

EOPEN

opEninterOperable Platform for unified access and analysis of Earth

observatioN data

H2020-776019

D4.3

Multimodal fusion for information retrieval

Dissemination level:	Public
Contractual date of delivery:	Month 31, 31/05/2020
Actual date of delivery:	Month 31, 29/05/2020
Workpackage:	WP4 Knowledge discovery and content extraction
Task:	T4.3 Similarity fusion from multiple sources for
	information retrieval
Туре:	Report
Approval Status:	Approved
Version:	1.0
Number of pages:	72

Filename:	D4.3-Multimodal fusion for information retrieval_2020- 29-05_v1.0.docx

Abstract

This deliverable reports on methods used for extracting content from EO and non-EO data and for finding similar EO and non-EO content. Specifically, it reports in depth the methodology and the research outputs for finding visually similar EO and non-EO data, and for retrieving data by combining multiple modalities found in each case. Finally, the deliverable contains a methodology for fusing Sentinel (EO data) and social data within the context of snow depth estimation.

The information in this document reflects only the author's views and the European Community is not liable for any use that may be made of the information contained therein. The information in this document is provided as is and no guarantee or warranty is given that the information is fit for any particular purpose. The user thereof uses the information at its sole risk and liability.



This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement 776019



History

Version	Date	Reason	Revised by	Approved By
0.1	02/4/2020	Initial Draft – ToC	Anastasia Moumtzidou (CERTH)	Stefanos Vrochidis (CERTH)
0.2	25/04/2020	Contributions (Section 4)	Damianos F. Mantsis (CERTH)	Ilias Gialampoukidis (CERTH)
0.5	19/05/2020	Contributions (Section 3)	Anastasia Moumtzidou (CERTH)	Stelios Andreadis (CERTH)
0.6	21/05/2020	Final Contributions (Section 2)	Ilias Gialampoukidis (CERTH) Stelios Andreadis (CERTH)	Stefanos Vrochidis (CERTH)
0.7	25/05/2020	Internal Review	Vasileios Sitokonstantinou (NOA)	Gabriella Scarpino (SERCO)
1.0	29/05/2020	Updated document after review for	Anastasia Moumtzidou (CERTH)	Stefanos Vrochidis (CERTH)
		submission	Stelios Andreadis (CERTH)	Ioannis Kompatsiaris (CERTH)
			Ilias Gialampoukidis (CERTH)	

Author list

Organization	Name	Contact Information
CERTH	Anastasia Moumtzidou	<u>moumtzid@iti.gr</u>
CERTH	Stelios Andreadis	andreadisst@iti.gr
CERTH	Ilias Gialampoukidis	heliasgj@iti.gr
CERTH	Damianos F. Mantsis	dmantsis@iti.gr
CERTH	Stefanos Vrochidis	<u>stefanos@iti.gr</u>



Executive Summary

This deliverable presents the similarity retrieval and multimodal fusion module that has been developed for handling both EO and non-EO data.

As far as the similarity of non-EO data is concerned, the methodology focuses mainly on data from social media platforms and specifically Twitter data. We start with an in-depth description of the modalities that can be found in Twitter data and provide examples of tweets for all EOPEN use cases. Then, the methods used for single modality search are presented along with state-of-the-art techniques for each case. In the sequel, a late fusion algorithm of multiple modalities is proposed, and the steps of the algorithm are described in detail. Finally, queries are realized for each EOPEN use case in the specific database collections by considering all single modalities, the fusion method and several state-of-the-art fusion techniques. Since the collection of tweets is very big and it is not possible to manually annotate the tweets as relevant or irrelevant, the methodology for evaluating the results is qualitative and is based on the visual inspection of the results for the different methods. The results show that the proposed method produces better results than single modalities and the majority of the existing fusion methods that it is compared against.

Regarding the similarity of EO data, the methodology and the analysis that is conducted focuses on data from satellite images and, specifically, Sentinel data. We begin with an analysis of the multi-label information retrieval task based on similarity that we are about to tackle. Some of the most recent works relative to the fusion of imagery's modalities are presented. Then, we describe the dataset used and the decisions we made to make it suitable for the task. We continue with the description of the modalities that can be found in satellite images, experimenting on both neural network approaches and classic remote sensing techniques. Thereinafter, a late fusion algorithm is used that combines the best performing methodologies of all the available modalities. Image patches are used as queries in order to retrieve the most relevant images from dataset by considering once all single modalities, then the fusion method and finally several other state-of-the-art fusion techniques. Extensive metrics per class for all the methodologies is presented, followed by qualitative analysis that is based on the visual inspection of the top fetched results for the different fusion methods. The quantitative and qualitative results show that the proposed method outperforms single-modality and fusion methods.

The fusion of Sentinel 1 and social media data has also been examined for the estimation of snow depth, where recent studies have shown that it can be estimated accurately on a global scale using satellite images through cross-polarisation and co-polarisation backscatter measurements. However, the existing methods have some limitations in lowland areas with dense forest coverage and shallow snow that is often found nearby urban areas. In these areas, citizen observations can be fused with satellite-based estimations to deliver more accurate solutions. To that end, we use snow-related tweets that have been annotated by artificial intelligence (AI) methods and are introduced in a novel regression model, aiming to increase the estimation accuracy of the state-of-the-art remote sensing method. The proposed model combines the estimated snow depth from Sentinel 1 images with the number of Twitter posts and Twitter images that are semantically relevant to snow. The use of social media data for purposes of snow depth estimation is investigated, validated and tested in Finland. Our results show that this approach does improve the snow depth



estimation, highlighting its potential for use in civil protection agencies in managing snow conditions, by fusing Sentinel 1 images and social data.



Abbreviations and Acronyms

ADC	Asymmetric Distance Computation
АР	Average Precision
ΑΡΙ	Application Programming Interface
BERT	Bidirectional Encoder Representation
BOW	Bag Of Words
BR	Backscatter Radiation
CBOW	Continuous Bag-of-Words
DCNN	Deep Convolutional Neural Network
СМС	Canadian Meteorological Centre
DNN	Deep Neural Network
CSN	Classification Similarity Networks
EO	Earth Observation
FC	Fully Connected
GeoJSON	Geographic JSON
JSON	JavaScript Object Notation
FoC	Forest Cover
mAP	Mean Average Precision
MSE	Mean Squared Error
NN	Neural Network
PUC	Pilot Use Case
NIR	Near-Infrared
SAR	Synthetic Aperture Radar
SC	Snow Cover
SD	Snow Depth
SQL	Structured Query Language
SWIR	Short-Wavelength Infrared
TF	Term Frequency model
TFIDF	Term Frequency Inversed Document Frequency
VSM	Vector Space Model



Table of Contents

1	INTRODUCTION	9
2	DATA FUSION FOR NON-EO CONTENT FOR INFORMATION RETRIEVAL	10
2.1 2. 2. 2. 2.	Methodology.1.1Similarity by textual content1.2Similarity using visual information1.3Similarity by time and geolocation metadata1.4Fusion of modalities	10 . 12 . 15 . 18 . 20
2.2	Results and Discussion	23
3	DATA FUSION FOR EO CONTENT FOR INFORMATION RETRIEVAL	26
3.1	Related work	26
3.2 3. 3. 3. 3. 3.	Methodology.2.1Similarity by visual content.2.2Similarity by time and geolocation metadata.2.3Similarity by visual concepts .2.4Fusion of modalities.	27 . 27 . 30 . 30 . 30
3.3 3. 3.	Results and Discussion 3.1 Quantitative analysis 3.2 Qualitative analysis	31 . 31 . 38
4	FUSION OF SENTINEL AND SOCIAL DATA FOR SNOW DEPTH ESTIMATION	42
4.1	Related work	43
4.2	Methodology	44
4.3	Results and discussion	47
5	CONCLUSIONS	53
6	REFERENCES	54
A	APPENDIX	57
A.1. A A A	Retrieval Results for Non-EO Content. 1.1 Flood Use Case 1.2 Food Use Case 1.3 Snow Use Case	57 . 57 . 61 . 66



A.2.	Information Retrieval in EOPEN and CANDELA	70)
------	--	----	---



1 INTRODUCTION

The amount of space-borne Earth observation data that is obtained increases day by day due to the multitude of sources orbiting around the globe. This advance of the satellite remote sensing technology produces the necessity of quick and precise generation of land cover maps that distinguish the characteristics of the underlying areas, providing beneficial information to global monitoring studies, resource management, and planning activities. To address this challenge, information retrieval undertakes to extract the attributes that characterize some satellite imagery in order to retrieve the most closely related images. Many characteristics can be used, varying from the visual content and the general concept that the areas depict, or even the location and the time of the data acquisition. Combining them together increase the possibilities to find areas with the same characteristics.

Within this context, EOPEN extracts knowledge from the collected EO and non-EO data in order to add value in data related to flood monitoring, food security and extreme weather conditions. This document presents the developed information retrieval techniques that consider either a single modality or fuse multiple modalities and which are applied both on EO and non-EO data. Furthermore, it presents a technique for combining EO with non-EO data for snow depth estimation.

In Section 2, we discuss the techniques for similarity retrieval for non-EO data, i.e. Twitter data. The techniques presented are single modality data retrieval techniques that differ per type of modality and a new multiple modalities data retrieval method that is basically a late fusion algorithm that considers the output of the single modalities. The results of the methods are discussed and compared against the ones of other well-known late fusion methods.

In Section 3, we analyse various similarity retrieval techniques focusing on EO data and more specifically on optical satellite imagery. The methodologies presented are single modality data retrieval techniques that differ per type of modality. A variety of both deep learning and classic remote sensing methods are explored. Eventually, a new multiple modalities data retrieval method is evaluated. The results of the method are compared against the ones of other well-known late fusion methods.

Section 4 focuses on using cross-polarisation and co-polarisation backscatter satellite measurements to estimate snow depth in Southern Finland. Due to the limitations of this method in lowland areas with dense forest coverage and shallow snow, we fuse the remote sensing data with citizen observations (snow-related Twitter posts which are annotated by deep learning methods) through a regression model, aiming to increase the estimation accuracy of the state-of-the-art remote sensing method.

Finally, Section 5 concludes the deliverable and discusses the main findings produced from each section.



2 DATA FUSION FOR NON-EO CONTENT FOR INFORMATION RETRIEVAL

The need to retrieve similar visual content from a set of observations in response to a query will be tackled in this task. Each item in the collection is equipped with several modalities (e.g. visual, textual, and spatiotemporal) that need to be fused in a scalable way, taking into account memory and computational complexity, in order to retrieve similar content. The output of this task is the EOPEN search engine, which will provide the top-k related EO products or social media posts, in response to multimodal query. Social media posts and EO imagery are associated and linked with metadata (tags, extracted concepts, text, time, location), but matching the similarities per modality for all modalities is not a scalable solution. The EOPEN fusion of similarities is based on the unsupervised fusion of similarities (Ah-Pine et al., 2015), which has been extended to multiple modalities (Gialampoukidis et al., 2016a), under the same memory complexity. This task will start with the development of an annotated dataset, for training purposes, in order to tune the parameters of the model in the context of the EOPEN use case scenarios. Tuning will be followed by an evaluation in the significance of each involved parameter and modality, and several directions towards the model simplification will be examined. The output of this task is a module, able to compare two multimodal objects, integrating all sources of information, effectively and quickly.

This section tackles the fusion and retrieval of multimodal non-EO content collected within EOPEN. As non-EO content, we consider data collected from social media platforms and in particular data from Twitter. While, the collection of data will be described in detail in EOPEN deliverable D3.3 "EOPEN Social Media Crawlers", this section focuses on the techniques applied for the efficient retrieval of such content in response to a query tweet. It should be noted that each tweet item is equipped with several modalities, including visual, textual, and spatiotemporal. The aim of this task is to consider all the aforementioned modalities, fuse them in a scalable way, taking into account memory and computational complexity, in order to retrieve similar content in real-time (i.e. 1-10 seconds maximum retrieval time) using AI.

2.1 Methodology

This section provides a detailed description of the approach followed for retrieving similar tweets. In order to make clear the reasons that led to the selection of the proposed approach, it is necessary to describe adequately the information linked to each tweet. Thus, each tweet contains the following information:

- A short text no longer that 140 characters that may contain non-standard terms, misspellings, "emojis", slang and abbreviations
- Possibly an image that is usually semantically related to the text
- The date and the time of the tweet publication

Figure 1 depicts examples of 3 tweets, one for each EOPEN Use Case, i.e. Floods, Food and Snow. The languages of the tweets are Italian for the Flood use case and Finnish for the Snow use cases, according to the country each Pilot focuses on. However, for the Food Security Use Case, the English language is opted instead of Korean because analysing ideograms is beyond the scope of the project.





Figure 1: Examples of 3 tweets, one for each EOPEN Use Case, i.e. flood monitoring, food security and snow observations.

Therefore, the retrieval of similar social media posts revolves around this information and any other information extracted by it after applying processing and analysis techniques.

Once a Twitter post is given as a query, several modalities are involved such as textual, visual, spatial and temporal information. Starting from the text information, textual representation of the tweet can be applied that will allow retrieval of similar text. Furthermore, after applying named entity recognition technique in the tweet text, locations and organization mentioned to the tweet can be identified which can be linked to a specific geo location and eventually allow the retrieval of geographically close tweets. As far as the image information is concerned, images can be described both with low level features and high-level visual concepts, thus allowing the retrieval of visually similar images to the image of the query and retrieval of images described with similar visual concepts respectively. Finally, temporal information can be used for retrieved tweets that are close in terms of date and timestamp.

Figure 2 depicts all the metadata that are produced after applying the techniques mentioned in the following section in order to describe a tweet, i.e. vector of visual concepts, text, time, location and visual similarity.







Given the heterogeneity of the metadata produced that describe a tweet from different perspectives, a late fusion approach was considered as a sole solution.

In the following, the methods for obtaining the metadata from the tweet and the fusion methods used are described in detail.

2.1.1 Similarity by textual content

Text similarity between two or more texts is the procedure of computing the similarity in meanings between them. There are several approaches that can be used for text similarity that involve as a first step, text representation, then as a second the distance function to calculate the distance among different texts. Finally, the distance measures of the texts are ranked from lowest to higher and the ranked set of documents is the output of the similarity by textual context module. In the following we describe some text representation techniques and distance functions used.

As far as text representation (Yan, 2009), is concerned the most commonly used text representation model is Vector Space Model (VSM) where documents are represented by vectors of words and a typical VSM is the Bag of Words (BOW) which uses all words of a given document set *D* as the index of the document vectors. Several term weighting schemas exist under the BOW model, including the Boolean model which involves the binary representation of documents, the Term Frequency model (TF) that uses the frequency of the terms, and the Term Frequency Inversed Document Frequency (TFIDF) model that considers

real values that capture the term distribution among documents to weight terms in each document vector. A more recent approach that generally outperforms the other methods in many cases, is word2vec (Mikolov, et al. 2013). word2Vec algorithm is a model that produces word embeddings (i.e. representation of words from a given vocabulary as vectors in a low-dimensional space) and builds distributed semantic representation of words, based on deep neural networks (NN), which are either the Continuous Bag-of-Words model (CBOW) or the Skip-gram. Both models are trained on large corpus, taking into consideration the neighbouring words in a sentence. The difference between these two architectures is that while in the CBOW the NN model tries to predict a word given the context of this word, in the Skip-gram given a word the NN model tries to predict the context of a word. The same idea of word2vec can be extended to sentences and documents where instead of learning feature representations for words, what the model learns is sentences (SentenceToVec) or documents (Doc2Vec) and that can be considered as a mathematical average of the word vector representations of all the words in the sentence. Another approach similar to word2vec is GloVe (Pennington, et al. 2014) which is an unsupervised learning algorithm for obtaining vector representations for words and thus no model is required. In GloVe, training is performed on aggregated global word-word co-occurrence statistics from a corpus. Finally, another more recent approach is the Bidirectional Encoder Representation from Transformers (BERT) algorithm (Devlin, et al. 2018). BERT is a non-directional or bidirectional model that involves an attention mechanism that learns contextual relations between words in a text and reads the entire sequence of words at once.

In order to calculate the similarity between two sequences of strings there are a number of string similarity measures. Some of the most popular term-based distance measures are the Manhattan distance, the cosine similarity, the Dice's coefficient, the Euclidean distance, the Jaccard Similarity, the Overlap coefficient and the Matching coefficient (Vijaymeena, 2016).

Apart from the aforementioned methods, there are some off-the-shelf text search engines with most prominent one, the Apache Lucene. Apache Lucene¹ is a full-text search engine which can be used from various programming languages and can be used for any application that that requires full text indexing and searching capability. Lucene is recognized for its utility in the implementation of Internet search engines and local, single-site searching. A list of the companies that use Lucene for their product or website can be is maintained by the Lucene team and it can be found <u>here</u>. Among the biggest deployments are Twitter that uses Lucene to power its real-time search over tweets, which is over a billion queries a day, LinkedIn which has also modified and enhanced Lucene for real-time search and faceted search, Hi5 and Comcast.

Lucene is able to achieve fast search responses because, instead of searching the text directly, it searches an index instead, which can be considered equivalent to a glossary at the end of any book. This type of index is called an inverted index, because it inverts a page-centric data structure (page->words) to a keyword-centric data structure (word->pages).

Indices consist of one or more documents, and search results are sets of best-matching documents. A document is a collection of fields, and each field has a value associated with it.

¹ <u>https://lucene.apache.org/</u>



This value is typically text which is converted into smaller and precise units during an analysis step in order to allow easy search. Specifically, the text goes through various operations which include extracting keywords, removing common words and punctuations, changing words to lower case, etc. For this purpose, there are multiple built-in analyzers:

- **StandardAnalyzer**: analyses based on basic grammar, removes stop words like "a", "an", lowercases the token and in general is the most sophisticated analyser
- **SimpleAnalyzer**: breaks the text based on no-letter character and converts in lowercase
- WhiteSpaceAnalyzer: breaks the text based on white spaces

It should be noted that there are Analyzers used that are dependent on language.

Finally, once an index is built, it is possible to search the created index using a Query and an IndexSearcher. The search result is typically a result set, containing the retrieved data. Finally, Lucene provides a very dynamic and easy to write query syntax that allows the user to specify which field(s) to search on, which fields to give more weight to (boosting) and also the ability to perform Boolean queries.

After this brief overview of the available solutions for text similarity, we opted for Apache Lucene within the context of EOPEN. The reason is that although the aforementioned techniques (e.g. BERT) may be more efficient in terms of quality of results, Apache Lucene allows very fast indexing and retrieval, which is of critical importance in the case in EOPEN where tweets are retrieved every second and thus the size of the collection is expanding extremely fast. In the Big Data context of EOPEN, it is necessary to have an index that can be updated very fast and also that allows fast and efficient retrieval over more than 10,000,000 tweets. Under the light of this requirements set by the EOPEN and after checking carefully all the possible solutions we concluded that Apache Lucene is more fitted. Furthermore, we should note that EOPEN we have three different languages, i.e. Italian, Finnish and Korean for each use case and English for easy and widespread demonstration of the platform. Thus, we considered the following language-specific analysers in order to handle efficiently the three aforementioned languages:

- org.apache.lucene.analysis.en.EnglishAnalyzer
- org.apache.lucene.analysis.fi.FinnishAnalyzer
- org.apache.lucene.analysis.it.ItalianAnalyzer
- org.apache.lucene.analysis.ko.KoreanAnalyzer

Finally, we should note that different Indexes were created for each pilot case and each language, that are updated whenever a new tweet is available, resulting in the six following Indexes:

- ItalianFloods
- EnglishFloods
- KoreanFood
- EnglishFood
- FinnishSnow
- EnglishSnow



2.1.2 Similarity using visual information

As far as similarity by visual information is concerned, it involves similarity by visual content and similarity by visual concepts. The framework used in both cases, i.e. a deep neural network, is the same, but the vectors used are taken from different layers of the network. Regarding the description of State-of-the-Art techniques, they were already provided in EOPEN deliverable D4.1 deliverable, entitled "Change detection techniques in Earth Observation", in Section 3.1.1 ("State of the art in Concept Detection") and in Section 4.1 ("State of the art in Similarity Fusion").

In the following, we will briefly describe the deep neural network used, as it was also described in D4.1. A 22-layer GoogleNet network (Szegedy, 2015) was trained on 5055 ImageNet concepts (Pittaras, et al. 2017), which are a subset of the ImageNet "fall" 2011 dataset² that was trained originally on 32,326 concepts. The subset of the 5055 concepts was produced by merging very similar concepts, removing concepts corresponding to scientific terms, and concepts with a very few number of positive images. Therefore, the dimension of classification layer of the trained network, which is a fully connected layer, equals to 5055. Following the GoogleNet architecture, Pittaras (2017) added after the classification layer a *softmax* function. The number of concepts identified was reduced even more in order to target the TRECVID Semantic Indexing SIN 2013 task³, and thus the authors ended up with 345 SIN TRECVID concepts⁴. In order to train these new concepts, fine-tuning was performed and after evaluating different fine-tuning methods, the one that performed the best involved replacing the classification layer with dimensionality 5055 with a classification layer with dimension equal to 345. It should be noted that GoogleNet has by default three classification layers. Thus, in order to keep the GoogleNet architecture, the authors considered three classification layers with dimension equal to 345. Finally, based on research realized on fine-tuning (Pittaras, 2017), an extra fully connected layer was added right before the classification layers, as it seems to boost its performance. Figure 3 depicts the original GoogleNet architecture and the described fine-tuned GoogleNet.

²<u>http://academictorrents.com/details/564a77c1e1119da199ff32622a1609431b9f1c47</u>

³<u>https://www-nlpir.nist.gov/projects/tv2013/index.html</u>

⁴<u>http://www-nlpir.nist.gov/projects/tv2012/tv11.sin.500.concepts_ann_v2.xls</u>



Figure 3: Original GoogleNet architecture and fine-tuned GoogleNet (layers in red have been added or replaced layers existing in the original GoogleNet).

Similarity by visual content

Regarding the visual features, they are DCNN-based descriptors and they are the output of the last pooling layer of the fine-tuned GoogleNet architecture (Pittaras, 2017) previously described. The dimension of the last pooling layer is 1024 and it is used as global image representation. The selection of a DCNN-based feature was based on the outcome of several studies that revealed the superiority of such features versus hand-crafted features both in terms of accuracy and time. Furthermore, as far as the selection of the last pooling layer for representing the image is concerned, it was evaluated both in terms of time and quality of results within the VERGE system (Moumtzidou, et al. 2018) that has participated in the Video Browser Showdown⁵ in 2018. The dataset, it was evaluated on, was the IACC.3 dataset⁶ that was used on the TRECVID 2018 AVS Task⁷ and which consists approximately of 4600 Internet Archive videos (144 GB, 600 h) with Creative Commons licenses with duration ranging from 6.5 min to 9.5 min and a mean duration of almost 7.8 min.



Figure 4 shows the layer of the GoogleNet architecture that is used as DCNN-feature.

Figure 4: Extraction of DCNN-based feature from the fine-tuned GoogleNet.

In order to retrieve visually similar images fast and efficient, we followed the Nearest Neighbour search which is the best performing approach between the query and database vectors described in (Jegou, et al. 2010; Jegou, et al. 2011) is applied. This approach involves initially, the construction of an inverted file and then combining it with Asymmetric Distance

⁵ htt<u>ps://videobrowsershowdown.org/</u>

⁶ https://www-nlpir.nist.gov/projects/tv2018/data/#IACC.3

⁷ https://www-nlpir.nist.gov/projects/tv2018/Tasks/ad-hoc/



Computation (ADC). Even though the existence of such an index, that is produced from the feature vector of the images and a unique identifier per image (i.e. tweet Id) speeds up significantly the querying time, the loading of the index to the RAM requires significant time, which might rise up to several minutes in large databases (i.e. number of records greater than 500,000) which is the case for several of the databases in EOPEN. Therefore, in order to eliminate the time required for the index loading, a simple REST web service is created that loads permanently this indexing structure in RAM, and also allows querying the index. By using this procedure, instant querying of the structure and eventually fast results retrieval is achieved each time a visual query is realized.

Finally, it should be noted that the indexing structure is updated on a daily basis since it is not time-efficient to update the index every time a new image is available. This is due to the fact that the time needed for reloading the index in the memory takes us to 5 minutes.

Similarity by visual concepts

Regarding the visual concepts, they are the output of the fine-tuned GoogleNet architecture (Pittaras, 2017) previously described. Thus, we have available the probabilities of 345 concepts. These probabilities are concatenated to a single vector with length 345, which is used for capturing the concepts found in each image.

Figure 3 shows the layer of the GoogleNet architecture that is used as concept vector. Similarly in Figure 4, the neural network layer that is used to extract the visual feature vector is presented. In order to retrieve visually similar images in a fast and efficient way, we followed the same indexing Nearest Neighbour search in both visual feature and visual concept search. Thus, an indexing is created that uses the concept vectors and a unique identifier per image (i.e. tweet Id) and then a simple REST service is created that loads the index to the RAM and also accepts requests.

Following the same pattern as before, the indexing structure is updated on a daily basis since it is not time-efficient to update the index every time a new image is available. This is due to the fact that the time needed for reloading the index in the memory takes about to 5 minutes (per day).

Figure 5 depicts the procedure described, starting from the generation of the feature vector or the concept vector, the query to the index and finally the retrieval of the results.



Figure 5: Visual Information Generation and retrieval procedure.



2.1.3 Similarity by time and geolocation metadata

Temporal information

The similarity considering time and geolocation information is tackled in a different manner compared to the other information. At this point, it should be noted that all the information that is related to the tweets and is either directly taken from the Twitter or is produced after analysing them is stored to a non-SQL database, and specifically MongoDB⁸. The exact information that is stored per tweet will be described in the upcoming deliverable D3.3 ("EOPEN Social Media Crawlers"). However, we should note that for each tweet, apart from the text, that was described in Section 2.1.1, the time of the publication is provided as well. This information is kept also in timestamp format thus allowing easy sorting using MongoDB.

Below there is an example of a date/time converted to a timestamp in millisecond.

05/05/2020018:06:56 ⇒ 1588691216000

Thus, by considering the timestamp of every tweet, we used the absolute value of the difference between the timestamp of the tweet query and the timestamp of each tweet in the database to sort the tweets. Then, we sorted these values in increasing order and kept the *N* smaller values which stand for the tweets that are closer to the tweet query in terms of its timestamp.

Spatial information

Similar to the time information, the spatial (geolocation) information is stored in the MongoDB is well. However, Twitter does not provide geographical information for the majority of tweets, because the twitter users do not enable location information as part of their Twitter post. To that end, moreover, the meaningful location that needs to be analysed is the location entity that appears in the text and not the place in which the tweet is posted on Twitter. The spatial information from Twitter content is produced as part of analysis realized on the Twitter's text.

Specifically, a named entity recognition (NER) method is employed in order to locate organization and location entities found in user tweets, which are then pinpointed to a map via the OpenStreetMap API. Currently, the deep neural networks-based approach exploits a bidirectional LSTM-CRF model (see D5.1 "The EOPEN ontology and semantic reasoning support", section 7.1) which will be updated with ELMO-based embeddings in the upcoming deliverable D5.2 ("Semantic reasoning for decision making"). Then, this information is stored as a geospatial data, and specifically a GeoJSON Point, using GeoJSON objects to the MongoDB.

The GeoJSON, as defined within MongoDB, has the following structure:

- a field named type that specifies the GeoJSON object type and
- a field named coordinates that specifies the object's coordinates
- latitude and longitude coordinates, which includes listing first the longitude and then the latitude. The types of GeoJSON objects that are supported from MongoDB are: Points, LineStrings, Polygons, MultiPoints, MultiLineStrings, MultiPolygons

⁸ https://www.mongodb.com/



<field>: { type: <GeoJSON type> , coordinates: <coordinates> }

Figure 6 depicts an example of the localisation procedure involving all the aforementioned steps.

	I	PUC: Flood	Language: English	/ Tweet i	d: 111154571	.0288216065
Initial Text	Major river snow melt a latest river f	flooding wil and addition flood foreca	l continue across par al rainfall will lead to sts visit: https://t.co	rts of the M o rising riv /YcNxqcIZ	Mississippi Riv ers in some loo PK https://t.co	er Basin. The combination of cations this week. For the /waZmInLJfk
				Named En	itity Recogniti	on (Location and Organisation)
			Mississip	oi		
			+	Open Str	eet Map	
			Full name: Mississ	ippi, USA		
			Latitude: 32.97	15645		
			Longitude: -89.73	348497		
			-	MongoDB	l GeoJSON obj	ect
		"estimate	d_locations" : [
		{ "loc "ge " " } }]	cation_in_text" : "Mi cation_fullname" : "M ometry" : { type" : "Point", coordinates" : [-89.7	ssissippi", √lississipp '348497, 3	, i, USA", 32.9715645]	

Figure 6: Overview of geolocation information extraction.

In order to obtain the tweets that are close in terms of geolocation, a built-in function of MongoDB is used that considers the information stored in the GeoJSON objects. Specifically, we consider $\$geoNear^9$ that returns documents in order of nearest to farthest from a specified point. Some important parameters that should be considered: a) the distanceField option should be used, and b) a geospatial index must exist.

Figure 7 depicts an example of the query send to MongoDB in order to retrieve the documents that are closer in terms of geolocation:

⁹ <u>https://docs.mongodb.com/manual/reference/operator/aggregation/geoNear/</u>



```
collection.aggregate([
    {
        '$geoNear': {
            'near': {
              'type': "Point",
              'coordinates': [
                 long,
                lat
            ]
        },
        'distanceField': "dist.calculated",
        'spherical': True
        }
    }
])
```

Figure 7: Example of *\$geoNear* MongoDB query

2.1.4 Fusion of modalities

This section describes the framework used for fusing the aforementioned information, textual, visual features, visual concepts, time and geolocation. An overview of the state of arts for similarity fusion was provided in EOPEN deliverable D4.1 "Change detection techniques in Earth Observation" in section 4.1 - State of the art in Similarity Fusion.

Due to the heterogeneity of the information/modalities used for describing a tweet, a late fusion approach was opted. In the following we describe in detail the proposed algorithm.

Algorithm and Notation

The algorithm proposed can be applied for fusing the output of *K* modalities, where $K \ge 2$. For each modality, we have *N* retrieved results and thus we have *K* such lists. We set as \underline{L} the *K*-order tensor of the retrieved lists, L_{θ} , $1 \le \theta \le K$. A single element \underline{L} of \underline{L} is addressed by providing its exact position through a series of indices $r_1, r_2, ..., r_K$ i.e.:

- $\underline{l}_{r_1,r_2,\dots,r_K} \equiv \underline{L}_{r_1,r_2,\dots,r_K}; 1 \le r_{\theta} \le N$
- $\underline{l}_{r_1,r_2,...,r_K} = 1$ if the same element w_n , $1 \le n \le N$ (e.g. Twitter ID) has rank r_1 in list L_1 , rank r_2 in list L_2 , ..., and rank r_K in list L_K .

The aim of the algorithm is to find the final list L^f of retrieved results. Thus, the first step of the algorithm is to compute tensor \underline{L} and the second is the computation of the final list L^f .

Algorithm 1: Compute tensor <u>L</u>

```
Input: L_{\theta}, 1 \le \theta \le K
for each element w_n, 1 \le n \le N
if rank(w_n) = \{r_1 \in L_1\} \land \{r_2 \in L_2\} \land \dots \land \{r_K \in L_K\}:
\underline{l}_{r_1, r_2, \dots, r_K} = 1
else:
\underline{l}_{r_1, r_2, \dots, r_K} = 0
Output: \underline{L}
```





Algorithm 2: Get the final list L^f

Input: <u>L</u>
j = 1
while $j \leq N$
$L^f = \emptyset$
$\text{if } \left\ \underline{L}_{r_1 \leq j, r_2 \leq j, \dots, r_K \leq j}\right\ _2 > 0$
which w_n s.t. $\underline{l}_{r_1 \leq j, r_2 \leq j,, r_K \leq j} = 1$ ($1 \leq n \leq N$)
$L^f = L^f \cup \{w_n\}$
else:
$L^f = L^f$
j = j + 1
Output: L ^f

Example of the Algorithm

In order to understand better how this algorithm, an example is provided. Thus, we consider that we have K = 4 modalities, i.e. text, time, location, and visual features, and that the number of retrieved results per modality is N = 5. Figure 8 depicts the lists with the retrieved results per modality.



Figure 8: Lists with the retrieved results per modality

Based on the list of retrieved results, we fill in the surfaces of the \underline{L} tensor as shown in Figure 9.



'4'		me				Text	/ Loo	atio	n			Text	/Vis	ual F	eatu	ires	
'4'	7	'8'	'5'	'1'	'2'		'5'	'4'	'10'	'7'	'8'		'2'	'6'	'7'	'4'	Γ
	0	0	0	0	0	'4'	0	1	0	0	0	'4'	0	0	0	1	t
'9'	0	0	0	0	0	'9'	0	0	0	0	0	'9'	0	0	0	0	t
'2'	0	0	0	0	1	'2'	0	0	0	0	0	'2'	1	0	0	0	t
'10'	0	0	0	0	0	'10'	0	0	1	0	0	'10'	0	0	0	0	t
'3'	0	0	0	0	0	'3'	0	0	0	0	0	'3'	0	0	0	0	t
ime/	Loca	tio	n			Time	e/ Vi	sual	Feat	ures							
4	5′ ′4	, '	10′	'7'	'8'		'2'	'6'	'7'	'4'	'3'						
'7' 0) 0	(D	1	0	'7'	0	0	1	0	0						
'8' 0	0	(D	0	1	'8'	0	0	0	0	0						
'5' 1	. 0	(D	0	0	'5'	0	0	0	0	0						
'1' 0) 0	0	D	0	0	'1'	0	0	0	0	0						
'2' 0) 0	0)	0	0	'2'	1	0	0	0	0						

Figure 9: Example of surfaces of \underline{L} tensor (result of 1^{st} Algorithm)

Finally, **Error! Reference source not found.** depicts the implementation of the 2^{nd} algorithm, which involves five steps till the final result. Specifically the first step is the bi-modal fusion of the retrieved results, the second is the bi-modal ranking of the retrieved results, the third involves the merging of the rankings, the fourth the duplicate removal and finally the fifth includes getting the final list L^{f} .



Figure 10: Steps of ranking procedure described in 2nd Algorithm.



2.2 **Results and Discussion**

This section presents the results retrieved from each single modality, and from the fusion of the modalities using the approach described in Section 2.1.4 and some well-known State-of-the-Art fusion methods. Specifically, the late fusion against which we will evaluate the proposed method are the seminal work of Borda fusion (Borda, 1784), Condorcet fusion (Montague and Aslam, 2002) and Reciprocal rank fusion (Cormack, et al. 2009). It should be noted that in order to evaluate the results of the different methods, we consider a qualitative method for the non-EO data, since it is not feasible to annotate the collected tweets collected. This involves the visual inspection of results and commenting on them. Regarding the quantitative results, we check and manually annotate, by considering the text of the tweet, whether a tweet is relevant or not to floods, food or snow, on the *top-N* retrieved results for each retrieval method and calculate the average precision for each query and mean average precision for 3 queries for each method. Specifically, for each different retrieval method, we will evaluate the *top-10* retrieved results.

As already mentioned, the tweets gathered are in 4 languages, i.e. Italian, Finnish, Korean and English and they cover different use cases (i.e. flood, food, snow). Thus, as defined in the Grant Agreement, the flood use case refers to the area of Italy, the snow case to the area of Finland and the food case to the area of Korea. However, as already mentioned analysing ideograms is a difficult task and beyond the scope of the project, we will consider English tweets for the case of food. Therefore, we will evaluate the results from the following queries:

- 1 query tweet in Italian language that is related to flood use case (Figure 11)
- 1 query tweet in Finnish language that is related to snow use case (Figure 12)
- 1 query tweet in English language that is related to food use case (Figure 13)



Figure 11: Query tweet in Italian language that is related to flood use case.



Figure 12: Query tweet in Finnish language that is related to snow use case.





Figure 13: Query tweet in English language that is related to food use case.

Table 1 contains the average precision scores for the different similarity methods for each query and the mean average precision (mAP) for each method. Moreover, in Appendix A.1, there are screenshots of the *top-10* tweets retrieved for all methods and for the 3 query tweets. In general, we can draw the following conclusions:

- The text modality has the lowest score when not fused with additional information. However, it is the only modality together with temporal, that exists in each tweet.
- The fact that time modality has better mAP compared to text is due to the fact that we retrieve the top-10 results only and thus it is more probable that tweets that are near in terms of time and have similar keywords to be related. However, it is expected that if we retrieve more results, this score (mAP) will fall.
- Visual features have very good mAP since it searches for visually similar results and isn't based on models (such as Visual Concepts) whose performance depends highly on how good the training set is.
- From the fusion techniques the ones that perform the best are the proposed EOPEN algorithm and the Borda fusion algorithm. However, the irrelevant retrieved results are ranked higher in Borda fusion algorithm, a fact which also affects the performance of a search engine. Qualitative analysis (Appendix A) with visual inspection on more than the top-10 retrieved results show superiority of our proposed method, when compared to single and multiple modality fusion methods.

		Ave	Average Precision@10						
		Flood (IT)	Food (EN)	Snow (FI)	Precision				
Single	Text	1.0	1.0	0.586	0.862				
retrieval	Time	0.839	0.867	1.0	0.902				
	Visual Features	0.878	1.0	1.0	0.959				
	Visual Concepts	0.638	1.0	1.0	0.879				
Multiple	EOPEN	0.906	1.0	1.0	0.969				
retrieval	Borda	0.906	1.0	1.0	0.969				
	Reciprocal	1.0	0.649	1.0	0.883				

Table 1: Average precision and mean Average Precision



Condorcet	1.0	0.947	0.947	0.965



3 DATA FUSION FOR EO CONTENT FOR INFORMATION RETRIEVAL

This section tackles the fusion and retrieval of multimodal EO content collected within EOPEN. As EO content, we consider the satellite products from the Copernicus Sentinel-2 mission that are annotated with multiple classes of the Corine Land Cover map. This section focuses on presenting the techniques that allow efficient retrieval of such content in response to a Sentinel-2 query. Each Sentinel-2 image is equipped with several modalities, including visual information (i.e. the RGB and other channels), and spatiotemporal information (i.e. the sentinel metadata that refer to the area that is depicted using geographical coordinates and timestamp that the image is taken) and the aim of this task is to consider all the aforementioned modalities, fuse them end eventually return similar content.

3.1 Related work

In remote sensing image retrieval task both traditionally extracted features and Convolutional Neural Networks have been investigated with the latter ones presenting performance advantage.

Specifically, CNN models that aim for both classification prediction and similarity estimation, called classification-similarity networks (CSNs), outputs class probability predictions and similarity scores at the same time (Liu et al., 2020). In order to further enhance performance, the authors combined information from two CSNs. "Double fusion" is used to indicate "feature fusion + score fusion".

Moreover, Liu et al. (2017) proposed a feature-level fusion method for adaptively combining the information from lower layers and FC layers, in which the fusion coefficients are automatically learned from data, and not designed beforehand. The fusion is performed via a linear combination of feature vectors instead of feature concatenation.

Another work is that of Wang et al. (2016), who performed multiple SAR-oriented visual features extraction and estimated the initial relevance scores. For the feature extraction, they constructed two bag-of-visual-words (BOVWs) features for the SAR images and another SAR-oriented feature, the local gradient ratio pattern histogram. The authors calculated a set of initial relevance scores and constructed the modal-image matrix, then they estimated the fusion similarity and eventually reranked the results returned based on this similarity.

Finally, Li et al. (2016) used multiple type of features to represent high-resolution remote sensing images. One fully connected graph and one corresponding locally connected graph were constructed for each type of feature. Furthermore, a fused graph was produced by implementing a cross-diffusion operation on all of the constructed graphs. Then, from the fused graph, the authors obtained an affinity value between two nodes that directly reflects the affinity between two corresponding images. Eventually, in order to retrieve the similar images retrieval, the affinity values between the query image and the other images in the image dataset are calculated.



3.2 Methodology

For the retrieval of most relative content in EO data content, three different modalities where combined, each one representing a different aspect of the images of the dataset. Similarity by 'visual content', 'visual concepts' and 'geolocation and time' are explored. Eventually they are fused to all together to extract a more precise discrimination among the classes of the dataset. Each modality returns a ranked similarity list. Performing late fusion on the formed lists returns the final sorted list with the closest images to the given query-image.

Supervised methods applied for the training of a custom and some well-known pretrained deep neural networks using Keras library. A more classic approach to extract features based on colour histogram of various bands of an image was also tested. The MongoDB is holding the images metadata allowing the execution of geolocation and time queries.

3.2.1 Similarity by visual content

The aim of this module is to generate a model that transforms images into embedding vectors where the Euclidean distance between vectors represents how visually similar the images are as it regards to the content. To extract the necessary features from satellite patches two different approaches were evaluated. The first involved deep neural networks more specifically three pre-trained ImageNet DCNNs and a custom DNN. The second involved a more classical method that relies on feature extraction.

We selected 10 test images for each of the seven classes parsed from the Corine Land Cover inventory, and thus we ended up with 70 test image patches. Adetailed description of the dataset and the classes selected can be found in Section 3.3.1 The procedure followed for obtaining the similarity according to the visual content involves the following steps: a) we extract feature vectors for each patch of the dataset, including the test images, b) we calculate the distance between the query image and the rest images of the dataset, c)we retrieve the imageswith the lowest distance from the query-test patch, and d) we calculate the mAP for the top 30 results. The full procedure is described in detail below.

For the feature extraction, we used layers closer to the top layers. Tested both with some well-known pre-trained networks and on a custom deep neural network:

- A) Deep neural networks:
 - Pretrained networks: Extracting features directly from specific intermediate layers of pretrained VGG19, ResNet-50 and Inception-ResNet-v2 networks. Three channel images were used as input. Since ImageNet is a dataset of RGB images we created an input dataset of same type of images. Red (band 4), Green (band 3) and Blue (band 2) Sentinel-2 bands are combined to form 3-channeled patches.
 - **Custom Deep Neural Network**: Trained a DNN network (see layers below) with a structure that resembles VGG. It contains blocks of convolutional layers with 3x3 filters followed by a max pooling layer. This pattern is repeating with a doubling in the number of filters with each block added. The model will produce a 7-element vector with a prediction between 0 and 1 for each output class. Since it is a multi-label problem, the sigmoid activation function was used in the output layer with the binary cross entropy loss function. For input we tested with both 3 channel images (as done with the pretrained networks) and also with images that consisted of 5



bands of Sentinel 2 images, i.e. the Red (band 4), Green (band 3), Blue (band 2) for the 3-channel input, with the addition of NIR (band 8) and SWIR (band 11) for the 5-channel input. After the training we extracted features of the 5-channel patches from some intermediate layers.

In Table 2 the summary of the used DNN is depicted. For each layer the output shape and the number of the trained parameters can be observed.

Layer type	Output Shape	Parameters #		
Conv2D	(None, 120, 120, 30)	1380		
Conv2D	(None, 120, 120, 30)	8130		
MaxPooling2D	(None, 60, 60, 30)	0		
Dropout	(None, 60, 60, 30)	0		
Conv2D	(None, 60, 60, 60)	16260		
Conv2D	(None, 60, 60, 60)	32460		
MaxPooling2	(None, 30, 30, 60)	0		
Dropout	(None, 30, 30, 60)	0		
Conv2D	(None, 30, 30, 120)	64920		
Conv2D	(None, 30, 30, 120)	129720		
MaxPooling2	(None, 15, 15, 120)	0		
Dropout	(None, 15, 15, 120)	0		
Flatten	(None <i>,</i> 27000)	0		
Dense	(None, 120)	3240120		
Dropout	(None, 120)	0		
Dense	(None <i>,</i> 7)	847		

Table 2: Layers summary of the Deep Neural Network

B) **Color histogram**: The histograms of a stack of bands were concatenated in a single vector. The same dataset of 3-channel and 5-channel images is used in here as well.

Three well known DCNNs were used for the feature extraction. For all of them we loaded a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as everyday objects and animals. As a result, the network has learned rich feature representations for a wide range of images.

VGG-19

VGG-19 is a convolutional neural network that is 19 layers deep. The network has an image input size of 224-by-224. Features extracted from fc1 (dense) and fc2 (dense) layers, with



feature size of 1 x 4096 float numbers per patch. The architecture of VGG19 is depicted in Figure 14.



Figure 14: VGG19 architecture

ResNet-50

ResNet-50 is a convolutional neural network that is 50 layers deep. The network has an image input size of 224-by-224. Features extracted from avg_pool (GlobalAveragingPooling2) layer, with feature size of 1 x 2048 float numbers per patch.

Inception-ResNet-v2

Inception-ResNet-v2 is a convolutional neural network that is 164 layers deep and is formulated based on a combination of the Inception structure and the Residual connection. The network has an image input size of 299-by-299. Features extracted from avg_pool (GlobalAveragingPooling2) layer, with feature size of 1 x 1536 float numbers per patch.

Deep neural network

For the visual similarity we need information of the "inside" layers of the NNs. For each network we extracted features from one or more intermediate lower level layers of the model in order to get the vectors that best describe each image just before the final prediction layer.

To obtain the best possible results we evaluated with did hyper parameter optimization and enabled dropout regulation. We used the models with the best validation scores at a 5-Fold Cross-Validation, achieved with following settings (Table 3):

Input	Optimizer	Learning	Batch	Epochs	F-Beta	F1 Score	Loss
Channels		Rate	Size		Score		
3ch	Adam	0.001	128	200	0.843	0.843	0.232
5ch	Adam	0.0005	256	200	0.864	0.861	0.214

Table 3: Best scores and settings for 3ch and 5ch input of the DNN

Colour Histogram



Apart from the DCNN-based features, we have investigated colour Histogram that was used in Candela Project¹⁰. In A.2 Appendix, there is a detailed table, which summarizes the aspects of the Similarity retrieval module in the EOPEN and Candela EU projects and thus makes clear the similarities and differences of the approaches proposed. In Candela project, raw Sentinel-2 band values were concatenated to form a long feature vector for each image query and normalisation was not applied. Thus, given that the data type of the initial bands is Uint16 meaning, the values may vary from 0-65,535. However, for the selected dataset the maximum value detected for any of the tiff files was below 21,000. These values were considered as the sub-vector length in order to reduce the concatenated vectors size, while at the same time preserving all the initial information. Thus, vector size for each query-image now is 1 x 63,000 for the 3 bands vectors (B04, B03, B02 Sentinel-2 bands) and 1 x 105,000 for the 5 bands vectors (B04, B03, B02, B08, B11 Sentinel-2 bands).

As a similarity measure the Euclidian Distance was used. For each query-image, its feature vector was generated and then the distance from all the feature vectors of the dataset was calculated. The *top-k* results with the less distance were kept.

3.2.2 Similarity by time and geolocation metadata

It is important to be able to find images that are timely and locally close to the query-image. For a quick retrieve of close images to the query we have used MongoDB queries. We have extracted all patches' datetime and geolocation metadata and inserted them in a MongoDB collection in the form of IsoDate and GeoJson respectively. Mongo allows quick indexing of the above data types. The Euclidean distance of the geolocations was used and then for images with the same distance, sorting by datetime was applied.

3.2.3 Similarity by visual concepts

In this module the concepts of an image are extracted. The methodology uses the deep neural networks of the Visual Content analysis module. This time we are using the last layer of each network that is responsible for predicting the class of the query-image and extract them as a vector. The Euclidean distance between vectors represents how visually similar the images are as it regards to the concept.

3.2.4 **Fusion of modalities**

In order to provide more consistent and accurate results on the retrieval task we combined the best performing methodology of Section 2.1.4 the previous sections, i.e. the similarity of visual content, visual concept and similarity by geolocation and time. For the fusion of the results we tested our algorithm against 3 know rank fusion algorithms; Borda count, Reciprocal and Condorcet fusion. For the extraction modality we used the VGG19 features, for the concept extraction the 5-channel custom DNN network's predictions. In our approach, that was described in detail in Section 2.1.4 , the fusion model was fed with the top 280 results of each of the previous modalities, due to limitations of MongoDB at the aggregation of the minimum distance of the geolocation query. For the evaluation of the various fusion methods we used the mean Average Precision (mAP) metric on the *top-30* results that were retrieved. Since our fusion method returns only strong candidates, there

¹⁰ <u>http://candela-h2020.eu/</u>



are cases that the returned results are fewer than the top-30 limit. When this happens the *top-N* results that are returned by our fusion methodology query is the length that we use for the rest fusion methods for this specific query.

3.3 **Results and Discussion**

3.3.1 **Quantitative analysis**

Dataset Description

The BigEarthNet (<u>http://bigearth.net/</u>) dataset was selected for our experiments. The dataset contains ground-truth annotation about Sentinel 2 level-2A satellite images and consisted of 590,326 patches. Each image patch was annotated by the multiple land-cover classes (i.e., multi-labels) that were extracted from the CORINE Land Cover inventory of the year 2018 (CLC 2018).

Based on the available Corine land cover classes we did the following grouping of the closely related sub-classes of the CLC, forming seven major classes. We selected around 130,000 patches, of resolution 120 x 120 pixels in order to preserve a balance among the number of items of the different classes/concepts:

- Class rice: 'Rice field'
- Class urban: 'Continuous urban fabric', 'Discontinuous urban fabric'
- Class bare rock: 'Bare rock'
- Class vineyards: 'Vineyards'
- Class forest: 'Broad-leaved forest', 'Mixed forest', 'Coniferous forest'
- Class water: 'Water courses', 'Water bodies', 'Sea and ocean'
- Class snow: 'Snow'

The selected classes are covering various PUCs subjects by including labels like water, rice and snow.

Results

The results for the feature extraction for the pretrained and the custom neural networks are shown at Table 4 using Mean Average Precision as metric and are computed against the Corine Land Cover (CLC) annotation of the BigEarthNet dataset. The VGG19 full convolutional layers are providing the best features for the retrieval problem. The flatten layer is underperforming. ResNet50 comes second with the Inception-ResNet_v2 falling behind. The custom DNN can't catch up with the performance of the pretrained networks. But the significance of the extra bands is apparent when comparing 5-channel to 3-channel input.

Table 4: Mean average precision comparison on Feature extraction of seven classes amongPretrained networks, custom DNN and Colour Histogram methodologies.

Pretrained Deep Neural Networks					Custom Deep Neural Network				Color Histogram		
classes	VGG19 fc2	VGG19 fc1	VGG19 flatten	ResNet50 avg_pool	Inception- ResNet_v2 avg_pool	5 bands flatten	5 bands dense	3 bands flatten	3 bands dense	3 bands	5 bands



					top #10						
forest	83.02%	84.05%	81.17%	81.66%	63.70%	76.52%	80.38%	49.22%	50.89%	85.28%	85.83%
rice	86.79%	85.00%	75.28%	57.68%	29.21%	25.89%	17.41%	30.40%	11.57%	36.19%	51.48%
rock	62.21%	62.80%	76.38%	59.04%	58.09%	58.37%	52.96%	86.56%	60.44%	71.68%	70.12%
snow	86.37%	86.65%	43.96%	91.85%	88.46%	74.93%	87.79%	48.03%	79.57%	90.77%	90.50%
urban	68.22%	60.53%	45.46%	68.25%	73.43%	73.71%	66.53%	34.60%	42.77%	76.09%	70.95%
vine	74.74%	79.58%	76.07%	67.85%	42.75%	45.44%	47.78%	59.67%	39.51%	74.09%	87.58%
water	98.78%	100.00%	100.00%	100.00%	96.20%	100.00%	97.11%	95.22%	92.68%	93.81%	97.79%
mAP	80.02%	79.80%	71.19%	75.19%	64.55%	64.98%	64.28%	57.67%	53.92%	75.41%	79.18%
					top #20						
forest	78.72%	82.37%	80.07%	77.63%	62.08%	76.12%	70.72%	45.98%	51.55%	82.75%	83.43%
rice	82.09%	81.77%	72.58%	49.74%	31.58%	21.01%	15.58%	30.40%	12.80%	32.32%	45.03%
rock	50.41%	53.52%	62.01%	51.59%	50.85%	46.30%	44.57%	83.94%	54.99%	62.80%	68.45%
snow	81.07%	80.39%	44.04%	90.92%	88.09%	74.52%	81.62%	49.20%	66.76%	90.00%	88.47%
urban	61.27%	53.65%	40.80%	64.92%	70.20%	69.26%	60.82%	30.85%	38.54%	74.52%	70.30%
vine	65.77%	69.36%	70.44%	61.53%	41.98%	41.55%	43.53%	44.75%	34.45%	67.64%	80.43%
water	98.83%	99.63%	100.00%	99.66%	97.00%	99.89%	96.58%	96.01%	92.27%	91.02%	95.98%
mAP	74.02%	74.39%	67.13%	70.86%	63.11%	61.24%	59.06%	54.45%	50.19%	71.58%	76.01%
					top #30						
forest	76.29%	81.08%	78.35%	76.66%	62.18%	75.57%	68.98%	42.66%	49.57%	81.78%	82.06%
rice	78.30%	77.92%	70.95%	46.78%	25.43%	18.39%	14.51%	30.40%	12.09%	27.93%	39.37%
rock	44.89%	50.31%	55.56%	49.26%	47.75%	39.45%	42.23%	76.41%	45.12%	59.42%	65.86%
snow	78.21%	77.31%	41.58%	88.92%	87.23%	74.40%	80.00%	48.13%	61.59%	88.76%	86.18%
urban	55.35%	50.58%	38.94%	63.60%	67.74%	67.07%	58.06%	29.58%	36.36%	71.23%	69.29%
vine	60.61%	63.57%	63.52%	57.70%	42.12%	40.76%	42.03%	36.70%	33.94%	63.29%	76.19%
water	98.94%	99.48%	100.00%	99.22%	97.54%	99.72%	95.90%	96.14%	92.22%	89.25%	95.22%
mAP	70.37%	71.47%	64.13%	68.88%	61.43%	59.34%	57.39%	51.43%	47.27%	68,81%	73.45%

Similar conclusions when using accuracy at K as metric as shown in Table 5.

Table 5: Accuracy at K comparison on Feature extraction of seven classes among Pretrained networks, custom DNN and Colour Histogram methodologies.

Pretrained Deep Neural Networks					Custom Deep Neural Network				Color Histogram		
					Incontion		-	2	2		
	VGG19	VGG19	VGG19	ResNet50	ResNet v2	5 bands	5 bands	5 bands	5 bands	3	5
classes	fc2	fc1	flatten	avg_pool	avg_pool	flatten	dense	flatten	dense	bands	bands
					100 #10	J					
forest	75.00%	77.00%	78.00%	73.00%	54.00%	71.00%	66.00%	38.00%	43.00%	80.00%	82.00%
rice	79.00%	81.00%	36.00%	38.00%	17.00%	12.00%	12.00%	13.00%	7.00%	15.00%	28.00%
rock	37.00%	40.00%	30.00%	43.00%	44.00%	23.00%	34.00%	20.00%	14.00%	53.00%	61.00%
snow	73.00%	72.00%	40.00%	86.00%	86.00%	73.00%	75.00%	38.00%	52.00%	89.00%	85.00%
urban	46.00%	43.00%	33.00%	59.00%	64.00%	66.00%	53.00%	22.00%	30.00%	70.00%	62.00%



vine	54.00%	57.00%	32.00%	53.00%	38.00%	27.00%	38.00%	19.00%	20.00%	60.00%	77.00%
water	99.00%	99.00%	100.00%	100.00%	97.00%	100.00%	97.00%	96.00%	92.00%	91.00%	95.00%
Average	66.14%	67.00%	49.86%	64.57%	57.14%	53.14%	53.57%	35.14%	36.86%	65.43%	70.00%
					top #20)					
forest	69.50%	78.50%	72.00%	73.50%	61.00%	73.50%	63.00%	33.50%	39.50%	78.00%	78.00%
rice	67.00%	68.00%	21.50%	30.00%	15.50%	10.50%	9.00%	6.50%	8.00%	10.50%	21.50%
rock	33.00%	36.00%	20.00%	42.00%	40.00%	18.00%	33.00%	10.50%	9.50%	48.00%	55.00%
snow	69.00%	69.00%	35.50%	82.50%	82.50%	74.00%	76.50%	35.50%	46.00%	86.00%	82.00%
urban	45.00%	41.00%	31.00%	59.00%	61.00%	61.50%	49.00%	23.50%	25.00%	64.00%	64.00%
vine	46.00%	50.50%	20.00%	47.00%	39.50%	26.50%	35.00%	13.50%	19.00%	53.00%	65.50%
water	99.00%	99.00%	100.00%	98.50%	98.00%	99.50%	94.50%	97.00%	91.50%	86.00%	93.50%
Average	61.21%	63.14%	42.86%	61.79%	56.79%	51.93%	51.43%	31.43%	34.07%	60.79%	65.64%
					top #30)					
forest	70.33%	76.33%	69.67%	72.00%	61.67%	73.33%	64.33%	36.00%	37.67%	78.67%	79.33%
rice	58.33%	60.33%	15.33%	24.67%	17.00%	11.00%	10.33%	4.33%	7.33%	10.00%	20.00%
rock	31.00%	33.33%	16.67%	40.33%	39.00%	17.00%	29.67%	8.00%	8.33%	48.00%	50.67%
snow	69.67%	68.00%	35.33%	80.67%	80.33%	74.00%	76.33%	33.33%	44.00%	84.00%	80.33%
urban	43.00%	41.33%	29.67%	57.67%	60.00%	58.33%	49.00%	20.33%	24.67%	62.67%	60.33%
vine	41.67%	46.67%	18.33%	48.33%	42.67%	26.00%	35.33%	12.00%	15.33%	48.33%	60.33%
water	99.00%	99.00%	100.00%	98.00%	98.67%	99.33%	94.67%	96.00%	92.33%	83.00%	93.00%
Average	59.00%	60.71%	40.71%	60.24%	57.05%	51.28%	51.38%	30.00%	32.81%	59.24%	63.43%

The results of the colour histogram are comparable with the best results obtained by the VGG layers.

Among the pretrained networks, the VGG19 fc2 layer managed to extract the best features for the task (Figure 15). The color histogram managed to outperform the VGG19 at top 20 and top 30 results, increasing the mAP score (Figure 16). On contrary the DNN modes with the 5-channel input was unable to follow (Figure 17).





Figure 15: Results at mAP metric on Feature extraction using VGG19 fc1 layer.



Figure 16: Results at mAP metric on Feature extraction using Color Histogram.





Figure 17: Results at mAP metric on Feature extraction using DNN 5 channel.

Comparing the pretrained VGG19 with the Colour Histogram methodology on most classes they perform the same. The only point that they greatly differentiate is that at rice identification VGG19 performs much better, while the color histogram method performs better at the Urban and at the rock areas.

Concept extraction

The results for the concept extraction for the pretrained and the custom neural networks are shown at Table 6 using Mean Average Precision as metric. Here the concepts are extracted directly by the last prediction layer. The 5-channel custom DNN presents the best results. The 3 channel one seems to be missing crucial information falling behind. For the pretrained networks the Inception-ResNet_v2 outperforms ResNet50 and VGG-19.

Table 6: Mean average precision comparison on Concept extraction of seven classes among Pretrained networks, custom DNN and Colour Histogram methodologies.

Pre	etrained Deep N	Custom Deep Neural Network				
classes	VGG19 sses predictions		.9 ResNet50 ResNet_v2 ctions fc1000 fc1000		5 bands dense (last)	3 bands dense (last)
		t	top #10			
forest	63.59%	71.28%	66.67%	forest	80.38%	49.22%
rice	19.60%	3.25%	34.16%	rice	17.41%	30.40%
rock	22.70%	14.13%	30.68%	rock	52.96%	86.56%
snow	63.48%	84.47%	91.14%	snow	87.79%	48.03%
urban	55.66%	69.17%	58.85%	urban	66.53%	34.60%
vine	44.78%	29.43%	48.55%	vine	47.78%	59.67%
water	93.44%	97.47%	99.77%	water	97.11%	95.22%



mAP	51.89%	52.74%	61.40%	All mAP:	64.28%	57.67%			
top #20									
forest	61.38%	66.58%	60.16%	forest	70.72%	45.98%			
rice	18.49%	3.54%	27.07%	rice	15.58%	30.40%			
rock	22.98%	15.85%	28.73%	rock	44.57%	83.94%			
snow	62.33%	83.91%	87.47%	snow	81.62%	49.20%			
urban	54.03%	65.62%	54.58%	urban	60.82%	30.85%			
vine	39.65%	28.15%	43.32%	vine	43.53%	44.75%			
water	93.49%	96.73%	98.52%	water	96.58%	96.01%			
mAP:	50.33%	51.48%	57.12%	All mAP:	59.06%	54.45%			
		to	p #30						
forest	59.34%	64.78%	58.30%	forest	68.98%	42.66%			
rice	16.92%	4.75%	27.02%	rice	14.51%	30.40%			
rock	22.13%	16.18%	26.54%	rock	42.23%	76.41%			
snow	62.42%	83.75%	86.36%	snow	80.00%	48.13%			
urban	52.17%	63.43%	48.42%	urban	58.06%	29.58%			
vine	35.01%	26.82%	39.82%	vine	42.03%	36.70%			
water	93.76%	95.95%	98.32%	water	95.90%	96.14%			
mAP:	48.82%	50.81%	54.97%	All mAP:	57.39%	51.43%			

Conclusions vary when using accuracy at K as metric (

Table 7). Here, the best results are demonstrated by Inception-ResNet_v2 and ResNet50, followed by 5-channel custom DNN.

Table 7: Accuracy at K comparison on Concept extraction of seven classes among Pretrained networks, custom DNN and Colour Histogram methodologies.

	Pretrained De	Custom Deep I	Custom Deep Neural Network								
classes	VGG19 predictions	ResNet50 fc1000	5 bands dense (last)	3 bands dense (last)							
	top #10										
forest	57.00%	62.00%	54.00%	61.00%	24.00%						
rice	10.00%	2.00%	13.00%	2.00%	2.00%						
rock	17.00%	13.00%	17.00%	30.00%	3.00%						
snow	57.00%	84.00%	81.00%	77.00%	17.00%						
urban	39.00%	60.00%	40.00%	34.00%	24.00%						
vine	23.00%	20.00%	33.00%	10.00%	4.00%						
water	94.00%	96.00%	97.00%	89.00%	87.00%						
Average	42.43%	48.14%	47.86%	43.29%	23.00%						
			top #20								


forest	54.50%	58.00%	53.50%	62.50%	22.00%
rice	9.00%	2.00%	12.50%	2.50%	2.50%
rock	17.00%	14.50%	15.00%	33.50%	3.50%
snow	61.00%	83.50%	79.50%	76.50%	19.00%
urban	36.00%	59.50%	39.00%	34.50%	25.50%
vine	20.00%	21.50%	29.50%	13.50%	8.50%
water	94.00%	94.50%	97.50%	87.00%	84.50%
Average	41.64%	47.64%	46.64%	44.29%	23.64%
top #30					
forest	53.67%	60.00%	52.33%	59.00%	22.33%
rice	10.67%	3.67%	9.67%	2.33%	2.33%
rock	16.67%	13.33%	13.67%	31.67%	3.33%
snow	62.67%	83.33%	75.33%	75.00%	20.00%
urban	35.67%	56.33%	39.33%	34.00%	26.00%
vine	20.33%	22.67%	29.00%	17.33%	10.33%
water	94.00%	93.67%	98.33%	86.33%	83.33%
Average	41.95%	47.57%	45.38%	43.67%	23.95%

Among the pretrained networks, the Concepts Inception-ResNet v2 (Figure 18) managed to extract the best concepts for the task. The DNN model with the 5-channel input provided similar results (Figure 19Figure 17).



Figure 18: Concepts Inception-ResNet v2 - mAP





Figure 19: Concepts DNN-5ch - mAP

Fusion

Our fusion method performs marginally better than the Borda fusion, leading the metrics array in the comparison results (

Table 8). Reciprocal and Condorcet were not able to complete the other two methods in any class metric.

Classes Method	Ours	Borda	Reciprocal	Condorcet
forest	89.56%	88.38%	60.11%	52.85%
rice	97.05%	98.92%	39.51%	66.61%
rock	62.90%	64.69%	26.53%	20.88%
snow	91.46%	89.44%	67.04%	15.22%
urban	79.96%	74.90%	53.72%	29.03%
vine	88.40%	88.25%	28.22%	19.54%
water	97.35%	97.97%	78.42%	76.05%
mAP:	86.67%	86.08%	50.51%	40.03%

Table 8: Comparison of fusion methods with mean Average Precision metric

3.3.2 **Qualitative analysis**

Here we present for each of the seven classes one representative query and its top-10 similar images. The first patch is the image-query, whereas the following 10 images are the more similar patches. Each row represents a single class. In the following, we provide example results for all four fusion algorithms (Figure 20, Figure 21, Figure 22, Figure 23).





Figure 20: EOPEN fusion – Query and top - 10 results.

Borda fu	ision: Quer	y and top	o-10 results



Figure 21: Borda fusion – Query and top - 10 results.





Reciprocal fusion: Query and top-10 results

Figure 22: Reciprocal fusion – Query and top - 10 results.

Condorcet fusion: Query and top-10 results



Figure 23: Condorcet fusion – Query and top - 10 results.



Based on the qualitative evaluation, the conclusions that can be drawn regarding the images misclassified in our approach.

Urban query: Most of the misclassified results are rice. Visually the two classes resemble to each other making difficult for the DCNNs to discriminate among them.

Forest query: The returned misclassified images are mostly water patches. Many queries contain water bodies like rivers or lakes.

Snow query: The returned misclassified images are mostly water. The main issue here is that some search-queries contain a small lake or river, resulting to the increased retrieval of water patches. Also, some of the retrieved images are of the forest class, because in some cases they depict sparse country-side areas mixed with snow.

Vine query: Almost all the misclassified images were actually urban patches. Visually, there is great similarity between these two classes.

Rock query: Rock queries are mostly rocky areas near water, resulting to fetching many water patches.

The overall conclusions that can be drawn from the experiments presented in this section are the following:

- For feature extraction VGG19 outperforms all the pretrained and custom DNNs that fail to catch the features with enough detail.
- For concept extraction, custom DNNs outperforms the other methods, while it comes second when comes to accuracy at K. Also, inception-ResNet_v2 and ResNet50 outperforms the VGG in this domain. In all cases the significance of moving from 5-channel to 3 channels is evident for the custom DNN as expected.
- For the fusion our method gives slightly better results than Borda fusion, with Reciprocal and Condorcet been proved inefficient for this task. Some classes are hard to be recognized cause many patches are multi-labelled with mixed characteristics or are difficult to discriminate due to great visual similarity.



4 FUSION OF SENTINEL AND SOCIAL DATA FOR SNOW DEPTH ESTIMATION

Northern European countries, such as Finland, experience a very long winter season which can last several months depending on the region, putting a lot of stress on infrastructure. Also, extreme snow events, besides the benefit it has on winter tourism, can also cause severe problems in electricity supply, traffic, and agriculture. Addressing these problems requires a well-organized civil protection agency, as well as significant financial resources.

Recently, civil protection agencies have adopted the use of remote sensing from a number of platforms (e.g. satellite images and UAVs) in extreme event management, with potential benefits in financial cost and decision making. However, very often the remote sensing data collected by these platforms are not available fast enough for the decision making required in such events. Additionally, malfunction of these platforms, or potentially deliberate attacks to ground segments of space systems, can lead to delayed decision making and ultimately can result in loss of life. Therefore, alternative data sources must be used to fill this gap. An example is given in Figure 24, with publicly available information on Twitter about snow observations.



Figure 24: Example of online social media data from Twitter posts in Finland.

During the last decade, publicly available information from social media (e.g. Twitter, Facebook, Instagram, and various blogs) have made their debut in civil protection agencies around the globe. They can be used as a snap-shot of the public response to an extreme event and they are instant, with a huge benefit to decision making. It turns out that when it comes to breaking news, Twitter appears to have outperformed traditional media. During the Sichuan 2008 earthquake, which was responsible for 70.000 deaths, information regarding an initial tremor was being disseminated by Twitter several minutes before the main burst (Li et al.2008), and a similar case took place during the 2008 Southern California earthquake as well.



Twitter was also used to disseminate information immediately after the Haiti 2010 earthquake providing an insight regarding injured and trapped victims as well as damaged buildings (Oh, et al.2010). Pollution related health issues is another potential field where Twitter could be used given that the public response through this platform is strongly correlated with the ambient air quality in major urban areas (Gurajala et al.2019). Terrorist attacks are also a field where microblogging (e.g like Twitter) has been shown to play a vital role in collective sense-making immediately after the first shock, significantly contributing to awareness and reducing the uncertainty associated with such events (Haverin et al.2012). Twitter can also be an effective source of data in other extreme events scenarios. For example, it has been shown as an effective source of data that can be used to identify flood "hot-spots" immediately after these take place, which will, in turn, be used to task remote sensing data collection (Satellites and UAVs) for a more detailed analysis during the crisis management (Cervone, et al.2015).

Furthermore, recent event-detection efforts regarding floods have shown that today's algorithms can detect floods, including those caused by major storms or hurricanes, with great accuracy on a global level (Bruijn, et al. 2019). Wildfire is another natural disaster that has attracted the attention of civil protection agencies. Wang et al. (2016) has shown that monitoring social media could benefit such crisis management especially by increasing situational awareness, and helping with the evacuation, damage assessment and rescuing efforts.

Given that microblogging has evolved into such a widespread tool during a crisis, we attempt to expand its use and highlight its potential in managing snowfall events. Our goal is to highlight possible correlation between snow depth and the amount of microblogging associated with this event. This would suggest that the amount of the related information that is shared among the public could be used as a proxy for the intensity of the meteorological event. For this, besides using snow depth derived from ground measurements and model simulations (described in the next section), we also adopt a method of estimating the snow depth based on satellite images of backscatter radiation. The proposed methodology is validated in Northern Europe (Finland), but can be directly extended to other high-latitude areas of interest. Given that snow related tweets are just a small subset of a larger pool or tweets covering all types of social life, an important tool used in this study is artificial intelligence and machine learning utilized to annotate thousands of tweets, which are then fused with the geophysical data to enhance our snow depth estimate.

4.1 Related work

The estimation of snow depth has been very popular using Synthetic Aperture Radar (SAR) images collected by the Copernicus Sentinel-1 constellation (satellites 1A and 1B), due to the lack of in-situ data in the area of interest. Sentinel 1 is a SAR mission that provides 5m×20m resolution backscatter measurements in co-polarization and cross-polarization. These are ground range detected (GRD) Interferometric Wide Swath (IW) backscatter (at C-band; 5.4 GHz). Both Sentinel 1 satellites (1A and 1B) have the same orbital plane, but have a 6-day offset with each other. Each satellite has a 12-day repeat cycle, and 175 orbits per cycle. Because of this, each observation from the Sentinel 1 constellation has a different incident angle relative to a flat surface (ranging between 29 and 46).



Traditionally, SAR C-band backscatter satellite measurements have been used to study snow melt (Nagler et al., 2016; Nagler et al., 2018), based on the high dielectric loses of water that lead to a reduced backscatter coefficient over wet snow compared to surfaces that are snow-free or covered by dry-snow. For snow depth, C-band satellite backscatter measurements were used early on in the past, but only in co-polarization σ_{vv}^0 , and showing only limited sensitivity (Bernier et al., 1999; Shi and Dozier, 2000).

On the other hand, cross-polarization backscatter σ_{vh}^0 has been used to estimate snow depth in the past, but only locally using tower installations (Kendra et al., 1998; Strozzi and Matzler, 1998). Recently, a new method that utilizes the ratio of co-polarization to crosspolarization backscatter $\sigma_{vh}^0/\sigma_{vv}^0$ has been implemented on Northern Hemisphere mountainous regions, exhibiting a promising snow depth estimate (Lievens et al., 2019). Cband σ_{vv}^0 measurements shows little variation during winter due to the limited absorption of scattering by dry snow, but exhibit a sharp decline during the melting period, due to the large absorption of backscatter by wet snow. In contrast, σ_{vh}^0 increases during winter as the snowpack intensifies. This is due to a raising path length of the radar signal, which results in increased backscattering. The logic behind the use of the ratio lies on the fact that it eliminates the effects of temporal changes in the ground surface, vegetation, and snow conditions, which affect both σ_{vv}^0 and σ_{vh}^0 the same way (Lievens et al., 2019). Furthermore, during winter snow accumulation (spring snow melt) increases (decreases) due to the higher increase (decrease) of σ_{vh}^0 compared to that of σ_{vv}^0 .

Despite the fact that the cross-polarization ratio method was implemented on a larger scale for conditions of deep snow (up to 1-3 meters) and mostly bare ground at high elevation, we attempt to use this method for estimating the snow depth on a much smaller scale (30Km × 40Km) for the low land area around the city of Helsinki, where additional data from citizen observations may be fused to further enhance the estimation capacity of the new model. Contrary to existing approaches, we fuse Twitter data with the snow depth estimation model of Lievens et al. (2019) to further improve the estimation of snow depth in high-latitude areas. The developed methodology is presented in the following section.

4.2 Methodology

The proposed methodology combines Sentinel 1 images and Twitter data that are highly correlated with actual snow conditions. The method fully exploits the citizen interactions in their social system, as they are expressed by short text and images on social media platforms





(e.g. Twitter). The overall framework is presented in Figure 25.

Figure 25: The proposed framework for snow depth estimation using EO and non-EO data.

4.2.1 Snow depth estimation using Earth Observation Data

The snow depth is estimated using Sentinel 1 images in the north of Helsinki. Preprocessing of the raw satellite data (Sentinel 1) is carried out through the Sentinel Application Platform (SNAP1) and includes radiometric calibration, speckle noise removal, terrain correction and linear to dB transform. Our area of interest is chosen more inland (north and northeast of Helsinki) to avoid the city centre, where snow is frequently cleared of the streets and roads. Two separate locations are chosen for this in order to validate the results from the satellite derived snow depth. Given that Southern Finland is covered to a large extent by forests, which attenuate backscatter, we mask out these areas till we are left with the open grassy and farmland areas. Additionally, we mask out water areas (lakes) regardless of whether the water bodies are frozen or not. Both forest and water have been masked out.

In order to properly process the backscatter data that often come from different orbits we need to remove the static bias. First, we average 1-year of backscatter data for each orbit separately, and then average for all orbits. The static bias for each orbit is estimated as the difference between the all orbit mean and the specific orbit mean, which is added to the backscatter time series for the corresponding orbit. Also, before computing their ratio, copolarized and cross-polarized backscatter are re-sampled and projected onto a coarser 1Km² grid by linear averaging, which also helps reduce speckle noise. If more than 20% of the pixels, corresponding to the native Sentinel 1 resolution, are assigned as water or forest when they are projected onto the coarser grid, the 1Km² average is automatically removed from the analysis.

The first step in estimating the snow depth is to estimate the snow index as follows:

$$SI(i,t) = \begin{cases} max(0, [SI(i,t-1) + BR(i,t) - BR(i,t-1)]) & if SC(i,t) = 0\\ 0 & if SC(i,t) = 0 \end{cases}$$
(1)

where SC is the snow cover, BR represents the ratio of backscatter radiation in crosspolarization (VH) and co-polarization (VV) if the backscatter is given in linear scale. However,



if the backscatter is given in dB the difference must be used instead. Next, we rescale the snow index into snow depth with:

$$SD(i,t) = \left(\frac{a}{1 - bFC(i)}\right)SI(i,t)$$
(2)

where a = $1.1dB^{-1}$, b = 0.6 and FC is the evergreen forest cover fraction (dimensionless).

4.2.2 Citizens observations about snow and reporting on social media

In this work we combine social media data from Twitter, that represent a public response to snow fall events and the accumulation of snow in the area of Finland, with the snow depth estimation, as it is presented in Equations (1) and (2).

Data Collection

11,024 tweets were collected, covering a period of 151 days, i.e. from November 2018 till March 2019. The Twitter Streaming API is used to collect relevant Twitter posts. The collection is keyword-based, where Finnish words for snow (e.g., lumi, lunta, lumeen) have been used as queries. Out of the collected data, 3,210 tweets have been manually annotated by the Finnish Meteorological Institute as relevant or irrelevant, based on whether the text content was indeed about snow weather or just included one of the keywords (e.g., a metaphor). This annotated dataset has been further used to train an algorithm that is able to automatically classify the text of a tweet as relevant or not.

Representation of Twitter text as a feature vector

Starting with the text representation, we used the state-of-art algorithm Bidirectional Encoder Representation from Transformers (BERT, Devlin et al. 2018). BERT involves an attention mechanism that learns contextual relations between words in a text. BERT's goal is to generate a language model, and the used mechanism reads the entire sequence of words at once, contrary to directional models (e.g. n- gram LMs (Rosenfeld, 2020), and neural network LMs (Mikolov et al. 2010; Bengio et al. 2003)) that read the text input sequentially. Therefore, it is considered bidirectional or non-directional. This characteristic allows the model to learn the context of a word based on its surroundings. In order to capture the text representation of the whole tweet, we used an existing pre-trained model in Finnish language called 'bert-base-finnish-cased-v1'. Thus, the input in the BERT model is a Twitter text and the output is a feature vector with a length of 768.

Logistic regression classification in Twitter text (tweet)

A Logistic Regression (LR) model is trained to classify Twitter posts (short text) as relevant or not to snow. This disambiguation allows the removal of tweets that refer to metaphoric meanings of the word "snow" or synonyms of it. The model is trained by using the manually annotated data provided by the Finnish Meteorological Institute and a grid search is realized in order to identify the best parameters. We report that a basic logistic regression model is developed with parameter C equal to 31.57. Eventually, the model is validated on a set of 11,024 new non-annotated data, and the model estimated 6,097 tweets (55%) as relevant and 4,927 (45%) as irrelevant.

Deep Learning for visual concept (snow) extraction on Twitter images

A frame- work different to text classification of the tweets has been used to extract visual concepts from the subset of tweets that include images. The target is to count the number



of Twitter images per day that illustrate snow. To that end, we used a 22-layer GoogleNet network (Szegedy et al., 2015) that was trained on 5,055 ImageNet concepts (Pittaras et al., 2017). At this stage, the classification layer of the network, which is a fully connected layer, has dimension equal to 5,055, i.e. the total number of given concepts. Thus, this framework receives as input an image, then the fined-tuned Deep Convolutional Neural Network is tested on the specific image and a list of concepts along with their probabilities is produced. If the concept "snow" is ranked among the top-10 concepts with probability higher than 0.01, then we consider that the image contains the concept. Eventually, concepts are extracted from all the Twitter images, and 1,118 have been found to contain the concept "snow".

4.2.3 Correlating social media observations with snow depth

The snow depth estimate can be, in some cases, strongly correlated with the actual measurements and weakly correlated in other. Even in the case when the correlation is significant, severe biases may exist due to an overestimation or underestimation of the actual measurements. To reduce these biases we use regression analysis:

$$\hat{Y} = \sum \alpha_i X_i + \beta_o \tag{3}$$

where \hat{Y} is the predicted snow depth from a linear regression model, a_i and β_i are coefficients derived through regression analysis between the predictor variables X_i and the observed snow depth Y. In our proposed approach, X_1 is the estimated snow depth SD. By Twitter data X_1 we mean either the number of relevant tweets T_t per day t or the number of Twitter images I_t per day t that contain snow. Our proposed model is formulated as follows:

$$\hat{Y} = \alpha_1 SD(t) + \alpha_2 I_t + \alpha_3 T_t + \beta \tag{4}$$

The proposed model of Eq. (3) is using SD(t), T_t and I_t , showing the added value of socialgenerated data assets, which is either estimated from Logistic regression classification in Twitter text or a Deep Convolutional Neural Network on Twitter images to count the number of posts that are relevant to snow. In the following Section, we compare the 1st order model which uses only satellite image-based estimations SD(t), with the proposed 3rd order model that fuses state-of-the-art snow depth estimations, social media images and social media short text (tweets).

4.3 **Results and discussion**

Validation data in Finland

Regarding snow depth, we use observations, as well as simulations, for validation purposes. First, we use direct snow depth measurements from four sites around the city of Helsinki (Figure 26). These were taken using instruments (SR50AH) that measure snow depth by emitting an ultrasonic pulse and then measuring the elapsed time between the emission and return of the pulse. The instrument also uses air temperature measurements to correct for sound speed variations. Snow depth is measured every ten minutes, and then it is averaged to provide daily mean snow depth. All four sites are located in areas with intense urban development, which is ideal for this study given that we need to accurately represent the snowfall conditions of the area where the public response (Twitter posts) takes place.





Figure 26: Area of interest and measurements from four pilot sites in Finland.

According to the snow depth measurements snow fall begins in mid-December and we have a constant snow build-up through the beginning of February due to several significant snow events (>4cm). This is followed by a melting period that extends till late April, with only one major snow event in between. Only one meteorological station (site 2) located in the centre of the city and close to the sea has a shorter (by roughly 10 days) snow cover period. All sites exhibit the same dynamic (variability), but differ in the snow amount, with the ones more inland experiencing heavier snowfall than the ones closer to the sea. The observed snow depth in the four considered sites and their average are illustrated in Figure 27.

Correlation between social media and snow depth.

For correlation purposes in the following analysis we use the average of all sites. A close inspection of the observed snow depth and the Twitter time series (text-based or image-based) we can see that the three largest snow events (during 09, 17, and 29 January 2019) coincide with peaks in tweeted snow images and number of relevant tweets which took place the same or the next day.

So far we have defined the variables T_t and I_t , which denote the number of relevant-tosnow tweets at day t and the number of Twitter images that contain snow at day t, respectively. We also denote by $\rho(A, B)$ the correlation coefficient between two variables Aand B. The corresponding estimated Pearson correlation is denoted by r(A, B), which results the following outcomes with the average observed snow depth Y:

• $r(Y, I_t)$ = 0.56, positive and statistically significant correlation



• $r(Y, T_t) = 0.51$, positive and statistically significant correlation



Figure 27: Daily snow depth from the four sites and their average during November 2018-March 2019.

Data fusion between social media and Sentinel 1 images.

The satellite derived snow depth of Equations (1) and (2), as expected, is less good and doesn't have the same time density and is only estimated based on Sentinel 1A measurements during Dec 2018-March 2019. During this period, Sentinel 1B satellite did not give any measurements for the area of Helsinki in IW mode, and are given in EW mode instead due to the Baltic Sea Ice campaign, limiting our snow depth estimate to every 6 days only in area A and a with slightly increased frequency in area B. Additionally, we exclude the snow depth computation during the period between late February to March, given the fact that the liquid water from melting snow during the melting period overwhelms any backscatter signal from shallow snow. The resulting estimated snow depth is poorly correlated with the observed one, i.e. r=0.25 for area A and r=0.41 for area B. This is most likely due to the fact that the snow was shallow in the area of Helsinki, which did not allow the Lievens' method to exhibit its full potential. However, here is exactly where the use of citizen observations through Twitter are fused with the satellite-based estimation to provide an improved estimation. The improvement is measured with the Mean Squared Error (MSE) evaluation measure that is able to quantify the deviation between the observed snow depth values with each model.

The positive correlation between the tweets and the snow observations is a necessary condition that allows us to fuse these two through a regression model in an attempt to improve our Sentinel 1 snow depth estimate. This can be seen in more detail as we build the regression model, based on the correlation between the observed snow depth and the number of tweets (variables I_t and T_t). The time series are shown in Figure 28.





Figure 28: Variation of observed (ground truth) and satellite derived snow depth for Area A (left) and Area B (right). The estimated snow depth based on the 1D, 2D and 3D regression model is also shown. The data are only presented for the dates when the Sentinel 1 backscatter is available.

The Sentinel 1 derived snow depth exhibits a large mean square error (MSE) when compared to the actual snow depth. This is mainly the result of outlier points like the one during February the 16th (Figure 29). Such large deviations are mainly the result of backscatter noise that overwhelms the signal from the snow cover, which is relatively low in our case. A 1st order (1D) regression model, which uses only the estimated snow depth, can remove the effect of such outliers by utilizing the linear relationship between the predictor X₁ and the observed snow depth Y. The resulting snow depth \hat{Y} has a much smaller MSE with no outliers. However, what needs to be examined is whether this can be improved by adding the information given by social media. It turns out that a 2nd order model (2D) expressed by the equation:

$$\hat{Y}_t = 0.17SD(t) + 0.98I_t + 6.07 \tag{5}$$

exhibits a smaller MSE, reduced by 50% compared to the 1st order model, highlighting the importance of social data. The regression coefficients show that the added value is mainly attributed to the Twitter data, which is because this variable has a larger correlation with the observed snow. So far we haven't distinguished between image-based or text-based tweets, which is due to the fact that both have a similar effect, i.e.:

$$\hat{Y}_t = 0.17SD(t) + 0.98I_t + 6.07 \tag{6}$$

The question raised here is whether using both Twitter variables Tt and It at the same time would make any sense. We can't assume that these two variables are independent, given that when someone will use text-based tweets is also likely to use image-based tweets for the same reason and vise versa. However, the best criterion on whether both these variables should be used together is the error minimization, as it is measured from the MSE. The resulting regression model is:

$$\hat{Y}_t = 0.16SD(t) + 0.43I_t + 0.11T_t + 3.53 \tag{7}$$

which further reduces the MSE by 10%, as it is shown in Table 1. This indicates that these variables can be used together. We can also see that the contribution of the information from social media is not shared equally, with a much larger contribution from the image-based tweets. This is due to the fact that I_t has a larger correlation with the actual snow, and a smaller weight is given to T_t which only accounts for the added skill to I_t .



For area B, despite the larger overestimation of the observed snow depth during February, the results are qualitatively similar with those of area A. Given the increased correlation of the Sentinel 1 derived snow depth, the MSE exhibits an even larger deflation, compared to area A, as we move from the raw estimate to the different versions of the regression model.

The comparison of the models, presented in Equations (4), (5) and (6) with respect to MSE are presented in Table 9.

Snow depth \hat{Y}	MSE (Area A)	MSE (Area B)
$\hat{Y}_t = \alpha_1 SD(t)$	2044.80	5656.35
$\hat{Y}_t = \alpha_1 SD(t) + \beta$	142.50	157.85
$\hat{Y}_t = \alpha_1 SD(t) + \alpha_2 T_t + \beta$	76.66	78.39
$\hat{Y}_t = \alpha_1 SD(t) + \alpha_2 I_t + \beta$	71.26	64.98
$\hat{Y}_t = \alpha_1 SD(t) + \alpha_2 I_t + \alpha_3 T_t + \beta$	67.33	64.97

Table 9: Mean Square Error (MSE) of observed snow depth with the proposed snow depthestimates.

Our approach aims to complement existing simulated models and not to replace them with social data. Sentinel 1 images, social media textual and visual content are combined to derive a novel model that is able to improve snow depth estimation in urban or near-urban areas. Citizens act as sensors generating multimodal (text-image) data, which can be further utilized to enhance existing state-of-the-art models for snow depth estimation.

Our study, and more particularly the satellite derived snow depth, does have some limitations that must be outlined. The Lievens' method works well for large barren (no trees) areas with deep snow (several meters). Unfortunately, these criteria are not fully met in this study. Our region is close to sea level, with small signal to noise ratio due to the relatively shallow snow (average 20-30cm), not ideal for using C-band satellite backscatter to estimate snow, but there was no alternative for this case. Additionally, the region used to carry out this study was relatively small (a total of 200Km²), and due to the extensive forest coverage, that strongly affects backscatter, roughly 50% of it had to be dismissed from the analysis making it even smaller for our purposes. Using Sentinel 1 images that cover a larger area would allow an even larger noise reduction. However, the presence of the Twitter data does allow some improvements when satellite-based estimations are combined with relevant tweets and images that contain snow.

Furthermore, the algorithm implemented to rescale the snow index into snow depth, was optimized (coefficients α and β) based on observations of deep snow from barren mountainous regions over the entire Northern Hemisphere. Future developments in remote sensing might address some of these issues, which could enhance the use of satellite backscatter in snow depth applications in small areas like ours.





Figure 29: Variation of observed and estimated snow depth

One may use daily snow depth simulations, e.g. the ones given by the Canadian Meteorological Centre (CMC), which use in-situ data measurements and sensor measurements from existing infrastructures from weather stations. This would exhibit a strong correlation with the observed snow depth, reaching values up to r = 0.92 (Figure 28). In this case, using a 1D regression model does reduce the MSE to less than a quarter of its original value, reducing the bias during almost the whole period. During days when the snow depth is larger than 25cm the bias is reduced to less than a few centimeters. Examining whether the social media data can improve this, it turns out that introducing the Twitter data in the 2D regression model does not have any effect on the snow depth estimate, and the resulting curve almost coincides with the one from the 1D model. In this case the model would be of the form:

$$\hat{Y}_t = 1.17SD^{simul} - 0.01T_t + 9.04 \tag{8}$$

This is because the correlation of the simulated and the observed snow depth is very high, and feeding additional information to the regression model does not add any new estimation capacity, hence the variable representing the Twitter data is represented by a coefficient that is close to zero.

As expected, social media data from citizen observations are utilized only for complementary purposes when sensor networks do not exist, taking into account that the social media data are openly available and free, and do not require system maintenance costs.





5 CONCLUSIONS

In this deliverable, we have presented the similarity retrieval for EO, non-EO data by considering single modalities, fusion methods that consider the intrinsic characteristics of the data and features produced after applying textual and visual analysis techniques. Also, a fusion approach that considers both EO and non-EO for estimating snow depth was presented.

Starting with the similarity retrieval in non-EO data, we compared the performance of single modalities, i.e. text, visual features, visual concepts, geolocation and time in the similarity retrieval task and the performance of several late fusion methods, including one that has been proposed within EOPEN. Given, that the datasets used for evaluating these methods were significantly large it wasn't possible to annotate them and thus the evaluation was limited to *top-10* results per modality. The results showed that the proposed fusion methods, while it has similar performance compared to Borda fusion when the order of retrieved results is not considered in the top-10 results.

As far the similarity retrieval in EO data, we compared the performance of various approaches in the fields of visual content similarity and similarity by content. The well-known pretrained networks proved useful at the extraction of features, with VGG19 achieving the best scores. At the same time the custom DNN failed to follow the performance of the VGG. Things seem to change to the concept extraction task. The Inception-ResNet v2 provides best results on par with the custom 5 channel DNN. Also, the significance of increasing from the 3 channels (classic RGB) to 5 channel images is evident in this case study. Moreover, we used the previous modalities paired with these of geolocation and time in order to form a late fusion method that improves the retrieved results. Finally, the results demonstrated the importance of combining multiple modalities of an image, managing to lead the board of metrics among 3 other known ranking methodologies.

Finally, we evaluated the potential for using space-borne SAR backscatter measurements to estimate snow depth in areas that experience a shallower snow and are much more densely forested, and how we can combine these with instant social media data to augment our estimate. Our results show that despite the limitations of the backscatter methodology to estimate snow depth, significant improvement can be achieved through the use of regression analysis and social media data. At first, the linear relationship between the snow depth estimate and the observed snow, allows the removal of most of the bias and the noise from the rough estimate. To a second degree a fusion of Twitter data into the regression model allows an additional bias removal. This approach shows that this fusion of social data and Sentinel images has a strong potential.



6 **REFERENCES**

Bernier, M., Fortin, J.-P., Gauthier, Y., Gauthier, R., Roy, R., Vincent, P., 1999. "Determination of snow water equivalent using radarsat SAR data in eastern Canada", Hydrological Processes 13(18), 3041–3051.

Borda, J. D. 1784. *"Mémoire sur les élections au scrutiny"*, Histoire de l'Academie Royale des Sciences pour 1781.

Cervone, G., Sava, E., Huang, Q., Schnebele, E., Harrison, J., Waters, N., 2016. *"Using twitter for tasking remote-sensing data collection and damage assessment: 2013 boulder flood case study"*, International Journal of Remote Sensing 37(1), 100–124.

Cormack, G. V., Clarke, C. L., & Buettcher, S. 2009. *"Reciprocal rank fusion outperforms condorcet and individual rank learning methods"*, In *Proceedings of the 32nd international* ACM SIGIR conference on Research and development in information retrieval (pp. 758-759).

de Bruijn, J. A., de Moel, H., Jongman, B., de Ruiter, M. C., Wagemaker, J., Aerts, J. C., 2019. "A global database of historic and real-time flood events based on social media", Scientific Data 6(1), 1–12.

Gialampoukidis, I., Liparas, D., Vrochidis S., and Kompatsiaris, I. 2016e. "*Query-based topic detection using concepts and named entities*", Proceedings of the 1st International Workshop on Multimodal Media Data Analytics (MMDA 2016), pp. 9–13.

Gialampoukidis, I., Moumtzidou, A., Tsikrika, T., Vrochidis, S., andKompatsiaris, I. 2016a. *"Retrieval of multimedia objects by fusing multiple modalities"*, Proceedings of the 2016 ACM on International Conference on Multimedia Retrieval (pp.359-362), ACM.

Gialampoukidis, I., Tsikrika, T., Vrochidis, S., andKompatsiaris, I. 2016b. "*Community detection in complex networks based on DBSCAN* and a Martingale process*", Semantic and Social Media Adaptation and Personalization (SMAP), 2016 11thInternational Workshop on (pp. 1-6), IEEE.

Gurajala, S., Dhaniyala, S., Matthews, J. N, 2019, *"Understanding public response to air quality using tweet analysis"*, Social Media+ Society 5(3), 2056305119867656.

Heverin, T., Zach, L., 2012, "Use of microblogging for collective sense-making during violent crises: A study of three campus shootings", Journal of the American Society for Information Science and Technology 63(1), 34–47.

Jégou, H., Douze, M., Schmid, C. 2011. "Product quantization for nearest neighbor search", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, pp. 117-128.

Jégou, H., Douze, M., Schmid, C., & Pérez, P. 2010. "Aggregating local descriptors into a compact image representation", In 2010 IEEE computer society conference on computer vision and pattern recognition (pp. 3304-3311). IEEE.

Kendra, J. R., Sarabandi, K., Ulaby, F. T., 1998. *"Radar measurements of snow: Experiment and analysis"*, IEEE Transactions on Geoscience and Remote Sensing 36(3), 864–879.

Lepy, E., Pasanen, L., 2017. "Observed regional climate variability during the last 50 years in reindeer herding cooperatives of Finnish fell Lapland", Climate 5 (4), 81.



Li, J., Rao, H. R., 2010. "Twitter as a rapid response news service: An exploration in the context of the 2008 china earthquake", The Electronic Journal of Information Systems in Developing Countries 42 (1), 1–22.

Li, Y., Zhang, Y., Tao, C., & Zhu, H., 2016. *"Content-based high-resolution remote sensing image retrieval via unsupervised feature learning and collaborative affinity metric fusion"*. *Remote Sensing*, *8*(9), pp. 709.

Lievens, H., Demuzere, M., Marshall, H.-P., Reichle, R. H., Brucker, L., Brangers, I., de Rosnay, P., Dumont, M., Girotto, M., Immerzeel, W. W., 2019. *"Snow depth variability in the northern hemisphere mountains observed from space"*, Nature communications 10(1), 1–12.

Liu, Y., Chen, C., Han, Z., Ding, L., & Liu, Y. 2020. *"High-Resolution Remote Sensing Image Retrieval Based on Classification-Similarity Networks and Double Fusion"*, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, pp 1119-1133.

Liu, Y., Liu, Y., & Ding, L., 2017. *"Scene classification based on two-stage deep feature fusion"*, IEEE Geoscience and Remote Sensing Letters, 15(2), pp 183-186.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. 2013. "*Distributed representations of words and phrases and their compositionality*", In Advances in neural information processing systems (pp. 3111-3119).

Montague, M., & Aslam, J. A. 2002. *"Condorcet fusion for improved retrieval"*, In *Proceedings of the eleventh international conference on Information and knowledge management* (pp. 538-548).

Moumtzidou, A., Andreadis, S., Markatopoulou, F., Galanopoulos, D., Gialampoukidis, I., Vrochidis, S., Mezaris, V., Kompatsiaris, I., Patras, I. 2018. *"VERGE IN VBS 2018"*, In 24th International Conference on Multimedia Modeling (pp. 444-450), Bangkok, Thailand. Springer, Cham.

Nagler, T., Rott, H., Ripper, E., Bippus, G., Hetzenecker, M., 2016. "Advancements for snowmelt monitoring by means of sentinel-1 SAR", Remote Sensing 8(4), 348.

Nagler, T., Rott, H., Schwaizer, G., Ossowska, J., Nemec, J., Fasching, U., 2018. "Operational monitoring of alpine snow cover within the European Copernicus programme", in: Proceedings of the International Snow Science Workshop, Vol. 1, pp. 348–252.

Oh, O., Kwon, K. H., Rao, H. R., 2010. "An exploration of social media in extreme events: Rumor theory and twitter during the Haiti earthquake 2010", in: Icis, Vol. 231, pp. 7332–7336.

Pennington, J., Socher, R., & Manning, C. D. 2014. *"Glove: Global vectors for word representation"*, In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP) (pp. 1532-1543).

Pittaras, N., Markatopoulou, F., Mezaris, V., Patras, I. 2017. *"Comparison of Fine-tuning and Extension Strategies for Deep Convolutional Neural Networks"*, Proc. 23rd Int. Conf. on MultiMedia Modeling (MMM'17), Reykjavik, Iceland, Springer LNCS vol. 10132, pp. 102-114.

Shi, J., and Dozier, J., 2000. *"Estimation of snow water equivalence using sir-c/x-sar. ii. inferring snow depth and particle size"*, IEEE Transactions on Geoscience and Remote sensing 38(6), 2475–2488.



Strozzi, T., Matzler, C., 1998. *"Backscattering measurements of alpine snowcovers at 5.3 and 35 GHz"*, IEEE Transactions on Geoscience and Remote Sensing 36(3), 838–848.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. and Rabinovich, A., 2015. *"Going deeper with convolutions"*, In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1-9).

Tang, X., & Jiao, L., 2016. *"Fusion similarity-based reranking for SAR image retrieval"*, IEEE Geoscience and Remote Sensing Letters, 14(2), pp. 242-246.

Turunen, M. T., Rasmus, S., Bavay, M., Ruosteenoja, K., Heiskanen, J., 2016. "Coping with di cult weather and snow conditions: Reindeer herders' views on climate change impacts and coping strategies", Climate Risk Management 11, 15–36.

Vijaymeena, M. K., and Kavitha, K., 2016. "A Survey on Similarity Measures in Text Mining", Machine Learning and Applications: An International Journal, 3 (1), 19-28.

Wang, Z., Ye, X., Tsou, M.-H., 2016. *"Spatial, temporal, and content analysis of twitter for wildfire hazards"*, Natural Hazards 83(1), 523–540.

Yan, J., 2009. "Text Representation", Encyclopedia of Database Systems, 3069-3072



A Appendix

A.1. Retrieval Results for Non-EO Content

In the following, we present for each use case the *top-10* results returned for each single modality and for the four different methods, i.e. the proposed fusion algorithm, the Borda fusion algorithm, the Reciprocal fusion algorithm, and the Condorcet fusion algorithm.

A.1.1 Flood Use Case

D4.3 - V1.0



Text	Tíme
La Lega: 'Nessuna commerrorazione pubblica per l'alluviane di Senigolila' <u>https://Lcg/GdFKAZaYHh https:// /TvKhnCcztr</u> /postar b/y.yllgo#	Cardoso di Stazzemo [Lucco] - L'alluvione in Alta Versilia del 19 giugno_ <u>https://t.co/kVV/I2/WEP</u> di @user posted by/SakyrC ✓ Mon, 04 May 2020 22:20
Lega: Nessuna commemorazione pubblico per l'alluvione di Senigaliio' <u>https://t.co/MCGLBgWWPC https://t. /LrdBiDUYY</u> poster by THdHOgg	Control 4 May 2020 2217 Outroom (4 May 2020 2217) Out
	ровев ву Охрнун У Тие, 05 Моу 2020 00:15
Sbc alla Lega Nord: Nessun flop per la serata in ricordo dell'alluvione" <u>https://t.co/XU9vfF0CTH https://t.co</u> /BS/CH4AptL posted by/MgoDEWK 9 Med, ON May 2018 1105 Cutador: (Lega Modelland) (Lega Suburbar) Blading (Urban Scenes: Magelation (Red. Scene Text: Coloroge	L'almanacco del 5 maggio: 1998 una valanga di fango dopo una violenta alluvione travalge Sarno - <u>https://t.co</u> //t//V4858/b https://t.co/ /bosted by:ngbT2UH ✓ Mon, o4 May 2020 2030 Mage Outdoor Eukoyotic Organize Vegetalon Piet Juni Frame Tendizage Doptime Outdoor Teners Mountain
Commemorazione alluvione Senigallia: "Un flop animato da divisioni e personalism" - Senigallia Notizie <u>https://t.co/F79HU7G76z</u> <i>posted by</i> 29L9Gek ✔ Mon, Ø7 May 2018 21:34	Domani è II 22º anniversorio dall'alluvione di #Sarno - Guel rischio sempre presente del Presidente #CNG Francesco Peduto https://Lco///rivDnEEnk di @user @user @user posted by ktMAm7D # Tue (30 May 2020 2024
"Visione apposizione su alluvione Senigallia non è comune". Comitato rinuncia a commemorazione - Senigallia Natizie <u>https://t.co/FRXx69B3p</u> posted by/JRawgi Y Thu, 03 May 2018 17:31	Domani è il 22º anniversorio dall'alluvione di #Sarno - Guet rischio sempre presente del Presidente #CNG Francesco Peduto <u>https://t.o/VrjvDnEEnk</u> di @user @user <i>posted</i> bySSThmm0
MLettersAllaGazatta' A Fornovalasco nessuna commemorazione della tragica alluvione del '96' di MAlbertaRebechi <u>https://t.co/2IPSURHDRu</u> postero by:unt2qMZ 9 Wed, 20 un 2018 12:24	Mon, 04 May 2020 1930 @user mi sono sempre detto, mo come forò tutta questa plastica ad andare negli oceani, noi che in europa abbiamo le discoriche e tutti bene o male si raccoglie.
L'alluvione del 2014 a Senigallia, Mangialardi: 'A oggi nessuno mi ha notificata https://t.co/AdbaCT&cFF https://t.co/MmCAUGRAYZ posted by/Juliqot y Thu; 24 Aug 2017 19:13 Cifice Male Reson Indoor Reson Science Technology Advocate Addit Fore Male Reporter Scientate	ported by Schriffh Tue, 05 May 2020 07:23 Quser Quser Guardando il filmato dell'alluvione lo trovà così commovente e così diverso da quanto stà accadedendo ai nostri giarni. La solidarietà che vedo, oggi non c². Non c² verso. Detudente ma è così posted by EMMGOrc Tue, 05 May 2020 08:06
Sibe alla Lega Nord: "Nessun flap per la serata in ricordo dell'alluvione" <u>https://t.co/XU9vfF0cTH https://t.co</u> / <u>H8G1CHAptL</u> /osted byT1HdHOQ y Tue, 08 May 2018 23:21	22 anni fa un evento catastrofico sconvolse la Campania e in mado particolare i comuni di Sarno, Guindici e Bracigliano, a causa dell'alluvione morirono più di 160 persone Konaggio Maccadeoggi <u>https://tco/vGP.WaZnGN</u> <i>postet By</i> delloakD y Tue, 05 May 2020 08:10
Culdor: Costine Culdor: Mags: Schurber: Building: Urben Scene: Megetation (Ref. Scene Ter) Chacope	Per non dimenticare #sorno #1998 Malluvione #storia @user @user @user #solerno @ Episcopio di Sarno [SA] <u>https://t.co/vmBoS02kdA</u> poster By/GHQgU 9 Tue, 05 May 2020 06:28
Proponiamo la nostra posizione in merito alle vicende accorse attorno alla commemorazione dell'alluvione del 2014 a #Senigallia. Come sempre siamo convint che la verità rende libet. <u>https://t.co/AczónMYD2w</u> #SenigalliaBeneComune #NoiCiSiamo #FiumeMisa #LaVeritàRendeLiberi posted grytAgaDEWX. I Tue, 15 May 2018 13:52	
Allwione 2017: faccolata di commemorazione #57100livorno <u>https://t.co/0wmBPlgeVa/6788-allwione-2017-faccolata-di-commemorazione.html</u> <i>posted by A</i> vigeZH 🗲 Sun, 09 Sep 2018 11:33	

Figure 30: *top-10* similar results retrieved using Text and Time modalities.

Page 58





	Visual Features	Viscol Concepts
	Estadoro Mangidardi. Jer Angebni ed altre sei persone a giuditio per fallurione di Senigalio <u>Hitos//too/018406518 Hitos//too/014606518 Hitos//too/01460518 Hitos//too/014605</u>	Esindano Mangialard i Be Angeloni ed obre sei persone o giuditio per falluoine di Senipsilio <u>(Hos/Hoo/24A06310) Hos/Hoo/2440344549</u> poster by Julgon Wesh Ti Doc 2019 2237 Ondest Displane Oudest Capazza (taking) Urban Scene Giv Taka (sabarlar) Galangati Oganing (Endential taking)
	a'i Onni da by grade f fabilitane, nai più una cotastrole similar. #Wendo Quaer 200 <u>Https://toa/u44T3HQH80 Https://toa/u0mu363.014</u> Dealerd SyrVisson V Mon, 30 Oct 2017 17:54 Otstag: Orgime Ouddaar, Ganny, Wan Modet Thing, Ways, Each, Galangatic Organise, Rast, Nepastran, Vehice	Gluer Holfer rama dican in spasso e chudo che Dio cè mont ben <u>999998</u> , in caso di alluione, ricordati di ne fAntonilo inditie 999999 <u>e Inter/I confectionen</u> poster dy OCE MUTI Jar Thu IA Nov 2019 10:24 Ordesti Titalini, Doytine Oussail Substati Chycargo (Uton Scene Cap Surry Baldeniat Falding) Casy
Nuit	Function of Admittanetace. No Disson of IDEU Ordinano ESPERIENZA 🖶 MISTICA 4: Store, #FinoAldFine 9:412Novembre 412Novembre	Uberose bestrade dale tagle che poj kreidabilinente, andranno ad astruire i tam bini contri ib uenda albilogamento della strade. Come vedete Struitfore Huserica Contro dale strade. Come vedete poeted by Kry BM V Man, 27 Jan 2020 I Soli Guidagi Organez Guidagi Gaburdon Graves Vahicle. Bast Ution Some, Etress Guinny Cahcel Pari
	Operatione Flumen Lute' inchiesto su alluione Carigilano e Rassana, 195 indagati <u>https://t.co/CR4.allub?e Hacs/H.co/PR4.blm3</u> poster byglic?: w Thu (5 Jul 208 1550 Cristop Cayline Cuidean flast) Galangati Caypine Galesape Galesape Sty Cayaanta flast (Watersape Waterfast)	Landon (hinyo hokokuli chi kuta anakanpoz kut Kalenzaneko unakanpoz kutaki (kutaki kutaz) (kojez) (kutaki (kuta Santo (n. 1937) Mina (a pikuli sinka) Canasa (masa) Canasa (kuta) (kuta) (kutaki
	And Benome A november 2015 onconcellents rooms per listicité dispeticipies Queer Madhempe Queer Aplaqué d'electrometes Penneme Revent de l'actes persont Queer <u>https://toc/sis/styles.le littes//toc/sis/styles.le littes//toc/sis</u> pender bys/VMCdp w Sun 24 los 2015 18.23 Cristion Gastagra Giv Less Watersage Waterfast Cased HI (bytme Outdoo) Fire Hannin	FLSHILpuoppa causo obgamento do naregoldo il actopossoggio della statione è chiuso <u>https://t.col/pdfledGV/https:/t.col/pdfledGV/https</u>
(Russia, sale a 340 i b ilon: to delle vittime defallurione nella obi posted bygom (ECr. \$F1 (S.S.J. 2019) [210] [210] Chair Quideon (Lan Model hing Furnicus Cologo (Lan Model hing Furnicus Cologo	ast di k luts <u>Htos//t.co/BoHT6VpHT Htos//t.co/NDN837#FD</u> NC-Oganilia (Mdaar) (Optime Guidear) (Femar) (Vagentia)	FLASH]Longyna causo obgomento do moregoido il astroposoggio della starbore è chiuso <u>https://t.co/UwiOeRsmoE https://t.co/UwiOeRsmoE https://t.co/UwiCeRsmoE https://t.co/UwiCeRsm</u>
	posted by Juni 251K 9 Ta: 22 Oct 2019 1135 Coydine Cuiddon Ouddon Time Weyesian Ratt Extenyate Organism Landscopp Field (R) Exteny	Archikida irchieda per oliwine 2011 <u>Hites//Ico/2h/SuWYanAW Hites//Ico/2ko5205564</u> poster by/Kirligh 3/ Sol 66 Jul 2019 13:41 Orddan Oxyder Ouddar) (Titlen) feran (follong lanning (fan Hade Thing) (Massager Materlant) (stantan) (finate (Malling
	Subnoron locale all grance for la modificazione fon previoere Kolluvore Allertaneetore. <u>Imper/for Hukevae w</u> Jonardo By//DBEO W Tux 22 Cot 2010 0.033 (orgine Custors) Tute: Wigestor Forth Calanyate Organiza (undersp: Feld) (11) (3117)	Viko sotto i fança una teom ba dacques colpisze fintera sere. Note officile per giabitanti soccarsi, in moltasimi casi, dai Vigil del Fusco in virtù degli snattamenti e Approtendiaci, segui il ini: <u>teles //t.col/stuk/Wigi s</u> falluvare scolbri a scovid ficabir a <u>Hos/It.col/stuk/Wigi s</u> paster by Noc 71 No 100 107 Outos in Gardine Castar Casi simitur intelling i Garangi fallo subatan interaciogana interacio i stating
	Som ocn focqua ale ginochia in horazzante non prevedere #allertaneteoPE <u>https://top/1404204EW</u> patter 50-021114 Y Ta; 22 Oct 2019 0149 Cognime Ondoor Time Vagestato Parti Extenyotic Olganem Landscope Field (H) Extenyo	FRolermo Marinea, II posse bobb dopo follwione per una voragine Vd <u>https://t.co//2.02.aK/MP https://t.co//2.07.aK/MP https://t.co//2.07.aK/MP https://t.co//2.07.ak/MP poster dop-TimeFr V Wed, 07 Nov 2018 TL41 Outdas) Daylee-Outdan (Table) Extenyatic Olganein (AmsteurVide) Extention (Checarje (Back/Gauss) (Matans Urban Scene</u>
	Senoro focquealle giacochia Imbaratzante non preedere. #alkvione #alkritameteoPE <u>https://tool1401204EW</u> posted by/Maninak 9 Tas 22 Coch 2011 00272 (byylimeCutdos) Quidos? Tees (Vajetsion Part) Extenyaic-Olganian Landscope (Edds IRI) Garny	Strade come fumi a 4 Pescasa Oui zona colii #olertameteo #matem po #10Lugilo <u>https://tcol#239F88ke</u> panted by Velitä Wed, 31 Juli 2019 18:01 Ouidas: Matica (optime Ouidass) distility (asatoputentia) distantas: Gas ed Velicie (Uton Scene

Figure 31: *top-10* similar results retrieved using Visual Features and Visual Concepts modalities.



and the second

te

s Road

Borda

2 novembre si terrà l'udienza preliminare per la tragic

Outdoor Building Urbon Scenes Resi

rosteo' by/ujtqo+ # Tue, 10 Jul 2018 15:52

Isindaco Mangialardi, Tex Angeloni ed altre sei persone a giuditio per fallurione di Senigalia https://t.co/0x6ADoS212 https://t.co/

	pomo oy yangoo Wed, The Vit Vit 12:25 Ondos) Goydae Outdos) Coycopy (Itidas) (Itidas Scene) Chy Cably Gabarlon Externatic Opanism Sectential Buldings		poraro of Ungen y Wesk (The Call Dir 2257 (Madean Cardenan Caldean Calence) (Tr Kling Urban Same) (Cay Table Calencer Calencer Cagastan Decidential Enklings
	Sic als Lega Noot, Nessan Rop per bærda in ricordodelalluvine <mark>l https://co/XU/#FicTH https://co/BO/BHAssi.</mark> Jostef og VegaCNU I Wed O H Nog XI II NS Ondesa Orytine Outdaar (Map) Salanbar (Tablia) (Kana Sates) Vegestran (Tar) Sate Tex Cepasije	art o	Socials Lega Need "Nessan Rop per la sercha in ricordo della luxime" <u>Inford //Lon/XU14/ENCH https://Lon/ACAOHApri.</u> poster by Angun Kay Nin Ios * Minko (H. May 2018 Ios (Indean Daylane Cuidean Heys Sabarban Infolg) (Inter Some Vegestich Ross Some Teo Organize
	Obe able pointed: "Nection flop per biseratio in ricordo delibilitation" https://co./KUM-KPOCH" Ortificity Obycline Outdoor Utility Utility Outdoor Outdoor Outdoor Outdoor		She ala lago kind "Hearmong per la perda in i condo defalluione" <u>https://co.XU.H=ThcTH https://co.XU.H=ThcTH </u>
	(Just Dollaruszadiczania posza e chuda che Dis că mani bon <u>99999</u>), in casi di alluióre, i condati in e #AntoneDiend Histopodegee # Mita/Histopide/Manih postor by VSE Malij # Thu H Nav 2019 19:24 Curtasa Mitalago (bytmeOutdaa) (situnta) (operare (Mani Scene (d) Sumy (situatio I siding) (dan)		Quee Do farstrand-loco in is passo e chuda che Do cià mani ban <u>999999</u> in cao di alluiore i kordati di ne Antonello/enditi pade 9 presi Mariji ♥ Thu 14 Nov 2019 10:24 Crador (Table) Optime Crustor Stanton Capazze Union Starte Cap Starty Radento (Lating) Cap
	her folknissend Samipalia inetto rischione il processo <u>https://tco/FokSY/Alay Https://tco/fokSY/Alay</u> podied foy/ulay PFT (21 No 2010 10003 COT6533 Coyline Cot6533 (Mag) (115/16) Statistica Scare for Ulicas Scare, Ulay Madel Theo (Reported Party Cot6533 Coyline Cot6533 (Mag) (115/16) Statistica Scare for Ulicas Scare, Ulay Madel Theo (Reported Party		Per tokutored identicalia inchional processo <u>Miss/Itco/ToHSY/Olisy Miss/Itco/Itco/Itco/Itco/Itco/Itco/Itco/Itco</u>
	113 nom ht ei lau hi fudema prelin inze per la tropica diuvice di Senigalia <u>Mess/Itco/mISH/MJ23E Mess/Itco/mISH/MJ23E</u> poster (by/julip) W Ten, D J J Mis 15 52 Ottosa) (MUBB) (Uton Scene) (Enstensis I Inzing) (Strent) (Velsio) (abunda) (Oysline Outcoa) (Gaund Velsio) (ass		Logo Hessanscon menorazione pubblica per folluxione di Senigalio' <u>Hittor / Kool Mol Bay Mino (Hittor / Kool Ma BOUWY</u> poster by THI 66800, 9º Tuo 65840, 2010 1641 (Tee Sansting Structure: Ox6500) Oprine Ox6600) (Sany Gip (Sans Teo, Teo, Copisio, Coast) (Teg
She a	113 nom ht ei lie nà fudiema preliminze per la trapica diuvare di Senigalia <u>Mess/Ico/InISH/MJ23E Mess/Ico/INIE mNLLaC2</u> podret /gr/glage 3 Ten 3 Jul 2018 ISSS CO16533 (INIERS) (Internet Endersoi Endersoi Endersoi Enderso) (Senison) (Gaust Malden, Cast		Meter STORED. Binaken bilakene dei Marro 2014 <u>Higo//t.co/v2/hdshibi Migo//t.co/43/kinyty</u> poster by 2013;9 June 18 Jul 2017 12:44 Cestern Ceysore Cey Galanten Orgener Cutden Orbon Scene Tataling (MMS) (SIM) Scene Test
Store .	Flasto per II Troven bre fusienzo preliminare per la tragica olluviore di Serigalio <u>Hitos//toolo?Oce42461 Hitos//toolo?Ukb2KHs</u> poster (s/) ujepor W Ten (b Juli 2018 ISS? Ordson (hitilitz) (hiton Scene) (hito) (trent) (asteritori Tuldago (skurbon) (bytien Ovtson) (Gaust Vihiden) (ast		Unance b blacker rei polern kare, ricordale b disciviline FOTO- <u>Hips//tco/Rei/HCorvett</u> #bbgic Korothe <u>Hips//tco/Rei/HCorvett</u> polet b/x5071 9 Sin C3 No 2019 13 22 Cedear Cadada Cadada Cadada (Sana Cadada Cadada Cadada Cadada Cadada Cadada Cadada Cadada Cadada (Sana Cadada (Sana Cadada Cada
LEG	Lage: The Result of Control of Section 2010 (Section 2010) (Sectio		117. cover bara i larrà fuel inna preliminare per la tragica allurbre di Senigalio <u>Hiss/Irco/mf3HV44785 [Hiss/Irco/Mf mHL452</u> pondre by/jica y Tae, 10.14 208 1818



EOPEN fuse

ll sindaco Mangiabrdi, Tex Angeloni ed altre sei persone a giudizio per Talluvione di Senigallia 📶

Figure 32: *top-10* similar results retrieved using EOPEN and Borda fusion algorithms.





Figure 33: top-10 similar results retrieved using Reciprocal and Condorcet fusion algorithms.

A.1.2 Food Use Case





	Text	Time
	Bit Startmers and an over the hugh the day producers they are quarking of our induced resources and born innovations. It moves in quarking the moves in the startment in moves in the startment of the startm	190230 Voorde Invidence Green Tao Seed Serum ASEAN Whydration Event 2019 and Fonmeet Highlights in Singapore High //LCO/IDVBJLAD #Voorde Jay Holdson poster by Hel 0387 Imu 11 Apr 2019 0211 © Singapore, Central 178157 Singapore (E 2904753, 102.6530259) Off Jacksone Central 178157 Singapore (E 2904753, 102.6530259)
<u> </u>	Control Reporting Yound Lastrynol Cogasta (Yeasa France Yeana Heasa) (Dytane Cuddar) (Han (Essa) deformers one un one thon just fixed produces they are guardinare of un indural resources and born introdential Engowering our formers and inseting in monotone key to achieving 42-existing # <u>Indurational Product (Indurational Product Produ</u>	giz Revisebe Geselischaft für internationale Zusummensighet (1022) Smith Thu TLAp 2019 (5807 International 2:445579245, 13020007711641) Text Operational Control (1:400) Text Operational Control (1:400) <t< td=""></t<>
<u>s</u> a	disfformers are on more than just food producers, they are guardians of our natural resources and born innocetors is provering our formers and inesting in innocetors is they to activeling #ZeroHunger (<u>bites/Loca/2eFa/BitLAH</u> #Agimoceton (<u>bites/Loca/2eFa/BitLAH</u> guarder dyt-KeroBite Just 0Feb 2019 0507 The 0Feb 2019 0507 Compare Statement Texame (SubaryoticOogase (Press) (Primote Press) (Dytaler Ontdoo) (Texa) (Soc	Ok what? There's gama be a DEPARTURE tax to leave Malanair ports? Why the fuck would i pay to kave the country, on top of airfore + airport taxes?? 6M20 to go to ASEAN countries and 6M40 togo to other international destinations, what builth if sithis parter dynatty Who and builth if sithis a parter dynatty who are a parter dynatty who and built a parter dynatty who are a parter dynamic who are a parter dynamic who are a parter dynamic when a parter dynamic who are a parter dynamic
<u>sa</u>	@dffarmers are our more than just food producers, they are guardians of our natural resources and born innovators it is powering our farmers and insetting in innovators is they to achieving #ZeroHunger <u>thes://co/2eFa98LAN</u> #Aginovation <u>thes://co/2EWitMreHJ</u> acated \$4\u00e9c00000 Wind, 13 Feb 2019 0231	coded by Vills(El w Thu II Apr 2019 06:22 Think Ing holdstolly about fait, means also to think holdstolly about inclusiveness and shared benefits of asstolinable food system, * Work/BFib h0G Dr Goeth-Johnstore of the #128AF This week. Learn more about the ASEAN region here: <a href="https://colorscOPV.442.https://colorscOPV.4</td>
	Control Contro Control Control Control Control Control Control Control Control Co	Colours Etherer word leader from Indonesia #ProbowsRecorc.ledTeWorld Quer Quer Quer Quer Quer Quer Quer Quer
		When you will file file and incoden ball months and prist the bools playing planaus or petons. This simple game is tool blood on hord surface as players throw metal bala cal a and incoden ball months as pick. Refore can be played by everyone regardless of oge and gender <u>Inter/Nool/2005/Disar</u> poster by USERHI Planage was
	disformers on our more than just food producers they are guardiance of our natural resources and born incodend. En powering our formers and installing in incodents is to foot heiving #ZeeHrunger - <u>Interal/Incodeguillineing</u> #Aginovation <u>thres/IncodentsEgree</u> poster dyn/veWbit wFr(123 Nov 2018 1342	Are you fan of watching Hollwood bick is basiners? But do you in ow that many ASEAN countries have produced movies that are internationally recognized by formous film festivals? Here is a. <u>Here //too/ffb/047EBB</u> Joader by/USASO The protect reflects on iterations for human rights and USBTOIN+ rights achocory in South East Asia AII140 ASEAN CSOs hope that Brune would uphold its name being on tobade of peocet, asc left that upholds and power by/USASO
	guardians of our natural resources and born innovators! Empowering our farmers and investing in innovation is key to achieving food security.	Are you booking to gran your business through digital transformation? Say hello to the futurel Register for ASEAN Virtual Claso Connect 2019 now pageter by 21mm (14, a) 99 7-38 © Register, Luzerne County, Pernaykania, 18622, USA (#1967499, -76.2732242)
	& Stormerscie our more than just food producers; they are guardians of our natural resources and born innovators! Empowering our formers and inexting in innovators is that born the storm of the	
	didFormersole our nore than just food producers they are guardiance four natural resources and born innovatoris Empowering our formersond innovatorial in the second seco	

Figure 34: *top-10* similar results retrieved using Text and Time modalities.

Page 62





Visual Features	Visual Concepts
Control of the second more than just body producers, they anguard board our natural resources and boar increated Exponenting our formers and increased our product on the second our product on the	Beformers down mone than just food producers they are guidence of an induction of an analysis of a monetane induced in the second and th
More thors 500 m Elion Cantury for ma worldwide are port of the solution to a source 4F uture/Food. #ZeroHunger <u>https://t.co/A.HW.BOogEZs</u> porter Upy/IC/WPBC San (14 aug 2008 1500 Rest (Vegester) Rever: Exterport: Organizm (Rest) frimste Geneti Hersis (Doytime-Outdoor) (Rev Food	Ead Africa is facing nagiot thread from 40 search cuts. The window of opportunity to help is all logan. At the nath is been pays tiller new or pays bit more laker games to game is upgrintly calling for \$328 M to help gave memets control these devicability pests <u>https://tcolv70e7/help.HFits.https://tcol</u> //tbo/b0/Leer //tb
With the decline of working oge employees threadening Jopon's economy, the ASEAN 43 Macroeconomic Research Office axid it bocks Jopon's mores to open is doors to foreign moviens to help address the issue of a shrinking working-oge population. READ: <a bindec.public.instr<="" bindec.public.instruction.nu="" href="https://control.org/licely.li</th><th>IAEA and @user are helping Zanzibar use nuclear science to grow nore of its own rice. Right now, around 70% of its rice is imported. 	
ASEAN think boxt vectores Japon policy shift to admit note foreign workers <u>https://t.co/vit/g2/cit/w</u> poster by mm//19 IF 107 June 2019 07-0 Japon [14 S74444, 13 12 23 417 7] Rest Greaters Extended Extended Foreign Rest Test Outdoor Stare	To makes, stracker risk, bittle card many other foods can be grown bload. Food is in hydroponics, plotts models the nutrients they need through a solution that deleves water and inicids directly to their roots #ZeroHunger <u>Hitsey/Loo/ENDSY/N32</u> pasted byHorMOND To 30 Aug 2019 10.88 Tom Registran Towner Extended to Control of the Control of Tood Towner (Control of Control of Contr
Hunger uplick in #Africo.com be reversed <u>https://t.co/AGBINTo2111</u> @user #UNFXO <u>https://t.co/aGBIOTo2110</u> @user #UNFXO <u>https://t.co/aGBIOTo21100</u> @User #UNFXO <u>https://t.co/aGBIOTo2110</u> @User #UNFXO <u>https:/t</u>	Control of the status of an analysis of the status of an analysis of the status of an analysis of the status of th
#Hunger uplick in #Africo.com be reversed <u>https://t.co/AGBINTo21ti@user</u> #UNFXO <u>https:/t</u>	However, the stand And Enderson (and the standard and the standard an
Food to me means., hoppiness We Maggle and her community in Mudzi #2 imbatwe have been growing fresh vegetables despite the world drought indexedse. WFPS realines activities such as community gardens?: and building::dams give people a route out of hunger! https://too/AlinoB/Despite Count of the despite out of hunger! https://too/AlinoB/Despite Wed, 14 Feb 2020 10:23 Wed, 14 Feb 2020 10:23 Ton Vegetable: Calgories Tree finance Camp feese (aspectable: Calgories Outdoor)	e stypistic diges in SLAM cooperation in tradiowedphiene <u>integration</u> poster byHHEC)+ ☞ Tie.12 Nov 2019 08:59 finit Tower: "trianguic Organism Magestism Daytime Outdoor" (Fild) (recon Outdoor) Animal Primate
Heads down and green thum be up "Ye A pill is #Gardenkkorth, so start planting awy! Like these students in #Moluku, indonesia, who are borning by doing at their owns:boolparten, <u>thios/It.cv/NINKSBBOS</u> pooler by Floorage 1 I S Sin I A pr. 2019 H43 Molacces, Indonesia (1984307, 198420756) Molacces, Indonesia (1984307, 198420756)	What & Agrobio Lot Marking and Why if mather if <u>missifica UNAdestantia</u> Gluer (Gluer
Sold, log bears, it ustard geers. Chiëten be to lok after their community gardens and see healty food growing. Queri is helping chiëten in flaces to born how how an unit itsus & diverse diek And the best way is to dig noter & grow their own boot if the <u>hear / toolgo theorem</u> parter by Encourse. If too X May 2019 1314 @ Loss (20107/109, 103.2724253) (may "weeting" Calory too Calory of Intel	Endet wedter has destuyed cops in the DiryCorr do of Central America, diffecting subsidence for mers who atrogge to feed their families WFP has supported over 160000 people for using on in medicle needs as well as helping them adapt to #climate hange <u>https://tcol/Mil/Odirs/W</u> patter by:Excap21 * Two, 20 aug 2011 1534 * Two 2011 au
SY Lania is tome to warm people, delicious food and beautiful scenery. It also has the 2nd highest rates of moderate acute mainutrition in the wort. WPP has been worting in 3Y Lania for 50 years to flight hunger, mainutrition & create a world where no child goes to bed hungry <u>https://too</u> //toospatible//	The P Ide of ASEAN Ploto Context Winners Announcement Full Album: <u>https://tcol/2rknb3/bp https://tcol/2018/b388.nm</u> poorter dryb/fica/c. If Tue, 04 Jun 2019 17:22 fant Rovers (Vegestant Eulerystic-Organism dunt Franz) Outdoor) fires (bytime Cutadoor) farest

Figure 35: *top-10* similar results retrieved using Visual Features and Visual Concepts modalities.





	EOPEN fuse		Borda
<u>see</u>	All-Formerszere our mote Honziad food jorduczes, they are guard fond our natural resources and horn incredule all maximum increasing in increasing in increasing in increasing increasing the second	S.A.	APEr metric record most thon just flood producers, they are guided from of our network resources and born introvolved. Empowering our for mers and immeding in improvements introvolved in the second se
	With the decline of text (is going employees theolening, Japonis eccompy, the ASEAM-0 Miccroscononic Research Office and R bock: Japonis mouse to open stadows: to being-monitories to help address the issue of a shrinking-working-age population. READ: <u>MiccroScAD: MiccroStAD: Miccr</u>		40% (hornlyformer protocies more than 80% of the % faco?) They are our #ZeroHunger heroes. 4F duroeFroot <u>https://t.co/HCo.H22326</u> porter by/wene ⊯ Mon 09 Jul 2018 07:18 Ten @quantan Enlangets Organism Fores: Felds Coyrime Oxidaan Primate Tree Oxidaan Otal
	ASEAN think tank webones Jopan pokryshift to admit more foreign workers <u>Hitse//too/y02/blub https://too/y1/y22/tlaw</u> poaked grang/p1 WFFLI U.J.n. 2016 U.F. Glapan (EX SAVAL 1332 24177 s) Glapan (Ex SAVAL 1332 24177 s) Glam (Meassian Galayatic Organiza frinance Towas Covinis Covidas s) (reco) (reco) (reco) (reco) (stery)		No formers = No food Without formers we wouldn't have the food on our plates. (#ZeroHunger <u>Https://t.co/fbo:/F0uMf</u> oparter by/HorWBD I Mon; 0 & Aug 2001 15:28 (*getation) from Externatic Organizm Romas: Atmater Resa: Coytime Outdoor) Time: Outdoor
	Volthare the future. The future of agriculture. The future of food. Our future without hunger. Investing in them is investing in our #ZeroHunger fouture #SDG# inforth0300 <u>https://t.co/m.Pad7V/Gim</u> posted Syndow1000 W Tue, 019 Apr 2019 18:24 (Ngestish Cast Guingetic Olgonian Power Primore Pennde Ferror Press) Two Paryle Crease Adult		Innocation is the certical driving bace which will © [Claration flood systems [Cluff family for mers out of powerty [Clifety the work to scheme load security and the 450cH low (Innocation is changing agriculture around the work) = <u>https://tco/2.674ELUA4</u> //tco/2.0745ELUA4 posted by how 100 for 53 © The Lift Skinka Soba, Himochal Prodesh 17000, India (D10/2135, 72174677) @ HELP, Tondou Ngoma, Madingo-Koyes, Koulbu, Congo-Brazzaille 13 562703, 113882163] esti (%getsita) (?inste Cataryotic Organize (recor) (inste (no ?easte (Male Reso) Sump) (data
	40X (bnik/formers produce more than 80% of the %s food? They are our #ZeroHunger heroes #FutureoFood <u>https://too/HON23310</u> postod y/HorM900 # Mon 99 J J 20 2018 Man (Magestian) (sharyoticlogesian) (Saver) (Edd) (bytine Ox663) (7/imst) (Tex) (Ox663) (C18)		Climite Charge is threedening the future of our filocate rule, But Mholl free boll you the answer could be in nature? How notart-based students con help us produces under Mail protecting our procision studio results. <i>Biol Strack Inter Charge Mail Strack Inter Charge Strack Inter Charg</i>
11 A	40% social forestrycon rollice poerty, imprate dod security and fight climate charge in ASEAN Member States? These positive impacts are what the ASE-ORCHARGENOR IN A States? These positive impacts are what the ASE-ORCHARGENOR IN The ASEA States? These positive impacts are what If the ASEA States in a state of the ASEA States in a state of the ASEA States? These positive impacts are what If the ASEA States in a state of the		Clinica change is threadening the future of our #Rodascurity. But Mrk 11 me bold you the answer could be in nature? How nature-based solutions can help us produce our food while protecting our precisus natural resources. <u>Miscuit Could Advancible</u> #Stice <u>Miscuit Could PCT/CBHki</u> posted by Hor Witten (*Thu (7 No. 2019) 1603 • Berbluck: Ria Jooguin Fibriona, faim Bib 1500 Poult, Regito Interlata de 550 Poults, Regito Intermedidina de 500 Poults, David Solutera Miscuit (*123 8384), 44.84033422444] *Cesation (*124)
	40% that social forestry considure deforestation, improve levelinoods, increase conservation, better forest governones & increase realience to climate charged These positive economic, social & environmental imports is what #ASPC/Chartnership has been working towards in #ASEAN <u>https://constituthitu</u> poster dys/q00000 V Tim; 25Feb 3020 06:23 Total: Guidescape Calibration Calibration Parameter Calibration Calibrat		With the decline of working age employees threadening Jopan's economy, the ASEAN +3 Macroeconomic Reason's Office soid it book is Jopan's moves to open its doors to foreign working to be address the issue of a strinking working age population. READ: https://controlstation.org (20110010120000000000000000000000000000
	Banglak tombs liyure 4 as Thalland hosts ASEAN summit with Pompeo <u>Hitos/Hco/PVmPdr@Wity Hitos/Hco/TUWHicloo</u> Jonded by Hoppeo W Fr1 (0 2 Aug 2011 I Lón (Hejestian Aset) Eukopolic Olganian Planem Raytine Octdaar Octdaar Teen Pensan Planate		ASEAN think tank wextomes logon policy shift to admit more foreign workers <u>https://t.co/ot/2.id/ub https://t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https://t.co/ot/p2.id/ub https://t.co/ot/p2.id/ub https://t.co/ot/p2.id/ub https://t.co/ot/p2.id/ub https://t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https://t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot /t.co/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub https:/t.co/ot/p2.id/ub http</u>
	Bangkio Kombs Injure 4 as Thabland hosts ASEAN summit with Pompeo <u>Hitos/Accol/N2DIKKiveo Hitos/Accol/NHCOGRIP</u> Joshed ZynATIN W FF10 2 Aug 2019 1844 © Bangkok, Thaband JS 2583924, 100.016.0003] (Ngestilah Asat) ExilopoticOlgansian Falverin Baytime Guidear) Guidear Tries (Risch Allinate		East Africa is facing major thread from #DesertLocuts. The window of opportunity to help is still-open & the math isc borr, pay a little row, or pay a bit more blar @Lawr is urgently asking for \$138.4 to help governments control these devastating peets <a href="https://conv/DeSUNFN.https://conv/DeSUNFN</th>
	No for mere 1No food Without for mers we would it have the food on our pibles #ZeroHunger <u>https://t.col/Sea/FOuld0</u> paded by/loc4W880 Mon (0 & Jug 2008 15 28 Wegetatian Rant: Exikingatic@ganiem Planes: Primate feature Condoan Tees Condoan		Votes Council

Figure 36: *top-10* similar results retrieved using EOPEN and Borda fusion algorithms.





Reciprocol	Condorcet
19030/ blonk-Green Teo Seed Serum ASEAN WHydraton Event 2019 and Panmeet ()) <u>https://tco/Uk/Brit/uk/Brit/uk/Brit/Uk/Brit/ Strat/Brit/Uk/Brit/Uk/Brit/Uk/Brit/Uk/Brit/Uk/Brit/Uk/Brit/Uk/Brit/Uk/Brit/Uk/Brit/Uk/Brit/Uk/Brit/Brit/Brit/Brit/Brit/Brit/Brit/Brit</u>	Generations of far mers have converted their natural surroundings into accellent bod production systems. Their traditional agricultural practices are vitation the #future#forced. #ZeroHunger https://confloads101n paded by bis/worked by W Fri 25 May 2018 08:21
So much beauty to explore in Singapore. Enjoyed our visit to Gordens by the Bay #ASEAN <u>https://t.co/artEvi38eu/</u> patter by chec/Vu If This 15 Not 2018 16:23 Checking Control Cont	Cases: Case
Central Control of formers have converted their natural sur pundings into excellent bool or od uction externs. Their toot tooplage is utilitied or or the second se	Image: Construction of the standing of
violator the #Future/Forced #ZeroHunger <u>https://tco/GH/D6ty/00</u> poder dyNo4W9R0 9 Sot 15 Sey 2000 247 Outdoor (Landscope Gouds) Sky Watercoope/Waterfort) (HB, Esca) (Hourson) Ront, Vegetarian	We need to recognize the value and knowledge of the people who produce our bod. Our #ZeroHunger heroes #Agroecology <u>https://tco ////HO456/i</u> and#df //wide/MBO
So much heauty to explore in Singapore. Enjoyed our visit to Gardens by the Bay, #ASEAN <u>https://t.colorefEwK3euv</u> posted byd01dC1n	M San, 13 May 2018 07:44 (Hisp:) Quidoon Ted, Junk From: Aans, Gogale, Negession, Animatian Conson, Eukaryotic-Organism, Landscope
Y That IS Nov 2008 Is 31 Vegestic: Olgonism Part Trees Parce Primate Guidson Doytime-Outdoon Urbon fairk Guid	Aguers supports the rollout of the ASEAN Guidelines on Promoting Responsible Investment in Food, Agriculture and Forestry #SDGs #biodiversity #foodescuit # More <u>Hitps://tcoi/uSEvi400b.https://tcoi/coi/sEROcaTY</u> poeted by/EGOCom #Fi(1) Apr 2020 06:30
Theibind becomes first ASEAN ration to grow industrial-scale medical controls https://tco/DWeGSAGEhtttps://tco/DWeGSAGEhttps:/	Vingestion Part Education Part Environment Environmen
(Inst) Existing in Control (Control) (Inst) (Existing Control) (Inst) (I	podráť byvlotvinnO S Tax, (7 Apr. 2020 11:55 Pares: Magessian Texn Fréds: Exlorgetic Ogonian Gandsospe Outdoor) Sky Qauds (baytine Outdoor)
Colling allwomen researchers in #ASEAN The ASEAN-US Science Prize for Women 2019 hos been bunched by @user & @user with @user to recognize ASEAN women scientists work. Curious? Learn more https://too/residencePrize https://too/TGSPGRLdg8 posted by/SWR2RV Image This (11 Apr 2019 0407)	It is pring story from Wis Christine Parfit on the Bottle for Botol project she founded to reduce plastic wate in Indonesia- and how @user's Australia- ASEAN Councils Emerging leaders program is supporting her to grow the business <u>https://conflimitin/Cemergine.tdoc.inter.com/Inter.com</u>
Generations of farmers have connerted their inclusion anoundings into excellent food production systems. Their traditional ogricultural practices a vital for the #Future/Erood #ZaroHunger https://toolaWa/SarHu poster byHorWWID If the: 10 Jul 2018 07:03	P VT Ta, 2 k Nov 2019 0230
Ondoor Endoor Could by Watercope Waterfant (HD) Haunoin Each Pant (Mice) So much beauty to explore in Singapore. Enjoyed our visit to Gordens by the Bay (ASEAN <u>Integriter/Jacobertalew</u>)	Quer Ak: Every day, & especially during this challenging period, we are more goteful than ever to all the #FoodHerces that are working to ensure that safe & nutritious food is available to all during these hard times https://too/?filkid.oc 4COVIDI® consult to a safe day loc ensure that safe & nutritious food is available to all during these hard times https://too/?filkid.oc 4COVIDI® consult to an ever to all the #FoodHerces that are working to ensure that safe & nutritious food is available to all during these hard times https://too/?filkid.oc 4COVIDI® consult to all during these hard times https://too/?filkid.oc 4COVIDI® consult to all during these hard times https://too/?filkid.oc 4COVIDI® consult to all during these hard times https://too/?filkid.oc 4COVIDI® consult to all during these hard times https://too/?filkid.oc 4COVIDI® consult to all during these hard times https://too/?filkid.oc 4COVIDI® consult to all during these hard times https://too/?filkid.oc 4COVIDI® consult to all during these hard times https://too/?filkid.oc 4COVIDI® consult to all during these hard times https://too/?filkid.oc 4COVIDI® consult to all during these hard times https://too/?filkid.oc 4COVIDI® consult to all during these hard times filkid.oc 4COVIDI® consult to all during these hard times filkid.oc 4COVIDI® consult to all during these hard times filkid.oc 4COVIDI® consult to all during these hard times filkid.oc 4COVID
ooster by d31172M ⊯ Thu 15 Nov 2018 18-41 (Najestian Eularyatic Citypatian (Ram) Times (Rama) (Rama) (Radoar) (Raytime Cutdoar) (Urban Brith) (Cite)	Romez (Negessión) (Rest. Fréds) Eskarpatic Organism (Landscape) Costdoar) Sile (Caudo) Goytime Cutodoar
Today @user Socio-Cultural Community and @user and organized the 'Platform on Challenges and Humanitarian Action in ASEAN, in Jokarta #ICRCASEANPlatform <u>Infect/I.co/Nhi#Sytmid</u> patient by Ugip "That 11 Apr 2019 1218	Guard AL Every day, & sepecially during this challenging period, we are more gradeful than even to all the #FoodPrecess that are working to ensure that sets AL Every day, & sepecially during these hard times the day of the CVDXDF docupatement (CVDXDF) packed by InderWith Day and the day of the
CRC 19: Avenue de la Poix, Sécheron, Rapuis, Geneva, 1202, Switzer bod (H4: 2277-46), £107276(H14248)	
Valors the Full sector and constructions in the data stand as a foreign of the sector and the sector in the data stand as a foreign of the sector and the sector in the data stand as a foreign of the sector and the sector in the data stand as a foreign of the sector and the sector in the data stand as a foreign of the sector and the sector in the data stand as a foreign of the sector and the sector in the data stand as a foreign of the sector and the sector in the data stand as a foreign of the sector and the sector in the data stand as a foreign of the sector and the sector in the data stand as a foreign of the sector and the sector in the sector in the sector and the sector in t	Partnership between ASEAN, Qiune; Qiuuer, Qiuer, Qiuer, Qiuer, Charles, Charlos Carcitas (* Southward Asia Leon how it is helping to preserve @ 49 and im prove helihoods for far mers and foreaters: <u>https://t.co/rMAGeWebs.https://t.co/UENZAVCo</u> poster by/14/902 If Thu (2 Mar 2020 2200 Versation Tast) Subgrate/Organism Sparts Tees Landscope Oxidan Rovers (bydier Oxidan) Centing
	Queer Queer Queer Queer While you enjoying of Theiland. <u>Hitos://t.co/ww0/lifFiff</u> poster/07/lif4/2] # Mon OH Nor 2019 5084 (Majantian Jian) Takanjanic/Oganism Quedan Timm (Landscope (Dytime Quedan Felds Str. Maja)

Figure 37: *top-10* similar results retrieved using Reciprocal and Condorcet fusion algorithms.

Page 65



A.1.3 Snow Use Case

Text	Time
Aurinkoista kevätpäivää kaikille +* #kevät #mökkeily #etelässäjopuunlehdet #lumi #jokivarsi #oulujoki https://tco/d0uBvOltRm posted by WINAMUE * Tue 28 Asr 2020 14/22	Kittilän yläkoulussa otettiin lumi hyötykäyttöön etäopetuksessa "On niin paljon lunta, sitä ei vain aina tule hyödynnettyä" <u>https://t.co/FRLPNyk9KC</u> posted by/p6fSoJ ¥ Tue, 28 Apr 2020 1422
	@user @user @user @user @user Nöytön tömön illalla Jalmarille ja kerron että tällaista lunta oli sillain kun isi oli nuori <i>posted by</i> kaG4XOH ♥ Tue, 28 Apr 2020 1420
Kevät tuli - lumi suli, purot lauloi - puli puli @ Aurinkoista ja turvallista vappua kaikille #, Mvappu Hjuhla Menklistä kumppani Häitätarjalla Mkevät <u>https://t.co/oknCCFFhfo</u> posted by 9f2MBn I Joista I Thu, 30 Apr 2020 1536	@user @user Köyvaan sellainen tuuli, että saas nähdä 😫 ja lunta sataa. Lunta!!! posted byun <mark>1250n</mark> ¥ Tue, 28 Apr 2020 14:30
UCEPUIA! www.exen Provers Text Overbid Text Computer Or Television Screens Background State Text On Artificial Background Synthetic Images Graphic Commercial Advertisement Professional Video	Täällä sotaa lunta _ poistaa aurinko_ai nyt sataa & poistaa samaan aikaan. Onneksi on SAUNA = #SUOMI <i>posted by</i> mtAshKG 🎔 Tue, 28 Apr 2020 13:58
Suomen kevät on sitä että otat aurinkoo pihalla joita kaikki lumi ei oo vielä ees sulanu <i>posted t</i> yr <mark>ijUltowi</mark> ✔ Wed, 09 May 2018 1631	@user Uusikoupunki, hetken sotoi lunto <mark>≌</mark> <i>posted by</i> dszcRMI ❤ Tue, 28 Apr 2020 14:48
https://t.co/miOLEMKwpE Tänään tiistaina on kevätpäivän tasaus ja uutta lunta tulee taivaan täydettä. Kevät keikkuen tulevi ja uusi lumi on vanhan surma ? #Kevätpäiväntasaus posted by sLRE?va y Tue, 20 Mar 2018 08:25	kenen vittusaatanan luvalla pihalla tulee lunta :3 <i>posted by</i> SCBRRCw ♥ Tue, 28 Apr 2020 13:50
Toiveissa päästä vappuna ulmaan≌ #kevät myöhässä. Paljan vietä lunta. #aurinkoinen #kevätpäivä taivas #sinnen <u>tutes/teo/sOWitkUV</u> poted bydo/sifiB ♥ Sat, 14 Apr 2018 21:39 ®oci) Wederscoje Mederfront Ouddoor Oceans Sty Londscope Sunny Lokes Clud's River	On lunto tulvillaon raikos takisādi <u>https://t.co/ZHOkjgEli9m</u> posted by Opgy44z
El lunta vaan aurinkaa. Upeaa viikonlappua kaikille j <u>https://t.co/f2PGuilULz</u> <i>posted by</i> <mark>fWPT</mark> //b ✔ Fri, 09 Feb 2018 19:40	©user Tammi-maaliskuu oli maninpaikain ihan kesäkeliä ja talvirajoitukset_ nyt on kesärajoitukset ja täällä mäkillä alka näemmä just sataa lunta_ Tarttis saada rajotukset voimaan kein mukaan, eikä kalenterin_ jos nyt lykkää lumet niin kesärenkailla kelin mukaan, ei 120_ <i>posted by</i> FrggS+0 ♥ Tue, 28.4pr 2020 13:38
https://t.co/miOLEMtkepE Tänään tiistaina on kevätpäivän tasaus ja uutta lunta tulee taivaan täydettä. Kevät keikkuen tulevi ja uusi lumi on vanhan surma ? Mkevätpäiväntasaus joosted tysERCudE S Tue, 20 Mar 2018 08:30	Woppu saapuu pian, vaikka isot juhlat onkin kielletty. MTilastat kertovat vapusta mm. että + Etelä-Suomesso sataa lunta tai räntää joka 10. vuosi + MTippaleipä sisättä 344 kerä/90 g + 2016 kulutettiin nakkeihin 33€/kotitalaus + Vappu-nimisiä on 3 219 <u>https://t.co/FUACBd1ane/https://t.co/dm./TeeVmSF</u> pooted by/WEly2Jb 9 Tue, 28 Apr 2020 13:38
Kevötpöivän tasaus. Eli Helsingissä tulppaanit pukkaavat maasta ja lunta on satanut. Ja kyllä se #koronorkin kohta väisty. #kevä Hhelsinki <u>https://co/mkigaonFults</u> posted of ylysäni ♥ Fri, 20 Mar 2020 0955 Filmers fizzt Eukarjets Organizm (keytelsize) Gudsor (tandizoje Store RicklyGloord) Egytime-Suddor (tines	Woppu saapuu pian, vaikka isot juhlat onkin kielletty. MTilastat kertovat vapusta mm. että ≗ Etelä-Suomesso sataa lunta tai räntää joka 10. vuosi ⇒ MTippaleipä sisättä 344 kerä/190g ÷ 2016 kulutettiin nakkeihin 33€/kotitalaus ⇒ Vappu-nimisiä on 3 219 <u>https://t.co/FUACR3/taw https://t.co/dmJ?eb/mSF</u> posted by://u2NN ♥ Tue, 28 Apr 2020 13:32
– Taiveissa päästä vappuna ulmaan®#kevät myöhässä. Paljon vielä lunta. Haurinkoinen #kevätpäivä taivas #sininen <u>https://t.co/dGWiztk1DY</u> posted byʻDDhiadJ ♥ Fri, 20 Jul 2018 1513	
Oulujski joulukuun lumisateessa. Täö siis toissapäivänä, lunta tuli ihan hulluna. <u>https://t.co/RdpA3.yrJO</u> <i>posted ty</i> /Pdjg/P ✓ Fri, 22 Dec 2017 09:18 Simo Cutadoo: Timo: Sil Waterscope Waterfront (Ther) Contine Cutadoo: Condiscope (Soch) Sip	

Figure 38: *top-10* similar results retrieved using Text and Time modalities.



Visual Features	Visual Concepts		
b. 1.600 Statusesso. politicaesso. pilulicaesso. pilulicaesso. # Luni https://t.co/ut5321n7228 politik type: # Luni https://t.co/ut5321n7228 politik type: # Luni https://t.co/ut5321n7228	Aprojum pop. 1953 rozna kurka per kele <u>https://t.col?idehSijel/</u> poster brynet/Sijel 1 Statistica Aproxima kurka per kele <u>https://t.col?idehSijel/</u> 1 Statistica Aproxima Ap		
Kydini venčasis joudanevelatis tibolih Sodorskylin puoleike, sto lunto muden sten on t <u>to https://tcolfwoil/tEitox</u> podret byblict_2048 ♥ Fri 27 Dec 2019 22:36 Gray ① Ontessy Sto	E links un likhenyt. Poriadetta ja pakkada. Tokoa on Voltoleeda jauluda <u>Inter//tcolk4/rOJETIC</u> porter VSF2/rOJA Fri (0 & bcc 2019 99:22 Gray 1) Onterop		
Kydiei venkasis joudere verketit bisili bisdonkylin puoleike, sitä lunto muuten siten on ill <u>o https://tco/fwoil.vE3tx</u> poster type/ <u>2014</u> ♥ Tru; 26 Dec 2019 2100 @@@ @ Ontestiti 610	Morrest uszar tulisza nyt kielis nyt kielis		
Tome postclikih pasa besitikih sataa namaa, halusat kaiki itasalimpöön tottuneet perheet Kuassa kesin 2019 netteellinen ensilumi 4 ± 2019 k b 0 600 (times/t) caldval/0/2019 orabet 9 (k) (Upri) Sata 94 kay 2019 6 5.8 (time) (tide) (times/t) caldval/0/2019 (tide) (times/t) caldval/0/2019 (tide) (times/t) caldval/0/2019	Morrard by VeCOVB		
	Morroskuussa tulispa nyt lunta että olis vabisaa ja kunnon tokki Helmi kuussa <u>https://t.co/HbECDdd/98</u> poster byyritiistu Vituo SSR-b 000 18 165 Gran Gradean 31		
() user Trevieted, 14 tata, Merkin banka on poljon errem mån 1° <u>https://t.co/f/SestHitm/X</u> poder / by 5100 S Sun 03 Feb 2019 2042 Total Cluster	Morroskuussa: tulisso nyt kinto etitä olis vabissa ja kunnon taki. Helmi kuussa: <u>https://t.co/HbEODxtyg</u> "odset vytyeli.201 ♥ Tue, 05Feb 2019 11:54 @@@@		
Nathtää laipurattason lainta <u>https://t.co/fin/EU/Loc/F</u>	Morraskuussz tulispo nył krito etitiolis vobisoo ja kunnon taki. Helmi kuussz <u>ktips //t.co/HitEOD.40%</u> øster bymili kluefe ♥ Tap, 05 Feb 2019 13.0 com cetsza cit		
✓ Thu; 22 Mor 2010 18:34 Grave Catalogy (1) ✓ Thu; 22 Mor 2010 18:34 Grave Catalogy (1) (1) (1)	Morrask usztz tulisjo nyi krito etiti olis vobisoo jo kunnon toki Helmi kuuszt <u>https://t.co/Hite/Obd/18</u> //t.co/Hite/Obd/19 /f.teo/SFR-0019877 Start College 2019877		
Uppe et ron nog uri n puranen not is tyljilion foketa, jobin oli satorut lunto van jonisen joliji fokyvat pitass #menories #winter 2016 #oskana di fitteri (rico Altartitelov poster bylgilian ¥ sin 16 feb 2007 2311	Morrast uussa: tulisso nyt lunto etitä olis vabisao ja lunnon taki Heini kuussa: <u>https://t.co/HbEOD.dt/rg</u> 		
Lundo Bjorthy, Horincinen nuto stickin rakkompi horrastus. Lopsuuden maisen iin ja nuistohinon aira ihara pabla 🗣 funi if fumikudalu ther the strong of the stickin rakkompi horrastus. Lopsuuden maisen iin ja nuistohinon aira ihara pabla 🗣 funi if fumikudalu therefore the strong of the stickin rakkompi horrastus. Lopsuuden maisen iin ja nuistohinon aira ihara pabla 🗣 funi if fumikudalu therefore the strong of the	Marrasiuussa tulispa nyi lunta etitä olis vabissa ja lunnon taki. Helin ikuussa <u>https://t.co/HhE.O.Write</u> // Joshen StyritZ Diefo // Tun OS Fek 2019 (7): 14 Composition of the state o		

Figure 39: *top-10* similar results retrieved using Visual Features and Visual Concepts modalities.





EOPEN fuse	Borda		
#lumion poempi luin #vesiton milito, silb tossute ikastu Mun lumiukot Morjo-Leeno ja Tööttijnä meri kasin sen saka kir pulitajvakoa leiklejä %. Wita dadu, bis of sarow and here discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu, bis of sarow and here discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu, bis of sarow and here discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu, bis of sarow and here discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu, bis of sarow and here discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu, bis of sarow and here discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu, bis of sarow and here discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu, bis of sarew and here discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu discovmane discovmane discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu discovmane discovmane discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu discovmane discovmane discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu discovmane discovmane discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u> Wita dadu discovmane discovmane discovmane #loira #takir#dag #sarew <u>Inters/Incontrol/Site/Asso</u>	(juser Huomentzi Sao nähdä, subala kaiki lumet Juhannukseksi filevät filumi <u>https://too/DPRLoyfing</u> //onter byfelsfill Syn 2 Skatz 2018 (913 Status 3 Shatzan 2 Shatz		
Olypo bei 4h fri tok kolle, vällilä lunto yli pokeen. # melähti #d izcpal https://t.col/Ahlfrei/KGM poster by?HVBAC I sun 03 Feb 2019 1601 I sano 310 (Misso)	What a day, bits of store and the discond that if dag \$2000 https://t.co/3109.55Mmc3 parter by Phyters What a Direct 2019 \$2006 Gene 301		
Token kuracida naisenaa #lavli # kura # larta # landacape # pirkonnoa <u>https://t.co/N527/Z.get</u> poster by://t.co/N527/Z.get > Tike; 23.don 2018 22.43 @rm:@rm:state:micro_context_pirkonnoa	Chipo Lei 44 hr fib al kallo villo gi la fan de jan		
Example of the information o	E Lick Kest Stoness biovekis terasikelt.n 80cm lunta #lumi #lievit.https://tco/tWal28m74 porter by//con/twi Wed, 21 Mar 2018 15:30 Grow Category (1)		
Tables h surcisio moisenoo #lok/# surce #lunta #londscope # pir kommoo https://t.co/HK02x7Eget porter by "poster by "poster" b	Tome porcitisiin jaas kesitiki in sato a normoo, holusat kaik it tastim pöön tottuneet perkeet Kisassa kesin 2019 netseellinen eratiumi 44.2019 ko 0400 http://toologi.ut/tool poleto brituget Sat 04 May 2019 64 SS Same Category @		
There is uncide noiseness #fail # ture # lands #fail # ture # lands #fail # faindscape # p in loam too https://too/NS02.7Eget There is uncide noiseness #fail # ture # lands # landscape # p in loam too https://too/NS02.7Eget There is uncide noiseness #fail # ture # lands # landscape # p in loam too https://too/NS02.7Eget There is uncide noiseness #fail # ture # lands # landscape # p in loam too https://too/NS02.7Eget There is uncide noiseness # lands # landscape # p in loam too https://too/NS02.7Eget There is uncide noiseness # lands # landscape # p in loam too https://too/NS02.7Eget There is uncide noiseness # lands # landscape # p in loam too https://too/NS02.7Eget There is uncide noiseness # lands # landscape # p in loam too https://too/NS02.7Eget There is uncide noiseness # lands # landscape # p in loam too https://too/NS02.7Eget There is uncide noiseness # landscape # p in loam too https://too/NS02.7Eget There is uncide noiseness # landscape # landscape # p in loam too https://too/NS02.7Eget There is uncide noiseness # landscape # landscape # landscape # p in loam too https://too/NS02.7Eget	Tortieri i jesee Miti kopitul No tiddi fihir nuhonine if uni if toki <u>i titos //t.co/Be/BB0KC</u> pode by/RE/T01 St. 05 Feb 30 19 18 33 20 € 06500		
Tablen 1: uuraista naiseenaa #lavii # tuura # lunta #londscape # pirkammaa <u>https://t.col/N527/Eged</u> Johen 1: uuraista naiseenaa #lavii # tuura # lunta #londscape # pirkammaa <u>https://t.col/N527/Eged</u> Voim 2: uuraista naiseenaa #lavii # tuura # lunta #londscape # pirkammaa <u>https://t.col/N527/Eged</u> Voim 2: uuraista naiseenaa #lavii # tuura # lunta #londscape # pirkammaa <u>https://t.col/N527/Eged</u> Voim 2: uuraista naiseenaa #lavii # tuura # lunta #londscape # pirkammaa <u>https://t.col/N527/Eged</u> Voim 2: uuraista naiseenaa #lavii # tuura #lunta #londscape # pirkammaa <u>https://t.col/N527/Eged</u> Voim 2: uuraista naiseenaa #lavii # tuura #lunta #londscape # pirkammaa <u>https://t.col/N527/Eged</u>	Toden kuvicida nicemoa Yduki 4 kuvi a kunita 4 bridscope 4 piktomoa <u>Hasz/AcoNKSty/Egek</u> podet by zizlebb ♥ Tus, 23 Jan 2018 22:43 Sara Catalar (1) Temo		
Eice Kesti Suomeso hanvieto texositeiti. näito m lunta. # luni # liveit <u>https://t.co/t.Wpl.2Bm74</u> poste/tyn/Orszie > Wog. 11 Mar 208 15:30	Todes kuuraida naisenaa fildhii if kuura if unto if bridscape if pikannoa <u>https://t.co/HSP//Egpt</u> poder by Hylca(A1) I Tup, 22 Jan 2018 2234 Georgi Gutterry (1) 1000		
Deven kuuraista maisenaa #laki#kuura#lunta#lantacape#pirkonmaa <u>htias//t.co/NK02x/Eae4</u> poeter by2/Pirinit >/ Moa 22 Jan 208 1945	Token industrial makemona #labi#i#i.sura #lunda #landacape # piklonnoa <u>https://t.co/HG27/Eap4</u> poster by/buk/d02 #line 23 and 108 23 th Georgi Galacian 410 fem		
Deven kur celab materna flavil # urc # lurts # brds:ope # p if kom as <u>https://t.co/HSD//Eged</u> John 21 Jan 208 IS 35 Image: State of the state o	Toden i kura oša na cisenco #toki # kura o #unto #bridscope # pirkonnoo <u>https://t.co/HKGP/Eget</u> John o toden i kura oša na secondarija		

Figure 40: *top-10* similar results retrieved using EOPEN and Borda fusion algorithms.





Reciprocal	Condorcet	
Ai, #stadījin ei tullut tarpesksi lunta vai_#partsīkuva <u>https://t.co/HPk2R8vMrx</u> pasted byvdmC08 ¥ Fri, 18 Jan 2019 09:27 Grow Coddoor) Gil (Tree) Coptine Ouddoor	Pyörä, lunta ja aurinkaa® Mhuruslahti Kvatuski Kwarkaus #2018 <u>https://t.co/NKspW461mx</u> <i>posted by</i> /RA/VD4 ♥ Fri, 06 Apr 2018 20:41 \$rom Guddoor 31 Stell Spots Staling Bapales Bapaling Website Gound Website	
Quser Ukkohallassa lunta riittää https://t.co/5wKkbZwgbP	Kouneinta takvea tässä tasiaan eletään; sopivasti asteita, vielä lunta ja jo aurinkoa * 0 * 0. <u>https://t.co/yimSBn85XA</u> <i>posted by</i> LPx8/rf Y Wed, 14 Mar 2018 1526	
¥ Vied, 14 Mar 2018 13:36 Grow St) Star Outdoor	Louekeskuksessa kelpaa lasketella! Aurinkoa, lunta jo hyvöä fiilistä riittöä. 🔮 #iloirtirinteestä #Louekeskus_ <u>https://tco/7PbvbJ2ype</u> posted by km+pPCL ¥ Fri, 23 Feb 2018 12:52	
Koronavuoren huiputusreissulla aurinko poistaa & lunta sataa - taitaa olla Vappul Mites siellä? Hauskaa & rentouttavaa Vappua sinulle rohkea intohimoinen edelläkävijäl 📽 🕐 Htyöelämä Hvappu Hrohkeus <u>htyps//t.co/MKQ1y07V5m</u>	lhanaa, että saatiin tännekin (kerrankin) oikea Htalvi 🔍 🙏 Hhelsinki Hlunta Hkytmä Haurinkoista <u>https://t.co/kgnZlSaetJ</u> posted by:42EUDrO 🕊 Wed, 21 Feb 2018 08:33	
posteo gy i rąski ¥ Thu, 30 Apr 2020 1505 Pyörä, lunta ja aurinkaati #huruslahti #vatuski #warkaus #2018 <u>https://t.co/NKspW461mx</u>	AIVAN IHANA SÄÄ, aurinkoa vähän ja lunta sataa silleen tosi kevyesti <u>https://t.co/HUHbSllhmZ</u> posted byR85c/UX ¥ Sun,18 Feb 2018 10:27	
posted by HB/VD4 ♥ Fri, 06 Apr 2018 20:41 Srow Outdoor 31) Stell Sports Stating Backets Backeting Nehicle Ground Vehicles	Mittakeppi el ulatu enää herkkuun. Tämä viittaa siihen, että lumi on vihdoinkin sulanut. #kevät #tiede https://t.co/NYGIIbéYtc posted by/XVFRKQ	
Miksi kukaan ei ole aiemmin hoksannut, että ne lumet voi kasata kadulle? Siinähän on tilaal #valkoinenkurittaja <u>https://t.co/y8ym/luCOO</u> <i>posted by</i> vNL445p ¥ Mon, 11 Feb 2019 14:14	Suc et reprizetto toco Eutorystic Organism Quodruped Ruminorit Animal Herbhore Domesticated Animal Dogs Mammal Corribore Wild Animal	
Story Outdoor Still (Resdential Buildings: Aportments) Suburbon Vähän enemmän lunta kuin viime vuonna Rukalla. Sopivasti pokkasta. <u>https://t.co/XuZvjälpv2</u> posted by:kkC2vjM V Ned, 27 Nov 2019 19:20 Story St. Ster: Outdoor	@user llimeeni tänöän kun lounoalle mennessä näin sen hetkisen söän_ #lumi #kevät <u>https://t.co/x3kdZTBkD3</u> > Fri, 06 Apr 2018 18:21 @ukorptic Organism foogo Carrivore @ukorptic Organism foogo Carrivore	
@user Mā sain just vaihdettua auton renkaat. Sanoin tuossa naopurille että varmaan sataa räntää ja lunta kun hommo on tehty, niin elkös se vaan niin körynykinäs. posted ör jöbövikk	Mustat kumpparit ja loskalumi. Mukavaa käyttää tähän oikaan vuodesta! #kumisaappaat #kevät #lumi <u>https:/tco/vDz4trLja7</u> posted 9y 2018/HDA IV Mon, 02 Apr 2018 18:35	
¥ Sun, 26 Apr 2020 12:45 Koureinta taivea tässä tasiaan eletään; sopivasti asteita, vielä lunta ja jo aurinkoa <u>*ii *ii, https://t.co/xjmSBn8SXA</u> <i>masteri tai</i> t ² elli (Kymmenennetsi tulut Määräinen: Uusi lumi teki ladusta hitaan ja raskaan, mutta soma se oli kaikille <u>https://t.co/zdSkrb4QSS</u> ⊅ Fri, 09 Mar 2018 20:11	
• Wed, 14 Mor 2018 1526 Oliko se Luontoõiti twitterissö? Mikö juttu? Ennusteisso 1-3 ostetta ja oikeasti -0,5 ja lunta 8 senttiö? Mappeenranta <u>Intre//Leo/EctFUZEbFO</u> posted by A4fDilu • Sun, Mar 2020 1809 • Sun, Mar 2020 1809	Mlumi #sulaninen #Oululssa keväällä 2018 ja vertailun vuoksi 2016. Käppyrät perustuvat #Forecdin julkaisemiin lumensyvysiäteläinin, Kevät #sää <u>https://tco/gHTUVis9w4e</u> posted tyvikeläise V Wed, 02 May 2018 19:26 Chots Computer CV TekvisionSceens Graphic Synthetic Images Ted Maps AnimationCarboon Scene Text	
Véhán enemnán lunta kuln vilme vuonno Rukalla. Sopivasti pokkasta. <u>https://t.co/XuZg3lpx2</u> postat by+/RKOMI S Sat, 30 Nov 2019 13:14 Com St Ster Satdoor		

Figure 41: *top-10* similar results retrieved using Reciprocal and Condorcet fusion algorithms.



A.2. Information Retrieval in EOPEN and CANDELA

Information Retrieval (CERTH-DLR)	EOPEN EO data	EOPEN non-EO data	CANDELA
Input data	Sentinel 2 images in GeoTIFF format	Twitter data in JSON format	Sentinel-2 and Sentinel-1 images, other multispectral and SAR sensors too
Query	Sentinel 2 patch (120x120)	One tweet	Image patch of a user-defined dimension, CBIR and semantic queries – concept search
Pre-processing	Multi-band GeoTIFF	Localization of named entities Concept extraction Visual feature extraction Lucene indexing	Spatial overlap between S1 and S2 images, for Data Fusion
Features extracted	 VGG19, fc2 (Dense) layer, 1x4096 ResNet50, avg_pool (Dense) layer, 1x2048 Inception-ResNet_v2, avg_pool_layer (Dense) layer, 1x1536 	 Text (Apache Lucene indexed) DCNN visual features (Extended GoogLe net) TRECVID 345 visual concepts Timestamp Location extracted 	 Multispectral histograms Gabor descriptors (MPEG standard) Weber features (WLD) for multispectral images Modified Weber features for SAR images
Similarity per modality	 Euclidean distance for the feature and concept vectors, 	 Text search (Lucene) Euclidean distance for the feature and 	Active learning based on SVM and Bayesian decision SQL multimodal queries (image



	 Sort by time for the timestamp Centroid-to-centroid for the location (GEOnear, mongoDB) 	 concept vectors, Sort by time for the timestamp Point-to-point for the location (GEOnear, mongoDB) 	semantics, EO product metadata, image descriptors)
Data Fusion	Late fusion on the order of results per modality	Late fusion on the order of results per modality	S 1& S2 data fusion with active learning at image feature level S1 &S2 fusion at semantics via SQL
Supervised/Unsupervised	 The fusion is unsupervised The feature extraction is supervised 	 The fusion is unsupervised The feature extraction is supervised 	 The data mining and fusion are supervised The feature extraction is unsupervised
Open/closed source	Open source at the end of the project	Open source at the end of the project	Open source
API or GUI available	Will be available as a web service	Will be available as a web service	GUI available
Use of Docker	No	No	Yes
Dataset	BigEarthNet (part of it with specific classes) • Water • Snow • Rice • Forest • Vineyards • Rock	~10,000,000 tweets regarding the EOPEN use cases	Sentinel 1 and 2 semantic annotation in active learning (user in the loop – dialog HMC) user is annotating the retrieved Open number of classes defined by the user adapted to the application (up to 100) Benchmark data sets created



	• Urban		in the project are available In the project have been analyzed up to 1Mkm^2 covered by S2 and S1
Evaluation metrics	Mean Average Precision	Precision@k	Precision and Recall