Zurich University
of Applied Sciences

School of
Engineering
InIT Institute of Applied
Information Technology

# Bachelor thesis Computer Science

## Dynamic Event Detection in Data Streams

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## Abstract

Detecting events in data streams can be difficult, especially if the definition, content, or properties of an event change over time.

This bachelor thesis focuses on the development and evaluation of an online clustering solution in which events are defined either as changes in existing clusters or as the formation of new clusters. The solution is a text mining software, which receives new news articles over a data stream and processes them. Articles are assigned to different clusters due to their similarity to other articles. The assumption is that very similar articles write about the same news story. In addition, the evaluation of the clustering quality is measured with a custom scoring function.

The first part of this work consists of determining a suitable data set, which will be the subject of the clustering and provides the ground truth for evaluating the results. The implemented solution uses HDBSCAN as the clustering method and compares it with the state-of-the-art method $k$-means. It turned out that the use of HDBSCAN has advantages over $k$-means in terms of both performance and precision. Furthermore, various text preprocessing methods and vector space models are evaluated, with text lemmatization and tf-idf providing the most promising results. Once applied in a simulated online setting, the final evaluation found that the noise rate in the overall clustering reduces the precision in the event detection.

The resulting precision of the clustering is 72% with a standard deviation of 12%. The precision for detecting new events results in 62% with a standard deviation of 43%. Detecting changes in existing events results in a precision 69% with a standard deviation of 16%. A continuation of this work should focus on improving the overall clustering to increase the precision of the event detection.

## Preface

The following bachelor thesis *Dynamic Event Detection in Data Streams* was written as part of our computer science studies at the ZHAW Zurich University of Applied Sciences.

After our lectures on artificial intelligence, we realized that we wanted to deepen our knowledge in this area. This thesis was the perfect opportunity to increase our expertise on topics such as natural language processing and cluster analysis.

Special thanks go to our two supervisors, Dr. Andreas Weiler and Prof. Dr. Kurt Stockinger, for their ongoing and effective support during the writing of this thesis.

We would also like to thank our two lecturers Prof. Dr. Thilo Stadelmann and Prof. Dr. Mark Cieliebak for their lectures on artificial intelligence.

At last but not least, we would like to thank our fellow students and the entire ZHAW staff for our great time at ZHAW.

Daniel Milenkovic and David Pacassi Torrico

# Contents

# 1 Introduction

## 1.1 Problem Formulation

How can events be recognized in a data stream? While searching for events in a data stream, the definition of an event is not always clear. Providing static definitions, as most approaches do, does not suffice for dynamic data streams, which change over time. Additionally, the behaviour of the data stream is an important factor in itself, since blockages of overflows in the system have to be prevented.

An example for a dynamic data stream can be found in a stream of news articles, which are published in irregular time intervals and different quantities over time. Thus detecting events based on an incoming stream of news articles is a challenging task.

The goal is to develop and evaluate a methodology to detect events in a dynamic stream of news articles.

## 1.2 Motivation

Today's environment is rapidly changing. With more devices being digitalized and connected to the internet, we are starting to have incredible amounts of data. Every smartphone, smartwatch and many other Internet of Things (IoT) devices start tracking every sensor data they record.

There is and will be no way to process all this data manually. This is where our work becomes relevant. We will try to detect events from a data stream, even when new and unknown events arise.

Our solution is based on text data, so any data in text form should be applicable. With technologies such as speech recognition, the data could also initially be acoustic and converted to text before being entered into our application.

That would open up use cases with smart speakers such as *Amazon Echo* or *Google Assistant*.

# 2 Related Work

Text based event detection is a diverse field and with increasingly large amounts of available information online a compelling topic for research. With the popularity of social media a lot of research around event detection has been done on micro blogs[1] such as Twitter[2], [3]. However, this thesis focuses on news articles as the primary data source. Text based clustering as a technique for event detection has already been explored with different approaches such as using custom methods based on neural networks[4] or by using a modified version of DBSCAN to account for its sensitivity for differences in cluster densities[5]. Based on the promising results with DBSCAN, we want to further explore text clustering using its successor HDBSCAN[6] and apply it in an online setting. Regarding the clustering validation, there has already been research into recognizing biases of different scoring functions[7] and developing custom scoring functions as a result[8].

TODO add related work for preprocessing

# 3 Theoretical Basics

In order to fully understand our work, it is important to ensure a few basics in the area of Natural Language Processing (NLP). In this chapter we will explain how the most important techniques used in our thesis work.

## 3.1 Text Preprocessing

When working with text data, many algorithms and methods will need to distinguish words from another. In most cases this is done by creating a dictionary of all known words and *vectorizing* the text data according to the dictionary.

While this works well in theory, we deal with tremendous amount of data in real world applications. This results in huge directories with many vector dimensions and does not only take up more disk space but also more text processing *(computation and comparison)* time.

What does that mean? Consider the following words:

- switzerland
- Switzerland
- SWITZERLAND

Anyone of us will be able to extract the same information out of these three words: The country *Switzerland*. However, for machines the terms are different to another because they are written differently. That is why in most cases it makes sense to lowercase all text data before processing it. That way we can ensure that the above words also share the same meaning for a machine and thus reduce the dictionary size.

**Exceptions** There are a few use cases where lowercasing a text is not desired. For example, when trying to detect the writer's sentiment. Someone who would write a few or all words of a sentence in all uppercase might be angrier than someone who does not.

**Reducing the dictionary size** Lowercasing text is just the beginning though. Depending on the size of a document, it might make sense to not use all text data inside a document. A good example for this would be books. Vectorizing books would take too much computational power and time to process. In such cases, the dictionary size needs to be reduced. This can be accomplished by processing a summary of the book instead of the book itself or by extracting the most relevant words from the whole book. Later can be done with Keyphrase Extraction or with Named Entity Recognition (NER).

**Normalizing text** If we are not dealing with books but with articles or papers, there are also other alternatives to Keyphrase Extraction and NER. Using Text Stemming (Section 3.1.3) or Text Lemmatization (Section 3.1.4), we can simplify terms and group them together to reduce the dictionary size.

### 3.1.1 Keyphrase Extraction

When having to describe data, one common approach is to tag the data with Keyphrases. Two of the most well-known tagging methods in social media are tagging content with Keyphrases marked with hash tags and user names marked with at signs. Let us check following Tweet from the *European Space Agency*[9]:

> This walking and hopping #**robot** is currently being tested in ESA's Mars Yard at our **@ESA_Tech** centre in the Netherlands. SpaceBok is a quadruped robot designed by a Swiss student team from **@ETH** and **@ZHAW**.

If we only read the hash tags and user names *#robot*, *@ESA_Tech*, *@ETH* and *@ZHAW*, we do not retrieve all information but we can already think of what the Tweet is about. These words would be our *Keyphrases*.

Now, in above example the Keyphrases were defined manually by a user. But in our data set (and most data sources), there are no Keyphrases defined. Luckily there are different approaches on how to extract Keyphrases from text data automatically.

We are using SGRank[10] in our thesis as it is currently one of the most used Keyphrase Extraction algorithms. Our goal is to check if working with Keyphrases alone is more, less or equal accurate than with working the whole text.

Since the dictionary size would be smaller, the data processing time could be improved.

### 3.1.2 Named Entity Recognition

Similar to *Keyphrase Extraction*, NER extracts relevant terms from a given text. However, it does not only extract terms but also states what kind of term it is. Consider following sentence:

> CERN in Geneva pays tribute to Murray Gell-Mann, who won the Nobel Prize in Physics in 1969.

When using spaCy's NER model, which is based on a transition-based Convolutional neural network (CNN)[11], we retrieve following entities:

- CERN (Organisation)
- Geneva (Location)
- Murray Gell-Mann (Person)
- the Nobel Prize in Physics (Work of art)
- 1969 (Date)

For comparison, when extracting the *Keyphrases* automatically, we receive following terms:

- Nobel Prize
- Murray Gell
- tribute
- Mann
- Geneva
- Physics
- CERN

Comparing the numbers of the extracted terms solely, Keyphrase Extraction seems to have delivered a better job. However, when evaluating the results, we can see that NER *understood* the terms and their relations better.

Not only was it able to correctly keep the subject's name, *Murray Gell-Mann*, but also the type of Nobel prize.

### 3.1.3 Text Stemming

Text Stemming is a form of Text Normalization which aims to simplify words by reducing the inflectional forms of each word into their word stems. For example, the words *connected*, *connecting*, *connection* share a similar meaning and could therefor be simplified to the base term **connect**.

The first paper describing a stemming algorithm was written by Julie Beth Lovins[12] as early as in 1968. In her algorithm she used an ordered list of 294 suffixes to strip them out and then applies one of 29 associated application rules followed by a set of 35 rules to check if the remaining stem has to be modified further.

Lovins' stemming algorithm was very successful but got mostly replaced by M.F. Porters stemming algorithm[13] published in 1980. In his paper, M.F. Porter was able to process his suffix stripping algorithm in 6,370 out of 10,000 words and thereby reducing the vocabulary size by **one third**. The algorithm simply follows 5 steps with replacement and/or removal rules and is therefor very easy and efficient.

M.F. Porter improved his stemming algorithm even further by publishing the Porter2 stemming algorithm[14] in 2002 which is widely known as the *Snowball stemming algorithm*.

There are even more stemming algoriths, very well known are the Lancester stemming algorithm[15] and the WordNet stemming algorithm[16]. Since M.F. Porter's snowball stemming algorithm is the most widely used one, we decided to go with his algorithm.

### 3.1.4 Text Lemmatization

Similar to *Text Stemming*, Text Lemmatization has the same goal to group together the inflected forms of a word but follows a different approach to do so. Instead of processing terms with fixed steps and defined rules, Text Lemmatization normally includes a dictionary lookup for the words and also takes in consideration to which part of a sentence a term belongs to. This results in more accurate root terms but also asks for more computational power than Text Stemming. See following table for a comparison:

| # | **Original word** | **Stemmed** | **Lemmatized** |
|---|---|---|---|
| 1 | written | written | write |
| 2 | greatest | greatest | great |
| 3 | best | best | best |
| 4 | fastest | fastest | fastest |
| 5 | highest | highest | high |
| 6 | compute | comput | compute |
| 7 | computer | comput | computer |
| 8 | computed | comput | compute |
| 9 | computing | comput | compute |
| 10 | studies | studi | study |
| 11 | studying | studi | study |
| 12 | university | univers | university |
| 13 | universities | univers | university |
| 14 | universe | univers | universe |
| 15 | universal | univers | universal |

Table 1: Comparison of Text Stemming and Text Lemmatization.

## 3.2 Vector Space Model

Comparing text documents with each other is not a straightforward task to do. This is the reason why the Vector space model (VSM) was developed.

When working with a VSM, text documents get vectorized. This is succeeded by assigning each unique term over all documents to one dimension.

When we now want to compare two documents with each other, we simply compare their vectors with each other.

But how do we vectorize each term of each document to a numerical value? Let us have a look at the two most used text vectorizers.

### 3.2.1 Term Frequency

The easiest vectorizer is the Term Frequency Vectorizer. After creating the dictionary of all used terms, it simply sums up the occurrences for each term. Consider following three sentences:

- Rosetta space probe scopes out landing zone.
- Landing site search for Rosetta narrows.
- Major Bank Shake-up At Bank of England.

After removing Stop words, we receive 13 unique terms over all documents. As the Term Frequency Vectorizer simply sums the occurences of each term up, the VSM looks as in Table 2.

| bank | england | landing | major | narrows | probe | rosetta | scopes | search | shake | site | space | zone |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 | 0.000 | 0.000 | 0.000 | 1.000 | 1.000 |
| 0.000 | 0.000 | 1.000 | 0.000 | 1.000 | 0.000 | 1.000 | 0.000 | 1.000 | 0.000 | 1.000 | 0.000 | 0.000 |
| 2.000 | 1.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 |

Table 2: Term Frequency VSM.

We can quickly see that the first two sentences share a few terms while they do not share any terms with the third sentence. At the same time we see that the term bank has been used twice in the third sentence.

### 3.2.2 tf-idf

Relying on the Term Frequency alone is a good start but can surely be improved. Consider following scenario: We have a document *d1* with 100 terms, 10 of them (10%) belong to one specific term *t1*. In a second document *d2* with 1,000 terms, 10 of them (1%) belong to the same term *t1*. When using Term Frequency as a Vectorizer, both documents will receive for the term *t1* a value of 10. However, in the first document *d1* the term should have received a higher value than in document *d2* as it covered a bigger percentage of the document.

This is what tf-idf tries to fix. Tf-idf was first introduced in 1975 by G. Salton, A. Wong and C. S. Yang[17] and defines the equation as displayed in Equation 1.

$$w_{x,y} = tf_{x,y} \cdot log(\frac{N}{df_x}) \tag{1}$$

where $tf_{x,y}$ is the Term Frequency of $x$ in $y$, $N$ the total number of documents and $df_x$ the documents containing $x$.

However, it is important to note that nowadays there are different tf-idf implementations. As we are using the scikit-learn[18] library, the tf-idf implementation[19] of the library is slightly different, see Equation 2.

$$w_{x,y} = tf_{x,y} \cdot (log(\frac{1+N}{1+df_x}) + 1) \tag{2}$$

where $tf_{x,y}$ is defined as the equal number of times that term $_x$ occurs in document $_y$.

If we now calculate the tf-idf value for the term *bank* inside the third document (sentence), we receive following value: 3.386. What scikit-learn now does is to normalize this value using the Euclidean norm:

$$v_{norm} = \frac{v}{||v||_2} = \frac{v}{\sqrt{{v_1}^2 + {v_2}^2 + \ldots + {v_n}^2}} \tag{3}$$

This results in following values in our VSM:

| bank | england | landing | major | narrows | probe | rosetta | scopes | search | shake | site | space | zone |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.000 | 0.000 | 0.335 | 0.000 | 0.000 | 0.440 | 0.335 | 0.440 | 0.000 | 0.000 | 0.000 | 0.440 | 0.440 |
| 0.000 | 0.000 | 0.373 | 0.000 | 0.490 | 0.000 | 0.373 | 0.000 | 0.490 | 0.000 | 0.490 | 0.000 | 0.000 |
| 0.756 | 0.378 | 0.000 | 0.378 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.378 | 0.000 | 0.000 | 0.000 |

Table 3: tf-idf VSM.

As we can see in Table 3, the term **bank** has in document *d3* a rather high value. This is because the term is not present in documents *d1* or *d2* but appears twice in document *d3*. We can also observe that the term **rosetta** has slightly different values for the documents *d1* and *d2*. The reason for this is that document *d2* has one term less than document *d1*, therefor the significance of one term is weighted heavier in document *d2*.

## 3.3 Clustering

Clustering finds similarities in different news articles based on their content and groups them together, while unrelated news are regarded as noise. The challenge now arises to find an appropriate clustering method, which is able to work with data of varying densities and of high dimensionality.

### 3.3.1 *k*-means clustering

*k*-means clustering is an iterative clustering method which assigns all data points in a given data set into k clusters, where k is a predefined number of clusters in the data set.

**How does *k*-means clustering work** At the very beginning, *k*-means creates k centroids at random locations. It then repeats following instructions until reaching convergence:

- For each data point: Find the nearest centroid
- Assign the data point to the nearest centroid (cluster)
- For each cluster: Compute a new cluster centroid with all assigned data points

**Advantages**

- Very simple and easy to understand algorithm

**Disadvantages**

- Initial (random) centroids have a strong impact on the results
- The number of clusters (k) has to be known beforehand
- Unable to handle noise (all data points will be assigned to a cluster)

### 3.3.2 DBSCAN

DBSCAN stands for *Density-Based Spatial Clustering of Applications with Noise* and is a density based clustering algorithm.

A big advantage of DBSCAN is that it is able to sort data into clusters of different shapes.

**How DBSCAN works** DBSCAN requires two parameters in order to work:

1. epsilon - The maximum distance between two data points for them to be considered as in the same cluster.
2. minPoints - The number of data points a neighbourhood has to contain in order to be considered as a cluster.

Having these two parameters defined, DBSCAN will iterate through the data points and try to assign them to clusters if the provided parameters match. If a data point can not be assigned to a cluster, it will be marked as noise point.

Data points that belong to a cluster but do not dense themselves are known as **border points**. Some border points could theoretically belong to two or more clusters if the distance from the point to the clusters do not differ.

**Advantages**

- Does not need to know the number of clusters beforehand.
- Is able to find shaped clusters.
- Is able to handle noise points.

**Disadvantages**

- DBSCAN is not entirely deterministic.
- Defining the right epsilon value can be difficult.
- Unable to cluster data sets with large differences in densities.

### 3.3.3 HDBSCAN

HDBSCAN is a hierarchical density-based clustering algorithm[6], based on DBSCAN and improves its sensitivity for clusters of varying densities. Therefore defining an epsilon parameter, which acts as a threshold for finding clusters, is no longer necessary. This makes the algorithm more stable and flexible for different applications.

**How HDBSCAN works** Since HDBSCAN is the focus for this thesis, we want to give a more detailed explanation of its inner workings, than for $k$-means or DBSCAN.

HDBSCAN only requires one parameter to be set beforehand:

1. minPoints - The number of data points a neighbourhood has to contain in order to be considered as a cluster.

The algorithm consist of five steps, which are as follows:

**1. Transforming the space** At its core HDBSCAN is a single linkage clustering, which are typically rather sensitive to noise. A single noise point between clusters could act a bridge, which would result in both clusters to be seen as one. To reduce this issue, the first step is to increase the distances of lower density points. This is achieved by to comparing the core distances between two points with the original distance to get the the mutual reachability distance. The core distance $core_k(x)$ is defined as the radius of a circle around point $x$, so that $k$ neighbours are contained within this circle. TODO describe example in Figure 1.

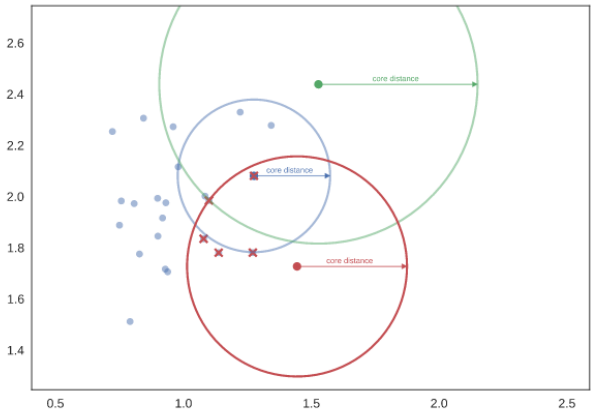



Figure 1: The core distances for three points shown as circles. Source[20]

Once the core distances are known, the mutual reachability distance between two points is defined as follows:

$$d_{mreach}(a,b) = max\{core_k(a), core_k(b), d(a,b)\}$$

where $d(a,b)$ is the original distance between $a$ and $b$. Therefore if two points are close together, but the density around one point is rather low, the core distance will be greater than the original distance and thus the two points appear to be less close together when considering the mutual reachability distance.

**2. Build the minimum spanning tree** Based on the mutual reachability distances, the next step is to find points close to each other. This is done by creating a minimum spanning tree, where edges are weighted according to the mutual reachability distance and a point is represented by a vertex. The minimum spanning tree is created one edge at a time, always choosing the lowest distance to a vertex not yet in the tree. This is done until each vertex is connected, which results in the minimal set of edges, such that dropping any edge will cause the disconnect of one or more vertices from the tree.

**3. Build the cluster hierarchy** Once the minimum spanning tree is complete, it is converted into a hierarchy of connected clusters, by sorting edges of the tree by distance and iterate through, creating a new merged cluster for each edge. The dendogram in Figure 2 shows a possible cluster hierarchy.

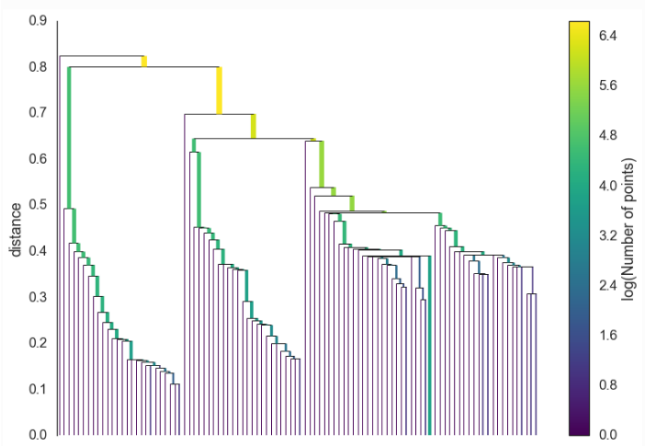



Figure 2: The cluster hierarchy shown as a dendogram. Source[20]

At this stage we have to flatten the hierarchy to get the final clusters, which provide the best representation of the current data set. DBSCAN simply cuts through the hierarchy using a fixed parameter, usually called epsilon, to get the final clusters. This approach does not work well with clusters of varying densities and the epsilon parameter itself is unintuitive, requiring further exploration to find optimal values. This is were HDBSCAN improves upon DBSCAN, by taking additional steps for finding relevant clusters.

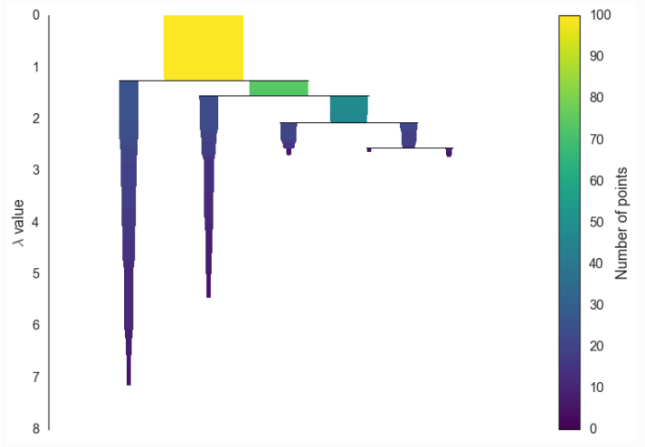



Figure 3: Condensed cluster hierarchy. Source[20]

**4. Condense the cluster tree** The fourth step consists of condensing the previously built cluster hierarchy into a smaller tree. The process starts at the top where all vertices still belong to the same cluster. Iterating through the hierarchy, for each split the two resulting clusters are compared against a predefined minimum cluster size. If the size of a cluster is below the minimum, its points will be discarded, while the other cluster remains in the parent cluster. If both cluster sizes are above or equal the minimum, the clusters are considered as true clusters. This is repeated until no more splits can be made.

**5. Extract the clusters** The extraction of the final clusters from the condensed tree is based on the stability per cluster and once it is selected, none of its subclusters can be chosen. The stability is

based on the persistence of a cluster, which is measured by $\lambda = \frac{1}{distance}$. The stability for a cluster $C$ is defined as

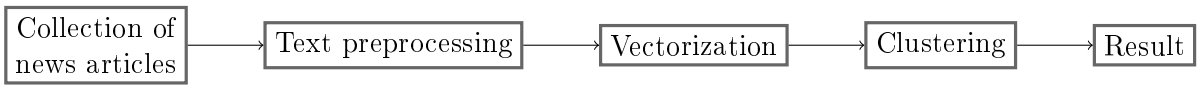
$$\sum_{p \in \mathrm{C}}^{|C|} (\lambda_p - \lambda_{birth}) \tag{4}$$

where $\lambda_p$ describes when point $p$ fell out of the cluster and $\lambda_{birth}$ describes when the cluster was created. Now calculating the stability for each cluster starts at the leaf nodes and ends when the root is reached. A cluster is selected if its stability is larger the sum of stabilities of its children. If the sum child stabilities is larger than that of its parent, the parent stability will be set to the value of the sum of its children, but no selection will be done. Based on this approach the final clusters will be selected, with regards to varying densities and noise.

# 4 Design and Implementation

The methodology consist of three parts, where each part builds upon the results from the previous one. Initially the test data is created, which will be used for all evaluations. Once the data is available, we evaluate HDBSCAN and determine the settings, which lead to optimal results regarding our specific use case. The final part applies the results obtained from the previous evaluation in an online setting.

## 4.1 Dataflow




TODO describe

## 4.2 Data Set

Before any clustering method can be implemented or evaluated, it is important to rely on the right data set for training and evaluation.

### 4.2.1 Data Set Candidates

As our goal is to detect events in data streams, we have evaluated different data sets and their possibilities to extract events from their data themselves.

| Data set | Number of rows | Description |
|---|---|---|
| GDELT 2.0 | 575,000,000+ | Print and web news from around the world. |
| ChallengeNetwork | 4,449,294 | Network packages including anomalies. |
| One Million Posts Corpus | 1,011,773 | User comments to news articles. |
| Online Retail Data Set | 541,909 | Customer retail purchases of one year. |
| News Aggregator Dataset | 422,937 | Clustered news articles. |
| Dodgers Loop Sensor Data Set | 50,400 | Number of cars driven through a ramp. |
| 10k German News Articles | 10,273 | German news articles. |

Table 4: Evaluated data set candidates ordered by data set size.

We could extract events from all data sets mentioned in Table 4.
The extracted events could be as follows:

- Network packages
  - Cyber attacks depending on suspicious packets.
- User comments
  - Change of public opinion during time.
- Retail purchases
  - Change of purchasing behavior based on product choices.
- Traffic
  - Traffic changes due to baseball games.
- News articles
  - Development of a certain news story.

However, from above data sets only two contained prelabeled events:

1. Dodgers Loop Sensor Data Set
   - 81 labeled events.
2. News Aggregator Dataset
   - 422,937 labeled events.

As we did not want to lose too much time in manually clustering data, we have decided to go with one of these two. Regarding our two options, our choice was simple:
We went for the **The News Aggregator Dataset** since it not only provided more data, but our work built on the news articles use case could later be continued with real live data. The **GDELT 2.0** data set for example, provides around 1,000 to 2,000 new news articles every 15 minutes.

### 4.2.2 Data Retrieval

Unfortunately the data set did not contain the news articles themselves but rather only the URL's to the news articles. This was done so due to copyright restrictions on the content. Fortunately there are web scraping tools designed to retrieve the content from news articles specifically. We decided to use Newspaper3k[21], a Python3 library that allows us to retrieve the text from news articles easily.

The library only requires an URL to download and extract the news article from a website, see following example:

```
from newspaper import Article

url = 'http://fox13now.com/2013/12/30/new-year-new-laws-obamacare-pot-guns-and-drones/'
article = Article(url)
article.download()
article.text # Contains the article's text.
```

Listing 1: Retrieve the news article from an URL.

All we had to do now is to run this code for all news articles. To speed this process up, we have loaded the data set into a database and run 8 concurrent processes which retrieved the news articles content from the web in different batches.

### 4.2.3 Data Cleansing

The data set contains news articles collected from March 10th to August 10th of 2014. Five years later, many resources are not online anymore or are not accessible from Europe due to GDPR. We have used following SQL query to filter out news articles that were most likely corrupt:

```
SELECT *
FROM news_article
WHERE
    newspaper_text IS NOT NULL
    AND TRIM(COALESCE(newspaper_text, '')) != ''
    AND hostname NOT IN ('newsledge.com', 'www.newsledge.com')
    AND newspaper_text NOT LIKE '%GDPR%'
    AND newspaper_text NOT LIKE '%javascript%'
    AND newspaper_text NOT LIKE '%404%'
    AND newspaper_text NOT LIKE '%cookie%'
```

```
11          AND newspaper_keywords NOT LIKE '%GDPR%'
12          AND newspaper_keywords NOT LIKE '%javascript%'
13          AND newspaper_keywords NOT LIKE '%404%'
14          AND newspaper_keywords NOT LIKE '%cookie%'
15          AND title_keywords_intersection = 1
```

Listing 2: Retrieve valid news articles.

## 4.3 Clustering Evaluation

### 4.3.1 Design

The goal of the clustering evaluation is to find the optimal parameters and preprocessing methods for applying HDBSCAN in an online setting. Therefore the clustering evaluation is designed to run HDBSCAN on our test data, using a combination of different text processing methods, vector space models and parameters. $k$-means is used to provide a benchmark for HDBSCAN evaluation. Once a clustering has been performed, the result is measured based on the ground truth and stored in a database for later analysis.

An important consideration is the variety of samples to use for a clustering run. Using only a single set of samples might bias the score against this specific set of samples and some methods might perform better or worse depending on the samples. To introduce variability, while still retaining repeatability, an evaluation run will be repeated multiple times. Each repetition will load a new set of sample, iterating linearly through the data set. For example if we define the number of repetitions as two with a sample size of 1000, the evaluation will first be done on the first 1000 samples with all possible settings and the second run will load the next 1000 samples, thus containing sample with indices ranging from 1001 to 2000. The reason we do not load random sets of samples is repeatability. If we make any changes in the implementation or the scoring function, we want to be able to compare the new results with the previous ones in a deterministic manner.

### 4.3.2 Scoring Function

The scoring function is essential for measuring the result of a clustering method. The score should reflect the quality of the individual clusters and of the clustering as a whole. The number of existing measures for clustering is vast and can be split into two main categories. Internal measures determine the score based on criteria derived from the data itself and external measures depend on criteria non-existent in the data itself such as class labels. Since the ground truth is known in our test data, we are going to apply an external measure.

Initially we used Normalized Mutual Information (NMI) as our primary scoring function. The NMI is an entropy-based measure and tries to quantify the amount shared information between the clusterings. The score proved to work well for our initial evaluations, but upon closer inspection certain anomalies were found. An example is given in Table 5, where $k$-means achieved a rather high score, regardless of the large difference between the true amount of clusters and the approximation using $\sqrt{n}$. We were not able to explain this behaviour, although there are multiple papers about the selection bias of NMI for higher numbers of clusters[22], [23]. Other scoring functions such as V-Measure or the Adjusted Rand Index showed similar unexpected results with different clusterings. Therefore we decided to develop our own scoring function based on the ideas of Maximum Matching[24] and the Jaccard Index, which we call MP-Score.

**Calculating the score** The scoring function first calculates the similarity between pairs of clusters, where each cluster belongs to a different clustering. We use the Jaccard Index to measure the similarity, which is defined as

| **Algorithm** | **Sample Size** | **NMI** | $\mathbf{n_{true}}$ | $\mid \mathbf{n_{true}} - \mathbf{n_{predicted}} \mid$ |
|---|---|---|---|---|
| $k$-means | 19255 | 0.754 | 600 | 457 |
| HDBSCAN | 19255 | 0.742 | 600 | 2 |

Table 5: $k$-means has a higher NMI score than HDBSCAN, while having a much larger difference in number of clusters.

$$\frac{|A \cap B|}{|A \cup B|} \tag{5}$$

To illustrate the process we start with an example. We use $T$ and $C$ as our clusterings, where $T$ is the ground truth and $C$ is the predicted clustering. The clusterings are defined as follows:

$$T = \{\{1,2,3\},\{4,5,6,7\},\{8,9\}\}$$
$$C = \{\{1,2\},\{3,4,5,6\},\{7\},\{8,9\}\}$$

We calculate the similarity as defined in Equation 5, for each possible pair between $T$ and $C$ starting with $t_1 = \{1,2,3\}$ and $c_1 = \{1,2\}$:

$$similarity(t_1, c_1) = \frac{|t_1 \cap c_1|}{|t_1 \cup c_1|} = \frac{|\{1,2\}|}{|\{1,2,3\}|} = \frac{2}{3} = 0.667$$

After doing this for each possible pair we get the similarity matrix $A$:

$$A = \begin{pmatrix} similarity(t_1,c_1) & \dots & \dots & similarity(t_1,c_4) \\ \vdots & \vdots & \vdots & \vdots \\ similarity(t_3,c_3) & \dots & \dots & similarity(t_3,c_4) \end{pmatrix} = \begin{pmatrix} 0.667 & 0.167 & 0 & 0 \\ 0 & 0.6 & 0.25 & 0.4 \\ 0 & 0 & 0 & 1.0 \end{pmatrix}$$

As a next step we have to select the most relevant similarity values from each row of the similarity matrix.

Finding relevant values in the similarity matrix is non-trivial, since clusters do not share labels across different clusterings. To solve this, we make two assumptions based on the principle of Maximum Matching:

1. The higher the similarity between two clusters, the more likely it is, that both clusters are describing the same group of documents.
2. Each cluster can be associated with a cluster from another clustering only once.

Based on those assumptions we select the highest similarity value per row, whose column is not already associated with another row. Applying this selection function $f$ to our previously calculated similarity matrix $A$ results in the set containing the most relevant similarity values.

$$f(A) = \begin{pmatrix} \mathbf{0.667} & 0.167 & 0 & 0 \\ 0 & \mathbf{0.6} & 0.25 & 0.4 \\ 0 & 0 & 0 & \mathbf{1.0} \end{pmatrix} = \{0.667, 0.6, 1\}$$

As we can see, there were no collisions between columns and we simply get the highest value per row. Consider the following example with a different similarity matrix $B$, which does contain a collision:

$$f(B) = \begin{pmatrix} \mathbf{0.75} & 0.375 & 0.427 & 0.375 \\ 0.4 & \mathbf{0.667} & 0.571 & 0.8 \\ 0.333 & 0.25 & 0.4 & \mathbf{1.0} \end{pmatrix} = \{0.75, 0.667, 1\}$$

The selected similarity for the second row is 0.667 instead of 0.8. This is because the fourth column is already associated with the third row, while having an similarity greater than 0.8. Therefore based on our assumption that clusters cannot be associated twice, the second highest similarity is used for the second column. In case no association could be found, the value would be set to zero.

As a third step we have to calculate the weights to be used for the weighted average. The weight is based on the number of elements inside the cluster and necessary to represent differences in predicted and true number of clusters in the final score. It is defined as follows:

$$w_{ij} = \frac{|t_i| + |c_j|}{|T| + |C|} \tag{6}$$

where $T$ is the ground truth with $t_i \in T$ and $C$ the predicted clustering with $c_j \in C$. Therefore the weight for a pairing $t_i c_j$ includes both the size of the true cluster and the size of the predicted cluster. The reason both sizes are used, is that we want to reflect the difference between the number of predicted clusters and the ground truth. Using only the true number of elements as the weight, would affect the score if $|C| < |T|$, but not $|C| > |T|$. Hence the number of predicted elements has to be included into the weight.

To continue our example, we have to calculate the weights based on the coordinates of the selected values from our similarity matrix $A$. The coordinates are $(1,1), (2,2), (3,4)$. As a result we calculate the following weights:

$$\begin{aligned} w_{1,1} &= \frac{|t_1| + |c_1|}{|T| + |C|} = \frac{3+2}{9+9} = \frac{5}{18} = 0.278 \\ w_{2,2} &= \frac{|t_2| + |c_2|}{|T| + |C|} = \frac{4+4}{9+9} = \frac{8}{18} = 0.444 \\ w_{3,4} &= \frac{|t_3| + |c_4|}{|T| + |C|} = \frac{2+2}{9+9} = \frac{4}{18} = 0.222 \end{aligned}$$

In the fourth and final step we calculate the weighted average

$$\text{MP-Score} = \sum_{i=0}^{|S|} w_i s_i \{w_i \in W \wedge s_i \in S\} \tag{7}$$

where $S$ contains the selected values from the similarity matrix with $s_i \in S$ and $W$ is the set of weights with $w_i \in W$. Using our previously selected similarity values $S = f(A) = \{0.667, 0.6, 1\}$ and the corresponding weights $W = \{0.278, 0.444, 0.222\}$, the calculation for the final average would be done as follows:

$$\text{MP-Score} = (0.278 \cdot 0.667) + (0.444 \cdot 0.6) + (0.222 \cdot 1) = \mathbf{0.674}$$

The final score for the evaluation of the predicted cluster $C$ with the true cluster is 0.674. The complete implementation of the scoring function can be found in the appendix as 6.

**Comparison against other measures** The test scenarios in Table 6 show the resulting scores of our similarity score, NMI and ARI. The second scenario results in a ARI score of 0.308, while the NMI with 0.564 and the MP-Score with 0.637 are both higher. Intuitively we would assume the higher score to better represent the predicted clustering, since the number of clusters is correct and only two out of nine elements are assigned to the wrong cluster. Scenario six shows a similar case. Scenarios four and especially five show the previously mentioned bias of NMI with regards to higher numbers of clusters. The seventh scenario gives an interesting result, where both NMI and ARI result in zero while the MP-Score results in 0.321. The relatively high MP-Score is because a true cluster with four elements is matched with the predicted cluster containing nine elements. This result in a similarity of 0.444, which is then lowered by the weight. The NMI does not infer any entropy, since every element ends up in the same cluster independently from the ground truth. The ARI results in zero because of its adjustment for chance. Overall the MP-Score behaves rather intuitively, although it is not corrected for randomness. This means even a completely random clustering would result in a MP-Score greater than 0, while an adjusted measure such as the ARI would be 0 in such a case.

| **Test scenarios with ground truth** $T = \{\{1,2,3\},\{4,5,6,7\},\{8,9\}\}$ | | | | |
|---|---|---|---|---|
| Nr. | Predicted Clustering $C$ | NMI | ARI | MP-Score |
| 1 | $C = \{\{1,2,3\},\{4,5,6,7\},\{8,9\}\}$ | 1.0 | 1.0 | 1.0 |
| 2 | $C = \{\{1,2\},\{3,4,5,6\},\{7,8,9\}\}$ | 0.564 | 0.308 | 0.637 |
| 3 | $C = \{\{1,2,3\},\{4,5,6\},\{7\},\{8,9\}\}$ | 0.895 | 0.771 | 0.847 |
| 4 | $C = \{\{1,2,3\},\{4,5\},\{6,7\},\{8\},\{9\}\}$ | 0.821 | 0.591 | 0.583 |
| 5 | $C = \{\{1\},\{2\},\{3\},\{4\},\{5\},\{6\},\{7\},\{8\},\{9\}\}$ | 0.651 | 0 | 0.227 |
| 6 | $C = \{\{1,2,3,4,5\},\{6,7,8,9\}\}$ | 0.434 | 0.182 | 0.433 |
| 7 | $C = \{\{1,2,3,4,5,6,7,8,9\}\}$ | 0.0 | 0 | 0.321 |
| 8 | $C = \{\{7,2,4\},\{8,9,6,3\},\{1,5\}\}$ | 0.219 | -0.108 | 0.392 |

Table 6: Direct comparison of different scoring functions

As a final note, repeating the evaluation shown in Table 5 a second time using the MP-Score, the score (Table 7) for $k$-means is much lower than HDBSCAN. This reflects what we would expect based on the big difference in the amount of predicted clusters.

| **Algorithm** | **Sample Size** | **Similarity** | $\mathbf{n_{true}}$ | $\mid \mathbf{n_{true}} - \mathbf{n_{predicted}} \mid$ |
|---|---|---|---|---|
| $k$-means | 19255 | 0.137 | 600 | 457 |
| HDBSCAN | 19255 | 0.605 | 600 | 2 |

Table 7: The similarity score reflects the difference in number of predicted clusters.

### 4.3.3 Implementation

The evaluation process is done with our own evaluation framework. The framework allows for automated and repeatable evaluation runs. Results are stored in a database for later analysis. The main features include:

- Defining the number of stories to run the evaluation with and load all news articles from those stories.

- Repeating evaluation runs with different sets of data.
- Providing different vector space models for converting the textual data into a vector space model.
- Defining a range for each parameter of a clustering method and running it with each possible combination of those parameters.
- Storing the result the result in a database and creating relations between news articles, clusters and evaluation runs. This allows for manual inspection and analysis of individual articles inside a predicted cluster.

The implementation is done with Python. Clustering methods and vector space models are provided by the scikit-learn library[18], while the specific HDBSCAN implementation is provided by a scikit-learn-contrib package[6]. scikit-learn-contrib is a collection of high quality third-party projects compatible with scikit-learn. We decided to use scikit-learn because of its rich documentation, the wide range of tools and algorithms it provides for clustering and our previous experience with it. Additionally the framework runs in a fully dockerized environment, which includes the database. This allows the framework to run independently from the underlying host, as long as the host supports docker. This principle was useful for developing and testing the framework in a local environment and deploying it on a remote server for long running evaluations, without worrying about setting up and installing all dependencies again.

**Defining cluster parameters** The parameters for each available clustering method are defined beforehand in a dictionary as can be seen in 3. Parameters are defined as a list of possible variations. For example if we want to run HDBSCAN with two different metrics *cosine* and *euclidean*, we define the metric parameter as "metric": ["cosine", "euclidean"]. When running a clustering method, it will be executed with each possible combination of parameters. This means a single evaluation of HDBSCAN, will include 16 different runs, since there are two different metrics and eight different options for *min_cluster_size*. This is important to consider for running clustering methods with long processing times or running evaluations on large sample sizes.

```
parameters_by_method = {
    self.kmeans: {
        "n_cluster": ["n_square", "n_true"]
    },
    self.hdbscan: {
        "min_cluster_size": range(2, 10),
        "metric": ["cosine", "euclidean"]
    },
    self.meanshift: {"cluster_all": [True, False]},
    self.birch: {
        "branching_factor": range(10, 100, 10),
        "threshold": range(2, 6),
    },
    self.affinity_propagation: {
        "affinity": ["euclidean"],
        "convergence_iter": [15],
        "damping": np.arange(0.5, 0.9, 0.1),
        "max_iter": [50, 100, 200, 500],
    },
    self.spectral_clustering: {
        "affinity": ["rbf"],
        "assign_labels": ["kmeans", "discretize"],
    },
}
```

Listing 3: Predefined parameters for different clustering methods

**CLI** The evaluation framework provides a command line interface to start evaluation runs and specify a number of settings. 4 shows the full interface.

```
usage: cluster_evaluation_framework.py [-h] [--rows ROWS] [--stories STORIES]
                                       [--methods METHODS]
                                       [--vectorizers VECTORIZERS]
                                       [--tokenizers TOKENIZERS] [--runs RUNS]

Run different clustering methods, with a variety of different settings.
data_mining
optional arguments:
  -h, --help            show this help message and exit
  --rows ROWS           number of samples to use for clustering
                        default: 1000
  --stories STORIES     number of stories to load samples from. This parameter
    overrides the rows parameter if set.
  --methods METHODS     options: kmeans, hdbscan, meanshift, birch,
    affinity_propagation, spectral_clustering
                        default: all available options
  --vectorizers VECTORIZERS
                        options: CountVectorizer, TfidfVectorizer
                        default: all available options
  --tokenizers TOKENIZERS
                        options: newspaper_text, text_keyterms, text_entities,
    text_keyterms_and_entities, text_lemmatized_without_stopwords,
    text_stemmed_without_stopwords
                        default: all available options
  --runs RUNS           number of runs per clustering method
                        default: 1
```

Listing 4: Command line interface for the evaluation framework

## 4.4 Online Clustering

### 4.4.1 Design

Detecting events in a stream of news articles will be achieved by using an online clustering approach. An event is described by the occurrence of multiple news articles about the same story. The events of interest for this application are the discovery of new stories and the extension of existing stories. Thus we define our two types events as follows:

- New event: A new cluster of news articles appears in the data stream, which describe the same story.
- Event extended: An existing story is extended by additional news articles.

HDBSCAN will be applied as the clustering method, using the optimal settings discovered in the clustering method evaluation. Additional preprocessing of news articles before clustering is going to be explored as part of evaluation as well and will be implemented accordingly for the online clustering.

The clustering will be done batchwise over time, since HDBSCAN only supports static data sets. Events are detected by comparing clusters from successive batches. Figure 4 illustrates this with three batches, where the resulting clusters from batch $t$ will be compared the previous result from batch $t-1$, while batch $t-1$ was previously compared with batch $t-2$. In this example each batch only contains samples from a limited time period, where $\triangle t$ stands for the time period between batches. Since a batch does not contain the full set of samples, we have to consider the overlap between batches. The size of the overlap is essential to find similar clusters different batches. If a similar cluster already exists

in the previous batch the differences between these clusters are detected as a change in an existing event. If no pair exists for a cluster from a current batch, this cluster will be regarded as a new event. The similarity between clusters is based on the same assumptions as for the scoring function described in Section 4.3.2.

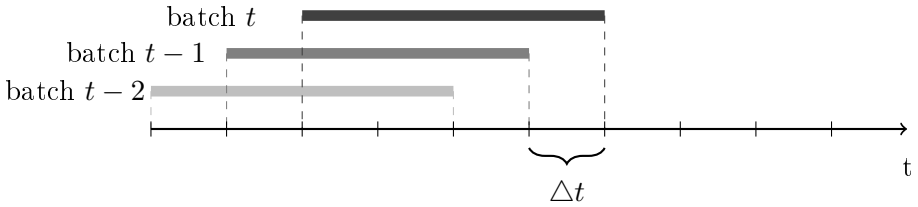



Figure 4: Timeline showing the sliding window approach

The overlap between batches depends on the batch size and the number of new samples in $\triangle t$. A high volume of incoming samples combined with a small batch sizes would result in an overlap too small to find pairs of clusters will. All clusters from the current batch will be detected as new in this case. To decrease the negative impact on the event detection by peaks in the data stream, we need a batch size which grows accordingly. The ideal batch size therefore provides enough overlap between batches to find pairs of clusters and small enough to allow for efficient processing. We explore three different methods for determining the ideal batch size:

1. **Fixed size**: The first method uses a fixed batch size, where each batch processes the most recent $n$ samples. This makes the clustering unstable against sudden peaks in the volume of incoming data, but we consider this method as useful benchmark for dynamic methods.
2. **Size by hours**: This method uses a dynamic batch size by loading the samples from the last $n$ hours. This enables the batch size to increase and decrease with the volume of the data stream. The number of samples will be limited by an upper bound, to keep the space and time consumption of the clustering method reasonable.
3. **Size by incoming data**: This method defines the batch size relative to the incoming data. We count the number of new samples since the last batch and multiply it by a predefined factor. For example we want the new samples to be 1% of the overall clustering and therefore define the factor as 100. The batch size will be limited by a lower and an upper bound. The lower bound prevents the overlap between batches from getting too small. The upper bound is based on the same reasoning as mentioned in the previous method.

The evaluation will use the MP-Score to measure the precision of the event detection, since our model represents an event as a cluster. True events can be extracted directly from the ground truth based on news articles from two successive batches.

### 4.4.2 Implementation

The online clustering implemented for this thesis does not operate in a true online setting, but rather it takes our existing test data and simulates a data stream over time. The simulated approach allows us to directly compare the resulting events with the ground truth and thus evaluate different settings. The implementation is done with Python and runs in a similar dockerized environment as the evaluation framework.

**Comparing clusters** To detect events between batches of clusterings, we have find pairs of clusters describing the same story. This problem is solved in the evaluation framework as part of the scoring function, by calculating the similarity for each possible cluster pair. The resulting time complexity is $O(n^2)$, which we deemed acceptable for the static evaluation. However in a dynamic setting such

as the online clustering, performance is an important factor, since it restricts the lengths of the time delta between batches and the overall batch size. Thus we decided to use Locality-Sensitive Hashing (LSH)[25] to find similar clusters. This reduces the time complexity to $O(log(n))$. The implementation for LSH is provided by the datasketch library[26].

**Detecting events** Once we have found pairs of clusters, which represent the same story, detecting events becomes trivial. For each pair we look for news articles, which are only present in the new cluster. These articles are then summarized in as an extension of an existing event. Clusters from the new batch without a matching cluster from the previous batch are seen as new events.

**Measuring the quality of events** Since events are themselves clusters of news articles, we apply the MP-Score to measure detected events against events taken from the ground truth. This gives an indication if the detected events contain the same news articles as true events and thus the rate of false positives and false negatives. Calculating the score is $O(n^2)$, but since the application runs on a simulated timeline, time complexity is only a minor concern.

**CLI** The application provides a command line interface to run the simulation with different parameters such as the start date, number of days to run and the batch size.

```
usage: online_clustering.py [-h] [--verbose] [--persist_in_db] [--rows ROWS]
    [--hours HOURS] [--factors FACTORS] --date DATE
    [--run_n_days RUN_N_DAYS] [--threshold THRESHOLD]

Run the batchwise clustering over a simulated stream of news articles.

optional arguments:
-h, --help              show this help message and exit
--verbose               default: False
--persist_in_db         default: False
--rows ROWS             numbers of samples to process per batch
--hours HOURS           numbers of hours to load samples
--factors FACTORS       factor to use for relative batch sizes
--date DATE             start date
--run_n_days RUN_N_DAYS number of days to run the batchwise clustering
                        default: 1
--threshold THRESHOLD   similarity threshold for cluster matching
                        default: 0.75
```

Listing 5: Command line interface for the online clustering

# 5 Results

## 5.1 Clustering Evaluation

The goal of this evaluation is to measure the precision of HDBSCAN, with different parameters and preprocessing methods. The most suitable settings will then be used for the online clustering approach to detect events in a news stream. The precision is be measured with the MP-Score.

### 5.1.1 Setup

**Text preprocessing** The first step in working with text is to apply preprocessing techniques for improving the quality of the data before clustering it. We look the five different preprocessing methods as described in Section 3.1 and evaluate each. The methods are:

- Full text with stop word removal
- Keyphrase Extraction
- NER
- Text Lemmatization
- Text Stemming

**Text vectorization** Before the text can be clustered, it has to be transformed into a vector space model. We look at two different models:

- Word Frequency
- tf-idf

**Parameters** HDBSCAN has a range of parameters, which can be tuned to fit our data set. We focus on the two primary ones:

- Min cluster size: The minimum size of a cluster. We run the evaluation with a range from two to nine as the $min\_cluster\_size$.
- Metric: The distance measure between points. We apply the metrics "cosine" and "euclidean".

The primary parameter for $k$-means is the number of clusters. Since $k$-means is used as a benchmark to evaluate HDBSCAN, we provide the true number of clusters for each run. Therefore $k$-means runs with an optimal starting point.

**Running evaluations** The evaluation is done with different sets of news articles per run. If we define a run to use 30 stories and set it to repeat five times, each repeat will load 30 different stories from the data set. This is done to get a more diverse set of samples. Each run will be repeated at least five times. Lower numbers of stories allow for more repetitions due to lower processing times.

### 5.1.2 Evaluation

The first run is done with 60 stories, which results in approximately 2000 news articles, over 20 repetitions. Table 8 shows the resulting MP-Score for each parameter in combination with each preprocessing method and vector space model. The highest score per parameter is highlighted as bold and the best score overall is underlined. The first insight we get is the variety of scores for different min cluster sizes. The lowest min cluster size results in the lowest score, while increasing this parameter leads to an increasingly better score. The highest score is reached with a min cluster size of six, while increasing it

further reduces the score again. The large difference in scores between different min cluster sizes, shows the importance this parameters has on the quality of the clustering and requires some knowledge of the data beforehand. In our case we have a wide range of different cluster sizes as shown in Figure 5, with clusters containing as few as two news articles. Based on this distribution we expected the ideal min size cluster size to be in a range from two to nine, which is why we chose this range. The distribution also explains the drop in the scores after a min cluster size of 6, since an increasingly number of clusters are being ignored.

| **Clustering** | **Word Frequency** | | | | | **tf-idf** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **HDBSCAN** | Full Text | Keyphrases | NER | Lemmatized | Stemmed | Full Text | Keyphrases | NER | Lemmatized | Stemmed |
| min_size: 2, metric: cosine | 0.446 | 0.456 | 0.409 | 0.452 | 0.451 | 0.477 | 0.450 | 0.398 | **0.499** | 0.479 |
| min_size: 2, metric: euclidean | 0.071 | 0.068 | 0.090 | 0.075 | 0.073 | 0.459 | 0.255 | 0.444 | **0.482** | 0.481 |
| min_size: 3, metric: cosine | 0.603 | 0.592 | 0.558 | 0.594 | 0.599 | 0.624 | 0.594 | 0.547 | **0.640** | 0.63 |
| min_size: 3, metric: euclidean | 0.071 | 0.067 | 0.090 | 0.073 | 0.073 | 0.595 | 0.304 | 0.549 | 0.609 | **0.613** |
| min_size: 4, metric: cosine | 0.656 | 0.639 | 0.613 | 0.647 | 0.657 | 0.684 | 0.654 | 0.604 | **0.691** | 0.686 |
| min_size: 4, metric: euclidean | 0.062 | 0.062 | 0.084 | 0.064 | 0.063 | 0.633 | 0.310 | 0.574 | 0.645 | **0.652** |
| min_size: 5, metric: cosine | 0.678 | 0.668 | 0.632 | 0.674 | 0.681 | 0.712 | 0.677 | 0.630 | **0.725** | 0.721 |
| min_size: 5, metric: euclidean | 0.048 | 0.057 | 0.081 | 0.051 | 0.051 | 0.650 | 0.303 | 0.578 | 0.66 | **0.674** |
| min_size: 6, metric: cosine | 0.695 | 0.672 | 0.636 | 0.685 | 0.686 | 0.731 | 0.695 | 0.630 | **0.738** | 0.735 |
| min_size: 6, metric: euclidean | 0.038 | 0.052 | 0.074 | 0.041 | 0.039 | 0.651 | 0.283 | 0.570 | 0.638 | **0.684** |
| min_size: 7, metric: cosine | 0.690 | 0.679 | 0.634 | 0.687 | 0.687 | 0.727 | 0.685 | 0.631 | **0.737** | 0.734 |
| min_size: 7, metric: euclidean | 0.032 | 0.049 | 0.072 | 0.034 | 0.033 | 0.654 | 0.269 | 0.555 | 0.659 | **0.676** |
| min_size: 8, metric: cosine | 0.683 | 0.669 | 0.628 | 0.683 | 0.685 | 0.729 | 0.689 | 0.626 | **0.733** | 0.733 |
| min_size: 8, metric: euclidean | 0.031 | 0.042 | 0.068 | 0.032 | 0.031 | 0.644 | 0.252 | 0.540 | 0.649 | **0.668** |
| min_size: 9, metric: cosine | 0.679 | 0.666 | 0.622 | 0.674 | 0.677 | 0.723 | 0.680 | 0.621 | **0.732** | 0.726 |
| min_size: 9, metric: euclidean | 0.029 | 0.036 | 0.064 | 0.031 | 0.032 | 0.640 | 0.234 | 0.527 | 0.648 | **0.660** |
| ***k*-means** | | | | | | | | | | |
| n_cluster: n_true | 0.364 | 0.437 | 0.289 | 0.358 | 0.361 | 0.643 | 0.632 | 0.466 | **0.651** | 0.649 |

Table 8: The average MP-Score for combinations of parameter and preprocessing methods with a sample size of 60 stories (approx. 2,000 articles)

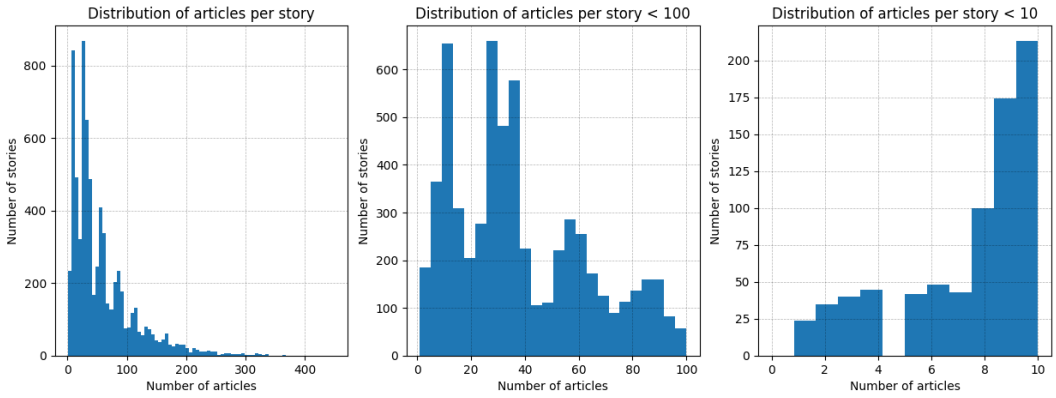



Figure 5: Distribution of cluster sizes.

Focusing on the two vector space models, shows that all of the best scores per parameter have been achieved by using tf-idf. Additionally the different metrics show a big difference when combined with word frequency. The best scores using the word frequency are 0.071 for the euclidean metric and 0.695 for the cosine metric. With tf-idf the difference between both metrics is still notable, but far less drastic than based on word frequency. This can be explained by considering that the word frequency model will weigh every word equally and therefore common words will have higher weights than less common ones. Based on these weights, the distance calculated by the euclidean metric does not correspond well with the actual similarity between documents. The cosine metric is less effected by these weights, since it already calculates the similarity of two vectors instead of their distance. Tf-idf balances out the term frequency with its inverse document frequency and therefore less common words are weighted higher than less common ones. As a result the euclidean distance is more effected by infrequent terms, which are similar for similar documents and hence better scores. Although the cosine similarity is still

superior in this case. This behaviour has already been studied in the past[27], [28] and is one of the reasons, why the cosine similarity is often preferred over the euclidean distance as a similarity measure in the field of text mining.

As for the optimal preprocessing, text lemmatization provides the highest overall mp-score with 0.738, although closely followed by text stemming. This is to be expected, since both lemmatization and stemming reduce the dimensions by grouping words into their base form, while still retaining most of the text. In contrast to Keyphrase Extraction and NER, which both result in a drastic reduction of the dimensions, and therefore less detail. It is also interesting to see how close the score from using the full text is compared to the best score per row. The difference between the overall best score of 0.738 achieved by Lemmatization and the score provided by the full text of 0.731 is only 0.007. This means text preprocessing has a lesser impact than initially expected. However it is important to note, that we used pretrained models for Keyphrase Extraction and NER. Specifically training on a news corpus might improve the performance of both methods, but it was decided as to be out of scope for this thesis.

After determining the optimal settings for text preprocessing and vectorization, we increase the sample sizes for our evaluation runs, to get a deeper insight into the behaviour of HDBSCAN with larger data sets. Figure 6 shows the scores achieved with different parameters over an increasingly large set of samples. Based on this Figure we see the metric *cosine* to be generally better than *euclidean* and significantly more stable based on the range of the score and the quality of the clustering seems to decrease with larger sample sizes.

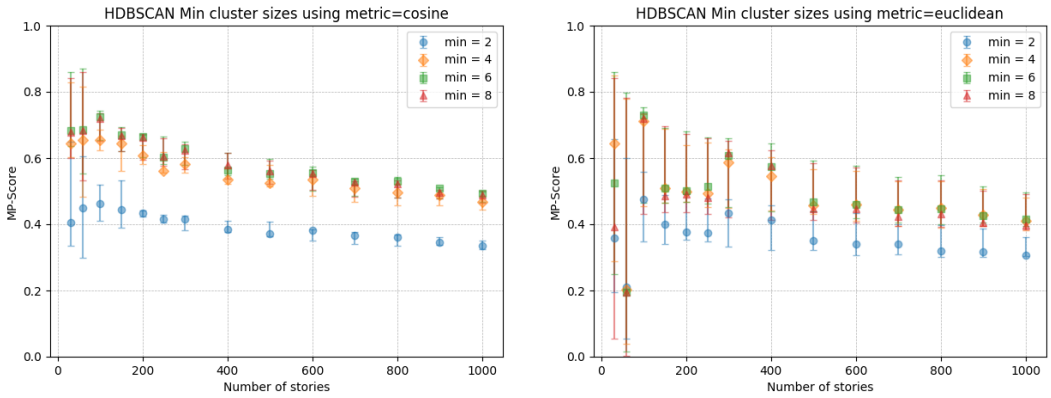



Figure 6: MP-Score for different parameters, where min stands for the min cluster size. The marker represents the median, while the vertical line indicates the range between the min and max values. Each run contains at least five repetitions.

Furthermore, the variance with smaller sample sizes can partially be explained through differences in the number of detected clusters, since missing a few clusters has a bigger impact if the overall number of clusters is small. Figure shows the difference between the number of predicted clusters and the number of true clusters. The Figure provides us with an interesting observation: While so far the minimum cluster size of six has given the best scores, the difference in the number of clusters is much smaller with a minimum cluster size of four. The MP-Score weights the similarity of a pair of clusters with their number of elements. This means ignoring smaller clusters has a lesser impact than ignoring larger clusters. We know our data set contains stories with news articles ranging from one up to 400. Based on this knowledge and the workings of the score, we can conclude that using a minimum cluster size of four gives us more clusters, which are ignored by using a larger minimum cluster size, but at the same time fragmenting larger clusters. Therefore resulting in a lower score, while having a better difference in the number of cluster predictions. This can be validated by analysing our data directly, where we observe the number of predicted cluster to be higher the lower the minimum cluster size

is. Using $min\_cluster\_size = 6$ tends to give a lower number compared the the true amount, while $min\_cluster\_size = 3$ gives usually a higher number than there are actual clusters.

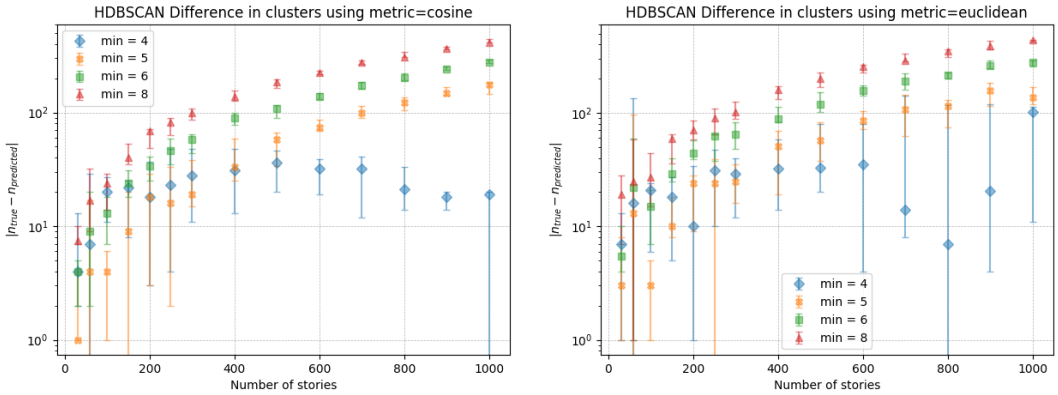



Figure 7: Difference between the predicted and true number of clusters.

One of the advantages HDBSCAN has over other clustering algorithms, is the ability to work with noise, since we intent on applying it in an online setting, where noisy data is to be expected. At the same time, the number of articles classified as noise should be kept to a minimum. However the noise ratio shown in Figure 8 is significantly higher, than we would expect it to be based on our test data. A variety of factors play into the high noise ratio. One influence is due to the $min\_cluster\_size$. Each news article belonging to a cluster, which has less articles than the minimum cluster size, will be counted as noise. Table 9 lists the calculated percentage of news articles, which would be ignored based on different minimum cluster sizes. Although the percentages show that the impact the minimum cluster size has on the overall noise ratio is very limited. It is reasonably to assume, that the test data still contains a fair amount noisy data, even after cleaning up the data to the best of our efforts. Decreasing the noise ratio is certainly an important part in future improvements.

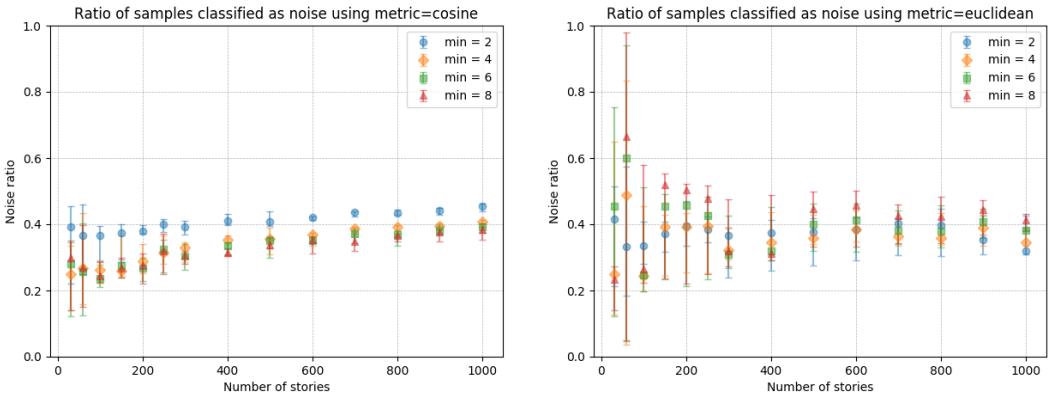



Figure 8: Number of news articles classified as noise.

Let us look closer at the data to get insights behind just the score or noise ratio. The first story we focus on is about the hacking of U.S firms by chinese military hackers. Table 10 shows a number of detected and missed news articles. Based on the text length, we see that the missed articles are generally shorter compared with detected articles with one major exception. Nr. 18 with a length of 13980 is nearly twice as long compared with the second longest article. The content of Nr. 18 is a collection of different stories, only the first being about the chinese hackers. It seems reasonable for this article to be missed in the clustering. Articles Nr. 17, 19 and 20 all have a significantly lower length than the others, which might already be enough to classify them as noise. Looking at the actual

| min cluster size | Ignored articles |
|---|---|
| 2 | 0.032% |
| 3 | 0.126% |
| 4 | 0.304% |
| 5 | 0.593% |
| 6 | 0.985% |
| 7 | 1.548% |
| 8 | 2.168% |
| 9 | 2.712% |

Table 9: Percentages of ignored news articles because of their cluster size. The values are calculated directly based on the test data.

contents reveals that Nr 17. is about the magazine's paywall, Nr. 19 appears to be a short summary of the publisher itself, and Nr. 20 contains only two sentences about the topic, a link to read more and a hint to download Acrobat Reader. Therefore these three news articles are actual noise and ideally should have been removed during the data cleansing. The remaining news articles appear to be valid articles about the story and do not provide any obvious reasons for why they were regarded as noise during the clustering.

**Detected Articles**

| Nr. | Title | Text length | Source |
|---|---|---|---|
| 1 | What were China's hacker spies after? | 3801 | CNNMoney |
| 2 | Chinese Cyberespionage Crackdown Prompts Look At Intellectual Property Theft | 5124 | CRN |
| 3 | FBI investigator: Many more US firms hit by Chinese military hackers | 5585 | Tribune-Review |
| 4 | State-sponsored business espionage decried | 3771 | Stars and Stripes |
| 5 | Westinghouse Among Companies in Chinese Trade Secret Hacking Case | 1364 | Nuclear Street |
| 6 | US charges on China hackers cap 3-year pressure drive | 7668 | Thanh Nien Daily |
| 7 | #ShotsFired in U.S.-China Cyberwar | 7352 | Daily Beast |
| 8 | Feds claim Chinese hackers hit US firms, including Westinghouse | 3746 | The Cranberry Eagle |
| 9 | America sues China over corporate spying | 4278 | Telegraph.co.uk |
| 10 | How China's army hacked America | 3427 | Ars Technica |

**Missed Articles**

| Nr. | Title | Text length | Source |
|---|---|---|---|
| 11 | Other views: China hacking indictments will create waves | 2968 | Monterey County Herald |
| 12 | How much damage has Chinese hacking done to the US government? | 785 | FederalNewsRadio.com |
| 13 | FBI Releases New Details In Cyber Espionage Case | 2885 | CBS Local |
| 14 | How 5 Chinese hackers stole American companies' most closely-guarded secrets | 3726 | ITProPortal |
| 15 | U.S. Charges 5 Chinese Army Members with Economic Spying | 1093 | Democracy Now |
| 16 | U.S. Charges Five Chinese Military Officers with Cyber Espionage | 1823 | eSecurity Planet |
| 17 | Prosecutors: Chinese targeted Western Pa. companies | 191 | Washington Observer Reporter |
| 18 | CNN's GUT CHECK for May 19, 2014 | 13980 | CNN |
| 19 | Nuclear Fallout From China's Alleged Espionage | 122 | Wall Street Journal |
| 20 | Charges Of Chinese Cybercrimes To Play Out In American Courts | 443 | KPBS |

Table 10: 10 correctly detected and 10 missed news articles, which all belong to the same story.

To find a possible explanation for the remaining new articles, we take a look at their tf-idf model. Table 11 lists the top 10 keywords per news article, based on the tf-idf model. There we see how the keywords from the detected news articles are quite similar, while the keywords from the missing news articles appear to be more varied with minimal overlap to the keywords from detected articles. This seems to give an indication as to why the articles were missing from the cluster. However it is important to note, that the tf-idf model in Table 11 was created from only those 20 articles and used the full text instead of lemmatization for better readability. The top keywords might differ in the model created for the whole clustering. Especially words such as *ap1000*, which is a name of a nuclear power plant, will be weighted higher in the full model. Based on this insight, we expect further work on text preprocessing to lead to considerable improvements in the quality of the clustering.

| Nr. | Top 10 Keywords |
|---|---|
| 1 | ['chinese', 'solar', 'steel', 'power', 'firms', 'hackers', 'solarworld', 'theft', 'plants', 'ap1000'] |
| 2 | ['theft', 'said', 'allegedly', 'data', 'security', 'businesses', 'officers', 'intellectual', 'property', 'indictment'] |
| 3 | ['said', 'companies', 'pittsburgh', 'don', 'chinese', 'company', 'security', 'accused', 'computer', 'hackers'] |
| 4 | ['said', 'companies', 'pittsburgh', 'don', 'security', 'know', 'university', 'computer', 'makes', 'chinese'] |
| 5 | ['ap1000', 'state', 'alleging', 'pipe', 'construction', 'design', 'chinese', 'westinghouse', 'china', 'owned'] |
| 6 | ['chinese', 'people', 'snowden', 'companies', 'said', 'china', 'indictment', 'evidence', 'administration', 'officials'] |
| 7 | ['chinese', 'said', 'house', 'white', 'cyber', 'department', 'indictments', 'way', 'defense', 'american'] |
| 8 | ['chinese', 'said', 'officials', 'indictment', 'company', 'mails', 'trade', 'companies', 'pennsylvania', 'stole'] |
| 9 | ['america', 'chinese', 'china', 'know', 'including', 'accused', 'targeted', 'company', 'trade', 'ap1000'] |
| 10 | ['messages', 'access', 'mail', 'according', 'indictment', 'attack', 'mails', 'spear', 'phishing', 'union'] |
| 11 | ['cyberspying', 'united', 'states', 'chinese', 'national', 'security', 'high', 'economic', 'aggressive', 'justice'] |
| 12 | ['report', 'world', 'cyber', 'technologies', 'economic', 'alleging', 'intended', 'links', 'programs', 'says'] |
| 13 | ['pittsburgh', 'cyber', 'allegedly', 'fbi', 'targeted', 'details', 'enforcement', 'officials', 'happens', 'threat'] |
| 14 | ['messages', 'access', 'group', 'attacks', 'like', 'mail', 'spear', 'unit', 'phishing', '61398'] |
| 15 | ['report', 'sponsored', 'state', 'states', 'economic', 'eric', 'holder', 'case', 'united', 'intelligence'] |
| 16 | ['allegedly', 'proprietary', 'sun', '2010', 'information', 'stole', 'market', 'solarworld', 'business', 'owned'] |
| 17 | ['account', 'create', 'log', 'continue', '000', '19', '20', '2008', '2010', '2012'] |
| 18 | ['com', 'leading', 'don', 'obama', 'new', 'house', 'oregon', 'years', 'people', 'state'] |
| 19 | ['news', 'leading', 'media', 'corp', 'network', 'information', 'companies', '000', '19', '20'] |
| 20 | ['alleging', 'order', 'pdf', '2014', 'alleges', 'filed', 'firms', 'chinese', 'documents', 'hacked'] |

Table 11: Top 10 keywords extracted from the tf-idf model.

So far we focused on HDBSCAN to determine the optimal settings to run it with. As a next step we can start comparing the overall performance with $k$-means. We use the follwing settings: Text Lemmatization with tf-idf, cosine as the similarity measure and six as the minimum size of clusters. Figure 9 shows a similar behaviour for both clustering methods in value and variance of the precision. Although HDBSCAN is generally more accurate than $k$-means, the difference gets smaller with an increase in the sample size. Additionally the increase in the number of samples results for both HDBSCAN and $k$-means in a small loss regarding the precision as can be seen in Figure 9 and which we have already observed when analysing HDBSCAN parameters.

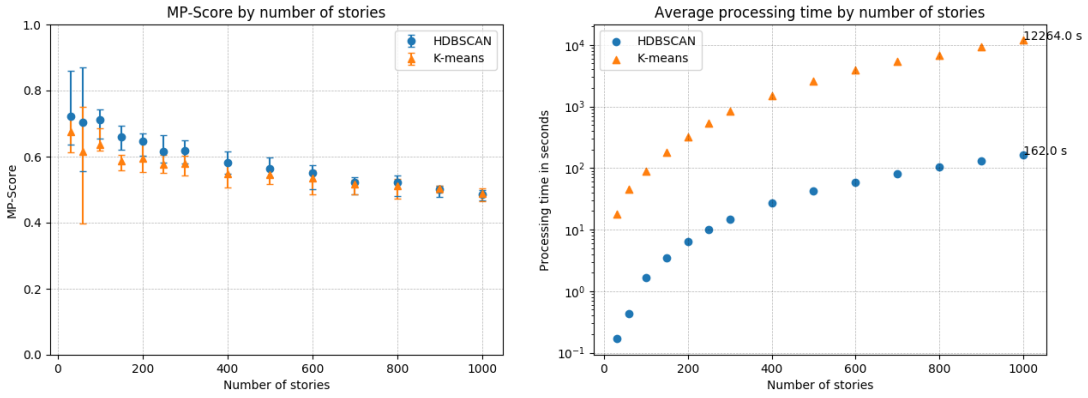



Figure 9: Comparison of the MP-Score and processing time between $k$-means and HDBSCAN

While HDBSCAN and $k$-means provide a similar score, the biggest difference can be noted in the processing time in relation to the number of samples. $k$-means has a time complexity of $O(n^2)$ in contrast to HDBSCAN with a time complexity of $O(nlog(n))$, which is illustrated by Figure 9. Although running the evaluation has also shown the space complexity for HDBSCAN to be substantially higher for larger amounts of samples than with $k$-means. Trying to run HDBSCAN with 100'000 news articles caused in a memory error, even with 64GB of RAM, while $k$-means was able to complete the clustering. The memory issue with large data sets is known and according to the author the current implementation of HDBSCAN is not optimised for memory[29]. This might be another area for further improvements, although it will not help to increase the score on larger data sets.

As a final evaluation, we compare HDBSCAN with six different clustering methods taken from scikit-learn. Each method is run with a variety of parameters and the best scores are shown in Figure 10. HDBSCAN provides the highest precision, while being still being one of the fastest algorithms. We are aware of our bias for HDBSCAN since we invested a significant amount understanding and analysing it, but it is still interesting to see how well it compares with other clustering methods out of the box.

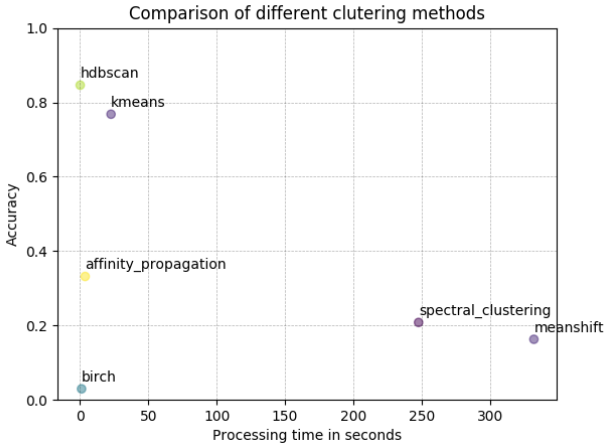



Figure 10: Comparison of different clustering methods with a sample size of approximately 1000 news articles

### 5.1.3 Conclusion

The evaluation has shown HDBSCAN to be a good candidate to use for text based clustering. It provides an better precision than $k$-means, while being significantly faster to process. The predicted number of clusters is consistent with an increasing number of samples and fairly close the truth. Additionally we have shown the required preprocessing and vectorization steps with the ideal parameters to achieve the most accurate results for our data set. However there is a substantial noise ratio, which causes almost a third of the processed samples to be classified as noise. We have also analysed individual clusters and discovered, that the vector space model can vary substantially between news articles of the same cluster. Another consideration is the space complexity with larger data sets, where we quickly ran into issues when clustering high number of samples. Overall HDBSCAN provides an acceptable precision, while still leaving room for further improvements.

## 5.2 Online Clustering

### 5.2.1 Setup

The online clustering is done on a simulated stream of news articles based on the same data set as used in the clustering evaluation. This allows for direct comparison between the detected events and the ground truth. The settings to run the clustering are as follows:

- Preprocessing: Text Lemmatization
- Vector space model: tf-idf
- Clustering method: HDBSCAN
- Minimum cluster size: 6
- Distance metric: cosine

The clustering is run over 30 days with a total of 42,916 news articles. The distribution of news articles this time period is illustrated in Figure 11. The time delta, which is the amount of time between two batches, is set to one hour.

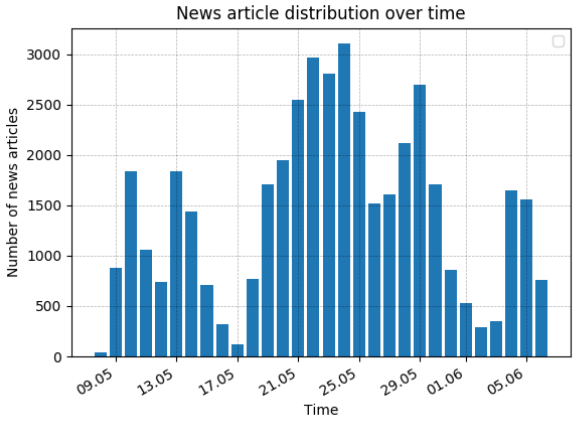



Figure 11: Incoming news articles over 30 days

### 5.2.2 Evaluation

The goal of the online clustering is to detect new events in an incoming stream of news articles and changes in existing events. This evaluation analyses the results of our simulated test runs with different batch sizes.

We start the evaluation with using a fixed batch size. Figure 12 shows the differences between the number of detected events and the number of true events for both new and existing topics. Based on this data we see the impact of different batch sizes for the accuracy in detected events. The difference with a batch size of 5,000 news articles is fairly lower than the batch size of 1,000. The difference is especially noticeable in the time period between the 21.05 and 25.05. The reason for this spike can be found in the distribution of incoming news articles as shown in Figure 11. During this period we receive up to 3,000 news articles in a single day. This means by using a lower batch size such as 1,000, the overlap between batches gets too small to reliably detect changes between batches, which causes too many new topics to be detected.

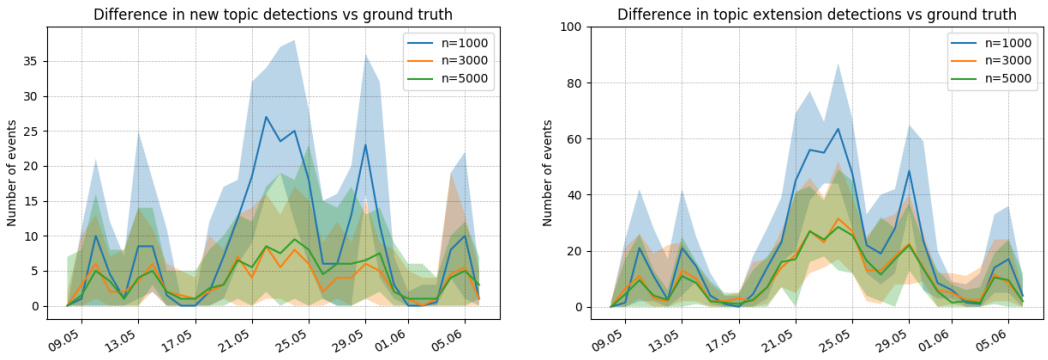



Figure 12: Comparison between the difference in detected and true events. The line represents the median, while the area shows the range from the minimum to the maximum value

Although a larger batch size does not simply equal a better difference, as can be seen in Figure 12 by

comparing the differences using a batch size of 3,000 with a batch size of 5,000. The batch size n=3000 shows a generally lower difference in the detection of new events than with n=5000. The differences between both batch sizes are less significant when detecting changes in existing events.

Based on the overall differences, we do not know the accuracy of those predictions. If the difference between newly detected events and true events is zero, there is still the possibility, that the events itself are different from the ground truth, and thus contain false positives. To measure the quality of events, we can look at the collection of events in a single batch as a subset of clusters, where each event is represented by a cluster containing all relevant news articles. Since we now have two clusterings, one containing detected events and the other with events taken from the ground truth, we can apply our MP-Score as a metric to get an insight into the quality of the detected events over the ground truth. Figure 13 shows the MP-Scores for an online clustering using a batch size of 1,000. Since there is quite a large variance, the score is shown as a boxplot, where a single box represents a full day. The large variance is already the first indication, that the quality is rather low. Meaning that there are still many false positives and false negatives.

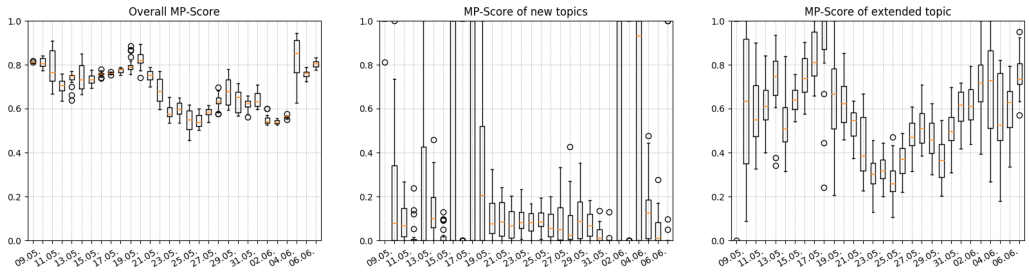



Figure 13: MP-Scores for clusterings using batch size of 1000

Looking at an increased batch size of 5000 in Figure 14, we note that there is less variance in the overall MP-Score, which compares the full clustering with the ground truth. Although the variance for new and existing event detections is still fairly high. Additionally while the variance is high, the median for new topics is mostly around 0.1. This tells us that most of the newly detected events do not correspond with new events according to the ground truth. The detection of extensions of existing events is generally more accurate with a median between 0.5 and 0.8 using n=5000, but there is still are wide variance noticeable.

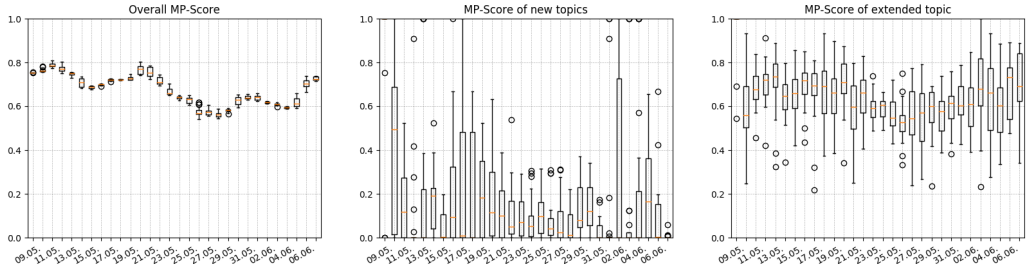



Figure 14: MP-Scores for clusterings using batch size of 5000

One of the reasons for the difference in the accuracy of the detection of new events and the extension of events might be explained by the *min_cluster_size*. In the current setting the *min_cluster_size* is set to 5, which means if an event occurs in batch one containing only four news articles, it will be discarded as noise. If the second batch contains additional news articles for the same event, it will be detected as a new occurrences, but the ground truth treats it as an existing event. To see how this

affects the result we run the same simulation with a batch size of n=3000 a second time, but only considering new events from the ground truth if the number of news articles is greater or equal to the *min_cluster_size*.

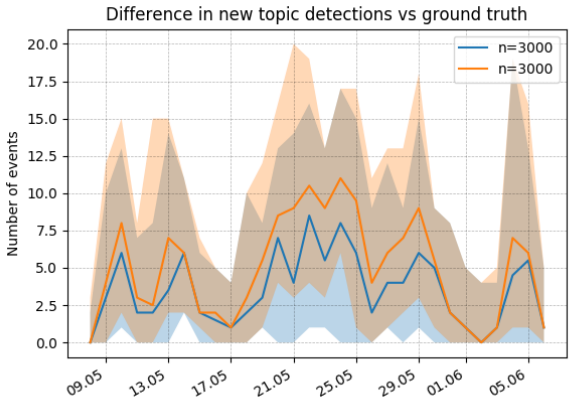



Figure 15: Differences in predictions vs ground truth using batch size of 3000.

Limiting new events in the ground truth based on the *min_cluster_size* gives the opposite result as initially expected. Figure 15 clearly shows an increase in the difference between predicted events and the adjusted ground truth. This means we already detected more new events than there were present in the ground truth and limiting it based on the *min_cluster_size* only lowered the true number of events, thus leading to an increase in the difference. A look at the raw data from an initial simulation run in Figure 16 validates this assumption.

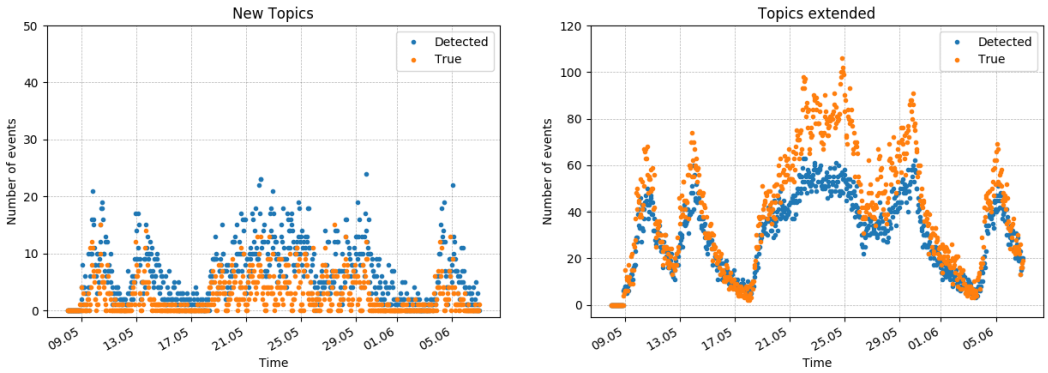



Figure 16: Number of events with a batch size of 3000

The raw data in Figure 16 also shows a direct correlation between the number of detected new events and the number of detected changes in events. The more changes we missed, the more new events are detected. This is to be expected, since the detection of changes depends upon finding similar pairs of clusters in two different batches. If a cluster in the current batch could not be matched to a cluster from the previous batch, the cluster from the current batch will be seen as a new event. Therefore the accuracy in finding pairs of clusters in crucial to a better performance. The online clustering makes use of Locality Sensitive Hashing as explained in Section 4.4.2. The current threshold value for determining the similarity is set to 0.75. To see the impact on the similarity threshold, we run the online clustering again with a batch size of n=3000 and different threshold values.

Figure 17 shows the effect of the threshold on the difference in decided over true events. We see how

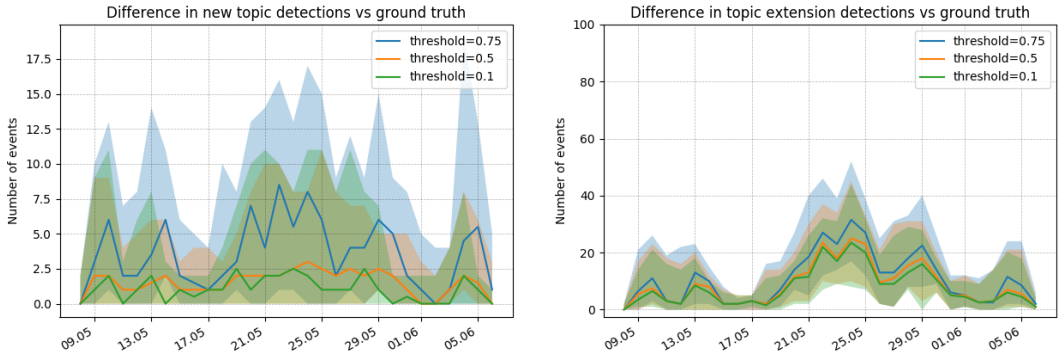



Figure 17: Differences in detected over true events with different thresholds and a batch size of 3000

the initial threshold of 0.75 was set too high, as lower threshold values such as 0.1 provide a significant lower difference. While there is still a substantial variance per day the median of 0.1 and 0.5 is generally more stable and lower than with a threshold value of 0.75. The reason for the better performance of lower threshold values, is that the overlap between batches decreases with an increase in the volume of news articles. This is clearly visible during the peaks in Figure 17. Thus a high similarity threshold cannot be met, since there exists only an overlap of a few news articles for the same cluster between batches. The MP-Score is also improved for new events as can be seen in Figure 18. While there is more variance than in similar plots from Figure 13 and Figure 14, the median from using threshold=0.1 clearly surpasses any measure from using threshold=0.75. The high variance in the boxplot is due to the fact, that there are only a few new events per hour, if any. This means detecting no events, when there are none leads to a score of 1, while detecting one event, when there is none leads to a score of 0.

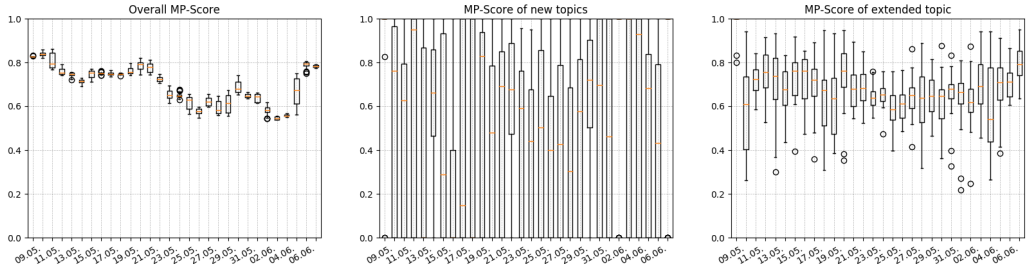



Figure 18: MP-Scores for online clustering with batch size n=3000 and threshold=0.1

After having analysed the impact of different batch sizes in detail and the similarity threshold, we want to explore the result of using a dynamic batch size. The first dynamic method loads the number of samples over $n$ hours. The second dynamic method calculates the batch size based on the incoming samples and a predefined factor. The dynamic methods will run with a similarity of 0.1 and an upper limit of 30,000 samples, which is approximately 1,000 stories. The number of the upper limit is based on observations from the clustering method evaluation. Higher number of samples resulted in frequent memory errors and while giving lower scores.

Figure 19 shows the difference in detected events compared with the true number of events using the first dynamic method. The variance is still quite high, especially during the peaks, where a lot of news articles are present in the data stream. The best performance is achieved by setting the time window to 24 hours. The average score for the overall clustering is 0.717 with a standard deviation of 0.119.

The detection of new events results in an average score of 0.618 with a standard deviation of 0.426 and the detection of changes results in an average score of 0.694 with a standard deviation of 0.16. The resulting scores are better than with using a fixed batch size of 3,000, but not by much. The biggest difference is in the average score of the detection of new events, where this method is better by 0.076. Increasing the time window to 48 or 72 hours results in slightly lower scores.

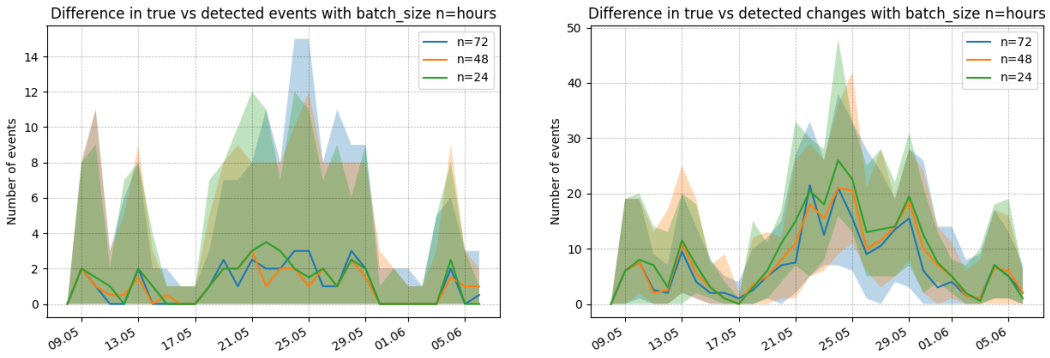



Figure 19: Difference in detected events vs predict events by using a dynamic batch size based on hours.

Since the first dynamic method only showed a marginal improvement over the static method, we move on to the second dynamic method. In addition to an upper bound, this method uses a lower bound as well, to prevent the overlap between batches from becoming too small. The lower bound is set to 3,000, since the evaluation of a fixed batch sizes proved 3,000 to provide the best results. Our initial assumption was, that having a good lower bound would give a good baseline and the relative factor allows the batch size to grow with the increase in the volume of samples. The overall performance should therefore be superior to using only the fixed batch size. The data proved our assumption to be incorrect as can be seen in Figure 19. The best scores are achieved by using a factor of 25. The overall score is 0.692 with a standard deviation of 0.091. The detection of new events results in a score of 0.589 with a standard deviation of 0.429. The score of detecting changes is 0.682 with a standard deviation of 0.136.

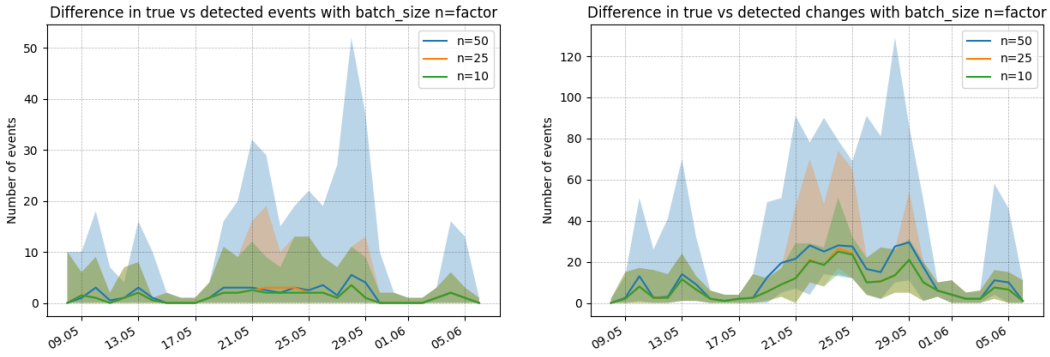



Figure 20: Difference in detected events vs predict events by using a dynamic batch size based on incoming samples.

In addition, the data shows an interesting observation, where using a factor of 50 results in some extreme outliers. The reason can be explained based on our previous clustering evaluation, where we showed the decrease in precision with larger number of samples. Figure 21 shows the maximum number of samples processed in a single batch. The factor 50 reaches the upper limit during most peaks in the

data stream. Clustering with 30,000 resulted in an lower average score of roughly 0.24 compared to the best result. Therefore an increasing amount of news articles is classified as noise and stories are further fragmented into multiple clusters. This leads to even bigger decreases in the event detection as this data shows.

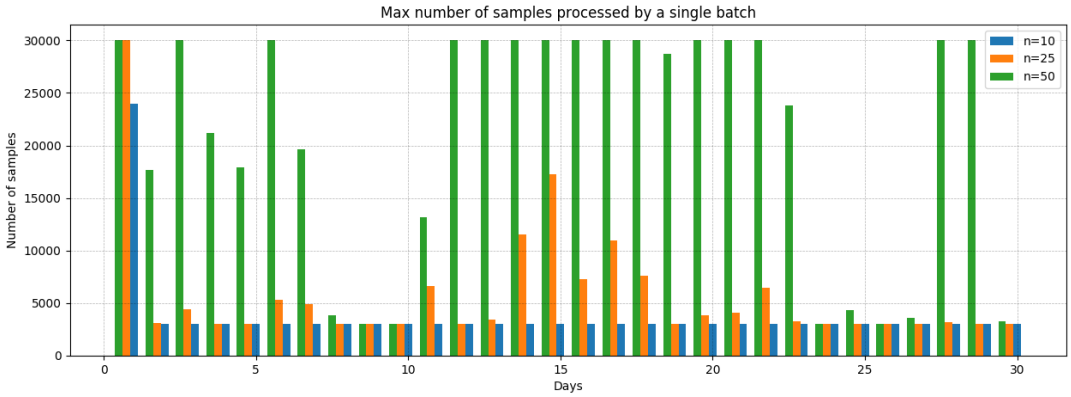



Figure 21: Maximum number of processed samples in a single batch per day and factor.

To conclude the evaluation of different methods for setting the batch size Table 12 shows the best approach per method. The highest scores are highlighted as bold. Based on this data, the time based method seems to provide the best results, although the differences between the methods are small. The high standard deviation for the detection of new events shows that the detection is quite unstable in its current form. Improving the precision and the stability for the event detection is therefore dependent on improving the overall clustering precision, since the dynamic methods for determining the batch size only show limited impact.

| **Batch size method** | **Overall clustering** | | **New events** | | **Changes in existing events** | |
|---|---|---|---|---|---|---|
| | Mean | Standard deviation | Mean | Standard deviation | Mean | Standard deviation |
| Fixed with n=3000 | 0.701 | **0.085** | 0.542 | 0.435 | 0.683 | 0.144 |
| Time based with hours=24 | **0.717** | 0.119 | **0.618** | **0.426** | **0.694** | 0.16 |
| Relative with factor=25 | 0.692 | 0.091 | 0.589 | 0.429 | 0.682 | **0.136** |

Table 12: Final scores obtained by each method for setting the batch size.

One of the major factors in the lower precision of event detection compared with the overall clustering is the noise rate. To demonstrate let us look at an online clustering over a simulated time period of five days. Overall the time period includes 364 stories with 12,603 news articles. During the online clustering we detected 275 new events and 4,080 changes. On average these events contain two news articles. Of the original 12,603 news articles only 8,626 have been assigned to clusters, with an average cluster size of 26.4. This results in a noise rate of 31.6%. If we now compare the average cluster size of 26.4 with the average event size of 2, we can see how single events are more likely to be missed than clusters due to their size.

During the analysis we also looked at two specific examples "Gmail redesign" and "Bad Neighbours". The first example was detected without errors, while the second example contained multiple news articles discarded as noise and a fragmentation in clusters. The fragmentation means that news articles from the same story got assigned to different clusters during the same batch, resulting in incorrect events.

The difference in the performance of both examples, can be explained based on the contents of their news articles. The first example about the "Gmail redesign" consists mostly of technology focused news sites such as *Ars Technica* or *PC Magazine*. Therefore the contents of the news articles are of good quality and share the same technical vocabulary. The second example with the new release of

the film "Bad Neighbours" has a wider variety of sources and types of articles. Some news articles are short summaries, while others are interviews or personal reviews. Additionally the vocabulary is more general than compared to technical articles and varies stronger between articles. This might lead to increased differences in the tf-idf model for entertainment articles than for technical articles, which we have already explored as part of clustering evaluation.

### 5.2.3 Conclusion

We explored different methods for determining the batch size, with one static and two dynamic approaches. The best results were achieved by using the dynamic method, which loads samples from the last 24 hours instead of defining an actual batch size. The resulting precision of the clustering using this method is 72% with a standard deviation of 12%. The precision for detecting new events results in 62% with a standard deviation of 43%. Detecting changes in existing events results in a precision 69% with a standard deviation of 16%. Although the differences in the resulting scores between the methods are marginal and all methods show similar deviation in the event detection. One of the reasons the dynamic methods did not perform better, is based on the overall decrease in precision of HDBSCAN with higher number of samples. Therefore increasing the batch size to react to high volumes of traffic resulted in a score similar or worse than the static batch size. In addition, we compared different thresholds for defining the similarity between samples and found 0.1 to be a good candidate. The noise rate is shown to impact the events even more then the clusters and therefore is a major influence regarding the precision of the event detection. In conclusion the high variance in correctly detecting event shows, that it is quite unstable in its current form and further optimizations should be focused on the overall clustering and on lowering the noise rate.

# 6 Conclusion

## 6.1 Summary

We started our work by searching for a suitable data set to create our clustering evaluations with. The primary requirement was, to have data points with their corresponding cluster labels. Having a labelled data set allows us to apply external measures and evaluate a resulting clustering against the ground truth. After selecting a few data set for closer inspection, we settled on the News Aggregator Dataset, which contains 422,937 labelled news articles, where a label describes the story the news article is about. Since the same story label applies to multiple news articles, we could use this as a cluster descriptor. Unfortunately the data set only contained headlines, which did not contain enough information for our approach. Therefore we collected the full text from each news article based on the provided source url. The content retrieval process turned out to generate a significant amount of noise, due to expired urls, paywalls, parsing errors or wrong redirects. To reduce the noise, we applied different cleansing techniques and ended up with approximately TODO usable news articles.

Once the data set was ready, we designed an evaluation framework to automatically run clustering methods with a variety of settings. The focus was to find a combination of text preprocessing methods, vector space model and parameters for the clustering method, which would provide the best clustering. Furthermore we developed a custom scoring function to measure the results of a clustering, since existing measures proved to be unintuitive and biased against certain results, such as the number of clusters. After having done many clustering evaluations based on our test data, we focused on analysing the collected data for our primary clustering method HDBSCAN and compared it to $k$-means. The analysis gave valuable insight into the behaviour of HDBSCAN with different vector space models combined with different preprocessing methods and parameters. We noted the initial good performance and the decrease in the quality of the clustering the bigger the sample size got. However the amount of news articles proved to be substantial with up to 30%. Possible explanations were explored, such as actual noisy data and different representations of articles belonging to the same cluster with tf-idf.

Having determined the optimal settings in the HDBSCAN evaluation, we applied them in a simulated online setting for event detection. The event detection was accomplished by running the clustering in batches over time. Events are detected by comparing a batch with its predecessor. If a batch contains clusters, which do not appear in the previous batch, than those clusters are considered as new events. If a cluster did exist in the previous batch, we look at the difference in assigned news articles and can therefore detect changes in existing event. The detection of events is measured against the ground truth. We explored different batch sizes and similarity thresholds for finding pairs of clusters between batches. Since finding pairs of clusters, requires a large enough overlap in identical news articles, the batch size has to account for this factor with regards to the volume of incoming news articles through the data stream. Additionally since events are represented as clusters, the sum of events can be regarded as a subclustering of the overall clustering. Although this makes the subclustering more sensitive to inaccuracies in the overall clustering, which explains the high error rate we observed in detecting new events. In conclusion we found the error rate in detected events to be rather high for our approach and therefore not applicable in a real world scenario in its current state.

## 6.2 Future Work

The approach in its current state still leaves different areas up for improvement. Further work on NER, might help in drastically reducing the dimensionality of the vector space model and condense a news article into only a few key entities. Using a pretrained model did not result in accurate results, but training a model specifically on a new corpus might improve the NER significantly. Another preprocessing technique, which we did not look at, would be word embeddings. Word embeddings allow

for the detection of similar words and therefore reduce the dimensionality of the vector space model substantially more than even Text Lemmatization. Thus leading to a potential improved clustering and reducing the noise rate.

As we have shown, the current implementation of HDBSCAN still leaves room for improvement in regards to space complexity. Finding potential optimizations in memory consumption would not necessarily improve our approach, since the quality of clusters decreases with larger sample sets, but might be a valuable contribution to the community and enable future work with larger data sets.

We focused mainly on HDBSCAN in our analysis, but the evaluation framework allows for many different clustering methods. Finding different methods suitable for text clustering or even a combination of different algorithms might lead to better results. Although we did try out some different variations such as HDBSCAN with LDA, but without any notable results.

Furthermore it would be interesting to see how HDBSCAN would perform using a data set based on a different kind of textual data. A possible alternative data set could be based on computer logs, which would also provide a source for data streams. Improvements in the overall performance of HDBSCAN will also significantly improve the event detection in data streams.

TODO dynamic batch interval based on incoming samples

TODO presegmentation of the data set based on categories

### 6.3 Lessons Learned

HDBSCAN

preprocessing

knowing your score

Good data set -> noise rate

# 7 Index

## 7.1 Bibliography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## 7.2 Glossary

**API** An application programming interface allowing access to data or features of an application.. 43

**Clustering** The task of grouping a set of objects based on their similarity.. 43

**Docker** A tool to package the application with all its dependencies as a single deployable unit and run it on independently from the underlying host.. 43

**Dockerized** An application environment running as a single or a collection of docker containers.. 43

**Stop word** A term that is overall so frequently used, that it is ignored in natural language processing.. 11, 43

**Vectorizer** A vectorizer transform a text into a numeric vector.. 43

## 7.3 List of Figures

## 7.4 List of Tables



## 7.5 List of Abbreviations

**CNN** Convolutional neural network. 9, 43

**IoT** Internet of Things. 6, 43

**NER** Named Entity Recognition. 8, 9, 27–29, 41, 43

**NLP** Natural Language Processing. 8, 43

**VSM** Vector space model. 11, 12, 43

# 8 Appendix

## 8.1 Algorithm for the MP-Score

```
import collections


def calculate_mp_score(true_clusters, predicted_clusters):
    """
    Calculate the mp_score of a clustering based on the contents of the clusters and the overall difference in
    predicted over true number of clusters. The calculation is based on three steps:
        1. Create an similarity matrix by calculating the difference between each cluster of both clusterings.
        2. Select the most relevant values from the similarity matrix and make sure no two clusters are being used
           at the same time.
        3. Calculate the weighted average, where the weight is based on the true and predicted amount of elements
           in a cluster.

    Parameters
    ----------
    true_clusters: array[clusters]
        2-dimensional array of true clusters

    predicted_clusters: array[clusters]
        2-dimensional array of predicted clusters
    """

    # If both clusters are empty, they are identical.
    if len(true_clusters) == 0 and len(predicted_clusters) == 0:
        return 1

    similarity_matrix = create_similarity_matrix(true_clusters, predicted_clusters)
    unique_indices = select_max_values(similarity_matrix)
    return calculate_weighted_average(unique_indices, true_clusters, predicted_clusters)


def create_similarity_matrix(true_clusters, predicted_clusters):
    similarity_matrix = []
    for true_cluster in true_clusters:
        true_set = set(true_cluster)
        n_true = float(len(true_set))
        row = []
        for predicted_cluster in predicted_clusters:
            cluster_set = set(predicted_cluster)

            # Calculate the similarity using the jaccard index
            similarity = len(true_set.intersection(cluster_set)) / len(
                true_set.union(cluster_set)
            )
            row.append(similarity)

        similarity_matrix.append(row)
    return similarity_matrix


def select_max_values(precision_matrix):
    unique_indices = dict()
    row_index = 0
```

```
    nrows = len(precision_matrix)

    while row_index < nrows:
        ignore_indices = set()
        max_value_found = False

        while not max_value_found:
            max_value = 0
            column = 0
            for col_index, value in enumerate(precision_matrix[row_index]):
                if value >= max_value and col_index not in ignore_indices:
                    max_value = value
                    column = col_index

            if (
                max_value > 0
                and column in unique_indices
                and unique_indices[column]["row_index"] != row_index
                and unique_indices[column]["max_value"] > 0
            ):
                if unique_indices[column]["max_value"] < max_value:
                    # The column is already used, but we found a better
                    # candidate. We use the new candidate and set the
                    # cursor to the old one to find a new max value.
                    old_row_index = unique_indices[column]["row_index"]
                    unique_indices[column]["row_index"] = row_index
                    row_index = old_row_index
                    unique_indices[column]["max_value"] = max_value
                    max_value_found = True
                else:
                    # The column is already used by a better candidate.
                    ignore_indices.add(column)
            else:
                # If max_value is greater than 0, we store the value as a
                # new candidate. Otherwise either the row does not match
                # any other column or the max_value was low and got
                # overridden by previous tries and no other match is available.
                if max_value > 0:
                    # The column is free to use
                    unique_indices[column] = {
                        "row_index": row_index,
                        "max_value": max_value,
                    }
                max_value_found = True
                row_index += 1

    return unique_indices


def calculate_weighted_average(unique_indices, true_clusters, predicted_clusters):
    mp_score = 0

    elements_per_true_cluster = [len(cluster) for cluster in true_clusters]
    elements_per_predicted_cluster = [len(cluster) for cluster in predicted_clusters]

    total_true_elements = sum(elements_per_true_cluster)
    total_pred_elements = sum(elements_per_predicted_cluster)
    total_elements = total_true_elements + total_pred_elements

    if total_elements > 0:
        for column, value in unique_indices.items():
```

```
115             # The row of the similarity matrix equals the index of the true cluster,
    while the column is the index of the predicted cluster
116             weight = (
117                 elements_per_true_cluster[value["row_index"]]
118                 + elements_per_predicted_cluster[column]
119             ) / (total_elements)
120             mp_score += value["max_value"] * weight
121
122     return mp_score
```

Listing 6: Calculate the MP-Score between two clusterings.

## 8.2 Code

The complete source code for this thesis can be accessed at https://github.com/dpacassi/ba2019. The repository contains the applications for the evaluation framework and the online clustering. Furthermore it contains the source of this document and the code to generate the plots and data tables from.

TODO make sure access is available