



**School of
Engineering**

InIT Institute of Applied
Information Technology

Bachelor thesis Computer Science

Dynamic Event Detection in Data Streams

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07.06.2019



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Abstract

How can events be recognized in a data stream? And what is the definition of an event? Current event recognition procedures define possible events (or event types) statically when the system starts. However, in data streams, the definition should develop dynamically over time as the data and their focus changes over time.

The first goal of this bachelor thesis is to define what an event is and how events can be recognized from static data. Depending on the definition, a suitable data set has to be found and chosen in order to create a system which is capable of recognizing events. In the second part, the events should be recognized from a data stream and therefore support dynamic event recognition.

This work uses news API's as data streams and tries to assign the received news articles to different events. An event is defined as a list of different news articles writing about the same story. A possible event could be "Brexit" or an upcoming election. It's important to keep in mind that new events can and should be created over time.

Assigning news articles to an event can be done by clustering the news articles. In order to achieve best possible results, a comparison between different clustering techniques has been completed. It was revealed that HDBSCAN is a promising candidate for our use case as it delivered the best results.

Unfortunately HDBSCAN was not made for data coming from data streams but this thesis will show one possible solution on how to deal with this. This work was able to process up to 20'000 news articles with HDBSCAN. A possible continuation of this work could try to extend this number to process more data at once.

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

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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 the application in dynamic data streams, which change over time. Additionally the behaviour of the data stream is an important factor in itself, since blockages or 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

Todo.

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 recognising biases of different scoring functions [7] and developing custom scoring functions as a result[8].

3 Theoretical basics

Todo.

3.1 Text preprocessing

Todo.

3.1.1 Keyterm extraction

Todo.

3.1.2 Entity extraction

Todo.

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. The original algorithm paper was written in 1979 by Martin Porter who aimed to improve performance of information retrieval systems. He stated that words such as *connect*, *connected*, *connecting*, *connection* and *connections* will usually have a similar meaning and can therefore be simplified for text vectorisation. In his paper he 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.

Snowball stemmer Todo

3.1.4 Text Lemmatisation

Text Lemmatisation is a form of Text Normalization which aims to simplify words by reducing the inflectional forms of each word into a common base or root.

3.2 Data Representation

Todo.

3.2.1 Word Frequency

Todo.

3.2.2 tf-idf

Todo.

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 does DBSCAN work 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't be assigned to a cluster, it will be marked as noise point.

Data points that belong to a cluster but don't 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 don't 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.

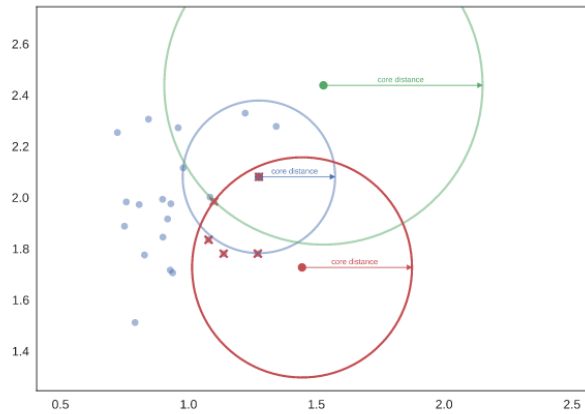


Figure 1: The core distances. TODO give more detailed explanation.

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 dendrogram in Figure 2 shows a possible cluster hierarchy.

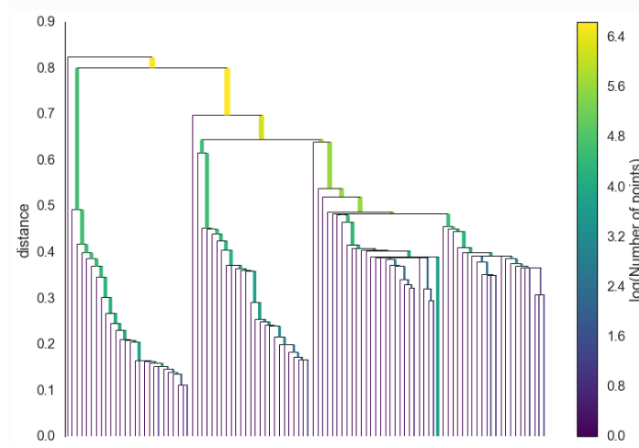


Figure 2: The cluster hierarchy shown as a dendrogram

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 where HDBSCAN improves upon DBSCAN, by taking additional steps for finding relevant clusters.

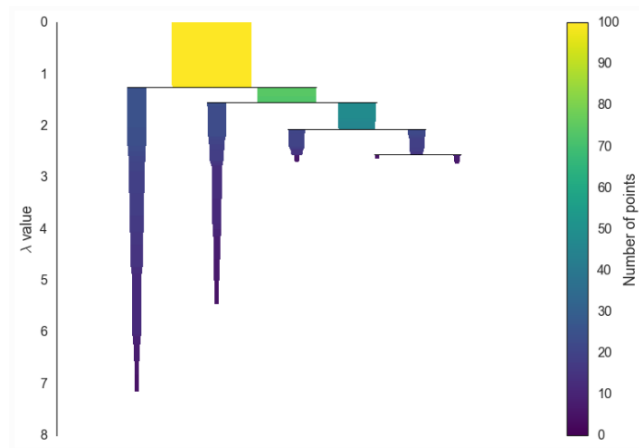


Figure 3: Condensed cluster hierarchy

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

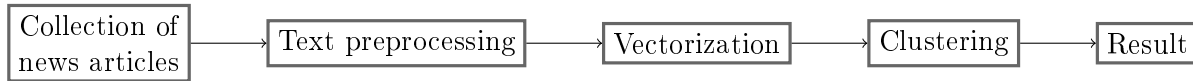
$$\sum_{p \in C}^{|C|} (\lambda_p - \lambda_{birth}) \quad (1)$$

where λ_p describes when point p fell out of the cluster and λ_{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 Methodology

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 Data flow



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've 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 1: Evaluated data set candidates ordered by data set size.

We could extract events from all data sets mentioned in Table 1. 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 didn't want to lose too much time in manually clustering data, we've 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[9], 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:

```

1  from newspaper import Article
2
3  url = 'http://fox13now.com/2013/12/30/new-year-new-laws-obamacare-pot-guns-and-drones/'
4  article = Article(url)
5  article.download()
6  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've 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've used following SQL query to filter out news articles that were most likely corrupt:

```

1  SELECT *
2  FROM news_article
3  WHERE
4      newspaper_text IS NOT NULL
5      AND TRIM(COALESCE(newspaper_text, '')) != ''
6      AND hostname NOT IN ('newsledge.com', 'www.newsledge.com')
7      AND newspaper_text NOT LIKE '%GDPR%'
8      AND newspaper_text NOT LIKE '%javascript%'
9      AND newspaper_text NOT LIKE '%404%'
10     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 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 2, where K-means achieved a rather high score, regardless of the significant difference between the true amount of clusters and the approximation using \sqrt{n} .

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

Table 2: K-Means has a higher NMI score than HDBSCAN, while having a much larger difference in number of clusters.

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 and the Jaccard index.

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

$$\frac{|A \cap B|}{|A \cup B|} \quad (2)$$

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:

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

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

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

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

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

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 non-trivial, since clusters do not share labels across different clusterings. To solve this, we make two assumptions:

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 an similarity matrix B , which does contain a collision:

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

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. The full algorithm for the selection process can be found in the appendix as listing 3.

As a third step we have to calculate the weights to be used for the final 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

$$w_{ij} = \frac{|t_i| + |c_j|}{|T| + |C|} \quad (3)$$

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 if the overall number of predicted clusters is different from the ground truth. Using only the true number of elements as the weight, would affect the

score if $|C| < |T|$, but not $|C| > |T|$. Therefore the number of predicted elements has to be included as well.

In the fourth and final step we calculate the weighted average

$$\text{MP-Score} = \sum_{i=0}^{|S|} w_i s_i \{w_i \in W \wedge s_i \in S\} \quad (4)$$

where S is the similarity matrix with $s_i \in S$ and w_i the corresponding weight 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:

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

The final score for the evaluation of the predicted cluster C with the true cluster is 0.674.

Comparison against other measures The test scenarios in table 3 show the resulting scores of our similarity score, NMI and completeness. It is important to note that NMI and completeness work with cluster labels assigned to each document, instead of considering elements inside a single cluster. This means the clustering will be flattened into one dimension, where each document is assigned the label of the cluster it appears in. The array containing the labels for the first scenario would look as follows: $C = [1, 1, 1, 2, 2, 2, 2, 3, 3]$.

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 3: Direct comparison of different scoring functions

As a final note, repeating the evaluation shown in table 2 a second time using the MP-Score, the score (Table 4) 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	n_{true}	$ n_{\text{true}} - n_{\text{predicted}} $
k-means	19255	0.137	600	457
HDBSCAN	19255	0.605	600	2

Table 4: The similarity score reflects the difference in number of predicted clusters.

4.3.1 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 vectorizers 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 vectorizers are provided by the scikit-learn library[10]. 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 running the final evaluations, without worrying about setting up and installing all dependencies again.

4.4 Online Clustering

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 to the same subject. The events of interest for this application are the discovery of new topics and the extension of existing topics. Thus we define our two events as follows:

- Topic added: A new cluster of news articles appears in the data stream.
- Topic extended: An existing topic is extended by additional news articles.

HDBSCAN will be applied as the clustering method, using the optimal settings as discovered in the previous 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.

Since HDBSCAN only supports static data sets, the clustering will be done in batches using a time based sliding window approach. Events are detected by comparing the resulting clusters with the previous ones.

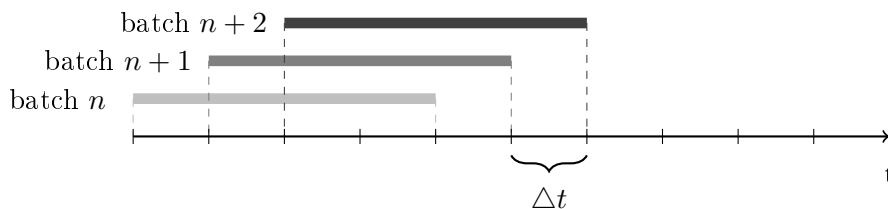


Figure 4: Timeline showing the sliding window approach

Finding pairs clusters Thus we define our two events as follows: To be able to compare clusters of different batches with each other, we have to find pairs of clusters between batches, which describe the same topic. This is done by applying the same assumptions as for the scoring function used in the evaluation. Therefore clusters are paired based on their similarity calculated with the Jaccard index as

shown in equation 2. If the similarity is above a certain threshold, both clusters are seen as describing the same topic.

Sliding window An important consideration for determining existing or new clusters is the overlap of samples between batches. If the overlap is too small, similar clusters will no longer be detected as such, which would result in an increasingly high error rate. Finding optimal values for the step size between batches and the number of samples for each batch is therefore essential for our online clustering approach.

4.4.1 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 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.

Comparing clusters To detect events between batches of clusterings, we have find pairs of clusters describing the same topic. 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)[11] to find similar clusters. This reduces the time complexity to $O(\log(n))$. The implementation for LSH is provided by the datasketch library[12].

Detecting Events Once we have found pairs of clusters, which represent the same topic, 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 the event *topic extended* for a specific topic. Clusters from the new batch without a matching cluster from the previous batch are seen as new topics and represented by the event *topic added*.

5 Results

5.1 Clustering Evaluation

The goal of this evaluation is to measure the accuracy of HDBSCAN, with different parameters and preprocessing methods. The most suitable approach will then be used for the online clustering to detect changes in a news stream.

5.1.1 Setup

Text Preprocessing The first step in working with text is to apply Natural Language Processing techniques for improving the quality of the data before clustering it. We look the five different preprocessing methods as described in section ?? and evaluate each. The methods are:

- Full text with stop word removal
- Key terms
- Named Entities
- Text Lemmatisation
- 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 baseline to evaluate HDBSCAN, we provide the true number of clusters for each run. Therefore K-Means runs with an optimal starting point.

Running the evaluation The evaluation is done with different sets of news articles per run. This means 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 three 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 five repetitions. Table 5 shows the resulting accuracy for each parameter in combination with each preprocessing method and vector space model. The highest score per parameter is highlighted as bold. The first insight we get is the variety in accuracy scores for different min cluster sizes. The lowest min cluster size results in the lowest accuracy, while increasing this parameter leads to an increasingly

better score. The highest accuracy is reached with a min cluster size of six, while increasing it further reduces the score again. The large difference in accuracy 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 little as two news articles. Based on this distribution we expected the min size cluster size to be low. The distribution also explains the drop in accuracy after a min cluster size of 6, since an increasingly number of clusters are being ignored.

Clustering	Word Frequency					tf-idf				
HDBSCAN	Full Text	Key terms	Entities	Lemmatised	Stemmed	Full Text	Key terms	Entities	Lemmatised	Stemmed
min_size: 2, metric: cosine	0.289	0.265	0.223	0.305	0.297	0.286	0.268	0.26	0.296	0.3
min_size: 2, metric: euclidean	0.101	0.093	0.110	0.101	0.106	0.301	0.170	0.241	0.306	0.301
min_size: 3, metric: cosine	0.488	0.456	0.465	0.48	0.487	0.472	0.446	0.457	0.493	0.478
min_size: 3, metric: euclidean	0.172	0.129	0.176	0.174	0.182	0.472	0.306	0.464	0.500	0.478
min_size: 4, metric: cosine	0.630	0.555	0.625	0.552	0.577	0.577	0.586	0.646	0.589	0.581
min_size: 4, metric: euclidean	0.320	0.182	0.214	0.315	0.332	0.611	0.416	0.559	0.613	0.615
min_size: 5, metric: cosine	0.716	0.652	0.656	0.718	0.718	0.688	0.664	0.632	0.686	0.692
min_size: 5, metric: euclidean	0.355	0.217	0.266	0.41	0.389	0.703	0.512	0.607	0.686	0.692
min_size: 6, metric: cosine	0.693	0.715	0.608	0.701	0.708	0.738	0.729	0.613	0.751	0.747
min_size: 6, metric: euclidean	0.179	0.280	0.292	0.202	0.164	0.738	0.408	0.622	0.778	0.763
min_size: 7, metric: cosine	0.631	0.611	0.552	0.643	0.634	0.689	0.685	0.553	0.718	0.722
min_size: 7, metric: euclidean	0.122	0.392	0.307	0.073	0.099	0.689	0.336	0.539	0.718	0.722
min_size: 8, metric: cosine	0.571	0.603	0.514	0.592	0.574	0.685	0.647	0.531	0.711	0.695
min_size: 8, metric: euclidean	0.056	0.339	0.338	0.025	0.057	0.685	0.286	0.522	0.711	0.695
min_size: 9, metric: cosine	0.542	0.569	0.476	0.544	0.541	0.602	0.614	0.499	0.637	0.640
min_size: 9, metric: euclidean	0.065	0.236	0.310	0.025	0.033	0.602	0.216	0.475	0.637	0.640
K-Means										
n_cluster: n_true	0.531	0.588	0.514	0.536	0.536	0.713	0.653	0.584	0.672	0.693

Table 5: Accuracy for combinations of parameter and preprocessing with a sample size of 60 stories (approx. 2000 articles)

Comparing the two vector models, shows the majority of best scores per parameter achieved by tf-idf. Additionally the different metrics show a significant difference when using the vector model based on word count. With tf-idf the difference between both metrics is often negligible.

As for the optimal preprocessing, text lemmatisation appears to provide the highest accuracy in general or at least being fairly close to the highest score. This is to be expected, since text lemmatisation reduces the dimensions by grouping words into their base form, while still retaining most of the text. In contrast to key term and entity extraction, which both result in a drastic reduction of the dimensions, and therefore less detail. It is important to note, that we used pretrained models for key term and entity extraction. 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.

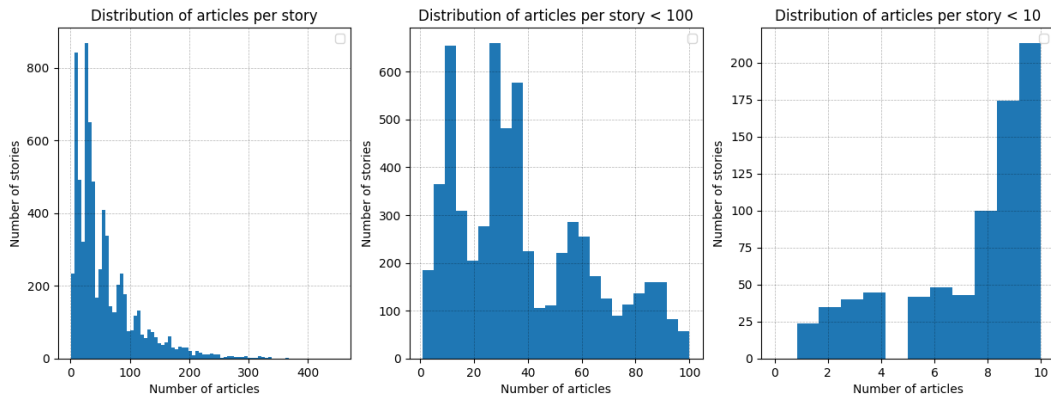


Figure 5: Distribution of cluster sizes.

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*, even if *euclidean* is occasionally more accurate.

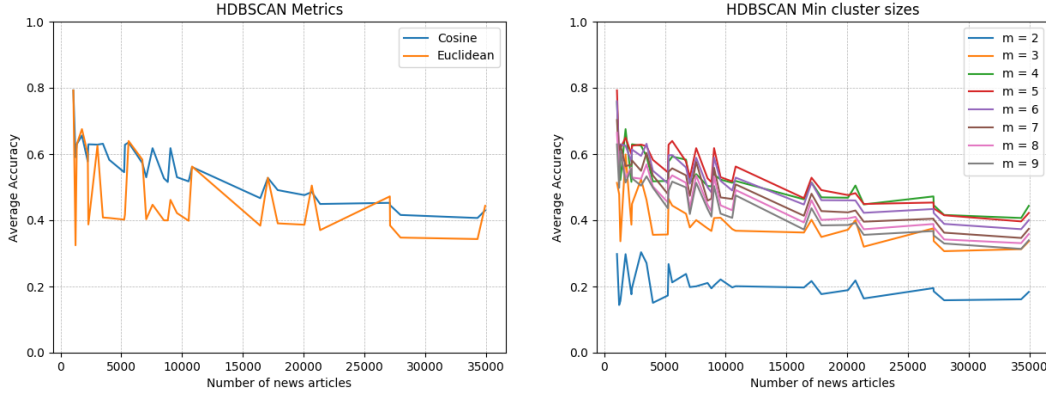


Figure 6: Accuracy for different parameters

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 7 is higher, than we would expect it to be based on our test data. A variety of factors play into the high noise ratio. One major influence is due to the used *min_cluster_size*. Each news article belonging to a cluster ignored due to a size too small, will be counted as noise. In addition to the false positives due to the min cluster size, the test data does still contain noisy data, even after our efforts in cleaning up the data as good as possible. Nonetheless the expected noise ratio based on the test data is less than 10%, nowhere close to the 20% of the current evaluation. Decreasing the noise ratio is certainly an important part in future improvements.

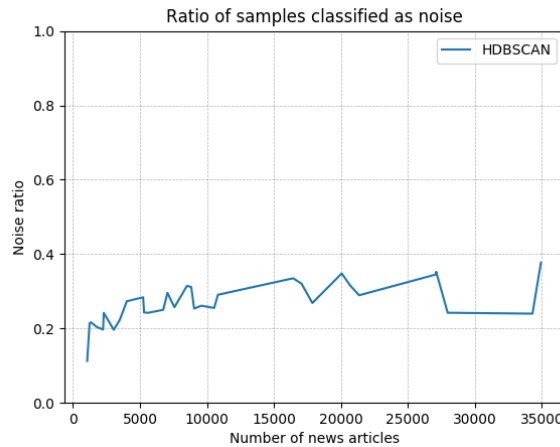


Figure 7: Number of news articles classified as noise.

Having found the optimal settings to run HDBSCAN with, we can start comparing the overall performance with K-Means. Figure 8 shows a similar behaviour for both clustering methods in value and variance of the accuracy. Although HDBSCAN is generally more accurate than K-Means, the difference gets smaller with an increase in the sample size.

Increasing the sample size results for both HDBSCAN and K-means in a small loss regarding the

accuracy as can be seen in Figure 8. However the accuracy seems to stabilize around the 0.7 mark.

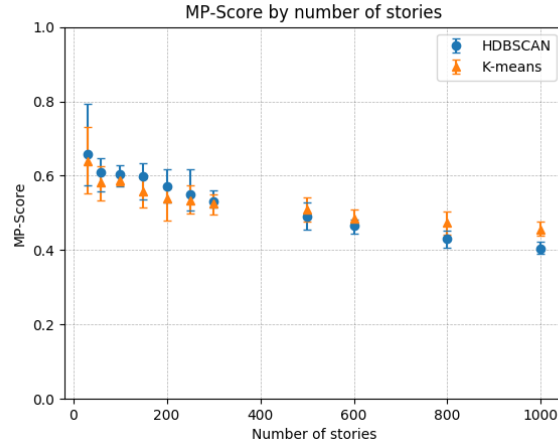


Figure 8: Comparison of the average accuracy between K-means and HDBSCAN

While HDBSCAN and K-means provide a similar accuracy, 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 $O(n \log(n))$, which is demonstrated 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.

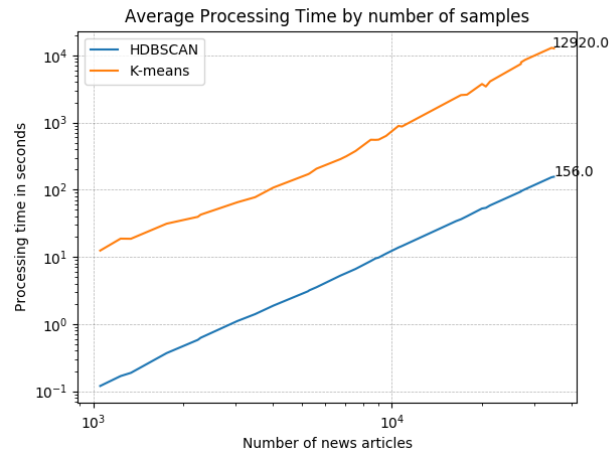


Figure 9: Processing time in seconds

Figure 10 shows, that the difference between predicted over the true number of clusters is fairly low and appears to be roughly linear with the overall number of clusters.

As a final note, 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 11. HDBSCAN provides the highest accuracy, while being still being one of the fastest algorithms. Based on this data, we can assume HDBSCAN to be a good candidate for our use case.

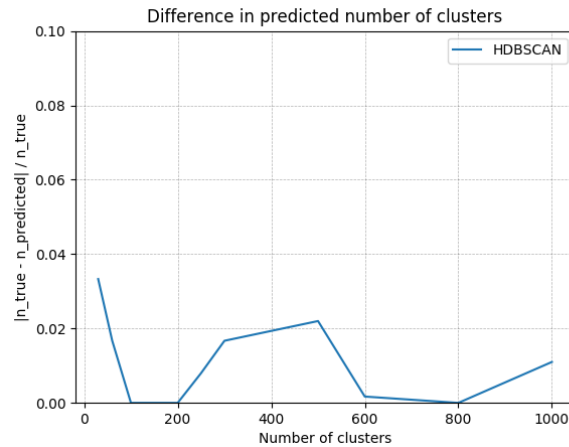


Figure 10: Ratio of difference over predicted with true number of clusters

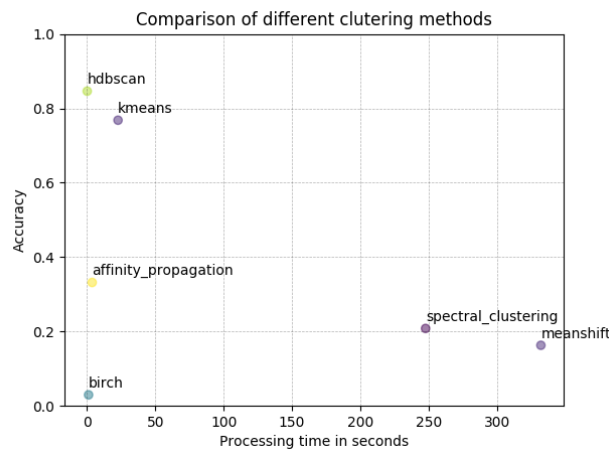


Figure 11: Comparison of different clustering methods with a sample size of approximately 1000 news articles

5.1.3 Conclusion

The evaluation has shown HDBSCAN to be a good candidate to use for news clustering. It provides a better accuracy 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 to 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. On the flip side, the noise ratio is quite high and the space complexity is problematic with larger data sets. Overall HDBSCAN provides an acceptable accuracy, 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:

- Text Lemmatisation
- Vectorizer: tf-idf

- Clustering method: HDBSCAN
- Min cluster size: 5
- 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 12.

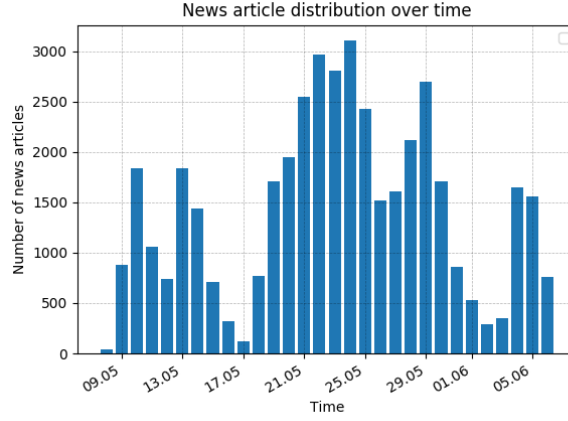


Figure 12: Incoming news articles over 30 days

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.

Figure 13 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 5000 news articles is significantly lower than the batch size of 1000. 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 12. During this period we receive up to 3000 news articles in a single day. This means by using a lower batch size such as 1000, the overlap between batches gets too small to reliably detect changes between batches, which causes too many new topics to be detected.

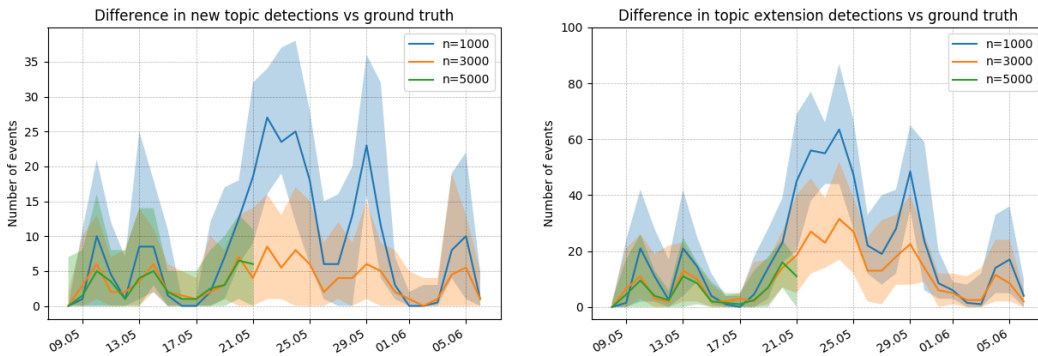


Figure 13: Comparison between the difference in detected and true events

Based on the overall differences, we still 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 14 shows the MP-Scores for an online clustering using a batch size of 1000. 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.

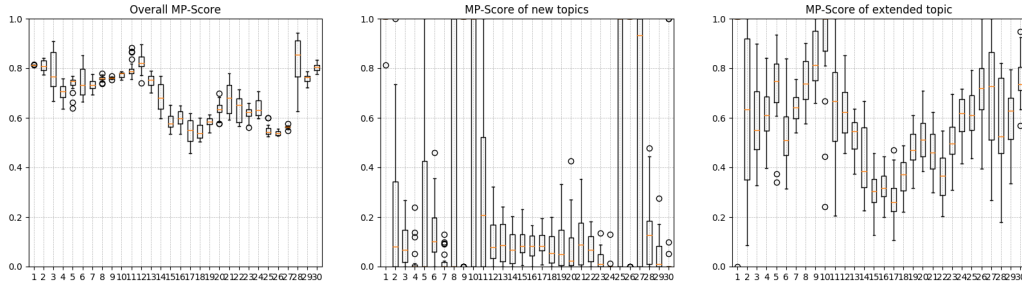


Figure 14: MP-Scores for clusterings using batch size of 1000

Looking at an increased batch size of 5000 in Figure 15, we note that there is less overall variance than with a batch size of 1000, but the variance is still fairly large for detected events. Additionally while the variance is large, the median for new topics is mostly below 0.2. 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, but there is still wide variance noticeable.

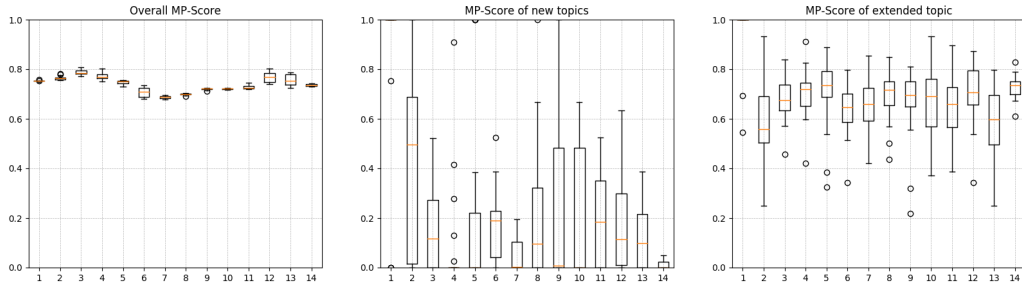


Figure 15: MP-Scores for clusterings using batch size of 5000

The difference in the accuracy of the detection of new events and the extension of events can be explained by bla bla bla,

5.2.3 Conclusion

6 Conclusion

6.1 Lessons learned

Todo.

6.2 Future work

How can this work be improved further?

- Improving space complexity and noise ratio of HDBSCAN.
- Alternatively, use HDBSCAN as an approximation for the number of clusters and a different clustering algorithm for the actual creation of the clusters.

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.. 29
- clustering** The task of grouping a set of objects based on their similarity.. 29
- docker** A tool to package the application with all its dependencies as a single deployable unit and run it on any host with docker installed.. 29
- dockerized** An application environment running as a single or a collection of docker containers.. 29
- vectorizer** A vectorizer transform a text into a numeric vector.. 29

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8 Appendix

8.1 Algorithm for MP-Score

```

1 import collections
2
3
4 def calculate_mp_score(true_clusters, predicted_clusters):
5     """
6     Calculate the mp_score of a clustering based on the contents of the clusters and
7     the overall difference in
8     predicted over true number of clusters. The calculation is based on three steps:
9     1. Create an similarity matrix by calculating the difference between each
10    cluster of both clusterings.
11    2. Select the most relevant values from the similarity matrix and make sure no
12    two clusters are being used
13    at the same time.
14    3. Calculate the weighted average, where the weight is based on the true and
15    predicted amount of elements
16    in a cluster.
17
18    Parameters
19    -----
20    true_clusters: array[clusters]
21    2-dimensional array of true clusters
22
23    predicted_clusters: array[clusters]
24    2-dimensional array of predicted clusters
25    """
26
27    # If both clusters are empty, they are identical.
28    if len(true_clusters) == 0 and len(predicted_clusters) == 0:
29        return 1
30
31    similarity_matrix = create_similarity_matrix(true_clusters, predicted_clusters)
32    unique_indices = select_max_values(similarity_matrix)
33    return calculate_weighted_average(unique_indices, true_clusters, predicted_clusters)
34
35
36 def create_similarity_matrix(true_clusters, predicted_clusters):
37     similarity_matrix = []
38     for true_cluster in true_clusters:
39         true_set = set(true_cluster)
40         n_true = float(len(true_set))
41         row = []
42         for predicted_cluster in predicted_clusters:
43             cluster_set = set(predicted_cluster)
44
45             # Calculate the similarity using the jaccard index
46             similarity = len(true_set.intersection(cluster_set)) / len(
47                 true_set.union(cluster_set)
48             )
49             row.append(similarity)
50
51         similarity_matrix.append(row)
52     return similarity_matrix
53
54
55 def select_max_values(precision_matrix):
56     unique_indices = dict()
57     row_index = 0

```

```

54     nrows = len(precision_matrix)
55
56     while row_index < nrows:
57         ignore_indices = set()
58         max_value_found = False
59
60         while not max_value_found:
61             max_value = 0
62             column = 0
63             for col_index, value in enumerate(precision_matrix[row_index]):
64                 if value >= max_value and col_index not in ignore_indices:
65                     max_value = value
66                     column = col_index
67
68             if (
69                 max_value > 0
70                 and column in unique_indices
71                 and unique_indices[column]["row_index"] != row_index
72                 and unique_indices[column]["max_value"] > 0
73             ):
74                 if unique_indices[column]["max_value"] < max_value:
75                     # The column is already used, but we found a better
76                     # candidate. We use the new candidate and set the
77                     # cursor to the old one to find a new max value.
78                     old_row_index = unique_indices[column]["row_index"]
79                     unique_indices[column]["row_index"] = row_index
80                     row_index = old_row_index
81                     unique_indices[column]["max_value"] = max_value
82                     max_value_found = True
83                 else:
84                     # The column is already used by a better candidate.
85                     ignore_indices.add(column)
86             else:
87                 # If max_value is greater than 0, we store the value as a
88                 # new candidate. Otherwise either the row does not match
89                 # any other column or the max_value was low and got
90                 # overridden by previous tries and no other match is available.
91                 if max_value > 0:
92                     # The column is free to use
93                     unique_indices[column] = {
94                         "row_index": row_index,
95                         "max_value": max_value,
96                     }
97                 max_value_found = True
98                 row_index += 1
99
100     return unique_indices
101
102
103 def calculate_weighted_average(unique_indices, true_clusters, predicted_clusters):
104     mp_score = 0
105
106     elements_per_true_cluster = [len(cluster) for cluster in true_clusters]
107     elements_per_predicted_cluster = [len(cluster) for cluster in predicted_clusters]
108
109     total_true_elements = sum(elements_per_true_cluster)
110     total_pred_elements = sum(elements_per_predicted_cluster)
111     total_elements = total_true_elements + total_pred_elements
112
113     if total_elements > 0:
114         for column, value in unique_indices.items():

```



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

Listing 3: Calculate the MP-Score between two clusterings.