Detecting Non-routine Customer Support E-Mails

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Keywords: E-Mail Outliers, Customer Support System, Outlier Detection, Machine Learning, Decision Support.

Abstract: Customer support can affect customer churn both positively and negatively. By identify non-routine e-mails to be handled by senior customer support agents, the customer support experience can potentially be improved. Complex e-mails, i.e. non-routine, might require longer time to handle, being more suitable for senior staff. Non-routine e-mails can be considered anomalous. This paper investigates an approach for context-based unsupervised anomaly detection that can assign each e-mail an anomaly score. This is investigated in customer support setting with 43523 e-mails. Context-based anomalies are investigated over different time resolutions, by multiple algorithms. The likelihood of anomalous e-mails can be considered increased when identified by several algorithms or over multiple time resolutions. The approach is suitable to implement as a decision support system for customer support agents in detecting e-mails that should be handled by senior staff.

1 INTRODUCTION

Maintaining a high-quality and cost-efficient interaction with customers is an important element for any corporation. Interactions between the organization and customer via customer support is especially important, and negative customer support experiences risk affecting the customers view of the organization negatively. This might lead to a worse reputation for the organization. Further, negative experiences with customer services can either deter potential new customers from a company or increase the risk of existing customers to drop out (Halpin, 2016).

E-mails still account for an important means of communication due to both its ease and widespread use (Kooti et al., 2015). As corporations receive large numbers of customer service e-mails, implementing efficient customer service processes that target customer E-mail communication is often a necessity. Furthermore, the customers expects quick responses (Church and de Oliveira, 2013).

Support errands are often sent to a generic customer service e-mail address. However, in this setting there are customer support agents with varying experience. Similarly, the content of the e-mails being received are of varying complexity. Complex e-mails, i.e. non-routine, might take longer time to handle given the cognitive load (Rafaeli et al., 2019). As such, they might be more suitably handled by senior customer support agents. Being able to identify non-routine customer support e-mails would enable senior customer support agents to focus on non-routine e-mails, and junior customer support agents to focus on routine e-mails. Given that routine e-mails can be interchanged with normal e-mails, non-routine e-mails can be considered anomalous. As such, this paper investigates an approach for detecting anomalous e-mails.

The study is conducted with one of the bigger telecom operators in Europe with over 200 million customers worldwide, and some 2.5 million in Sweden. E-mail based customer support is one of the primary means of resolving issues customers experience. The company utilizes a semi-automated customer service E-mail management system to sort and handle support errands. Customer service E-mails, provided by the telecom company, contains support errands with different topics. As such, an E-mail topic could be sorted as *Invoice*, *TechicalIssue*, and *Order*.

What can be considered anomalous in this setting is context-dependant and affected by different factors, e.g. campaigns conducted or system roll-outs. Consequently, what can be considered anomalies is contextual (Chandola et al., 2009). I.e. an e-mail considered anomalous during a week might not be considered anomalous during a longer time period. Another challenge is that the data available is unlabeled, i.e.

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Borg, A. and Ahlstrand, J.
Detecting Non-routine Customer Support E-Mails.
DOI: 10.5220/0010396203870394
In *Proceedings of the 23rd International Conference on Enterprise Information Systems (ICEIS 2021) - Volume 1*, pages 387-394
ISBN: 978-989-758-509-8

no labeled anomalies exists. As such, this study investigates unsupervised approaches to context-based anomaly detection and discusses how such an approach might be implemented in a customer support system.

2 RELATED WORK

The overlap between outlier detection and anomaly detection should be pointed out, and the terms are often used interchangeably (Chandola et al., 2007; Chandola et al., 2009). While anomaly detection is an active research area, the research has mostly focused on areas e.g. intrusion detection, traffic analysis, fault detection, or fraud detection (Chandola et al., 2007; Chandola et al., 2009).

Document anomaly detection has been suggested for detecting anomalies among e.g. web sites using document clustering (Friedman et al., 2007). But it has also been used to detect novel topics in documents, e.g. news data (Allan et al., 1998).

A contextual anomaly is a data point that is only considered anomalous in a certain context, e.g. a subset of the data or from within a certain feature set (Chandola et al., 2009). The same data point can be considered normal in another context. This type of anomaly detection has been investigated in e.g. time series, where seasonality can affect normality (Chandola et al., 2009). Contextual anomalies can be compared to point anomalies and collective anomalies. In the former a data point is considered an anomaly compared to the whole dataset, and in the latter a collection of related data points are considered anomalous compared to the whole dataset (Chandola et al., 2009).

Semantic anomaly detection has been investigated to detect normal and abnormal documents. This has used SVM to model normal documents based on semantic features, and then classify new documents as on- or off-topic based on their semantic similarity to normality (Yilmazel et al., 2005). Semantic features include e.g. entities and named entities.

There is, to the best of the authors knowledge, little research on how to detect context-based anomalies, routine, or non-routine e-mails in customer support settings.

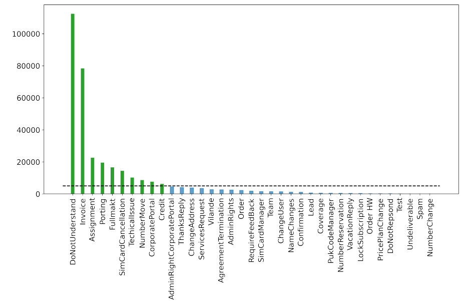


Figure 1: Topic distribution. Dashed line denotes threshold of 5000 e-mails.

Table 1: Example E-mail with multiple classes (Borg et al., 2020). The keyword-based rule system could make the following associations: terminate, termination → Simcardcancellation.

Header	Sent	2031-02-31 08:00:00
	Thread	234
	Mail	3
	From	customer_service@company.org
Content	Subject	RE Termination
	Content	Hello Ralph, Thank you for your email. Do they want us to terminate the subscription immediately, so they are left without a subscription or shall we set a future termination date so that they are able to port their numbers? Please get back to us. Have a nice day.
	Class	Simcardcancellation

3 METHODOLOGY

3.1 Data

The dataset consists of 333700 e-mails in 68238 threads, divided over 36 different topics. Figure 1 shows the number of e-mails for each topic. The most frequent topic is DoNotUnderstand, followed by Invoice. DoNotUnderstand contains e-mails that the classifier is unable to correctly classify, and as such can contain a vast number of topics. The investigation in this study is focused on the invoice class, as it is the highest homogeneous class.

The Invoice topic consists of 78386 e-mails. The features available in the dataset is the subject, content, sent time, from address, mail id, and thread id. The data set does not contain any label concerning anomalies.

3.2 Preprocessing

The content has been anonymized by removing numbers (e.g. phone nr, invoice nr, etc), names and other identifying content. Further, header information and attachments have also been removed.

While, the content of the e-mails are primarily written in Swedish, other languages can exist in the dataset. The customer support e-mails are from corporate clients, i.e. no individual customers. This should be noted as it affects the manner of how the e-mails are written, i.e. a more formal or professional writing style is expected.

From this subset, e-mails from the customer support agents are removed. I.e. only e-mails from customers are kept. The resulting dataset consists of 43523 e-mails in 21866 threads. Swedish stop words have been removed from the e-mail content[1].

The data is divided into multiple subsets based on their date. The data is divided into 12 one month periods and from each month a one week subset were extracted. This chronological division is chosen instead of e.g. 10-fold cross-validation to adjust for seasonality (Chandola et al., 2009). The time periods were chosen in collaboration with domain experts. The resulting data sets consists of 12 month sets and 12 week sets.

For each data set, the text were represented as a bag-of-words using a term-frequency and inverse document frequency (TF-IDF) vectorizer, where the words have been transformed into uni-, bi-, and tri-grams (I.H. Witten and Hall, 2011). A TF-IDF algorithm weights each word based on the term frequency, i.e. how frequent each word is in each document, and the inversed document frequency, i.e. the inverse fraction of documents that contain the word. The term frequency indicates if a word is indicative of a document and the inverse document frequency normalizes each word according to how frequent it is occurring in all documents.

3.3 Algorithms

Several algorithms for anomaly detection are investigated in this paper, the majority of which is available through PyOD (Zhao et al., 2019). The algorithms has been chosen because the work according to different assumptions, or have different weaknesses. When of relevance, the assumptions or weaknesses are described below.

MINISOM[2] is an implementation of Self Organizing Maps (SOM), that can be used for outlier detection (Vettigli,). SOM is an unsupervised Artificial Neural Network. It is also able to conduct dimension reduction.

K-Means-based anomaly detection, denoted *K-means Outlier detector* (KOD) significance levels. The assumption for both KOD and MiniSOM is that normal data instances lie close to their closest cluster centroid. Anomalies, on the other hand, lies further from the cluster centroid (Chandola et al., 2009). KOD, however, is unable to locate anomalies if the anomalies are grouped as small clusters of their own (Chandola et al., 2007). Using K-means for anomaly detection has been done previously, e.g. by calculating a distance-based outlier score (Pamula et al., 2011). The implementation used in this paper computes the likelihood (p-value) of an instance being an anomaly based on the standard deviation from the cluster center. Significance levels of 0.05 and 0.1 are used. The number of clusters is set to $k = 5$ after a manual investigation of the data.

Local Outlier Factor (LOF), measures the local deviation of density for a instance compared to its k nearest neighbors (Chandola et al., 2009; Zhao et al., 2019). The algorithm assumes a certain amount of *contamination*, i.e. number of anomalies, when setting the threshold of the decision function. This is left to the default value of 0.1.

Connectivity-Based Outlier Factor (COF), is similar to LOF, but rather looking at the k-nearest neighbors of the instance, the neighborhood is increased incrementally k times and each time the instance nearest the neighborhood is added (Chandola et al., 2009; Zhao et al., 2019). A contamination value of 0.1 is used.

Stochastic Outlier Selection (SOS), is based on the concept of affinity. Affinity is defined as a decreasing function of the dissimilarity value. Each instance have a certain affinity for other instances, i.e. an affinity distribution. All instances simultaneous decide which instances they have the highest affinity towards, i.e. chosen by an instance. Instances which do not get chosen are considered outliers (Janssens et al., 2011). This is repeated to get the probability of an outlier being true. A contamination value of 0.1 is used.

One-class SVM, is a kernel based functions where the model learns what is normal data, delineated by a learnt boundary. Instances considered outside of the normal data boundary is considered anomalous (Chandola et al., 2009). A contamination value of 0.1 is used.

Isolation Forest is built on the assumptions that trees constructed from anomalies will be different from trees constructed from normal data, with regard to tree number of splits and nodes (Zhao et al., 2019). A contamination value of 0.1 is used.

[1] https://gist.github.com/peterdalle/8865eb918a824a475b7ac5561f2f88e9

[2] https://github.com/JustGlowing/minisom/blob/master/minisom.py

3.4 Experiment Setup

Two experiments are conducted based on the two time resolutions, month and week.

The first experiment investigates anomalies using a month resolution. In the preprocessing stage, the TF-IDF algorithm were applied to each data set independently, as opposed to a global bag-of-words representation. This ensures that any context-shift that might have occurred over time do not affect the current data. For a data set, the algorithms described in Section 3.3 were run and which instances were considered anomalies by the different algorithms saved. The second experiment is similar to the first, but instead uses data sets based on the week resolution.

Since this data set is not labeled, i.e. there is no known anomalies, using traditional evaluation metrics (i.e. quantitative) is difficult. Further, given that context-based anomaly detection is investigated, the labels might have changed given e.g. the time resolution. Instead algorithm agreement and visualization is used to evaluate the anomalies detected. Manual verification of random anomalies in their context has also been done in cooperation with domain experts.

The anomalies are visualized in two ways. First, data sets were visualized in a 2D space with normal instances along with anomalies detected by different algorithms. The dimensional reduction is done using T-SNE (Maaten and Hinton, 2008). Second, The results are visualized using Upset Plots (Lex et al., 2014). Upset plots are used instead of Venn diagram and help visualize the uniqueness and overlap between algorithms with regard to anomalies found. For each time resolution, an upset plot of the mean overlap is constructed.

Algorithm agreement denotes the number of anomalies that are shared between algorithms for a data set. Anomalies detected by multiple algorithms are considered stronger anomalies. Similarly, anomalies detected by only one algorithm is considered a weak anomaly. This is similar to the approach used by Boldt et al. (Boldt et al., 2020).

Finally, anomalies shared over time resolutions are shown. The assumption being that if an instance is identified as an anomaly in both a shorter and longer time resolution, the likelihood of it being an anomaly increase (Boldt et al., 2020).

4 RESULTS

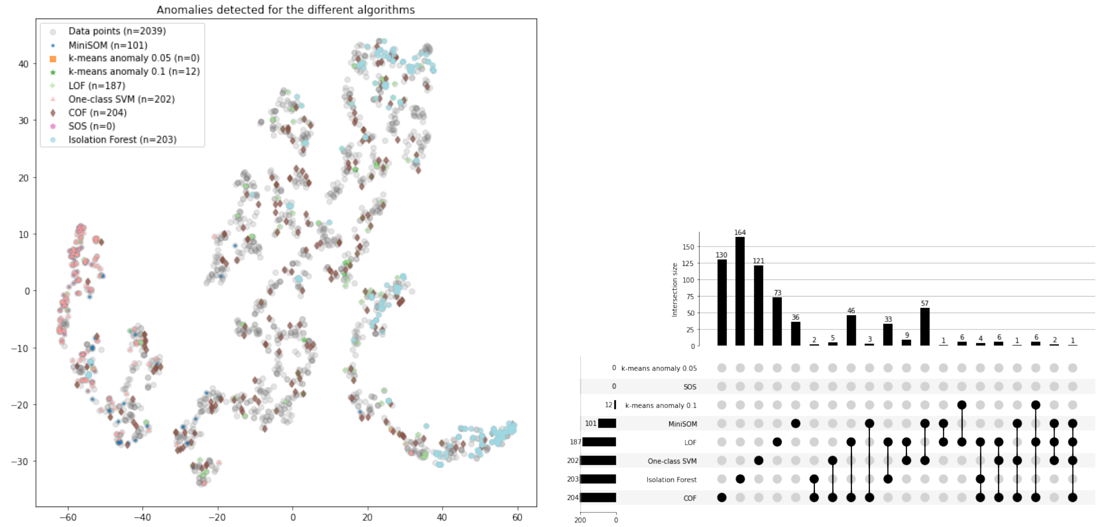
The results are divided into two subsections. The first subsection presents the results for the outlier detection for the month resolution along with the mean results. The second, similarly, presents the results but for the week resolution.

4.1 Month

One of the data sets investigated can be seen, visualized in a 2D space, in Figure 2a. The outliers suggested by the algorithms investigated are shown in the 2D-space, denoted using different colors and markers. Non outliers are shown as grey dots. In this example, e.g. Isolation Forest and One-class SVM seems to suggest anomalies located in denser clusters, whereas COF seems to suggest a sparser, more spread out solution. However, this might be a result of the dimensional reduction and, given another way of reducing the dimensions, should be generalized from with some scepticism. A qualitative investigation of the found anomalies for Isolation forest suggests that there are indeed three clusters of detected outliers.

As can be seen in Figure 2b, the results suggests that for most algorithms the suggested outliers are not shared with other algorithms. Columns with lines between point/rows indicate that n instance are considered anomalies by the algorithms denoted by the points. A column with a single point indicates that the outliers found aren't found by any other algorithm. E.g. for Isolation Forest, out of 203 anomalies, only 39 are designated outliers by, at least, one other algorithm. The numbers are higher for other algorithms. However, e.g. LOF and COF agree on 50 data points, which might be because of the similar approach for the two algorithms. It should also be noted that K-means 0.1 only found shared anomalies, which can be considered stronger anomalies. K-means 0.05 and SOS found no anomalies.

As Figure 2 only shows an example month, it doesn't give an overview of all month data sets. To give an overview of detected anomalies over all twelve month data sets, an mean Upset plot was created. This plot can be seen in Figure 3. The bars on top and to the left denotes mean anomalies and can be interpreted similar to Figure 2b. However, the top bars also show error bars denoting the standard deviation for each bar. As can be seen in the sixth column, K-means anomaly 0.1 have a large standard deviation, indicating that the algorithm vary a lot with regards to the number of anomalies detected for the different data sets. Similar results can also be seen for the overlaps between different algorithms. However, e.g. in the case of COF and One-Class SVM, it might be expected that algorithms do not detect the same outliers, as they are from different families of algorithms.



(a) Data points plotted together with found outliers for an example month. Dimensional reduction by using T-SNE. Colors denote algorithm.

(b) Upset plot showing number of outliers found for each algorithm, as well as to what extent algorithms denoted the same data points as outliers.

Figure 2: Example of findings for a random month data set.

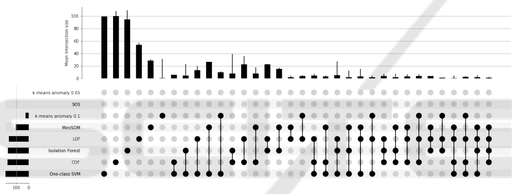


Figure 3: The mean upset plot for all month data sets.

4.2 Week

Anomalies in a week time span is shown similar to the results of the month data set. Figure 4a shows a 2D visualization of the data-points and the anomalies detected by the different algorithms for an random week data set. E.g. Isolation Forest seem to have found at least one denser area of anomalies. Similar to Figure 2b, Figure 4b indicates that a majority of the anomalies detected are only detected by one algorithm, i.e. the number of shared outliers is quite low. MiniSOM detected anomalies shared with other algorithms for 75% of the anomalies found, increasing the likelihood of them actually being outliers. The K-means based algorithm did not detect any anomalies.

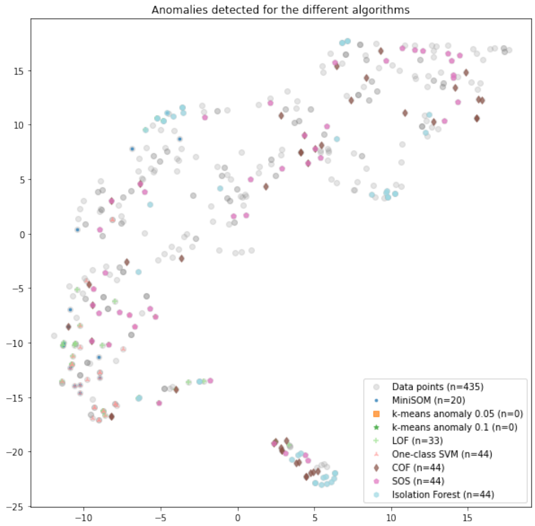
Similar to Figure 3, Figure 5 shows the mean findings for the week data sets. The results indicates that there is a larger overlap between algorithms for week data sets, indicated by the higher number of columns (34 columns for Figure 3 and 43 columns for Figure 5). The error bars shown in Figure 5 are also larger compared to the month data set. Both of these findings can indicate that there is a larger variation between the data sets, i.e. the email contents tend to differ between different weeks.

4.3 Combined Results

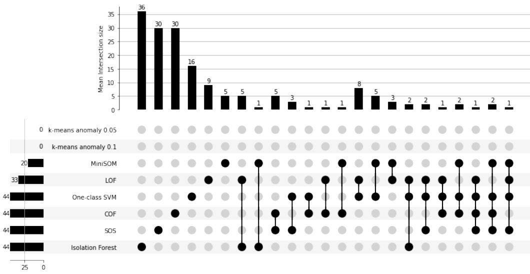
The idea of strengthening the anomaly detection by investigating anomalies over different temporal resolutions has been done before (Boldt et al., 2020). Given a longer time span, the context which the anomaly has been detected in is different. Consequently, if an data point is considered anomalous in both time resolutions (i.e. contexts) the certainty of the prediction is increased. Similarly, a data point that is considered anomalous by several different types of algorithms could be considered a more likely anomaly.

Anomalies detected by several different algorithms has been shown to exist in e.g. Figure 2b and Figure 4b. In Figure 6a the anomalies found by at least two and three algorithms are visualized. This is for the same data set as used in Figure 4. What is possible to discern from this picture, and looking at the data, is that, for most anomalies, the anomalies detected by three algorithms are a subset of the ones detected by two algorithms. I.e. the emails are from the same thread where some might be considered more anomalous than others (detected by more algorithms). It should be noted that there are emails in the threads not considered anomalous.

Similarly, Figure 6 visualizes anomalies detected in both a week and month context. Additionally, the



(a) Data points plotted together with found outliers for an example week. Dimensional reduction by using T-SNE. Colors denote algorithm.



(b) Upset plot showing number of outliers found for each algorithm, as well as to what extent algorithms denoted the same data points as outliers.

Figure 4: Example of findings for a random week data set.

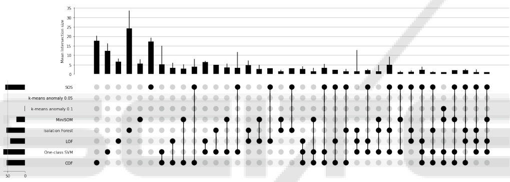


Figure 5: The mean upset plot for all week data sets.

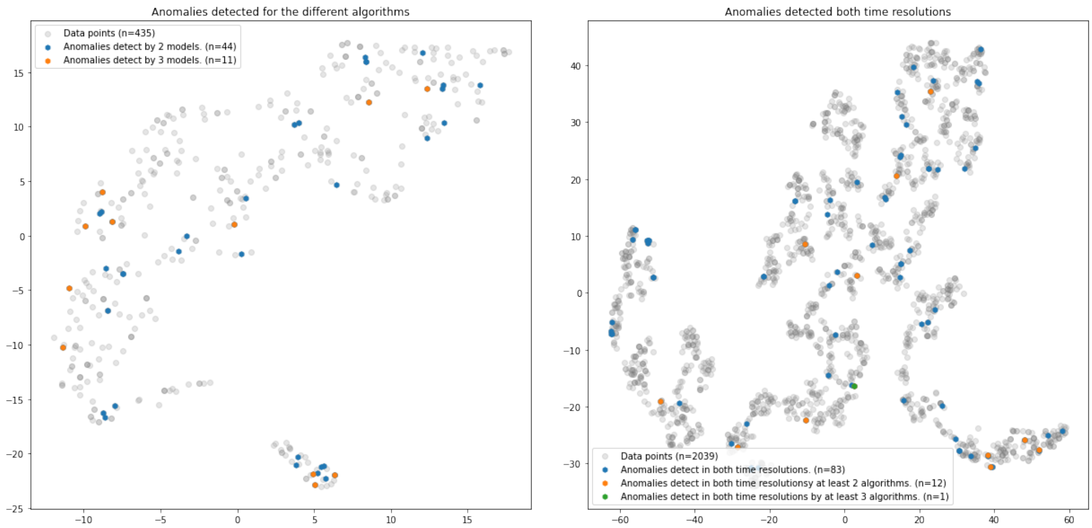
anomalies are colored according to the number of algorithms that have detected it. There are 83 anomalies detect in both time resolutions by at least one algorithm (out of 2039 data points). 12 anomalies are detected by at least two algorithms, and one anomaly is detect by at least three algorithms. Similar results can be seen for all the data sets in Table 2.

5 ANALYSIS & DISCUSSION

Different anomaly detection algorithms are based on different assumptions. As such, having multiple types of algorithms investigate anomalies enables anomalies to be found from different point-of-views (e.g. based on different assumptions). Anomalies detected by multiple algorithms could as such be considered stronger anomalies. Similarly, anomalies detected in multiple time resolutions might also be considered as stronger anomalies. As the type of contents change over different weeks the context from week to week might be different. Similarly, the context over a month might be different from the context of weeks within that month. As such, anomalies detected in multiple time resolutions could be considered stronger candidates as they are anomalies in multiple contexts (Boldt et al., 2020).

It should be noted that LOF, One-class SVM, COF, SOS and Isolation forests uses the contamination parameter to set the threshold on the decision function. This is an assumption on the proportion of outliers in the dataset. In this case it is left to it's default value, i.e. 0.1. Consequently, a weakness of these algorithms are that they require the user to have some sort of knowledge about the level of contamination in the data. This is of course not feasible in a live setting, especially a customer support system where the contamination can differ between different topics. Further, this assumes that there actually exists anomalies in the dataset. As can be seen in Figure 4, this is not certain. Both K-means 0.05 and K-means 0.1 report zero anomalies, and MiniSOM reports 20.

Implementing anomaly detection in a customer support system could be done as a scoring system, where a point is awarded for each time resolutions the anomaly is detected in and for each algorithm the anomaly is detected by. A data point can be awarded between $0-2$ point for the time resolutions and between $0-8$ for the algorithms. A data point can as such have a score between 0 and 10. In practice it is unlikely that an anomaly will get a score of 10, Figure 6 shows that one anomaly with a score of 5, and 12 anomalies with a score of 4 have been found. By using this approach, it is possible to implement a scoring system for e-mails in a customer support setting.



(a) Example week showing outliers detected by at least two and three algorithms.

(b) Example month showing outliers detected in both week and month data sets. Number of shared algorithms denoted by color.

Figure 6: Data points plotted together with found outliers for an example week and month.

Table 2: Anomalies detected in both Week and Month dataset. *+2* and *+3* denotes anomalies detected by more than one and two algorithms respectively in each time resolution. A *+1* anomaly is only detected by one algorithm in each time resolution.

Nr of alg.	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	Mean
+1	83	16	74	89	74	54	52	87	83	36	64.8
+2	12	2	5	9	14	10	12	10	10	3	8.7
+3	1	0	2	0	1	0	0	2	0	2	0.8

A higher score would indicate a likelier anomaly, and as such should be directed to a more experienced customer support agent.

Given different kinds of data, algorithms might be more or less suited for the problem. By using a combined algorithm approach, i.e. an ensemble approach (Flach, 2012), where scores are utilized to highlight anomalies, algorithms unsuited for the data set will be marginalized by the combined findings of algorithms suited for the data set. However, it is quite possible that an anomaly detected by just one algorithm should be on par with an anomaly detected by multiple algorithms. As such, they shouldn't be discarded.

When inspecting the found anomalies, a minority of the e-mails are spam messages that were not caught by the spam filter. Consequently, single message threads that are considered anomalies could be also be investigated as spam again, either manually or automatic. This would be an additional benefit to customer support agents, as context switching, manually reading e-mails, and then discarding spam messages could become a workload bottleneck (Woods et al., 2002). Especially as complex messages can put an increased cognitive load on the customer support agents (Rafaeli et al., 2019).

6 CONCLUSION & FUTURE WORK

This paper has investigated an approach for anomaly detection in an e-mail based customer support setting. The suggested approach utilizes two different assumptions. First, different time resolutions to investigate anomalies in different contexts. And second, different types of anomaly detection algorithms to investigate anomalies based on different assumptions. By assigning scores to the anomalies found, depending on the number of algorithms detected the anomaly and in how many time resolutions it was detected, the likelihood of an anomaly is quantified. This would enable senior customer support agents to focus on e-mails that are considered highly anomalous, i.e. non-normal, and junior customer support agents to focus on routine, i.e. normal, e-mails.

Future work is two fold. First, implementing and evaluating the practical use of this approach as a decision support system. Second, investigating the possibility of predicting the likelihood that an e-mail in a thread is an anomaly. As an e-mail thread becomes larger, it would then be possible to assign a senior customer support agent to the e-mail thread before it becomes anomalous. And thus, possibly, improving the customer support experience for the customer.

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