AOEC: A Tool for Automated Online Email Categorization

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1. INTRODUCTION

More and more people are using email as a daily communication tool for their work and daily lives. Its growing importance has inspired many attempts to develop intelligent tools for classifying, organizing, and presenting email messages (e.g., Bellotti etal., 2003 [2]; Murakoshi et al., 1999 [8]; Sproat et al., 1998 [11]). Among these tools, Email automatic categorization has became a basic and important part for email applications. That is because, for most people, there will be hundreds of emails flowing into the mailboxes everyday, while people usually don't have the patience to read such a large amount of emails one by one. So automatic categorizations and classifications for email are crucial to improve the efficiency of dealing with the flow of emails.

1.1 Problems

There are two main problems in existing email applications. First of all, for most popular Email applications like Outlook, Gmail and Yahoo Mail, they only automatically categorize emails into several default folders, such as Promotions, Updates, Social, Forums and so on. While users do not have the option to create their own folders that have the automatic categorization feature. It is true that these default folders have covered the need for common email users, but it is far away from "enough" for heavy email users who have to categorize their emails in a more detailed way.

Another problem we notice is that the existing automatic categorization systems only ask for users' feedback in a quite passive way, which means they seldom ask feedback from the user for their auto-categorization result, or they put their feedback buttons in the second or third level of the user interface. Even worse, some email applications do not have a feedback mechanism at all for their automatic categorization.

1.2 User

Based on the problems above, our target users are those who gave to deal with emails everyday, who need more flexibility to manage their email folders, and who also need their emails be automatically categorized into the folders by their own.

1.3 Tool

Email client receiving real-time email streams, and monitor user behaviors to provide non-intrusive notification asking for user feedback.

Besides the basic structure of Gmail, we will add the following features: a) user can create new folders with any arbitrary name; b) incoming emails will be automatically classified into each folders; c) one emails may appear in multiple folders d) a folder named "Confusing" will store the most confusing emails that the classifiers are confused about and wait for the user's judgement. e) implicit feedback: if user opened one email under a folder without moving it to other folders, we will treat this as an implicit feedback.

1.4 Goal

For this project, our goal is to offer users a more flexible, active and automatic email categorization. To achieve this, a new categorization logic is needed. Like other email applications, we will first classify emails into several default folders, which is based on massive email training set. Then, we will actively ask the user for feedback in a non-disturbing way. User can choose the right folder to put the new incoming mail or create new folder if they like. Finally, after collecting the new categorization record, we will re-train our classifiers to adapt the new user-specific features.

All the materials for this project can be found at our Github repository[1].

2. CHALLENGES

Literature and several user experiences are studied to identify the challenges we may face to achieve our goal. Start with one seed paper [1], each member of the team reviewed three papers, either highly cited or most recent. In addition to literature review, several users are interviewed to express their difficulties using existing tools. The following problems are summarized to provide a guideline for the next step of our project.

2.1 Lack of Training Examples

2.1.1 Challenge

Most of the text mining classifiers requires thousands of training examples to build a reliable model. However, more than half the users we interviewed expressed their unwillingness to provide such a great amount of training examples. The number of training examples acceptable is dozens for each folder and hundreds in total according to our interview. This leads to the lack of training examples in the initial step. For a text categorization task, the dimensionality for feature is usually thousands, which is a lot higher than the available training examples. The classifier trained on such a feature matrix will have a huge bias.

[1]https://github.com/azhe825/CSC510.git

2.1.2 Solution

There are three methods we proposed to solve the problem:

a) try different types of classifiers to see if anyone works better in this scenario;

b) implement incremental learning, we may have bad performance at beginning but will keep learning until saturation.

c) apply LDA first to get a topic model before training, so that the dimension of features can be reduced to less than the number of training examples;

The result of these three solutions are presented in Section 3.3.

2.2 Compensation to Explicit Feedback

2.2.1 Challenge

In most of the email categorization tools, the implicit feedback events are underutilized. When the classifier is not confident, positive feedback confirming the correctness of predictions would be helpful. It is a good compensation to explicit feedback. Users do not like to be asked to provide corrections frequently, especially if they are working quickly or are deeply engaged in a task. Under such conditions, self training is risky [10]. This was the motivation to explore *implicit feedback*. The implicit events/interactions are defined as follows:

a) user add or remove a tag on the message;
b) user add or remove a flag from the message;
c) user move the message to a folder;
d) user copy, reply, forward, or print a message;
e) user save an attachment from the message.

2.2.2 Solution

The study shows most of the bad labels are corrected almost immediately within a few interactions [10]. One way to use these events for implicit feedback events is to keep a threshold on these events. When it exceeds a total number of events, the labels are assumed to be correctly predicted and the classifier trains on that message. We can set less threshold for good confident labels and more threshold for bad confident labels. This made us to explore [10] and found 4 methods to tackle implicit feedback events:

a) No Implicit Feedback (NoIF): This creates a training example for a label if the user adds or removes that label from the email message. This doesn't change the confidence level of the other labels.

b) Simple Implicit Feedback (SIF): When the user changes any label, immediately treats all remaining labels as correct and creates implicit feedback training examples. This changes the confidence level of the other labels.

c) Implicit Feedback without SIF (IFwoSIF): This maintains a count of the total number of implicit feedback events. When this count exceeds a specified threshold, then it creates the implicit feedback training examples.

d) Implicit Feedback with SIF (IFwSIF): If the user changes a label, then implicit feedback examples are immediately created. Otherwise, continue to count up implicit events to reach a specified threshold.

With the addition of implicit feedback on top of explicit feedback, the system is more adaptive and produce less errors as time passes by.

2.3 Importance of Folders may Vary

2.3.1 Challenge

Users definitely do not want to miss a single important email. Some of the folders can be of high importance that False Negative costs much more than False Positive. This phenomenon is commonly described in the binary classification case of email categorization– spam filtering [5]. Failure to identify a spam is always less important to failure to identify non-spam.

2.3.2 Solution

One possible solution for this problem would be to allow each incoming email belongs to several folders. This will change the problem to multi-label, multi-classification problem.

In addition, different weight can be addressed on the labels. User can be asked to put an importance rank when creating folders. For the folders with high rank, the threshold can be reduced to allow emails to go into that folder more easily.

2.4 Not Every Folder is Content-aware

2.4.1 Challenge

There are three types of email folders– content-aware, time-aware, and participants-aware– while most of the existing methods can only correctly classify emails with content-aware folders [6].

Content-aware: Folders contain emails of the same topic, e.g. "sports", "music".

Time-aware: Emails in this type of folders are categorized regarding the time they are received, e.g. "2012 Summer".

Participants-aware: This type of folders contain emails with the sender or recipients from a particular group of users, e.g. "Supervisor", "PhD Council".

2.4.2 Solution

Suggested by [6], three separate models can be built. Each one of the models focuses on one type of folders by constructing the feature set and classifiers specifically according to the characteristic of the target folder type. In the prediction step, the predicted probability of the three models will be used to make a decision fusion and thus decide which folder the incoming email belongs to.

In addition, users will be asked to select the type when they are creating new folders. This simple action of users can greatly facilitate the system in training.

2.5 Non-text Content can be Useful

2.5.1 Challenge

The expressions of email nowadays are not just confined to the text content. Instead, with the convenience of GUI and embedded HTML as well as the support of MIME (multipurpose Internet mail extension), lots of emails can carry graphical attachments, linkages to on-line information and non-text characters [4]. For example, many people use email to share and discuss photos taken together with their friends or families. And they also suggest interesting on-line videos to friends by providing website linkages. Also, people today prefer to use non-text characters such as Emoji to convey

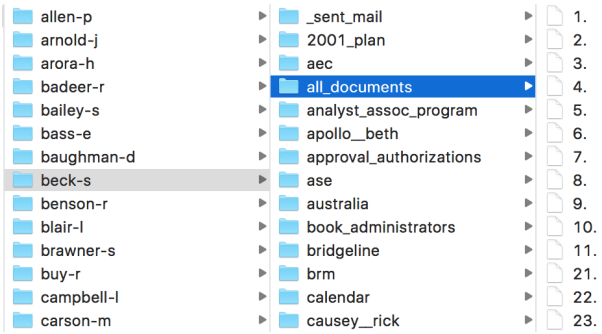


Figure 1: Structure of Enron Data Set

```
Message-ID: <3812348.1075849811001.JavaMail.evans@thyme>
Date: Wed, 29 Nov 2000 15:48:00 -0800 (PST)
From: brenda.herod@enron.com
To: sally.beck@enron.com
Subject: Accomplishments - 2000
Mime-Version: 1.0
Content-Type: text/plain; charset=us-ascii
Content-Transfer-Encoding: 7bit
X-From: Brenda F Herod
X-To: Sally Beck
X-cc:
X-bcc:
X-Folder: \Sally_Beck_Nov2001\Notes Folders\All documents
X-Origin: BECK-S
X-FileName: sbeck.nsf

Sally,

Seems like it's been so long since we have talked or seen each other!  i hope
you and your family had a wonderful Thanksgiving holiday!  We certainly did!
Attached are my accomplishments for 2000.  Please let me know if you have any
questions.
```

Figure 2: Email Content

emotions and ideas. In these situations, even the names of the attached files and domains of website links might be more useful than the whole text content to determine the email categorizations. And considering these files or websites are probably viewed by thousands of people who share the same interesting, they are more precise to describe the themes of the parent emails. In addition, some emails even contain only the non-text contents. Instead, they embed HTML codes inside email to present the information neatly.

2.5.2 *Solution*

A thorough analysis of the non-text content in the emails is not practical due to the computational speed requirements. Instead, we will extract partial information in those non-text parts and convert them into text labels. For example, instead of analyzing the attached graphs using computer visions, we only extract the text properties such as file names, authors, create dates, graph formats and so on.

3. EXPERIMENT

We divide our experiment into two phases:

a) In February, data is collected and preprocessed. Then we focus on the primary problem, lack of training examples, and try all three solutions. Statistical results are collected and compared to determine the best solution for this problem.

b) In March, we build a GUI to implement our best solution from February. Then we define our telemetry and repeatedly test on our GUI. Find small problems that matters most from user experience and build smallest solutions for them. We keep adding features and end up with a satisfiable product.

As a result, we solve the first problem described in Section 2.1 by the end of February and the second and third problem described in Section 2.2, 2.3 by the end of March. The last two problem described in Section 2.4, 2.5 remain unsolved because they are of least importance according to user experience.

3.1 Data Collection

The Enron Corpus is a large database of over 600,000 emails generated by 158 employees [7] of the Enron Corporation and acquired by the Federal Energy Regulatory Commission during its investigation after the company's collapse. It is sized to about 400Mb, tarred and gzipped. The May 7, 2015 Version of Enron Email Data will be used as our data set[2]. The data set here does not include attachments. The Enron data set which we will be using is preprocessed and provided after the classification of these emails into few categories [1]. The structure of the mail looks into various folders according to the user's name and each of these folders are further classified into folders of categories as shown in Figure 1. An example of the content of one email is presented in Figure 2.

We extract data from seven different users for the experiment. Each user is treated as an independent data set. Within each data set, folder names are used as the true label of emails inside. Within each folder, ten randomly picked emails are treated as initial training examples, all the other emails are treated as test examples with labels unknown.

All the emails was stored in the text file of the MIME standard of email format. To grab the email subject and body texts, we use the 'email' python package to separate the email subject and body from other components. This package could accurately parse the email of standard format into text segmentation. And then we apply the regular expressions to filter out digits and non-character tokens and also remove common words to reduce noise and computational consumptions. Finally, we save the processed email subject and body as list of words for each email document, and convert those words into a numeric word vector as features for later categorization using techniques such as tf-idf (term frequency - inverse document frequency) and Word2Vec.

3.2 Performance Metrics

Accuracy: accuracy is the most commonly applied performance metric when comparing multi-classification results. Its problem is that the performance on minority classes are barely reflected in accuracy [9].

F_M: F-score on each class can be calculated after the trained classifier is tested on test set. The mean of F-score on each class is then calculated to represent the overall performance of the classifier. Regardless of the population within each class, the F_M represents performance on each class equally [9].

We are using F_M in the comparison of performance.

3.3 Three Solutions for Lack of Training Examples

[2]https://www.cs.cmu.edu/ ./enron/

3.3.1 *Supervised Learning*

For supervised learning, we assume that we have gotten some emails categorized by uses, and predict the new coming emails based on the categorized one. In this solution, we totally test 3 classifiers incrementally among 7 different users.

Specifically, we first selected 7 users from Enron Email data set that have the most sub-folders. Then, we removed the sub-folders that contain less than 10 emails. After that, we only select 10 emails as our training dataset for each sub-folder per user, so that we could simulate the real-life scenery of predicting email folders based on limited categorized emails. Finally, we use three different classifiers to train and predict the emails.

The results are shown in Figure below. As you can see in Figure 3, the prediction performance varies among different users. It is because some users may label them emails more generally, while the others more precisely. Also, the content of the email sub-folders also matters. In spite of that, we can know that SVM performs better than DT and KNN.

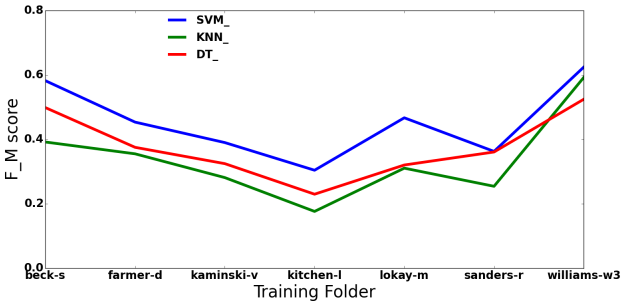


Figure 3: Performance among different users.

3.3.2 *Incremental Learning*

In this experiment, we assume that somehow we can get the true label of emails as time passing by. Therefore the training set can be enriched and thus a better classifier can be retrained. The size of training set starts with 100 and grows to 1000. The classifier is retrained every 100 new training examples and is tested on a holdout test set. Seven different users are treated as seven data set. We also implement three different ways to select examples that would be included in the training.

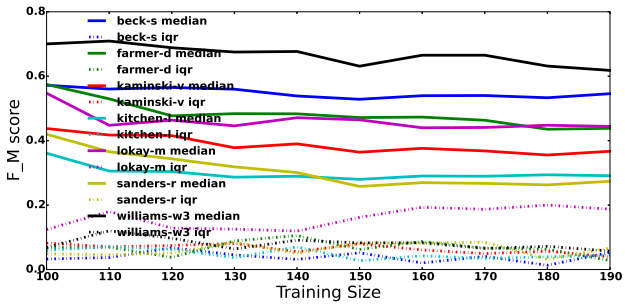
Brutal: every new coming email that that are labeled goes into the training set. **Benefit:** simple.

Credit: every new coming email is assigned with a credit of $1-Probability(label)$. Emails with top N credits will goes into the training set. **Benefit:** more balanced over folders, wrongly predicted emails, which means $Probability(label)$ is low, have more chance to get into the training set.

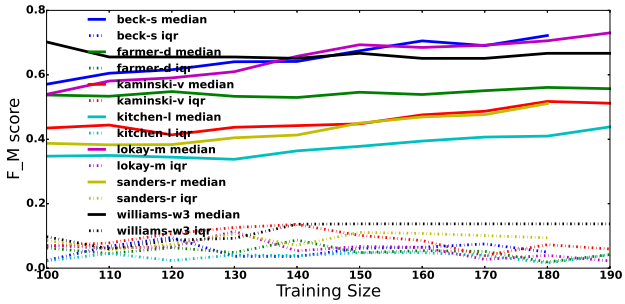
Wrong: only the wrongly predicted emails go into the training set. **Benefit:** wrongly predicted emails are guaranteed to be put into training set, correctly predicted emails will be totally ignored.

As shown in Fig 4, incremental learning is helpful in solving our problem and Credit is the best way to select examples.

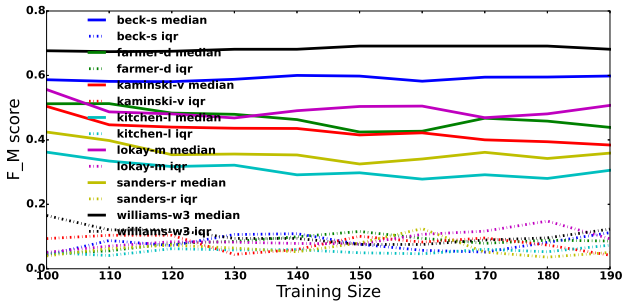
3.3.3 *Unsupervised Learning*



(a) Brutal



(b) Credit



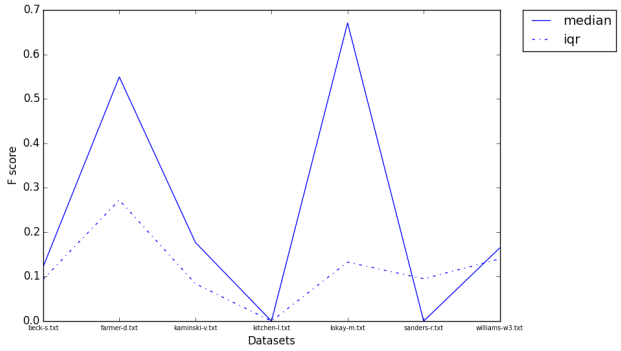
(c) Wrong

Figure 4: Performance of three different example selection ways. Only Credit has a stable increase of performance while training size increases.

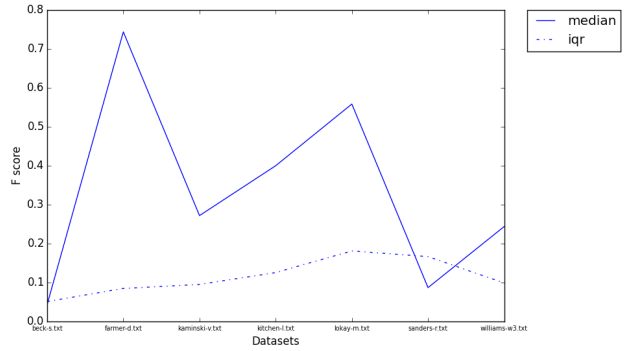
Unsupervised learning is the machine learning task of inferring a function to describe hidden structure from unlabeled data. There are various tools of doing unsupervised learning, and we used Latent Dirichlet allocation [3]. We used LDA because of its useful importance and advantages for finding useful topics from an unlabeled data. LDA features were extracted and given as input to SVM learner. LDA is used as a feature extractor. We have already shown in Figure 4 that SVM performs better than the other classifiers.

The Famous Enron email dataset is used and have already specified about the pre-processing steps and its final structure above. We tested the data on 7 different users. There are different labels already defined for the mails. We selected 5 top labels for each user dataset, and converted it into a binary classifier where those 5 labels are given "YES" label and others as "NO" label. And we also selected different ranges of cluster size namely 20, 50 and 100. Respective results can

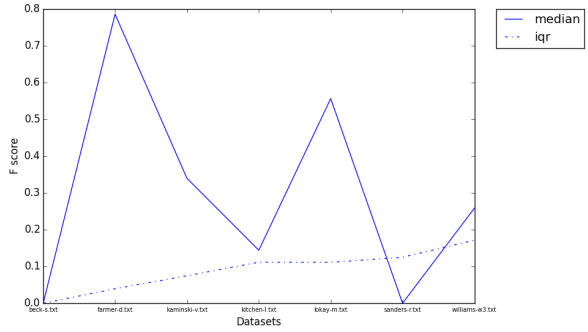
be seen for all the different cluster size given below.



(a) Performance of LDA with 12 clusters



(b) Performance of LDA with 50 clusters



(c) Performance of LDA with 100 clusters

Figure 5: Performance of dimensionality reduction with LDA

Following results show highly instability of F-Score across different datasets. The reason for that is, if we have large data for positive class then it gets you good results but if number of negative labels dominant over positive labels, it performs poorly. The other problem which we saw, the instability of these clusters even if there was no changes in the data or the parameters of the algorithm. These results made us to not use unsupervised features to train a classifier.

3.3.4 Comparisons of Three Solutions

Judging from the previous sections, we have learned that
a) SVM is the best choice for our problem;
b) incremental learning is helpful in solving our problem and Credit is the best way to select examples;
c) dimensionality reduction by unsupervised learning is not helpful in our problem.

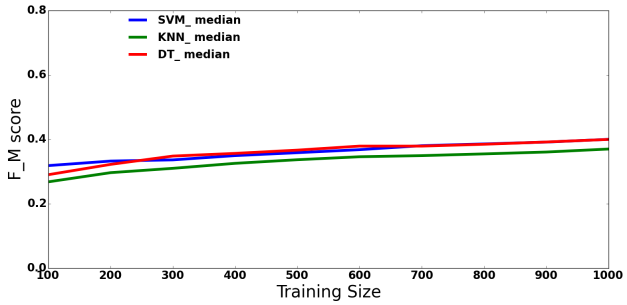


Figure 6: Performance of classifiers with incremental learning.

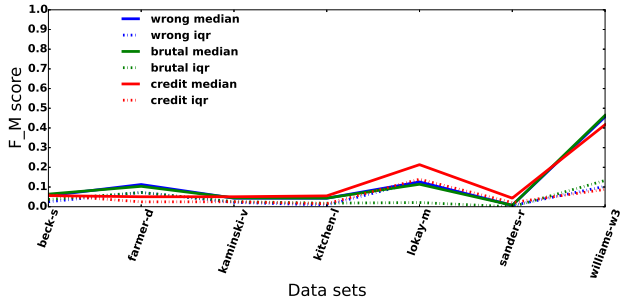


Figure 7: Performance of incremental learning with dimensionality reduction by LDA.

We have also experimented on some combination of these three method, as shown in Fig 6 and Fig 7 and still found the same conclusion.

3.4 GUI Development

The GUI is developed using Python Tkinter package. We took Gmail as our sample for making the Mailbox GUI. See Figure 9 for our mailbox interface.

We have provided users with read mails, move mails to different folders, creation of user defined folders. We have also provided the user with different features to select on demand. These features are Implicit User Feedback, Explicit User Feedback, Multi-folders. The GUI is designed to not only load local email files for training classifier, but also read email from the online email account for different users. Under the hood, it will connect the server at preset frequency, fetch emails from the online account, categorize them using local classifier and refresh the emails saved on local folders. Currently, it support Gmail accounts only for security settings.

3.5 Telemetry for GUI Test

GUI test requires actual users to operate on it and gather their experience and feedback. It is more difficult than the previous tests which only need to run a script and wait for the result. Due to the lack of time, we use a much smaller test set for GUI test.

Setup: when the GUI is opened, a fixed set of emails is loaded as the initial training set for the classifier. There

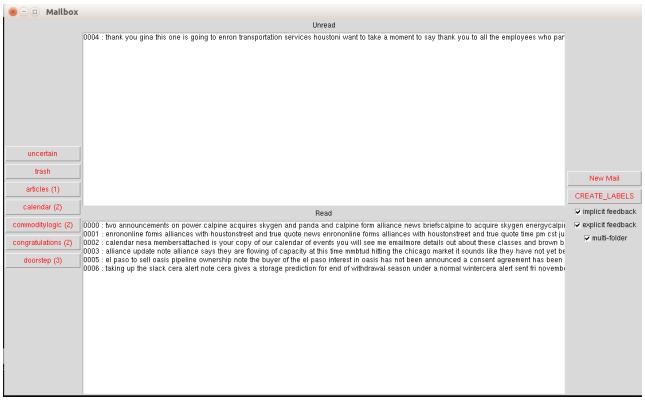


Figure 8: Graphical User Interface

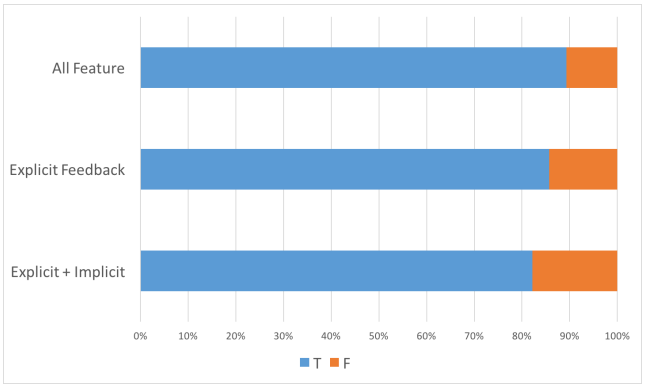


Figure 9: Telemetry Report

are five predefined folders, each comes from the user Beck-s, Enron data set. There are about 10 emails in each folder and we have 47 in total.

Test: users will operate on this GUI, pretending they are using a email client. By hitting a New Email button, one email will comes in and be predicted by the classifier, appear in one (or more) of the folders. Users will read the email, move it into another folder if they think it is wrongly predicted, otherwise do nothing. The new email pool is fixed, all the emails in that pool also come from Beck-s, Enron data set. The size of the new email pool is 51.

Sum up: after the user has drilled out the new email pool, a performance score will be returned by counting how many emails are wrongly predicted. The performance score will be in the form of accuracy. The performance score is used along with user experience feedback for further improvement of the product.

3.6 Explicit User Feedback

According to the experiment result in February, the first version of our GUI utilizes an SVM classifier, and gathers true label of new coming emails via explicit user feedback. If our classifier is pretty sure that the new coming email should belong to a particular folder ($Probability(folder)$ is higher than a threshold), that email will appear in that folder, otherwise, it will appear in a folder called "uncertain" and ask user to determine the true label of it.

Tested by four users, a median of accuracy of 0.821 is achieved, as shown in Figure 9.

3.7 Implicit User Feedback

For the next step, we decide to add one additional feature to solve the second problem mentioned in Section 2.2, which is of most importance and also requires least effort among the remaining unsolved problems.

Our solution for this problem is to introduce implicit user feedback, which is a kind of feedback that will not cost user any extra effort. When user read an unread email, that email will have the current folder as its true label and a credit of $1 - Probability(currentfolder)$. When user move an email to another folder, the true label of that email will be set to the target folder and have a credit of $1 - Probability(targetfolder)$. These two strategy work amazingly well in our tests. By having more true labels identified with implicit user feedback, the classifier will be retrained more frequently and result in a decrease of the number of emails appear in "uncertain" folder. Thus allow user to use the GUI more smoothly.

Tested by four users, a median of accuracy of 0.857 is achieved, as shown in Figure 9.

3.8 Multi-folder

The final problem we choose is the one described in Section 2.3, which again, is of most importance and also requires least effort among the remaining unsolved problems. The rest of the problems described in Section 2 are too complicated to be finished in time, thus will be the future work of our project.

Our solution for this problem is to allow new coming emails to appear in multiple folders. For each folder we have, once the $Probability(folder)$ is higher than the threshold (0.35 in our experiments), the email will appear in that folder. This feature will increase Recall by sacrificing Precision. It is a good trade-off since we sure do not want to miss any important email. In this scenario, false positive is much more tolerable than false negative.

Tested by four users, a median of accuracy of 0.892 is achieved, as shown in Figure 9.

We are detecting increasing accuracy as we add new features in.

4. DISCUSSION

After three-month work, our project has finally ended and we are satisfied with our result. It is an amazing experience since each month has a totally different type of work.

In January, we focused on discussions about ideas and literature reviews. Thanks to the huge amount of literature reviews, we have plenty of problems to work on in the following two months. We laid a good foundation in January.

In February, we worked on pure data without GUI and user feedback. This is the kind of work our whole team is familiar with and as a result, we worked efficiently with equally distributed work load. The result is also satisfiable. Although dimensionality reduction by LDA did not work well, which is frustrating, we still improved the performance by finding the right classifier and implementing incremental learning.

March is a real challenge, none of us has worked on software development before. We lose efficiency because the work load is no longer separable and we need to work on each others' code. Testing with telemetry is also a challenge

for us. Communications become a huge issue and Github does help a lot on that. Gladly, we finished our project in the last minute and we are proud to present you this report, along with our working demo.

4.1 Validity Threads

There are several validity threads in our experiment:

1: all the tests, in both February and March, use data from Enron data set. The result and method may thus rely on this specific data set a lot. Need more tests on different data sets in the future. Testing with real user and their true email account would be the best.

2: all the tests in March are conducted within our team. We are developers and users. Usually this should not happen, tests need to be conducted outside the team.

3: right now we run our tests in March on a fixed test set with very few examples (51). The result can be unstable since the size is too small.

4: due to the limitation of our knowledge, there sure exists options that we have not explored yet.

5. CONCLUSIONS

In this project, we developed a working demo that can automatically classify new coming emails into user predefined folders. We proposed three methods to solve the primary problem, which is the lack of training examples. Experiment results on Enron data set show that SVM and incremental learning are helpful in solving the problem while dimensionality reduction with LDA is not. Furthermore, we add features of implicit user feedback and multi-folder to solve the next two problems. With our telemetry, the new features are helpful in the overall user experience.

In our future work, we will continue working on the rest of the challenges mentioned in Section 2. More importantly, we will enhance our user tests by having real users outside our team (by using Mechanical Turk maybe) to test our product on real email account. In this way, the result can be more reliable.

6. REFERENCES

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