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AUTHOR DETECTION ON A MOBILE PHONE

by

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March 2011

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Traditional author detection is conducted on powerful computers using documents such as books and articles. With the explosion of mobile phone computing use, modern author detection needs to be lean enough to operate on a resource restrained mobile phone and robust enough to handle the terse and non-standard wording in text messages, Tweets, and emails. By testing natural language and machine learning techniques for size and speed, not just effectiveness, this thesis identifies feature and technique combinations appropriate for author detection on a mobile phone. Specifically this thesis will examine effectiveness versus storage size for word grams of size 1, 2, and 5 as well as Gappy Bigrams and Orthogonal Sparse Bigrams. To deal with the robust nature of Tweets and text message, the Google Web1T corpus will be tested for size versus effectiveness in combination with the word grams. Once appropriate feature and technique combinations are found, those combinations will be tested on actual Android mobile phones to gauge how effective the chosen techniques are on a real mobile phone.

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AUTHOR DETECTION ON A MOBILE PHONE

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Submitted in partial fulfillment of the
requirements for the degree of

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CHAPTER 1:
Introduction

Mobile devices have become ubiquitous throughout the world. Mobile phones, in particular, have evolved from large clumsy devices available to only a select few to miniature computers in the hands of millions of people. Communications on mobile devices encompasses more than just phone calls. Short messages using SMS and Twitter services are used in increasing numbers everyday. E-mail, once solely reserved for personal computers and workstations, is now widely used from mobile phones and tablets.

While the versatile and always-on communications provided by mobile devices have been a boost to society, it has also been a powerful tool for terrorists, child predators, and other criminals. Disposable phones make nefarious communications anonymous and bad people more difficult to find. To combat that, author detection tools capable of analyzing the preferred text communications, short messages and e-mail, of mobile devices is needed.

1.1 Using Mobile Devices to Locate Persons of Interest

Eavesdropping on text communications across millions of cell phones is difficult at best. With an estimated 1.81 trillion SMS text messages sent in 20101, processing the massive amount of data created by such an eavesdropping capability is overwhelming for a central processing facility. With the growth of other short message services like Twitter, text messaging on mobile devices is only growing more prevalent. Central processing of data this massive can create a severe bottleneck.

A better approach could be to decentralize author detection against mobile text communications. In short, empower mobile phones to process text data for persons of interest on the mobile phone itself, not at a central processing facility. Whether the intent is to screen the text messages of a teen for known child predators or to locate terrorists in a combat error using cell phones to coordinate attacks, the computing ability of millions of cell phone processors is a powerful resource to tap.

The challenge with author detection on a mobile device is managing very limited resources. Even though modern smart phones are much more powerful than their predecessors, CPU speed and quantity are not on par with a high performance computing facility. RAM on a smart phone has grown as well, but many mobile operating systems like Android impose severe limits on the allowed heap space. To detect authors on a mobile device the combination of classification methods, feature types, and vocabularies must be selected more than high accuracy in mind. Storage, processing, and even power requirements must be taken into account.

1.2 Research Questions

This thesis asks one basic question: can author detection be accomplished on a mobile device? To answer that question, several supporting questions must be answered first:

- For the two dominant mobile phone text mediums, short message and e-mail, what combination of classification method and feature type provides the best accuracy?

- What is the storage requirement for each combination of method and feature type?

- What is the relative value of classification accuracy versus storage requirement for each classification method and feature type?

- Does the relative prolificity of each author in a detection group significantly affect the accuracy of each classification method and feature type?

- Does a highly effective method-feature type combination exist with a small enough storage requirement to be executed on a mobile device?

To answer these research questions, two corpora will be used as test data: the Enron E-mail Corpus and the NPS Twitter Short Message Corpus. The Enron E-mail Corpus will be treated as a representative sample of e-mail communications. The NPS Twitter Short Message Corpus will be used as a representative sample of short messages. Since Twitter has identical character limits to SMS messages, the NPS Twitter Short Message Corpus will be considered representative of both SMS and Twitter communications.

To account for the widely varied nature of English language use in e-mail and short messages, the Google Web1T N-Grams corpus will be used as a vocabulary to build n-gram models for this thesis. This will provide an a language reference populated with standard English as well as the evolving language habits on Internet and mobile device users.

1.3 Significant Findings

The testing of all classification method, feature type, and vocabulary combinations resulted in 19,782 tests producing 286,050 measurements for f-score and 19,782 measurements for accuracy. After analysis of these results the following significant findings were made:

- The method-feature type combination that suited mobile devices best for the Enron E-mail Corpus was Support Vector Machine classification using 1-grams as a feature type and no reference to the Google Web1T Corpus for vocabulary. This combination produced an average accuracy of 0.7735 and average f-score of .6257 requiring 4.83MB of storage on the device.

- The method-feature type combination that suited mobile devices best for the Twitter Short Message Corpus was Support Vector Method using Gappy Bigrams with a word distance of 3 and no reference to the Google Web1T Corpus for vocabulary. This combination produce an average accuracy of 0.5203 and average f-score of 0.4820 requiring 3.59MB of storage on the device.

- Very prolific authors were detected with greater accuracy and f-score than less prolific authors, even when a prolific author was in a group with other very prolific authors.

- Author detection accuracy and f-score against the Enron E-mail Corpus was significantly higher than author detection accuracy and f-score against the Twitter Short Message Corpus. However, it was not clear from the results if this disparity in accuracy is due to language differences between e-mail and short message or due to having a large amount of e-mail text compared to the amount of short message text.

- Similarly prolific authors had lower accuracies, but higher f-scores than dissimilarly prolific authors.

- Storage requirements for many of the model-feature combinations were too large for use on a mobile device. The most powerful method-feature combinations often had storage requirements above 2GB.

- There is a small number of method-feature combinations that can meet the storage limitations of a mobile device and still produce reasonable accuracy for author detection.

1.4 Thesis Structure

This thesis is organized as follows:

- Chapter I covers the motivation for this research, the research questions being answered in this thesis, and key findings of the research conducted.
- Chapter II discusses prior work in authorship detection, machine learning, the corpora used, details of the Google Web1T corpus, and hashing strategies for managing the Google Web1T corpus.
- Chapter III describes the combinations of classification methods, feature types, and vocabularies used during experimentation. The limitations of the experimentation approach are discussed along with the metrics to be used to measure author detection performance.
- Chapter V contains conclusions drawn from the results and recommended future work.

CHAPTER 2:
Prior and Related Work

2.1 Introduction

Author detection is the process of analyzing documents to determine if that document was created by a pre-determined set of authors. Detecting authors on mobile devices requires identification of a combination of classification methods, feature types, and vocabularies that effectively identifies specific authors amongst a body of text created by many authors.

2.2 Author Detection

"Automated authorship attribution is the problem of identifying the author of an anonymous text, or text whose authorship is in doubt" [1]. Classic examples of documents whose authorship was subjected to author attribution are the Federalist Papers and the works of Shakespeare. In the case of the Federalist Papers, the likely pool of authors was known, but exactly which author wrote specific issues of the Federalist Papers was not known.[2] This was strictly a case of authorship attribution. In the case of the works of Shakespeare, some scholars have expressed doubts that all of Shakespeare's collected works were really written by only one person.[3] Author attribution has been used to investigate these claims with a focus on authorship verification.

For this thesis, author detection and authorship attribution are synonymous, but author detection has the additional requirement of being able to state that none of the text provided was authored by the specific authors being sought. This rejection of all text as being authored by the specific author requires a "noise" group be included in the classifier training. The explosive growth of communications and document storage on the Internet provides a vast amount of data to draw on for author detection.

Books, articles, blogs, tweets, and emails are posted for public viewing in an electronic format every day. Some of these postings have verifiable authors. By verifiable, there is reasonable proof that the posted content was created by the stated author. For example a book published by an established publishing house from an author with no charges of plagiarism can be considered a document written by that author. Many Internet authors use nom de plumes or are posted anonymously. Matching verified authors to anonymous Internet authors or mobile phone text authors has numerous practical applications. The increased speed and storage capacity of computing devices allow analysis of these corpora for author detection. The methods of author detection fall within the science of machine learning.

2.3 Machine Learning

"Machine learning is programming computers to optimize a performance criterion using example data or past experience" [4]. Machine learning has been used famously to determine the authors of the Federalist papers, allow computers to "read" human handwriting, and to mine sales data for profitable trends. Two broad categories of machine learning are supervised learning and unsupervised learning. Supervised learning is "learning with a teacher." The teacher can show the learner what to do based on examples or experience. Unsupervised learning is "learning with a critic" [4].

This thesis relies exclusively on supervised learning. Construction of machine learning models is a resource intensive process. Current mobile devices would be severely challenged to create large machine learning models within a reasonable amount of time. Current mobile device limitations demand author identification models be constructed on a platform more powerful than a mobile device. That model is then put on a device for ongoing author identification. Current mobile devices such as smart phones and tablet computers are capable of running machine learning models against smaller datasets for supervised learning processes. This capability is currently limited to supervised learning on mobile devices because supervised models require previous "teaching" instead of predictive "criticizing". Evolving the structure and content of a model using predictive "criticizing may still be beyond the capability of current mobile

Machine learning can be used for many tasks. Often, machine learning is used to assign a given data set to a specific class or predict an outcome value over a continuous range of values. This thesis uses machine learning to assign a given data set, a document, to a given class, an author. Classification machine learning is comprised of a set of classes, a classifier, a feature set, and data. In supervised learning, the machine learner uses a data input comprised of features trained to (or owned by) by a specific class. Based on creatively counting these features, the machine learner creates a model for each class based on the the behavior of the classifier. Finally, test data, consisting of sets of features, are processed by the classifier based on the previously built models. The classifier provides an output of the most likely class that fits the given features.

Machine learning is central to this thesis. Modeling corpora of emails and tweets from numerous authors on traditional workstation or server computers, and, then, testing prediction capability on mobile devices requires not just accurate machine learning, but efficient machine learning. The efficiency is needed due to the limits of even the most advanced mobile devices. Hardware specifications are not the only limiting factor in machine learning. There are competing strengths and weaknesses in the techniques chosen, as well. Different classification methods make varying demands on memory, processor cycles, and non-volatile storage. These varying demands may be trivial on a high performance computer or modern desktop, but a mobile device implementation must be keenly aware of these resource demands.

In addition to accuracy and efficiency, author detection on a mobile device must be robust. Both e-mail and short message communications make use of new words and new phrases constantly. A workable author detection tool must be able to deal with tokens not seen during training. Whether the method to deal with unseen words is use of a smoothing technique, labeling as an ”unknown” token, or simply dropping the token from consideration, the model must have a strategy to manage previously unseen text.

2.3.1 Machine Learning Techniques

The techniques in this thesis are all supervised machine learning techniques. Specifically, the two supervised techniques used are naive Bayes and Support Vector Machine (SVM). Naive bayes was chosen because it is computationally lightweight compared to many other methods. Support Vector Machine was chosen because data for SVM can be stored in ”sparse format”. Sparse means that every feature does not have to be represented in the stored data for a model or test case. Features with a zero count can simply be excluded. SVM has been successful in many other authorship attribution experiments [5].

Naive Bayes

Naive bayes is explained in this section specifically using author attribution variables instead of general variables to help show the applicability of naive Bayes for the bad of words model used in this thesis. Specifically a document, D, is defined as a vector of tokens $\mathbf{t}$, where the dimensions of the vector are the types found in the document and the magnitude of each dimension is the count for that type. Specifically, $\mathbf{t} = c_i t_i$ for $0 < i < n$ where n is the total number of types in the document, t_i is a type in D, and c_i is the count of occurrences of type t_i in D.

$$D = \mathbf{t} \tag{2.1}$$

With the definition of a document as a vector of tokens, the desired end result is determine which author a_i out of possible authors, A, has the highest probability of having written document, D. This conditional probability is expressed as $P(A|D)$. To get $P(A|D)$, we need to use Bayes Rule. Using variables A and D to express Bayes Rule, we begin with the realization that the probability we are seeking is the probability that both A and D are true. This probability can be expressed as $P(A \wedge B)$. Using the probability product rule, $P(A \wedge B)$ can be expressed as:

$$P(A \wedge D) = P(A|D)P(D) \tag{2.2}$$

$$P(A \wedge D) = P(D|A)P(A) \tag{2.3}$$

Using equations 2.2 and 2.3, we get:

$$P(A|D)P(D) = P(D|A)P(A) \tag{2.4}$$

Solving for $P(A|D)$ we get:

$$P(A|D) = \frac{P(D|A)P(A)}{P(D)} \tag{2.5}$$

At this point, we use our definition of a document, as a vector of tokens, and a strong conditional independence assumption. The strong conditional independence assumption states that when a single effect, E, results from multiple causes, c_i in C, for $0 \leq i \leq n$, where there is no probability relationship between any c_i in C:

$$P(E|C) = P(E|c_i) = \prod_i^n P(E|c_i) \tag{2.6}$$

Substituting our definition that a document is a vector of tokens into Equation 2.6 and then further into Equation 2.5 yields:

$$P(A|\mathbf{t}) = \frac{P(\mathbf{t}|A)P(A)}{P(\mathbf{t})} \tag{2.7}$$

$$P(A|\mathbf{t}) = \frac{P(A)\prod_i^n P(t_i|A)}{\prod_i^n P(t_i)} \tag{2.8}$$

Since the objective in using naive Bayes as a classifier is not to arrive at the precise probability for each author given a document, but rather to determine which author has the highest probability, Equation 2.8 can be simplified by converting Equation 2.8 from an equation to a proportion. Namely, note that $\prod_i^n P(t_i)$ is constant for a given document and, therefore, does not contribute to finding the maximum probability author. Equation 2.8 now becomes:

$$P(A|\mathbf{t}) \propto P(A) \prod_i^n P(t_i|A) \tag{2.9}$$

Since our classifier has to arrive at probabilities in a methodical way, that probability is calculated by counting tokens, $\hat{P}(A|t_i)$, in a training document:

$$\hat{P}(A|t_i) = \frac{count(t_i)}{\sum_{j=0}^{n} count(t_j)} \tag{2.10}$$

Also, the prior probability of an author, $P(A)$, is defined for each author as the proportion of total count of documents in the training corpus written by an author, a_i to the total count of documents of all authors a_i in A. As calculated specifically for a set of documents with know authors as a training set:

$$\hat{P}(a_i) = \frac{count(documents_{a_i})}{count(document_{allauthors})} \tag{2.11}$$

To use the naive Bayes classifier, when a test document is processed for author attribution, $\hat{P}(A|t_i)$ by the count of each t_i in the test document. The a in A with the maximum score, s, from

$$s_a = \hat{P}(a) \prod_i^n \hat{P}(a|t_i) \tag{2.12}$$

To implement the above equations, the naive Bayes classifier algorithm provided by the Stanford Natural Language Lab [6] was implemented using Java. This algorithm is shown in Figure 2.1.

As a practical matter, the values produced by Equation 2.12 are very small. Successively multiplying such small value can result in underflow. To avoid that underflow, each $\hat{P}(a|t_i)$ is converted to its log value. This also allows successive $\hat{P}(a|t_i)$ to be added instead of multiplied.

```
TrainMultinomialNB(C, D)
V ← ExtractVocabulary(D)
N ← CountDocs(D)
for each c ∈ C
do N_c ← CountDocsInClass(D, c)
   prior[c] ← N_c / N
   text_c ← ConcatenateTextOfAllDocsInClass(D, c)
   for each t ∈ V
   do T_ct ← CountTokensOfTerm(text_c, t)
   for each t ∈ V
   do condprob[t][c] ← (T_ct + 1) / Σ_t'(T_ct' + 1)
return V, prior, condprob

ApplyMultinomialNB(C, V, prior, condprob, d)
W ← ExtractTokensFromDoc(V, d)
for each c ∈ C
do score[c] ← log prior[c]
   for each t ∈ W
   do score[c] += log condprob[t][c]
return arg max_{c∈C} score[c]
```

Figure 2.1: Standford Naive Bayes Classifier Algorithm

With these changes, 2.12 becomes:

$$\log(s_a) = \log \hat{P}(a) \sum_{i}^{n} \log \hat{P}(a|t_i) \tag{2.13}$$

This makes the final goal of the naive Bayes classifier:

$$\arg\max_{a}[\log(s_a)] = \arg\max_{a}[\log \hat{P}(a) \sum_{i}^{n} \log \hat{P}(a|t_i)] \tag{2.14}$$

Support Vector Machine

A Support Vector Machine (SVM) is a supervised machine learning method that finds a hyperplane in some n-dimensional space then classifies based on maximizing the margin between the hyperplane and the support vectors around that hyperplane. This is based on finding a hyperplane between two types of data in a dataset, then computing the largest margin between closest data points and the hyperplane. In cases where a clear hyperplane between two data sets is not possible, a ”slack variable” provides an allowance of data points to be on the wrong side of the hyperplane. SVM seeks to minimize the slack variable while increasing the margin between hyperplane and closest data points. To create the hyperplane, SVM ”maps the input vectors into some high dimensional feature space, Z, often through some non-linear mapping chosen a priori” [7]

For the two situations that a SVM can encounter: data can be separated without error and data cannot be separated without error, the same equation can be used. In the first situation, where data can be separated without error, the SVM optimizes the SVM base equation with $C = 0$. For the second situation, where the training data cannot be strictly separated, $C > 0$:

$$\min_{w,\alpha} \frac{1}{2}||\mathbf{w}||^2 + C\sum_{i}^{n}\xi \tag{2.15}$$

where ξ is known as the slack variable, C is the error penalty, and the entire term $C\sum_i^n \xi$ is the soft margin. This is a quadratic programming problem to find ξ and C, often accomplished by a logarithmic grid search ($C = 2^{-5}, 2^{-3}, 2^{-1}, 2^{1}, 2^{3}, 2^{5}$ and $\xi = 2^{-15}, 2^{-10}, 2^{-5}, 2^{0}, 2^{5}$) with the best accuracy or F-Score determining where to continue refining the grid.

Optimal Hyperplane in Feature Space

The core of SVM is finding an optimal hyperplane in the higher dimension space mapped from the original feature space. That hyperplane is defined as:

$$\mathbf{w_0} \cdot \mathbf{z} + b_0 = 0 \tag{2.16}$$

where w_0 are weights, z is the space, and b_0 is a scalar value which shifts the values of $\mathbf{w} \cdot \mathbf{x_i}$ such that:

$$\mathbf{w} \cdot \mathbf{x_i} \geq 1\text{if } y_i = 1 \tag{2.17}$$

and

$$\mathbf{w} \cdot \mathbf{x_i} \leq 1\text{if } y_i = -1. \tag{2.18}$$

To that end, $\mathbf{w_0}$ ”can be written as some linear combination of support vectors.” This uses the following equation:

$$\mathbf{w_0} = \sum_{support\ vectors} \alpha_i \mathbf{z_i} \tag{2.19}$$

and the decision function using those weights is given by

$$I(z) = sign\left(\sum_{support\ vectors} \alpha_i \mathbf{z_i} \cdot \mathbf{z} + b_0\right) \tag{2.20}$$

meaning that $I(z) < 0$ for one class and $I(z) > 0$ for the other class.

For distance ρ between projections defined by the support vectors, ρ is defined as:

$$\rho(\mathbf{w}, b) = \min_{x:y=1} \frac{\mathbf{x} \cdot \mathbf{w}}{|\mathbf{w}|} - \max_{x:y=-1} \frac{\mathbf{x} \cdot \mathbf{w}}{|\mathbf{w}|} \tag{2.21}$$

given that 2.16 it follows that the weights needed to create the optimal hyperplane are given by

$$\rho(\mathbf{w_0}, b_0) = \frac{2}{|\mathbf{w_0}|} \tag{2.22}$$

The best solution maximizes the distance ρ. To maximize ρ, you must minimize the magnitude of $\mathbf{w_0}$. Find that minimum $\mathbf{w_0}$ is a quadratic programming issue.[7]

Procedure ”Divide the training data into a number of portions with a reasonable small number of training vectors in each portion. Start out by solving the quadratic programming problem determined by the first portion of training data. For this problem there are two possible outcomes: either this portion of the data cannot be separated by a hyperplane (in which case the full set of data as well cannot be separated), or the optimal hyperplane for separating the first portion of the training data is found.” If this first set is found to be linearly separable, then all the non-support vector values are discarded, a new batch of values are put into this set (these values do not meet the constraint of $y_i(\mathbf{w} \cdot \mathbf{x_i} + b) \geq 1, i = 1, ..., l$)

Soft Margins In cases where the data is not linearly separable, the goal becomes to minimize the number of errors (the number of values on the wrong side of the hyperplane). Now a new variable $\xi \geq 0, i = 1, ..., l$ is introduced along with the function $\Phi(\xi) = \sum_{i=1}^{l} \xi_i^{\sigma}$. The constraints are that the value ξ_i does not push values in the non-negative quadrant out of the negative quadrant ($y_i(\mathbf{w} \cdot \mathbf{x_i} + b) \geq 1 - \xi_i, i = 1, ..., l$. Also, ξ_i is zero or a positive number ($\xi_i \geq 0$). ξ here represents "the sum of deviations of training errors" The central equation for minimizing the number of errors is:

$$\frac{1}{2}\mathbf{w^2} + CF(\sum_{i=1}^{l} \xi_i^{\sigma}) \tag{2.23}$$

In cases for ξ_i^{σ} where $\sigma = 1$, we are dealing with the soft margin hyperplane. Cases where $\sigma < 1$, there may not be a unique solution. For values of $\sigma > 1$, there are also unique solutions, but $\sigma = 1$ is the smallest value and that allows the term $CF(\sum_{i=1}^{l} \xi_i^{\sigma})$ from (2.23) to not overwhelm the $\frac{1}{2}\mathbf{w}^2$.[7]

Multi-Class SVM SVM is an inherently binary classifier. However, SVM can process multi-class data sets using SVM. There are two approaches to applying a binary classifier to a multi-class data set: one-versus-all and one-versus-one. In one-versus-all, each class in the training set is singled out against the conglomerated remaining classes in the training set. Whichever class achieves the best separation is labeled as the correct class for that data. In one-versus-one, the data classes in the training set are paired against each other and the best comparison among pairs is labeled as the correct class for that data.

It is important to define what is meant by "best" in the classification process. Best is defined as the class that nets the most positive results from individual data instances in the training set. Settling ties, should they occur is implementation dependent, sometimes as simple as making a random choice among the tied classes.[8].

SVM was chose for this thesis because it has been implemented in a number of open source tools, so it is easily available for us. SVM takes a non-probability approach to classification, so it is a distinctly different method from naive Bayes. SVM also appears often in a search of literature for natural language processing, making it a reasonable choice for attempting author detection in e-mail and short messages.

2.3.2 Machine Learning Tools

There are many machine learning toolkits available. These tools come in both open source and proprietary forms. Tools are chosen based on techniques used, so, for this thesis, libSVM and libLinear were examined as SVM tools. Naive bayes was constructed from scratch for customization with Google Web1T.

LibSVM

LibSVM attempts to optimize the basic SVM equation:

$$\min_{\mathbf{w},b,\xi} \frac{1}{2}\mathbf{w}^{\mathbf{t}}\mathbf{w} + C\sum_{i=1}^{l} \xi_i \tag{2.24}$$

$$\text{subject to } y_i(\mathbf{w}^{\mathbf{t}}\phi(\mathbf{x}_i) + b) > 1 - \xi_i \tag{2.25}$$

$$\text{and } \xi_i > 0 \tag{2.26}$$

For all kernels used in SVM a variable that must be solved for prior to optimization, the penalty term, C. Other kernels have additional variables that must be solved for prior to optimization, such as γ in the radial basis function kernel. While there are sophisticated methods to find C and other required variables, LibSVM takes a simple, straightforward approach: grid search. The grid for this search is a log grid search. As the local minimum is found on each pass of the grid search, libSVM reduces the grid size to home in on the minimum C value.

To make libSVM more efficient and more likely to converge on a solution, data in the training set should be scaled to either span 0 to +1 or -1 to +1. While test data may show up outside the original training data range, libSVM will extend the normalized range to accommodate. For example, if the range of the training data was -100 to +100, libSVM would scale that range to -1 to +1 by dividing by 100. If there was test datum with a value of -110, then libSVM would scale that datum to -1.1. LibSVM does not automatically scale, but rather relies on scripts provided with the libSVM package to do the scaling. If those scripts are bypassed, as they will be for this thesis, it is up to the user of libSVM to conduct the scaling.

LibSVM was originally constructed in C and employed with python tools to support. LibSVM is not available in a wide array of languages, including Java. A Java version of libSVM makes libSVM functional on many of the mobile operating systems available today, including Android. For this reason, libSVM was originally chosen as the SVM tool for this thesis.

LibLinear

While libSVM has numerous kernels to improve results, the inclusion of code to accommodate these kernels slows libSVM down. To increase processing speed for libSVM for linear kernels, libLinear was created. LibLinear is heavily modeled on libSVM but without non-linear kernel support. The kernels, represented within the ϕ function in SVM equations is not dealt with at all in libLinear, thus cutting down on checks and processing time. A linear kernel has been found to give as good or nearly as good a result as other kernels such as RBF, parabolic, and radial for text classification, especially when the corpus being used is large. The reduction in code can produce results 100-200 times faster that using LibSVM.

LibLinear has also been studied for large data sets that produces models which cannot be fit into memory. the application of ”chunked” data on a mobile platform with very limited RAM, but significant storage (due to microSD cards) makes libLinear even more attractive for mobile device use.

2.4 Features

For this thesis, it is necessary to carefully distinguish between types of features, types, and tokens. For purposes of brevity, types of features will be called ”feature types” in this thesis. Types are the distinct items within data. Feature types are the structure used to determine what constitutes a distinct item. Tokens are the count for each type encountered within the data.

For the phrase ”the quick brown fox” each word can be considered a type if the feature type is a single word. ”the”, ”quick”, ”brown” and ”fox” are types within the data ”the quick brown fox”. ”the 1”, ”quick 1”, ”brown 1”, and ”fox 1” would be tokens – a type accompanied by its count. A type would be the each distinct letter if the feature type was individual characters. For the individual character feature type, the type ”t” would have only one token of ”t” encountered in ”the quick brown fox”. The specific feature types used in this thesis are described in detail in the following sections.

2.4.1 Feature Types

Feature types for natural language processing can be as simple as keeping counts of individual characters within a document to complex tracking of word combinations. There are three feature types used in this thesis, N-Grams, Gappy Bigrams, and Orthogonal Sparse Bigrams. These feature types vary in complexity and effectiveness for author detection.

N-Grams

N-grams are word groups or character groups of size N within a document. These word groups can include sentence boundaries, often denoted as $< S >$ for sentence start and $< /S >$ for sentence end. For instance, in the phrase the ”the quick brown fox” the set of 2-grams (bigrams) are shown in Table 2.1:

1.	$< S >$ the
2.	the quick
3.	quick brown
4.	brown fox
5.	fox $< /S >$

Table 2.1: The Five N-grams (N=2) of ”the quick brown fox” with sentence boundaries

To further illustrate, the 3-grams (N=3 N-grams) of the phrase ”the quick brown fox” are shown in Table 2.2:

1.	$< S >$ the quick
2.	the quick brown
3.	quick brown fox
4.	brown fox $< /S >$

Table 2.2: The Four N-grams (N=3) of ”the quick brown fox” with sentence boundaries

The larger the N-Gram, the lower the probability of finding that N-Gram in a document. A specific 5-Gram may be very rarely repeated, even by the same author. That makes a 5-gram distinctive, but unreliable for author detection. A 1-Gram like ”the”, ”of”, ”a”, etc occurs frequently across almost all authors, but is not discriminating. Finding discriminating words groupings without the unreliable low probability of large-N N-Grams drove the creation of a modified N-Gram grouping called a Gappy Bigram.

Gappy Bigrams

Gappy Bigram definitions vary between the sources cited in this thesis. For the purposes of this thesis, a Gappy Bigram will be composed of two tokens (words) found within a distance of words. A Gappy Bigram of distance 0 reduces to an identical set to 2-Grams (also know as bigrams). Just like N-Grams, Gappy Bigrams can extend beyond a sentence boundary, include punctuation, etc. However, for larger distances, the distinction between Gappy Bigrams and regular bigrams is clear. For instance, in the phrase ”the quick brown fox” and a Gappy Bigram distance of 2, the Gappy Bigrams are given in Table 2.3:

To further illustrate, Gappy Bigrams of distance 1 are given in Table 2.4:

1. $< S >$ the
2. $< S >$ quick
3. $< S >$ brown
4. the quick
5. the brown
6. the fox
7. quick brown
8. quick fox
9. quick $< /S >$
10. brown fox
11. brown $< /S >$
12. fox $< /S >$

Table 2.3: The Twelve Gappy Bigrams (of distance 2) of ”the quick brown fox” with sentence boundaries

1. $< S >$ the
2. $< S >$ quick
3. the quick
4. the brown
5. quick brown
6. quick fox
7. brown fox
8. brown $< /S >$
9. fox $< /S >$

Table 2.4: The Nine Gappy Bigrams (of distance 1) of ”the quick brown fox” with sentence boundaries

The Gappy Bigram is able to preserve distinctive word groups for an author without the extremely low probability of occurrence. However, an author may distinctively used a two word group at exactly an interval of 3 words or 2 words or 1 word. That distinctiveness could be a key attribute for that grouping and is lost in Gappy Bigrams. To capture that distinctiveness, Orthogonal Sparse Bigrams are employed.

Orthogonal Sparse Bigrams

Orthogonal Sparse Bigrams (OSB) are similar to Gappy Bigrams in how they are constructed except that the distance between words in the OSB is included in the OSB. Just like N-Grams, Orthogonal Sparse Bigrams can extend beyond a sentence boundary, include punctuation, etc. For instance, in the phrase ”the quick brown fox” and a OSB distance of 2, the OSBs are given in Table 2.5:

To further illustrate, OSBs of distance 1 are given in Table 2.6:

1. $<$ S $>$ the 0
2. $<$ S $>$ quick 1
3. $<$ S $>$ brown 2
4. the quick 0
5. the brown 1
6. the fox 2
7. quick brown 0
8. quick fox 1
9. quick $<$ /S $>$ 2
10. brown fox0
11. brown $<$ /S $>$ 1
12. fox $<$ /S $>$ 0

Table 2.5: Orthogonal Sparse Bigrams (of distance 2) of ”the quick brown fox” with sentence boundaries

1. $<$ S $>$ the 0
2. $<$ S $>$ quick 1
3. the quick 0
4. the brown 1
5. quick brown 0
6. quick fox 1
7. brown fox 0
8. brown $<$ /S $>$ 1
9. fox $<$ /S $>$ 0

Table 2.6: Orthogonal Sparse Bigrams (of distance 1) of ”the quick brown fox” with sentence boundaries

It is important to note that in the cited references, the distance for OSBs is place between token 1 and token 2 instead of after token 1 and token 2 as shown in Tables 2.5 and 2.6. The distance is placed after the tokens in this thesis for more convenient parsing within reference files. Also, for OSBs, there is an issue of how to count OSBs. There two approaches for counting OSBs are: strict distance and lesser-included distance. For the strict distance approach, the OSB distance value record is the distance encountered in the text only. By contrast the lesser-included distances approach counts the distance encountered in the text and allows all OSB values greater than the distance encountered to count that encounter as well.

The concept of strict distance and lesser-included distance can be made clearer by example. In ”the quick brown fox”, the OSB of distance 2 of ”quick brown” has one instance, with a distance of 0. For the strict distance approach, only ”quick brown 0” would be recorded. For the lesser included approach, using a maximum OSB distance of 2 , ”quick brown” has three instances: ”quick brown 0”, ”quick brown 1”, and ”quick brown 2” because ”quick brown” is a lesser included OSB of distance 2. For this thesis, the lesser included distance approach is used.

If a file or database of OSBs is constructed, then a file or database of Gappy Bigrams also exists by default. The count of maximum distance OSBs equals the count of Gappy Bigrams, assuming the lesser included version of OSBs is used. This can be useful for conserving space in a system when both OSBs and Gappy Bigrams are needed.

2.4.2 Vocabularies

Once a scheme is determined for managing features types, the actual features required must be selected. Feature selection is the process of deciding which features to include during classification. A set of features can be built from the training set, such as selecting the N most used words in a training set. Features can be further refined by using outside vocabularies. For instance, a feature set could be built as the N most used words in a training set and filtered for ”stop” words. In this case, ”stop” words could be defined by other researchers work or some standard ”stop word” list where ”stop words” are words like ”the”, ”a”, or ”an” that occur very frequently but provide no real help in modeling the text. Another option is to build all features from a reference vocabulary. A reference vocabulary is a list of types that could be used to filter for only the most useful words in the expected text or as a reference to smooth predictions for an expected body of text. This thesis made heavy use of the Google Web1T Corpus to act as a reference vocabulary.

Google Web1T Corpus

The Google Web1T Corpus is a massive corpus of English language N-grams ranging from N=1 to N=5. The collection of these N-Grams focused on sites within Google’s databases that used English as their language, but there is no guarantee that non-English words are not present in the corpus. Many of the types in the Web1T corpus are not really words at all but web addresses, memory addresses, and emoticons. However, there are no non-UTF-8 characters in the corpus, which at least excludes languages like Chinese, Japanese, Thai, and Russian.

The corpus was created from a snapshot of Google’s search databases that took place during January 2006. The corpus consists of text files with the N-grams accompanied by a count of those N-grams. Each set of N-grams is stored in its own uniquely named folder. The N-Grams are organized alphabetically by the first word in the N-Gram. For instance, ”a cat” comes before ”a dog” in the 2-Grams of the corpus.

For natural language processing in general, and for this thesis in particular, each N-Gram in the Web1T corpus is a type. Each N-Gram paired with a count is a token. The process of creating these tokens is called tokenization.[9]

All folders in the Web1T corpus are structured the same except for the 1-Gram folder. There are two files within the 1-Gram folder. One file is organized alphabetically like the rest of the corpus, but the other file is organize by count. The largest count comes first. This folder serves as both a 1-Gram source and an authoritative reference of all types within the Google Web1T corpus.[9]

Punctuation is included in the corpus. Sentence boundaries are indicated by <S> and < \S >. To qualify for corpus inclusion, a 1-Gram needed to appear in the Google search databases at least 200 times. Additionally, to appear in a 2-Gram or greater, a gram had to appear in the database at least 40 times. For 2-Grams and greater that appeared 40 times or more, but one of the words in the gram did not individually appear at least 200 times, the tag <UNK> is used to replace that word. The characters used in the corpus are UTF 8. Tokenization was ”similar” to Penn Tree Bank except that hyphenated words were separated.[9] From working with the corpus, it becomes apparent that contraction within the corpus does not exactly match Penn Tree Bank. No ”'t” contractions were kept intact during tokenization. The authors were contacted regarding this tokenization issue, to determine if this was intentional, but no reply has been received.

The Google Web1T is massive. This size makes Web1T both powerful to employ and cumbersome to use. The statistics for this corpus are listed in Table 2.7.

Number of tokens:	1,024,908,267,229
Number of sentences:	95,119,665,584
Number of unigrams:	13,588,391
Number of bigrams:	314,843,401
Number of trigrams:	977,069,902
Number of fourgrams:	1,313,818,354
Number of fivegrams:	1,176,470,663

Table 2.7: Token and Type Counts in Google Web1T Corpus

2.4.3 Feature Compression Techniques

Due to the large size of the corpora and feature reference used in this thesis, an efficient way to represent words and N-grams was needed. After surveying general literature on representing large data sets, the search for this thesis was narrowed. Two methods of efficiently representing large sets were investigated: bloom filters and minimal perfect hash functions. Minimal perfect hash functions were ultimately chosen as the tool for representing data in this thesis.

Bloom Filters

Representing a large dataset in a small memory space requires trading off between probability of a false positive, probability of a false negative, processing time, and size of representation. Bloom filters allow efficient storage of a list of values with zero probability of false negatives and a configurable probability of false positives. A Bloom filter consists of an array of m bits and k hash functions. Each hash function has an output range of 0 to $m - 1$. Each hash function must provide an equal probability distribution for each value 0 to $m - 1$. At the beginning of the construction of the Bloom filter, all m bits are set to 0. Each value to be a member of the Bloom filter is processed by each hash function. The output of the hash function corresponds to the array position of one of the m bits, which is then set to 1. If an output bit is already set to 1, that bit remains a 1. After all Bloom filter member values have been processed by the hash functions, the array of bits should be a mix of 0's and 1's.

To determine if a value belongs to the Bloom filter, that value is run through all k hash functions. If each array position output by the k hash function contains a bit set to 1, then the value probably belongs to the membership set. If any of the m bits is a 0, that value does not belong.

There are variations on the Bloom filter that can use parallel architectures to advantage. For example, if the array of m bits is a multiple of k, then each hash function can have a range of 0 to $\frac{m}{k}$. Then each hash function can be run in parallel instead of in series. This scheme has no effect on the probability of a false positive, but can be appreciably faster to process in parallel processing platforms.

The work in a Bloom filter comes from determining the minimum values required for k and m to represent the expected set of values for a required false positive rate. The trade offs are, the larger the number of bits, the lower the probability of a false positive, but the larger the storage of the Bloom filter becomes. Likewise, an increased number of hash functions provides a lower probability of false positives, but larger numbers of hash functions increases the computational cost of the Bloom filter. Given a required maximum false positive probability, p, and a maximum number of items, n, the minimum number of bits, m, is given by:

$$m = \frac{n \ln p}{(\ln 2)^2}. \tag{2.27}$$

Once the number of bits, m, is determined, the minimum number of hash functions, k, must be found. The required minimum of hash functions is given by:

$$k = \ln \frac{m}{n}. \tag{2.28}$$

Bloom filters are flexible and compressible. They are flexible because the number of bits, m, can be changed on the fly based on a changing number of items, n. Various compression techniques can be used to compress the bits, m, in the filters for transmission between computers. The filters can be processed in serial or parallel based on hardware architecture. Unfortunately, while flexible, Bloom filters are not as compact as their closely related cousin, the minimal perfect hash function.

Minimal Perfect Hash Functions

A minimal perfect hash function is the culmination of three concepts: a hash, a perfect hash, and a minimal hash. A hash function is a function that maps values from a set, U, with a number of values, k, to a range of values, m [10]. Hashes are normally associated with mapping a large universe to a small universe, but hashes can map between spaces of equal size. Hashes are often used in computer science for cryptography, efficiently mapping values, and myriad other tasks.

A hash function is a perfect hash function if there are no hashing collisions. A collision occurs when different values from U result in the same output value. More formally, in perfect hashes, there are m distinct values resulting from applying the hash function to all k values in U such that $k = m$. In short there must be a 1-1 mapping between each value in U to each resulting value in the range, m – no collisions to be handled (load factor $\alpha = 1$. A perfect hash function is called a k-perfect hash function if the ratio of possible values in the mapped space is not larger than k times the original space. This means the range, m, must be k times larger than U to ensure there are no collisions.

A perfect hash function is called a minimal perfect hash function if there are no ”blank” spaces in the hash table – meaning that no space is wasted in storing the hash. This is the same as a k-perfect hash function where k=1. Less formally, the size of the range, m is equal to n, the size of the universe, U.

The time required to compute a value in m from a value in U is known as evaluation time. The time required to construct the minimal perfect hash function is known as construction time. Along with representation space, evaluation time and construction time are the three performance parameters used to judge the efficiency of a minimal perfect hash function.

Minimal perfect hash functions (MPHF) are comprised of a set of hashing functions and a lookup data structure. The set of values (the universe, U)to be hashed must be known in advance. Those values are mapped, one-to-one to a unique range of numbers. At the end of the mapping, there is exactly one unique numerical hash for every provided input. The required number of bits for the hash is the minimum number of bits possible to uniquely identify all the items. The theoretical lower bound is 1.44n bits, where n is the number of elements in U.

A lower bound of 1.44n bits is the advantage of the MPHF, the data structure is extremely compact once created. The disadvantage is that any value submitted to the MPHF will result in a hash value. This requires a second discriminating function to determine member in the correct value set, such as a second, traditional, hash. This second hash undermines the compact size of the MPHF. However, combining a MPHF with a single traditional hash provides an extremely small probability of a false positive during a membership check and a fast lookup time.

In general, there are three stages of creating a minimal perfect hash function or any k-perfect hash function. These three stages are mapping, ordering, and searching. The mapping stage maps the set of keys in universe, U, to some other values. For example mapping a set of strings to an integer value or creating a set of vertices in a graph could serve as the mapping step. Ordering involves finding the buckets, vertices, etc that have been mapped with the most keys. These highly mapped entries become levels or child graphs in a further refined hashing scheme to develop into the final data structure. The final step, searching, involves assigning keys to positions within the mapping. The mapping is often multilevel allowing duplication from hashing to be ”backed off” and retried to continue building the hash.

There are many MPHF implementations available in the open source world. The implementation claiming to be the closest to the theoretical minimum for representation space is called the Compress, Hash, and Displace (CHD) algorithm[11]. CHD maps keys into buckets. Each bucket is assigned its own hash function, ϕ to create an index into the final data structures. The buckets are ordered by magnitude (number of values in the bucket) for placement into the data structure. The theoretical lower bound of storage for a minimal perfect hash is 1.44n bits [10]. CHD's lower bound of storage is 2.07n to 3.56n bits depending on generation time allowed for the data structure.

2.5 Evaluation Criteria

Results from classifying data are computed from four basic categories of results: true positives, (tp), true negatives (tn), false positives (fp), and false negatives (fn). These four basic results are combined into accuracy, precision recall and F-Score for this thesis. While there are other evaluation criteria, these chosen criteria are clear enough and sufficient for measuring results.

2.5.1 Accuracy

Accuracy is a widely used and intuitive performance measure for classification. Accuracy, however, is flawed. Accuracy poorly represents the effectiveness of a classifier when the number of true negatives is large compared to the number of true positives. Missing all the true positives, but calling everything a negative, true or otherwise, yields a high accuracy without actually being effective at finding correctly labeled positives. Accuracy is defined as:

$$accuracy = \frac{tp + tn}{tp + fp + tn + fn} \tag{2.29}$$

[12] In a confusion matrix, accuracy is the total of all values on the diagonal of the confusion matrix divided by total of all values in the confusion matrix.

2.5.2 Precision and Recall

Due to the weakness of accuracy as an evaluation criteria, precision and recall (also known as sensitivity) is used. Precision measures how often a document that belongs to the class being sought is actually labeled as that class. In other words, for all the actual documents written by the target author, how often are those documents labeled by the classifier as being written by the author. For all the documents said to be true by the classifier, what percentage are actually true.

$$precision = \frac{tp}{tp + fp} \tag{2.30}$$

Recall determines how well the classifier picks out true documents. In other words, for all the true documents in the set, how often does the classifier detect those true documents? Recall is given by:

$$recall = \frac{tp}{tp + fn} \tag{2.31}$$

[12]

2.5.3 F-Score

F-score is a tool to better evaluate the results of testing. Unlike accuracy, where a high number can actually mask poor recall, f-score balances precision and recall. In the form in Equation 2.32, f-score is the harmonic mean of precision and recall. It is a superior indicator to accuracy in evaluating a classifier. The definition of f-score used in this thesis is:

$$F - Score = \frac{2}{\frac{1}{p} + \frac{1}{r}} \tag{2.32}$$

This definition is a variant of the standard definition of:

$$F - Score = \frac{(\beta^2 + 1) * 2pr}{\beta^2 * (p + r)} \tag{2.33}$$

The full definition of f-score involves an additional term, β, which is a weighting value. A β value greater than one favors precision and a β value less than one favors recall. This thesis values precision and recall equally. This makes $\beta = 1$, thus the simpler equation for F-Score is used:

$$\frac{2pr}{p + r} = \frac{2}{\frac{1}{p} + \frac{1}{r}} \tag{2.34}$$

F-score and accuracy will be the primary evaluation criteria for this thesis.[12]

2.6 Mobile Device Platforms

There are numerous mobile device platforms ranging from the near ubiquitous mobile phones to tablets to personal digital assistants. Even within the category of mobile phones, there is a wide ranging array of capability and popularity. For newer mobile phones, capabilities often include access to storage, a network, phone services, GPS, and multimedia. Storage can be both onboard phone storage or removable storage such as a micro-SD card.

Often, there is network access to more than just the mobile provider GSM or CDMA network. Modern phones often have WiFi access. GPS services provide position updates to the phone.

Multimedia capability varies dependent on display size, resolution, battery consumption, processing speed, memory, and network availability. Mobile phones have not yet reached the level of commonality expected in desktop and laptop computing devices. Commonality here refers to similar features being available at similar price points across many manufacturers. In a desktop computer, the list of features is fairly predictable for a given price. The same can be said for laptop computers. The variation in packaged features and capabilities still varies greatly between mobile devices as the mobile device market matures.

2.6.1 Mobile Devices by Popularity

To determine an effective development strategy for author detection on a mobile phone, it is sensible to determine what development language would support the largest number of mobile phones. By device popularity, the most dominant mobile operating systems, in order, are Symbian (Nokia phones), Research In Motion (Blackberry), iOS (Apple iPhone, iPad, iPod), and Android (Droid, Evo, Galaxy Tab). These four OS platforms constitute 88% of the mobile device market for first quarter of 2010.[13] Symbian, RIM, and Android all accept applications built on Java, or at least a variant of Java. Based on this vast market share, using Java as the development language for author detection on a mobile device has the largest potential for use.[14][15][16] Only iOS uses exclusively Objective C.[17]

2.6.2 Android Operating System

Based on its popularity and ease of installing test applications, Android is used as the development platform for this thesis. Android applications are not written, strictly speaking, in Java. Android applications are written in Dalvik which implements most of the syntax and structure of Java. Dalvik development is targeted at mimicking recent stable releases of the Java Development Kit (JDK). The core of the Android operating system is built on Linux, but is not built as a traditional Linux environment.[16]

Android applications consist of a combination of Activities, Services, Intents, and Content Providers. Activities are processes that users can see and interact with. Activities create the windows, tabs, and dialogs for user interaction.

Services run in the background with no user graphical user interface (GUI). Android Services are not equivalent to traditional Unix services (daemons). Unix services are, by nature, persistent process within the operating system. Android Services are just as prone to being killed by the operating system as an Activity.

Intents are messages passed around by processes and Java Virtual Machines within the Android operating System. Typical Intents are created by Content Providers for actions such as incoming calls, incoming Short Messaging Service (SMS) messages, GPS, etc. Other typical Intents are passed between Activities in an application or between Services and Activities in an application. Intents can start, stop, and pause Activities as well as just pass along data such as a String or integer. Applications use Activities, Services, and Intents in combination to provide functionality on an Android Mobile device.

The lifecycle of an application in Android varies from a standard PC application lifecycle. Activities and Services continue to run in Android while sufficient resources remain on the mobile device. When resources become exhausted, the Android operating system will shut down Activities and Services it deems as less important or less used. This is why Android applications often lack a ”Quit” or ”Exit” function in their menus – developers expect that the application can continue to run so long as the operating system has sufficient resources. Contents providers, on the other hand, are persistent processes driven by items such as GPS receivers, mobile networks, and WiFi networks. Content providers are accessed and listened to by applications. A Content Provider can also be built by a developer to act as a data provider for other application as an abstraction instead of an actual physical device like GPS or WiFi.[18]

2.7 Corpora

A major portion of validating a method of author attribution is securing a corpus of usable data. There are some tried and true corpora openly available, such as the ENRON E-mail Corpus, which are well know, well studied, and useful for comparison. With a focus on mobile devices, this thesis needed a more short text relevant corpus. For this need an in-house corpus of Twitter posts, known as Tweets, was used. Using these two corpora provides a standard corpus to judge effectiveness and a newer corpus to anticipate future capability in the evolving medium of mobile computing.

2.7.1 ENRON E-mail Corpus

The ENRON e-mail corpus is a set of emails collected by the Cognitive Assistant that Learns and Organizes (CALO) Project. The original corpus contains 619,446 emails from 158 users. These emails were posted on the web by the Federal Energy regulatory Commission during the investigation of ENRON. Issues with the raw posting were corrected by several people at MIT and SRI to arrive at the form of the current corpus. The emails are organized in folders, by user. The folder organization used by the original user is kept mostly intact (Inbox, Sent Items, etc) except for some computer generated folders that were seldom used by the actual users. Each e-mail is contained in its own text file. Each text file contains the full e-mail header as well as any threaded conversation headers (replies and forwards).[19]

The ENRON corpus is a frequent target for natural language processing. Author detection performance for character and word N-grams, SVM, naive Bayes and other classifiers on the ENRON corpus is well documented. For this reason, all methods used in this thesis were attempted on the ENRON e-mail corpus as a benchmark of performance, before moving on to the more mobile-centric corpus of Twitter.

2.7.2 Twitter

Twitter is a short message micro-blogging services that users can access from traditional computers as well as mobile devices. Originally designed for use over Short Message Service (SMS), Tweets (vernacular for message sent on Twitter) are limited to 140 characters. Unlike other social networking sites, Twitter has no requirement for users to post their real names. Author detection on a corpus of Tweets will be challenged by the short duration of each Tweet (Tweets would constitute a document in this case) and the non-standard use of language. Also, users do not have to formulate original content for their Tweets. Just like as e-mail forward, users can re-Tweet a Tweet they have already received.

Tweets are formatted for use with a JavaScript Object Notation (JSON) format. The JSON formatting provides numerous fields containing language, Twitter id, geocode (latitude and longitude of sender). The Twitter API contains both streaming and RESTful methods. Using the Twitter API, Tweets can be pulled from the TwitterSphere using a free, rate limited service called Garden Hose or via a fee-based, rate unlimited service called Fire Hose. The rate limit for Garden Hose is 150 messages per hour. Those messages are randomly chosen from Twitter accounts that make themselves viewable by the public. The Twitter API allows for filters to affect the stream of Tweets to avoid getting Tweets that do not meet your needs and would otherwise impact your rate limit. The length limitation and mobile nature of Tweeting, makes Twitter a reasonable model of SMS behavior for testing purposes.[20]

2.8 Recent Work in Author Detection, Google Web1T, and Mobile Devices

Using minimum perfect hash functions and signature hash functions in a method similar to this thesis was discussed by Talbot and Brants. [21] This paper on using hash functions with Web1T is additionally interesting because Brants is one of the researcher who created the Google Web1T corpus. Other structures have been proposed for managing the vast size of the Web1T corpus such as using block compression and variable length bit compression to reduce the size of stored Web1T data.[22]

Google Web1T has been used as a smoothing reference in other machine learning studies. Yuret et all used a backoff method based on Google Web1T counts to smooth using a Dirichlet prior form and a Kneser-May backoff model.[23] Google Web1T has also been a reference for spelling correction[24] and semantic classification[25]. References to Web1T are numerous for natural language processing, spam detection, and spelling correction. Some papers such as Islam et al. simply discusses how to manage a large corpus like Web1T.[26]

Author detection across varied information sources using a normalized compressor distance has been patented. This method creates a bitwise compression of content from web pages, emails, texts, or any electronic document and uses clustering, based on this patented distance measure, to arrive at probability of various documents being from the same author.[**?**] Author detection on mobile devices has not shown up in patent or paper searches. However, author attribution for Twitter messages was addressed by Layton et al. These researchers used a method called SCAP to get an author attribution accuracy of 0.70 for group sizes of 6 authors and an accuracy of 0.20 in group sizes of 50.[27]

Recent SVM work shows a focus on making SVM faster to accommodate ”online” processing and capable of being distributed across multiple processors. A concept called Cascade SVM was improved upon by Yang to allow independent SVM processes feed back results of the SVM calculation without carrying the entire weight of the processed data set with that feedback.[28]. In the effort to have SVM ”adapt” in an online fashion, Bordes et al. develop fast SVM classifiers that use only a portion of the training data and ensure that the classification is conducted in a single pass. [29]

2.9 Conclusion

There is a rich body of work on author attribution, SVM, naive Bayes, and on the ENRON E-mail corpus. Applying traditional document and e-mail author attribution tools to the short message environment of mobile phones is an area ripe for exploration.

CHAPTER 3:
Experimental Design

This chapter document the concepts and technical approaches used in this thesis, as well as procedural concepts for understanding the experiments of this thesis.

3.1 Experimental Design Overview

Thesis Goals The central goal of this thesis's experiments is to compare size and speed of different author detection methods against the effectiveness of those same author detection methods on a resource constrained device such as a mobile phone. Size and speed are critical to this thesis. This is due to the restrictive nature of mobile phones. However, the nature of these experiments allows the results to be applied to other computing platforms with limited resources such as nano-computers, mobile sensors, or yet unimagined devices.

Experimentation Phases To achieve the thesis goal, experimentation will be conducted in two phases: parameter evaluation and mobile phone performance evaluation. In parameter evaluation, the effectiveness of different combinations of classification methods, features sets, group sizes, and smoothing/filtering to compare prediction performance against model size and processing requirements. During the mobile phone performance evaluation, the combinations of classification methods that are both feasible and effective are used on mobile phones to determine the overall performance and impact of running author detection on an actual mobile phone.

3.2 Phase One: Parameter Evaluation

This phase will evaluate numerous combinations of two classification methods, five feature sets, six grouping sizes, three grouping methods, and two corpora to determine the computing requirements and effectiveness of these combinations. Preparing for these evaluations takes several steps including determining the required combinations, organizing and compressing the feature references, preparing the training and prediction data, building the models, and, finally, running the prediction tests. The results for all prediction test will be stored in a mySQL database which will also store the resulting f-score, precision, recall, and size of model for each test.

3.2.1 Creating the Testing Combinations

The classification methods to be compared are naive Bayes and Support Vector machines (SVM). Naive bayes is fast and uses a relatively small amount of RAM and disk storage. SVMs, are slower, use greater RAM and disk storage, but often yield higher f-scores. There are numerous feature sets that can be chosen. For this thesis, 1-grams, 2-grams, 5-grams, gappy bigrams, and orthogonal Sparse bigrams will be examined. The intuition is that 1-grams are simple and use less space, but will be less effective than bigger feature sets such as gappy bigrams or 5-grams.

For this thesis, two feature reference sets will be examined, a bootstrapped bag of words and the Google Web1T corpus. Bootstrapped bag of words simply means finding all the unique types within a training set and making each type a feature in the feature set. Since the Google Web1T corpus is huge, a parameter of that feature reference which can be adjusted is the percentage of a given feature set that might be used. These experiments will permute through these numerous options to determine size, speed, precision and f-score. The end result will be an analysis of the utility of these various approaches to author detection on a mobile phone. A graphic of the parameter combinations is given in Figure 3.1.

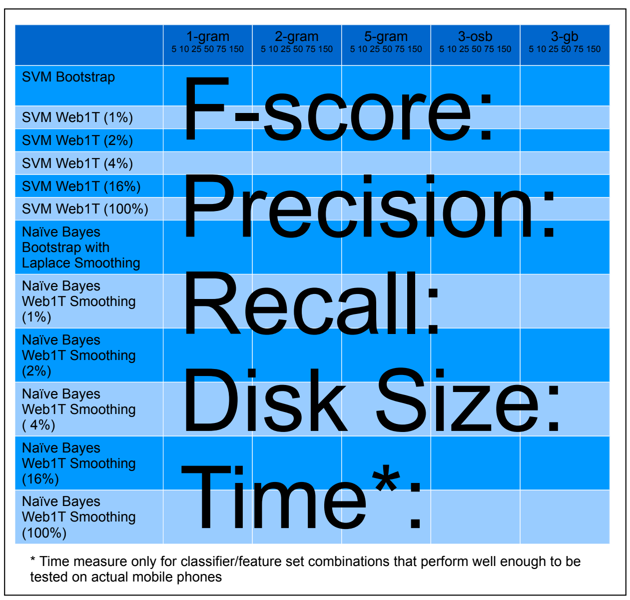


Figure 3.1: Parameter Combinations for Testing

The small numbers ”5 10 25 50 75 150” given under each column heading in Figure 3.1 indicate that all authors will be tested in groups of 5, 10, 25, 50, 75, and 150 using three different grouping strategies: small-to-large, small-and-large, and random. In small-to-large, the authors with the smallest amount of training data are grouped together. In small-and-large, small authors and large authors are paired together. In the random grouping, the authors are grouped together by a pseudo-random selection. The reasoning for these three grouping strategies is to provide insight into the effect of prolific authors versus less prolific authors. If results are similar for the same author for each group, the prolific writing may not impact the outcome of author detection with these methods. This is needed information to rule out that the test author detection methods simply select the most prolific author instead of the actual author.

3.2.2 Organizing and Compressing Feature References

A key element to this testing is the use of the Google Web1T corpus. The Web1T corpus contains billions of types with a token mass of just over 1 trillion. The size and breadth of the Web1T corpus makes it appealing as a source for smoothing in naive Bayes and a tool for creating models in SVM. However, due to the huge size of the Web1T corpus, the text files comprising the corpus must be compressed and managed for use on desktop workstations, servers, and especially mobile devices. Managing the corpus requires determining what portions of the Web1T corpus will be used. Using the choice of 5-grams as an example for illustration purposes, suppose only the 5-grams portion of the Web1T corpus might be used. The 5-grams constitutes 118 text files containing up to 10 million lines of text each. Each line of the Web1T 5-gram files contains space separated words (making up the type) followed by a count, separated from the words by a tab. The lines of text are organized alphabetically by token where uppercase letters are distinct from lowercase letters. Even using only one size of gram from Web1T, a reverence of this size is slow and bulky for machine learning use. Therefore, a subset of the reference is needed.

Sizing the Feature Reference Set To manage the size of Web1T, a small portion of the 5-grams could be chosen – 1%, 2%, 4%, etc. To choose which part of the reference to use (largest, smallest, random) this thesis takes advantage of Zipf's Law. Zipf's law states that the highest frequency word occurs approximately twice as often as the next most frequent word. By that reasoning, a list of the types with the highest counts is needed to capture the largest use of words in a natural language corpus. To get this count ordered list, the complete set of Web1T n-grams are recreated. The recreated files list each type organized by count instead of alphabetically. If two or more types have the same count, then those types are list alphabetically. The types are still listed first as a group of space separated words followed by a tab and ended with a count.

Three Tiered Hashing Scheme Even once the feature set of types to be used for classification has been determined, the smaller set of text is still too slow to process and very bulky to store. To further compress the data, a three tiered hashing scheme is used. The structure of the three tiered hashing scheme is shown in Figure 3.2.

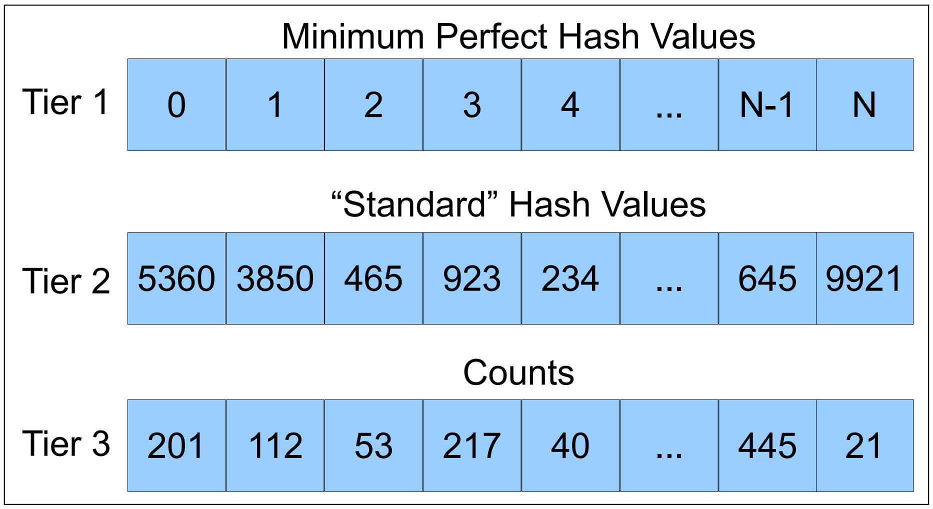


Figure 3.2: Three Tiered Hashing Scheme Structure

The first tier is comprised of minimal perfect hash (MPH) values of the selected feature set. The second tier of the scheme is comprised of a 64 bit hash of the original type. This second tier's job is to reduce the probability of a false positive in the fist tier. This issue arises because no matter what string is input to the MPH function, a valid MPH value will be produced. The second tier's traditional hash is accessed by mapping the MPH value to the index of an array that comprises the second tier. That array cell contains the 64 bit hash of the original text used to create the MPH value. This make the false positive rate for a given type $\frac{1}{2^{64}} * \frac{1}{\text{range of MPH values}}$ which is deemed an appropriate risk of collision in this hashing scheme. The third tier is simply an array of long values. The MPH value from tier 1 is used to access this array which hold the count value for a given type. An example of converting a phrase, ”the quick brown”, is shown in Figure 3.3.

These different tiers are not contained in a single data structures. The MPH data structure, tier 1, is contained in a file called ”keys.mph”. The array of hash values, tier 2, is contained in a file called ”signature”. The counts are contained in a Java object file call LongCountsArrayFile. The naive Bayes experiments use all three tiers of this structure for smoothing values. The SVM experiments only use tier 1 and tier 2 to verify that a string encountered actually belongs to the

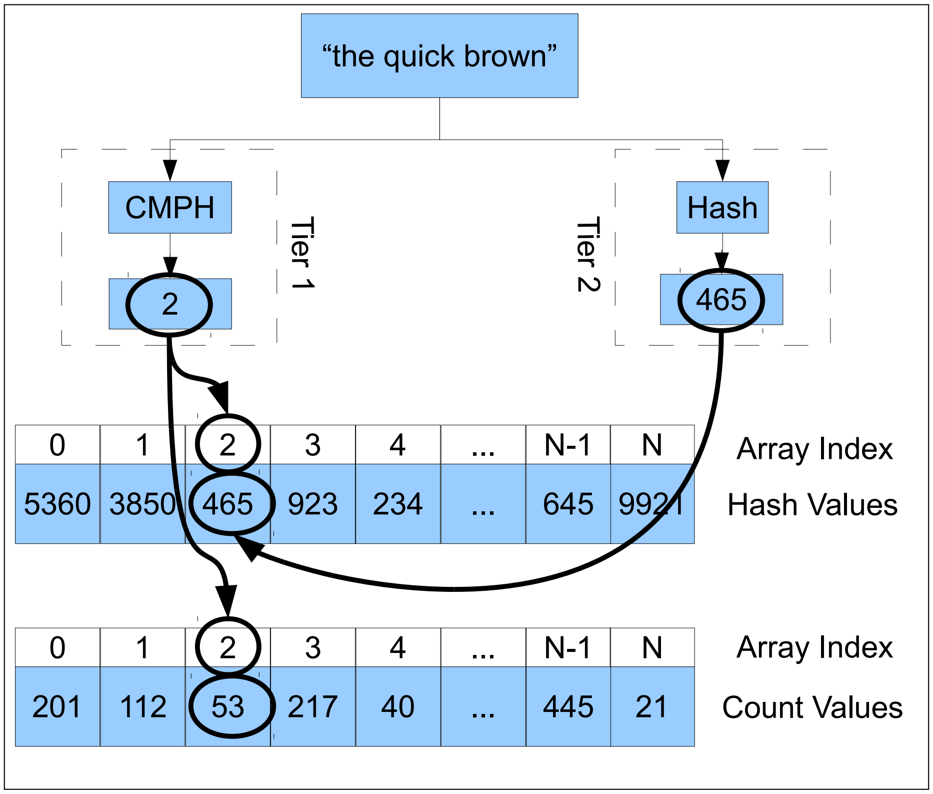


Figure 3.3: Three Tiered Hashing Scheme Example

feature set. These hefty data files comprise the bulk of storage required on the mobile device. Since these data files get loaded into RAM during the prediction process, the file sizes also impact RAM requirements. The impact on RAM and disk storage makes management of the size of keys.mph, signature, and LongCountsArrayFile an important aspect of the experiments.

Choosing Artifacts for the Three Tiered Hashing Scheme One impact of using MPH to reduce the size of storing types is a loss of flexibility with the text artifact selection process. Before the MPH data structure is created, the creator must determine if punctuation, capitalization, sentence boundaries, or ”unknown” words will be allowed. The omission of each of these artifact types brings its own unique challenges. A binary style number scheme was adopted for each of these features where capital letters hold the 1 position, punctuation the 2 position, unknown word tags the 4 position, and sentence boundaries hold the 8 position. The complete matrix of artifacts allowed in the MPH model is included in Figure 3.4.

MPH Label	Remove Sentence Boundary Tags	Remove Unknown Word Tags	Remove Punctuation	Remove Capital Letters
0	FALSE	FALSE	FALSE	FALSE
1	FALSE	FALSE	FALSE	TRUE
2	FALSE	FALSE	TRUE	FALSE
3	FALSE	FALSE	TRUE	TRUE
4	FALSE	TRUE	FALSE	FALSE
5	FALSE	TRUE	FALSE	TRUE
6	FALSE	TRUE	TRUE	FALSE
7	FALSE	TRUE	TRUE	TRUE
8	TRUE	FALSE	FALSE	FALSE
9	TRUE	FALSE	FALSE	TRUE
10	TRUE	FALSE	TRUE	FALSE
11	TRUE	FALSE	TRUE	TRUE
12	TRUE	TRUE	FALSE	FALSE
13	TRUE	TRUE	FALSE	TRUE
14	TRUE	TRUE	TRUE	FALSE
15	TRUE	TRUE	TRUE	TRUE

Figure 3.4: Matrix of CMPH Models by Artifacts Included

Omitting Punctuation Omitting punctuation provides two options for dealing with the corpus: replace punctuation with "$<$ UNK $>$" or drop the punctuation altogether. If punctuation is dropped, then any type containing a punctuation mark in the feature reference set must be completely ignored. If the punctuation is replaced with $<$ UNK $>$, then a search within the existing count structure must be conducted for a corresponding entry for $<$ UNK $>$ and any non-punctuation words in the type. While dropping punctuation is much simpler to implement than employing "$<$ UNK $>$" tags, however, Google did count punctuation as a word in type construction, so correlation between n-gram counts in the Web1T corpus and the trained/predicted documents is slightly affected. To maintain simplicity, the simple drop approach was used in these experiments.

Omitting Capitalization Omitting capitalization is straightforward for construction of tier 1 and tier 2, the inputted text for the type is converted to all lower case and a check is conducted to see if that type is already in the MPH data structure. For tier 3, which contains the counts, the lower case versions of the word must have its count mass added with its corresponding uppercase types. This adds complexity to the insertion process for MPH but is easily managed. Another option would be to simply drop all types that contained capitalization, but that would remove a large count mass from the Web1T corpus. Adding counts was the method used in this thesis to deal with omitting capitalization.

Omitting Sentence Boundaries Sentence boundaries are denoted in the Web1T corpus as $< S >$ and $< \backslash S >$. Dropping sentence boundaries is straightforward since there is no replacement or count mass issues to deal with. Since the tools for locating sentence boundaries make use of their own machine learning processes, no sentence boundaries were used in these experiments.

Omitting Unknown Words In the Web1T corpus, ”unknown” words have a specific meaning. To be included in any corpus n-gram set, a word must have appeared as a 1-gram at least 200 times in the Google database. By contrast, to be 2-gram, 3-gram, 4-gram, or 5-gram, that gram had to appear at least 40 times in the Google database. This created as situation where a word would need to appear in a 2-or-higher-gram, but was not allowed into the corpus because it did not appear 200 times in the overall database. Words that fall into that category are replaced with the tag $< UNK >$ in the Web1T corpus. Removing $< UNK >$ words from the MPH has no effect on the counts in tier3 and is a straightforward process.

Choosing N-Grams N-grams can be as small as a 1-gram and grow, theoretically, to any size N imaginable. The preferred reference set for this thesis, the Web1T corpus, uses 1, 2, 3, 4, and 5-grams. While it is tempting to test all 5 N-gram sizes available in the corpus, only three were used. 1-grams and 5-grams were chosen to represent opposite ends of the size N gram spectrum available. 2-grams were used as a strong comparison to gappy bigrams and orthogonal sparse bigrams discussed below. Future work could focus on 3 and 4-grams to determine if there is a performance to size advantage in using those size of N-grams.

Gappy Bigram and Orthogonal Sparse Bigram Construction Once the 3 tier structure is created and functional, there are still two type of features remaining to be created. The Web1T corpus only contains standard n-grams, not gappy bigrams or orthogonal sparse bigrams. To create these more exotic types of bigrams, a rule for counting distance and a notation scheme was needed. It was decided to use ”lesser included counts” for both the gappy bigrams and the orthogonal sparse bigrams. This means that a word1 word2 pair would count for osb-0, osb-1, osb2, etc. While previous papers placed the distance for an OSB between word1 and word2 [30], this thesis constructed the OSBs with the distance after word2 for easier parsing. The gappy bigrams and OSBs were constructed from the 2, 3, 4, and 5-grams in the Web1T Corpus. Word pairs from a distance of 0 (a traditional bigram or an OSB-0) to a distance of 3 (an OSB-3 or the first and last word in a 5-gram) were built from the Web1T corpus. This process only looks at the first and last words in a 3-gram, 4-gram, or 5-gram since the inner words of this gram are already captured in the 2-gram. Using the inner 2-grams would double count 2-grams and throw off the count mass. The same is true for 3-grams inside of 4 and 5-grams as well as 4-grams inside of 5-grams.

Grouping By Size With references built and sized, an efficient structuring of the authors and documents needs to be devised. During data file construction, the grouping and conversion processes happened simultaneously. The grouping sets built were: small-to-large, small-and-large, and random.

Small-To-Large The small-to-large group matched the least prolific authors together with increasing size up to the most prolific authors. For example, of the 5 authors in the ENRON corpus with 5 total kilobytes worth of text are group together while the 5 authors with greater than 1 total megabyte of text are group together. No author is picked more than once. An example is shown in Figure 3.5.

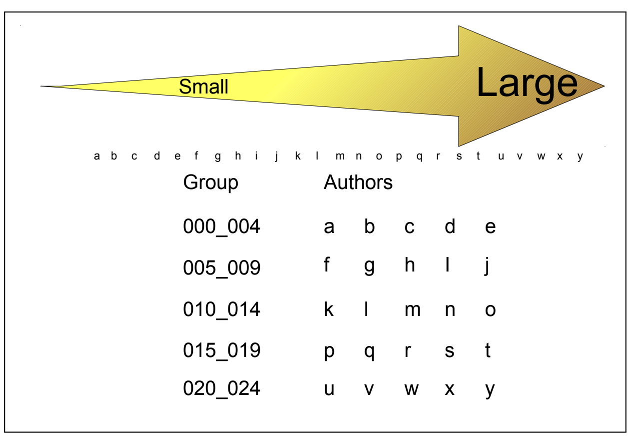


Figure 3.5: Small-To-Large Group for Group Size 5, 25 Authors

Small-And-Large The next group, small-and-large, is created by binning the authors by size. Then one author from each bin is picked to be group with one author from each other bin. For example the least prolific author is paired with one author from the most prolific bin and one author from each bin in between. In this situation, the selection from each bin is not random. The least prolific remaining author from each bin is picked for grouping. No author is picked more than once. An example is shown in Figure 3.6.

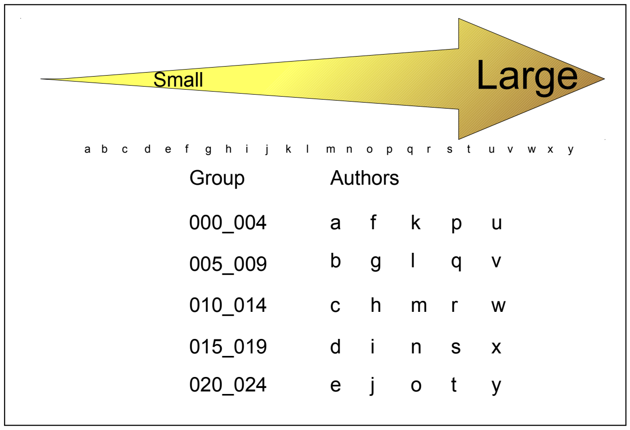
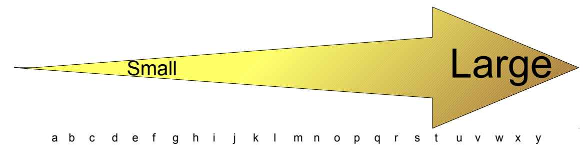


Figure 3.6: Small-And-Large Group for Group Size 5, 25 Authors

Random This grouping simply produces a random number in the range of available authors and places the selected author into a group until that group is full. Then the next group is filled the same way until no authors remain. No author is picked more than once. No author is picked more than once. An example is shown in Figure 3.7.

Group Sizes Based on having 150 authors in the ENRON Corpus, the six following group sizes were used: 5, 10, 25, 50, 75 150. These six group sizes coupled with the three grouping types, small-to-large, small-and-large, and random creates 18 grouping types. Examples of these grouping types are 5 small-to-large, 5 small-and-large, 5 random, 10 small-to-large, ..., 150 small-to-large, 150 random. Although using all 150 authors in a grouping set makes the procedure of how the 150 were grouped redundant, all three size 150 tests were conducted as a check on the experiments. If the 150 author grouping provides different reslts, then there may be an issue with the classifiers.



Group	Authors				
000_004	u	q	m	r	e
005_009	a	g	s	y	h
010_014	w	j	t	b	f
015_019	c	i	n	v	x
020_024	d	k	l	o	p

Figure 3.7: Random Group for Group Size 5, 25 Authors

After these grouping types were constructed, there were 171 totals sets (30 sets of 5 small-to-large, 15 sets of 10 small-to-large, ..., 1 set of 150 small-to-large, 1 set of 150 random.) Each of these sets were intended to be run through Bootstrapped SVM, Web1T SVM, Laplace Smoothed naive Bayes, and Web1T Smoothed naive Bayes. Assuming that only one MPH model is chosen to represent Google Web1T, that results in 684 experiments. Since there are 16 different MPH models based on the combinations punctuation, capitalization, sentence boundaries, and unknown words, the number of experiments could rise drastically. However, only two MPH models will be used during the experiments resulting in only 1,368 per feature type. Using 1-grams, 2-grams, 5-grams, 3-gb, and 3-osb results in 6,840 totals experiments.

Data File Format With combinations of features, artifacts, and group sizes chosen and the MPH data structures created, the actual documents must be converted into a format that can be used by the classifiers. The LibSVM file format was used since that it is the native format for libLinear, the tool used for SVM in this thesis. The naive Bayes classifier was built specifically for this thesis and was designed to use LibSVM format for convenience. The format of the data files consisted of an integer representing the author followed by a space, followed by a number representing the MPH value, followed by a colon, followed by another number representing the count. Each succeeding instance of a MPH value coupled with a count is separated by a space. Each document in the corpus is represented by a single line. Each line's mph number is in increasing order from left to right. The data files store the word/count pairs in a sparse fashion. This means that a zero count is not included in the data file. Absence of a word/count pair constitutes a zero count without needlessly using up space in the file. An example of this file format is provide in Figure 3.8.

```
83 362112:1 2216672:1 4609969:1 5582887:1 6141348:1 13588391:0
115 2334923:1 4077269:1 4759253:1 10878308:1 13069356:1 13588391:0
47 902626:1 1820755:1 10686459:1 12596717:1 13588391:0
80 1648944:1 1979998:1 2205090:1 2334923:1 2478205:2 13588391:0
```

Figure 3.8: LibSVM File Format

Running SVM With the data files created, the classifiers can be applied. The chosen tool for author detection using SVM is libLinear. libLinear was chosen for its speed compared to LibSVM. The libLinear source code was slightly modified to allow training a model from a data set, then running prediction on a separate set without using the built-in cross validation function. During the training phase, each author has a SVM model built for it from a training file in a directory labeled ”train”. During the prediction phase, document contained in another file are used to predict the mostly likely author. That file is contained in a folder called ”predict”. The SVM author result is printed to a result file in a directory labeled ”result”. The f-score, precision, and recall for each file is recorded in a file inside a folder labeled ”analysis”. The analysis file also contains a full confusion matrix, time of prediction, size of original file, and other statistics. This file is finally pulled into a mySQL database for storage and calculation of precision, recall, and f-score..

The size of the author models impacts RAM usage and disk space. libLinear stores SVM models as an array. RAM and storage are not the only limits. An array of integers representing token counts can be sizable, especially when token counts are long numbers (64 bits) instead of integers (32 bits).

RAM and disk storage are not the only limits. By specification, arrays in Java are limited to $2^{31} - 1$ entries. This means the model cannot contain more than $2^{31} - 1$ features. Also, the model must be loaded into RAM, so the number of authors coupled with the size of the author model must be weighed against the available RAM and disk storage.

Running Naive Bayes The naive Bayes classifier has been specifically built for this thesis. The classifier reads in a pre-built array of long values from a file. The two types of arrays are a Laplace Smoothing array, which is comprised of all 1’s. the second type of array is the Google Smoothing array comprised of the count values from the Web1T corpus. Using an array to hold the smoothing values for naive Bayes has an impact on RAM usage. There must be enough available RAM to hold the smoothing array. To prevent having numerous copies of the smoothing array in memory (one for each author being trained) a hashmap is used to create the author models instead. The process for training put each encountered feature type into a hashmap along with a count of $1plus$the array smoothing value. If that feature type is encountered, the the count is simply incremented. Once all the training documents have been read and counted, the hashmaps of feature types and counts is converted into a hashmap of feature types and log of probability.

During the prediction process, each encountered feature type is queried against the author hashmap first. If the feature type is found in the hashmap, then the hashmap $\log probability$ is used. If not, then the smoothing array containing log of probabilities is used. An example of this hashmap/array process is shown in Figure 3.9. The result of the prediction process is outputted to a file in the corresponding results directory. Those results are then processed into a file in the corresponding analysis folder where all data is then read into a mySQL database for evaluation of precision, recall, and f-score.

3.3 Phase Two: Android Implementation

To manage files on the mobile device, a rudimentary file manager was built with a text viewer added. A button was also added to the File Manager to execute prediction against a document on the phone. An Android Service was also constructed that listens for incoming SMS messages. When an SMS Message is "heard", it is processed for author detection. The Service can be turned on and off using a button on the File Manager.

To measure CPU and RAM impact caused by the author detection processing, the third party applications, and Memory Usage, was installed on the phones. The method is to take a baseline of the phone's CPU and RAM usage with no Widgets or Applications running, the phone is attached to a recharging device, and no calls or texts are being sent. The same phone conditions are being set for the processing tests where the only application that will run on the phone will be the SMS capture and author detection application for this thesis. This will yield some basic metrics of author detection impact on the phone's capabilities.

3.4 Corpora

Two corpora are used for this thesis: the ENRON E-mail Corpus and the Naval Postgraduate School (NPS) Twitter Corpus. The aim of this thesis is to examine author detection using a mobile device. Two of the most common text communications on a mobile device are e-mail

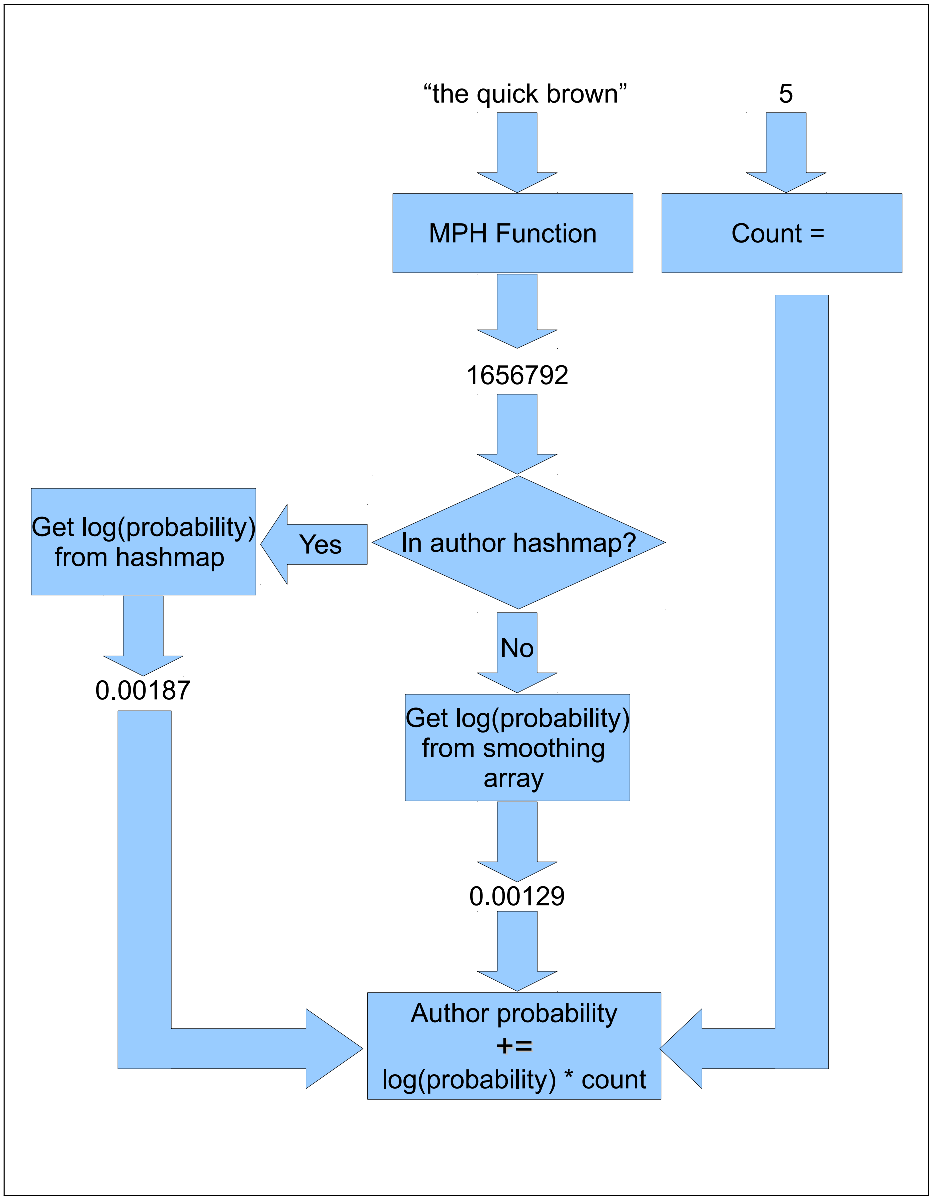


Figure 3.9: Naive Bayes Hashmap and Smoothing Array Flow Chart

and SMS (texting). The ENRON E-mail Corpus has been widely examined and has been used to author attribution in other studies. This makes the ENRON Corpus a suitable standard to measure the author detection techniques used in this thesis. The NPS Twitter Corpus is smaller and newer than the ENRON e-mail corpus, but texting is extremely popular as a communications medium. Determining the effectiveness of author detection over this rapidly expanding text standard is important for analyzing the effectiveness of author detection on mobile devices.

ENRON E-mail Corpus Each ENRON e-mail was stored in a single text file within a folder labeled with the author's first initial, second initial, and last name. Prior to processing each ENRON e-mail, a systematic attempt was made to distill each e-mail down into just the author's words. To support this distillation, the e-mail header was stripped from each e-mail. A search was conducted throughout the remaining text to find additional e-mail headers. These are the embedded headers caused by e-mail replies and forwards. Also to prevent biasing the author attribution, an attempt was made to systematically detect an e-mail closing such as ”Sincerely, Dave” or ”Yours Truly, Jane”.

Naval Postgraduate School Twitter Short Message Corpus All tweets from a single author were stored in a single text file. Each tweet from that author was contained on its own line. Each line begins with a date-time stamp with the content of the text following. Prior to constructing the corpus, all ”re-tweets” were removed to ensure the text came from a single author, not just from a single Twitter account.

3.5 Intended Comparison

Once all tests are complete, performance of the different combinations of feature and classifiers will be compared for both the ENRON e-mail corpus and the Twitter Corpus. This is to allow any differences in performance against the two primary media used on mobile phones. The completed test results should provide insight into the possibility of author detection on a mobile phone against both e-mail and short messages.

CHAPTER 4:
Results and Analysis

After 19,782 tests producing 286,050 measurements for f-score and 19,782 measurements for accuracy, several notable results emerged. Most importantly, a small number of method-feature combinations do exist that both provide a reasonable author detection accuracy and have a storage requirement of less than 16MB. Further, in studying the effects of using the Google Web1T Corpus, Web1T did not provide enough benefit to accuracy to justify its large storage requirement. This does not mean that Web1T did not have a positive impact on accuracy, especially for the Enron corpus and naive Bayes. It was also found that Web1T had different impacts on dissimilarly prolific authors than on similarly prolific authors. This chapter provides specific details about usable method-feature combinations and the impacts of Web1T.

There is one notation convention used in this chapter that requires explanation. The notation Web1T% refers to the top percentage of the Web1T corpus used as the vocabulary in testing. For instance, Web1T% of 1 for OSB3 means that the top 1% of orthogonal sparse bigrams of distance three (OSB3) were used as the vocabulary. Web1T% of 2 for GB3 means that the top 2% of gappy bigrams of distance three (GB3) are used. This pattern continues for Web1T% of 4, 8, and 16 and feature types of 1-grams (GM1), 2-grams (GM2), and 5-grams (GM5). The only special case is for Web1T% of 0. In this case, there was no reference to the Google Web1T Corpus at all in constructing the vocabulary. The vocabulary is built using any and all tokens found in the training set.

4.1 Most Effective Combination of Classification Methods, Feature Types, and Vocabulary

Two measurements of effectiveness were used in this thesis: accuracy and f-score. Since the accuracy for each author is not the focus of this thesis, but rather the overall effectiveness of each classifier, feature type, and vocabulary combination, f-score is averaged, over the set of authors, for each combination. In each test set, average accuracy was higher than MLE. Likewise, average f-score was always lower than average accuracy.

At this point, it would be natural to simply compare the highest accuracy for each method-feature-vocabulary combination in the thesis and determine which combination performed best.

This analysis would be flawed. Due to the underlying data structure in the libLinear model, there is an absolute maximum number, 2^{31}, of elements allowed. The libLinear tool creates one element created in its model for each feature-classifier combination. This means that the number of for each author, there is a dedicated cell for each feature. The data structure impact for the libLinear tool is array size become the number of authors multiplied by the number of features. Array size in Java cannot exceed 2^{31}. This limits the of features that can be used with libLinear for a given number of authors. Figure 4.1 shows the value of each feature-vocabulary-group combination. Cells highlighted in red cannot be used with the LibLinear model. If only the top 2^{31} features from each Web1T% was used, then large Web1T% values would have identical features. For instance, two very large set are OSB3 for Web1T% of 8 and Web1T% of 16. If only the top 2^{31} features were used from each of these features sets, then both of these sets, which far exceed 2^{31} features, would hold the same 2^{31} features. This would create identical results and provide no additional insight into the true performance of that vocabulary. Therefore, due to the data structure limitation of the libLinear tool, there will be no LibLinear results for feature-author combinations that require an array larger than 2^{31} elements in the libLinear model.

While libLinear is the chosen SVM tool for this thesis, the classifier method being test is SVM. For the rest of this chapter, results will be analyzied by method instead of by tool. For this reason, results will be discussed in terms of SVM and naive Bayes instead of in terms of libLinear and naive Bayes.

The impact of this hard maximum is large vocabularies show a higher accuracy and f-score than smaller vocabularies. This is not necessarily because the large vocabularies are more effective, but because the larger vocabularies do not have the lower accuracy and f-score outcomes of the large group sizes. To illustrate this, the top twenty feature-method combinations are show in Table 4.1 for the ENRON E-mail Corpus. The performance of each SVM OSB3-vocabulary combination is shown in Figure 4.2. Using Table 4.2 to evaluate accuracy would lead to a conclusion that SVM OSB3 has the best accuracy and f-score in this thesis. However, plotting all OSB3 results for each Web1t % in 4.2 shows that all OSB3-vocabulary combinations perform along a similar curve. The Web1T $\% \ of 0$ is actually able to perform against all group sizes (5, 10, 25, 50, 75, and 150) and, thus, appears to perform worse than other OSB3s in the table, but clearly performs similarly from Figure 4.2. From this example, it becomes clear that simply using the table values in Appendix A through Appendix D provides an insufficient analysis. A better analysis is provided by examining the plots in Appendix Q through Appendix T.

Feature Type	Web1T %	Liblinear Limits Due to Vocabulary Size (Web1T %) and Group Size					
		Group Size					
		5	10	25	50	75	150
GM1	1	679415	1358830	3397075	6794150	10191225	20382450
	2	1358835	2717670	6794175	13588350	20382525	40765050
	4	2717675	5435350	13588375	27176750	40765125	81530250
	8	5435355	10870710	27176775	54353550	81530325	163060650
	16	10870710	21741420	54353550	108707100	163060650	326121300
GM2	1	15488310	30976620	77441550	154883100	232324650	464649300
	2	30976620	61953240	154883100	309766200	464649300	929298600
	4	61953240	123906480	309766200	619532400	929298600	1858597200
	8	123906480	247812960	619532400	1239064800	1858597200	3717194400
	16	247812960	495625920	1239064800	2478129600	3717194400	7434388800
GM5	1	57357075	114714150	286785375	573570750	860356125	1720712250
	2	114714155	229428310	573570775	1147141550	1720712325	3441424650
	4	229428310	458856620	1147141550	2294283100	3441424650	6882849300
	8	458856620	917713240	2294283100	4588566200	6882849300	13765698600
	16	917713245	1835426490	4588566225	9177132450	13765698675	27531397350
GB3	1	30275425	60550850	151377125	302754250	454131375	908262750
	2	60550850	121101700	302754250	605508500	908262750	1816525500
	4	121101700	242203400	605508500	1211017000	1816525500	3633051000
	8	242203405	484406810	1211017025	2422034050	3633051075	7266102150
	16	484406810	968813620	2422034050	4844068100	7266102150	14532204300
OSB3	1	117215100	234430200	586075500	1172151000	1758226500	3516453000
	2	234430200	468860400	1172151000	2344302000	3516453000	7032906000
	4	468860400	937720800	2344302000	4688604000	7032906000	14065812000
	8	937720805	1875441610	4688604025	9377208050	14065812075	28131624150
	16	1875441615	3750883230	9377208075	18754416150	28131624225	56263248450

Figure 4.1: Liblinear Limits Due to Vocabulary Size and Group Size

It is important to note that this is not an issue for combinations using naive Bayes as a classification method. However, naive Bayes did not outperform SVM in these tests, so a careful analysis of SVM using the plots in Appendix Q through Appendix T is required.

By examining the plots in Appendix Q through Appendix T, a clear trend emerges that the bootstrapped models, meaning models that made no use of the Web1T corpus as a vocabulary reference) performed similarly for SVM to Web1T vocabularies. In all cases, the bootstrapped SVM tests are usable for all group sizes. In this case, a good comparison would be to drop all SVM combinations that are not usable for all group sizes, then compare these remaining SVM tests against all naive Bayes tests. Since all naive Bayes tests were usable for all group sizes, this makes the comparison fair.

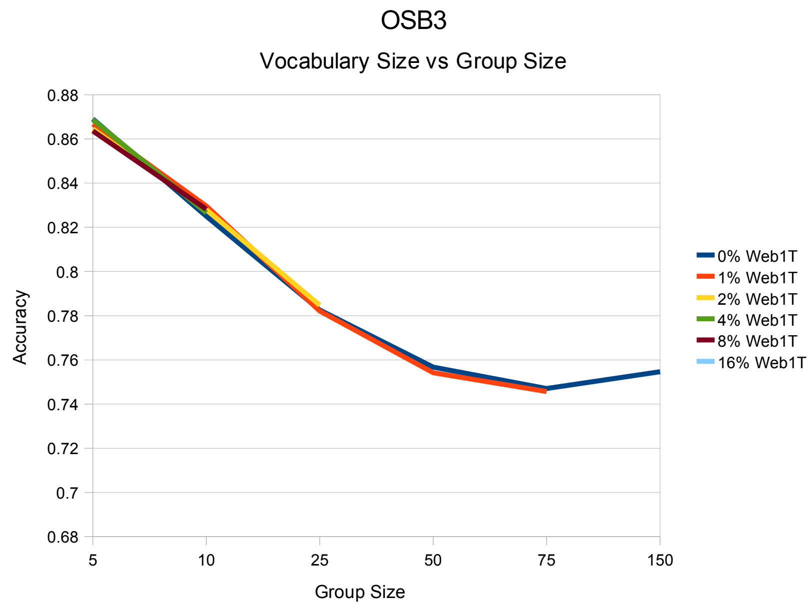


Figure 4.2: Accuracy of SVM OSB3 for the ENRON E-mail Corpus

After extracting out SVM tests that were not usable against all groups sizes, the highest accuracy method-feature combination show the most accurate results for the ENRON E-mail Corpus in Table 4.1. The highest accuracy method-feature combination show the most accurate results for the Twitter Short Message Corpus in Table 4.2.

From Table 4.1 orthogonal sparse bigrams and gappy bigrams perform very well overall, with a traditional bigram making an entry at number five. The best performing method-feature combination is SVM OSB3 with a Web1t% of 0. The next three combinations are naive Bayes classifiers using OSB3 with large Web1T% vocabulary sizes. The results are similar for gappy bigrams, but at a reduced accuracy of approximately one percent.

From Table 4.2, the top performing method-feature combination is naive Bayes OSB3 with a Web1T % of 0. The next four positions are filled with gappy bigrams with sizable Web1T% vocabularies. Why Twitter responds better to naive Bayes as opposed to e-mail responding better to SVM is left to future work.

While the above table shows the best performing, accuracy is not always a solid measure of classification effectiveness. A better measure is f-score. As shown repeatedly by the tables in Appendix A through Appendix D, the relative performance of average f-score matched the relative performance of accuracy for each test set. In all cases, f-score was lower than the

Combinations		Accuracy				
Method	Feature Type	Web1T %	AVG	MIN	MAX	STDDEV
SVM	OSB3	0	0.8362	0.5106	0.9732	0.1043
NB	OSB3	16	0.8325	0.5213	0.9823	0.0890
NB	OSB3	8	0.8315	0.5213	0.9714	0.0893
NB	OSB3	4	0.8274	0.5197	0.9587	0.0924
SVM	GM2	0	0.8262	0.4824	0.9753	0.1087
SVM	GB3	0	0.8212	0.4787	0.9835	0.1121
NB	GB3	16	0.8195	0.5201	0.9674	0.0947
NB	GB3	4	0.8194	0.5340	0.9522	0.0941
SVM	GB3	1	0.8191	0.4731	0.9673	0.1110
SVM	GB3	2	0.8184	0.4765	0.9805	0.1113
NB	GB3	8	0.8172	0.5255	0.9782	0.0935
NB	OSB3	1	0.8126	0.3615	0.9574	0.1185
NB	OSB3	2	0.8095	0.3526	0.9575	0.1283
NB	OSB3	0	0.8058	0.5185	0.9592	0.0970
SVM	GM5	16	0.7918	0.3908	0.9676	0.1204
SVM	GM5	8	0.7872	0.3908	0.9513	0.1193
NB	GB3	2	0.7857	0.4790	0.9669	0.1166
SVM	GM5	4	0.7755	0.3908	0.9455	0.1241
SVM	GM1	4	0.7742	0.4006	0.9590	0.1212
SVM	GM1	8	0.7740	0.4074	0.9570	0.1223
SVM	GM1	0	0.7735	0.3776	0.9531	0.1222

Table 4.1: Highest Accuracy Method-Feature Type Combinations for the ENRON E-mail Corpus

average accuracy. Even more telling about the results is every test set shows a minimum f-score of 0. That means that at least one author had an f-score of zero in each test. This accounts for the high standard deviation for f-scores across all tests. For f-scores of approximately 0.65 the standard deviation was approximately 0.25.

An examination of the confusion matrices for each test can provide insight into whether there was a ”poison” author that never got selected or if there was an author who was a selection ”magnet” always getting too many selections for documents. Due to the large number of confusions matrices in this thesis (nearly 19,782 confusion matrices created from 57 tests * 3 size groupings * 6 vocabulary sizes * 5 feature types * 2 corpora * 2 methods - 738 unusable SVM tests) the confusions matrices are not presented in this thesis, but are archived by the NPS Natural Language Processing lab in comma separated value files.

Combinations		Accuracy				
Method	Feature Type	Web1t %	AVG	MIN	MAX	STDDEV
NB	OSB3	0	0.5525	0.2320	0.8164	0.1339
NB	GB3	16	0.5327	0.2216	0.8216	0.1351
NB	GB3	4	0.5271	0.2190	0.8546	0.1375
NB	GB3	8	0.5256	0.2176	0.8474	0.1362
NB	GB3	2	0.5249	0.2186	0.7823	0.1324
SVM	GM2	4	0.5228	0.1809	0.8210	0.1477
NB	GB3	1	0.5204	0.2148	0.8125	0.1319
NB	GB3	0	0.5203	0.1973	0.8021	0.1389
SVM	GM2	1	0.5197	0.1882	0.8454	0.1483
SVM	GM1	8	0.5187	0.1743	0.9026	0.1525
SVM	GM2	2	0.5186	0.1830	0.8232	0.1495
SVM	GM1	1	0.5159	0.1768	0.8211	0.1494
SVM	GM1	4	0.5149	0.1874	0.8546	0.1485
SVM	GM1	0	0.5141	0.1802	0.8089	0.1485
NB	GM1	0	0.5140	0.1247	0.7714	0.1631
SVM	GM1	16	0.5134	0.1865	0.8324	0.1483
SVM	GM1	2	0.5131	0.1818	0.8966	0.1487
SVM	GM5	1	0.4768	0.1398	0.8362	0.1521
NB	GM2	0	0.4750	0.1630	0.7890	0.1406
NB	OSB3	2	0.4739	0.1790	0.7734	0.1370
NB	OSB3	8	0.4707	0.1787	0.7790	0.1373

Table 4.2: Highest Accuracy Method-Feature Type Combinations for the Twitter Short Message Corpus

4.2 Impact of Author Relative Prolificity on Classifier Effectiveness

While identifying the best accuracy results for method-feature combinations is important, these results could mask a weakness in the method-feature combinations. Does the relative prolificity of each author impact the results? To answer this question, the tests in this thesis were conducted in three groupings: small-to-large, small-and-large, and random. As explained fully in Chapter 3, these groupings were based on a rank-ordering by size for each author's total document collection. For small-to-large, the least prolific authors are grouped together, while the most prolific authors are grouped together. The idea behind the small-to-large group is to keep the difference in total documents size between the authors to a minimum. For small-and-large, the opposite idea is employed. The smallest authors are combined with the largest authors using a bucket strategy. Each bucket contains rank-ordered by size authors of similar size. One author is picked from each bucket to provide a maximum variety of author document collections sizes. In the random group, the authors are grouped together using a pseudo-random number generator, where each author has been assigned a number.

The results of testing in this thesis for accuracy and f-score, broken out by small-to-large, small-and-large, and random are given in Appendix E through Appendix H. The results from Appendix E, SVM Results for the ENRON E-mail Corpus, show the accuracy for small-to-large is always lower than the accuracy for small-and-large and random. However, the f-score for small-to-large is always higher than the f-score for small-and-large and random. This result shows how accuracy is dominated by the MLE author, since allowing a more prolific author into a group with less prolific authors tends to raise accuracy, but hurts f-score. To illustrate the effect of author prolificity on accuracy and f-score Table 4.3 shows the confusion matrix for a small-to-large grouping of size 10 for GB3, Web1T%=0. Table 4.4 shows the confusion matrix for a small-and-large grouping of size 10 for GB3, Web1T%=0.

		Label									
		11	111	119	14	146	15	48	60	71	91
Truth	11	0	0	0	0	0	0	2	0	1	0
	111	0	0	1	0	0	0	0	0	0	0
	119	0	0	8	1	0	0	0	0	0	6
	14	0	0	0	4	0	0	0	0	0	10
	146	0	0	0	1	0	0	1	0	0	1
	15	0	0	0	1	0	4	1	0	0	4
	48	0	0	0	2	0	0	9	0	0	2
	60	0	0	2	0	0	0	1	4	0	2
	71	0	0	0	2	0	0	0	0	0	4
	91	0	0	0	2	0	0	1	0	0	17

Table 4.3: Confusion Matrix for Small-To-Large Grouping, Feature Type: GB3, Group Size: 10, Web1T%: 0

Table 4.3 represents a group of similarly prolific authors. One author, author 91, not only has the highest number of true positives, 17, but has a large number of false positives. The combined false positives for all other authors is 21, compared to author 91's 29 false positives. That counts as 29 false negatives spread across the other 9 authors, impacting their false negative value. For calculating f-score, a higher false negative rate decreases recall and, since true positives remain constant, false positives fall, increasing precision. In the small-to-large grouping, one author has very few false positives, creating a high precision. The other authors end up with a high

		Label									
		11	113	47	49	58	75	76	86	88	95
Truth	11	0	0	0	0	0	1	0	0	2	0
	113	0	203	43	23	3	6	0	4	19	0
	47	0	7	2510	2	4	2	0	3	61	0
	49	0	16	52	1180	2	6	0	2	48	1
	58	0	1	16	2	508	0	0	0	7	0
	75	0	5	19	4	0	338	0	1	16	0
	76	0	0	1	3	0	0	9	0	1	0
	86	0	14	12	14	2	9	0	36	15	0
	88	0	11	129	12	1	7	0	0	277	1
	95	0	4	2	7	3	2	0	1	9	4

Table 4.4: Confusion Matrix for Small-And-Large Grouping, Feature Type: GB3, Group Size: 10, Web1T%: 0

recall. As the f-score for each author is average for the group, these unbalanced numbers drive the f-score higher while maintaining a lower accuracy.

Table 4.4 represents a group of dissimilarly prolific authors. In this grouping, one author does not dominate the number of false positives. This more evenly spread set of false positives and false negatives keeps the overall f-score lower, while maintaining a higher accuracy. The bottom line is the high outlier precision score for one author in the small-to-large group gives a higher f-score, but lower accuracy. A median measurement of f-score might provide a better picture of overall f-score behavior than an average f-score.

The other issue that arises from the f-score average is the small-to-large f-score has a smaller standard deviation than the small-and-large f-score. This points to a tighter grouping of values. This arises from all but one author having similar f-score values. The small-and-large group has no single outlier f-score to drag the f-score higher, but the values do have greater variation among all points.

The above paragraphs make use of a cursory examination of the behavior of author detection due to author prolificity. An in-depth statistical analysis of the difference between the author groupings is warranted as future work. The goal of using these different groupings was to ensure that the tools chosen in this thesis behaved predictably with respect to varying author prolificity within a detection group. To examine that behavior, plots of accuracy, average f-score, MLE, precision, and recall for each method-feature combination across all usable Web1T% vocabularies is included in Appendix Q through Appendix U. To illustrate that the impact of author prolificity is predictable across method-feature combinations and corpora, Figure 4.3 and Figure 4.4 are shown as representative samples of overall classifier and corpora results.

Figure 4.3: SVM Limits Due to Vocabulary Size and Group Size

From Figure 4.3 some trends become apparent. As the small-to-large graph for the Enron corpus moves from left to right, the accuracy, f-score, precision, and recall all increase in tight agreement. This correlates to the wide variation in prolificity between the least prolific group on the far left, file 000_009, and the last file on the far right, file 140_149. In the Enron corpus,

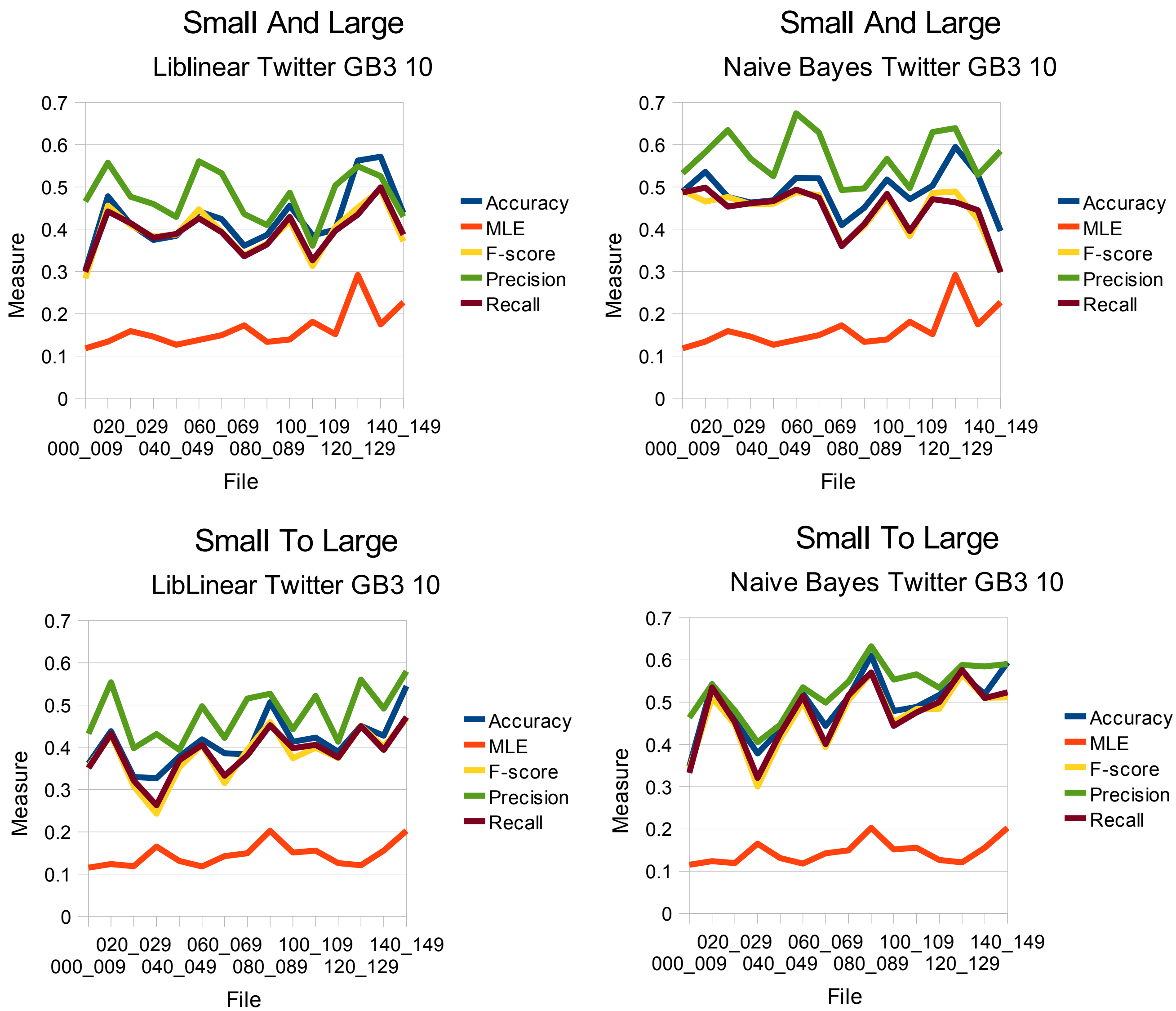


Figure 4.4: SVM Limits Due to Vocabulary Size and Group Size

the least prolific author's document total size is measured in a few kilobytes where the most prolific author's document total size is measured in megabytes. Most striking is that the trend holds for both SVM and naive Bayes. Also, with a group size of 10, the most prolific authors have a high accuracy, high f-score, high precision, and high recall. The impact of prolificity is predictable and significant for the Enron Corpus.

The results for the Enron corpus small-and-large group are largely flat as the graph moves from left to right. This shows that in a mixed group of varying prolificity, both SVM and naive Bayes maintain fairly consistent results. Clearly, having an author who is significantly more prolific than other authors in his detection group hurts the average f-score for that group while raising the accuracy. This rise in accuracy is not a good indicator of improved performance. For the Enron E-mail Corpus, prolific authors are more detectable than less prolific authors, even in the presence of other prolific authors.

4.2.1 Cumulative Distribution of Authors Over F-Scores Due to Grouping

In the Enron small-and-large figures, precision and accuracy are close in value where f-score and recall are always close in value. The accuracy and precision values are also always above the f-score and recall values. Investigation into the underlying reasons for this pattern warrants future work in an in-depth statistical analysis of the effects of grouping on author detection.

The story from Figure 4.4 is markedly different than the story from Figure 4.3. All results are lower for the Twitter Short Message Corpus than for the Enron E-mail Corpus, as indicated by the top value on for graphs in Figure 4.4 being 0.7 versus 1.0 for Figure 4.3. The relative flatness of measures in the Twitter corpus compared to the Enron corpus can be explained by the difference in relative sizes of an author in the Twitter corpus and an author in the Enron corpus. The most prolific author in the Twitter corpus has only 15.2KB of text as opposed to 2.5MB for the most prolific Enron author. Future work of gathering a larger Twitter corpus of original, not re-tweeted, short messages could supply a similar size and variation of the Enron corpus.

The further illustrate the impact of grouping similarly profilic, dissimilarly prolific, and randomly prolific authors together, cumulative distribution graphs were constructed for four scenarios: SVM for Enron in Figure 4.5, naive Bayes for Enron in Figure 4.6, SVM for Twitter in Figure 4.7, and naive Bayes for Twitter in Figure 4.8. Each of these plots are displayed as six panels in one figure. Each panel represent a different Web1T% for that method-corpus combination. The panel Web1T% values are, from upper left to lower right by row, 0, 1, 2, 4, 8, and 16. Each panel has three lines plotted as the cumulative distribution of authors over f-score. The f-scores in these panels are per-author, not averaged, and not weighted f-scores. For the sake of consistency, all four figures use GB3 as the feature type and a group size of 10. The graphs show are representative of all feature types (GM1, GM2, GM5, GB3, OSB3). Group size has a significant impact on the shape and position of the graphs. The impact of group size on the will be demonstrated in the next subsection. There are some blank panels in the graphs. Blank graphs occurs when the number of authors coupled with the number of types exceeds 2^{31} elements and cannot fit into the array used by libLinear model.

The characteristics being examined in these cumulative distribution graphs how are the lines curved, how closely the lines are grouped, and how far the lines are to the left or right.

- For curvature, a line curving to the bottom right shows that a large number of authors have higher f-scores. A line curving to the upper left corner show that a larger number of authors have lower f-scores. A line curving to the bottom right demonstrates a better performing method-feature combination.

- For close grouping of lines, the closer the lines are grouped together, the more negligible the effect of author prolficity has on f-score. For instance, if the small-to-large line curves to the lower right while the small-and-large line curves to the upper left, the having authors of dissimilar size had a detrimental effect on author f-score. More closely grouped lines demonstrates a better performing method-feature combination because that combination performs more consistently across groupings by author prolificity.

- In examining the position of the lines to the left or right, lines positioned further to the right indicated more authors with a higher f-score, even at the bottom of the curve. For instance, a line starting at a f-score of 0.0 shows that at least one author had a f-score of 0.0. A line starting at 0.4 show the worst f-score for any author was 0.4, which demonstrates a a better performing method-feature combination.

The panels in Figure 4.5 shows a representative set of curves for all SVM tests on the Enron E-Mail Corpus. Looking at the first panel, the curvature of all three lines, small-to-large, small-and-large, and random are all of similar shape. That shape curves down and to the right. The small-to-large curve slightly outperforms the small-and-large and random curve up to a f-score of 0.7. This similarity in curvature is consistent as the Web1T% increase through the next five panels. All three lines are grouped closely together. The close grouping is consistent through the next five panels. The left to right positioning of the curves is nearly identical. This positioning does not shift as the Web1T% increases.

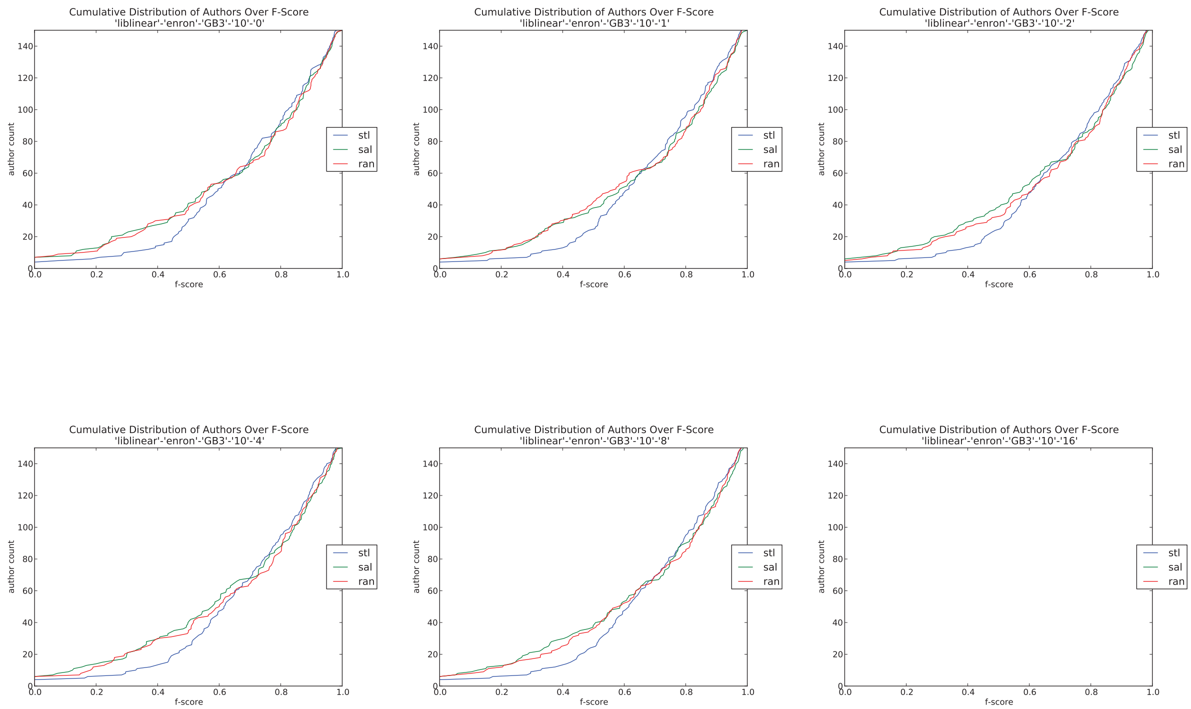


Figure 4.5: plot-tiled-cdf-summary-liblinear-enron-gb3-10

These panels show that the results of SVM on Enron are consistent and generally positive with or without Web1T%. It also shows that SVM performance against Enron is consistent for both similarly and dissimilarly prolific authors.

The panels in Figure 4.6 shows a representative set of curves for all naive Bayes tests on the Enron E-Mail Corpus. Looking at the first panel, the curvature of the small-to-large line is down and to the right. The small-and-large line and the random line curve up and to the left. This shows the small-to-large line performing significantly better than the other two lines. This pattern is not consistent moving from the first panel, Web1T% of 0, to the second panel, Web1T% of 1. In the second panel the small-and-large line and the random line both curve down and to the right. At this point all three lines are grouped closer together, but not as closely as in SVM for Enron. The grouping varies slightly through the next four panels with small-to-large alway outperforming small-and-large and random. The left to right positioning of the curves is nearly identical for the second through sixth panels. The position on the small-and-large line and the random line improved from the first panel to the second panel.

There are three observations from the naive bayes for Enron panels in Figure 4.6, first moving from a bootstrap naive bayes using Laplace plus one smoothing to a Web1T% smoothing greatly

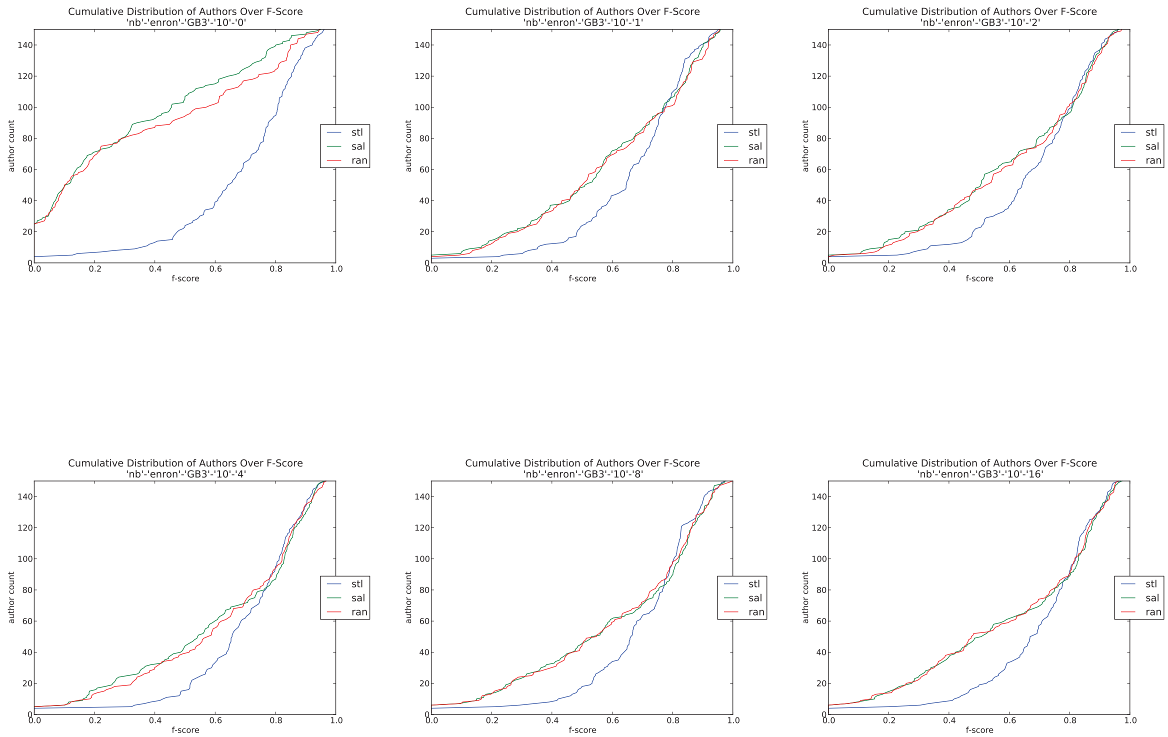


Figure 4.6: plot-tiled-cdf-summary-nb-enron-gb3-10

improves the performance of the small-and-large and random lines without any appreciable change to the small-to-large line. This shows that Web1T% has is useful as a smoothing tool for naive bayes for the Enron Email corpus. Second, there is no further significant performance improvement to any line as the Web1T% increase beyond 1%. This implies that only the most common terms in the Web1T corpus have a significant impact on smoothing. Third, using naive bayes, f-score performas similary for small-to-large with Web1T or without Web1T. This speaks to the power of having similarly sized speakers in the same author detection group.

The panels in Figure 4.7 shows a representative set of curves for all SVM tests on the Twitter Short Message Corpus. The panels in Figure 4.7 shows a representative set of curves for all naive Bayes test on the Twitter Short Message Corpus. Both figures are nearly identical. Looking at the first panel of both figures, the curvature of all three lines, small-to-large, small-and-large, and random are all of similar shape. That shape curves is an "S" shape showing that there are few authors with low f-scores and few authors with high f-scores. No curve regularly outperforms the others. This similarity in curvature is consistent as the Web1T% increase through the next five panels. All three lines are grouped closely together. The close grouping is consistent through the next five panels. The left to right positioning of the curves is nearly

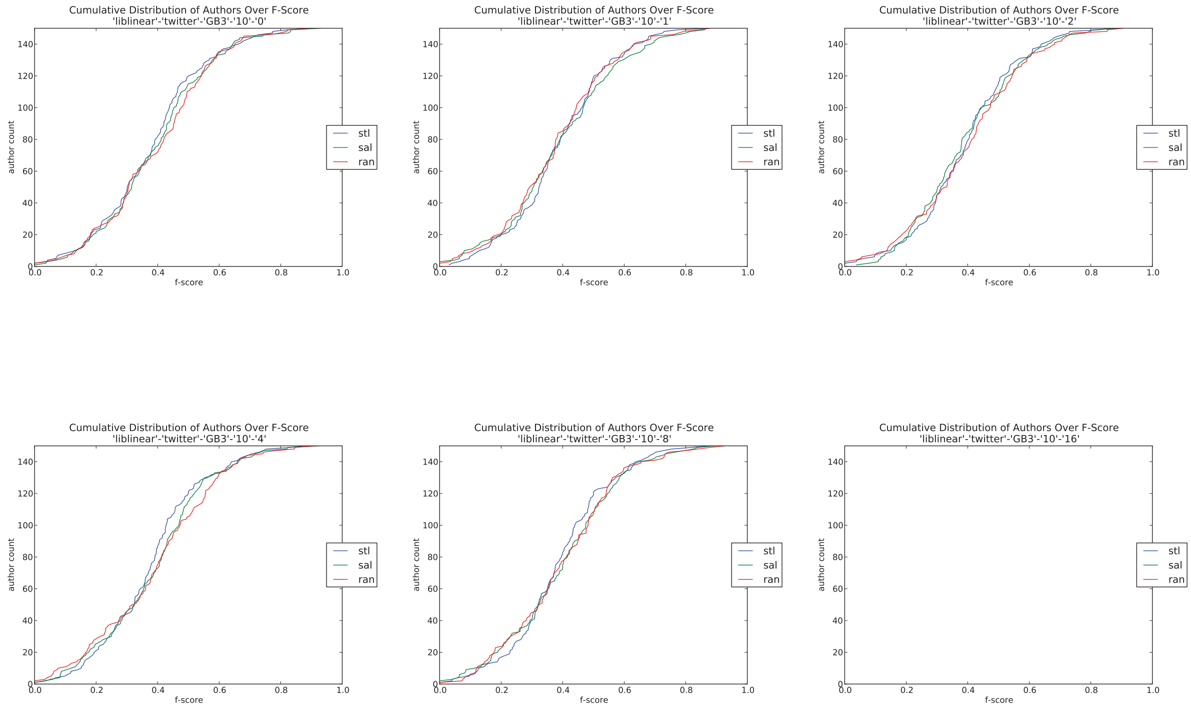


Figure 4.7: plot-tiled-cdf-summary-liblinear-twitter-gb3-10

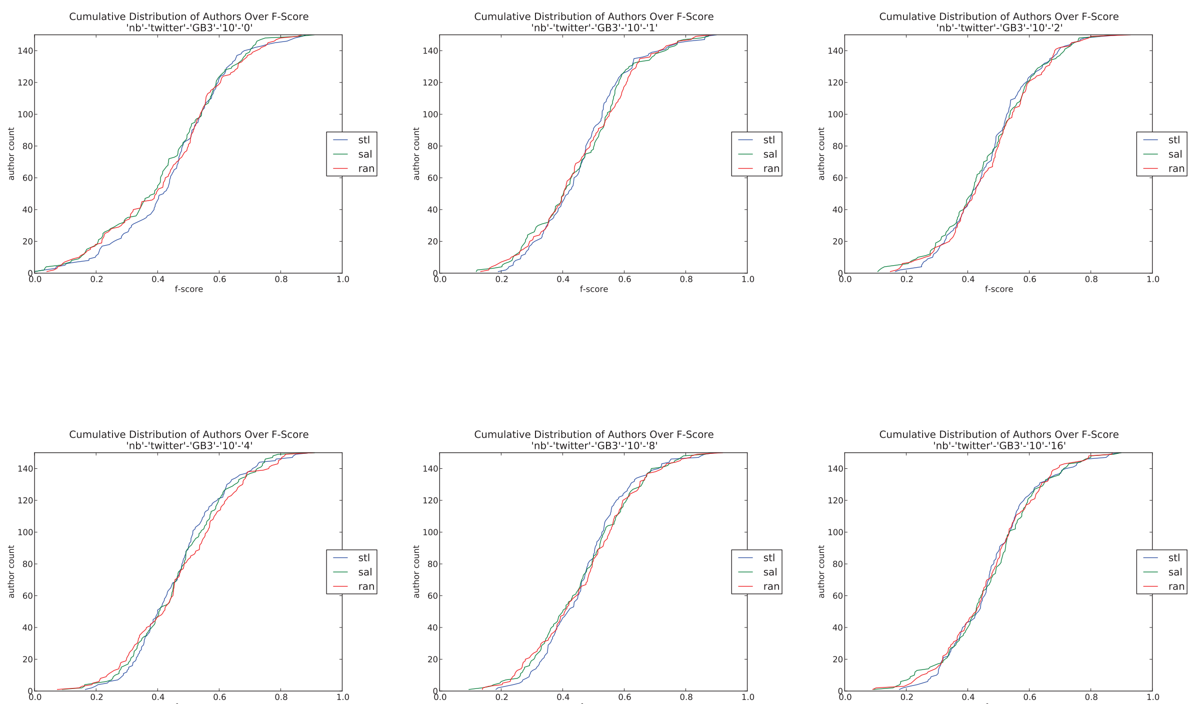


Figure 4.8: plot-tiled-cdf-summary-nb-twitter-gb3-10

identical except that introducing a Web1T% of 1 into 4.7 shifts the line further to the right, improving overall performance. This positioning does not shift as the Web1T% increases.

These panels show that the results of SVM and naive Bayes on Twitter are consistent and generally mediocre with or without Web1T%. It also shows that SVM performance against Twitter is consistent for both similarly and dissimilarly prolific authors.

4.2.2 Cumulative Distribution of Authors Over F-Score Due to Group Sizes

Figures 4.9, 4.10, 4.11, fig:plot-tiled-cdf-summary-nb-enron-GB3-ALL-1, and fig:plot-tiled-cdf-summary-nb-twitter-GB3-ALL-0 are representative examples of the impact of changing group size on authors being grouped by prolificity. There are six panels in each figure. The panels progress from upper left to bottom right through group sizes 5, 10, 25, 50, 75, and 150. All of these figures except Figure 4.11 display a Web1T% of 0. Figure reffig:plot-tiled-cdf-summary-nb-enron-GB3-ALL-1 displays a Web1T% of 1 to present the difference in general shape between naive Bayes against Enron for both Web1T% of 0 (Figure 4.10) and 1 (Figure 4.11).

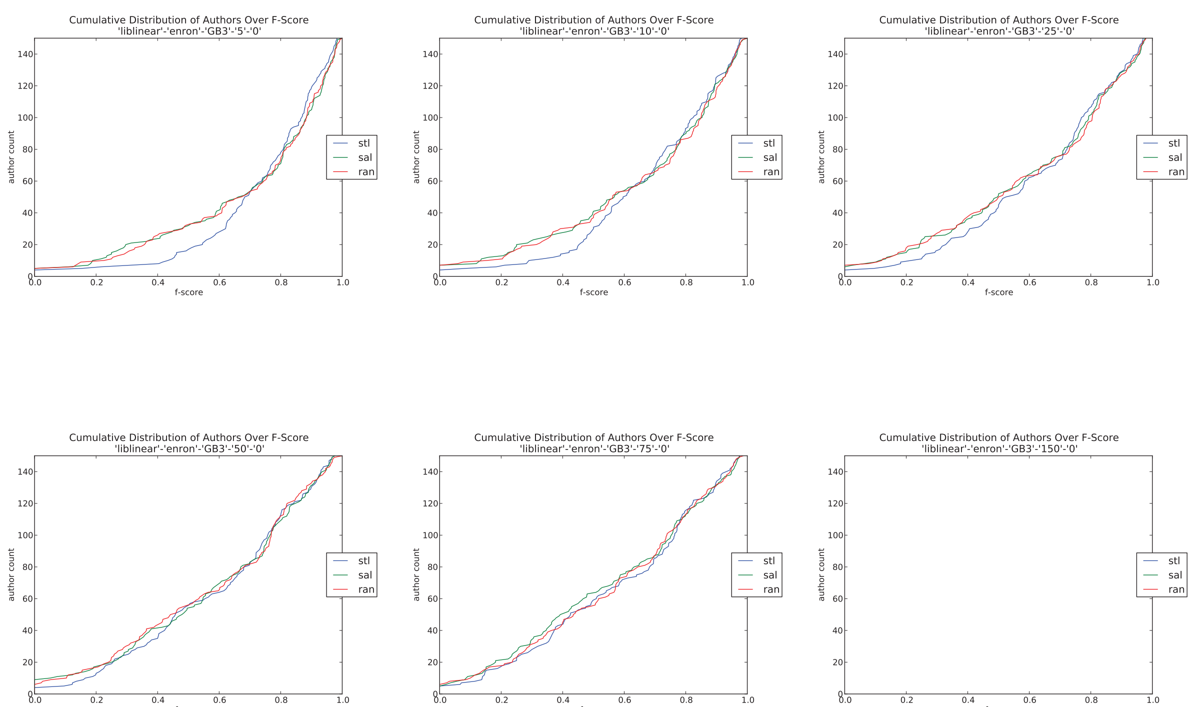


Figure 4.9: plot-tiled-cdf-summary-liblinear-enron-GB3-ALL-0

Figure 4.9 shows the typical progression as group size increase from an initial value of 5 to a final value of 150. The curvature of all three lines shifts from curving down and right to up and left. None of the feature-group size combination ever curve left and up past a basically straight line. The grouping of the lines gets tighter as the group size increases. Specifically, the small-to-large curve gets worse at a faster rate as the group sizes increase, causing the small-to-large line to decrease the distance between it and the small-and-large and random lines. This shows that group size impacts the small-to-large line more than the small-and-large and random lines. The left to right position of the endpoints of all three lines remain relatively fixed through all group sizes. This shows that the worst and best f-scores remains relatively constant through the group sizes while f-scores in the middle f-score authors worsens.

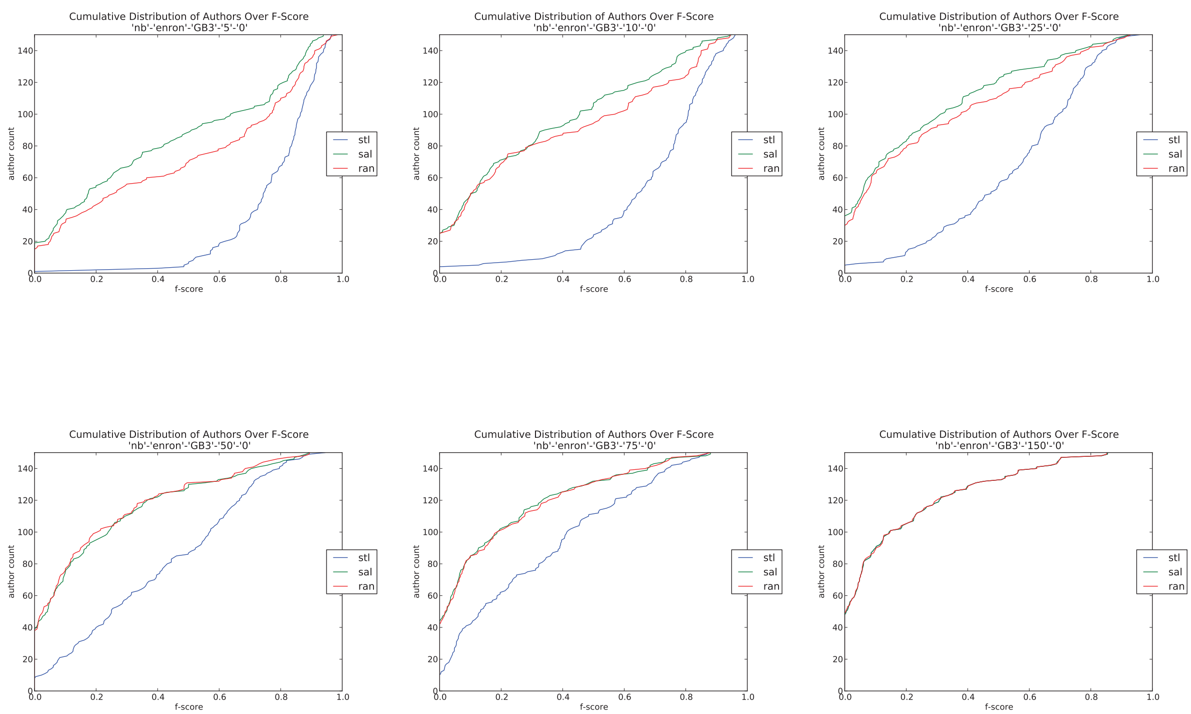


Figure 4.10: plot-tiled-cdf-summary-nb-enron-GB3-ALL-0

Figures 4.10 and fig:plot-tiled-cdf-summary-nb-enron-GB3-ALL-1 both show the cumulative distribution of authors over f-score for naive Bayes against Enron. The two plots start with different shapes. The first panel of Figure 4.10 start with with separation between the small-to-large line and the small-and-large lines. The small-to-large curvature is down and right where the small-and-large curve is up and left. As group size increases, the curvature of all lines increases, but not at the same rate. The small-to-large line closes the gap between lines until all lines are merged in the last panel, group size of 150. It makes sense that the last panel shows

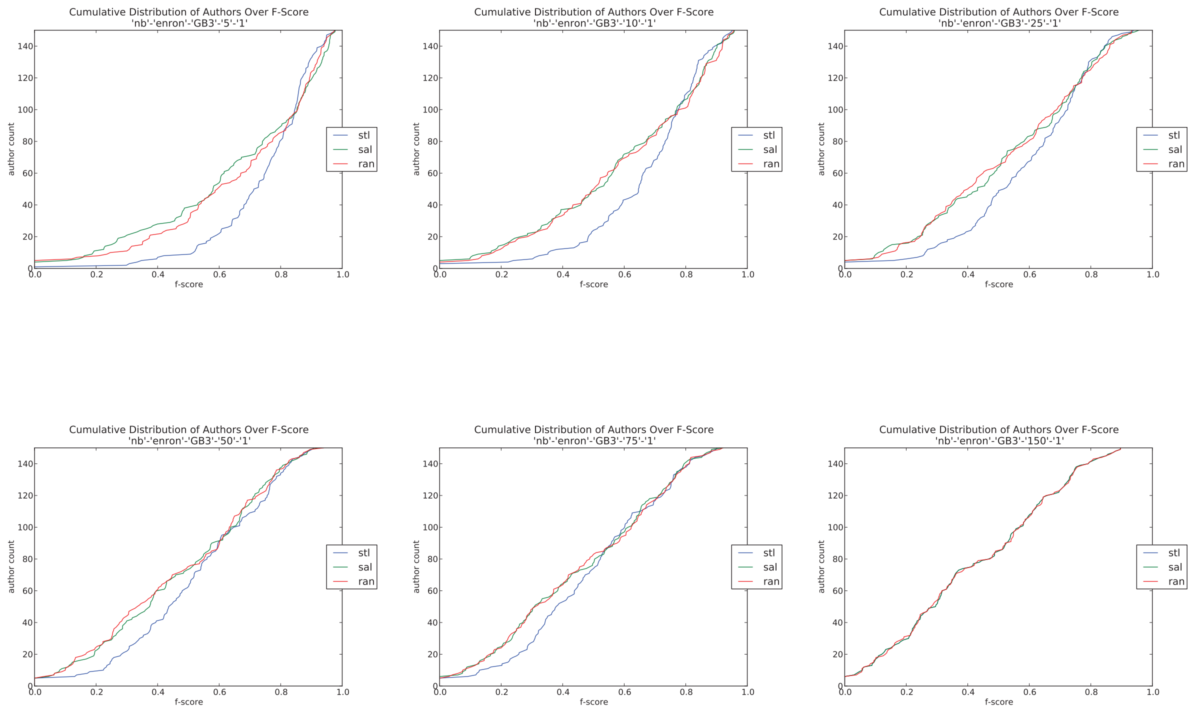


Figure 4.11: plot-tiled-cdf-summary-nb-enron-GB3-ALL-1

all lines on top of each other because all 150 author are included in all three lines. If these lines show different curvature, that would indicate a problem with the methodogy, since the only difference between the training and test sets of these three lines is the order that documents are read by the classifier. For group sizes of 5 through 75, each line contains groups unique combinations of authors.

Figurefig:plot-tiled-cdf-summary-nb-enron-GB3-ALL-1 begins with all three line cloesly grouped. Just like in Figure 4.10, the curvature of all three lines progresses from down and right to more up and left as group size increases. The grouping of the three lines becomes closer as group size increases with all three lines merging at a group size of 150. However, the group size of 150 for Figure fig:plot-tiled-cdf-summary-nb-enron-GB3-ALL-0 is essentially a diagonal line in Figure fig:plot-tiled-cdf-summary-nb-enron-GB3-ALL-1 where it is a up and left curve for Figure 4.10. This indicates that naive Bayes benefits from the use of Web1T% of 1 over naive Bayes with a Web1t% of 0. This result is typical of all the naive Bayes against Enron cumulative distribution graphs. This begs the question of whether Web1T smoothing performs better than other smoothing techniques such as Witten-Bell or Good-Turing. Witten-Bell and Good-Turing do not bring the large storage requirement of Web1T smoothing, but may produce similar results.

Determining this result is left for future work.

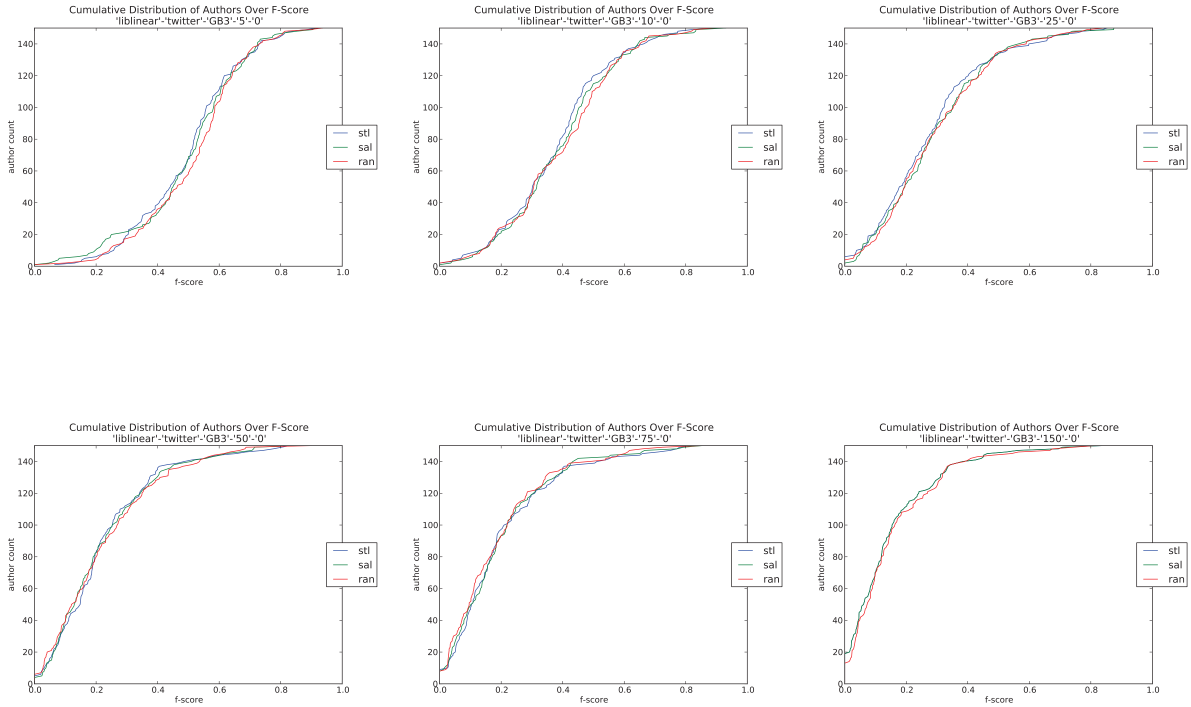


Figure 4.12: plot-tiled-cdf-summary-liblinear-twitter-GB3-ALL-0

For Twitter GM2 with naive Bayes, applying Web1T% of 1 makes STL worse, but leaves SAL and RAN intact. Additional Web1T% makes the damage to STL less severe, but does not get back to STL results of Web1T% of 0.

Impact of CDF? Twitter was barely on the scene in 2006 when the Google Web1T snapshot was taken. There was no significant Twitter corpus for Google to crawl. Twiiter language has evolved significantly since its inception and may differ appreciably from standard English or even standard web verbiage. Could a new Web1T built from a Google database that has crawled Twitter term................

4.3 Storage Requirements for Combinations of Classification Methods, Feature Types, and Vocabulary

While the effectiveness of the method-feature combinations are important, these tools are of no use on a mobile device unless the tool can actually fit on the disk and within the RAM on the mobile device. An important fact about determining the size of classifier models is that

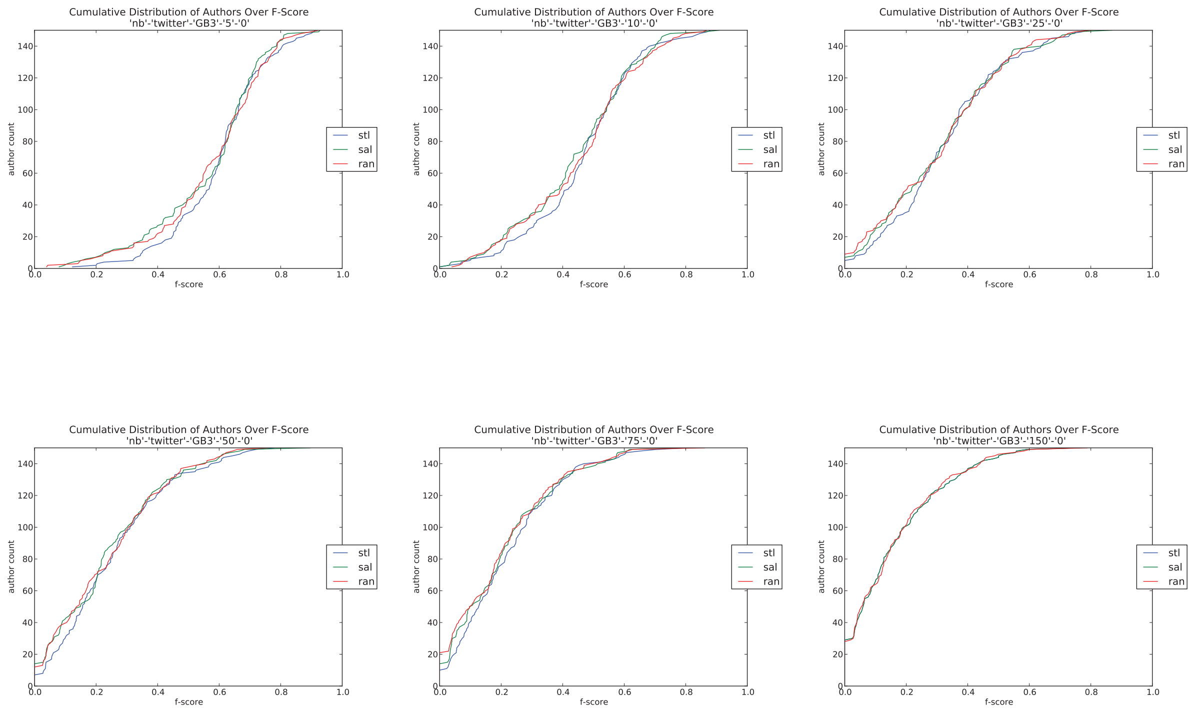


Figure 4.13: plot-tiled-cdf-summary-nb-twitter-GB3-ALL-0

the size of the model in RAM does not equal the size of the model when written to a file. For instance, a Java long (primitive) of 1 uses 8 bytes of RAM, but is represented in a file using only 4 bytes. Similarly, there is a disparity between the UTF-8 values byte size on disk and the object representation in RAM for many Java objects. This is why heap size could not be used as an accurate measurement of model size.

To determine if any of these method-feature combinations will fit on a mobile device, a few combinations had exhaustive outputs of their model sizes computed. After determining that the standard deviation for models with a vocabulary size greater than a Web1T% of 0 was trivial, only a small sample of the remaining method-feature combinations were computed. Due to the large size of many models, only one model size was calculated for many method-feature combinations.

Actually writing out these models to disk would have been extremely time consuming and a load on the already taxed Hamming High Performance Cluster. To conduct the size measurements, the SVM models were written to a Java ByteArrayOutputStream. Once the write was complete, the size of the ByteArrayOutputStream buffer was measured. The worked well for models smaller than 2GB. Models larger than 2GB caused the ByteArrayOutputStream to be

”full” since the index for an ByteArrayOutputStream is limited to 2^{31} elements and each element in that array is a byte. For any model larger than 2GB, the size for that model was not recorded and thus has no size record in Appendix M through Appendix P nor a score in the scoring tables in Appendix I through Appendix L.

What constitutes a storage requirement for the method-feature combinations in this thesis depends on the vocabulary size and method used. A Web1T% of 0 in SVM requires no keys.mph or signature file, but does require a sizable vocabulary map. For naive Bayes, a Web1T% of 0 does not require a keys.mph file, signature file, count file, nor logprobs file. However a sizable vocabulary map is needed. The sizes for each combination’s keys.mph, signature, counts, logprobs, and average author size are included with totals in Appendix M through Appendix P. To provide an intuition on the magnitude of sizes involved, Table 4.5 shows sizes for keys.mph, signature, counts, logprobs, and vocabmap for a few method-feature combinations. Table 4.5 shows only the vocabmap size for the Web1T% of 0. This is because Web1T% of 0 does not use keys.mph, signature, counts, or logprobs references, but does create it own vocabulary map. Complete size tables are provided in Appendix M through Appendix P.

It is quickly apparent from this table that few of these files could be loaded into the RAM of a 16MB Dalvik VM. If these files were to be used, they would have to be read directly from the microSD card, which is an expensive operation compared to reading from RAM. A more thorough discussion of method-feature combinations is discussed in the last section of this chapter.

Apart from the vocabulary references needed for the method-feature combinations, each method-feature combination produces a different authors model size. Unlike the vocabulary reference files, the authors model file sizes vary greatly. The model constructed for SVM consists of an array populated with the support vector values for each author. The model for naive Bayes consists of a Java hashmap. That hashmap has an Integer object for a key and a Double object for its value. The Integer object is the mapped integer value for a given token. The Double object is the probability for that token during the training process.

The impact of authors model size for a mobile device is important. Even if the vocabulary reference files can be accommodate by a mobile device, a large authors model can push the storage requirement beyond the 16MB Dalvik VMs capability or even the capacity of common microSD cards. It is important to note here that size on a file only provides a relative indicator of size in RAM for a given method-feature combination. Actually measuring the impact of

Method	Feature Type	Web1T%	Size (MB)					
			keys.mph	signature	counts	logprobs	vocabmap	Total
SVM	GB3	0	0.00	0.00	0.00	0.00	54.31	54.31
SVM	GB3	1	3.21	12.11	0.00	0.00	0.00	15.32
SVM	GB3	2	6.41	24.22	0.00	0.00	0.00	30.63
SVM	GB3	4	12.82	48.44	0.00	0.00	0.00	61.27
SVM	GB3	8	25.64	96.89	0.00	0.00	0.00	122.53
SVM	GB3	16	51.31	193.85	0.00	0.00	0.00	245.15
SVM	GM1	0	0.00	0.00	0.00	0.00	1.40	1.40
SVM	GM1	1	0.07	0.27	0.00	0.00	0.00	0.34
SVM	GM1	2	0.14	0.54	0.00	0.00	0.00	0.69
SVM	GM1	4	0.29	1.09	0.00	0.00	0.00	1.37
SVM	GM1	8	0.58	2.17	0.00	0.00	0.00	2.75
SVM	GM1	16	1.15	4.35	0.00	0.00	0.00	5.50
NB	GB3	0	0.00	0.00	0.00	0.00	54.31	54.31
NB	GB3	1	3.21	12.11	48.44	48.44	0.00	112.20
NB	GB3	2	6.41	24.22	96.88	96.88	0.00	224.39
NB	GB3	4	12.82	48.44	193.78	193.78	0.00	448.83
NB	GB3	8	25.64	96.89	387.55	387.55	0.00	897.64
NB	GB3	16	51.31	193.85	775.39	775.39	0.00	1795.94
NB	GM1	0	0.00	0.00	0.00	0.00	1.40	1.40
NB	GM1	1	0.07	0.27	1.09	1.09	0.00	2.52
NB	GM1	2	0.14	0.54	2.17	2.17	0.00	5.04
NB	GM1	4	0.29	1.09	4.35	4.35	0.00	10.07
NB	GM1	8	0.58	2.17	8.70	8.70	0.00	20.14
NB	GM1	16	1.15	4.35	17.40	17.40	0.00	40.29

Table 4.5: Sample of Vocabulary Reference File Sizes

Dalvik VM in terms of RAM used versus storage requirements is left to future work as this study involves how model referencing is handled and how values on the file are converted to objects in memory. Table 4.6 shows a sample of author sizes for both SVM and naive Bayes authors models. A complete list of average authors models sizes is provided in Appendix M through Appendix P.

Corpus	Method	Feature Type	Group Size	Web1T%	Size (MB)			
					AVG	MIN	MAX	STDDEV
enron	SVM	OSB3	5	0	15.254	8.020	31.368	5.840
enron	SVM	OSB3	5	1	259.320	211.231	262.991	7.944
enron	SVM	OSB3	5	2	521.039	422.022	530.023	11.188
enron	SVM	OSB3	5	4	1031.477	844.102	1039.616	26.316
enron	NB	OSB3	5	0	5.328	0.068	34.479	7.090
enron	NB	OSB3	5	1	8.528	0.075	54.680	11.243
enron	NB	OSB3	5	2	8.544	0.075	54.939	11.286
enron	NB	OSB3	5	4	8.550	0.075	55.054	11.305
enron	NB	OSB3	5	8	8.553	0.075	55.100	11.314
enron	NB	OSB3	5	16	8.554	0.075	55.121	11.317
twitter	SVM	GM1	5	0	0.088	0.076	0.108	0.007
twitter	SVM	GM1	5	1	1.568	1.546	1.614	0.013
twitter	SVM	GM1	5	2	3.064	3.043	3.109	0.013
twitter	SVM	GM1	5	4	6.050	6.013	6.099	0.015
twitter	SVM	GM1	5	8	12.034	12.011	12.079	0.013
twitter	SVM	GM1	5	16	23.952	23.869	24.038	0.037
twitter	NB	GM1	5	0	0.024	0.016	0.045	0.005
twitter	NB	GM1	5	1	0.040	0.034	0.050	0.003
twitter	NB	GM1	5	2	0.040	0.035	0.051	0.003
twitter	NB	GM1	5	4	0.040	0.036	0.052	0.003
twitter	NB	GM1	5	8	0.040	0.034	0.053	0.003
twitter	NB	GM1	5	16	0.040	0.035	0.050	0.003

Table 4.6: Sample of Authors Model File Sizes

4.4 Classification Effectiveness Versus Storage Requirements

With the resource constraints of mobile devices and the author detection requirements of this thesis, some method must be used to evaluate the tradeoff between accuracy and size. For this thesis, effectiveness will be divided by the full storage requirement for each method-feature combination. The storage requirements will be computed as the sum of keys.mph, signature, counts, logprobs, vocabmap, and average authors model size for each method-feature combination. The complete set of scores for this thesis are included in Appendix I through Appendix L.

*It is important to note that there are no scores for any authors model size over 2GB. This is due to the limitations of measuring on-disk size for authors models with a ByteArrayOutputStream, but this limitation will not adversely affect the conclusions of this thesis. Any authors model larger than 2GB is impractical for current mobile devices. Also a 2GB divisor for the score computation would put that method-feature combination out of contention for a top performer in this thesis.

The top performing method-feature combination for the Enron E-mail Corpus was naive Bayes method using GM1 for group size 5 with a score of 0.4495. Table 4.7 shows the top 20 scores along with accuracy and size information for the Enron E-mail Corpus. All of these top performers use the GM1 feature type. The accuracy of these combinations is in the same range as the most accurate method-feature combinations. However, these accuracies are mostly for group sizes of 5, 10, and 25, which limits the applicability of the tools in this thesis. There is only one combination for group size 50 and only one combination of group size 75. All of these top 20 scores have storage requirements under 16MB.

The top performing method-feature combination for the Twitter Short Message Corpus was naive Bayes using feature type GM1 for a group size of 5. Table 4.8 shows the top 20 scores along with accuracy and size information for the Twitter Short Message Corpus. The accuracy of these combinations is in the same range as the most accurate method-feature combinations. The range of groups sizes that made the top 20 scores is much larger than for the ENRON E-mail Corpus. There are three combinations for group size 50, two combinations of group size 75, and two combinations of group size 150. All of the top 20 performing score combinations have a storage requirement of less than 16MB.

With the scores measure for each method-feature combination in hand, the shortcoming of using $score = \frac{accuracy}{size}$ become apparent. Table 4.7 indicates that naive Bayes using GM1 for group size 5 is the best feature-combination to choose for a mobile device. However, the second highest score, SVM using GM1 for group size 5 has an accuracy of 0.8269 where the top scoring combination has an accuracy of 0.7215, a full 0.1 worse than the second top scorer. An even more important limitation to this approach if the heavy bias of group size on the scoring process. To address this, Table 4.9 for the Enron E-mail Corpus and Table 4.10 for the Twitter Short Message Corpus were constructed to show the score for each feature-method-percentage combination that could cover all group sizes with score averaged over all group sizes.

Method	Corpus	Feature Type	Group Size	Web1T %	Score	Accuracy	Size(MB)
NB	enron	GM1	5	0	0.4495	0.7215	1.60
SVM	enron	GM1	5	0	0.4374	0.8269	1.89
SVM	enron	GM1	5	1	0.3685	0.8233	2.23
NB	enron	GM1	10	0	0.3186	0.5768	1.81
SVM	enron	GM1	10	0	0.2789	0.7611	2.73
NB	enron	GM1	5	1	0.2262	0.6441	2.85
SVM	enron	GM1	5	2	0.2017	0.8216	4.07
SVM	enron	GM1	10	1	0.1800	0.7610	4.23
NB	enron	GM1	25	0	0.1683	0.4083	2.43
NB	enron	GM1	10	1	0.1634	0.5189	3.18
NB	enron	GM1	5	2	0.1212	0.6505	5.37
SVM	enron	GM1	25	0	0.1124	0.6845	6.09
SVM	enron	GM1	5	4	0.1071	0.8298	7.75
SVM	enron	GM1	10	2	0.1024	0.7594	7.42
NB	enron	GM1	25	1	0.0950	0.3956	4.16
NB	enron	GM1	10	2	0.0915	0.5215	5.70
NB	enron	GM1	50	0	0.0903	0.3126	3.46
SVM	enron	GM1	25	1	0.0648	0.6847	10.56
NB	enron	GM1	75	0	0.0648	0.2912	4.50
NB	enron	GM1	5	4	0.0635	0.6610	10.40

Table 4.7: Highest Scoring Method-Feature Combinations for the Enron E-mail Corpus

The top method-feature combinations in Table 4.9 are still dominated by GM1 as a feature type. naive Bayes using GM1 and a Web1T%=0 had a higher score than SVM using GM1 and a Web1T%=0, but the SVM accuracy is 0.1284 higher than the naive Bayes accuracy. This shows again that this scoring method by itself does not produce an optimal feature-method combination on its own.

Similarly, the top method-feature combinations for the Twitter Short Message Corpus in Table 4.10 are GM1. However, there is a much wider mix of feature types in the Twitter Corpus than was seen in the Enron Corpus. Also, naive Bayes outperforms its SVM counterparts in some situations. Just like with Enron, the highest scoring method-feature combination is not necessarily the most appropriate combination for deployment on a mobile phone. For the Twitter Corpus,

Method	Corpus	Feature Type	Group Size	Web1T %	Score	Accuracy	Size(MB)
NB	twitter	GM1	5	0	2.8233	0.6264	0.22
NB	twitter	GM1	10	0	1.9815	0.4869	0.25
SVM	twitter	GM1	5	0	2.1731	0.6212	0.29
NB	twitter	GM1	25	0	1.0593	0.3357	0.32
NB	twitter	GM1	50	0	0.5347	0.2326	0.43
SVM	twitter	GM1	10	0	1.0850	0.4762	0.44
NB	twitter	GM1	75	0	0.3291	0.1820	0.55
NB	twitter	GM1	150	0	0.1375	0.1252	0.91
SVM	twitter	GM1	25	0	0.3301	0.3461	1.05
NB	twitter	GM2	5	0	0.4866	0.5711	1.17
NB	twitter	GM2	10	0	0.3644	0.4439	1.22
NB	twitter	GM2	25	0	0.2380	0.3215	1.35
SVM	twitter	GM2	5	0	0.3503	0.4844	1.38
NB	twitter	GM2	50	0	0.1598	0.2509	1.57
NB	twitter	GM2	75	0	0.1207	0.2162	1.79
SVM	twitter	GM1	5	1	0.3257	0.6228	1.91
SVM	twitter	GM2	10	0	0.1911	0.3700	1.94
SVM	twitter	GM1	50	0	0.1153	0.2693	2.34
NB	twitter	GM2	150	0	0.0696	0.1709	2.46
NB	twitter	GM1	5	1	0.1945	0.4974	2.56

Table 4.8: Highest Scoring Method-Feature Combinations for the Twitter Short Message Corpus

SVM using OSB3 and a Web1T%=0 has a .6127 accuracy with a size of 11.3466MB. This is the highest accuracy on the top 20 list that is still below 16MB. There are several accuracies above 0.5 that have significantly smaller storage requirements.

To more clearly illustrate the results of accuracy and storage size on the Enron E-mail Corpus and the Twitter Short Message Corpus, Figures 4.14 and 4.15 were generated. In these figures:

- Circles are tests using SVM
- Triangles are test using naive Bayes
- Red symbols are tests using GM1

Method	Corpus	Feature Type	Web1T %	Score	Accuracy	Size(MB)
NB	enron	GM1	0	0.3998	0.6792	1.6986
SVM	enron	GM1	0	0.3388	0.8076	2.3840
SVM	enron	GM1	1	0.2528	0.8047	3.1834
NB	enron	GM1	1	0.2030	0.6083	2.9969
SVM	enron	GM1	2	0.1424	0.8033	5.6421
NB	enron	GM1	2	0.1113	0.6140	5.5165
SVM	enron	GM1	4	0.0776	0.8097	10.4301
NB	enron	GM1	4	0.0593	0.6260	10.5528
NB	enron	GM2	0	0.0437	0.7804	17.8759
SVM	enron	GM1	8	0.0397	0.8092	20.3672
SVM	enron	GM2	0	0.0383	0.8477	22.1173
NB	enron	GM1	8	0.0300	0.6192	20.6262
SVM	enron	GM1	16	0.0203	0.8057	39.6953
NB	enron	GM1	16	0.0154	0.6298	40.7717
SVM	enron	GM2	1	0.0142	0.8007	56.5585
NB	enron	GB3	0	0.0131	0.7631	58.1904
SVM	enron	GB3	0	0.0119	0.8413	70.6541
NB	enron	GM2	1	0.0106	0.6206	58.8138
SVM	enron	GB3	1	0.0083	0.8429	101.9446
SVM	enron	GM2	2	0.0072	0.8011	111.2368

Table 4.9: Highest Scoring Method-Feature Combinations Over All Groups for the Enron E-mail Corpus

- Cyan symbols are tests using GM2
- Yellow symbols are tests using GM5
- Green symbols are tests using GB3
- Blue symbols are tests using OSB3
- The smallest symbols are for a group size of 5
- The largest symbols are for a group size of 150
- The x-axis, Storage Size (MB), is a logarithmic scale to better distinguish items on the left of the graph

Method	Corpus	Feature Type	Web1T %	Score	Accuracy	Size(MB)
NB	twitter	GM1	0	2.5176	0.5858	0.2327
SVM	twitter	GM1	0	1.5509	0.5806	0.3744
NB	twitter	GM2	0	0.4482	0.5351	1.1939
SVM	twitter	GM2	0	0.2607	0.4524	1.7353
SVM	twitter	GM1	1	0.2244	0.5827	2.5972
NB	twitter	GM1	1	0.1772	0.4565	2.5758
NB	twitter	GB3	0	0.1729	0.5822	3.3669
SVM	twitter	GM1	2	0.1142	0.5773	5.0542
NB	twitter	GM5	0	0.1006	0.3167	3.1482
SVM	twitter	GB3	0	0.0995	0.5074	5.0984
NB	twitter	GM1	2	0.0927	0.4721	5.0936
NB	twitter	OSB3	0	0.0797	0.6127	7.6833
SVM	twitter	GM5	0	0.0599	0.2488	4.1559
SVM	twitter	GM1	4	0.0581	0.5792	9.9645
NB	twitter	GM1	4	0.0467	0.4728	10.1292
SVM	twitter	OSB3	0	0.0449	0.5100	11.3466
SVM	twitter	GM1	8	0.0296	0.5862	19.8001
NB	twitter	GM1	8	0.0239	0.4823	20.2023
SVM	twitter	GM1	16	0.0147	0.5789	39.4154
NB	twitter	GM1	16	0.0116	0.4694	40.3477

Table 4.10: Highest Scoring Method-Feature Combinations Over All Groups for the Twitter Short Message Corpus

- The more accurate method-feature combinations are higher in the graph
- The method-feature combinations with a smaller storage requirement are further left on the graph

Figure 4.14 shows several notable trends for accuracy in the Enron E-Mail Corpus. These are:

- There is little white space at the top of the graph. While the graph tops out at 0.9, the bulk of symbols in the graph are toward the top of the graph. This shows that both naive Bayes and SVM performed well against the Enron E-Mail Corpus.

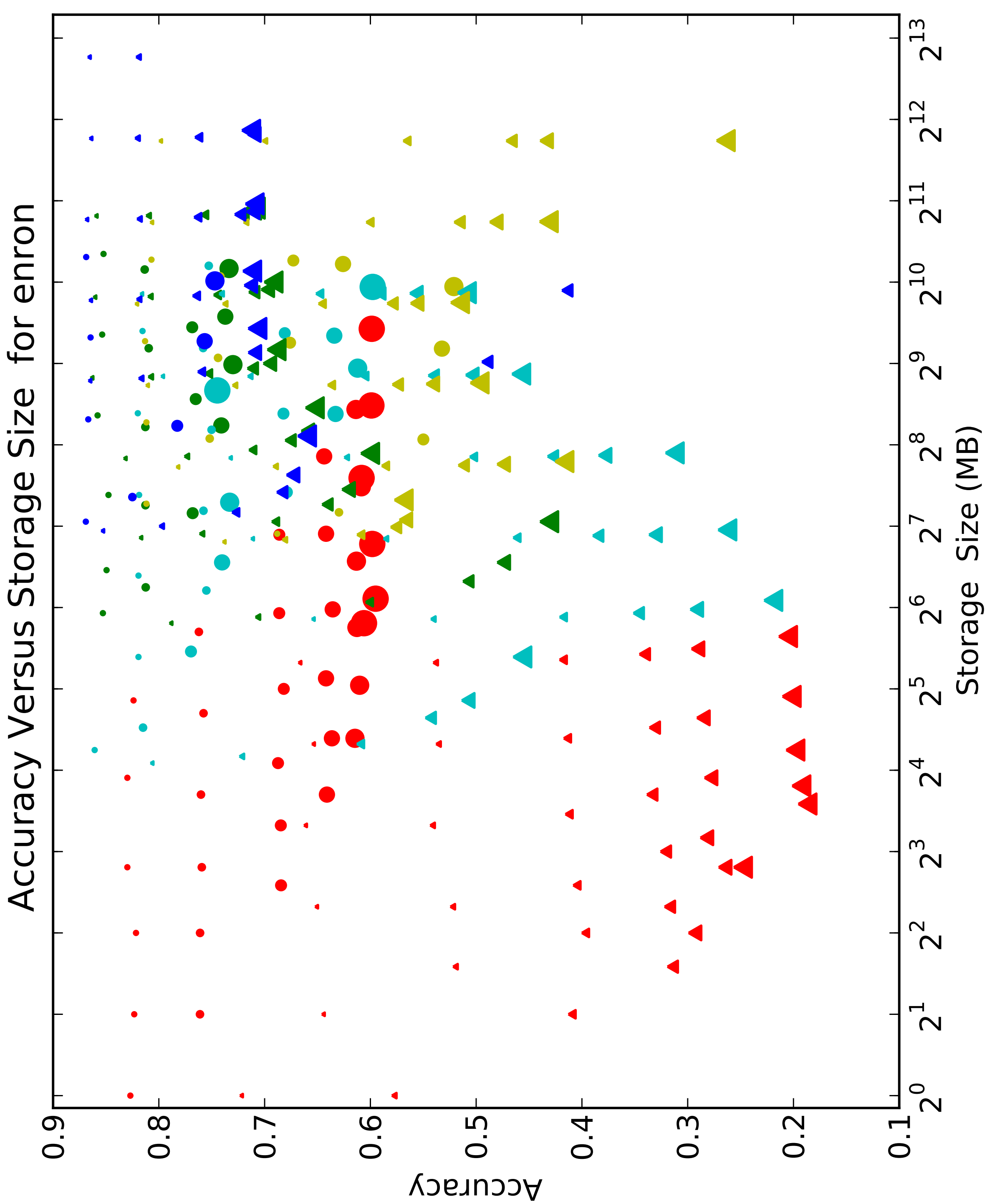


Figure 4.14: Scatter-Plot of Enron Email Corpus Tests

- The upper leftmost point represent SVM using GM1 with Web1T% of 0. The trail of red circles to the right of this point represent SVM using GM1 with Web1T% values of 1,2,4,8, and 16. The points provide roughly the same accuracy at an increasing cost of storage. This could be represented as a horizontal line through the Web1T% values for SVM for GM1. This pattern repeats itself for most symbols to the left of 2^6MB.

- The upper leftmost point is not the highest accuracy point on the graph. There are numerous light blue (GM2), dark blue (OSB3), and green (GB3) circles with higher accuracies. Also there are some dark blue (OSB3) and green (GB3) triangles with higher accuracies. However, the storage requirement for the first point encountered with a higher accuracy than the upper leftmost point is 16 times large than the upper leftmost red circle. This is a significant storage cost compared to the increase in accuracy. The size penalty versus improved accuracy only gets worse as this line of maximum values moves right.

- All of the highest accuracy points are dark blue (OSB3) and green (GB3) symbols. Both triangles (naive Bayes) and circles (SVM) are represented. This shows that OSB3 and GB3 give high accuracies using both SVM and naive Bayes. This shows the potential of more complex feature types like GB3 and OSB3 for author detection.

- There are numerous symbols to the left of 2^4MB. 2^4MB is an important line because the default heap size limit for a Dalvik VM is 16MB. While it is true that a storage size of 16MB does not necessarily equate to 16MB of heap, 16MB is still a good relative indicator of how well a model could fit into a Dalvik VM.

- The circles (SVM) generally hold higher positions in the plot while triangles (naive Bayes) generally hold lower positions in the graph. These relative positions show that SVM generally outperforms naive Bayes for the Enron E-mail corpus.

- There are diagonal lines, from upper left to lower right, of same shape, same color, different size symbols representing the fall in accuracy and increase in size for a method-feature combination as the group size increase from 5 to 150. For example, there is a clear line of increasingly large, red circles from the uppermost red circle at (accuracy=0.82, size=2^0MB) fall successively to the large red circle at (accuracy=0.61, size=2^4MB). This pattern is repeated through the graph with the slope becoming steeper as the graph progresses to the right. As an example of a steep slope for this line, take the small light blue triangle at (accuracy=0.6, size=2^4MB). There is a steep line of increasingly large, light blue triangles down to (accuracy=0.45, size=2^5MB). The increasing slope is due to the logarithmic scale of the graph, but shows that increasing group size has an adverse effect on accuracy.

- The triangles (naive Bayes), do not get into the upper part of the graph until after 2^7MB. Also, these more accurate naive Bayes points are competing well with their SVM counterparts for accuracy, but carry a lot more size as there are no circles past 2^{11}MB, but there are triangles all the way out to 2^{13}. This is an artifact of naive Bayes for Web1T% ≥ 1 having to carry a large keys.mph file, large signature file, as well as large counts and logprob files. It is important to remember that any storage model with an authors model size of $\geq$ 2GB did not get plotted on this graph, which explains the lack of large blue triangle continuing down the 2^{13}MB line.

- One symbol stands out on the graph, the light blue, large circle at (accuracy=0.74, size=2^9MB). This is circle represents a group size of 150 with a very high accuracy compared to other circles representing a group size of 150. At 2^9MB, this method-feature combination is by no means, light on storage, but produces an accuracy of over 0.70 for a group size of 150 authors. that is a standout achievement compared to the other symbols with a group size of 150.

- There are fewer circles than triangles on the graph. This is due to the internal model limitations of libLinear. Naive Bayes is able to handle all sizes of authors and models where the libLinear limit of author-feature pairs is 2^31 pairs.

- No symbols, circle or triangle, sit on the bottom line of the graph. The worst accuracy shown is just below 0.2. No symbol made it to the top of the graph meaning no accuracy equaled 1.0.

Figure 4.15 shows several notable trends for accuracy in the Twitter Short Message Corpus. These are:

- There is significant whitespace at the top of the graph. This shows that both naive Bayes and SVM produced lower accuracies against the Twitter Short Message Corpus than against the Enron Email Corpus.

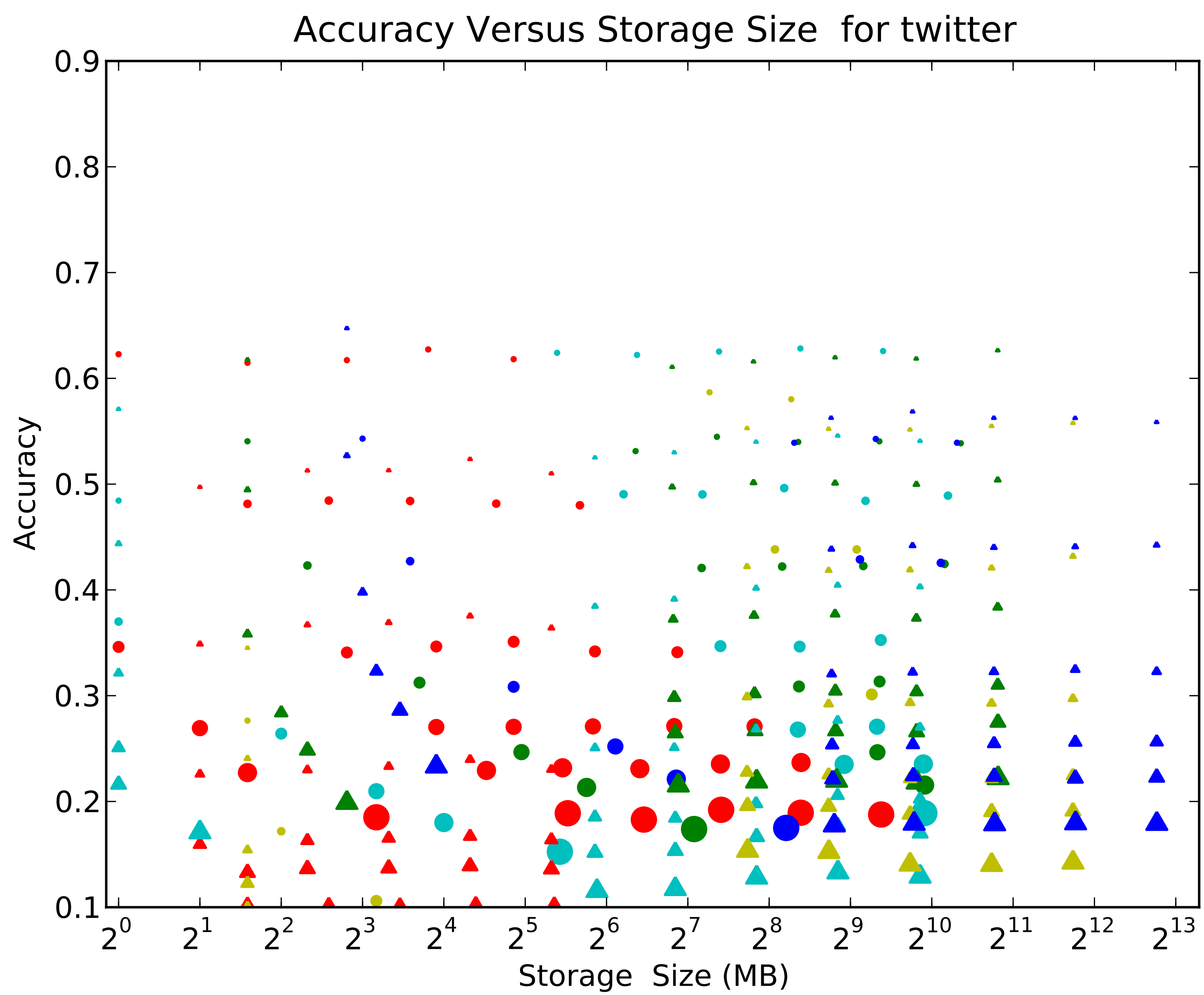


Figure 4.15: Scatter-Plot of Twitter Short Message Corpus Tests

- The upper leftmost point is SVM for GM1 using Web1T% of 0. This leftmost point is not the highest accuracy on the graph. The highest accuracy belongs to the dark blue triangle, representing naive Bayes for OSB3. While there is still a line of red circles extending right from the left most red circle, there is also a line of dark blue and green triangles as well light blue circles extending to the right. This indicates that multiple feature type, GM1, GM2, OSB3, and GB3 all performed similarly well for group sizes of 5.

- There are many symbols to the left of 2^4MB. 2^4MB is an important line because the default heap size limit for a Dalvik VM is 16MB. While it is true that a storage size of 16MB does not necessarily equate to 16MB of heap, 16MB is still a good relative indicator of how well a model could fit into a Dalvik VM.

- No symbols on the Twitter graph stand out as unusual or noteworthy. The entire graph progresses downward by group size.

- There is no clear grouping of triangle and circles in any portion of the Twitter graph. This show that neither SVM nor naive Bayes held a clear accuracy advantage at any part of the graph.

Comparing the performance of the method-feature combinations in this thesis against the Enron E-Mail Corpus and the Twitter Short Message Corpus yields some significant differences:

- The symbols in the Enron graph tend higher in accuracy than the symbols in the Twitter graph. This shows that the method-feature combinations in this thesis produced higher accuracies for an email corpus than against a short message corpus.

- There is significant mixture of colors of different shapes and sizes at the top of the right side of the Enron graph. The large, light blue circle at (accuracy=0.74, size=2^9MB) is a notable data point showing high accuracy for a group size of 150. The Twitter graph has no such exceptional data points. The data in the Twitter graph is very regular. Accuracies fall as group sizes fall nearly identically across all method-feature combinations. This result means that the test either had too little Twitter text to train on, the wrong types of feature types to use against the 140 character limited structure of short messages, or the compact language of Twitter was not well represented by Web1T or sample well by the bootstrapping (Web1T% of 0) method.

- There is no clear grouping of triangle and circles in the Twitter graph. On the left side of the Enron graph, there was a clear delineation between circles at the top of the graph and triangles at the bottom of the graph. This show that neither SVM nor naive Bayes held a clear accuracy advantage at any part of the graph. The top performing method-feature combinations all fell in a nearly straight line across the the 0.62 accuracy line for Twitter. This is noticeably different than the top performance line for Enron of 0.85.

- There are fewer circles than triangles on the graph. This is due to the internal model limitations of libLinear. Naive Bayes is able to handle all sizes of authors and models where the libLinear limit of author-feature pairs is 2^31 pairs.

- There are symbols, circles and triangles, sitting on the bottom line of the graph. The worst accuracies shown are on the 0.1 line.

4.5 Ability to Execute on an Android Mobile Phone

With scores calculated alongside accuracy and storage requirements, feasibility on a mobile device must be determined. The previous section clearly showed that $score = \frac{accuracy}{size}$ by itself does not provide an optimal solution for choosing an author detection method-feature combination on a mobile device. Tables 4.11 and 4.12 show the highest scoring method-feature combinations that have storage requirements less than 16MB and then ordered by accuracy. For the Enron Corpus Table 4.12 shows that the best accuracy achievable using the tools of thesis is 0.7735. For the Twitter Corpus, Table 4.12 shows that the best accuracy achievable using the tools of this thesis is 0.5525.

The Enron E-mail Corpus has 7 method-feature combinations with a storage requirement of less than 16MB. The Twitter Short Message Corpus has 14 method-feature combinations across all group sizes with a storage requirement under 16MB. Looking closely at the values of size and accuracy, there is little difference between the three highest accuracies in Table 4.11 but the third highest accuracy is more than double the size of the highest accuracy. That makes the choice of SVM GM1 0 clearly the most appropriate choice for a mobile device. For the Twitter corpus, the top accuracy of .5525 for naive Bayes using OSB3 is only slightly higher than 0.5203 for naive Bayes using GB3 with a size that is which is less than half of OSB3. naive Bayes using GB3 would be more appropriate for a mobile device.

Method	Corpus	Feature Type	Web1T %	Score	Accuracy	Size(MB)	MLE	F-Score
SVM	enron	GM1	0	0.1601	0.7735	4.83	0.3842	0.6257
SVM	enron	GM1	1	0.1113	0.7710	6.93	0.3859	0.6235
SVM	enron	GM1	2	0.0658	0.7704	11.71	0.3849	0.6255
NB	enron	GM1	0	0.2954	0.6055	2.05	0.3842	0.3399
NB	enron	GM1	4	0.0507	0.5640	11.12	0.3793	0.4771
NB	enron	GM1	2	0.0908	0.5520	6.08	0.3849	0.4719
NB	enron	GM1	1	0.1536	0.5462	3.56	0.3859	0.4649

Table 4.11: Highest Scoring Method-Feature Combinations Over All Groups for the Enron E-mail Corpus

Method	Corpus	Feature Type	Web1T %	Score	Accuracy	Size(MB)	MLE	F-Score
NB	twitter	OSB3	0	0.0680	0.5525	8.13	0.1978	0.5338
NB	twitter	GB3	0	0.1451	0.5203	3.59	0.1990	0.4820
SVM	twitter	GM1	1	0.0992	0.5159	5.20	0.1960	0.4953
SVM	twitter	GM1	0	0.6402	0.5141	0.80	0.1975	0.4934
NB	twitter	GM1	0	1.8823	0.5140	0.27	0.1975	0.4708
SVM	twitter	GM1	2	0.0515	0.5131	9.97	0.1944	0.4915
NB	twitter	GM2	0	0.3743	0.4750	1.27	0.1978	0.4350
SVM	twitter	GB3	0	0.0411	0.4522	11.01	0.1990	0.4207
NB	twitter	GM1	4	0.0399	0.4070	10.20	0.1957	0.3838
NB	twitter	GM1	2	0.0786	0.4059	5.16	0.1944	0.3833
SVM	twitter	GM2	0	0.1121	0.4002	3.57	0.1978	0.3726
NB	twitter	GM1	1	0.1484	0.3922	2.64	0.1960	0.3672
NB	twitter	GM5	0	0.0845	0.2726	3.22	0.1995	0.1902
SVM	twitter	GM5	0	0.0240	0.2095	8.73	0.1995	0.1547

Table 4.12: Highest Scoring Method-Feature Combinations Over All Groups for the Twitter Short Message Corpus

The only remaining question is whether these method-feature combinations are stable performers across the group sizes. While standard deviation is one indicator, a plot of the accuracy, f-score, and MLE for each of these choices would be informative for consistent performance across group sizes. These plots can be compared to other method-feature combinations that have similar accuracy and size values.

Figure 4.16 shows that SVM GM1 has a steady decline from just above 0.8 to 0.6 from a groups size of 5 to a group size of 75. The accuracy for SVM GM1 for the Enron corpus is virtually identical for groups sizes of 75 and 150. Figure 4.17 shows that SVM OSB3 for Twitter has declining accuracy from just above 0.6 to slightly above 0.2 as group size increases from 5 authors to 150 authors.

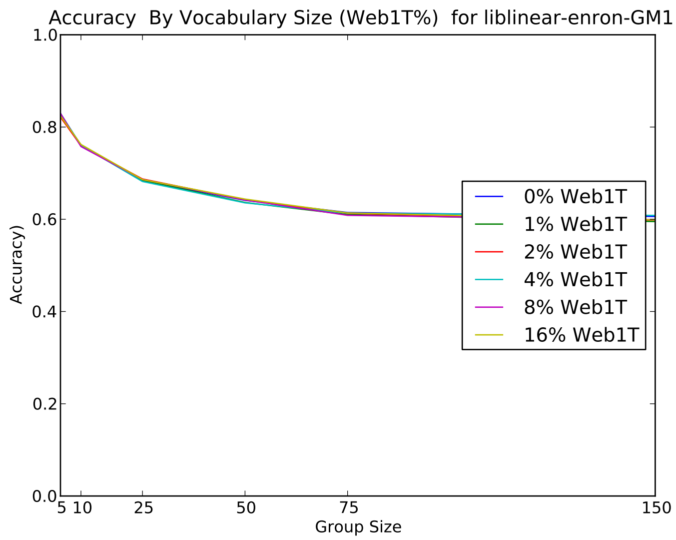


Figure 4.16: Accuracy Results over Group Size Using SVM GM1 for the Enron E-mail Corpus

The results for author detection over the Enron E-mail Corpus are far higher than for the Twitter Short Message Corpus for the selected method-feature combinations. This is not unexpected since results for the Enron E-mail Corpus have been higher than the Twitter Short Message Corpus across all test sets. With both selections having storage requirements of less than 1MB, execution of actual author detection on a mobile phone is practical as a next stage in future work.

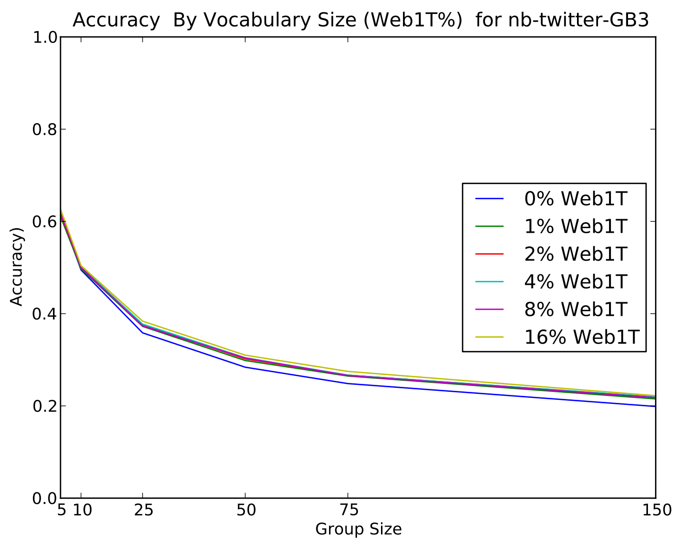


Figure 4.17: Accuracy Results over Group Size Using SVM OSB3 for the Twitter Short Message Corpus

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CHAPTER 5:
Conclusions and Future Work

5.1 Summary

This thesis asked one basic question: can author detection be accomplished on a mobile device? To answer that question, several supporting questions had to be answered:

- For the two dominant mobile phone text mediums, short message and e-mail, what combination of classification method and feature type provides the best accuracy?
- What is the storage requirement for each combination of method and feature type?
- What is the relative value of classification accuracy versus storage requirement for each classification method and feature type?
- Does the relative prolificity of each author in a detection group significantly affect the accuracy of each classification method and feature type?
- Does a highly effective method-feature type combination exist with a small enough storage requirement to be executed on a mobile device?

Two classification methods, naive Bayes and SVM using the Liblinear tool, were tested against five feature types: 1-grams (GM1), 2-grams (GM2), 5-grams (GM5), gappy bigrams of distance 3 (GB3), and orthogonal sparse bigrams of distance 3 (OSB3). For each of these combinations, six vocabularies were used. Five of the vocabularies were drawn from a specific percentage of the highest count features found in the Google Web1T corpus. Specifically, the top 1%, 2%, 4%, 8%, and 16% of Google Web1T were used as vocabularies. The sixth vocabulary was a ”bootstrapped” vocabulary that was drawn directly from the training corpus with no reference to a outside set of features. This vocabulary was represented as Web1T% 0 since the bootstrapped vocabulary used 0% of the Google Web1T corpus as a vocabulary reference.

Testing was conducted using a 80/20 cross validation against each set of selected authors. Each author was tested in group sizes of 5, 10, 25, 50, 75, and 150 authors. The grouping of authors was selected in three ways, similarly prolific authors, dissimilarly prolific authors, and randomly chosen authors. To determine prolificity, authors were put in rank order based on total size of all their documents.

The testing of all these combinations resulted in 19,782 tests producing 286,050 measurements for f-score and 19,782 measurements for accuracy. After analysis of these results:

- Author detection accuracy and f-score against the Enron E-mail Corpus was significantly higher than author detection accuracy and f-score against the Twitter Short Message Corpus.
- Similarly prolific authors had lower accuracies, but higher f-scores than dissimilarly prolific authors.
- Very prolific authors were detected with greater accuracy and f-score than less prolific authors, even when a prolific author was in a group with other very prolific authors.
- Storage requirements for many of the model-feature combinations were too large for use on a mobile device.
- There is a small number of method-feature combinations that can meet the storage limitations of a mobile device and still produce reasonable accuracy for author detection.
- The method-feature type combination that suited mobile devices best for the Enron E-mail Corpus was SVM using GM1 and a Web1T%=0.
- The method-feature type combination that suited mobile devices best for the Twitter Short Message Corpus was SVM using GB3 and a Web1T%=0.

These results show that author detection on a mobile device can be implemented and test knowing that . A working author detection capability is worthy of future work.

5.2 Future Work

This thesis sets the stage for several future work efforts. Some future work should focus specifically on implementation of mobile device author detection tools. Other efforts could focus on the natural language processing impacts of the model-feature combinations. Specific items of future work are:

- Actually Test the Top Scoring Method-Feature Combinations on Android Phones and other Java-Capable Mobile Platforms
- Rewrite LibLinear Data Structures
- Determine Accuracy and F-Score for Web1T Vocabulary Variations
- Apply Good Turing and Witten-Bell Smoothing to naive Bayes
- Increase Size of the Twitter Short Message Corpus
- Deliver Author Detection Tools to Mobile Device
- Determine Appropriate Group Size for Target Authors
- Study ”Stealthiness” for Author Detection Software
- Study Public Tweets of Former ENRON Employees
- Study of Disk Storage to RAM Usage for Mobile Phones
- Statistical Study of Small-To-Large Versus Small-And-Large Groupings Results
- Conduct SVM and naive Bayes Tests Again with a Large ”Noise” Group
- Test Spoken Keyword Recognition Techniques

5.2.1 Actually Test the Top Scoring Method-Feature Combinations on Android Phones and other Java-Capable Mobile Platforms

As part of the preparation for this thesis, an Android application was written to record SMS messages as they were received on an Android phone. This application had a rudimentary file browser to manage the captured SMS messages. The tools for this thesis were all written in Java to make the transition to an Android phone seamless. Even the libLinear version used was written in Java for use on an Android phone.

With these preparations and the results of this thesis, the only limiting factor to running author detection tests on a variety of Android phones is time. Another researcher with access to a small number of Android phones or tablets could conduct these these tests in a few weeks. The tests should span the range of Android versions from Android version 1.6 all the way up to Android version 3.0. Underpowered phones such as the HTC ADP2 should be tested along with higher end phones like the Google ADP3 or the Motorola Xoom. These tests could determine not only the feasibility of author detection on a mobile device, but the impact on CPU usage, battery life, and sdcard life.

5.2.2 Rewrite LibLinear Data Structures

A limiting factor in testing method-feature combinations with libLinear was the maximum number of elements the libLinear model was able to hold. Since the core of the libLinear model is an array of float values, that array is limited to 2^{31} elements. When libLinear initializes the model, each author is combined with each feature and assigned an element in the array. When # authors $*$ # features $> 2^{31}$, libLinear cannot process that method-feature combination.

To fix this situation, the array of integers in libLinear could be replaced with a vector of integers or list of integers. Locating a value within the list or vector would be more complex than using an array, so an additional author-feature tracking mechanism might be needed. Another options would be to change the one dimensional array of integers to a two dimensional array of integers and divide the expected index into the array by 2^{31} to determine what row of the two dimensional array should be accessed.

Simply changing the data structure of libLinear would not suffice for adapting libLinear to extremely large method-feature type combination. The performance impact of using a more complex data structure would need to be measured. A more complex data structure could slow libLinear to the point of being unusable, which would undermine the purpose of modifying libLinear in the first place.

5.2.3 Determine Accuracy and F-Score for Other Web1T Vocabulary Variations

To support this thesis, minimum perfect hash data structure files and hash signature files were created for every permutation of allowing punctuation, capitalization, sentence boundaries, and handling Web1T "unknown word" tag. Each permutation was assigned a number between "0" and ”15” to identify that permutation. Only permutation ”0”, which allows punctuation, capitalization, sentence boundaries, and the Web1T unknown word tag was used in this thesis. The remaining permutations of ”1” through ”15” could also be test to determine their accuracy, f-score, and storage requirements.

Handling punctuation, capitalization, and the Web1T ”unknown word” tag is already coded into the Java code used for this thesis. Sentence boundaries are more difficult to deal with. Tools that use maximum entropy to find sentence boundaries are available, but were deemed to computationally expensive to use in the already processing and memory intensive environment of this thesis. An efficient means of sentence boundary detection would need to be found before making actual use of sentence boundaries. To that end, permutation ”8” should give identical results to this thesis since this thesis allowed for sentence boundaries in the Web1T vocabulary, but had no mechanism to train to sentence boundaries.

5.2.4 Apply Good-Turing or Witten-Bell Smoothing to Naive Bayes

Laplace Smoothing was used for naive Bayes in this thesis. In the case of Web1T% of 1 and higher, the actual counts within the chosen Web1T% corpus were used to smooth unseen words in the authors model. (There are lots of GB3 features, so the assigned value was relatively small. There are relatively few GM1 features, so the value was relatively large.) For Web1T% of 0, a single value was assigned for smoothing based on the feature type used. In the scoring of accuracy versus size, the Web1T% of 0 produced higher scores than it Web1T% of 1 and higher.

Since Web1T% of 0 scored better relative to its more storage intensive counterparts, further exploration of the Web1T% of 0 space is warranted. Instead of the very basic Laplace Smoothing, Good-Turing or Witten-Bell could be used over the all the feature types for Web1T% of 0 to see if performance is significantly improved. Since Good-Turing and Witten-Bell would likely have little impact on the storage requirements for any given feature type, a higher accuracy would result in a higher score for that feature type.

5.2.5 Increase Size of the Twitter Short Message Corpus

The large difference in accuracy and f-score between the ENRON E-mail Corpus and Twitter Short Message Corpus may be a function of how few tokens are present in the Twitter Corpus compared to the ENRON E-mail Corpus. If the most prolific Tweeters could be recorded for several months, a large enough body of tokens could be created to put the token count of some

Tweeter on par with the average ENRON e-mail author's token count. Testing a Twitter corpus with a larger amount of text could clarify whether Twitter is inherently different from e-mail or is simply less predictable when there is a smaller sample to analyze.

A large Twitter corpus would need to find a few hundred Twitter authors who regularly create original content that is publicly accessible. The Twitter Garden Hose would need to gather Tweets for a few weeks to identify these prolific Tweeters. After the initial gathering, the identified prolific Tweeters would be collected on exclusively while screening out re-Tweets. A good faith effort to identify if any of the prolific Tweeters was a corporation or public figure know to use group of writers for their Tweets would need to be made. The analysis of Twitter only works if there is truly one person creating the content for each Twitter account tracked.

Once there are a few Twitter authors that have approximately 15MB of Twitter text and numerous Twitter authors with at least 500K of Twitter text, the Twitter corpus could be considered equivalent to the Enron E-mail Corpus for size of text and relative author prolificity. At this point, this new Twitter corpus could be tested again using all the method-feature combinations of this thesis to determine if the new Twitter accuracy and f-score more closely resemble the Enron corpus. If the Twitter results being to more closely resemble Enron results, then there may not be a significant signal difference between short message posts and e-mail messages.

5.2.6 Deliver Author Detection Tools to Mobile Device

Having a working author detection tool is a step toward implementation, however, that tool still must be delivered to mobile devices. There are different delivery methods for varying purposes. Two major categories of delivery are deliberate and covert.

An example of a deliberate installation would be as a child predator detector on a teen's mobile phone. To support a parent's desire to know if a child predator is texting their teen, simply packaging author detection tools for the Android marketplace is only one step. Text authored by local child predators would need to be gathered and trained into models. This would be a non-trivial collections and organization effort. Finding an effective strategy for this collection and organization would be a valuable avenue of study.

An example of a covert installation would be saturating a combat operations area's mobile devices author detection tool containing models of high value enemies. This delivery to an unknowing device user poses many more difficulties than the deliberate installation. Many questions must be answered for a covert delivery: Is the local cell tower controlled by an independent entity? Are their popular applications used by the target demographic? Can the author detection tools be joined with that popular application? Is it easy to detect the tools once installed?

Each of these delivery categories is worthy of their study to determine feasibility and to develop methods to accomplish placement on a mobile device efficiently and reliably. Each of these delivery categories would also need extensive legal and administrative review to ensure compliance with federal, state, and local laws as well as intelligence collection constraints.

5.2.7 Determine Appropriate Group Size for Target Authors

Training to a large number of authors may not be necessary. Do most mobile device users often have a social network of 150 people they routinely communicate with? While a mobile device user may have hundreds of "friends" on Facebook, they may only send text messages and emails to a small number of people. If a reasonable number can be determined for expected authors to be detected, then the choice of method-feature combination can be specifically refined to that number of people. This would keep the authors model size minimized for disk storage as well.

5.2.8 Study "Stealthiness" for Author Detection Software

For a covert delivery of author detection tools, it is important to keep the presence of author detection tools unnoticed by the user. If the author detection tool cause lag in the user interface, noticeably reduces batter time, consumes a large portion of storage, or increases a user's wireless bill, that tool will get noticed.

Methods to conceal the author detection tools could be as simple as storing e-mail and short messages throughout the day, then process them only when the device is on a charger during night hours. The covert mechanism could be very sophisticated and learn user patterns to find an optimal time to process. The covert portion of the tools should cease operation if the user picks up the phone or receives a call.

Even if the act of author detection process is concealed, alerting an outside facility that an author has been detected must avoid detection as well. Sending an SMS could attract attention. Creating a data connection over wireless unexpectedly could draw attention as well. Using some covert channel to alert an outside facility would be an important part of using these author detection tools in a covert delivery environment.

5.2.9 Study Public Tweets of Former ENRON Employees

If former ENRON employees maintain public Twitter posts, their compiled Tweets could be tested against author detection models created from their Enron emails. This could be a straightforward check of signal similarity between short messages and e-mail.

5.2.10 Study of Disk Storage to RAM Usage for Mobile Phones

The storage requirement measurement in this thesis focused heavily on the standard Dalvik VM limit of 16MB. To reduce the impact of large vocabularies on the Dalvik VM, the vocabulary could be read directly from non-volatile storage like a microSD card. This would slow processing of intercepted emails or short messages, but could greatly expand the number of mobile device appropriate method-feature combinations.

Studying techniques of accessing vocabulary files direct from disk would entail more than just developing a random access file to hold the vocabulary objects. The impact on processing time, stealthiness, and possible interruption of applications on the mobile device would need to be examined. Also, the behavior of Liblinear and naive Bayes would need to be changed to handle a random access file instead of directly accessing RAM.

5.2.11 Statistical Study of Small-To-Large Versus Small-And-Large Groupings Results

A detailed study of how much difference in author prolificity alters the accuracy and f-score for author detection could reveal important breakpoints between authors. By this, a set of modeled authors who are all highly prolific put into an environment where authors are not prolific could produce an extremely high number of false positive. By the same token, a set of modeled authors who are not prolific put into an environment of very prolific authors could produce a high number of false negatives. Studying breakpoints in the variation between authors in prolificity and its impacts on the standard deviation of accuracy and f-score would all people building models of authors to determine if the collected documents of the target authors provide an appropriate amount of text compared to the amount of text in the detecting environment.

This study would not necessarily need to be conducted by a natural language processing researcher. An operations research analyst may be better suited to analyze the data already produced in this thesis using natural language processing techniques.

5.2.12 Conduct LibLinear and Naive Bayes Tests Again with a Large ”Noise” Group

One of the most important tests that could be run against the data in this thesis would be to create noise groups to test the accuracy and f-score of the author detection tools in this thesis. To do this, the 150 author groups could have all but 5 authors relabeled as ”author X”. This would create a six author test set where one author is actually a mix of 145 authors. This would provide an indication of how well these tools work in an environment filled with many non-targets authors and a few target authors.

This same test could be conducted with 10 authors and an ”author X”, 25 authors with an ”author X”, etc. This is a more realistic test scenario than the 5 versus 5, 10 versus 10, etc tests conducted in this thesis.

These tests would likely be very time consuming. Tests run as 150 versus 150 in this thesis often took hours to execute, though having a large number of documents to process against only six classifications of author would reduce the overall time required to process. While time consuming, the noise group tests are an important next step towards implementation.

5.2.13 Test Spoken Keyword Recognition Techniques

With text processing examined for use on mobile devices, a natural progression is to detect key words on a mobile device. While conducting author detection using voice recognition is likely beyond the reach of current mobile devices, detecting key words or combinations of key words may not be.

For example, detecting words often associated with an attack on a convoy could be incorporated on a mobile device which then sends a signal to a central alert center to warn nearby convoys. A teenager’s phone could recognize key words associated with drug use or other dangerous behaviors. Parents could then receive an alert.

Voice processing is much more difficult than text processing and would require a substantially different approach from this thesis. Also, accounting for voice tenor and variation in phonemes between languages would be complex. In the end, the operations task of creating author text models may be more daunting than the complexity of keyword recognition from phonemes, buts making keyword recognition a viable path of research.

5.3 Concluding Remarks

With millions of mobile phones across the world, leveraging the power of those millions of processors to identify persons of interest could be of enormous use to governments, organizations, and families. This thesis has shown that viable combinations of methods and feature types do exist as author detection tools for today's mobile devices. With additional testing and engineering, the model of centralized analysis of data collected from distribute mobile devices could be changed dramatically. This centralized model could be changed to distributed collection, distribute processing, and distributed notification. This distributed model offers great promise for detecting persons of interest via mobile devices.

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APPENDIX A: LibLinear Accuracy and F-Score Results for the ENRON Email Corpus

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.8269	0.9531	0.4815	0.0979	0.6864	0.9842	0.0000	0.2414
	1	0.8233	0.9578	0.4444	0.1003	0.6859	0.9826	0.0000	0.2384
	2	0.8216	0.9570	0.4444	0.0971	0.6881	0.9819	0.0000	0.2377
	4	0.8298	0.9590	0.4444	0.0949	0.6950	0.9821	0.0000	0.2315
	8	0.8298	0.9570	0.4444	0.0980	0.6878	0.9819	0.0000	0.2406
	16	0.8239	0.9732	0.4444	0.0987	0.6901	0.9878	0.0000	0.2316

Table A.1: liblinear-enron-GM1-ALL-ALL-5

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.7611	0.9312	0.3776	0.1130	0.6122	0.9778	0.0000	0.2463
	1	0.7610	0.8890	0.3878	0.1109	0.6081	0.9699	0.0000	0.2490
	2	0.7594	0.9068	0.4388	0.1080	0.6093	0.9660	0.0000	0.2437
	4	0.7602	0.9086	0.4388	0.1074	0.6093	0.9692	0.0000	0.2451
	8	0.7578	0.9025	0.4388	0.1080	0.6113	0.9684	0.0000	0.2415
	16	0.7622	0.9187	0.3878	0.1142	0.6116	0.9698	0.0000	0.2425

Table A.2: liblinear-enron-GM1-ALL-ALL-10

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.6845	0.8073	0.4430	0.1031	0.5251	0.9640	0.0000	0.2550
	1	0.6847	0.8064	0.4574	0.1071	0.5233	0.9572	0.0000	0.2567
	2	0.6873	0.8364	0.4500	0.1092	0.5256	0.9645	0.0000	0.2538
	4	0.6819	0.7836	0.4483	0.1057	0.5237	0.9558	0.0000	0.2554
	8	0.6862	0.8013	0.4599	0.1044	0.5291	0.9566	0.0000	0.2512
	16	0.6861	0.7925	0.4483	0.1033	0.5223	0.9568	0.0000	0.2620

Table A.3: liblinear-enron-GM1-ALL-ALL-25

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.6411	0.7476	0.4341	0.0905	0.4800	0.9509	0.0000	0.2558
	1	0.6364	0.7280	0.4234	0.0982	0.4746	0.9561	0.0000	0.2571
	2	0.6420	0.7214	0.4287	0.0911	0.4764	0.9475	0.0000	0.2577
	4	0.6356	0.7052	0.4327	0.0888	0.4751	0.9532	0.0000	0.2578
	8	0.6419	0.7127	0.4376	0.0917	0.4780	0.9559	0.0000	0.2608
	16	0.6437	0.7524	0.4406	0.0913	0.4771	0.9504	0.0000	0.2576

Table A.4: liblinear-enron-GM1-ALL-ALL-50

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.6146	0.7024	0.4155	0.0921	0.4492	0.9437	0.0000	0.2588
	1	0.6101	0.7011	0.3880	0.1031	0.4407	0.9453	0.0000	0.2633
	2	0.6127	0.6858	0.3995	0.0978	0.4462	0.9511	0.0000	0.2584
	4	0.6132	0.6814	0.4006	0.0969	0.4417	0.9402	0.0000	0.2609
	8	0.6085	0.6836	0.4074	0.0921	0.4432	0.9392	0.0000	0.2574
	16	0.6137	0.6716	0.4030	0.0948	0.4403	0.9413	0.0000	0.2595

Table A.5: liblinear-enron-GM1-ALL-ALL-75

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.6060	0.6074	0.6033	0.0020	0.4000	0.9316	0.0000	0.2610
	1	0.5951	0.6155	0.5849	0.0144	0.3968	0.9402	0.0000	0.2678
	2	0.5982	0.6049	0.5949	0.0047	0.3958	0.9389	0.0000	0.2676
	4	0.6083	0.6093	0.6065	0.0013	0.4037	0.9488	0.0000	0.2640
	8	0.5990	0.6008	0.5982	0.0012	0.4023	0.9451	0.0000	0.2639
	16	0.5987	0.6011	0.5975	0.0017	0.3991	0.9489	0.0000	0.2664

Table A.6: liblinear-enron-GM1-ALL-ALL-150

GM2									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.8607	0.9753	0.5185	0.0980	0.7309	1.0000	0.0000	0.2402
	1	0.8193	0.9544	0.4444	0.1034	0.6761	0.9781	0.0000	0.2389
	2	0.8192	0.9448	0.4444	0.1004	0.6782	0.9778	0.0000	0.2400
	4	0.8187	0.9560	0.4444	0.1014	0.6747	0.9834	0.0000	0.2412
	8	0.8199	0.9547	0.4444	0.1024	0.6747	0.9817	0.0000	0.2419
	16	0.8154	0.9606	0.4444	0.1037	0.6782	0.9881	0.0000	0.2379

Table A.7: liblinear-enron-GM2-ALL-ALL-5

GM2									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.8150	0.9369	0.5000	0.1044	0.6869	0.9811	0.0000	0.2443
	1	0.7551	0.9093	0.3936	0.1114	0.5942	0.9711	0.0000	0.2510
	2	0.7578	0.9255	0.3936	0.1129	0.6001	0.9711	0.0000	0.2510
	4	0.7502	0.8969	0.3936	0.1126	0.5998	0.9675	0.0000	0.2480
	8	0.7581	0.8739	0.3936	0.1122	0.6003	0.9678	0.0000	0.2488
	16	0.7528	0.9065	0.3936	0.1138	0.5986	0.9728	0.0000	0.2510

Table A.8: liblinear-enron-GM2-ALL-ALL-10

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.7696	0.8989	0.4824	0.1111	0.6317	0.9814	0.0000	0.2630
	1	0.6790	0.8075	0.4512	0.1045	0.5171	0.9632	0.0000	0.2591
	2	0.6822	0.8065	0.4562	0.1023	0.5212	0.9612	0.0000	0.2558
	4	0.6810	0.7994	0.4465	0.1055	0.5174	0.9674	0.0000	0.2565

Table A.9: liblinear-enron-GM2-ALL-ALL-25

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.7402	0.8240	0.5252	0.0987	0.6002	0.9780	0.0000	0.2678
	1	0.6329	0.7216	0.4211	0.0925	0.4682	0.9505	0.0000	0.2616
	2	0.6341	0.7156	0.4119	0.0963	0.4709	0.9504	0.0000	0.2581

Table A.10: liblinear-enron-GM2-ALL-ALL-50

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.7330	0.7969	0.5437	0.0867	0.5832	0.9786	0.0000	0.2721
	1	0.6120	0.6959	0.3872	0.1035	0.4454	0.9564	0.0000	0.2650
	2	0.5987	0.6677	0.3874	0.0974	0.4385	0.9523	0.0000	0.2653

Table A.11: liblinear-enron-GM2-ALL-ALL-75

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.7447	0.7456	0.7429	0.0013	0.5516	0.9737	0.0000	0.2791
	1	0.5978	0.6047	0.5841	0.0097	0.3979	0.9387	0.0000	0.2697

Table A.12: liblinear-enron-GM2-ALL-ALL-150

GM5									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.6881	0.9636	0.3017	0.1576	0.5062	1.0000	0.0000	0.3012
	1	0.8117	0.9685	0.4000	0.1167	0.6773	0.9869	0.0000	0.2407
	2	0.8118	0.9550	0.4000	0.1133	0.6725	0.9836	0.0000	0.2423
	4	0.8130	0.9455	0.4000	0.1142	0.6772	0.9821	0.0000	0.2398
	8	0.8070	0.9513	0.4000	0.1152	0.6749	0.9824	0.0000	0.2367

Table A.13: liblinear-enron-GM5-ALL-ALL-5

GM5									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.6297	0.8560	0.2548	0.1432	0.4605	0.9870	0.0000	0.2997
	1	0.7519	0.9022	0.3908	0.1141	0.5979	0.9782	0.0000	0.2478
	2	0.7440	0.9221	0.3908	0.1128	0.5981	0.9733	0.0000	0.2487
	4	0.7418	0.9256	0.3908	0.1161	0.5992	0.9729	0.0000	0.2479

Table A.14: liblinear-enron-GM5-ALL-ALL-10

GM5									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.5499	0.7076	0.3305	0.1318	0.4372	1.0000	0.0000	0.3073
	1	0.6759	0.7867	0.4371	0.1075	0.5242	0.9554	0.0000	0.2557
	2	0.6728	0.7759	0.4371	0.0982	0.5252	0.9599	0.0000	0.2552

Table A.15: liblinear-enron-GM5-ALL-ALL-25

GM5									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.5323	0.6564	0.3088	0.1049	0.4262	0.9870	0.0000	0.3097
	1	0.6259	0.7342	0.4304	0.0929	0.4757	0.9572	0.0000	0.2655

Table A.16: liblinear-enron-GM5-ALL-ALL-50

GM5									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.5211	0.6206	0.3240	0.0953	0.4148	0.9870	0.0000	0.3171

Table A.17: liblinear-enron-GM5-ALL-ALL-75

GB3									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.8529	0.9835	0.5185	0.1014	0.7203	1.0000	0.0000	0.2469
	1	0.8494	0.9673	0.5185	0.1016	0.7172	0.9854	0.0000	0.2459
	2	0.8476	0.9805	0.5185	0.1040	0.7152	0.9890	0.0000	0.2470
	4	0.8579	0.9762	0.5185	0.1007	0.7174	0.9844	0.0000	0.2516
	8	0.8536	0.9786	0.5185	0.1003	0.7152	0.9921	0.0000	0.2501
	16	0.8523	0.9756	0.5185	0.1028	0.7136	0.9886	0.0000	0.2520

Table A.18: liblinear-enron-GB3-ALL-ALL-5

GB3									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.8124	0.9538	0.4787	0.1149	0.6699	1.0000	0.0000	0.2599
	1	0.8127	0.9341	0.4894	0.1084	0.6712	1.0000	0.0000	0.2545
	2	0.8128	0.9297	0.4894	0.1074	0.6753	0.9870	0.0000	0.2509
	4	0.8096	0.9426	0.4894	0.1079	0.6723	1.0000	0.0000	0.2548
	8	0.8134	0.9512	0.4894	0.1100	0.6725	0.9870	0.0000	0.2545

Table A.19: liblinear-enron-GB3-ALL-ALL-10

GB3									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.7680	0.8882	0.5215	0.1068	0.6218	0.9797	0.0000	0.2675
	1	0.7652	0.8744	0.5158	0.1136	0.6188	0.9816	0.0000	0.2657
	2	0.7684	0.8788	0.5130	0.1119	0.6208	0.9772	0.0000	0.2646

Table A.20: liblinear-enron-GB3-ALL-ALL-25

GB3									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.7409	0.8465	0.4980	0.1063	0.5914	1.0000	0.0000	0.2725
	1	0.7372	0.8204	0.4731	0.1083	0.5865	0.9753	0.0000	0.2732

Table A.21: liblinear-enron-GB3-ALL-ALL-50

GB3									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.7300	0.7955	0.5220	0.0947	0.5710	0.9870	0.0000	0.2783
	1	0.7336	0.8161	0.5273	0.0952	0.5773	0.9763	0.0000	0.2722

Table A.22: liblinear-enron-GB3-ALL-ALL-75

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.8690	0.9732	0.5185	0.0928	0.7386	1.0000	0.0000	0.2435
	1	0.8667	0.9741	0.5185	0.0964	0.7375	0.9921	0.0000	0.2396
	2	0.8645	0.9765	0.5185	0.0991	0.7369	0.9923	0.0000	0.2424
	4	0.8687	0.9762	0.5185	0.0958	0.7367	0.9884	0.0000	0.2416

Table A.23: liblinear-enron-OSB3-ALL-ALL-5

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.8250	0.9469	0.5106	0.1028	0.6886	0.9867	0.0000	0.2502

Table A.24: liblinear-enron-OSB3-ALL-ALL-10

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.7826	0.8954	0.5385	0.1038	0.6374	0.9815	0.0000	0.2599

Table A.25: liblinear-enron-OSB3-ALL-ALL-25

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.7567	0.8569	0.5160	0.1016	0.6056	0.9793	0.0000	0.2645

Table A.26: liblinear-enron-OSB3-ALL-ALL-50

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.7470	0.7931	0.5547	0.0862	0.5858	0.9786	0.0000	0.2703

Table A.27: liblinear-enron-OSB3-ALL-ALL-75

APPENDIX B: LibLinear Accuracy and F-Score Results for the Twitter Short Message Corpus

GM1									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.6212	0.8089	0.4737	0.0739	0.6023	0.9696	0.1791	0.1416
	1	0.6228	0.8211	0.4713	0.0778	0.6034	0.9597	0.1429	0.1445
	2	0.6147	0.8966	0.4218	0.0888	0.5948	0.9697	0.0000	0.1514
	4	0.6172	0.8546	0.3846	0.0850	0.5992	0.9811	0.1200	0.1450
	8	0.6273	0.9026	0.4661	0.0813	0.6087	0.9735	0.1404	0.1419
	16	0.6181	0.8324	0.4458	0.0816	0.6013	0.9600	0.1515	0.1386

Table B.1: liblinear-twitter-GM1-ALL-ALL-5

GM1									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.4762	0.6234	0.3448	0.0725	0.4537	0.9556	0.0385	0.1607
	1	0.4813	0.6389	0.3627	0.0662	0.4605	0.9482	0.0755	0.1592
	2	0.4845	0.6567	0.3358	0.0699	0.4617	0.9699	0.0702	0.1615
	4	0.4841	0.6900	0.3184	0.0750	0.4628	0.9517	0.0299	0.1639
	8	0.4816	0.7194	0.3080	0.0784	0.4576	0.9621	0.0000	0.1637
	16	0.4800	0.6362	0.2846	0.0723	0.4567	0.9474	0.0370	0.1613

Table B.2: liblinear-twitter-GM1-ALL-ALL-10

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.3461	0.4816	0.2735	0.0562	0.3197	0.9344	0.0000	0.1697
	1	0.3408	0.4390	0.2408	0.0596	0.3160	0.9221	0.0000	0.1740
	2	0.3465	0.4309	0.2714	0.0430	0.3225	0.9225	0.0000	0.1717
	4	0.3510	0.4402	0.2811	0.0476	0.3264	0.9358	0.0000	0.1724
	8	0.3419	0.4296	0.2591	0.0483	0.3189	0.9231	0.0000	0.1707
	16	0.3411	0.4296	0.2651	0.0417	0.3133	0.9011	0.0000	0.1705

Table B.3: liblinear-twitter-GM1-ALL-ALL-25

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.2693	0.3371	0.2190	0.0369	0.2496	0.8798	0.0000	0.1754
	1	0.2704	0.3173	0.2219	0.0365	0.2483	0.9153	0.0000	0.1747
	2	0.2705	0.3338	0.2180	0.0415	0.2419	0.8922	0.0000	0.1753
	4	0.2710	0.3272	0.2032	0.0457	0.2464	0.8889	0.0000	0.1716
	8	0.2712	0.3171	0.2274	0.0281	0.2431	0.9119	0.0000	0.1727
	16	0.2710	0.3326	0.2344	0.0308	0.2458	0.9035	0.0000	0.1713

Table B.4: liblinear-twitter-GM1-ALL-ALL-50

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.2273	0.2738	0.1810	0.0371	0.2100	0.8687	0.0000	0.1713
	1	0.2293	0.2626	0.1768	0.0320	0.2092	0.9157	0.0000	0.1718
	2	0.2318	0.2730	0.1818	0.0364	0.2127	0.8750	0.0000	0.1729
	4	0.2310	0.2776	0.1874	0.0313	0.2101	0.8971	0.0000	0.1687
	8	0.2354	0.2910	0.1743	0.0406	0.2097	0.8873	0.0000	0.1720
	16	0.2368	0.2780	0.1910	0.0361	0.2091	0.9037	0.0000	0.1740

Table B.5: liblinear-twitter-GM1-ALL-ALL-75

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.1851	0.1875	0.1802	0.0034	0.1629	0.8582	0.0000	0.1623
	1	0.1888	0.1932	0.1802	0.0061	0.1642	0.8212	0.0000	0.1636
	2	0.1829	0.1833	0.1821	0.0006	0.1595	0.7807	0.0000	0.1575
	4	0.1921	0.1943	0.1910	0.0016	0.1665	0.8792	0.0000	0.1594
	8	0.1893	0.1913	0.1884	0.0014	0.1640	0.8139	0.0000	0.1650
	16	0.1877	0.1883	0.1865	0.0008	0.1644	0.8143	0.0000	0.1614

Table B.6: liblinear-twitter-GM1-ALL-ALL-150

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.4844	0.7282	0.2664	0.0887	0.4501	0.9272	0.0000	0.1676
	1	0.6241	0.8454	0.4664	0.0780	0.6029	0.9886	0.1159	0.1482
	2	0.6221	0.8232	0.3934	0.0867	0.6054	0.9697	0.1071	0.1423
	4	0.6253	0.8210	0.4245	0.0791	0.6077	0.9545	0.1639	0.1405
	8	0.6282	0.8489	0.4773	0.0734	0.6130	0.9773	0.1818	0.1373
	16	0.6258	0.8544	0.4094	0.0877	0.6119	0.9603	0.2157	0.1348

Table B.7: liblinear-twitter-GM2-ALL-ALL-5

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.3700	0.5725	0.1985	0.0775	0.3455	0.9150	0.0000	0.1686
	1	0.4904	0.6219	0.3429	0.0665	0.4657	0.9575	0.0000	0.1636
	2	0.4903	0.6491	0.3560	0.0628	0.4689	0.9549	0.0879	0.1585
	4	0.4962	0.6924	0.3379	0.0711	0.4711	0.9771	0.0000	0.1639
	8	0.4842	0.6693	0.3593	0.0623	0.4622	0.9524	0.0857	0.1603
	16	0.4891	0.6961	0.3142	0.0737	0.4684	0.9421	0.0000	0.1581

Table B.8: liblinear-twitter-GM2-ALL-ALL-10

GM2									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.2641	0.3285	0.1882	0.0346	0.2437	0.8473	0.0000	0.1734
	1	0.3468	0.4945	0.2702	0.0518	0.3226	0.9299	0.0000	0.1737
	2	0.3464	0.4433	0.2642	0.0508	0.3219	0.9542	0.0000	0.1678
	4	0.3526	0.4450	0.2665	0.0470	0.3304	0.9438	0.0000	0.1692

Table B.9: liblinear-twitter-GM2-ALL-ALL-25

GM2									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.2097	0.2745	0.1587	0.0304	0.2006	0.8333	0.0000	0.1732
	1	0.2679	0.3381	0.2275	0.0404	0.2453	0.8750	0.0000	0.1712
	2	0.2707	0.3221	0.2116	0.0373	0.2470	0.8777	0.0000	0.1796

Table B.10: liblinear-twitter-GM2-ALL-ALL-50

GM2									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.1800	0.2186	0.1277	0.0302	0.1729	0.7926	0.0000	0.1664
	1	0.2350	0.2861	0.1960	0.0331	0.2147	0.8914	0.0000	0.1715
	2	0.2354	0.2697	0.1867	0.0293	0.2130	0.8397	0.0000	0.1710

Table B.11: liblinear-twitter-GM2-ALL-ALL-75

GM2									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.1525	0.1554	0.1466	0.0042	0.1439	0.8092	0.0000	0.1605
	1	0.1889	0.1893	0.1882	0.0006	0.1659	0.7742	0.0000	0.1627

Table B.12: liblinear-twitter-GM2-ALL-ALL-150

GM5									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.2764	0.5119	0.1687	0.0560	0.1995	0.6715	0.0000	0.1509
	1	0.5868	0.8362	0.4040	0.0830	0.5657	0.9498	0.1667	0.1468
	2	0.5802	0.7639	0.3689	0.0835	0.5594	0.9457	0.0845	0.1488

Table B.13: liblinear-twitter-GM5-ALL-ALL-5

GM5									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.1718	0.2811	0.0961	0.0371	0.1238	0.5625	0.0000	0.1172
	1	0.4383	0.5825	0.3247	0.0648	0.4150	0.9237	0.0519	0.1609
	2	0.4382	0.5657	0.3108	0.0643	0.4182	0.9302	0.0000	0.1577

Table B.14: liblinear-twitter-GM5-ALL-ALL-10

GM5									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.1060	0.1677	0.0717	0.0254	0.0886	0.6154	0.0000	0.1141
	1	0.3011	0.3718	0.2378	0.0356	0.2784	0.9105	0.0000	0.1619

Table B.15: liblinear-twitter-GM5-ALL-ALL-25

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.0805	0.1060	0.0666	0.0149	0.0792	0.5373	0.0000	0.1124

Table B.16: liblinear-twitter-GM5-ALL-ALL-50

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.0643	0.0792	0.0421	0.0123	0.0658	0.5392	0.0000	0.1018

Table B.17: liblinear-twitter-GM5-ALL-ALL-75

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.0636	0.0667	0.0573	0.0044	0.0707	0.5443	0.0000	0.1076

Table B.18: liblinear-twitter-GM5-ALL-ALL-150

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.5405	0.8313	0.3737	0.0845	0.5059	0.9360	0.0000	0.1665
	1	0.5312	0.7360	0.3734	0.0752	0.4996	0.9308	0.0000	0.1684
	2	0.5447	0.7269	0.3850	0.0702	0.5125	0.9375	0.0000	0.1630
	4	0.5399	0.7538	0.3571	0.0834	0.5093	0.9354	0.0000	0.1684
	8	0.5404	0.8297	0.3908	0.0842	0.5085	0.9290	0.0000	0.1665
	16	0.5386	0.7564	0.3780	0.0768	0.5020	0.9416	0.0000	0.1740

Table B.19: liblinear-twitter-GB3-ALL-ALL-5

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.4231	0.5716	0.3021	0.0666	0.3913	0.9302	0.0000	0.1732
	1	0.4207	0.5795	0.2998	0.0632	0.3868	0.8806	0.0000	0.1734
	2	0.4221	0.6907	0.3259	0.0717	0.3938	0.9049	0.0000	0.1711
	4	0.4226	0.5960	0.3114	0.0682	0.3899	0.9231	0.0000	0.1757
	8	0.4246	0.5868	0.3045	0.0706	0.3961	0.9266	0.0000	0.1732

Table B.20: liblinear-twitter-GB3-ALL-ALL-10

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.3123	0.4116	0.2218	0.0525	0.2865	0.8750	0.0000	0.1770
	1	0.3087	0.4029	0.2379	0.0469	0.2837	0.9147	0.0000	0.1726
	2	0.3134	0.4094	0.2569	0.0423	0.2829	0.8949	0.0000	0.1782

Table B.21: liblinear-twitter-GB3-ALL-ALL-25

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.2467	0.2968	0.1960	0.0322	0.2240	0.8992	0.0000	0.1676
	1	0.2465	0.3082	0.1949	0.0353	0.2250	0.8864	0.0000	0.1729

Table B.22: liblinear-twitter-GB3-ALL-ALL-50

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.2132	0.2497	0.1842	0.0224	0.1963	0.8530	0.0000	0.1675
	1	0.2155	0.2477	0.1803	0.0310	0.1916	0.8803	0.0000	0.1659

Table B.23: liblinear-twitter-GB3-ALL-ALL-75

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.1739	0.1825	0.1696	0.0061	0.1514	0.8357	0.0000	0.1507

Table B.24: liblinear-twitter-GB3-ALL-ALL-150

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.5430	0.7559	0.3680	0.0818	0.5144	0.9513	0.0000	0.1641
	1	0.5391	0.7747	0.4000	0.0729	0.5062	0.9362	0.0000	0.1647
	2	0.5427	0.7651	0.3731	0.0790	0.5084	0.9425	0.0000	0.1687
	4	0.5391	0.7747	0.3934	0.0793	0.5085	0.9434	0.0000	0.1673

Table B.25: liblinear-twitter-OSB3-ALL-ALL-5

OSB3									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.4271	0.5520	0.3216	0.0587	0.3987	0.9261	0.0000	0.1669
	1	0.4288	0.5847	0.3219	0.0646	0.3973	0.9453	0.0000	0.1774
	2	0.4255	0.5802	0.3280	0.0579	0.3936	0.9125	0.0000	0.1768

Table B.26: liblinear-twitter-OSB3-ALL-ALL-10

OSB3									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.3084	0.4086	0.2331	0.0532	0.2849	0.8731	0.0000	0.1766

Table B.27: liblinear-twitter-OSB3-ALL-ALL-25

OSB3									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.2520	0.2913	0.2023	0.0296	0.2293	0.8686	0.0000	0.1728

Table B.28: liblinear-twitter-OSB3-ALL-ALL-50

OSB3									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.2211	0.2493	0.1815	0.0254	0.2009	0.8839	0.0000	0.1709

Table B.29: liblinear-twitter-OSB3-ALL-ALL-75

OSB3									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.1750	0.1839	0.1705	0.0063	0.1580	0.8239	0.0000	0.1531

Table B.30: liblinear-twitter-OSB3-ALL-ALL-150

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APPENDIX C:
Naive Bayes Accuracy and F-Score Results for the ENRON Email Corpus

GM1									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.7215	0.9114	0.4815	0.0960	0.4350	0.9730	0.0000	0.3637
	1	0.6441	0.8864	0.2937	0.1462	0.5404	0.9453	0.0000	0.2494
	2	0.6505	0.8877	0.2256	0.1460	0.5510	0.9467	0.0000	0.2474
	4	0.6610	0.8724	0.2898	0.1378	0.5526	0.9483	0.0000	0.2501
	8	0.6534	0.8864	0.2950	0.1387	0.5461	0.9494	0.0000	0.2482
	16	0.6663	0.8698	0.2551	0.1438	0.5567	0.9513	0.0000	0.2472

Table C.1: nb-enron-GM1-ALL-ALL-5

GM1									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.5768	0.7663	0.3311	0.1086	0.3121	0.9164	0.0000	0.3137
	1	0.5189	0.7117	0.2923	0.1220	0.4421	0.9655	0.0000	0.2343
	2	0.5215	0.7192	0.2904	0.1215	0.4446	0.9157	0.0000	0.2344
	4	0.5406	0.7545	0.2715	0.1269	0.4554	0.9500	0.0000	0.2372
	8	0.5349	0.7164	0.2647	0.1192	0.4534	0.9157	0.0000	0.2351
	16	0.5377	0.7174	0.2763	0.1209	0.4537	0.9500	0.0000	0.2354

Table C.2: nb-enron-GM1-ALL-ALL-10

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.4083	0.5192	0.2996	0.0581	0.1852	0.8796	0.0000	0.2424
	1	0.3956	0.5915	0.2745	0.0983	0.3457	0.9870	0.0000	0.2139
	2	0.4037	0.5964	0.2822	0.0958	0.3488	0.9870	0.0000	0.2137
	4	0.4111	0.5966	0.2402	0.1037	0.3583	0.9870	0.0000	0.2154
	8	0.4127	0.5982	0.2544	0.0957	0.3586	0.9870	0.0000	0.2151
	16	0.4166	0.5986	0.2909	0.0903	0.3600	0.9870	0.0000	0.2143

Table C.3: nb-enron-GM1-ALL-ALL-25

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.3126	0.4130	0.2686	0.0462	0.1093	0.8718	0.0000	0.1906
	1	0.3153	0.4779	0.2307	0.0905	0.2918	0.9157	0.0000	0.1973
	2	0.3191	0.4838	0.2549	0.0879	0.2950	0.9157	0.0000	0.1989
	4	0.3320	0.4842	0.2526	0.0846	0.3011	0.9157	0.0000	0.1974
	8	0.3296	0.4864	0.2641	0.0844	0.3030	0.9157	0.0000	0.1999
	16	0.3391	0.4875	0.2587	0.0825	0.3052	0.9157	0.0000	0.2014

Table C.4: nb-enron-GM1-ALL-ALL-50

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.2912	0.3441	0.2603	0.0293	0.0791	0.8705	0.0000	0.1658
	1	0.2627	0.4048	0.2087	0.0663	0.2566	0.8085	0.0000	0.1816
	2	0.2800	0.4078	0.2011	0.0679	0.2625	0.8172	0.0000	0.1861
	4	0.2761	0.4106	0.2256	0.0626	0.2641	0.8000	0.0000	0.1848
	8	0.2833	0.4115	0.2237	0.0632	0.2677	0.8261	0.0000	0.1856
	16	0.2884	0.4136	0.2282	0.0599	0.2699	0.7917	0.0000	0.1887

Table C.5: nb-enron-GM1-ALL-ALL-75

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.2451	0.2451	0.2450	0.0000	0.0488	0.8674	0.0000	0.1402
	1	0.1840	0.1841	0.1839	0.0001	0.1938	0.6728	0.0000	0.1576
	2	0.1898	0.1901	0.1893	0.0003	0.1971	0.6773	0.0000	0.1591
	4	0.1955	0.1956	0.1955	0.0001	0.2016	0.6844	0.0000	0.1604
	8	0.1990	0.1991	0.1989	0.0001	0.2034	0.6986	0.0000	0.1616
	16	0.2024	0.2028	0.2018	0.0004	0.2055	0.6926	0.0000	0.1627

Table C.6: nb-enron-GM1-ALL-ALL-150

GM2									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.8061	0.9337	0.5185	0.0740	0.5732	0.9781	0.0000	0.3272
	1	0.6536	0.8763	0.2766	0.1482	0.5529	0.9529	0.0000	0.2414
	2	0.7111	0.9132	0.3035	0.1071	0.5998	1.0000	0.0000	0.2359
	4	0.7320	0.8899	0.4797	0.0958	0.6136	0.9656	0.0000	0.2288
	8	0.7961	0.9224	0.5879	0.0753	0.6670	0.9755	0.0000	0.2165
	16	0.8158	0.9489	0.5926	0.0732	0.6752	0.9759	0.0000	0.2286

Table C.7: nb-enron-GM2-ALL-ALL-5

GM2									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.7209	0.9024	0.5381	0.0843	0.4862	0.9710	0.0000	0.3227
	1	0.5399	0.7902	0.2541	0.1209	0.4571	0.8932	0.0000	0.2309
	2	0.5847	0.7330	0.3271	0.0972	0.4919	0.9655	0.0000	0.2301
	4	0.6218	0.8022	0.4823	0.0733	0.5176	0.9241	0.0000	0.2273
	8	0.7130	0.8440	0.5489	0.0735	0.5794	0.9410	0.0000	0.2168
	16	0.7401	0.8961	0.5735	0.0780	0.5951	0.9759	0.0000	0.2308

Table C.8: nb-enron-GM2-ALL-ALL-10

GM2									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.6083	0.7145	0.4523	0.0791	0.3700	0.9737	0.0000	0.2992
	1	0.4166	0.5881	0.2742	0.0901	0.3675	0.8975	0.0000	0.2180
	2	0.4604	0.6078	0.3110	0.0756	0.3983	0.9231	0.0000	0.2158
	4	0.5015	0.5873	0.4101	0.0446	0.4157	0.9188	0.0000	0.2200
	8	0.6042	0.7139	0.5254	0.0555	0.4851	0.9257	0.0000	0.2108
	16	0.6469	0.7904	0.5391	0.0804	0.5119	0.9867	0.0000	0.2294

Table C.9: nb-enron-GM2-ALL-ALL-25

GM2									
		Accuracy				F-Score			
Group Size	Web1T %	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.5414	0.5970	0.4515	0.0438	0.3014	0.9296	0.0000	0.2763
	1	0.3448	0.4884	0.2742	0.0729	0.3118	0.8958	0.0000	0.2072
	2	0.3831	0.5023	0.3151	0.0632	0.3371	0.8347	0.0000	0.2062
	4	0.4259	0.4894	0.3918	0.0335	0.3585	0.8974	0.0000	0.2119
	8	0.5386	0.5911	0.4971	0.0315	0.4249	0.8941	0.0000	0.2059
	16	0.5891	0.6972	0.4888	0.0593	0.4577	0.9589	0.0000	0.2284

Table C.10: nb-enron-GM2-ALL-ALL-50

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.5056	0.5296	0.4925	0.0127	0.2486	0.8921	0.0000	0.2603
	1	0.2896	0.4085	0.2295	0.0576	0.2701	0.8282	0.0000	0.1918
	2	0.3286	0.4265	0.2711	0.0521	0.3018	0.8235	0.0000	0.1963
	4	0.3762	0.4361	0.3264	0.0411	0.3246	0.8706	0.0000	0.2057
	8	0.5018	0.5650	0.4625	0.0392	0.3901	0.8737	0.0000	0.2020
	16	0.5547	0.6703	0.4654	0.0744	0.4239	0.9144	0.0000	0.2307

Table C.11: nb-enron-GM2-ALL-ALL-75

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.4536	0.4537	0.4535	0.0001	0.1706	0.8573	0.0000	0.2302
	1	0.2164	0.2164	0.2163	0.0000	0.2159	0.6874	0.0000	0.1776
	2	0.2598	0.2601	0.2593	0.0004	0.2403	0.7682	0.0000	0.1823
	4	0.3096	0.3097	0.3095	0.0001	0.2659	0.8385	0.0000	0.1969
	8	0.4547	0.4552	0.4539	0.0006	0.3333	0.8334	0.0000	0.2012
	16	0.5061	0.5063	0.5058	0.0002	0.3734	0.8657	0.0000	0.2351

Table C.12: nb-enron-GM2-ALL-ALL-150

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.7379	0.9618	0.4180	0.1274	0.5485	0.9870	0.0000	0.2951
	1	0.7817	0.9380	0.5353	0.0824	0.6598	0.9693	0.0000	0.2188
	2	0.8104	0.9554	0.6325	0.0755	0.6798	1.0000	0.0000	0.2241
	4	0.8206	0.9436	0.6265	0.0684	0.6644	0.9698	0.0000	0.2503
	8	0.8064	0.9372	0.6265	0.0717	0.6376	0.9718	0.0000	0.2640
	16	0.7980	0.9380	0.6325	0.0661	0.6032	0.9676	0.0000	0.2833

Table C.13: nb-enron-GM5-ALL-ALL-5

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.6803	0.9091	0.3708	0.1247	0.4987	0.9870	0.0000	0.2958
	1	0.6890	0.8903	0.5165	0.0795	0.5668	0.9505	0.0000	0.2148
	2	0.7274	0.8888	0.5714	0.0818	0.5972	0.9466	0.0000	0.2218
	4	0.7367	0.8857	0.5526	0.0816	0.5871	0.9444	0.0000	0.2447
	8	0.7169	0.8473	0.5485	0.0822	0.5357	0.9737	0.0000	0.2631
	16	0.6991	0.8389	0.4791	0.0845	0.5001	0.9867	0.0000	0.2822

Table C.14: nb-enron-GM5-ALL-ALL-10

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.6081	0.7309	0.4074	0.1104	0.4596	0.9744	0.0000	0.2962
	1	0.5847	0.7185	0.5079	0.0608	0.4678	0.9268	0.0000	0.2132
	2	0.6358	0.7188	0.5047	0.0590	0.5079	0.9620	0.0000	0.2145
	4	0.6445	0.7459	0.4969	0.0651	0.4997	0.9444	0.0000	0.2432
	8	0.5994	0.7127	0.5000	0.0450	0.4316	0.9867	0.0000	0.2539
	16	0.5644	0.6254	0.4921	0.0331	0.3775	0.9730	0.0000	0.2620

Table C.15: nb-enron-GM5-ALL-ALL-25

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.5742	0.6977	0.3783	0.0964	0.4284	0.9600	0.0000	0.3010
	1	0.5103	0.5454	0.4597	0.0311	0.4061	0.9136	0.0000	0.2113
	2	0.5726	0.6422	0.4907	0.0445	0.4482	0.9067	0.0000	0.2148
	4	0.5775	0.6355	0.4732	0.0590	0.4415	0.8986	0.0000	0.2432
	8	0.5142	0.5991	0.3952	0.0546	0.3477	0.9045	0.0000	0.2448
	16	0.4650	0.5206	0.3570	0.0466	0.2839	0.9072	0.0000	0.2414

Table C.16: nb-enron-GM5-ALL-ALL-50

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.5646	0.6346	0.3780	0.0866	0.4135	0.9444	0.0000	0.3021
	1	0.4722	0.5150	0.4403	0.0244	0.3675	0.8622	0.0000	0.2053
	2	0.5391	0.5894	0.4776	0.0370	0.4175	0.8857	0.0000	0.2106
	4	0.5539	0.5833	0.4791	0.0360	0.4111	0.8831	0.0000	0.2429
	8	0.4791	0.5279	0.4349	0.0306	0.3050	0.9046	0.0000	0.2378
	16	0.4316	0.4690	0.3988	0.0246	0.2359	0.8950	0.0000	0.2281

Table C.17: nb-enron-GM5-ALL-ALL-75

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.5659	0.5661	0.5657	0.0002	0.3826	0.9085	0.0000	0.3068
	1	0.4139	0.4141	0.4137	0.0002	0.3098	0.8095	0.0000	0.1997
	2	0.4941	0.4945	0.4938	0.0003	0.3648	0.8586	0.0000	0.2071
	4	0.5126	0.5127	0.5125	0.0001	0.3545	0.8444	0.0000	0.2491
	8	0.4287	0.4287	0.4285	0.0001	0.2321	0.8650	0.0000	0.2195
	16	0.2613	0.3703	0.0433	0.1542	0.1063	0.8920	0.0000	0.1732

Table C.18: nb-enron-GM5-ALL-ALL-150

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.7882	0.9709	0.5772	0.0823	0.5680	0.9852	0.0000	0.3232
	1	0.8167	0.9561	0.4360	0.1118	0.6987	0.9776	0.0000	0.2271
	2	0.8314	0.9669	0.4790	0.1051	0.7097	0.9833	0.0000	0.2332
	4	0.8629	0.9522	0.5556	0.0727	0.7273	0.9823	0.0000	0.2303
	8	0.8601	0.9782	0.5556	0.0716	0.7232	0.9889	0.0000	0.2342
	16	0.8589	0.9674	0.5556	0.0755	0.7174	1.0000	0.0000	0.2428

Table C.19: nb-enron-GB3-ALL-ALL-5

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.7057	0.8951	0.5319	0.0855	0.4602	0.9610	0.0000	0.3217
	1	0.7586	0.8962	0.5359	0.1064	0.6283	0.9579	0.0000	0.2354
	2	0.7729	0.9138	0.5161	0.1115	0.6415	0.9724	0.0000	0.2406
	4	0.8070	0.9251	0.5532	0.0816	0.6616	0.9688	0.0000	0.2407
	8	0.8074	0.9456	0.5638	0.0816	0.6570	1.0000	0.0000	0.2453
	16	0.8091	0.9198	0.5426	0.0873	0.6539	0.9744	0.0000	0.2535

Table C.20: nb-enron-GB3-ALL-ALL-10

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.5999	0.7052	0.4270	0.0712	0.3626	0.9600	0.0000	0.2942
	1	0.6887	0.8258	0.5542	0.0827	0.5541	0.9561	0.0000	0.2343
	2	0.7102	0.8493	0.5610	0.0850	0.5667	0.9620	0.0000	0.2413
	4	0.7520	0.8607	0.5501	0.0854	0.5903	0.9620	0.0000	0.2444
	8	0.7436	0.8614	0.5528	0.0834	0.5875	0.9690	0.0000	0.2452
	16	0.7557	0.8677	0.5556	0.0898	0.5906	0.9620	0.0000	0.2545

Table C.21: nb-enron-GB3-ALL-ALL-25

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.5059	0.5463	0.4256	0.0386	0.2735	0.9444	0.0000	0.2672
	1	0.6391	0.7451	0.5289	0.0627	0.5008	0.9394	0.0000	0.2375
	2	0.6740	0.7769	0.5262	0.0732	0.5194	0.9620	0.0000	0.2443
	4	0.7097	0.8163	0.5340	0.0834	0.5407	0.9539	0.0000	0.2486
	8	0.7083	0.7993	0.5255	0.0840	0.5406	0.9650	0.0000	0.2482
	16	0.7185	0.8277	0.5201	0.0886	0.5469	0.9744	0.0000	0.2574

Table C.22: nb-enron-GB3-ALL-ALL-50

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.4721	0.4962	0.4403	0.0198	0.2291	0.8811	0.0000	0.2484
	1	0.6188	0.7176	0.5323	0.0608	0.4748	0.9209	0.0000	0.2367
	2	0.6573	0.7352	0.5324	0.0684	0.4933	0.9308	0.0000	0.2453
	4	0.6932	0.7345	0.5359	0.0707	0.5118	0.9385	0.0000	0.2529
	8	0.6952	0.7491	0.5359	0.0725	0.5148	0.9615	0.0000	0.2520
	16	0.7075	0.7559	0.5311	0.0793	0.5192	0.9500	0.0000	0.2610

Table C.23: nb-enron-GB3-ALL-ALL-75

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.4282	0.4284	0.4279	0.0002	0.1611	0.8550	0.0000	0.2175
	1	0.5976	0.5978	0.5971	0.0004	0.4265	0.8973	0.0000	0.2451
	2	0.6499	0.6499	0.6499	0.0000	0.4496	0.9190	0.0000	0.2533
	4	0.6860	0.6862	0.6859	0.0001	0.4648	0.9348	0.0000	0.2606
	8	0.6889	0.6891	0.6885	0.0003	0.4701	0.9593	0.0000	0.2600
	16	0.7056	0.7059	0.7052	0.0003	0.4750	0.9287	0.0000	0.2688

Table C.24: nb-enron-GB3-ALL-ALL-150

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.8527	0.9592	0.5185	0.0752	0.6957	1.0000	0.0000	0.2611
	1	0.8648	0.9574	0.5556	0.0741	0.7266	1.0000	0.0000	0.2416
	2	0.8642	0.9575	0.5556	0.0736	0.7269	0.9870	0.0000	0.2424
	4	0.8678	0.9587	0.5556	0.0712	0.7238	0.9870	0.0000	0.2446
	8	0.8638	0.9714	0.5556	0.0728	0.7260	1.0000	0.0000	0.2407
	16	0.8653	0.9823	0.5556	0.0732	0.7261	1.0000	0.0000	0.2417

Table C.25: nb-enron-OSB3-ALL-ALL-5

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.7967	0.9336	0.5532	0.0802	0.6298	1.0000	0.0000	0.2738
	1	0.8161	0.9317	0.5213	0.0818	0.6584	0.9744	0.0000	0.2605
	2	0.8180	0.9272	0.5213	0.0844	0.6596	0.9731	0.0000	0.2606
	4	0.8177	0.9307	0.5213	0.0832	0.6618	0.9685	0.0000	0.2586
	8	0.8195	0.9332	0.5213	0.0841	0.6623	0.9744	0.0000	0.2606
	16	0.8186	0.9318	0.5213	0.0830	0.6590	0.9870	0.0000	0.2615

Table C.26: nb-enron-OSB3-ALL-ALL-10

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.7263	0.8437	0.5711	0.0810	0.5621	1.0000	0.0000	0.2761
	1	0.7586	0.8489	0.5514	0.0850	0.5931	0.9870	0.0000	0.2674
	2	0.7635	0.8600	0.5514	0.0856	0.5964	0.9744	0.0000	0.2664
	4	0.7621	0.8551	0.5514	0.0858	0.5947	0.9744	0.0000	0.2644
	8	0.7613	0.8618	0.5556	0.0853	0.5951	0.9744	0.0000	0.2659

Table C.27: nb-enron-OSB3-ALL-ALL-25

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.6818	0.7570	0.5190	0.0722	0.5105	1.0000	0.0000	0.2815
	1	0.4880	0.6819	0.3615	0.1021	0.3943	0.9744	0.0000	0.2598
	2	0.4123	0.5087	0.3526	0.0473	0.3243	0.9730	0.0000	0.2273
	4	0.7216	0.7899	0.5197	0.0866	0.5483	0.9744	0.0000	0.2701

Table C.28: nb-enron-OSB3-ALL-ALL-50

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.6713	0.7004	0.5504	0.0542	0.4870	1.0000	0.0000	0.2883
	1	0.7074	0.7478	0.5376	0.0762	0.5221	0.9287	0.0000	0.2748
	2	0.7112	0.7531	0.5390	0.0771	0.5218	0.9341	0.0000	0.2757
	4	0.7089	0.7621	0.5393	0.0773	0.5199	0.9352	0.0000	0.2757
	8	0.7079	0.7860	0.5389	0.0829	0.5230	0.9290	0.0000	0.2750

Table C.29: nb-enron-OSB3-ALL-ALL-75

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.6572	0.6574	0.6571	0.0002	0.4441	0.9867	0.0000	0.3023
	1	0.7041	0.7042	0.7040	0.0001	0.4789	0.9127	0.0000	0.2855
	2	0.7091	0.7092	0.7089	0.0001	0.4787	0.9146	0.0000	0.2875
	4	0.7068	0.7071	0.7066	0.0003	0.4769	0.9189	0.0000	0.2874
	8	0.7101	0.7101	0.7100	0.0001	0.4778	0.9151	0.0000	0.2878

Table C.30: nb-enron-OSB3-ALL-ALL-150

APPENDIX D:
Naive Bayes Accuracy and F-Score Results for the Twitter Short Message Corpus

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.6264	0.7714	0.4580	0.0794	0.5886	0.9618	0.0000	0.1854
	1	0.4974	0.7500	0.1965	0.1176	0.4734	0.9421	0.0000	0.1630
	2	0.5130	0.8101	0.2785	0.1138	0.4936	0.9463	0.0615	0.1538
	4	0.5132	0.7749	0.2637	0.1029	0.4914	0.9518	0.1190	0.1537
	8	0.5238	0.7913	0.2861	0.1088	0.5019	0.9562	0.1311	0.1531
	16	0.5102	0.7778	0.2885	0.1105	0.4904	0.9501	0.1649	0.1509

Table D.1: nb-twitter-GM1-ALL-ALL-5

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.4869	0.6411	0.2738	0.0831	0.4345	0.9282	0.0000	0.2191
	1	0.3490	0.5598	0.1297	0.1163	0.3227	0.9152	0.0000	0.1697
	2	0.3671	0.6005	0.1623	0.1142	0.3407	0.9209	0.0000	0.1662
	4	0.3693	0.5990	0.1997	0.1045	0.3437	0.9151	0.0274	0.1600
	8	0.3755	0.5902	0.1692	0.1023	0.3498	0.9002	0.0000	0.1644
	16	0.3642	0.5588	0.1639	0.1141	0.3398	0.8667	0.0000	0.1616

Table D.2: nb-twitter-GM1-ALL-ALL-10

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.3357	0.4389	0.2200	0.0642	0.2848	0.8560	0.0000	0.2063
	1	0.2260	0.3653	0.0731	0.0991	0.2007	0.8185	0.0000	0.1561
	2	0.2299	0.3574	0.0817	0.0963	0.2042	0.8385	0.0000	0.1556
	4	0.2332	0.3539	0.0956	0.0918	0.2088	0.8615	0.0000	0.1559
	8	0.2398	0.3882	0.0848	0.0934	0.2132	0.8615	0.0000	0.1571
	16	0.2304	0.3517	0.0733	0.0965	0.2023	0.8803	0.0000	0.1535

Table D.3: nb-twitter-GM1-ALL-ALL-25

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.2326	0.3191	0.1395	0.0509	0.1920	0.8426	0.0000	0.1850
	1	0.1595	0.2449	0.0387	0.0799	0.1323	0.8116	0.0000	0.1393
	2	0.1631	0.2501	0.0460	0.0790	0.1366	0.8615	0.0000	0.1368
	4	0.1653	0.2507	0.0556	0.0779	0.1404	0.8000	0.0000	0.1355
	8	0.1671	0.2522	0.0504	0.0757	0.1418	0.8750	0.0000	0.1409
	16	0.1638	0.2436	0.0486	0.0807	0.1387	0.8485	0.0000	0.1426

Table D.4: nb-twitter-GM1-ALL-ALL-50

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.1820	0.2356	0.1399	0.0310	0.1439	0.7876	0.0000	0.1695
	1	0.1328	0.2014	0.0254	0.0707	0.1070	0.7324	0.0000	0.1289
	2	0.1364	0.2167	0.0303	0.0723	0.1115	0.8000	0.0000	0.1310
	4	0.1370	0.2184	0.0400	0.0691	0.1132	0.7941	0.0000	0.1283
	8	0.1390	0.2275	0.0404	0.0698	0.1156	0.7617	0.0000	0.1309
	16	0.1360	0.2114	0.0315	0.0731	0.1109	0.7680	0.0000	0.1268

Table D.5: nb-twitter-GM1-ALL-ALL-75

GM1									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.1252	0.1254	0.1247	0.0003	0.0855	0.7565	0.0000	0.1448
	1	0.0982	0.1353	0.0239	0.0525	0.0745	0.7500	0.0000	0.1112
	2	0.0979	0.1344	0.0248	0.0517	0.0738	0.7027	0.0000	0.1102
	4	0.0975	0.1351	0.0231	0.0526	0.0760	0.7324	0.0000	0.1091
	8	0.0986	0.1350	0.0274	0.0504	0.0754	0.7123	0.0000	0.1101
	16	0.0983	0.1386	0.0200	0.0554	0.0758	0.6923	0.0000	0.1095

Table D.6: nb-twitter-GM1-ALL-ALL-150

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.5711	0.7890	0.3875	0.0853	0.5299	0.9486	0.0000	0.1822
	1	0.5253	0.7643	0.2871	0.1167	0.5135	0.9250	0.1667	0.1530
	2	0.5301	0.7467	0.3114	0.1090	0.5175	0.9328	0.1284	0.1495
	4	0.5401	0.7926	0.3519	0.0979	0.5259	0.9237	0.1522	0.1468
	8	0.5459	0.7992	0.2906	0.1085	0.5313	0.9457	0.1944	0.1512
	16	0.5409	0.8437	0.2975	0.1141	0.5249	0.9560	0.1481	0.1537

Table D.7: nb-twitter-GM2-ALL-ALL-5

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.4439	0.6304	0.2809	0.0749	0.4032	0.8824	0.0000	0.1885
	1	0.3847	0.5960	0.1816	0.1107	0.3716	0.8974	0.0377	0.1667
	2	0.3914	0.5446	0.1842	0.1064	0.3781	0.8988	0.0519	0.1705
	4	0.4018	0.6610	0.2146	0.1041	0.3879	0.8947	0.0588	0.1657
	8	0.4046	0.6051	0.1764	0.1088	0.3866	0.9231	0.0250	0.1688
	16	0.4031	0.6179	0.1855	0.1147	0.3832	0.9170	0.0357	0.1759

Table D.8: nb-twitter-GM2-ALL-ALL-10

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.3215	0.3855	0.2617	0.0382	0.2821	0.8462	0.0000	0.1846
	1	0.2508	0.4249	0.0872	0.1062	0.2406	0.8755	0.0000	0.1721
	2	0.2510	0.3846	0.0963	0.1036	0.2406	0.8745	0.0000	0.1694
	4	0.2686	0.4173	0.1121	0.0960	0.2559	0.8364	0.0000	0.1681
	8	0.2768	0.4602	0.1198	0.1051	0.2597	0.8681	0.0000	0.1714
	16	0.2703	0.4437	0.1105	0.1007	0.2545	0.8619	0.0000	0.1747

Table D.9: nb-twitter-GM2-ALL-ALL-25

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.2509	0.2992	0.2038	0.0282	0.2175	0.8438	0.0000	0.1705
	1	0.1854	0.3044	0.0507	0.0938	0.1758	0.8288	0.0000	0.1584
	2	0.1843	0.2660	0.0413	0.0909	0.1743	0.8300	0.0000	0.1629
	4	0.1980	0.3055	0.0578	0.0901	0.1844	0.8037	0.0000	0.1614
	8	0.2058	0.2880	0.0771	0.0883	0.1919	0.8362	0.0000	0.1619
	16	0.2023	0.3031	0.0786	0.0892	0.1891	0.8438	0.0000	0.1662

Table D.10: nb-twitter-GM2-ALL-ALL-50

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.2162	0.2621	0.1630	0.0338	0.1846	0.7879	0.0000	0.1622
	1	0.1518	0.2358	0.0368	0.0823	0.1431	0.8036	0.0000	0.1514
	2	0.1535	0.2255	0.0328	0.0831	0.1448	0.8293	0.0000	0.1501
	4	0.1666	0.2477	0.0477	0.0835	0.1550	0.8073	0.0000	0.1516
	8	0.1770	0.2535	0.0578	0.0825	0.1648	0.8106	0.0000	0.1596
	16	0.1700	0.2579	0.0573	0.0808	0.1573	0.8571	0.0000	0.1580

Table D.11: nb-twitter-GM2-ALL-ALL-75

GM2									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.1709	0.1719	0.1690	0.0013	0.1379	0.7619	0.0000	0.1484
	1	0.1155	0.1655	0.0190	0.0683	0.1074	0.7593	0.0000	0.1354
	2	0.1173	0.1659	0.0206	0.0684	0.1104	0.7967	0.0000	0.1397
	4	0.1282	0.1789	0.0276	0.0712	0.1169	0.7477	0.0000	0.1385
	8	0.1331	0.1819	0.0363	0.0684	0.1236	0.7414	0.0000	0.1437
	16	0.1290	0.1760	0.0357	0.0660	0.1169	0.7519	0.0000	0.1425

Table D.12: nb-twitter-GM2-ALL-ALL-150

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.3453	0.5293	0.2431	0.0531	0.2306	0.7931	0.0000	0.1930
	1	0.5530	0.7495	0.4066	0.0794	0.5324	0.9106	0.1096	0.1415
	2	0.5523	0.7220	0.4000	0.0789	0.5279	0.9231	0.1212	0.1530
	4	0.5516	0.7077	0.3814	0.0714	0.5223	0.9052	0.0426	0.1564
	8	0.5550	0.7094	0.3968	0.0687	0.5262	0.9254	0.0779	0.1559
	16	0.5579	0.7680	0.4106	0.0777	0.5299	0.9245	0.0571	0.1643

Table D.13: nb-twitter-GM5-ALL-ALL-5

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.2408	0.3357	0.1748	0.0354	0.1711	0.8136	0.0000	0.1595
	1	0.4222	0.5466	0.3065	0.0630	0.3994	0.8571	0.0556	0.1545
	2	0.4187	0.5806	0.3035	0.0642	0.3954	0.8889	0.0267	0.1652
	4	0.4191	0.5954	0.3069	0.0590	0.3913	0.8618	0.0286	0.1711
	8	0.4209	0.5239	0.3269	0.0506	0.3953	0.8750	0.0303	0.1673
	16	0.4319	0.5606	0.3228	0.0590	0.4062	0.8932	0.0267	0.1710

Table D.14: nb-twitter-GM5-ALL-ALL-10

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.1543	0.2141	0.1224	0.0232	0.1288	0.7931	0.0000	0.1443
	1	0.2990	0.3613	0.2514	0.0302	0.2770	0.8190	0.0000	0.1613
	2	0.2923	0.3493	0.2405	0.0324	0.2728	0.8710	0.0000	0.1661
	4	0.2935	0.3300	0.2133	0.0306	0.2689	0.8750	0.0000	0.1720
	8	0.2929	0.3552	0.2278	0.0293	0.2722	0.8438	0.0000	0.1707
	16	0.2973	0.3765	0.2032	0.0395	0.2768	0.8615	0.0000	0.1740

Table D.15: nb-twitter-GM5-ALL-ALL-25

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.1226	0.1558	0.0999	0.0157	0.1079	0.7719	0.0000	0.1390
	1	0.2277	0.2534	0.1808	0.0276	0.2096	0.7961	0.0000	0.1528
	2	0.2252	0.2637	0.1996	0.0205	0.2084	0.8000	0.0000	0.1630
	4	0.2216	0.2441	0.1770	0.0182	0.2031	0.8254	0.0000	0.1658
	8	0.2217	0.2573	0.1871	0.0212	0.2033	0.8224	0.0000	0.1637
	16	0.2245	0.2608	0.1540	0.0308	0.2059	0.8710	0.0000	0.1644

Table D.16: nb-twitter-GM5-ALL-ALL-50

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.0977	0.1069	0.0836	0.0086	0.0908	0.7719	0.0000	0.1280
	1	0.1960	0.2111	0.1780	0.0121	0.1782	0.6739	0.0000	0.1457
	2	0.1952	0.2113	0.1803	0.0122	0.1767	0.8710	0.0000	0.1520
	4	0.1878	0.1984	0.1777	0.0069	0.1725	0.7937	0.0000	0.1565
	8	0.1902	0.1945	0.1861	0.0029	0.1729	0.8065	0.0000	0.1565
	16	0.1908	0.2060	0.1689	0.0135	0.1741	0.7937	0.0000	0.1585

Table D.17: nb-twitter-GM5-ALL-ALL-75

GM5									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.0787	0.0792	0.0784	0.0004	0.0754	0.6429	0.0000	0.1186
	1	0.1535	0.1542	0.1531	0.0005	0.1370	0.6392	0.0000	0.1359
	2	0.1524	0.1531	0.1520	0.0005	0.1360	0.7879	0.0000	0.1427
	4	0.1404	0.1414	0.1399	0.0007	0.1276	0.7500	0.0000	0.1459
	8	0.1401	0.1404	0.1399	0.0002	0.1267	0.7463	0.0000	0.1443
	16	0.1424	0.1430	0.1420	0.0005	0.1294	0.7813	0.0000	0.1465

Table D.18: nb-twitter-GM5-ALL-ALL-150

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.6179	0.8021	0.4745	0.0729	0.5813	0.9284	0.0392	0.1654
	1	0.6109	0.8125	0.4585	0.0734	0.5959	0.9480	0.2000	0.1296
	2	0.6160	0.7823	0.4606	0.0699	0.5986	0.9347	0.2340	0.1291
	4	0.6199	0.8546	0.4694	0.0819	0.6043	0.9613	0.2444	0.1330
	8	0.6187	0.8474	0.4669	0.0770	0.6040	0.9409	0.2222	0.1266
	16	0.6265	0.8216	0.4648	0.0773	0.6098	0.9512	0.2154	0.1322

Table D.19: nb-twitter-GB3-ALL-ALL-5

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.4948	0.6108	0.3477	0.0607	0.4543	0.9091	0.0000	0.1799
	1	0.4975	0.6356	0.3297	0.0644	0.4760	0.9002	0.1190	0.1515
	2	0.5015	0.7366	0.3748	0.0712	0.4809	0.9289	0.1075	0.1444
	4	0.5011	0.6671	0.3665	0.0723	0.4801	0.9102	0.0741	0.1521
	8	0.4999	0.6359	0.3732	0.0716	0.4801	0.9197	0.0952	0.1489
	16	0.5041	0.6385	0.3876	0.0636	0.4838	0.8986	0.0909	0.1465

Table D.20: nb-twitter-GB3-ALL-ALL-10

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.3584	0.4401	0.2988	0.0397	0.3164	0.8696	0.0000	0.1861
	1	0.3724	0.4429	0.3147	0.0367	0.3490	0.8824	0.0202	0.1557
	2	0.3760	0.4394	0.3271	0.0352	0.3530	0.8155	0.0227	0.1507
	4	0.3773	0.4834	0.3207	0.0466	0.3539	0.8504	0.0227	0.1554
	8	0.3733	0.4633	0.3186	0.0447	0.3528	0.8355	0.0244	0.1524
	16	0.3838	0.4431	0.2890	0.0417	0.3600	0.8649	0.0270	0.1619

Table D.21: nb-twitter-GB3-ALL-ALL-25

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.2839	0.3292	0.2411	0.0265	0.2457	0.8955	0.0000	0.1769
	1	0.2984	0.3356	0.2686	0.0234	0.2746	0.8219	0.0000	0.1569
	2	0.3019	0.3366	0.2770	0.0222	0.2778	0.7529	0.0000	0.1500
	4	0.3044	0.3376	0.2728	0.0237	0.2803	0.7895	0.0000	0.1540
	8	0.3038	0.3409	0.2618	0.0312	0.2805	0.8067	0.0000	0.1536
	16	0.3100	0.3411	0.2813	0.0236	0.2858	0.8696	0.0000	0.1595

Table D.22: nb-twitter-GB3-ALL-ALL-50

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.2484	0.2862	0.2169	0.0247	0.2120	0.8615	0.0000	0.1667
	1	0.2648	0.3021	0.2254	0.0309	0.2414	0.8000	0.0000	0.1551
	2	0.2668	0.3023	0.2297	0.0295	0.2423	0.7333	0.0000	0.1481
	4	0.2667	0.3128	0.2263	0.0300	0.2433	0.7368	0.0000	0.1541
	8	0.2657	0.2990	0.2368	0.0235	0.2434	0.7478	0.0171	0.1481
	16	0.2748	0.3096	0.2389	0.0259	0.2512	0.8116	0.0000	0.1578

Table D.23: nb-twitter-GB3-ALL-ALL-75

GB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.1988	0.1995	0.1973	0.0011	0.1613	0.7879	0.0000	0.1550
	1	0.2152	0.2154	0.2148	0.0003	0.1910	0.7105	0.0000	0.1454
	2	0.2190	0.2191	0.2186	0.0002	0.1945	0.6458	0.0000	0.1397
	4	0.2197	0.2200	0.2190	0.0005	0.1954	0.6914	0.0000	0.1450
	8	0.2180	0.2187	0.2176	0.0006	0.1942	0.7000	0.0000	0.1418
	16	0.2221	0.2233	0.2216	0.0008	0.1976	0.7297	0.0000	0.1476

Table D.24: nb-twitter-GB3-ALL-ALL-150

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	0.6475	0.8164	0.4983	0.0673	0.6308	0.9254	0.1481	0.1296
	1	0.5628	0.8293	0.3913	0.0878	0.5296	0.9419	0.0597	0.1640
	2	0.5687	0.7734	0.3836	0.0833	0.5328	0.9243	0.0597	0.1675
	4	0.5627	0.7768	0.3836	0.0856	0.5292	0.9419	0.0597	0.1656
	8	0.5626	0.7790	0.3429	0.0915	0.5272	0.9419	0.0597	0.1677
	16	0.5587	0.7479	0.3857	0.0802	0.5251	0.9458	0.0351	0.1636

Table D.25: nb-twitter-OSB3-ALL-ALL-5

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	0.5271	0.6410	0.4333	0.0545	0.5077	0.9069	0.0988	0.1454
	1	0.4387	0.6071	0.3160	0.0682	0.3977	0.9122	0.0000	0.1724
	2	0.4420	0.5840	0.2883	0.0688	0.4002	0.9098	0.0000	0.1752
	4	0.4403	0.6238	0.2876	0.0767	0.3971	0.9228	0.0000	0.1777
	8	0.4410	0.5966	0.2853	0.0690	0.3983	0.9228	0.0000	0.1771
	16	0.4425	0.5954	0.3245	0.0614	0.3991	0.9265	0.0000	0.1757

Table D.26: nb-twitter-OSB3-ALL-ALL-10

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	0.3979	0.4848	0.3207	0.0464	0.3752	0.8824	0.0000	0.1648
	1	0.3206	0.4237	0.2419	0.0407	0.2744	0.8341	0.0000	0.1689
	2	0.3223	0.3951	0.2704	0.0365	0.2776	0.8386	0.0000	0.1695
	4	0.3228	0.3814	0.2773	0.0359	0.2759	0.8571	0.0000	0.1679
	8	0.3249	0.3937	0.2570	0.0369	0.2814	0.8389	0.0000	0.1682
	16	0.3229	0.4016	0.2749	0.0351	0.2785	0.8629	0.0000	0.1698

Table D.27: nb-twitter-OSB3-ALL-ALL-25

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	0.3233	0.3739	0.2838	0.0259	0.3004	0.7895	0.0000	0.1641
	1	0.2535	0.2797	0.2254	0.0177	0.2115	0.7556	0.0000	0.1573
	2	0.2538	0.2810	0.2332	0.0177	0.2114	0.7712	0.0000	0.1569
	4	0.2548	0.2819	0.2296	0.0181	0.2126	0.7511	0.0000	0.1594
	8	0.2561	0.2831	0.2305	0.0200	0.2144	0.7585	0.0000	0.1587
	16	0.2564	0.2913	0.2300	0.0216	0.2136	0.7609	0.0000	0.1594

Table D.28: nb-twitter-OSB3-ALL-ALL-50

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	0.2861	0.3048	0.2582	0.0180	0.2634	0.7945	0.0000	0.1605
	1	0.2212	0.2444	0.1972	0.0198	0.1818	0.7364	0.0000	0.1513
	2	0.2242	0.2654	0.1806	0.0267	0.1840	0.8051	0.0000	0.1513
	4	0.2237	0.2615	0.1851	0.0269	0.1851	0.7229	0.0000	0.1512
	8	0.2219	0.2611	0.1870	0.0237	0.1831	0.7077	0.0000	0.1500
	16	0.2228	0.2482	0.1973	0.0209	0.1838	0.7360	0.0000	0.1515

Table D.29: nb-twitter-OSB3-ALL-ALL-75

OSB3									
Group Size	Web1T %	Accuracy				F-Score			
		AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	0.2332	0.2337	0.2320	0.0008	0.2104	0.7778	0.0000	0.1561
	1	0.1775	0.1776	0.1773	0.0001	0.1402	0.6337	0.0000	0.1314
	2	0.1791	0.1792	0.1790	0.0001	0.1422	0.6250	0.0000	0.1322
	4	0.1786	0.1788	0.1784	0.0002	0.1412	0.6244	0.0000	0.1329
	8	0.1795	0.1810	0.1787	0.0011	0.1422	0.6570	0.0000	0.1328
	16	0.1789	0.1797	0.1785	0.0006	0.1411	0.6540	0.0000	0.1329

Table D.30: nb-twitter-OSB3-ALL-ALL-150

APPENDIX E: Grouped Results LibLinear Results for the ENRON Email Corpus

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.8581	0.9505	0.6630	0.0607	0.6718	0.9795	0.0000	0.2650
		SAL	0.8767	0.9531	0.7526	0.0517	0.6663	0.9842	0.0000	0.2625
		STL	0.7460	0.9246	0.4815	0.1113	0.7211	0.9653	0.0000	0.1841
	1	RAN	0.8475	0.9362	0.6603	0.0762	0.6682	0.9737	0.0000	0.2516
		SAL	0.8797	0.9578	0.7977	0.0363	0.6682	0.9826	0.0000	0.2670
		STL	0.7426	0.9332	0.4444	0.1129	0.7215	0.9712	0.0000	0.1845
	2	RAN	0.8400	0.9275	0.5742	0.0747	0.6716	0.9672	0.0000	0.2570
		SAL	0.8810	0.9570	0.8049	0.0337	0.6701	0.9819	0.0000	0.2621
		STL	0.7437	0.9291	0.4444	0.1080	0.7226	0.9692	0.0000	0.1817
	4	RAN	0.8639	0.9590	0.7444	0.0553	0.6833	0.9799	0.0000	0.2500
		SAL	0.8800	0.9582	0.7877	0.0365	0.6766	0.9821	0.0000	0.2535
		STL	0.7455	0.9314	0.4444	0.1089	0.7250	0.9676	0.0000	0.1807
	8	RAN	0.8656	0.9485	0.7321	0.0656	0.6705	0.9760	0.0000	0.2671
		SAL	0.8810	0.9570	0.7848	0.0347	0.6720	0.9819	0.0000	0.2592
		STL	0.7427	0.9237	0.4444	0.1087	0.7208	0.9651	0.0000	0.1829
	16	RAN	0.8550	0.9555	0.6913	0.0616	0.6795	0.9744	0.0000	0.2492
		SAL	0.8789	0.9732	0.7844	0.0369	0.6731	0.9878	0.0000	0.2536
		STL	0.7379	0.9269	0.4444	0.1127	0.7178	0.9668	0.0000	0.1827

Table E.1: grouped-liblinear-enron-GM1-ALL-ALL-5

GM1										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.8024	0.9312	0.6768	0.0655	0.5981	0.9778	0.0000	0.2636
		SAL	0.8227	0.9043	0.7375	0.0531	0.6038	0.9660	0.0000	0.2671
		STL	0.6582	0.8234	0.3776	0.1228	0.6346	0.9618	0.0000	0.2012
	1	RAN	0.8123	0.8862	0.7168	0.0572	0.6040	0.9699	0.0000	0.2686
		SAL	0.8209	0.8890	0.7641	0.0360	0.5922	0.9620	0.0000	0.2714
		STL	0.6499	0.8117	0.3878	0.1172	0.6282	0.9397	0.0000	0.1990
	2	RAN	0.7988	0.9068	0.6456	0.0668	0.5900	0.9660	0.0000	0.2655
		SAL	0.8246	0.8905	0.7788	0.0331	0.6025	0.9633	0.0000	0.2633
		STL	0.6547	0.8168	0.4388	0.1124	0.6353	0.9488	0.0000	0.1932
	4	RAN	0.8083	0.9086	0.6986	0.0481	0.6013	0.9692	0.0000	0.2674
		SAL	0.8221	0.8922	0.7372	0.0367	0.5968	0.9652	0.0000	0.2651
		STL	0.6502	0.8177	0.4388	0.1127	0.6299	0.9428	0.0000	0.1943
	8	RAN	0.8027	0.8736	0.6660	0.0616	0.6055	0.9678	0.0000	0.2555
		SAL	0.8182	0.9025	0.7224	0.0426	0.5966	0.9684	0.0000	0.2683
		STL	0.6525	0.8144	0.4388	0.1125	0.6319	0.9511	0.0000	0.1923
	16	RAN	0.8160	0.9187	0.7108	0.0618	0.6036	0.9698	0.0000	0.2591
		SAL	0.8231	0.9158	0.7345	0.0406	0.6039	0.9691	0.0000	0.2614
		STL	0.6473	0.8219	0.3878	0.1176	0.6273	0.9485	0.0000	0.2013

Table E.2: grouped-liblinear-enron-GM1-ALL-ALL-10

GM1										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.7373	0.8073	0.6803	0.0411	0.5176	0.9640	0.0000	0.2682
		SAL	0.7414	0.7815	0.7195	0.0219	0.5144	0.9546	0.0000	0.2664
		STL	0.5747	0.7400	0.4430	0.1079	0.5435	0.9337	0.0000	0.2273
	1	RAN	0.7300	0.8064	0.6522	0.0486	0.5081	0.9572	0.0000	0.2699
		SAL	0.7511	0.7905	0.7100	0.0280	0.5241	0.9551	0.0000	0.2654
		STL	0.5730	0.7486	0.4574	0.1109	0.5376	0.9347	0.0000	0.2323
	2	RAN	0.7442	0.8364	0.6904	0.0527	0.5211	0.9606	0.0000	0.2637
		SAL	0.7450	0.7880	0.7076	0.0280	0.5141	0.9645	0.0000	0.2666
		STL	0.5728	0.7472	0.4500	0.1120	0.5415	0.9427	0.0000	0.2285
	4	RAN	0.7306	0.7668	0.6556	0.0452	0.5175	0.9558	0.0000	0.2668
		SAL	0.7454	0.7836	0.7137	0.0219	0.5147	0.9496	0.0000	0.2689
		STL	0.5696	0.7409	0.4483	0.1095	0.5390	0.9388	0.0000	0.2277
	8	RAN	0.7383	0.8013	0.6680	0.0407	0.5254	0.9566	0.0000	0.2590
		SAL	0.7476	0.7933	0.7244	0.0245	0.5183	0.9565	0.0000	0.2656
		STL	0.5727	0.7454	0.4599	0.1051	0.5437	0.9441	0.0000	0.2264
	16	RAN	0.7364	0.7925	0.6755	0.0386	0.5113	0.9525	0.0000	0.2764
		SAL	0.7455	0.7776	0.7148	0.0232	0.5132	0.9568	0.0000	0.2719
		STL	0.5764	0.7487	0.4483	0.1090	0.5424	0.9388	0.0000	0.2344

Table E.3: grouped-liblinear-enron-GM1-ALL-ALL-25

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.6872	0.7476	0.6382	0.0454	0.4701	0.9509	0.0000	0.2677
		SAL	0.6889	0.7028	0.6648	0.0171	0.4733	0.9426	0.0000	0.2611
		STL	0.5472	0.6660	0.4341	0.0948	0.4966	0.9455	0.0000	0.2368
	1	RAN	0.6765	0.7280	0.5821	0.0669	0.4680	0.9486	0.0000	0.2701
		SAL	0.6918	0.7114	0.6621	0.0214	0.4689	0.9561	0.0000	0.2625
		STL	0.5408	0.6699	0.4234	0.1010	0.4870	0.9423	0.0000	0.2372
	2	RAN	0.6981	0.7214	0.6835	0.0167	0.4779	0.9475	0.0000	0.2691
		SAL	0.6834	0.6975	0.6662	0.0130	0.4600	0.9426	0.0000	0.2633
		STL	0.5443	0.6732	0.4287	0.1003	0.4912	0.9330	0.0000	0.2388
	4	RAN	0.6734	0.7052	0.6472	0.0240	0.4622	0.9395	0.0000	0.2671
		SAL	0.6928	0.7026	0.6810	0.0089	0.4727	0.9532	0.0000	0.2677
		STL	0.5407	0.6664	0.4327	0.0962	0.4904	0.9396	0.0000	0.2365
	8	RAN	0.6889	0.7127	0.6465	0.0301	0.4727	0.9511	0.0000	0.2694
		SAL	0.6921	0.7013	0.6753	0.0119	0.4700	0.9559	0.0000	0.2724
		STL	0.5447	0.6779	0.4376	0.0998	0.4911	0.9341	0.0000	0.2389
	16	RAN	0.6861	0.7524	0.6315	0.0500	0.4633	0.9416	0.0000	0.2699
		SAL	0.6920	0.7105	0.6715	0.0160	0.4732	0.9504	0.0000	0.2648
		STL	0.5530	0.6826	0.4406	0.0996	0.4948	0.9381	0.0000	0.2358

Table E.4: grouped-liblinear-enron-GM1-ALL-ALL-50

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.6490	0.6499	0.6482	0.0009	0.4426	0.9437	0.0000	0.2615
		SAL	0.6631	0.7024	0.6239	0.0393	0.4462	0.9388	0.0000	0.2682
		STL	0.5316	0.6478	0.4155	0.1162	0.4589	0.9217	0.0000	0.2459
	1	RAN	0.6585	0.6724	0.6446	0.0139	0.4423	0.9365	0.0000	0.2678
		SAL	0.6565	0.7011	0.6118	0.0447	0.4354	0.9394	0.0000	0.2714
		STL	0.5155	0.6430	0.3880	0.1275	0.4445	0.9453	0.0000	0.2500
	2	RAN	0.6511	0.6786	0.6237	0.0275	0.4416	0.9511	0.0000	0.2647
		SAL	0.6618	0.6858	0.6378	0.0240	0.4435	0.9286	0.0000	0.2644
		STL	0.5253	0.6511	0.3995	0.1258	0.4534	0.9104	0.0000	0.2454
	4	RAN	0.6570	0.6793	0.6347	0.0223	0.4415	0.9402	0.0000	0.2681
		SAL	0.6581	0.6814	0.6347	0.0234	0.4337	0.9281	0.0000	0.2662
		STL	0.5245	0.6484	0.4006	0.1239	0.4501	0.9380	0.0000	0.2476
	8	RAN	0.6445	0.6632	0.6259	0.0186	0.4324	0.9392	0.0000	0.2626
		SAL	0.6585	0.6836	0.6334	0.0251	0.4495	0.9275	0.0000	0.2627
		STL	0.5226	0.6378	0.4074	0.1152	0.4479	0.9339	0.0000	0.2462
	16	RAN	0.6553	0.6716	0.6391	0.0163	0.4339	0.9413	0.0000	0.2676
		SAL	0.6593	0.6655	0.6531	0.0062	0.4362	0.9401	0.0000	0.2647
		STL	0.5264	0.6497	0.4030	0.1233	0.4507	0.9156	0.0000	0.2452

Table E.5: grouped-liblinear-enron-GM1-ALL-ALL-75

GM1										
Group Size	Web1T %	Group Type	Accuracy AVG	Accuracy MAX	Accuracy MIN	Accuracy STDEV	F-Score AVG	F-Score MAX	F-Score MIN	F-Score STDEV
150	0	RAN	0.6033	0.6033	0.6033	0.0000	0.3951	0.9144	0.0000	0.2613
		SAL	0.6074	0.6074	0.6074	0.0000	0.4025	0.9316	0.0000	0.2607
		STL	0.6074	0.6074	0.6074	0.0000	0.4025	0.9316	0.0000	0.2607
	1	RAN	0.6155	0.6155	0.6155	0.0000	0.4059	0.9176	0.0000	0.2649
		SAL	0.5849	0.5849	0.5849	0.0000	0.3923	0.9402	0.0000	0.2691
		STL	0.5849	0.5849	0.5849	0.0000	0.3923	0.9402	0.0000	0.2691
	2	RAN	0.6049	0.6049	0.6049	0.0000	0.3968	0.9342	0.0000	0.2654
		SAL	0.5949	0.5949	0.5949	0.0000	0.3954	0.9389	0.0000	0.2686
		STL	0.5949	0.5949	0.5949	0.0000	0.3954	0.9389	0.0000	0.2686
	4	RAN	0.6065	0.6065	0.6065	0.0000	0.4026	0.9132	0.0000	0.2608
		SAL	0.6093	0.6093	0.6093	0.0000	0.4042	0.9488	0.0000	0.2656
		STL	0.6093	0.6093	0.6093	0.0000	0.4042	0.9488	0.0000	0.2656
	8	RAN	0.6008	0.6008	0.6008	0.0000	0.4015	0.9394	0.0000	0.2651
		SAL	0.5982	0.5982	0.5982	0.0000	0.4028	0.9451	0.0000	0.2632
		STL	0.5982	0.5982	0.5982	0.0000	0.4028	0.9451	0.0000	0.2632
	16	RAN	0.6011	0.6011	0.6011	0.0000	0.4038	0.9274	0.0000	0.2614
		SAL	0.5975	0.5975	0.5975	0.0000	0.3968	0.9489	0.0000	0.2689
		STL	0.5975	0.5975	0.5975	0.0000	0.3968	0.9489	0.0000	0.2689

Table E.6: grouped-liblinear-enron-GM1-ALL-ALL-150

GM2										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.8948	0.9753	0.7918	0.0485	0.7299	1.0000	0.0000	0.2440
		SAL	0.9091	0.9599	0.8276	0.0336	0.7160	0.9901	0.0000	0.2660
		STL	0.7782	0.9509	0.5185	0.1226	0.7467	0.9847	0.0000	0.2057
	1	RAN	0.8538	0.9413	0.6271	0.0733	0.6626	0.9781	0.0000	0.2548
		SAL	0.8745	0.9544	0.7669	0.0413	0.6615	0.9780	0.0000	0.2644
		STL	0.7294	0.9356	0.4444	0.1127	0.7042	0.9676	0.0000	0.1876
	2	RAN	0.8520	0.9448	0.7456	0.0570	0.6654	0.9771	0.0000	0.2605
		SAL	0.8758	0.9369	0.7792	0.0411	0.6651	0.9778	0.0000	0.2601
		STL	0.7300	0.9133	0.4444	0.1143	0.7041	0.9658	0.0000	0.1903
	4	RAN	0.8487	0.9560	0.7092	0.0660	0.6539	0.9834	0.0000	0.2618
		SAL	0.8775	0.9366	0.7835	0.0366	0.6662	0.9789	0.0000	0.2620
		STL	0.7298	0.9381	0.4444	0.1136	0.7041	0.9672	0.0000	0.1896
	8	RAN	0.8532	0.9547	0.7217	0.0652	0.6544	0.9817	0.0000	0.2670
		SAL	0.8783	0.9366	0.7688	0.0411	0.6671	0.9781	0.0000	0.2608
		STL	0.7281	0.9262	0.4444	0.1120	0.7028	0.9609	0.0000	0.1869
	16	RAN	0.8440	0.9606	0.6183	0.0813	0.6695	0.9881	0.0000	0.2538
		SAL	0.8733	0.9428	0.7773	0.0434	0.6605	0.9789	0.0000	0.2653
		STL	0.7291	0.9077	0.4444	0.1101	0.7047	0.9680	0.0000	0.1842

Table E.7: grouped-liblinear-enron-GM2-ALL-ALL-5

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.8552	0.9369	0.7431	0.0453	0.6870	0.9789	0.0000	0.2520
		SAL	0.8708	0.9297	0.8023	0.0350	0.6791	0.9811	0.0000	0.2612
		STL	0.7188	0.9258	0.5000	0.1243	0.6945	0.9802	0.0000	0.2174
	1	RAN	0.8038	0.9093	0.6536	0.0624	0.5769	0.9711	0.0000	0.2683
		SAL	0.8177	0.8707	0.7580	0.0376	0.5879	0.9616	0.0000	0.2696
		STL	0.6438	0.8086	0.3936	0.1151	0.6178	0.9592	0.0000	0.2084
	2	RAN	0.8181	0.9255	0.7252	0.0584	0.5925	0.9711	0.0000	0.2721
		SAL	0.8107	0.8651	0.7298	0.0394	0.5878	0.9641	0.0000	0.2621
		STL	0.6447	0.8129	0.3936	0.1184	0.6199	0.9537	0.0000	0.2138
	4	RAN	0.7917	0.8918	0.6272	0.0747	0.5913	0.9675	0.0000	0.2618
		SAL	0.8148	0.8969	0.7263	0.0476	0.5891	0.9622	0.0000	0.2704
		STL	0.6440	0.8130	0.3936	0.1141	0.6191	0.9535	0.0000	0.2057
	8	RAN	0.8112	0.8739	0.6976	0.0508	0.5855	0.9634	0.0000	0.2628
		SAL	0.8194	0.8722	0.7347	0.0398	0.5958	0.9678	0.0000	0.2667
		STL	0.6437	0.8110	0.3936	0.1181	0.6195	0.9561	0.0000	0.2120
	16	RAN	0.8008	0.9065	0.6550	0.0763	0.5866	0.9728	0.0000	0.2670
		SAL	0.8128	0.8887	0.6917	0.0460	0.5886	0.9615	0.0000	0.2704
		STL	0.6448	0.8073	0.3936	0.1155	0.6205	0.9596	0.0000	0.2093

Table E.8: grouped-liblinear-enron-GM2-ALL-ALL-10

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.8191	0.8989	0.7154	0.0639	0.6266	0.9810	0.0000	0.2710
		SAL	0.8224	0.8598	0.7468	0.0363	0.6270	0.9814	0.0000	0.2725
		STL	0.6674	0.8551	0.4824	0.1262	0.6416	0.9748	0.0000	0.2442
	1	RAN	0.7356	0.7693	0.6908	0.0296	0.5124	0.9610	0.0000	0.2729
		SAL	0.7309	0.8075	0.6765	0.0392	0.5039	0.9632	0.0000	0.2700
		STL	0.5704	0.7427	0.4512	0.1123	0.5351	0.9518	0.0000	0.2313
	2	RAN	0.7394	0.8065	0.6931	0.0411	0.5174	0.9526	0.0000	0.2680
		SAL	0.7353	0.8036	0.6822	0.0411	0.5119	0.9612	0.0000	0.2695
		STL	0.5718	0.7216	0.4562	0.0986	0.5343	0.9441	0.0000	0.2270
	4	RAN	0.7403	0.7758	0.6806	0.0344	0.5097	0.9512	0.0000	0.2696
		SAL	0.7324	0.7994	0.7053	0.0327	0.5094	0.9674	0.0000	0.2643
		STL	0.5701	0.7473	0.4465	0.1126	0.5329	0.9510	0.0000	0.2334
	8	RAN	0.7192	0.8331	0.6238	0.0661	0.5093	0.9655	0.0000	0.2689
		SAL	0.7362	0.8000	0.6915	0.0359	0.5106	0.9562	0.0000	0.2677
		STL	0.5751	0.7448	0.4486	0.1055	0.5390	0.9492	0.0000	0.2269
	16	RAN	0.7317	0.8142	0.6307	0.0670	0.5174	0.9613	0.0000	0.2645
		SAL	0.7302	0.8380	0.6722	0.0531	0.5027	0.9628	0.0000	0.2685
		STL	0.5661	0.7312	0.4470	0.1040	0.5286	0.9518	0.0000	0.2300

Table E.9: grouped-liblinear-enron-GM2-ALL-ALL-25

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.7702	0.8240	0.6807	0.0637	0.5973	0.9747	0.0000	0.2689
		SAL	0.7940	0.8240	0.7423	0.0367	0.5922	0.9780	0.0000	0.2791
		STL	0.6564	0.8029	0.5252	0.1139	0.6109	0.9731	0.0000	0.2545
	1	RAN	0.6743	0.7015	0.6543	0.0199	0.4607	0.9505	0.0000	0.2681
		SAL	0.6892	0.7216	0.6673	0.0234	0.4598	0.9480	0.0000	0.2718
		STL	0.5354	0.6679	0.4211	0.1016	0.4843	0.9348	0.0000	0.2432
	2	RAN	0.6817	0.7054	0.6572	0.0197	0.4625	0.9318	0.0000	0.2650
		SAL	0.6890	0.7156	0.6716	0.0191	0.4677	0.9504	0.0000	0.2658
		STL	0.5317	0.6701	0.4119	0.1062	0.4826	0.9357	0.0000	0.2425
	4	RAN	0.6806	0.7174	0.6552	0.0266	0.4638	0.9460	0.0000	0.2712
		SAL	0.6808	0.7030	0.6581	0.0183	0.4587	0.9540	0.0000	0.2726
		STL	0.5343	0.6607	0.4211	0.0983	0.4837	0.9347	0.0000	0.2387
	8	RAN	0.6771	0.7296	0.6471	0.0372	0.4545	0.9333	0.0000	0.2730
		SAL	0.6883	0.7290	0.6577	0.0300	0.4729	0.9402	0.0000	0.2669
		STL	0.5325	0.6714	0.4092	0.1076	0.4786	0.9327	0.0000	0.2393

Table E.10: grouped-liblinear-enron-GM2-ALL-ALL-50

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.7667	0.7969	0.7365	0.0302	0.5812	0.9747	0.0000	0.2717
		SAL	0.7747	0.7839	0.7656	0.0092	0.5797	0.9786	0.0000	0.2763
		STL	0.6576	0.7716	0.5437	0.1139	0.5887	0.9737	0.0000	0.2682
	1	RAN	0.6565	0.6959	0.6171	0.0394	0.4408	0.9313	0.0000	0.2716
		SAL	0.6640	0.6751	0.6528	0.0112	0.4415	0.9564	0.0000	0.2767
		STL	0.5156	0.6440	0.3872	0.1284	0.4539	0.9444	0.0000	0.2453
	2	RAN	0.6439	0.6625	0.6253	0.0186	0.4317	0.9523	0.0000	0.2687
		SAL	0.6329	0.6677	0.5980	0.0349	0.4301	0.9428	0.0000	0.2722
		STL	0.5194	0.6514	0.3874	0.1320	0.4538	0.9377	0.0000	0.2538
	4	RAN	0.6397	0.6441	0.6352	0.0045	0.4354	0.9450	0.0000	0.2725
		SAL	0.6565	0.6913	0.6216	0.0349	0.4427	0.9492	0.0000	0.2666
		STL	0.5209	0.6467	0.3950	0.1259	0.4609	0.9304	0.0000	0.2508
	8	RAN	0.6570	0.6647	0.6492	0.0077	0.4352	0.9490	0.0000	0.2731
		SAL	0.6420	0.6681	0.6158	0.0262	0.4304	0.9344	0.0000	0.2696
		STL	0.5112	0.6471	0.3752	0.1359	0.4470	0.9428	0.0000	0.2535

Table E.11: grouped-liblinear-enron-GM2-ALL-ALL-75

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.7429	0.7429	0.7429	0.0000	0.5493	0.9731	0.0000	0.2777
		SAL	0.7456	0.7456	0.7456	0.0000	0.5528	0.9737	0.0000	0.2798
		STL	0.7456	0.7456	0.7456	0.0000	0.5528	0.9737	0.0000	0.2798
	1	RAN	0.5841	0.5841	0.5841	0.0000	0.3870	0.9285	0.0000	0.2690
		SAL	0.6047	0.6047	0.6047	0.0000	0.4034	0.9387	0.0000	0.2698
		STL	0.6047	0.6047	0.6047	0.0000	0.4034	0.9387	0.0000	0.2698
	2	RAN	0.6134	0.6134	0.6134	0.0000	0.4057	0.9311	0.0000	0.2653
		SAL	0.6105	0.6105	0.6105	0.0000	0.4030	0.9283	0.0000	0.2668
		STL	0.6105	0.6105	0.6105	0.0000	0.4030	0.9283	0.0000	0.2668
	4	RAN	0.6057	0.6057	0.6057	0.0000	0.4016	0.9327	0.0000	0.2717
		SAL	0.6073	0.6073	0.6073	0.0000	0.4010	0.9391	0.0000	0.2709
		STL	0.6073	0.6073	0.6073	0.0000	0.4010	0.9391	0.0000	0.2709

Table E.12: grouped-liblinear-enron-GM2-ALL-ALL-150

GM5										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.7207	0.9636	0.4010	0.1429	0.5052	1.0000	0.0000	0.3099
		SAL	0.7744	0.9271	0.5114	0.1158	0.5026	1.0000	0.0000	0.3307
		STL	0.5692	0.8742	0.3017	0.1344	0.5108	1.0000	0.0000	0.2582
	1	RAN	0.8487	0.9685	0.7000	0.0784	0.6751	0.9869	0.0000	0.2565
		SAL	0.8705	0.9378	0.7535	0.0455	0.6656	0.9824	0.0000	0.2587
		STL	0.7160	0.9274	0.4000	0.1367	0.6913	0.9590	0.0000	0.2018
	2	RAN	0.8515	0.9550	0.5736	0.0716	0.6635	0.9836	0.0000	0.2600
		SAL	0.8636	0.9498	0.7201	0.0609	0.6591	0.9824	0.0000	0.2612
		STL	0.7201	0.9287	0.4000	0.1304	0.6949	0.9613	0.0000	0.1986
	4	RAN	0.8531	0.9421	0.6677	0.0616	0.6730	0.9714	0.0000	0.2549
		SAL	0.8696	0.9455	0.7224	0.0535	0.6671	0.9821	0.0000	0.2582
		STL	0.7163	0.9264	0.4000	0.1352	0.6915	0.9666	0.0000	0.2014
	8	RAN	0.8383	0.9513	0.6020	0.0744	0.6728	0.9700	0.0000	0.2452
		SAL	0.8705	0.9470	0.7557	0.0454	0.6656	0.9824	0.0000	0.2597
		STL	0.7122	0.9284	0.4000	0.1349	0.6864	0.9639	0.0000	0.2006
	16	RAN	0.8522	0.9676	0.6954	0.0732	0.6686	0.9874	0.0000	0.2547
		SAL	0.8676	0.9463	0.7557	0.0519	0.6630	0.9824	0.0000	0.2603
		STL	0.7138	0.9276	0.4000	0.1365	0.6881	0.9630	0.0000	0.2014

Table E.13: grouped-liblinear-enron-GM5-ALL-ALL-5

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.6930	0.8560	0.4644	0.0931	0.4657	0.9867	0.0000	0.3066
		SAL	0.7104	0.8020	0.5628	0.0630	0.4652	0.9870	0.0000	0.3143
		STL	0.4857	0.7801	0.2548	0.1328	0.4507	0.9870	0.0000	0.2766
	1	RAN	0.8095	0.9022	0.7286	0.0564	0.5826	0.9782	0.0000	0.2630
		SAL	0.8057	0.8903	0.6153	0.0603	0.5886	0.9727	0.0000	0.2639
		STL	0.6406	0.8044	0.3908	0.1168	0.6225	0.9604	0.0000	0.2110
	2	RAN	0.7999	0.9145	0.7189	0.0572	0.5902	0.9684	0.0000	0.2723
		SAL	0.7957	0.9221	0.6462	0.0685	0.5860	0.9733	0.0000	0.2568
		STL	0.6365	0.7796	0.3908	0.1135	0.6181	0.9529	0.0000	0.2119
	4	RAN	0.7865	0.9187	0.5834	0.0723	0.5908	0.9714	0.0000	0.2641
		SAL	0.7985	0.9256	0.5951	0.0810	0.5848	0.9729	0.0000	0.2634
		STL	0.6405	0.7866	0.3908	0.1150	0.6220	0.9551	0.0000	0.2108
	8	RAN	0.8017	0.9272	0.6714	0.0691	0.5895	0.9764	0.0000	0.2584
		SAL	0.8020	0.9232	0.5924	0.0707	0.5874	0.9736	0.0000	0.2637
		STL	0.6394	0.8052	0.3908	0.1191	0.6214	0.9565	0.0000	0.2104
	16	RAN	0.8086	0.9142	0.6593	0.0748	0.6006	0.9770	0.0000	0.2613
		SAL	0.8080	0.9191	0.6835	0.0576	0.5901	0.9734	0.0000	0.2652
		STL	0.6422	0.8006	0.3908	0.1194	0.6246	0.9573	0.0000	0.2122

Table E.14: grouped-liblinear-enron-GM5-ALL-ALL-10

GM5										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.5816	0.7076	0.4018	0.1110	0.4370	1.0000	0.0000	0.3091
		SAL	0.6305	0.6898	0.5050	0.0599	0.4377	0.9744	0.0000	0.3124
		STL	0.4377	0.6993	0.3305	0.1268	0.4368	0.9870	0.0000	0.3003
	1	RAN	0.7379	0.7867	0.6328	0.0574	0.5186	0.9523	0.0000	0.2697
		SAL	0.7247	0.7775	0.6392	0.0455	0.5128	0.9554	0.0000	0.2673
		STL	0.5652	0.7111	0.4371	0.1041	0.5413	0.9412	0.0000	0.2270
	2	RAN	0.7282	0.7445	0.7007	0.0137	0.5224	0.9551	0.0000	0.2684
		SAL	0.7287	0.7759	0.6819	0.0279	0.5155	0.9599	0.0000	0.2666
		STL	0.5616	0.7027	0.4371	0.0970	0.5378	0.9395	0.0000	0.2282
	4	RAN	0.7235	0.8209	0.6430	0.0658	0.5187	0.9488	0.0000	0.2720
		SAL	0.7320	0.7808	0.6872	0.0288	0.5180	0.9629	0.0000	0.2654
		STL	0.5607	0.7156	0.4371	0.1032	0.5388	0.9390	0.0000	0.2273

Table E.15: grouped-liblinear-enron-GM5-ALL-ALL-25

GM5										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.5793	0.6564	0.4924	0.0673	0.4272	0.9870	0.0000	0.3154
		SAL	0.5812	0.6174	0.5616	0.0256	0.4256	0.9870	0.0000	0.3083
		STL	0.4365	0.5943	0.3088	0.1185	0.4259	0.9870	0.0000	0.3052
	1	RAN	0.6659	0.7342	0.5793	0.0646	0.4697	0.9572	0.0000	0.2773
		SAL	0.6784	0.7134	0.6323	0.0340	0.4698	0.9571	0.0000	0.2709
		STL	0.5333	0.6441	0.4304	0.0874	0.4877	0.9281	0.0000	0.2470
	2	RAN	0.6780	0.7022	0.6515	0.0208	0.4747	0.9584	0.0000	0.2702
		SAL	0.6825	0.7004	0.6661	0.0140	0.4729	0.9610	0.0000	0.2749
		STL	0.5452	0.6611	0.4442	0.0892	0.4976	0.9399	0.0000	0.2503

Table E.16: grouped-liblinear-enron-GM5-ALL-ALL-50

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.5703	0.6206	0.5199	0.0503	0.4193	0.9870	0.0000	0.3119
		SAL	0.5454	0.5772	0.5136	0.0318	0.4086	0.9870	0.0000	0.3215
		STL	0.4475	0.5710	0.3240	0.1235	0.4164	0.9744	0.0000	0.3177
	1	RAN	0.6525	0.7194	0.5856	0.0669	0.4427	0.9513	0.0000	0.2758
		SAL	0.6549	0.6679	0.6419	0.0130	0.4445	0.9497	0.0000	0.2763
		STL	0.5350	0.6489	0.4211	0.1139	0.4672	0.9421	0.0000	0.2567
	2	RAN	0.6511	0.6739	0.6283	0.0228	0.4460	0.9437	0.0000	0.2699
		SAL	0.6461	0.6551	0.6371	0.0090	0.4410	0.9494	0.0000	0.2737
		STL	0.5341	0.6451	0.4230	0.1111	0.4674	0.9380	0.0000	0.2542

Table E.17: grouped-liblinear-enron-GM5-ALL-ALL-75

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.5418	0.5418	0.5418	0.0000	0.4035	0.9737	0.0000	0.3182
		SAL	0.5478	0.5478	0.5478	0.0000	0.4034	0.9870	0.0000	0.3169
		STL	0.5478	0.5478	0.5478	0.0000	0.4034	0.9870	0.0000	0.3169
	1	RAN	0.6091	0.6091	0.6091	0.0000	0.4141	0.9493	0.0000	0.2691
		SAL	0.5875	0.5875	0.5875	0.0000	0.4043	0.9502	0.0000	0.2656
		STL	0.5875	0.5875	0.5875	0.0000	0.4043	0.9502	0.0000	0.2656

Table E.18: grouped-liblinear-enron-GM5-ALL-ALL-150

GB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.8782	0.9835	0.6177	0.0747	0.7112	1.0000	0.0000	0.2621
		SAL	0.9047	0.9706	0.7487	0.0431	0.7088	1.0000	0.0000	0.2663
		STL	0.7758	0.9533	0.5185	0.1190	0.7410	0.9839	0.0000	0.2063
	1	RAN	0.8781	0.9673	0.7660	0.0609	0.7147	0.9822	0.0000	0.2540
		SAL	0.9020	0.9662	0.7589	0.0466	0.7005	0.9854	0.0000	0.2721
		STL	0.7682	0.9664	0.5185	0.1219	0.7364	0.9837	0.0000	0.2054
	2	RAN	0.8740	0.9805	0.6998	0.0747	0.7114	0.9890	0.0000	0.2549
		SAL	0.9014	0.9658	0.7589	0.0460	0.6988	0.9840	0.0000	0.2736
		STL	0.7675	0.9632	0.5185	0.1215	0.7354	0.9834	0.0000	0.2061
	4	RAN	0.9046	0.9762	0.8386	0.0344	0.7172	0.9821	0.0000	0.2684
		SAL	0.9016	0.9666	0.7585	0.0461	0.6994	0.9843	0.0000	0.2733
		STL	0.7676	0.9663	0.5185	0.1220	0.7355	0.9844	0.0000	0.2062
	8	RAN	0.8921	0.9786	0.8128	0.0426	0.7116	0.9921	0.0000	0.2628
		SAL	0.9025	0.9666	0.7581	0.0466	0.6999	0.9881	0.0000	0.2751
		STL	0.7661	0.9641	0.5185	0.1210	0.7341	0.9826	0.0000	0.2057
	16	RAN	0.8881	0.9756	0.7216	0.0591	0.7070	0.9884	0.0000	0.2677
		SAL	0.9025	0.9666	0.7605	0.0466	0.6996	0.9886	0.0000	0.2750
		STL	0.7663	0.9643	0.5185	0.1218	0.7343	0.9821	0.0000	0.2063

Table E.19: grouped-liblinear-enron-GB3-ALL-ALL-5

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.8618	0.9407	0.7427	0.0577	0.6638	1.0000	0.0000	0.2742
		SAL	0.8626	0.9538	0.7131	0.0564	0.6593	1.0000	0.0000	0.2753
		STL	0.7128	0.9326	0.4787	0.1349	0.6867	0.9816	0.0000	0.2261
	1	RAN	0.8550	0.9341	0.7705	0.0454	0.6599	0.9818	0.0000	0.2701
		SAL	0.8680	0.9242	0.6904	0.0569	0.6658	1.0000	0.0000	0.2701
		STL	0.7151	0.9302	0.4894	0.1248	0.6880	0.9806	0.0000	0.2189
	2	RAN	0.8550	0.9265	0.7683	0.0454	0.6737	0.9819	0.0000	0.2588
		SAL	0.8657	0.9221	0.6941	0.0562	0.6610	0.9870	0.0000	0.2715
		STL	0.7176	0.9297	0.4894	0.1254	0.6912	0.9796	0.0000	0.2185
	4	RAN	0.8471	0.9426	0.7322	0.0584	0.6681	0.9870	0.0000	0.2658
		SAL	0.8640	0.9204	0.7026	0.0546	0.6572	1.0000	0.0000	0.2751
		STL	0.7177	0.9300	0.4894	0.1253	0.6915	0.9806	0.0000	0.2187
	8	RAN	0.8560	0.9512	0.7510	0.0590	0.6667	0.9808	0.0000	0.2654
		SAL	0.8664	0.9185	0.6894	0.0577	0.6595	0.9870	0.0000	0.2748
		STL	0.7177	0.9292	0.4894	0.1253	0.6912	0.9799	0.0000	0.2187
	16	RAN	0.8525	0.9215	0.7137	0.0541	0.6616	0.9831	0.0000	0.2682
		SAL	0.8690	0.9264	0.7208	0.0513	0.6629	0.9870	0.0000	0.2722
		STL	0.7170	0.9288	0.4894	0.1248	0.6906	0.9801	0.0000	0.2184

Table E.20: grouped-liblinear-enron-GB3-ALL-ALL-10

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.8190	0.8758	0.7683	0.0365	0.6151	0.9797	0.0000	0.2800
		SAL	0.8195	0.8882	0.7559	0.0473	0.6142	0.9774	0.0000	0.2768
		STL	0.6657	0.8529	0.5215	0.1221	0.6361	0.9700	0.0000	0.2437
	1	RAN	0.8158	0.8744	0.6640	0.0708	0.6150	0.9812	0.0000	0.2762
		SAL	0.8235	0.8733	0.7936	0.0248	0.6158	0.9816	0.0000	0.2720
		STL	0.6562	0.8501	0.5158	0.1235	0.6255	0.9717	0.0000	0.2480
	2	RAN	0.8268	0.8600	0.7862	0.0291	0.6207	0.9765	0.0000	0.2693
		SAL	0.8258	0.8788	0.8011	0.0253	0.6174	0.9772	0.0000	0.2709
		STL	0.6527	0.8497	0.5130	0.1264	0.6242	0.9721	0.0000	0.2533
	4	RAN	0.8230	0.9056	0.7260	0.0568	0.6185	0.9802	0.0000	0.2705
		SAL	0.8238	0.8793	0.7973	0.0262	0.6152	0.9771	0.0000	0.2723
		STL	0.6534	0.8498	0.5144	0.1258	0.6243	0.9721	0.0000	0.2526
	8	RAN	0.8088	0.8812	0.7701	0.0363	0.6109	0.9750	0.0000	0.2702
		SAL	0.8230	0.8563	0.7995	0.0177	0.6137	0.9776	0.0000	0.2718
		STL	0.6546	0.8535	0.5144	0.1255	0.6251	0.9720	0.0000	0.2507

Table E.21: grouped-liblinear-enron-GB3-ALL-ALL-25

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.7902	0.8149	0.7445	0.0323	0.5839	1.0000	0.0000	0.2793
		SAL	0.7905	0.8465	0.7234	0.0509	0.5898	0.9761	0.0000	0.2784
		STL	0.6421	0.8024	0.4980	0.1248	0.6004	0.9754	0.0000	0.2590
	1	RAN	0.7853	0.8094	0.7482	0.0266	0.5776	0.9753	0.0000	0.2820
		SAL	0.7918	0.8204	0.7663	0.0222	0.5864	0.9709	0.0000	0.2792
		STL	0.6344	0.8026	0.4731	0.1346	0.5955	0.9727	0.0000	0.2576
	2	RAN	0.7908	0.8058	0.7743	0.0129	0.5867	0.9753	0.0000	0.2803
		SAL	0.7891	0.8100	0.7663	0.0179	0.5836	1.0000	0.0000	0.2756
		STL	0.6326	0.8017	0.4765	0.1331	0.5960	0.9747	0.0000	0.2584
	4	RAN	0.7895	0.8628	0.7357	0.0537	0.5897	0.9759	0.0000	0.2759
		SAL	0.7884	0.8137	0.7670	0.0193	0.5833	1.0000	0.0000	0.2790
		STL	0.6305	0.7973	0.4735	0.1324	0.5938	0.9725	0.0000	0.2604

Table E.22: grouped-liblinear-enron-GB3-ALL-ALL-50

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.7731	0.7764	0.7698	0.0033	0.5722	0.9870	0.0000	0.2775
		SAL	0.7662	0.7955	0.7368	0.0294	0.5603	0.9758	0.0000	0.2858
		STL	0.6507	0.7794	0.5220	0.1287	0.5805	0.9744	0.0000	0.2711
	1	RAN	0.7762	0.8161	0.7364	0.0399	0.5810	0.9712	0.0000	0.2717
		SAL	0.7740	0.7836	0.7644	0.0096	0.5735	0.9763	0.0000	0.2786
		STL	0.6506	0.7739	0.5273	0.1233	0.5774	0.9718	0.0000	0.2662
	2	RAN	0.7734	0.7886	0.7583	0.0152	0.5686	0.9726	0.0000	0.2874
		SAL	0.7756	0.7820	0.7692	0.0064	0.5733	0.9764	0.0000	0.2804
		STL	0.6482	0.7712	0.5251	0.1230	0.5736	0.9719	0.0000	0.2658
	4	RAN	0.7715	0.7715	0.7715	0.0000	0.5690	0.9714	0.0000	0.2787
		SAL	0.7756	0.7808	0.7704	0.0052	0.5748	0.9742	0.0000	0.2780
		STL	0.6480	0.7723	0.5237	0.1243	0.5763	0.9713	0.0000	0.2661

Table E.23: grouped-liblinear-enron-GB3-ALL-ALL-75

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.7472	0.7472	0.7472	0.0000	0.5470	0.9701	0.0000	0.2839
		SAL	0.7440	0.7440	0.7440	0.0000	0.5326	0.9711	0.0000	0.2882
		STL	0.7440	0.7440	0.7440	0.0000	0.5326	0.9711	0.0000	0.2882
	1	RAN	0.7453	0.7453	0.7453	0.0000	0.5413	0.9700	0.0000	0.2850
		SAL	0.7426	0.7426	0.7426	0.0000	0.5358	0.9867	0.0000	0.2903
		STL	0.7426	0.7426	0.7426	0.0000	0.5358	0.9867	0.0000	0.2903
	2	RAN	0.7432	0.7432	0.7432	0.0000	0.5451	0.9666	0.0000	0.2813
		SAL	0.7417	0.7417	0.7417	0.0000	0.5376	0.9867	0.0000	0.2848
		STL	0.7417	0.7417	0.7417	0.0000	0.5376	0.9867	0.0000	0.2848

Table E.24: grouped-liblinear-enron-GB3-ALL-ALL-150

OSB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.8946	0.9696	0.6599	0.0718	0.7269	1.0000	0.0000	0.2605
		SAL	0.9147	0.9732	0.7892	0.0337	0.7246	0.9903	0.0000	0.2633
		STL	0.7979	0.9579	0.5185	0.1085	0.7643	0.9841	0.0000	0.1994
	1	RAN	0.8970	0.9619	0.6565	0.0575	0.7324	0.9869	0.0000	0.2481
		SAL	0.9147	0.9673	0.7777	0.0410	0.7227	0.9921	0.0000	0.2643
		STL	0.7885	0.9741	0.5185	0.1165	0.7573	0.9853	0.0000	0.2004
	2	RAN	0.8904	0.9765	0.6446	0.0710	0.7325	0.9923	0.0000	0.2548
		SAL	0.9142	0.9673	0.7812	0.0387	0.7203	0.9877	0.0000	0.2642
		STL	0.7891	0.9740	0.5185	0.1187	0.7579	0.9851	0.0000	0.2020
	4	RAN	0.9027	0.9762	0.7346	0.0487	0.7313	0.9884	0.0000	0.2534
		SAL	0.9142	0.9677	0.7777	0.0392	0.7208	0.9877	0.0000	0.2634
		STL	0.7893	0.9738	0.5185	0.1187	0.7582	0.9856	0.0000	0.2019
	8	RAN	0.8876	0.9706	0.7021	0.0675	0.7249	0.9840	0.0000	0.2584
		SAL	0.9144	0.9673	0.7777	0.0396	0.7207	0.9877	0.0000	0.2642
		STL	0.7889	0.9740	0.5185	0.1191	0.7581	0.9853	0.0000	0.2020
	16	RAN	0.8916	0.9848	0.7284	0.0649	0.7327	0.9924	0.0000	0.2513
		SAL	0.9143	0.9677	0.7777	0.0392	0.7206	0.9877	0.0000	0.2640
		STL	0.7889	0.9744	0.5185	0.1185	0.7578	0.9853	0.0000	0.2017

Table E.25: grouped-liblinear-enron-OSB3-ALL-ALL-5

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.8643	0.9469	0.7573	0.0505	0.6814	0.9867	0.0000	0.2595
		SAL	0.8758	0.9462	0.7660	0.0419	0.6788	0.9867	0.0000	0.2647
		STL	0.7349	0.9353	0.5106	0.1231	0.7054	0.9841	0.0000	0.2236
	1	RAN	0.8669	0.9516	0.7406	0.0518	0.6841	0.9849	0.0000	0.2616
		SAL	0.8813	0.9316	0.7407	0.0470	0.6847	0.9888	0.0000	0.2642
		STL	0.7405	0.9363	0.5319	0.1154	0.7122	0.9844	0.0000	0.2126
	2	RAN	0.8638	0.9432	0.7652	0.0573	0.6847	1.0000	0.0000	0.2616
		SAL	0.8801	0.9319	0.7410	0.0459	0.6804	0.9870	0.0000	0.2642
		STL	0.7401	0.9368	0.5319	0.1174	0.7120	0.9817	0.0000	0.2119
	4	RAN	0.8600	0.9446	0.7783	0.0549	0.6809	0.9854	0.0000	0.2616
		SAL	0.8804	0.9319	0.7448	0.0450	0.6814	0.9870	0.0000	0.2628
		STL	0.7393	0.9369	0.5319	0.1172	0.7114	0.9812	0.0000	0.2121
	8	RAN	0.8652	0.9482	0.7428	0.0554	0.6859	0.9851	0.0000	0.2573
		SAL	0.8793	0.9317	0.7381	0.0450	0.6782	0.9870	0.0000	0.2670
		STL	0.7401	0.9372	0.5319	0.1174	0.7119	0.9817	0.0000	0.2121

Table E.26: grouped-liblinear-enron-OSB3-ALL-ALL-10

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.8300	0.8954	0.7736	0.0457	0.6303	0.9815	0.0000	0.2729
		SAL	0.8320	0.8928	0.7447	0.0480	0.6334	0.9810	0.0000	0.2650
		STL	0.6858	0.8664	0.5385	0.1179	0.6486	0.9771	0.0000	0.2403
	1	RAN	0.8262	0.8850	0.7908	0.0382	0.6321	0.9867	0.0000	0.2703
		SAL	0.8379	0.8634	0.8210	0.0132	0.6345	0.9801	0.0000	0.2718
		STL	0.6823	0.8636	0.5350	0.1156	0.6498	0.9752	0.0000	0.2362
	2	RAN	0.8349	0.8516	0.8018	0.0171	0.6336	1.0000	0.0000	0.2708
		SAL	0.8388	0.8775	0.8140	0.0207	0.6377	0.9787	0.0000	0.2689
		STL	0.6806	0.8630	0.5350	0.1162	0.6485	0.9769	0.0000	0.2372

Table E.27: grouped-liblinear-enron-OSB3-ALL-ALL-25

OSB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.8012	0.8280	0.7684	0.0247	0.5999	0.9727	0.0000	0.2719
		SAL	0.8063	0.8569	0.7447	0.0465	0.6051	0.9793	0.0000	0.2726
		STL	0.6625	0.8147	0.5160	0.1220	0.6119	0.9785	0.0000	0.2481
	1	RAN	0.8024	0.8343	0.7672	0.0275	0.5976	0.9717	0.0000	0.2769
		SAL	0.8025	0.8219	0.7801	0.0172	0.6010	0.9764	0.0000	0.2706
		STL	0.6575	0.8132	0.5126	0.1230	0.6096	0.9771	0.0000	0.2493

Table E.28: grouped-liblinear-enron-OSB3-ALL-ALL-50

OSB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.7842	0.7888	0.7796	0.0046	0.5802	0.9741	0.0000	0.2784
		SAL	0.7852	0.7931	0.7774	0.0079	0.5874	0.9786	0.0000	0.2708
		STL	0.6715	0.7884	0.5547	0.1169	0.5898	0.9766	0.0000	0.2615
	1	RAN	0.7832	0.8011	0.7653	0.0179	0.5876	0.9705	0.0000	0.2710
		SAL	0.7859	0.7894	0.7823	0.0035	0.5870	0.9751	0.0000	0.2726
		STL	0.6678	0.7898	0.5458	0.1220	0.5950	0.9758	0.0000	0.2582

Table E.29: grouped-liblinear-enron-OSB3-ALL-ALL-75

OSB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.7553	0.7553	0.7553	0.0000	0.5537	0.9754	0.0000	0.2782
		SAL	0.7543	0.7543	0.7543	0.0000	0.5563	0.9716	0.0000	0.2778
		STL	0.7543	0.7543	0.7543	0.0000	0.5563	0.9716	0.0000	0.2778

Table E.30: grouped-liblinear-enron-OSB3-ALL-ALL-150

APPENDIX F:
Grouped LibLinear Results for the Twitter Short Message Corpus

GM1										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.6283	0.8081	0.4918	0.0706	0.6077	0.9696	0.1892	0.1404
		SAL	0.6321	0.7631	0.5068	0.0720	0.6100	0.9363	0.2195	0.1374
		STL	0.6032	0.8089	0.4737	0.0758	0.5893	0.9391	0.1791	0.1458
	1	RAN	0.6333	0.8037	0.5031	0.0723	0.6074	0.9588	0.1449	0.1479
		SAL	0.6259	0.8211	0.5083	0.0802	0.6013	0.9597	0.1429	0.1523
		STL	0.6093	0.8117	0.4713	0.0787	0.6015	0.9347	0.1690	0.1326
	2	RAN	0.6223	0.8966	0.4754	0.0969	0.6070	0.9602	0.2000	0.1431
		SAL	0.6025	0.8093	0.4441	0.0877	0.5720	0.9697	0.1509	0.1636
		STL	0.6195	0.8049	0.4218	0.0796	0.6055	0.9328	0.0000	0.1442
	4	RAN	0.6126	0.7957	0.3846	0.0918	0.5914	0.9811	0.1200	0.1514
		SAL	0.6266	0.8546	0.4823	0.0837	0.6041	0.9560	0.1695	0.1486
		STL	0.6123	0.8062	0.4659	0.0781	0.6021	0.9347	0.1972	0.1342
	8	RAN	0.6356	0.8084	0.4848	0.0714	0.6088	0.9718	0.1613	0.1491
		SAL	0.6321	0.9026	0.4828	0.0909	0.6121	0.9735	0.1404	0.1448
		STL	0.6143	0.8117	0.4661	0.0789	0.6052	0.9347	0.1972	0.1310
	16	RAN	0.6179	0.8112	0.4645	0.0902	0.5989	0.9470	0.1818	0.1455
		SAL	0.6219	0.8324	0.4563	0.0781	0.6022	0.9600	0.2182	0.1413
		STL	0.6145	0.8062	0.4458	0.0756	0.6028	0.9347	0.1515	0.1283

Table F.1: grouped-liblinear-twitter-GM1-ALL-ALL-5

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.4768	0.6234	0.3448	0.0817	0.4500	0.9556	0.0702	0.1651
		SAL	0.4978	0.5788	0.3952	0.0572	0.4670	0.9527	0.0385	0.1615
		STL	0.4540	0.6063	0.3578	0.0697	0.4443	0.9389	0.1250	0.1545
	1	RAN	0.4943	0.5836	0.3936	0.0629	0.4682	0.9482	0.0755	0.1626
		SAL	0.4773	0.6389	0.3627	0.0640	0.4545	0.9405	0.0923	0.1607
		STL	0.4724	0.6329	0.3766	0.0695	0.4587	0.9384	0.0889	0.1539
	2	RAN	0.4914	0.5881	0.3884	0.0627	0.4631	0.9513	0.0833	0.1706
		SAL	0.4859	0.6567	0.3888	0.0779	0.4582	0.9699	0.0702	0.1608
		STL	0.4761	0.6321	0.3358	0.0673	0.4638	0.9381	0.1446	0.1524
	4	RAN	0.4947	0.6310	0.3849	0.0544	0.4729	0.9517	0.1250	0.1570
		SAL	0.4853	0.6900	0.3778	0.0916	0.4542	0.9487	0.0714	0.1781
		STL	0.4722	0.6362	0.3184	0.0728	0.4613	0.9402	0.0299	0.1551
	8	RAN	0.4946	0.6282	0.3895	0.0632	0.4639	0.9472	0.0000	0.1622
		SAL	0.4787	0.7194	0.3994	0.0862	0.4495	0.9621	0.1034	0.1636
		STL	0.4714	0.6362	0.3080	0.0821	0.4593	0.9402	0.0400	0.1648
	16	RAN	0.4904	0.6124	0.3844	0.0675	0.4600	0.9363	0.0769	0.1604
		SAL	0.4817	0.5909	0.3985	0.0591	0.4534	0.9474	0.0370	0.1659
		STL	0.4679	0.6362	0.2846	0.0859	0.4568	0.9402	0.1026	0.1576

Table F.2: grouped-liblinear-twitter-GM1-ALL-ALL-10

GM1										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.3441	0.4816	0.2912	0.0644	0.3144	0.9344	0.0000	0.1658
		SAL	0.3544	0.4245	0.2735	0.0484	0.3248	0.8820	0.0000	0.1725
		STL	0.3399	0.4550	0.2916	0.0538	0.3199	0.8806	0.0000	0.1707
	1	RAN	0.3377	0.4119	0.2408	0.0661	0.3121	0.9167	0.0000	0.1736
		SAL	0.3531	0.4352	0.3091	0.0518	0.3188	0.9221	0.0000	0.1782
		STL	0.3318	0.4390	0.2660	0.0582	0.3170	0.9052	0.0000	0.1699
	2	RAN	0.3535	0.4084	0.3176	0.0279	0.3207	0.8960	0.0377	0.1672
		SAL	0.3477	0.4309	0.2878	0.0500	0.3197	0.9225	0.0000	0.1779
		STL	0.3382	0.4245	0.2714	0.0463	0.3271	0.8969	0.0000	0.1696
	4	RAN	0.3566	0.4015	0.3092	0.0320	0.3249	0.9119	0.0000	0.1747
		SAL	0.3486	0.4402	0.2859	0.0583	0.3213	0.9358	0.0000	0.1729
		STL	0.3478	0.4372	0.2811	0.0482	0.3331	0.8851	0.0000	0.1694
	8	RAN	0.3442	0.4118	0.3082	0.0327	0.3166	0.9051	0.0000	0.1671
		SAL	0.3520	0.4186	0.2944	0.0498	0.3267	0.9231	0.0000	0.1788
		STL	0.3294	0.4296	0.2591	0.0566	0.3135	0.8851	0.0000	0.1656
	16	RAN	0.3482	0.3976	0.3137	0.0335	0.3136	0.9011	0.0000	0.1701
		SAL	0.3375	0.4094	0.2879	0.0373	0.3074	0.8981	0.0000	0.1742
		STL	0.3376	0.4296	0.2651	0.0514	0.3188	0.8851	0.0000	0.1670

Table F.3: grouped-liblinear-twitter-GM1-ALL-ALL-25

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.2776	0.3371	0.2451	0.0421	0.2566	0.8780	0.0000	0.1768
		SAL	0.2659	0.2759	0.2510	0.0107	0.2405	0.8759	0.0000	0.1688
		STL	0.2645	0.3273	0.2190	0.0459	0.2518	0.8798	0.0000	0.1799
	1	RAN	0.2736	0.3120	0.2219	0.0380	0.2521	0.9153	0.0000	0.1736
		SAL	0.2769	0.3173	0.2438	0.0305	0.2506	0.8788	0.0000	0.1745
		STL	0.2606	0.3142	0.2249	0.0386	0.2421	0.8647	0.0000	0.1758
	2	RAN	0.2741	0.3248	0.2180	0.0438	0.2398	0.8905	0.0000	0.1723
		SAL	0.2644	0.3100	0.2250	0.0350	0.2351	0.8922	0.0000	0.1718
		STL	0.2731	0.3338	0.2284	0.0445	0.2510	0.8838	0.0000	0.1814
	4	RAN	0.2826	0.3236	0.2287	0.0398	0.2524	0.8766	0.0000	0.1675
		SAL	0.2717	0.3272	0.2032	0.0515	0.2452	0.8889	0.0000	0.1676
		STL	0.2586	0.3155	0.2162	0.0418	0.2416	0.8880	0.0000	0.1793
	8	RAN	0.2773	0.2996	0.2637	0.0159	0.2504	0.9119	0.0000	0.1770
		SAL	0.2742	0.2924	0.2446	0.0211	0.2381	0.8449	0.0000	0.1686
		STL	0.2623	0.3171	0.2274	0.0393	0.2409	0.9010	0.0000	0.1722
	16	RAN	0.2759	0.2963	0.2501	0.0192	0.2525	0.9035	0.0000	0.1689
		SAL	0.2698	0.2920	0.2504	0.0171	0.2370	0.8832	0.0000	0.1713
		STL	0.2672	0.3326	0.2344	0.0463	0.2480	0.8906	0.0000	0.1733

Table F.4: grouped-liblinear-twitter-GM1-ALL-ALL-50

GM1										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.2396	0.2738	0.2054	0.0342	0.2200	0.8390	0.0000	0.1619
		SAL	0.2165	0.2521	0.1810	0.0356	0.1989	0.8321	0.0000	0.1745
		STL	0.2257	0.2633	0.1881	0.0376	0.2112	0.8687	0.0000	0.1765
	1	RAN	0.2337	0.2554	0.2120	0.0217	0.2063	0.8630	0.0000	0.1679
		SAL	0.2347	0.2595	0.2098	0.0249	0.2140	0.9157	0.0000	0.1727
		STL	0.2197	0.2626	0.1768	0.0429	0.2074	0.8435	0.0000	0.1746
	2	RAN	0.2313	0.2641	0.1986	0.0327	0.2093	0.8722	0.0000	0.1780
		SAL	0.2367	0.2648	0.2086	0.0281	0.2173	0.8417	0.0000	0.1683
		STL	0.2274	0.2730	0.1818	0.0456	0.2114	0.8750	0.0000	0.1723
	4	RAN	0.2299	0.2328	0.2271	0.0028	0.2063	0.8971	0.0000	0.1665
		SAL	0.2391	0.2776	0.2006	0.0385	0.2150	0.8387	0.0000	0.1719
		STL	0.2240	0.2605	0.1874	0.0365	0.2091	0.8343	0.0000	0.1674
	8	RAN	0.2451	0.2487	0.2416	0.0035	0.2157	0.8873	0.0000	0.1741
		SAL	0.2413	0.2910	0.1915	0.0498	0.2100	0.8429	0.0000	0.1686
		STL	0.2199	0.2654	0.1743	0.0456	0.2033	0.8116	0.0000	0.1729
	16	RAN	0.2372	0.2745	0.2000	0.0372	0.2064	0.9037	0.0000	0.1756
		SAL	0.2387	0.2639	0.2136	0.0252	0.2094	0.9034	0.0000	0.1691
		STL	0.2345	0.2780	0.1910	0.0435	0.2114	0.8621	0.0000	0.1771

Table F.5: grouped-liblinear-twitter-GM1-ALL-ALL-75

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.1802	0.1802	0.1802	0.0000	0.1609	0.8582	0.0000	0.1599
		SAL	0.1875	0.1875	0.1875	0.0000	0.1640	0.8127	0.0000	0.1634
		STL	0.1875	0.1875	0.1875	0.0000	0.1640	0.8127	0.0000	0.1634
	1	RAN	0.1802	0.1802	0.1802	0.0000	0.1554	0.8071	0.0000	0.1605
		SAL	0.1932	0.1932	0.1932	0.0000	0.1687	0.8212	0.0000	0.1650
		STL	0.1932	0.1932	0.1932	0.0000	0.1687	0.8212	0.0000	0.1650
	2	RAN	0.1821	0.1821	0.1821	0.0000	0.1617	0.7698	0.0000	0.1628
		SAL	0.1833	0.1833	0.1833	0.0000	0.1585	0.7807	0.0000	0.1548
		STL	0.1833	0.1833	0.1833	0.0000	0.1585	0.7807	0.0000	0.1548
	4	RAN	0.1943	0.1943	0.1943	0.0000	0.1702	0.8792	0.0000	0.1668
		SAL	0.1910	0.1910	0.1910	0.0000	0.1647	0.7697	0.0000	0.1556
		STL	0.1910	0.1910	0.1910	0.0000	0.1647	0.7697	0.0000	0.1556
	8	RAN	0.1913	0.1913	0.1913	0.0000	0.1649	0.8139	0.0000	0.1687
		SAL	0.1884	0.1884	0.1884	0.0000	0.1636	0.7644	0.0000	0.1631
		STL	0.1884	0.1884	0.1884	0.0000	0.1636	0.7644	0.0000	0.1631
	16	RAN	0.1865	0.1865	0.1865	0.0000	0.1592	0.8143	0.0000	0.1666
		SAL	0.1883	0.1883	0.1883	0.0000	0.1671	0.7732	0.0000	0.1588
		STL	0.1883	0.1883	0.1883	0.0000	0.1671	0.7732	0.0000	0.1588

Table F.6: grouped-liblinear-twitter-GM1-ALL-ALL-150

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.4955	0.7162	0.3041	0.0815	0.4553	0.9272	0.0000	0.1764
		SAL	0.4834	0.7282	0.2664	0.1007	0.4476	0.9272	0.0000	0.1688
		STL	0.4744	0.6572	0.3283	0.0813	0.4474	0.8897	0.0000	0.1570
	1	RAN	0.6339	0.8454	0.4772	0.0813	0.6069	0.9886	0.1159	0.1596
		SAL	0.6252	0.7790	0.4664	0.0795	0.6051	0.9771	0.1739	0.1438
		STL	0.6133	0.7656	0.4881	0.0714	0.5967	0.9202	0.1250	0.1404
	2	RAN	0.6219	0.8172	0.4335	0.0934	0.6025	0.9697	0.1071	0.1478
		SAL	0.6324	0.7629	0.3934	0.0813	0.6130	0.9524	0.2143	0.1385
		STL	0.6120	0.8232	0.4517	0.0838	0.6006	0.9202	0.2716	0.1400
	4	RAN	0.6420	0.8157	0.5014	0.0783	0.6202	0.9545	0.2258	0.1400
		SAL	0.6196	0.8210	0.4820	0.0810	0.5996	0.9488	0.1951	0.1453
		STL	0.6144	0.7669	0.4245	0.0751	0.6035	0.9202	0.1639	0.1351
	8	RAN	0.6415	0.7996	0.5168	0.0782	0.6205	0.9732	0.2326	0.1453
		SAL	0.6309	0.8489	0.4951	0.0678	0.6136	0.9773	0.1818	0.1390
		STL	0.6123	0.7669	0.4773	0.0707	0.6048	0.9202	0.2667	0.1265
	16	RAN	0.6358	0.8544	0.4986	0.0831	0.6204	0.9603	0.2985	0.1281
		SAL	0.6272	0.8015	0.4094	0.1010	0.6102	0.9579	0.2157	0.1468
		STL	0.6144	0.7870	0.5018	0.0758	0.6051	0.9202	0.2368	0.1282

Table F.7: grouped-liblinear-twitter-GM2-ALL-ALL-5

GM2										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.3685	0.5557	0.1985	0.0875	0.3390	0.9150	0.0000	0.1702
		SAL	0.3721	0.5725	0.2590	0.0864	0.3469	0.8176	0.0000	0.1686
		STL	0.3695	0.4854	0.2646	0.0539	0.3506	0.8539	0.0000	0.1669
	1	RAN	0.5044	0.6219	0.3851	0.0668	0.4737	0.9575	0.0357	0.1671
		SAL	0.4832	0.5897	0.3429	0.0674	0.4514	0.9531	0.0000	0.1722
		STL	0.4836	0.6154	0.3430	0.0631	0.4721	0.8945	0.1667	0.1498
	2	RAN	0.4934	0.5992	0.3683	0.0549	0.4690	0.9509	0.0923	0.1542
		SAL	0.5073	0.6491	0.4107	0.0599	0.4802	0.9549	0.0923	0.1667
		STL	0.4700	0.6213	0.3560	0.0672	0.4575	0.8963	0.0879	0.1536
	4	RAN	0.4989	0.6303	0.3851	0.0732	0.4696	0.9771	0.0303	0.1692
		SAL	0.5058	0.6924	0.4116	0.0731	0.4763	0.9363	0.0000	0.1648
		STL	0.4840	0.6013	0.3379	0.0650	0.4676	0.8928	0.0714	0.1573
	8	RAN	0.4895	0.6693	0.3939	0.0782	0.4646	0.9524	0.1463	0.1658
		SAL	0.4870	0.5608	0.4050	0.0400	0.4583	0.9502	0.1042	0.1627
		STL	0.4762	0.6163	0.3593	0.0619	0.4638	0.8980	0.0857	0.1519
	16	RAN	0.4965	0.6961	0.3142	0.0889	0.4709	0.9421	0.0000	0.1724
		SAL	0.4962	0.6383	0.3804	0.0677	0.4714	0.9358	0.1111	0.1564
		STL	0.4746	0.6163	0.3733	0.0591	0.4628	0.8980	0.1379	0.1440

Table F.8: grouped-liblinear-twitter-GM2-ALL-ALL-10

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.2618	0.3285	0.2022	0.0403	0.2437	0.8399	0.0000	0.1704
		SAL	0.2694	0.3163	0.2364	0.0237	0.2376	0.7742	0.0000	0.1790
		STL	0.2613	0.3004	0.1882	0.0369	0.2498	0.8473	0.0000	0.1706
	1	RAN	0.3556	0.3991	0.3017	0.0342	0.3266	0.9299	0.0000	0.1729
		SAL	0.3512	0.4945	0.2926	0.0698	0.3227	0.9037	0.0000	0.1790
		STL	0.3338	0.4079	0.2702	0.0418	0.3186	0.8871	0.0000	0.1689
	2	RAN	0.3525	0.4076	0.2881	0.0379	0.3219	0.8880	0.0000	0.1689
		SAL	0.3555	0.4433	0.2642	0.0587	0.3285	0.9542	0.0000	0.1683
		STL	0.3313	0.4132	0.2655	0.0500	0.3154	0.8618	0.0241	0.1658
	4	RAN	0.3577	0.4149	0.3246	0.0338	0.3291	0.8548	0.0000	0.1675
		SAL	0.3598	0.4450	0.3107	0.0441	0.3372	0.9438	0.0345	0.1718
		STL	0.3403	0.4418	0.2665	0.0576	0.3249	0.8463	0.0000	0.1681
	8	RAN	0.3551	0.4446	0.2818	0.0548	0.3224	0.9011	0.0000	0.1673
		SAL	0.3533	0.4469	0.3027	0.0480	0.3249	0.9136	0.0000	0.1711
		STL	0.3253	0.4172	0.2535	0.0541	0.3132	0.8767	0.0682	0.1608
	16	RAN	0.3463	0.4218	0.2916	0.0476	0.3175	0.9213	0.0000	0.1831
		SAL	0.3572	0.4682	0.2755	0.0805	0.3310	0.8782	0.0313	0.1664
		STL	0.3276	0.4381	0.2419	0.0648	0.3166	0.8436	0.0000	0.1707

Table F.9: grouped-liblinear-twitter-GM2-ALL-ALL-25

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.2089	0.2220	0.1947	0.0112	0.1974	0.8315	0.0000	0.1739
		SAL	0.2107	0.2265	0.1860	0.0177	0.2008	0.8333	0.0000	0.1720
		STL	0.2095	0.2745	0.1587	0.0484	0.2034	0.8333	0.0000	0.1736
	1	RAN	0.2702	0.3381	0.2310	0.0482	0.2478	0.8592	0.0000	0.1705
		SAL	0.2781	0.3185	0.2483	0.0296	0.2458	0.8750	0.0000	0.1685
		STL	0.2555	0.3090	0.2275	0.0378	0.2424	0.8661	0.0000	0.1744
	2	RAN	0.2701	0.2863	0.2559	0.0125	0.2423	0.8521	0.0000	0.1803
		SAL	0.2794	0.3221	0.2116	0.0484	0.2533	0.8777	0.0000	0.1780
		STL	0.2625	0.3178	0.2331	0.0391	0.2454	0.8571	0.0000	0.1802
	4	RAN	0.2742	0.3019	0.2591	0.0196	0.2442	0.8473	0.0000	0.1724
		SAL	0.2842	0.3006	0.2567	0.0195	0.2510	0.8760	0.0000	0.1741
		STL	0.2662	0.3236	0.2372	0.0406	0.2441	0.8689	0.0000	0.1759
	8	RAN	0.2773	0.3057	0.2445	0.0252	0.2490	0.8218	0.0000	0.1678
		SAL	0.2780	0.2855	0.2718	0.0057	0.2494	0.8686	0.0000	0.1742
		STL	0.2767	0.3297	0.2427	0.0380	0.2578	0.8571	0.0000	0.1806

Table F.10: grouped-liblinear-twitter-GM2-ALL-ALL-50

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.1731	0.2186	0.1277	0.0455	0.1724	0.7893	0.0000	0.1690
		SAL	0.1869	0.1948	0.1789	0.0079	0.1742	0.7926	0.0000	0.1712
		STL	0.1801	0.2027	0.1576	0.0225	0.1721	0.7589	0.0000	0.1587
	1	RAN	0.2398	0.2568	0.2227	0.0170	0.2098	0.8914	0.0000	0.1693
		SAL	0.2410	0.2861	0.1960	0.0451	0.2205	0.8647	0.0000	0.1747
		STL	0.2242	0.2523	0.1960	0.0282	0.2137	0.8402	0.0000	0.1703
	2	RAN	0.2430	0.2518	0.2341	0.0088	0.2147	0.8397	0.0000	0.1748
		SAL	0.2395	0.2697	0.2093	0.0302	0.2119	0.8027	0.0000	0.1694
		STL	0.2238	0.2609	0.1867	0.0371	0.2124	0.8353	0.0000	0.1688
	4	RAN	0.2424	0.2688	0.2160	0.0264	0.2097	0.8372	0.0000	0.1712
		SAL	0.2356	0.2556	0.2156	0.0200	0.2082	0.8615	0.0000	0.1710
		STL	0.2309	0.2778	0.1841	0.0469	0.2155	0.8291	0.0000	0.1666
	8	RAN	0.2359	0.2575	0.2143	0.0216	0.2135	0.8259	0.0000	0.1699
		SAL	0.2445	0.2672	0.2219	0.0227	0.2155	0.8600	0.0000	0.1805
		STL	0.2257	0.2672	0.1843	0.0415	0.2150	0.8160	0.0000	0.1737

Table F.11: grouped-liblinear-twitter-GM2-ALL-ALL-75

GM2										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.1466	0.1466	0.1466	0.0000	0.1383	0.7754	0.0000	0.1565
		SAL	0.1554	0.1554	0.1554	0.0000	0.1466	0.8092	0.0000	0.1624
		STL	0.1554	0.1554	0.1554	0.0000	0.1466	0.8092	0.0000	0.1624
	1	RAN	0.1882	0.1882	0.1882	0.0000	0.1610	0.7742	0.0000	0.1642
		SAL	0.1893	0.1893	0.1893	0.0000	0.1683	0.7241	0.0000	0.1618
		STL	0.1893	0.1893	0.1893	0.0000	0.1683	0.7241	0.0000	0.1618
	2	RAN	0.1874	0.1874	0.1874	0.0000	0.1584	0.8385	0.0000	0.1714
		SAL	0.1830	0.1830	0.1830	0.0000	0.1612	0.7421	0.0000	0.1653
		STL	0.1830	0.1830	0.1830	0.0000	0.1612	0.7421	0.0000	0.1653
	4	RAN	0.1809	0.1809	0.1809	0.0000	0.1573	0.7458	0.0000	0.1599
		SAL	0.1888	0.1888	0.1888	0.0000	0.1662	0.7143	0.0000	0.1638
		STL	0.1888	0.1888	0.1888	0.0000	0.1662	0.7143	0.0000	0.1638

Table F.12: grouped-liblinear-twitter-GM2-ALL-ALL-150

GM5										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.2775	0.4753	0.1687	0.0584	0.1980	0.6443	0.0000	0.1541
		SAL	0.2754	0.5119	0.1805	0.0606	0.1990	0.6715	0.0000	0.1498
		STL	0.2763	0.4075	0.2085	0.0483	0.2016	0.5846	0.0000	0.1488
	1	RAN	0.5972	0.8029	0.4040	0.0855	0.5712	0.9498	0.1887	0.1491
		SAL	0.5876	0.8362	0.4503	0.0896	0.5650	0.9494	0.1667	0.1503
		STL	0.5756	0.7406	0.4249	0.0715	0.5609	0.9286	0.2373	0.1405
	2	RAN	0.5836	0.7339	0.4037	0.0852	0.5587	0.9237	0.0845	0.1523
		SAL	0.5885	0.7639	0.3689	0.0879	0.5700	0.9457	0.1017	0.1449
		STL	0.5686	0.7365	0.4480	0.0755	0.5496	0.9105	0.2000	0.1483
	4	SAL	0.5900	0.7832	0.4274	0.0883	0.5684	0.9064	0.1967	0.1439
		STL	0.5635	0.7406	0.3838	0.0707	0.5481	0.9147	0.1972	0.1421
		RAN	0.5905	0.7827	0.4317	0.0894	0.5716	0.9389	0.2295	0.1456
	8	SAL	0.5784	0.7253	0.4162	0.0701	0.5546	0.9506	0.1818	0.1419
		STL	0.5757	0.7365	0.4249	0.0657	0.5596	0.9105	0.2059	0.1438
		RAN	0.5819	0.8039	0.4245	0.0911	0.5643	0.9278	0.1231	0.1463
	16	SAL	0.5800	0.7916	0.4084	0.0966	0.5632	0.9104	0.1765	0.1517
		STL	0.5661	0.7365	0.4176	0.0710	0.5534	0.9105	0.0625	0.1389

Table F.13: grouped-liblinear-twitter-GM5-ALL-ALL-5

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.1740	0.2808	0.1212	0.0355	0.1302	0.5538	0.0000	0.1202
		SAL	0.1727	0.2811	0.0961	0.0439	0.1221	0.5294	0.0000	0.1157
		STL	0.1688	0.2530	0.1313	0.0304	0.1192	0.5625	0.0000	0.1155
	1	RAN	0.4394	0.5487	0.3428	0.0598	0.4153	0.8931	0.0519	0.1602
		SAL	0.4520	0.5825	0.3247	0.0719	0.4245	0.9237	0.0741	0.1673
		STL	0.4234	0.5439	0.3402	0.0588	0.4053	0.8485	0.0597	0.1544
	2	RAN	0.4501	0.5657	0.3178	0.0665	0.4290	0.9272	0.0000	0.1542
		SAL	0.4401	0.5567	0.3453	0.0618	0.4169	0.9302	0.0519	0.1657
		STL	0.4244	0.5439	0.3108	0.0618	0.4088	0.8640	0.0345	0.1521
	4	RAN	0.4540	0.5758	0.3693	0.0569	0.4296	0.9272	0.0000	0.1579
		SAL	0.4499	0.5550	0.3482	0.0490	0.4219	0.8923	0.0000	0.1614
		STL	0.4198	0.5439	0.3059	0.0623	0.4063	0.8500	0.0328	0.1522
	8	RAN	0.4431	0.6007	0.3683	0.0619	0.4227	0.9219	0.1067	0.1521
		SAL	0.4519	0.5438	0.3591	0.0466	0.4204	0.9134	0.0741	0.1611
		STL	0.4246	0.5439	0.3375	0.0579	0.4122	0.8485	0.0385	0.1483
	16	RAN	0.4564	0.5563	0.3924	0.0554	0.4276	0.9213	0.0370	0.1635
		SAL	0.4538	0.6258	0.3294	0.0925	0.4311	0.9160	0.0779	0.1685
		STL	0.4142	0.5366	0.2951	0.0649	0.3996	0.8321	0.0328	0.1502

Table F.14: grouped-liblinear-twitter-GM5-ALL-ALL-10

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.1053	0.1493	0.0851	0.0211	0.0916	0.6154	0.0000	0.1161
		SAL	0.1088	0.1677	0.0717	0.0319	0.0881	0.5075	0.0000	0.1101
		STL	0.1039	0.1480	0.0816	0.0217	0.0861	0.5758	0.0000	0.1157
	1	RAN	0.2969	0.3466	0.2487	0.0297	0.2722	0.8872	0.0000	0.1590
		SAL	0.3133	0.3718	0.2607	0.0398	0.2856	0.9105	0.0000	0.1670
		STL	0.2932	0.3498	0.2378	0.0332	0.2773	0.8346	0.0000	0.1593
	2	RAN	0.3113	0.3874	0.2285	0.0510	0.2880	0.8913	0.0000	0.1678
		SAL	0.3080	0.3700	0.2576	0.0447	0.2838	0.8973	0.0000	0.1609
		STL	0.2958	0.3352	0.1840	0.0518	0.2801	0.8197	0.0196	0.1655
	4	RAN	0.3019	0.3746	0.2493	0.0436	0.2771	0.8613	0.0000	0.1570
		SAL	0.3050	0.3749	0.2491	0.0413	0.2808	0.8627	0.0000	0.1655
		STL	0.2897	0.3382	0.2324	0.0348	0.2701	0.8217	0.0000	0.1613

Table F.15: grouped-liblinear-twitter-GM5-ALL-ALL-25

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.0827	0.1043	0.0668	0.0158	0.0793	0.5205	0.0000	0.1092
		SAL	0.0809	0.1060	0.0666	0.0178	0.0835	0.5333	0.0000	0.1187
		STL	0.0780	0.0908	0.0678	0.0096	0.0749	0.5373	0.0000	0.1089
	1	RAN	0.2249	0.2511	0.1950	0.0231	0.2079	0.8759	0.0000	0.1559
		SAL	0.2266	0.2574	0.1834	0.0315	0.2066	0.8636	0.0000	0.1527
		STL	0.2220	0.2457	0.1952	0.0207	0.2042	0.7729	0.0000	0.1499
	2	RAN	0.2190	0.2327	0.2035	0.0120	0.2011	0.8803	0.0000	0.1486
		SAL	0.2329	0.3069	0.1935	0.0524	0.2146	0.8519	0.0000	0.1633
		STL	0.2190	0.2430	0.1884	0.0228	0.2020	0.7846	0.0000	0.1528

Table F.16: grouped-liblinear-twitter-GM5-ALL-ALL-50

GM5										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.0633	0.0681	0.0585	0.0048	0.0625	0.4571	0.0000	0.0971
		SAL	0.0607	0.0792	0.0421	0.0186	0.0624	0.4595	0.0000	0.0943
		STL	0.0690	0.0764	0.0617	0.0073	0.0725	0.5392	0.0000	0.1127
	1	RAN	0.1991	0.2074	0.1907	0.0084	0.1790	0.8326	0.0000	0.1519
		SAL	0.1901	0.1943	0.1859	0.0042	0.1714	0.8669	0.0000	0.1535
		STL	0.1815	0.2133	0.1496	0.0318	0.1668	0.7969	0.0000	0.1486
	2	RAN	0.1944	0.2180	0.1708	0.0236	0.1707	0.8211	0.0000	0.1469
		SAL	0.1925	0.1979	0.1870	0.0054	0.1668	0.8201	0.0000	0.1520
		STL	0.1789	0.1904	0.1673	0.0115	0.1680	0.7333	0.0000	0.1446

Table F.17: grouped-liblinear-twitter-GM5-ALL-ALL-75

GM5										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.0573	0.0573	0.0573	0.0000	0.0623	0.5363	0.0000	0.1016
		SAL	0.0667	0.0667	0.0667	0.0000	0.0749	0.5443	0.0000	0.1102
		STL	0.0667	0.0667	0.0667	0.0000	0.0749	0.5443	0.0000	0.1102
	1	RAN	0.1402	0.1402	0.1402	0.0000	0.1270	0.7500	0.0000	0.1360
		SAL	0.1398	0.1398	0.1398	0.0000	0.1388	0.7399	0.0000	0.1426
		STL	0.1398	0.1398	0.1398	0.0000	0.1388	0.7399	0.0000	0.1426

Table F.18: grouped-liblinear-twitter-GM5-ALL-ALL-150

GB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.5516	0.8313	0.3737	0.0851	0.5171	0.9360	0.0000	0.1613
		SAL	0.5413	0.7271	0.4077	0.0823	0.5003	0.9125	0.0000	0.1754
		STL	0.5286	0.7248	0.3916	0.0846	0.5004	0.9206	0.0656	0.1620
	1	RAN	0.5237	0.7348	0.3734	0.0767	0.4901	0.9308	0.0000	0.1701
		SAL	0.5472	0.7360	0.3782	0.0744	0.5070	0.9213	0.0385	0.1749
		STL	0.5227	0.6789	0.3935	0.0718	0.5016	0.9237	0.0000	0.1594
	2	RAN	0.5529	0.6855	0.3850	0.0687	0.5190	0.9375	0.0800	0.1623
		SAL	0.5518	0.7269	0.4286	0.0748	0.5138	0.8897	0.0435	0.1701
		STL	0.5295	0.6789	0.4142	0.0642	0.5047	0.9231	0.0000	0.1559
	4	RAN	0.5455	0.7530	0.3571	0.0896	0.5146	0.9344	0.0370	0.1655
		SAL	0.5573	0.7538	0.4223	0.0816	0.5217	0.9354	0.0435	0.1705
		STL	0.5167	0.6748	0.3966	0.0730	0.4917	0.9237	0.0000	0.1677
	8	RAN	0.5486	0.8297	0.4236	0.0909	0.5209	0.9290	0.0513	0.1596
		SAL	0.5487	0.7169	0.3908	0.0828	0.5056	0.8930	0.0385	0.1772
		STL	0.5241	0.6789	0.3935	0.0756	0.4989	0.9237	0.0000	0.1616
	16	RAN	0.5473	0.7285	0.3780	0.0773	0.5080	0.9105	0.0000	0.1802
		SAL	0.5471	0.7564	0.4084	0.0801	0.5015	0.9416	0.0000	0.1787
		STL	0.5214	0.6775	0.3966	0.0698	0.4965	0.9237	0.0000	0.1623

Table F.19: grouped-liblinear-twitter-GB3-ALL-ALL-5

GB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.4323	0.5419	0.3306	0.0708	0.3973	0.8931	0.0000	0.1751
		SAL	0.4251	0.5716	0.3021	0.0693	0.3946	0.9302	0.0000	0.1727
		STL	0.4118	0.5448	0.3267	0.0572	0.3819	0.9015	0.0000	0.1714
	1	RAN	0.4203	0.5008	0.3237	0.0515	0.3793	0.8806	0.0000	0.1743
		SAL	0.4268	0.5795	0.2998	0.0774	0.3916	0.8655	0.0000	0.1846
		STL	0.4150	0.5289	0.3373	0.0573	0.3897	0.8727	0.0308	0.1603
	2	RAN	0.4277	0.6907	0.3418	0.0837	0.3982	0.9049	0.0000	0.1809
		SAL	0.4239	0.5714	0.3259	0.0686	0.3921	0.8947	0.0385	0.1685
		STL	0.4146	0.5289	0.3365	0.0600	0.3910	0.8750	0.0000	0.1634
	4	RAN	0.4325	0.5960	0.3114	0.0791	0.3947	0.9127	0.0000	0.1880
		SAL	0.4286	0.5818	0.3194	0.0625	0.3922	0.9231	0.0000	0.1746
		STL	0.4066	0.5280	0.3317	0.0584	0.3827	0.8750	0.0000	0.1635
	8	RAN	0.4295	0.5868	0.3045	0.0738	0.3980	0.9266	0.0000	0.1783
		SAL	0.4298	0.5508	0.3273	0.0758	0.3988	0.8947	0.0000	0.1798
		STL	0.4145	0.5297	0.3274	0.0600	0.3914	0.8750	0.0000	0.1606
	16	RAN	0.4380	0.5621	0.3144	0.0690	0.4078	0.9183	0.0000	0.1714
		SAL	0.4291	0.5633	0.3351	0.0633	0.3887	0.9147	0.0000	0.1798
		STL	0.4043	0.5297	0.3278	0.0622	0.3826	0.8750	0.0000	0.1642

Table F.20: grouped-liblinear-twitter-GB3-ALL-ALL-10

GB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.3201	0.3997	0.2486	0.0509	0.2917	0.8433	0.0000	0.1746
		SAL	0.3170	0.3983	0.2658	0.0472	0.2898	0.8750	0.0000	0.1755
		STL	0.2998	0.4116	0.2218	0.0567	0.2781	0.8531	0.0000	0.1804
	1	RAN	0.3143	0.3864	0.2626	0.0412	0.2831	0.9147	0.0000	0.1686
		SAL	0.3172	0.3813	0.2666	0.0401	0.2907	0.8923	0.0000	0.1777
		STL	0.2946	0.4029	0.2379	0.0547	0.2772	0.8689	0.0000	0.1712
	2	RAN	0.3193	0.3680	0.2569	0.0437	0.2910	0.8949	0.0000	0.1861
		SAL	0.3118	0.3603	0.2839	0.0301	0.2706	0.8622	0.0000	0.1778
		STL	0.3090	0.4094	0.2572	0.0500	0.2872	0.8647	0.0000	0.1696
	4	RAN	0.3191	0.3886	0.2582	0.0424	0.2805	0.8973	0.0000	0.1748
		SAL	0.3203	0.3957	0.2714	0.0492	0.2893	0.8841	0.0000	0.1716
		STL	0.3002	0.4082	0.2461	0.0557	0.2794	0.8593	0.0000	0.1724
	8	RAN	0.3240	0.3914	0.2693	0.0388	0.3031	0.9286	0.0000	0.1813
		SAL	0.3225	0.3795	0.2862	0.0348	0.2910	0.8806	0.0000	0.1714
		STL	0.2982	0.4164	0.2594	0.0554	0.2794	0.8657	0.0000	0.1702

Table F.21: grouped-liblinear-twitter-GB3-ALL-ALL-25

GB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.2506	0.2968	0.2038	0.0379	0.2256	0.8992	0.0000	0.1710
		SAL	0.2483	0.2688	0.2372	0.0145	0.2229	0.8540	0.0000	0.1659
		STL	0.2411	0.2883	0.1960	0.0377	0.2235	0.8298	0.0000	0.1658
	1	RAN	0.2412	0.2821	0.2077	0.0309	0.2161	0.8679	0.0000	0.1683
		SAL	0.2572	0.2728	0.2349	0.0161	0.2292	0.8561	0.0000	0.1686
		STL	0.2412	0.3082	0.1949	0.0485	0.2299	0.8864	0.0000	0.1811
	2	RAN	0.2494	0.2622	0.2352	0.0110	0.2229	0.8812	0.0000	0.1712
		SAL	0.2558	0.2942	0.2224	0.0295	0.2295	0.8872	0.0000	0.1661
		STL	0.2344	0.3034	0.1923	0.0492	0.2205	0.9008	0.0000	0.1717
	4	RAN	0.2532	0.2633	0.2403	0.0096	0.2284	0.8978	0.0000	0.1686
		SAL	0.2626	0.2964	0.2126	0.0361	0.2320	0.8699	0.0000	0.1670
		STL	0.2520	0.3163	0.2019	0.0478	0.2396	0.8764	0.0000	0.1725

Table F.22: grouped-liblinear-twitter-GB3-ALL-ALL-50

GB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.2035	0.2139	0.1931	0.0104	0.1888	0.8496	0.0000	0.1631
		SAL	0.2193	0.2325	0.2060	0.0133	0.1972	0.8530	0.0000	0.1658
		STL	0.2170	0.2497	0.1842	0.0328	0.2029	0.8235	0.0000	0.1732
	1	RAN	0.2184	0.2477	0.1891	0.0293	0.1915	0.8071	0.0000	0.1657
		SAL	0.2143	0.2442	0.1845	0.0299	0.1898	0.8803	0.0000	0.1667
		STL	0.2138	0.2472	0.1803	0.0335	0.1934	0.8561	0.0000	0.1654
	2	RAN	0.2193	0.2448	0.1937	0.0256	0.2010	0.8989	0.0000	0.1717
		SAL	0.2243	0.2421	0.2065	0.0178	0.1980	0.8520	0.0000	0.1678
		STL	0.2085	0.2433	0.1736	0.0348	0.1924	0.8692	0.0000	0.1746
	4	RAN	0.2226	0.2324	0.2128	0.0098	0.1930	0.8846	0.0000	0.1698
		SAL	0.2244	0.2648	0.1840	0.0404	0.1947	0.8722	0.0000	0.1672
		STL	0.2120	0.2428	0.1812	0.0308	0.1985	0.8682	0.0000	0.1696

Table F.23: grouped-liblinear-twitter-GB3-ALL-ALL-75

GB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.1825	0.1825	0.1825	0.0000	0.1573	0.8100	0.0000	0.1522
		SAL	0.1696	0.1696	0.1696	0.0000	0.1484	0.8357	0.0000	0.1498
		STL	0.1696	0.1696	0.1696	0.0000	0.1484	0.8357	0.0000	0.1498
	1	RAN	0.1813	0.1813	0.1813	0.0000	0.1581	0.8192	0.0000	0.1611
		SAL	0.1796	0.1796	0.1796	0.0000	0.1562	0.8125	0.0000	0.1509
		STL	0.1796	0.1796	0.1796	0.0000	0.1562	0.8125	0.0000	0.1509
	2	RAN	0.1758	0.1758	0.1758	0.0000	0.1528	0.7723	0.0000	0.1577
		SAL	0.1746	0.1746	0.1746	0.0000	0.1568	0.8182	0.0000	0.1558
		STL	0.1746	0.1746	0.1746	0.0000	0.1568	0.8182	0.0000	0.1558

Table F.24: grouped-liblinear-twitter-GB3-ALL-ALL-150

OSB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.5481	0.6885	0.3680	0.0785	0.5141	0.9272	0.0941	0.1632
		SAL	0.5564	0.7559	0.3794	0.0880	0.5289	0.9513	0.0000	0.1634
		STL	0.5245	0.6680	0.3774	0.0752	0.5001	0.9206	0.0299	0.1644
	1	RAN	0.5480	0.7148	0.4186	0.0746	0.5107	0.9362	0.0952	0.1659
		SAL	0.5525	0.7747	0.4000	0.0710	0.5169	0.9290	0.0000	0.1637
		STL	0.5168	0.6748	0.4059	0.0676	0.4911	0.9237	0.0000	0.1633
	2	RAN	0.5426	0.7221	0.3867	0.0812	0.5010	0.9302	0.0400	0.1739
		SAL	0.5623	0.7651	0.3934	0.0786	0.5259	0.9425	0.0000	0.1714
		STL	0.5233	0.6734	0.3731	0.0720	0.4984	0.9194	0.0000	0.1591
	4	RAN	0.5435	0.6757	0.3967	0.0789	0.5120	0.9434	0.0435	0.1691
		SAL	0.5509	0.7747	0.3934	0.0845	0.5152	0.9333	0.0000	0.1704
		STL	0.5230	0.6762	0.4059	0.0712	0.4983	0.9237	0.0000	0.1619
	8	RAN	0.5520	0.7570	0.4263	0.0827	0.5113	0.9457	0.0000	0.1743
		SAL	0.5549	0.7747	0.4000	0.0893	0.5177	0.9425	0.0000	0.1794
		STL	0.5211	0.6775	0.4143	0.0701	0.4961	0.9280	0.0000	0.1609
	16	RAN	0.5459	0.7647	0.3704	0.0862	0.5088	0.9333	0.0000	0.1626
		SAL	0.5557	0.7773	0.4372	0.0780	0.5218	0.9278	0.0000	0.1649
		STL	0.5200	0.6775	0.4022	0.0665	0.4963	0.9280	0.0000	0.1672

Table F.25: grouped-liblinear-twitter-OSB3-ALL-ALL-5

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.4272	0.5191	0.3284	0.0617	0.3974	0.9261	0.0000	0.1711
		SAL	0.4408	0.5520	0.3268	0.0575	0.4043	0.8621	0.0000	0.1739
		STL	0.4135	0.5473	0.3216	0.0532	0.3944	0.8759	0.0426	0.1547
	1	RAN	0.4373	0.5798	0.3328	0.0678	0.4050	0.9453	0.0000	0.1793
		SAL	0.4370	0.5847	0.3219	0.0643	0.4003	0.8832	0.0000	0.1769
		STL	0.4122	0.5331	0.3226	0.0581	0.3864	0.8664	0.0299	0.1756
	2	RAN	0.4246	0.5667	0.3483	0.0546	0.3893	0.9125	0.0000	0.1763
		SAL	0.4369	0.5802	0.3380	0.0629	0.4012	0.8812	0.0000	0.1809
		STL	0.4151	0.5322	0.3280	0.0536	0.3902	0.8633	0.0000	0.1727
	4	RAN	0.4239	0.6093	0.3043	0.0825	0.3891	0.9375	0.0000	0.1804
		SAL	0.4318	0.6031	0.3051	0.0734	0.3947	0.8679	0.0000	0.1812
		STL	0.4193	0.5322	0.3495	0.0479	0.3956	0.8664	0.0392	0.1696
	8	RAN	0.4326	0.5522	0.3042	0.0617	0.3967	0.9358	0.0000	0.1841
		SAL	0.4344	0.6031	0.3219	0.0814	0.4011	0.9057	0.0000	0.1818
		STL	0.4178	0.5322	0.3247	0.0555	0.3939	0.8664	0.0328	0.1734

Table F.26: grouped-liblinear-twitter-OSB3-ALL-ALL-10

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.3047	0.3761	0.2584	0.0478	0.2748	0.8722	0.0000	0.1747
		SAL	0.3148	0.3923	0.2331	0.0595	0.2924	0.8647	0.0000	0.1755
		STL	0.3055	0.4086	0.2393	0.0511	0.2876	0.8731	0.0000	0.1790
	1	RAN	0.3188	0.4382	0.2234	0.0653	0.2824	0.8837	0.0000	0.1826
		SAL	0.3235	0.3714	0.2589	0.0388	0.2919	0.8945	0.0000	0.1816
		STL	0.3012	0.4021	0.2604	0.0501	0.2873	0.8571	0.0000	0.1722
	2	RAN	0.3146	0.3747	0.2557	0.0390	0.2824	0.9112	0.0000	0.1774
		SAL	0.3142	0.3713	0.2617	0.0436	0.2833	0.8741	0.0000	0.1792
		STL	0.2898	0.4078	0.2144	0.0593	0.2733	0.8529	0.0000	0.1705

Table F.27: grouped-liblinear-twitter-OSB3-ALL-ALL-25

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.2524	0.2630	0.2319	0.0145	0.2311	0.8550	0.0000	0.1770
		SAL	0.2589	0.2913	0.2137	0.0329	0.2327	0.8686	0.0000	0.1697
		STL	0.2446	0.2880	0.2023	0.0350	0.2242	0.8456	0.0000	0.1715
	1	RAN	0.2527	0.3057	0.2138	0.0388	0.2268	0.8727	0.0000	0.1742
		SAL	0.2521	0.2849	0.2251	0.0247	0.2250	0.8464	0.0000	0.1739
		STL	0.2505	0.3164	0.2046	0.0478	0.2323	0.8897	0.0000	0.1766

Table F.28: grouped-liblinear-twitter-OSB3-ALL-ALL-50

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.2263	0.2300	0.2227	0.0037	0.2002	0.8374	0.0000	0.1650
		SAL	0.2221	0.2493	0.1949	0.0272	0.1998	0.8839	0.0000	0.1735
		STL	0.2148	0.2482	0.1815	0.0334	0.2028	0.8561	0.0000	0.1740
	1	RAN	0.2217	0.2519	0.1916	0.0302	0.1933	0.8692	0.0000	0.1698
		SAL	0.2370	0.2722	0.2019	0.0351	0.2077	0.7818	0.0000	0.1640
		STL	0.2177	0.2498	0.1856	0.0321	0.1992	0.8303	0.0000	0.1736

Table F.29: grouped-liblinear-twitter-OSB3-ALL-ALL-75

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.1839	0.1839	0.1839	0.0000	0.1609	0.8043	0.0000	0.1509
		SAL	0.1705	0.1705	0.1705	0.0000	0.1566	0.8239	0.0000	0.1542
		STL	0.1705	0.1705	0.1705	0.0000	0.1566	0.8239	0.0000	0.1542

Table F.30: grouped-liblinear-twitter-OSB3-ALL-ALL-150

APPENDIX G:
Grouped Naive Bayes Results for the ENRON Email Corpus

GM1										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.7112	0.8965	0.5604	0.0942	0.3205	0.9529	0.0000	0.3517
		SAL	0.6942	0.8457	0.4841	0.0881	0.2498	0.9165	0.0000	0.3264
		STL	0.7591	0.9114	0.4815	0.0937	0.7347	0.9730	0.0000	0.1714
	1	RAN	0.6223	0.8864	0.2937	0.1626	0.4969	0.9407	0.0000	0.2549
		SAL	0.6009	0.8448	0.2985	0.1576	0.4483	0.9110	0.0000	0.2488
		STL	0.7091	0.8601	0.4875	0.0791	0.6762	0.9453	0.0000	0.1760
	2	RAN	0.6337	0.8877	0.2256	0.1662	0.5208	0.9420	0.0000	0.2563
		SAL	0.6075	0.8704	0.2926	0.1574	0.4534	0.9173	0.0000	0.2476
		STL	0.7103	0.8612	0.5096	0.0766	0.6787	0.9467	0.0000	0.1729
	4	RAN	0.6545	0.8717	0.2898	0.1469	0.5182	0.9198	0.0000	0.2631
		SAL	0.6134	0.8724	0.3059	0.1559	0.4570	0.9186	0.0000	0.2476
		STL	0.7150	0.8606	0.5176	0.0764	0.6827	0.9483	0.0000	0.1730
	8	RAN	0.6253	0.8864	0.2950	0.1491	0.4916	0.9398	0.0000	0.2540
		SAL	0.6184	0.8729	0.3070	0.1541	0.4618	0.9235	0.0000	0.2480
		STL	0.7167	0.8622	0.5217	0.0756	0.6850	0.9494	0.0000	0.1714
	16	RAN	0.6658	0.8698	0.2551	0.1582	0.5233	0.9173	0.0000	0.2575
		SAL	0.6172	0.8599	0.2724	0.1629	0.4627	0.9276	0.0000	0.2480
		STL	0.7158	0.8628	0.5256	0.0752	0.6840	0.9513	0.0000	0.1715

Table G.1: grouped-nb-enron-GM1-ALL-ALL-5

GM1										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.5658	0.7384	0.3311	0.1193	0.1854	0.8975	0.0000	0.2631
		SAL	0.5240	0.7271	0.3841	0.0955	0.1419	0.9164	0.0000	0.2302
		STL	0.6406	0.7663	0.5204	0.0710	0.6089	0.9144	0.0000	0.1999
	1	RAN	0.4851	0.6974	0.2923	0.1199	0.3867	0.8844	0.0000	0.2229
		SAL	0.4615	0.6259	0.3234	0.0999	0.3605	0.8191	0.0000	0.2192
		STL	0.6101	0.7117	0.3748	0.0867	0.5791	0.9655	0.0000	0.1960
	2	RAN	0.4861	0.7192	0.2904	0.1308	0.3905	0.8919	0.0000	0.2318
		SAL	0.4692	0.5976	0.2952	0.0933	0.3642	0.8037	0.0000	0.2161
		STL	0.6091	0.7137	0.3918	0.0828	0.5793	0.9157	0.0000	0.1920
	4	RAN	0.5304	0.7545	0.2715	0.1535	0.4113	0.8797	0.0000	0.2443
		SAL	0.4767	0.6021	0.3353	0.0915	0.3706	0.8056	0.0000	0.2167
		STL	0.6145	0.7146	0.4003	0.0822	0.5843	0.9500	0.0000	0.1907
	8	RAN	0.5051	0.6994	0.2647	0.1301	0.3973	0.8365	0.0000	0.2348
		SAL	0.4832	0.6110	0.3375	0.0936	0.3763	0.8063	0.0000	0.2187
		STL	0.6166	0.7164	0.4038	0.0820	0.5864	0.9157	0.0000	0.1897
	16	RAN	0.5172	0.6935	0.2763	0.1387	0.3980	0.9015	0.0000	0.2364
		SAL	0.4788	0.6056	0.3219	0.0886	0.3762	0.8341	0.0000	0.2178
		STL	0.6170	0.7174	0.4079	0.0812	0.5869	0.9500	0.0000	0.1899

Table G.2: grouped-nb-enron-GM1-ALL-ALL-10

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.4141	0.5192	0.3471	0.0548	0.1008	0.8796	0.0000	0.1952
		SAL	0.3826	0.4585	0.2996	0.0622	0.0896	0.8666	0.0000	0.1791
		STL	0.4280	0.5172	0.3652	0.0466	0.3652	0.8750	0.0000	0.2397
	1	RAN	0.3598	0.4587	0.2930	0.0601	0.2919	0.8148	0.0000	0.2012
		SAL	0.3306	0.3737	0.2745	0.0367	0.2805	0.8205	0.0000	0.1863
		STL	0.4964	0.5915	0.3156	0.0916	0.4648	0.9870	0.0000	0.2020
	2	RAN	0.3504	0.4163	0.3035	0.0373	0.2879	0.7757	0.0000	0.1908
		SAL	0.3618	0.4662	0.2822	0.0656	0.2896	0.7686	0.0000	0.1969
		STL	0.4989	0.5964	0.3246	0.0906	0.4688	0.9870	0.0000	0.2005
	4	RAN	0.3616	0.4911	0.2402	0.0871	0.3053	0.8243	0.0000	0.2001
		SAL	0.3690	0.4729	0.2850	0.0654	0.2957	0.7718	0.0000	0.1986
		STL	0.5026	0.5966	0.3294	0.0883	0.4739	0.9870	0.0000	0.1990
	8	RAN	0.3580	0.4243	0.2544	0.0568	0.3017	0.8513	0.0000	0.1990
		SAL	0.3758	0.4772	0.3050	0.0630	0.2989	0.7813	0.0000	0.1991
		STL	0.5041	0.5982	0.3330	0.0871	0.4753	0.9870	0.0000	0.1979
	16	RAN	0.3729	0.4546	0.3235	0.0407	0.3039	0.8175	0.0000	0.1978
		SAL	0.3715	0.4700	0.2909	0.0603	0.2998	0.7713	0.0000	0.1978
		STL	0.5055	0.5986	0.3372	0.0857	0.4761	0.9870	0.0000	0.1981

Table G.3: grouped-nb-enron-GM1-ALL-ALL-25

GM1										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.3205	0.4130	0.2686	0.0656	0.0672	0.8599	0.0000	0.1603
		SAL	0.3237	0.3750	0.2792	0.0394	0.0685	0.8667	0.0000	0.1647
		STL	0.2936	0.2978	0.2901	0.0032	0.1921	0.8718	0.0000	0.2142
	1	RAN	0.2744	0.3331	0.2307	0.0431	0.2497	0.8040	0.0000	0.1828
		SAL	0.2623	0.2763	0.2495	0.0110	0.2404	0.7367	0.0000	0.1724
		STL	0.4092	0.4779	0.2728	0.0965	0.3853	0.9157	0.0000	0.2012
	2	RAN	0.2681	0.2885	0.2549	0.0146	0.2486	0.7320	0.0000	0.1797
		SAL	0.2749	0.2802	0.2681	0.0051	0.2459	0.7417	0.0000	0.1773
		STL	0.4144	0.4838	0.2781	0.0964	0.3904	0.9157	0.0000	0.2032
	4	RAN	0.2862	0.3415	0.2526	0.0394	0.2552	0.6896	0.0000	0.1749
		SAL	0.2922	0.3067	0.2778	0.0118	0.2533	0.7423	0.0000	0.1804
		STL	0.4176	0.4842	0.2850	0.0937	0.3949	0.9157	0.0000	0.2014
	8	RAN	0.2819	0.3057	0.2641	0.0175	0.2593	0.7625	0.0000	0.1854
		SAL	0.2865	0.2916	0.2824	0.0038	0.2524	0.7513	0.0000	0.1779
		STL	0.4203	0.4864	0.2885	0.0932	0.3973	0.9157	0.0000	0.2013
	16	RAN	0.2952	0.3505	0.2587	0.0398	0.2585	0.7603	0.0000	0.1842
		SAL	0.3001	0.3139	0.2898	0.0101	0.2596	0.7871	0.0000	0.1854
		STL	0.4218	0.4875	0.2919	0.0919	0.3975	0.9157	0.0000	0.2015

Table G.4: grouped-nb-enron-GM1-ALL-ALL-50

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.3069	0.3441	0.2696	0.0373	0.0618	0.8578	0.0000	0.1515
		SAL	0.2796	0.2988	0.2603	0.0193	0.0579	0.8647	0.0000	0.1534
		STL	0.2871	0.3076	0.2667	0.0204	0.1177	0.8705	0.0000	0.1836
	1	RAN	0.2345	0.2603	0.2087	0.0258	0.2265	0.7585	0.0000	0.1717
		SAL	0.2287	0.2468	0.2106	0.0181	0.2236	0.7277	0.0000	0.1686
		STL	0.3250	0.4048	0.2451	0.0798	0.3197	0.8085	0.0000	0.1872
	2	RAN	0.2518	0.3025	0.2011	0.0507	0.2314	0.7606	0.0000	0.1766
		SAL	0.2589	0.2968	0.2210	0.0379	0.2328	0.6919	0.0000	0.1773
		STL	0.3293	0.4078	0.2509	0.0785	0.3235	0.8172	0.0000	0.1888
	4	RAN	0.2410	0.2438	0.2382	0.0028	0.2283	0.7446	0.0000	0.1714
		SAL	0.2535	0.2814	0.2256	0.0279	0.2354	0.7226	0.0000	0.1774
		STL	0.3337	0.4106	0.2569	0.0768	0.3285	0.8000	0.0000	0.1880
	8	RAN	0.2462	0.2688	0.2237	0.0225	0.2343	0.6904	0.0000	0.1723
		SAL	0.2678	0.3051	0.2305	0.0373	0.2393	0.7048	0.0000	0.1788
		STL	0.3359	0.4115	0.2604	0.0755	0.3295	0.8261	0.0000	0.1896
	16	RAN	0.2676	0.2869	0.2483	0.0193	0.2396	0.7419	0.0000	0.1833
		SAL	0.2588	0.2895	0.2282	0.0307	0.2381	0.7295	0.0000	0.1771
		STL	0.3388	0.4136	0.2639	0.0748	0.3319	0.7917	0.0000	0.1901

Table G.5: grouped-nb-enron-GM1-ALL-ALL-75

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.2450	0.2450	0.2450	0.0000	0.0487	0.8668	0.0000	0.1401
		SAL	0.2451	0.2451	0.2451	0.0000	0.0488	0.8674	0.0000	0.1403
		STL	0.2451	0.2451	0.2451	0.0000	0.0488	0.8674	0.0000	0.1403
	1	RAN	0.1839	0.1839	0.1839	0.0000	0.1942	0.6636	0.0000	0.1582
		SAL	0.1841	0.1841	0.1841	0.0000	0.1935	0.6728	0.0000	0.1572
		STL	0.1841	0.1841	0.1841	0.0000	0.1935	0.6728	0.0000	0.1572
	2	RAN	0.1893	0.1893	0.1893	0.0000	0.1965	0.6773	0.0000	0.1592
		SAL	0.1901	0.1901	0.1901	0.0000	0.1974	0.6735	0.0000	0.1591
		STL	0.1901	0.1901	0.1901	0.0000	0.1974	0.6735	0.0000	0.1591
	4	RAN	0.1956	0.1956	0.1956	0.0000	0.2016	0.6844	0.0000	0.1612
		SAL	0.1955	0.1955	0.1955	0.0000	0.2016	0.6801	0.0000	0.1600
		STL	0.1955	0.1955	0.1955	0.0000	0.2016	0.6801	0.0000	0.1600
	8	RAN	0.1989	0.1989	0.1989	0.0000	0.2031	0.6986	0.0000	0.1618
		SAL	0.1991	0.1991	0.1991	0.0000	0.2036	0.6801	0.0000	0.1615
		STL	0.1991	0.1991	0.1991	0.0000	0.2036	0.6801	0.0000	0.1615
	16	RAN	0.2018	0.2018	0.2018	0.0000	0.2052	0.6794	0.0000	0.1622
		SAL	0.2028	0.2028	0.2028	0.0000	0.2056	0.6926	0.0000	0.1630
		STL	0.2028	0.2028	0.2028	0.0000	0.2056	0.6926	0.0000	0.1630

Table G.6: grouped-nb-enron-GM1-ALL-ALL-150

GM2										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.8114	0.9270	0.6573	0.0662	0.4915	0.9781	0.0000	0.3374
		SAL	0.7950	0.9010	0.6311	0.0598	0.4441	0.9555	0.0000	0.3345
		STL	0.8119	0.9337	0.5185	0.0910	0.7841	0.9670	0.0000	0.1661
	1	RAN	0.6333	0.8675	0.2766	0.1733	0.5020	0.9370	0.0000	0.2578
		SAL	0.6308	0.8528	0.2883	0.1638	0.4829	0.9281	0.0000	0.2506
		STL	0.6968	0.8763	0.5445	0.0787	0.6739	0.9529	0.0000	0.1532
	2	RAN	0.7264	0.9132	0.4417	0.1062	0.5780	0.9545	0.0000	0.2582
		SAL	0.6882	0.8550	0.3035	0.1284	0.5210	0.9321	0.0000	0.2516
		STL	0.7186	0.8705	0.6072	0.0766	0.7004	1.0000	0.0000	0.1422
	4	RAN	0.7356	0.8675	0.4845	0.1042	0.5817	0.9253	0.0000	0.2450
		SAL	0.7410	0.8782	0.4797	0.1032	0.5602	0.9559	0.0000	0.2553
		STL	0.7194	0.8899	0.5837	0.0757	0.6987	0.9656	0.0000	0.1439
	8	RAN	0.8166	0.9224	0.6607	0.0680	0.6420	0.9642	0.0000	0.2402
		SAL	0.8242	0.9216	0.5879	0.0723	0.6286	0.9755	0.0000	0.2477
		STL	0.7474	0.8784	0.6321	0.0597	0.7304	0.9630	0.0000	0.1242
	16	RAN	0.8333	0.9489	0.6951	0.0657	0.6524	0.9759	0.0000	0.2473
		SAL	0.8572	0.9347	0.7479	0.0455	0.6354	0.9746	0.0000	0.2634
		STL	0.7571	0.8821	0.5926	0.0649	0.7377	0.9630	0.0000	0.1422

Table G.7: grouped-nb-enron-GM2-ALL-ALL-5

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.7271	0.8713	0.5381	0.0877	0.4106	0.9710	0.0000	0.3276
		SAL	0.6963	0.8205	0.5599	0.0675	0.3439	0.9394	0.0000	0.3055
		STL	0.7393	0.9024	0.5745	0.0901	0.7041	0.9679	0.0000	0.1959
	1	RAN	0.5131	0.7902	0.2541	0.1471	0.4019	0.8853	0.0000	0.2319
		SAL	0.4976	0.6377	0.3167	0.1058	0.3901	0.8932	0.0000	0.2245
		STL	0.6089	0.6987	0.4849	0.0610	0.5794	0.8749	0.0000	0.1824
	2	RAN	0.5793	0.7090	0.3424	0.1013	0.4527	0.8739	0.0000	0.2388
		SAL	0.5539	0.7023	0.3271	0.1131	0.4278	0.8901	0.0000	0.2287
		STL	0.6209	0.7330	0.5128	0.0545	0.5951	0.9655	0.0000	0.1823
	4	RAN	0.6270	0.8022	0.4944	0.0828	0.4931	0.9196	0.0000	0.2395
		SAL	0.6081	0.7190	0.4823	0.0745	0.4607	0.9005	0.0000	0.2312
		STL	0.6302	0.7094	0.5207	0.0585	0.5991	0.9241	0.0000	0.1836
	8	RAN	0.7474	0.8440	0.6015	0.0625	0.5565	0.9400	0.0000	0.2302
		SAL	0.7311	0.8202	0.5846	0.0722	0.5474	0.9410	0.0000	0.2332
		STL	0.6605	0.7617	0.5489	0.0532	0.6345	0.9286	0.0000	0.1705
	16	RAN	0.7656	0.8961	0.5957	0.0807	0.5709	0.9759	0.0000	0.2469
		SAL	0.7818	0.8610	0.6899	0.0460	0.5656	0.9471	0.0000	0.2546
		STL	0.6728	0.7552	0.5735	0.0520	0.6487	0.9500	0.0000	0.1723

Table G.8: grouped-nb-enron-GM2-ALL-ALL-10

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.5975	0.7145	0.4636	0.0953	0.2695	0.9293	0.0000	0.2761
		SAL	0.5942	0.7023	0.4523	0.0743	0.2636	0.9152	0.0000	0.2805
		STL	0.6331	0.7088	0.5554	0.0571	0.5768	0.9737	0.0000	0.2225
	1	RAN	0.3720	0.4786	0.2837	0.0763	0.3161	0.8705	0.0000	0.2091
		SAL	0.3766	0.4937	0.2742	0.0667	0.3146	0.8975	0.0000	0.2092
		STL	0.5011	0.5881	0.4209	0.0580	0.4717	0.8636	0.0000	0.1968
	2	RAN	0.4446	0.5200	0.3110	0.0839	0.3586	0.8620	0.0000	0.2170
		SAL	0.4214	0.4976	0.3305	0.0498	0.3458	0.8644	0.0000	0.2116
		STL	0.5153	0.6078	0.4446	0.0534	0.4907	0.9231	0.0000	0.1869
	4	RAN	0.4960	0.5403	0.4444	0.0348	0.3808	0.8547	0.0000	0.2260
		SAL	0.4878	0.5873	0.4101	0.0570	0.3748	0.9188	0.0000	0.2253
		STL	0.5207	0.5802	0.4948	0.0302	0.4916	0.8941	0.0000	0.1864
	8	RAN	0.6310	0.7008	0.5261	0.0557	0.4663	0.9257	0.0000	0.2214
		SAL	0.6211	0.7139	0.5706	0.0442	0.4560	0.8951	0.0000	0.2196
		STL	0.5605	0.6335	0.5254	0.0355	0.5331	0.9009	0.0000	0.1806
	16	RAN	0.6782	0.7517	0.6019	0.0625	0.4939	0.9191	0.0000	0.2378
		SAL	0.6826	0.7904	0.5595	0.0833	0.4880	0.9275	0.0000	0.2514
		STL	0.5799	0.6454	0.5391	0.0428	0.5538	0.9867	0.0000	0.1885

Table G.9: grouped-nb-enron-GM2-ALL-ALL-25

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.5627	0.5970	0.5242	0.0299	0.2547	0.9063	0.0000	0.2697
		SAL	0.5338	0.5932	0.4515	0.0601	0.2180	0.8959	0.0000	0.2590
		STL	0.5278	0.5459	0.4946	0.0236	0.4315	0.9296	0.0000	0.2511
	1	RAN	0.3025	0.3280	0.2742	0.0220	0.2681	0.7377	0.0000	0.1933
		SAL	0.3090	0.3163	0.3044	0.0052	0.2728	0.8958	0.0000	0.2016
		STL	0.4228	0.4884	0.3114	0.0792	0.3945	0.8132	0.0000	0.2012
	2	RAN	0.3539	0.3809	0.3151	0.0281	0.2984	0.8045	0.0000	0.1988
		SAL	0.3547	0.3661	0.3448	0.0088	0.2971	0.8347	0.0000	0.1989
		STL	0.4408	0.5023	0.3303	0.0783	0.4158	0.8128	0.0000	0.1979
	4	RAN	0.4102	0.4249	0.3939	0.0127	0.3252	0.8479	0.0000	0.2087
		SAL	0.4134	0.4192	0.4044	0.0064	0.3268	0.8974	0.0000	0.2160
		STL	0.4542	0.4894	0.3918	0.0442	0.4233	0.8176	0.0000	0.1953
	8	RAN	0.5480	0.5908	0.5177	0.0311	0.4041	0.8840	0.0000	0.2085
		SAL	0.5554	0.5911	0.5344	0.0253	0.4017	0.8618	0.0000	0.2118
		STL	0.5124	0.5370	0.4971	0.0175	0.4688	0.8941	0.0000	0.1896
	16	RAN	0.6202	0.6477	0.5704	0.0353	0.4438	0.9051	0.0000	0.2349
		SAL	0.6169	0.6972	0.5731	0.0568	0.4410	0.9356	0.0000	0.2435
		STL	0.5301	0.5543	0.4888	0.0294	0.4883	0.9589	0.0000	0.2016

Table G.10: grouped-nb-enron-GM2-ALL-ALL-50

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.5153	0.5296	0.5010	0.0143	0.2140	0.8921	0.0000	0.2510
		SAL	0.5030	0.5128	0.4932	0.0098	0.1989	0.8916	0.0000	0.2485
		STL	0.4987	0.5048	0.4925	0.0062	0.3328	0.8700	0.0000	0.2604
	1	RAN	0.2635	0.2643	0.2626	0.0008	0.2461	0.6999	0.0000	0.1890
		SAL	0.2678	0.3060	0.2295	0.0382	0.2480	0.7862	0.0000	0.1931
		STL	0.3375	0.4085	0.2664	0.0711	0.3161	0.8282	0.0000	0.1847
	2	RAN	0.3145	0.3434	0.2857	0.0289	0.2789	0.7465	0.0000	0.1964
		SAL	0.3092	0.3473	0.2711	0.0381	0.2752	0.8037	0.0000	0.1951
		STL	0.3620	0.4265	0.2974	0.0645	0.3514	0.8235	0.0000	0.1879
	4	RAN	0.3731	0.4061	0.3401	0.0330	0.3039	0.8706	0.0000	0.2099
		SAL	0.3657	0.4049	0.3264	0.0392	0.3012	0.8670	0.0000	0.2100
		STL	0.3900	0.4361	0.3439	0.0461	0.3687	0.8291	0.0000	0.1892
	8	RAN	0.5275	0.5650	0.4901	0.0374	0.3768	0.8579	0.0000	0.2108
		SAL	0.5069	0.5458	0.4681	0.0388	0.3722	0.8737	0.0000	0.2070
		STL	0.4710	0.4795	0.4625	0.0085	0.4212	0.8429	0.0000	0.1836
	16	RAN	0.5897	0.6703	0.5092	0.0806	0.4142	0.9144	0.0000	0.2394
		SAL	0.5758	0.6406	0.5111	0.0647	0.4100	0.8824	0.0000	0.2412
		STL	0.4985	0.5315	0.4654	0.0331	0.4475	0.9143	0.0000	0.2082

Table G.11: grouped-nb-enron-GM2-ALL-ALL-75

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.4535	0.4535	0.4535	0.0000	0.1703	0.8555	0.0000	0.2304
		SAL	0.4537	0.4537	0.4537	0.0000	0.1708	0.8573	0.0000	0.2301
		STL	0.4537	0.4537	0.4537	0.0000	0.1708	0.8573	0.0000	0.2301
	1	RAN	0.2163	0.2163	0.2163	0.0000	0.2158	0.6874	0.0000	0.1767
		SAL	0.2164	0.2164	0.2164	0.0000	0.2160	0.6834	0.0000	0.1780
		STL	0.2164	0.2164	0.2164	0.0000	0.2160	0.6834	0.0000	0.1780
	2	RAN	0.2593	0.2593	0.2593	0.0000	0.2403	0.7671	0.0000	0.1822
		SAL	0.2601	0.2601	0.2601	0.0000	0.2403	0.7682	0.0000	0.1824
		STL	0.2601	0.2601	0.2601	0.0000	0.2403	0.7682	0.0000	0.1824
	4	RAN	0.3097	0.3097	0.3097	0.0000	0.2657	0.8364	0.0000	0.1964
		SAL	0.3095	0.3095	0.3095	0.0000	0.2660	0.8385	0.0000	0.1972
		STL	0.3095	0.3095	0.3095	0.0000	0.2660	0.8385	0.0000	0.1972
	8	RAN	0.4539	0.4539	0.4539	0.0000	0.3333	0.8287	0.0000	0.2013
		SAL	0.4552	0.4552	0.4552	0.0000	0.3333	0.8334	0.0000	0.2011
		STL	0.4552	0.4552	0.4552	0.0000	0.3333	0.8334	0.0000	0.2011
	16	RAN	0.5058	0.5058	0.5058	0.0000	0.3738	0.8657	0.0000	0.2349
		SAL	0.5063	0.5063	0.5063	0.0000	0.3733	0.8657	0.0000	0.2352
		STL	0.5063	0.5063	0.5063	0.0000	0.3733	0.8657	0.0000	0.2352

Table G.12: grouped-nb-enron-GM2-ALL-ALL-150

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.7692	0.9618	0.6018	0.1082	0.5340	0.9802	0.0000	0.3121
		SAL	0.8106	0.9055	0.6539	0.0704	0.5305	0.9528	0.0000	0.3241
		STL	0.6339	0.8767	0.4180	0.1223	0.5810	0.9870	0.0000	0.2393
	1	RAN	0.7957	0.9380	0.6322	0.0867	0.6377	0.9693	0.0000	0.2332
		SAL	0.8073	0.9197	0.5353	0.0788	0.6169	0.9586	0.0000	0.2497
		STL	0.7421	0.8766	0.6145	0.0651	0.7247	0.9600	0.0000	0.1426
	2	RAN	0.8289	0.9554	0.6859	0.0629	0.6597	0.9806	0.0000	0.2434
		SAL	0.8519	0.9318	0.7022	0.0562	0.6470	1.0000	0.0000	0.2618
		STL	0.7504	0.9077	0.6325	0.0657	0.7327	0.9540	0.0000	0.1362
	4	RAN	0.8427	0.9428	0.6772	0.0533	0.6313	0.9698	0.0000	0.2783
		SAL	0.8553	0.9436	0.7293	0.0428	0.6143	0.9693	0.0000	0.2859
		STL	0.7638	0.9006	0.6265	0.0668	0.7478	0.9500	0.0000	0.1351
	8	RAN	0.8120	0.9372	0.6667	0.0776	0.5955	0.9718	0.0000	0.2812
		SAL	0.8325	0.9241	0.7240	0.0472	0.5585	0.9582	0.0000	0.2960
		STL	0.7747	0.9218	0.6265	0.0740	0.7590	0.9559	0.0000	0.1401
	16	RAN	0.8068	0.9380	0.6991	0.0625	0.5363	0.9676	0.0000	0.3012
		SAL	0.8126	0.9073	0.6810	0.0567	0.5136	0.9494	0.0000	0.3063
		STL	0.7746	0.9065	0.6325	0.0718	0.7596	0.9557	0.0000	0.1391

Table G.13: grouped-nb-enron-GM5-ALL-ALL-5

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.7371	0.9091	0.5956	0.0726	0.4816	0.9491	0.0000	0.3135
		SAL	0.7413	0.8168	0.6452	0.0565	0.4794	0.9396	0.0000	0.3142
		STL	0.5624	0.8320	0.3708	0.1317	0.5353	0.9870	0.0000	0.2520
	1	RAN	0.7178	0.8903	0.5807	0.0706	0.5411	0.9505	0.0000	0.2318
		SAL	0.7020	0.8310	0.5165	0.0841	0.5309	0.9173	0.0000	0.2269
		STL	0.6472	0.7498	0.5462	0.0643	0.6284	0.9250	0.0000	0.1657
	2	RAN	0.7544	0.8888	0.6724	0.0622	0.5753	0.9466	0.0000	0.2423
		SAL	0.7632	0.8734	0.6045	0.0724	0.5702	0.9409	0.0000	0.2430
		STL	0.6647	0.7891	0.5714	0.0708	0.6460	0.9275	0.0000	0.1618
	4	RAN	0.7575	0.8857	0.6151	0.0698	0.5545	0.9315	0.0000	0.2608
		SAL	0.7746	0.8638	0.6282	0.0632	0.5451	0.9359	0.0000	0.2748
		STL	0.6779	0.7848	0.5526	0.0761	0.6616	0.9444	0.0000	0.1664
	8	RAN	0.7310	0.8473	0.5485	0.0869	0.4717	0.9418	0.0000	0.2702
		SAL	0.7329	0.8184	0.6297	0.0669	0.4656	0.9433	0.0000	0.2772
		STL	0.6869	0.8005	0.5586	0.0830	0.6696	0.9737	0.0000	0.1759
	16	RAN	0.7199	0.8389	0.4791	0.0847	0.4327	0.9548	0.0000	0.2947
		SAL	0.6940	0.8021	0.5511	0.0835	0.3992	0.9386	0.0000	0.2790
		STL	0.6834	0.7931	0.5616	0.0810	0.6685	0.9867	0.0000	0.1765

Table G.14: grouped-nb-enron-GM5-ALL-ALL-10

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.6434	0.7309	0.5130	0.0775	0.4455	0.9297	0.0000	0.3071
		SAL	0.6732	0.7168	0.5666	0.0525	0.4418	0.9178	0.0000	0.3076
		STL	0.5076	0.7289	0.4074	0.1105	0.4916	0.9744	0.0000	0.2698
	1	RAN	0.6028	0.7185	0.5085	0.0748	0.4394	0.9144	0.0000	0.2220
		SAL	0.5991	0.6973	0.5529	0.0464	0.4385	0.8812	0.0000	0.2177
		STL	0.5522	0.6382	0.5079	0.0417	0.5254	0.9268	0.0000	0.1864
	2	RAN	0.6698	0.6963	0.6157	0.0272	0.4917	0.8946	0.0000	0.2253
		SAL	0.6673	0.7188	0.6446	0.0239	0.4889	0.8985	0.0000	0.2270
		STL	0.5702	0.6659	0.5047	0.0519	0.5431	0.9620	0.0000	0.1840
	4	RAN	0.6709	0.7459	0.5991	0.0609	0.4703	0.9324	0.0000	0.2584
		SAL	0.6765	0.7014	0.6575	0.0159	0.4689	0.8822	0.0000	0.2598
		STL	0.5861	0.6627	0.4969	0.0600	0.5599	0.9444	0.0000	0.1940
	8	RAN	0.6294	0.7127	0.5875	0.0421	0.3859	0.9066	0.0000	0.2616
		SAL	0.5961	0.6366	0.5724	0.0224	0.3662	0.9130	0.0000	0.2548
		STL	0.5726	0.6436	0.5000	0.0465	0.5428	0.9867	0.0000	0.2030
	16	RAN	0.5891	0.6076	0.5691	0.0148	0.3203	0.9140	0.0000	0.2634
		SAL	0.5466	0.5729	0.5154	0.0211	0.2859	0.9126	0.0000	0.2409
		STL	0.5575	0.6254	0.4921	0.0406	0.5264	0.9730	0.0000	0.2115

Table G.15: grouped-nb-enron-GM5-ALL-ALL-25

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.6165	0.6977	0.5449	0.0628	0.4160	0.9251	0.0000	0.3096
		SAL	0.6224	0.6475	0.5970	0.0206	0.4147	0.9096	0.0000	0.3081
		STL	0.4838	0.6288	0.3783	0.1060	0.4544	0.9600	0.0000	0.2827
	1	RAN	0.5128	0.5454	0.4620	0.0364	0.3799	0.8700	0.0000	0.2134
		SAL	0.5173	0.5303	0.4917	0.0181	0.3783	0.8631	0.0000	0.2125
		STL	0.5007	0.5410	0.4597	0.0332	0.4600	0.9136	0.0000	0.1971
	2	RAN	0.5942	0.6422	0.5384	0.0427	0.4341	0.9067	0.0000	0.2238
		SAL	0.5959	0.6162	0.5765	0.0162	0.4326	0.8889	0.0000	0.2218
		STL	0.5277	0.5604	0.4907	0.0286	0.4779	0.9041	0.0000	0.1944
	4	RAN	0.5791	0.6349	0.4732	0.0749	0.4192	0.8708	0.0000	0.2509
		SAL	0.6179	0.6355	0.6059	0.0127	0.4192	0.8923	0.0000	0.2568
		STL	0.5356	0.5698	0.4859	0.0360	0.4860	0.8986	0.0000	0.2134
	8	RAN	0.5125	0.5991	0.3952	0.0860	0.2985	0.8772	0.0000	0.2387
		SAL	0.5315	0.5655	0.5055	0.0251	0.3084	0.9045	0.0000	0.2436
		STL	0.4985	0.5234	0.4773	0.0190	0.4363	0.8986	0.0000	0.2272
	16	RAN	0.4494	0.5206	0.3570	0.0685	0.2269	0.9072	0.0000	0.2189
		SAL	0.4740	0.5064	0.4419	0.0263	0.2237	0.8982	0.0000	0.2247
		STL	0.4717	0.5027	0.4357	0.0276	0.4012	0.8986	0.0000	0.2360

Table G.16: grouped-nb-enron-GM5-ALL-ALL-50

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.6083	0.6216	0.5951	0.0132	0.4086	0.9157	0.0000	0.3082
		SAL	0.5978	0.6346	0.5609	0.0368	0.4000	0.9017	0.0000	0.3079
		STL	0.4877	0.5973	0.3780	0.1096	0.4317	0.9444	0.0000	0.2888
	1	RAN	0.4809	0.4897	0.4722	0.0087	0.3491	0.8622	0.0000	0.2108
		SAL	0.4856	0.5150	0.4562	0.0294	0.3503	0.8414	0.0000	0.2088
		STL	0.4500	0.4597	0.4403	0.0097	0.4031	0.8246	0.0000	0.1910
	2	RAN	0.5593	0.5894	0.5291	0.0301	0.4092	0.8707	0.0000	0.2188
		SAL	0.5609	0.5746	0.5471	0.0138	0.4055	0.8847	0.0000	0.2155
		STL	0.4973	0.5170	0.4776	0.0197	0.4377	0.8857	0.0000	0.1953
	4	RAN	0.5787	0.5833	0.5741	0.0046	0.3985	0.8586	0.0000	0.2468
		SAL	0.5722	0.5798	0.5647	0.0076	0.3930	0.8831	0.0000	0.2525
		STL	0.5108	0.5426	0.4791	0.0318	0.4419	0.8720	0.0000	0.2255
	8	RAN	0.4814	0.5279	0.4349	0.0465	0.2771	0.9046	0.0000	0.2352
		SAL	0.4896	0.5072	0.4719	0.0176	0.2744	0.8724	0.0000	0.2384
		STL	0.4664	0.4738	0.4590	0.0074	0.3636	0.8848	0.0000	0.2289
	16	RAN	0.4317	0.4459	0.4176	0.0142	0.1951	0.8947	0.0000	0.2138
		SAL	0.4290	0.4481	0.4100	0.0191	0.1969	0.8697	0.0000	0.2133
		STL	0.4339	0.4690	0.3988	0.0351	0.3157	0.8950	0.0000	0.2352

Table G.17: grouped-nb-enron-GM5-ALL-ALL-75

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.5661	0.5661	0.5661	0.0000	0.3832	0.9077	0.0000	0.3073
		SAL	0.5657	0.5657	0.5657	0.0000	0.3823	0.9085	0.0000	0.3065
		STL	0.5657	0.5657	0.5657	0.0000	0.3823	0.9085	0.0000	0.3065
	1	RAN	0.4141	0.4141	0.4141	0.0000	0.3101	0.8081	0.0000	0.2001
		SAL	0.4137	0.4137	0.4137	0.0000	0.3097	0.8095	0.0000	0.1995
		STL	0.4137	0.4137	0.4137	0.0000	0.3097	0.8095	0.0000	0.1995
	2	RAN	0.4945	0.4945	0.4945	0.0000	0.3653	0.8565	0.0000	0.2067
		SAL	0.4938	0.4938	0.4938	0.0000	0.3645	0.8586	0.0000	0.2073
		STL	0.4938	0.4938	0.4938	0.0000	0.3645	0.8586	0.0000	0.2073
	4	RAN	0.5127	0.5127	0.5127	0.0000	0.3546	0.8444	0.0000	0.2496
		SAL	0.5125	0.5125	0.5125	0.0000	0.3545	0.8440	0.0000	0.2489
		STL	0.5125	0.5125	0.5125	0.0000	0.3545	0.8440	0.0000	0.2489
	8	RAN	0.4285	0.4285	0.4285	0.0000	0.2320	0.8633	0.0000	0.2195
		SAL	0.4287	0.4287	0.4287	0.0000	0.2322	0.8650	0.0000	0.2195
		STL	0.4287	0.4287	0.4287	0.0000	0.2322	0.8650	0.0000	0.2195
	16	RAN	0.0433	0.0433	0.0433	0.0000	0.0024	0.1148	0.0000	0.0130
		SAL	0.3703	0.3703	0.3703	0.0000	0.1583	0.8920	0.0000	0.1919
		STL	0.3703	0.3703	0.3703	0.0000	0.1583	0.8920	0.0000	0.1919

Table G.18: grouped-nb-enron-GM5-ALL-ALL-150

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.7853	0.9709	0.5772	0.0870	0.5006	0.9852	0.0000	0.3368
		SAL	0.7730	0.9016	0.6315	0.0687	0.4223	0.9392	0.0000	0.3270
		STL	0.8062	0.9319	0.6075	0.0863	0.7812	0.9660	0.0000	0.1475
	1	RAN	0.8290	0.9432	0.5311	0.1033	0.6821	0.9757	0.0000	0.2415
		SAL	0.8449	0.9561	0.4360	0.1173	0.6614	0.9776	0.0000	0.2596
		STL	0.7761	0.9485	0.4815	0.1023	0.7527	0.9776	0.0000	0.1564
	2	RAN	0.8492	0.9669	0.5602	0.1006	0.6945	0.9833	0.0000	0.2540
		SAL	0.8578	0.9550	0.4790	0.1102	0.6722	0.9820	0.0000	0.2637
		STL	0.7874	0.9494	0.5556	0.0891	0.7623	0.9757	0.0000	0.1571
	4	RAN	0.8901	0.9483	0.8122	0.0359	0.7044	0.9757	0.0000	0.2564
		SAL	0.8930	0.9522	0.7851	0.0455	0.6939	0.9823	0.0000	0.2622
		STL	0.8055	0.9459	0.5556	0.0870	0.7835	0.9763	0.0000	0.1410
	8	RAN	0.8854	0.9782	0.8101	0.0419	0.6996	0.9889	0.0000	0.2607
		SAL	0.8904	0.9579	0.7796	0.0422	0.6893	0.9870	0.0000	0.2652
		STL	0.8045	0.9528	0.5556	0.0849	0.7806	0.9771	0.0000	0.1456
	16	RAN	0.8777	0.9674	0.7354	0.0531	0.6874	1.0000	0.0000	0.2686
		SAL	0.8915	0.9528	0.7770	0.0457	0.6786	0.9870	0.0000	0.2758
		STL	0.8075	0.9473	0.5556	0.0903	0.7863	0.9765	0.0000	0.1467

Table G.19: grouped-nb-enron-GB3-ALL-ALL-5

GB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.7209	0.8310	0.5989	0.0743	0.3650	0.9456	0.0000	0.3224
		SAL	0.6704	0.8012	0.5652	0.0738	0.3254	0.9493	0.0000	0.2913
		STL	0.7258	0.8951	0.5319	0.0953	0.6902	0.9610	0.0000	0.2041
	1	RAN	0.7835	0.8924	0.5487	0.1081	0.6067	0.9558	0.0000	0.2524
		SAL	0.7793	0.8962	0.5359	0.1160	0.5999	0.9579	0.0000	0.2547
		STL	0.7129	0.8734	0.5638	0.0755	0.6784	0.9519	0.0000	0.1842
	2	RAN	0.7969	0.9087	0.5466	0.1090	0.6218	0.9724	0.0000	0.2542
		SAL	0.7994	0.8989	0.5161	0.1149	0.6141	0.9637	0.0000	0.2592
		STL	0.7225	0.9138	0.5532	0.0917	0.6887	0.9594	0.0000	0.1963
	4	RAN	0.8314	0.9251	0.7516	0.0528	0.6422	0.9688	0.0000	0.2545
		SAL	0.8502	0.9004	0.7678	0.0372	0.6340	0.9648	0.0000	0.2669
		STL	0.7395	0.9189	0.5532	0.0938	0.7087	0.9663	0.0000	0.1855
	8	RAN	0.8343	0.9456	0.7188	0.0573	0.6320	1.0000	0.0000	0.2648
		SAL	0.8504	0.9029	0.7455	0.0378	0.6338	0.9744	0.0000	0.2681
		STL	0.7374	0.9109	0.5638	0.0883	0.7052	0.9772	0.0000	0.1874
	16	RAN	0.8336	0.9165	0.6203	0.0721	0.6227	0.9632	0.0000	0.2742
		SAL	0.8500	0.8999	0.7729	0.0369	0.6262	0.9744	0.0000	0.2755
		STL	0.7437	0.9198	0.5426	0.0988	0.7127	0.9686	0.0000	0.1909

Table G.20: grouped-nb-enron-GB3-ALL-ALL-10

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.6238	0.7052	0.5110	0.0638	0.2828	0.9304	0.0000	0.2843
		SAL	0.5608	0.6636	0.4270	0.0765	0.2493	0.9253	0.0000	0.2652
		STL	0.6151	0.6894	0.5403	0.0542	0.5556	0.9600	0.0000	0.2281
	1	RAN	0.7123	0.8258	0.6218	0.0757	0.5320	0.9329	0.0000	0.2465
		SAL	0.7184	0.8183	0.5719	0.0860	0.5347	0.9561	0.0000	0.2462
		STL	0.6352	0.6956	0.5542	0.0558	0.5955	0.9383	0.0000	0.2017
	2	RAN	0.7365	0.8493	0.6077	0.0752	0.5446	0.9415	0.0000	0.2548
		SAL	0.7453	0.8321	0.6359	0.0740	0.5483	0.9409	0.0000	0.2533
		STL	0.6487	0.7517	0.5610	0.0697	0.6071	0.9620	0.0000	0.2077
	4	RAN	0.7956	0.8607	0.7353	0.0444	0.5743	0.9528	0.0000	0.2585
		SAL	0.7939	0.8307	0.7504	0.0261	0.5702	0.9514	0.0000	0.2595
		STL	0.6663	0.8136	0.5501	0.0905	0.6264	0.9620	0.0000	0.2075
	8	RAN	0.7805	0.8614	0.7359	0.0430	0.5716	0.9575	0.0000	0.2592
		SAL	0.7891	0.8112	0.7535	0.0199	0.5687	0.9647	0.0000	0.2588
		STL	0.6612	0.8189	0.5528	0.0916	0.6221	0.9690	0.0000	0.2107
	16	RAN	0.7973	0.8677	0.7348	0.0417	0.5712	0.9620	0.0000	0.2693
		SAL	0.8016	0.8327	0.7752	0.0195	0.5698	0.9465	0.0000	0.2712
		STL	0.6681	0.8462	0.5556	0.1027	0.6307	0.9500	0.0000	0.2141

Table G.21: grouped-nb-enron-GB3-ALL-ALL-25

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.5052	0.5421	0.4843	0.0262	0.1996	0.8947	0.0000	0.2422
		SAL	0.5059	0.5463	0.4256	0.0567	0.2082	0.8943	0.0000	0.2474
		STL	0.5067	0.5326	0.4752	0.0238	0.4126	0.9444	0.0000	0.2554
	1	RAN	0.6608	0.7451	0.5709	0.0712	0.4806	0.9394	0.0000	0.2483
		SAL	0.6613	0.7140	0.6267	0.0379	0.4868	0.9222	0.0000	0.2433
		STL	0.5952	0.6454	0.5289	0.0489	0.5351	0.9077	0.0000	0.2158
	2	RAN	0.7032	0.7629	0.6679	0.0425	0.5026	0.9152	0.0000	0.2543
		SAL	0.7040	0.7769	0.6296	0.0602	0.5069	0.9456	0.0000	0.2517
		STL	0.6148	0.7059	0.5262	0.0734	0.5487	0.9620	0.0000	0.2229
	4	RAN	0.7465	0.8163	0.6789	0.0561	0.5280	0.9539	0.0000	0.2619
		SAL	0.7485	0.7770	0.7042	0.0317	0.5268	0.9419	0.0000	0.2586
		STL	0.6341	0.7525	0.5340	0.0902	0.5674	0.9467	0.0000	0.2210
	8	RAN	0.7456	0.7993	0.6834	0.0477	0.5262	0.9637	0.0000	0.2594
		SAL	0.7495	0.7739	0.7146	0.0253	0.5304	0.9650	0.0000	0.2577
		STL	0.6298	0.7552	0.5255	0.0950	0.5652	0.9637	0.0000	0.2239
	16	RAN	0.7533	0.8277	0.7077	0.0531	0.5326	0.9410	0.0000	0.2718
		SAL	0.7629	0.7801	0.7349	0.0200	0.5322	0.9392	0.0000	0.2685
		STL	0.6392	0.7742	0.5201	0.1044	0.5761	0.9744	0.0000	0.2270

Table G.22: grouped-nb-enron-GB3-ALL-ALL-50

GB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.4676	0.4949	0.4403	0.0273	0.1844	0.8811	0.0000	0.2307
		SAL	0.4682	0.4766	0.4598	0.0084	0.1812	0.8809	0.0000	0.2314
		STL	0.4805	0.4962	0.4647	0.0157	0.3218	0.8709	0.0000	0.2559
	1	RAN	0.6370	0.7176	0.5564	0.0806	0.4643	0.9202	0.0000	0.2460
		SAL	0.6396	0.6479	0.6313	0.0083	0.4636	0.9209	0.0000	0.2436
		STL	0.5797	0.6272	0.5323	0.0474	0.4966	0.9021	0.0000	0.2181
	2	RAN	0.6822	0.7352	0.6293	0.0529	0.4818	0.9308	0.0000	0.2558
		SAL	0.6820	0.7254	0.6387	0.0433	0.4829	0.9281	0.0000	0.2524
		STL	0.6076	0.6827	0.5324	0.0752	0.5153	0.9301	0.0000	0.2252
	4	RAN	0.7239	0.7331	0.7147	0.0092	0.5013	0.9378	0.0000	0.2647
		SAL	0.7261	0.7345	0.7178	0.0083	0.5004	0.9382	0.0000	0.2623
		STL	0.6296	0.7232	0.5359	0.0936	0.5338	0.9385	0.0000	0.2288
	8	RAN	0.7270	0.7491	0.7049	0.0221	0.5057	0.9615	0.0000	0.2607
		SAL	0.7284	0.7350	0.7217	0.0067	0.5036	0.9550	0.0000	0.2627
		STL	0.6302	0.7245	0.5359	0.0943	0.5350	0.9597	0.0000	0.2300
	16	RAN	0.7417	0.7559	0.7275	0.0142	0.5076	0.9369	0.0000	0.2714
		SAL	0.7437	0.7479	0.7395	0.0042	0.5091	0.9250	0.0000	0.2735
		STL	0.6370	0.7428	0.5311	0.1059	0.5410	0.9500	0.0000	0.2348

Table G.23: grouped-nb-enron-GB3-ALL-ALL-75

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.4279	0.4279	0.4279	0.0000	0.1609	0.8518	0.0000	0.2174
		SAL	0.4284	0.4284	0.4284	0.0000	0.1612	0.8550	0.0000	0.2176
		STL	0.4284	0.4284	0.4284	0.0000	0.1612	0.8550	0.0000	0.2176
	1	RAN	0.5971	0.5971	0.5971	0.0000	0.4266	0.8973	0.0000	0.2455
		SAL	0.5978	0.5978	0.5978	0.0000	0.4264	0.8962	0.0000	0.2449
		STL	0.5978	0.5978	0.5978	0.0000	0.4264	0.8962	0.0000	0.2449
	2	RAN	0.6499	0.6499	0.6499	0.0000	0.4491	0.9160	0.0000	0.2541
		SAL	0.6499	0.6499	0.6499	0.0000	0.4498	0.9190	0.0000	0.2528
		STL	0.6499	0.6499	0.6499	0.0000	0.4498	0.9190	0.0000	0.2528
	4	RAN	0.6862	0.6862	0.6862	0.0000	0.4657	0.9348	0.0000	0.2595
		SAL	0.6859	0.6859	0.6859	0.0000	0.4644	0.9331	0.0000	0.2612
		STL	0.6859	0.6859	0.6859	0.0000	0.4644	0.9331	0.0000	0.2612
	8	RAN	0.6885	0.6885	0.6885	0.0000	0.4703	0.9593	0.0000	0.2593
		SAL	0.6891	0.6891	0.6891	0.0000	0.4700	0.9583	0.0000	0.2604
		STL	0.6891	0.6891	0.6891	0.0000	0.4700	0.9583	0.0000	0.2604
	16	RAN	0.7052	0.7052	0.7052	0.0000	0.4745	0.9287	0.0000	0.2686
		SAL	0.7059	0.7059	0.7059	0.0000	0.4752	0.9278	0.0000	0.2689
		STL	0.7059	0.7059	0.7059	0.0000	0.4752	0.9278	0.0000	0.2689

Table G.24: grouped-nb-enron-GB3-ALL-ALL-150

OSB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.8658	0.9592	0.7085	0.0647	0.6505	1.0000	0.0000	0.2854
		SAL	0.8678	0.9558	0.7158	0.0494	0.6314	1.0000	0.0000	0.2889
		STL	0.8244	0.9564	0.5185	0.0956	0.8052	0.9798	0.0000	0.1462
	1	RAN	0.8825	0.9533	0.7244	0.0602	0.7007	1.0000	0.0000	0.2649
		SAL	0.8912	0.9566	0.7746	0.0434	0.6783	0.9832	0.0000	0.2763
		STL	0.8207	0.9574	0.5556	0.0896	0.8008	0.9781	0.0000	0.1418
	2	RAN	0.8786	0.9398	0.7018	0.0585	0.7039	0.9870	0.0000	0.2643
		SAL	0.8928	0.9575	0.7781	0.0397	0.6756	0.9835	0.0000	0.2781
		STL	0.8210	0.9487	0.5556	0.0915	0.8013	0.9785	0.0000	0.1429
	4	RAN	0.8892	0.9587	0.7664	0.0446	0.6944	0.9773	0.0000	0.2691
		SAL	0.8930	0.9578	0.7772	0.0400	0.6759	0.9870	0.0000	0.2784
		STL	0.8211	0.9560	0.5556	0.0914	0.8012	0.9789	0.0000	0.1430
	8	RAN	0.8764	0.9714	0.7461	0.0546	0.6986	0.9881	0.0000	0.2581
		SAL	0.8932	0.9582	0.7772	0.0411	0.6767	1.0000	0.0000	0.2786
		STL	0.8219	0.9564	0.5556	0.0920	0.8026	0.9786	0.0000	0.1431
	16	RAN	0.8806	0.9823	0.7683	0.0558	0.7004	0.9913	0.0000	0.2600
		SAL	0.8930	0.9582	0.7763	0.0401	0.6752	1.0000	0.0000	0.2794
		STL	0.8224	0.9564	0.5556	0.0922	0.8028	0.9786	0.0000	0.1433

Table G.25: grouped-nb-enron-OSB3-ALL-ALL-5

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.8152	0.9272	0.6736	0.0637	0.5782	0.9867	0.0000	0.2980
		SAL	0.8133	0.8925	0.6713	0.0544	0.5763	1.0000	0.0000	0.2895
		STL	0.7616	0.9336	0.5532	0.1020	0.7350	0.9722	0.0000	0.1888
	1	RAN	0.8423	0.9261	0.7550	0.0474	0.6266	0.9744	0.0000	0.2812
		SAL	0.8511	0.9143	0.7614	0.0386	0.6205	0.9635	0.0000	0.2861
		STL	0.7549	0.9317	0.5213	0.1034	0.7281	0.9682	0.0000	0.1880
	2	RAN	0.8472	0.9178	0.7590	0.0516	0.6301	0.9731	0.0000	0.2804
		SAL	0.8514	0.9140	0.7625	0.0392	0.6190	0.9636	0.0000	0.2867
		STL	0.7555	0.9272	0.5213	0.1063	0.7297	0.9667	0.0000	0.1886
	4	RAN	0.8447	0.9260	0.7648	0.0470	0.6368	0.9655	0.0000	0.2737
		SAL	0.8526	0.9149	0.7624	0.0389	0.6195	0.9637	0.0000	0.2878
		STL	0.7557	0.9307	0.5213	0.1060	0.7291	0.9685	0.0000	0.1895
	8	RAN	0.8492	0.9332	0.7598	0.0492	0.6363	0.9744	0.0000	0.2794
		SAL	0.8524	0.9152	0.7617	0.0382	0.6194	0.9744	0.0000	0.2876
		STL	0.7570	0.9315	0.5213	0.1071	0.7312	0.9694	0.0000	0.1889
	16	RAN	0.8458	0.9123	0.7765	0.0452	0.6265	0.9870	0.0000	0.2801
		SAL	0.8525	0.9154	0.7615	0.0388	0.6191	0.9870	0.0000	0.2881
		STL	0.7574	0.9318	0.5213	0.1073	0.7315	0.9694	0.0000	0.1891

Table G.26: grouped-nb-enron-OSB3-ALL-ALL-10

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.7452	0.8205	0.6445	0.0623	0.5169	1.0000	0.0000	0.2949
		SAL	0.7481	0.8048	0.6397	0.0565	0.5206	0.9867	0.0000	0.2891
		STL	0.6854	0.8437	0.5711	0.1006	0.6488	0.9794	0.0000	0.2163
	1	RAN	0.7937	0.8378	0.7226	0.0378	0.5639	0.9870	0.0000	0.2906
		SAL	0.7999	0.8301	0.7640	0.0205	0.5692	0.9349	0.0000	0.2831
		STL	0.6822	0.8489	0.5514	0.1050	0.6463	0.9744	0.0000	0.2137
	2	RAN	0.8030	0.8257	0.7623	0.0212	0.5716	0.9445	0.0000	0.2858
		SAL	0.8027	0.8350	0.7624	0.0243	0.5691	0.9386	0.0000	0.2848
		STL	0.6846	0.8600	0.5514	0.1078	0.6483	0.9744	0.0000	0.2146
	4	RAN	0.8015	0.8546	0.7614	0.0285	0.5681	0.9620	0.0000	0.2803
		SAL	0.8010	0.8349	0.7537	0.0268	0.5689	0.9326	0.0000	0.2844
		STL	0.6839	0.8551	0.5514	0.1067	0.6471	0.9744	0.0000	0.2149
	8	RAN	0.7950	0.8534	0.7415	0.0337	0.5675	0.9744	0.0000	0.2823
		SAL	0.8028	0.8354	0.7625	0.0243	0.5681	0.9366	0.0000	0.2867
		STL	0.6860	0.8618	0.5556	0.1077	0.6498	0.9744	0.0000	0.2140
	16	RAN	0.7977	0.8377	0.7485	0.0324	0.5689	0.9744	0.0000	0.2881
		SAL	0.8034	0.8359	0.7622	0.0248	0.5686	0.9384	0.0000	0.2867
		STL	0.6867	0.8627	0.5556	0.1083	0.6504	0.9744	0.0000	0.2144

Table G.27: grouped-nb-enron-OSB3-ALL-ALL-25

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.7132	0.7408	0.6774	0.0265	0.4868	0.9730	0.0000	0.2978
		SAL	0.7089	0.7570	0.6429	0.0483	0.4869	0.9730	0.0000	0.2922
		STL	0.6234	0.7305	0.5190	0.0864	0.5579	1.0000	0.0000	0.2457
	1	RAN	0.4410	0.4869	0.3615	0.0565	0.3216	0.8700	0.0000	0.2438
		SAL	0.4123	0.4347	0.3781	0.0246	0.3063	0.8458	0.0000	0.2268
		STL	0.6105	0.6819	0.5204	0.0672	0.5550	0.9744	0.0000	0.2296
	2	RAN	0.4316	0.5087	0.3695	0.0578	0.3103	0.8427	0.0000	0.2371
		SAL	0.4273	0.4539	0.3784	0.0346	0.3078	0.8506	0.0000	0.2314
		STL	0.3779	0.4000	0.3526	0.0195	0.3548	0.9730	0.0000	0.2091
	4	RAN	0.7562	0.7820	0.7072	0.0346	0.5324	0.9320	0.0000	0.2844
		SAL	0.7651	0.7899	0.7354	0.0225	0.5311	0.9343	0.0000	0.2854
		STL	0.6437	0.7829	0.5197	0.1080	0.5814	0.9744	0.0000	0.2344

Table G.28: grouped-nb-enron-OSB3-ALL-ALL-50

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.6983	0.6992	0.6975	0.0009	0.4726	1.0000	0.0000	0.3006
		SAL	0.6939	0.7004	0.6874	0.0065	0.4724	0.9867	0.0000	0.2986
		STL	0.6216	0.6927	0.5504	0.0712	0.5160	0.9870	0.0000	0.2620
	1	RAN	0.7370	0.7448	0.7293	0.0077	0.5072	0.9287	0.0000	0.2889
		SAL	0.7425	0.7444	0.7407	0.0018	0.5108	0.9094	0.0000	0.2868
		STL	0.6427	0.7478	0.5376	0.1051	0.5481	0.9181	0.0000	0.2445
	2	RAN	0.7408	0.7414	0.7402	0.0006	0.5051	0.9341	0.0000	0.2895
		SAL	0.7467	0.7488	0.7447	0.0020	0.5117	0.9101	0.0000	0.2873
		STL	0.6461	0.7531	0.5390	0.1070	0.5486	0.9197	0.0000	0.2461
	4	RAN	0.7378	0.7621	0.7135	0.0243	0.5014	0.9352	0.0000	0.2906
		SAL	0.7444	0.7475	0.7412	0.0032	0.5112	0.9077	0.0000	0.2862
		STL	0.6446	0.7500	0.5393	0.1054	0.5471	0.9208	0.0000	0.2460
	8	RAN	0.7295	0.7860	0.6730	0.0565	0.5098	0.9290	0.0000	0.2863
		SAL	0.7477	0.7512	0.7441	0.0036	0.5109	0.9119	0.0000	0.2886
		STL	0.6465	0.7541	0.5389	0.1076	0.5484	0.9193	0.0000	0.2463
	16	RAN	0.7489	0.7604	0.7374	0.0115	0.5121	0.9315	0.0000	0.2889
		SAL	0.7485	0.7515	0.7455	0.0030	0.5117	0.9131	0.0000	0.2887
		STL	0.6471	0.7551	0.5391	0.1080	0.5491	0.9223	0.0000	0.2467

Table G.29: grouped-nb-enron-OSB3-ALL-ALL-75

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.6574	0.6574	0.6574	0.0000	0.4442	0.9867	0.0000	0.3023
		SAL	0.6571	0.6571	0.6571	0.0000	0.4441	0.9730	0.0000	0.3023
		STL	0.6571	0.6571	0.6571	0.0000	0.4441	0.9730	0.0000	0.3023
	1	RAN	0.7040	0.7040	0.7040	0.0000	0.4788	0.9127	0.0000	0.2863
		SAL	0.7042	0.7042	0.7042	0.0000	0.4790	0.9118	0.0000	0.2851
		STL	0.7042	0.7042	0.7042	0.0000	0.4790	0.9118	0.0000	0.2851
	2	RAN	0.7089	0.7089	0.7089	0.0000	0.4786	0.9126	0.0000	0.2879
		SAL	0.7092	0.7092	0.7092	0.0000	0.4787	0.9146	0.0000	0.2873
		STL	0.7092	0.7092	0.7092	0.0000	0.4787	0.9146	0.0000	0.2873
	4	RAN	0.7071	0.7071	0.7071	0.0000	0.4767	0.9189	0.0000	0.2885
		SAL	0.7066	0.7066	0.7066	0.0000	0.4770	0.9154	0.0000	0.2869
		STL	0.7066	0.7066	0.7066	0.0000	0.4770	0.9154	0.0000	0.2869
	8	RAN	0.7100	0.7100	0.7100	0.0000	0.4769	0.9130	0.0000	0.2881
		SAL	0.7101	0.7101	0.7101	0.0000	0.4782	0.9151	0.0000	0.2877
		STL	0.7101	0.7101	0.7101	0.0000	0.4782	0.9151	0.0000	0.2877
	16	RAN	0.7120	0.7120	0.7120	0.0000	0.4793	0.9187	0.0000	0.2893
		SAL	0.7112	0.7112	0.7112	0.0000	0.4789	0.9175	0.0000	0.2881
		STL	0.7112	0.7112	0.7112	0.0000	0.4789	0.9175	0.0000	0.2881

Table G.30: grouped-nb-enron-OSB3-ALL-ALL-150

APPENDIX H:
Grouped Naive Bayes Results for the Twitter Short Message Corpus

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.6173	0.7548	0.4740	0.0779	0.5706	0.9069	0.0000	0.1942
		SAL	0.5952	0.7598	0.4580	0.0747	0.5405	0.9063	0.0000	0.2002
		STL	0.6667	0.7714	0.5326	0.0678	0.6548	0.9618	0.2333	0.1351
	1	RAN	0.5577	0.7500	0.4421	0.0738	0.5255	0.9178	0.1455	0.1516
		SAL	0.5636	0.7495	0.4514	0.0654	0.5363	0.9421	0.1493	0.1474
		STL	0.3709	0.5720	0.1965	0.0878	0.3585	0.7213	0.0000	0.1229
	2	RAN	0.5704	0.8101	0.4545	0.0764	0.5474	0.9412	0.1481	0.1393
		SAL	0.5746	0.7657	0.4759	0.0721	0.5448	0.9463	0.1000	0.1450
		STL	0.3939	0.5815	0.2785	0.0807	0.3885	0.7899	0.0615	0.1181
	4	RAN	0.5590	0.7400	0.4291	0.0699	0.5261	0.9518	0.1379	0.1505
		SAL	0.5657	0.7749	0.4217	0.0807	0.5385	0.9421	0.1538	0.1518
		STL	0.4149	0.5671	0.2637	0.0766	0.4097	0.8108	0.1190	0.1227
	8	RAN	0.5672	0.7454	0.4291	0.0799	0.5344	0.9393	0.1311	0.1544
		SAL	0.5733	0.7913	0.4667	0.0796	0.5469	0.9562	0.1639	0.1415
		STL	0.4309	0.6667	0.2861	0.0991	0.4245	0.8169	0.1573	0.1319
	16	RAN	0.5652	0.7597	0.3969	0.0868	0.5387	0.9501	0.1667	0.1489
		SAL	0.5682	0.7778	0.4675	0.0738	0.5405	0.9500	0.1967	0.1418
		STL	0.3972	0.6022	0.2885	0.0670	0.3919	0.7105	0.1649	0.1070

Table H.1: grouped-nb-twitter-GM1-ALL-ALL-5

GM1										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.4629	0.6043	0.2738	0.0849	0.3920	0.8720	0.0000	0.2385
		SAL	0.4538	0.5875	0.3167	0.0744	0.3872	0.9129	0.0000	0.2225
		STL	0.5441	0.6411	0.4658	0.0549	0.5242	0.9282	0.0222	0.1598
	1	RAN	0.4195	0.5598	0.2964	0.0646	0.3892	0.9152	0.0000	0.1589
		SAL	0.4184	0.5570	0.3208	0.0647	0.3818	0.9016	0.0000	0.1623
		STL	0.2090	0.3092	0.1297	0.0534	0.1970	0.6731	0.0000	0.1054
	2	RAN	0.4386	0.5517	0.3314	0.0597	0.4009	0.8797	0.0351	0.1602
		SAL	0.4308	0.6005	0.3629	0.0699	0.3938	0.9209	0.0000	0.1563
		STL	0.2320	0.3820	0.1623	0.0573	0.2274	0.6727	0.0270	0.1162
	4	RAN	0.4290	0.5693	0.3675	0.0556	0.3916	0.9151	0.0370	0.1558
		SAL	0.4299	0.5990	0.3043	0.0787	0.3940	0.9150	0.0364	0.1627
		STL	0.2490	0.3628	0.1997	0.0417	0.2456	0.6429	0.0274	0.1078
	8	RAN	0.4357	0.5521	0.3576	0.0534	0.4005	0.8968	0.0000	0.1604
		SAL	0.4276	0.5902	0.3372	0.0742	0.3915	0.9002	0.0000	0.1587
		STL	0.2632	0.3752	0.1692	0.0642	0.2573	0.7893	0.0000	0.1316
	16	RAN	0.4334	0.5562	0.3275	0.0642	0.3996	0.8664	0.0980	0.1537
		SAL	0.4319	0.5588	0.3415	0.0676	0.3957	0.8667	0.0714	0.1558
		STL	0.2271	0.3321	0.1639	0.0468	0.2241	0.6105	0.0000	0.1015

Table H.2: grouped-nb-twitter-GM1-ALL-ALL-10

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.3215	0.3906	0.2200	0.0511	0.2534	0.8340	0.0000	0.2091
		SAL	0.2995	0.4110	0.2265	0.0685	0.2393	0.8560	0.0000	0.2029
		STL	0.3861	0.4389	0.3553	0.0316	0.3616	0.8430	0.0000	0.1839
	1	RAN	0.2926	0.3653	0.2279	0.0465	0.2572	0.8185	0.0000	0.1560
		SAL	0.2900	0.3541	0.2492	0.0347	0.2553	0.7879	0.0222	0.1510
		STL	0.0953	0.1352	0.0731	0.0212	0.0895	0.5030	0.0000	0.0860
	2	RAN	0.2942	0.3371	0.2473	0.0266	0.2566	0.7992	0.0000	0.1540
		SAL	0.2951	0.3574	0.2445	0.0408	0.2588	0.8385	0.0290	0.1576
		STL	0.1005	0.1333	0.0817	0.0177	0.0971	0.5591	0.0000	0.0827
	4	RAN	0.2913	0.3444	0.2572	0.0330	0.2530	0.8356	0.0000	0.1567
		SAL	0.2964	0.3539	0.2271	0.0448	0.2626	0.8615	0.0000	0.1639
		STL	0.1119	0.1248	0.0956	0.0101	0.1107	0.6250	0.0000	0.0837
	8	RAN	0.2996	0.3882	0.2327	0.0475	0.2595	0.8249	0.0000	0.1521
		SAL	0.2985	0.3701	0.2388	0.0466	0.2615	0.8615	0.0000	0.1629
		STL	0.1213	0.1617	0.0848	0.0263	0.1186	0.6557	0.0000	0.1046
	16	RAN	0.2987	0.3319	0.2712	0.0229	0.2537	0.8168	0.0274	0.1516
		SAL	0.2937	0.3517	0.2543	0.0349	0.2548	0.8803	0.0000	0.1574
		STL	0.0988	0.1172	0.0733	0.0139	0.0984	0.5714	0.0000	0.0820

Table H.3: grouped-nb-twitter-GM1-ALL-ALL-25

GM1										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.2120	0.2566	0.1395	0.0517	0.1665	0.8214	0.0000	0.1818
		SAL	0.2079	0.2373	0.1680	0.0293	0.1610	0.8426	0.0000	0.1748
		STL	0.2779	0.3191	0.2359	0.0340	0.2485	0.8333	0.0000	0.1849
	1	RAN	0.2158	0.2421	0.1936	0.0200	0.1786	0.8116	0.0000	0.1462
		SAL	0.2131	0.2449	0.1897	0.0233	0.1755	0.7368	0.0000	0.1450
		STL	0.0495	0.0593	0.0387	0.0084	0.0428	0.4078	0.0000	0.0618
	2	RAN	0.2145	0.2501	0.1686	0.0341	0.1768	0.8615	0.0000	0.1393
		SAL	0.2186	0.2465	0.2018	0.0199	0.1809	0.7857	0.0000	0.1458
		STL	0.0563	0.0652	0.0460	0.0079	0.0522	0.5000	0.0000	0.0689
	4	RAN	0.2154	0.2507	0.1683	0.0346	0.1773	0.7924	0.0000	0.1411
		SAL	0.2174	0.2467	0.1665	0.0361	0.1818	0.8000	0.0000	0.1444
		STL	0.0632	0.0746	0.0556	0.0082	0.0621	0.5902	0.0000	0.0716
	8	RAN	0.2195	0.2522	0.1986	0.0234	0.1816	0.7917	0.0000	0.1439
		SAL	0.2181	0.2460	0.1960	0.0208	0.1823	0.8750	0.0000	0.1515
		STL	0.0637	0.0796	0.0504	0.0121	0.0615	0.4940	0.0000	0.0789
	16	RAN	0.2213	0.2436	0.1849	0.0259	0.1845	0.7883	0.0000	0.1489
		SAL	0.2183	0.2289	0.2064	0.0092	0.1805	0.8485	0.0000	0.1482
		STL	0.0520	0.0585	0.0486	0.0046	0.0510	0.5417	0.0000	0.0729

Table H.4: grouped-nb-twitter-GM1-ALL-ALL-50

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.1644	0.1890	0.1399	0.0246	0.1233	0.7876	0.0000	0.1582
		SAL	0.1678	0.1846	0.1509	0.0169	0.1259	0.7807	0.0000	0.1713
		STL	0.2137	0.2356	0.1917	0.0220	0.1825	0.7818	0.0000	0.1721
	1	RAN	0.1846	0.2014	0.1679	0.0167	0.1487	0.7324	0.0000	0.1373
		SAL	0.1785	0.1964	0.1606	0.0179	0.1441	0.7027	0.0000	0.1387
		STL	0.0351	0.0448	0.0254	0.0097	0.0281	0.3841	0.0000	0.0492
	2	RAN	0.1798	0.2120	0.1475	0.0323	0.1445	0.8000	0.0000	0.1412
		SAL	0.1885	0.2167	0.1604	0.0282	0.1537	0.7647	0.0000	0.1404
		STL	0.0408	0.0512	0.0303	0.0105	0.0362	0.3975	0.0000	0.0572
	4	RAN	0.1855	0.1888	0.1822	0.0033	0.1467	0.7598	0.0000	0.1332
		SAL	0.1813	0.2184	0.1442	0.0371	0.1494	0.7941	0.0000	0.1432
		STL	0.0441	0.0483	0.0400	0.0042	0.0435	0.5357	0.0000	0.0619
	8	RAN	0.1876	0.1927	0.1825	0.0051	0.1529	0.7037	0.0000	0.1392
		SAL	0.1813	0.2275	0.1350	0.0462	0.1487	0.7617	0.0000	0.1399
		STL	0.0481	0.0559	0.0404	0.0077	0.0453	0.4713	0.0000	0.0709
	16	RAN	0.1854	0.1928	0.1779	0.0074	0.1493	0.6950	0.0000	0.1318
		SAL	0.1881	0.2114	0.1647	0.0233	0.1509	0.7680	0.0000	0.1382
		STL	0.0347	0.0379	0.0315	0.0032	0.0324	0.3111	0.0000	0.0503

Table H.5: grouped-nb-twitter-GM1-ALL-ALL-75

GM1										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.1247	0.1247	0.1247	0.0000	0.0843	0.7565	0.0000	0.1440
		SAL	0.1254	0.1254	0.1254	0.0000	0.0860	0.7458	0.0000	0.1451
		STL	0.1254	0.1254	0.1254	0.0000	0.0860	0.7458	0.0000	0.1451
	1	RAN	0.1353	0.1353	0.1353	0.0000	0.1021	0.6933	0.0000	0.1224
		SAL	0.1353	0.1353	0.1353	0.0000	0.1042	0.7500	0.0000	0.1246
		STL	0.0239	0.0239	0.0239	0.0000	0.0172	0.3232	0.0000	0.0410
	2	RAN	0.1344	0.1344	0.1344	0.0000	0.1003	0.6753	0.0000	0.1222
		SAL	0.1344	0.1344	0.1344	0.0000	0.1019	0.7027	0.0000	0.1219
		STL	0.0248	0.0248	0.0248	0.0000	0.0192	0.3333	0.0000	0.0463
	4	RAN	0.1342	0.1342	0.1342	0.0000	0.1028	0.6933	0.0000	0.1212
		SAL	0.1351	0.1351	0.1351	0.0000	0.1028	0.7324	0.0000	0.1225
		STL	0.0231	0.0231	0.0231	0.0000	0.0224	0.3182	0.0000	0.0414
	8	RAN	0.1335	0.1335	0.1335	0.0000	0.1004	0.7027	0.0000	0.1209
		SAL	0.1350	0.1350	0.1350	0.0000	0.1029	0.7123	0.0000	0.1220
		STL	0.0274	0.0274	0.0274	0.0000	0.0230	0.4013	0.0000	0.0522
	16	RAN	0.1386	0.1386	0.1386	0.0000	0.1053	0.6753	0.0000	0.1198
		SAL	0.1363	0.1363	0.1363	0.0000	0.1039	0.6923	0.0000	0.1242
		STL	0.0200	0.0200	0.0200	0.0000	0.0181	0.1991	0.0000	0.0343

Table H.6: grouped-nb-twitter-GM1-ALL-ALL-150

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.5732	0.7657	0.3986	0.0847	0.5224	0.9486	0.0351	0.1884
		SAL	0.5623	0.7890	0.3875	0.0874	0.5087	0.9105	0.0000	0.1956
		STL	0.5778	0.7356	0.4151	0.0831	0.5585	0.9231	0.0606	0.1564
	1	RAN	0.5874	0.7616	0.3830	0.0780	0.5716	0.9250	0.2222	0.1359
		SAL	0.5877	0.7643	0.4103	0.0877	0.5718	0.9153	0.2059	0.1392
		STL	0.4007	0.5500	0.2871	0.0618	0.3970	0.8182	0.1667	0.1099
	2	RAN	0.5820	0.7467	0.4236	0.0878	0.5651	0.9328	0.1687	0.1425
		SAL	0.5844	0.7114	0.4590	0.0751	0.5671	0.9043	0.2078	0.1333
		STL	0.4240	0.5590	0.3114	0.0733	0.4203	0.8000	0.1284	0.1214
	4	RAN	0.5888	0.7574	0.4727	0.0702	0.5667	0.9237	0.2368	0.1398
		SAL	0.5806	0.7926	0.4336	0.0883	0.5599	0.9167	0.2381	0.1499
		STL	0.4510	0.6162	0.3519	0.0639	0.4511	0.8615	0.1522	0.1193
	8	RAN	0.6026	0.7797	0.4710	0.0839	0.5817	0.9457	0.1944	0.1470
		SAL	0.6003	0.7992	0.4743	0.0699	0.5806	0.9237	0.2626	0.1369
		STL	0.4348	0.6199	0.2906	0.0696	0.4316	0.7950	0.2329	0.1155
	16	RAN	0.6003	0.8437	0.4465	0.0858	0.5808	0.9560	0.3143	0.1318
		SAL	0.5884	0.7737	0.4029	0.0999	0.5632	0.9492	0.2118	0.1585
		STL	0.4340	0.5185	0.2975	0.0667	0.4307	0.8186	0.1481	0.1224

Table H.7: grouped-nb-twitter-GM2-ALL-ALL-5

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.4438	0.6199	0.2809	0.0829	0.3966	0.8710	0.0000	0.1959
		SAL	0.4346	0.6304	0.3645	0.0752	0.3817	0.8429	0.0000	0.1963
		STL	0.4532	0.5707	0.3270	0.0643	0.4313	0.8824	0.0357	0.1684
	1	RAN	0.4539	0.5810	0.3958	0.0511	0.4332	0.8974	0.0377	0.1542
		SAL	0.4511	0.5960	0.3042	0.0716	0.4328	0.8642	0.0702	0.1585
		STL	0.2489	0.3478	0.1816	0.0377	0.2489	0.6765	0.0513	0.1089
	2	RAN	0.4536	0.5446	0.3374	0.0619	0.4356	0.8988	0.0822	0.1631
		SAL	0.4624	0.5246	0.4006	0.0383	0.4402	0.8947	0.0519	0.1549
		STL	0.2582	0.3644	0.1842	0.0450	0.2586	0.7869	0.0594	0.1230
	4	RAN	0.4538	0.5885	0.3429	0.0805	0.4318	0.8947	0.0759	0.1613
		SAL	0.4641	0.6610	0.3768	0.0696	0.4397	0.8848	0.0698	0.1629
		STL	0.2875	0.3425	0.2146	0.0396	0.2922	0.8116	0.0588	0.1266
	8	RAN	0.4715	0.6051	0.3775	0.0751	0.4482	0.9231	0.0976	0.1628
		SAL	0.4696	0.5573	0.4150	0.0468	0.4424	0.9217	0.1290	0.1593
		STL	0.2727	0.3638	0.1764	0.0402	0.2690	0.7102	0.0250	0.1136
	16	RAN	0.4653	0.6179	0.3557	0.0767	0.4388	0.9043	0.0357	0.1733
		SAL	0.4692	0.6117	0.3640	0.0867	0.4367	0.9170	0.0811	0.1741
		STL	0.2748	0.3317	0.1855	0.0372	0.2742	0.7718	0.0426	0.1210

Table H.8: grouped-nb-twitter-GM2-ALL-ALL-10

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.3179	0.3833	0.2853	0.0318	0.2706	0.8182	0.0000	0.1887
		SAL	0.3253	0.3855	0.2750	0.0415	0.2745	0.8462	0.0000	0.1864
		STL	0.3212	0.3755	0.2617	0.0401	0.3013	0.8182	0.0000	0.1769
	1	RAN	0.3223	0.3457	0.2971	0.0175	0.3091	0.8571	0.0000	0.1664
		SAL	0.3218	0.4249	0.2574	0.0537	0.3045	0.8755	0.0377	0.1658
		STL	0.1082	0.1254	0.0872	0.0126	0.1083	0.5600	0.0000	0.0857
	2	RAN	0.3176	0.3636	0.2754	0.0346	0.3024	0.8745	0.0645	0.1616
		SAL	0.3238	0.3846	0.2684	0.0404	0.3092	0.8308	0.0000	0.1584
		STL	0.1116	0.1358	0.0963	0.0132	0.1103	0.7368	0.0000	0.0967
	4	RAN	0.3338	0.3673	0.3033	0.0250	0.3104	0.8000	0.0278	0.1652
		SAL	0.3317	0.4173	0.2733	0.0458	0.3092	0.8364	0.0270	0.1673
		STL	0.1404	0.1616	0.1121	0.0162	0.1480	0.7879	0.0000	0.1096
	8	RAN	0.3426	0.4296	0.3064	0.0470	0.3186	0.8681	0.0513	0.1623
		SAL	0.3463	0.4602	0.2814	0.0561	0.3200	0.8671	0.0455	0.1730
		STL	0.1415	0.1684	0.1198	0.0164	0.1404	0.6600	0.0000	0.1023
	16	RAN	0.3351	0.3989	0.2781	0.0353	0.3077	0.8358	0.0299	0.1709
		SAL	0.3339	0.4437	0.2787	0.0644	0.3114	0.8619	0.0000	0.1785
		STL	0.1418	0.1603	0.1105	0.0168	0.1445	0.7048	0.0000	0.1111

Table H.9: grouped-nb-twitter-GM2-ALL-ALL-25

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.2499	0.2846	0.2213	0.0262	0.2128	0.8438	0.0000	0.1727
		SAL	0.2531	0.2662	0.2349	0.0133	0.2069	0.7941	0.0000	0.1716
		STL	0.2497	0.2992	0.2038	0.0390	0.2328	0.7826	0.0000	0.1661
	1	RAN	0.2522	0.3044	0.2198	0.0373	0.2375	0.7753	0.0000	0.1531
		SAL	0.2467	0.2626	0.2193	0.0194	0.2326	0.8288	0.0000	0.1600
		STL	0.0573	0.0611	0.0507	0.0047	0.0573	0.5106	0.0000	0.0718
	2	RAN	0.2477	0.2533	0.2367	0.0077	0.2329	0.8189	0.0000	0.1636
		SAL	0.2481	0.2660	0.2241	0.0177	0.2351	0.8300	0.0000	0.1627
		STL	0.0571	0.0730	0.0413	0.0129	0.0550	0.4783	0.0000	0.0707
	4	RAN	0.2583	0.2667	0.2498	0.0069	0.2344	0.7944	0.0000	0.1647
		SAL	0.2617	0.3055	0.2335	0.0314	0.2398	0.8037	0.0420	0.1618
		STL	0.0739	0.0946	0.0578	0.0154	0.0789	0.7419	0.0000	0.0904
	8	RAN	0.2674	0.2880	0.2415	0.0194	0.2451	0.8117	0.0250	0.1623
		SAL	0.2678	0.2806	0.2607	0.0090	0.2465	0.8362	0.0000	0.1669
		STL	0.0822	0.0891	0.0771	0.0051	0.0840	0.5241	0.0000	0.0836
	16	RAN	0.2629	0.3031	0.2405	0.0285	0.2408	0.8438	0.0204	0.1690
		SAL	0.2624	0.2887	0.2138	0.0344	0.2419	0.8313	0.0000	0.1745
		STL	0.0817	0.0870	0.0786	0.0038	0.0846	0.5310	0.0000	0.0866

Table H.10: grouped-nb-twitter-GM2-ALL-ALL-50

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.2125	0.2621	0.1630	0.0496	0.1744	0.7385	0.0000	0.1610
		SAL	0.2195	0.2291	0.2100	0.0095	0.1828	0.7397	0.0000	0.1634
		STL	0.2164	0.2458	0.1871	0.0293	0.1965	0.7879	0.0000	0.1614
	1	RAN	0.2051	0.2181	0.1922	0.0129	0.1938	0.8000	0.0000	0.1548
		SAL	0.2126	0.2358	0.1895	0.0232	0.2000	0.8036	0.0000	0.1578
		STL	0.0375	0.0382	0.0368	0.0007	0.0356	0.3158	0.0000	0.0500
	2	RAN	0.2131	0.2229	0.2034	0.0098	0.2012	0.8000	0.0000	0.1539
		SAL	0.2104	0.2255	0.1953	0.0151	0.1989	0.8293	0.0000	0.1513
		STL	0.0370	0.0413	0.0328	0.0043	0.0344	0.3721	0.0000	0.0516
	4	RAN	0.2255	0.2477	0.2033	0.0222	0.2067	0.8073	0.0000	0.1553
		SAL	0.2244	0.2291	0.2197	0.0047	0.2044	0.7500	0.0000	0.1582
		STL	0.0501	0.0524	0.0477	0.0024	0.0540	0.5000	0.0000	0.0671
	8	RAN	0.2342	0.2535	0.2149	0.0193	0.2152	0.7887	0.0000	0.1659
		SAL	0.2346	0.2503	0.2189	0.0157	0.2144	0.8106	0.0000	0.1664
		STL	0.0622	0.0666	0.0578	0.0044	0.0648	0.5275	0.0000	0.0788
	16	RAN	0.2253	0.2316	0.2190	0.0063	0.2031	0.8182	0.0000	0.1665
		SAL	0.2257	0.2579	0.1935	0.0322	0.2079	0.8571	0.0000	0.1675
		STL	0.0590	0.0607	0.0573	0.0017	0.0609	0.4786	0.0000	0.0716

Table H.11: grouped-nb-twitter-GM2-ALL-ALL-75

GM2										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.1690	0.1690	0.1690	0.0000	0.1355	0.7619	0.0000	0.1476
		SAL	0.1719	0.1719	0.1719	0.0000	0.1390	0.7500	0.0000	0.1488
		STL	0.1719	0.1719	0.1719	0.0000	0.1390	0.7500	0.0000	0.1488
	1	RAN	0.1621	0.1621	0.1621	0.0000	0.1521	0.7593	0.0000	0.1450
		SAL	0.1655	0.1655	0.1655	0.0000	0.1541	0.7321	0.0000	0.1426
		STL	0.0190	0.0190	0.0190	0.0000	0.0160	0.2629	0.0000	0.0336
	2	RAN	0.1659	0.1659	0.1659	0.0000	0.1565	0.7748	0.0000	0.1487
		SAL	0.1655	0.1655	0.1655	0.0000	0.1580	0.7967	0.0000	0.1488
		STL	0.0206	0.0206	0.0206	0.0000	0.0169	0.2623	0.0000	0.0337
	4	RAN	0.1789	0.1789	0.1789	0.0000	0.1611	0.7477	0.0000	0.1467
		SAL	0.1781	0.1781	0.1781	0.0000	0.1611	0.7455	0.0000	0.1481
		STL	0.0276	0.0276	0.0276	0.0000	0.0286	0.3750	0.0000	0.0491
	8	RAN	0.1810	0.1810	0.1810	0.0000	0.1658	0.7414	0.0000	0.1522
		SAL	0.1819	0.1819	0.1819	0.0000	0.1662	0.7339	0.0000	0.1541
		STL	0.0363	0.0363	0.0363	0.0000	0.0388	0.4483	0.0000	0.0648
	16	RAN	0.1753	0.1753	0.1753	0.0000	0.1570	0.7293	0.0000	0.1544
		SAL	0.1760	0.1760	0.1760	0.0000	0.1589	0.7519	0.0000	0.1543
		STL	0.0357	0.0357	0.0357	0.0000	0.0348	0.3692	0.0000	0.0559

Table H.12: grouped-nb-twitter-GM2-ALL-ALL-150

GM5										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.3442	0.4815	0.2431	0.0621	0.2258	0.7931	0.0000	0.1935
		SAL	0.3544	0.5293	0.2909	0.0486	0.2280	0.7931	0.0000	0.1947
		STL	0.3374	0.4555	0.2564	0.0456	0.2380	0.7719	0.0000	0.1905
	1	RAN	0.5553	0.7495	0.4139	0.0861	0.5284	0.8703	0.1096	0.1466
		SAL	0.5531	0.7345	0.4227	0.0845	0.5285	0.9106	0.1379	0.1473
		STL	0.5506	0.6907	0.4066	0.0661	0.5404	0.8750	0.2330	0.1296
	2	RAN	0.5544	0.7220	0.4161	0.0765	0.5230	0.9206	0.1975	0.1587
		SAL	0.5492	0.6859	0.4000	0.0843	0.5206	0.9231	0.1212	0.1572
		STL	0.5534	0.7087	0.4254	0.0755	0.5403	0.8629	0.1975	0.1417
	4	RAN	0.5595	0.7021	0.4539	0.0604	0.5220	0.9021	0.0426	0.1629
		SAL	0.5396	0.7077	0.3814	0.0809	0.5031	0.9052	0.0588	0.1619
		STL	0.5558	0.6981	0.4280	0.0698	0.5420	0.8689	0.2162	0.1409
	8	RAN	0.5533	0.7071	0.3968	0.0677	0.5163	0.9224	0.0779	0.1625
		SAL	0.5432	0.6912	0.4127	0.0717	0.5057	0.8972	0.1067	0.1596
		STL	0.5686	0.7094	0.4029	0.0642	0.5566	0.9254	0.2338	0.1398
	16	RAN	0.5562	0.7680	0.4106	0.0869	0.5202	0.8713	0.0870	0.1730
		SAL	0.5416	0.6900	0.4373	0.0803	0.5070	0.9245	0.0571	0.1704
		STL	0.5758	0.6852	0.4322	0.0594	0.5626	0.8833	0.1690	0.1425

Table H.13: grouped-nb-twitter-GM5-ALL-ALL-5

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.2462	0.3357	0.2000	0.0395	0.1752	0.8136	0.0000	0.1570
		SAL	0.2450	0.3185	0.1748	0.0312	0.1683	0.7931	0.0000	0.1598
		STL	0.2313	0.3245	0.1759	0.0331	0.1700	0.7719	0.0000	0.1617
	1	RAN	0.4266	0.5466	0.3396	0.0669	0.3998	0.8175	0.0556	0.1588
		SAL	0.4247	0.5410	0.3065	0.0655	0.3970	0.8571	0.0833	0.1555
		STL	0.4151	0.5362	0.3212	0.0552	0.4015	0.8400	0.0976	0.1490
	2	RAN	0.4105	0.5806	0.3103	0.0674	0.3807	0.8571	0.0811	0.1638
		SAL	0.4215	0.5522	0.3041	0.0613	0.3940	0.8889	0.0267	0.1706
		STL	0.4240	0.5371	0.3035	0.0631	0.4115	0.8618	0.1167	0.1596
	4	RAN	0.4182	0.5954	0.3220	0.0724	0.3833	0.8618	0.0635	0.1716
		SAL	0.4140	0.4774	0.3069	0.0481	0.3792	0.8468	0.0286	0.1768
		STL	0.4252	0.5124	0.3368	0.0531	0.4114	0.8583	0.1096	0.1629
	8	RAN	0.4235	0.5239	0.3269	0.0573	0.3906	0.8367	0.0656	0.1687
		SAL	0.4108	0.4825	0.3302	0.0447	0.3796	0.8515	0.0303	0.1709
		STL	0.4283	0.5090	0.3364	0.0474	0.4156	0.8750	0.1429	0.1601
	16	RAN	0.4333	0.5369	0.3519	0.0559	0.3979	0.8571	0.0278	0.1758
		SAL	0.4207	0.5606	0.3228	0.0716	0.3916	0.8932	0.0267	0.1750
		STL	0.4418	0.5221	0.3723	0.0446	0.4291	0.8480	0.1067	0.1592

Table H.14: grouped-nb-twitter-GM5-ALL-ALL-10

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.1534	0.1780	0.1256	0.0193	0.1293	0.7931	0.0000	0.1450
		SAL	0.1580	0.2141	0.1224	0.0292	0.1265	0.7931	0.0000	0.1413
		STL	0.1516	0.1929	0.1335	0.0192	0.1307	0.7719	0.0000	0.1464
	1	RAN	0.2966	0.3293	0.2781	0.0196	0.2711	0.7500	0.0000	0.1594
		SAL	0.3041	0.3472	0.2514	0.0357	0.2775	0.7143	0.0000	0.1652
		STL	0.2962	0.3613	0.2703	0.0322	0.2824	0.8190	0.0357	0.1592
	2	RAN	0.2945	0.3486	0.2405	0.0335	0.2728	0.8125	0.0000	0.1682
		SAL	0.2923	0.3478	0.2644	0.0319	0.2684	0.8710	0.0000	0.1646
		STL	0.2901	0.3493	0.2411	0.0317	0.2772	0.8571	0.0278	0.1654
	4	RAN	0.2924	0.3272	0.2133	0.0394	0.2601	0.8750	0.0000	0.1673
		SAL	0.2909	0.3271	0.2491	0.0297	0.2614	0.8710	0.0000	0.1761
		STL	0.2972	0.3300	0.2718	0.0187	0.2851	0.8571	0.0357	0.1712
	8	RAN	0.2914	0.3552	0.2278	0.0417	0.2652	0.8438	0.0000	0.1689
		SAL	0.2885	0.3166	0.2632	0.0203	0.2655	0.8125	0.0000	0.1721
		STL	0.2987	0.3288	0.2746	0.0194	0.2860	0.8387	0.0308	0.1701
	16	RAN	0.2906	0.3765	0.2488	0.0417	0.2659	0.8615	0.0000	0.1761
		SAL	0.2946	0.3568	0.2032	0.0506	0.2694	0.8254	0.0000	0.1723
		STL	0.3068	0.3309	0.2810	0.0154	0.2953	0.8438	0.0286	0.1721

Table H.15: grouped-nb-twitter-GM5-ALL-ALL-25

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.1269	0.1351	0.1218	0.0059	0.1106	0.7719	0.0000	0.1421
		SAL	0.1247	0.1558	0.0999	0.0232	0.1081	0.6909	0.0000	0.1359
		STL	0.1162	0.1298	0.1065	0.0099	0.1052	0.7241	0.0000	0.1390
	1	RAN	0.2254	0.2481	0.1808	0.0315	0.2063	0.7200	0.0000	0.1517
		SAL	0.2287	0.2534	0.1825	0.0327	0.2067	0.7071	0.0000	0.1527
		STL	0.2289	0.2484	0.2129	0.0147	0.2159	0.7961	0.0000	0.1538
	2	RAN	0.2268	0.2327	0.2218	0.0045	0.2069	0.7647	0.0000	0.1617
		SAL	0.2242	0.2637	0.2009	0.0281	0.2027	0.8000	0.0000	0.1624
		STL	0.2246	0.2511	0.1996	0.0210	0.2156	0.8000	0.0132	0.1645
	4	RAN	0.2215	0.2282	0.2133	0.0062	0.1986	0.8065	0.0000	0.1654
		SAL	0.2170	0.2441	0.1770	0.0288	0.1953	0.7937	0.0000	0.1634
		STL	0.2263	0.2336	0.2141	0.0087	0.2153	0.8254	0.0000	0.1678
	8	RAN	0.2212	0.2573	0.2010	0.0256	0.1959	0.7353	0.0000	0.1593
		SAL	0.2160	0.2452	0.1871	0.0237	0.1992	0.8065	0.0000	0.1649
		STL	0.2280	0.2374	0.2198	0.0073	0.2148	0.8224	0.0000	0.1662
	16	RAN	0.2187	0.2328	0.1954	0.0166	0.1973	0.8710	0.0000	0.1596
		SAL	0.2240	0.2608	0.1540	0.0495	0.2010	0.8254	0.0000	0.1653
		STL	0.2308	0.2400	0.2226	0.0071	0.2194	0.8182	0.0000	0.1674

Table H.16: grouped-nb-twitter-GM5-ALL-ALL-50

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.0974	0.1049	0.0898	0.0075	0.0914	0.7241	0.0000	0.1239
		SAL	0.0942	0.1047	0.0836	0.0106	0.0875	0.7719	0.0000	0.1280
		STL	0.1014	0.1069	0.0960	0.0054	0.0935	0.7273	0.0000	0.1318
	1	RAN	0.1964	0.2086	0.1843	0.0122	0.1753	0.6588	0.0000	0.1446
		SAL	0.1970	0.2006	0.1934	0.0036	0.1803	0.6735	0.0000	0.1471
		STL	0.1946	0.2111	0.1780	0.0166	0.1790	0.6739	0.0000	0.1454
	2	RAN	0.1957	0.2027	0.1887	0.0070	0.1734	0.7647	0.0000	0.1476
		SAL	0.1934	0.2066	0.1803	0.0132	0.1750	0.8710	0.0000	0.1553
		STL	0.1966	0.2113	0.1819	0.0147	0.1818	0.8254	0.0000	0.1529
	4	RAN	0.1881	0.1984	0.1777	0.0103	0.1705	0.7619	0.0000	0.1595
		SAL	0.1860	0.1880	0.1839	0.0021	0.1709	0.7813	0.0000	0.1564
		STL	0.1895	0.1945	0.1844	0.0051	0.1760	0.7937	0.0000	0.1533
	8	RAN	0.1897	0.1904	0.1890	0.0007	0.1679	0.7576	0.0000	0.1559
		SAL	0.1871	0.1880	0.1861	0.0009	0.1701	0.7813	0.0000	0.1553
		STL	0.1939	0.1945	0.1932	0.0007	0.1806	0.8065	0.0000	0.1581
	16	RAN	0.1858	0.2027	0.1689	0.0169	0.1673	0.7937	0.0000	0.1581
		SAL	0.1881	0.1987	0.1775	0.0106	0.1699	0.7500	0.0000	0.1590
		STL	0.1985	0.2060	0.1910	0.0075	0.1852	0.7937	0.0000	0.1579

Table H.17: grouped-nb-twitter-GM5-ALL-ALL-75

GM5										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.0792	0.0792	0.0792	0.0000	0.0765	0.6429	0.0000	0.1203
		SAL	0.0784	0.0784	0.0784	0.0000	0.0749	0.6182	0.0000	0.1178
		STL	0.0784	0.0784	0.0784	0.0000	0.0749	0.6182	0.0000	0.1178
	1	RAN	0.1542	0.1542	0.1542	0.0000	0.1380	0.6392	0.0000	0.1370
		SAL	0.1531	0.1531	0.1531	0.0000	0.1364	0.6263	0.0000	0.1354
		STL	0.1531	0.1531	0.1531	0.0000	0.1364	0.6263	0.0000	0.1354
	2	RAN	0.1531	0.1531	0.1531	0.0000	0.1363	0.7692	0.0000	0.1425
		SAL	0.1520	0.1520	0.1520	0.0000	0.1358	0.7879	0.0000	0.1428
		STL	0.1520	0.1520	0.1520	0.0000	0.1358	0.7879	0.0000	0.1428
	4	RAN	0.1414	0.1414	0.1414	0.0000	0.1295	0.7500	0.0000	0.1463
		SAL	0.1399	0.1399	0.1399	0.0000	0.1266	0.7500	0.0000	0.1456
		STL	0.1399	0.1399	0.1399	0.0000	0.1266	0.7500	0.0000	0.1456
	8	RAN	0.1404	0.1404	0.1404	0.0000	0.1268	0.7463	0.0000	0.1457
		SAL	0.1399	0.1399	0.1399	0.0000	0.1267	0.7302	0.0000	0.1436
		STL	0.1399	0.1399	0.1399	0.0000	0.1267	0.7302	0.0000	0.1436
	16	RAN	0.1430	0.1430	0.1430	0.0000	0.1292	0.7500	0.0000	0.1467
		SAL	0.1420	0.1420	0.1420	0.0000	0.1295	0.7813	0.0000	0.1464
		STL	0.1420	0.1420	0.1420	0.0000	0.1295	0.7813	0.0000	0.1464

Table H.18: grouped-nb-twitter-GM5-ALL-ALL-150

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.6189	0.8011	0.4860	0.0817	0.5761	0.9234	0.0392	0.1733
		SAL	0.6135	0.8021	0.5154	0.0624	0.5689	0.9284	0.0800	0.1732
		STL	0.6215	0.7500	0.4745	0.0731	0.5991	0.9112	0.1231	0.1466
	1	RAN	0.6132	0.8125	0.4816	0.0678	0.5976	0.9480	0.2051	0.1291
		SAL	0.6155	0.7584	0.4585	0.0765	0.5967	0.9118	0.2000	0.1344
		STL	0.6040	0.7840	0.4606	0.0752	0.5933	0.9126	0.2783	0.1250
	2	RAN	0.6183	0.7311	0.4954	0.0638	0.5982	0.9347	0.3077	0.1280
		SAL	0.6223	0.7823	0.5029	0.0766	0.5998	0.9130	0.2340	0.1377
		STL	0.6075	0.7653	0.4606	0.0678	0.5978	0.9228	0.2824	0.1210
	4	RAN	0.6257	0.8546	0.4694	0.0850	0.6075	0.9613	0.2444	0.1387
		SAL	0.6291	0.8187	0.5164	0.0874	0.6085	0.9320	0.2500	0.1387
		STL	0.6048	0.7781	0.4953	0.0700	0.5969	0.9208	0.3218	0.1204
	8	RAN	0.6210	0.8474	0.4717	0.0767	0.6035	0.9409	0.2500	0.1318
		SAL	0.6247	0.8013	0.4734	0.0831	0.6055	0.9203	0.2222	0.1310
		STL	0.6106	0.7813	0.4669	0.0699	0.6029	0.9208	0.2459	0.1164
	16	RAN	0.6345	0.8216	0.4648	0.0810	0.6169	0.9512	0.2299	0.1355
		SAL	0.6346	0.7564	0.5229	0.0711	0.6104	0.9070	0.2154	0.1368
		STL	0.6106	0.7867	0.4795	0.0770	0.6021	0.9208	0.2526	0.1235

Table H.19: grouped-nb-twitter-GB3-ALL-ALL-5

GB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.5006	0.6108	0.3844	0.0595	0.4537	0.8696	0.0400	0.1853
		SAL	0.4898	0.5952	0.3958	0.0491	0.4434	0.9091	0.0000	0.1827
		STL	0.4940	0.6108	0.3477	0.0709	0.4658	0.8817	0.0000	0.1708
	1	RAN	0.5038	0.6000	0.4232	0.0499	0.4769	0.8871	0.1333	0.1549
		SAL	0.4977	0.6266	0.3297	0.0742	0.4743	0.8745	0.1190	0.1562
		STL	0.4909	0.6356	0.3796	0.0661	0.4769	0.9002	0.1905	0.1430
	2	RAN	0.5092	0.7366	0.4142	0.0746	0.4865	0.9289	0.1481	0.1447
		SAL	0.5019	0.6596	0.3845	0.0773	0.4754	0.8716	0.1075	0.1510
		STL	0.4935	0.6094	0.3748	0.0594	0.4809	0.9031	0.1647	0.1371
	4	RAN	0.5100	0.6671	0.4123	0.0825	0.4850	0.9066	0.0741	0.1637
		SAL	0.5039	0.6517	0.3665	0.0703	0.4782	0.9102	0.0899	0.1496
		STL	0.4895	0.6067	0.3939	0.0608	0.4770	0.8994	0.1649	0.1419
	8	RAN	0.5061	0.6355	0.4196	0.0675	0.4813	0.9197	0.1389	0.1561
		SAL	0.5013	0.6359	0.3893	0.0788	0.4774	0.8854	0.0952	0.1534
		STL	0.4924	0.6218	0.3732	0.0671	0.4818	0.8994	0.1831	0.1363
	16	RAN	0.5038	0.6205	0.3986	0.0662	0.4811	0.8696	0.0909	0.1464
		SAL	0.5098	0.6137	0.3997	0.0550	0.4842	0.8986	0.0941	0.1517
		STL	0.4987	0.6385	0.3876	0.0682	0.4861	0.8975	0.1778	0.1412

Table H.20: grouped-nb-twitter-GB3-ALL-ALL-10

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.3602	0.4185	0.3076	0.0371	0.3105	0.8000	0.0000	0.1891
		SAL	0.3614	0.4401	0.3153	0.0393	0.3135	0.8696	0.0000	0.1888
		STL	0.3535	0.4211	0.2988	0.0421	0.3253	0.7904	0.0000	0.1799
	1	RAN	0.3788	0.4236	0.3384	0.0317	0.3517	0.8473	0.0256	0.1581
		SAL	0.3764	0.4429	0.3147	0.0411	0.3518	0.8824	0.0202	0.1576
		STL	0.3619	0.4222	0.3190	0.0344	0.3436	0.8393	0.0449	0.1511
	2	RAN	0.3817	0.4394	0.3367	0.0397	0.3563	0.7629	0.0253	0.1525
		SAL	0.3796	0.4232	0.3464	0.0266	0.3512	0.7858	0.0227	0.1501
		STL	0.3667	0.4361	0.3271	0.0360	0.3516	0.8155	0.0440	0.1493
	4	RAN	0.3882	0.4834	0.3428	0.0447	0.3599	0.8504	0.0294	0.1609
		SAL	0.3832	0.4562	0.3207	0.0522	0.3561	0.7828	0.0227	0.1530
		STL	0.3604	0.4353	0.3245	0.0369	0.3457	0.8121	0.0440	0.1519
	8	RAN	0.3733	0.4633	0.3186	0.0511	0.3512	0.8355	0.0588	0.1528
		SAL	0.3824	0.4558	0.3353	0.0409	0.3565	0.7815	0.0244	0.1536
		STL	0.3642	0.4361	0.3206	0.0394	0.3508	0.8117	0.0842	0.1506
	16	RAN	0.3868	0.4290	0.2890	0.0469	0.3595	0.8649	0.0400	0.1685
		SAL	0.3915	0.4422	0.3474	0.0357	0.3625	0.8451	0.0270	0.1651
		STL	0.3730	0.4431	0.3184	0.0395	0.3580	0.8493	0.0449	0.1515

Table H.21: grouped-nb-twitter-GB3-ALL-ALL-25

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.2849	0.3171	0.2642	0.0231	0.2400	0.7606	0.0000	0.1753
		SAL	0.2831	0.3015	0.2612	0.0166	0.2401	0.8955	0.0000	0.1791
		STL	0.2837	0.3292	0.2411	0.0360	0.2569	0.7788	0.0000	0.1759
	1	RAN	0.3022	0.3356	0.2757	0.0249	0.2751	0.7892	0.0000	0.1555
		SAL	0.3002	0.3108	0.2923	0.0078	0.2742	0.8219	0.0235	0.1583
		STL	0.2928	0.3354	0.2686	0.0302	0.2744	0.8073	0.0000	0.1568
	2	RAN	0.3029	0.3256	0.2865	0.0165	0.2765	0.7529	0.0000	0.1511
		SAL	0.3058	0.3300	0.2823	0.0195	0.2782	0.7218	0.0256	0.1513
		STL	0.2970	0.3366	0.2770	0.0280	0.2786	0.7519	0.0000	0.1475
	4	RAN	0.3074	0.3132	0.2995	0.0058	0.2800	0.7895	0.0000	0.1573
		SAL	0.3107	0.3376	0.2755	0.0260	0.2831	0.7111	0.0241	0.1521
		STL	0.2952	0.3361	0.2728	0.0290	0.2778	0.7627	0.0000	0.1525
	8	RAN	0.3086	0.3409	0.2618	0.0339	0.2812	0.8067	0.0000	0.1571
		SAL	0.3044	0.3349	0.2666	0.0283	0.2781	0.7229	0.0385	0.1532
		STL	0.2984	0.3407	0.2721	0.0302	0.2824	0.7965	0.0185	0.1503
	16	RAN	0.3144	0.3272	0.2895	0.0176	0.2860	0.8333	0.0267	0.1597
		SAL	0.3128	0.3371	0.2813	0.0233	0.2860	0.7733	0.0233	0.1605
		STL	0.3028	0.3411	0.2835	0.0271	0.2855	0.8696	0.0000	0.1584

Table H.22: grouped-nb-twitter-GB3-ALL-ALL-50

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.2437	0.2633	0.2241	0.0196	0.2035	0.8615	0.0000	0.1692
		SAL	0.2499	0.2646	0.2351	0.0147	0.2094	0.7941	0.0000	0.1661
		STL	0.2515	0.2862	0.2169	0.0347	0.2230	0.8125	0.0000	0.1641
	1	RAN	0.2693	0.2953	0.2433	0.0260	0.2433	0.7416	0.0000	0.1541
		SAL	0.2637	0.3021	0.2254	0.0384	0.2394	0.8000	0.0000	0.1577
		STL	0.2612	0.2873	0.2352	0.0260	0.2414	0.7368	0.0000	0.1533
	2	RAN	0.2660	0.3023	0.2297	0.0363	0.2407	0.7333	0.0000	0.1509
		SAL	0.2724	0.2949	0.2500	0.0225	0.2439	0.7292	0.0000	0.1484
		STL	0.2619	0.2891	0.2347	0.0272	0.2423	0.6869	0.0000	0.1450
	4	RAN	0.2686	0.2787	0.2584	0.0101	0.2427	0.6875	0.0000	0.1541
		SAL	0.2696	0.3128	0.2263	0.0433	0.2442	0.7263	0.0000	0.1560
		STL	0.2619	0.2881	0.2356	0.0262	0.2432	0.7368	0.0000	0.1523
	8	RAN	0.2650	0.2663	0.2638	0.0013	0.2401	0.7325	0.0196	0.1503
		SAL	0.2685	0.2990	0.2381	0.0305	0.2439	0.7013	0.0235	0.1469
		STL	0.2636	0.2903	0.2368	0.0268	0.2462	0.7478	0.0171	0.1470
	16	RAN	0.2788	0.2923	0.2653	0.0135	0.2526	0.7500	0.0000	0.1603
		SAL	0.2787	0.3096	0.2479	0.0308	0.2524	0.7568	0.0000	0.1575
		STL	0.2668	0.2948	0.2389	0.0280	0.2487	0.8116	0.0000	0.1554

Table H.23: grouped-nb-twitter-GB3-ALL-ALL-75

GB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.1973	0.1973	0.1973	0.0000	0.1600	0.7879	0.0000	0.1540
		SAL	0.1995	0.1995	0.1995	0.0000	0.1619	0.7647	0.0000	0.1554
		STL	0.1995	0.1995	0.1995	0.0000	0.1619	0.7647	0.0000	0.1554
	1	RAN	0.2148	0.2148	0.2148	0.0000	0.1910	0.7105	0.0000	0.1453
		SAL	0.2154	0.2154	0.2154	0.0000	0.1910	0.6923	0.0000	0.1455
		STL	0.2154	0.2154	0.2154	0.0000	0.1910	0.6923	0.0000	0.1455
	2	RAN	0.2186	0.2186	0.2186	0.0000	0.1956	0.6458	0.0000	0.1411
		SAL	0.2191	0.2191	0.2191	0.0000	0.1940	0.6437	0.0000	0.1390
		STL	0.2191	0.2191	0.2191	0.0000	0.1940	0.6437	0.0000	0.1390
	4	RAN	0.2190	0.2190	0.2190	0.0000	0.1947	0.6585	0.0000	0.1449
		SAL	0.2200	0.2200	0.2200	0.0000	0.1958	0.6914	0.0000	0.1451
		STL	0.2200	0.2200	0.2200	0.0000	0.1958	0.6914	0.0000	0.1451
	8	RAN	0.2187	0.2187	0.2187	0.0000	0.1953	0.6914	0.0000	0.1426
		SAL	0.2176	0.2176	0.2176	0.0000	0.1936	0.7000	0.0000	0.1414
		STL	0.2176	0.2176	0.2176	0.0000	0.1936	0.7000	0.0000	0.1414
	16	RAN	0.2233	0.2233	0.2233	0.0000	0.1989	0.6829	0.0000	0.1459
		SAL	0.2216	0.2216	0.2216	0.0000	0.1969	0.7297	0.0000	0.1485
		STL	0.2216	0.2216	0.2216	0.0000	0.1969	0.7297	0.0000	0.1485

Table H.24: grouped-nb-twitter-GB3-ALL-ALL-150

OSB3										
			Accuracy				F-Score			
Group Size	Web1T %	Group Type	AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
5	0	RAN	0.6437	0.7942	0.4983	0.0675	0.6224	0.9170	0.2813	0.1354
		SAL	0.6529	0.8164	0.5263	0.0725	0.6323	0.9254	0.1481	0.1378
		STL	0.6459	0.7520	0.5284	0.0612	0.6376	0.9175	0.2326	0.1137
	1	RAN	0.5594	0.8293	0.4149	0.1044	0.5264	0.9336	0.1370	0.1726
		SAL	0.5725	0.7768	0.3913	0.0853	0.5334	0.9419	0.0597	0.1610
		STL	0.5564	0.7425	0.4484	0.0694	0.5290	0.9064	0.0896	0.1580
	2	RAN	0.5741	0.7734	0.4230	0.0814	0.5321	0.9243	0.0597	0.1702
		SAL	0.5746	0.7698	0.3836	0.0949	0.5340	0.9172	0.0597	0.1770
		STL	0.5575	0.7412	0.4452	0.0705	0.5323	0.9045	0.0896	0.1544
	4	RAN	0.5555	0.7413	0.4019	0.0820	0.5197	0.9315	0.0800	0.1651
		SAL	0.5734	0.7768	0.3836	0.1005	0.5335	0.9419	0.0597	0.1787
		STL	0.5592	0.7439	0.4484	0.0704	0.5344	0.9064	0.1270	0.1515
	8	RAN	0.5613	0.7762	0.3429	0.0956	0.5209	0.9160	0.0896	0.1660
		SAL	0.5662	0.7790	0.3942	0.1056	0.5261	0.9419	0.0597	0.1794
		STL	0.5602	0.7439	0.4484	0.0692	0.5346	0.9064	0.1449	0.1566
	16	RAN	0.5534	0.7395	0.3857	0.0860	0.5170	0.9427	0.0351	0.1675
		SAL	0.5669	0.7479	0.4126	0.0824	0.5264	0.9458	0.0606	0.1700
		STL	0.5559	0.7425	0.4484	0.0706	0.5318	0.9064	0.0896	0.1524

Table H.25: grouped-nb-twitter-OSB3-ALL-ALL-5

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
10	0	RAN	0.5287	0.6236	0.4526	0.0468	0.5043	0.9069	0.0988	0.1461
		SAL	0.5283	0.6316	0.4333	0.0606	0.5052	0.8555	0.1481	0.1516
		STL	0.5242	0.6410	0.4355	0.0552	0.5136	0.8996	0.1075	0.1380
	1	RAN	0.4405	0.6071	0.3160	0.0821	0.4016	0.9122	0.0000	0.1771
		SAL	0.4509	0.5714	0.3189	0.0666	0.4070	0.9018	0.0000	0.1669
		STL	0.4247	0.5138	0.3461	0.0495	0.3844	0.8610	0.0000	0.1723
	2	RAN	0.4500	0.5798	0.2883	0.0749	0.4064	0.8989	0.0000	0.1790
		SAL	0.4516	0.5840	0.3535	0.0755	0.4076	0.9098	0.0000	0.1744
		STL	0.4245	0.5163	0.3461	0.0494	0.3866	0.8591	0.0000	0.1712
	4	RAN	0.4429	0.6238	0.3309	0.0860	0.3974	0.8846	0.0000	0.1835
		SAL	0.4499	0.5940	0.2876	0.0863	0.4039	0.9228	0.0000	0.1790
		STL	0.4281	0.5172	0.3455	0.0505	0.3899	0.8610	0.0000	0.1700
	8	RAN	0.4480	0.5315	0.3264	0.0581	0.4033	0.8857	0.0000	0.1802
		SAL	0.4459	0.5966	0.2853	0.0911	0.4015	0.9228	0.0000	0.1778
		STL	0.4289	0.5172	0.3461	0.0490	0.3902	0.8610	0.0000	0.1729
	16	RAN	0.4520	0.5954	0.3539	0.0628	0.4055	0.8785	0.0317	0.1824
		SAL	0.4475	0.5826	0.3245	0.0693	0.4015	0.9265	0.0000	0.1731
		STL	0.4278	0.5163	0.3438	0.0470	0.3902	0.8610	0.0000	0.1712

Table H.26: grouped-nb-twitter-OSB3-ALL-ALL-10

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
25	0	RAN	0.4008	0.4626	0.3364	0.0404	0.3727	0.8824	0.0000	0.1687
		SAL	0.3985	0.4848	0.3207	0.0592	0.3731	0.8219	0.0000	0.1681
		STL	0.3945	0.4509	0.3359	0.0360	0.3798	0.8529	0.0215	0.1572
	1	RAN	0.3270	0.4237	0.2419	0.0557	0.2795	0.8238	0.0000	0.1742
		SAL	0.3207	0.3673	0.2870	0.0337	0.2706	0.8341	0.0000	0.1677
		STL	0.3142	0.3626	0.2818	0.0254	0.2730	0.7892	0.0000	0.1646
	2	RAN	0.3274	0.3719	0.2897	0.0267	0.2796	0.8333	0.0000	0.1735
		SAL	0.3248	0.3951	0.2704	0.0501	0.2789	0.8386	0.0000	0.1704
		STL	0.3146	0.3618	0.2824	0.0259	0.2742	0.7768	0.0000	0.1643
	4	RAN	0.3257	0.3685	0.2773	0.0365	0.2736	0.7942	0.0000	0.1666
		SAL	0.3251	0.3814	0.2859	0.0424	0.2764	0.8571	0.0000	0.1721
		STL	0.3176	0.3655	0.2818	0.0266	0.2776	0.7830	0.0000	0.1650
	8	RAN	0.3303	0.3894	0.2570	0.0400	0.2864	0.8219	0.0000	0.1702
		SAL	0.3280	0.3937	0.2782	0.0417	0.2810	0.8389	0.0000	0.1702
		STL	0.3164	0.3622	0.2849	0.0250	0.2769	0.7795	0.0000	0.1639
	16	RAN	0.3269	0.4016	0.2749	0.0389	0.2800	0.8629	0.0000	0.1718
		SAL	0.3246	0.3746	0.2837	0.0368	0.2782	0.8444	0.0000	0.1728
		STL	0.3172	0.3659	0.2786	0.0281	0.2774	0.7792	0.0000	0.1647

Table H.27: grouped-nb-twitter-OSB3-ALL-ALL-25

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
50	0	RAN	0.3221	0.3322	0.3156	0.0072	0.2965	0.7792	0.0000	0.1680
		SAL	0.3265	0.3739	0.2838	0.0369	0.3002	0.7895	0.0000	0.1637
		STL	0.3212	0.3505	0.2914	0.0241	0.3046	0.7826	0.0000	0.1603
	1	RAN	0.2549	0.2620	0.2507	0.0051	0.2147	0.7119	0.0000	0.1596
		SAL	0.2553	0.2797	0.2254	0.0225	0.2085	0.7556	0.0000	0.1540
		STL	0.2504	0.2786	0.2361	0.0199	0.2113	0.7250	0.0000	0.1582
	2	RAN	0.2546	0.2797	0.2360	0.0184	0.2082	0.7712	0.0000	0.1553
		SAL	0.2566	0.2674	0.2427	0.0103	0.2142	0.7350	0.0000	0.1598
		STL	0.2502	0.2810	0.2332	0.0218	0.2118	0.7244	0.0000	0.1555
	4	RAN	0.2549	0.2751	0.2296	0.0189	0.2110	0.7511	0.0000	0.1598
		SAL	0.2569	0.2670	0.2385	0.0130	0.2136	0.7412	0.0000	0.1620
		STL	0.2524	0.2819	0.2343	0.0211	0.2132	0.7289	0.0000	0.1563
	8	RAN	0.2596	0.2831	0.2305	0.0218	0.2154	0.7585	0.0000	0.1604
		SAL	0.2575	0.2741	0.2398	0.0140	0.2151	0.7511	0.0000	0.1583
		STL	0.2512	0.2819	0.2314	0.0220	0.2128	0.7261	0.0000	0.1574
	16	RAN	0.2601	0.2913	0.2410	0.0223	0.2134	0.7609	0.0000	0.1602
		SAL	0.2572	0.2795	0.2335	0.0188	0.2140	0.7429	0.0000	0.1620
		STL	0.2518	0.2831	0.2300	0.0227	0.2133	0.7248	0.0000	0.1560

Table H.28: grouped-nb-twitter-OSB3-ALL-ALL-50

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
75	0	RAN	0.2854	0.3004	0.2704	0.0150	0.2607	0.7945	0.0000	0.1585
		SAL	0.2912	0.3039	0.2786	0.0127	0.2656	0.7941	0.0000	0.1645
		STL	0.2815	0.3048	0.2582	0.0233	0.2638	0.7887	0.0000	0.1585
	1	RAN	0.2241	0.2444	0.2038	0.0203	0.1842	0.7364	0.0000	0.1536
		SAL	0.2200	0.2427	0.1972	0.0228	0.1767	0.7042	0.0000	0.1510
		STL	0.2196	0.2347	0.2044	0.0152	0.1844	0.6905	0.0000	0.1493
	2	RAN	0.2285	0.2345	0.2226	0.0060	0.1854	0.8051	0.0000	0.1548
		SAL	0.2230	0.2654	0.1806	0.0424	0.1796	0.7176	0.0000	0.1496
		STL	0.2210	0.2378	0.2042	0.0168	0.1868	0.7160	0.0000	0.1493
	4	RAN	0.2268	0.2464	0.2072	0.0196	0.1886	0.7229	0.0000	0.1523
		SAL	0.2233	0.2615	0.1851	0.0382	0.1797	0.7213	0.0000	0.1506
		STL	0.2209	0.2383	0.2035	0.0174	0.1869	0.7073	0.0000	0.1504
	8	RAN	0.2212	0.2226	0.2198	0.0014	0.1824	0.6875	0.0000	0.1489
		SAL	0.2240	0.2611	0.1870	0.0371	0.1812	0.7077	0.0000	0.1508
		STL	0.2205	0.2376	0.2033	0.0172	0.1859	0.7073	0.0000	0.1502
	16	RAN	0.2274	0.2482	0.2065	0.0209	0.1861	0.7330	0.0000	0.1534
		SAL	0.2204	0.2435	0.1973	0.0231	0.1791	0.7360	0.0000	0.1509
		STL	0.2207	0.2382	0.2033	0.0174	0.1863	0.6905	0.0000	0.1501

Table H.29: grouped-nb-twitter-OSB3-ALL-ALL-75

OSB3										
Group Size	Web1T %	Group Type	Accuracy				F-Score			
			AVG	MAX	MIN	STDEV	AVG	MAX	MIN	STDEV
150	0	RAN	0.2320	0.2320	0.2320	0.0000	0.2087	0.7778	0.0000	0.1539
		SAL	0.2337	0.2337	0.2337	0.0000	0.2113	0.7467	0.0000	0.1571
		STL	0.2337	0.2337	0.2337	0.0000	0.2113	0.7467	0.0000	0.1571
	1	RAN	0.1773	0.1773	0.1773	0.0000	0.1407	0.6337	0.0000	0.1319
		SAL	0.1776	0.1776	0.1776	0.0000	0.1400	0.6058	0.0000	0.1311
		STL	0.1776	0.1776	0.1776	0.0000	0.1400	0.6058	0.0000	0.1311
	2	RAN	0.1792	0.1792	0.1792	0.0000	0.1413	0.6250	0.0000	0.1336
		SAL	0.1790	0.1790	0.1790	0.0000	0.1427	0.6058	0.0000	0.1316
		STL	0.1790	0.1790	0.1790	0.0000	0.1427	0.6058	0.0000	0.1316
	4	RAN	0.1788	0.1788	0.1788	0.0000	0.1413	0.6244	0.0000	0.1336
		SAL	0.1784	0.1784	0.1784	0.0000	0.1412	0.6184	0.0000	0.1325
		STL	0.1784	0.1784	0.1784	0.0000	0.1412	0.6184	0.0000	0.1325
	8	RAN	0.1810	0.1810	0.1810	0.0000	0.1442	0.6570	0.0000	0.1339
		SAL	0.1787	0.1787	0.1787	0.0000	0.1412	0.6087	0.0000	0.1322
		STL	0.1787	0.1787	0.1787	0.0000	0.1412	0.6087	0.0000	0.1322
	16	RAN	0.1797	0.1797	0.1797	0.0000	0.1416	0.6540	0.0000	0.1334
		SAL	0.1785	0.1785	0.1785	0.0000	0.1408	0.6377	0.0000	0.1326
		STL	0.1785	0.1785	0.1785	0.0000	0.1408	0.6377	0.0000	0.1326

Table H.30: grouped-nb-twitter-OSB3-ALL-ALL-150

APPENDIX I: Liblinear Scores (Accuracy / Size) for the ENRON Email Corpus

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.4374	0.8269	1.8907
	1	0.2700	0.8233	3.0491
	2	0.1440	0.8216	5.7048
	4	0.0754	0.8298	11.0081
	8	0.0384	0.8298	21.6131
	16	0.0192	0.8239	42.8058

Table I.1: liblinear-enron-GM1-ALL-ALL-5

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.2789	0.7611	2.7294
	1	0.1509	0.7610	5.0430
	2	0.0839	0.7594	9.0498
	4	0.0445	0.7602	17.0733
	8	0.0229	0.7578	33.1029
	16	0.0117	0.7622	65.0962

Table I.2: liblinear-enron-GM1-ALL-ALL-10

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.1124	0.6845	6.0891
	1	0.0602	0.6847	11.3773
	2	0.0353	0.6873	19.4874
	4	0.0191	0.6819	35.6598
	8	0.0101	0.6862	67.9353
	16	0.0052	0.6861	132.4731

Table I.3: liblinear-enron-GM1-ALL-ALL-25

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0474	0.6411	13.5303
	1	0.0282	0.6364	22.5920
	2	0.0171	0.6420	37.5149
	4	0.0095	0.6356	67.2513
	8	0.0051	0.6419	126.8646
	16	0.0026	0.6437	246.0215

Table I.4: liblinear-enron-GM1-ALL-ALL-50

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0280	0.6146	21.9684
	1	0.0179	0.6101	34.1738
	2	0.0110	0.6127	55.8602
	4	0.0062	0.6132	98.2967
	8	0.0033	0.6085	185.8852
	16	0.0017	0.6137	359.8159

Table I.5: liblinear-enron-GM1-ALL-ALL-75

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0107	0.6060	56.6487
	1	0.0085	0.5951	69.9670
	2	0.0053	0.5982	112.2744
	4	0.0031	0.6083	196.3090
	8	0.0016	0.5990	364.9695
	16	0.0009	0.5987	701.2420

Table I.6: liblinear-enron-GM1-ALL-ALL-150

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0451	0.8607	19.0724
	1	0.0133	0.8193	61.7992
	2	0.0067	0.8192	121.3905
	4	0.0034	0.8187	242.0133
	8	0.0017	0.8199	483.7247
	16	0.0008	0.8154	975.2060

Table I.7: liblinear-enron-GM2-ALL-ALL-5

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0344	0.8150	23.7182
	1	0.0080	0.7551	93.8882
	2	0.0041	0.7578	184.0112
	4	0.0020	0.7502	366.0065
	8	0.0010	0.7581	732.8332
	16	0.0005	0.7528	1477.4525

Table I.8: liblinear-enron-GM2-ALL-ALL-10

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0173	0.7696	44.4495
	1	0.0036	0.6790	190.3109
	2	0.0018	0.6822	372.1569
	4	0.0009	0.6810	738.3009

Table I.9: liblinear-enron-GM2-ALL-ALL-25

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0078	0.7402	94.3040
	1	0.0018	0.6329	352.2680
	2	0.0009	0.6341	686.3251

Table I.10: liblinear-enron-GM2-ALL-ALL-50

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0047	0.7330	157.4604
	1	0.0012	0.6120	511.3843
	2	0.0006	0.5987	1001.0303

Table I.11: liblinear-enron-GM2-ALL-ALL-75

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0018	0.7447	407.3896
	1	0.0006	0.5978	1001.9953

Table I.12: liblinear-enron-GM2-ALL-ALL-150

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0057	0.6881	120.7109
	1	0.0036	0.8117	224.1507
	2	0.0018	0.8118	448.0959
	4	0.0009	0.8130	895.4960
	8	0.0005	0.8070	1792.4125

Table I.13: liblinear-enron-GM5-ALL-ALL-5

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0044	0.6297	144.1015
	1	0.0022	0.7519	339.2591
	2	0.0011	0.7440	675.1472
	4	0.0005	0.7418	1350.7320

Table I.14: liblinear-enron-GM5-ALL-ALL-10

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0021	0.5499	268.0080
	1	0.0010	0.6759	680.7577
	2	0.0005	0.6728	1369.3669

Table I.15: liblinear-enron-GM5-ALL-ALL-25

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0009	0.5323	581.8953
	1	0.0005	0.6259	1263.9173

Table I.16: liblinear-enron-GM5-ALL-ALL-50

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0005	0.5211	986.9350

Table I.17: liblinear-enron-GM5-ALL-ALL-75

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0138	0.8529	61.9115
	1	0.0068	0.8494	124.5811
	2	0.0035	0.8476	240.5565
	4	0.0018	0.8579	475.1952
	8	0.0009	0.8536	946.3660
	16	0.0005	0.8523	1883.6282

Table I.18: liblinear-enron-GB3-ALL-ALL-5

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0106	0.8124	76.9171
	1	0.0043	0.8127	190.2863
	2	0.0022	0.8128	371.0244
	4	0.0011	0.8096	728.4382
	8	0.0006	0.8134	1431.6209

Table I.19: liblinear-enron-GB3-ALL-ALL-10

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0054	0.7680	143.4930
	1	0.0018	0.7652	415.2456
	2	0.0010	0.7684	770.3589

Table I.20: liblinear-enron-GB3-ALL-ALL-25

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0024	0.7409	302.6619
	1	0.0009	0.7372	799.7790

Table I.21: liblinear-enron-GB3-ALL-ALL-50

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0014	0.7300	507.8629
	1	0.0006	0.7336	1186.7074

Table I.22: liblinear-enron-GB3-ALL-ALL-75

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0065	0.8690	133.2758
	1	0.0019	0.8667	459.2738
	2	0.0009	0.8645	920.9545
	4	0.0005	0.8687	1831.4047

Table I.23: liblinear-enron-OSB3-ALL-ALL-5

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0050	0.8250	164.5371

Table I.24: liblinear-enron-OSB3-ALL-ALL-10

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0026	0.7826	301.6652

Table I.25: liblinear-enron-OSB3-ALL-ALL-25

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0012	0.7567	619.0632

Table I.26: liblinear-enron-OSB3-ALL-ALL-50

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0007	0.7470	1035.0252

Table I.27: liblinear-enron-OSB3-ALL-ALL-75

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APPENDIX J:
Liblinear Scores (Accuracy / Size) for the Twitter Short Message Corpus

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	2.1731	0.6212	0.2859
	1	0.2283	0.6228	2.7276
	2	0.1142	0.6147	5.3818
	4	0.0578	0.6172	10.6855
	8	0.0294	0.6273	21.3067
	16	0.0145	0.6181	42.4984

Table J.1: liblinear-twitter-GM1-ALL-ALL-5

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	1.0850	0.4762	0.4389
	1	0.1143	0.4813	4.2117
	2	0.0589	0.4845	8.2212
	4	0.0298	0.4841	16.2411
	8	0.0149	0.4816	32.3032
	16	0.0075	0.4800	64.3495

Table J.2: liblinear-twitter-GM1-ALL-ALL-10

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.3301	0.3461	1.0483
	1	0.0390	0.3408	8.7461
	2	0.0206	0.3465	16.8384
	4	0.0106	0.3510	33.0149
	8	0.0052	0.3419	65.3817
	16	0.0026	0.3411	130.0523

Table J.3: liblinear-twitter-GM1-ALL-ALL-25

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.1153	0.2693	2.3366
	1	0.0165	0.2704	16.4318
	2	0.0086	0.2705	31.3058
	4	0.0044	0.2710	61.0727
	8	0.0022	0.2712	120.6237
	16	0.0011	0.2710	239.7010

Table J.4: liblinear-twitter-GM1-ALL-ALL-50

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0585	0.2273	3.8856
	1	0.0095	0.2293	24.1926
	2	0.0051	0.2318	45.8821
	4	0.0026	0.2310	89.2325
	8	0.0013	0.2354	175.9403
	16	0.0007	0.2368	349.3536

Table J.5: liblinear-twitter-GM1-ALL-ALL-75

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0194	0.1851	9.5448
	1	0.0040	0.1888	47.7363
	2	0.0020	0.1829	89.8071
	4	0.0011	0.1921	173.9928
	8	0.0006	0.1893	342.2109
	16	0.0003	0.1877	678.6646

Table J.6: liblinear-twitter-GM1-ALL-ALL-150

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.3503	0.4844	1.3830
	1	0.0101	0.6241	61.5521
	2	0.0051	0.6221	121.0065
	4	0.0026	0.6253	241.9295
	8	0.0013	0.6282	483.6331
	16	0.0006	0.6258	976.1899

Table J.7: liblinear-twitter-GM2-ALL-ALL-5

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.1911	0.3700	1.9363
	1	0.0053	0.4904	93.1498
	2	0.0027	0.4903	183.0523
	4	0.0014	0.4962	365.9331
	8	0.0007	0.4842	731.3270
	16	0.0003	0.4891	1475.9678

Table J.8: liblinear-twitter-GM2-ALL-ALL-10

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0600	0.2641	4.4027
	1	0.0018	0.3468	188.0281
	2	0.0009	0.3464	369.2436
	4	0.0005	0.3526	738.0104

Table J.9: liblinear-twitter-GM2-ALL-ALL-25

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0210	0.2097	9.9997
	1	0.0008	0.2679	346.2943
	2	0.0004	0.2707	679.7548

Table J.10: liblinear-twitter-GM2-ALL-ALL-50

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0107	0.1800	16.7491
	1	0.0005	0.2350	504.6377
	2	0.0002	0.2354	990.5135

Table J.11: liblinear-twitter-GM2-ALL-ALL-75

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0035	0.1525	43.1187
	1	0.0002	0.1889	979.9898

Table J.12: liblinear-twitter-GM2-ALL-ALL-150

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0814	0.2764	3.3953
	1	0.0026	0.5868	223.5723
	2	0.0013	0.5802	447.1519

Table J.13: liblinear-twitter-GM5-ALL-ALL-5

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0398	0.1718	4.3228
	1	0.0013	0.4383	338.7141
	2	0.0006	0.4382	677.8461

Table J.14: liblinear-twitter-GM5-ALL-ALL-10

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0109	0.1060	9.7684
	1	0.0004	0.3011	682.9173

Table J.15: liblinear-twitter-GM5-ALL-ALL-25

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0033	0.0805	24.4182

Table J.16: liblinear-twitter-GM5-ALL-ALL-50

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0015	0.0643	42.2738

Table J.17: liblinear-twitter-GM5-ALL-ALL-75

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0006	0.0636	114.3282

Table J.18: liblinear-twitter-GM5-ALL-ALL-150

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.1364	0.5405	3.9613
	1	0.0045	0.5312	118.6950
	2	0.0023	0.5447	237.0721
	4	0.0011	0.5399	473.4116
	8	0.0006	0.5404	946.5430
	16	0.0003	0.5386	1893.1607

Table J.19: liblinear-twitter-GB3-ALL-ALL-5

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0737	0.4231	5.7396
	1	0.0023	0.4207	180.5003
	2	0.0012	0.4221	359.6409
	4	0.0006	0.4226	717.1286
	8	0.0003	0.4246	1431.7552

Table J.20: liblinear-twitter-GB3-ALL-ALL-10

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0228	0.3123	13.6973
	1	0.0008	0.3087	366.6181
	2	0.0004	0.3134	728.8935

Table J.21: liblinear-twitter-GB3-ALL-ALL-25

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0077	0.2467	31.9322
	1	0.0004	0.2465	681.2334

Table J.22: liblinear-twitter-GB3-ALL-ALL-50

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0039	0.2132	54.4683
	1	0.0002	0.2155	999.3930

Table J.23: liblinear-twitter-GB3-ALL-ALL-75

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0013	0.1739	135.6456

Table J.24: liblinear-twitter-GB3-ALL-ALL-150

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0609	0.5430	8.9203
	1	0.0012	0.5391	458.6561
	2	0.0006	0.5427	916.6625
	4	0.0003	0.5391	1832.3842

Table J.25: liblinear-twitter-OSB3-ALL-ALL-5

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0338	0.4271	12.6292
	1	0.0006	0.4288	696.0890
	2	0.0003	0.4255	1387.3440

Table J.26: liblinear-twitter-OSB3-ALL-ALL-10

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0103	0.3084	29.8123

Table J.27: liblinear-twitter-OSB3-ALL-ALL-25

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0036	0.2520	69.4942

Table J.28: liblinear-twitter-OSB3-ALL-ALL-50

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0019	0.2211	116.9183

Table J.29: liblinear-twitter-OSB3-ALL-ALL-75

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0006	0.1750	296.1385

Table J.30: liblinear-twitter-OSB3-ALL-ALL-150

APPENDIX K:
Naive Bayes Scores (Accuracy / Size) for the ENRON Email Corpus

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.4495	0.7215	1.6050
	1	0.2262	0.6441	2.8472
	2	0.1212	0.6505	5.3662
	4	0.0635	0.6610	10.4023
	8	0.0319	0.6534	20.4755
	16	0.0164	0.6663	40.6210

Table K.1: nb-enron-GM1-ALL-ALL-5

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.3186	0.5768	1.8103
	1	0.1634	0.5189	3.1761
	2	0.0915	0.5215	5.6963
	4	0.0504	0.5406	10.7329
	8	0.0257	0.5349	20.8064
	16	0.0131	0.5377	40.9520

Table K.2: nb-enron-GM1-ALL-ALL-10

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.1683	0.4083	2.4263
	1	0.0950	0.3956	4.1628
	2	0.0604	0.4037	6.6867
	4	0.0351	0.4111	11.7248
	8	0.0189	0.4127	21.7989
	16	0.0099	0.4166	41.9447

Table K.3: nb-enron-GM1-ALL-ALL-25

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0903	0.3126	3.4631
	1	0.0543	0.3153	5.8074
	2	0.0383	0.3191	8.3373
	4	0.0248	0.3320	13.3779
	8	0.0141	0.3296	23.4531
	16	0.0078	0.3391	43.5993

Table K.4: nb-enron-GM1-ALL-ALL-50

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0648	0.2912	4.4965
	1	0.0353	0.2627	7.4519
	2	0.0280	0.2800	9.9879
	4	0.0184	0.2761	15.0311
	8	0.0113	0.2833	25.1073
	16	0.0064	0.2884	45.2539

Table K.5: nb-enron-GM1-ALL-ALL-75

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0323	0.2451	7.5810
	1	0.0149	0.1840	12.3856
	2	0.0127	0.1898	14.9398
	4	0.0098	0.1955	19.9905
	8	0.0066	0.1990	30.0698
	16	0.0040	0.2024	50.2177

Table K.6: nb-enron-GM1-ALL-ALL-150

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0461	0.8061	17.4811
	1	0.0111	0.6536	58.6657
	2	0.0062	0.7111	115.1229
	4	0.0032	0.7320	229.9337
	8	0.0017	0.7961	459.5158
	16	0.0009	0.8158	926.7927

Table K.7: nb-enron-GM2-ALL-ALL-5

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0393	0.7209	18.3377
	1	0.0092	0.5399	58.9909
	2	0.0051	0.5847	115.4482
	4	0.0027	0.6218	230.2592
	8	0.0016	0.7130	459.8414
	16	0.0008	0.7401	927.1183

Table K.8: nb-enron-GM2-ALL-ALL-10

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0290	0.6083	20.9885
	1	0.0069	0.4166	59.9664
	2	0.0040	0.4604	116.4243
	4	0.0022	0.5015	231.2357
	8	0.0013	0.6042	460.8180
	16	0.0007	0.6469	928.0949

Table K.9: nb-enron-GM2-ALL-ALL-25

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0214	0.5414	25.3013
	1	0.0056	0.3448	61.5922
	2	0.0032	0.3831	118.0511
	4	0.0018	0.4259	232.8632
	8	0.0012	0.5386	462.4457
	16	0.0006	0.5891	929.7227

Table K.10: nb-enron-GM2-ALL-ALL-50

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0170	0.5056	29.8167
	1	0.0046	0.2896	63.2180
	2	0.0027	0.3286	119.6779
	4	0.0016	0.3762	234.4907
	8	0.0011	0.5018	464.0733
	16	0.0006	0.5547	931.3504

Table K.11: nb-enron-GM2-ALL-ALL-75

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0106	0.4536	42.5965
	1	0.0032	0.2164	68.0954
	2	0.0021	0.2598	124.5583
	4	0.0013	0.3096	239.3732
	8	0.0010	0.4547	468.9564
	16	0.0005	0.5061	936.2337

Table K.12: nb-enron-GM2-ALL-ALL-150

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0065	0.7379	112.9389
	1	0.0037	0.7817	212.9081
	2	0.0019	0.8104	425.6461
	4	0.0010	0.8206	851.1609
	8	0.0005	0.8064	1704.9937
	16	0.0002	0.7980	3410.7224

Table K.13: nb-enron-GM5-ALL-ALL-5

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0059	0.6803	114.5784
	1	0.0032	0.6890	213.2250
	2	0.0017	0.7274	425.9630
	4	0.0009	0.7367	851.4779
	8	0.0004	0.7169	1705.3107
	16	0.0002	0.6991	3411.0393

Table K.14: nb-enron-GM5-ALL-ALL-10

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0051	0.6081	119.3005
	1	0.0027	0.5847	214.1756
	2	0.0015	0.6358	426.9138
	4	0.0008	0.6445	852.4287
	8	0.0004	0.5994	1706.2616
	16	0.0002	0.5644	3411.9902

Table K.15: nb-enron-GM5-ALL-ALL-25

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0045	0.5742	127.4399
	1	0.0024	0.5103	215.7599
	2	0.0013	0.5726	428.4984
	4	0.0007	0.5775	854.0134
	8	0.0003	0.5142	1707.8464
	16	0.0001	0.4650	3413.5750

Table K.16: nb-enron-GM5-ALL-ALL-50

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0042	0.5646	135.6983
	1	0.0022	0.4722	217.3442
	2	0.0013	0.5391	430.0830
	4	0.0006	0.5539	855.5982
	8	0.0003	0.4791	1709.4312
	16	0.0001	0.4316	3415.1599

Table K.17: nb-enron-GM5-ALL-ALL-75

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0035	0.5659	160.2268
	1	0.0019	0.4139	222.0971
	2	0.0011	0.4941	434.8369
	4	0.0006	0.5126	860.3524
	8	0.0003	0.4287	1714.1856
	16	0.0001	0.2613	3419.9143

Table K.18: nb-enron-GM5-ALL-ALL-150

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0138	0.7882	56.9801
	1	0.0070	0.8167	116.4139
	2	0.0036	0.8314	228.6381
	4	0.0019	0.8629	453.0841
	8	0.0010	0.8601	901.9044
	16	0.0005	0.8589	1800.2036

Table K.19: nb-enron-GB3-ALL-ALL-5

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0118	0.7057	59.6121
	1	0.0063	0.7586	120.6296
	2	0.0033	0.7729	232.8820
	4	0.0018	0.8070	457.3419
	8	0.0009	0.8074	906.1696
	16	0.0004	0.8091	1804.4721

Table K.20: nb-enron-GB3-ALL-ALL-10

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0089	0.5999	67.7286
	1	0.0052	0.6887	133.2767
	2	0.0029	0.7102	245.6138
	4	0.0016	0.7520	470.1153
	8	0.0008	0.7436	918.9651
	16	0.0004	0.7557	1817.2774

Table K.21: nb-enron-GB3-ALL-ALL-25

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0062	0.5059	80.9739
	1	0.0041	0.6391	154.3553
	2	0.0025	0.6740	266.8334
	4	0.0014	0.7097	491.4044
	8	0.0008	0.7083	940.2910
	16	0.0004	0.7185	1838.6197

Table K.22: nb-enron-GB3-ALL-ALL-50

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0050	0.4721	94.5262
	1	0.0035	0.6188	175.4338
	2	0.0023	0.6573	288.0529
	4	0.0014	0.6932	512.6934
	8	0.0007	0.6952	961.6169
	16	0.0004	0.7075	1859.9620

Table K.23: nb-enron-GB3-ALL-ALL-75

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0032	0.4282	133.7770
	1	0.0025	0.5976	238.6693
	2	0.0018	0.6499	351.7116
	4	0.0012	0.6860	576.5604
	8	0.0007	0.6889	1025.5946
	16	0.0004	0.7056	1923.9889

Table K.24: nb-enron-GB3-ALL-ALL-150

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0069	0.8527	123.3505
	1	0.0020	0.8648	442.9132
	2	0.0010	0.8642	877.3292
	4	0.0005	0.8678	1746.3302
	8	0.0002	0.8638	3484.0829
	16	0.0001	0.8653	6966.6684

Table K.25: nb-enron-OSB3-ALL-ALL-5

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0062	0.7967	128.6443
	1	0.0018	0.8161	451.4412
	2	0.0009	0.8180	885.8726
	4	0.0005	0.8177	1754.8804
	8	0.0002	0.8195	3492.6359
	16	0.0001	0.8186	6970.0526

Table K.26: nb-enron-OSB3-ALL-ALL-10

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0050	0.7263	144.8636
	1	0.0016	0.7586	477.0252
	2	0.0008	0.7635	911.5027
	4	0.0004	0.7621	1780.5309
	8	0.0002	0.7613	3518.2948

Table K.27: nb-enron-OSB3-ALL-ALL-25

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0040	0.6818	171.3725
	1	0.0009	0.4880	519.6651
	2	0.0004	0.4123	954.2195
	4	0.0004	0.7216	1823.2817

Table K.28: nb-enron-OSB3-ALL-ALL-50

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0034	0.6713	198.4913
	1	0.0013	0.7074	562.3051
	2	0.0007	0.7112	996.9363
	4	0.0004	0.7089	1866.0326
	8	0.0002	0.7079	3603.8247

Table K.29: nb-enron-OSB3-ALL-ALL-75

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0024	0.6572	276.9361
	1	0.0010	0.7041	690.2250
	2	0.0006	0.7091	1125.0867
	4	0.0004	0.7068	1994.2851
	8	0.0002	0.7101	3732.1196

Table K.30: nb-enron-OSB3-ALL-ALL-150

APPENDIX L:
Naive Bayes Scores (Accuracy / Size) for the Twitter Short Message Corpus

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	2.8233	0.6264	0.2219
	1	0.1945	0.4974	2.5578
	2	0.1011	0.5130	5.0756
	4	0.0508	0.5132	10.1112
	8	0.0260	0.5238	20.1842
	16	0.0127	0.5102	40.3296

Table L.1: nb-twitter-GM1-ALL-ALL-5

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	1.9815	0.4869	0.2457
	1	0.1344	0.3490	2.5972
	2	0.0718	0.3671	5.1151
	4	0.0364	0.3693	10.1508
	8	0.0186	0.3755	20.2239
	16	0.0090	0.3642	40.3693

Table L.2: nb-twitter-GM1-ALL-ALL-10

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	1.0593	0.3357	0.3169
	1	0.0832	0.2260	2.7157
	2	0.0439	0.2299	5.2329
	4	0.0227	0.2332	10.2692
	8	0.0118	0.2398	20.3426
	16	0.0057	0.2304	40.4876

Table L.3: nb-twitter-GM1-ALL-ALL-25

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.5347	0.2326	0.4350
	1	0.0547	0.1595	2.9149
	2	0.0300	0.1631	5.4320
	4	0.0158	0.1653	10.4665
	8	0.0081	0.1671	20.5404
	16	0.0040	0.1638	40.6876

Table L.4: nb-twitter-GM1-ALL-ALL-50

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.3291	0.1820	0.5530
	1	0.0426	0.1328	3.1132
	2	0.0242	0.1364	5.6325
	4	0.0128	0.1370	10.6678
	8	0.0067	0.1390	20.7389
	16	0.0033	0.1360	40.8821

Table L.5: nb-twitter-GM1-ALL-ALL-75

GM1				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.1375	0.1252	0.9104
	1	0.0265	0.0982	3.7007
	2	0.0157	0.0979	6.2278
	4	0.0087	0.0975	11.2574
	8	0.0046	0.0986	21.3302
	16	0.0024	0.0983	41.4726

Table L.6: nb-twitter-GM1-ALL-ALL-150

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.4866	0.5711	1.1738
	1	0.0090	0.5253	58.3788
	2	0.0046	0.5301	114.8358
	4	0.0024	0.5401	229.6465
	8	0.0012	0.5459	459.2286
	16	0.0006	0.5409	926.5055

Table L.7: nb-twitter-GM2-ALL-ALL-5

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.3644	0.4439	1.2181
	1	0.0066	0.3847	58.4174
	2	0.0034	0.3914	114.8738
	4	0.0017	0.4018	229.6847
	8	0.0009	0.4046	459.2667
	16	0.0004	0.4031	926.5439

Table L.8: nb-twitter-GM2-ALL-ALL-10

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.2380	0.3215	1.3508
	1	0.0043	0.2508	58.5325
	2	0.0022	0.2510	114.9893
	4	0.0012	0.2686	229.7997
	8	0.0006	0.2768	459.3819
	16	0.0003	0.2703	926.6588

Table L.9: nb-twitter-GM2-ALL-ALL-25

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.1598	0.2509	1.5700
	1	0.0032	0.1854	58.7240
	2	0.0016	0.1843	115.1800
	4	0.0009	0.1980	229.9909
	8	0.0004	0.2058	459.5747
	16	0.0002	0.2023	926.8513

Table L.10: nb-twitter-GM2-ALL-ALL-50

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.1207	0.2162	1.7905
	1	0.0026	0.1518	58.9138
	2	0.0013	0.1535	115.3732
	4	0.0007	0.1666	230.1851
	8	0.0004	0.1770	459.7666
	16	0.0002	0.1700	927.0460

Table L.11: nb-twitter-GM2-ALL-ALL-75

GM2				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0696	0.1709	2.4569
	1	0.0019	0.1155	59.4939
	2	0.0010	0.1173	115.9487
	4	0.0006	0.1282	230.7586
	8	0.0003	0.1331	460.3425
	16	0.0001	0.1290	927.6131

Table L.12: nb-twitter-GM2-ALL-ALL-150

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.1104	0.3453	3.1278
	1	0.0026	0.5530	212.6251
	2	0.0013	0.5523	425.3632
	4	0.0006	0.5516	850.8778
	8	0.0003	0.5550	1704.7107
	16	0.0002	0.5579	3410.4392

Table L.13: nb-twitter-GM5-ALL-ALL-5

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0759	0.2408	3.1727
	1	0.0020	0.4222	212.6591
	2	0.0010	0.4187	425.3972
	4	0.0005	0.4191	850.9119
	8	0.0002	0.4209	1704.7446
	16	0.0001	0.4319	3410.4732

Table L.14: nb-twitter-GM5-ALL-ALL-10

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0467	0.1543	3.3068
	1	0.0014	0.2990	212.7613
	2	0.0007	0.2923	425.4981
	4	0.0003	0.2935	851.0135
	8	0.0002	0.2929	1704.8464
	16	0.0001	0.2973	3410.5747

Table L.15: nb-twitter-GM5-ALL-ALL-25

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0347	0.1226	3.5298
	1	0.0011	0.2277	212.9303
	2	0.0005	0.2252	425.6690
	4	0.0003	0.2216	851.1809
	8	0.0001	0.2217	1705.0156
	16	0.0001	0.2245	3410.7461

Table L.16: nb-twitter-GM5-ALL-ALL-50

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0260	0.0977	3.7547
	1	0.0009	0.1960	213.0992
	2	0.0005	0.1952	425.8394
	4	0.0002	0.1878	851.3518
	8	0.0001	0.1902	1705.1849
	16	0.0001	0.1908	3410.9148

Table L.17: nb-twitter-GM5-ALL-ALL-75

GM5				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0178	0.0787	4.4242
	1	0.0007	0.1535	213.6106
	2	0.0004	0.1524	426.3482
	4	0.0002	0.1404	851.8602
	8	0.0001	0.1401	1705.6951
	16	0.0000	0.1424	3411.4199

Table L.18: nb-twitter-GM5-ALL-ALL-150

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.1868	0.6179	3.3084
	1	0.0054	0.6109	112.4031
	2	0.0027	0.6160	224.5981
	4	0.0014	0.6199	449.0306
	8	0.0007	0.6187	897.8441
	16	0.0003	0.6265	1796.1397

Table L.19: nb-twitter-GB3-ALL-ALL-5

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.1440	0.4948	3.4368
	1	0.0044	0.4975	112.6054
	2	0.0022	0.5015	224.8053
	4	0.0011	0.5011	449.2383
	8	0.0006	0.4999	898.0512
	16	0.0003	0.5041	1796.3457

Table L.20: nb-twitter-GB3-ALL-ALL-10

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0937	0.3584	3.8242
	1	0.0033	0.3724	113.2226
	2	0.0017	0.3760	225.4217
	4	0.0008	0.3773	449.8555
	8	0.0004	0.3733	898.6658
	16	0.0002	0.3838	1796.9620

Table L.21: nb-twitter-GB3-ALL-ALL-25

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0636	0.2839	4.4620
	1	0.0026	0.2984	114.2444
	2	0.0013	0.3019	226.4522
	4	0.0007	0.3044	450.8849
	8	0.0003	0.3038	899.6969
	16	0.0002	0.3100	1797.9942

Table L.22: nb-twitter-GB3-ALL-ALL-50

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0487	0.2484	5.1018
	1	0.0023	0.2648	115.2803
	2	0.0012	0.2668	227.4728
	4	0.0006	0.2667	451.9111
	8	0.0003	0.2657	900.7211
	16	0.0002	0.2748	1799.0202

Table L.23: nb-twitter-GB3-ALL-ALL-75

GB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0283	0.1988	7.0186
	1	0.0018	0.2152	118.3712
	2	0.0009	0.2190	230.5749
	4	0.0005	0.2197	455.0150
	8	0.0002	0.2180	903.8222
	16	0.0001	0.2221	1802.1037

Table L.24: nb-twitter-GB3-ALL-ALL-150

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
5	0	0.0856	0.6475	7.5640
	1	0.0013	0.5628	434.7978
	2	0.0007	0.5687	869.2005
	4	0.0003	0.5627	1738.1940
	8	0.0002	0.5626	3475.9425
	16	0.0001	0.5587	6958.5295

Table L.25: nb-twitter-OSB3-ALL-ALL-5

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
10	0	0.0673	0.5271	7.8277
	1	0.0010	0.4387	435.2158
	2	0.0005	0.4420	869.6175
	4	0.0003	0.4403	1738.6111
	8	0.0001	0.4410	3476.3611
	16	0.0001	0.4425	6958.9458

Table L.26: nb-twitter-OSB3-ALL-ALL-10

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
25	0	0.0462	0.3979	8.6114
	1	0.0007	0.3206	436.4719
	2	0.0004	0.3223	870.8699
	4	0.0002	0.3228	1739.8607
	8	0.0001	0.3249	3477.6101
	16	0.0000	0.3229	6960.2009

Table L.27: nb-twitter-OSB3-ALL-ALL-25

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
50	0	0.0326	0.3233	9.9031
	1	0.0006	0.2535	438.5595
	2	0.0003	0.2538	872.9681
	4	0.0001	0.2548	1741.9419
	8	0.0001	0.2561	3479.6877
	16	0.0000	0.2564	6962.2798

Table L.28: nb-twitter-OSB3-ALL-ALL-50

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
75	0	0.0255	0.2861	11.1995
	1	0.0005	0.2212	440.6614
	2	0.0003	0.2242	875.0073
	4	0.0001	0.2237	1744.0464
	8	0.0001	0.2219	3481.7927
	16	0.0000	0.2228	6964.3666

Table L.29: nb-twitter-OSB3-ALL-ALL-75

OSB3				
Group Size	Web1T %	Score	Accuracy	Size(MB)
150	0	0.0154	0.2332	15.0982
	1	0.0004	0.1775	446.8905
	2	0.0002	0.1791	881.2573
	4	0.0001	0.1786	1750.2371
	8	0.0001	0.1795	3488.0249
	16	0.0000	0.1789	6970.5827

Table L.30: nb-twitter-OSB3-ALL-ALL-150

APPENDIX M: Liblinear Storage Requirements for the ENRON Email Corpus

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	1.40	0.49	1.89
	1	0.07	0.00	0.00	1.09	0.00	1.89	3.05
	2	0.14	0.00	0.00	2.17	0.00	3.39	5.70
	4	0.29	0.00	0.00	4.35	0.00	6.37	11.01
	8	0.58	0.00	0.00	8.70	0.00	12.34	21.61
	16	1.15	0.00	0.00	17.40	0.00	24.26	42.81

Table M.1: liblinear-enron-GM1-ALL-ALL-5

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	1.40	1.33	2.73
	1	0.07	0.00	0.00	1.09	0.00	3.88	5.04
	2	0.14	0.00	0.00	2.17	0.00	6.73	9.05
	4	0.29	0.00	0.00	4.35	0.00	12.44	17.07
	8	0.58	0.00	0.00	8.70	0.00	23.83	33.10
	16	1.15	0.00	0.00	17.40	0.00	46.55	65.10

Table M.2: liblinear-enron-GM1-ALL-ALL-10

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	1.40	4.69	6.09
	1	0.07	0.00	0.00	1.09	0.00	10.22	11.38
	2	0.14	0.00	0.00	2.17	0.00	17.17	19.49
	4	0.29	0.00	0.00	4.35	0.00	31.02	35.66
	8	0.58	0.00	0.00	8.70	0.00	58.66	67.94
	16	1.15	0.00	0.00	17.40	0.00	113.93	132.47

Table M.3: liblinear-enron-GM1-ALL-ALL-25

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	1.40	12.13	13.53
	1	0.07	0.00	0.00	1.09	0.00	21.43	22.59
	2	0.14	0.00	0.00	2.17	0.00	35.20	37.51
	4	0.29	0.00	0.00	4.35	0.00	62.62	67.25
	8	0.58	0.00	0.00	8.70	0.00	117.59	126.86
	16	1.15	0.00	0.00	17.40	0.00	227.48	246.02

Table M.4: liblinear-enron-GM1-ALL-ALL-50

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	1.40	20.57	21.97
	1	0.07	0.00	0.00	1.09	0.00	33.01	34.17
	2	0.14	0.00	0.00	2.17	0.00	53.54	55.86
	4	0.29	0.00	0.00	4.35	0.00	93.66	98.30
	8	0.58	0.00	0.00	8.70	0.00	176.61	185.89
	16	1.15	0.00	0.00	17.40	0.00	341.27	359.82

Table M.5: liblinear-enron-GM1-ALL-ALL-75

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	1.40	55.25	56.65
	1	0.07	0.00	0.00	1.09	0.00	68.81	69.97
	2	0.14	0.00	0.00	2.17	0.00	109.96	112.27
	4	0.29	0.00	0.00	4.35	0.00	191.67	196.31
	8	0.58	0.00	0.00	8.70	0.00	355.70	364.97
	16	1.15	0.00	0.00	17.40	0.00	682.70	701.24

Table M.6: liblinear-enron-GM1-ALL-ALL-150

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	16.61	2.46	19.07
	1	1.67	0.00	0.00	25.19	0.00	34.94	61.80
	2	3.28	0.00	0.00	49.56	0.00	68.55	121.39
	4	6.56	0.00	0.00	99.13	0.00	136.32	242.01
	8	13.12	0.00	0.00	198.25	0.00	272.35	483.72
	16	26.47	0.00	0.00	400.00	0.00	548.74	975.21

Table M.7: liblinear-enron-GM2-ALL-ALL-5

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	16.61	7.11	23.72
	1	1.67	0.00	0.00	25.19	0.00	67.03	93.89
	2	3.28	0.00	0.00	49.56	0.00	131.17	184.01
	4	6.56	0.00	0.00	99.13	0.00	260.31	366.01
	8	13.12	0.00	0.00	198.25	0.00	521.46	732.83
	16	26.47	0.00	0.00	400.00	0.00	1050.99	1477.45

Table M.8: liblinear-enron-GM2-ALL-ALL-10

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	16.61	27.84	44.45
	1	1.67	0.00	0.00	25.19	0.00	163.46	190.31
	2	3.28	0.00	0.00	49.56	0.00	319.31	372.16
	4	6.56	0.00	0.00	99.13	0.00	632.61	738.30

Table M.9: liblinear-enron-GM2-ALL-ALL-25

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	16.61	77.69	94.30
	1	1.67	0.00	0.00	25.19	0.00	325.41	352.27
	2	3.28	0.00	0.00	49.56	0.00	633.48	686.33

Table M.10: liblinear-enron-GM2-ALL-ALL-50

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	16.61	140.85	157.46
	1	1.67	0.00	0.00	25.19	0.00	484.53	511.38
	2	3.28	0.00	0.00	49.56	0.00	948.19	1001.03

Table M.11: liblinear-enron-GM2-ALL-ALL-75

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	16.61	390.78	407.39
	1	1.67	0.00	0.00	25.19	0.00	975.14	1002.00

Table M.12: liblinear-enron-GM2-ALL-ALL-150

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	111.31	9.40	120.71
	1	6.07	0.00	0.00	91.79	0.00	126.29	224.15
	2	12.15	0.00	0.00	183.63	0.00	252.31	448.10
	4	24.31	0.00	0.00	367.35	0.00	503.84	895.50
	8	48.70	0.00	0.00	735.99	0.00	1007.72	1792.41

Table M.13: liblinear-enron-GM5-ALL-ALL-5

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	111.31	32.79	144.10
	1	6.07	0.00	0.00	91.79	0.00	241.40	339.26
	2	12.15	0.00	0.00	183.63	0.00	479.36	675.15
	4	24.31	0.00	0.00	367.35	0.00	959.08	1350.73

Table M.14: liblinear-enron-GM5-ALL-ALL-10

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	111.31	156.70	268.01
	1	6.07	0.00	0.00	91.79	0.00	582.90	680.76
	2	12.15	0.00	0.00	183.63	0.00	1173.58	1369.37

Table M.15: liblinear-enron-GM5-ALL-ALL-25

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	111.31	470.59	581.90
	1	6.07	0.00	0.00	91.79	0.00	1166.06	1263.92

Table M.16: liblinear-enron-GM5-ALL-ALL-50

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	111.31	875.63	986.94

Table M.17: liblinear-enron-GM5-ALL-ALL-75

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	54.31	7.61	61.91
	1	3.21	0.00	0.00	48.44	0.00	72.93	124.58
	2	6.41	0.00	0.00	96.88	0.00	137.26	240.56
	4	12.82	0.00	0.00	193.78	0.00	268.59	475.20
	8	25.64	0.00	0.00	387.55	0.00	533.17	946.37
	16	51.31	0.00	0.00	775.39	0.00	1056.93	1883.63

Table M.18: liblinear-enron-GB3-ALL-ALL-5

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	54.31	22.61	76.92
	1	3.21	0.00	0.00	48.44	0.00	138.64	190.29
	2	6.41	0.00	0.00	96.88	0.00	267.73	371.02
	4	12.82	0.00	0.00	193.78	0.00	521.84	728.44
	8	25.64	0.00	0.00	387.55	0.00	1018.42	1431.62

Table M.19: liblinear-enron-GB3-ALL-ALL-10

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	54.31	89.19	143.49
	1	3.21	0.00	0.00	48.44	0.00	363.60	415.25
	2	6.41	0.00	0.00	96.88	0.00	667.07	770.36

Table M.20: liblinear-enron-GB3-ALL-ALL-25

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	54.31	248.36	302.66
	1	3.21	0.00	0.00	48.44	0.00	748.13	799.78

Table M.21: liblinear-enron-GB3-ALL-ALL-50

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	54.31	453.56	507.86
	1	3.21	0.00	0.00	48.44	0.00	1135.06	1186.71

Table M.22: liblinear-enron-GB3-ALL-ALL-75

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	118.02	15.25	133.28
	1	12.41	0.00	0.00	187.54	0.00	259.32	459.27
	2	24.82	0.00	0.00	375.10	0.00	521.04	920.95
	4	49.65	0.00	0.00	750.28	0.00	1031.48	1831.40

Table M.23: liblinear-enron-OSB3-ALL-ALL-5

APPENDIX N:
Liblinear Storage Requirements for the Twitter Short Message Corpus

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	0.20	0.09	0.29
	1	0.07	0.00	0.00	1.09	0.00	1.57	2.73
	2	0.14	0.00	0.00	2.17	0.00	3.06	5.38
	4	0.29	0.00	0.00	4.35	0.00	6.05	10.69
	8	0.58	0.00	0.00	8.70	0.00	12.03	21.31
	16	1.15	0.00	0.00	17.40	0.00	23.95	42.50

Table N.1: liblinear-twitter-GM1-ALL-ALL-5

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	0.20	0.24	0.44
	1	0.07	0.00	0.00	1.09	0.00	3.05	4.21
	2	0.14	0.00	0.00	2.17	0.00	5.90	8.22
	4	0.29	0.00	0.00	4.35	0.00	11.61	16.24
	8	0.58	0.00	0.00	8.70	0.00	23.03	32.30
	16	1.15	0.00	0.00	17.40	0.00	45.80	64.35

Table N.2: liblinear-twitter-GM1-ALL-ALL-10

GM1								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	0.20	0.85	1.05
	1	0.07	0.00	0.00	1.09	0.00	7.59	8.75
	2	0.14	0.00	0.00	2.17	0.00	14.52	16.84
	4	0.29	0.00	0.00	4.35	0.00	28.38	33.01
	8	0.58	0.00	0.00	8.70	0.00	56.11	65.38
	16	1.15	0.00	0.00	17.40	0.00	111.51	130.05

Table N.3: liblinear-twitter-GM1-ALL-ALL-25

GM1								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	0.20	2.14	2.34
	1	0.07	0.00	0.00	1.09	0.00	15.27	16.43
	2	0.14	0.00	0.00	2.17	0.00	28.99	31.31
	4	0.29	0.00	0.00	4.35	0.00	56.44	61.07
	8	0.58	0.00	0.00	8.70	0.00	111.35	120.62
	16	1.15	0.00	0.00	17.40	0.00	221.15	239.70

Table N.4: liblinear-twitter-GM1-ALL-ALL-50

GM1								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	0.20	3.69	3.89
	1	0.07	0.00	0.00	1.09	0.00	23.03	24.19
	2	0.14	0.00	0.00	2.17	0.00	43.56	45.88
	4	0.29	0.00	0.00	4.35	0.00	84.60	89.23
	8	0.58	0.00	0.00	8.70	0.00	166.67	175.94
	16	1.15	0.00	0.00	17.40	0.00	330.81	349.35

Table N.5: liblinear-twitter-GM1-ALL-ALL-75

GM1								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	0.20	9.35	9.54
	1	0.07	0.00	0.00	1.09	0.00	46.58	47.74
	2	0.14	0.00	0.00	2.17	0.00	87.49	89.81
	4	0.29	0.00	0.00	4.35	0.00	169.36	173.99
	8	0.58	0.00	0.00	8.70	0.00	332.94	342.21
	16	1.15	0.00	0.00	17.40	0.00	660.12	678.66

Table N.6: liblinear-twitter-GM1-ALL-ALL-150

GM2								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	1.13	0.25	1.38
	1	1.67	0.00	0.00	25.19	0.00	34.70	61.55
	2	3.28	0.00	0.00	49.56	0.00	68.16	121.01
	4	6.56	0.00	0.00	99.13	0.00	136.24	241.93
	8	13.12	0.00	0.00	198.25	0.00	272.26	483.63
	16	26.47	0.00	0.00	400.00	0.00	549.72	976.19

Table N.7: liblinear-twitter-GM2-ALL-ALL-5

GM2								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	1.13	0.81	1.94
	1	1.67	0.00	0.00	25.19	0.00	66.29	93.15
	2	3.28	0.00	0.00	49.56	0.00	130.21	183.05
	4	6.56	0.00	0.00	99.13	0.00	260.24	365.93
	8	13.12	0.00	0.00	198.25	0.00	519.95	731.33
	16	26.47	0.00	0.00	400.00	0.00	1049.50	1475.97

Table N.8: liblinear-twitter-GM2-ALL-ALL-10

GM2								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	1.13	3.27	4.40
	1	1.67	0.00	0.00	25.19	0.00	161.17	188.03
	2	3.28	0.00	0.00	49.56	0.00	316.40	369.24
	4	6.56	0.00	0.00	99.13	0.00	632.32	738.01

Table N.9: liblinear-twitter-GM2-ALL-ALL-25

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	1.13	8.87	10.00
	1	1.67	0.00	0.00	25.19	0.00	319.44	346.29
	2	3.28	0.00	0.00	49.56	0.00	626.91	679.75

Table N.10: liblinear-twitter-GM2-ALL-ALL-50

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	1.13	15.62	16.75
	1	1.67	0.00	0.00	25.19	0.00	477.78	504.64
	2	3.28	0.00	0.00	49.56	0.00	937.67	990.51

Table N.11: liblinear-twitter-GM2-ALL-ALL-75

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	1.13	41.99	43.12
	1	1.67	0.00	0.00	25.19	0.00	953.13	979.99

Table N.12: liblinear-twitter-GM2-ALL-ALL-150

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	3.08	0.31	3.40
	1	6.07	0.00	0.00	91.79	0.00	125.71	223.57
	2	12.15	0.00	0.00	183.63	0.00	251.37	447.15

Table N.13: liblinear-twitter-GM5-ALL-ALL-5

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	3.08	1.24	4.32
	1	6.07	0.00	0.00	91.79	0.00	240.86	338.71
	2	12.15	0.00	0.00	183.63	0.00	482.06	677.85

Table N.14: liblinear-twitter-GM5-ALL-ALL-10

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	3.08	6.69	9.77
	1	6.07	0.00	0.00	91.79	0.00	585.06	682.92

Table N.15: liblinear-twitter-GM5-ALL-ALL-25

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	3.08	21.34	24.42

Table N.16: liblinear-twitter-GM5-ALL-ALL-50

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	3.08	39.19	42.27

Table N.17: liblinear-twitter-GM5-ALL-ALL-75

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	3.08	111.25	114.33

Table N.18: liblinear-twitter-GM5-ALL-ALL-150

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	3.18	0.78	3.96
	1	3.21	0.00	0.00	48.44	0.00	67.05	118.69
	2	6.41	0.00	0.00	96.88	0.00	133.78	237.07
	4	12.82	0.00	0.00	193.78	0.00	266.81	473.41
	8	25.64	0.00	0.00	387.55	0.00	533.35	946.54
	16	51.31	0.00	0.00	775.39	0.00	1066.46	1893.16

Table N.19: liblinear-twitter-GB3-ALL-ALL-5

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	3.18	2.56	5.74
	1	3.21	0.00	0.00	48.44	0.00	128.85	180.50
	2	6.41	0.00	0.00	96.88	0.00	256.35	359.64
	4	12.82	0.00	0.00	193.78	0.00	510.53	717.13
	8	25.64	0.00	0.00	387.55	0.00	1018.56	1431.76

Table N.20: liblinear-twitter-GB3-ALL-ALL-10

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	3.18	10.52	13.70
	1	3.21	0.00	0.00	48.44	0.00	314.97	366.62
	2	6.41	0.00	0.00	96.88	0.00	625.60	728.89

Table N.21: liblinear-twitter-GB3-ALL-ALL-25

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	3.18	28.75	31.93
	1	3.21	0.00	0.00	48.44	0.00	629.59	681.23

Table N.22: liblinear-twitter-GB3-ALL-ALL-50

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	3.18	51.29	54.47
	1	3.21	0.00	0.00	48.44	0.00	947.75	999.39

Table N.23: liblinear-twitter-GB3-ALL-ALL-75

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	3.18	132.47	135.65

Table N.24: liblinear-twitter-GB3-ALL-ALL-150

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	7.30	1.62	8.92
	1	12.41	0.00	0.00	187.54	0.00	258.70	458.66
	2	24.82	0.00	0.00	375.10	0.00	516.75	916.66
	4	49.65	0.00	0.00	750.28	0.00	1032.46	1832.38

Table N.25: liblinear-twitter-OSB3-ALL-ALL-5

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	7.30	5.33	12.63
	1	12.41	0.00	0.00	187.54	0.00	496.13	696.09
	2	24.82	0.00	0.00	375.10	0.00	987.43	1387.34

Table N.26: liblinear-twitter-OSB3-ALL-ALL-10

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	7.30	22.51	29.81

Table N.27: liblinear-twitter-OSB3-ALL-ALL-25

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	7.30	62.19	69.49

Table N.28: liblinear-twitter-OSB3-ALL-ALL-50

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	7.30	109.61	116.92

Table N.29: liblinear-twitter-OSB3-ALL-ALL-75

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	7.30	288.83	296.14

Table N.30: liblinear-twitter-OSB3-ALL-ALL-150

APPENDIX O: Naive Bayes Storage Requirements for the ENRON Email Corpus

GM1								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	1.40	0.21	1.60
	1	0.07	0.27	1.09	1.09	0.00	0.33	2.85
	2	0.14	0.54	2.17	2.17	0.00	0.33	5.37
	4	0.29	1.09	4.35	4.35	0.00	0.33	10.40
	8	0.58	2.17	8.70	8.70	0.00	0.33	20.48
	16	1.15	4.35	17.40	17.40	0.00	0.33	40.62

Table O.1: nb-enron-GM1-ALL-ALL-5

GM1								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	1.40	0.41	1.81
	1	0.07	0.27	1.09	1.09	0.00	0.66	3.18
	2	0.14	0.54	2.17	2.17	0.00	0.66	5.70
	4	0.29	1.09	4.35	4.35	0.00	0.66	10.73
	8	0.58	2.17	8.70	8.70	0.00	0.66	20.81
	16	1.15	4.35	17.40	17.40	0.00	0.66	40.95

Table O.2: nb-enron-GM1-ALL-ALL-10

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	1.40	1.03	2.43
	1	0.07	0.27	1.09	1.09	0.00	1.64	4.16
	2	0.14	0.54	2.17	2.17	0.00	1.65	6.69
	4	0.29	1.09	4.35	4.35	0.00	1.65	11.72
	8	0.58	2.17	8.70	8.70	0.00	1.65	21.80
	16	1.15	4.35	17.40	17.40	0.00	1.65	41.94

Table O.3: nb-enron-GM1-ALL-ALL-25

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	1.40	2.07	3.46
	1	0.07	0.27	1.09	1.09	0.00	3.29	5.81
	2	0.14	0.54	2.17	2.17	0.00	3.30	8.34
	4	0.29	1.09	4.35	4.35	0.00	3.31	13.38
	8	0.58	2.17	8.70	8.70	0.00	3.31	23.45
	16	1.15	4.35	17.40	17.40	0.00	3.31	43.60

Table O.4: nb-enron-GM1-ALL-ALL-50

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	1.40	3.10	4.50
	1	0.07	0.27	1.09	1.09	0.00	4.93	7.45
	2	0.14	0.54	2.17	2.17	0.00	4.95	9.99
	4	0.29	1.09	4.35	4.35	0.00	4.96	15.03
	8	0.58	2.17	8.70	8.70	0.00	4.96	25.11
	16	1.15	4.35	17.40	17.40	0.00	4.96	45.25

Table O.5: nb-enron-GM1-ALL-ALL-75

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	1.40	6.18	7.58
	1	0.07	0.27	1.09	1.09	0.00	9.87	12.39
	2	0.14	0.54	2.17	2.17	0.00	9.90	14.94
	4	0.29	1.09	4.35	4.35	0.00	9.92	19.99
	8	0.58	2.17	8.70	8.70	0.00	9.93	30.07
	16	1.15	4.35	17.40	17.40	0.00	9.93	50.22

Table O.6: nb-enron-GM1-ALL-ALL-150

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	16.61	0.87	17.48
	1	1.67	6.30	25.19	25.19	0.00	0.33	58.67
	2	3.28	12.39	49.56	49.56	0.00	0.33	115.12
	4	6.56	24.78	99.13	99.13	0.00	0.33	229.93
	8	13.12	49.56	198.25	198.25	0.00	0.33	459.52
	16	26.47	100.00	400.00	400.00	0.00	0.33	926.79

Table O.7: nb-enron-GM2-ALL-ALL-5

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	16.61	1.73	18.34
	1	1.67	6.30	25.19	25.19	0.00	0.65	58.99
	2	3.28	12.39	49.56	49.56	0.00	0.65	115.45
	4	6.56	24.78	99.13	99.13	0.00	0.65	230.26
	8	13.12	49.56	198.25	198.25	0.00	0.65	459.84
	16	26.47	100.00	400.00	400.00	0.00	0.65	927.12

Table O.8: nb-enron-GM2-ALL-ALL-10

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	16.61	4.38	20.99
	1	1.67	6.30	25.19	25.19	0.00	1.63	59.97
	2	3.28	12.39	49.56	49.56	0.00	1.63	116.42
	4	6.56	24.78	99.13	99.13	0.00	1.63	231.24
	8	13.12	49.56	198.25	198.25	0.00	1.63	460.82
	16	26.47	100.00	400.00	400.00	0.00	1.63	928.09

Table O.9: nb-enron-GM2-ALL-ALL-25

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	16.61	8.69	25.30
	1	1.67	6.30	25.19	25.19	0.00	3.25	61.59
	2	3.28	12.39	49.56	49.56	0.00	3.25	118.05
	4	6.56	24.78	99.13	99.13	0.00	3.26	232.86
	8	13.12	49.56	198.25	198.25	0.00	3.26	462.45
	16	26.47	100.00	400.00	400.00	0.00	3.26	929.72

Table O.10: nb-enron-GM2-ALL-ALL-50

GM2								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	16.61	13.21	29.82
	1	1.67	6.30	25.19	25.19	0.00	4.88	63.22
	2	3.28	12.39	49.56	49.56	0.00	4.88	119.68
	4	6.56	24.78	99.13	99.13	0.00	4.88	234.49
	8	13.12	49.56	198.25	198.25	0.00	4.88	464.07
	16	26.47	100.00	400.00	400.00	0.00	4.88	931.35

Table O.11: nb-enron-GM2-ALL-ALL-75

GM2								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	16.61	25.99	42.60
	1	1.67	6.30	25.19	25.19	0.00	9.75	68.10
	2	3.28	12.39	49.56	49.56	0.00	9.76	124.56
	4	6.56	24.78	99.13	99.13	0.00	9.77	239.37
	8	13.12	49.56	198.25	198.25	0.00	9.77	468.96
	16	26.47	100.00	400.00	400.00	0.00	9.77	936.23

Table O.12: nb-enron-GM2-ALL-ALL-150

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	111.31	1.63	112.94
	1	6.07	22.95	91.79	91.79	0.00	0.32	212.91
	2	12.15	45.91	183.63	183.63	0.00	0.32	425.65
	4	24.31	91.84	367.35	367.35	0.00	0.32	851.16
	8	48.70	184.00	735.99	735.99	0.00	0.32	1704.99
	16	97.43	368.11	1472.43	1472.43	0.00	0.32	3410.72

Table O.13: nb-enron-GM5-ALL-ALL-5

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	111.31	3.27	114.58
	1	6.07	22.95	91.79	91.79	0.00	0.63	213.23
	2	12.15	45.91	183.63	183.63	0.00	0.63	425.96
	4	24.31	91.84	367.35	367.35	0.00	0.63	851.48
	8	48.70	184.00	735.99	735.99	0.00	0.63	1705.31
	16	97.43	368.11	1472.43	1472.43	0.00	0.63	3411.04

Table O.14: nb-enron-GM5-ALL-ALL-10

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	111.31	7.99	119.30
	1	6.07	22.95	91.79	91.79	0.00	1.58	214.18
	2	12.15	45.91	183.63	183.63	0.00	1.58	426.91
	4	24.31	91.84	367.35	367.35	0.00	1.58	852.43
	8	48.70	184.00	735.99	735.99	0.00	1.58	1706.26
	16	97.43	368.11	1472.43	1472.43	0.00	1.59	3411.99

Table O.15: nb-enron-GM5-ALL-ALL-25

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	111.31	16.13	127.44
	1	6.07	22.95	91.79	91.79	0.00	3.17	215.76
	2	12.15	45.91	183.63	183.63	0.00	3.17	428.50
	4	24.31	91.84	367.35	367.35	0.00	3.17	854.01
	8	48.70	184.00	735.99	735.99	0.00	3.17	1707.85
	16	97.43	368.11	1472.43	1472.43	0.00	3.17	3413.58

Table O.16: nb-enron-GM5-ALL-ALL-50

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	111.31	24.39	135.70
	1	6.07	22.95	91.79	91.79	0.00	4.75	217.34
	2	12.15	45.91	183.63	183.63	0.00	4.75	430.08
	4	24.31	91.84	367.35	367.35	0.00	4.75	855.60
	8	48.70	184.00	735.99	735.99	0.00	4.75	1709.43
	16	97.43	368.11	1472.43	1472.43	0.00	4.75	3415.16

Table O.17: nb-enron-GM5-ALL-ALL-75

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	111.31	48.92	160.23
	1	6.07	22.95	91.79	91.79	0.00	9.51	222.10
	2	12.15	45.91	183.63	183.63	0.00	9.51	434.84
	4	24.31	91.84	367.35	367.35	0.00	9.51	860.35
	8	48.70	184.00	735.99	735.99	0.00	9.51	1714.19
	16	97.43	368.11	1472.43	1472.43	0.00	9.51	3419.91

Table O.18: nb-enron-GM5-ALL-ALL-150

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	54.31	2.67	56.98
	1	3.21	12.11	48.44	48.44	0.00	4.22	116.41
	2	6.41	24.22	96.88	96.88	0.00	4.24	228.64
	4	12.82	48.44	193.78	193.78	0.00	4.26	453.08
	8	25.64	96.89	387.55	387.55	0.00	4.27	901.90
	16	51.31	193.85	775.39	775.39	0.00	4.27	1800.20

Table O.19: nb-enron-GB3-ALL-ALL-5

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	54.31	5.31	59.61
	1	3.21	12.11	48.44	48.44	0.00	8.43	120.63
	2	6.41	24.22	96.88	96.88	0.00	8.49	232.88
	4	12.82	48.44	193.78	193.78	0.00	8.52	457.34
	8	25.64	96.89	387.55	387.55	0.00	8.53	906.17
	16	51.31	193.85	775.39	775.39	0.00	8.54	1804.47

Table O.20: nb-enron-GB3-ALL-ALL-10

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	54.31	13.42	67.73
	1	3.21	12.11	48.44	48.44	0.00	21.08	133.28
	2	6.41	24.22	96.88	96.88	0.00	21.22	245.61
	4	12.82	48.44	193.78	193.78	0.00	21.29	470.12
	8	25.64	96.89	387.55	387.55	0.00	21.33	918.97
	16	51.31	193.85	775.39	775.39	0.00	21.34	1817.28

Table O.21: nb-enron-GB3-ALL-ALL-25

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	54.31	26.67	80.97
	1	3.21	12.11	48.44	48.44	0.00	42.16	154.36
	2	6.41	24.22	96.88	96.88	0.00	42.44	266.83
	4	12.82	48.44	193.78	193.78	0.00	42.58	491.40
	8	25.64	96.89	387.55	387.55	0.00	42.65	940.29
	16	51.31	193.85	775.39	775.39	0.00	42.68	1838.62

Table O.22: nb-enron-GB3-ALL-ALL-50

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	54.31	40.22	94.53
	1	3.21	12.11	48.44	48.44	0.00	63.24	175.43
	2	6.41	24.22	96.88	96.88	0.00	63.66	288.05
	4	12.82	48.44	193.78	193.78	0.00	63.87	512.69
	8	25.64	96.89	387.55	387.55	0.00	63.98	961.62
	16	51.31	193.85	775.39	775.39	0.00	64.03	1859.96

Table O.23: nb-enron-GB3-ALL-ALL-75

GB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	54.31	79.47	133.78
	1	3.21	12.11	48.44	48.44	0.00	126.47	238.67
	2	6.41	24.22	96.88	96.88	0.00	127.32	351.71
	4	12.82	48.44	193.78	193.78	0.00	127.73	576.56
	8	25.64	96.89	387.55	387.55	0.00	127.96	1025.59
	16	51.31	193.85	775.39	775.39	0.00	128.05	1923.99

Table O.24: nb-enron-GB3-ALL-ALL-150

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	118.02	5.33	123.35
	1	12.41	46.89	187.54	187.54	0.00	8.53	442.91
	2	24.82	93.77	375.10	375.10	0.00	8.54	877.33
	4	49.65	187.57	750.28	750.28	0.00	8.55	1746.33
	8	99.29	375.14	1500.55	1500.55	0.00	8.55	3484.08
	16	198.81	751.03	3004.14	3004.14	0.00	8.55	6966.67

Table O.25: nb-enron-OSB3-ALL-ALL-5

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	118.02	10.62	128.64
	1	12.41	46.89	187.54	187.54	0.00	17.06	451.44
	2	24.82	93.77	375.10	375.10	0.00	17.09	885.87
	4	49.65	187.57	750.28	750.28	0.00	17.10	1754.88
	8	99.29	375.14	1500.55	1500.55	0.00	17.11	3492.64
	16	198.81	751.03	3004.14	3004.14	0.00	11.94	6970.05

Table O.26: nb-enron-OSB3-ALL-ALL-10

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	118.02	26.84	144.86
	1	12.41	46.89	187.54	187.54	0.00	42.64	477.03
	2	24.82	93.77	375.10	375.10	0.00	42.72	911.50
	4	49.65	187.57	750.28	750.28	0.00	42.75	1780.53
	8	99.29	375.14	1500.55	1500.55	0.00	42.77	3518.29

Table O.27: nb-enron-OSB3-ALL-ALL-25

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	118.02	53.35	171.37
	1	12.41	46.89	187.54	187.54	0.00	85.28	519.67
	2	24.82	93.77	375.10	375.10	0.00	85.43	954.22
	4	49.65	187.57	750.28	750.28	0.00	85.50	1823.28

Table O.28: nb-enron-OSB3-ALL-ALL-50

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	118.02	80.47	198.49
	1	12.41	46.89	187.54	187.54	0.00	127.92	562.31
	2	24.82	93.77	375.10	375.10	0.00	128.15	996.94
	4	49.65	187.57	750.28	750.28	0.00	128.25	1866.03
	8	99.29	375.14	1500.55	1500.55	0.00	128.30	3603.82

Table O.29: nb-enron-OSB3-ALL-ALL-75

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	118.02	158.91	276.94
	1	12.41	46.89	187.54	187.54	0.00	255.84	690.22
	2	24.82	93.77	375.10	375.10	0.00	256.30	1125.09
	4	49.65	187.57	750.28	750.28	0.00	256.51	1994.29
	8	99.29	375.14	1500.55	1500.55	0.00	256.59	3732.12

Table O.30: nb-enron-OSB3-ALL-ALL-150

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APPENDIX P:
Naive Bayes Storage Requirements for the Twitter Short Message Corpus

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	0.20	0.02	0.22
	1	0.07	0.27	1.09	1.09	0.00	0.04	2.56
	2	0.14	0.54	2.17	2.17	0.00	0.04	5.08
	4	0.29	1.09	4.35	4.35	0.00	0.04	10.11
	8	0.58	2.17	8.70	8.70	0.00	0.04	20.18
	16	1.15	4.35	17.40	17.40	0.00	0.04	40.33

Table P.1: nb-twitter-GM1-ALL-ALL-5

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	0.20	0.05	0.25
	1	0.07	0.27	1.09	1.09	0.00	0.08	2.60
	2	0.14	0.54	2.17	2.17	0.00	0.08	5.12
	4	0.29	1.09	4.35	4.35	0.00	0.08	10.15
	8	0.58	2.17	8.70	8.70	0.00	0.08	20.22
	16	1.15	4.35	17.40	17.40	0.00	0.08	40.37

Table P.2: nb-twitter-GM1-ALL-ALL-10

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	0.20	0.12	0.32
	1	0.07	0.27	1.09	1.09	0.00	0.20	2.72
	2	0.14	0.54	2.17	2.17	0.00	0.20	5.23
	4	0.29	1.09	4.35	4.35	0.00	0.20	10.27
	8	0.58	2.17	8.70	8.70	0.00	0.20	20.34
	16	1.15	4.35	17.40	17.40	0.00	0.20	40.49

Table P.3: nb-twitter-GM1-ALL-ALL-25

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	0.20	0.24	0.43
	1	0.07	0.27	1.09	1.09	0.00	0.40	2.91
	2	0.14	0.54	2.17	2.17	0.00	0.40	5.43
	4	0.29	1.09	4.35	4.35	0.00	0.39	10.47
	8	0.58	2.17	8.70	8.70	0.00	0.40	20.54
	16	1.15	4.35	17.40	17.40	0.00	0.40	40.69

Table P.4: nb-twitter-GM1-ALL-ALL-50

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	0.20	0.36	0.55
	1	0.07	0.27	1.09	1.09	0.00	0.60	3.11
	2	0.14	0.54	2.17	2.17	0.00	0.60	5.63
	4	0.29	1.09	4.35	4.35	0.00	0.60	10.67
	8	0.58	2.17	8.70	8.70	0.00	0.59	20.74
	16	1.15	4.35	17.40	17.40	0.00	0.59	40.88

Table P.5: nb-twitter-GM1-ALL-ALL-75

GM1								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	0.20	0.71	0.91
	1	0.07	0.27	1.09	1.09	0.00	1.18	3.70
	2	0.14	0.54	2.17	2.17	0.00	1.19	6.23
	4	0.29	1.09	4.35	4.35	0.00	1.19	11.26
	8	0.58	2.17	8.70	8.70	0.00	1.19	21.33
	16	1.15	4.35	17.40	17.40	0.00	1.18	41.47

Table P.6: nb-twitter-GM1-ALL-ALL-150

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	1.13	0.04	1.17
	1	1.67	6.30	25.19	25.19	0.00	0.04	58.38
	2	3.28	12.39	49.56	49.56	0.00	0.04	114.84
	4	6.56	24.78	99.13	99.13	0.00	0.04	229.65
	8	13.12	49.56	198.25	198.25	0.00	0.04	459.23
	16	26.47	100.00	400.00	400.00	0.00	0.04	926.51

Table P.7: nb-twitter-GM2-ALL-ALL-5

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	1.13	0.09	1.22
	1	1.67	6.30	25.19	25.19	0.00	0.08	58.42
	2	3.28	12.39	49.56	49.56	0.00	0.08	114.87
	4	6.56	24.78	99.13	99.13	0.00	0.08	229.68
	8	13.12	49.56	198.25	198.25	0.00	0.08	459.27
	16	26.47	100.00	400.00	400.00	0.00	0.08	926.54

Table P.8: nb-twitter-GM2-ALL-ALL-10

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	1.13	0.22	1.35
	1	1.67	6.30	25.19	25.19	0.00	0.19	58.53
	2	3.28	12.39	49.56	49.56	0.00	0.19	114.99
	4	6.56	24.78	99.13	99.13	0.00	0.19	229.80
	8	13.12	49.56	198.25	198.25	0.00	0.19	459.38
	16	26.47	100.00	400.00	400.00	0.00	0.19	926.66

Table P.9: nb-twitter-GM2-ALL-ALL-25

GM2								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	1.13	0.44	1.57
	1	1.67	6.30	25.19	25.19	0.00	0.38	58.72
	2	3.28	12.39	49.56	49.56	0.00	0.38	115.18
	4	6.56	24.78	99.13	99.13	0.00	0.38	229.99
	8	13.12	49.56	198.25	198.25	0.00	0.38	459.57
	16	26.47	100.00	400.00	400.00	0.00	0.38	926.85

Table P.10: nb-twitter-GM2-ALL-ALL-50

GM2								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	1.13	0.66	1.79
	1	1.67	6.30	25.19	25.19	0.00	0.57	58.91
	2	3.28	12.39	49.56	49.56	0.00	0.58	115.37
	4	6.56	24.78	99.13	99.13	0.00	0.58	230.19
	8	13.12	49.56	198.25	198.25	0.00	0.58	459.77
	16	26.47	100.00	400.00	400.00	0.00	0.58	927.05

Table P.11: nb-twitter-GM2-ALL-ALL-75

GM2								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	1.13	1.33	2.46
	1	1.67	6.30	25.19	25.19	0.00	1.15	59.49
	2	3.28	12.39	49.56	49.56	0.00	1.15	115.95
	4	6.56	24.78	99.13	99.13	0.00	1.15	230.76
	8	13.12	49.56	198.25	198.25	0.00	1.15	460.34
	16	26.47	100.00	400.00	400.00	0.00	1.15	927.61

Table P.12: nb-twitter-GM2-ALL-ALL-150

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	3.08	0.04	3.13
	1	6.07	22.95	91.79	91.79	0.00	0.03	212.63
	2	12.15	45.91	183.63	183.63	0.00	0.03	425.36
	4	24.31	91.84	367.35	367.35	0.00	0.03	850.88
	8	48.70	184.00	735.99	735.99	0.00	0.03	1704.71
	16	97.43	368.11	1472.43	1472.43	0.00	0.03	3410.44

Table P.13: nb-twitter-GM5-ALL-ALL-5

GM5								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	3.08	0.09	3.17
	1	6.07	22.95	91.79	91.79	0.00	0.07	212.66
	2	12.15	45.91	183.63	183.63	0.00	0.07	425.40
	4	24.31	91.84	367.35	367.35	0.00	0.07	850.91
	8	48.70	184.00	735.99	735.99	0.00	0.07	1704.74
	16	97.43	368.11	1472.43	1472.43	0.00	0.07	3410.47

Table P.14: nb-twitter-GM5-ALL-ALL-10

GM5								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	3.08	0.22	3.31
	1	6.07	22.95	91.79	91.79	0.00	0.17	212.76
	2	12.15	45.91	183.63	183.63	0.00	0.17	425.50
	4	24.31	91.84	367.35	367.35	0.00	0.17	851.01
	8	48.70	184.00	735.99	735.99	0.00	0.17	1704.85
	16	97.43	368.11	1472.43	1472.43	0.00	0.17	3410.57

Table P.15: nb-twitter-GM5-ALL-ALL-25

GM5								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	3.08	0.45	3.53
	1	6.07	22.95	91.79	91.79	0.00	0.34	212.93
	2	12.15	45.91	183.63	183.63	0.00	0.34	425.67
	4	24.31	91.84	367.35	367.35	0.00	0.34	851.18
	8	48.70	184.00	735.99	735.99	0.00	0.34	1705.02
	16	97.43	368.11	1472.43	1472.43	0.00	0.34	3410.75

Table P.16: nb-twitter-GM5-ALL-ALL-50

GM5								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	3.08	0.67	3.75
	1	6.07	22.95	91.79	91.79	0.00	0.51	213.10
	2	12.15	45.91	183.63	183.63	0.00	0.51	425.84
	4	24.31	91.84	367.35	367.35	0.00	0.51	851.35
	8	48.70	184.00	735.99	735.99	0.00	0.51	1705.18
	16	97.43	368.11	1472.43	1472.43	0.00	0.51	3410.91

Table P.17: nb-twitter-GM5-ALL-ALL-75

GM5								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	3.08	1.34	4.42
	1	6.07	22.95	91.79	91.79	0.00	1.02	213.61
	2	12.15	45.91	183.63	183.63	0.00	1.02	426.35
	4	24.31	91.84	367.35	367.35	0.00	1.02	851.86
	8	48.70	184.00	735.99	735.99	0.00	1.02	1705.70
	16	97.43	368.11	1472.43	1472.43	0.00	1.01	3411.42

Table P.18: nb-twitter-GM5-ALL-ALL-150

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	3.18	0.13	3.31
	1	3.21	12.11	48.44	48.44	0.00	0.21	112.40
	2	6.41	24.22	96.88	96.88	0.00	0.20	224.60
	4	12.82	48.44	193.78	193.78	0.00	0.20	449.03
	8	25.64	96.89	387.55	387.55	0.00	0.21	897.84
	16	51.31	193.85	775.39	775.39	0.00	0.20	1796.14

Table P.19: nb-twitter-GB3-ALL-ALL-5

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	3.18	0.26	3.44
	1	3.21	12.11	48.44	48.44	0.00	0.41	112.61
	2	6.41	24.22	96.88	96.88	0.00	0.41	224.81
	4	12.82	48.44	193.78	193.78	0.00	0.41	449.24
	8	25.64	96.89	387.55	387.55	0.00	0.41	898.05
	16	51.31	193.85	775.39	775.39	0.00	0.41	1796.35

Table P.20: nb-twitter-GB3-ALL-ALL-10

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	3.18	0.64	3.82
	1	3.21	12.11	48.44	48.44	0.00	1.02	113.22
	2	6.41	24.22	96.88	96.88	0.00	1.03	225.42
	4	12.82	48.44	193.78	193.78	0.00	1.03	449.86
	8	25.64	96.89	387.55	387.55	0.00	1.03	898.67
	16	51.31	193.85	775.39	775.39	0.00	1.03	1796.96

Table P.21: nb-twitter-GB3-ALL-ALL-25

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	3.18	1.28	4.46
	1	3.21	12.11	48.44	48.44	0.00	2.05	114.24
	2	6.41	24.22	96.88	96.88	0.00	2.06	226.45
	4	12.82	48.44	193.78	193.78	0.00	2.06	450.88
	8	25.64	96.89	387.55	387.55	0.00	2.06	899.70
	16	51.31	193.85	775.39	775.39	0.00	2.06	1797.99

Table P.22: nb-twitter-GB3-ALL-ALL-50

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	3.18	1.92	5.10
	1	3.21	12.11	48.44	48.44	0.00	3.08	115.28
	2	6.41	24.22	96.88	96.88	0.00	3.08	227.47
	4	12.82	48.44	193.78	193.78	0.00	3.08	451.91
	8	25.64	96.89	387.55	387.55	0.00	3.08	900.72
	16	51.31	193.85	775.39	775.39	0.00	3.09	1799.02

Table P.23: nb-twitter-GB3-ALL-ALL-75

GB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	3.18	3.84	7.02
	1	3.21	12.11	48.44	48.44	0.00	6.17	118.37
	2	6.41	24.22	96.88	96.88	0.00	6.18	230.57
	4	12.82	48.44	193.78	193.78	0.00	6.19	455.02
	8	25.64	96.89	387.55	387.55	0.00	6.18	903.82
	16	51.31	193.85	775.39	775.39	0.00	6.17	1802.10

Table P.24: nb-twitter-GB3-ALL-ALL-150

OSB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
5	0	0.00	0.00	0.00	0.00	7.30	0.26	7.56
	1	12.41	46.89	187.54	187.54	0.00	0.41	434.80
	2	24.82	93.77	375.10	375.10	0.00	0.41	869.20
	4	49.65	187.57	750.28	750.28	0.00	0.41	1738.19
	8	99.29	375.14	1500.55	1500.55	0.00	0.41	3475.94
	16	198.81	751.03	3004.14	3004.14	0.00	0.42	6958.53

Table P.25: nb-twitter-OSB3-ALL-ALL-5

OSB3								
Group Size	Web1T %	Size (MB)						
		keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
10	0	0.00	0.00	0.00	0.00	7.30	0.52	7.83
	1	12.41	46.89	187.54	187.54	0.00	0.83	435.22
	2	24.82	93.77	375.10	375.10	0.00	0.83	869.62
	4	49.65	187.57	750.28	750.28	0.00	0.83	1738.61
	8	99.29	375.14	1500.55	1500.55	0.00	0.83	3476.36
	16	198.81	751.03	3004.14	3004.14	0.00	0.83	6958.95

Table P.26: nb-twitter-OSB3-ALL-ALL-10

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
25	0	0.00	0.00	0.00	0.00	7.30	1.31	8.61
	1	12.41	46.89	187.54	187.54	0.00	2.09	436.47
	2	24.82	93.77	375.10	375.10	0.00	2.08	870.87
	4	49.65	187.57	750.28	750.28	0.00	2.08	1739.86
	8	99.29	375.14	1500.55	1500.55	0.00	2.08	3477.61
	16	198.81	751.03	3004.14	3004.14	0.00	2.09	6960.20

Table P.27: nb-twitter-OSB3-ALL-ALL-25

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
50	0	0.00	0.00	0.00	0.00	7.30	2.60	9.90
	1	12.41	46.89	187.54	187.54	0.00	4.17	438.56
	2	24.82	93.77	375.10	375.10	0.00	4.18	872.97
	4	49.65	187.57	750.28	750.28	0.00	4.16	1741.94
	8	99.29	375.14	1500.55	1500.55	0.00	4.16	3479.69
	16	198.81	751.03	3004.14	3004.14	0.00	4.17	6962.28

Table P.28: nb-twitter-OSB3-ALL-ALL-50

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
75	0	0.00	0.00	0.00	0.00	7.30	3.90	11.20
	1	12.41	46.89	187.54	187.54	0.00	6.28	440.66
	2	24.82	93.77	375.10	375.10	0.00	6.22	875.01
	4	49.65	187.57	750.28	750.28	0.00	6.27	1744.05
	8	99.29	375.14	1500.55	1500.55	0.00	6.26	3481.79
	16	198.81	751.03	3004.14	3004.14	0.00	6.25	6964.37

Table P.29: nb-twitter-OSB3-ALL-ALL-75

OSB3								
		Size (MB)						
Group Size	Web1T %	keys.mph	signature	counts	logprobs	vocabmap	Authors Model	TOTAL
150	0	0.00	0.00	0.00	0.00	7.30	7.79	15.10
	1	12.41	46.89	187.54	187.54	0.00	12.51	446.89
	2	24.82	93.77	375.10	375.10	0.00	12.47	881.26
	4	49.65	187.57	750.28	750.28	0.00	12.46	1750.24
	8	99.29	375.14	1500.55	1500.55	0.00	12.50	3488.02
	16	198.81	751.03	3004.14	3004.14	0.00	12.47	6970.58

Table P.30: nb-twitter-OSB3-ALL-ALL-150

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