My Comprehensive Evaluation

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in
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Abstract

This paper examines the effectiveness of six machine learning algorithms built to classify textual data. Decision Trees, Bagging, Random Forests, Support Vector Machines (SVMs), Logistic Regression, and Linear Discriminat Analysis (LDA) are evaluated by their respective error rates and learning speeds. The data set is a description of over 100,000 happy moments; each response is given a predefined label that is predicted by the six classifiers, after considerations to train and test sets. SVMs outperformance of the other models supports the theoretical discussion of each algorithm, and demonstrates the challenges associated with unstructured data. I conclude by exploring alternative methods that may provide improved outcomes for text classification.

Introduction

By 2022, 93% of all data in the digital universe will be unstructured. As the wealth of information stored in comments, tweets, and reviews increases, so does the growing interest in extracting insights from this textual data. Organizations such as Amazon, Apple, and Facebook have begun recruiting researchers to investigate how data can be used to better reach their customers. Over the years, this research has led to break throughs in text categorization – the assignment of natural language texts to predefined categories based on content – which has applications in areas such as search engines and customer relationship management. Some of the biggest challenges when working with unstructured data pertain to the volume of data. By nature, a large percentage of the data companies collect is unverified, and remains in its uncleaned, user generated state. When drawing insights from this data, it is vital that the data is transformed into an actionable form. There is currently 171,476 words in the English language, making natural language processing a difficult task when considerations are made dimensionality. In this paper, I look to find the most computationally efficient methods of analyzing natural language.

Six supervised methods were used in this analysis: Support Vector Machines (SVM), Multinomial Logistic Regression, Decision Trees, Bagging, Random Forests, and Linear Discriminant Anlaysis (LDA). Misclassification rates, precision-recall, and runtimes were used to evaluated each algorithm's computational efficiency. Missclassification rate is defined as 1 minus classification accuracy (the proportion of corrected predicted categories). The report is organized as follows:

- Chapter 1 provides background information on the chosen dataset, how it was mined, how it was transformed, and an exploratory analysis of the features within the data
- Chapter 2 provides the theoretical background of each learning algorithm used in the experiment
- Chapter 3 shows and interprets the results, and concludes

0.1 Previous Work

My exposition draws from several noteworthy analyses of textual data. This list includes the role of SVMs in learning text classifiers (Joachim, 1994), the use of semantic orientation in classifying documents (Pang et al., 2002), and the benefits of term-frequency transformations (Leopold and Kinderman, 2002).

Chapter 1

Data

The data used in this analysis is a series happy moments. In collaboration with the University of Tokyo, Massachusetts Institute of Technology researchers interviewed thousands of people and asked them to list ten happy moments that occurred within the last 24 hours. Their responses were recorded and compiled into *HappyDB*, a corpus of 100,535 happy moments. The data set is hosted publicly on github as a zip file (`https://rit-public.github.io/HappyDB/`).

It is important to note that this curated data set contains cleaned textual data. The variables of interest in this analysis are cleaned_hm, the list of happy moments, and its associated predicted category (achievement, affection, bonding, enjoying the moment, exercise, leisure, or nature). For my analysis, I sampled 10,000 of these responses and trained on 80% of the data.

1.1 Data Preprocessing

In order to analyze how words influence a predicted category, the data set had to be transformed. First, each character vector response is converted into a corpus. A corpus is simply a collection of natural langauge constructed with a specific purpose. The corpus consists of 10,000 responses samples from the larger dataset.

Table 1.1: Happy DB

Responses	Category
I went on a successful date with someone I felt sympathy and connection with.	affection
I was happy when my son got 90% marks in his examination	affection
I went to the gym this morning and did yoga.	exercise

Table 1.2: Term Document Matrix for First Three Responses

farm	fruit	sale	store
1	1	1	1
0	0	0	0
0	0	0	0

```
as.character(corpus[[1]])
```

```
[1] "i went to the farm store and found fruit trees on sale for 70% off. "
```

Entries in the corpus are then cleaned of symbols, punctuations, and stop words. Once accomplished the corpus is reduced to a collection of key words.

```
as.character(a[[1]])
```

```
[1] "    farm store   fruit trees  sale   "
```

The next step is to create a document term matrix. A document term matrix is a corpus transformation that represents each word as a feature, and each response as a row. The matrix is populated with values 0 or 1, depending on the absence or presence of that word in the document. Traditionally, document term matrices are highly dimensional due to the thousands of words that can be used as features. Often times many of these cells are empty indicating the absence of a word from that document. High sparsity (the proportion of entries which are zero) is another known condition of document terms matrices.

1.2 Exploratory Data Analysis:

In this section, I further explore the properties of the cleaned data above. First we look at the response variable **category**. Next, I explore statistics related to the explanatory variable **terms**.

1.2.1 Category

Affection and achievement were the most talked about categories (33.9% and 34.1% respectively). This follows conventional logic given that love and sense of accomplishment are vital traits to a good quality of life. Nature and exercises accounted for just 1.2% and 1.8% of labeled responses in the entire data set.

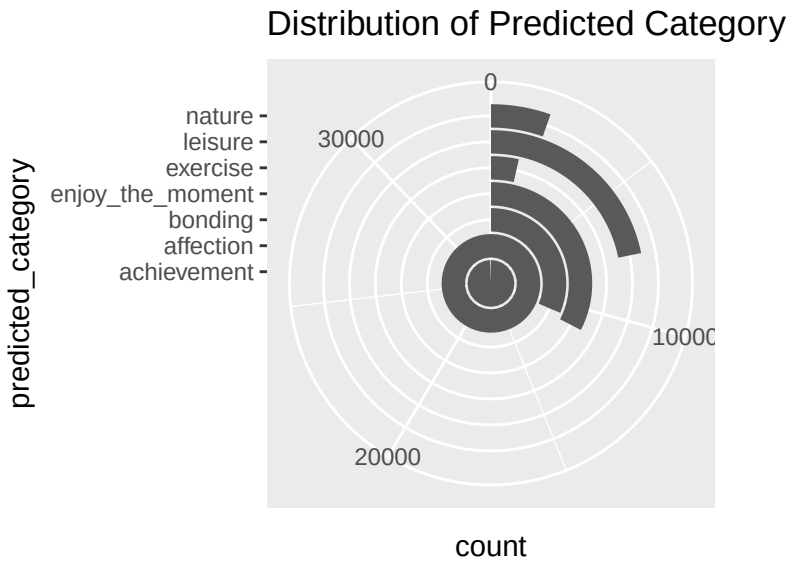


Figure 1.1: Pie Chart

In a predictive setting, having highly disproportionate classes can lead to errors when making predictions based on that training data. When classes are unequally represented, models may simply decide to always predict a certain class in order to achieve a high accuracy. This accuracy paradox does not reflect effective predictions for the model, but rather the state of the underlying distribution. While this is not the case for our data set, consideration must be taken for the classifications of minority labels.

1.2.2 Term Count

Figure 1.2 shows the majority of entries are between 5 and 14 words. Over 4,000 reviews contain over 50 words. Many of these words add little to no value to an algorithmic interpretation of the sentence. These are the commonly used words such as “a”, “I”, and “was” that were removed from the corpus.

1.2.3 Term Frequency - Inverse Document Frequency

Two metrics frequently used to quantify the importance of a word are it’s term frequency (tf), and inverse document frequency (idf). Term frequency measures how frequently a word appears in a document, while idf weights frequently used words less than words rarely used (Leopold, 2002). When combined, the tf-idf is the frequency of a term adjusted by how rarely it is used.

Figure 1.3 shows a breakdown of the highest tf-idf word per category and yields

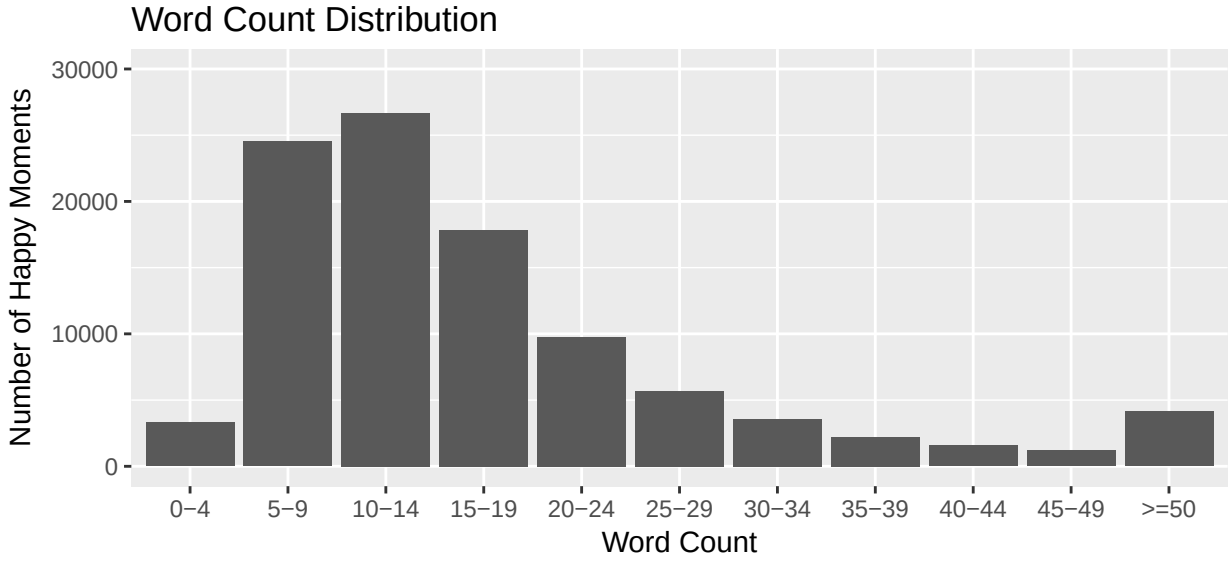


Figure 1.2: Word Count Distribution

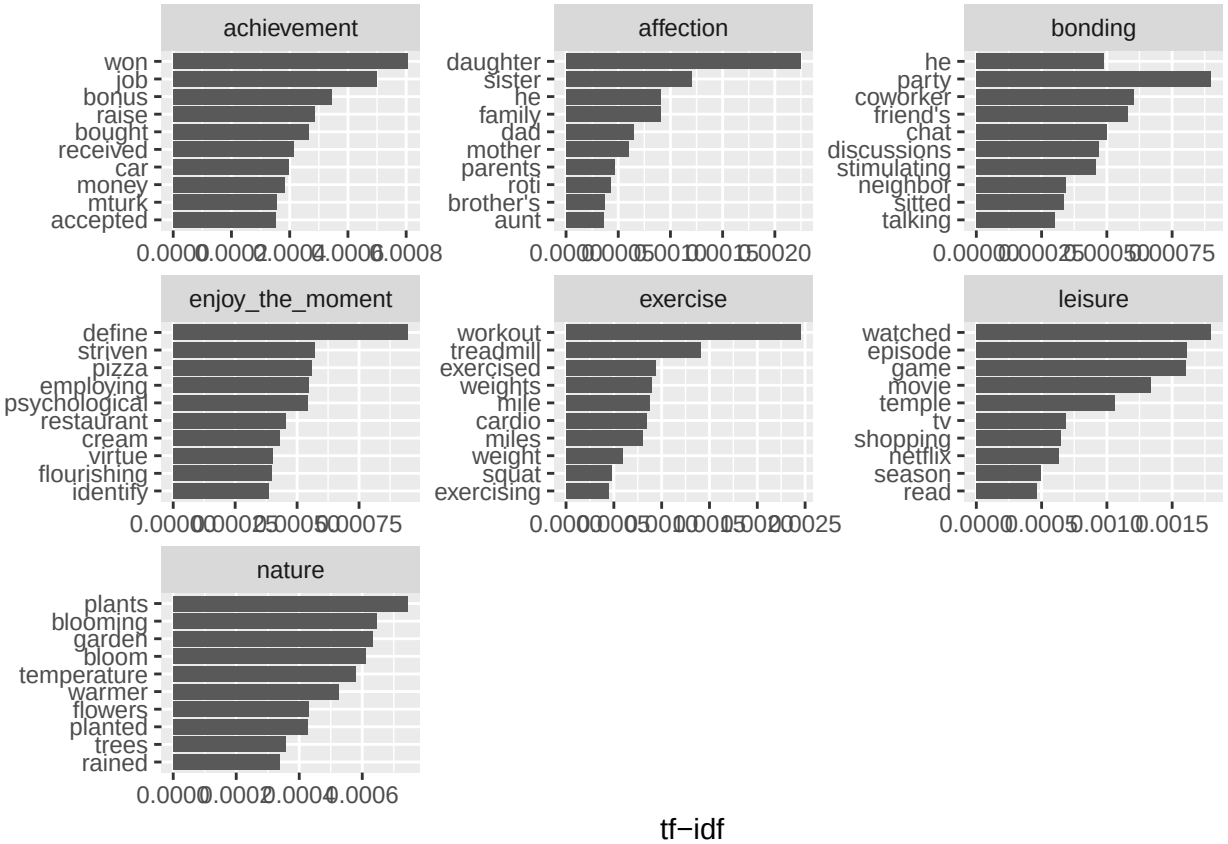


Figure 1.3: TD-IDF per Category

further insight into words associated with each label. For phrases related to achievement, words like “won”, “job”, and “bonus” have the highest adjusted usage. In responses categorized as exercise, we see terms related to working out and equipment used. These key terms provide natural separators by which the algorithms can uses to classify future responses. In the next section, I discuss some of the methods used to predict the categories of happy moments.

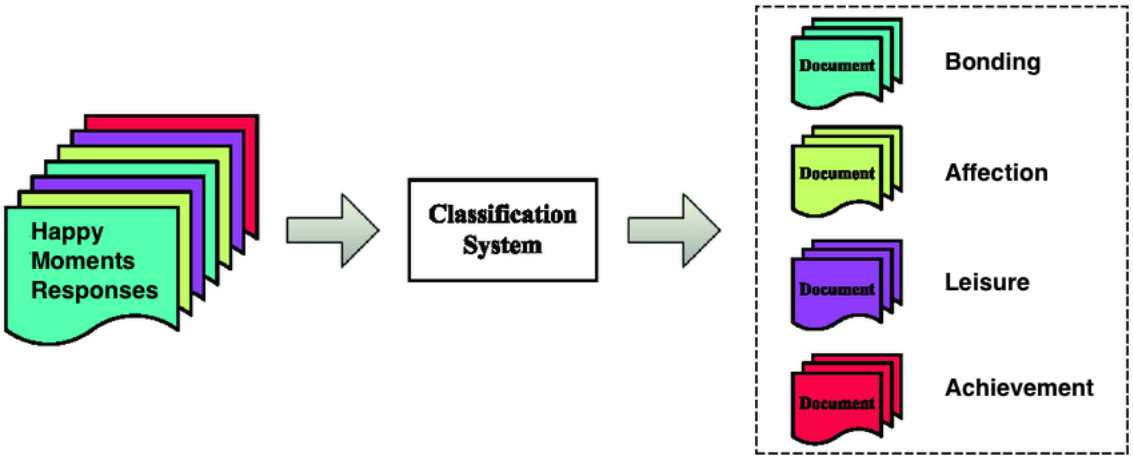


Figure 1.4: Framework of Text Classification

Chapter 2

Theoretical Background

Broadly speaking, there are two types of machine learning techniques: supervised, and unsupervised methods. In a supervised setting, inputs are mapped to a predefined label, and models are trained to predict labels for a new set of inputs. In the case of text classification, each response and associated category are learned by a classifier which then predicts labels for new responses. In an unsupervised setting, there is no corresponding labels to the inputs. These methods cluster responses based on associations between them. Given that this study aims to compare the performance of classifiers when labeling texts, we remain in a supervised setting.

2.1 Support Vector Machines

The Support Vector Machines (SVM) approach to classification is a generalization of the maximal margin classifier to non-linear decision boundaries. It is first defined by a hyperplane, which is a flat subspace existing in a $p-1$ dimensional setting. The mathematical definition of a hyperplanes is a line with:

$$\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p = 0$$

The hyperplane essentially divides a p-dimensional space into two halves depending on whether or not the linear equation is greater than zero or less than zero for a given $X = (X_1, X_2, ..., X_p)^T$. In the scenario where X is an $n * p$ matrix where observations fall into two classes $y_1, y_2, ...y_n$ between $-1, 1$. If a separating hyperlane exists, it can be used to construct an intuitive classifier based on the $G(x) = sign[x_i^T \beta + \beta_0]$. The optimization problem

$$maxM$$

subject to

$$y_i(x_i^T\beta + \beta_0) \geq M, i = 1, ..., N$$

Where M is the width of the margin.

In a high dimensional setting however, this is unlikely to be the case. A soft margin classifier aims to address this by allowing some observations to fall on the wrong side of the margin or even hyperplane. These observations correspond to training points that have been misclassified by the support vector classifier. This constraint can now be modified to be:

$$y_i(x_i^T\beta + \beta_0) \geq M - \xi$$

.

Where ξ is a slack variable representing observations on the wrong side of the margin/hyperplane. In this setting, points on the wrong side of the margin are penalized proportionally to the distance from the boundary.

Tuning parameter, C can be introduced restraining the number of points that violate the hyperplane. As C increases we allow for more observations to appear on the wrong side of the hyperplane so the margin widens. Conversely, as C decreases less violations result in a smaller margin. Increasing the cost parameter additionally makes models more expensive and increases the risk of losing model generability.

In situations where there are more than $k > 2$ classes, k SVMs are fit and compared to the remaining k-1 classes. Observations are assigned to a class based on which $\beta_0 k + \beta_{1k}X_{1k} + ... + \beta_{pk}X_{pk}$ is the greatest (Hastie, 337-356).

SVMs hold a unique property in that they can classify observations independent of the dimensionality of the feature space (Joachim). By separating the data on the largest margin rather than the number of features, our model can be easily generalized, irrespective of the size of the feature space.

2.2 Decision Trees

Decision trees partition a feature space into a number of simpler regions. Decision trees are composed of two main parts: a node and leaf. Each node in a decision tree represents a variable by which observations can be group based on conditions associated with that variable. In this setting, every node is a word in the document term matrix. In a classification setting, the tree is split based on which variable minimizes the classification error rate. If we let $\hat{p}_{mk} = 1/N_m * \Sigma I(y_i = k)$ be the proportion of class k observations in node m, observsations are classified to the class

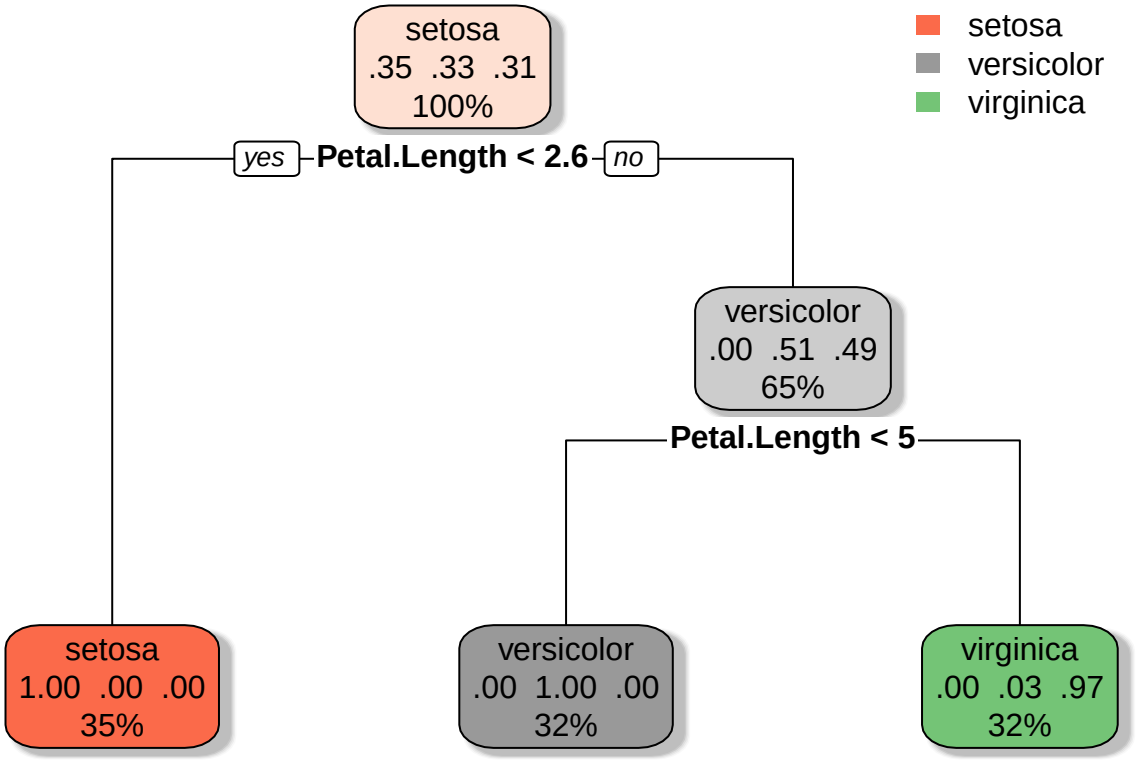


Figure 2.1: Decision Tree to Determine Plant Species

where $k(m) =_{argmax}\ \hat{p}_{mk}$ (Hastie, 312). This can also be described as the majority class for node m. This greedy algorithm chooses which variable to split on based on the largest drop in misclassification rate.

Figure **x** is a simple decision tree that chooses petal length and width as nodes. Do to their high variance, resulting trees can vary greatly if the training data is modified, and can lead to drastically different test labels. Traditionally, classification and regression decision trees are associated with high variance and low bias.

Table 2.1: Decision Tree Confusion Matrix

	setosa	versicolor	virginica
setosa	50	0	0
versicolor	0	48	6
virginica	0	2	43

2.3 Bagging

Bootstrap aggregation (bagging) is an ensemble method that combines the predictions of several smaller algorithms to make an improve estimate. Given a set of independent observations $X_1...X_n$ each with variance σ^2, the variance of the mean $\bar{X}$ is $\frac{\sigma^2}{n}$. This illustrates how averaging over a set of observations can reduce variance. In this approach, several samples are taken from the training data with replacement and a classification tree is trained on each. Given a new data set, the bagging method aggregates the average prediction across the models for each observation and assigns it to the class with the majority vote (Hastie, 317).

Because the prediction is an average of several trees, we are less concerned with one tree overfitting. This allows for trees to remain unpruned, with high variance. In this setting the only adjustable parameter is the number of samples drawn, in essence, how many decision trees are averaged. Traditionally, this number is chosen through cross-validation (increased until accuracy stops showing improvement). It must be kept in consideration however that more samples will require more time to train the models, and may be computational infeasible.

Due to the algorithms greedy nature, a series of decision trees may have highly correlated predictions as a result of the method dividing the data based on the largest drop in missclassification rate. Imagine a scenario where there is only one strongly correlated predictor. Even with a high number of samples, we can expect most trees generated to split the first node on this variable. Situations where there is structural similarity between bootstrap samples can lead to predictions that are highly correlated. **Note**: The Bagging model did not provide reproducible results, therefore it is omitted from the remainder of this experiment. Nonetheless, it is an important algorithm that establishes the framework for the next method discussed in this chapter.

2.4 Random Forests

Random Forests algorithms improve on the bootstrap aggregation by decorrelating trees. The main differences is that in a random forest setting, only a random sample of m predictors from p variables can be chosen as a splitting feature. This alleviates the issue described earlier by not considering the one strong predictor in approximately $(p-m)/p$ of the splits. Situations where $m = p$ is simply a bootstrap aggregation (Hastie, 319). Smaller values of m are traditionally helpful when there is a large number of correlated features.

2.5 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is most commonly used as a dimension reduction technique. In the case of $p > 1$ classes, each class density is assumed to follow a multivariate gaussian distribution $N(\mu_k, \Sigma)$, where μ_k is a class mean vector , and Σ is common covariance matrix.

$$log(Pr(G = k|X = x)/Pr(G = l|X = x) =$$

$$log(f_k(x)/f_l(x) + log(\pi_k/\pi_l)$$

$$log(\pi_k/\pi_l) - 1/2(\mu_k + \mu_l)^T\Sigma^{-1}(\mu_k - \mu_l) + x^T\Sigma^{-1}(\mu_k - \mu_l)$$

When simplified further, the above becomes:

$$\delta_k(x) = x^T\Sigma^{-1}\mu_k - 1/2\mu_k^T\Sigma^{-1} + log\pi_k$$

This equation assigns an observation to the class for which the its $\delta_k(x)$ is the largest (Hastie, 143). Since the parameters of the gaussian are unknown, following estimates are used:

$\hat{\pi}_k = N_k/N$ where N_k is the number of class-k observations

$$\hat{\mu}_k = \Sigma_{g=k}x_i/N_k$$

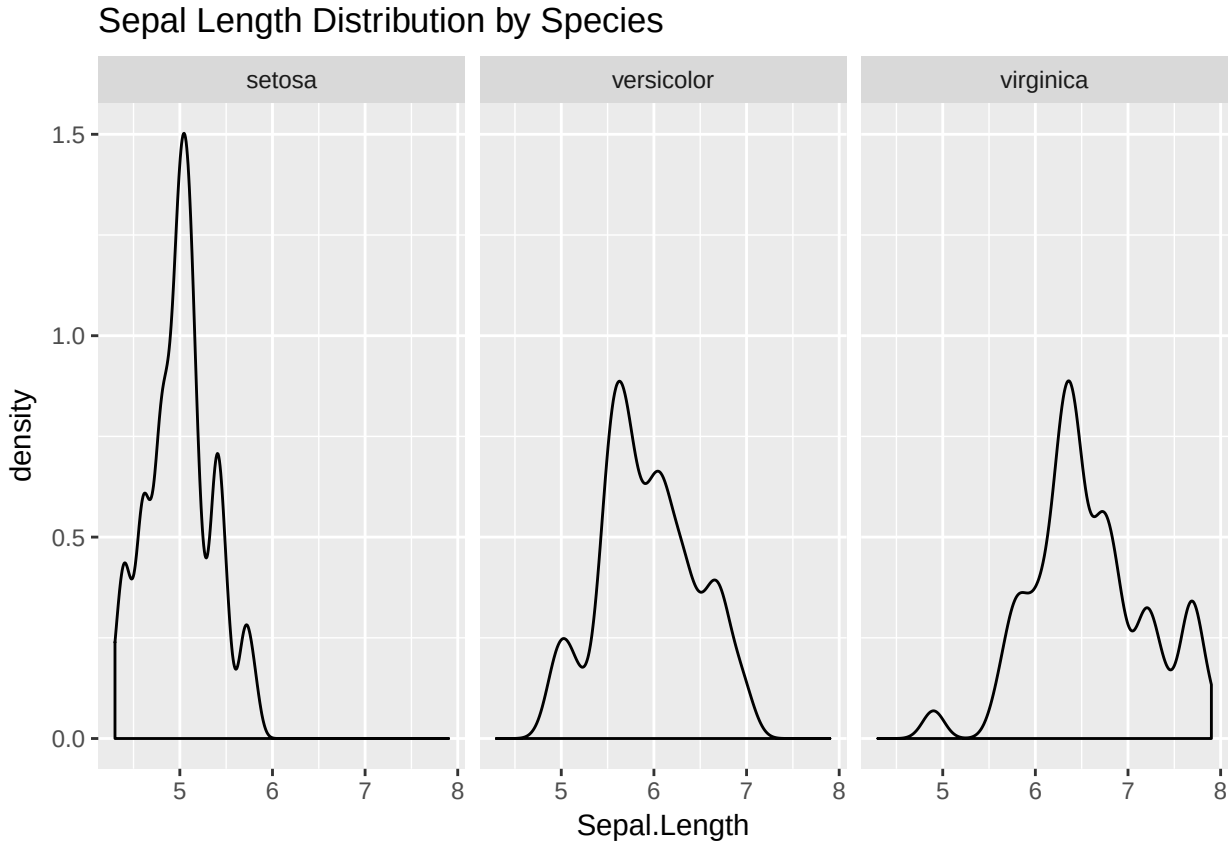
$$\hat{\Sigma}_k = \Sigma_{k=1}^K$$

$$_k(x_i - \hat{\mu}_k(x_i - \hat{\mu}_k)^T/(N - K)$$

The decision rule cast by LDA depends on x only through a linear combination of its elements. One drawback however of the LDA is the restrictive conditions associated with the algorithm. LDA assumes that features within the data set are a series of independent multivariate gaussians with identical covariance matrices. Additionally, LDA requires the number of features to be less than the sample size. As p approaches n, the performance of the model declines. If the assumption of uniform variance is highly off, then LDA can suffer high bias (Hastie, 153). When tested on the iris dataset, the LDA model had a missclassification rate of 0.0201342. Further exploratory data analysis shows that the variable sepal length does not satisfy the normality assumption across all categories. Such violations may become more apparent in a highly sparse setting.

Table 2.2: Linear Discriminant Analysis Confusion Matrix

	setosa	versicolor	virginica
setosa	50	0	0
versicolor	0	48	1
virginica	0	2	48



Chapter 3

Results

The goal of this analysis is to compare the ability of different learning algorithms tasked with text categorization. Responses have been transformed into document term matrices, accounting for the presence of each word in the description of happy moments. Five models are trained on a random sample of 8,000 observations, and one of five categories is predicted on a unlabeled test set of 2,000 responses.

3.1 Run Times

The amount of time taken to learn the 8,000 responses varied substantially across all methods. The linear SVM and decision tree were amongst the fastest trained models taking just 43.576 and 54.37 seconds respectively. The multinomial logistic was the fastest model, taking just 32.501 seconds.

The higher runtime for the random forest model follows convention given that it is an aggregation of several learning methods. The runtime of the LDA model initially came as a surprise, however LDA computes discriminant scores $\delta_k(x)$ by finding a linear combination of the independent variables. In a highly sparse setting, this becomes a linear combination of over 10,000 variables for each of the 6 categories. The training time of the SVM, decision tree, and multinomial models were quite impressive, given the nature of the problem when applied to larger data sets.

model	accuracy	runtime
SVM	0.2000	43.57646
Multinomial	0.2250	32.50130
Decision Trees	0.6430	54.37009
Random Forests	0.2565	2304.62833
LDA	0.2610	7392.19593

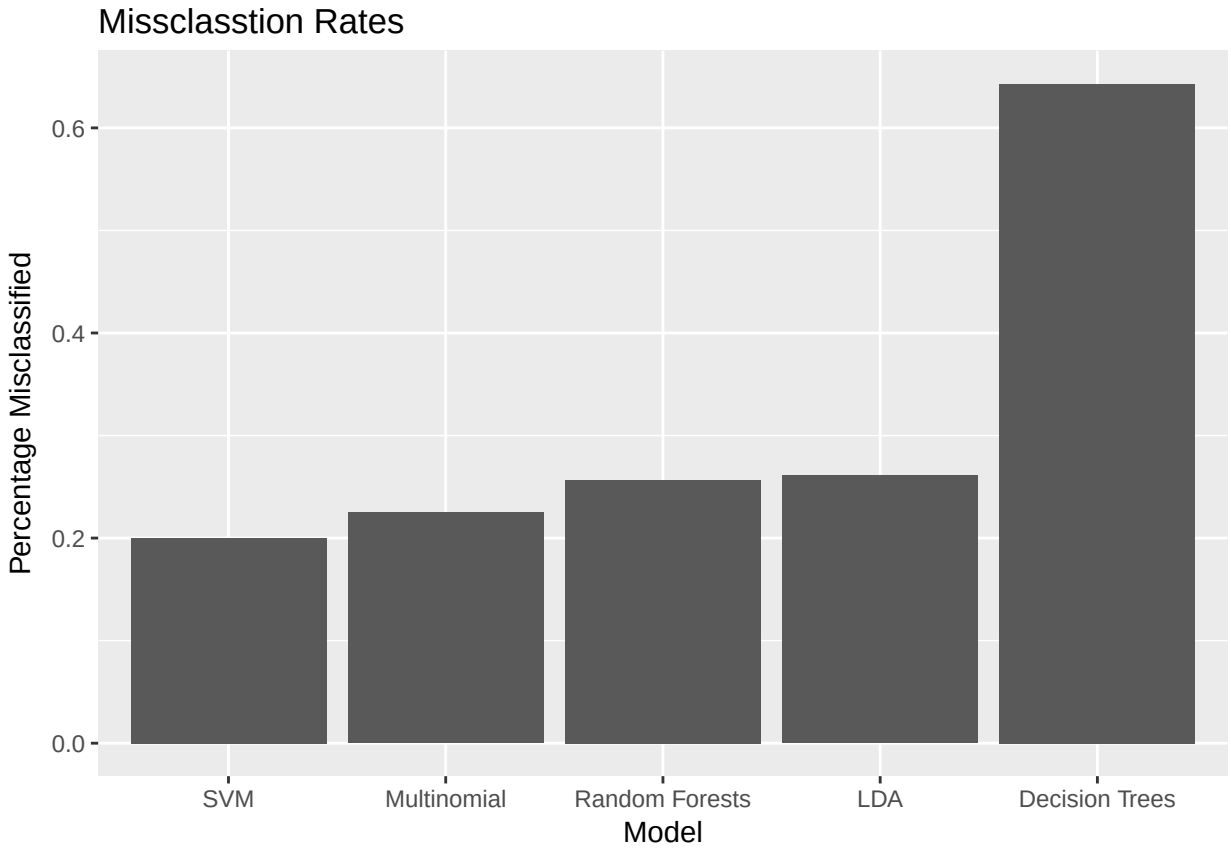


Figure 3.1: Bar Plot of Missclasification Rate

3.2 Classification Accuracy

As stated in the introduction the goal of this analysis was to compare classification error rates between models. The classification error rate is defined as the proportion of training observations in the region that do not belong to the most common class. SVMs had the lowest misclassification rate of 0.2. This was a slight improvement on the multinomial model (0.225 misclassification rate). LDA and Random Forests performed suprisingling well (0.261 for LDA and 0.256 for Random Forests). The decision tree produced the highest misclassification rate with 0.643 incorrectly categorized. Figure 3.1 shows the misclassification rates for all five algorithms tested.

While accuracy is a valid measure for information retrieval, in situations where classes are imbalanced, always predicting one class may yield a high accuracy. Precision and recall can be used to focus the evaluation on the correctly label categories (true positives). Precision is defined as the proportion of items i placed in the category correctly out of every algorithmic declaration of i, while recall is the proportion of items correctly guessed that truly belong in the category (Platt, 5). Low precision-high

Table 3.1: Precision-Recall Table for Achievement Category

	SVM_PRECISION	SVM_RECALL
SVM	0.81	0.88
Multinomial	0.64	0.96
Decision Tree	0.49	0.95
Random Forests	0.72	0.89
LDA	0.75	0.78

Table 3.2: Decision Tree Confusion Matrix

	achievement	affection	bonding	enjoy_the_moment	exercise	leisure
achievement	625	242	34	208	13	110
affection	19	400	1	1	0	2
bonding	0	20	180	2	0	0
leisure	13	16	2	5	7	62

recall systems guess a label frequently, however a significant portion of labels are incorrect. High precision-low recall systems are the opposite, predicting a class less frequently but more accurately. Ideal systems have both high precision and high recall. Table 3.1 shows precision-recall values for the category achievement, across for all 5 algorithms.

The most efficient classifier (SVM) had high precision and high recall for the category achievement. Although the decision tree predicted achievement frequently, only 0.49 were correctly labeled. Interestingly enough, this was also this case for the multinomial model, which had a low precision of 0.64 and high recall of 0.96. However unlike the decision tree, the overall misclassification rate for the multinomial was quite low (0.225% labeled incorrectly). When their confusion matrices are compared, it is immediately apparent that two classes were not predicted in the decision tree model. Due to its greedy nature, the decision tree appeared to overfit on the noise in the training data. This led to poor generalizability, and the algorithm only predicting the majority categories acheivement, affection and bonding. On the other hand, the multinomial model accurately predicted a higher proportion of the other classes.

Table 3.3: Multinomial Confusion Matrix

	achievement	affection	bonding	enjoy_the_moment	exercise	leisure
achievement	633	93	27	140	9	71
affection	16	567	5	13	0	14
bonding	1	7	183	1	0	0
enjoy_the_moment	5	5	1	58	1	2
exercise	0	0	0	0	9	0
leisure	2	6	1	4	1	87
nature	0	0	0	0	0	0

Conclusion

This experiment compares the performance of six machine learning algorithms tasked with classifying unstructured textual data. First, I discuss how the transformation of texts into document term matrices allows for words to be used as features in supervised methods. I also show how to each of the algorithms creates a classifier based on these features, and predicts labels for new data. Due to issues with reproducibility, the bagging model discussed theoretically and was not evaluated further. My results demonstrate that accurate text classifiers can be trained from relatively simple models. Following Joachim's findings, it was emprically shown that SVM models consistently outperform competing methods in precision, recall. The high number of features and sparsity of the data aided in the creation of decision boundaries cast by the SVM by relying on the fact that the features are linearly separable. Although other methods such as Random Forests and LDA had low misclassification rates, their runtimes made them poor alternatives. A more detailed look at precision and recall for the LDA model highlights how its failed assumptions impacted the accuracy of the model. Likewise, the high variance of the decision tree is evident in its high error rate.

The two most important aspects of this experiment are the structure of the data, and the assumptions of the models. Further exploratory analysis may have shown why methods like LDA were not suitable for this data. Most of the limitations are a result of the high dimensionality of the data, or its incompatiability with the algorithms. The presence of the zero value in a sparse matrix provides no information while allocating memory for each 32-bit value. A document term matrix of the entire dataset occupies 25 megabytes of space. Using 10,000 observations, a more manageable 3.1 mb document term matrix is created. While this made computations feasible, reducing the size of the corpus and document term matrix reduces the number of unique words encountered in the training data.

For future studies, it would be advisable to test other natural language processing techniques. For example, how might multi-word (n-grams), noun phrases, and weighting affect the classification accuracy? Another interesting factor to consider is

the role of dimension reduction techniques such as principal component analysis and support vector decomposition. By projecting data onto lower dimensional subspaces, these methods may alleviate some of the issues related to sparse matrices, and provide improved algorithmic runtimes.

Appendix A

Main Appendix

In the main Rmd file:

```
library(acstats)
library(RJSONIO)
library(RCurl)
library(ngram)
library(tm)
library(wordcloud)
library(ggplot2)
library(glmnet)
library(text2vec)
library(data.table)
library(magrittr)
library(dplyr)
library(mosaic)
library(RTextTools)
library(e1071)
# library(caret)
library(tidyr)
library(stringr)
library(jsonlite)
library(tidytext)
library(rpart)
library(broom)
library(kableExtra)
```

```
library(rpart.plot)
#library(MASS) #lda
```

```
#Loading Data

setwd("~/Desktop/Statistics/Comps/Comps - Fayorsey/Comps-Fayorsey19E")
data <- read.csv("cleaned_hm.csv", stringsAsFactors = FALSE)

happydb <- cbind(data[1:3,"cleaned_hm"], data[1:3,9])
colnames(happydb) <- c("Responses", "Category")
kable(happydb, caption = "Happy DB")
data$predicted_category <- as.factor(data$predicted_category)
```

```
#Creating Term Document Matrix

set.seed(7)
random_hm <- sample(1:nrow(data), 15000)
corpus    <- Corpus(VectorSource(data$cleaned_hm[random_hm]))
skipWords <- function(x) removeWords(x,
            words = c(stopwords(kind = "en"),'happy',
            'day', 'got', 'went', 'today', 'made', 'one',
            'two', 'time', 'last', 'first', 'going', 'getting',
            'took', 'found', 'lot', 'really', 'saw', 'see', 'month',
            'week', 'day', 'yesterday', 'year', 'ago', 'now', 'still',
            'since', 'something', 'great', 'good', 'long', 'thing',
            'toi', 'without', 'yesteri', '2s', 'toand', 'ing'))
funcs <- list(skipWords, stripWhitespace, removeNumbers,
              removePunctuation, tolower)
a         <- tm_map(corpus, FUN = tm_reduce, tmFuns = funcs)
a_tdm     <- TermDocumentMatrix(a)
m         <- as.matrix(a_tdm)
v         <- sort(rowSums(m), decreasing = TRUE)
d         <- data.frame(word = names(v), freq = v)
d <- head(d, 10);d
```

```
#Displaying TDM for first three observations

a_dtm <- DocumentTermMatrix(a)
wa <- as.matrix(a_dtm)


kable(wa[1:3,1:4], caption = "Term Document Matrix for First Three Responses", for
```

```
#PieChart of Categories

ggplot(data, aes(x=predicted_category, fill=predicted_category))+
  geom_bar()+
  labs(title = "Distribution of Predicted Category")+
  guides(fill="none")+
  coord_polar(theta = "y", start=0)
```

```
#Summary of wordcount

count <- sapply(data$cleaned_hm, wordcount) # Counts number of words
summary(count)
```

```
#Distribution of Word Counts

category <- c("0-4","5-9","10-14","15-19","20-24","25-29","30-34",
              "35-39",
              "40-44","45-49",">=50")
count_class <- cut(count, breaks = c(0,4,9,14,19,24,29,34,39,44,49,
              Inf),
              labels = category, include.lowest = TRUE)
ggplot()+
  geom_bar(aes(x = count_class, fill = count_class))+
  ylim(0,30000)+
  labs(x = "Word Count", y = "Number of Happy Moments",
       title = "Word Count Distribution")+
  guides(fill = "none")
```

```
#TD-IDF

words <- data %>%
  unnest_tokens(word, cleaned_hm) %>%
  count(predicted_category, word, sort = TRUE) %>%
  ungroup()

totalwords <- words %>%
  group_by(predicted_category) %>%
  summarize(total = sum(n))

words <- left_join(words, totalwords);words

tf <- words %>%
  bind_tf_idf(word, predicted_category, n);tf

tf %>%
  select(-total) %>%
  filter(n >=30) %>%
  arrange(desc(tf_idf));tf
```

```
#TD-IDF Graph

tf %>%
  arrange(desc(tf_idf)) %>%
  mutate(word = factor(word, levels = rev(unique(word)))) %>%
  group_by(predicted_category) %>%
  top_n(10) %>%
  ungroup %>%
  ggplot() +
  geom_col(aes(word, tf_idf, fill = predicted_category),
           show.legend = FALSE) +
  labs(x = NULL, y = "tf-idf") +
  facet_wrap(~predicted_category, ncol = 3, scales = "free") +
  coord_flip()
```

```
#Creating containers for models

set.seed(57)

bin_data <- data[sample(1:nrow(data), 15000), ]
my.matrix1 <- create_matrix(bin_data$cleaned_hm, language="english",
                            removeNumbers=TRUE, stemWords=FALSE,
                            weighting=tm::weightTfIdf)

container1 <- create_container(my.matrix1, bin_data$predicted_category,
                               trainSize=1:8000, testSize =8001:10000,
                               virgin = FALSE)
```

```
#SVM model

set.seed(6)
start_svm <- Sys.time()
svm_model <- train_model(container1, "SVM")
end_svm <- Sys.time()

svm_results <- classify_model(container1, svm_model)
ac_svm <- mean(svm_results$SVM_LABEL != bin_data[8001:10000,9])

table(svm_results$SVM_LABEL, bin_data[8001:10000,9])


end_svm - start_svm

pr_svm <- create_precisionRecallSummary(container1, svm_results)
```

```
#Tree Model

set.seed(1)
start_tree <- Sys.time()
tree_model <- train_model(container1, "TREE")
end_tree <- Sys.time()
```

```
tree_results <- classify_model(container1, tree_model)
table(tree_results$TREE_LABEL, bin_data[8001:10000,9])

ac_tree <- (682+363+202+39)/2000
end_tree - start_tree

pr_tree <- create_precisionRecallSummary(container1, tree_results)
```

```
#Multinomial Model

set.seed(2)
start_multi <- Sys.time()
multinomial_model <- train_model(container1, "GLMNET",
                                 family="multinomial")
end_multi <- Sys.time()

multi_results <- classify_model(container1, multinomial_model)
table(multi_results$GLMNET_LABEL, bin_data[8001:10000,9])
ac_multi <- mean(multi_results$GLMNET_LABEL != bin_data[8001:10000,9])
end_multi - start_multi

pr_multi <- create_precisionRecallSummary(container1, multi_results)
```

```
#Bagging Model

# set.seed(3)
# start_bagging <- Sys.time()
# lda_model <- train_model(container1, "BAGGING")
# end_bagging <- Sys.time()
#
# bagging_results <- classify_model(container1, lda_model)
# table(bagging_results$BAGGING_LABEL, bin_data[8001:10000,9])
# ac_bagging <- mean(bagging_results$BAGGING_LABEL != bin_data[8001:10000,9])
#
# end_bagging - start_bagging
```

```
# pr_bag <- create_precisionRecallSummary(container1, bagging_results)
```

```
#Random Forests Model

set.seed(4)
start_rf <- Sys.time()
rf_model <- train_model(container1, "RF", ntree=10)
end_rf <- Sys.time()

rf_results <- classify_model(container1, rf_model)
table( rf_results$FORESTS_LABEL, bin_data[8001:10000,9])
ac_rf <- mean(rf_results$FORESTS_LABEL != bin_data[8001:10000,9])
end_rf-start_rf

pr_rf <- create_precisionRecallSummary(container1, rf_results)
```

```
#LDA Model

set.seed(5)
start_lda <- Sys.time()
lda_model <- train_model(container1, "SLDA")
end_lda <- Sys.time()

lda_results <- classify_model(container1, lda_model)
table(lda_results$SLDA_LABEL, bin_data[8001:10000,9])
ac_lda <- mean(lda_results$SLDA_LABEL != bin_data[8001:10000,9])
end_lda - start_lda

pr_lda <- create_precisionRecallSummary(container1, lda_results)
```

```
#Runtime table

time_svm <- end_svm - start_svm

# time_bagging <- end_bagging - start_bagging
```

```
time_rf <- end_rf - start_rf

time_multi <- end_multi - start_multi

time_lda <- end_lda - start_lda

time_tree <- end_tree - start_tree

times <- c(time_svm, time_multi, time_tree, time_rf, time_lda)
accuracy <- c(ac_svm, ac_multi, ac_tree, ac_rf, ac_lda)

times <- as.data.frame(as.numeric(unlist(times)))

colnames(times) <- c("runtime")


model <- c("SVM", "Multinomial", "Decision Trees", "Random Forests",
           "LDA")

run_table <- cbind(model, accuracy, times)
```

```
#Plot of Misclassification rate

ggplot()+
  geom_bar(aes(x= reorder(run_table$model, run_table$accuracy),
               y=run_table$accuracy),
           stat="identity")+
  labs(x="Model", y="Percentage Misclassified",
       title="Missclasstion Rates")+
  guides(fill="none")
```

```
#Precision Recall Table for achievement category

pr_table <- rbind(pr_svm[1,], pr_multi[1,], pr_tree[1,], pr_rf[1,],
                  pr_lda[1,])
```

```
rownames(pr_table) <- c("SVM", "Multinomial", "Decision Tree",
                        "Random Forests", "LDA")

pr_table
```

```
#Decision Tree Confusion Matrix

table(tree_results$TREE_LABEL, bin_data[8001:10000,9])
kable(table1[,1:6], format= "latex", caption=
        "Decision Tree Confusion Matrix \\label{tab:treeconfusion}")
```

```
#Multinomial Confusion Matrix

table(multi_results$GLMNET_LABEL, bin_data[8001:10000,9])
kable(table2[,1:6], format = "latex", caption =
        "Multinomial Confusion Matrix \\label{tab:multi}")
```

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