Improving Workplace Accident Fatality Classification Models with Text Mining and Ensemble Methods

Thomas S. Wilk, Jr.

A Thesis

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science in Data Mining

Department of Mathematical Sciences

Central Connecticut State University

New Britain, Connecticut

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Thesis Advisor:

Dr. Daniel T. Larose

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Key Words: Data Mining, Text Mining, Predictive Modeling, Natural Language Processing, Ensemble Methods, Python, IPython Notebook, Pandas, Scikit-Learn

ABSTRACT

Using publically available OSHA accident investigation data and open source Python scientific computing tools this applied research project asserts the value of exploiting all types of data available when constructing predictive models. The goal of this project was to build the best classification model of accident outcome, either fatal or non-fatal, using data available for catastrophic accident investigations conducted by OSHA over the last few decades. Multiple feature sets were engineered using a variety of techniques that leveraged all types of data available, including structured, semi-structured and unstructured accident attributes.

This thesis proposes that features mined from each accident's text-based attributes will capture concepts and information that are not present in each accident's structured data attributes and that this infusion of new information will enable classification algorithms to better discriminate between fatal and non-fatal accidents, thereby improving model accuracy. Baseline classification models of accident outcome were trained on a feature set created from the structured accident attributes only. With the goal of improving baseline classification accuracy, a variety of text mining and data mining techniques were employed to create statistics-based and linguistics-based feature sets from accident keywords, descriptions and summaries. These efforts resulted in a measurable improvement in model accuracy.

This thesis also asserts the value of ensemble methods and proposes that combining multiple predictive models trained on the same feature set will obtain better performance than could be obtained from any of the component models independently. Ensemble methods in the form of voting models and mean response probability models capitalized on a confluence of results from multiple classifiers. Classifiers that internalized boosting techniques and ensemble

learning, such as AdaBoost and Random Forest, were also utilized. Finally, combined feature sets composed of top performing predictors selected across the various text-based and structured data feature sets engineered in this thesis provided the greatest lift to model accuracy.

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INTRODUCTION

Statement of Purpose

The primary purpose of this study was to conduct applied research using publically available data that combined text mining and machine learning, two related areas of academic and professional interest. Mining features from unstructured data to enhance the performance of predictive models built initially upon structured data only was a topic expected to be of considerable interest amongst members of the data mining community. A parallel purpose was to implement all phases of the analysis with freely available open source data mining tools, and by doing so demonstrate their viability as an alternative to proprietary applications. The Python scientific computing ecosystem comprises a set of powerful and flexible tools that were selected to implement this thesis. All project phases, including data wrangling, data analysis, machine learning and visualization, were implemented with Python based tools. The result of using publically available data and free, open source tools to conduct this particular project is a completely transparent, accessible and (hopefully) interesting thesis. In this spirit, project code, imperfections and all, are available to the reader should he or she desire to improve, reproduce or leverage any aspect of this project. All assets created to implement this thesis, in the form of IPython Notebooks and a single Python code module, are accessible by the reader at an online public GitHub repository.

In 1970, the Unites States Congress created the Occupational Safety and Health Administration (OSHA), a national public health agency dedicated to the basic proposition that no worker should have to choose between their life and their job. OSHA's mission is "to assure safe and healthful conditions for working men and women by setting and enforcing standards and providing training, outreach, education and compliance assistance." [*All About OSHA*]. To

enforce standards OSHA conducts approximately 100,000 inspections annually and conducts investigations when catastrophic workplace accidents occur. Datasets comprising inspection and accident investigation case detail are made available to the general public via the U.S. Department of Labor's Data Enforcement website [*OSHA Enforcement Data*]. The inspection dataset "includes information regarding the impetus for conducting the inspection, and details on citations and penalty assessments resulting from violations of OSHA standards." The accident investigation dataset includes "textual descriptions of the accident, and details regarding the injuries and fatalities which occurred. " The OSHA accident data is stable, voluminous, of high integrity, and publically available. Each accident contains a robust set of attributes that provide a mix of structured, semi-structured and unstructured data types. The OSHA accident data was well suited for a combined application of machine learning and text mining techniques, and was an ideal dataset for this thesis.

The goal of this project was to build the best classification model of accident outcome, either fatal or non-fatal, given a workplace accident occurred and was investigated by OSHA. Multiple feature sets used to model accident outcome leveraged all types of data available, including structured, semi-structured and unstructured accident attributes. Although not as actionable in its raw form, the unstructured data, after being pre-processed, transformed and optimized for modeling, was expected to embody new information not present in the structured data that would improve classification model performance beyond that of models built with the structured data only. This is in fact the central research question and project challenge.

Stated Hypothesis/Research Questions

The central hypothesis of this thesis is that features mined from each accident's text-based attributes would capture concepts and information that were not present in each accident's structured data attributes and that this additional information would enable classification algorithms to better discriminate between fatal and non-fatal accidents, thereby improving model accuracy. Stated as a question,

> **Research Question One:** Will inclusion of features mined from unstructured data attributes associated with each accident improve the accuracy of predictive models constructed with structured accident data attributes only?

Initial exploration of the OSHA accident data as a foundation for this thesis revealed that answering this question and validating the hypothesis would not prove to be a straight-forward task. OSHA has been in operation for decades. Their efforts have decreased workplace accidents and fatalities over time and have contributed to safer workplace conditions for all employees in most industries. Analysis of data collected routinely by OSHA enables identification of the causes of catastrophic workplace accidents and the detection of emerging trends. As would be expected, the accident and injury data captured by OSHA was comprehensive along multiple dimensions. Using a data mining platform of choice and a minimal investment of time, a proficient practitioner is able to download the structured accident data, apply minimal transformation, and generate predictive models that classify accidents as fatal or non-fatal with accuracy rates of 80%+ on a test holdout set. Although the text-based OSHA accident data was ideally suited for an application of predictive text mining techniques, the structured data attributes on their own were already strong

predictors of accident outcome. Features mined from the text-based accident data would not be expected to prove their worth easily. Although a cause of initial hesitation, the OSHA data was ultimately selected for his thesis precisely because the structured variables were so information-rich. Top performing models fit to structured data features only would provide solid baselines from which to gauge the efficacy of models infused with features derived from unstructured text.

Ensemble methods combine multiple predictive models to obtain better performance than could be obtained from any of the component models independently. Ensemble methods in the form of voting models and mean response probability models capitalize on a confluence of results from multiple classifiers. Combined feature sets that leverage top predictors from constituent feature sets are another example of ensemble methods. Additionally, classification models, such as AdaBoost and Random Forest classifiers, internalize boosting techniques and ensemble learning to achieve greater predictive gains. The secondary hypothesis of this thesis was that application of ensemble methods, in the three forms stated above, would in fact provide additional lift to classification model performance. Stated as a question,

> **Research Question Two:** Will a confluence of model results from different classification algorithms trained on the same feature set, each independently deployed to address the challenge of research question one, produce more accurate classifications of accident outcome in concert than on their own? Additionally, will the combination of top-performing predictor variables from statistics-based text mining feature sets, a linguistics-based text mining feature set and the structured data feature set achieve yet more gains?

Statement of Need

The proprietary nature of successful text mining and machine learning models deployed by for-profit organizations tends to inhibit their publication. Likewise, the cost associated with proprietary data mining applications tends to limit their ownership and broad usage by individuals. By contrast, this study offers up a transparent application of text mining and machine learning methods, using publically available datasets of a serious nature, implemented with software that any individual can download and use. This author believes that veteran data miners and newcomers alike can benefit from exposure to this project and the publication of its code, methodology and results. This project is a small contribution of thanks to the open source data science community whose hard work made it possible.

Related Research

This thesis is an application of mainstream data mining and text mining techniques. There is nothing exotic or controversial happening here. Related research for this project can be segmented into three categories. The first category was comprised of Python scientific computing books, documentation and tutorials. The second category was comprised of eight foundational data mining, text mining and natural language processing books. A plethora of online, open-source publications, examples, tutorials, question-answer forums and blogs comprised the third category.

A large chunk of background research required an investment of hundreds of hours of learning to implement in the Python scientific computing environment general data analysis and predictive modeling techniques implemented by this author in past projects using proprietary applications such as Excel, SQL Server and IBM SPSS Modeler. An additional investment of

time was required to learn how to leverage advanced functionality that distinguished the Python scientific computing environment from other applications. Appendix A lists the various resources and packages that comprised the scientific computing ecosystem of the Python programming language used in this thesis. These resources were utilized to implement all project phases. Scikit-learn, a machine learning library, and Pandas, a data analysis toolset, were two Python resources that were used extensively in this project and required a considerable investment of time researching and hacking to earn a level of modest proficiency required to implement most phases of this project. One awesome benefit of the open source nature and popularity of the Python ecosystem is freely available software, online documentation, tutorials and examples. In lieu of citing resources here, the interested reader is encouraged to follow the links provided in Appendix A, or conduct a quick web search, to learn more.

Foundational data mining, text mining and natural language processing textbooks provided guidance for the various techniques, decisions and approaches used in this analysis. In the data mining category were two general data mining books authored by Daniel Larose and a machine learning book implemented in Python and authored by Willi Richert. In the text mining category were two text mining books authored by Sholom Weiss, et al., a text mining book authored by Roger Bilisoly, and a text mining book authored by Gary Miner, et al. On the natural language processing front was a book written by the authors of the Natural Language Toolkit, a popular Python NLP resource.

Data Sources

The main sources of data used in this project were publically available files downloaded from the U.S. Department of Labor's Data Enforcement website, OSHA Enforcement Data page [*OSHA Enforcement Data*]. The OSHA data used in this project was last refreshed in early November 2013. The interested reader is encouraged to navigate to the site to learn more about the OSHA datasets, to query and browse accident case detail, and to download the actual data files used in this thesis, if desired. A dozen or so files were available for download. The files spanned four main categories: violations, inspections, accidents and metadata. This study focused on the three accident investigation datasets only. One additional publically available online resource used in this project was the SentiWordNet file. SentiWordNet is a lexical resource for opinion mining that assigns to each synset of WordNet three sentiment scores: positivity, negativity, objectivity [*SentiWordNet]*. SentiWordNet was leveraged to extract linguistic features from accident text summaries.

Table 1 below is a snapshot of output for a selected accident from OSHA's online Accident Search tool. Although not a complete representation of all attributes available for each accident, the main types of data used in this analysis are present. Examples of structured data attributes that comprised the Structured feature set are the *Event Date* and categorical variables such as *Occupation* and *Nature of Injury*. Many other structured data fields existed in the raw accident investigation files beyond that which is shown here. The *Keywords* field included with each accident is a great example of semi-structured data.

Table 1: Example Accident Investigation Summary

Accident Investigation Summary				
Summary Nr: 508937	Event: 08/11/1997	Employee Drowns While Scuba Diving		
While Employee #1 was SCUBA diving in approximately 120 feet of water, using equipment that was marginally/poorly maintained, his high pressure hose was inadvertently cut and he drowned. Causal factors include: no standby diver was available to render assistance; Employee #1 was not line tended; Employee #1 was not wearing a required personal flotation device; and no supplemental air supply was provided.				
Keywords: inadequate maint, scuba, diving, severed, drown, water, work rules, air hose, diver				
	Inspection	**Degree**	**Nature**	**Occupation**
1	301494159	Fatality	Other	Occupation not reported

The number of keywords and keyword categories vary considerably across accidents but there is still a pattern that one quickly intuits – each keyword associated with an accident is separated by commas. Transformation of the list of keywords needs to be performed before the keywords can be leveraged for modeling. The transformed keywords across accidents comprised the Keyword feature set. Each accident contains two unstructured data fields, the *Event Description* and *Text Summary*. The short phrase on the top right, the *Event Description*, contains a brief description of each accident. The center box, the *Text Summary*, contains a lengthier, more detailed description of each accident. More effort will be required to extract features from these unstructured text fields to use as predictors during the modeling phase. The *Degree of Injury* field represents the target variable. Note the unique accident and inspection identifier numbers on the left side corners. These identifiers were not used as modeling input variables but were retained on all records throughout the analysis and provided reference back to specific accidents.

Online Project Repository

All project datasets, Python code and IPython Notebooks are posted at a freely available public GitHub repository created especially for this project and will remain there indefinitely. The interested reader can view all project IPython Notebooks online via links provided below. A zip file of all project assets can be downloaded from the repository homepage with one simple click. Provided that a compatible Python distribution with the requisite packages listed in Appendix A is installed on a local computer, the interested reader can execute, modify and extend this project in its entirety. The Anaconda Scientific Python Distribution used for this project is freely available to download and comes preloaded with most of the requisite packages. Additional posts on the project wiki, accessible from the homepage, will provide guidance on execution of all project resources in the correct sequence.

Project repository homepage

https://github.com/tswilk/ccsu-thesis-project-osha

IPython Notebook links

https://github.com/tswilk/ccsu-thesis-project-osha/wiki/Links-to-view-IPython-Notebooks-online

Anaconda Scientific Python Distribution

https://store.continuum.io/cshop/anaconda/

ANALYSIS

Structured Feature Set

Section IPython Notebook link: osha_01_structured_feature_set.ipynb

The goal of this section was to transform the raw OSHA data files into a single feature set with one row per accident, or observation, and carefully selected features, or predictor variables, as columns, in preparation for subsequent modeling efforts. The predictor variables were fashioned out of the raw structured data attributes. Feature sets created in subsequent sections leveraged the raw semi-structured and unstructured accident attributes. Additional actions were taken to filter out accident observations and accident attributes not suitable for modeling, create new, more optimal features based on existing features, replace codes with meaningful labels and address missing values.

The files *osha_accident.csv* and *osha_accident_injury.csv,* located on the project repository page, were downloaded from the OSHA website in early November 2013. The Accident file contained one row per accident and multiple attributes that pertained to the accident. The Injury file contained multiple rows per accident, one for each injured person involved in each accident, along with attributes of the injury. The manually created file, entitled *osha_code_map.csv*, also housed on the project repository, provided a mapping of codes to descriptions for fields relevant to this analysis and was used to replace codes present in the raw data fields with more legible and meaningful descriptions.

The raw Accident file comprised 103,771 accidents over the last 40 years. Each accident contained a field indicating fatality or non-fatality. This field was transformed into a binary

indicator (1=fatal accident, 0 = non-fatal accident) and served as the target variable throughout the analysis. Figure 1 is a histogram of accidents by year with outcome overlay. Note the large jump in the number of accidents between 1989 and 1990, with no significant trend in the years leading up to 1989 and the years following 1990. Documentation on the OSHA website indicated that data for accidents occurring in 2008 and prior were fully represented in the online datasets but not so for accidents that occurred in 2009 and later. This explained the steep drop in total accidents for years 2009 to 2012, as the most current years were most incomplete. The normalized histogram of accidents by event year depicted in Figure 2 indicated a very slight downward trend in the proportion of fatal accidents. This trend may be due to a delay in the reporting of more serious, fatal accidents. Despite this potential systematic difference, a decision was made to partition data from the incomplete years of 2009 to 2012 into a validation holdout set and to use data from years 1990 to 2008 for training and testing classification models.

Figure 1: Histogram of Accidents by Year with Outcome Overlay

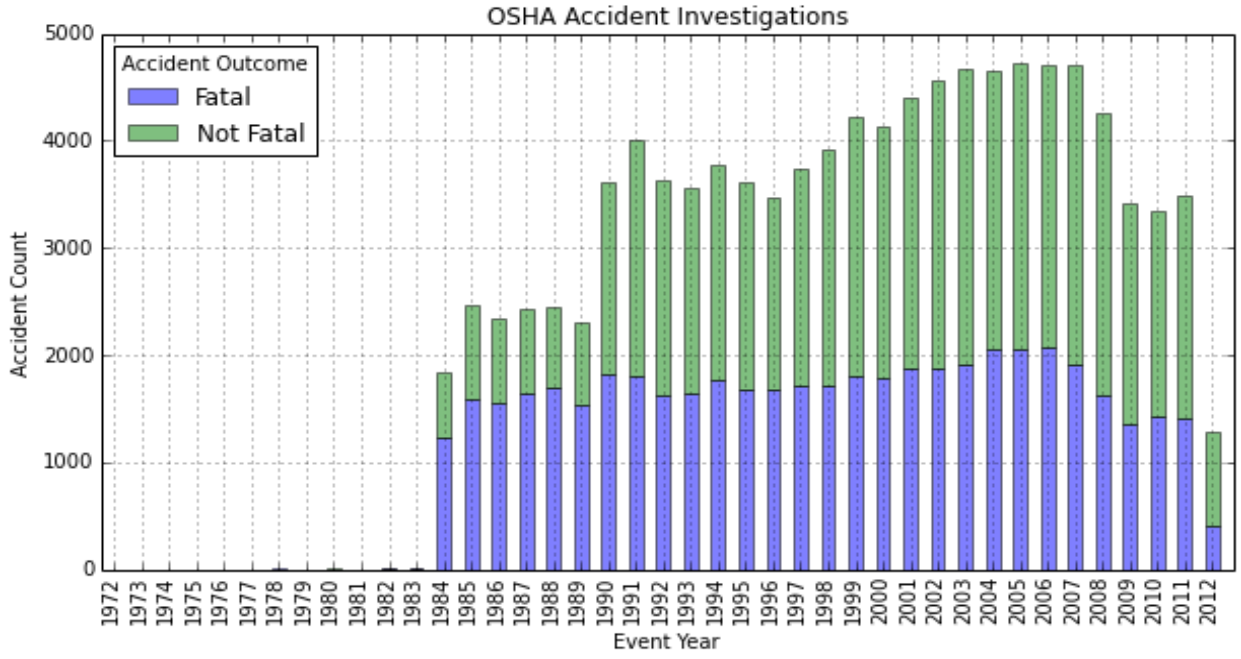
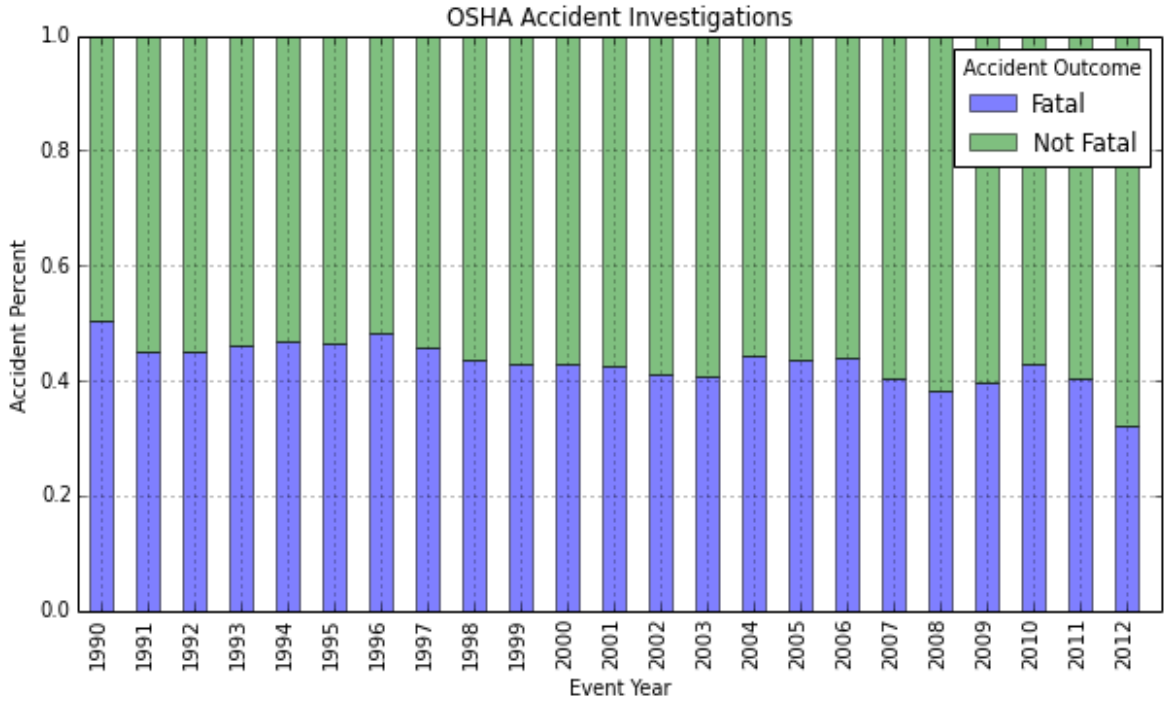


Figure 2: Normalized Histogram of Accidents by Year with Outcome Overlay



A few more data preparation steps were taken to refine the raw Accident data. A trinary variable with values of fatality, hospitalization and non-hospitalization was dropped as it was a proxy for the fatality indicator and the focus of this project was binary classification of accident outcomes as fatal or non-fatal. Time based variables *event year*, *event month*, *event weekday* and *event hour* were derived from the raw *event date* timestamp. SIC codes were replaced with SIC descriptions. Empty accident variables, unnecessary variables, and variables that did not contain information relative to the majority of accidents were omitted. This step excluded a set of variables pertaining to construction specific accidents that would likely be of interest for projects with a construction segment focus. Finally, the semi-structured and unstructured fields associated with each accident were temporarily omitted for purposes of the Structured feature set, but were utilized in the construction of text-based feature sets in later sections.

The raw Injury file comprised 130,410 injuries. Injury data associated with accidents out of scope were immediately filtered out. Table 2 provides statistics on the number of injuries per accident. A decision was made to retain accidents with single injuries and exclude accidents with two or more injuries. This action removed 7.8% of the total recorded accidents from 1990 to 2012. Note that 43% of all single-injury accidents were fatal. Not having to accommodate multiple injuries per accident simplified the construction of the Structured feature set, as single rows of accident data and injury data could be merged into one observation easily.

Table 2: Number of Injuries per Accident Distribution

Number Injuries Per Accident	Accident Count	Portion Total Accidents	Average Fatalities
1	82,840	92.2%	0.43
2	4,130	4.6%	1.08
3	1,356	1.5%	1.36
4	578	0.6%	1.68
5	282	0.3%	1.74
6	168	0.2%	1.75
7	122	0.1%	2.35
8	70	0.1%	2.06
9	62	0.1%	2.47
10	67	0.1%	2.39
11	30	0.0%	2.57
12 to 153	190	0.2%	6.14

A few more data preparation steps were taken to refine the raw Injury data. Injury variables that contained information relative to a minority of accidents, such as construction specific variables, a hazardous substance variable associated with a subset of accidents, and fall

distance metrics, were omitted. Clearly, projects with a more narrow focus could likely benefit from inclusion of these variables. The *age* and *sex* variables were dropped as they contained unary values of zero and null, respectively. Eight injury attributes were retained and their coded values were mapped to descriptions. Finally, 939 observations were dropped due to missing codes, and therefore missing descriptions, for all injury attributes.

The next step was to merge the retained accident and single injury attributes into a single feature set with one record per accident. The resulting table of 81,874 single-injury accidents formed the basis of the Structured feature set after data preparation. A few more transformations were applied during the upcoming exploratory data analysis phase prior to modeling. Table 3 below depicts a sample record from the feature set.

All predictor variables that comprised the Structured feature set were categorical or binary in nature. For exploratory data analysis histograms, heatmaps, distribution charts and bar charts were generated to help gauge how useful the categorical variables might prove to be as predictors of accident outcome. The target variable was included as a graphical dimension to aid diagnosis. A review of all visualizations suggested that the majority of categorical variables and indicators would likely be useful as predictors of accident outcome.

Table 3: Sample Record from the Structured Feature Set After Data Preparation

Full Name	Variable Name	Typical Variable Value
Accident ID Number	summary_nr	508937
Fatality Indicator	fatality_ind	1
Event Timestamp	event_ts	8/11/97 10:30
Event Year	event_year	1997
Event Month	event_month	8
Event Weekday	event_weekday	0
Event Hour	event_hour	10
SIC Description	sic_desc	Amusement and Recreation Services
Inspection Number	rel_insp_nr	301494159
Nature of Injury	nature_of_inj	OTHER
Part of Body	part_of_body	LUNG
Source of Injury	src_of_injury	WATER
Event Type	event_type	CARD-VASC/RESP FAIL.
Environmental Factor	evn_factor	OTHER
Human Factor	hum_factor	PERCEPTION MALFUNC,TASK-ENVIR.
Occupation Code	occ_code	Occupation not reported
Task Assigned	task_assigned	TASK OTHER THAN REGULARLY ASSIGNED
OSHA Detail URL	osha_detail_url	Accident Detail Link

Figures 3 and 4 depict heatmaps for two selected categorical variables. The number of fatalities by accident year and categorical value are represented by color, with darker colors indicating higher fatality counts. Similar visualizations for the other categorical variables can be viewed within the IPython Notebook accompanying this section. Injuries with an *Event Type* of 'Struck By' are the top cause of fatalities, followed by 'Fall (From Elevation)' and 'Caught In Or Between'. The remaining event types vary by the number of fatalities over time. The last five event types appear to rarely result in fatality, if at all. It is interesting that the greatest number of fatalities for *Source of Injury* was attributed to an 'Other' category. Accidents involving motor vehicles were the next greatest source of fatalities.

Figure 3: *Event Type* Heatmap

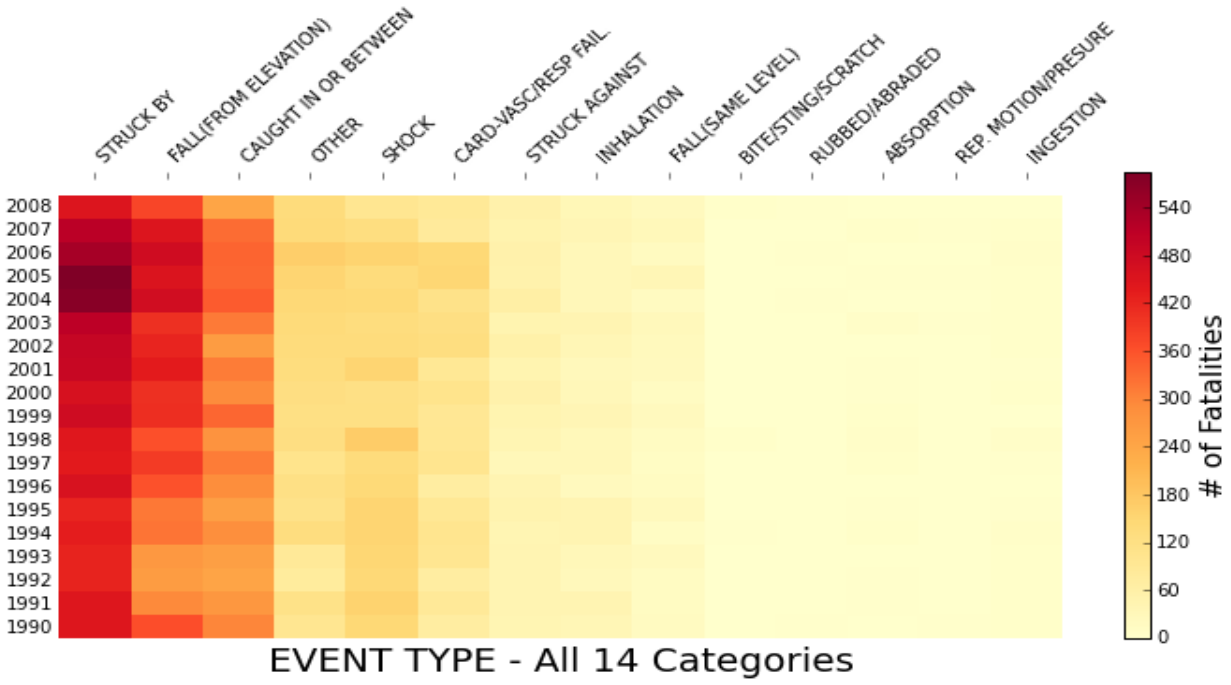
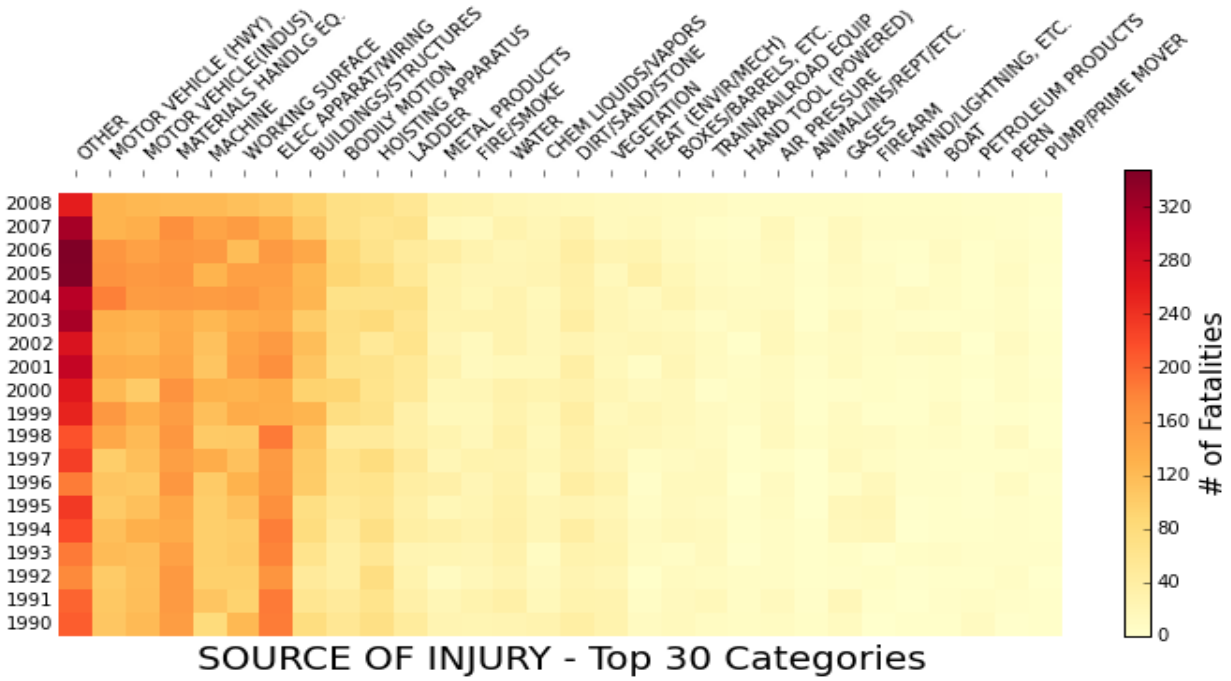


Figure 4: *Source of Injury* Heatmap



Figures 5 and 6 depict bar charts of the number of accidents across all years with outcome overlay for two selected categorical variables. A normalized distribution of accidents by outcome accompanies each bar chart to help discern the proportion of fatal and non-fatal outcomes by category. The top ten categories are shown separately with remaining categories aggregated into a single category. The proportion of fatalities varied significantly across categories for both the *Nature of Injury* and *Part of Body* variables. These variables were expected to aid classification models to discriminate between accident outcomes. Again, similar visualizations for the other categorical variables can be viewed within the IPython Notebook accompanying this section.

Figure 5: *Nature of Injury* Distribution Chart

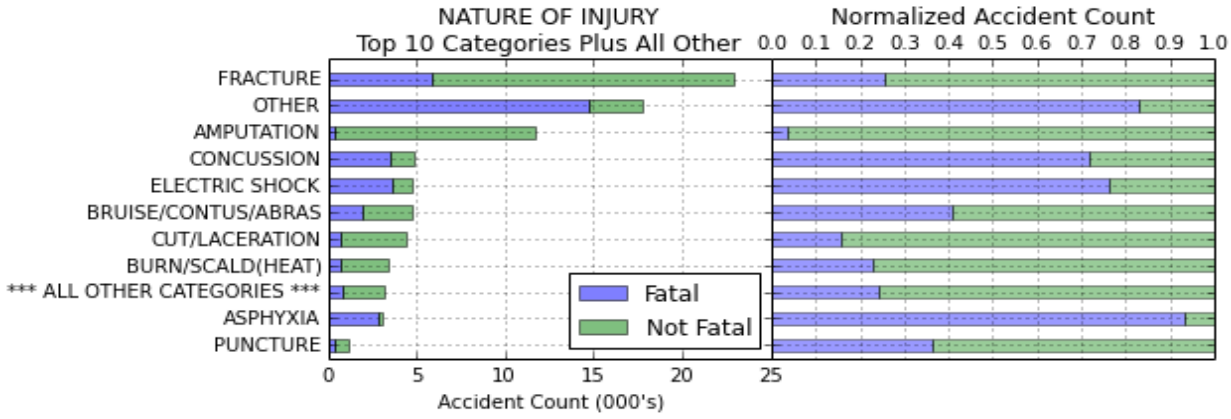


Figure 6: *Part of Body* Distribution Chart

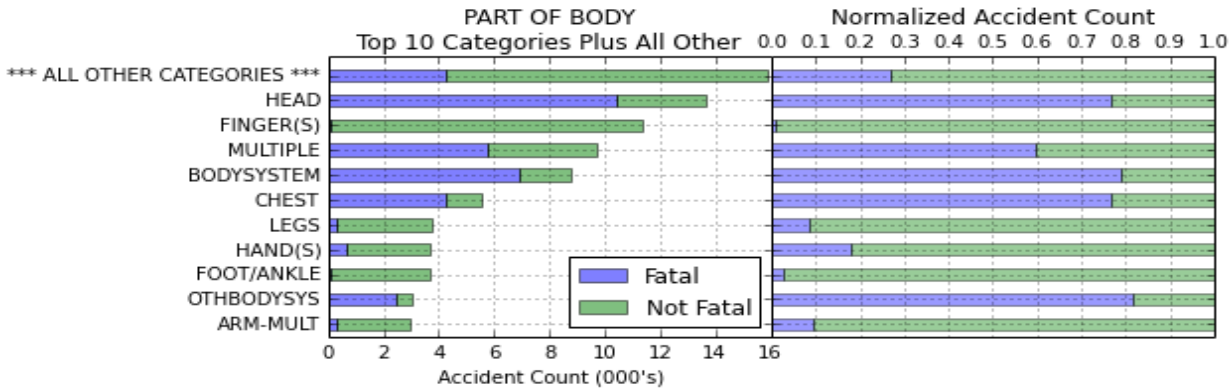


Figure 7 depicts histograms of the time variables *year, month, weekday* and *hour.* A normalized histogram with accident outcome overlay accompanies each plot. Although the number of accidents peaks during the summer and early fall, the proportion of accidents that result in fatality is fairly constant throughout the year. The number of accidents and proportion of fatal accidents is level during the weekdays with the fewest accidents occurring on Friday. Although the number of accidents on weekend days is less than half of accidents that occur on weekdays the proportion of fatalities given an accident occurred is slightly greater. As would be expected most accidents occur during daytime working hours with a lull during the noontime lunch hours. The fewest accidents occur during the early morning hours with slightly more occurring during the late evening hours. The spike in accidents at midnight is due to a large portion of accidents with accurate dates but without accompanying time information. A decision was made to not adjust for this feature.

Additional actions were taken as a result of exploratory data analysis to prepare the Structured feature set for modeling. The *year* and *month* variables were dropped. The *weekday* variable was transformed into a binary *weekend indicator* (1=weekend, 0=not weekend). The two-state categorical variable *task assigned* was transformed into a binary *regular task indicator* (1=regular task, 0=not regular task). Figure 8 depicts plots of the binary indicator values for the two newly transformed variables by average fatality.

Figure 7: Time Variable Histograms with Accident Outcome Overlay

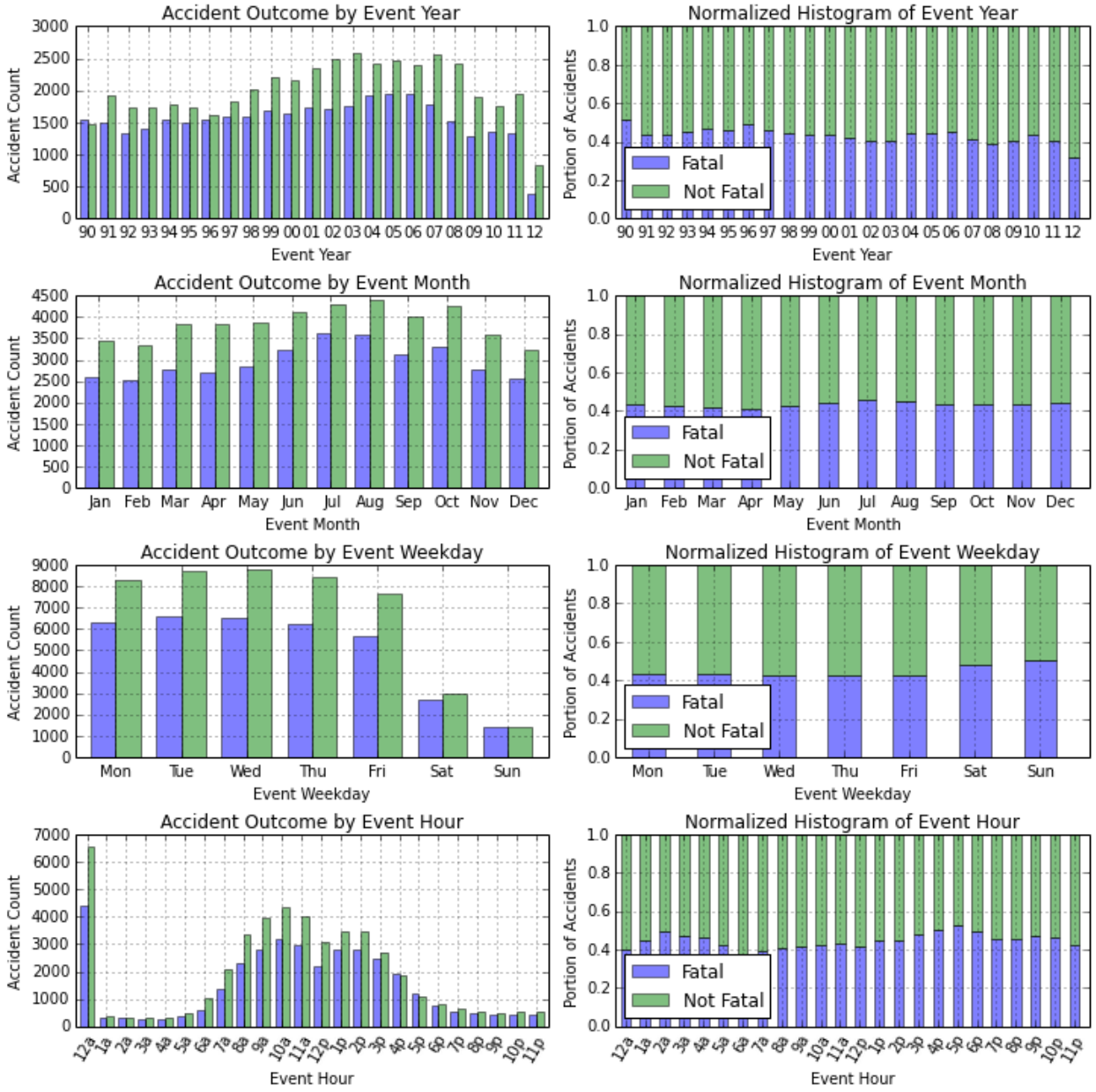
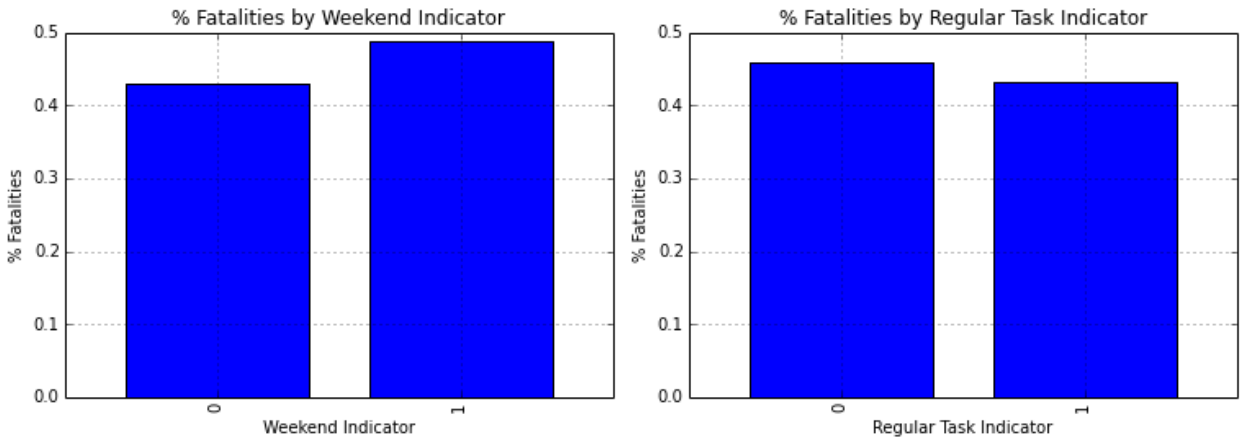


Figure 8: Binary Indicator Variables



The final Structured feature set for modeling contained 263 predictor variables spanning 81,874 accident observations. The predictor variables were comprised of the nine categorical variables converted into 261 binary indicators and the two binary variables *weekend indicator* and *regular task indicator*. Transforming each categorical feature with *m* possible values into *m* binary features, with only one active, was necessary as the classification algorithms used in this project required continuous input variables. The categorical variables are listed in Table 4 along with the number of distinct values that equated to the number of binary indicators created for each variable. Each observation contained a binary target variable indicating whether the accident resulted in a fatality or not. This was the target variable. Classification models will attempt to predict whether or not a fatality occurred given the set of predictor variables provided for each accident.

Table 4: Categorical Variables Transformed Into Flag Indicators for Modeling

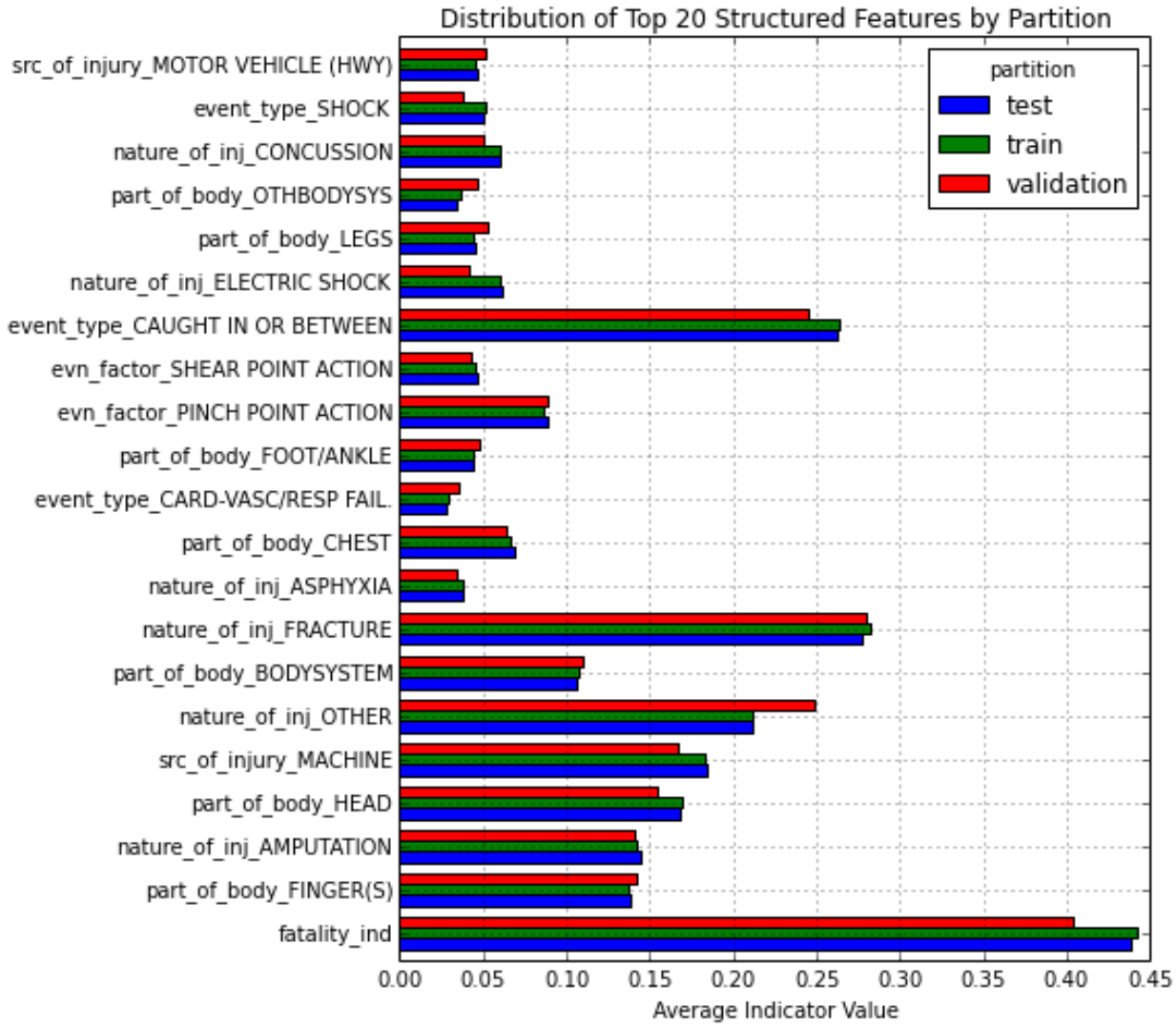
Categorical Variable	Distinct Values
Part of Body	31
Environmental Factor	18
Event Type	14
Event Hour	24
Human Factor	20
Nature of Injury	22
SIC Group	84
Source of Injury	48

At this point data preparation and EDA was performed on the Structured feature set and the structured data predictors and target variable were set and stable. Before modeling accident outcomes with the Structured feature set, partitioning the feature set into a train, test and validation set was indicated. Due to the information-rich nature of the feature set, and to guard against model over-fitting, a 30% / 70% train and test set partition was selected. Recall that accidents from years 2009 to 2012 were earmarked to serve as a holdout validation set. After setting the validation set accidents aside, the train and test partitions comprised 71,101 accidents in total. Accidents were randomly assigned to train and test partitions based on the 30% / 70% split. The data was split relatively evenly with respect to the target variable as indicated by the mean percentage of fatal accidents across partitions in Table 5. To ensure that distributions of variables across the train and test set were similar, the top 20 most important features were selected by computing ANOVA F-value statistics between each binary predictor variable and the binary target variable. Figure 9 depicts a similar distribution of the top 20 features and fatality indicator across the train, test and validation partitions as measured by each feature's average indicator value.

Table 5: Distribution of Accidents into Train, Test and Validation Partitions

Partition	Accident Count	Percent Fatalities
Train	21,331	44.2%
Test	49,770	43.8%
Validation	10,773	40.4%
Overall	81,874	43.5%

Figure 9: Similar Distribution of Top Features Across Train and Test Partitions



Five classification algorithms were employed in this project for model training of all feature sets. These algorithms were selected for their speed and for their availability within the *scikit-learn* machine learning library. For simplicity and for consistency across all feature sets, the *scikit-learn* default model configurations for each classification model were selected. Table 6 lists the five classification algorithms, the short name used to refer to each classifier throughout the remainder of this analysis, and a brief description.

Table 6: Classification Models

Classifier	Brief Description
Descision Tree (Dtree)	Non-parametric supervised learning method often used for classification. The algorithm generates a model that predicts outcomes of new input cases by learning simple decision rules inferred from the dataset features the classifier was trained on.
AdaBoost (AdaBst)	Popular boosting algorithm used for classification that fits a sequence of weak learners on repeatedly modified versions of the training data. Examples of weak learners are small decision trees and other simple models that perform only slightly better than random guessing. The algorithm is inherently an ensemble method as the multiple predictions generated internally are combined through a weighted majority vote to produce a final prediction.
Random Forest (RanFst)	Another popular algorithm that internalizes an ensemble learning method for classification. The algorithm fits a multitude of decision tree classifiers on various sub-samples of the training dataset and uses averaging to improve the accuracy of its predictions.
K-Nearest Neighbors (KNN)	Instance-based learning algorithm often used for classification. K-Nearest Neighbor classifiers find a predefined number of training samples and predict each test case outcome as a function of the k nearest training sample outcomes.
Logistic Regression (LogReg)	Well-known probabilistic statistical classification model often used to predict a dichotomous outcome with continuous predictor variables.

Two types of combination models were generated during the modeling phase of each feature set based on the aggregated test results of the five base classification models:

- The voting models counted the number of fatal accident predictions from each of the five base models for each accident test case and predicted fatality if the count of fatal predictions was equal to or greater than a set number of models. The voting model with threshold of 4+, for example, predicted fatality if 4 or 5 of the models predicted fatality, and predicted non-fatality otherwise. To identify the optimal threshold, five models were generated with thresholds 1+, 2+, 3+, 4+ and 5.

- The mean response probability models (MRP) capitalized on the confidence measures, between 0 and 1, which each model delivered with its predictions. The MRP model with threshold 40, for example, predicted fatality if the average confidence in fatal predictions for a given accident test case from each of the five classification models was greater than or equal to 0.40, and predicted non-fatality otherwise. To identify the optimal threshold, eleven models were generated with MRP thresholds of 25 to 75 incremented by 5.

Each of the five classification algorithms was fit to the train partition data of the Structured feature set and evaluated on the test partition data. Table 7 lists the eight evaluation metrics computed, along with their definition. Model evaluation statistics for the five base classification models and top performing combination models are summarized in Table 8.

Table 7: Classification Model Evaluation Metrics

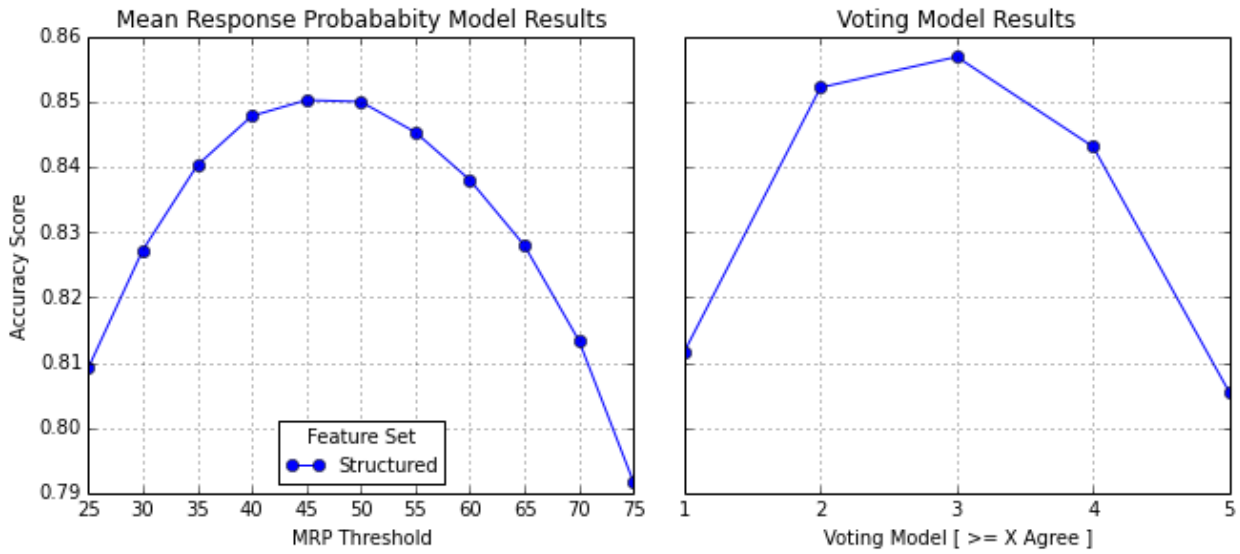
Classification Model Evaluation Metric	Evaluation Metric Definition
Accuracy	Number of correct accident outcome predictions divided by the number of total accident outcomes.
True Negative (TN)	Number of test cases where the accident outcome was non-fatal and the model predicted non-fatal.
False Negative (FN)	Number of test cases where the accident outcome was fatal and the model predicted non-fatal.
False Positive (FP)	Number of test cases where the accident outcome was non-fatal and the model predicted fatal.
True Positive (TP)	Number of test cases where the accident outcome was fatal and the model predicted fatal.
Precision	Positive predictive value (PPV) TP / (TP + FP)
Recall	True positive rate or sensitivity TP / (TP + FN)
F Measure	Combined measure of precision and recall (evenly weighted)

Table 8: Base Model and Combination Model Results

Model Name	Accuracy	Precision	Recall	F Measure	TN	FN	FP	TP
Base Classification Models								
Structured - LogReg	0.853	0.815	0.861	0.837	23,687	3,024	4,269	18,790
Structured - AdaBst	0.843	0.813	0.835	0.824	23,761	3,605	4,195	18,209
Structured - RanFst	0.843	0.825	0.814	0.820	24,193	4,058	3,763	17,756
Structured - KNN	0.817	0.757	0.857	0.804	21,946	3,109	6,010	18,705
Structured - DTree	0.813	0.784	0.792	0.788	23,189	4,547	4,767	17,267
Top 3 Mean Response Probability Models								
Structured - MRP 45	0.850	0.795	0.887	0.838	22,975	2,472	4,981	19,342
Structured - MRP 50	0.850	0.812	0.856	0.833	23,630	3,139	4,326	18,675
Structured - MRP 40	0.848	0.778	0.914	0.840	22,252	1,870	5,704	19,944
Top 3 Voting Models								
Structured - Vote 3+	0.857	0.821	0.862	0.841	23,853	3,019	4,103	18,795
Structured - Vote 2+	0.852	0.785	0.912	0.844	22,513	1,914	5,443	19,900
Structured - Vote 4+	0.843	0.848	0.783	0.814	24,885	4,737	3,071	17,077

The Logistic Regression model was the top performer with a classification accuracy score of 85.3%. This model was selected as the baseline structured data only model from which to measure the performance of models trained on text-based feature sets in upcoming sections. Note that the top MRP model came close and that the 3+ voting model earned a slight 0.4% improvement in accuracy. Accuracy scores at different thresholds for the combination models are plotted in Figure 10.

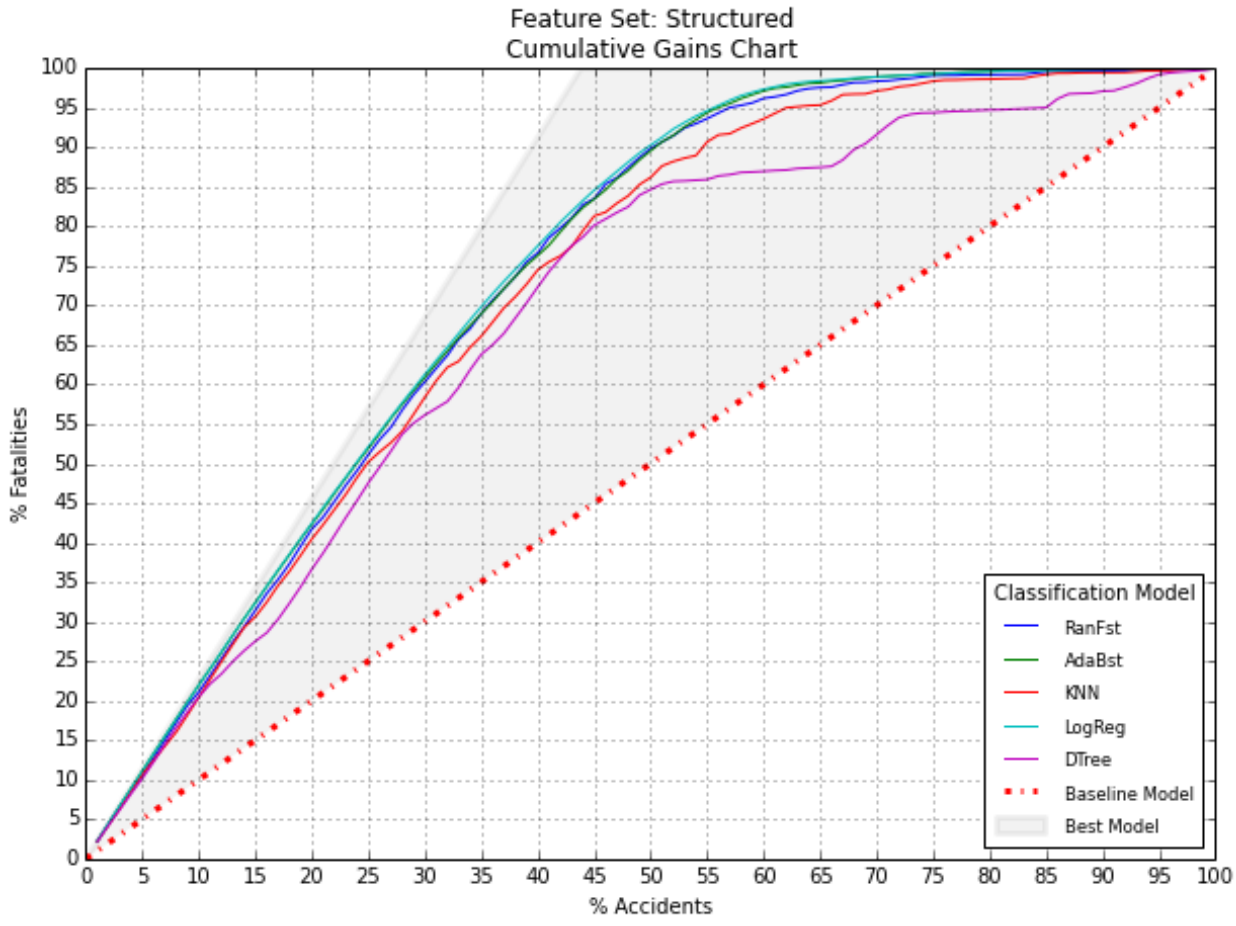
Figure 10: Combination Model Results



A cumulative gains chart for each of the five classification models is depicted in Figure 11. A cumulative gains chart is a graphical method for assessing model performance of one or more classification models. An explanation is in order here. The baseline model randomly selects test cases and predicts fatality each time such that x% of actual fatal accidents would, on average, be captured after sampling x% of the total accidents. To create the gains curve for each model, the model's confidence in predictions of fatal outcome for each test case is ranked from

high to low and the cumulative number of correct fatal predictions divided by the cumulative number of total predictions made is calculated at increasing percentages of overall accidents. Accidents that comprised the test partition resulted in fatality 43.8% of the time. The best model makes all accurate predictions such that 100% of fatal accidents are captured from 43.8% of all accidents scored. The two top performing models, Logistic Regression and Random Forest, captured about 90% of all fatal accidents in the first 50% of accidents scored.

Figure 11: Base Classification Model Cumulative Gains Chart



Figures 12 and 13 are plots of feature importance for the top 20 features of the Random Forest and Logistic Regression models, respectively. Importance for logistic regression input variables was computed from the regression coefficients provided by the model for each variable. Greater positive coefficient values indicated stronger influence on fatal outcome and greater negative values indicated stronger influence on non-fatal outcome. Calculation of feature importance of random forest input variables was more esoteric. *Scikit-learn* returns an array of feature importance for input variables fit to a random forest classifier. The importance of each feature is roughly the average rank, or depth of a feature from the root node, calculated from multiple randomized decision trees utilized in the random forest classifier.

Figure 12: Random Forest Classification Model Feature Importance

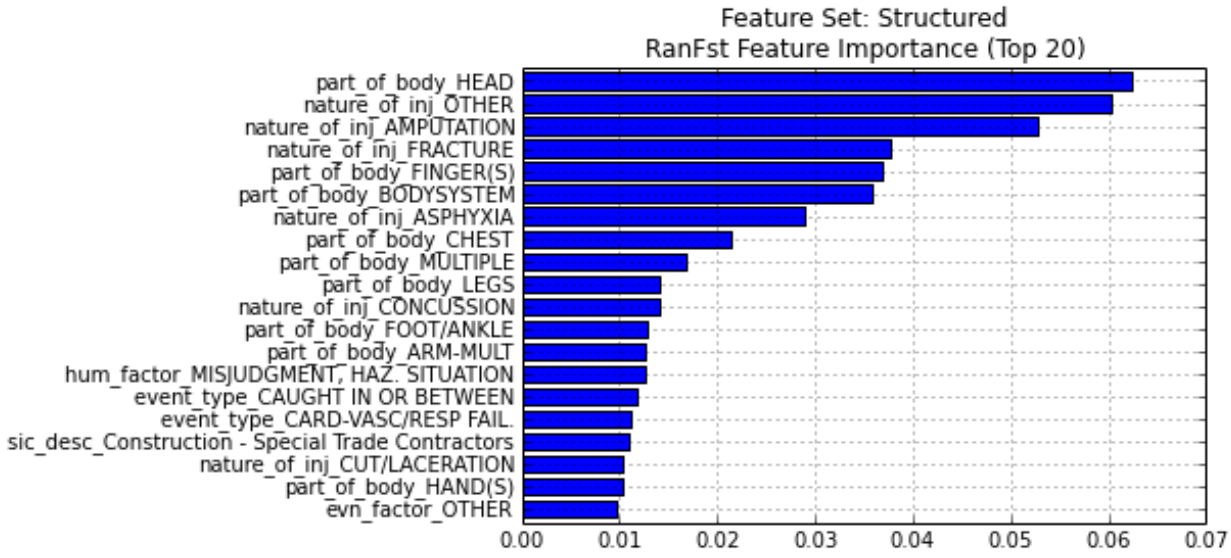
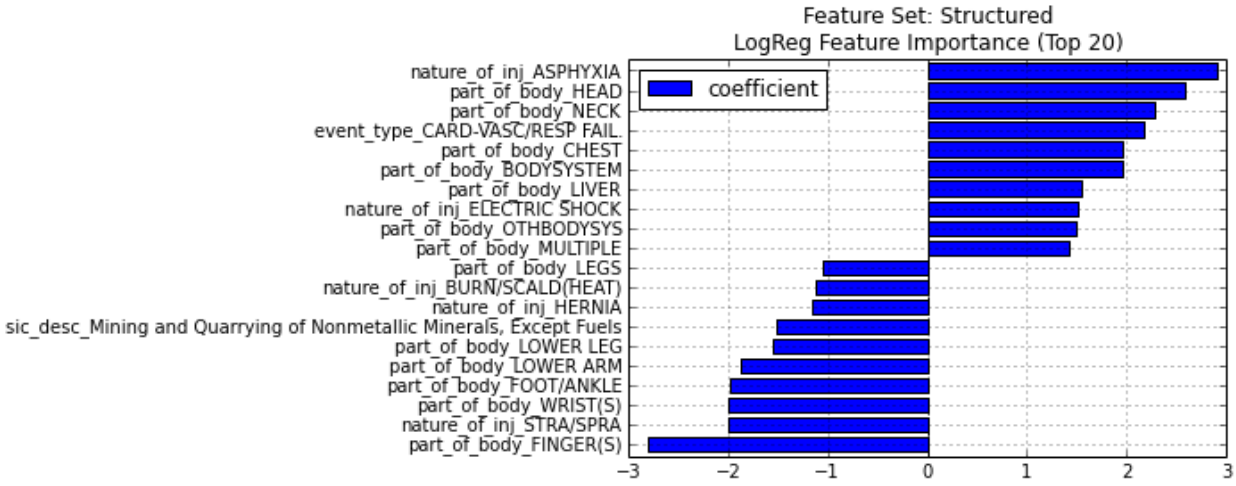


Figure 13: Logistic Regression Classification Model Feature Importance



Unstructured Text Preprocessing

Section IPython Notebook link: [osha_02_unstructured_preprocessing.ipynb]

The OSHA accident abstract data contained multiple rows of text per accident. The raw abstract file, entitled *osha_accident_abstract.csv,* is located on the project repository. The first text pre-processing task was to combine these multiple lines of text into one text field per accident. Table 9 depicts a sample accident's abstract records before and after transformation.

The second text pre-processing task involved removal of words from the Keywords, Event Description and Text Summary fields that were both highly correlated with fatality and of similar semantic meaning. Allowing these words to remain in the text would provide the text-based feature sets with a distinct advantage over the Structured feature set. Models initially generated with these words included achieved accuracy scores between 98% and 99%. Table 10 lists the two most frequent stemmed tokens from the Event Description field that were highly

correlated with fatality and of similar semantic meaning. Over 96.6% of the time that the stemmed tokens *kill* and *die* occurred in the description the accident outcome was fatal.

Table 9: Merging Multiple Text Lines into a Single Text Field Per Accident

508937	1	While Employee #1 was SCUBA diving in approximately 120 feet of water, using
508937	2	equipment that was marginally/poorly maintained, his high pressure hose was
508937	3	inadvertently cut and he drowned. Causal factors include: no standby diver was
508937	4	available to render assistance; Employee #1 was not line tended; Employee #1
508937	5	was not wearing a required personal flotation device; and no supplemental air
508937	6	supply was provided.

508937	While Employee #1 was SCUBA diving in approximately 120 feet of water, using equipment that was marginally/poorly maintained, his high pressure hose was inadvertently cut and he drowned. Causal factors include: no standby diver was available to render assistance; Employee #1 was not line tended; Employee #1 was not wearing a required personal flotation device; and no supplemental air supply was provided.

Table 10: Top Two Stemmed Words from Event Description Highly Correlated with Fatality

Stemmed Token	# Occurrences in Non-Fatal Accident Descriptions	# Occurrences in Fatal Accident Descriptions	Percentage Fatal Accident Occurrence
kill	101	20,344	99.5%
die	260	7,427	96.6%

On the other side of the spectrum words that were a variant of *hospital* resulted in fatalities 14% of the time, and were likewise removed. Variants of the word *employee* were also removed as they occurred in a majority of accidents and were essentially stopwords for purposes of this project. Table 11 lists all word variants that were removed from the unstructured text fields. Table 12 depicts a sample accident's text fields before and after word removal. Although

the resulting text is not always grammatically correct the application of subsequent text mining techniques used in this project were expected to tolerate these modifications without issue.

Table 11: Stemmed Word Proxies for Fatality and Corresponding Word Variants Removed

Stemmed Words Highly Correlated With Fatality	All Word Variants With Stem Highly Correlated with Fatality Removed From the Unstructured Text Fields			
asphyxi	asphyxia	demise	electrocuting	hospitalized
asphyxia	asphyxiant	die	electrocution	hospitalizes
dead	asphyxiate	died	electrocutions	hospitalizing
death	asphyxiated	dies	fatal	hospitals
deceas	asphyxiates	drown	fatalities	kill
demis	asphyxiating	drowned	fatality	killed
die	asphyxiation	drownes	fatally	killing
drown	dead	drowning	hospitable	kills
electrocut	deadly	drowns	hospital	suffocate
fatal	death	dying	hospitality	suffocated
hospit	deaths	electrocute	hospitalization	suffocates
kill	decease	electrocuted	hospitalizations	suffocating
suffoc	deceased	electrocutes	hospitalize	suffocation

Table 12: Sample Accident Text Fields Before and After Modification

Summary Nr 508937	Raw Text	Cleaned Text
Keywords	INADEQUATE MAINT, SCUBA, DIVING, SEVERED, DROWN, WATER, WORK RULES, AIR HOSE, DIVER	inadequate maint, scuba, diving, severed, water, work rules, air hose, diver
Event Description	Employee drowns while SCUBA diving	while scuba diving
Text Summary	While Employee #1 was SCUBA diving in approximately 120 feet of water, using equipment that was marginally/poorly maintained, his high pressure hose was inadvertently cut and he drowned. Causal factors include: no standby diver was available to render assistance; Employee #1 was not line tended; Employee #1 was not wearing a required personal flotation device; and no supplemental air supply was provided.	while was scuba diving in approximately 120 feet of water, using equipment that was marginally/poorly maintained, his high pressure hose was inadvertently cut and he . causal factors include: no standby diver was available to render assistance; was not line tended; was not wearing a required personal flotation device; and no supplemental air supply was provided.

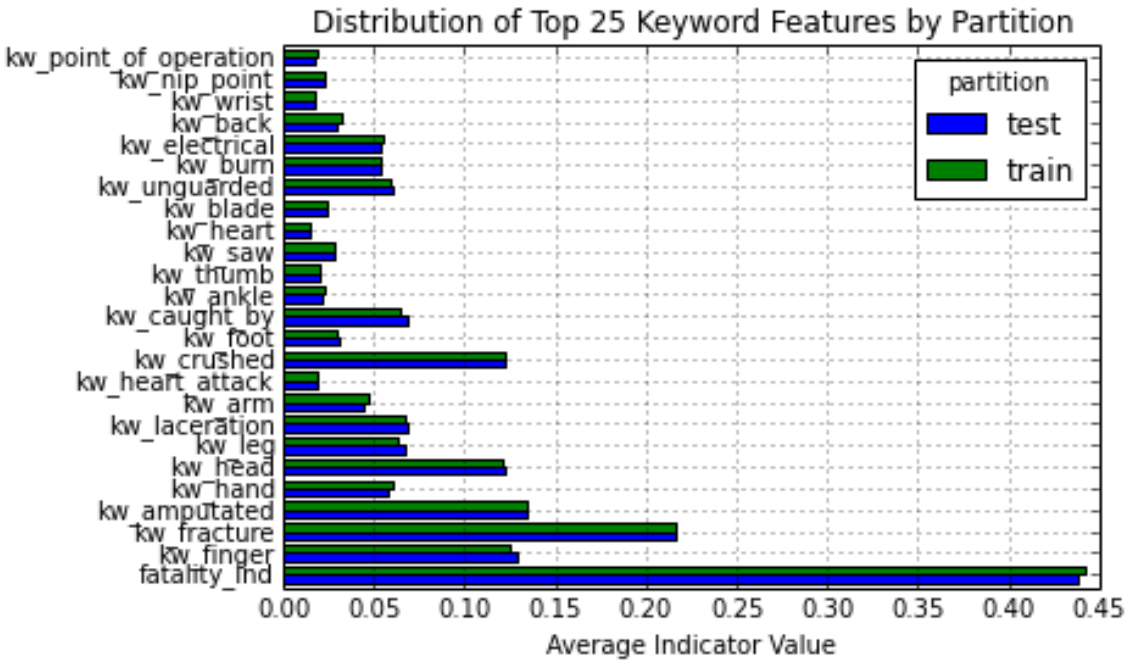
Keyword Feature Set

Section IPython Notebook link: osha_03_keyword_feature_set.ipynb

Keywords associated with each accident were provided as a single text field separated by commas in the raw accident data file. The pre-processing task here was quite simple as the data was already semi-structured. The feature set created from the keywords data was a binary matrix with accidents as rows and the set of 1,300+ keywords extracted from all accidents in the train partition as columns. Iterating through each accident a value of 1 was assigned to each keyword column associated with the accident and 0 was assigned for all other keyword columns. To ensure that distributions of keyword occurrences were similar across the train and test set the top 25 most important features were selected by computing ANOVA F-value statistics between each binary keyword indicator and the binary target variable. Figure 14 depicts a similar distribution of the top 25 features and fatality indicator across the train and test partitions as measured by each keyword's average occurrence.

A K-Means cluster model with four clusters was fit to the train partition and evaluated on the test partition. Figure 15 demonstrates that the distribution of clusters across the train and test set was remarkably similar. Mean value distributions for each of the top 25 keywords and the fatality indicator were plotted by partition and cluster to facilitate inspection of the results. Inspection of the results from Figures B.1 and B.2 of Appendix B indicated that the K-Means cluster membership would likely prove to be an important predictor for the accident outcome classification models. In preparation for modeling, the cluster membership field was converted into flag indicators and added to the Keyword feature set.

Figure 14: Distribution of Top 25 Keywords by Partition



Each of the five classification algorithms was trained on the train partition data of the Keyword feature set and evaluated on the test partition data. Model evaluation statistics for the base and combination models are summarized in Table 13.

Figure 15: K-Means Cluster Membership and Counts by Partition

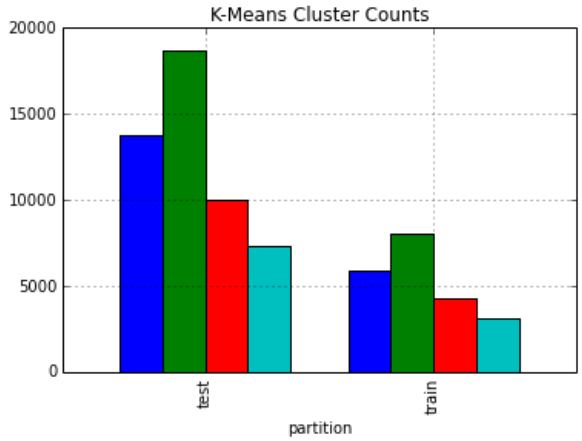


Table 13: Base Model and Combination Model Results

Model Name	Accuracy	Precision	Recall	F Measure	TN	FN	FP	TP
Base Classification Models								
Keyword - LogReg	0.862	0.819	0.880	0.848	23,711	2,613	4,245	19,201
Structured - LogReg	**0.853**	**0.815**	**0.861**	**0.837**	**23,687**	**3,024**	**4,269**	**18,790**
Keyword - AdaBst	0.847	0.796	0.874	0.833	23,082	2,754	4,874	19,060
Keyword - RanFst	0.844	0.832	0.806	0.819	24,417	4,234	3,539	17,580
Keyword - DTree	0.813	0.788	0.784	0.786	23,350	4,704	4,606	17,110
Keyword - KNN	0.777	0.686	0.907	0.781	18,888	2,030	9,068	19,784
Top 3 Mean Response Probability Models								
Keyword - MRP 50	0.852	0.810	0.867	0.837	23,508	2,911	4,448	18,903
Keyword - MRP 45	0.851	0.790	0.898	0.841	22,756	2,221	5,200	19,593
Keyword - MRP 55	0.850	0.828	0.831	0.829	24,182	3,697	3,774	18,117
Top 3 Voting Models								
Keyword - Vote 3+	0.861	0.816	0.881	0.847	23,614	2,595	4,342	19,219
Keyword - Vote 4+	0.854	0.851	0.808	0.829	24,882	4,199	3,074	17,615
Keyword - Vote 2+	0.845	0.767	0.929	0.840	21,807	1,550	6,149	20,264

The Logistic Regression model was again the top performer with a classification accuracy score of 86.2%, a 0.9% improvement in accuracy from the baseline structured data only model. The combination models did not provide additional lift for this feature set. A cumulative gains chart for each of the five classification models is depicted in Figure 16. Accuracy scores at different thresholds for the combination models are plotted in Figure 17. Figures 18 and 19 are plots of feature importance for the top 20 features of the Random Forest and Logistic Regression models, respectively.

Figure 16: Base Classification Model Cumulative Gains Chart

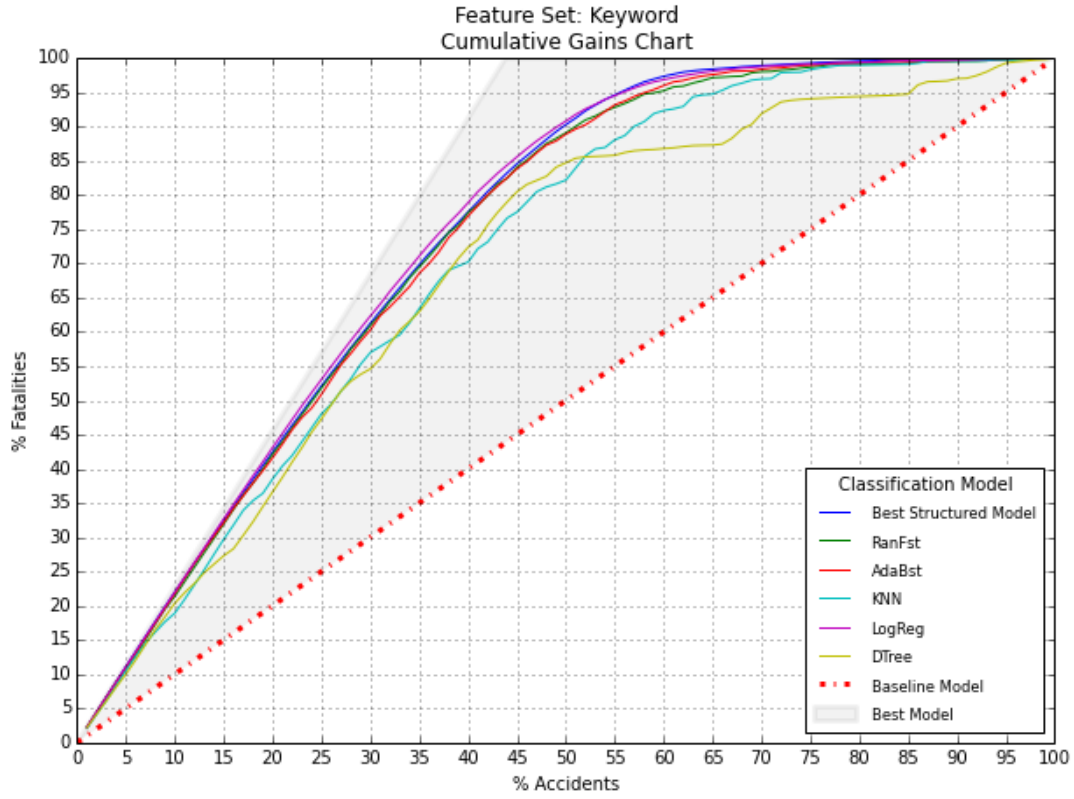


Figure 17: Combination Model Results

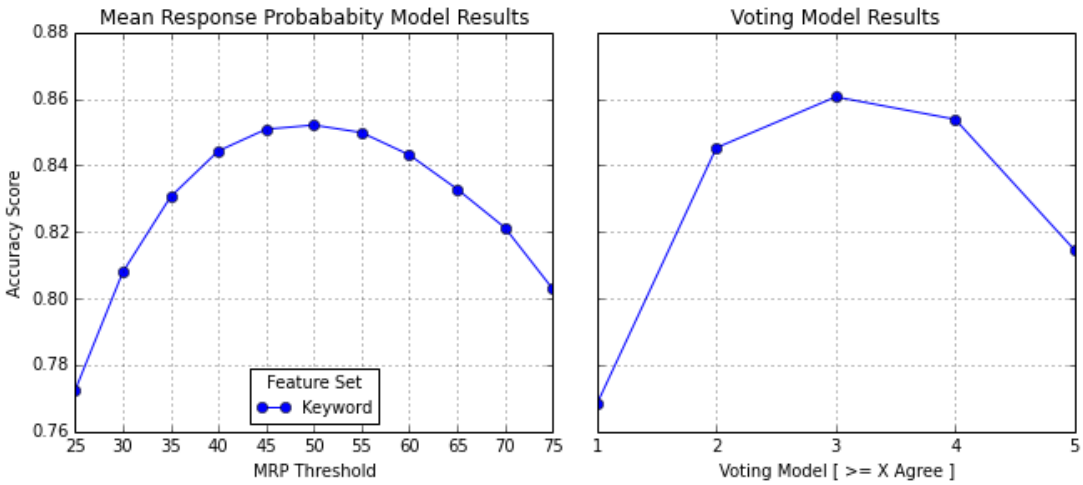


Figure 18: Random Forest Classification Model Feature Importance

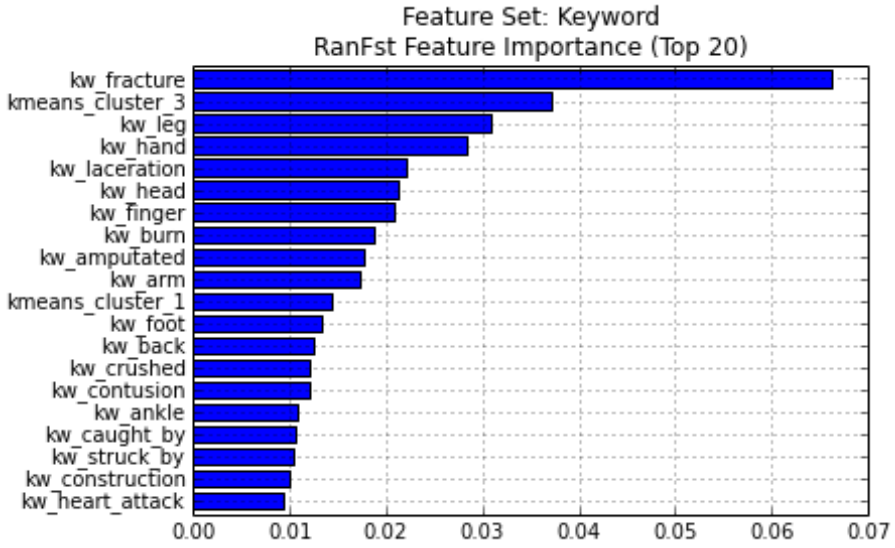
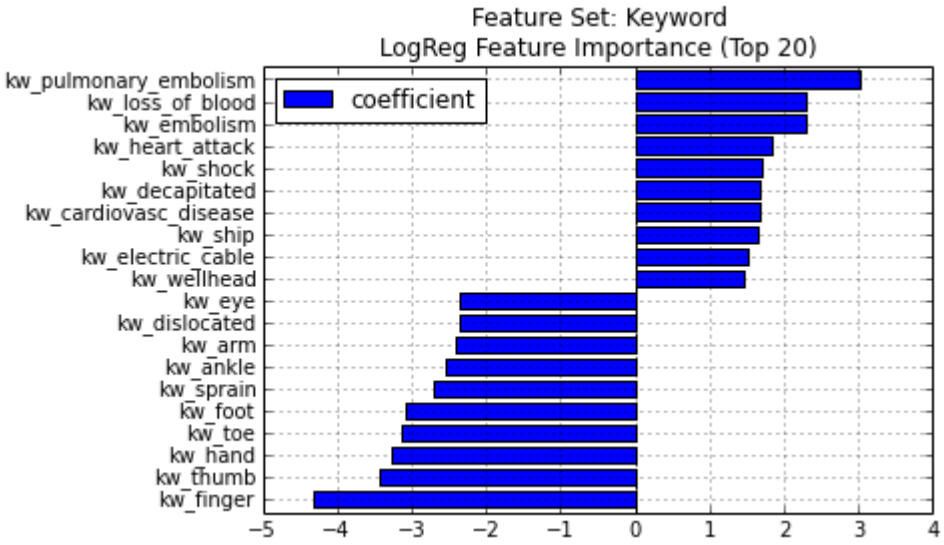


Figure 19: Logistic Regression Classification Model Feature Importance



Linguistic Feature Set

Section IPython Notebook link: osha_04_linguistic_feature_set.ipynb

This feature set was created by application of simple natural language processing techniques to extract linguistic features present within the unstructured accident summary data. The rationale was that linguistic features embedded within accident summaries might vary across accident outcomes in a manner that would enable classifiers to better discern between fatal and non-fatal accidents. With this goal in mind various features were extracted and assembled into a single feature set for subsequent modeling. The linguistic features might not prove to be strong predictors of accident outcome on their own but a few of them might provide an edge when combined with features from other feature sets at later stages of this project.

Features based on the main parts of speech (POS) from language used in the accident summaries were extracted. The rationale for inclusion was that a greater proportion of nouns might be used in less serious accident summaries and a greater proportion of adjectives and verbs might be used in more serious accident summaries. The POS tagger from the NLTK package was employed to extract counts of nouns, adjectives, verbs and adverbs from each accident summary. Another possibility was that fatal accidents might on average be lengthier, more descriptive and more lexically diverse. With this possibility in mind features such as summary text length, number of tokens and number of unique tokens were extracted from each accident summary. As the *sex* variable from the raw injury data was empty, counts of female prepositions and male prepositions were also extracted and fashioned into features.

The final two linguistic features were measures of average positive sentiment and average negative sentiment contained in each accident summary. Measures of sentiment were derived as

features based on the reasoning that severe accidents might exhibit greater negative sentiment than less severe accidents and therefore assist models to better discriminate between accident outcomes. The idea, code base and implementation used to extract these particular features came from Richert's excellent book *Building Machine Learning Systems with Python* (pg. 138). In fact, the book was inspiration for most of this project. SentiWordNet is a publically available resource file built on WordNet that assigns the majority of English words a positive and negative value and takes into consideration the part-of-speech of each word. The overall average negative value and overall average positive value of each word from the accident summaries comprised the two features. Figure 20 is a plot of average negative sentiment versus average positive sentiment for each accident in the train and test set with accident outcome overlay. Although the results were stable across partition, the measures of sentiment were not expected to be strong predictors of accident outcome. These measures were included as modeling inputs nonetheless.

Figure 20: Average Positive and Negative Sentiment Scatterplot with Accident Outcome Overlay

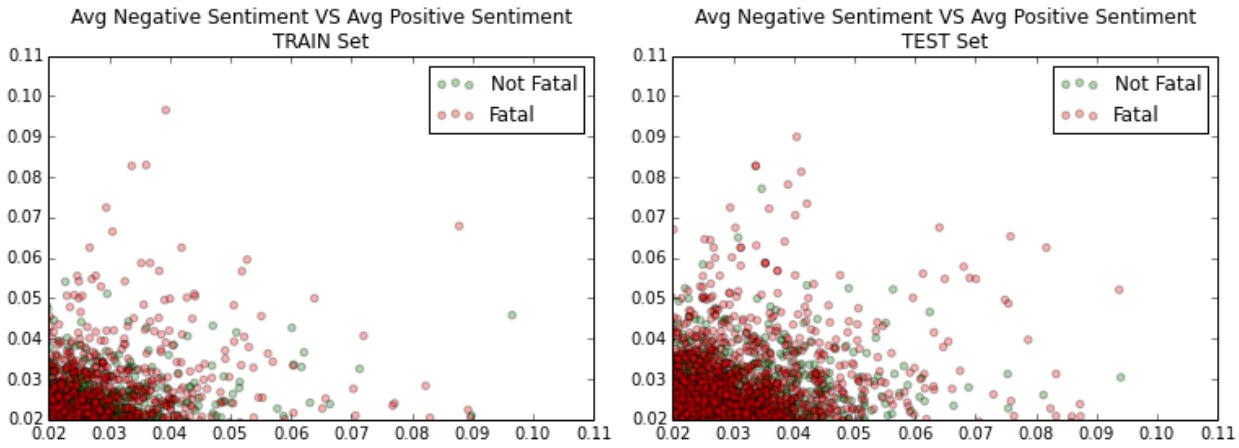


Table 14 lists the linguistic features extracted from all accidents in the train and test partitions along with their mean values. As all of the linguistic features were numerical and

clearly correlated, principal components analysis was indicated. A PCA model was fit to the scaled predictor variables of the train set and evaluated on the test set. Figure 21 depicts a scree plot of the principal components. Figure 22 is a plot of the first and second principal components with accident outcome overlay. Similar to measures of sentiment, the principal components derived from this feature set were not expected to be strong predictors of accident outcome. The final Linguistic feature set for modeling was created with the first 10 principal components. The original variables were omitted.

Table 14: Linguistic Feature Set Statistics

	Test Partition		Train Partition	
Linguistic Set Feature	Not Fatal	Fatal	Not Fatal	Fatal
Summary Length	567.5	475.4	575.5	469.5
Sentence Count	5.7	4.9	5.7	4.9
Character Count	442.1	369.9	448.7	365.5
Token Count	94.0	79.3	95.4	78.3
Unique Token Count	58.8	49.8	59.5	49.3
Average Positive Sentiment	0.01197	0.01242	0.01198	0.01229
Average Negative Sentiment	0.01403	0.01453	0.01410	0.01441
Noun Count	30.4	25.0	30.7	24.8
Adjective Count	4.5	4.1	4.6	4.0
Verb Count	18.8	16.0	19.1	15.8
Adverb Count	2.4	2.0	2.5	2.0
Female Preposition Count	0.3	0.1	0.3	0.1
Male Preposition Count	3.3	2.4	3.3	2.3

Figure 21: Principal Components Scree Plot

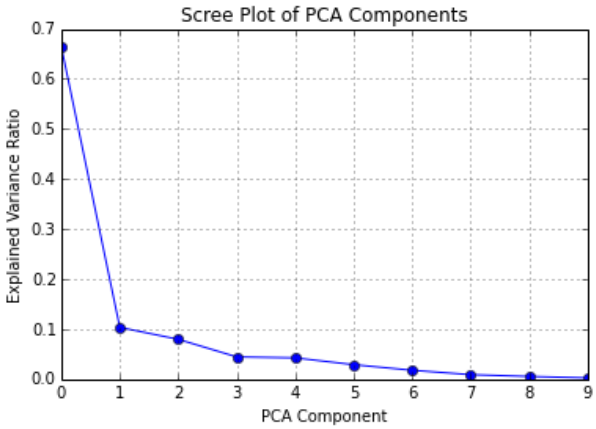
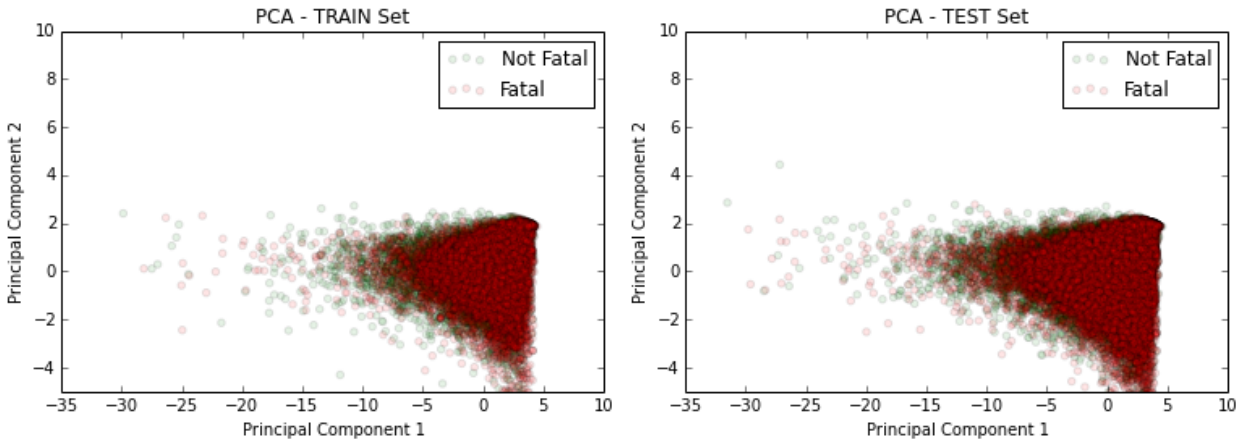


Figure 22: Scatterplot of Top Two Principal Components with Accident Outcome Overlay



Each of the five classification algorithms was trained on the train partition data of the Linguistic feature set and evaluated on the test partition data. Model evaluation statistics for the base and combination models are summarized in Table 15.

The Logistic Regression model was again the top performer with a classification accuracy score of 64.0%, a dismal 21.3% drop in accuracy from the baseline structured data only model. The combination models did not provide additional lift for this feature set. A cumulative

gains chart for each of the five classification models is depicted in Figure 24. Accuracy scores at different thresholds for the combination models are plotted in Figure 23. Figure 25 is a plot of feature importance for the top 20 features of the Random Forest model.

Table 15: Base Model and Combination Model Results

Model Name	Accuracy	Precision	Recall	F Measure	TN	FN	FP	TP
Base Classification Models								
Structured - LogReg	**0.853**	**0.815**	**0.861**	**0.837**	**23,687**	**3,024**	**4,269**	**18,790**
Linguistic - LogReg	0.640	0.601	0.529	0.562	20,302	10,284	7,654	11,530
Linguistic - AdaBst	0.632	0.598	0.487	0.537	20,806	11,181	7,150	10,633
Linguistic - RanFst	0.608	0.573	0.417	0.483	21,188	12,723	6,768	9,091
Linguistic - KNN	0.592	0.538	0.493	0.515	18,734	11,064	9,222	10,750
Linguistic - DTree	0.561	0.499	0.505	0.502	16,916	10,803	11,040	11,011
Top 3 Mean Response Probability Models								
Linguistic - MRP 60	0.612	0.614	0.313	0.414	23,667	14,997	4,289	6,817
Linguistic - MRP 55	0.609	0.577	0.404	0.475	21,500	13,002	6,456	8,812
Linguistic - MRP 65	0.606	0.649	0.219	0.328	25,367	17,026	2,589	4,788
Top 3 Voting Models								
Linguistic - Vote 3+	0.634	0.604	0.482	0.536	21,061	11,299	6,895	10,515
Linguistic - Vote 4+	0.625	0.639	0.329	0.435	23,900	14,628	4,056	7,186
Linguistic - Vote 2+	0.620	0.559	0.635	0.594	17,032	7,971	10,924	13,843

Figure 23: Combination Model Results

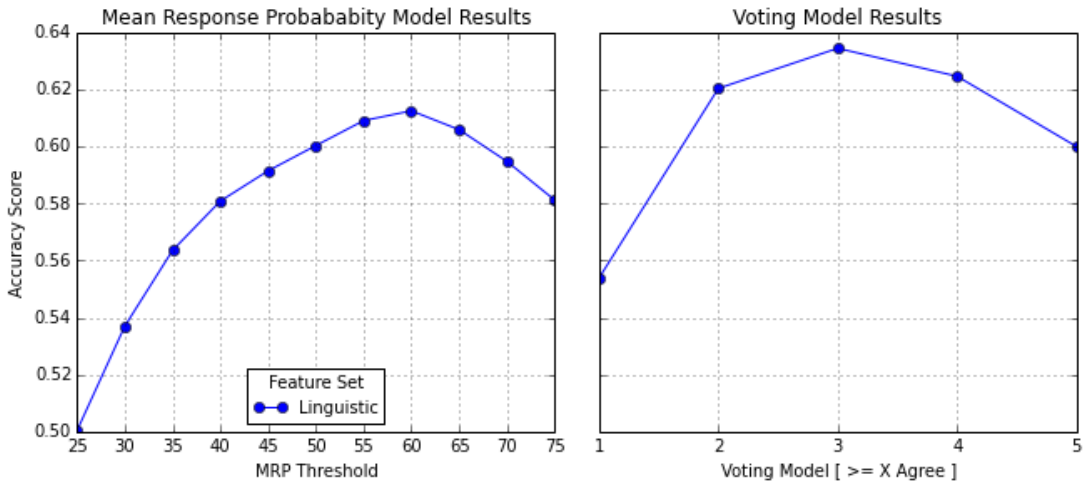


Figure 24: Base Classification Model Cumulative Gains Chart

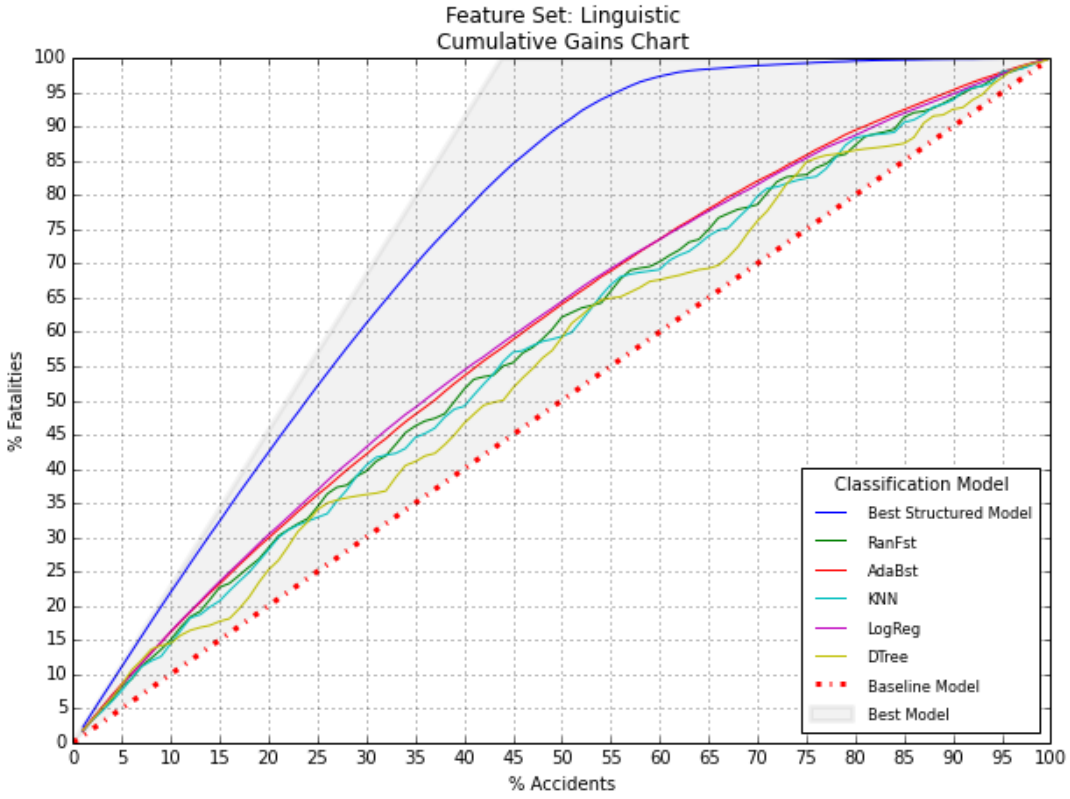
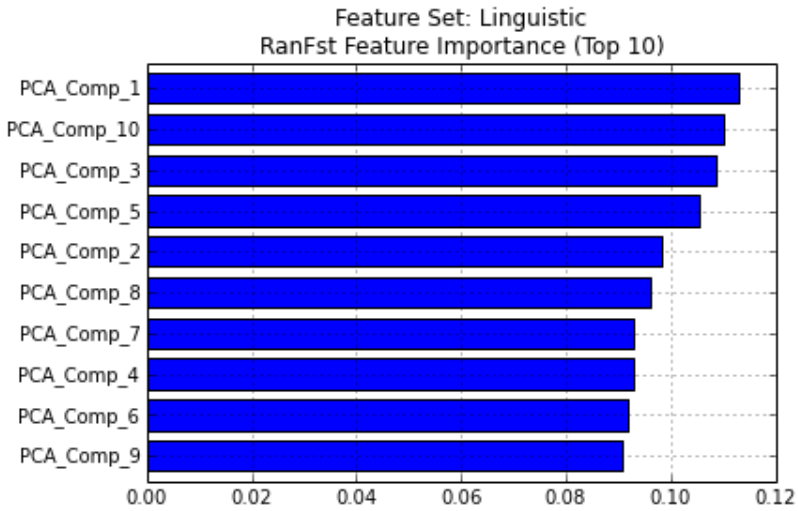


Figure 25: Random Forest Classification Model Feature Importance



Topic Feature Set

Section IPython Notebook link: osha_05_topic_feature_set.ipynb

For this feature set a Python implementation of Latent Dirichlet Allocation from the Gensim package was used to develop a topic model based on the accident summary content of each accident in the training set. Unlike unsupervised clustering where each observation is assigned to one cluster, LDA assigns each text observation to a small set of groups, or topics. Furthermore, the degree of membership in each topic is weighted, with a large weight indicating strong membership, and vice versa. LDA does not require a priori knowledge of topics and configures topics based on a supplied parameter.

The topic model is a sparse model where many topics define the overall corpus but only a few are assigned to each text. The topics are multinomial distributions over words, with each topic giving each word in the corpus a probability. Words with higher probability are more associated with certain topics than words with lower probability (Richert, pg. 79). Topic composition can be summarized by the most highly weighted words associated with it. Accident summaries can be compared in topic space by creating an accident-topic matrix with each accident as a row, each topic as a column, and topic weights as cell values. Two accident summaries are similar if they refer to the same topics. For purposes of this project, the desired effect was that some topics would be more associated with fatal accidents than non-fatal accidents and this difference would enable classification algorithms to better discriminate between the two. As the number of topics was far less than the number of words that comprised the corpus of all accident summaries another benefit of the topic space model was dimensionality reduction.

Prior to fitting a topic model with 200 topics to the train partition data the accident summary text was pre-processed. NLTK was employed to exclude stopwords, stem words, remove punctuation, and retain words with all alphabetical characters only. A histogram of the number of resulting topics per accident is depicted in Figure 26. A large percentage of accidents had 6 to 8 topics a piece with no accident having more than 35 topics. Figure 27 depicts the proportion of accident outcomes for the first 25 topics. Based on the variance in proportions of fatality exhibited across the first 25 topics the Topic model feature set was expected to add predictive power during the modeling stage.

Figure 26: Histogram of the Number of Topics Per Accident

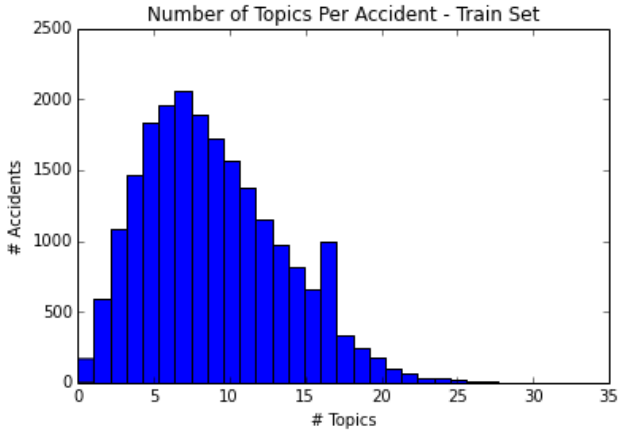


Table 16 depicts an example accident's summary along with the top 7 topic memberships and weights. The overall topic composition for the top 7 topics is included to aid interpretation. Not all content words from the accident summary are matched with the "highest probability" words that comprise the topic and vice versa. But one can see why the accident was assigned to most of the topics nonetheless. What might seem like a weakness is actually a strength, as accidents that allude to similar concepts with different wording can converge on the same topics

and allow models to detect similarities across text from separate observations in cases where the bag-of-words model would fail.

Figure 27: Proportion of Fatal Accidents for the First 25 Topics

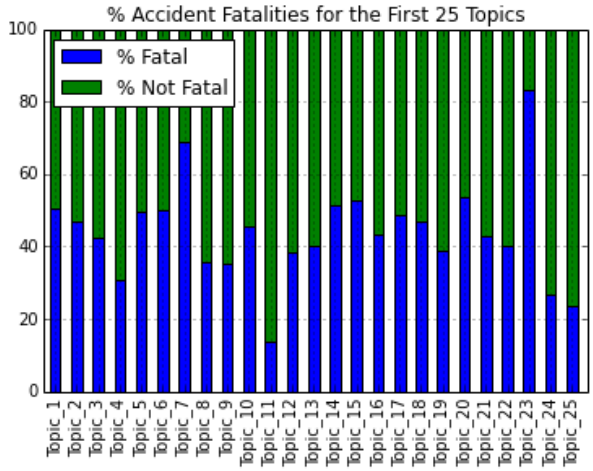


Table 16: Example Accident Topic Membership and Weight

Accident 200924264 - Cleaned Text Summary		
on december 17, 2005, was working for an automobile dealer as an auto mechanic assigned to perform routine vehicle maintenance. he was working underneath a car raised on a lift, and he had removed the lower oil pan. he was cleaning the interior of the upper oil pan section with an aerosol degreasing compound containing that was 80 to 90 percent heptane. the degreaser had a flash point of -18 degrees c. for some reason, the vapor ignited, and was surrounded by a flash fire. the oil on the oil pan and on the floor beneath the car ignited as well. coworkers in adjacent work stations extinguished the flames on and in the other areas. he was not wearing safety glasses or other personal protective equipment. he was transported to a local , where he was . he returned to work six days later after treatment for his facial burns.		
Topic #	Weight	Topic Composition
194	0.287	0.036*oil + 0.020*tank + 0.016*comput + 0.016*gallon + 0.011*slowli + 0.011*burn + 0.011*contain + 0.011*horn + 0.010*leader + 0.010*lumbar
192	0.132	0.034*well + 0.034*kitchen + 0.033*fire + 0.033*vapor + 0.032*burn + 0.031*brush + 0.029*clinic + 0.027*ignit + 0.022*flame + 0.020*unrespons
160	0.095	0.077*backho + 0.026*bucket + 0.025*like + 0.020*spool + 0.014*mari + 0.011*oper + 0.011*seek + 0.011*danger + 0.011*dog + 0.010*capacitor
98	0.064	0.040*truck + 0.029*park + 0.021*lot + 0.018*vehicl + 0.015*driver + 0.015*trash + 0.013*number + 0.013*compactor + 0.012*via + 0.011*roll
22	0.063	0.026*hitch + 0.023*wood + 0.022*junction + 0.021*rip + 0.019*correct + 0.019*shop + 0.018*automobil + 0.016*box + 0.016*narrow + 0.015*thumb
42	0.058	0.115*window + 0.059*balanc + 0.050*lost + 0.049*walkway + 0.037*pan + 0.037*raymond + 0.031*ladder + 0.028*summon + 0.023*sideway + 0.021*chainsaw
81	0.036	0.070*surgeri + 0.059*underw + 0.058*auger + 0.037*grind + 0.031*movement + 0.029*thigh + 0.021*nois + 0.020*wheel + 0.014*collect + 0.013*grinder

Each of the five classification algorithms was trained on the train partition data of the Topic feature set and evaluated on the test partition data. Model evaluation statistics for the base and combination models are summarized in Table 17.

The Logistic Regression model was again the top performer with a classification accuracy score of 70.9%, a significant drop in accuracy from the baseline structured data only model. The 3+ voting model earned a slight 0.3% improvement in accuracy over the top performing Topic base model. The MRP models did not provide additional lift for this feature set. A cumulative gains chart for each of the five classification models is depicted in Figure 28. Accuracy scores at different thresholds for the combination models are plotted in Figure 29. Figures 30 and 31 are plots of feature importance for the top 20 features of the Random Forest and Logistic Regression models, respectively.

Table 17: Base Model and Combination Model Results

Model Name	Accuracy	Precision	Recall	F Measure	TN	FN	FP	TP
Base Classification Models								
Structured - LogReg	**0.853**	**0.815**	**0.861**	**0.837**	**23,687**	**3,024**	**4,269**	**18,790**
Topic - LogReg	0.709	0.692	0.605	0.645	22,070	8,620	5,886	13,194
Topic - AdaBst	0.702	0.672	0.625	0.648	21,308	8,180	6,648	13,634
Topic - RanFst	0.689	0.686	0.536	0.602	22,606	10,112	5,350	11,702
Topic - KNN	0.663	0.631	0.560	0.593	20,803	9,606	7,153	12,208
Topic - DTree	0.636	0.586	0.579	0.582	19,058	9,194	8,898	12,620
Top 3 Mean Response Probability Models								
Topic - MRP 55	0.686	0.686	0.522	0.593	22,752	10,432	5,204	11,382
Topic - MRP 50	0.684	0.652	0.597	0.623	21,010	8,790	6,946	13,024
Topic - MRP 60	0.682	0.728	0.440	0.548	24,362	12,215	3,594	9,599
Top 3 Voting Models								
Topic - Vote 3+	0.712	0.700	0.598	0.645	22,368	8,766	5,588	13,048
Topic - Vote 2+	0.706	0.644	0.739	0.688	19,045	5,702	8,911	16,112
Topic - Vote 4+	0.693	0.755	0.443	0.558	24,824	12,160	3,132	9,654

Figure 28: Base Classification Model Cumulative Gains Chart

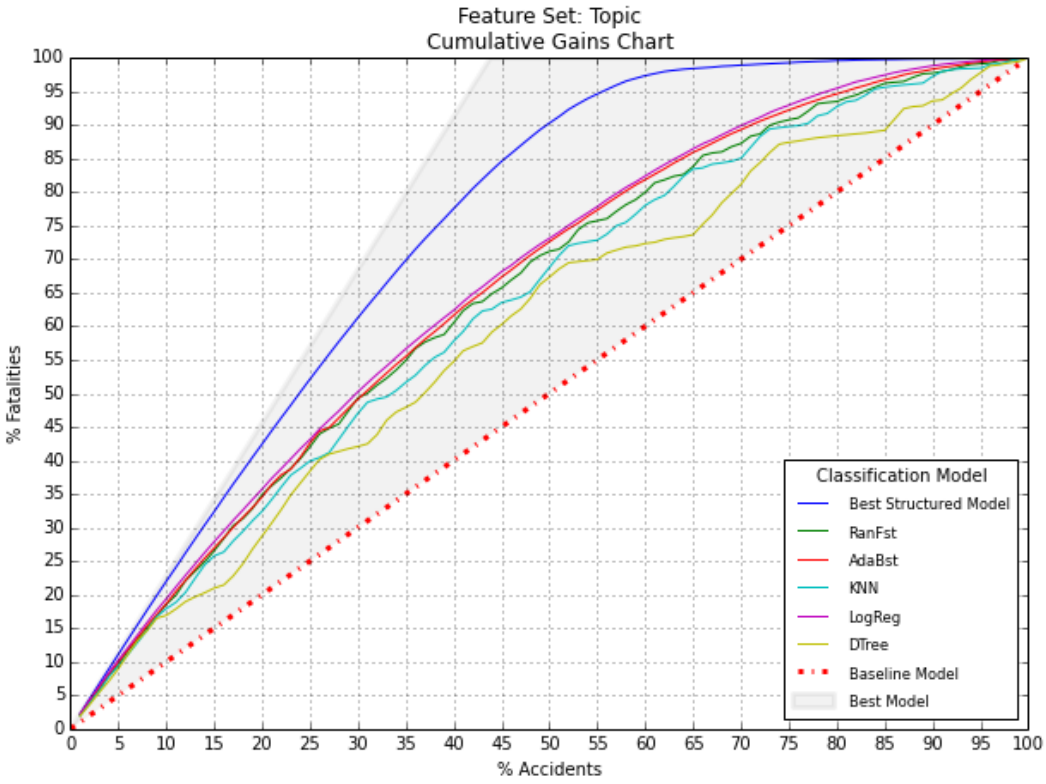


Figure 29: Combination Model Results

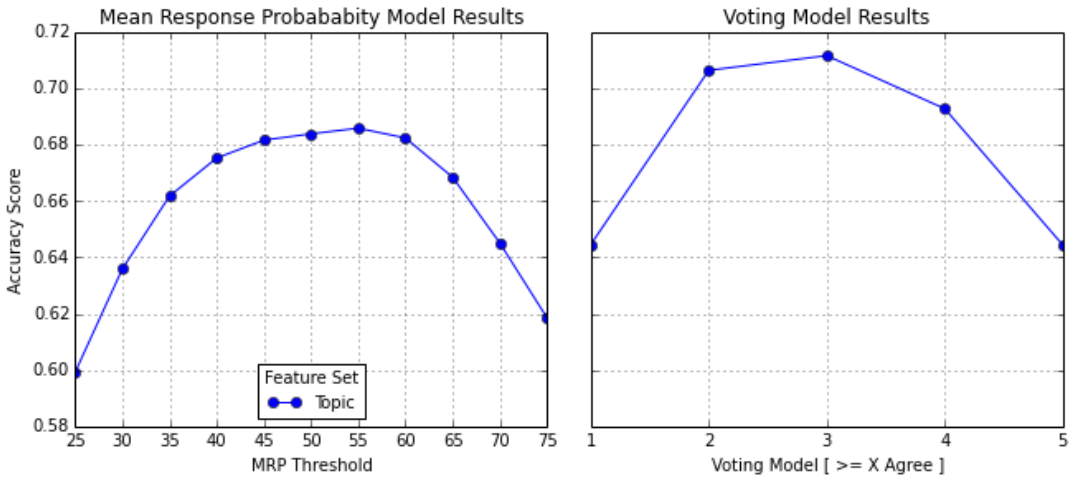


Figure 30: Random Forest Classification Model Feature Importance

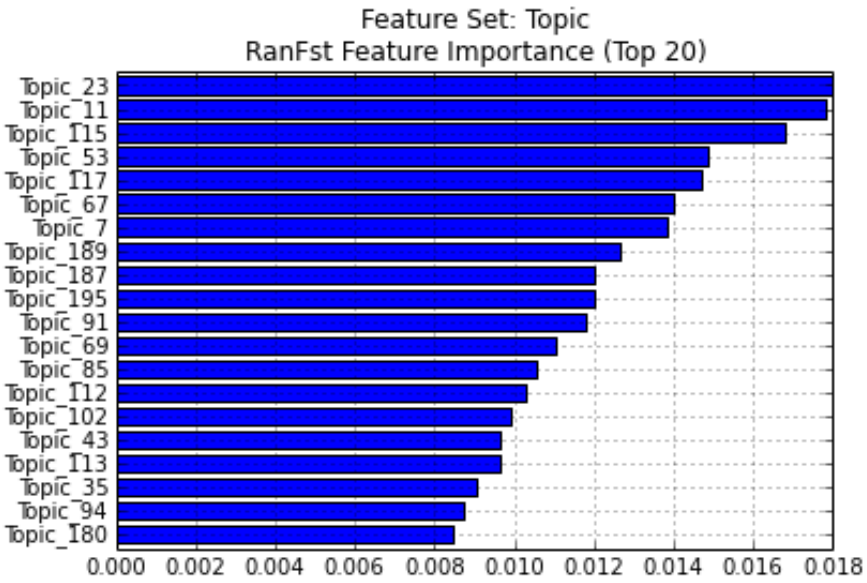
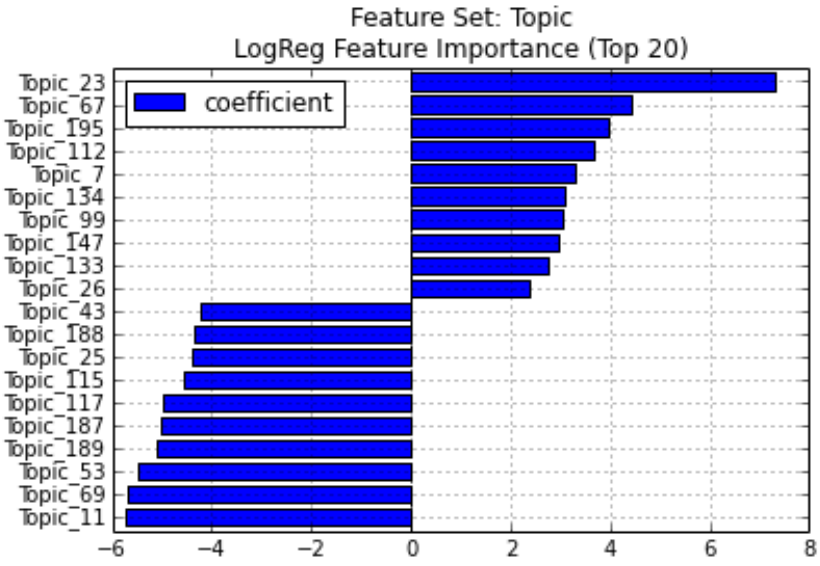


Figure 31: Logistic Regression Classification Model Feature Importance



Description SVD Feature Set

Section IPython Notebook link: osha_06_svd_description_feature_set.ipynb

Four feature sets were created by applying singular value decomposition (SVD) to vectorized matrices of terms contained in the Event Description field. Because additional steps were taken to apply TF-IDF transformation to the vectorized document-term matrices the technique in this context is known as Latent Semantic Analysis. According to Wikipedia, "Latent semantic analysis (LSA) is a technique in natural language processing, in particular in vectorial semantics, of analyzing relationships between a set of documents and the terms they contain by producing a set of concepts related to the documents and terms. LSA assumes that words that are close in meaning will occur in similar pieces of text."

There are various approaches for pre-processing raw text prior to vectorization. Table 18 below summarizes the four different configurations experimented with in this project. The four feature sets created from application of SVD to each of these vectorized document-term matrices were used during modeling to allow results to pass judgment on the optimal configuration.

Table 18: Vectorization Parameters and Resulting SVD Feature Sets

Feature Set Short Name	Ngram Features	Corpus Transform Method	Term Reduction Method	Minimum Document Frequency	# Rows in Vectorized Matrix	# Columns in Vectorized Matrix	# SVD Components Selected
desc_stem_n1	Unigrams	TF-IDF	Stem	5	21,331	1,092	50
desc_stem_n123	Unigrams, Bigrams, Trigrams	TF-IDF	Stem	5	21,331	3,524	50
desc_lem_n1	Unigrams	TF-IDF	Lemma	5	21,331	1,203	50
desc_lem_n123	Unigrams, Bigrams, Trigrams	TF-IDF	Lemma	5	21,331	3,567	50

Singular value decomposition is a dimensionality reduction technique and also a feature extraction technique. Like principal components analysis, SVD constructs a linear combination of variables, a small number of which contain the majority of all information resident in the original variables. When used as an intermediate step prior to predictive modeling it is customary to retain many components, as the models themselves will discern which components are useful and which are not. Like PCA, the components are uncorrelated so multicollinearity is not an issue. An arbitrary decision was made to retain the first 50 components. As indicated in Table 18 the largest document-term vector prior to application of SVD contained 3,567 features. A matrix of features this size is unmanageable, but becomes much more manageable and informative after application of SVD.

SVD can be thought of as a process that uncovers "latent dimensions of meaning" in the linear combinations of input variables. Each document, an accident description in this case, is assigned a score, or weight, with each component. The document score for each component denotes that documents influence on the component. Weights range from negative to neutral to positive, indicating the sign of the relationship. The anticipated effect here is that some components will be associated with a higher likelihood of fatality and that classification algorithms will be able to better discriminate between accident outcomes based on the document-component scores.

Figures E.1 and E.2 in Appendix E are scatterplots of the top four components containing the majority of information resident in the underlying document-term matrices. Note that the plots are remarkably similar across the train and test partitions, especially as the SVD model was fit to the train partition data and subsequently used to transform the test partition data into component space. The overlay of accident outcome, with red indicating fatality, on each

component-to-component scatterplot, helps show why the SVD feature sets are expected to be strong predictors of accident outcome. If all the documents' scores were clustered together around the point of origin, or if document scores from accidents with different outcomes were plotted together away from the point of origin, the components would not be expected to be strong predictors of accident outcome. Further analysis of document clusters farthest away from the point of origin may uncover additional insight, and could be an interesting area of further research.

Each of the five classification algorithms was trained on the train partition data of the Description SVD feature set and evaluated on the test partition data. Of the four feature sets created, the *desc_stem_n1* feature set was selected to go forward with. Model evaluation statistics for the base and combination models are summarized in Table 19.

Table 19: Base Model and Combination Model Results

Model Name	Accuracy	Precision	Recall	F Measure	TN	FN	FP	TP
Base Classification Models								
desc_stem_n1 - LogReg	0.900	0.844	0.946	0.892	24,135	1,175	3,821	20,639
desc_stem_n1 - RanFst	0.898	0.873	0.897	0.885	25,121	2,252	2,835	19,562
desc_stem_n1 - KNN	0.887	0.839	0.918	0.877	24,120	1,786	3,836	20,028
desc_stem_n1 - DTree	0.867	0.840	0.861	0.850	24,381	3,042	3,575	18,772
desc_stem_n1 - AdaBst	0.881	0.837	0.904	0.869	24,102	2,092	3,854	19,722
Structured - LogReg	**0.853**	**0.815**	**0.861**	**0.837**	**23,687**	**3,024**	**4,269**	**18,790**
Top 3 Mean Response Probability Models								
desc_stem_n1 - MRP 40	0.901	0.841	0.956	0.895	24,011	962	3,945	20,852
desc_stem_n1 - MRP 45	0.906	0.855	0.947	0.898	24,443	1,167	3,513	20,647
desc_stem_n1 - MRP 50	0.905	0.865	0.929	0.896	24,789	1,540	3,167	20,274
Top 3 Voting Models								
desc_stem_n1 - Vote 2+	0.901	0.839	0.958	0.895	23,951	922	4,005	20,892
desc_stem_n1 - Vote 3+	0.908	0.863	0.939	0.899	24,691	1,320	3,265	20,494
desc_stem_n1 - Vote 4+	0.900	0.880	0.892	0.886	25,302	2,347	2,654	19,467

The Logistic Regression model was once again the top performer with a classification accuracy score of 90.0%, a 4.7% improvement in accuracy from the baseline structured data only model. The best MRP combination model provided an additional lift of 0.6% for this feature set. The best voting combination model provided an additional lift of 0.8%. A cumulative gains chart for each of the five classification models is depicted in Figure 32. Accuracy scores at different thresholds for the combination models are plotted in Figure 33. Figures 34 and 35 are plots of feature importance for the top 20 features of the Random Forest and Logistic Regression models, respectively.

Figure 32: Base Classification Model Cumulative Gains Chart

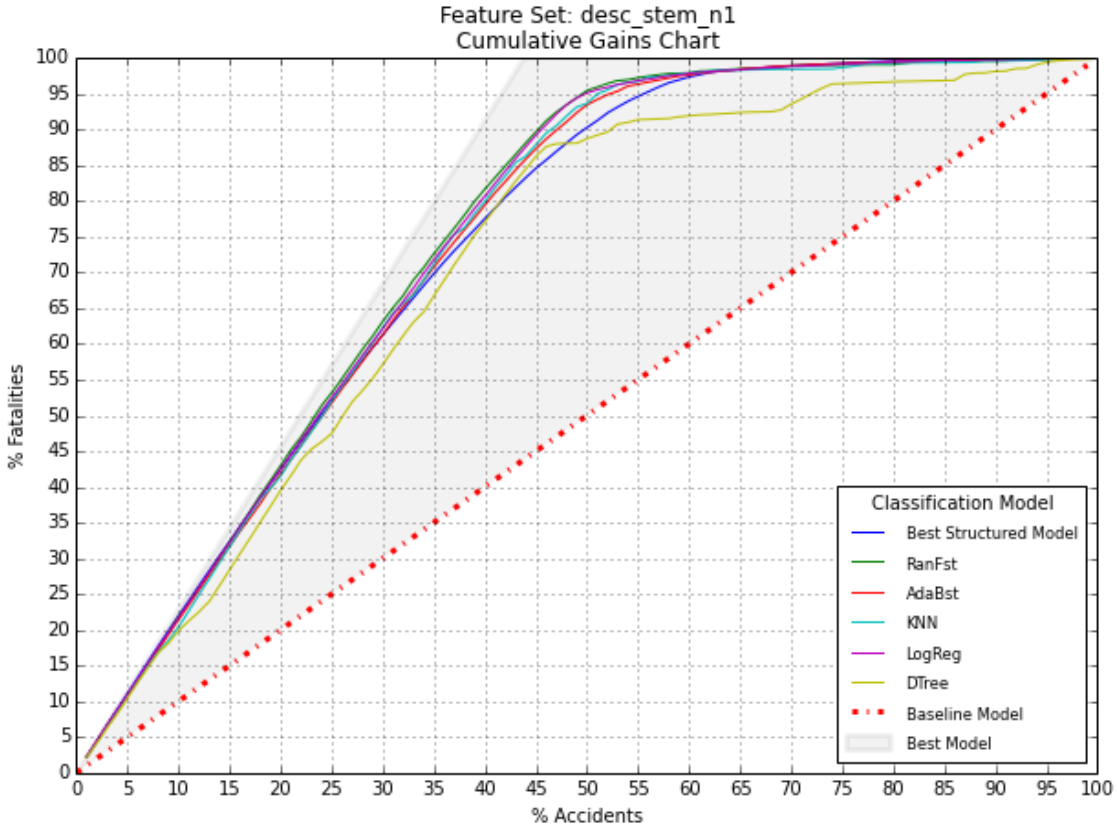


Figure 33: Combination Model Results

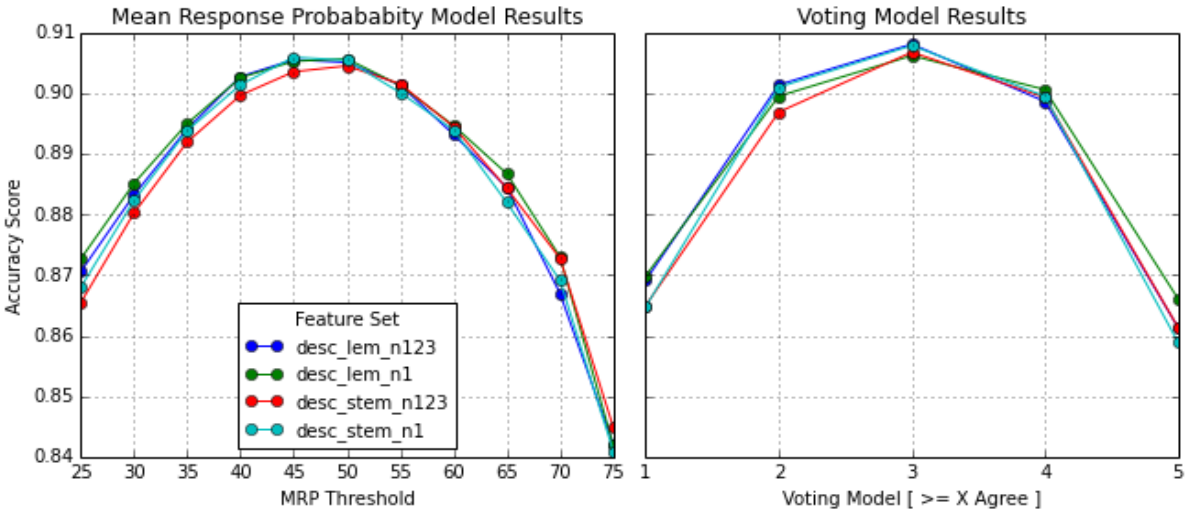


Figure 34: Random Forest Classification Model Feature Importance

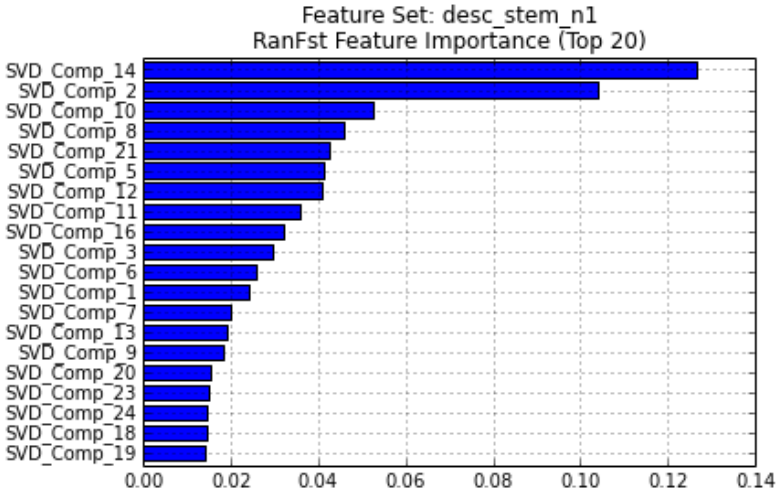
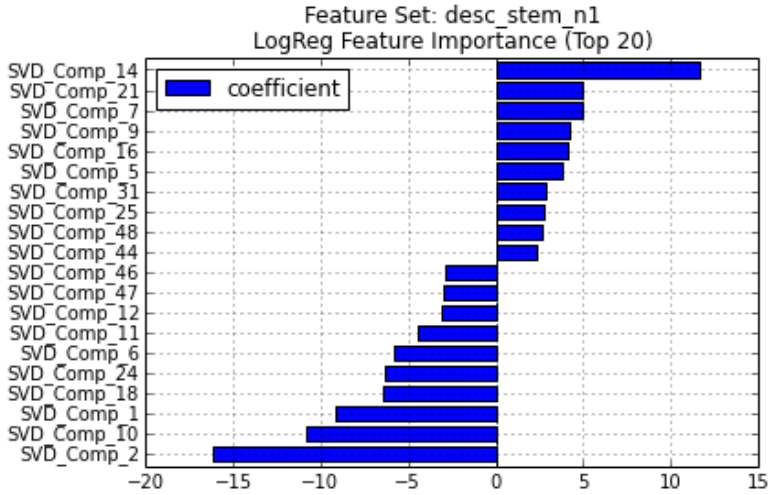


Figure 35: Logistic Regression Classification Model Feature Importance



Summary SVD Feature Set

Section IPython Notebook link: osha_07_svd_summary_feature_set.ipynb

Similar to the process followed in the previous section for the Event Description field, applying singular value decomposition to vectorized matrices of terms contained in the Summary Text field created four feature sets. Table 20 below summarizes the four different configurations experimented with in this project. The four feature sets created from application of SVD to each of these vectorized document-term matrices were used during modeling to allow results to pass judgment on the optimal configuration.

Table 20: Vectorization Parameters and Resulting SVD Feature Sets

Feature Set Short Name	Ngram Features	Corpus Transform Method	Term Reduction Method	Minimum Document Frequency	# Rows in Vectorized Matrix	# Columns in Vectorized Matrix	# SVD Components Selected
summ_stem_n1	Unigrams	TF-IDF	Stem	20	21,331	3,120	50
summ_stem_n123	Unigrams, Bigrams, Trigrams	TF-IDF	Stem	20	21,331	9,154	50
summ_lem_n1	Unigrams	TF-IDF	Lemma	20	21,331	3,925	50
summ_lem_n123	Unigrams, Bigrams, Trigrams	TF-IDF	Lemma	20	21,331	9,464	50

Figures F.1 and F.2 in Appendix F are scatterplots of the top four components containing the majority of information resident in the underlying document-term matrices. Note that, like the Description SVD, the Summary SVD plots are remarkably similar across the train and test partitions. However, the document score plots are more blurred and not as distinctive. This is likely due to the much larger variety of words and concepts contained in the summary text. These Summary SVD feature sets are expected to be weaker predictors of accident outcome then those from the Description SVD feature sets, but still predictive nonetheless. There are clear clusters of documents with similar accident outcomes in concept-to-concept space removed from the origin. Concepts contained in the Summary SVD features might complement the Description SVD features during the upcoming combined feature set modeling phase and provide a distinctive edge.

Each of the five classification algorithms was trained on the train partition data of the Summary SVD feature set and evaluated on the test partition data. Of the four feature sets

created, the *summ_stem_n1* feature set was selected to go forward with. Model evaluation statistics for the base and combination models are summarized in Table 21.

Table 21: Base Model and Combination Model Results

Model Name	Accuracy	Precision	Recall	F Measure	TN	FN	FP	TP
Base Classification Models								
Structured - LogReg	**0.853**	**0.815**	**0.861**	**0.837**	**23,687**	**3,024**	**4,269**	**18,790**
summ_stem_n1 - LogReg	0.837	0.799	0.841	0.819	23,336	3,468	4,620	18,346
summ_stem_n1 - AdaBst	0.798	0.761	0.784	0.773	22,588	4,701	5,368	17,113
summ_stem_n1 - RanFst	0.775	0.771	0.692	0.729	23,468	6,725	4,488	15,089
summ_stem_n1 - KNN	0.771	0.726	0.768	0.746	21,639	5,070	6,317	16,744
summ_stem_n1 - DTree	0.718	0.682	0.671	0.676	21,118	7,174	6,838	14,640
Top 3 Mean Response Probability Models								
summ_stem_n1 - MRP 45	0.799	0.736	0.844	0.786	21,348	3,404	6,608	18,410
summ_stem_n1 - MRP 50	0.800	0.765	0.783	0.774	22,721	4,733	5,235	17,081
summ_stem_n1 - MRP 55	0.792	0.792	0.713	0.750	23,874	6,260	4,082	15,554
Top 3 Voting Models								
summ_stem_n1 - Vote 2+	0.809	0.731	0.895	0.805	20,762	2,291	7,194	19,523
summ_stem_n1 - Vote 3+	0.823	0.791	0.810	0.800	23,287	4,144	4,669	17,670
summ_stem_n1 - Vote 4+	0.800	0.843	0.669	0.746	25,244	7,228	2,712	14,586

The Logistic Regression model was once again the top performer with classification accuracy score of 83.7%, a slight 1.6% drop in accuracy from the baseline structured data only model. The combination models did not provide additional lift for this feature set. A cumulative gains chart for each of the five classification models is depicted in Figure 36. Accuracy scores at different thresholds for the combination models are plotted in Figure 37. Figures 38 and 39 are plots of feature importance for the top 20 features of the Random Forest and Logistic Regression models, respectively.

Figure 36: Base Classification Model Cumulative Gains Chart

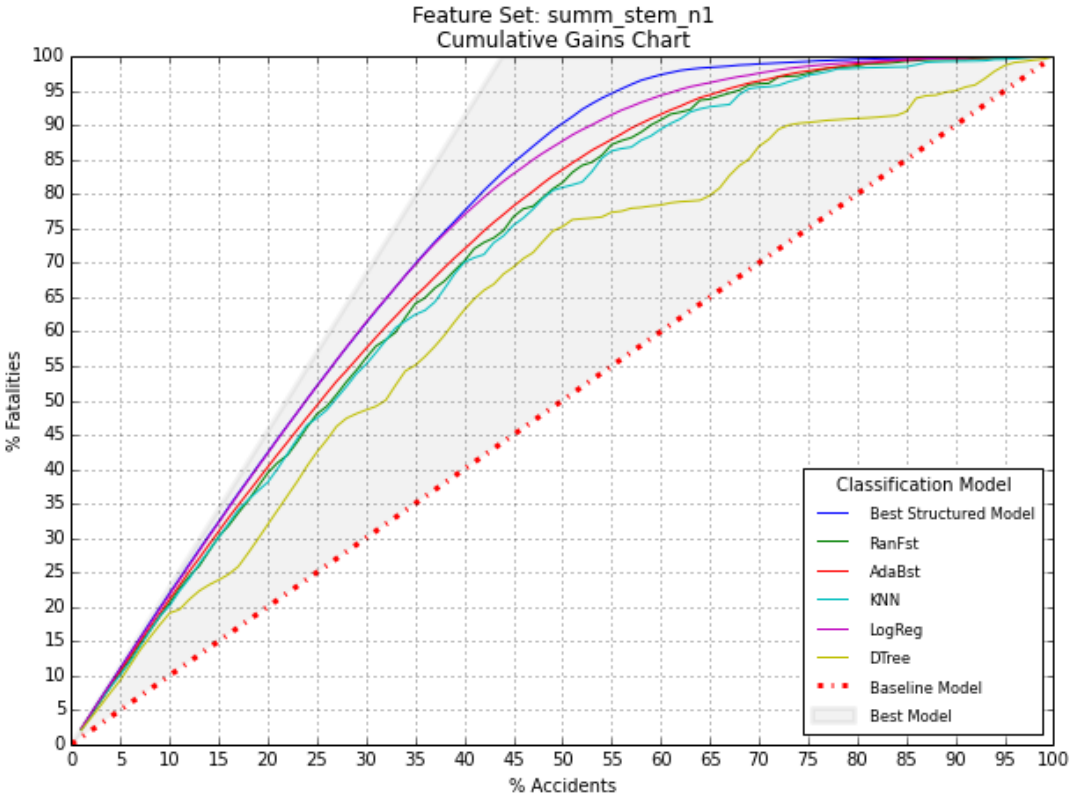


Figure 37: Combination Model Results

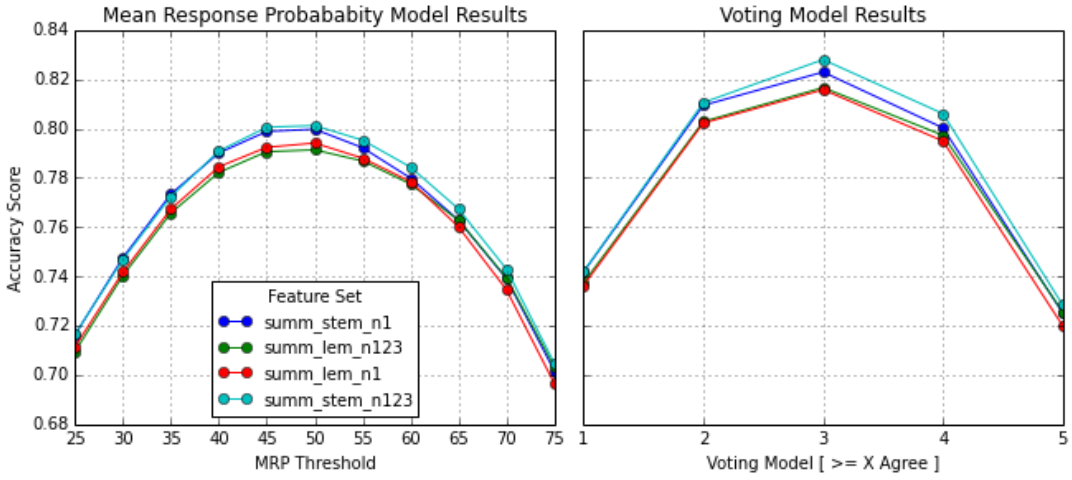


Figure 38: Random Forest Classification Model Feature Importance

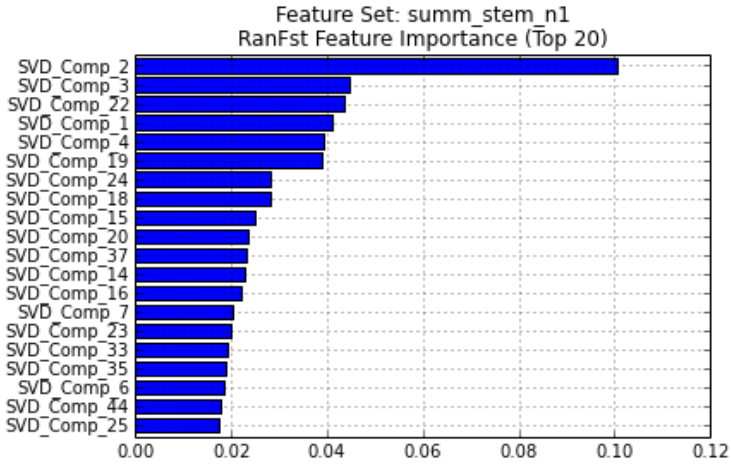
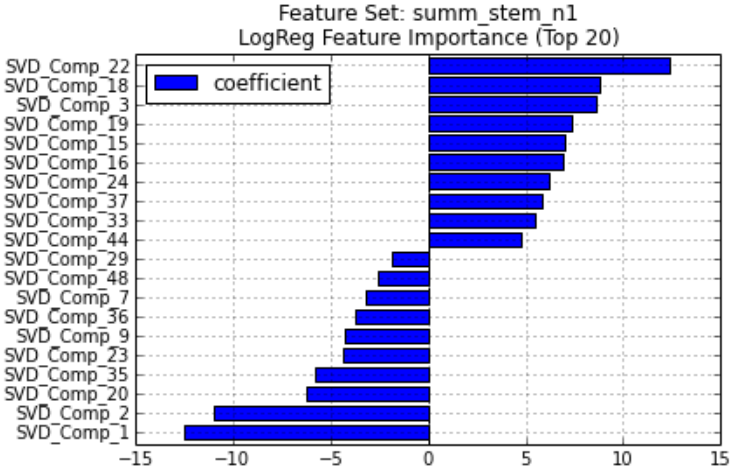


Figure 39: Logistic Regression Classification Model Feature Importance



Combined Feature Set

Section IPython Notebook link: osha_08_combined_feature_set.ipynb

In this final section combined feature sets comprised of top predictors selected across the various text-based and structured data feature sets were created and used as input to the five base classification models. The goal was to create synergies by joining together the best-of-predictors into combined feature sets and achieve potentially greater gains in classification accuracy. Combined feature sets were created based on various predictors selected from the Structured, Keyword, Linguistic, Topic, Description SVD and Summary SVD feature sets. Two feature selection methods and two methods of applying the feature selection method to the underlying feature sets were employed. Table 22 lists the 28 combined feature sets and the logic used in their construction.

Each of the five classification algorithms was trained on the train partition data of each combined feature set and evaluated on the test partition data. Five classifiers trained on 28 feature sets resulted in 140 distinct classification models. Model evaluation statistics for the base and combination models from selected top performing combined feature sets are summarized in Table 23. The Logistic Regression model was once again the top performer with classification accuracy score of 94.0%, a 4% gain in accuracy from the top performing standalone feature set model, and a 8.7% gain in accuracy from the baseline structured data only model. The combination models did not provide additional lift. A cumulative gains chart for each of the five classification models of the top performing combined feature set is depicted in Figure 41. Accuracy scores at different thresholds for the selected combination models are plotted in Figure

40. Figures 42, 43 and 44 are plots of feature importance for the top 20 features of the top performing combined model and two other combined models.

Table 22: Configuring the Combined Feature Sets

Combined Feature Sets	
Main Utd Ptile 1	All Utd Ptile 1
Main Utd Ptile 2	All Utd Ptile 2
Main Utd Ptile 5	All Utd Ptile 5
Main Utd Ptile 10	All Utd Ptile 10
Main Utd Ptile 20	All Utd Ptile 20
Main Utd Ptile 30	All Utd Ptile 30
Main Utd Ptile 40	All Utd Ptile 40
Main Utd Ptile 50	All Utd Ptile 50
Main Sep Ptile 5	All Sep Ptile 5
Main Sep Ptile 10	All Sep Ptile 10
Main Sep Ptile 20	All Sep Ptile 20
Main Sep Kbest 10	All Sep Kbest 10
Main Sep Kbest 5	All Sep Kbest 5
Main Sep Kbest 2	All Sep Kbest 2

[Main] = Feature sets used: Structured, Linguistic, Topic, Keywords
[All] = [Main] + [Description SVD stem/n1] + [Summary SVD stem/n1]

[Utd] = Combine feature sets into single united set prior to feature selection
[Sep] = Apply feature selection to each feature set before combining features

[Ptile X] = Feature selection of most important X percent of features
[Kbest X] = Feature selection of most important X number of features

Table 23: Base Model and Combination Model Results

Model Name	Accuracy	Precision	Recall	F Measure	TN	FN	FP	TP
Base Classification Models								
All Utd P40 - LogReg	0.940	0.925	0.940	0.933	26,302	1,309	1,654	20,505
All Utd P50 - LogReg	0.940	0.925	0.940	0.933	26,295	1,306	1,661	20,508
All Utd P30 - LogReg	0.940	0.924	0.940	0.932	26,279	1,315	1,677	20,499
All Utd P20 - LogReg	0.936	0.918	0.939	0.928	26,121	1,339	1,835	20,475
All Utd P10 - LogReg	0.933	0.913	0.937	0.925	26,003	1,368	1,953	20,446
Structured - LogReg	**0.853**	**0.815**	**0.861**	**0.837**	**23,687**	**3,024**	**4,269**	**18,790**
Honorable Mention Base Classification Models								
All Sep P20 - RanFst	0.920	0.911	0.906	0.909	26,027	2,041	1,929	19,773
All Utd P05 - RanFst	0.918	0.907	0.906	0.906	25,918	2,042	2,038	19,772
All Sep P20 - AdaBst	0.914	0.893	0.912	0.902	25,580	1,928	2,376	19,886
All Sep P10 - LogReg	0.912	0.887	0.917	0.901	25,397	1,812	2,559	20,002
All Utd P02 - RanFst	0.912	0.899	0.900	0.899	25,752	2,187	2,204	19,627
All Sep P10 - AdaBst	0.908	0.887	0.906	0.896	25,440	2,060	2,516	19,754
All Sep K10 - RanFst	0.907	0.892	0.896	0.894	25,602	2,271	2,354	19,543
All Sep K10 - LogReg	0.906	0.884	0.904	0.894	25,364	2,084	2,592	19,730
All Sep K10 - AdaBst	0.902	0.881	0.896	0.889	25,329	2,273	2,627	19,541
Top 3 Mean Response Probability Models								
All Utd P30 - MRP 50	0.934	0.917	0.934	0.925	26,114	1,448	1,842	20,366
All Utd P50 - MRP 50	0.934	0.917	0.933	0.925	26,101	1,451	1,855	20,363
All Utd P30 - MRP 55	0.933	0.933	0.912	0.922	26,519	1,909	1,437	19,905
Top 3 Voting Models								
All Utd P50 - Vote 3+	0.936	0.921	0.936	0.928	26,202	1,407	1,754	20,407
All Utd P30 - Vote 3+	0.936	0.920	0.935	0.928	26,193	1,410	1,763	20,404
All Utd P40 - Vote 3+	0.936	0.920	0.934	0.927	26,192	1,433	1,764	20,381

Figure 40: Combination Model Results

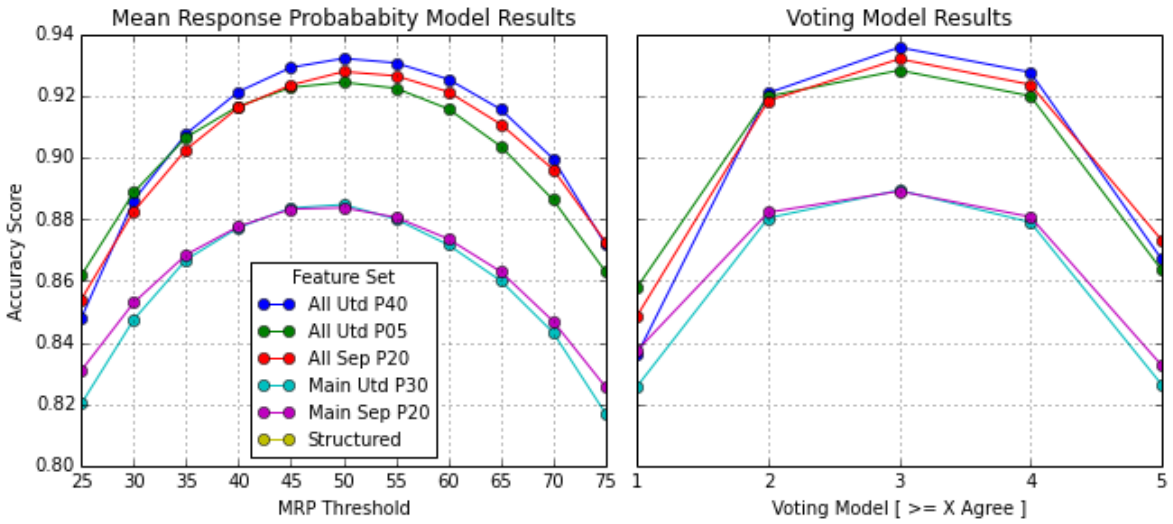


Figure 41: Base Classification Model Cumulative Gains Chart

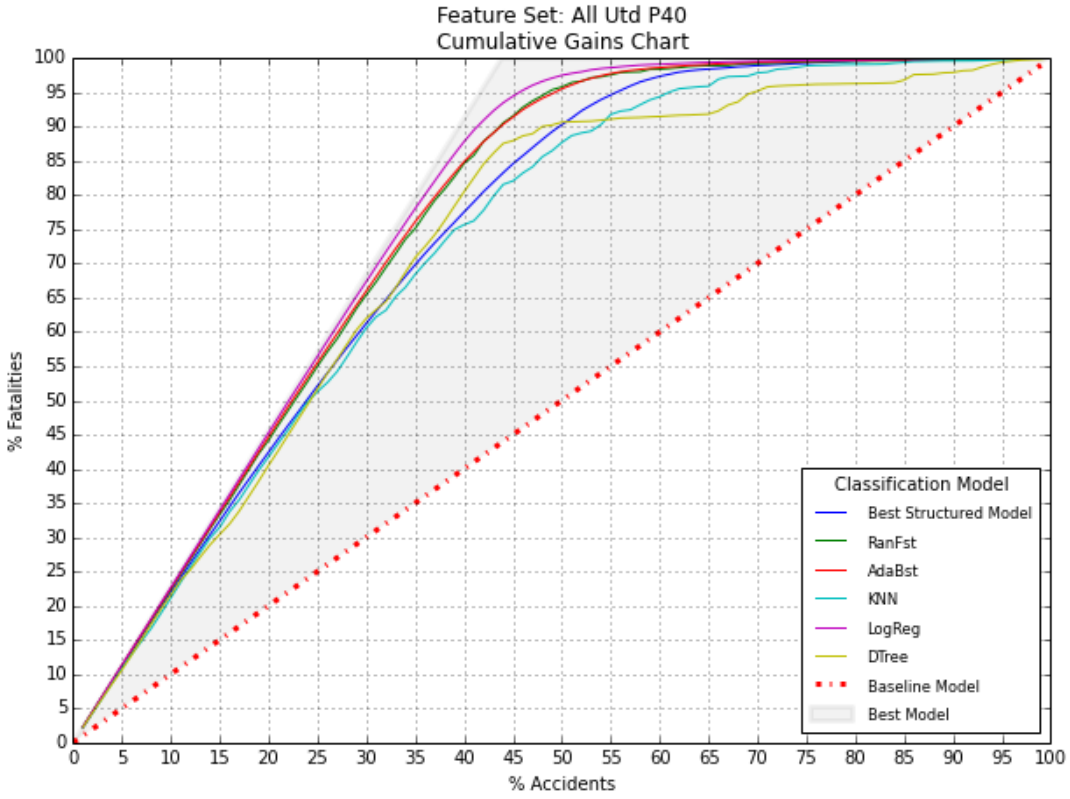


Figure 42: Classification Model Feature Importance of Top Performing Combined Model

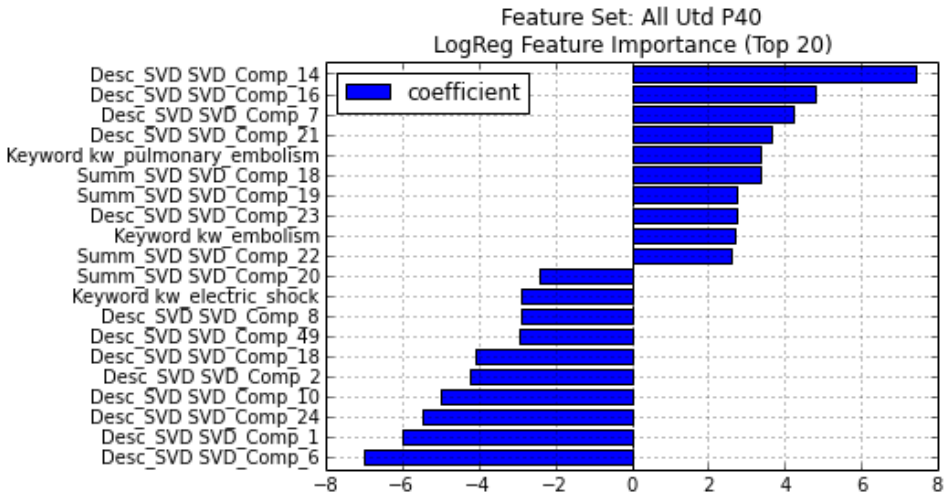


Figure 43: Logistic Regression Feature Importance of a Selected Combined Model

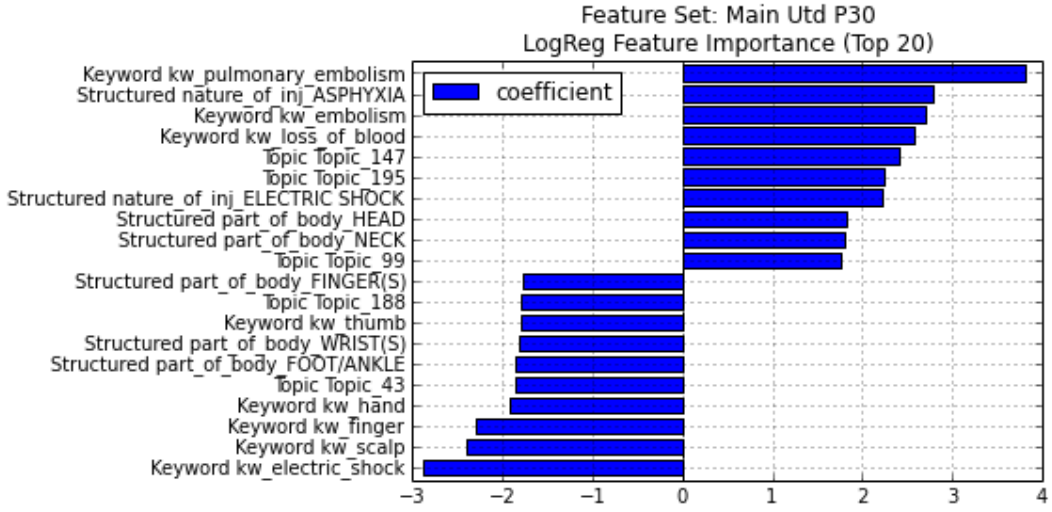
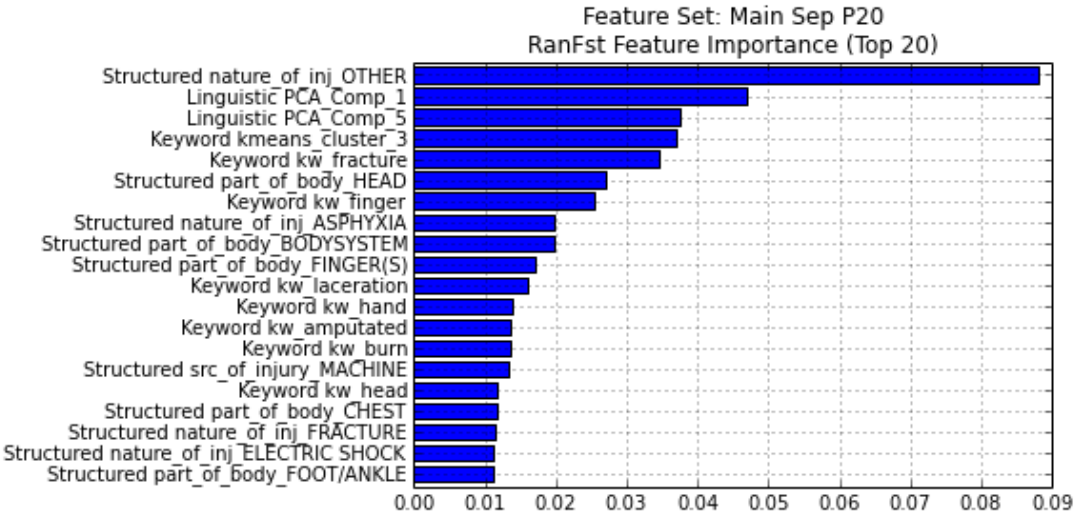


Figure 44: Random Forest Feature Importance of a Selected Combined Model



CONCLUSION

This thesis demonstrated that features mined from text-based attributes captured concepts and information not present in the structured data attributes and that this infusion of new information enabled classification algorithms to better discriminate between target variable outcomes, thereby improving model accuracy. Feature sets created from a medley of statistics-based and linguistics-based text mining techniques resulted in a measurable improvement in classification model accuracy in some cases beyond that of models trained on structured data attributes only. This thesis also demonstrated that combining multiple predictive models trained on the same features set obtained better performance than was obtained from any of the constituent models independently. Finally, combined feature sets composed of top predictors selected across the various text-based and structured data feature sets provided the greatest lift to classification model accuracy.

FURTHER RESEARCH

This analysis placed equal importance on the classification of accident outcomes and evaluated models based on their overall accuracy rate. The misclassification cost ratio is the ratio of false positive misclassification costs to false negative misclassification costs, which was implicitly one for this project. However, classifying a true-death as non-death should be more costly. Future work could investigate the effect of asymmetric misclassification costs on classifier results. Correct application of misclassification costs would likely decrease false negative outcomes at the expense of increased false positive outcomes, an acceptable tradeoff.

Recall that the raw data contained a trinary variable with injury outcomes of fatal, hospitalized and non-hospitalized. This trichotomous variable was omitted in favor of a dichotomous target variable with values of fatal or non-fatal. Development of a trinary classification model based on this trinary target, with application of trinary evaluation measures for model goodness, such as sensitivity, is another area ripe for future work.

Assumptions and decisions made during the data preparation phase dictated the quality of feature sets used to train classification models and exerted considerable influence on predictive performance. The breadth and depth of this project reduced feature extraction and selection, two critical components of any predictive modeling project, to arbitrary decisions at certain steps in the analytical pipeline. Examples are the selection of 50 singular value decomposition components and four K-Means clusters, text pre-processing procedures, simplified sentiment computations, exclusion of structured accident attributes and default classification algorithm parameters. The only way to thoroughly test whether assumptions and decisions made throughout this analysis were optimal would be to evaluate the impact of each unique path of

decisions against some common metric, such as model accuracy on the test set. Of course this is not feasible, as the number of paths to evaluate would grow exponentially with each decision made. With time, dedication and a flexible framework, running iterations of the entire project from start to end along multiple decision paths would help determine optimal thresholds and make important decisions less arbitrary and more scientific.

This author believes that the Python scientific computing environment is an ideal framework for programming such iterations over complex analytical pipelines, and that the publically available project code, and the powerful open source Python capabilities that this project is built upon, offer an ideal foundation from which to expand and manage analytical complexity of this nature.

Furthermore, default classification model configurations were used in this study as the modeling framework and feature engineering tasks were complex enough. Time spent experimenting with different parameters and discovering optimal configurations may be worth the effort. In a similar manner the five classification models used in this study were selected in part for their speed. Experimenting with different classifiers, including those with longer run times, may improve results beyond that which was achieved in this project.

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APPENDIX A: Python Scientific Computing Resources and Packages

Resource		URL	Description
Python	Programming Language	http://www.python.org	Powerful dynamic programming language that is used in a wide variety of application domains
IPython / IPython Notebook	Interactive Computing	http://ipython.org http://ipython.org/notebook	Web-based interactive computational environment that combines code execution, text, mathematics, plots and rich media into a single document.
Pandas	Python for Data Analysis	http://pandas.pydata.org	High-performance, easy-to-use data structures and data analysis tools for the Python programming language.
Scikit-Learn	Machine Learning in Python	http://scikit-learn.org/stable/	Simple and efficient tools for data mining and data analysis; Built on NumPy, SciPy, and Matplotlib.
NLTK	Natural Language Toolkit	http://nltk.org	Leading platform for building Python programs to work with human language data.
Gensim	Topic Modeling	http://radimrehurek.com/gensim/	Scalable statistical semantics and analysis of documents for semantic structure.
Matplotlib	Visualization and Graphing	http://matplotlib.org	Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms
SciPy	Mathematical Algorithms and Functions	http://www.scipy.org	Python-based ecosystem of open-source software for mathematics, science, and engineering
NumPy	Base N-Dimensional Arrays	http://www.numpy.org	Fundamental package for scientific computing with Python

APPENDIX B: Keyword Feature Set Additional Figures

Figure B.1

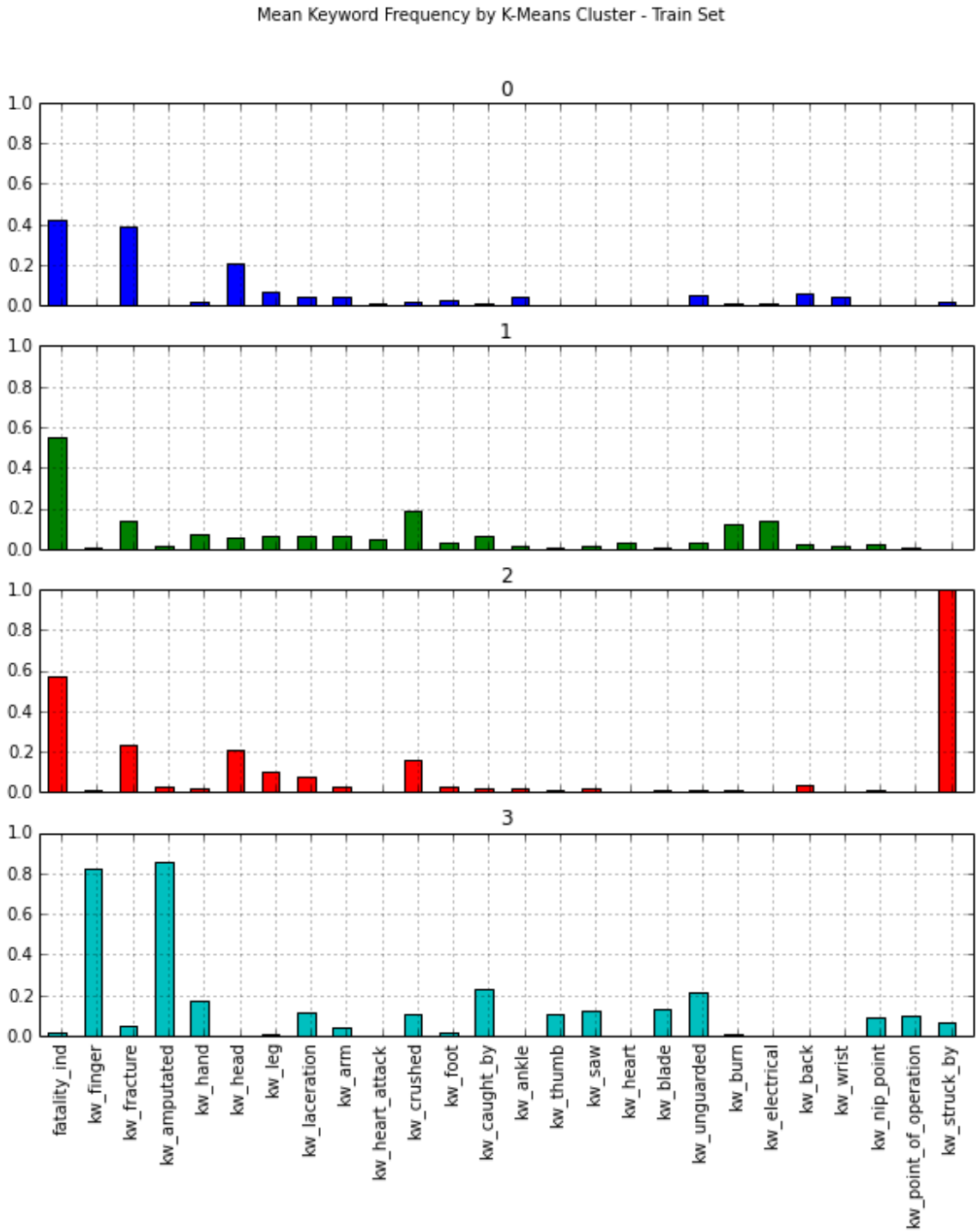
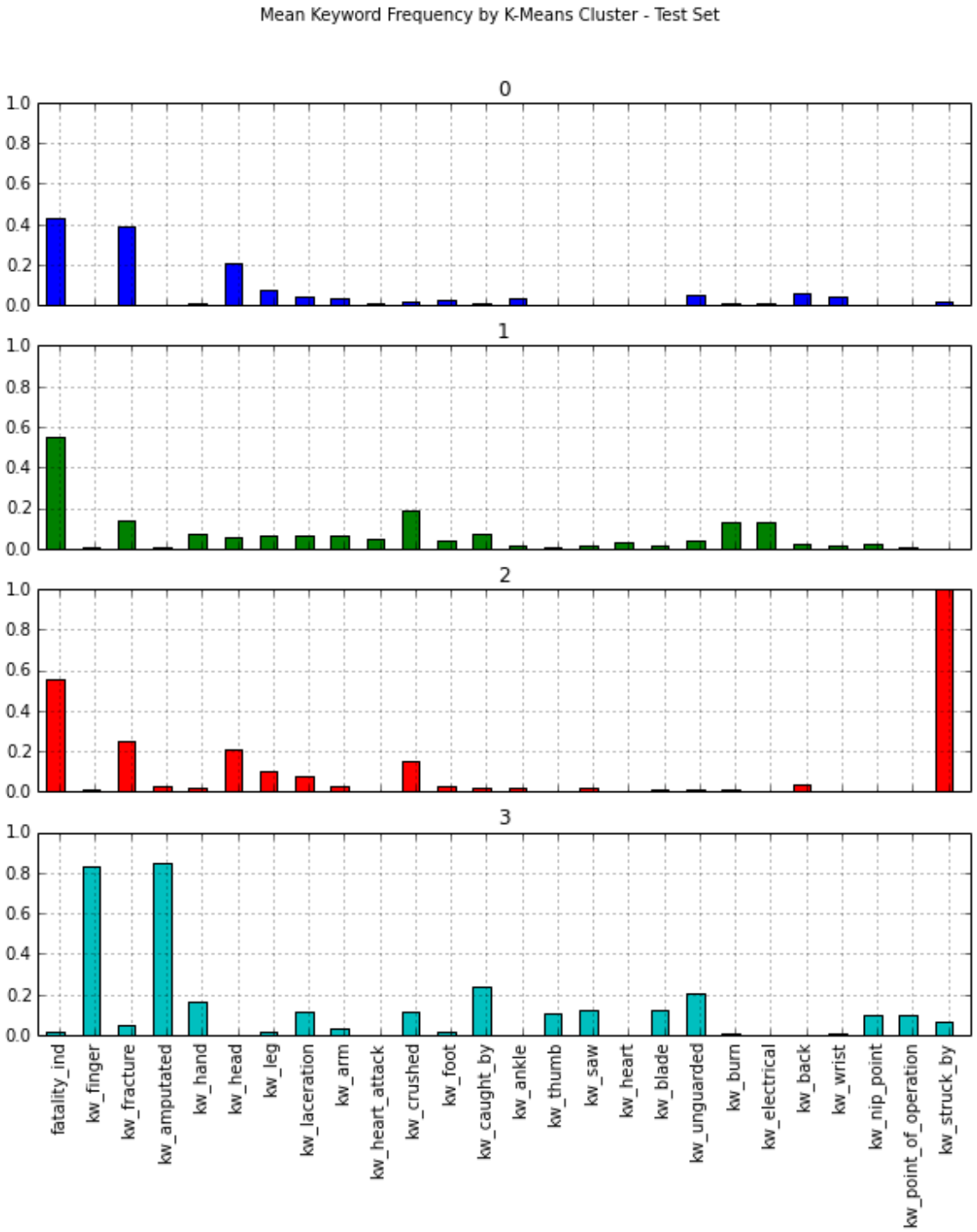
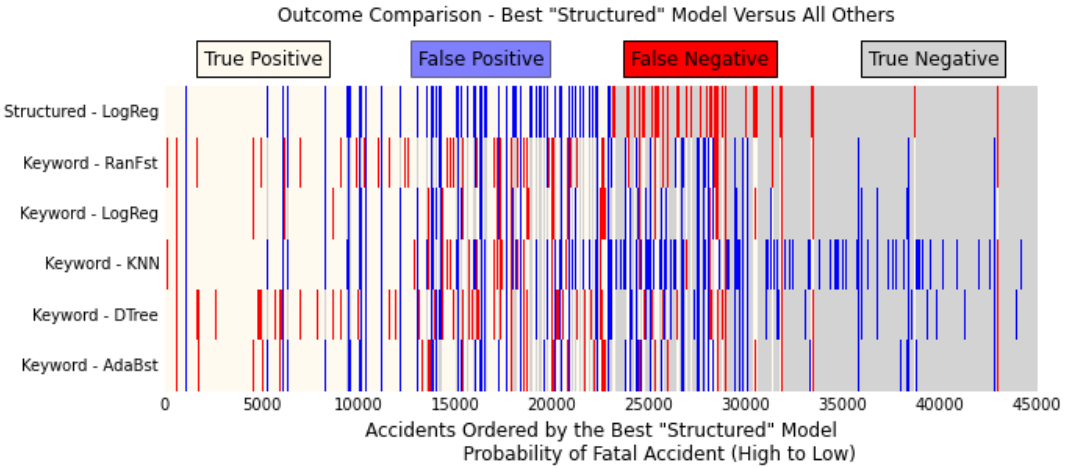
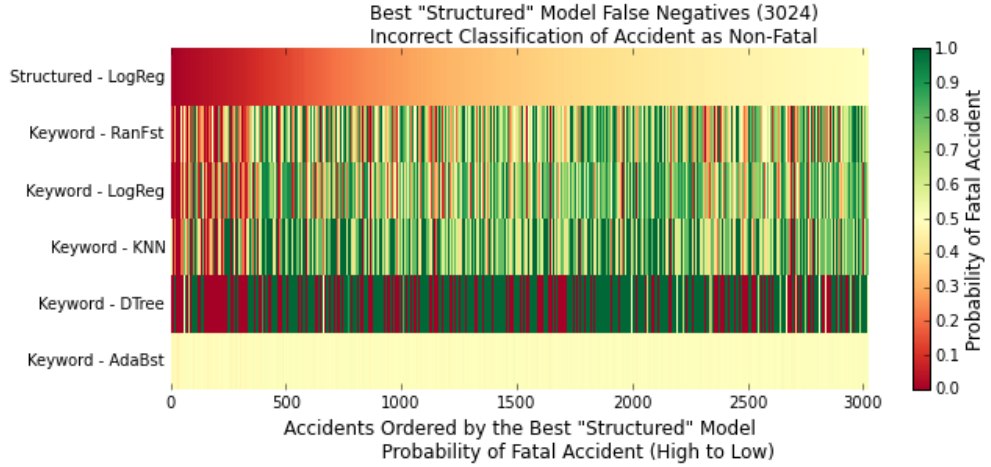
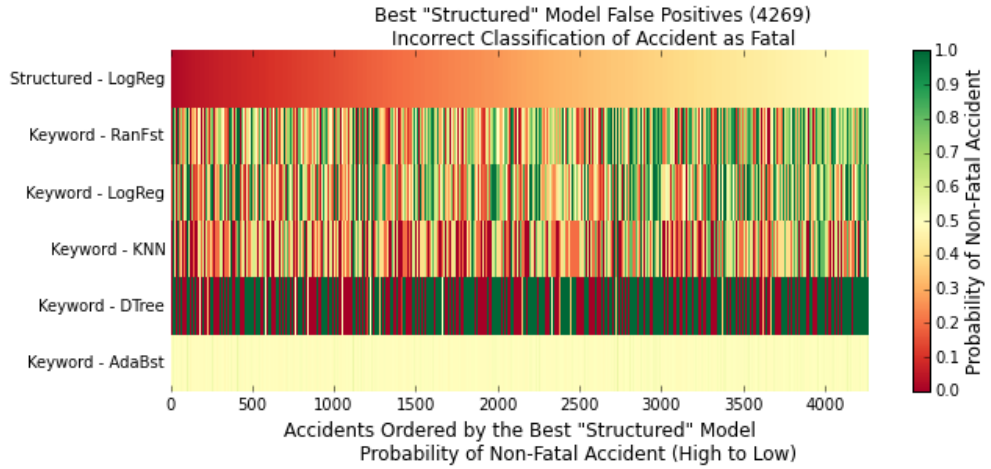


Figure B.2

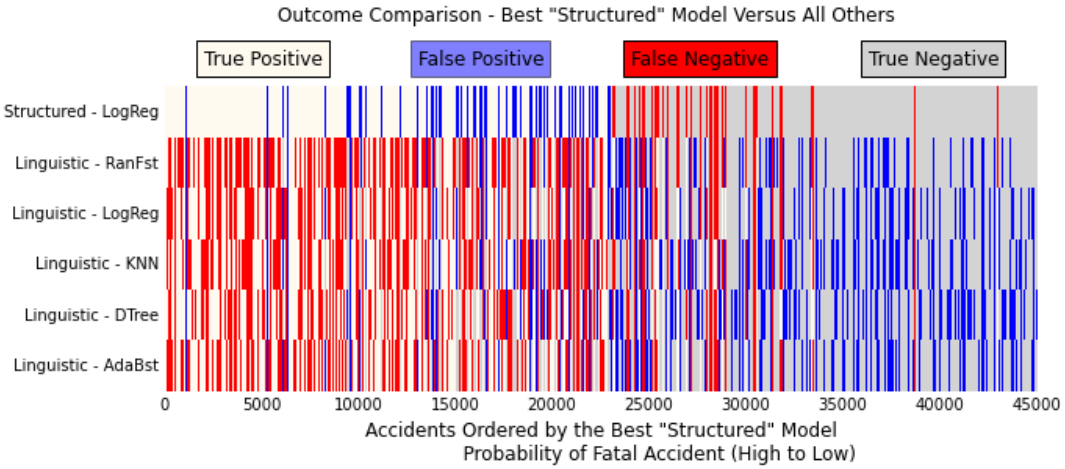

Mean Keyword Frequency by K-Means Cluster - Test Set
0
1
2
3
1.0
0.8
0.6
0.4
0.2
0.0
fatality_ind
kw_finger
kw_fracture
kw_amputated
kw_hand
kw_head
kw_leg
kw_laceration
kw_arm
kw_heart_attack
kw_crushed
kw_foot
kw_caught_by
kw_ankle
kw_thumb
kw_saw
kw_heart
kw_blade
kw_unguarded
kw_burn
kw_electrical
kw_back
kw_wrist
kw_nip_point
kw_point_of_operation
kw_struck_by

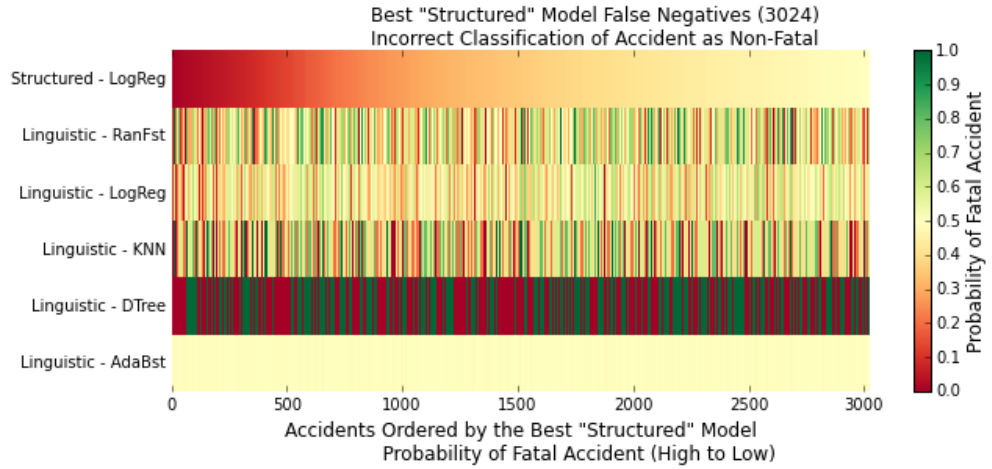

Outcome Comparison - Best "Structured" Model Versus All Others
True Positive
False Positive
False Negative
True Negative
Structured - LogReg
Keyword - RanFst
Keyword - LogReg
Keyword - KNN
Keyword - DTree
Keyword - AdaBst
0
5000
10000
15000
20000
25000
30000
35000
40000
45000
Accidents Ordered by the Best "Structured" Model
Probability of Fatal Accident (High to Low)

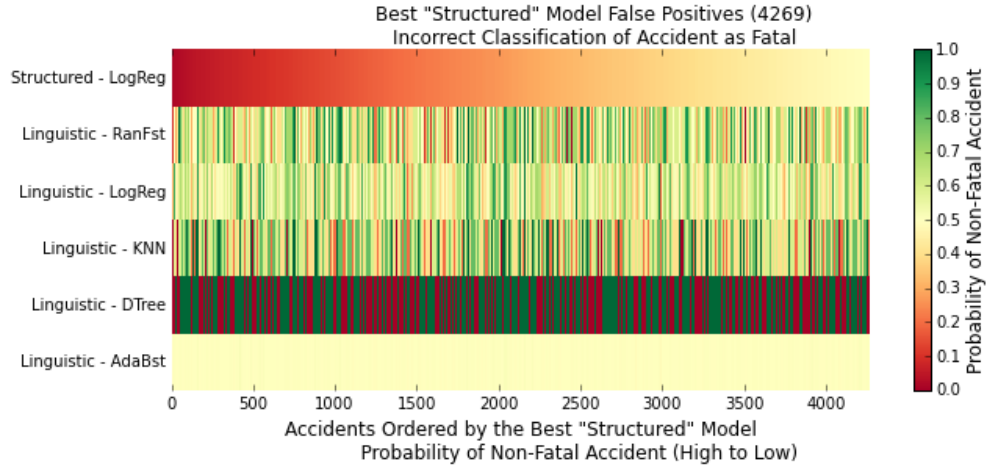

Best "Structured" Model False Negatives (3024)
Incorrect Classification of Accident as Non-Fatal
Structured - LogReg
Keyword - RanFst
Keyword - LogReg
Keyword - KNN
Keyword - DTree
Keyword - AdaBst
0
500
1000
1500
2000
2500
3000
Accidents Ordered by the Best "Structured" Model
Probability of Fatal Accident (High to Low)
Probability of Fatal Accident
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0


Best "Structured" Model False Positives (4269)
Incorrect Classification of Accident as Fatal
Structured - LogReg
Keyword - RanFst
Keyword - LogReg
Keyword - KNN
Keyword - DTree
Keyword - AdaBst
0
500
1000
1500
2000
2500
3000
3500
4000
Accidents Ordered by the Best "Structured" Model
Probability of Non-Fatal Accident (High to Low)
Probability of Non-Fatal Accident
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0

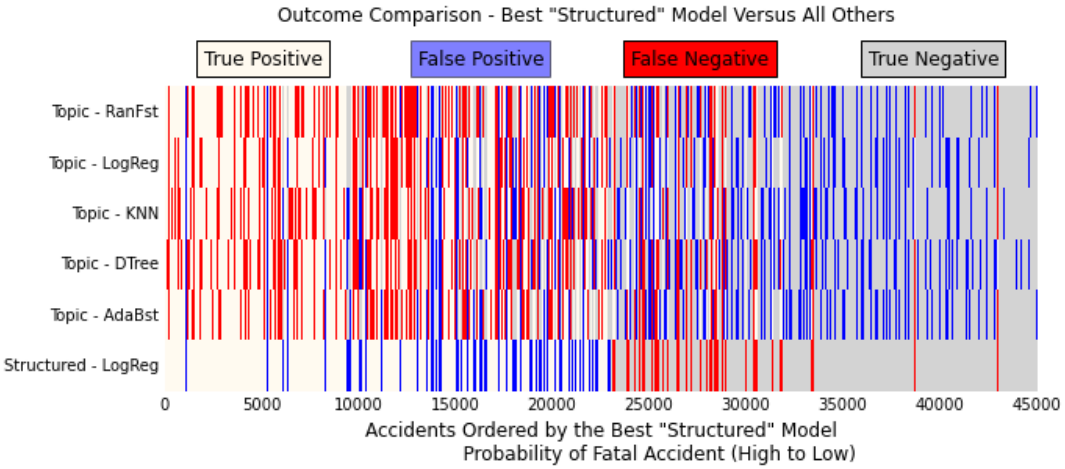
APPENDIX C: Linguistic Feature Set Additional Figures

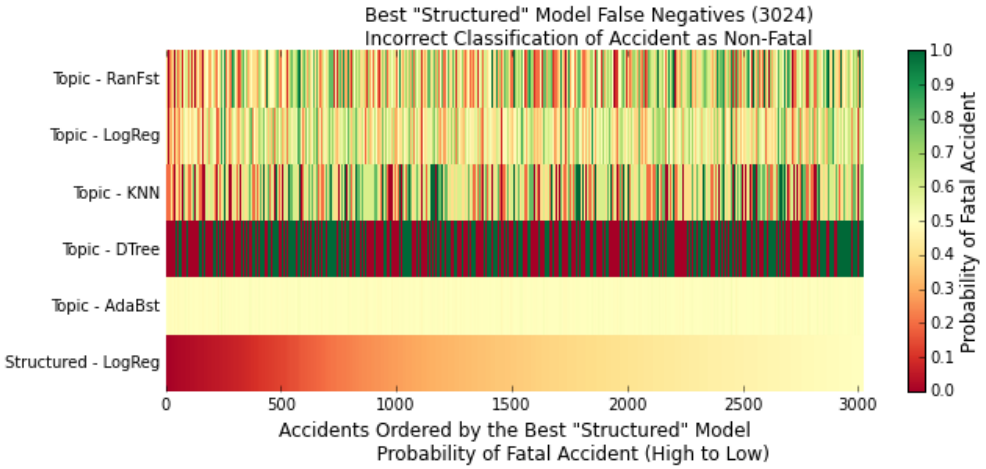


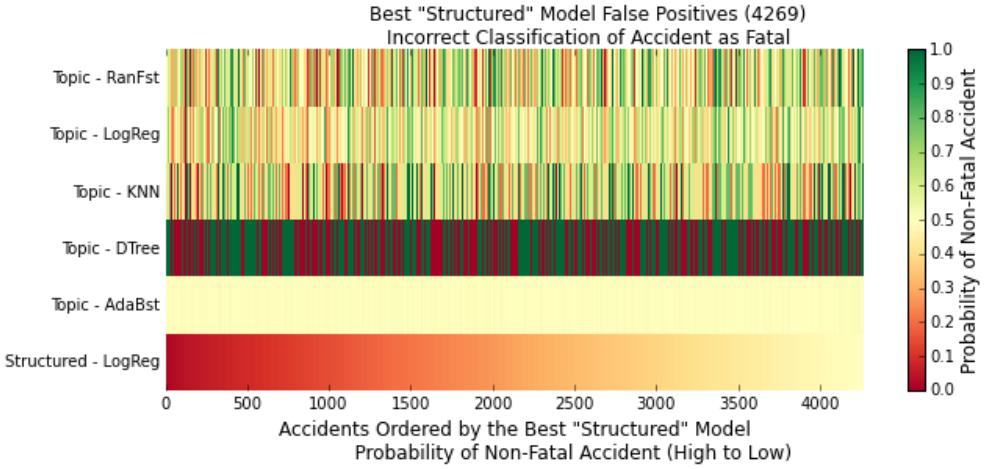




APPENDIX D: Topic Feature Set Additional Figures







APPENDIX E: Description SVD Feature Set Additional Figures

Figure E.1

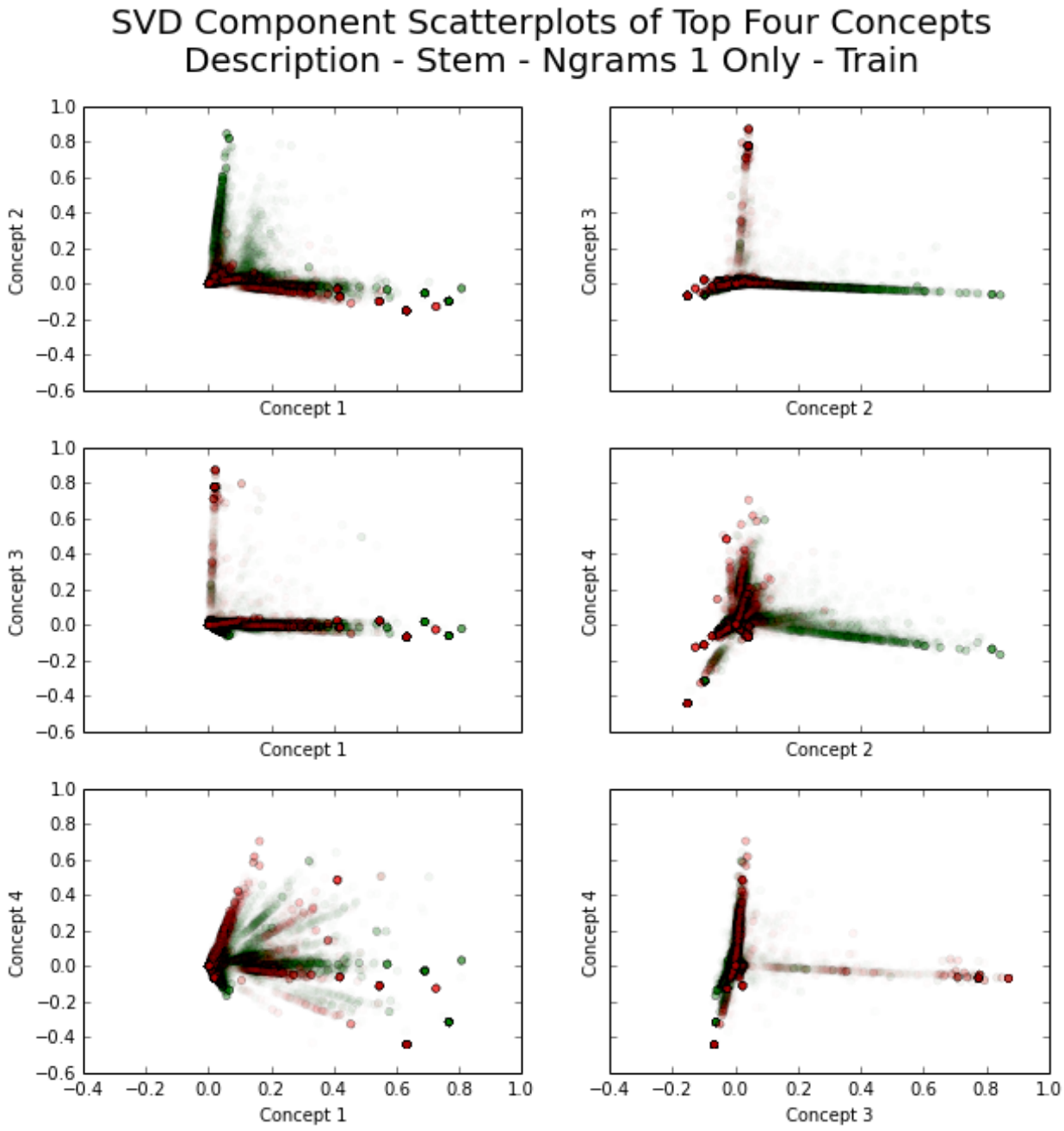
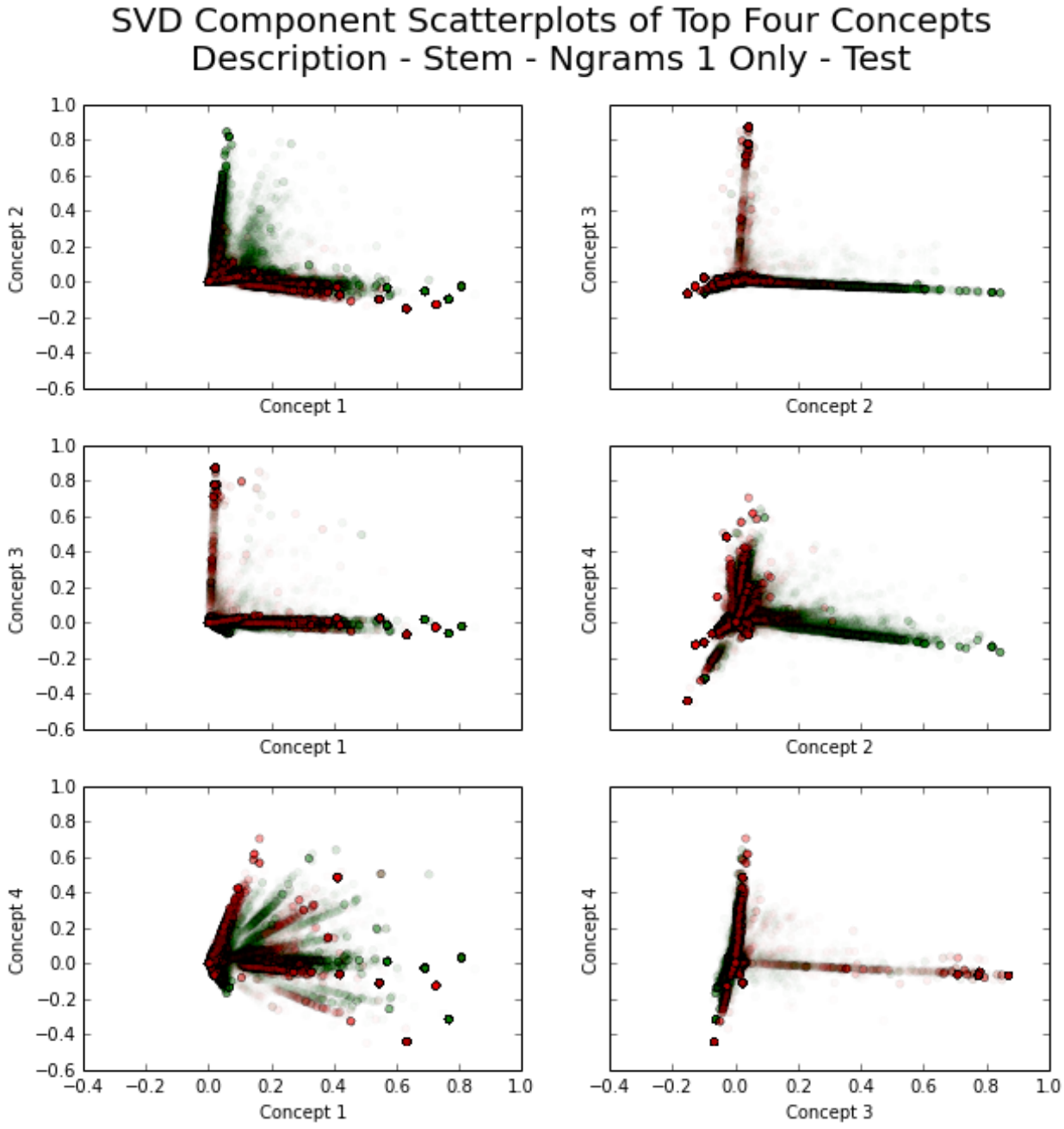
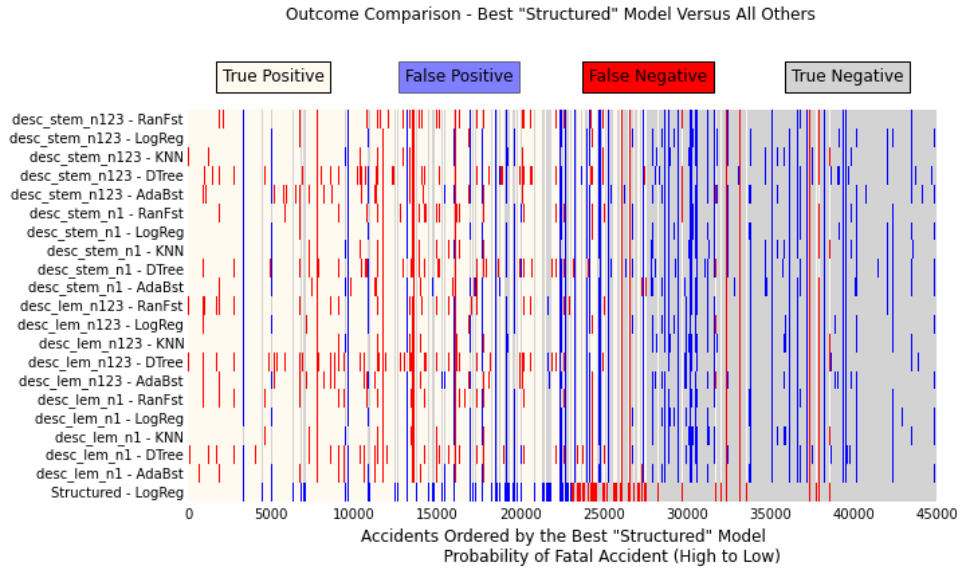
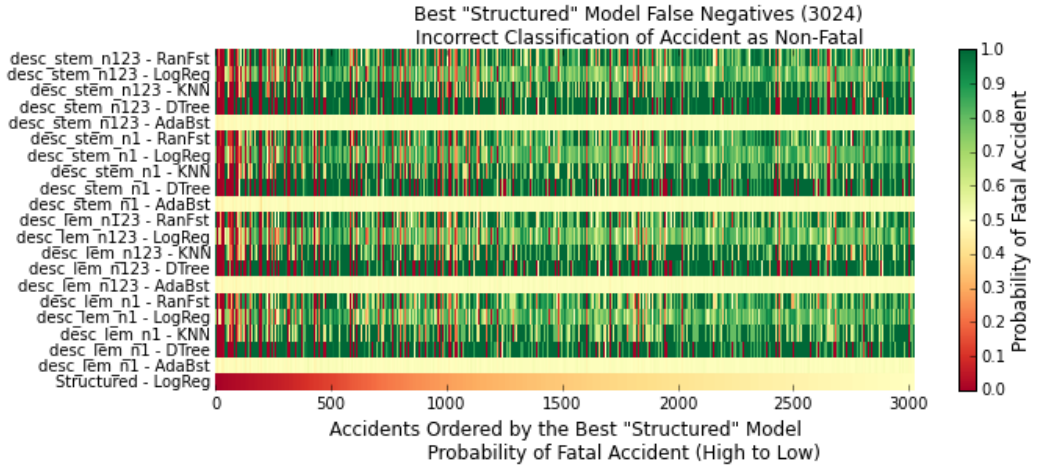
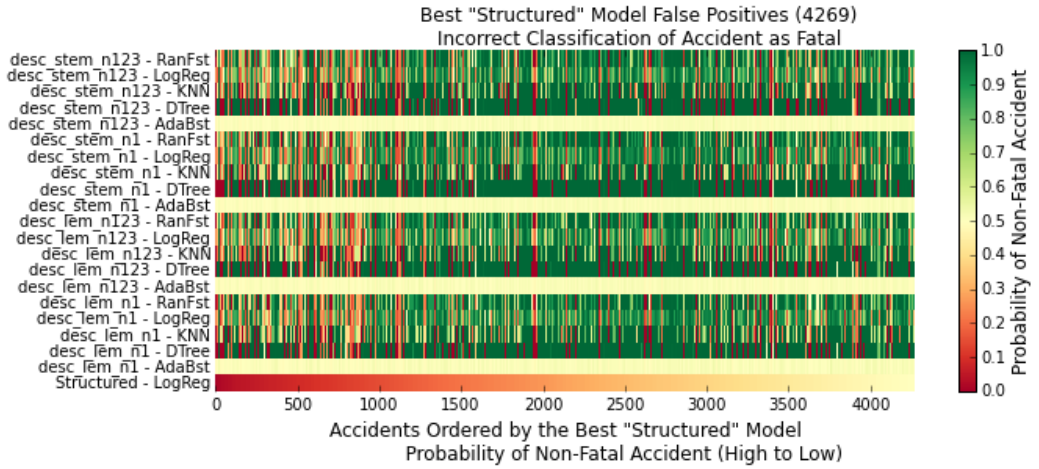


Figure E.2


SVD Component Scatterplots of Top Four Concepts
Description - Stem - Ngrams 1 Only - Test
Concept 2
Concept 1
Concept 3
Concept 2
Concept 3
Concept 1
Concept 4
Concept 2
Concept 4
Concept 1
Concept 4
Concept 3


Outcome Comparison - Best "Structured" Model Versus All Others
True Positive
False Positive
False Negative
True Negative
desc_stem_n123 - RanFst
desc_stem_n123 - LogReg
desc_stem_n123 - KNN
desc_stem_n123 - DTree
desc_stem_n123 - AdaBst
desc_stem_n1 - RanFst
desc_stem_n1 - LogReg
desc_stem_n1 - KNN
desc_stem_n1 - DTree
desc_stem_n1 - AdaBst
desc_lem_n123 - RanFst
desc_lem_n123 - LogReg
desc_lem_n123 - KNN
desc_lem_n123 - DTree
desc_lem_n123 - AdaBst
desc_lem_n1 - RanFst
desc_lem_n1 - LogReg
desc_lem_n1 - KNN
desc_lem_n1 - DTree
desc_lem_n1 - AdaBst
Structured - LogReg
0
5000
10000
15000
20000
25000
30000
35000
40000
45000
Accidents Ordered by the Best "Structured" Model
Probability of Fatal Accident (High to Low)


Best "Structured" Model False Negatives (3024)
Incorrect Classification of Accident as Non-Fatal
desc_stem_n123 - RanFst
desc_stem_n123 - LogReg
desc_stem_n123 - KNN
desc_stem_n123 - DTree
desc_stem_n123 - AdaBst
desc_stem_n1 - RanFst
desc_stem_n1 - LogReg
desc_stem_n1 - KNN
desc_stem_n1 - DTree
desc_stem_n1 - AdaBst
desc_lem_n123 - RanFst
desc_lem_n123 - LogReg
desc_lem_n123 - KNN
desc_lem_n123 - DTree
desc_lem_n123 - AdaBst
desc_lem_n1 - RanFst
desc_lem_n1 - LogReg
desc_lem_n1 - KNN
desc_lem_n1 - DTree
desc_lem_n1 - AdaBst
Structured - LogReg
0
500
1000
1500
2000
2500
3000
Accidents Ordered by the Best "Structured" Model
Probability of Fatal Accident (High to Low)
Probability of Fatal Accident
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0


Best "Structured" Model False Positives (4269)
Incorrect Classification of Accident as Fatal
desc_stem_n123 - RanFst
desc_stem_n123 - LogReg
desc_stem_n123 - KNN
desc_stem_n123 - DTree
desc_stem_n123 - AdaBst
desc_stem_n1 - RanFst
desc_stem_n1 - LogReg
desc_stem_n1 - KNN
desc_stem_n1 - DTree
desc_stem_n1 - AdaBst
desc_lem_n123 - RanFst
desc_lem_n123 - LogReg
desc_lem_n123 - KNN
desc_lem_n123 - DTree
desc_lem_n123 - AdaBst
desc_lem_n1 - RanFst
desc_lem_n1 - LogReg
desc_lem_n1 - KNN
desc_lem_n1 - DTree
desc_lem_n1 - AdaBst
Structured - LogReg
0
500
1000
1500
2000
2500
3000
3500
4000
Accidents Ordered by the Best "Structured" Model
Probability of Non-Fatal Accident (High to Low)
Probability of Non-Fatal Accident
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0

APPENDIX F: Summary SVD Feature Set Additional Figures

Figure F.1

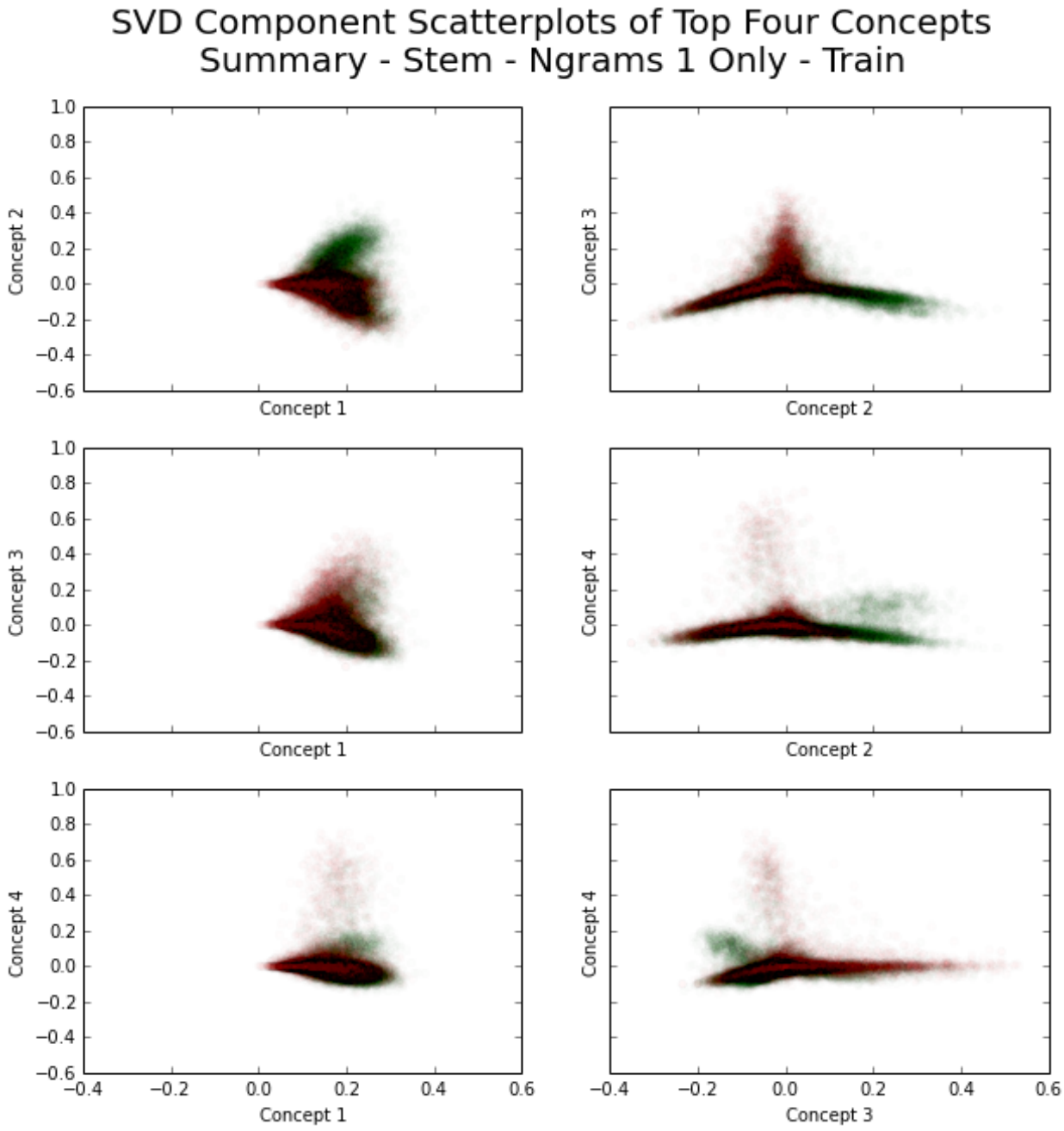
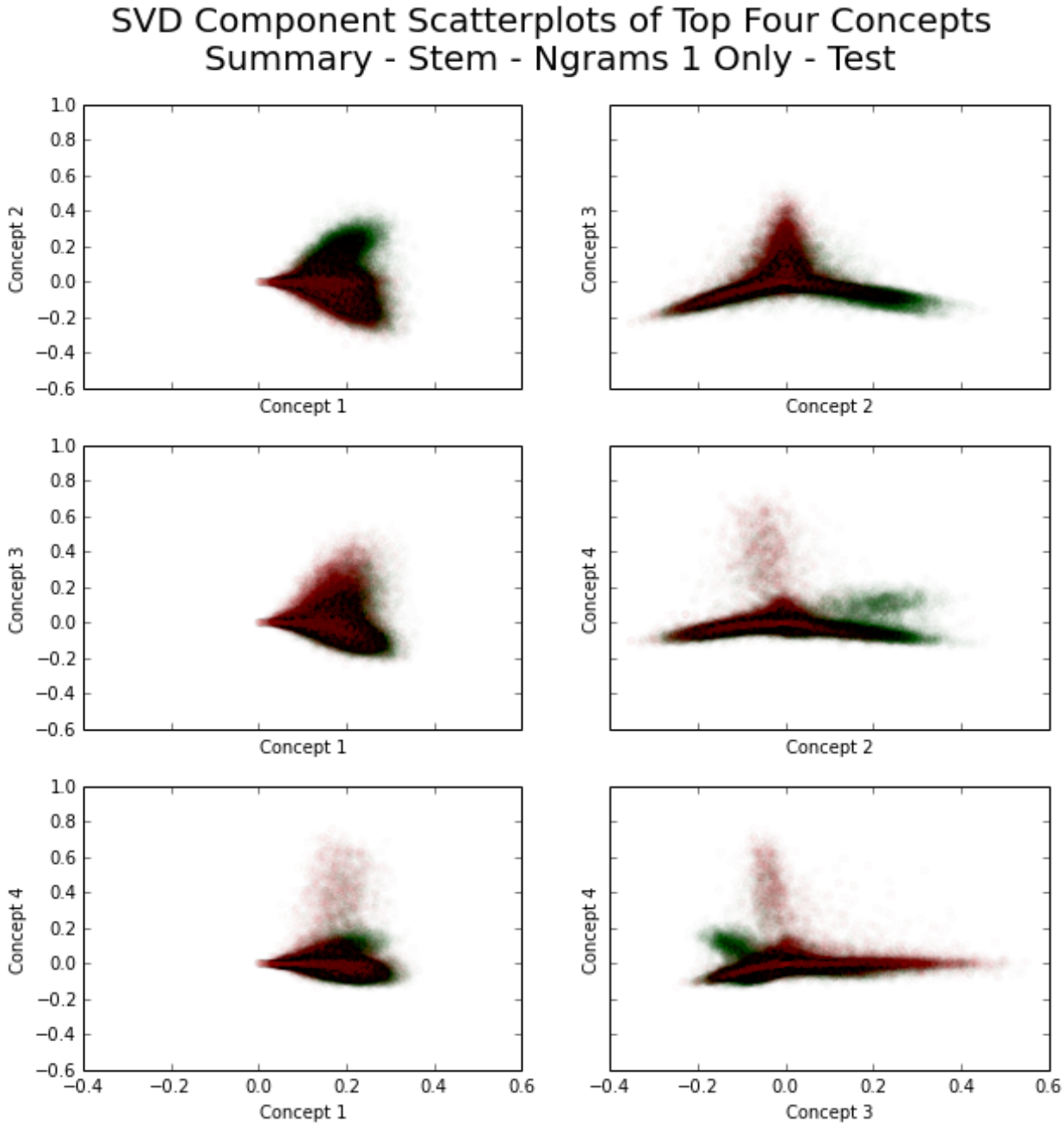
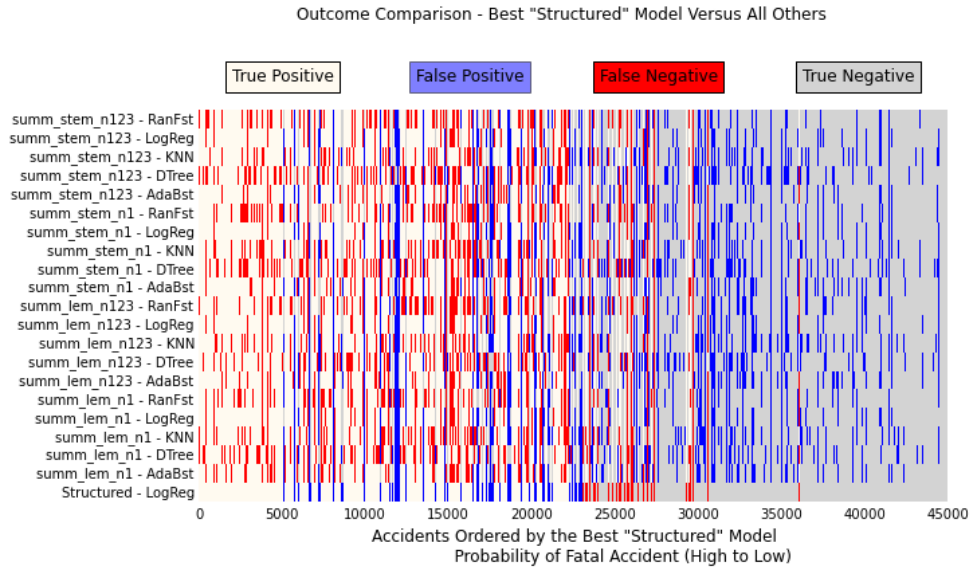
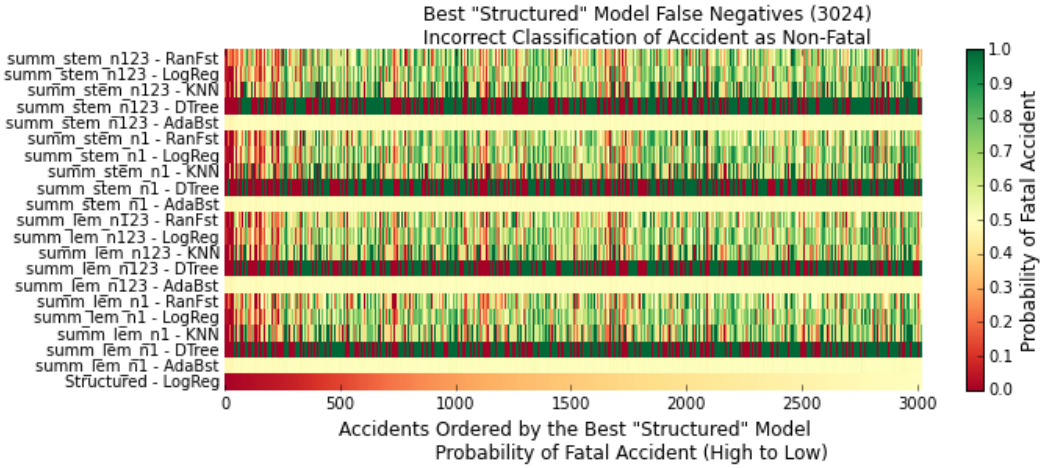
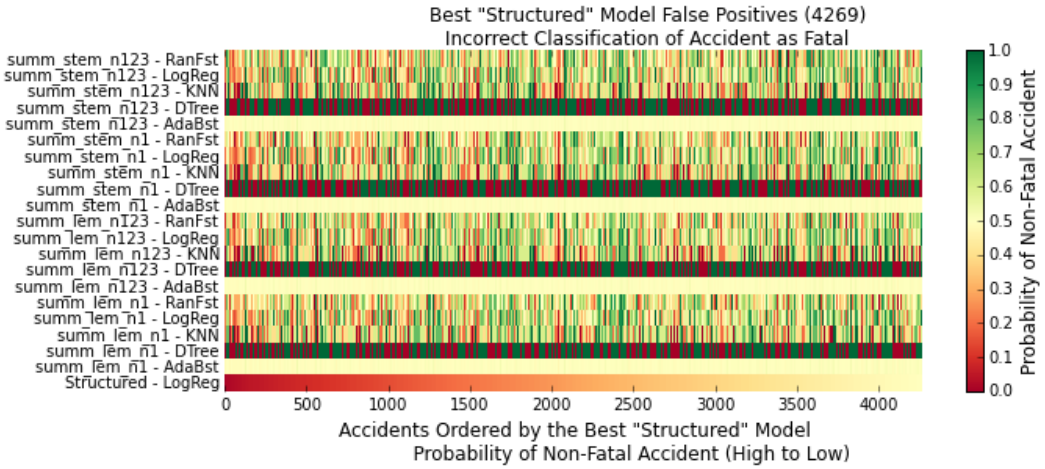


Figure F.2


SVD Component Scatterplots of Top Four Concepts
Summary - Stem - Ngrams 1 Only - Test
Concept 2
Concept 1
Concept 3
Concept 2
Concept 3
Concept 1
Concept 4
Concept 2
Concept 4
Concept 1
Concept 4
Concept 3


Outcome Comparison - Best "Structured" Model Versus All Others
True Positive
False Positive
False Negative
True Negative
summ_stem_n123 - RanFst
summ_stem_n123 - LogReg
summ_stem_n123 - KNN
summ_stem_n123 - DTree
summ_stem_n123 - AdaBst
summ_stem_n1 - RanFst
summ_stem_n1 - LogReg
summ_stem_n1 - KNN
summ_stem_n1 - DTree
summ_stem_n1 - AdaBst
summ_lem_n123 - RanFst
summ_lem_n123 - LogReg
summ_lem_n123 - KNN
summ_lem_n123 - DTree
summ_lem_n123 - AdaBst
summ_lem_n1 - RanFst
summ_lem_n1 - LogReg
summ_lem_n1 - KNN
summ_lem_n1 - DTree
summ_lem_n1 - AdaBst
Structured - LogReg
0
5000
10000
15000
20000
25000
30000
35000
40000
45000
Accidents Ordered by the Best "Structured" Model
Probability of Fatal Accident (High to Low)


Best "Structured" Model False Negatives (3024)
Incorrect Classification of Accident as Non-Fatal
summ_stem_n123 - RanFst
summ_stem_n123 - LogReg
summ_stem_n123 - KNN
summ_stem_n123 - DTree
summ_stem_n123 - AdaBst
summ_stem_n1 - RanFst
summ_stem_n1 - LogReg
summ_stem_n1 - KNN
summ_stem_n1 - DTree
summ_stem_n1 - AdaBst
summ_lem_n123 - RanFst
summ_lem_n123 - LogReg
summ_lem_n123 - KNN
summ_lem_n123 - DTree
summ_lem_n123 - AdaBst
summ_lem_n1 - RanFst
summ_lem_n1 - LogReg
summ_lem_n1 - KNN
summ_lem_n1 - DTree
summ_lem_n1 - AdaBst
Structured - LogReg
0
500
1000
1500
2000
2500
3000
Accidents Ordered by the Best "Structured" Model
Probability of Fatal Accident (High to Low)
Probability of Fatal Accident
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0


Best "Structured" Model False Positives (4269)
Incorrect Classification of Accident as Fatal
summ_stem_n123 - RanFst
summ_stem_n123 - LogReg
summ_stem_n123 - KNN
summ_stem_n123 - DTree
summ_stem_n123 - AdaBst
summ_stem_n1 - RanFst
summ_stem_n1 - LogReg
summ_stem_n1 - KNN
summ_stem_n1 - DTree
summ_stem_n1 - AdaBst
summ_lem_n123 - RanFst
summ_lem_n123 - LogReg
summ_lem_n123 - KNN
summ_lem_n123 - DTree
summ_lem_n123 - AdaBst
summ_lem_n1 - RanFst
summ_lem_n1 - LogReg
summ_lem_n1 - KNN
summ_lem_n1 - DTree
summ_lem_n1 - AdaBst
Structured - LogReg
0
500
1000
1500
2000
2500
3000
3500
4000
Accidents Ordered by the Best "Structured" Model
Probability of Non-Fatal Accident (High to Low)
Probability of Non-Fatal Accident
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0

APPENDIX G: Combined Feature Set Additional Figures