# Predictive Analytics Executed through the Use of Social Big Data and Machine Learning: An Imperious Result

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**Abstract:** *Instability in important socioeconomic indicators can have far-reaching effects on global development. This thesis offers a set of one-of-a-kind big data analytics algorithms that operate on unstructured Web data streams to automatically infer events, knowledge graphs, and predictive models, allowing for a better understanding, definition, and anticipation of the volatility of socioeconomic indicators. This paper we presents four major results that expand previous knowledge. Given a large volume of diverse unstructured news streams, we first describe novel models for collecting events and learning spatio-temporal features of events from news streams. We explore two different kinds of event models: one that is based on the concept of event triggers, and another that is probabilistic and learns a generic class of meta-events by extracting named entities from text streams. The second piece of work investigates the challenge of gleaning knowledge graphs from time-sensitive data like news and events as they happen. Event graphs produce a condensed depiction of a chronology of events pertinent to a news query by characterizing linkages between them using "event-phenomenon graphs," while spatio-temporal article graphs capture innate links between news stories. In this paper we present the various result outcome for predictive result analysis.*

**Keywords:** Big data, Machine Learning

## I. INTRODUCTION

Some countries, especially those in the developing world, have historically shown high levels of volatility across a range of socioeconomic indicators. High levels of volatility in important economic indicators can have a devastating effect on a country's economy. These indicators include commodity prices, the unemployment rate, currency exchange rates, and others. Commodity price fluctuations have a negative impact on GDP growth, national budgets, and wealth distribution, and may actually increase poverty levels rather than reducing them. In a large number of countries, including India, commodity sales make up more than 90% of overall revenue. Currency exchange rate fluctuations may also play a role in commodity price volatility. Consequently, maintaining a stable and robust economy necessitates keeping a watch on these socioeconomic indicators and learning the volatility they exhibit. Despite the fact that many fluctuations have been recorded over the course of decades, we still do not have a fundamental understanding of why a particular socio-economic index fluctuates at a given time and location, or how fluctuations across different indices connect to one another. Many years of noticing these variations. Economists who have done research on these types of challenges often rely on preexisting economic models to help them understand and predict the volatility of a given socioeconomic indicator. Scientists from computer-related disciplines who have studied this sort of thing have typically used computational modelling techniques to analyse structured time series data. Exploring hitherto inaccessible data reflecting societal and economic shifts has become possible thanks to the recent explosion of unstructured data streams on the internet and the development of increasingly complicated computational linguistics algorithms over the course of the past decade. This thesis's study contributes significantly to our understanding of the following topics: In the realm of big data analytics, we provide a collection of one-of-a-kind algorithms with the ability to automatically infer events, knowledge graphs, and prediction models from unstructured news streams.

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### 1.1 Objective

Create a self-driving inference engine that can sift through online data to find the most pertinent trends for a particular region, time period, and topic.

In order to properly categorise and depict email events, it is required to process a massive corpus of news articles.

Making knowledge graphs that (a) reveal latent relationships between phenomena for predictive purposes and (b) make the broader socioeconomic implications of news events more readily apparent (like food prices) (c) a method for visually depicting article-appearing terms to help determine their interrelationships (d) Creating structured domain-specific content from unstructured text It is possible to make predictions about economic and social variables by using these connections as a starting point.

## II. LITERATURE SURVEY

### 2.1 Big Text Figurative Schemes

Several sparse, low-dimensional representational systems for text documents have been developed as a result of recent developments in text mining techniques. In topic models like pLSI [1] and LDA [2], a huge document corpus with a vocabulary of 100,000 words may be represented by only 100 topics. These models have greatly improved the efficiency with which information may be gleaned from texts written in natural languages. Such document representation has proven useful in internet news items.

### 2.2 News Analytics and Submissions

New information is used by several current initiatives to improve existing applications. Radinsky and Horvitz [5] offer a paradigm that can be used to predict events like the spread of disease in the wake of natural disasters. Rudin et al. [6] focus on applying association rule mining and Bayesian analysis to predict the next event in a sequentially arranged data set.

Combining a traditional statistical model with machine learning techniques, the New York Times database is used to create forecasts. In order to analyse the Twitter data following the Haiti disaster, FBLG modified their algorithm for discovering temporal dependence from time series data. Luo et al. [7] also provided evidence for the connection between events and time series data.

By examining the effect of uncommon news events on stock prices, Hogenboom et al. [8] improved the efficacy of Value-at-Risk (VaR), a common technique for gauging portfolio risk.

Some efforts have been made to foretell some factors, such stock price, using news data. Presenting a revolutionary approach that incorporates financial news and market reaction into stock price predictions.

### 2.3 Methodology

In this piece, we'll examine the process that leads to a shortened answer to a user's search query on the internet. Foremost, our summarizing engine pulls the top 64 (customizable) search result pages from Google using the Google Search API. The summarizing engine's primary function is to analyses the text of each search result page in order to compile a streamlined summary page. The final search response is an abbreviated version of the original text that includes only the most important information from the longer text, relevant graphics, and related references to the individual search result pages, should the user feel compelled to click on any result page. Each page's relevant summaries are extracted by the Text Summarization Engine, relevant images are extracted by the Image Extraction Engine, and the aggregated summaries and photos are presented by the Aggregation and Presentation layer. Next, we go into the specifics of each subsystem.

### 2.4 Extraction Using Domain-Specific Large Datasets:

We will look at how to extract structured information from unstructured data in a specific domain. Each key corresponds to an attribute of the underlying domain, and the value is supplied as a pair consisting of a key and its associated value. Unstructured short-message ad-postings on online portals like Craigslist contain a large quantity of user-defined information in current Web content, making this a pressing concern. Writing style of these ad-postings lacks a well-defined lexicon or syntax, and the quality of the textual material is often fairly unpredictable and noisy due to factors like users using different acronyms and forms for expressing the same information.

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Such classified advertising would likely be incomprehensible to a computer programmer, but not to a human. Improving machine analysis of such adverts requires a solution to the pressing problem of converting such advertisements into structured data with defined keys and values.

Our aim is to create a system that can automatically generate a structured document from a collection of adverts on a given topic, such as those found in online car classifieds.

Two distinct algorithms are provided by us for squeezing information out of raw, unlabeled data. Sporadic commercials that don't amount to anything. The advertised item is usually defined by a handful of broad qualities. Apartment features commonly advertised in rental ads include square footage, monthly rent, neighbourhood, and number of bathrooms. Private spaces include bedrooms and bathrooms. Each classified ad filed under a particular subject has the same fundamental pattern, and under any given classified ad, you'll find a detailed analysis of a feature or features presented in a haphazard method. To this end, we will describe a data structure in which "keys" are qualities (such as monthly rent) and "values" are values of $2,000 or more. The elements of the converted, structured form of an advertising are displayed.

Combinations of keys and values that are distinct an unsupervised technique is used to generate a word-affinity network, where each edge represents a different word. These weights make it so that synonyms, antonyms, word pairings, etc., that have a higher amount of mutual information, are more likely to be connected with one another. Binary keys, numeric key phrases, and descriptive keys are the three types of keys defined in the unsupervised algorithm. Binary keys are used to represent features, and their values are expressed by binary outputs on whether or not the feature is present. Keys for numeric attributes have numerical values. Output Descriptive keys are those that characterize a broad category and its associated set of values.

### 2.5 Datasets

Our algorithms were tested on a collection of Craigslist advertisements for both automobiles and housing. A total of 12,984 ads for automobiles and 10,784 for housing were gathered from Craigslist. These classified ads were culled from the Boston, New York, Chicago, and Los Angeles sections of Craigslist, website 1. About 80% of the ads were used to train the models, and the rest were saved for evaluation. Performance was evaluated using a manually labelled test set.

## III. UNSUPERVISED TECHNIQUE

In this section, a graph-based unsupervised algorithm is proposed. The words in the advertising serve as vertices in a graph that captures the associations between those phrases; an edge between the vertices represents an affinity between those terms. This method is based on the premise that, generally speaking, keys may be broken down into three distinct types: descriptive, binary, and numeric. The structure of the affinity graph makes it simple to identify the various categories of keys. To this end, we offer a rule-based inference mechanism that can reliably identify the group of topic-specific keys in the affinity network and the values they represent.

**Table 3.1:** Different Keys and Their Occurrence in the ads

| Label | Type | Example |
|---|---|---|
| Color | Numeric | Grey with black interior<br>shiney red paint<br>the color is black<br>Red with black racing stripe |
| Price | Desc | Best Offer $5000<br>Cost $2952<br>Asking $22(K) firm<br>value is 3(XM)S<br>price for quick sale 3500 $ |
| Miles | Numeric | Under 62, 000 miles<br>approx 170k miles<br>has 144,000 miles |

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| | | |
|---|---|---|
| Power | Binary | new power steering |
| steering | | Power Steering. Cruise Control<br>Power Steering - Power .Brakes |

**Table 3.2** Corresponding < key, value> pairs

| Label (Type) | Value |
|---|---|
| Make (Desc) | BMW |
| Color (Desc) | black |
| Miles (Num) | 114,000 |
| Transmission (Desc) | automatic |
| Alloy wheels (Bin) | yes |
| Air conditioning (Bin) | yes |
| Leather Seals (Bin) | yes |
| Poor window (Bin) | yes |
| AM/FM radio (Bin) | yes |
| CD player (Bin) | yes |
| Price (Num) | 11.488 |

## IV. FINDING CONSISTENT LABELS AND VALUES IN AN AFFINITY GRAPH

The terms within the affinity graph determine the type of vertex it contains: descriptive, binary, or numeric. According to the hypotheses supporting this grouping,

- In a graph, a descriptive key takes the shape of a star with the central word serving as the key and the surrounding terms as its values.
- In a graph, a descriptive key takes the shape of a star with the central word serving as the key and the surrounding terms as its values.
- All the terms in a binary key component will have comparable edge weights since they all belong to the same group. All the bits of a binary key are combined into a single value. Binary values can be inferred from their appearance as keys.
- Under these premises, we offer an algorithm that, given an affinity graph as input, can label each vertex as either descriptive, binary, or numeric. The proposed approach, referred to here as Algorithm 2, is a deterministic one.

The vertex degrees are used to categories the three distinct groups. The hypotheses predict that various key types will exhibit distinct graph orientations. The presence of many edges at a vertex, for instance, suggests that it may serve as a descriptive key. One of the most important clues in finding the (key, value) pairings is the connection between the words (or an edge between the words). Therefore, the graph must be refined by removing the edges that do not provide adequate evidence of semantic similarity.

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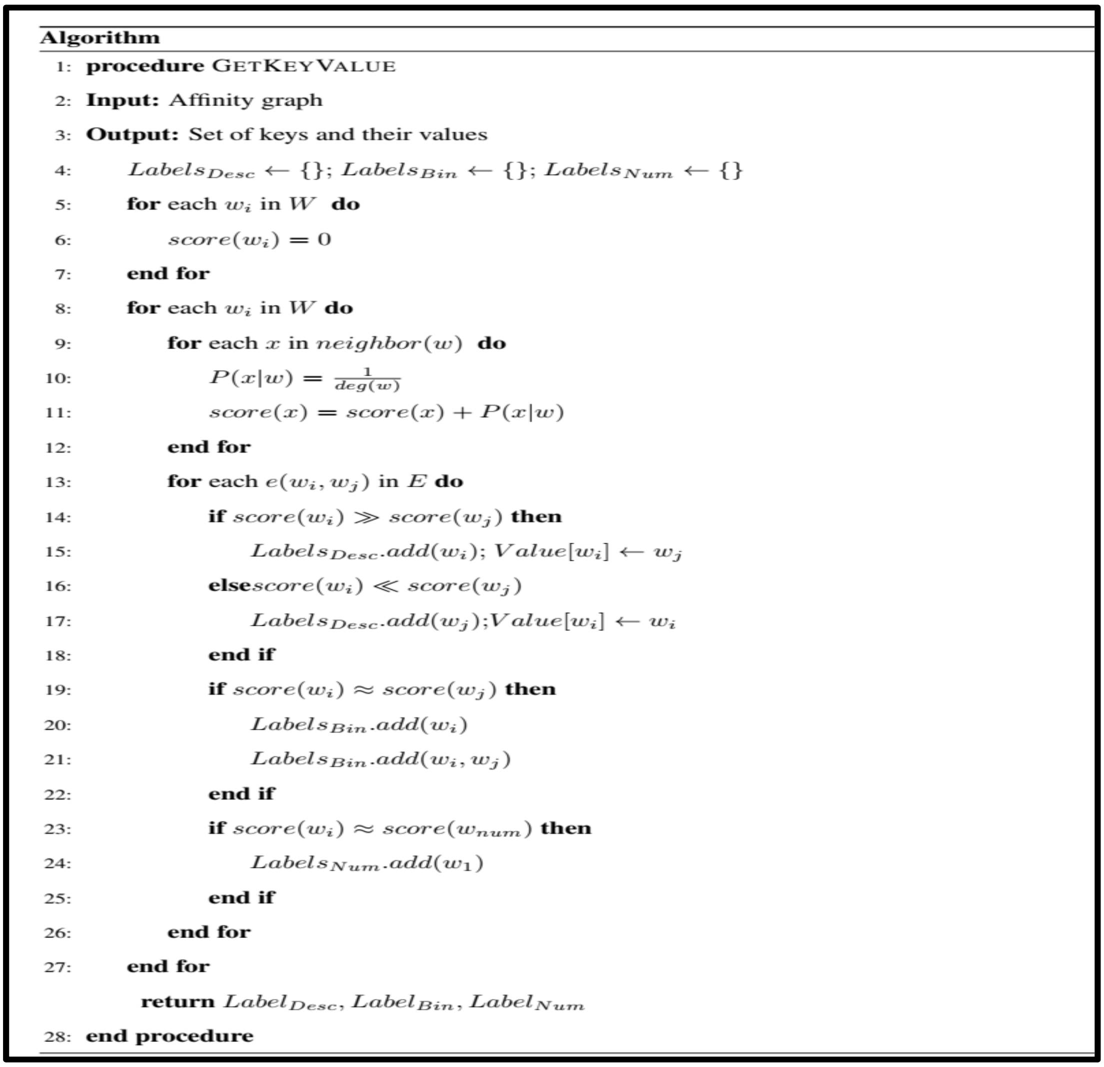
An edge $e(wi;\ wj)$ was pruned if $MI(wi;\ wj) > \lambda threshold$ . By measuring the average edge weights of randomly selected word pairs, an empirical cutoff is established. The cases of strong affinity were sampled separately from those with no known relationships between the couples.



```
Algorithm
procedure GETKEYVALUE
Input: Affinity graph
Output: Set of keys and their values
    $Labels_{Desc} \leftarrow \{\}; Labels_{Bin} \leftarrow \{\}; Labels_{Num} \leftarrow \{\}$
    for each $w_i$ in $W$ do
        $score(w_i) = 0$
    end for
    for each $w_i$ in $W$ do
        for each $x$ in $neighbor(w)$ do
            $P(x|w) = \frac{1}{deg(w)}$
            $score(x) = score(x) + P(x|w)$
        end for
        for each $e(w_i, w_j)$ in $E$ do
            if $score(w_i) \gg score(w_j)$ then
                $Labels_{Desc}.add(w_i); Value[w_i] \leftarrow w_j$
            else$score(w_i) \ll score(w_j)$
                $Labels_{Desc}.add(w_j);Value[w_i] \leftarrow w_i$
            end if
            if $score(w_i) \approx score(w_j)$ then
                $Labels_{Bin}.add(w_i)$
                $Labels_{Bin}.add(w_i, w_j)$
            end if
            if $score(w_i) \approx score(w_{num})$ then
                $Labels_{Num}.add(w_1)$
            end if
        end for
    end for
      return $Label_{Desc}, Label_{Bin}, Label_{Num}$
end procedure
```

The difference in distributional dispersion between the two measures of dispersion. If we assume that both distributions are normally distributed, then the threshold is the mean of the values of the data points at the 95th percentile of the weak association distribution and the 5th percentile of the strong association distribution. For a normal distribution with mean and standard deviation, we have the quantile function for a given probability, If q norm(p; μ; σ)

$$\lambda_{threshold} = \frac{qnorm(0.05,\mu_s,\sigma_s)+qnorm(0.95,\mu_w,\sigma_w)}{2}$$

## V. PERFORMANCE

In order to learn a set of keys (descriptive, binary, and numeric) for the two separate themes, the graph-based technique was applied to a corpus of 10,000 Craigslist advertising on vehicles and 8,000 ads on apartment rentals. In order to gauge the effectiveness of the training keys, they were applied to a database consisting of 2,984 automobile advertising and 2,784 apartment rental postings. We created a "golden set" by manually extracting key-value pairs from test data. A human annotator reviewed the training and testing data and assigned each label descriptive, binary, and numeric to generate the golden set. Extracting (key, value) pairs from the testing set using the affinity network built during training allowed us to assess the unsupervised method. Precision-recall values were used to evaluate the effectiveness of the extracted key-value pairs in comparison to the manually produced golden set.

The F-value computed from the precision and recall values for the car and apartment ad sets are shown in Figure 5.1 and 5.2 respectively.

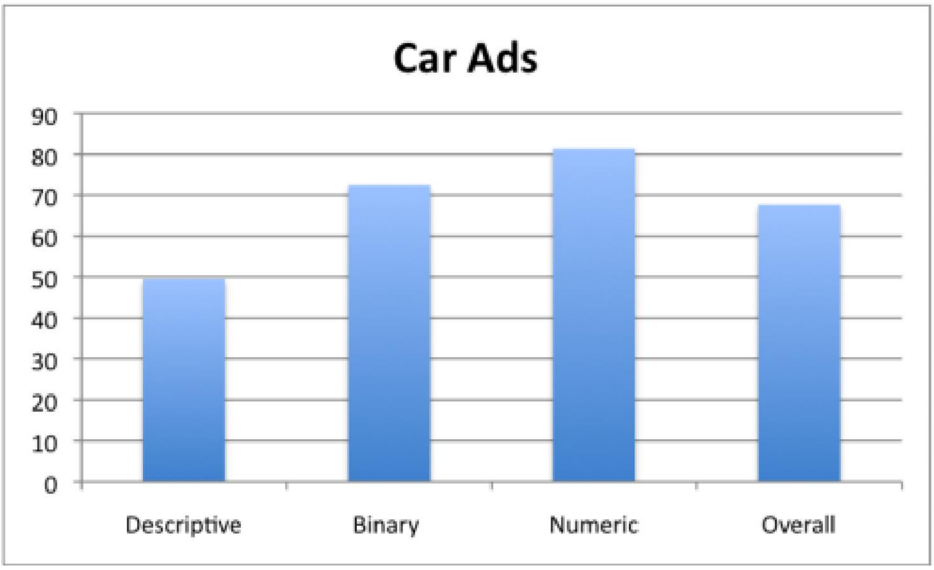


**Figure 1:** Overall and per-category accuracy (F-measure) for automotive advertising

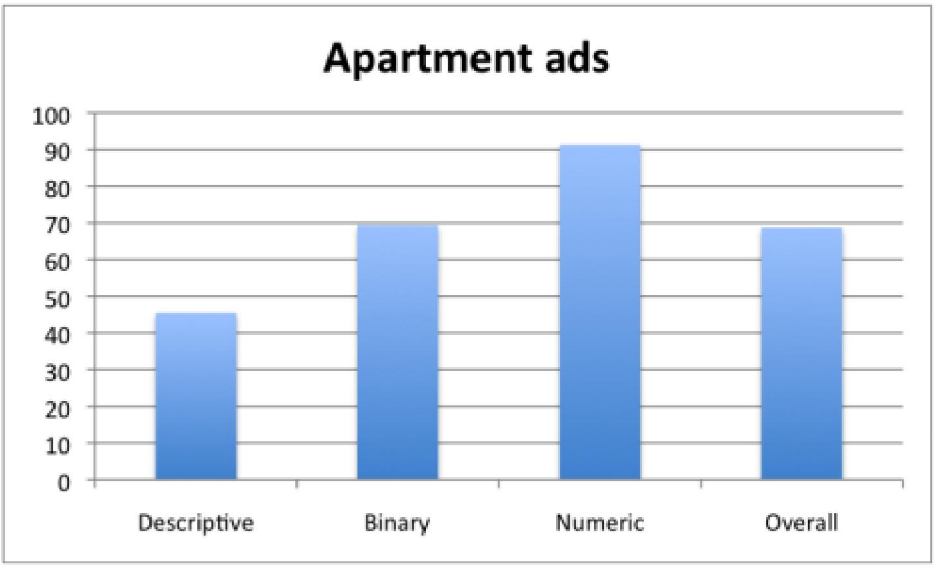


**Figure 2:** Total accuracy (F-measure) for apartment ads and under each category

## VI. RESEARCH AND FINDINGS

600 adverts from a training set were used to train the model. To assess the model, 200 more ads were annotated in the same manner. Due to the significant cost of creating such sets, the training and testing set was tiny in size. Based on the accuracy calculated on the test set of 200 ads, the final findings are presented. The X axis in Figure 5.4 displays the performance for various tests. In ten separate studies, we tested different feature combinations, including varied word window sizes. Based on several word surface traits, we examined the mistake cases and added a few more features. Most of these features were binary. Examples of such attributes include whether a word contains a numeral, a symbol, etc. The performance was enhanced by nearly 0.6 by adding the digit functionality. The symbol feature, however, did not improve the accuracy. On the basis of this finding, we developed features involving symbols like "$" and "-." The addition of these features worked well, increasing accuracy to 73.66%.

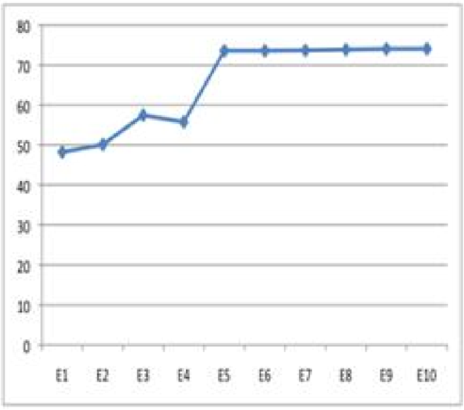


Figure 3 : Accuracy for each experiment. There were 10 experiments performed on car ads with combinations of different word-window size and feature sets. Y-axis shows the accuracy in percentage.

### 6.1 Newscast Trainings for Investigative and Forecasting Future Proceedings

Our objective is to create a system that can automatically extract data about real-world occurrences from news sources and then use that data to foresee changes in broad economic indices. In order to infer and perhaps anticipate changes in selected macroeconomic indices, we aim to create a system that can automatically form event-driven predictive models. Assuming we have access to a large corpus of real-world events that can be extracted from news sources and a structured time series about a specific macro-economic index of interest, we ask if it is possible to learn a predictive model for the macro-economic index by connecting it with the appropriate events that relate closely to it.

Estimating various macroeconomic indexes calls for information from a wide range of sources. However, in research seeking to estimate such variables [62], analysis and forecasting are often performed using structured data sources, with only a select few of such aspects included (and chosen manually).

The indices' extreme swings could be due to unknown reasons or a convergence of known and unknown ones that increase volatility. The sensitivity of these indicators can be better understood by keeping tabs on global happenings. We owe a great deal of our understanding of these events to unstructured text streams, such as those seen in the news, online, and on social media. There have been a plethora of studies that have used information gleaned from the media to predict future events.

### 6.2 Models of Events

The news provides information about events from all over the world. Therefore, news stories can be used as a database to extract information about the real world. Numerous works have drawn inspiration from events reported in the news. These works provide a variety of interpretations and depictions of the same event.

Case in point: Radinsky et al. [73] based their models on news stories.

- Cyclone in Rwanda, floods in Africa, etc. A different approach involved representing events as a whole, which included objects (or actors), actions, and time. Automatic Content Extraction (ACE) defines 8 main types of events and 33 sub-types of events for usage in event extraction by considering entities, event triggers, timings, event mention argument, etc. In order to isolate the relevant triggers, it is often required to zero in on a certain type of domain-specific event. A few examples of the most common occurrences in the financial world are hiring, firing, resignation, acquisition, loss, growth or decrease in profits, etc.

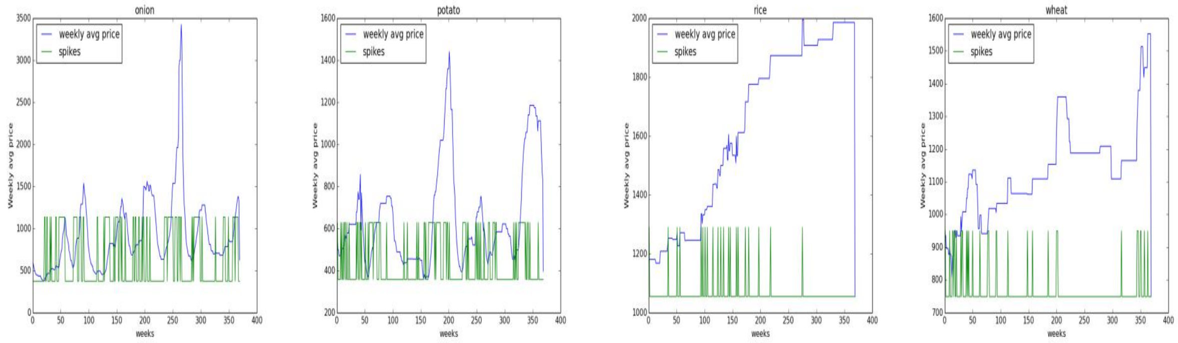
In this section, we present a novel probabilistic model to characterise events that can be extracted from a corpus of news articles. News is typically assumed to be a brief report of a singular occurrence because most news stories follow a consistent format. On the basis of this assumption, we make an attempt to simulate the incident in question using data from the news account. We also assume that in any given time period, only a small subset of possible event types will actually occur. When it comes to events, news stories fall into a specific category. "Event classes" are a useful tool for organising a wide variety of events. For example, an accident can be seen of as both a category of events and a single instance of that category, depending on the exact location, nature, and other factors involved (such as actors, objects, etc.). The primary action, or trigger, of an event is the most crucial aspect of the event class. In the preceding instance, the word "accident" functions as the trigger; however, other words or phrases, such as "crash," "collision," "rammed," and so on, may also act as triggers for the same class.

### 6.3 Prediction Correctness

Our dataset includes 7 years (2557 days). Using the event model, we retrieved daily events over 7 years to anticipate food price spikes and stock price fluctuations.

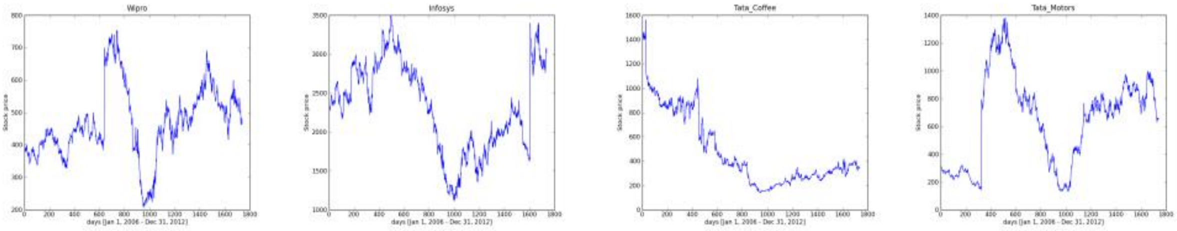
The model's predictive accuracy is evaluated. Accuracy is the ratio of correct predictions to data points. We compare our event model's performance across baselines and text mining approaches (Section 6.4).

Our event model uses a pipeline method, with event triggers extracted first and subsidiary events added subsequently. First, the benefit of adding subsidiary events to the event model was tested. So, performance was compared to a naive event trigger-based model (TRIGG). We compared performance with LDA-based predictor (section 6.4.4). We examined adding subsidiary events vs. subjects in our model. We combined TRIGG and LDA to observe the secondary events' benefits. Finally, we assess all these models with another model that uses past and current events to predict indicator changes. Model HIST (6.4.3). Tables 6.2, 6.3, and 6.4 summaries the food price and stock price tests.



(a) Onion price (b) Potato price (c) Rice price (d) Wheat price

**Figure 4:** 2012-2018 weekly average agricultural prices. The spikes represent a 10% price increase. The horizontal axis shows the weeks between January 2012 and December 2016, from 0 to 364.



(a) Wipro (b) Infosys (c) Tata Coffee (d) Tata Motors

**Figure 5:** Stock price variation of 4 Indian concerns

wheat, potato (events: attack on railways, railway strike etc.). Wheat and potatoes aren't grown equally across the country and rely largely on transportation for distribution. Any occurrence that affects agricultural movement affects supply, raising prices. Festivals only impact onion and wheat. Festivals enhance demand for these two commodities, driving up prices.

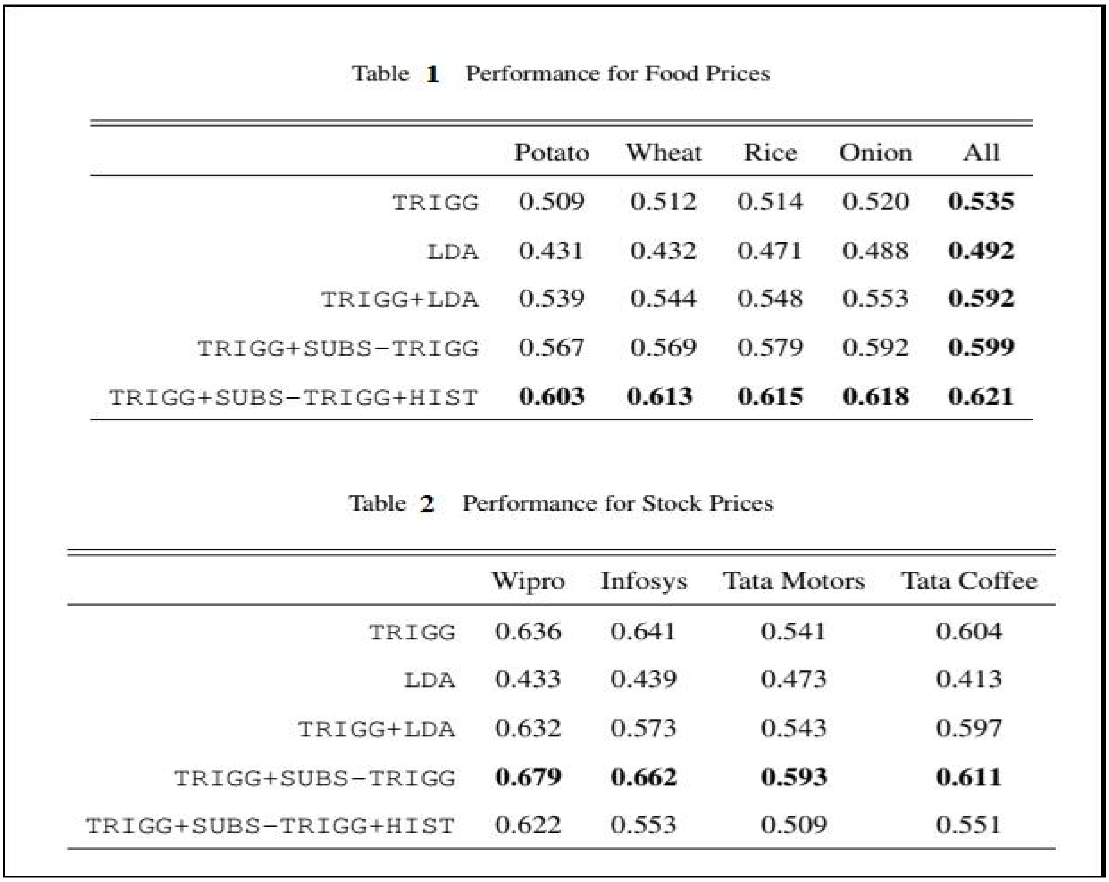


Table **1** Performance for Food Prices

| | Potato | Wheat | Rice | Onion | All |
|---|---|---|---|---|---|
| TRIGG | 0.509 | 0.512 | 0.514 | 0.520 | **0.535** |
| LDA | 0.431 | 0.432 | 0.471 | 0.488 | **0.492** |
| TRIGG+LDA | 0.539 | 0.544 | 0.548 | 0.553 | **0.592** |
| TRIGG+SUBS−TRIGG | 0.567 | 0.569 | 0.579 | 0.592 | **0.599** |
| TRIGG+SUBS−TRIGG+HIST | **0.603** | **0.613** | **0.615** | **0.618** | **0.621** |

Table **2** Performance for Stock Prices

| | Wipro | Infosys | Tata Motors | Tata Coffee |
|---|---|---|---|---|
| TRIGG | 0.636 | 0.641 | 0.541 | 0.604 |
| LDA | 0.433 | 0.439 | 0.473 | 0.413 |
| TRIGG+LDA | 0.632 | 0.573 | 0.543 | 0.597 |
| TRIGG+SUBS−TRIGG | **0.679** | **0.662** | **0.593** | **0.611** |
| TRIGG+SUBS−TRIGG+HIST | 0.622 | 0.553 | 0.509 | 0.551 |

## VII. CONCLUSION

To this purpose, we looked into the viability of using news articles as a source for event extraction and the creation of knowledge graphs to characterize event dependencies for different kinds of analytics. Two distinct event model types and five knowledge graph building approaches were provided in the thesis.

These knowledge graphs can be used in a number of automated and human-driven methods to examine historical news archives. An important use of both event models and knowledge graphs is the modelling of the behavior of external variables and indicators. We show how knowledge graphs may be utilized to build predictive models that take into account the relationships between news events.

This paper relies primarily on the utilization of unstructured online data in order to extract events, knowledge graphs, and predictive models for socio-economic indicators. We intend to expand upon this contribution by looking into related areas of research. We'd like to look into various news data sources and reporting methodologies so that we can make more well-informed and persuasive assertions. When creating this thesis, I ignored a lot of evidence. Think about the possibility that one news organization is biased.

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