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Abstract

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Keywords

Deep learning for text, news, redundancy, content popularity.

I. INTRODUCTION

News articles are very dynamic in nature due to continuously developing nature of the event and parallel reporting of the same thus they have a very short span of life. The ease and low cost of online content creation and sharing have changed the traditional rules of competition for public attention. News sources now concentrate a large portion of attention on online mediums where they can disseminate their news effectively and to a large population. Due to the time-sensitive post aspect and intense competition for attention in the socially connected digital platform, accurately estimating the extent to which a news article will spread on the web is extremely valuable to journalists, content providers, advertisers and news recommended systems. However, predicting the online popularity of online news articles is a challenging task. First, context outside the web is often not readily accessible and elements such as local and geographical conditions and various circumstances that affect the population to make this prediction difficult. Furthermore, network properties such as the structure of social networks that are propagating the news, influence variations among members and interplay between different sections of the web add other layers of complexity to this problem. Most significantly, intuition suggests that content of an article must play a significant role in its popularity. Content that resonates with a majority of readers such as a major worldwide event can be expected to garner wide attention while specific content relevant only to a few may not be as successful. Content that is up-to-date and highlights all aspect of that article.

The news data for our study was collected from AG's news corpus and Financial News Dataset. To generate features for the articles, we used Character level convolution network. To remove redundant information, we perform specific topic-wise clustering in a certain timeframe. For each cluster, we analyze its contents and use those for prediction of the popularity of upcoming articles before publishing. Our work will also help the content writer to remove irrelevant contents.

The rest of the paper is organized as follows. Section II describes the business motivation behind the problem. Section III gives a glimpse of the related academic work surveyed. Section IV details the solution framework to the problem. After that, in Section V we describe the experimental evaluation criteria. Finally, we conclude with a summary of this work in Section VI and Future possibilities in Section VII.



Kanpur train derailment: Hundreds of kin rush to Patna Junction

Times of India - Nov 20, 2016

If the number of such people would not be more, railways would arrange their transportation up to **Kanpur** from Patna Junction in any other mail and express **trains**, Danapur DRM R K Jha said, adding, railways arranged a special **train** from **Kanpur** for Patna ...



Indore-Patna express train derailes in Kanpur: 96 killed, over 100 injured

Times of India - Nov 20, 2016

The ministry said that the stranded passengers are being moved from site to the Malasa station, adding that the injured passengers are being taken to the **Kanpur** Dehat hospital. "All hospitals have been asked to be on alert. More than 30 ambulances have ...



Kanpur train tragedy: List of passengers killed

Hindustan Times - Nov 20, 2016

As many as 120 people were killed and more than 200 injured early Sunday when 14 coaches of the Indore-Patna Express **train** flew off the rails in **Kanpur** Dehat district of Uttar Pradesh. The toll in one of India's worst **train** accidents in six years was ...

Kanpur train tragedy: Toll mounts to 146 in Indore-Patna Express derailment

The New Indian Express - Nov 21, 2016

North Central **Railway** General Manager Arun Srivastava had said yesterday that traffic on **Kanpur**-Jhansi section will be opened in 36 hours. Four **trains** were cancelled and fourteen diverted yesterday after the derailment disrupted traffic on the route ...



116 killed in train accident near Kanpur

Business Standard - Nov 20, 2016

India's creaking **railway** system is the world's fourth largest. The central government runs 11,000 **trains** a day, including 7,000 passenger **trains** that ferry more than 20 million people, but it has a poor safety record, with thousands of people dying in ...



A Bang And The Entire Coach Overturned, Says Kanpur Train Accident Survivor

NDTV - Nov 19, 2016

Deepika Tripathi, travelling on the Indore-Patna Express **train** with around 45 relatives, had slept just hours ago. She jerked awake to a bang and felt everything tumbling around her in pitch dark. Moments later, she realized that her coach was north ...

Fig. 1: Google News results on query Kanpur train on 26 Nov. 2016 at 16:44 IST.

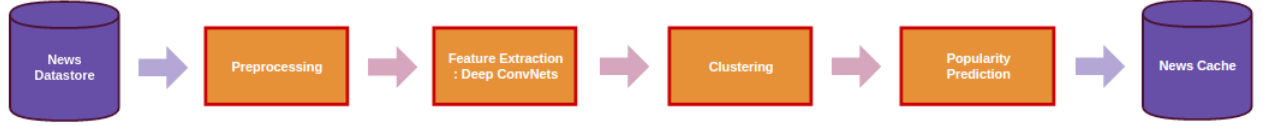


Fig. 2: Solution Framework

II. BUSINESS

- **Content Caching and Traffic Management** There is a hidden cost to publishing content, the cost to review and maintain the content. The millions of articles also affect the usability and maintainability of the site. In the long run, it is necessary to tackle redundant, outdated and trivial content which has been cursing the site.
- **Advertising** This work finds it's use in media advertising and ad placement.
- **News Aggregation**
- **Trends Forecasting**

III. RELATED WORK

Previous research on news content analysis for forecasting its popularity before publishing takes a lot of factors besides content. Often, factors like social network links, inorganic links undermines content of articles. We believe that content is still king of any article. In haystack clustering paper, a news article on any particular topic according to static, dynamic and social factors. We just consider static and dynamic factors to design a framework that does event based clustering and filters duplicate and less relevant news, making it easier to read the more interesting news in less time. Traditionally, feature extraction for articles clustering is done using self-design features such as name entity relation, Tf IDF. On the other hand, researchers have found convolutional networks [1][2] are useful in extracting information from raw signals, ranging from computer vision applications to speech recognition and others Zhang et. al. [3] explored treating the text as a kind of raw signal at the character level and applying temporal (one-dimensional) ConvNets to it. It has been shown that ConvNets can be directly applied to distributed[4][5] or discrete[6] embedding of words, without any knowledge on the syntactic or semantic structures of a language. These approaches have been proven to be competitive to traditional models. This simplification of engineering could be crucial for a single system that can work for different language since characters always constitute a necessary construct regardless of whether segmentation into words is possible. Working on only characters also has the advantage that abnormal character combinations such as spelling mistakes and emoticons may be naturally learned. Finally, we predict the most popular articles in different clusters by different factors such as news source that generates those articles, the subjectivity of the language in the article, factual completeness of the article, name entities mentioned in the article.

IV. SOLUTION FRAMEWORK

A. Preprocessing

We preprocess the data to make processing more meaningful [7].

- **Filtering** Removal of markup, punctuation and special characters from sentences.
- **Tokenization** Splitting of text into individual units.

- **Stemming** Reduction of words to their base forms [8].
- **Stopwords removal** Deletion of words that do not convey any special meaning.
- **Pruning** Removal of words that do appear with a low frequency throughout the text.

The result of these preprocessing steps is a set of feature words.

B. Text Understanding

[3] [9] [2].

C. Clustering

[7] [10].

D. Popularity Prediction

[11].

- **Age** The date of publication of news given by the dataset. We remove few records with missing dates.
- **Text Quality** The ratio of size of document before and after preprocessing.
- **Source Quality** The popularity of source of the content given by initial number of hits provided by the source. If missing, we use the popularity of news agent as a whole. This is log-normalized to account for high range of hits.
- **Subjectivity** The ratio of size of document before and after preprocessing.
- **Named Entities** The ratio of size of document before and after preprocessing.
- **Factual Density** The ratio of size of document before and after preprocessing [12].

V. EXPERIMENTAL EVALUATION

A. Dataset

- 1) **AG's news corpus** We obtained AG's corpus of news articles on the web¹. It contains more than 1 million news articles from more than 2000 sources. We use the source, title, description, rank and pubdate fields for our experiments.
- 2) **Financial News Dataset** We obtained financial news dataset of Bloomberg and Reuters². It contains 450,341 articles from Bloomberg and 109,110 articles from Reuters. It provides us title, content, date and author of the article.
- 3) **20 Newsgroups Dataset** The 20 Newsgroups data set is a collection of approximately 20,000 newsgroup documents, partitioned (nearly) evenly across 20 different newsgroups. The data is organized into 20 different newsgroups, each corresponding to a different topic.³

¹https://www.di.unipi.it/~gulli/AG_corpus_of_news_articles.html

²<https://github.com/philipperemy/financial-news-dataset>

³http://scikit-learn.org/stable/datasets/twenty_newsgroups.html

B. Baseline

- 1) **News Aggregators** We conduct an internal survey to verify initial results of the pipeline when compared with different news agents and aggregators like Google News, Feedly, Digg etc.
- 2) **TF-IDF Comparison** We use an obvious baseline based on sum of tf-idf scores of entities in the document to rank it's importance.
- 3) **Bandari et. al.** We use an obvious baseline based on sum of tf-idf scores of entities in the document to rank it's importance.[11]
- 4) **Clustering Metrics** We use an obvious baseline based on sum of tf-idf scores of entities in the document to rank it's importance. [13] [14]

VI. CONCLUSION

In this paper, we improve the quality of news cache and recommendations by predicting popularity of articles prior to publishing. The need for the same arises from the stiff competition among different news agencies and aggregators. Through deep convolutional neural networks, we extract features of articles at character-level. To remove redundant information, we make highly specific clusters of news items. Finally, we predict the most popular pieces in different clusters to provide the set of most popular articles, which is then used for multiple use-cases in content caching, advertising, forecasting and recommendation. With an initial survey, we ensure inception results of the pipeline versus different competitors. Lastly, we compare with different baselines to ascertain quality of our work.

VII. FUTURE WORK

- 1) Information explosion is prevalent not only in news items, but across different content classes. There rises the opportunity to extend the current work for multiple such classes.
- 2) There are abundant works [15] [16] which when given initial popularity of some content, are better able to forecast popularity. With that notion, we want to adapt the predictions to incoming hits.
- 3) With growing amount of personalization in different news agents [17] [18], there exists a demand and an opportunity for the same in this work.
- 4) Growing number of events and articles pose the need for concise summaries of multiple articles. We believe, successful summarization of one cluster can generate concise, clear and helpful news articles.

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