Temporal Analysis of News Feeds using Phrase Position

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***Abstract*— This paper describes a method to identify temporal relationships between news articles using phrase position analysis. The words from the news feed were tokenized using special character and space delimiters. The word-tokens were tagged by the type such as noun, verb, preposition and adverb. The location of each word and its distance from the verb on the left, right and previous and next sentence was recorded as a feature. The links between multiple sentences using noun as the anchor and verbs as the event was established. The link count was measured and the connected graph was stored as a decision tree. The model was tested using temporal questions and event sequence queries. The results indicated 67% accuracy in terms of correct event sequencing and recall rate. Additionally emotion based categorization of the news event was performed to test whether the weighted graph linking based on phrase position technique could be used for sentiment analysis with fear and happiness categorization showing clear thresholds for certain event pair and their temporal relation type.**

***Keywords*— Tokenization, linked graph, phrase position, anchor action verb**

I. Introduction

In the last decade, millions of websites have emerged on the internet and many newspapers now have a dedicated website for current news feeds. There is a need to identify the temporal relation between various events. Such temporal analysis has applications ranging from historical data evaluation, forensic studies and archaeological examination. Many times the actual time specific word, data and information such as seconds, minutes, hours, days, week, month and year, is not found in the text. The system has to rely on presence of event specific words such as before, after, soon, later, at, since then, ago etc. It is important to develop ability to automatically answer questions about event occurrence using machines.

This paper focuses on answering the event chronology related questions from a news feed using decision tree model and weighted graphical links. We formulated the problem of event sequencing as given an event A the system must be able to create a chronological order of events and place the event in the correct location on the time scale. Additionally, the system must be able to identify unique events and similar events even when the token representing the event is different or separated by more than one sentence. Tatu and Srikanth [1] examined the temporal links between various events and methods to provide reasons for answering ‘why’ based queries and for information retrieval.

Various methods have been explored [2], [3], [4] to identify the temporal events from text with high accuracy. But identifying the temporal links between these events is a time consuming and laborious task even for human annotators. Automatically detecting the temporal sequence of events is challenging and only few studies have succeeded in accurately establishing the chronology of events. The problem with accurately detecting temporal relation between series of sentences is that the same sentence could have a different meaning. In addition, many times the context is important to evaluate the association of events with specific time and the context information is not available. Thus, an exhaustive semantic analysis needs to be performed on the narrative, text, news, blogs and articles to be able to detect and associate the correct time sequence of various events in the text. Depending on the techniques applied, whether it is computational, probabilistic, or supervised learning, the accuracy changes for time based analysis of events. Researchers [5], [6], [7], [8] have developed temporal corpus and evaluated techniques for temporal relation identification between consecutive sentence but accuracy of such systems is limited to the corpus because of lack of machine understanding about common knowledge that humans have. The studies have concentration mostly on consecutive sentence event tagging.

This paper proposed a graph based tree-linking technique with position of temporal phrases serving as weights for the links. Thus the system is able to traverse the tree given two events and estimate whether the event 1 is before, after or at the same time as event 2. The traversal also used dynamic adjustment to weights based on over lapping events to generate optimized graphs for temporal tagging of event relationships. Additionally this paper also evaluated sentiment analysis and effects of temporal characteristics of events on the emotion expressed in the text. For instance whether news about certain events and the sequence of occurrence in time, affects the sentiment and polarity of emotions expressed in the text. Several multimodal emotion recognition studies have focussed on audio-visual emotion recognition. This paper examines the emotions from text based news feeds and the effect of chronology of events invoking emotions such as rebellions, accidents, coups, natural disasters, calamities, political events and social events.

II. Method

For the purpose of temporal analysis of news feeds, data from various popular news websites was gathered. Specifically political events articles were chosen. A total of 862 articles containing 600 to 1000 words were recorded. The articles were annotated using event linking and manual graph development. This data served as the ground truth. The automatic linking process was dependent on correct tokenization and action verb identification. For tokenization special character and space based delimiters were used. After the tokenization each word token was tagged with properties such as noun, verb, adverb and adjective. Additionally, the word frequency and the location of words from each action verb was measured. The list of temporal words used for position based analysis is shown in Table. 1. The weighted graph was constructed with each event as the node and the number of hops taken to reach the node as the weight of the link. To determine the time sequence between the events the phrases from the temporal word list were used and the pointer to the event was moved in the paragraph based on the occurrence of the phrase in the sentence and a hop count in both directions was maintained with the current timestamp as the reference point. To establish the sequencing of events on a time series the events were ordered by the number of hops taken to reach the words from the current timestamp.

Table. 1 Temporal words

Temporal word list used for phrase detection		
Before	between	shortly after that
After	by	then
later	during	henceforth
yesterday	earlier	tomorrow
Back then	eventually	lately
ago	except	next
same time	finally	next week
simultaneously	following	suddenly
at that moment	for	in addition
at first	from then on	not a moment too soon
at last	in the meantime	now
as soon as	in the end	

The event identification was based on action verbs which were used to create nodes for 4 events with the highest frequency in the news feed. The four different categories to group similar events together were natural disaster, accident, politics and sports. First the events were identified using action and noun words such as { won, championship, defeated, series} for sports, {tremor, rocked, shook, earthquake, scale} for disaster, {hit, run, crash, interstate, pile, traffic, light, cops, bumper, hurt} for accident, and {election, speech, controversy, run, voter, senate, politician, businessman} for politics were used. After the event specific nodes were identified the linking was done by moving around the paragraph using search and count method to navigate from event to event using temporal words from the list and counting as the search progressed. The count served as the weights for the links and the links with the highest count established the relation type such as before, after, simultaneously or unrelated.

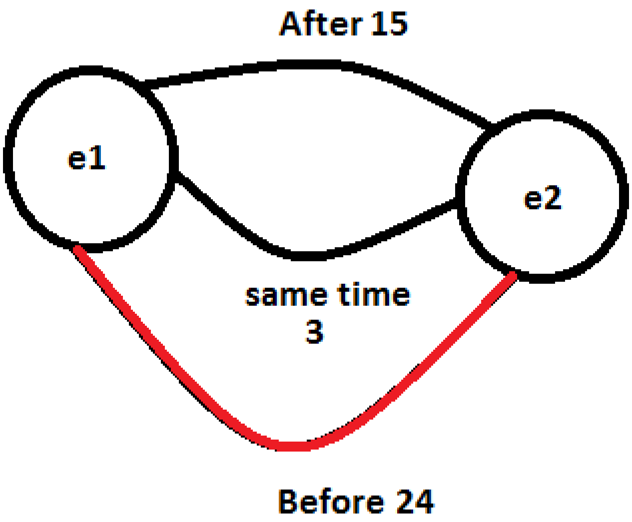

Fig. 1. Weighted event linking based on word hops

In Fig. 1. The event relationship between e1-e2 was determined to be e1 occurred before e2 because the before category links had the highest weight and hop count. To calculate the weight of the relationship category, the hop count and the time specific word weight was used. Hence the before type relation weight was given by the sum of hops found for before type of links + weight of day, year, month, week and time within the e1 and e2 occurrences. For each different location of e1 and e2 in the entire news feed the link weight was calculated. The average of the weights was used to determine the overall link weight. Once the relationship was determined between various events then the events were allocated in chronological order. In case of conflicts, the relation with higher weight was chosen as the final relation type.

The same process was repeated in both directions and for a range of words with the event as the reference point. The graph based relationship type linking was also done for emotion category recognition between the events. To establish co-relation between the various news feeds and the corresponding emotions, manual annotation was done by 5 annotators. For instance, the news about natural disaster was more likely to invoked sadness and fear. News about a sports championship win was more likely to invoke happiness for the local news feed supporting the winning team. The news on politics was likely to invoke anger, disgust or surprise.

An odd number of annotators was used to avoid contradictory classification and avoiding inter-annotator disagreement. For emotion analysis, the six basic emotions were used: Angry, sad, happy, afraid, disgust, surprise and neutral for fact based news reporting. The next section discusses various metrics such as accuracy comparison, hop count comparison, intra-event emotion category recognition.

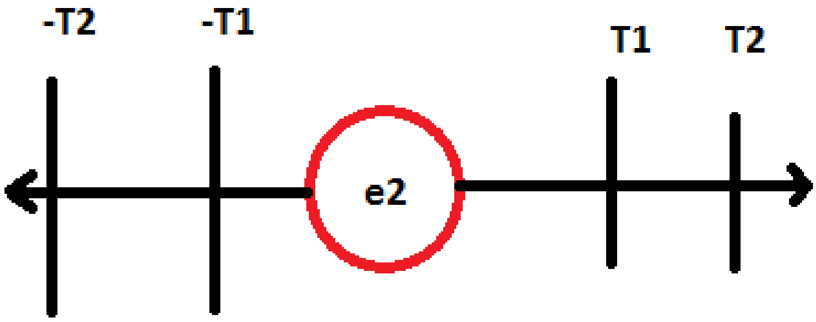

Fig. 2. Bi-directional scan for phrase position

III. Result

The results below show the assigned weights for hops because of know time specific words.

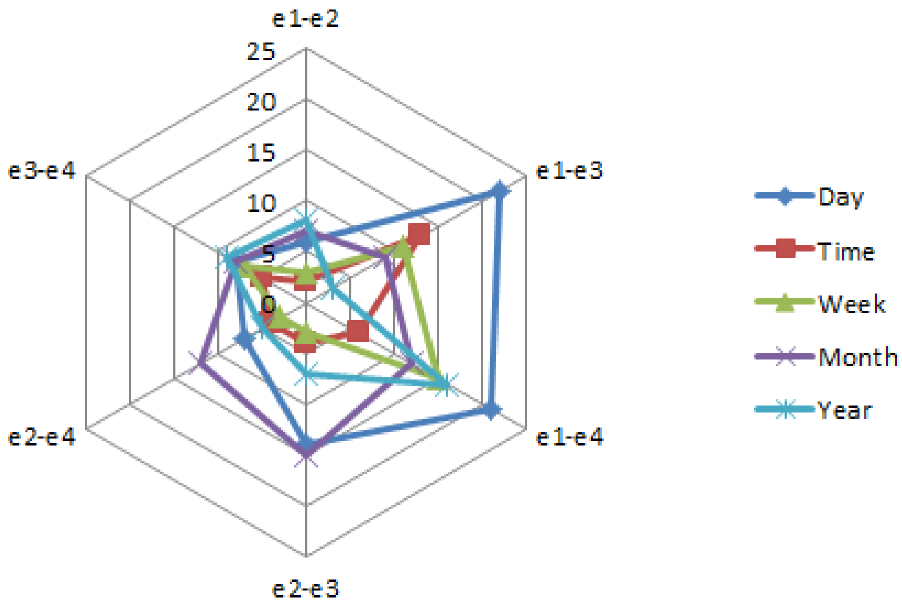

Fig. 3. Weighted hops between event i to j

The results below show the comparison between weighted hops on the time scale because of phrase positions. The temporal relation scans for the events related by direct dates in the news articles was the highest between e1-e3 and e1-e4. The event relationship between e1-e4 was well defined with day, year and week specific words existing mostly for this relation. Based on the direct time specific words there was no clear consistency between the weights for the event relationships. This indicated that a wider range of temporal word analysis needed to be performed using non-time specific words.

The overall hops found for time-specific words was low compared to the available words from the 800+ news feed articles with each containing 1000s of words. This was another indicator that there was a need to use phrases instead of specific words that describe time for a more accurate temporal event relationship prediction.

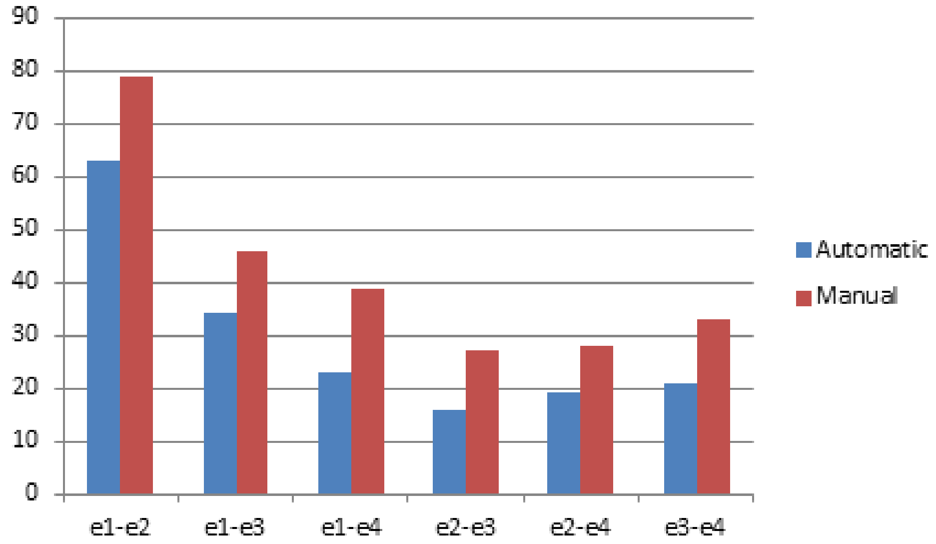

Fig. 4. Automatic vs manual relation identification performance.

The automatic temporal relation detection recall rate was 79.74, 73.91, 58.97, 59.25, 67.85 for e1-e2, e1-e3, e1-e4, e2-e3, e3-e4 respectively for an average of 67% recall rate. Fig, 4 shows the average hop count using various relation type qualifier words for the 6 event pairs between e1 and e4.

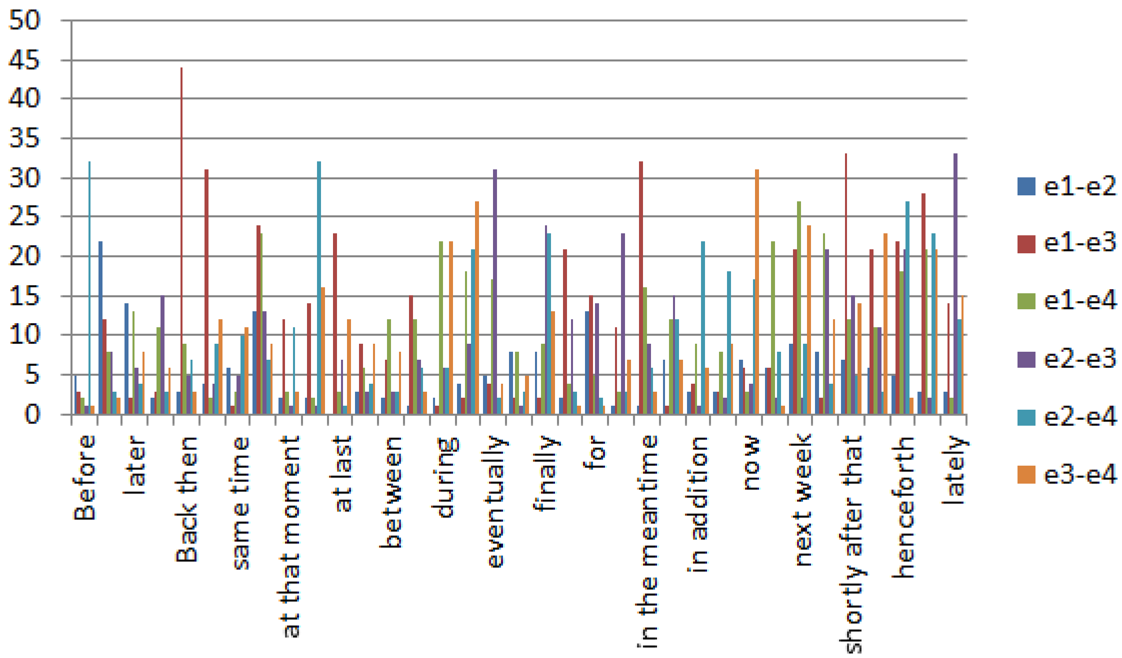

Fig. 5. Hop count by phrase position

Some of the hop count were above 30 which indicated that the news feeds contained two events far apart in the text. One advantage of the phrase postion weighted graph based technique was that even if the hop count was high, it was weighted so the processing was instantaneous with minimum traversal in subsequent tree traversals. There was no clear threshold or pattern among the weights of the temporal phrase based hops. As a result the various phrases and their hops had to be evaluated separately instead of grouping them into before, after, same time and unrelated categories.

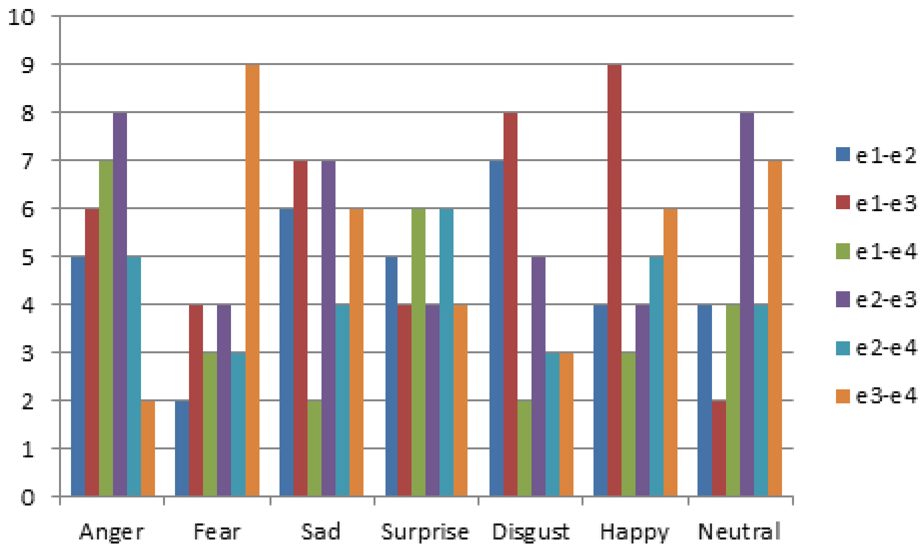

Fig. 6. Emotion occurrence between event relationships

Based on the ranking of emotions found between pairs of events there was no clear threshold to determine the overall emotion expressed in the sentences containing the events across the various event pairs. In case of event e1-e3 happiness was identified as the highest ranking emotion, which indicates that the news was most likely about a sports championship victory. Similarly fear was identified as the prominent emotion for the event e3-e4 pair indicating the news was most likely related to a natural disaster.

IV. Conclusions

The automatic estimation of temporal relationship between action verbs from the news feed showed 67% accuracy in terms of recall rate. The weighted-frequency based linked graphical models of phrase positions allowed the automatic estimation to travel bi-directionally while searching for occurrence of events before, after or at the same time as the input event. The estimation performance and processing time was merely seconds, thus making the automatic time sequence prediction steps feasible for real time applications. One such application that we plan to work as future scope is recommender system based on time sequencing where based on the search keyword, the system could suggest news articles related to the event in chronological order. Additionally the emotion categorization of the event pairs based on the relationship type and the weighted graph traversal technique showed that sentiment analysis could also be performed on the text using the same technique.

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