Socially-Informed Timeline Generation for Complex Events

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Abstract

Existing timeline generation systems for complex events consider only information from traditional media, ignoring the rich social context provided by user-generated content that reveals representative public interests or insightful opinions. We instead aim to generate socially-informed timelines that contain both news article summaries and selected user comments. We present an optimization framework designed to balance topical cohesion between the article and comment summaries along with their informativeness and coverage of the event. Automatic evaluations on real-world datasets that cover four complex events show that our system produces more informative timelines than state-of-the-art systems. In human evaluation, the associated comment summaries are furthermore rated more insightful than editor’s picks and comments ranked highly by users.

1 Introduction

Social media sites on the Internet provide increasingly more, and increasingly popular, means for people to voice their opinions on trending events. Traditional news media — the New York Times and CNN, for example — now provide online mechanisms that allow and encourage readers to share reactions, opinions, and personal experiences relevant to a news story. For complex emerging events, in particular, user comments can provide relevant, interesting and insightful information beyond the facts reported in the news. But their large volume and tremendous variation in quality make it impossible for readers to efficiently digest the user-generated content, much less integrate it with reported facts from the dozens or hundreds of news reports produced on the event each day.

In this work, we present a socially-informed timeline generation system that jointly generates a news article summary and a user comment summary for each day of an ongoing complex event. A sample (gold standard) timeline snippet for Ukraine Crisis is shown in Figure 1. The event timeline is on the left; the comment summary for March 17th is on the right.
While generating timelines from news articles and summarizing user comments have been studied as separate problems (Yan et al., 2011; Ma et al., 2012), their joint summarization for timeline generation raises new challenges. Firstly, there should be a tight connection between the article and comment portion of the timeline. By definition, users comment on socially relevant events. So the important part of articles and insightful comments should both cover these events. Moreover, good reading experience requires that the article summary and comment summary demonstrate evident connectivity. For example, Comment C in Figure 1 ("Sanctions are effective and if done in unison with the EU") is obscure without knowing the context that "sanctions are imposed by U.S". Simply combining the outputs from a timeline generation system and a comment summarization system may lead to timelines that lack cohesion. On the other hand, articles and comments are from intrinsically different genres of text: articles emphasize facts and are written in a professional style; comments reflect opinions in a less formal way. Thus, it could be difficult to recognize the connections between articles and comments. Finally, it is also challenging to enforce continuity in timelines with many entities and events.

To address the challenges mentioned above, we formulate the timeline generation task as an optimization problem, where we maximize topic cohesion between the article and comment summaries while preserving their ability to reflect important concepts and subevents, adequate coverage of mentioned topics, and continuity of the timeline as it is updated with new material each day. We design a novel alternating optimizing algorithm that allows the generation of a high quality article summary and comment summary via mutual reinforcement. We demonstrate the effectiveness of our algorithm on four disparate complex event datasets collected over months from the New York Times, CNN, and BBC. Automatic evaluation using ROUGE (Lin and Hovy, 2003) and gold standard timelines indicates that our system can effectively leverage user comments to outperform state-of-the-art approaches on timeline generation. For example, we achieve an NDCG@3 of 0.88 on the Ukraine crisis dataset, compared to 0.77 from Yang et al. (2011) which also conducts joint learning between articles and social context using factor graphs.

Finally, to encourage continuity in the generated timeline, we propose an entity-centered event threading algorithm. Human evaluation demonstrates that users who read timelines with event threads write more informative answers than users who do not see the threads while answering the same questions. This implies that our system constructed threads can help users better navigate the timelines and collect relevant information in a short time.

For the rest of the paper, we first describe data collection (Section 2). We then introduce the joint learning model for importance prediction (Section 3). The full timeline generation system is presented in Section 4, which is followed by evaluations (Section 5). Related work and conclusion are in Sections 6 and 7.

2 Data Collection and Preprocessing

We crawled news articles from New York Times (NYT), CNN, and BBC on four trending events: the missing Malaysia Airlines Flight MH370 (MH370), the political unrest in Ukraine (Ukraine), the Israel-Gaza conflict (Israel-Gaza), and the NSA surveillance leaks (NSA). For each event, we select a set of key words (usually entities’ name), which are used to filter out irrelevant articles. We collect comments for NYT articles through NYT community API, and comments for CNN articles via Disqus.
API. NYT comments come with information on whether a comment is an editor’s-pick. The statistics on the four datasets are displayed in Table 1.

| Time Span       | # Articles | # Comments |
|-----------------|------------|------------|
| MH370           | 03/08 - 06/30 | 955        | 406,646    |
| Ukraine         | 03/08 - 06/30 | 3,779      | 646,961    |
| Israel-Gaza     | 07/20 - 09/30 | 909        | 322,344    |
| NSA             | 03/23 - 06/30 | 145        | 60,481     |

Table 1: Statistics on the four event datasets.

We extract parse trees, dependency trees, and coreference resolution results of articles and comments with Stanford CoreNLP (Manning et al., 2014). Sentences in articles are labeled with timestamps using SUTime (Chang and Manning, 2012).

We also collect all articles with comments from NYT in 2013 (henceforth NYT2013) to form a training set for learning importance scoring functions on articles sentences and comments (see Section 3). NYT2013 contains 3,863 articles and 833,032 comments.

3 Joint Learning for Importance Scoring

We first introduce a joint learning method that uses graph-based regularization to simultaneously learn two functions — a sentence scorer and a comment scorer — that predict the importance of including an individual news article sentence or a particular user comment in the timeline.

We train the model on the aforementioned NYT2013 dataset, where 20% of the articles and their comments are reserved for parameter tuning. Formally, the training data consists of a set of articles $D = \{d_i\}_{i=1}^{|D|}$. Each article $d_i$ contains a set of sentences $x_{di} = \{x_{s_{di},j}\}_{j=0}^{|s_{di}|-1}$ and a set of associated comments $x_{cdi} = \{x_{c_{cdi},k}\}_{k=0}^{|c_{cdi}|-1}$, where $|s_{di}|$ and $|c_{cdi}|$ are the numbers of sentences and comments for $d_i$. For simplicity, we use $x_s$ or $x_c$ to denote a sentence or a comment wherever there is no ambiguity.

In addition, each article has a human-written abstract. We use the ROUGE-2 (Lin and Hovy, 2003) score of each sentence computed against the associated abstract as its gold-standard importance score.

Each comment is assigned a gold-standard value of 1.0 if it is an editor’s pick, or 0.0 otherwise.

The sentence and comment scorers rely on two classifiers, each designed to handle the special characteristics of news and user comments, respectively; and a graph-based regularizing constraint that encourages similarity between selected sentences and comments. We describe each component below.

Article Sentence Importance. Each sentence $x_s$ in a news article is represented as a $k$-dimensional feature vector $x_s \in \mathbb{R}^k$, with a gold-standard label $y_s$. We denote the training set as a feature matrix $\tilde{X}_s$, with a label vector $\tilde{y}_s$. To produce the sentence scoring function $f_s(x_s) = x_s \cdot w_s$, we use ridge regression to learn a vector $w_s$ that minimizes $||\tilde{X}_s w_s - \tilde{y}_s||_2^2 + \beta_s \cdot ||w_s||_2^2$. Features used in the model are listed in Table 2. We also impose the following position-based regularizing constraint to encode the fact that the first sentence in a news article usually conveys the most essential information: $\lambda_s \cdot \sum_{j=1}^{|s_d|} \sum_{j \neq j'} (||x_{s_{di},0} - x_{s_{dj},j}|| \cdot w_s - (y_{s_{di},0} - y_{s_{dj},j})|| \cdot w_s)^2$, where $x_{s_{di},j}$ is the $j$-th sentence in document $d_i$. Term $(x_{s_{di},0} - x_{s_{dj},j}) \cdot w_s$ measures the difference in predicted scores between the first sentence and any other sentence. This value is expected to be close to the true difference. We further construct $\tilde{X}'_s$ to contain all difference vectors $(x_{s_{di},0} - x_{s_{dj},j})$, with $\tilde{y}'_s$ as label difference vector. The objective function to minimize becomes

$$J_s(w_s) = ||\tilde{X}_s w_s - \tilde{y}_s||_2^2 + \lambda_s \cdot ||\tilde{X}'_s w_s - \tilde{y}'_s||_2^2 + \beta_s \cdot ||w_s||_2^2$$

(1)

User Comment Importance. Similarly, each comment $x_c$ is represented as an $l$-dimensional feature vector $x_c \in \mathbb{R}^l$, with label $y_c$. Comments in the training data are denoted with a feature matrix $\tilde{X}_c$ with a label vector $\tilde{y}_c$. Likewise, we learn $f_c(x_c) = x_c \cdot w_c$ by minimizing $||\tilde{X}_c w_c - \tilde{y}_c||_2^2 + \beta_c \cdot ||w_c||_2^2$. Features are listed in Table 3. We apply a pairwise preference-based regularizing constraint (Joachims, 2002) to incorporate a bias toward editor’s picks: $\lambda_c \cdot \sum_{d_i} \sum_{x_{cdi},j \in E_{di}} x_{cdi,j} \cdot (x_{cdi,j} \cdot w_c - 1)||^2$, where $E_{di}$ are the editor’s picks for $d_i$. Term $(x_{cdi,j} \cdot w_c)$ enforces the separation of editor’s picks from regular comments. We further construct $\tilde{X}'_c$ to contain all the pairwise differences.
The interplay between the two types of data is encoded in the following regularizing constraint:

$$J_{s,c}(w_s, w_c) = \lambda_{sc} \cdot \sum_{d_i} \sum_{x_s \in x_{sd_i}, x_c \in x_{cd_i}} Q_{x_s, x_c} \cdot (x_s \cdot w_s - x_c \cdot w_c)^2$$

(3)

**Full Objective Function.** Thus, the full objective function consists of the three parts discussed above:

$$J(w_s, w_c) = J_s(w_s) + J_c(w_c) + J_{s,c}(w_s, w_c)$$

(4)

Furthermore, using the following notation,

$$\tilde{X} = \begin{bmatrix} \tilde{X}_s & 0 \\ 0 & \tilde{X}_c \end{bmatrix}, \tilde{Y} = \begin{bmatrix} \tilde{Y}_s \\ \tilde{Y}_c \end{bmatrix}, \tilde{X}' = \begin{bmatrix} \tilde{X}_s' & 0 \\ 0 & \tilde{X}_c' \end{bmatrix}, \tilde{Y}' = \begin{bmatrix} \tilde{Y}_s' \\ \tilde{Y}_c' \end{bmatrix}$$

we can show a **closed form solution** to Equation 4 as follows:

$$\hat{w} = (\tilde{X}^T \tilde{L} \tilde{X} + \tilde{X}^T \tilde{X}' + \tilde{X}'^T \tilde{L} \tilde{X}' + \tilde{X}'^T \tilde{X}' + \tilde{X}'^T \tilde{Y} + \tilde{X}'^T \tilde{Y}' + \beta)^{-1}(\tilde{X}^T \tilde{Y} + \tilde{X}'^T \tilde{Y}')$$

(5)
in Section 4.4. In general, we alternately search for a better article summary \( S \) with hill climbing search and a better comment summary \( C \) with Ford-Fulkerson algorithm until convergence.

In the rest of this section, we first describe an entity-centered event threading algorithm to construct event threads \( T \) which are used to boost article timeline continuity. Then we explain how to compute \( S_{\text{qual}}(S; T) \) and \( C_{\text{qual}}(C) \) in Section 4.2 followed by \( \chi(S, C) \) in Section 4.3.

### 4.1 Entity-Centered Event Threading

We present an event threading process where each thread connects sequential events centered on a set of relevant entities. For instance, the following thread connects events about Obama’s action towards the annexation of Crimea by Russia:

Day 1: Obama declared sanctions on Russian officials.
Day 2: President Obama warned Russian.
Day 3: Obama urges Russian to move back its troops.
Day 4: Obama condemns Russian aggression in Ukraine.

We first collect relation extractions as \( \text{(entity, relation, entity)} \) triples from OLLIE \cite{mausam2012}, a dependency relation based open information extraction system. We retain extractions with confidence scores higher than 0.5. We further design syntactic patterns based on \cite{fader2011} to identify relations expressed as a combination of a verb and nouns. Each relation contains at least one event-related word \cite{ritter2012}.

The entity-centered event threading algorithm works as follows: on the first day, each sentence in the summary becomes an individual cluster; thereafter, each sentence in the current day’s article summary either gets attached to an existing thread or starts a new thread. The updated threads then become the input to next day’s summary generation process. On day \( n \), we have a set of threads \( T = \{ \tau : s_1, s_2, \ldots, s_{n-1} \} \) constructed from previous \( n - 1 \) days, where \( s_i \) represents the set of sentences attached to thread \( \tau \) from day \( i \). The cohesion between a new sentence \( s \in S \) and a thread \( \tau \) is denoted as \( \text{cohn}(s, \tau) \). A sentence \( s \) is attached to \( \tau \) if there exists an \( \hat{\tau} = \max_{\tau \in T} \text{cohn}(s, \tau) \) and \( \text{cohn}(s, \hat{\tau}) > 0.0 \). Otherwise, \( s \) becomes a new thread. We define \( \text{cohn}(s, \tau) = \min_{s_i \in \tau, s_i \neq s} \text{tf} \text{sim}(s_i, s) \), where \( \text{tf} \text{sim}(s_i, s) \) measures the TF similarity between \( s_i \) and \( s \). We consider unigrams/bigrams/trigrams generated from the entities of our event extractions.

### 4.2 Summary Quality Measurement

Recall that we learned two separate importance scoring functions for sentences and comments, which will be denoted here as \( \text{imp}_s(s) \) and \( \text{imp}_c(c) \). With an article summary \( S \) and threads \( T = \{ \tau \} \), the article summary quality function \( S_{\text{qual}}(S; T) \) has the following form:

\[
S_{\text{qual}}(S; T) = \sum_{s \in S} \text{imp}_s(s) + \theta_{\text{cov}} \sum_{s' \in V_s} \min(\sum_{s \in S} \text{tfidf}(s, s'), \alpha \sum_{s \in V_s} \text{tfidf}(\hat{s}, s'))
+ \theta_{\text{cont}} \sum_{s \in T} \max_{\tau \in S} \text{cohn}(s_\tau, \tau)
\]

\( \text{tfidf}(\cdot, \cdot) \) is the TF-IDF similarity function. \( S_{\text{qual}}(S; T) \) captures three desired qualities of an article summary: importance (first item), coverage (second item), and the continuity of the current summary to previously generated summaries. The coverage function has been used to encourage summary diversity and reduce redundancy \cite{lin2011, wang2014}. The continuity function considers how well article summary \( S \) can be attached to each event thread, thus favors summaries that can be connected to multiple threads.

Parameters \( \theta_{\text{cov}} \) and \( \alpha \) are tuned on multidocument summarization dataset DUC 2003 \cite{over2003}. Experiments show that system performance peaks and is stable for \( \theta_{\text{cont}} \in [1.0, 5.0] \). We thus fix \( \theta_{\text{cont}} \) to 1.0. We discard sentences with more than 80% of content words covered by historical summaries. We use BASIC to denote a system that only optimizes on importance and coverage (i.e. first two items in \( S_{\text{qual}}(S; T) \)). The system optimizing \( S_{\text{qual}}(S; T) \) is henceforth called THREAD.

The comment summary quality function simply takes the form \( C_{\text{qual}}(C) = \sum_{c \in C} \text{imp}_c(c) \).

### 4.3 Connectivity Measurement

We encode two objectives in the connectivity function \( \chi(S, C) \): (1) encouraging topical cohesion (i.e. connectivity) between article summary and comment summary; and (2) favoring comments that cover diversified events.

Let \( \text{conn}(s, c) \) measure content similarity between a sentence \( s \in S \) and a comment \( c \in C \). Connectivity between article summary \( S \) and comment summary \( C \) is computed as follows. We build a bipartite graph \( G \) between \( S \) and \( C \) with edge weight as \( \text{conn}(s, c) \).
We then find an edge set $\mathcal{M}$, the best matching of $\mathcal{G}$. $\mathcal{X}(S, C)$ is defined as the sum over edge weights in $\mathcal{M}$, i.e. $\mathcal{X}(S, C) = \sum_{e \in \mathcal{M}} \text{weight}(e)$. An example is illustrated in Figure 2.

### Table: Article Summary vs. Comment Summary

| Article Summary                          | Comment Summary                          |
|-----------------------------------------|-----------------------------------------|
| S_5: The Crimean parliament officially declared independence and requested full access to the Russian Federation. | C_6: The “Crimean Parliament”, headed by an ethnic Russian separatist, has voted for Crimea to be annexed into Russia… |
| S_6: Obama declared sanctions on Russian officials considered responsible for the crisis. | C_3: The Obama administration has warned of “increasingly harsh sanctions”, but it is unlikely that Europe will comply… |

Figure 2: An example on computing the connectivity between an article summary (left) and a comment summary (right) via best matching in bipartite graph. Number on each edge indicates the content similarity between a sentence and a comment. Solid lines are edges in the best matching graph. For this example, the connectivity $\mathcal{X}(S, C)$ is $0.8 + 0.8 = 1.6$.

We consider two options for $conn(s, c)$. One is lexical similarity which is based on TF-IDF vectors. Another is semantic similarity. Let $R_s = \{ (a_s, r_s, b_s) \}$ and $R_c = \{ (a_c, r_c, b_c) \}$ be the sets of dependency relations in $s$ and $c$. $conn(s, c)$ is calculated as:

$$\sum_{(a_s, r_s, b_s) \in R_s} \max_{(a_c, r_c, b_c) \in R_c} \text{simi}(a_s, a_c) \times \text{simi}(b_s, b_c)$$

where $\text{simi}(\cdot, \cdot)$ is a word similarity function. We experiment with shortest path based similarity defined on WordNet (Miller, 1995) and Cosine similarity with word vectors trained on Google news (Mikolov et al., 2013). Systems using the three metrics that optimize $\mathcal{Z}(S, C; T)$ are henceforth called THREAD+OPTTFIDF, THREAD+OPTWordNet and THREAD+OPTWordVec.

### 4.4 An Alternating Optimization Algorithm

To maximize the full objective function $\mathcal{Z}(S, C; T)$, we design a novel alternating optimization algorithm (Alg. 1) where we alternately find better $S$ and $C$.

We initialize $S_0$ by a greedy algorithm (Lin and Bilmes, 2011) with respect to $S_{qual}(S; T)$. Notice that $S_{qual}(S; T)$ is a submodular function, so that the greedy solution is a $1 - 1/e$ approximation to the optimal solution of $S_{qual}(S; T)$. Fixing $S_0$, we model the problem of finding $C_0$ that maximizes $C_{qual}(C) + \delta \mathcal{X}(S_0, C)$ as a maximum-weight bipartite graph matching problem. This problem can be reduced to a maximum network flow problem, and then be solved by Ford-Fulkerson algorithm (details are discussed in (Kleinberg and Tardos, 2005)). Thereafter, for each iteration, we alternately find a better $S_t$ with regard to $S_{qual}(S; T) + \delta \mathcal{X}(S, C_{t-1})$ using hill climbing, and an exact solution $C_t$ to $C_{qual}(C) + \delta \mathcal{X}(S, C)$ with Ford-Fulkerson algorithm. Iteration stops when the increase of $\mathcal{Z}(S, C)$ is below threshold $\epsilon$ (set to 0.01). System performance is stable when we vary $\delta \in \{1.0, 10.0\}$, so we set $\delta = 1.0$.

#### Algorithm 1: Generate article summary and comment summary for a given day via alternating optimization

```
Input: sentences $V_s$, comments $V_c$, threads $T$, $\delta$, threshold $\epsilon$, functions $\mathcal{Z}(S, C; T)$, $S_{qual}(S; T)$, $C_{qual}(C)$, $\mathcal{X}(S, C)$
Output: article summary $S$, comment summary $C$

/* Initialize $S$ and $C$ by greedy algorithm and Ford-Fulkerson algorithm */
$S_0 \leftarrow \max_S S_{qual}(S; T)$;
$C_0 \leftarrow \max_C C_{qual}(C) + \delta \mathcal{X}(S_0, C)$;
$t \leftarrow 1$;

while $\Delta Z > \epsilon$ do
  /* Step 1: Hill climbing algorithm */
  $S_t \leftarrow \max_S S_{qual}(S; T) + \delta \mathcal{X}(S, C_{t-1})$;
  /* Step 2: Ford-Fulkerson algorithm */
  $C_t \leftarrow \max_C C_{qual}(C) + \delta \mathcal{X}(S_t, C)$;
  $\Delta Z = \mathcal{Z}(S_t, C_t; T) - \mathcal{Z}(S_{t-1}, C_{t-1}; T)$;
  $t \leftarrow t + 1$;
end
```

Algorithm 1 is guaranteed to find a solution at least as good as $S_0$ and $C_0$. It progresses only if Step 1 finds $S_t$ that improves upon $\mathcal{Z}(S_{t-1}, C_{t-1}; T)$, and Step 2 finds $C_t$ where $\mathcal{Z}(S_t, C_t; T) \geq \mathcal{Z}(S_{t-1}, C_{t-1}; T)$.

### 5 Experimental Results

#### 5.1 Evaluation of Sentence and Comment Importance Scorers

We test importance scorers (Section 3) on single document sentence ranking and comment ranking.

For both tasks, we compare with two previous systems on joint ranking and summarization of news articles and tweets. Yang et al. (2011) employ supervised learning based on factor graphs to model content similarity between the two types of data. We use the same features for this model. Gao et al. (2012) summarize by including the complementary information between articles and
tweets, which is estimated by an unsupervised topic model. We also consider two state-of-the-art rankers: RankBoost (Freund et al., 2003) and LambdaMART (Burges, 2010). Finally, we use a position baseline that ranks sentences based on their position in the article, and a rating baseline that ranks comments based on positive user ratings.

We evaluate using normalized discounted cumulative gain at top 3 returned results (NDCG@3). Sentences are considered relevant if they have ROUGE-2 scores larger than 0.0 (computed against human abstracts), and comments are considered relevant if they are editor’s picks. Figure 3 demonstrates that our joint learning model uniformly outperforms all the other comparisons for both ranking tasks. In general, supervised learning based approaches (e.g. our method, Yang et al. (2011), RankBoost, and LambdaMART) produce better results than unsupervised method (e.g. Gao et al. (2012)).

Figure 3: Evaluation of sentence and comment ranking on the four datasets by using normalized discounted cumulative gain at top 3 returned results (NDCG@3). Our joint learning based approach uniformly outperforms all the other comparisons.

5.2 Leveraging User Comments

In this section, we test if our system can leverage comments to produce better article-based summaries for event timelines. We collect gold-standard timelines for each of the four events from the corresponding Wikipedia page(s), NYT topic page, or BBC news page.

We consider two existing timeline creation systems that only utilize news articles, and a timeline generated from single-article human abstracts: (1) CHIEU AND LEE (2004) select sentences with high “interestingness” and “burstiness” using a likelihood ratio test to compare word distributions of sentences with articles in neighboring days. (2) YAN ET AL. (2011) design an evolutionary summarization system that selects sentences based on on coverage, coherence, and diversity. (3) We construct a timeline from the human abstracts provided with each article: we sort them chronologically according to article timestamps and add abstract sentences into each daily summary until reaching the word limit.

We test on five variations of our system. The first two systems generate article summaries with no comment information by optimizing \( S_{qual}(S; T) \) using a greedy algorithm: BASIC ignores event threading; THREAD considers the threads. THREAD+OPT\_TFIDF, THREAD+OPT\_WordNet and THREAD+OPT\_WordVec (see Section 4.3) leverage user comments to generate article summaries as well as comment summaries based on alternating optimization of Equation 3. Although comment summaries are generated, they are not used in the evaluation.

For all systems, we generate daily article summaries of at most 100 words, and select 5 comments for the corresponding comment summary. We employ ROUGE (Lin and Hovy, 2003) to automatically evaluate the content coverage (in terms of ngrams) of the article-based timelines vs. gold-standard timelines. ROUGE-2 (measures bigram overlap) and ROUGE-SU4 (measures unigram and skip-bigrams separated by up to four words) scores are reported in Table 4. As can be seen, under the alternating optimization framework, our systems, employing both articles and comments, consistently yield better ROUGE scores than the three baseline systems and our systems that do not leverage comments. Though constructed from single-article abstracts, baseline ABSTRACT is found to contain redundant information and thus limited in content coverage. This is due to the fact that different media tend to report on the same important events.

5.3 Evaluating Socially-Informed Timelines

We evaluate the full article+comment-based timelines on Amazon Mechanical Turk. Turkers are presented with a timeline consisting of five consecutive days’ article summaries and four variations of the accompanying comment summary.
Table 5: Human evaluation results on the comment portion of socially-informed timelines. **Boldface** indicates statistical significance vs. other results in the same column using a Wilcoxon signed-rank test (\( p < 0.05 \)). On average, the output from our system is ranked higher than all other alternatives.

Table 4: ROUGE-2 (R-2) and ROUGE-SU4 (R-SU4) scores (multiplied by 100) for different timeline generation approaches on four event datasets. Systems that statistically significantly outperform the three baselines (\( p < 0.05 \), paired \( t \)-test) are in italics. Numbers in **bold** are the highest score for each column.

| Method | ROUGE-2 | ROUGE-SU4 |
|--------|---------|-----------|
| Basic | 5.93 | 9.80 |
| Thread | 6.55 | 10.86 |
| - Alternating Optimization (leveraging comments) | 6.73 | 11.87 |
| Thread+OPTWordVec | 6.74 | 11.63 |
| Thread+OPTWordVec | 8.74 | 11.63 |

Turkers are asked to rank the comment summary variations according to informativeness and insightfulness. For informativeness, we ask the Turkers to judge based only on knowledge displayed in the timeline, and to rate each comment summary based on how much relevant information they learn from it. For insightfulness, Turkers are required to focus on insights and valuable opinions. They are requested to leave a short explanation of their ranking.

15 five-day periods are randomly selected. We solicit four distinct Turkers located in the U.S. to evaluate each set of timelines. An inter-rater agreement of Krippendorff’s \( \alpha \) of 0.63 is achieved for informativeness ranking and \( \alpha = 0.50 \) for insightfulness ranking.

Table 5 shows the percentage of times a particular method is selected as producing the best comment portion of the timeline, as well as the micro-average rank of each method, for both informativeness and insightfulness. Our system is selected as the best in 66.7% of the evaluations for informativeness and 51.7% for insightfulness. In both cases, we statistically significantly outperform (\( p < 0.05 \) using a Wilcoxon signed-rank test) the editor’s-picks and user’s-picks. Turkers’ explanations indicate that they prefer our comment summaries mainly because they are “very informative and insightful to what was happening”, and “show the sharpness of the commenter”. Turkers sometimes think the summaries randomly selected from editor’s-picks “lack connection”, and characterize user’s-picks as “the information was somewhat limited”.

Figure 4 shows part of the timeline generated by our system for the Ukraine crisis.
variation of our system. We designed one question for each timeline. Sample questions are: “describe the activities for searching for the missing flight MH370”, and “describe the attitude and action of Russian Government on Eastern Ukraine”. We recruited 10 undergraduate and graduate students who are native speakers of English. Each student first read one question and its corresponding timeline for 5 minutes. The timeline was then removed, and the student wrote down an answer for the question. We asked each student to answer the question for each of four timelines (one for each event dataset). Two timelines are displayed with threads, and two without threads. We presented threads by adding a thread number in front of each sentence.

We then used Amazon Mechanical Turk to evaluate the informativeness of students’ answers. Turkers were asked to read all 10 answers for the same question, with five answers based on timelines with threads and five others based on timelines without threads. After that, they rated each answer with an informativeness score on a 1-to-5 rating scale (1 as “not relevant to the query”, and 5 as “very informative”). We also added two quality control questions. Table 6 shows that the average rating for answers written after reading timelines with threads is 3.29 (43% are rated ≥ 4), higher than the 2.58 for the timelines with no thread exhibited (30% are rated ≥ 4).

| Answer Type | Avg ± STD | Rated 5 (%) | Rated 4 (%) |
|-------------|-----------|-------------|-------------|
| No Thread   | 2.58 ± 1.20 | 7%          | 23%         |
| With Threads| 3.29 ± 1.28 | 17%         | 26%         |

Table 6: Human evaluation on the informativeness of answers written after reading timelines with threads vs. with no thread. Answers written with access to threads are rated higher (3.29) than the ones with no thread (2.58).

6 Related Work

There is a growing interest in generating article summaries informed by social context. Existing work focuses on learning users’ interests from comments and incorporates the learned information into a news article summarization system (Hu et al., 2008). Zhao et al. (2013) instead estimate word distributions from tweets, and bias a Page Rank algorithm to give higher restart probability to sentences with similar distributions. Generating tweet+article summaries has been recently investigated in Gao et al. (2011). They propose a factor graph to allow sentences and tweets to mutually reinforce each other. Gao et al. (2012) exploit a co-ranking model to identify sentence-tweet pairs with complementary information estimated from a topic model. These efforts handle a small number of documents and tweets, while we target a larger scale of data.

In terms of timeline summarization, the Chieu and Lee (2004) system ranks sentences according to “burstiness” and “interestingness” estimated by a likelihood ratio test. Yan et al. (2011) explore an optimization framework that maximizes the relevance, coverage, diversity, and coherence of the timeline. Neither system has leveraged the social context. Our event threading algorithm is also inspired by work on topic detection and tracking (TDT) (Allan et al., 1998), where efforts are made for document-level link detection and topic tracking. Similarly, Nallapati et al. (2004) investigate event threading for articles, where they predict linkage based on causal and temporal dependencies. Shahaf et al. (2012) instead seek for connecting articles into one coherent graph. To the best of our knowledge, we are the first to study sentence-level event threading.

7 Conclusion

We presented a socially-informed timeline generation system, which constructs timelines consisting of article summaries and comment summaries. An alternating optimization algorithm is designed to maximize the connectivity between the two sets of summaries as well as their importance and information coverage. Automatic and human evaluations showed that our system produced more informative timelines than state-of-the-art systems. Our comment summaries were also rated as very insightful.

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