Utilizing Microblogs for Automatic News Highlights Extraction

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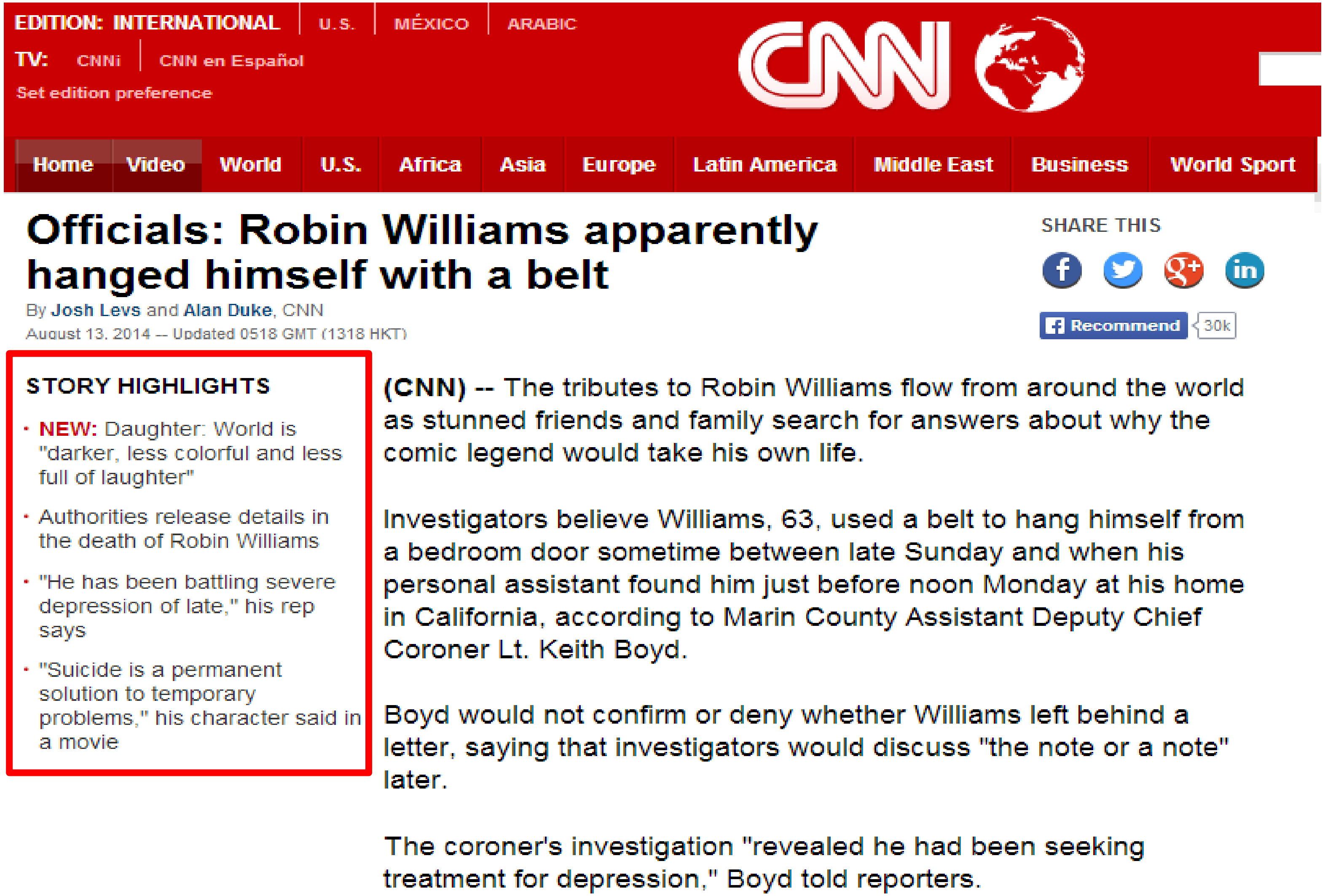
**Work conducted at Qatar Computing Research Institute*

Outline

- **Background**
- Motivation
- Related Work
- Our Approach
- Evaluation
- Conclusion and Feature Work

What are News Highlights?



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Officials: Robin Williams apparently hanged himself with a belt

By Josh Levs and Alan Duke, CNN

August 13, 2014 -- Updated 0518 GMT (1318 HKT)

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STORY HIGHLIGHTS

- **NEW:** Daughter: World is "darker, less colorful and less full of laughter"
- Authorities release details in the death of Robin Williams
- "He has been battling severe depression of late," his rep says
- "Suicide is a permanent solution to temporary problems," his character said in a movie

(CNN) -- The tributes to Robin Williams flow from around the world as stunned friends and family search for answers about why the comic legend would take his own life.

Investigators believe Williams, 63, used a belt to hang himself from a bedroom door sometime between late Sunday and when his personal assistant found him just before noon Monday at his home in California, according to Marin County Assistant Deputy Chief Coroner Lt. Keith Boyd.

Boyd would not confirm or deny whether Williams left behind a letter, saying that investigators would discuss "the note or a note" later.

The coroner's investigation "revealed he had been seeking treatment for depression," Boyd told reporters.

Challenges

- Difficult to locate the original content of highlights in a news article
  - *Sophisticated systems in Document Understanding Conference (DUC) task cannot significantly outperform the naïve baseline by extracting the first n sentences*
- Original sentences extracted as highlights are generally verbose
  - *Sentence compression suffers from poor readability or grammaticality*

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Increased Cross-Media Interaction

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Motivating Example

- **Social media recasts the highlights extraction**

❑ Indicative effect: Microblog users' mentioning about the news is indicative of the importance of the corresponding sentences

- Highlight: A third person has died from the bombing, Boston Police Commissioner Ed Davis says.
- Sentence: Boston Police Commissioner Ed Davis said Monday night that the death toll had risen to three.
- Tweet: Death toll from bombing at Boston Marathon rises to three.

Motivating Example (cont.’)

- **Social media recasts the highlights extraction**

❑ Human compression effect: Important portions of a news article might be rewritten by microblog users in a condensed style

- Highlight: Obama vows those guilty “will fell the full weight of justice”
- Sentence: In Washington, President Barack Obama vowed, “any responsible individuals, any responsible groups, will feel the full weight of justice.”
- Tweet: Obama: Those who did this will fell the full weight of justice.

Our Contributions

- Linking tweets to utilize the timely information as assistance to extract news sentences as highlights
- Extracting tweets as highlights to generate condensed version of news summary
- Treat with the problem as ranking which is more suitable for highlights extraction than classification

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Related Work

- News-tweets correlation
  - Content analysis across news and twitter (Petrovic et al., 2010; Subavsic and Berendt, 2011; Zhao et al., 2011)
  - Joint topic model for summarization (Gao et al., 2012)
  - News recommendation using tweets (Phelan et al., 2012)
  - News comments detection from tweets (Kothari et al., 2013; Stajner et al., 2013)
  - Link news to tweets (Guo et al., 2013)

Related Work (cont.')

- Single-document summarization
  - Using local content: Classification (Wong et al., 2008), ILP (Li et al., 2013), Sequential Model (Shen et al., 2007), Graphical model (Litvak and Last, 2008)
  - Using external content: Wikipedia (Svore et al., 2007), comments on news (Hu el al., 2008), clickthrough data (Sun et al., 2005; Svore et al., 2007)
  - Compression-based: Sentence selection and compression (Knight and Marcu, 2002), Joint model (Woodsend and Lapata, 2010; Li et al., 2013)

Related Work (cont.')

- Microblog summarization
  - Algorithm for short text collection: Phrase reinforcement algorithm (PRA) (Sharifi et al. 2010), Hybrid TF-IDF (Sharifi et al. 2010), Improved PRA (Judd and Kalita, 2013)
  - Sub-event-based: Using statistical methods for sub-event detection (Shen et al. 2013; Nichols et al. 2012; Zubiaga et al., 2012; Duan et al., 2012)

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Problem Statement

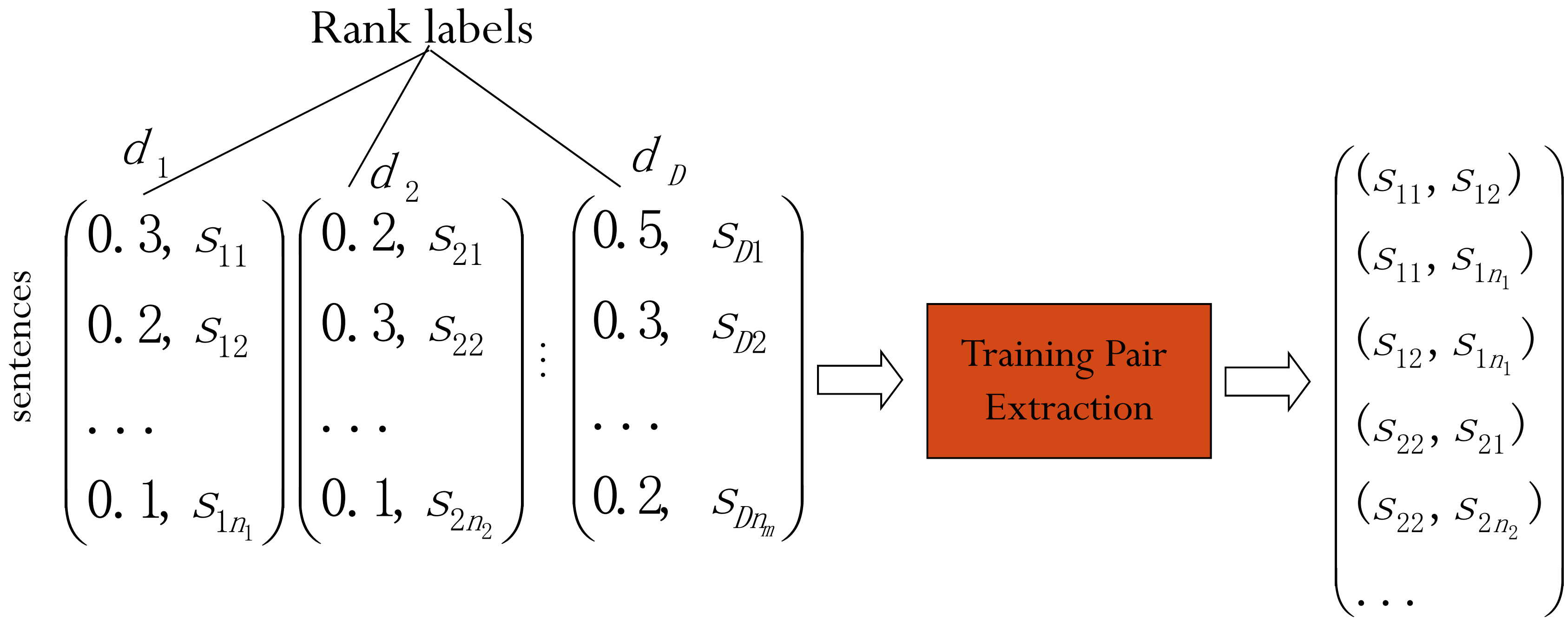
- Given a news article $S = \{s_1, s_2, \dots, s_n\}$ and relevant tweets set $T = \{t_1, t_2, \dots t_m\}$.

- **Task 1 - sentences extraction**: Given auxiliary T, extract x elements $H(S) = \left\{s^{(1)}, s^{(2)}, \dots, s^{(x)} | s^{(i)} \in S, 1 \le i \le x\right\}$ from S as highlights.
- **Task 2 - tweets extraction**: Given auxiliary S, extract x elements $H(T) = \left\{t^{(1)}, t^{(2)}, \dots, t^{(x)} | t^{(i)} \in T, 1 \le i \le x\right\}$ from T as highlights.

Ranking-based Highlights Extraction

- Instance: a news sentence (task 1); a tweet (task 2)
- Algorithm: RankBoost (Freund et al., 2003)
- Rank labeling: Given the ground-truth highlights $H_g = \{h_1, h_2, \ldots, h_x\}$ the label of an instance I_i is fixed as $max_k\{ROUGE(I_i, h_k)\}$

Training Corpus Construction



Feature Design

- Local sentence features (LSF)
- Local tweet features (LTF)
- Cross-media correlation features (CCF)
- Task 1 : LSF + CCF
- Task 2 : LTF + CCF

Feature set

Category	Name	Description
Local Sentence Feature (LSF)	IsFirst	Whether s is the first sentence in the news
	Pos	The position of s in the news
	TitleSimi	Token overlap between s and news title
	ImportUnigram	Importance score of s according to the unigram distribution in the news
	ImportBigram	Importance score of s according to the bigram distribution in the news
Local Tweet Feature (LTF)	Length	Token number in t
	HashTag	HashTag related features (presence and count)
	URL	URL related features (count)
	Mention	Mention related features (presence and count)
	ImportTFIDF	Importance score of t based on unigram Hybrid TF-IDF algorithm (Sharifi et al., 2010)
	ImportPRA	Importance score of t based on phrase reinforcement algorithm (Sharifi et al., 2010)
	TopicNE	Named entity related features (NE count and seven binary values indicating the presence of each category)
	TopicLDA	LDA-based topic model features (maximum relevance with sub-topics, etc.)
	QualityOOV	Out-of-vocabulary words related features (count and percentage)
	QualityLM	Quality score of t according to language model (Unigram, bigram and trigram)
	QualityDepend	Quality score of t according to dependency bank (Han and Baldwin, 2011)
Cross-Media Feature (CCF)	MaxCosine	Maximum cosine value between the target instance and auxiliary instances
	MaxROUGE1F	Maximum ROUGE-1 F score between the target instance and auxiliary instances
	MaxROUGE1P	Maximum ROUGE-1 precision value between the target instance and auxiliary instances
	MaxROUGE1R	Maximum ROUGE-1 recall value between the target instance and auxiliary instances
	LeadSenSimi*	ROUGE-1 F score between leading news sentences and t
	TitleSimi*	ROUGE-1 F score between news title and t
	MaxSenPos*	The position of sentences that obtain maximum ROUGE-1 F score with t
	SimiUnigram	Similarity based on the distribution of (local) unigram frequency in the auxiliary resource
	SimiUniTFIDF	Similarity based on the distribution of (local) unigram TF-IDF in the auxiliary resource
	SimiTopEntity	Similarity based on the (local) presence and count of most frequent entities in the auxiliary resource
	SimiTopUnigram	Similarity based on the (local) presence and count of most frequent unigrams in the auxiliary resource

Cross-media features

Category	Name	Description
Instance-level similarities	MaxSimilarity	Maximum similarity value between the target instance and auxiliary instances (Cosine, ROUGE1)
	LeadSenSimi*	ROUGE-1 F score between leading news sentences and t
	TitleSimi*	ROUGE-1 F score between news title and t
	MaxSenPos*	The position of sentences obtained maximum ROUGE-1 F score with t
Semantic-space-level similarities	SimiUnigram	Similarity based on the distribution of (local) unigram frequency in the auxiliary resource
	SimiUniTFIDF	Similarity based on the distribution of (local) unigram TF-IDF in the auxiliary resource
	SimiTopEntity	Similarity based on the (local) presence and count of most frequent entities in the auxiliary resource
	SimiTopUnigram	Similarity based on the (local) presence and count of most frequent unigrams in the auxiliary resource

Features with * are used for task 2 only.

Local Sentence Feature

Name	Description
IsFirst	Whether sentence *s* is the first sentence in the news
Pos	The position of sentence *s* in the news
TitleSum	Token overlap between sentence *s* and news title
SumUnigram	Importance of *s* according to the unigram distribution in the news
SumBigram	Importance of *s* according to the bigram distribution in the news

Local Tweet Feature

Category	Name	Description
Twitter specific features	Length	Token number in *t*
	HashTag	HashTag related features
	URL	URL related features
	Mention	Mention related features
	ImportTFIDF	Importance score of *t* based on unigram Hybrid TF-IDF
	ImportPRA	Importance score of *t* based on phrase reinforcement algorithm
Topical features	TopicNE	Named entity related features
	TopicLDA	LDA-based topic model features
Writing-quality features	QualiOOV	Out-of-vocabulary words related features
	QualiLM	Quality degree of t according to language model
	QualiDependency	Quality degree of t according to dependency bank

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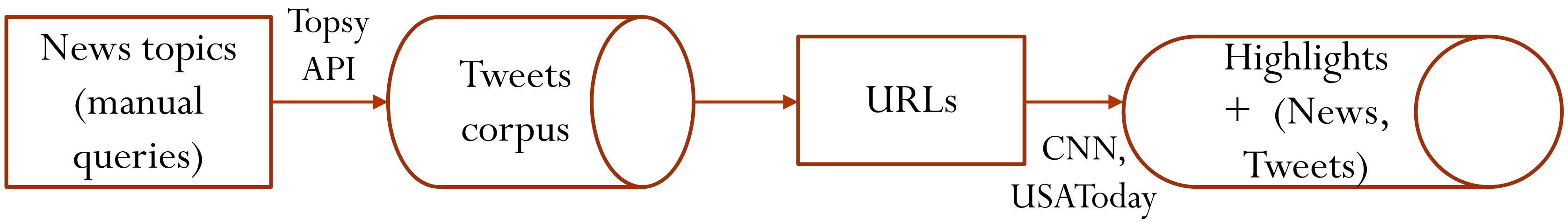
Data Collection

- Tweets gathering using Topsy API for17 topics
- News articles from CNN.com and USAToday.com



- Link news and tweets using embedded URLs
- Corpus Filtering
  - Remove the tweet if:
    1. Suspected copies from news title and highlights, e.g., “RT @someone HIGHLIGHT URL”;
    2. Token # < 5
  - Keep the news article if # of tweets linked to it > 100

Data Collection (cont.')

- Distribution of documents, highlights, and tweets per topic

Topic	Doc #	Highlight #	Tweet #	Topic	Doc #	Highlight #	Tweet #
Aurora shooting	14	54	12463	African runner murder	8	29	9461
Boston bombing	38	147	21683	Syria chemical weapons use	1	4	331
Connecticut shooting	13	47	3021	US military in Syria	2	7	719
Edward Snowden	5	17	1955	DPRK Nuclear Test	2	8	3329
Egypt balloon crash	3	12	836	Asiana Airlines Flight 214	11	42	8353
Hurricane Sandy	4	15	607	Moore Tornado	5	19	1259
Russian meteor	3	11	6841	US Flu Season	7	23	6304
Chinese Computer Attacks	2	8	507	Williams Olefins Explosion	1	4	268
cause of the Super Bowl blackout	2	8	482	Total	121	455	78419

- Length statistics

	Documents	Highlights	Tweets
Total#	121	455	78,419
Sentence # per news	53.6±25.6	3.7±0.4	648.1±1161.7
Token # per news	1123.0±495.8	49.6±10.0	10364.5±24749.2
Token # per sentence	21.0±11.6	13.2±3.2	16.0±5.3

Compared Approaches

- Task 1: from news articles
  - **Lead Sentence**: the first *x* sentences
  - **PhraseILP, SentenceILP**: joint model combining sentence compression and selection (Woodsend et al., 2010)
  - **Lexrank (news)**: Lexrank with news sentences as input
  - **Ours (LSF)**: Our method based on LSF features
  - **Ours (LSF+CCF)**: Our method combining LSF and CCF

- Task 2: from tweets
  - **Lexrank (tweets)**: Lexrank with tweets as input
  - **Ours (LTF)**: Our method based on LTF features
  - **Ours (LTF+CCF)**: Our method combining LTF and CCF

Experiment Setup

- Five-fold-cross validation for supervised methods
- MMR (Maximal Marginal Relevance) for methods in task 2
- Use ROUGE-1 as evaluation metric, ROUGE-2 as reference

Results on CNN/USAToday

Method	ROUGE-1			ROUGE-2		
	F	P	R	F	P	R
Lead sentence	<u>0.263</u>	<u>0.211</u>	0.374	0.101	0.080	0.147
Lexrank (news)	*0.264*	0.226	<u>0.332</u>	<u>0.088</u>	*0.074*	<u>0.112</u>
SentenceILP	<u>0.238</u>	<u>0.209</u>	<u>0.293</u>	<u>0.068</u>	<u>0.058</u>	<u>0.088</u>
PhraseILP	<u>0.236</u>	*0.215*	<u>0.281</u>	<u>0.069</u>	<u>0.061</u>	<u>0.086</u>
Ours (LSF)	<u>0.256</u>	<u>0.214</u>	<u>0.345</u>	<u>0.093</u>	<u>0.076</u>	<u>0.129</u>
Ours (LSF+CCF)	**0.292**	**0.239**	**0.398**	**0.110**	**0.089**	**0.155**
Lexrank (tweets)	<u>0.212</u>	<u>0.204</u>	<u>0.226</u>	<u>0.064</u>	<u>0.061</u>	<u>0.068</u>
Ours (LTF)	<u>0.264</u>	<u>0.280</u>	<u>0.274</u>	0.095	0.106	0.098
Ours (LTF+CCF)	**0.295**	**0.320**	**0.295**	**0.105**	**0.118**	**0.105**

Overall performance (Bold: best performance of the task; Underlined: significance ($p < 0.01$) compared to our best model; Italic: significance ($p < 0.05$) compared to our best model)

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Comparison of Summary Length

- Length of extracted highlights vs. that of ground truth

	Tokens # per sentence	Tokens # per summary
Ground-truth highlights	13.2±3.2	49.6±10.0
Ours (LSF+CCF) (sentence extraction)	24.3±11.8	91.3±18.4
Ours (LTF+CCF) (tweet extraction)	16.1±5.4	55.3±16.1

Contribution of Ranking Features

Task1: Ours (LSF+CCF)		Task2: Ours (LTF+CCF)	
Feature	**Weight**	**Feature**	**Weight**
ImportUnigram	4.7912	<u>SimiTopUnigram (count)</u>	1.9300
<u>MaxROUGE1R</u>	2.1049	<u>LeadSenSimi (third)</u>	1.8367
<u>MaxROUGE1F</u>	0.6511	QualityLM (Bigram)	0.4513
<u>SimiTopUnigram (count)</u>	0.6260	<u>MaxROUGE1R</u>	1.1925
<u>SimiUnigram</u>	0.5424	QualityLM (Unigram)	0.9441
<u>MaxROUGE1P</u>	0.1922	<u>LeadSenSimi (second)</u>	0.9224
<u>SimiTFIDF</u>	0.1534	QualityDepend	0.8306
<u>SimiTopEntity (count)</u>	0.0311	TopicNE (person)	0.7937
<u>SimiTopEntity (presence)</u>	0.0051	ImportTFIDF	0.7423
TitleSimi	0.0050	<u>LeadSenSimi (fourth)</u>	0.6072

Top 10 features and their weights resulting from the best ranking models in the two tasks (<u>underline</u>: Cross-media correlation features)

Outline

- Background
- Motivation
- Related Work
- Our Approach
- Evaluation
- **Conclusion and Future Work**

Conclusion and future work

- Successfully extract highlights from news article by taking advantage of indicative effect of relevant tweets associated with the article
- Successfully extract highlights from the relevant tweets set associated with the given article by taking the advantage of the fact that tweets are comparably concise as highlights

- ❑ Enlarge the relevant tweets collection by including potentially important tweets without explicit links to articles
- ❑ Strengthen the model by capturing deeper or latent linguistic and semantic correlations, e.g., using deep neural networks

Q & A