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Document analysis by means of data mining techniques

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Motivation and Research Context



- ▶ Information overload
- ▶ Unstructured form
- ▶ Different aspects of information

- ▶ Data mining and IR techniques
- ▶ **Automatic Summary**
- ▶ Text Summarization

ItemSum

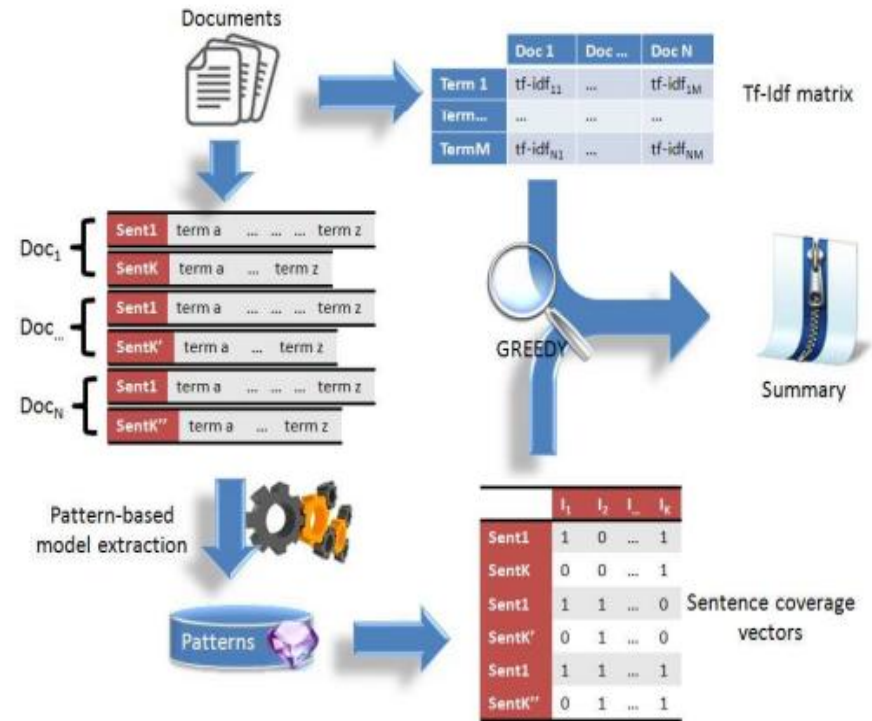
▶ Research Problem(s)

- Previous approaches typically focus **single-word** significance

▶ Need for capturing correlations among multiple-words

▶ Novel Contributions

- Frequent itemset mining to discover correlations in TS
- The usage of an itemset-based model to represent the most relevant and not redundant correlations among document terms
- The selection of minimal set of representative sentences based on:
 - Sentence coverage – Transactional data format
 - Sentence relevance score – Score based on tf-idf statistics



Performance Comparison–ItemSum

Performance comparison in terms of ROUGE-2 score

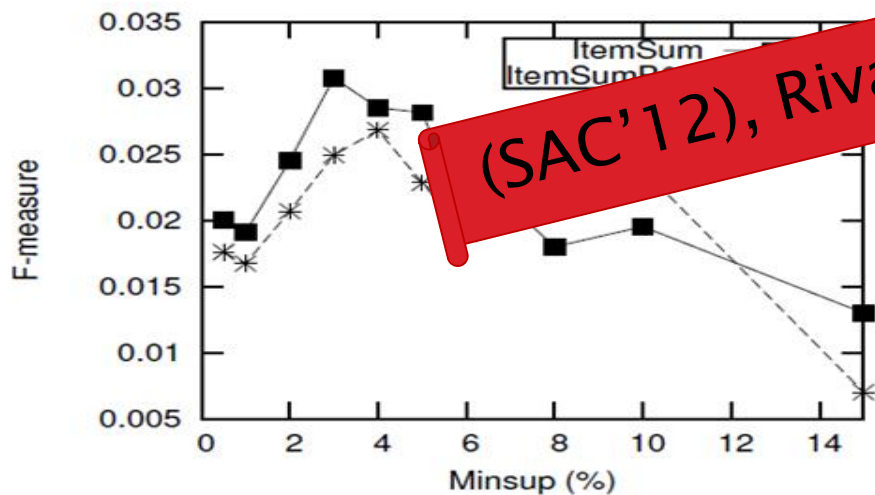
dataset	PATeXSUM				OTS			TexLexAn		
	p	R	Pr	F	R	Pr	F	R	Pr	F
Natural Disaster	16	0.116	0.288	0.141	0.040	0.120	0.053	0.038	0.114	0.045
Royal Wedding	12	0.036	0.215	0.058	0.034	0.174	0.054	0.030	0.150	0.047
Technology	5	0.141	0.465	0.210	0.042	0.208	0.067	0.042	0.172	0.065
Sports	10	0.145	0.297	0.189	0.055	0.133	0.075	0.071	0.149	0.093
Education	8	0.039	0.241	0.064	0.036	0.170	0.051	0.036	0.151	0.047

MCP 2011, (AI*AI'11), Palermo (Italy)

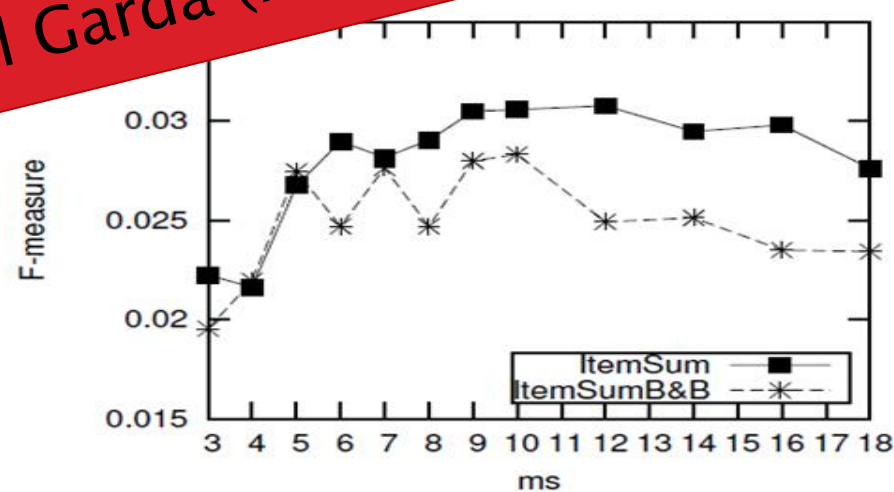
dataset	PATeXSUM				OTS			TexLexAn		
	p	R	Pr	F	R	Pr	F	R	Pr	F
Natural-Disaster	16	0.060	0.125	0.068	0.005	0.012	0.006	0.005	0.011	0.006
Royal-wedding	12	0.009	0.082	0.015	0.003	0.018	0.005	0.003	0.018	0.005
Technology	5	0.113	0.356	0.167	0.009	0.065	0.016	0.003	0.011	0.005
Sports	10	0.059	0.112	0.077	0.004	0.010	0.006	0.022	0.036	0.027
Education	8	0.017	0.141	0.030	0.003	0.012	0.005	0.003	0.009	0.004

Performance Comparison–ItemSum

Summarizer		ROUGE-2			ROUGE-3			ROUGE-4		
		R	Pr	F	R	Pr	F	R	Pr	F
OTS		0.0746*	0.0740*	0.0743*	0.0236*	0.0234*	0.0235*	0.0087*	0.0086*	0.0087*
TexLexAn		0.0655*	0.0643*	0.0649*	0.0197*	0.0193*	0.0195*	0.0071*	0.0069*	0.0070*
DUC'04 competitors	peer102	0.0840	0.0846	0.0843	0.0264	0.0267	0.0265	0.0103*	0.0104*	0.0104*
	peer103	0.0774*	0.0896	0.0826	0.0243*	0.0284	0.0260*	0.0092*	0.0108	0.0099*
	peer140	0.0685*	0.0692*	0.0688	0.0218*	0.0220*	0.0219*	0.0093*	0.0094*	0.0093*
ItemSum		0.0864	0.0869	0.0866	0.0307	0.0309	0.0308	0.0136	0.0136	0.0135



(a) $ms=12$. Impact of the support threshold.



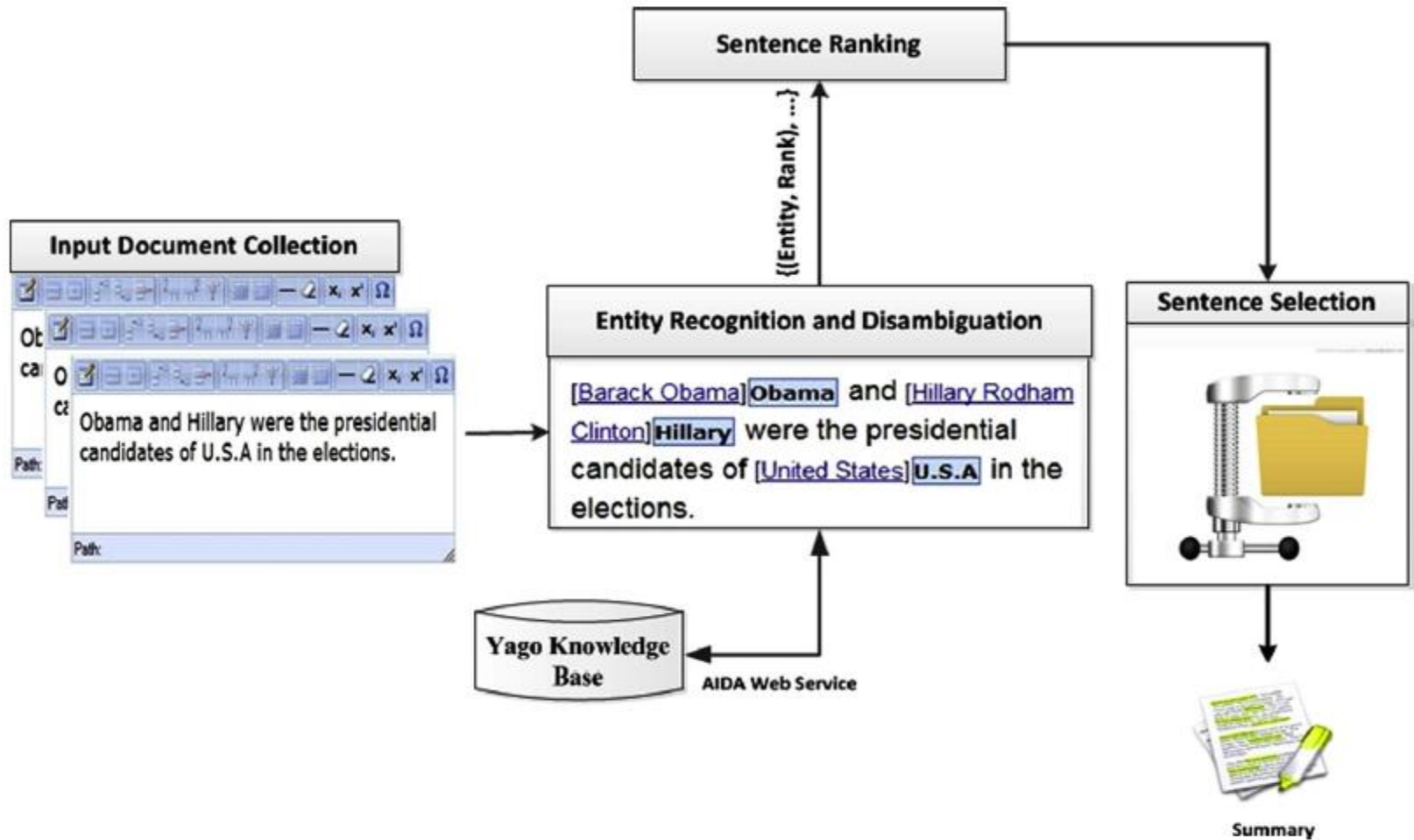
(b) $min_sup=3\%$. Impact of the model size.

The Yago-based summarizer

- ▶ Research Problem(s)
 - Unsatisfactory soundness and readability of summaries
 - Semantic models were used only in preprocessing
 - Domain specific ontologies/taxonomies, dictionaries were used
- ▶ Need of a generic summarizer based on a generic knowledgebase
- ▶ Novel Contribution(s):
 - Integration of a semantics-based model into document summarization
 - Use Yago ontology to **evaluate** and **select** document sentences
- ▶ Results:

YagoSum outperforms many state-of-the-art summarizers in terms of ROUGE scores on benchmark collections

The Yago-based summarizer



Performance Comparison–YagoSum

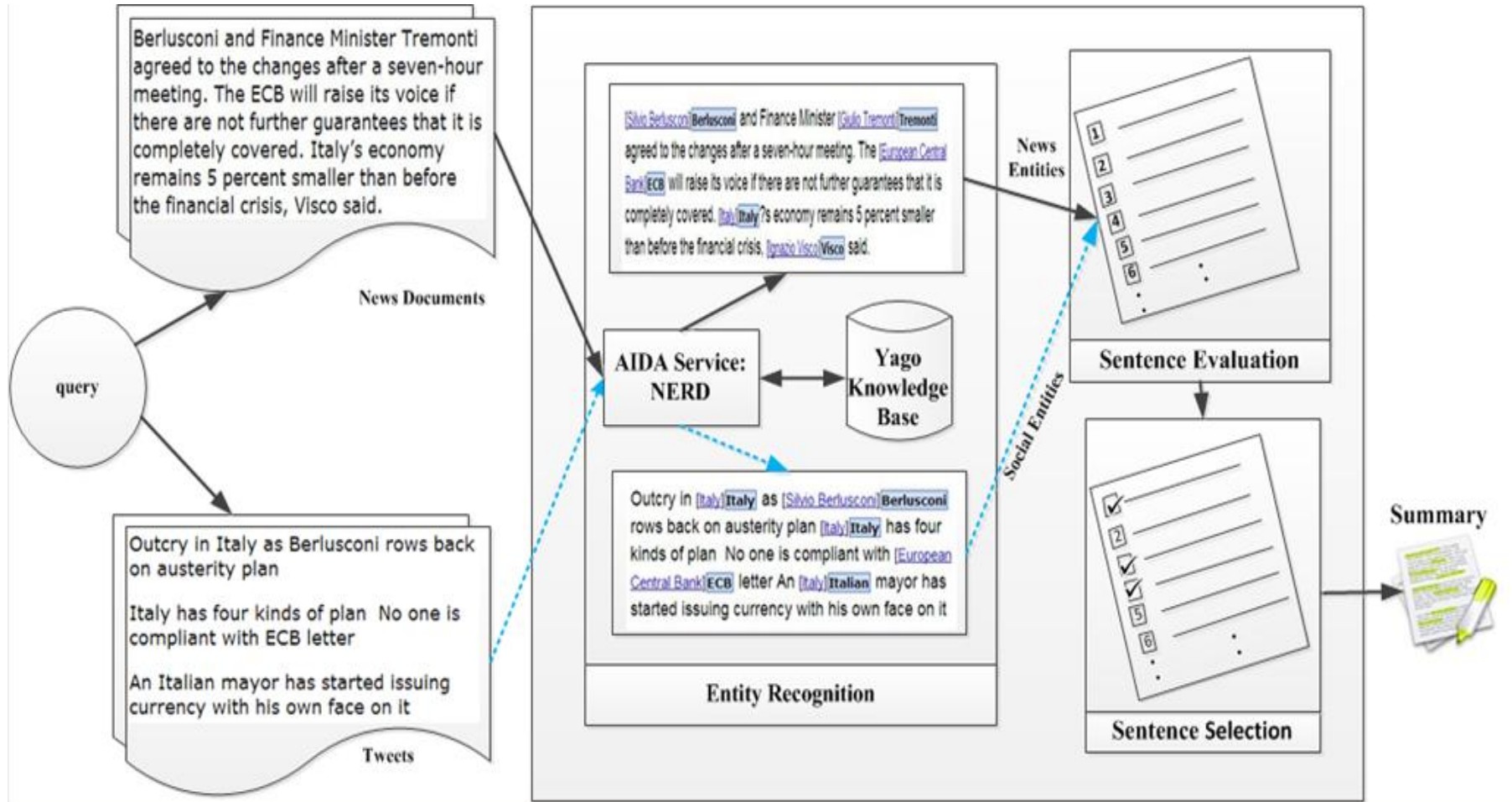
Summarizer		ROUGE-2			ROUGE-4		
		R	Pr	F	R	Pr	F
TOP RANKED DUC'04 PEERS	peer120	0.076*	0.103	0.086*	0.014*	0.019	0.016
	peer65	0.091*	0.090*	0.091*	0.015*	0.015	0.015*
	peer19	0.080*	0.080*	0.080*	0.010*	0.010*	0.010*
	peer121	0.071*	0.085*	0.077*	0.012*	0.014*	0.013*
	peer11	0.070*	0.087*	0.077*	0.012*	0.015*	0.012*
	peer44	0.075*	0.080*	0.078*	0.012*	0.013*	0.012*
	peer81	0.077*	0.080*	0.078*	0.012*	0.013*	0.012*
	peer104	0.086*	0.084*	0.085*	0.012*	0.013*	0.012*
	peer124	0.083*	0.084*	0.083*	0.012*	0.013*	0.012*
	peer35	0.076*	0.085*	0.080*	0.012*	0.013*	0.012*
DUC'04 HUMANS	A	0.094	0.102	0.098	0.009*	0.010*	0.010*
	B	0.096	0.102	0.099	0.013*	0.013*	0.013*
	C	0.094	0.102	0.098	0.011*	0.012*	0.012*
	D	0.100	0.106	0.102	0.010*	0.010*	0.010*
	E	0.094	0.099	0.097	0.011*	0.012*	0.012*
	F	0.086*	0.090*	0.088*	0.008*	0.009*	0.009*
	G	0.082*	0.087*	0.084*	0.008*	0.008*	0.007*
	H	0.101	0.105	0.103	0.012*	0.013*	0.012*
OTS		0.075*	0.074*	0.074*	0.009*	0.009*	0.009*
texLexAn		0.067*	0.067*	0.067*	0.007*	0.007*	0.007*
ItemSum		0.083*	0.085*	0.084*	0.012*	0.014*	0.014*
Baseline		0.092*	0.091*	0.092*	0.014*	0.014*	0.014*
Yago-based Summarizer		0.095	0.094	0.095	0.017	0.017	0.017

Expert Systems With Applications. ISSN 0957-4174

SocioNewSum

- ▶ Research Problem(s)
 - correlations among relevant concepts are missed
 - Reader's expectations and current interests
- ▶ With the advent of social media, user's interest can easily be identified
- ▶ Novel Contribution(s)
 - Combining Semantic and social knowledge for news TS
 - Preliminary analysis of Twitter messages to discover the actual user's interests
 - Identifying ontological concepts in both genres
 - Summarization of news collections driven by social knowledge to generate appealing news summaries
- ▶ Results:
 - Integration of social knowledge substantially improves news document summarization performance

Overview of SocioNewSum



Performance Comparison–SocioNewSum

Dataset (Tuned setting)	TexLexAn			OTS			Baseline			SocioNewSum Standard result (Tuned result)		
	R	P	F1	R	P	F1	R	P	F1	R	P	F1
Debt Crisis (K=50, $\delta=0.1$, $\alpha=0.6$)	0.068	0.541	0.121	0.077	0.581	0.135	0.070	0.518	0.121	0.081* (0.082*)	0.569 (0.582)	0.141* (0.143*)
Irene (K=30, $\delta=0.1$, $\alpha=0.2$)	0.062	0.577	0.110	0.064	0.602	0.116	0.055	0.532	0.099	0.066* (0.070*)	0.612* (0.646*)	0.119* (0.127*)
Steve Jobs (K=40, $\delta=0.2$, $\alpha=0.8$)	0.057	0.533	0.102	0.060	0.573	0.109	0.068	0.615	0.122	0.072* (0.072*)	0.625* (0.645*)	0.126* (0.128*)
Terrorism (K=70, $\delta=0.1$, $\alpha=0.7$)	0.047	0.447	0.086	0.052	0.479	0.093	0.045	0.444	0.082	0.055* (0.058*)	0.517* (0.544*)	0.099* (0.104*)
UK riots (K=10, $\delta=0.1$, $\alpha=0.2$)	0.060	0.522	0.107	0.065	0.586	0.117	0.052	0.456	0.092	0.065 (0.067)	0.578 (0.578)	0.117 (0.120*)
US Open (K=40, $\delta=0.1$, $\alpha=0.5$)	0.076	0.651	0.136	0.065	0.545	0.116	0.065	0.492	0.114	0.080* (0.082*)	0.654 (0.663*)	0.142* (0.145*)

SocioNewSum: Performance comparison in terms of ROUGE-1

Dataset (Tuned setting)	TexLexAn			OTS			Baseline			SocioNewSum		
	R	P	F1	R	P	F1	R	P	F1	R	P	F1
Debt Crisis (K=50, $\delta=0.1$, $\alpha=0.6$)	0.021	0.175	0.037	0.021	0.175	0.037	0.021	0.175	0.037	0.023* (0.024*)	0.221* (0.230*)	0.041* (0.043*)
Irene (K=30, $\delta=0.1$, $\alpha=0.2$)	0.022	0.195	0.039	0.022	0.203	0.040	0.015	0.139	0.027	0.023 (0.024)	0.211* (0.211*)	0.043* (0.043*)
Steve Jobs (K=40, $\delta=0.2$, $\alpha=0.8$)	0.022	0.195	0.039	0.022	0.203	0.040	0.015	0.139	0.027	0.023 (0.024)	0.211* (0.211*)	0.043* (0.043*)
Terrorism (K=70, $\delta=0.1$, $\alpha=0.7$)	0.015	0.147	0.028	0.017	0.161	0.031	0.014	0.142	0.025	0.014 (0.019*)	0.142 (0.188*)	0.025 (0.035*)
UK riots (K=10, $\delta=0.1$, $\alpha=0.2$)	0.022	0.195	0.039	0.022	0.203	0.040	0.015	0.139	0.027	0.023 (0.024)	0.211* (0.211*)	0.043* (0.043*)
US Open (K=40, $\delta=0.1$, $\alpha=0.5$)	0.025	0.221	0.045	0.021	0.182	0.038	0.025	0.198	0.044	0.032* (0.034*)	0.264* (0.278*)	0.056* (0.059*)

Data Mining and Analysis in Engineering Field. IGI
Global, Hershey, USA

Concluding remarks

- ▶ frequent itemsets
- ▶ semantic-based
- ▶ Social document analysis
- ▶ Effectiveness of the proposed approaches
- ▶ Future developments
 - Incremental Updated summaries
 - Extension to multi-lingual document collections

Thanks for the attention!

