

Getting Emotional About News Summarization

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Motivation

Introducing Emotion into Automatic Text Summarization

- Summarization of news has focused on facts
 - Other domains, such as blogs have worked on sentiment/emotion more
- The emotion of a story is also important to its meaning
- Make summaries more emotional, could make summaries:
 - More interesting to read and so score higher in readability
 - Contain more relevant information – Pyramid Score
- Will it work? – Interesting negative result



Automatic Text Summarization

Guided Summaries

- Text Analysis Conference (TAC)
 - Query-driven multi-document summarization
 - Guided Summarization – 5 categories of news
 - Each containing its own topic statement and a list of aspects
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- Accidents/Natural Disasters
 - e.g. *Plane Crash Indonesia*
 - Attacks
 - e.g. *Amish Shooting*
 - Health and Safety
 - e.g. *Internet Security*
 - Endangered Resources
 - e.g. *Tuna Fishing*
 - Investigations and Trials
 - e.g. *Michael Vick Dog Fight*

Automatic Text Summarization

Update Summaries

- Update Summarization – two data sets A and B
 - Summarize A normally – Summarize B to only contain information not found in A
- Tuning Data – TAC 2010
 - Human written “model summaries” – 4 per topic
 - Source documents to be summarized – 10 per topic
- Testing Data – TAC 2011
 - Source documents to be summarized – 10 per topic

	Tuning 2010	Testing 2011
Accidents	7	9
Attacks	7	9
Health	12	10
Resources	10	8
Trial	10	8
Total	46	44

Automatic Text Summarization

Evaluation

- Pyramid Evaluation
 - Human annotators find Summary Content Units (SCUs) in model summaries
 - Annotate automatically generated summaries with these SCUs
 - Rank based on SCU recall
 - We used a corpus of SCU annotated sentences to evaluate our sentence ranker
- Readability
 - Evaluates summaries for grammaticality, non-redundancy, referential clarity, focus, and structure/coherence
- ROUGE
 - Measures bigram overlap between model and automatic summaries
 - Two versions used ROUGE-2 and ROUGE-SU4
- Responsiveness
 - Overall summary quality

Emotional Corpus

- NRC Emotion Lexicon v0.5 [Mohammad and Turney(2012)]
- Emotion: 2283 words
 - Joy: 353
 - Sadness: 600
 - Fear: 749
 - Surprise: 275
 - Disgust: 540
 - Anger: 647
 - Trust: 641
 - Anticipation: 439
 - No emotion: 4808
- Sentiment: 2821 words
 - Positive: 1183
 - Negative: 1675
 - No sentiment: 4270



Measuring Relevant Emotions

- Are some emotions more common in summaries than source documents?
- Calculate *Emotional Density* (ED)

$$ED(E_i) = \frac{\text{count}(E_i)}{\text{count}(E_{1..N}) + \text{count}(\neg E)}$$

- ED can be calculated for each emotion E_i or no emotion $\neg E$
- ED can be calculated for model summaries and for source documents: $ED_M(E_i)$ and $ED_D(E_i)$
- For each news category calculate an emotional ratio: $\frac{ED_M(E_i)}{ED_D(E_i)}$

Discovering Significant Emotions: TAC 2010

	Emotional Ratio				
	Accidents	Attacks	Health	Resources	Trial
Joy	1.070	0.801	1.127	1.202	0.797
Sad	1.349	1.220	1.171	0.906	1.561
Fear	1.079	1.242	1.163	1.120	1.157
Surprise	1.036	0.996	0.973	0.622	1.372
Disgust	0.998	1.201	1.158	1.197	1.453
Anger	1.254	0.593	1.271	1.070	1.458
Trust	0.842	0.593	0.790	1.073	0.818
Anticipation	0.966	0.590	0.726	1.021	0.841
None	0.917	0.908	0.971	0.968	0.686
Positive	1.039	0.908	0.932	1.305	0.999
Negative	1.195	1.323	1.271	1.123	1.522
None	0.924	0.885	0.951	0.901	0.807

Discovering Significant Emotions: TAC 2010

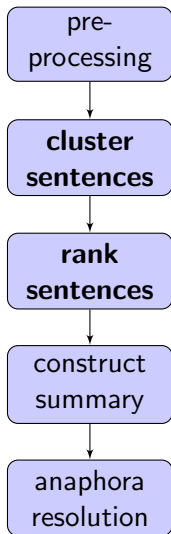
(Continued)

Maximize these emotions for each news category:

- Accidents: Sadness
- Attacks: Sadness, Fear & Anger
- Health: None, but strongly Negative
- Resources: None, but strongly Positive
- Trials: Sadness, Fear, Surprise, Disgust & Anger

Our System

Overview



- Two main components
 - Sentence Clustering: clusters related sentences
 - Sentence Ranker: ranks sentences based on their relatedness to the query
- Use Emotion to improve sentence ranking:
 - Baseline summarizer – no emotion
 - Emotionally Aware summarizer – use emotion words for query expansion

Our System

Clustering

- Objective: identify sub-topics in each collection of documents
- Representation: BOW vectors with stop-words removed, weighted by tf.idf
- Clustering algorithm: Affinity Propagation [Givoni and Frey(2009)]
 - Sentences are clustered into clusters of topics based on vocabulary
 - Each cluster has an exemplar - the most representative sentence
- Output: topical clusters.

Our System

Sentence Ranking



- *Roget's Thesaurus* based sentence ranking [Kennedy and Szpakowicz(2010)]
- For each word q in query Q , find the most related word w in a sentence S

$$\text{score}(S) = \sum_{q \in Q} \max(\text{SemDist}(w, q) : w \in S)$$

- *SemDist* gives a relatedness score from 0..18
- Create summaries out of the top ranked sentences selecting at most one per cluster.

Our System

The Query for Baseline and Emotional Summaries

- What belongs in the query?
- Baseline Summarizer
 - use topic statement as query
- Emotionally Aware Summarizer
 - use topic statement as query
 - use emotional words – given much lower weight than topic words
 - only use exact matches
 - i.e. $SemDist(w, q) > 0 \iff w = q$
- These parameters were discovered using the TAC 2010 data
 - include topic statement, but leave aspects out

Intermediate Results Ranking Sentences

- Evaluate Sentence Ranking component on tuning (TAC 2010) data
- Macro-average precision (MAP)

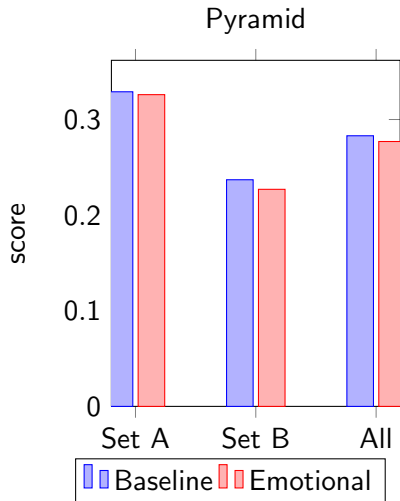
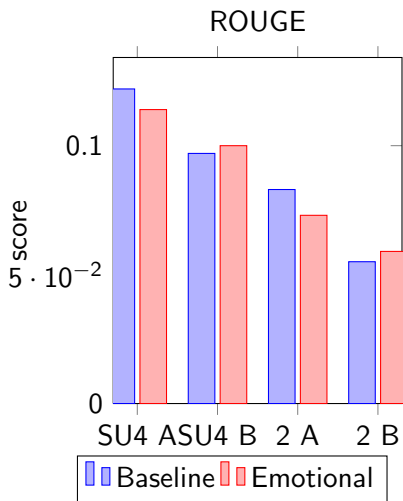
Category	Baseline	Emotion	p -value
Accidents	0.603	0.637	0.008
Attacks	0.519	0.552	0.087
Health	0.422	0.476	0.014
Resources	0.479	0.485	0.562
Trial	0.559	0.591	0.065
All	0.506	0.539	0.000

Evaluation on TAC 2011 data

Emotional Ratio

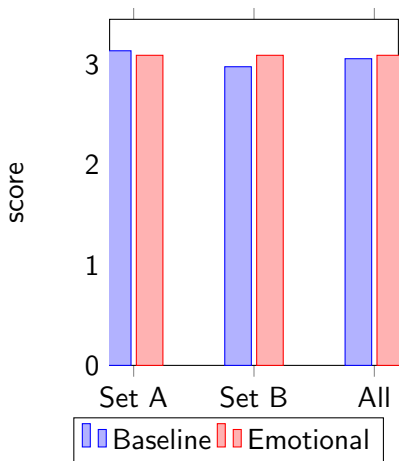
	Emotional Ratio $\frac{emotionCount(emotionalSummaries)}{emotionCount(baselineSummaries)}$				
	Accidents	Attacks	Health	Resources	Trial
Joy	1.000	1.667	0.913	2.833	1.00
Sad	3.847	1.900	1.920	0.923	2.296
Fear	2.167	2.182	2.038	0.857	1.596
Surprise	2.364	1.125	1.000	1.400	2.727
Disgust	3.125	2.500	2.154	1.200	2.368
Anger	2.200	1.921	2.059	0.923	1.837
Trust	1.278	1.190	0.895	2.136	0.581
Anticipation	0.905	1.417	1.047	2.500	1.500
None	0.953	0.888	1.072	1.094	0.911
Positive	1.143	1.286	0.949	2.310	1.00
Negative	2.267	1.878	2.244	1.077	1.816
None	0.923	0.932	0.950	1.012	0.931

Results

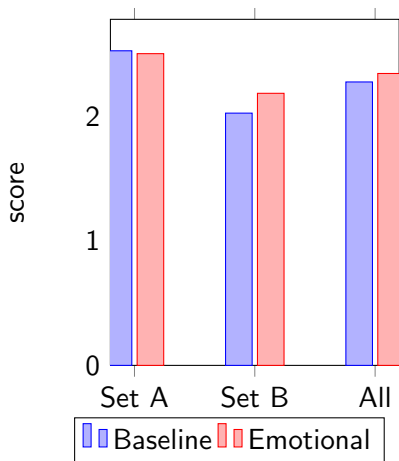


Results

Readability



Responsiveness



Associated Emotions: 2010 vs 2011

Category	Emotions – 2010	Emotions – 2011
Accidents	Sadness	None
Attacks	Sadness , Fear & Anger	Fear & Anger
Health	None – strongly Negative	None – strongly Negative
Resources	None – strongly Positive	None – strongly Negative
Trials	Sadness, Fear, Surprise , Disgust & Anger	Sadness, Fear & Anger

Conclusion

- What worked
 - Created summaries with more emotional words
 - Some improvement for sentence ranking on the tuning data
 - Did not hurt TAC evaluation
- What did not work
 - No meaningful improvement on TAC evaluation
 - Some emotions from tuning data were not correct for the testing data
- Are ROUGE, Pyramids, etc really the right evaluation for such work?
 - Evaluate for emotional content instead?
 - Is this the right way to be using emotion?
- Future directions for research
 - Summarizing reviews, short stories, etc. instead of news
 - Make non-emotional summaries – would still need emotional awareness

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