To leverage the sentiment which traditional approaches may not catch

Motivation

<table>
<thead>
<tr>
<th>What we want</th>
<th>vs.</th>
<th>What we don’t want</th>
</tr>
</thead>
<tbody>
<tr>
<td>I missed my flight, that's great</td>
<td>Encouragement, Happiness</td>
<td></td>
</tr>
<tr>
<td>Anger, Embarrassment, Sadness</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Power, Pride, Happiness, Achievement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I finished my exam, I killed it</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Gun, Evil, Fear, Death</td>
<td></td>
</tr>
<tr>
<td>I broke up with my girlfriend, how awesome is it?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Insecurity, Sadness</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Pride, Happiness, Peace</td>
<td></td>
</tr>
</tbody>
</table>
Pipeline

Data
- Queries
- Documents

Feature Extraction
- Extracting Emotion Features
- Basic Features, i.e. TF*IDF

Learning to Rank
- RankLib (MART, LambdaMart)

Evaluation
- NDCG@10, P@10
Datasets

- **Emoji-labeled tweets**
  - 1.2 billion tweets (English, Text + Emoji)

- **Microblog TREC 2011**
  - 10 millions tweets
  - 50 queries
  - Each query has 1000 tweets with corresponding relevance score
Data Preprocessing

- Stop words, punctuation, numbers, urls removal
- Non-English character and word removal
- Stemming
Emotion Extraction

• For each tweet in the document set:
  ○ Predict the probability of each emotion
  ○ Total of 64 emotion classes

• Do the same for each tweet in the query set

• We get two vectors of 64 emotion class probabilities

* Emotion extraction paper [felbo2017]
Features used for LTR (MART, LambdaMART)

- **Baseline**
  - Cosine similarity between query and doc
  - Retweet counts
  - Favorited or not

- **Our Feature Vector**
  - Features from baseline
  - Emotion from query (64 classes)
  - Emotion from tweet/doc (64 classes)
<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Baseline + Emoji</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MART</td>
<td>LambdaM ART</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDCG@10</td>
<td>0.4049</td>
<td>0.3779</td>
</tr>
<tr>
<td>P@10</td>
<td>0.149</td>
<td>0.1367</td>
</tr>
</tbody>
</table>
## Improvement

<table>
<thead>
<tr>
<th></th>
<th>MART</th>
<th>Lambda MART</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDCG</td>
<td>6.05%</td>
<td>25.35%</td>
</tr>
<tr>
<td>MAP</td>
<td>9.59%</td>
<td>28.38%</td>
</tr>
</tbody>
</table>
Potential Improvements

- More evaluation data from TREC 2013
- 60 additional queries
- More documents
Conclusion

➢ Extracted emotion features from Microblog TREC dataset
➢ Fed it into the pipeline
➢ Got improvements over the baseline

Thank you!
Challenges

- Evaluation Dataset
- Are Emotions Effective for other datasets?