Automatically Determining Review Helpfulness

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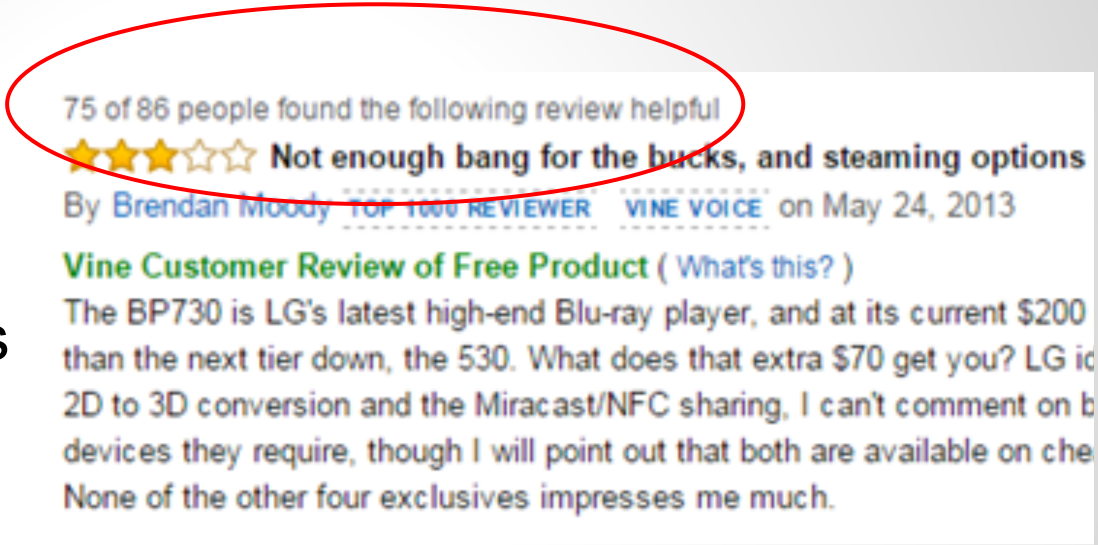
Motivation

- ➢ Too many reviews
- ➢ Automatically find the helpful reviews



Goal

- ➢ Determining the “features” of reviews
- ➢ Learning algorithm for prediction

Research Question

- ➢ What are the features of reviews that are indicative of their helpfulness?

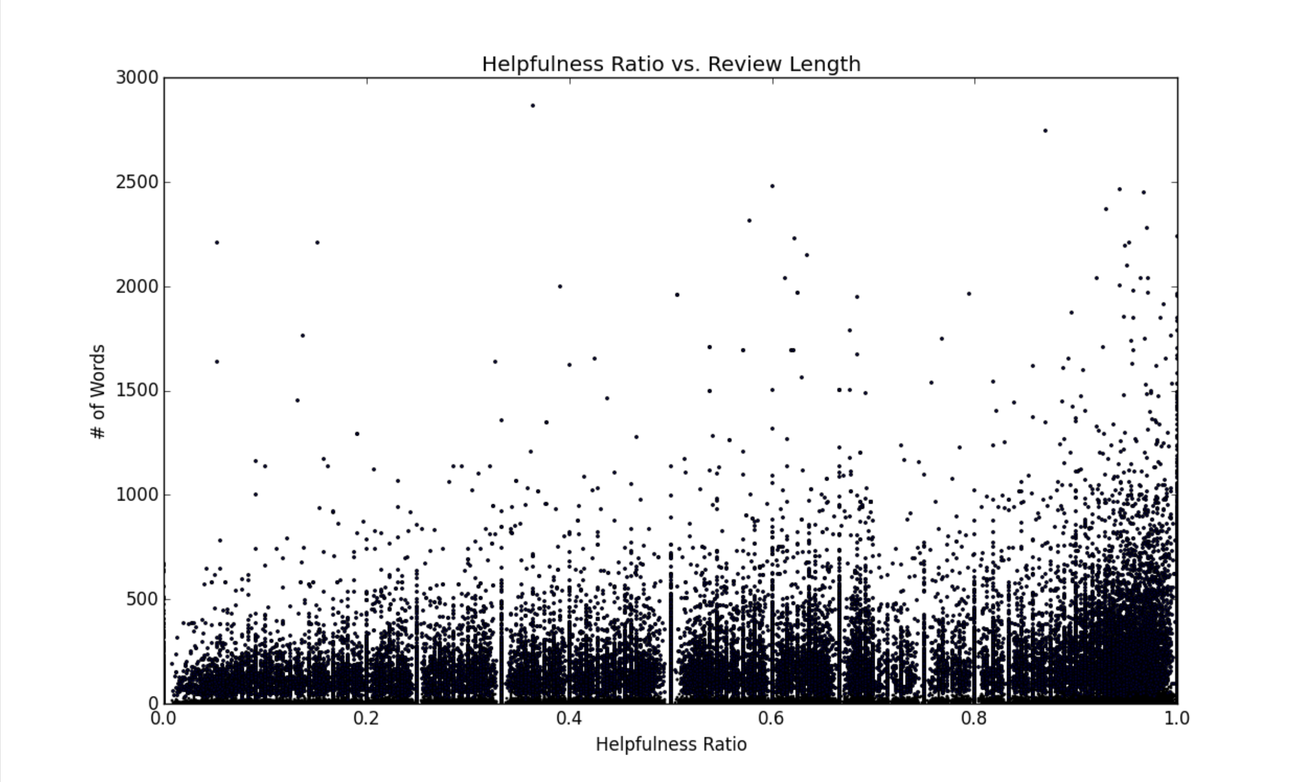
Dataset

- Helpfulness Ratio = $\dfrac{\text{\# of votes found helpful}}{\text{\# of total votes}}$

- Reviews tested for Pearson's r
  - Have at least 10 total votes **and** at least 5 sentences

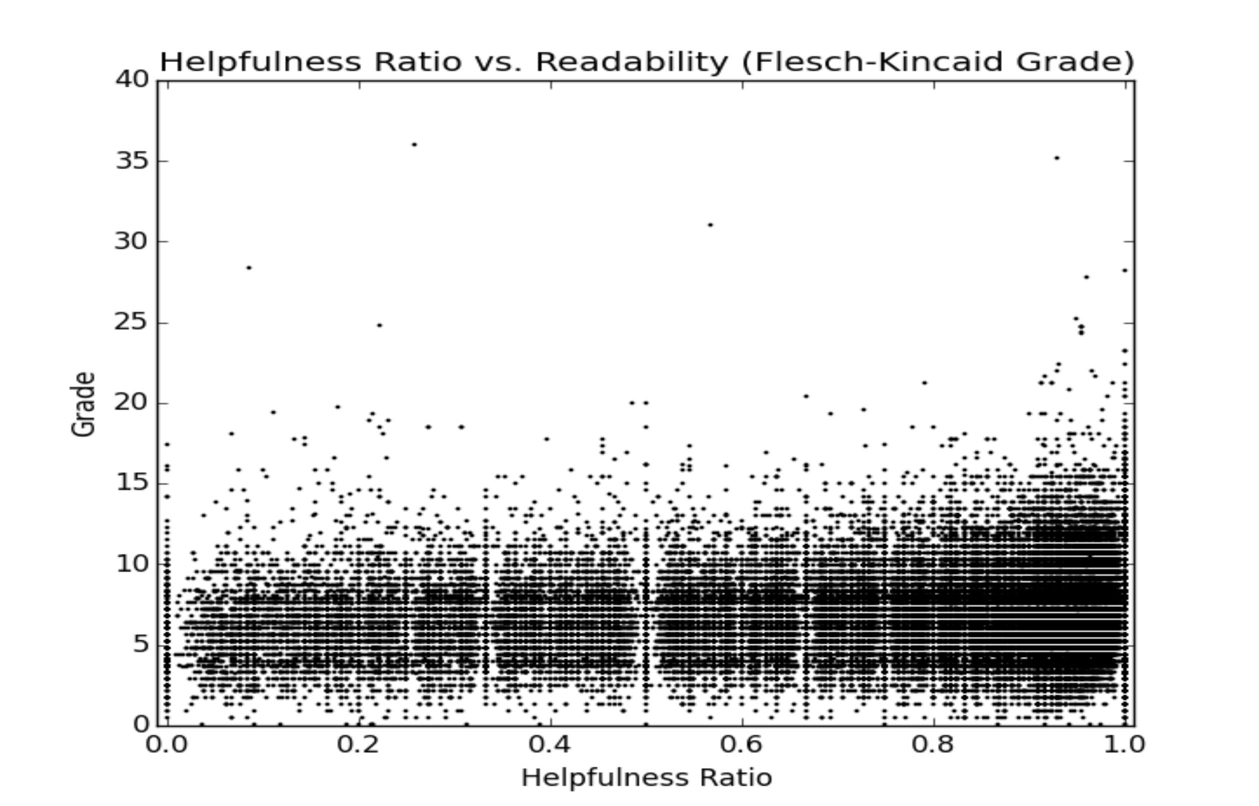
Total # of Reviews	**1241778**
# of Reviews, ≥ 10 Votes	**167604**
# of Reviews, ≥ 10 Votes and ≥ 5 sentences	**116680**
Average Helpfulness Ratio	**0.78**
Average Length of Review	**108 words**

Feature: length of review (# of words)



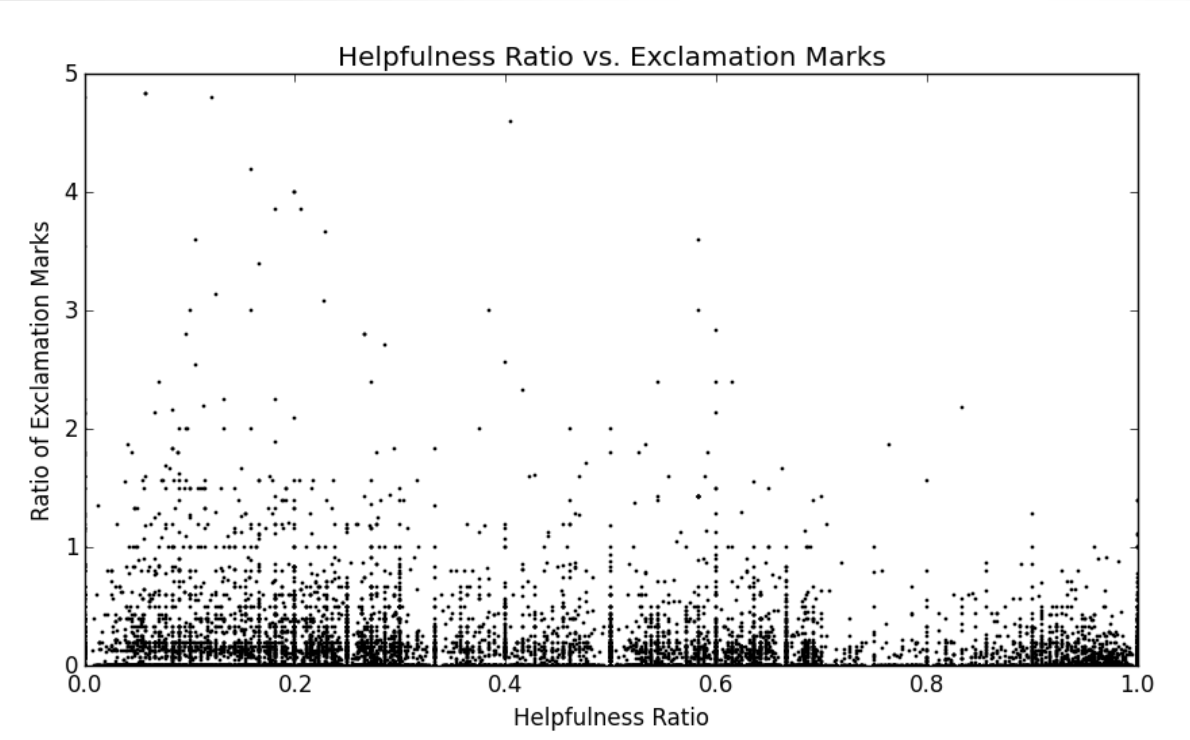
r = 0.26

Feature: Flesch-Kincaid Grade Level Test



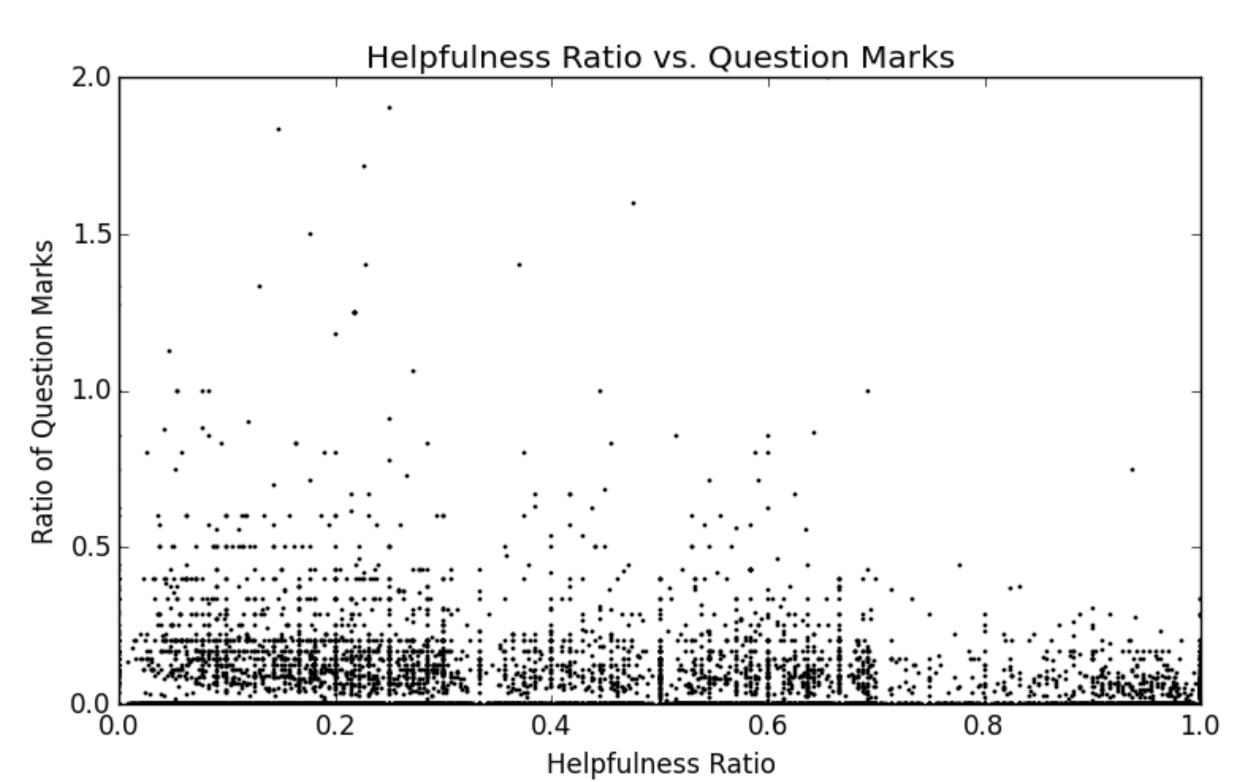
r = 0.17

Feature: punctuation, exclamation mark



r = -0.21

Feature: punctuation, question mark



r = -0.32

Other Features

Sentiment Polarity ● less helpful reviews use emotionally charged language	$r = -0.15$
Number of Sentences ● helpful reviews are longer	$r = 0.26$
Average Sentence Length ● sentence length has little correlation to helpfulness	$r = 0.07$
Grammatical part-of-speech Categories ● noun, verb, adjective use has little correlation to helpfulness	$r \approx \pm 0.05$

Results

- ➢ Prediction model
- ➢ Random baseline accuracy: 33.3%
- ➢ Decision tree: 42.9%

Decision Tree Confusion Matrix				
		Predicted		
		Poor	Neutral	Good
Actual	Poor	308	146	133
	Neutral	217	201	169
	Good	192	187	208

Current Work

- ➢ Subsets of features
- ➢ Different # of classifications
- ➢ Different learning algorithms

Future Work

- More possible features can be explored
  - Lexical information
  - Information beyond review text

Conclusion

- ➢ Desire to collect helpful reviews
- ➢ Finding useful features
- ➢ Using features for helpfulness prediction