A Piece of My Mind: A Sentiment Analysis Approach for Online Dispute Detection

Lu Wang and Claire Cardie Department of Computer Science Cornell University



Cornell University

Introduction





- According to Wikipedia, there are more than 4.5M articles in English Wikipedia alone.
- About 21.6M users.
- About 130K registered editors.

A Disputed Discussion

Emy: I think everyone is forgetting that my previous image was the lead image for well over a year! ... *Massimo is the one who began the "edit war"*...

Massimo: I'm not going to start a debate about who started the fight, since it is childish and pointless... As for your new image... I'm sorry to say so, but it is grossly over processed...

Emy: Yes, your camera has slightly higher resolution than mine. <u>I'm glad you</u> paid more money for a camera than I did. Congrats. I appreciate your constructive criticism. Thank you.

Massimo: First of all, I want to make clear that this is not personal. I just want to have the best picture as a lead for the article.

Emy: <u>Wow, I am really enjoying this photography debate. It is seriously making</u> <u>my work day so much more enjoyable!</u>... don't make assumptions you know nothing about. <u>Really, grow up.</u>... <u>Sound good?</u>

Massimo: *I do feel it is a pity, that you turned out to be a sore loser.*

The Problem: Online Dispute Detection



"Sometimes I think the collaborative process would work better without you."

[Credit: https://www.cartoonbank.com]

The Problem: Online Dispute Detection

Facilitate collaboration



[Credit: http://wondermark.com]

- Identify controversial topics
- Analyze user relations
- Predict stance

Our Objectives

Detecting the online disputes automatically

- Predicting disputes on a newly constructed dataset of scale.
- Understanding whether linguistic features, e.g. sentiment flow, are importance for dispute detection.

Previous Work

- Analyzed dispute-laden content to discover features correlated with conflicts and disputes
 - Kittur et al. (2007): edit history
 - Billings and Watts (2010): dispute resolution
 - Yasseri et al. (2012): temporal characteristics
 - Kraut and Resnick (2012): design of successful online communities
- However, they all rely on small number of manually selected discussions known to involve disputes.

Roadmap

- A dispute corpus constructed from Wikipedia
- Online dispute detection
 - Sentence-level sentiment prediction
 - Dispute detection
- Conclusion

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A Dispute Corpus Constructed from Wikipedia

The Pixar universe

From Wikipedia, the free encyclopedia



This article's factual accuracy is disputed. Please help to ensure that disp

A Dispute Corpus Constructed from Wikipedia

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- Disputed
- TotallyDisputed
- DisputedSection
- TotallyDisputedSection
- POV
- 2013-03-04 Wikipedia data dump
- Result in 19,071 talk pages

A Dispute Corpus Constructed from Wikipedia

Step 1: Get Talk Pages of Disputed Articles

Step 2: Get Discussions with Disputes.

3609 discussions are collected

Step 3: Get Discussions without Disputes.

- 3609 non-dispute discussions are randomly selected.
- We consider non-dispute discussions with at least 3 distinct speakers and 10 turns.
- The average turn numbers for dispute and non-dispute discussions are 45.03 and 22.95, respectively

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Sentence-Level Sentiment Prediction

- Input: sentences $x = \{x \not\mid 1, \dots, x \not\mid n\}$ from a single turn
- Output: sequence of sentiment labels $y = \{y \nmid 1, ..., y \nmid n\}$, where $y \nmid i \in \{NN, N, O, P, PP\}$
- NN: very negative
- N: negative
- O: neutral
- P: positive
- PP: very positive

• Partial order: $NN \le N \le O \le P \le PP$

Sentence-Level Sentiment Prediction

- Isotonic Conditional Random Fields (CRF)
 - Mao and Lebanon (2007) proposed isotonic CRF to predict sentiment in movie reviews.
 - Encode domain knowledge through isotonic constraints on model parameters.

Isotonic CRF

- $\begin{array}{l}pyx = 1/Z(x) \exp\left(\sum i \uparrow f f \sigma, \tau \uparrow f \lambda \downarrow < \sigma, \tau > f \downarrow < \sigma, \tau > (y \downarrow i 1, y \downarrow i)\right) \\ +\sum i \uparrow f f \sigma, w \uparrow f \mu \downarrow < \sigma, w > g \downarrow < \sigma, w > (y \downarrow i 1, x \downarrow i)\end{array}$
- $f \downarrow < \sigma, \tau >$, $g \downarrow < \sigma, w >$ are feature functions, $\lambda \downarrow < \sigma, \tau >$, $\mu \downarrow < \sigma, w >$ are the parameters when $y \downarrow i - 1$, $y \downarrow i$, $x \downarrow i$ take values of λ , τ , w.
- Lexicon $M = M \downarrow p \cup M \downarrow n$, where $M \downarrow p$ (or $M \downarrow n$) contain features associated with positive (or negative) sentiments.
- Monotonicity constraints:
 - $\sigma \leq \sigma \uparrow' \Rightarrow \mu \downarrow < \sigma, w > \leq \mu \downarrow < \sigma', w > , w \in M \downarrow p$
 - $\sigma \geq \sigma \uparrow' \Rightarrow \mu \downarrow < \sigma, w > \leq \mu \downarrow < \sigma', w > , w \in M \downarrow n$

Isotonic CRF

 $\begin{array}{l}pyx = 1/Z(x) \exp\left(\sum i \widehat{l} \sum \sigma, \tau \widehat{l} \right) \\ y \downarrow i \right) + \sum i \widehat{l} \sum \sigma, w \widehat{l} = \mu \downarrow < \sigma, w > g \downarrow < \sigma, w > (y \downarrow i - 1, x \downarrow i) \end{array}$

"totally agree" is observed in the training data

• $\mu \downarrow < PP$, totally agree> $\geq \mu \downarrow < NN$, totally agree>

 We collect a lexicon compiled from MPQA (Wilson et al., 2005), General Inquirer (Stone et al., 1966), and SentiWordNet (Esuli and Sebastiani, 2006).

Training A Sentiment Classifier

- Authority and Alignment in Wikipedia Discussions (AAWD) corpus (Bender et al., 2011)
- 221 English Wikipedia discussions with positive and negative alignment annotations.

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Online Dispute Detection

Sentiment features

- Sentiment distribution
 - *P*(*S*), where *S*∈{*NN*, *N*,*O*,*P*,*PP*}
- Sentiment transition distribution
 - $P(S \downarrow t \rightarrow S \downarrow t+1)$, where $S \downarrow t$, $S \downarrow t+1 \in \{NN, N, O, P, PP\}$

Two versions

- Global version: estimated from whole discussion
- Local version: segment a discussion into three stages equally
 - For future work, we can leverage other topic segmentation techniques.

Online Dispute Detection

- Lexical Features
 - Unigram, bigram
- Topic Features
 - Category information
- Discussion Features
 - Number of turns
 - Number of participants
 - Average number of words in each turn

Experimental Setup

- Logistic regression
- Linear SVM
- RBF kernel SVM
- 5-fold cross-validation

Results

	Precision	Recall	F1	Accuracy
Baseline (Random)	50.0	50.0	50.0	50.0
Baseline (All dispute)	50.0	100.0	66.7	50.0
Logistic Regression	74.8	72.3	73.5	73.9
SVM + Linear	69.8	71.9	70.8	70.4
SVM + RBF	77.4	79.1	78.3	80.0

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 \square

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Feature Analysis

	Precision	Recall	F1	Accuracy
Lexical	75.86	34.66	47.58	61.82
Торіс	68.44	71.46	69.92	69.26
Discussion	69.73	76.14	72.79	71.54
Sentiment (Senti _{g+/})	72.54	69.52	71.00	71.60

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Topic + Discussion	68.49	71.79	70.10	69.38
Topic + Discussion + Senti _g	77.39	78.36	77.87	77.74
Topic + Discussion + Senti _{g+/}	77.38	79.14	78.25	80.00
Lexical + Topic + Discussion + Senti $_{g+l}$	78.38	75.12	76.71	77.20

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Discussions

- Dialog structure varies.
 - The recall for resolved dispute discussions is 0.86; and it is 0.78 for unresolved ones.

- The sentiment classifier has limitations.
 - *"I told you over and over again..."*: neutral or negative?
 - "Wow, I am really enjoying this photography debate!": sarcasm is hard to detect.

Conclusion

- We present a sentiment analysis-based approach to online dispute detection.
- We create a dispute corpus from Wikipedia Talk pages to study the problem.
- Experiments demonstrate that classifiers trained with sentiment tagging features outperform others that do not.

Thank you!

Features for Sentence-Level Sentiment Prediction

- Lexical Features: unigrams/bigrams, number of words all uppercased, number of words
- Discourse Features: initial ngrams, repeated punctuations, number of negators
- Conversation Features: quote overlap with target, TFIDF similarity with target
- Sentiment Features: sentiment words

Evaluation on Sentiment Prediction

	Positive	Negative	Neutral
Baseline (Polarity)	22.53	38.61	66.45
Baseline (Distance)	33.75	55.79	88.97
SVM (3-way)	44.62	52.56	80.84
CRF (3-way)	56.28	56.37	89.41
CRF (5-way)	58.39	56.30	90.10
isotonic CRF	68.18	62.53	88.87