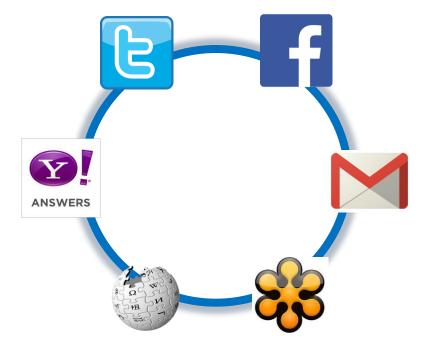
Improving Agreement and Disagreement Identification in Online Discussions with A Socially-Tuned Sentiment Lexicon

Lu Wang and Claire Cardie Department of Computer Science Cornell University



Cornell University

Introduction



Discussion Forums

Image: state state

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IamA Teenager living in Syria, War is outside my window AMA! (No politics) (self.IAmA) submitted 3 months ago by RTheodory 🔞

My short bio:

Yes. I live in Aleppo Syria, and i'm a student. During the three years of war, we have lost so much and learned a lot and even had some amazing experiences. I've got a lot of stories to tell ! So Ask me anything about our past and recent life, about our experiences and culture. (I Prefer not to answer Political Questions because we have suffered enough from It !)

My Proof:

Feel free to browse through my Instagram Pictures:

Http://Instagram.com/RTheodory

Or tweet me on:

Http://Twitter.com/TheodoryFollow

NSFW 2254 comments share

top 200 comments show 500

sorted by: best **v**

- [-] MagikMitch 362 points 3 months ago
- How hard is it to find food? Are there regular restaurants and things still open?

permalink

- [-] RTheodory [S] 510 points 3 months ago
- Last year, we got circled by terrorists that stopped every food truck from entering our town, we didn't see fresh vegetables or fruits for a whole month, but now, we 've got everything. restaurants outside of town got closed, but those who are in the safe areas are still open !

permalink parent

- ▲ [-] MagikMitch 190 points 3 months ago
- Thanks for the answer! Since we're on the subject, what's your favorite food?

permalink parent

- ▲ [-] RTheodory [S] 454 points 3 months ago
- Hmm, Syrian food is wonderful, You might not know this, but we have different versions of the foods you eat, We have our own style of burgers, macaronie, pizza, cheese, and chicken. If you try to eat these in syria, they would

Discussion Forums

Image: Second state
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Debate Forums

Should students be able to listen to music in class? Music help them focusing on their works and ignoring all the noise around them like people talking, laughing, object stuff noise. They hear nothing but music. i love music and it help me focus alot Yes No Side Score: 609 Side Score: 423 SeekSeven (30) 36 points 🚺 🎧 mego63(23) 34 points 🚺 🎧 Many people may argue yes, because they find their classes to be dull, and want an alternative to the Recent studies proved that people produce effectively and happily when they listen to music. I myself like droning noise of their teachers voice. I don't take such a cynical stance of class, but actually believe that this idea. However, the case of getting students to listen to music IN THE CLASSROOM is completely listening to music can help certain individuals to concentrate and work more efficiently - for example, when irrelevant. Students should be busy all the time listening to the teacher, listening to each other or even revising, I find low volume music can help me to work faster and, actually, better. Whenever a teacher speaking to each other. Therefore, it is illogical to allow students listen to music DURING CLASSES. allows music in class, I work much better than without it - people are going to concentrate more on their 43 days ago | Side: No work than speaking to classmates, and get more work done. Support | Dispute | Clarify Of course, I cannot argue that students be allowed to just come into a lesson and start listening to music immediately - first, the teacher must be allowed to do their job (teach the lessons content), and set tasks † Hide Replies - but proceeding this, I see no possible harm that can be caused. As soon as a task has been set, students, in my opinion, should be allowed to listen to music (at a suitable noise level, of course). 20 points 🚺 🎧 Opai (63) 43 days ago | Side: Yes sir., if the students was very bored ... what is the problem if they refresh their mind ? Support | Dispute | Clarify 25 days ago | Side: No † Hide Replies Support | Dispute | Clarify 8 points 🚺 🎧 Opai (63) 19 points 🕛 🎧 Mopai (63) Disputed Thank you .. and i hope that the music be able in the school :)

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The Problem

 Agreement and disagreement identification in online discussions

Zer0faults: I just hope we can remove the assertions that WMDs were in fact the sole reason for the US invasion ...

Mr. Tibbs: No. Just because things didn't turn out the way theBush administration wanted doesn't give you license to rewrite history.

MONGO: Regardless, the article is an antiwar propaganda tool.

Mr. Tibbs: So what? That wasn't the casus belli and trying to give that impression After the Fact is Untrue.

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Our Contributions

- We propose an sentence-/segment-level agreement and disagreement identification model based on isotonic Conditional Random Fields.
- We learn a new lexicon from Wikipedia Talk pages using label propagation algorithm.
- We show that the learned lexicon significantly improves performance over systems that use existing generalpurpose lexicons

The Problem

- Agreement and disagreement identification in online discussions
- Given a target turn, we aim to determine whether the current sentence is an agreement or a disagreement to the target.

- Public opinion mining
 - Popular topic detection
- Stance prediction
 - Subgroup detection
 - User relation analysis
- Discourse analysis
 - Debate strategy

Related Work

- Sentiment Analysis
 - Online debate (Yin et al., 2012)
 - Discussion forums (Hassan et al., 2010)
- Agreement and disagreement Identification
 - Conditional Markov models in Spoken meetings (Galley et al., 2004)
 - CRF in broadcast conversations (Wang et al., 2011)
 - Online debate (Abbott et al., 2011; Misra and Walker, 2013)

Related Work

- Agreement and disagreement used as features:
 - Stance prediction (Thomas et al., 2006; Somasundaran and Wiebe, 2009; Walker et al., 2012b)
 - Subgroup detection (Hassan et al., 2012; Abu-Jbara et al., 2012).

Roadmap

- The Model
 - Sentence-/Segment-Level Sentiment Prediction
 - Online Discussion Sentiment Lexicon Construction
 - Feature Set
- Experiments
- Conclusion

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Sentence-/Segment-Level Sentiment Prediction

- Input: sentences $x = \{x_1, ..., x_n\}$ from a single turn
- Output: sequence of sentiment labels $y = \{y_1, ..., y_n\}$, where $y_i \in \{NN, N, O, P, PP\}$
- NN: very negative
- N: negative
- O: neutral
- P: positive
- PP: very positive
- Partial order: $NN \le N \le 0 \le P \le PP$
- NN, N -> disagreement
- PP, P -> agreement

Sentence-/Segment-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

$$p(y|x) = \frac{1}{Z(x)} \exp\left(\sum_{i} \sum_{\sigma,\tau} \lambda_{<\sigma,\tau>} f_{<\sigma,\tau>}(y_{i-1}, y_i) + \sum_{i} \sum_{\sigma,w} \mu_{<\sigma,w>} g_{<\sigma,w>}(y_{i-1}, x_i)\right)$$

- $f_{<\sigma,\tau>}$, $g_{<\sigma,w>}$ are feature functions, $\lambda_{<\sigma,\tau>}$, $\mu_{<\sigma,w>}$ are the parameters when y_{i-1}, y_i, x_i take values of λ, τ, w .
- Lexicon $M = M_p \cup M_n$, where M_p (or M_n) contain features associated with positive (or negative) sentiments.

Isotonic CRF

$$p(y|x) = \frac{1}{Z(x)} \exp\left(\sum_{i} \sum_{\sigma,\tau} \lambda_{<\sigma,\tau>} f_{<\sigma,\tau>}(y_{i-1}, y_i) + \sum_{i} \sum_{\sigma,w} \mu_{<\sigma,w>} g_{<\sigma,w>}(y_{i-1}, x_i)\right)$$

• "totally agree" is observed in the training data

• $\mu_{<PP,totally agree>} \ge \mu_{<NN,totally agree>}$

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Online Discussion Sentiment Lexicon Construction

- Why we want to build a socially-tuned lexicon?
 - "So what?"
 - "told you!"
 - "Whatever!"
 - ...

Online Discussion Sentiment Lexicon Construction

- Label propagation (Zhu and Ghahramani, 2002) algorithm is a semi-supervised learning method.
- Input: a set of seed samples (e.g. sentiment words in this work), similarity between pairwise samples
- Output: label for each sample.
- **Data**: English Wikipedia (4.4M talk pages)

Graph Construction

- Node Set V
 - Unigrams
 - E.g. royalty, sunlight
 - Bigrams
 - E.g. in contrast, by facts
 - Dependency relations
 - E.g. Rel (informative, less)
 - Sentiment dependency relations
 - E.g. Rel (SentiWord_{NEG}, your) (from Rel (crap, your))
- We replace all relation names with a general label.
- Text units that appear in at least 10 discussions are retained

Graph Construction

Edge Set E

- We aim to construct a sparsely connected graph.
- **Step 1**: Each text unit is represented by the top 50 co-occurring text units computed by Pointwise Mutual Information.
 - "Co-occur" is defined as appearance in the same sentence.
- Step 2: An edge is created between two text units only if they ever co-occur.
- **Step 3**: The similarity between two text units is calculated as the Cosine similarity between them.

Graph Construction

Seed words

- General Inquirer (Stone et al., 1966)
- MPQA (Wilson et al., 2005)
- SentiWordNet (Esuli and Sebastiani, 2006)

Sample Terms in New Lexicon

Positive

nod, from experiences, anti-war, profits, royalty, sunlight, conclusively, badges, prophecies, in vivo, tesla, pioneer, published material, from god, lend itself, geek, intuition, morning, endorsements, testable, source carefully

Negative

: (, TOT, in contrast, ought to, whatever, Rel(nothing, you), anyway, by facts, disproven, opt for, subdue to, disinformation, tornado, heroin, Rel(newbies, the), Rel (intentional, is), watergate, perjury, Rel(lock, article), contrast with, censoring information, Rel(informative, less), clowns, Rel(feeling, mixed), never-ending

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Features

Lexical features

Unigram, bigram, has any uppercased words

Syntactic/Semantic features

- Dependency relations, generalized dependency relations
- E.g. nsubj(wrong, you), nsubj(ADJ, you), nsubj(wrong, PRP)

Discourse features

Initial unigram/bigram/trigram, hedge words

Conversation features

Number of words in quote, TFIDF similarity with target

Sentiment features

- Sentiment words, sentiment dependency relations
- E.g. "nsubj(wrong, you)" becomes "nsubj(SentiWordneg, you)"

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Datasets

Wikipedia Talk pages

- Authority and Alignment in Wikipedia Discussions (AAWD) (Bender et al., 2011)
- 221 English Wikipedia discussions with agreement and disagreement annotations on sentence-level or turn-level.
- For utterances that are annotated as agreement by at least two annotators → "strongly agree" (PP)
- Utterance is only selected as agreement by one annotator or it gets the label by turn-level annotation → "agree" (P)
- Similarly for "strongly disagree" (NN) and "disagree" (N)
- All others are "neutral" (O).

Datasets

Online debates

- Internet Argument Corpus (IAC) (Walker et al., 2012), collected from 4forums.com.
- Each discussion in IAC consists of multiple posts, where we treat each post as a turn.
- Most posts (72.3%) contain quoted content from target post, which naturally break the post into multiple segments.
- Each segment is annotated for agreement level in [-5, 5]. We thus divide it into equal intervals, and map it onto our 5-point scale labels.

Comparisons

- Baselines:
 - **Baseline (Polarity)**: an utterance or segment is predicted as agreement if it contains more positive words than negative words; otherwise, it is disagreement.
 - **Baseline (Distance)**: is extended from (Hassan et al., 2010).
 - Each sentiment word is associated with the closest second person pronoun, and a surface distance can be computed between them.
 - SVM is trained with the features of sentiment words, minimum/maximum/average of the distances.

Comparisons

- Support Vector Machines (SVMs) with RBF kernel
 - Sentiment prediction (Hassan et al., 2010), and (dis)agreement detection (Yin et al., 2012) in online debates.
- Linear Conditional Random Fields (CRFs)
 - (dis)agreement identification in broadcast conversations (Wang et al., 2011).

Results on Wikipedia Talk Page

	Agreement	Disagreement	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

Results on Wikipedia Talk Page

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Isotonic CRF	68.18	62.53	88.87

Results on Online Debates

	Agreement	Disagreement	Neutral
Baseline (Polarity)	3.33	5.96	65.61
Baseline (Distance)	1.65	5.07	85.41
SVM (3-way)	25.62	69.10	31.47
CRF (3-way)	29.46	74.81	31.93
CRF (5-way)	24.54	69.31	39.60
Isotonic CRF	53.40	76.77	44.10

Results on Online Debates

	Agreement	Disagreement	Neutral
Baseline (Polarity)	3.33	5.96	65.61
Baseline (Distance)	1.65	5.07	85.41
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CRF (5-way)	24.54	69.31	39.60
Isotonic CRF	53.40	76.77	44.10

New Lexicon on Online Debates

	Agreement	Disagreement	Neutral
SVM (3-way)	25.62	69.10	31.47
+ new lexicon features	28.35	72.58	34.53
CRF (5-way)	24.54	69.31	39.60
+ new lexicon features	28.85	71.81	39.14
Isotonic CRF	53.40	76.77	44.10
+ new lexicon	61.49	77.80	51.43

New Lexicon on Online Debates

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SVM (3-way)	25.62	69.10	31.47
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Isotonic CRF	53.40	76.77	44.10
+ new lexicon	61.49	77.80	51.43

Feature Analysis

Wikipedia Talk page

<u>Positive</u>: agree, nsubj (right, you), thanks, amod (idea, good), nsubj(glad, I), good point, concur, happy with, advmod (good, pretty)

<u>Negative</u>: you, your, numberOfNegator, don't, nsubj (disagree, I), actually as SentInitial, please stop as SentInitial, what? as SentInitial, should

Online Debate

<u>Positive</u>: amod (conclusion, logical), Rel (agree, on), Rel (have, justified), Rel (work, out), one might as SentInitial, to confirm, women

Negative: their kind, the male, the female, the scientist, according to, is stated, poss (understanding, my), hell as SentInitial, whatever as SentInitial

Discussions

- Disagreement as contradictory example.
 - deeper understanding of the semantic information embedded in the text.
- Sarcasm is hard to detect.
 - "Bravo, my friends! Bravo! Goebbles would be proud of your abilities to whitewash information."

Conclusion

- We present an agreement and disagreement detection model based on isotonic CRFs that outputs labels at the sentence- or segment-level.
- We bootstrap the construction of a sentiment lexicon for online discussions.
- We encode the lexicon in the form of domain knowledge for the isotonic CRF learner, and outperform other compared approaches.

Thank you!