Analyzing Debaters’ Persuasion Strategies on Change My View (CMV)

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Overview

- Background and Motivation
- Approach
    - Dataset Preparation
    - Analysis of Debaters on CMV
    - Predicting Debaters’ Effectiveness in Persuasion
- Conclusion and Future Work

Background and Motivation

Persuasion

- An attempt to influence someone’s beliefs, attitudes, intentions, motivations, or behaviors
- Omnipresent in our society

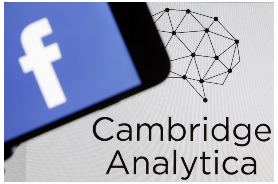
Psychology

History

Politics

Marketing

- A deeper understanding of persuasion could help:
  - Assess its impact on society
  - Detect and mitigate its unethical uses



Change My View(CMV)

- Discussion forum with > 1.2 million users
- Intended to expose people to contrasting views
- *A place to post an opinion you accept may be flawed, in an effort to understand other perspectives on the issue. Enter with a mindset for conversation, not debate.*
- Examples:

CMV: Congress needs term limits and age limits.

CMV: Politicians should make the minimum wage of the state they live in.

CMV: Car headlights are becoming too bright

How CMV works

Original Post (OP)

CMV: Every fine should be income based, without any exceptions

How CMV works

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CMV: Every fine should be income based, without any exceptions

Debater #1's reply

This would not really work because most of the liquid income for the millionaires are pretty small.

How CMV works

Original Post (OP)

CMV: Every fine should be income based, without any exceptions

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OP's reply

Target their capital gains then.

How CMV works

Original Post (OP)
CMV: Every fine should be income based, without any exceptions

Debater #2's reply
Linking fines to wealth makes plenty of sense until you realize that you're then directly linking a crime's punishment to something that has nothing to do with the crime itself.

Debater #1's reply
This would not really work because most of the liquid income for the millionaires are pretty small.

OP's reply
Target their capital gains then.

How CMV works

Original Post (OP)
CMV: Every fine should be income based, without any exceptions

Debater #2's reply
Linking fines to wealth makes plenty of sense until you realize that you're then directly linking a crime's punishment to something that has nothing to do with the crime itself.

OP's reply
That's a perfectly valid point! Δ

Debater #1's reply
This would not really work because most of the liquid income for the millionaires are pretty small.

OP's reply
Target their capital gains then.

Related Work

- Relevance of Argumentative Units in persuasion (Egawa et al. [2019], Hidey et al. [2017])
- Predicting OP’s susceptibility in online discussions (Mensal et al. [2019])
- Predicting persuasiveness in online discussions (Tan et al. [2016], Wei et al. [2016], Guo et al. [2020])
- Predicting word repetition in persuasion explanations (Atkinson et al. [2019])

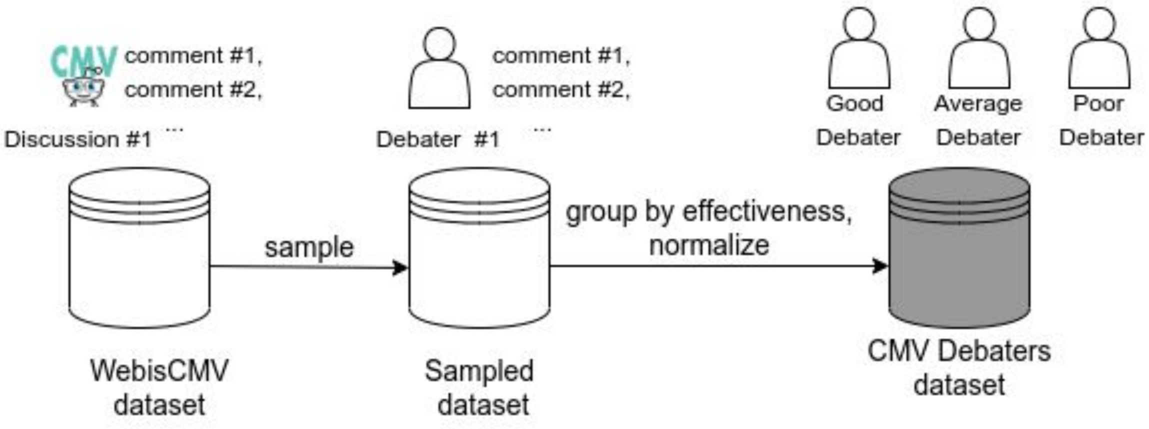
Motivation and Research Questions

- Past works focus on comment-level persuasion in isolated discussions, little emphasis on debater-level persuasion over several discussions
- *What makes some debaters more successful in persuasion than others?*
- In this regard, we address the following research questions:
  - **RQ1**: How do the persuasion strategies of effective and ineffective debaters **differ**?
  - **RQ2**: How do the debaters’ persuasion strategies **evolve** with experience in persuasion?
  - **RQ3**: How effectively can we **predict** CMV debaters’ effectiveness in persuasion?

Approach - Overview

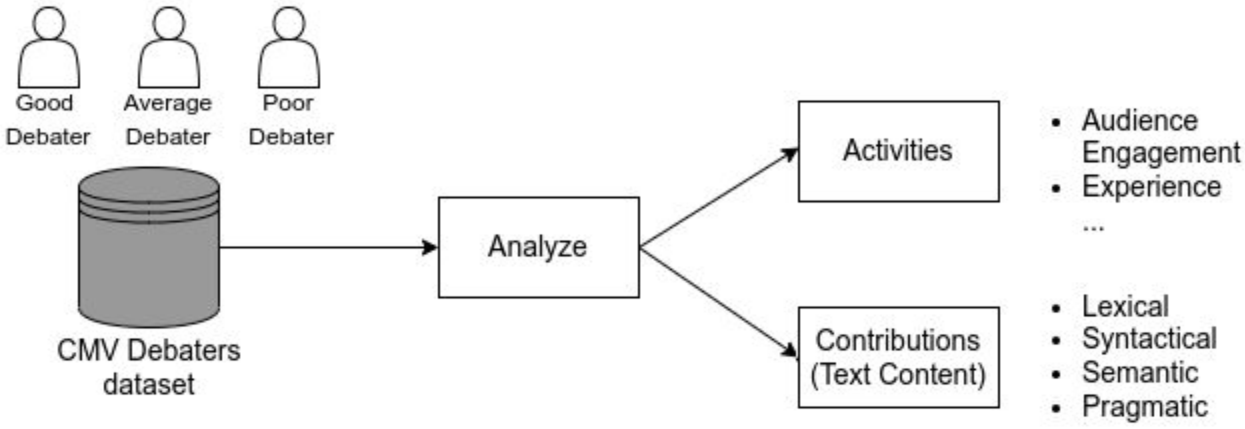
1. Data **Preparation** 
2. **Analysis** of Debaters on CMV 
3. **Prediction** of Debaters’ Effectiveness in Persuasion 

Approach - Data Preparation



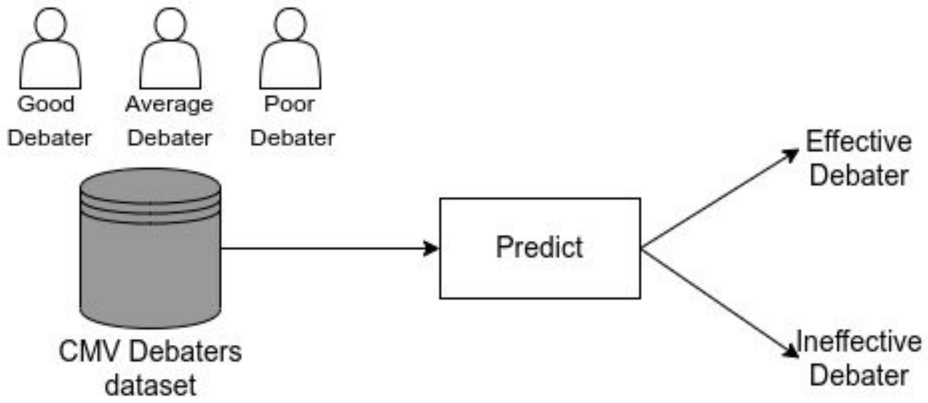
Step #1 Data Preparation

Approach - Analysis



Step #2 Analysis

Approach - Prediction

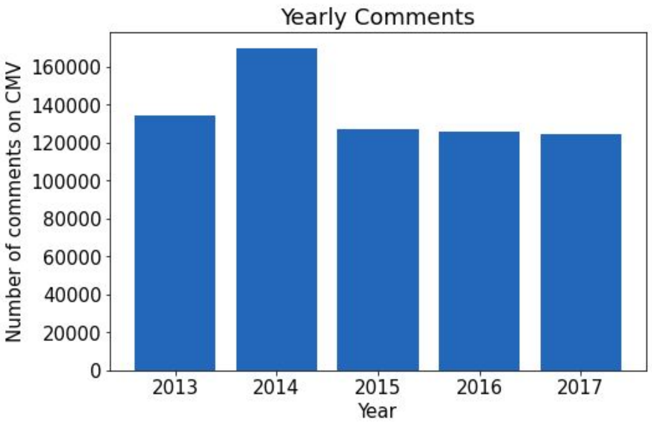


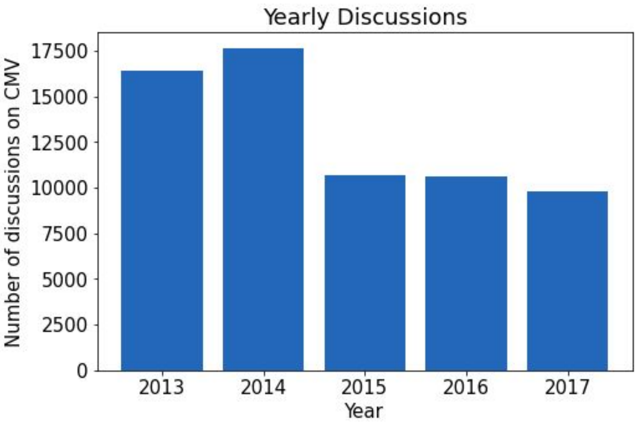
Step #3 Prediction

1. Dataset Preparation
    1.1. Dataset Sampling
    1.2. Dataset Categorization
    1.3. Dataset Normalization

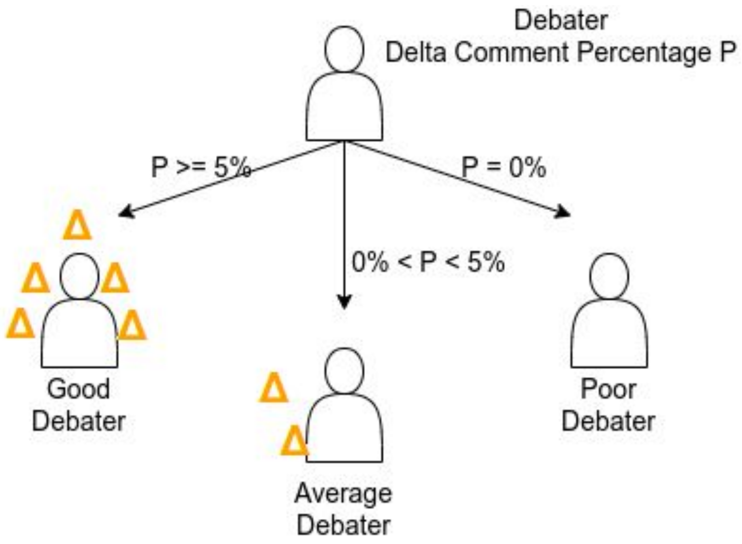
Dataset Sampling

- Sample from WebisCMV dataset by Khatib et al.[2020]
- Consists of 13254 CMV debaters and their top-level argumentative comments (inner comments could be non-argumentative)
- Discard debaters with less than 10 top-level comments





Dataset Categorization - Grouping Debaters by Effectiveness

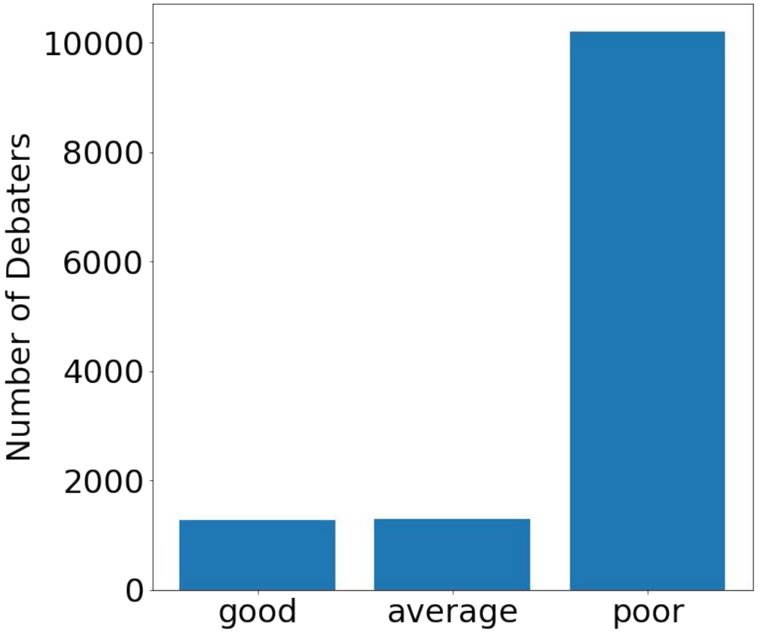


- Compute debaters' persuasion effectiveness from delta comment percentage
- Calculated for each debater as:

$$\frac{\#\ \text{delta comments}}{\#\ \text{total comments}} \times 100$$

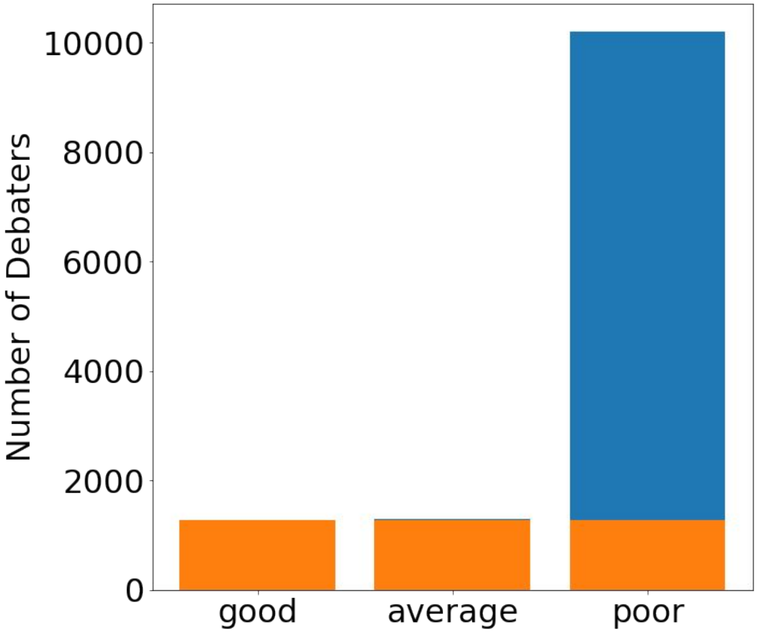
- Represents success rate normalized w.r.t. varying number of comments by different debaters

Dataset Normalization - 1



- > 80% of debaters don't achieve any success

Dataset Normalization - 2



- Balance the dataset by creating triplets of (good, average, poor) such that:
    - Number of comments are similar
    - If multiple entries, break ties by average comment length
- Balanced dataset contains 3801 debaters evenly distributed between 3 classes

2. Analysis of Debaters on Change My View

2.1 Analysis of Debaters' Activities

2.1.1 Audience Engagement

2.1.2 Experience

2.2 Analysis of Debaters' Contributions (Text Content)

2.2.1 Text Semantics

2.2.2 Text Pragmatics - Arguments

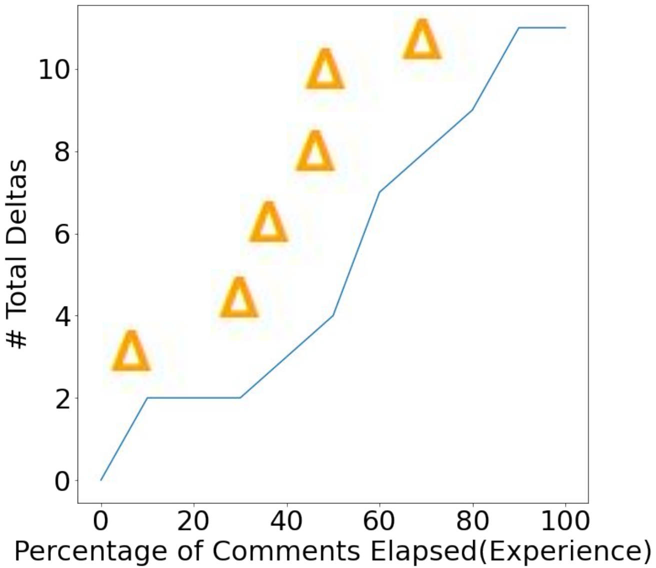
2.2.3 Text Pragmatics - Frames

Quantifying Debaters' Experience in Persuasion

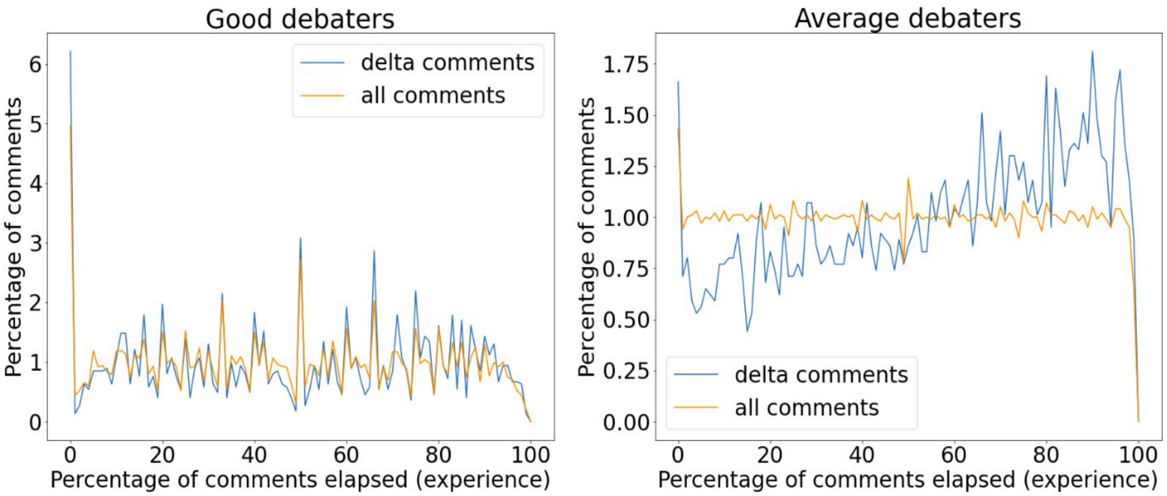
- Experience in persuasion quantified as percentage of total comments elapsed
- For debater *D* with temporally ordered comments $\{C_0, C_1 \ldots C_n\}$, value for comment C_i:

$$percentage\_comments\_elapsed(Ci, D) = \frac{i}{|C_0, C_1 ... C_n|} \times 100$$

- Model evolution of debaters with varying levels of activities on a static scale

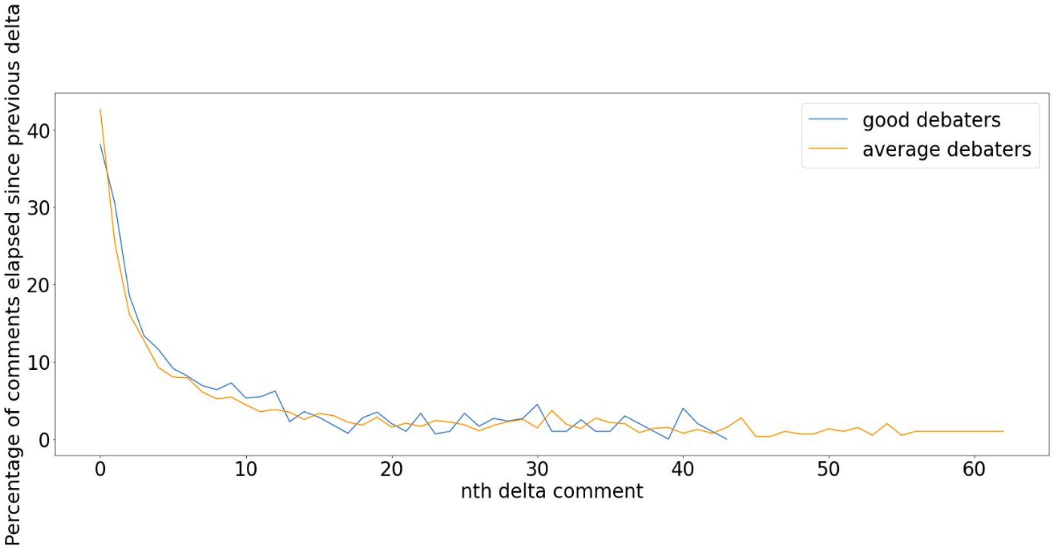


Evolution of Activity and Success with Experience



- Average debaters show improved success at similar activity levels with experience
- Persuasion is a skill that can be acquired and improved upon with experience

Amount of Experience between Consecutive Deltas



Methods

- Experience gained between each new delta
- Amount of experience required for the n^{th} delta, having achieved (n - 1) deltas

Results

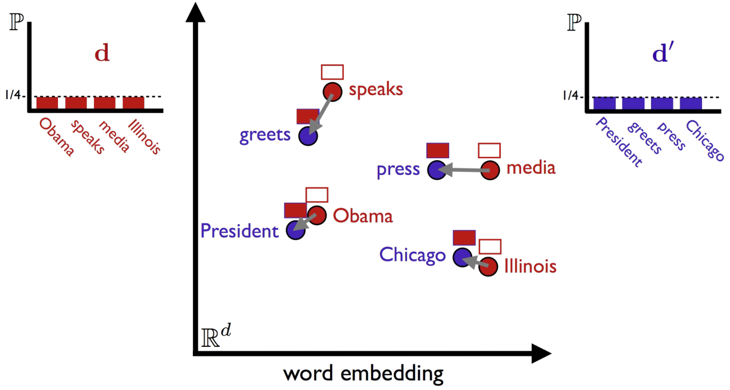
- Experience required for next delta decreases as debater accumulates deltas
- Once a threshold level of success is achieved, achieving further success becomes significantly easier

Analysis of Debaters’ Contributions (Text Content)

- Lexical
  - Distribution of stop and content words
  - Content words’ type token ratio and comment length
- Syntactical
  - Text complexity metrics
  - Parts of speech tags
- **Semantic**
  - Comment OP WMD
  - Average comment sentence pair WMD
- **Pragmatic**
  - Distribution of argumentative units’ semantic types
  - Frames

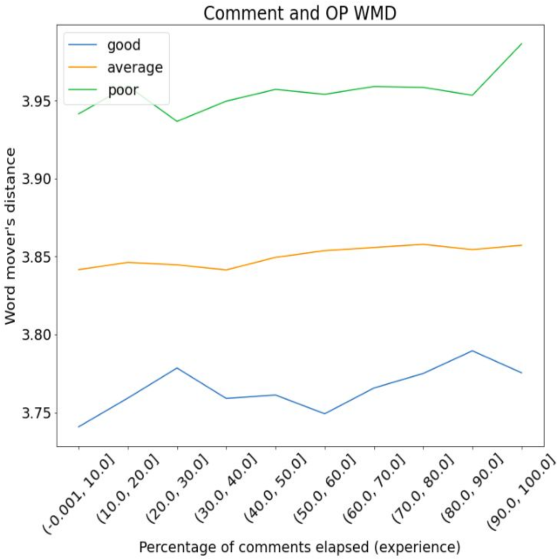
Comment Semantics and Persuasion - Methods

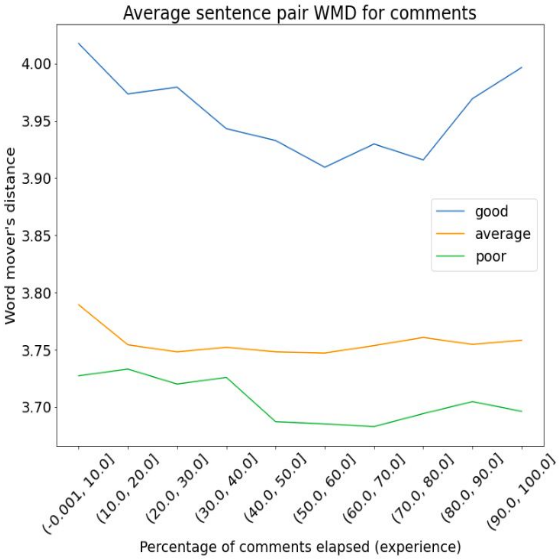
- Represent debaters' comments as 300 dimensional vectors using fasText's word embeddings
- Word Mover's Distance(WMD) to compute anti-similarities between texts
- Compute 2 WMD based metrics:
  - **Comment-OP WMD** - Semantic similarity between debater's comment and its OP
  - **Average comment sentence pair WMD** - Semantic variability in the debater's comment



$$avg\_sentence\_pair\_wmd(C) = \frac{\sum_{i=1}^{i=n-1} \sum_{j=i+1}^{j=n} wmd(Si, Sj)}{n(n-1)/2}$$

Comment Semantics and Persuasion - Results

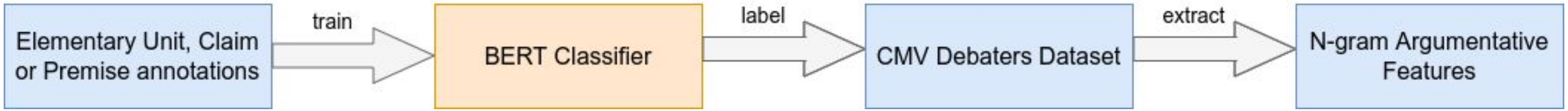




- Semantic similarity with OP and higher semantic variability in comment’s sentences characteristic of effective persuasion

- Effective debaters’ comments are informatically closer to OP while having higher overall information

Argumentative Features - Methods 1



- Consider two classes of argumentative units:
    - Elementary Units(EU) - Testimony, Fact, Value, Policy, Rhetorical Statement
      [Egawa et al.]
    - Claims, Premises - Interpretation, Evaluation, (Dis-)Agreement, Ethos, Logos, Pathos
      [Hidey et al.]
- Sentence level classification
- For EU, best macro and micro accuracies of 0.55 and 0.75 after oversampling training set
- For Claims/Premises, train 5 classifiers with accuracies ranging from 0.33 to 0.94

Argumentative Features - Analysis

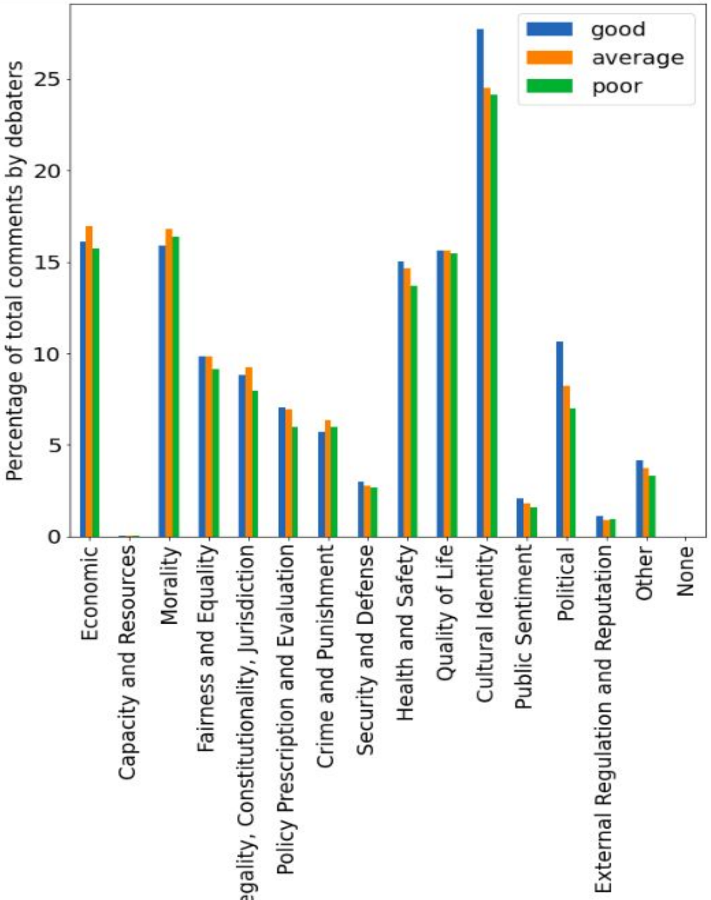
- Compute Pearson correlation coefficients for argument type n-grams and effectiveness
- Most argument type n-grams don’t correlate significantly with effectiveness in persuasion
- Use of rhetorics and stating subjective opinions slightly correlates with effectiveness in persuasion
- Mere presence of argument types doesn’t indicate effectiveness in persuasion, their effective use might

Framing and Persuasion - Methods

1. *Economic*
2. *Capacity and Resources*
3. *Morality*
4. *Fairness and Equality*
5. *Legality*
6. *Policy*
7. *Crime and Punishment*
8. *Security and Defense*
9. *Health and Safety*
10. *Quality of Life*
11. *Cultural Identity*
12. *Public Opinion*
13. *Political*
14. *External Regulation and Reputation*
15. *Other*

- Framing - Focus on some aspects while ignoring others
- Media Frames Corpus by Card et al. contains news articles with 15 frame-type annotations
- Train BERT model to detect frames with macro and micro accuracies of 0.51 and 0.68

Framing and Persuasion - Analysis



- Similar usage by all debaters for most frame types
- Good debaters more prominent in ‘Cultural Identity’ and ‘Political’ frame types
- Connecting with audience(OP) along socio-cultural and/or political beliefs can yield higher effectiveness in persuasion

Or

Effective debaters more inclined towards political and socio-cultural themed discussions

Features Indicative of Effectiveness

- Lexical
  - Distribution of stop and content words
  - Content words’ type token ratio and **comment length**
- Syntactical
  - **Text complexity metrics**
  - Parts of speech tags
- Semantic
  - **Comment OP WMD**
  - **Average comment sentence pair WMD**
- Pragmatic
  - Distribution of argumentative units’ semantic types
  - **Frames**

3. Predicting Debaters’ Effectiveness in Persuasion

3.1 Background and Motivation

3.2 Features For Predicting Effectiveness in Persuasion

3.3 Vocabulary Interplay Features

3.4 Experiments

3.5 Results

Background and Motivation

- Past works have successfully predicted persuasiveness at comment/discussion level using 4 main feature types:
    - Surface level text based - lexical, syntactical, semantic attributes of the text
    - User interaction based - interaction dynamics between users
    - Pragmatic - explore higher level contextual properties of text
    - User level - past activity, established credibility
- *Can similar success be achieved in predicting debaters' effectiveness in persuasion?*

Features for Predicting Effectiveness in Persuasion

- Semantic
  - Word Mover's Distance based metrics
- Pragmatic
  - Frame types distribution(absolute and relative)
  - N-grams of argumentative semantic types
- Lexical
- Syntactical
  - N-grams of parts of speech tags
  - Text complexity metrics
- Vocabulary Interplay
- Bag of Words (baseline)

[Tan et. al]

Experiments

- ***Classification task*** - Given a CMV debater, predict whether they are highly effective at persuasion (success rate >= 5%) or not
- 3 experimental settings:
  - Good vs Average
  - Good vs Poor
  - Good vs (Average + Poor)
- Compute feature vectors for debaters by averaging vectors for all comments

Experimental Setting	# Positive Samples	# Negative Samples
Good vs Poor	1267	1267
Good vs Average	1267	1267
Good vs (Poor + Average)	1267	2534

Results

Feature Type	Feature	Good vs Average + Poor	Good vs Average	Good vs Poor
-	Bag of Words	0.64	0.60	0.68
-	Vocabulary Interplay	0.61	0.58	0.67
Lexical	Lexical	0.61	0.62	0.67
Pragmatic	Elementary Units	0.57	0.51	0.59
Pragmatic	Claim and Premise	0.52	0.47	0.55
Pragmatic	Claim Semantic Type	0.57	0.48	0.58
Pragmatic	Premise Semantic Type	0.56	0.48	0.58
Pragmatic	Claim and Premise with Semantic Types	0.56	0.48	0.58
Pragmatic	**Frames**	**0.74**	**0.70**	**0.72**
Semantic	Word Mover's Distance features	0.57	0.59	0.63
Syntactical	Parts of Speech	0.52	0.57	0.51
Syntactical	Text Complexity	0.53	0.65	0.61

- Bag of words yields stronger baseline than for classifying persuasive comments - fewer debaters yet more data per debater

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- Distribution of argument types poor predictor of effectiveness

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- Relative and absolute frequency of frames in comments best predictor of effectiveness
- High usage of ’Quality of Life’, ’Morality’, and ’Health and Safety’ frames by ineffective debaters

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- Easier to separate good debaters from poor debaters

Conclusion and Future Work

- Curated dataset of CMV debaters grouped by effectiveness in persuasion
- Analysis of CMV debaters’ activities and contributions - insights on effective persuasion strategies
- Prediction experiments for effectiveness - comparison of features

- Factor in OP’s subjectivity in evaluating debater’s persuasiveness
- Explore role of features beyond comments’ text content(interaction dynamics with other users)
- Features capturing effective use of argumentative units - interdependencies, relative ordering