Frame Semantics for Stance Classification

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Stance Classification

Determine the stance (i.e., for or against) of a post written for a two-sided topic discussed in an online debate forum.
# A Sample Debate

## Should abortion be allowed?

<table>
<thead>
<tr>
<th>Yes <em>(for)</em></th>
<th>No <em>(against)</em></th>
</tr>
</thead>
<tbody>
<tr>
<td>Women should have the ability to choose what they do with their bodies.</td>
<td>Technically abortion is murder. They are killing the baby without a justified motive.</td>
</tr>
</tbody>
</table>
Our Debate Setting:

Ideological Debates

• Various social, political, and ideological issues
  – Abortion, gay rights, gun rights, god’s existence
Goal

To improve the state of the art in supervised stance classification of ideological debates

– by proposing a linguistic and an extra-linguistic extension to state-of-the-art baseline systems
Plan for the Talk

• Two baseline stance classification systems
• Linguistic extension to the baselines
• Extra-linguistic extension to the baselines
• Evaluation
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Baseline 1: Anand et al., 2011 ($C_b$)

- Supervised approach, one stance classifier per domain
  - SVM in our implementation
  - One training/test instance for each post
  - Two labels – *for* and *against*

<table>
<thead>
<tr>
<th>Feature Type</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic</td>
<td>Unigrams, bigrams, syntactic and POS generalized dependencies</td>
</tr>
<tr>
<td>Sentiment</td>
<td>LIWC counts, opinion dependencies</td>
</tr>
<tr>
<td>Argument</td>
<td>Cue words, repeated punctuation, context</td>
</tr>
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</table>
Baseline 2: Anand et al.’s system enhanced with Author Constraints ($C_b + AC$)

• **Author constraints (ACs)**
  – a type of constraints for postprocessing the output of a stance classifier
  – ensure that all test posts written for the same domain by an author have the *same stance*

• **How to postprocess Anand et al.’s output with ACs?**
  – For each author, sum up classification values of her test posts
    • Classification value is the signed distance from the hyperplane
  – If sum > 0, assign *for* to all her test posts; else *against*
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Linguistic Extension: Semantic Generalization

- **Aim**: improve a learner’s ability to generalize by inducing patterns based on semantic frames and use them as features so that semantically similar sentences can be detected.

- **FrameNet** (https://framenet.icsi.berkeley.edu/)

**Example 1**: Some people hate guns.  
**Example 2**: Some people do not like guns.  
—Anand et al.’s features cannot detect these semantically similar sentences
Pattern Induction

• Three types of patterns from each sentence:
  1. Subject-Frame-Object (SFO)
  2. Dependency-Frame (DF)
  3. Frame-Element-Topic (FET)
Subject-Frame-Object (SFO)

Capture how a verb (i.e., a frame target) is connected with the topics/frames used as its subject/object.

<Subj_Topic_Fr : Frame : Obj_Topic_Fr : V_Neg : V_Sent>

Example 1: Some people hate guns.
SFO pattern: <people : EF : Weapon : Not_Neg : [-]>

Example 2: Some people do not like guns.
Subject-Frame-Object (SFO)

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Dependency-Frame (DF)

Capture how a topic/frame is connected to another topic/frame via a dependency relation.

<Dep_Rel : Head_Topic_Fr : Dep_Topic_Fr : H_Neg : H_Sent>

**Example 1:** Some people hate guns.
**DF pattern:** <dobj : EF : Weapon : Not_Neg : [-]>

**Example 2:** Some people do not like guns.
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Capture how a topic/frame is connected to another topic/frame via a dependency relation.

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Dependency-Frame (DF)

Capture how a topic/frame is connected to another topic/frame via a dependency relation.

Example 1: Some people *hate* guns.
DF pattern: `<dobj : EF : Weapon : Not_Neg : [-]>`

Example 2: Some people *do not like* guns.
Dependency-Frame (DF)

Capture how a topic/frame is connected to another topic/frame via a dependency relation.

Example 1: Some people hate guns.
DF pattern: <dobj : EF : Weapon : Not_Neg : [-]>

Example 2: Some people do not like guns.
Frame-Element-Topic (FET)

Capture how a topic/frame is contained in an element of another frame.

Example 1: Some people hate guns.
FET pattern: `<Weapon : Content : EF : Not_Neg : [-]>`

Example 2: Some people do not like guns.
Combine $C_b$ and $C_s$’s output heuristically

- $C_b$: Anand et al.’s system
- $C_s$: Classifier trained with patterns only

- **Rule 1**: if $C_b$ can classify a test post $p$ confidently, then use $C_b$’s prediction.
- **Rule 2**: if $C_s$ can classify $p$ confidently, use $C_s$’s prediction.
- **Rule 3**: use $C_b$’s prediction.

**Note:**
The rules favor $C_b$ than $C_s$ because $\text{Accuracy}(C_b) > \text{Accuracy}(C_s)$.
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Extra-linguistic Extension: Exploiting Same-stance Posts

**Aim:** to improve the classification of a post by exploiting information from other posts in the test set that are likely to have the same stance

\[P_1 \text{ – Pro-abortion}\] I don’t think abortion should be illegal.

\[P_2 \text{ – Pro-abortion}\] What will you do if a woman’s life is in danger while she’s pregnant?

\(P_1\) is arguably easier to classify than \(P_2\) and may help classify \(P_2\).
Using Similar-minded Authors

• Goal: for each author in the test set, identify the $k$ authors most likely to have the same stance

• Train an **author-agreement** classifier
  – Each instance corresponds to a pair of authors
  – Labels - **same** or **different** stance
  – $k$ to be determined using development data
Using Similar-minded Authors

Other **test** posts by \( p \)'s author & her \( k \)-NNs →

**Test** post \( p \) to be classified
Using Similar-minded Authors

Other test posts by $p$’s author & her $k$-NNs

Test post $p$ to be classified

All possible subsets with $p$
Using Similar-minded Authors

Other test posts by p’s author & her k-NNs

Test post p to be classified

All possible subsets with p

Stance Classifier
Using Similar-minded Authors

Other test posts by p’s author & her k-NNs

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All possible subsets with p

Stance Classifier

Sum SVM confidence

Stance for
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Experimental Setup

• 4 Datasets
  – Collected from http://www.createdebate.com

<table>
<thead>
<tr>
<th>Domain</th>
<th>Posts</th>
<th>“for” %</th>
<th>Thread Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABO (support abortion?)</td>
<td>1741</td>
<td>54.9</td>
<td>4.1</td>
</tr>
<tr>
<td>GAY (support gay rights?)</td>
<td>1376</td>
<td>63.4</td>
<td>4.0</td>
</tr>
<tr>
<td>OBA (support Obama?)</td>
<td>985</td>
<td>53.9</td>
<td>2.6</td>
</tr>
<tr>
<td>MAR (legalize marijuana?)</td>
<td>626</td>
<td>69.5</td>
<td>2.5</td>
</tr>
</tbody>
</table>
Experimental Setup

- Performance metric – accuracy
- 5-fold cross validation
Summary of Results

• Anand+AC significantly outperforms Anand by 4.6 points
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• Anand+Patterns+AC significantly beats Anand+AC by 2.5 points
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• Two extensions yield an overall improvement of 6.4 points over Anand+AC
Conclusions

• Proposed a linguistic and an extra-linguistic extension to our two baselines
  1. Semantic generalization
  2. Exploiting same-stance posts

• Outperformed an improved version of Anand et al.’s approach significantly by $2.6–7.0$ accuracy points