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?

| Yes *(for)* | No *(against)* |
|-------------|---------------|
| Women should have the ability to choose what they do with their bodies. | Technically abortion is murder. They are killing the baby without a justified motive. |
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*

| Feature Type   | Features                                              |
|----------------|--------------------------------------------------------|
| Basic          | Unigrams, bigrams, syntactic and POS generalized dependencies |
| Sentiment      | LIWC counts, opinion dependencies                      |
| Argument       | Cue words, repeated punctuation, context               |
Baseline 2: Anand et al.’s system enhanced with Author Constraints (C₉+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/](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.
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\[
\begin{align*}
&<\text{Subj\_Topic\_Fr} : \text{Frame} : \text{Obj\_Topic\_Fr} : \text{V\_Neg} : \text{V\_Sent}> \\
&\uparrow \hspace{1cm} \uparrow \hspace{1cm} \uparrow \hspace{1cm} \uparrow \hspace{1cm} \uparrow \\
&\text{Topic/Frame as subject} \hspace{1cm} \text{Frame} \hspace{1cm} \text{Topic/Frame as object} \hspace{1cm} \text{Verb negated?} \hspace{1cm} \text{Verb sentiment}
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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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Frame-Element-Topic (FET)

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

<Topic_Frame : Frame_Element : Frame : V_Neg : V_Sent>

Topic/Frame Frame element Frame Verb negated? Verb sentiment

**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

[P₁ – Pro-abortion] I don’t think abortion should be illegal.

[P₂ – Pro-abortion] What will you do if a woman’s life is in danger while she’s pregnant?

P₁ is arguably easier to classify than P₂ and may help classify P₂.
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

Test post $p$ to be classified

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

| Domain                  | Posts | “for” % | Thread Length |
|-------------------------|-------|---------|---------------|
| ABO (support abortion?) | 1741  | 54.9    | 4.1           |
| GAY (support gay rights?) | 1376 | 63.4    | 4.0           |
| OBA (support Obama?)    | 985   | 53.9    | 2.6           |
| MAR (legalize marijuana?) | 626  | 69.5    | 2.5           |
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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• Anand+Patterns+AC significantly beats Anand+AC by 2.5 points

• 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