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# Stance Classification of Tweets in Online Debates

## 1 Introduction

My research project in Research Track Exploration Internship is about Predicting Stance for Tweets, a task in International Workshop of Semantic Evaluation 2016. I worked under my mentor Prof Vincent Ng, Department of Computer Science, UTD.

After having a look at all the tweets in the data set for Target **Legalization of Abortion**, I found that many of them were expressing views about abortion but not in an explicit way. There were some tweets that expressed views directly like “*Abortion is morally wrong and should be banned*” but a lot of them expressed views in an indirect way like ‘*We must speak for the unborn*’. So here we need to relate that caring for unborn needs is against the legalization of abortion.

The various other entities about which a tweet can express the opinion, I call them as secondary targets. We need to relate the opinion expressed on secondary target to the main target. Hence we first find stance of a tweet on the secondary target and then relate it to the stance for the main target.

I classify all tweets into 5 categories: one primary and four secondaries. The primary category is where the opinion is expressed directly about Abortion and the rest are those where opinion is expressed about the secondary targets. A list of all secondary targets is described in Section 2.

The problem is that we do not have any explicit relation given between tweets and secondary targets. If we do not know the secondary target of a tweet, then there is no way we can predict the local stance and relate it with the main stance. I am working on a solution to this problem as stated below.

I first manually annotate the training set tweets with the entities toward which they express opinion i.e classify the training set tweets over secondary targets. After classifying the training set manually, I try to find some pattern among certain words, Hashtags, and secondary targets. This can help us as using these special knowledge sources we will classify the Test Set tweets into their secondary targets, then determine stance for secondary targets and ultimately convert this local stance into the main stance by using the relation between secondary targets and primary targets. This is further elaborated in Section 3.

## 2 Secondary targets

- |                |  |
|----------------|--|
| 1-Women Rights | [ Tweets which target the rights of women over her own body and her health ] |
| 2-Baby's Right | [ Tweets which target the right to live of unborn child ]                    |
| 3-Christianity | [ Tweets which target Christian views on life and choices]                   |
| 4-Adoption     | [ Tweets where target is adoption of children ]                              |

## 3 Objectives

### 3.1 Classifying tweets regarding Abortion in test set into Secondary Categories

If we can classify tweets of Test Set into above secondary categories, then we remove the problem of determining stance from tweets where opinion is not directly expressed about the main target. As now we know the Local Targets of each tweet, we will determine stance of each tweet on its Local Target first and then relate this Local Stance to Main Stance. Local Stance can be converted to Main Stance by knowing the relation between Local Targets and Main Targets.

**Example:** If a tweet is labeled Pro for Women's Right to Choose then it is Pro for Abortion. While a tweet labeled Pro for Baby's Rights will be Against Abortion.

We can classify Test Set into categories by using some special additional information in the form of some words, phrases, and Hashtag that have been observed to occur with a particular category in the Training Set.

My work is centered around generating some special knowledge sources from the training set, that can help me classify the tweets of Test Set over the secondary target set.

**Example:** The phrases like “speak for voiceless”, “ Every Life Matters” are observed to occur with category Baby’s Right in Training Set, so we can use it as tweets containing these phrases in Test Set are likely to be of category Baby’s Rights.

So, my approach is to classify the Test Set tweets into their secondary targets, then determine stance about secondary targets and ultimately relate this local stance to the main stance.

### 3.2 Expanding our current training set

We can expand our current training set by classifying tweets in Test Set as Pro or Con directly by using some special information in the form of words, phrases and Hashtags as in above case 1. A particular word in tweets of the training set is observed to occur with a particular category say “Pro” then tweets with that word in Test Set can also be classified as “Pro”. This way we can expand our current training set.

**NOTE:** Case 2 is likely to more error prone than Case1. In both cases, we use some information that can be used to classify tweets directly, in Case 1 we only categorize the tweets on which entity is an opinion expressed and then further use algorithms to find Stance. But in Case 2 we directly classify tweets on Basis of Stance which can be more error prone.

## 4 Relation Between Local Stance and Main Stance

Below is the list where have information on how local stance is related to main stance. Here the label ‘Positive’ means Local Stance is same as Main Stance while label ‘Negative’ means Local Stance is opposite of Main Stance.

1-Women Rights	Positive
2-Baby’s Right	Negative
3-Christianity	Negative
4-Adoption	Negative

## 5 Word Target Associations

Here is the list of special information in the form of words and phrases that can be used to classify tweets into categories on the basis of about what entity the opinion is expressed.

### Important Notes

1- I have only chosen those words, phrases, and hashtags which can are observed to occur only with that particular category and in large frequency. Those information pieces that happen to overlap with categories were rejected. This can be seen as many words seem to relate to category ‘Women’s right to choose’ and frequently in a training set, they do relate also but sometimes they also relate to category ‘ Baby’s Rights ’.

Here is a list of these Hashtags that I do not take for further analysis.

#choose, #rights, #pregnancy, #mother, #aborted, #extremist, #liberty, #liberalism, #LiberalLogic, #happiness, #EndDiscrimination, #righttochoose, #standforchoice, #prochoice

2- Most of the tweets had targets relating first two categories ‘Women Rights’ and ‘Baby Rights’ and fewer tweets on last two categories ‘Adoption’ and ‘Christianity’ . But the last two topics are useful because tweets belonging to any of these topics largely have the same stance. Almost all tweets in ‘Adoption’ had stance ‘Against’.

### 5.1 Women Rights

Words:

Profeminist, Prochoice, Bodily Autonomy, Rapeculture, Win for women

Hashtags:

#Rapeculture, #WomensRights, #ReproductiveRights, #MyBodyMyRights, #Reprojustice, #Reprorights, #Rape, #YourBody, #AbortionRight, #NoChoiceIsNeverEasy, #womenshealth, #reprohealth, #ReproJustice

## 5.2 Baby Rights

Words:

Murder, Killing, Fight for Unborn, ProLife, Promurder, ProLifeYouth, Protect Voiceless, Protect Life, Legalised Murder, Innocent Human Life, Hitler

Hashtags:

#murder, #voiceless, #AbortionIsMurder, #prolifegen, #ProLifeYouth, #killing, #child, #Life, #Mother, #InnocentLives, #ProtectLife, #LifeIsBeautiful, #AllLivesMatter, #BlackLivesMatter, #LifeWins, #Unborn, #MotherTeresa, #ISIS

## 5.3 Christianity

Words:

God, Catholic, God's Laws

Hashtags:

#jesus, #bible, #God, #Catholic, #Christian, #GodIsLoveSoLoveWins

## 5.4 Adoption

Words:

Fostering

Hashtags:

#adopt,

# 6 Implementation

The procedure suggested in above section for selecting words that will be used for making feature sets has one limitation that it is only specific to my current Training Set as it was made manually, so it needs to be converted such that code generates a list of unique words for any training data set.

To automate the process of selecting features for classifiers, I calculated Pointwise Mutual Information (PMI) of all the unique words in all tweets with stance or secondary target (depending on which classifier is to be used). Those words that had PMI greater than or equal to 0.7 were chosen for forming the feature vectors.

Finally, I used Support Vector Machines for classifying tweets on the basis of secondary targets and stance. I used a linear kernel with feature set generated from words chosen as explained in above paragraph. Also, after classifying tweets on the basis of secondary targets, I did not find stance related to particular secondary targets but directly towards main targets. So, I use one SVM classifier to predict secondary targets for tweets and then other SVM classifiers for tweets belonging to a particular secondary target in predicting stance toward the main target.

All this was implemented in Python, I used Pandas library to work Training and Test Datasets and I used the sklearn library to implement Support Vector Machine.

## 7 Results

### Analysis for Classifier for Secondary Targets

Total number of tweets with Secondary Targets as Baby Rights: 29

Total number of tweets with Secondary Targets as Baby Rights: 24

Total number of tweets with Secondary Targets as Women Rights: 18

Total number of tweets with Secondary Targets as Women Rights: 10

Total number of tweets with Secondary Targets as Christianity: 7

Total number of tweets with Secondary Targets as Christianity: 1

Total number of tweets with Secondary Targets as Adoption: 3

Total number of tweets with Secondary Targets as Adoption: 0

Total number of tweets with Secondary Targets as Abortion: 16

Total number of tweets with Secondary Targets as Abortion: 11

Total number of tweets with Secondary Targets as Other: 29

Total number of tweets with Secondary Targets as Other: 58

Total Wrongly Predicted Cases: 47

Accuracy: 0.548076923077

### Analysis for Classifier for Baby Rights

Total number of tweets with Baby Rights as FAVOR: 2

Total number of tweets with Baby Rights as FAVOR: 2

Total number of tweets with Baby Rights as AGAINST: 22

Total number of tweets with Baby Rights as AGAINST: 22

Total number of tweets with Baby Rights as NONE: 0

Total number of tweets with Baby Rights as NONE: 0

Total Wrongly Predicted Cases: 4

Accuracy: 0.833333333333

### Analysis for Classifier for Women Rights

Total number of tweets with Women Rights as FAVOR: 7

Total number of tweets with Women Rights as FAVOR: 10

Total number of tweets with Women Rights as AGAINST: 3

Total number of tweets with Women Rights as AGAINST: 0

Total number of tweets with Women Rights as NONE: 0

Total number of tweets with Women Rights as NONE: 0

Total Wrongly Predicted Cases: 3

Accuracy: 0.7

### Analysis for Classifier for Christianity

Total number of tweets with Christianity as FAVOR: 0

Total number of tweets with Christianity as FAVOR: 0

Total number of tweets with Christianity as AGAINST: 1

Total number of tweets with Christianity as AGAINST: 1

Total number of tweets with Christianity as NONE: 0  
Total number of tweets with Christianity as NONE: 0

Total Wrongly Predicted Cases: 0  
Accuracy: 1.0

### **Analysis for Classifier for Abortion**

Total number of tweets with Abortion as FAVOR: 2  
Total number of tweets with Abortion as FAVOR: 1

Total number of tweets with Abortion as AGAINST: 8  
Total number of tweets with Abortion as AGAINST: 10

Total number of tweets with Abortion as NONE: 1  
Total number of tweets with Abortion as NONE: 0

Total Wrongly Predicted Cases: 2  
Accuracy: 0.818181818182

### **Analysis for Classifier for Other**

Total number of tweets with Other as FAVOR: 10  
Total number of tweets with Other as FAVOR: 4

Total number of tweets with Other as AGAINST: 36  
Total number of tweets with Other as AGAINST: 12

Total number of tweets with Other as NONE: 12  
Total number of tweets with Other as NONE: 42

Total Wrongly Predicted Cases: 36  
Accuracy: 0.379310344828

## **8 Scope for Improvement and Further Work**

The results I got so far can be improved to a greater extent by implementing the SVM in better ways. There is a lot of work that can be done to improve the feature set for SVM.

Also, the technique of Distant Supervision in section 3.2 has not been implemented by me yet and this is another area where I can work on and see if it leads to better results.

Another area for work is automating the procedure for generating a class of secondary targets from Training Set and annotating tweets with their secondary targets. Currently, I manually annotated all tweets of Training Set with their secondary targets

Furthermore, my approach of first finding stance in particular to secondary targets was not achieved. I only classified tweets on the basis of their secondary targets and found stance for the main target separately for each class of secondary target. So, this is another area where work can be done.