

Sentiment and Topic Analysis

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Goal

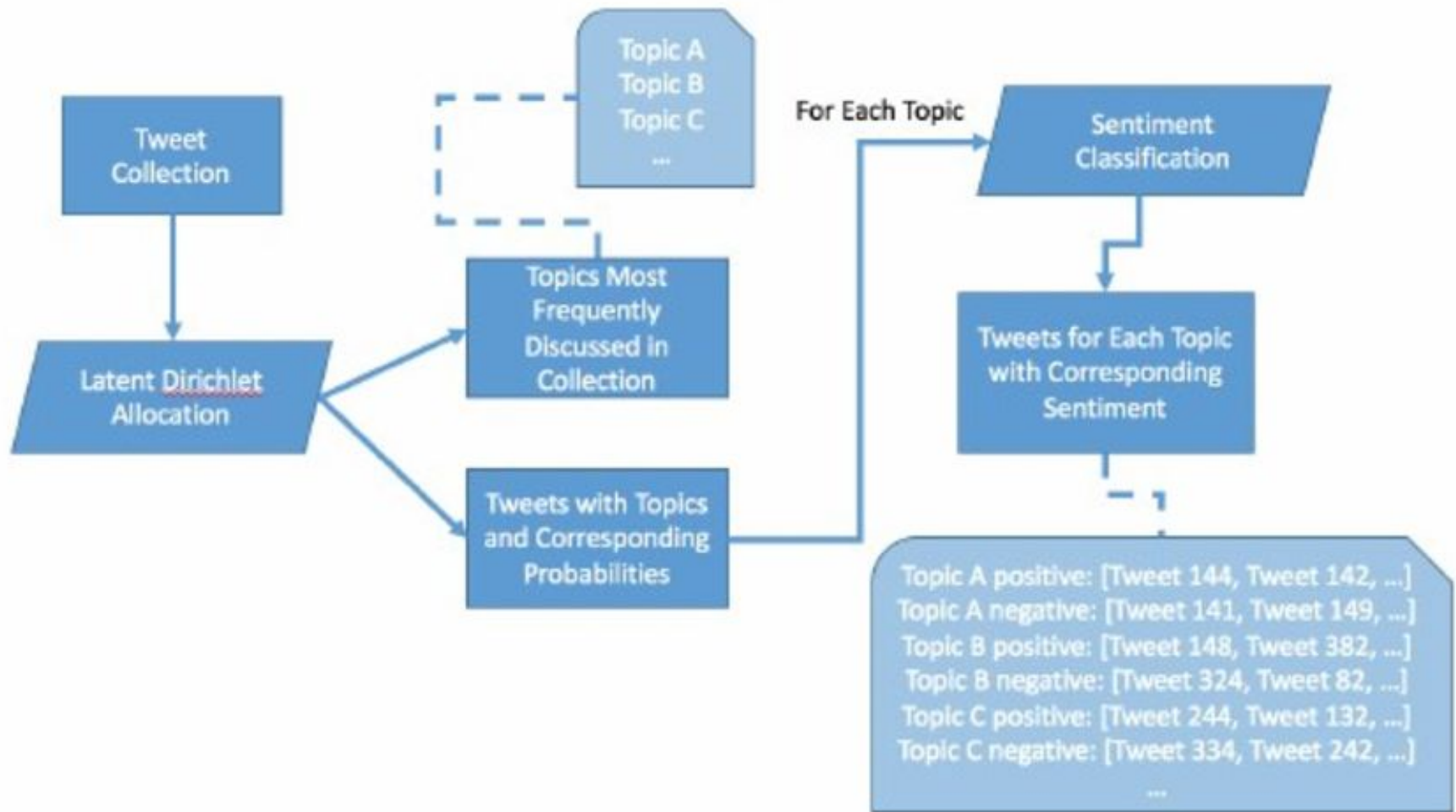
To build an effective tool that will allow linguists and sociologists to find topics of interest within a collection of tweets and explore the sentiments of the tweets relating to each topic

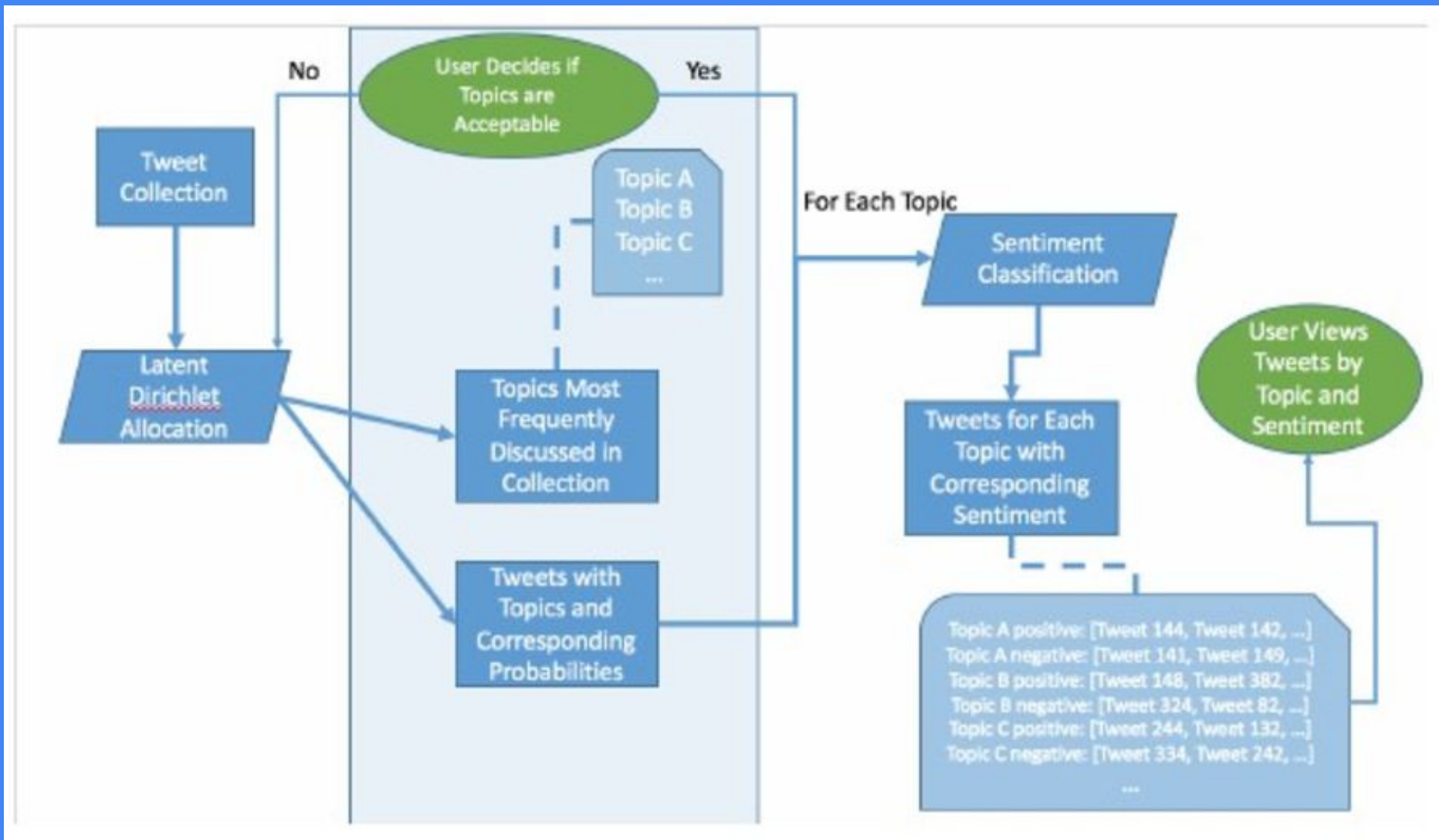
- Extract and Clean Tweets
- Latent Dirichlet Allocation
- Allow User Interaction
- Sentiment Analysis
- User Interface

Outline

- Workflow
- Preprocessing and Latent Dirichlet Allocation
- Emoji Labeled Sentiment Classification
- Dependency Tree Based Sentiment Classification
- Topic Analysis Interface
- Future Work

Workflow



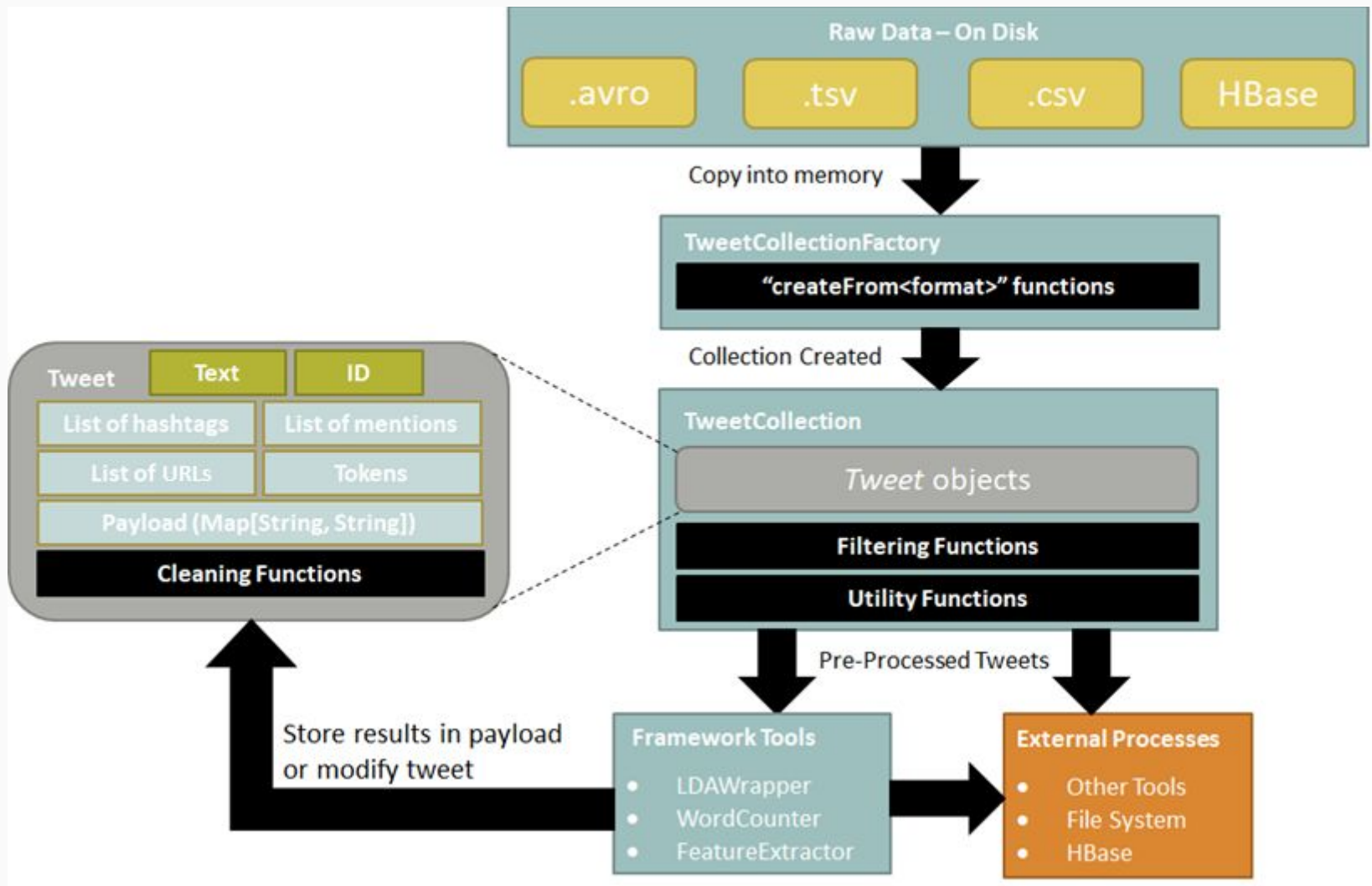


The planned flow of user interaction with our system's tools

Preprocessing Tweet Collections and Running LDA

Matthew's Thesis Framework

- Preprocesses collections of tweet text
 - Handles reading data from source files
 - Processing data into data structures
- Runs LDA
 - Framework provides wrapper for running Spark's LDA implementation on tweet collections
 - Automatically returns overall topic results and topic tags for each tweet



Reading Twitter Data

- Utilize *TweetCollectionFactory*
 - Read data from any supported source
 - Simplifies development - easy to change data source
 - Creates a collection of *Tweet* data structures
- Run analysis on *TweetCollection* data structure
 - No need to do any raw text processing manually
 - Use provided functionalities to simplify cleaning and pre-processing

Cleaning Twitter Data

LDA only	Both	Sentiment only
Stopwords	URLs	Mentions
	lowercase	Hashtags
	punctuation	
	RT marker	

- Separate cleaning for LDA and Sentiment Analysis
- Stop words hinder LDA results, but are necessary for our Sentiment Analysis
- Mentions/hashtags hinder sentiment results, but are common topic-defining terms

LDAWrapper

- Wrapper around Spark's LDA implementation - works with *TweetCollections*
- Two sets of results: overall topic results and individual tags for each tweet

Overall topic results

```
Topic number 0:  
#travel: 0.019037395276840414  
va: 0.017585128058131682  
sunrise: 0.01737546103835172  
catawba: 0.017162258743414125  
halfway: 0.016313580408116864  
Topic number 1:  
5: 0.01571722876285292  
thruhikers: 0.012579547329638608  
thruhiker: 0.012566871814079542  
thruhike: 0.010651317950181937  
thru: 0.010626772087766138  
Topic number 2:  
#tairp: 0.026796846204839297  
#indigenous: 0.026796846204839297  
@americanindian8: 0.026146256569298542  
mcafee: 0.017894562390441637  
knob: 0.017894562390441637
```



Topic tags for each tweet

Result	Example
Probability that this tweet belongs to each topic	[0.851, 0.13, 0.019]
Topic number assigned to this tweet	0
Topic label assigned to this tweet	"#travel va sunrise catawba halfway"

Emoji-Labeled Sentiment Classification

Emoji Extraction

- UTF-8 format containing non-alphanumeric codes
 - E.g.,

ðŸ~	\xF0\x9F\x98\xA0	Angry	Negative	
ðŸ~,,	\F0\x9F\x98\x84	Smiling face with open mouth and smiling eyes	Positive	

- Used a lookup table to identify if emoji was positive or negative

Sentiment Classifier

- Binomial logistic regression model
- Word2Vec
- Not enough labeled data to train classifier
 - Too many false-negatives

Dependency Tree Based Sentiment Classification

Basics

Lexicon Used:

- VADER (Valence Aware Dictionary and sEntiment Reasoner)
- General Inquirer (polarity reversal words)

A way to compute overall polarity using Lexicon

- Parse Tree created by Syntaxnet
- Our Focus: Impact of polarity reversal words and negation in the overall polarity of tweet

Polarity reversal words with VADER

Tested VADER with tweets that had polarity reversal words.

We focused on very limited words because we were testing the polarity of tweets manually.

We focused on words such as “depression,” “anxiety,” and “stress”

These words have negative sentiment scores.

Then we started looking for tweets which had these negative words along with polarity reversal words like “abate,” “diminish,” “reduce,” and “decrease.”

Polarity reversal words with VADER

Following are subset of tweets that we tested with VADER:

1. "Study shows a significant decrease in depression after taking psilocybin"
Vader score = -.4404
2. "Escape to nature, even if just for a 30 minute walk.. it will greatly lower your stress levels and reduce risk of depression"
Vader score = -.309
3. "Singing helps reduce feelings of depression and anxiety, increases oxygen to your lungs."
Vader score = -.4215
4. "Listening to music for an hour every day can reduce chronic pain by up to 21% and depression by up to 25%"
Vader score = -.7906

Our Observation on VADER

When we have polarity reversal words in tweets with a negative sentiment word, then the output of VADER is different from the expected value.

This list of tweets is not sufficient to draw any concrete conclusion, and hence we cannot make any claims about the accuracy of VADER.

Our objective of such a test was to find a category of tweets for which it is difficult to predict sentiment.

This led to our search for a method that can determine sentiment of tweets with polarity reversal words.

Parse Tree Based Approach (Rule 1)

Voting with Polarity Reversal

Polarities of nodes in a parse tree are reversed if they have odd numbers of reversal phrases in their ancestors.

Add polarities of all nodes

Word node in a tree

$r_j = 1$ if there is a reverse polarity word in Ancestor list
Else $r_j = 0$

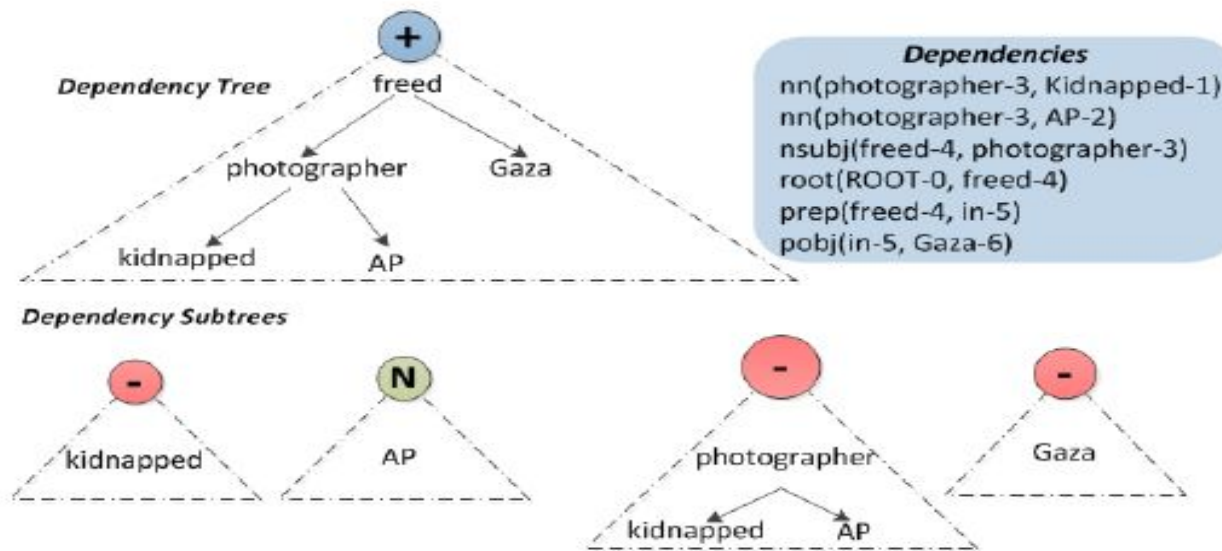
$p = \text{pos}$, when $\text{sum} > 0$
 $p = \text{neg}$, when $\text{sum} < 0$
else $p = \text{neutral}$

$$p = \text{val} \left(\sum_{i=1}^n m_i \prod_{j \in A_i} (-1)^{r_j} \right)$$

Set of ancestors

Parse Tree Based Approach (Rule 2)

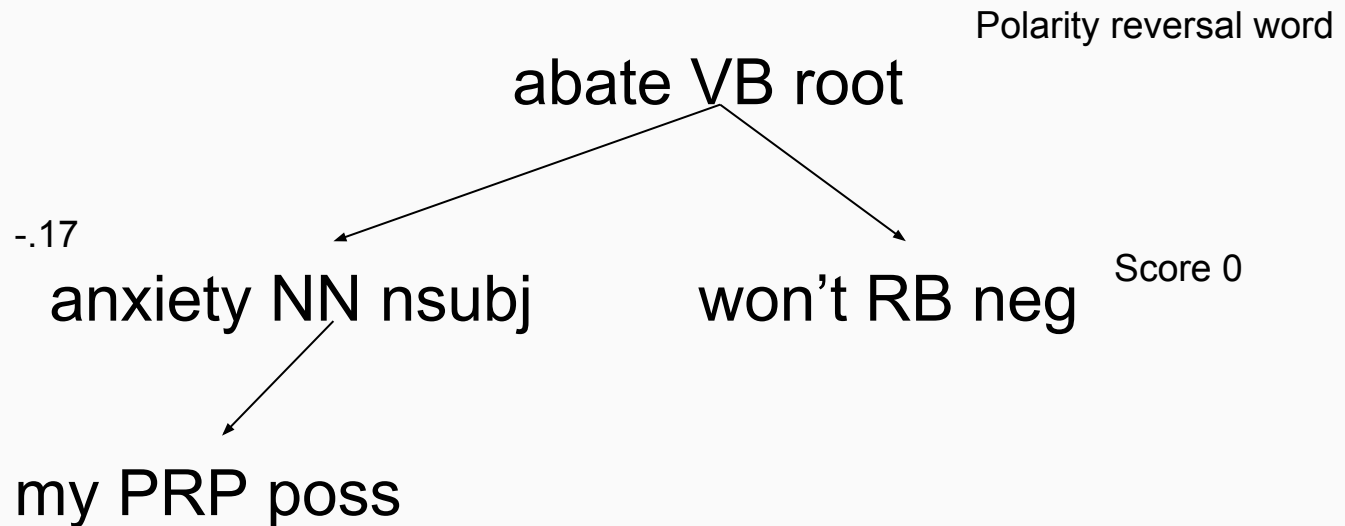
Reverse polarity of subtrees if head is a polarity reversal word.
Add sub trees polarity to get the polarity of overall sentence (Root)



Rule 1 Fails

Both in sentiwordnet and VADER
Score of Negation words in Lexicon is 0.

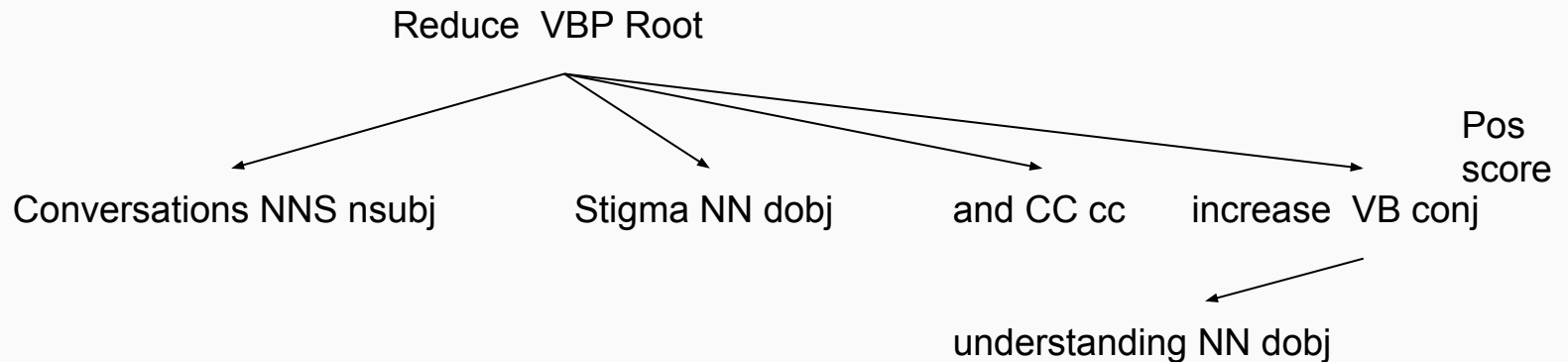
Tweet -> My Anxiety won't abate



Rule 2 Fails

Tweet ->Conversations reduce stigma and increase understanding.

Polarity of increase should not be reversed due to word 'reduce'



And here 'and' is connecting two clauses and not two words.

How to detect that in parse tree?

Improvement

Straightforward application of Rules will give wrong results

Approach 1.

Detection of two independent clauses from a Parse tree.

Compute sentiment on each of them separately and add them.

Example :

Conversation reduces stigma

Conversation increases understanding

Improvement Continued

Approach 2

Do a sentential analysis. Find subject, verb, and object.

And decide when to reverse polarity based on the head node.

Our Approach :

1. Do further analysis only if the conjunction is connecting two clauses rather than two words.
2. Do not reverse polarity due to a polarity reversal word in head node, if
 - a. The child is a verb and accompanied by a subject in its neighbor
 - b. The child has an object as its dependent

Our Approach Continued...

3. Use 'neg' part of speech to negate the overall polarity of head node.

Verification of Results:

We compared our results with VADER

Files after Topic Analysis	Tweet Count	Our Approach Accuracy
Topics_0	654	97.7%
Topics_1	552	96.3
Topics_2	688	99.56

Conclusions

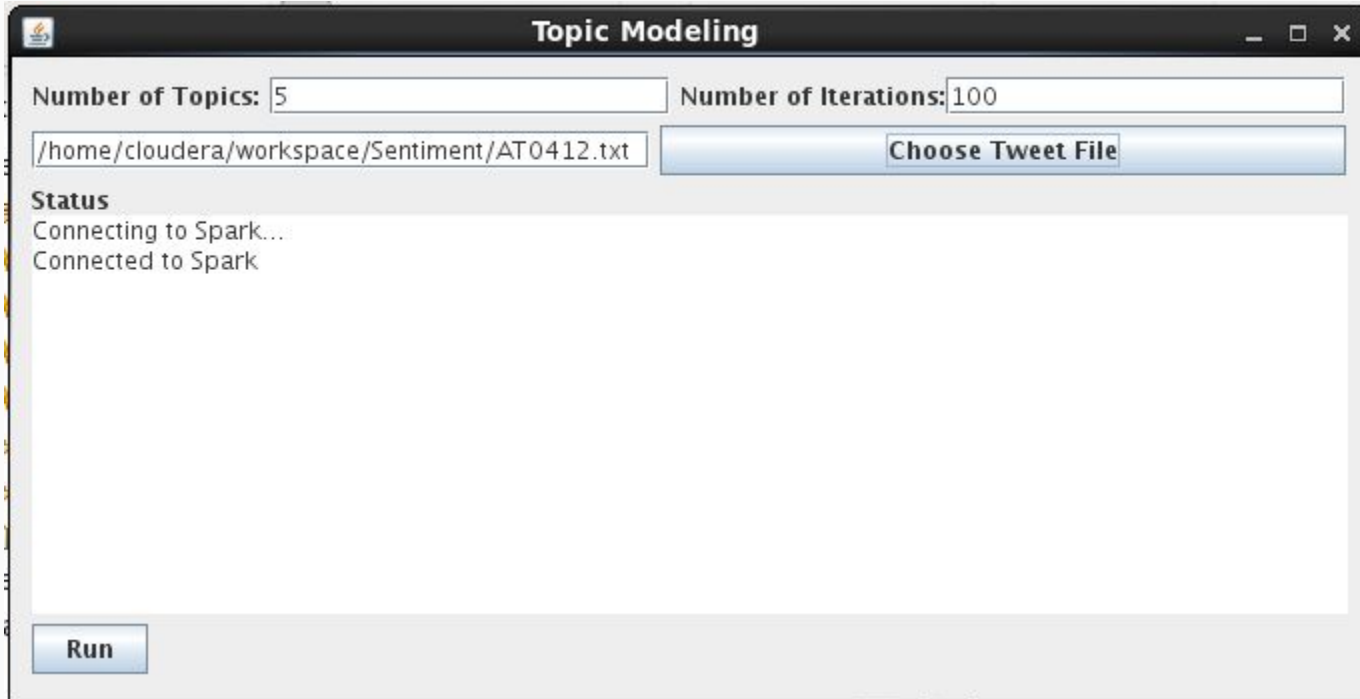
We found limitation in state of art tool VADER

Presented limitations in existing parse tree based approaches

Presented a better rule based approach which overcomes problems in previous approaches

Our approach showed good accuracy for general English tweets and not just tweets related to polarity reversal words.

Topic Analysis Interface (demo)



Topic Results

Identified Topics

Topic number 0:
trail: 0.09220212604989712
hike: 0.050863271207284594
appalachian: 0.04511902467057008
things: 0.01510387714694663
appalachiantrail: 0.011492325681921317
Topic number 1:
rt: 0.14814471530496667
appalachian: 0.09972351456072094
#tairp: 0.02119881798427045
#indigenous: 0.02119881798427045
@americanindian8: 0.020684473097603753
Topic number 2:
#at2017: 0.07303230498965986
@thetrek: 0.05524829300352795
hiking: 0.0426188621483663
rt: 0.025782707438967364
hiker: 0.025257788415450563
Topic number 3:
appalachian: 0.06360684000577974
trail: 0.036898654684377384
#hiking: 0.035171289819039754
#trail: 0.019847861983220368
gear: 0.019156876215699854
Topic number 4:

trail
hike
appalachian
things
appalachiantrail
rt
#tairp
#indigenous
@americanindian8
#at2017
@thetrek
hiking
hiker
#hiking
#trail
gear
#appalachiantrail
new
va

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Re-Run

Finish

First Pass Results - Reasonable results but not all meaningful

Topic Results

Identified Topics

Topic number 0:
 trail: 0.09220212604989712
 hike: 0.050863271207284594
 appalachian: 0.04511902467057008
 things: 0.01510387714694663
 appalachiantrail: 0.011492325681921317

Topic number 1:
 rt: 0.14814471530496667
 appalachian: 0.09972351456072094
 #tairp: 0.02119881798427045
 #indigenous: 0.02119881798427045
 @americanindian8: 0.020684473097603753

Topic number 2:
 #at2017: 0.07303230498965986
 @thetrekat: 0.05524829300352795
 hiking: 0.0426188621483663
 rt: 0.025782707438967364
 hiker: 0.025257788415450563

Topic number 3:
 appalachian: 0.06360684000577974
 trail: 0.036898654684377384
 #hiking: 0.035171289819039754
 #trail: 0.019847861983220368
 gear: 0.019156876215699854

Topic number 4:

<p>#indigenous #at2017 va gear @thetrekat new @americanindian8 #tairp</p>	<p>trail #hiking rt appalachian appalachiantrail hike hiker things #appalachiantrail #trail hiking</p>
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Filtering topic words that don't contribute meaning

Topic Results

Identified Topics

Topic number 1:
 5: 0.01571722876285292
 thruhikers: 0.012579547329638608
 thruhiker: 0.012566871814079542
 thruhike: 0.010651317950181937
 thru: 0.010626772087766138

Topic number 2:
 #tairp: 0.026796846204839297
 #indigenous: 0.026796846204839297
 @americanindian8: 0.026146256569298542
 mcafee: 0.017894562390441637
 knob: 0.017894562390441637

Topic number 3:
 new: 0.01777387473398445
 80yearold: 0.015484849801179451
 get: 0.014742714609189444
 #hike: 0.014106336249658978
 long: 0.013363491743750979

Topic number 4:
 #at2017: 0.0886827521727909
 @thetrek: 0.06533404525834756
 along: 0.018372529016660744
 im: 0.018219858766484225
 gear: 0.017024598806752077

<p>#travel va sunrise catawba halfway 5 thruhikers thruhiker thruhike thru #tairp #indigenous @americanindian8 mcafee knob new 80yearold get #hike long #at2017 @thetrek</p>	<p>trail #hiking rt appalachian appalachiantrail hike hiker things #appalachiantrail #trail hiking</p>
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Second Pass Results - Topics start to become more defined

Topic Results

Identified Topics

Topic number 0:
#travel: 0.019037395276840414
va: 0.017585128058131682
sunrise: 0.01737546103835172
catawba: 0.017162258743414125
halfway: 0.016313580408116864
Topic number 1:
5: 0.01571722876285292
thruhikers: 0.012579547329638608
thruhiker: 0.012566871814079542
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#tairp: 0.026796846204839297
#indigenous: 0.026796846204839297
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mcafee: 0.017894562390441637
knob: 0.017894562390441637
Topic number 3:
new: 0.01777387473398445
80yearold: 0.015484849801179451
get: 0.014742714609189444
#hike: 0.014106336249658978
long: 0.013363491743750979
Topic number 4:

catawba
#indigenous
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@thetrekat
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#travel
new
sunrise
thru
@americanindian8
get
#tairp
along

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#hiking
rt
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appalachiantrail
hike
hiker
things
#appalachiantrail
#trail
hiking
5
im
thruhike
#hike
thruhiker

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Re-Run

Finish

Repeat as Necessary

- Process can be repeated any number of times
- Continue to remove uninteresting terms until topics become meaningful
- Finish button writes result sets to file for sentiment processing

Future Work

Future Work

- Lemmatization and stemming for topic analysis
- More labeled data
 - Incorporate specialized hand-labeled data
 - Use pre-defined dictionary
- Combine NER with parse trees technique to get the polarity of entities
- Use part of speech tags and apply machine learning techniques to determine sentiment of tweet
- Add more granular controls and sentiment analysis to user interface

Questions?

