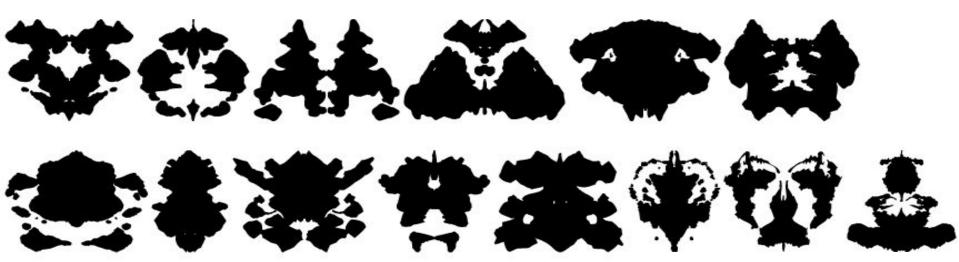


# **Emotional Impacts of Viral Content**

Sentiment Analysis of Social Media Comments



As user comments have grown in popularity to become a staple of internet behavior, the visibility of consumer content has only increased. Given the reputation of the comments section as an emotionally fraught place, what are the emotional impacts of the most popular

internet content?

Collect comment data

Train a model on Emotion vocabulary Feed comment data to the model

Interpret model results

Tag posts with associated emotions

#### **Data Sources:**

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YouTube.com + Reddit.com

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National Research Council Canada

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Logistic Regression

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### A Note on Virality...

### Data Sources

### **Data Sources**







### Data Collection

### Data Collection: Social Media Posts

- Calls to the YouTube and Reddit APIs
- Search for posts that fit "viral" criteria
- Account for the nested nature of comment threads
- Structure the JSON output appropriately

### What was in the data sets?

#### NRC Emotion Lexicon:

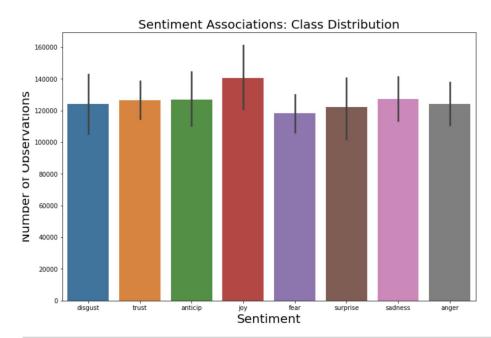
- 19236 rows of terms
- Between 2 and 5 synonyms for each term
- Associations of each term with one or more of eight emotions:
  - anger, fear, anticipation, trust, surprise, sadness, joy, or disgust
- Associations of each term with either a negative or positive sentiment

#### Social Media Data:

- 651 rows of unique social media posts
- Title, description, likes/dislikes, view count, total comment count, date published
- 50+ comments per post

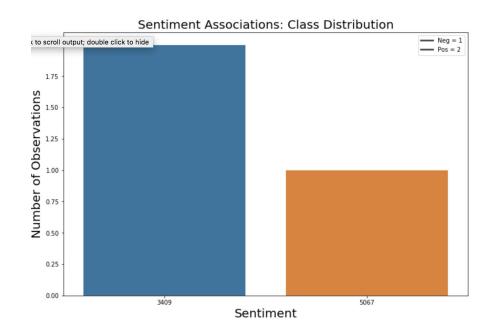
### Visualizing the NRC Class Distributions

fear	1939
anger	1623
trust	1589
sadness	1513
disgust	1343
joy	1104
anticip	1016
surprise	633



### Visualizing the NRC Class Distributions

negative 5067 positive 3409



### Data Structure

	Term	AffectCategory	Flag	Synonym_1	Synonym_2	Synonym_3	Synonym_4
30	guide	fear	0	teaching	direct	breed	None
31	guide	anger	0	teaching	direct	breed	None
32	guide	anticip	0	teaching	direct	breed	None
33	guide	trust	1	teaching	direct	breed	None
34	guide	surprise	0	teaching	direct	breed	None
35	guide	positive	1	teaching	direct	breed	None
36	guide	negative	0	teaching	direct	breed	None
37	guide	sadness	0	teaching	direct	breed	None
38	guide	disgust	0	teaching	direct	breed	None
39	guide	joy	0	teaching	direct	breed	None

#### Data Structure

		Term	AffectCategory	Flag	Synonym_1	Synonym_2	Synonym_3	Synonym_4
3	30	guide	fear	0	teaching	direct	breed	None
3	31	guide	anger	0	teaching	direct	breed	None
3	32	guide	anticip	0	teaching	direct	breed	None
3	33	guide	trust	1	teaching	direct	breed	None
3	34	guide	surprise	0	teaching	direct	breed	None
[3	35	guide	positive	1	teaching	direct	breed	None
3	36	guide	negative	0	teaching	direct	breed	None
3	37	guide	sadness	0	teaching	direct	breed	None
3	38	guide	disgust	0	teaching	direct	breed	None
3	39	guide	joy	0	teaching	direct	breed	None

Process

Train a model on Emotion vocabulary Feed comment data to the model

**Process** 

Phase 1

Train a model on Emotion vocabulary

- Emotion + Sentiment data from the NRC Lexicon
- Supervised

Feed comment data to the model

**Process** 

#### Phase 1

Train a model on Emotion vocabulary

- Emotion + Sentiment data from the NRC Lexicon
- Supervised

#### Phase 2

Feed comment data to the model

- Comment text data from YouTube + Reddit
- Unsupervised

Part I: Sentiment

Part I: Sentiment

Baseline Accuracy:

Part I: Sentiment

#### Baseline Accuracy:

negative 0.597806 positive 0.402194

Part I: Sentiment

Baseline	Accuracy:	Overall Accuracy:			
negative	0.597806	Sentiment Train Score: 0.991977347805568			

positive 0.402194 Sentiment Test Score: 0.8876828692779613

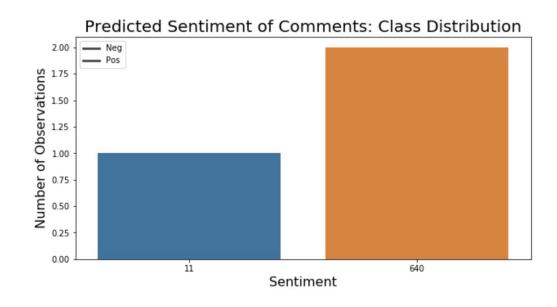
Part I: Sentiment

Test Data: Class

Distribution

Negative: 11 comments

Positive: 640 comments



Part II: Emotion

Part II: Emotion

Approach # 1

Part II: Emotion

Approach # 1

Multiclass Classification

Predict all emotion categories at the same time

Part II: Emotion

Approach # 1

Multiclass Classification

Predict all emotion categories at the same time

#### Baseline Accuracy:

fear	0.180204
anger	0.150836
trust	0.147677
sadness	0.140613
disgust	0.124814
joy	0.102602
anticip	0.094424
surprise	0.058829

Part II: Emotion

Approach # 1

**Multiclass Classification** 

Predict all emotion categories at the same time

#### Baseline Accuracy:

fear	0.180204
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#### Train-Test Split Accuracy:

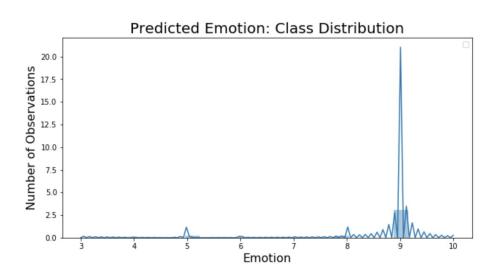
Emotion Train Score: 0.6509293680297398 Emotion Test Score: 0.2382899628252788

Part II: Emotion

Approach # 1

Multiclass Classification

Predict all emotion categories at the same time



Part II: Emotion

Part II: Emotion

Approach # 2

Part II: Emotion

Approach # 2

Multiple Binary Classifications

#### Part II: Emotion

Emotion Train Score, Target_ Emotion Test Score, Target_4		Approach # 2
Emotion Train Score, Target_ Emotion Test Score, Target_5	•	Multiple Binary Classifications
Emotion Train Score, Target_ Emotion Test Score, Target_6		One binary regression per emotion category
Emotion Train Score, Target_ Emotion Test Score, Target_7	The state of the s	
Emotion Train Score, Target_ Emotion Test Score, Target_8		
Emotion Train Score, Target_ Emotion Test Score, Target_9		

#### Part II: Emotion

Emotion Train Score, Target\_4:
Emotion Test Score, Target\_4:

Emotion Train Score, Target\_5:
Emotion Test Score, Target\_5:

Emotion Train Score, Target\_6:
Emotion Test Score, Target 6:

Emotion Train Score, Target\_7:
Emotion Test Score, Target 7:

Emotion Train Score, Target\_8: Emotion Test Score, Target 8:

Emotion Train Score, Target\_9:
Emotion Test Score, Target 9:

0.8807930607187113 0.8182156133828996

0.9313<mark>5</mark>06815365551 0.8460<mark>9</mark>6654275093

0.8947955390334572 0.8412639405204461

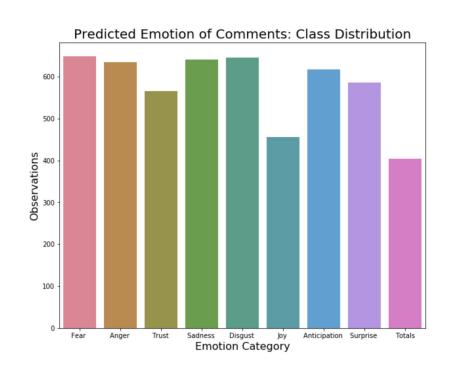
0.9017348203221809 0.866542750929368

0.9293<mark>68029739777</mark> 0.8680<mark>297397769516</mark>

0.9240<mark>396530359356</mark> 0.8947955390334572 Approach # 2

Multiple Binary Classifications

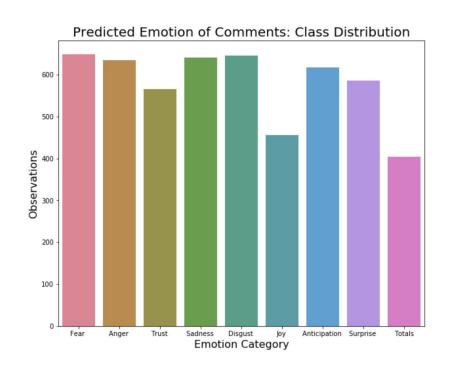
#### Part II: Emotion



Approach # 2

Multiple Binary Classifications

#### Part II: Emotion



#### Approach # 2

#### Multiple Binary Classifications

```
649 comments associated with Fear
634 comments associated with Anger
565 comments associated with Trust
640 comments associated with Sadness
646 comments associated with Disgust
456 comments associated with Joy
617 comments associated with Anticipation
586 comments associated with Surprise
```

Conclusion:

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 NLP and logistic regression can be used to model emotional sentiment in text data with reasonably reliable results.

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 NLP and logistic regression can be used to model emotional sentiment in text data with reasonably reliable results.

Suggestions for Future Iterations:

#### Conclusion:

• NLP and logistic regression **can** be used to model emotional sentiment in text data with reasonably reliable results.

#### Suggestions for Future Iterations:

- Utilize advanced modeling techniques, such as clustering and neural networks
- Incorporate token coefficients into the results, in order to create a valence of emotional intensity
- Experiment with different preprocessing and embedding methods, such as sentence2vec, in order to improve accuracy

# Thank You.