MID SEMESTER PROGRESS REPORT ON

Predicting Psychological Impact of Famous Speeches On People

Submitted by

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Introduction

Famous speeches are powerful tools of persuasion and influence. They can inspire, motivate, challenge, or even manipulate the emotions of the listeners. However, not all speeches have the same effect on different people. Some may find a speech uplifting, while others may find it boring or offensive. How can we measure and predict the psychological impact of famous speeches on people?

In this project, we aim to build a model that can predict the psychological impact of famous famous speeches on people. We define psychological impact as the emotional response of the listeners to the speech, such as happiness, sadness, anger, fear, or surprise. We use a survey method to collect people's emotions on various famous speeches, such as Martin Luther King Jr.'s "I Have a Dream", Barack Obama's "Yes We Can", or Narendra Modi's "Make in India". We then use natural language processing techniques to convert the speeches into word vectors, which are numerical representations of the words and their meanings.

The main objectives of this project are:

- To collect data on people's emotions on various famous speeches using surveys.
- To preprocess and vectorize the speeches using natural language processing techniques.
- To create a dataset that has word vectors of the speeches as input features and emotions of the listeners as output labels.
- To develop a classification model that can predict the psychological impact of famous speeches on people.

The expected outcomes of this project are:

- A dataset that contains word vectors of famous famous speeches and emotions of the listeners.
- A classification model that can predict the psychological impact of famous speeches on people.
- A report that summarizes the findings and limitations of the project.

Motivation

We believe that by building a model that can predict the psychological impact of famous famous speeches on people, we will contribute to the understanding of how language and emotion interact in famous communication. We also hope that our project will have practical applications for famous speechwriters, analysts, or researchers who want to craft or assess famous speeches based on their desired or expected psychological impact. Key motivations to do this project are:

1. To explore the relationship between language and emotion in famous communication.
2. To evaluate the effectiveness and impact of famous speeches on public opinion and social change.
3. To develop a tool that can help famous speechwriters, analysts, or researchers to craft or assess famous speeches based on their desired or expected psychological impact.

Problem statement

The psychological impact of famous speeches on people is not well understood. How do people react emotionally to different famous speeches? What factors affect their emotional response? How can we measure and predict their psychological impact using machine learning?

The problem we want to solve is challenging because:

- famous speeches are complex and nuanced texts that convey various messages and arguments.
- People’s emotions are subjective and influenced by many factors, such as their background, beliefs, values, and expectations.
- The dataset we create may be imbalanced, noisy, or incomplete.
- The classification model we develop may have limitations in generalization, accuracy, or interpretability.

LITERATURE SURVEY

PAPER	DESCRIPTION	REFERENCE
Deep Learning Techniques for Speech Emotion Recognition, from Databases to Models	This paper provides a summary of the datasets, techniques, and strategies used in SER, followed by the difficulties. They talk about the datasets and techniques described in the research in the first section before moving on to the difficulties SER faces.	https://www.mdpi.com/1424-8220/21/4/1249
Research on the dissemination of celebrities' opinions based on speech act theory and potential category analysis	This research paper aims to investigate the influence of celebrity language style on user behavior and opinions in the context of social media.	https://www.frontiersin.org/articles/10.3389/fpsyg.2022.1041644/full#B42

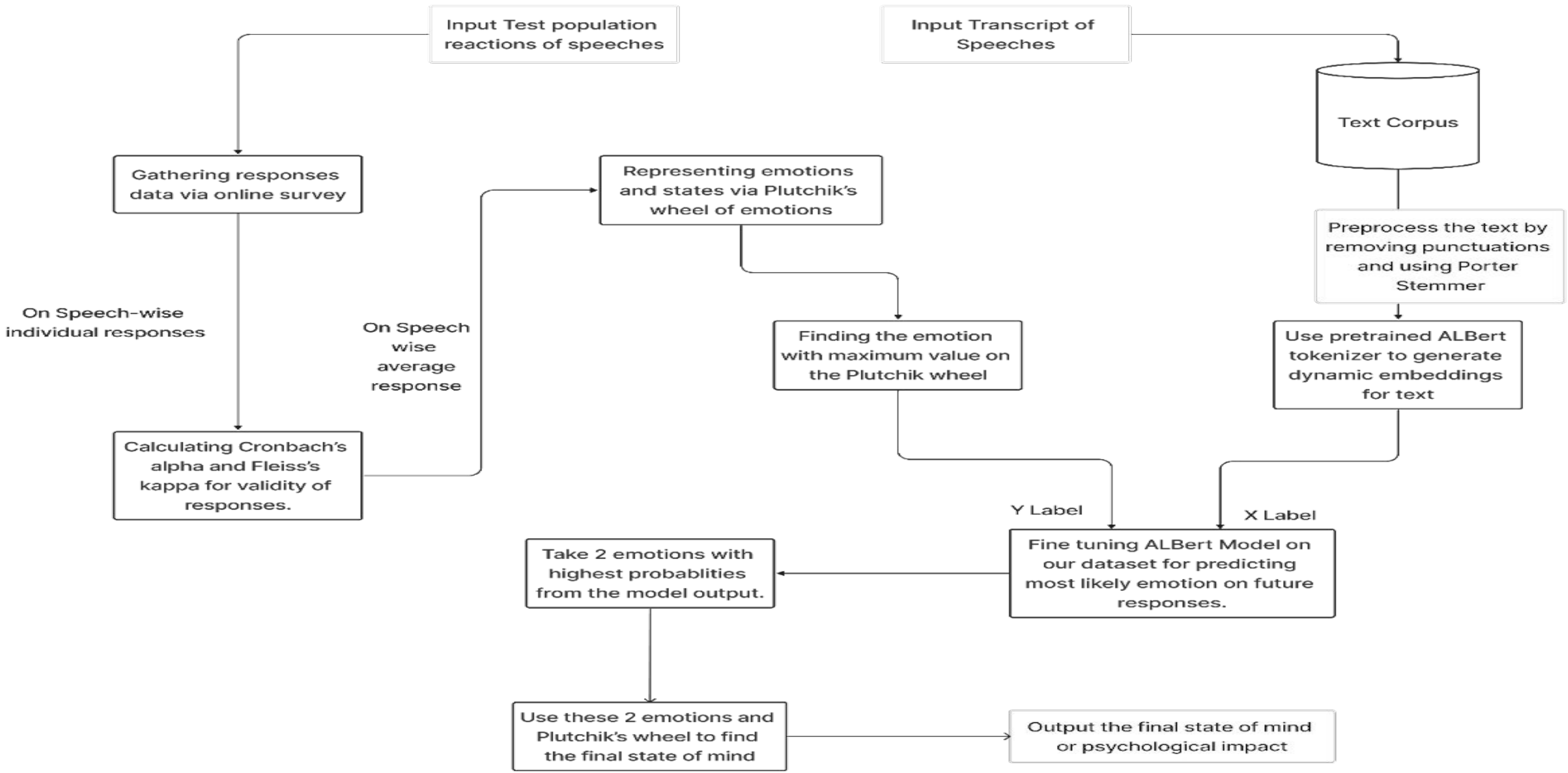
Speech Emotion Recognition Ashish B. Ingale, D. S. Chaudhari	This research paper reviews voice emotion recognition technologies using classifiers to distinguish between emotions like surprise, happiness, sorrow, and rage.	http://surl.li/lyjux
Summarizing Emotions from Text Using Plutchik's Wheel of Emotions	This paper analyzes an online blog post about online shopping using Plutchik's wheel of emotions, a 1980 theory that categorizes emotions into eight main groups.	https://ieeexplore.ieee.org/document/9336534
Mining Emotions on Plutchik's Wheel Abhijit Mondal, Swapna S. Gokhale	This paper proposes a supervised machine learning approach to detect emotions from tweets, based on a Crowdflower data set of 40,000 tweets labeled with 13 distinct emotions	https://ieeexplore.ieee.org/document/9336534

Cronbach's Alpha (α)using SPSS Statistics	This paper looks into Cronbach's Alpha as a index for assessing the internal consistency and reliability of scales with multiple elements.	https://link.springer.com/article/10.3758/BF03192845
Likert Scales and Data Analyses	This paper analyses likert scales as a standard rating method, ranging from least to most, with respondents indicating their agreement or disagreement.	https://www.bayviewanalytics.com/reports/asq/likert-scales-and-data-analyses.pdf
Fleiss' kappa statistic without paradoxes	This work provides a novel way to avoid the dilemma of the Fleiss' kappa statistic, which may behave inconsistently under strong agreement, and investigates the problem of kappa confidence intervals	https://link.springer.com/article/10.1007/s11135-014-0003-1
Albert - A Lite Bert For Self-Supervised Learning of Language Representations	The study provides two parameter reduction methodologies for lowering memory consumption and enhancing BERT training speed, addressing memory limits, and training for extended periods of time.	https://openreview.net/pdf?id=H1eA7AEtvS

Methodology

The project is wholly divided into 2 parts:

1. Gathering surveys and creating dataset
2. Implementing the classification model.


Input Test population reactions of speeches
Input Transcript of Speeches
Text Corpus
Gathering responses data via online survey
Representing emotions and states via Plutchik's wheel of emotions
Preprocess the text by removing punctuations and using Porter Stemmer
On Speech-wise individual responses
On Speech wise average response
Finding the emotion with maximum value on the Plutchik wheel
Use pretrained ALBert tokenizer to generate dynamic embeddings for text
Calculating Cronbach's alpha and Fleiss's kappa for validity of responses.
Y Label
X Label
Take 2 emotions with highest probablities from the model output.
Fine tuning ALBert Model on our dataset for predicting most likely emotion on future responses.
Use these 2 emotions and Plutchik's wheel to find the final state of mind
Output the final state of mind or psychological impact

Implementation

Till now, we have done the following parts of the project:

1. Collecting transcripts of the following famous speeches:

    1) Winston Churchill's "We Shall Fight on the Beaches" Speech (1940):
    2) Martin Luther King Jr.'s "I Have a Dream" Speech (1963):
    3) John F. Kennedy's Inaugural Address (1961):
    4) Nelson Mandela's Inaugural Address (1994):
    5) Malala Yousafzai's United Nations Speech (2013):
    6) Steve Jobs' Stanford Commencement Speech (2005):
    7) Elie Wiesel's Nobel Peace Prize Acceptance Speech (1986):
    8) Greta Thunberg's Climate Change Speeches (Various):
    9) Barack Obama's Farewell Address (2017):
    10) Aung San Suu Kyi's Nobel Lecture (2012):

2. Create and distribute surveys in public so people can listen to speeches and rate their emotions on the same : https://forms.gle/Aus62EJepvc7oX358

Questionnaire

beetleeater2711@gmail.com Switch account

Not shared

Which speech have you listened to/read?

- Winston Churchill's "We Shall Fight on the Beaches" Speech (1940):
- Martin Luther King Jr.'s "I Have a Dream" Speech (1963):
- John F. Kennedy's Inaugural Address (1961):
- Steve Jobs' Stanford Commencement Speech (2005):
- Nelson Mandela's Inaugural Address (1994)
- Malala Yousafzai's United Nations Speech (2013):
- Elie Wiesel's Nobel Peace Prize Acceptance Speech (1986):
- Aung San Suu Kyi's Nobel Lecture (2012):
- Other:

How much time did you spend reading the speech/hearing the speech?(In Minutes)

Your answer

On a scale of 0-10(0 being strongly disagree,10 being strongly agree), how much do you agree with these statements?

1. the speech was trying to convey feelings of Anger

0 1 2 3 4 5 6 7 8 9 10

strongly disagree ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ strongly agree

2. the speech was trying to convey feelings of Anticipation

0 1 2 3 4 5 6 7 8 9 10

strongly disagree ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ strongly agree

3. the speech was trying to convey feelings of Joy

0 1 2 3 4 5 6 7 8 9 10

strongly disagree ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ strongly agree

4. the speech was trying to convey feelings of Trust

0 1 2 3 4 5 6 7 8 9 10

strongly disagree ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ strongly agree

5. the speech was trying to convey feelings of Fear

0 1 2 3 4 5 6 7 8 9 10

strongly disagree ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ strongly agree

6. the speech was trying to convey feelings of Surprise

0 1 2 3 4 5 6 7 8 9 10

strongly disagree ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ strongly agree

7. the speech was trying to convey feelings of Sadness

0 1 2 3 4 5 6 7 8 9 10

strongly disagree ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ strongly agree

8. the speech was trying to convey feelings of Disgust

0 1 2 3 4 5 6 7 8 9 10

strongly disagree ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ strongly agree

Submit

Clear form

3.Write python code to input responses from the survey, preprocess the form data and then use a python library called **Pyplutchik** to plot the Plutchik wheel of emotions using the emotion values from the survey for each speech. The python script does the following tasks:

a. Read survey responses from google sheets file. Figure 2 shows the first five values from the dataset.

b. Replace and fix columns names

c. Delete Null and partially empty responses

d. Calculate speechwise average values for emotions. Figure 3 shows the average of all the emotions for each speech.

```
[2]: df=pd.read_csv("responses.csv", header=1)
```

```
[3]: df
```

[3]:

	Timestamp	Which speech have you listened to/read?	How much time did you spend reading the speech/hearing the speech?(In Minutes)	1. the speech was trying to convey feelings of Anger	2. the speech was trying to convey feelings of Anticipation	3. the speech was trying to convey feelings of Joy	4. the speech was trying to convey feelings of Trust	5. the speech was trying to convey feelings of Fear	6. the speech was trying to convey feelings of Surprise	7. the speech was trying to convey feelings of Sadness	8. the speech was trying to convey feelings of Disgust
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	10/17/2023 22:58:21	Martin Luther King Jr.'s "I Have a Dream" Spee...	6.0	7.0	5.0	7.0	10.0	4.0	4.0	7.0	8.0
3	10/17/2023 23:01:44	Barack Obama's Farewell Address (2017):https:/...	NaN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	10/17/2023 23:03:00	Steve Jobs' Stanford Commencement Speech (2005...	75.0	0.0	6.0	2.0	10.0	1.0	3.0	5.0	0.0

4 . Next, we want to create the dataset on which we want to train our classification model. We chose the speech transcripts as the X labels and the strongest emotion or emotion with highest value on the Plutchik wheel as our Y label.

```
df=pd.read_csv('one_output_dataset.csv')
df
```

	speech	emotion
0	From the moment that the French defenses at Se...	anger
1	We observe today not a victory of party but a ...	joy
2	Your Majesties, Your Highnesses, Distinguished...	trust
3	I am honored to be with you today at your comm...	anticipation
4	Honorable UN Secretary General Mr Ban Ki-moon,...	sadness

5. We had taken responses on only 10 individual speeches, so our final dataset consisted of only 10 datapoints or 10 rows.

6. To combat with this shortage of data, we decided to use a pre trained transformer model, Google's ALBert in this case, to generate dynamic word embeddings for our transcripts and also use it for the classification task.

7. In the next steps, we focused on doing the following tasks:

a. We load out X and Y label dataset using pandas

b. We encode our labels by converting them from string to float starting from 0.0 to 5.0 using a Python dict to

```
dict={'anger':0.0, 'joy':1.0, 'trust':2.0, 'anticipation':3.0, 'sadness':4.0, 'fear':5.0}
df=df.replace(dict)
df['emotion'] = df['emotion'].apply(pd.to_numeric)
df
```

	speech	emotion
0	From the moment that the French defenses at Se...	0.0
1	We observe today not a victory of party but a ...	1.0
2	Your Majesties, Your Highnesses, Distinguished...	2.0
3	I am honored to be with you today at your comm...	3.0
4	Honorable UN Secretary General Mr Ban Ki-moon,...	4.0

C. . Next, we perform preprocessing on the speech transcripts using the following steps:

i. Perform lowercase conversion
ii. Remove punctuation marks
iii. Tokenize the text
iv. Remove stopwords
v. Perform stemming on the tokens

D. Then we split the dataset into train and test datasets in 80:20 ratio.

E. Here, we use the pretrained ALBert tokenizer to generate word embedding and attention masks of the text we preprocessed before. Figure 9 shows the code for albert tokenizer.

F. Finally, we convert the train and test features and labels into tensor slices and subsequently convert them into tensorflow Datasets for seamless compatibility with tensorflow. Figure 10 shows the code for the same.

8. Now we need to fine tune the ALBert model. For this task, we will use the transformers library api which allows us to download pre trained weights for the ALBert model for sequence classification tasks.

9. We initiate the model, specifying the number of labels as 6 in our case. This ensures that the dense output layer at the end of the model has 6 neurons. The model metrics are defined and the model is compiled and subsequently fit on the train dataset, validating the results on the test dataset.

```
#define model metrics
optimizer = tf.keras.optimizers.Adam(learning_rate=3e-5)
loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
metrics = ['accuracy']
```

```
model.summary()
```

```
Model: "tf_albert_for_sequence_classification"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 albert (TFAlbertMainLayer)  multiple                  17683968

 dropout_4 (Dropout)         multiple                  0

 classifier (Dense)          multiple                  6150

=================================================================
Total params: 17690118 (67.48 MB)
Trainable params: 17690118 (67.48 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

10. We then save the model weights using tensorflow. The outputs are then passed through a softmax layer so that we get the probabilities of each emotion being classified by the model.

11. To predict the psychological state of mind, we take the top two emotions from the model output which have the 2 highest probabilities, and then compare it in our Plutchik wheels Primary, Secondary and tertiary dyads to get the final state of mind.

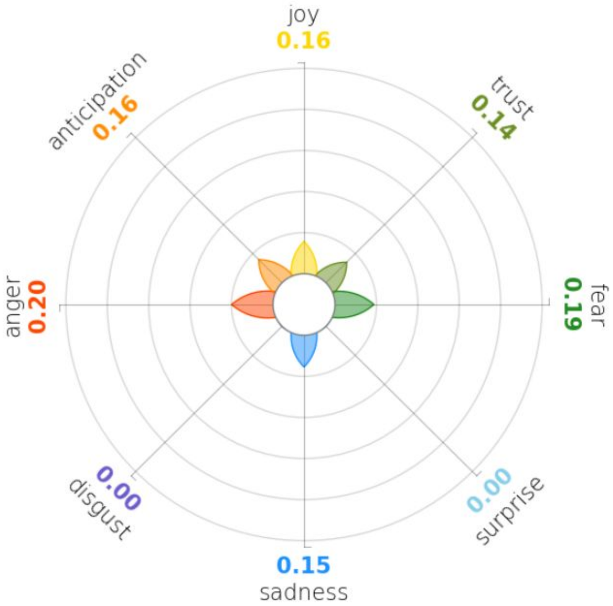
12. Checking validity of the data collected using Fleiss’ kappa and Cronhach’s Alpha. These coefficients are being used to assess the agreement between different respondents for a particular speech and the similarity between questions asked in the questionnaire.

Fleiss’ kappa was calculated separately by segregating the form responses for each speech, while Cronbach’s alpha was calculated for all the responses.

Results

The ALBERT model was trained on a dataset of speech samples, each labeled with one of the target emotions. The model achieved an accuracy of 12.5%. This metric is misleading since we did not have enough and diverse training data to finetune our model on.

Despite the overall high performance, the model showed some difficulty in distinguishing between certain emotions. This could be due to the similarities in the speech patterns associated with these emotions. Another reason for this could be our constrained training data, since our survey consisted of very limited number of speeches.



Plutchik wheel of emotions plot on test data

Conclusion

This research aimed to understand the psychological impact of famous speeches by exploring subtle language details, emotional resonances, and audience-specific variables. The study faced challenges such as a small dataset, hindering model accuracy, and difficulties in data collection due to lengthy speeches. Findings emphasized the subjective nature of psychological responses, influenced by individual differences, cultural backgrounds, and contextual factors. The need for a predictive model accommodating diversity was highlighted, acknowledging the importance of multimodal elements like tone and gestures. The field's future potential lies in generalizability across cultural contexts, adapting to the changing media landscape, and incorporating advanced technologies for model enhancement. In conclusion, interdisciplinary collaboration is essential for developing robust models that contribute to both academic understanding and the responsible use of persuasive rhetoric in shaping informed and empathetic societies.

Thank You!