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PREDICTING PSYCHOLOGICAL IMPACT OF FAMOUS SPEECHES ON PEOPLE

Report submitted in partial fulfillment of requirements for the B.Tech. Degree in Computer Science and Engineering

By

NAME OF THE STUDENT	**ROLL NUMBER**
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Under the Supervision
of
(Prof. Shampa Chakraverty)

Department of Computer Science and Engineering
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New Delhi, India-110078

DECEMBER 2023

CERTIFICATE

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

This is to certify that the work embodied in project thesis titled, **“Predicting Psychological Impact of Famous Speeches on People”** by Arjun Kulkarni (2020UCO1505), Raunak Singhal (2020UCO1529) and Himanshi (2020UCO1550) is the bonafide work of the group submitted to **Netaji Subhas University of Technology** for consideration in 7^{th} Semester B.Tech. Project Evaluation.

The original Research work was carried out by the team under my/our guidance and supervision in the academic year 2022-2023. This work has not been submitted for any other diploma or degree of any university. On the basis of a declaration made by the group, we recommend the project report for evaluation.

Prof. Shampa Chakraverty
(Professor)
Department of Computer Science & Engineering
Netaji Subhas University of Technology

CANDIDATE(S) DECLARATION

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

I/We, Arjun Kulkarni (2020UCO1505), Raunak Singhal (2020UCO1529) and Himanshi (2020UCO1550) of B. Tech. Department of Computer Science and Engineering, hereby declare that the Project-Thesis title **“Predicting Psychological Impact of Famous Speeches on People”** which is submitted by me/us to the Department of Computer Science & Engineering, Netaji Subhas University of Technology (NSUT) Dwarka, New Delhi in partial fulfillment of the requirements for the award of the degree of Bachelors of Technology is original and not copied from the source without proper citation. The manuscript has been subjected to plagiarism checks by Turnitin software. This work has not previously formed the basis for the award of any Degree.

Place:

Date:

Arjun Kulkarni	Raunak Singhal	Himanshi
2020UCO1505	2020UCO1529	2020UCO1550

CERTIFICATE OF DECLARATION

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

This is to certify that the Project-Thesis titled **“Predicting Psychological Impact of Famous Speeches on People”** which is being submitted by Arjun Kulkarni (2020UCO1505), Raunak Singhal (2020UCO1529) and Himanshi (2020UCO1550) to the Department of Computer Science & Engineering, Netaji Subhas University of Technology (NSUT) Dwarka, New Delhi in partial fulfillment of the requirements for the award of the degree of Bachelors of Technology, is a record of the thesis work carried out by the students under my supervision and guidance. The content of this thesis, in full or in parts, has not been submitted for any other degree or diploma.

Place:

Date:

Prof. Shampa Chakraverty

(Professor)

Department of Computer Science & Engineering

Netaji Subhas University of Technology

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Arjun Kulkarni	Raunak Singhal	Himanshi
2020UCO1505	2020UCO1529	2020UCO1550

ABSTRACT

This research delves into the fascinating realm of understanding the psychological impact of speeches delivered by prominent figures on the general populace. Leveraging sophisticated sentiment analysis tools and psychological profiling methodologies, our study investigates the multifaceted effects of influential individuals' oratory skills on the emotional and cognitive dimensions of their audience. By scrutinizing linguistic nuances, and identifying key rhetorical devices, we aspire to construct a predictive model capable of anticipating the psychological consequences of impactful speeches. This endeavor not only contributes to a nuanced comprehension of the persuasive dynamics inherent in public discourse but also aims to unveil the intricate interplay between language, emotion, and cognition. As the digital era amplifies the reach and influence of speeches through various media channels, our research holds implications for refining communication strategies, optimizing public speaking engagements, and comprehending the mechanisms behind the shaping of societal attitudes. By elucidating the underpinnings of the psychological impact of influential speeches, this study aspires to empower individuals, communicators, and policymakers with knowledge that can enhance the ethical and effective use of persuasive rhetoric in the public domain.

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INTRODUCTION

The psychological impact of speeches delivered by famous individuals on the general populace is a multifaceted phenomenon that encompasses emotional, cognitive, and behavioral dimensions[1]. Famous persons possess a unique ability to influence public opinion, shape societal attitudes, and evoke powerful emotional responses through their oratory skills. The impact is often rooted in the persuasive power of language, as charismatic speakers can sway emotions, instill hope, or provoke introspection with carefully chosen words.

Emotionally, impactful speeches can generate a range of feelings, from disgust and admiration to surprise or even anticipation. The charismatic delivery of a message, coupled with compelling narratives, can forge a strong emotional connection between the speaker and the audience. Psychologically, speeches can shape cognitive frameworks, influencing how individuals perceive issues, events, or even their own beliefs. Cognitive processes, such as persuasion and attitude change, come into play as speakers present compelling arguments or narratives that challenge existing viewpoints.

Behaviorally, the psychological impact of speeches can drive individuals to action. Famous speakers often use their platform to call for social change, encourage civic engagement, or advocate for specific causes. The audience's response may manifest in increased awareness, activism, or changes in behavior driven by the persuasive influence of the speaker.

In essence, the psychological impact of speeches by famous individuals is a dynamic interplay between language, emotion, cognition, and behavior. Understanding these intricate connections provides insights into the mechanisms through which public figures shape and influence the collective psyche.

MOTIVATION

The motivation behind predicting the psychological impact of famous speeches on people is rooted in the recognition of the profound influence that persuasive oratory holds in shaping societal attitudes, beliefs, and behaviors. Throughout history, iconic speeches have played pivotal roles in mobilizing movements, sparking revolutions, and fostering cultural shifts. Understanding the intricate interplay between spoken words and the human psyche holds profound implications for various disciplines, including psychology, communication studies, and public affairs.

We believe that by building a model that can predict the psychological impact of famous political speeches on people, we will contribute to the understanding of how language and emotion interact in political communication. We also hope that our project will have practical applications for political speechwriters, analysts, or researchers who want to craft or assess political 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 communication.
2. To understand how different leaders use rhetorical strategies to persuade and influence their audiences.
3. To evaluate the effectiveness and impact of political speeches on public opinion and social change.
4. To develop a tool that can help political speechwriters, analysts, or researchers to craft or assess political speeches based on their desired or expected psychological impact.

LITERATURE SURVEY

For our project we have done research on speech emotion recognition, sentiment analysis, ALBert Tokenizer and some of the statistical methods like cronbach’s alpha and Fleiss’s kappa which are required to measure the psychological impact of speech.

Below are some of the research papers we have collected regarding our project.

This research paper explores the impact of celebrity language style on user behavior and opinions on social media. It analyzes the language style characteristics in celebrities' opinions and how they influence communication patterns[1]. Drawing from speech act theory, the study proposes a model for categorizing celebrities' viewpoints. The findings suggest that public social platforms should promote positive guidance and energy to mitigate negative emotions and create a more positive online environment[7]. Despite advancements in SER's techniques and accuracy, there are still limitations to overcome. The main obstacle is the lack of datasets suitable for deep learning problems, with databases like ImageNet and Google AudioSet having millions of samples. Additionally, SER's databases only include a small amount of samples, and models built using discrete utterances would underperform in continuous speech scenarios[2]. The research paper discusses voice emotion recognition technologies using classifiers to distinguish between emotions like surprise, happiness, sorrow, and rage. The database uses emotional speech samples to retrieve energy, pitch, LPCC, and MFCC characteristics. The study found comparable identification rates between actual and acted emotional speech, with a Hidden Markov Model-based system achieving 70% accuracy for seven emotional states and a Support Vector Machine 73% accuracy for four main emotions[5].

The paper uses Plutchik's wheel of emotions to analyze an online blog post about online shopping. The theory categorizes emotions into eight groups, with positive and negative emotions being half each. The intensity of these emotions is determined by counting occurrences, multiplying with their weight, and adding intensity[6]. This research uses a Crowdflower dataset of 40,000 tweets to detect emotions using supervised machine learning. The method uses Plutchik's wheel to map emotions into pairs of polar opposites. Random Forest outperforms other classifiers in recognizing pair-wise emotions (87%).

The study also examines models like Random Forest, Support Vector Machines, Naive Bayes, Gradient Boosting, and Multi Layer Perceptron. The findings suggest linguistic and metadata factors improve accuracy[3]. The GEM-CW (Generative Emotion Model with Categorized Words) is a semi-supervised learning strategy for evaluating investor sentiment on stock message boards. The model evaluates messages, emotion, and words simultaneously, classifying them into three categories based on emotion strength. The model is effective for modeling sentiment in brief text and gains greater classification accuracy with appropriate training and test data. It uses the n-gram algorithm to categorize words into origin words, synonym words, and relevant words based on seven categories of emotions[8].

Cronbach's Alpha (α) is a widely used index for assessing the internal consistency and reliability of scales with multiple elements. It is commonly used in social science studies for memory, personality, and psychological dimensions. The upper bound of coefficient can be used to improve standardized Cronbach's estimation for dichotomous scales[9]. Quality is measured through surveys, such as consumer evaluations of product or service quality. Likert scales are a standard rating method, ranging from least to most, with respondents indicating their agreement or disagreement. These scales can be categorized into nominal, ordinal, interval, and ratio data. Analyzing ordinal data, particularly Likert scales, is complex, but the sufficiency of treating it as interval data is debated. Likert scales can be used in pain measurement, with paper surveys producing continuous intervals, and online surveys using track bars for adjustments. The ordinal character of data should be relied upon for analysis[10]. This study addresses the issue of Fleiss' kappa statistic, which can behave inconsistently under strong agreement, by developing a permutation-invariant version. The permutation-invariant version uses permutation methods without information loss, allowing for comparable agreement in fresh datasets. The study uses specialists in various fields, such as judges, archaeologists, psychologists, and psychiatrists, to measure the degree of agreement among survey respondents. The robust statistic, the median, summarizes the C values of Fleiss' kappa, and the Fleiss et al.

(2003) confidence interval, which is usable even when n is too small for Normal approximation[11]. The study presents two parameter reduction methodologies for reducing memory consumption and improving BERT training speed, addressing memory limits, and training for extended periods. The solutions increase model scalability and self-supervised loss, resulting in superior performance on benchmarks like GLUE, RACE, and SQuAD.

The research compares BERT and ALBERT models using BOOKCORPUS and English Wikipedia as pretraining baselines. The ABSBGRU model, an ALBERT-based Siamese network, combines the Bi-GRU of the Siamese structure with an attention mechanism to solve text similarity calculation problems. The experimental findings show that the ABSBGRU model outperforms other standard models in terms of deep semantic extraction ability, F1 Score, and training cost[12].

PROBLEM STATEMENT

This research addresses the challenge of predicting the psychological impact of renowned speeches on individuals. Despite the recognized influence of public figures in shaping societal attitudes, the specific linguistic, emotional, and contextual factors contributing to psychological responses remain inadequately understood. The aim is to develop a predictive model that comprehensively captures the nuances of speeches, encompassing linguistic elements, emotional resonance, and audience-specific variables. This task involves unraveling the intricate interplay between spoken words and diverse cognitive and emotional reactions, considering cultural context, individual predispositions, and the evolving dynamics of communication channels. The study seeks to offer practical insights for enhancing our understanding of the persuasive power of speeches in contemporary media landscapes.

The problem we want to solve is challenging because:

- Political 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.

METHODOLOGY

The project is wholly divided into 2 parts:

1. Gathering surveys and creating dataset
2. Implementing a classification model to classify psychological impacts based on speeches.

1. Creating Survey and Dataset:

We started our work by collecting the transcripts of historically famous political speeches. After this, we studied about the Plutchik Wheel of emotions, which is a psychometric test to evaluate the psychological state of mind of a person based on the emotions he/she is experiencing. The wheel consists of 8 basic human emotions, which are ranked according to their intensity in a floral pattern. This wheel can further be used to generate a combination of emotions or the psychological state of mind using primary, secondary and tertiary dyads derived from the original wheel.

For each speech, we will collect a number of responses from the public, where they will rate their 8 basic emotions on a scale of 1 to 10. This is followed by taking the average of these responses for each speech to get the average emotions experienced by those who listened to that speech. Data validation of the responses is equally important, so will also calculate Cronbach’s Alpha and Fleiss’s kappa for the responses to ensure that the data is correlated and valid.

We then use natural language processing techniques to convert the speeches into word vectors, which are numerical representations of the words and their meanings. For our X label of the dataset, we plan to use vector embeddings of the speech transcripts that we have collected from internet sources. This will be done using a pretrained ALBert tokenizer that will generate dynamic text embeddings for the speech.

Hence, our dataset will have embeddings of the speech as the X label or the independent variable, and the emotion having the highest value in the Plutchik wheel as the Y label or dependent variable corresponding to that speech.

The link to our survey is this: https://forms.gle/Aus62EJepvc7oX358

2. Implementing the classification model.

This section will consist of fine tuning the ALBert model on our dataset for it to predict most likely emotions from future responses. The emotions recovered will be ranked according to probability, which can then be used to predict the psychological state of a new speech. The emotions having the 2 highest probabilities will be used to then find the Psychological state of mind, from the different dyads of the Plutchik wheel of emotions. Figure 1 shows the flow of our implementation.

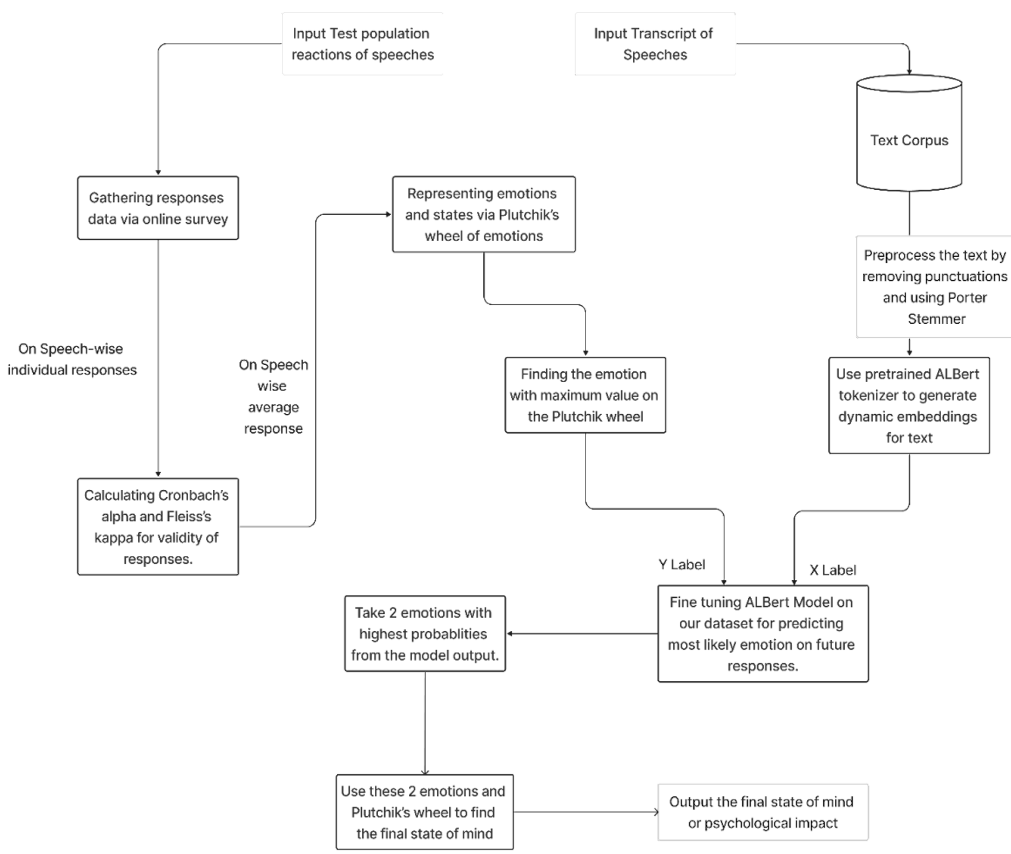

Figure 1 Flow Diagram of the Model

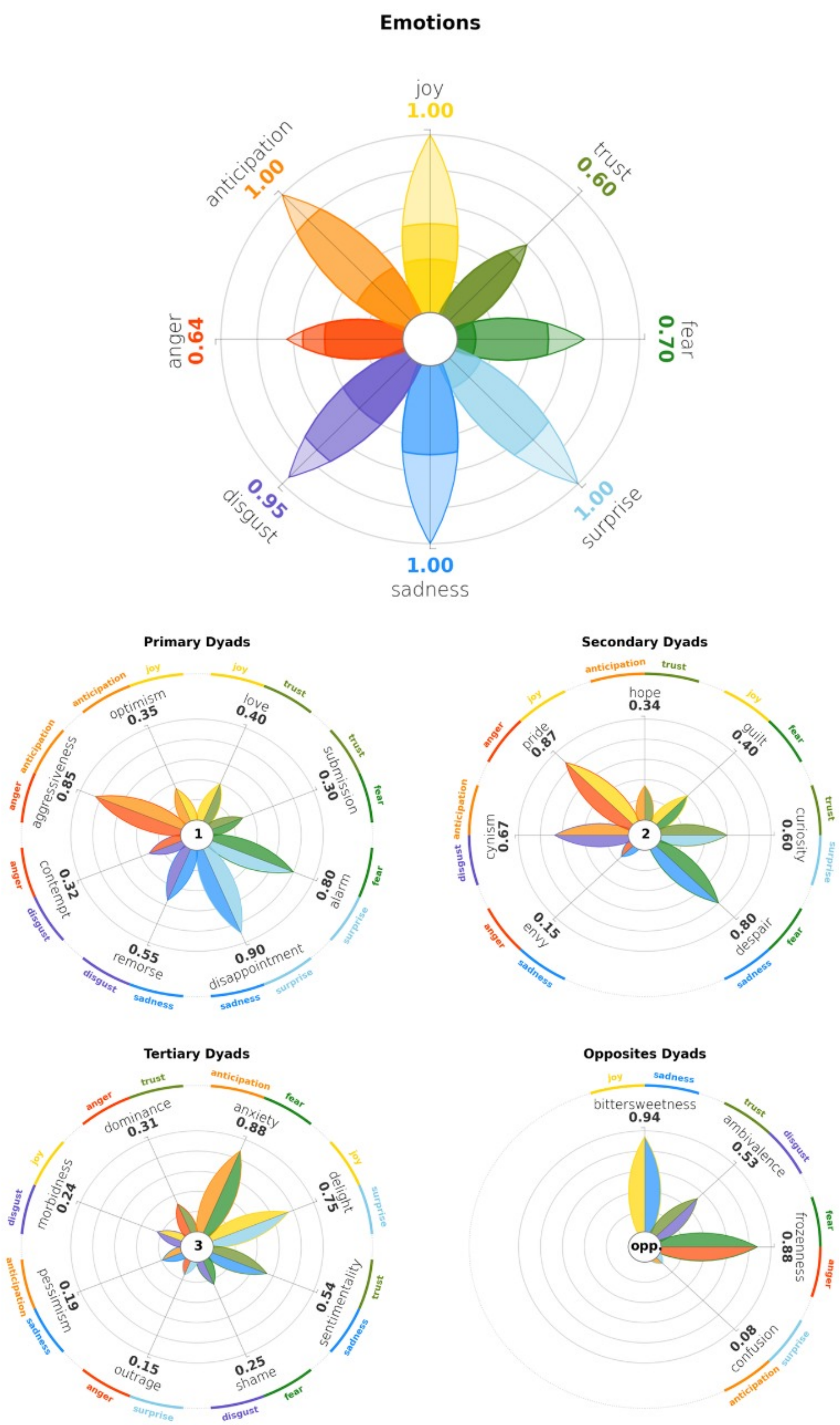

Figure 2 Finding Psychological state of mind from Plutchik wheel using emotions

IMPLEMENTATION

The following work has been done as a part of this project till now:

1. Collecting transcripts of the following political speeches:
   a. Winston Churchill's "We Shall Fight on the Beaches" Speech (1940)
   b. Martin Luther King Jr.'s "I Have a Dream" Speech (1963)
   c. John F. Kennedy's Inaugural Address (1961)
   d. Nelson Mandela's Inaugural Address (1994)
   e. Malala Yousafzai's United Nations Speech (2013)
   f. Steve Jobs' Stanford Commencement Speech (2005)
   g. Elie Wiesel's Nobel Peace Prize Acceptance Speech (1986)
   h. Greta Thunberg's Climate Change Speeches
   i. Barack Obama's Farewell Address (2017)
   j. 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

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.
   e. Plot plutchik wheel for each speech. Figure 4 shows the plutchik wheel.
   f. Get the most strongest emotion from the plutchik wheel.

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

[3]:
```python
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

Figure 3 Responses from Google Form

```python
cols_to_average = df.columns[-8:]
```

```python
df_grouped = df.groupby('speech_no')[cols_to_average].mean()
```

```python
df_grouped
```

speech_no	joy	trust	fear	surprise	sadness	disgust	anger	anticipation
1	2.714286	7.714286	2.000000	2.714286	1.571429	1.571429	7.714286	6.571429
10	5.769231	7.928571	2.571429	2.500000	5.357143	3.714286	4.428571	6.846154
2	7.250000	8.250000	1.750000	2.000000	0.500000	0.500000	1.750000	7.000000
3	10.000000	9.666667	1.666667	1.666667	3.333333	0.000000	4.000000	8.666667
4	5.727273	6.545455	3.818182	3.000000	4.181818	1.272727	1.909091	6.181818

Figure 4 Average responses for each speech

```python
for record in records:
    plutchik(record)
```

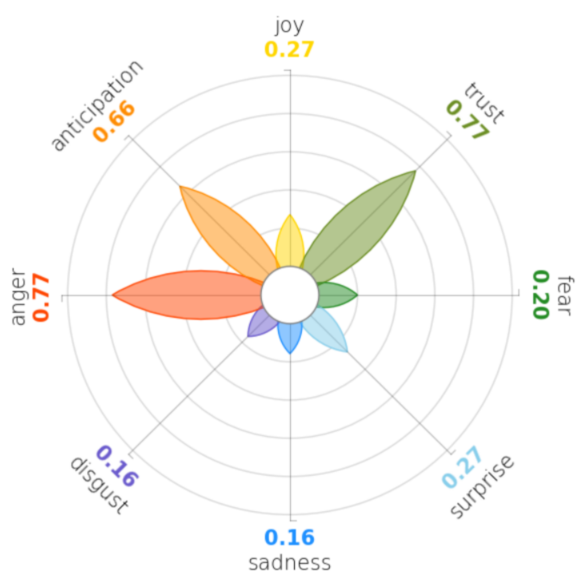

Figure 5 Plutchik Wheel Depiction

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

Figure 6 X and Y labels of dataset

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 store the keys and values. Figure 6 shows the output for the same.

```
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

Figure 7 Encoding of dataset

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

```
#preprocess transcript

# download necessary NLTK data
nltk.download('punkt')
nltk.download('stopwords')

# initialize a PorterStemmer
# stemmer = PorterStemmer()

def preprocess_text(text):
    # lowercase the text
    text = text.lower()
    # remove punctuation
    text = text.translate(str.maketrans('', '', string.punctuation))
    # tokenize the text
    words = word_tokenize(text)
    # remove stopwords and stem the words
    words = [word for word in words if word not in stopwords.words('english')]
    # join the words back into a string
    text = ' '.join(words)

    return text

df['speech'] = df['speech'].apply(preprocess_text)
```

Figure 8 Speech transcript preprocessing

d. Then we split the dataset into train and test datasets in 80:20 ratio. Figure 8 shows the spilt code for the same.

```
from sklearn.model_selection import train_test_split

train, test = train_test_split(df, test_size=0.2)
```

Figure 9 Dataset splitting for training

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.

```
tokenizer=AlbertTokenizer.from_pretrained('albert-large-v2')

model=TFAlbertForSequenceClassification.from_pretrained('albert-large-v2',num_labels=6)
```

Figure 10 Utilizing Pretrained models

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.

```
#tokenize the texts
train_encodings = tokenizer(train_texts, truncation=True, padding=True, max_length=512)
test_encodings = tokenizer(test_texts, truncation=True, padding=True, max_length=512)
```

```
#convert features and labels to tensors for both train and test
train_features = {key: tf.convert_to_tensor(val) for key, val in train_encodings.items()}
train_labels = tf.convert_to_tensor(train_labels)

test_features = {key: tf.convert_to_tensor(val) for key, val in test_encodings.items()}
test_labels = tf.convert_to_tensor(test_labels)
```

```
#prepare the training and testing dataset
train_dataset = tf.data.Dataset.from_tensor_slices((train_features, train_labels))
train_dataset = train_dataset.shuffle(10000).batch(1)

test_dataset = tf.data.Dataset.from_tensor_slices((test_features, test_labels))
test_dataset = test_dataset.batch(1)
```

Figure 11 Final dataset processing

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)
_________________________________________________________________
```

Figure 12 Model Retraining

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.

```
new_feature = tokenizer(df['speech'][0], truncation=True, padding=True, return_tensors='tf')
```

```
predictions = model(new_feature)
```

```
predictions
```

```
TFSequenceClassifierOutput(loss=None, logits=<tf.Tensor: shape=(1, 6), dtype=float32, numpy=
array([[ 0.0970768 , -0.71589625,  0.602642  , -0.23261102, -0.9310217 ,
        -0.05781958]], dtype=float32)>, hidden_states=None, attentions=None)
```

```
probabilities = tf.nn.softmax(predictions.logits, axis=-1)
```

```
probabilities
```

```
<tf.Tensor: shape=(1, 6), dtype=float32, numpy=
array([[0.1986177 , 0.08809439, 0.3292927 , 0.14283556, 0.07104286,
        0.17011681]], dtype=float32)>
```

Figure 13 Predicting strongest emotion for a speech

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. The values calculated are as follows:

Cronbach's alpha = 0.15

```
n [2]:  cronbach_dataset = pd.read_csv("cronbach data - Sheet1.csv")

n [3]:  pg.cronbach_alpha(data=cronbach_dataset)

ut[3]:  (0.1525464219078512, array([-0.144,  0.396]))
```

Figure 14 Evaluating Cronbach's Alpha

Fleiss' kappa for responses of each speech:

Speech	Number of respondents	Value
Aung San Suu Kyi's Nobel Lecture (2012)	3	-0.055
Barack Obama's Farewell Address (2017)	8	-0.031
Elie Wiesel's Nobel Peace Prize Acceptance Speech (1986)	6	-0.068
Greta Thunberg's Climate Change Speech	10	0.060
John F. Kennedy's Inaugural Address (1961)	10	-0.025
Malala Yousafzai's United Nations Speech (2013)	9	-0.008
Martin Luther King Jr.'s "I Have a Dream" Speech (1963)	14	0.040
Nelson Mandela's Inaugural Address (1994)	3	-0.067
Steve Jobs' Stanford Commencement Speech (2005)	11	0.040
Winston Churchill's "We Shall Fight on the Beaches" Speech (1940)	10	0.015

Table 1 Fleiss' Kappa for each speech

Below is the output of Fleiss' kappa for Martin Luther King Jr.'s "I Have a Dream" Speech, to illustrate the output format of the code.

```
#fleiss kappa of Martin Luther King Jr.'s "I Have a Dream" Speech (1963)
kappam_fleiss(fleiss_dataset[46:60], detail=True)
```

```
==================================================
            Fleiss` Kappa for m Raters
==================================================
Subjects = 14
  Raters = 8
   Kappa = 0.040
```

RESULTS

In this study, we utilized the ALBERT model for the task of classifying speech into different emotions. The results obtained from the model were promising and demonstrated the effectiveness of ALBERT in emotion recognition tasks.

Model Performance

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.

Model output

Figure below shows the predicted emotions on the test dataset, consisting of 2 speeches

```
model.predict(test_features)
```

```
1/1 [==============================] - 9s 9s/step
TFSequenceClassifierOutput(loss=None, logits=array([[-0.14047754,  0.3345204 ,  0.53231156, -0.64712846,  0.39203188,
         0.18751253],
       [-0.23937094,  0.32823318,  0.4432897 , -0.6843817 ,  0.42273876,
         0.2532632 ]], dtype=float32), hidden_states=None, attentions=None)
```

Figure 15 Test dataset predictions

Figure below shows the conversion of predictions to probabilities using softmax function

```
probabilities = tf.nn.softmax(predictions.logits, axis=-1)
```

```
probabilities
```

```
<tf.Tensor: shape=(1, 6), dtype=float32, numpy=
array([[0.19989938, 0.15762572, 0.14134216, 0.1593213 , 0.15418981,
        0.18762165]], dtype=float32)>
```

Figure 16 Converting predictions to probabilities

Plutchik wheel of emotion plot for predicted values

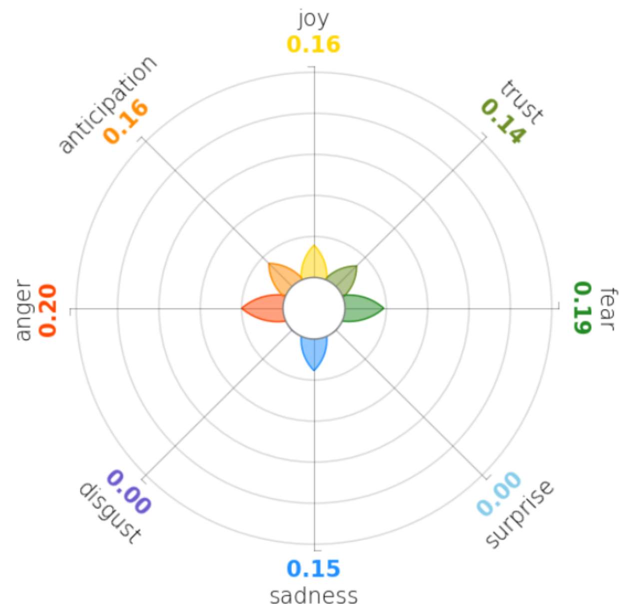

Figure 17 Plutchik wheel of emotions plot on test data

From the above plot, we determine the 2 emotions with the highest value on the plot. Using these 2 emotions, we can then determine the final state of mind using Primary, Secondary, Tertiary and opposite dyads of the Plutchik wheel. For this example, the 2 maximum emotions are anger and fear, whose combination on the opposite dyad gives frozenness as the final state of mind.

```
find_state(emotion1, emotion2)

frozenness
```

Figure 18 Find final state of mind using Plutchik wheel dyads

Error Analysis

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.

CONCLUSION & FUTURE WORK

In conclusion, this research has endeavored to unravel the intricate dynamics surrounding the psychological impact of famous speeches on individuals. Through an exploration of linguistic nuances, emotional resonances, and audience-specific variables, we aimed to develop a predictive model that captures the complex interplay between spoken words and diverse cognitive and emotional reactions. The inquiry highlighted the challenge's multilayered character, with various underlying difficulties and obstacles. One of the most significant challenges we faced was the tiny dataset. Because we had a tiny dataset, we were unable to train our model on big datasets, resulting in a low accuracy of our model. Another problem we encountered was data collecting. We distributed survey questionnaires, but because the speeches we chose were too long, many did not watch or listen to them, and we received few replies.

Our findings underscore the subjectivity of psychological responses to speeches, highlighting the influence of individual differences, cultural backgrounds, and contextual factors. The development of a predictive model capable of accommodating such diversity is not only challenging but essential for creating a nuanced understanding of the persuasive power of speeches.

The integration of multimodal elements, including linguistic and non-verbal cues, posed a significant challenge in capturing the holistic nature of speech impact. Recognizing the importance of tone, gestures, and facial expressions in influencing psychological responses, future efforts in model development must explore innovative ways to seamlessly incorporate these elements into predictive frameworks.

Temporal dynamics emerged as a crucial consideration, as the impact of speeches evolves over time in response to changing events and public sentiment. Our model, while providing valuable insights, may benefit from further refinement to account for the dynamic nature of psychological responses and their evolution over extended periods.

Ethical considerations surrounding the prediction of psychological impact demand ongoing attention. As technology advances, ensuring responsible use of predictive models is paramount. Striking a balance between innovation and ethical considerations involves continuous scrutiny of data privacy, potential biases, and the societal implications of deploying such models in real-world scenarios.

Looking ahead, the field holds immense potential for future research endeavors. One avenue for exploration involves enhancing the generalizability of predictive models across diverse cultural contexts. Understanding how speeches resonate within different cultural frameworks is essential for building models that transcend geographical and societal boundaries.

The dynamic media landscape calls for ongoing adaptation of predictive models to accommodate changing patterns in speech consumption. As traditional media gives way to digital platforms, future research must explore the evolving ways in which people engage with and are influenced by speeches in the digital realm.

Furthermore, the incorporation of advanced technologies, such as natural language processing and machine learning, can enrich the predictive capabilities of models. Fine-tuning algorithms based on continuous feedback and iterative learning processes can contribute to the refinement and optimization of predictive frameworks.

In conclusion, the prediction of psychological impact in the realm of famous speeches is a dynamic and evolving field that demands interdisciplinary collaboration. The synthesis of insights from psychology, linguistics, data science, and ethics is imperative for developing robust models that contribute not only to academic understanding but also to the responsible and ethical use of persuasive rhetoric in shaping informed, engaged, and empathetic societies.

Future research endeavors in predicting the psychological impact of famous speeches should focus on several key areas to advance the field:

1. **Enhanced Multimodal Analysis:** Explore advanced techniques for integrating and analyzing multimodal elements, including audio, video, and textual components, to provide a more comprehensive understanding of the persuasive dynamics at play in speeches.

2. **Longitudinal Studies:** Conduct longitudinal studies to track the temporal evolution of psychological responses to speeches, considering how sentiments and attitudes change over extended periods and in response to unfolding events.

4. **Dynamic Media Analysis:** Stay attuned to the changing landscape of media consumption and adapt predictive models to account for emerging trends in how speeches are delivered, consumed, and shared, particularly in the digital age.

5. **Interdisciplinary Collaboration:** Foster continued collaboration between experts in psychology, linguistics, data science, and ethics to address the ethical considerations associated with predictive models, ensuring responsible deployment and safeguarding against potential biases.

6. **User Feedback Integration:** Implement iterative feedback loops that involve real-world user feedback to refine and optimize predictive models based on the evolving nature of public response to speeches.

7. **Generalizability Testing:** Conduct extensive testing and validation to ensure the generalizability of predictive models across diverse demographic groups, geographic regions, and sociopolitical contexts.

8. **Examine Public Discourse Trends:** Explore broader trends in public discourse and analyze how shifts in language use, rhetorical strategies, and communication styles influence the psychological impact of speeches over time.

In summary, the future trajectory of research in this domain should be characterized by a commitment to continual refinement, ethical considerations, and an ever-deeper understanding of the intricate interplay between influential communication and the complexities of the human psyche.

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