Sentiment Score Construction with Facebook Comments on US Politics

Presentation by Ching-Yao Lin (林璟耀)

Executive Summary

Propose a Way to construct Sentiment Score with Social Media Comments

- Five SOTA deep learning models are adopted and combined for score construction
  - distilBERT, RoBERTa-large, RoBERTa-tweet, BERT-star, BERT-emotion
- Three types of sentiment score are constructed
  - Aspect-based Sentiment: scores on different emotions (within 0, 1)
  - Binary Sentiment Label: positive or negative labels (-1, +1)
  - Continuous Sentiment Score: scores for binary sentiment labels (within -1, +1)
- A full recipe for Sentiment Score Construction
  - Preprocessing: Deal with Emojis & Emoticons
  - Model-Mining: Score distributions, Keyword sanity checks
  - Score Construction & Analytical Results: Predicting Trump winning the US Presidential Election in 2016 with Social Media Comments

Research Topic

Data Introduction

Data Preprocessing

Score Building

Analysis Results

Future Work

Research Topic

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Research Topic

Propose a Way to Construct Sentiment Score with respect to Social Media Comments

Research Topic

Propose a Way to Construct Sentiment Score

with respect to Social Media Comments

Data: Facebook Comments on US Politics

Models: BERT and its variants

2016 US Presidential Election: Nov 8, 2016 (Tue)

		
Nominee	**Donald Trump**	Hillary Clinton
Party	Republican	Democratic
Home state	New York	New York
Running mate	**Mike Pence**	Tim Kaine
Electoral vote	**304**[a]	227[a]
States carried	**30 + ME-02**	20 + DC
Popular vote	62,984,828[2]	**65,853,514**[2]
Percentage	46.1%	**48.2%**

There are 4 kinds of data.

- Page
- Post
- Reaction
- Comment

US Presidential Election Process

Source: https://en.wikipedia.org/wiki/2016_United_States_presidential_election

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Data Introduction

There are 4 kinds of data.

- **Page**
  - 1000-page-info
  - politician-info
  - 1000-page-and-politician-info
- **Post**
  - 1000-page
  - politician
- **Reaction**
  - 1000-page: LIKE by us-political-user
  - 20-min: LIKE, LOVE, HAHA, WOW, SAD, ANGRY, THANKFUL
  - Politician: LIKE by us-political-user
- **Comment**
  - Only on 1000-page!

Data Introduction

us-political-user: A total of 29,410,568 unique users that ever liked a post from US national politicians in 2015 and 2016

US national politicians

1. Senators: Current members and all 2016 Senate election candidates
2. House of Representatives: Current members and all 2016 House election candidates
3. Governors: Current and former Governor (last one).

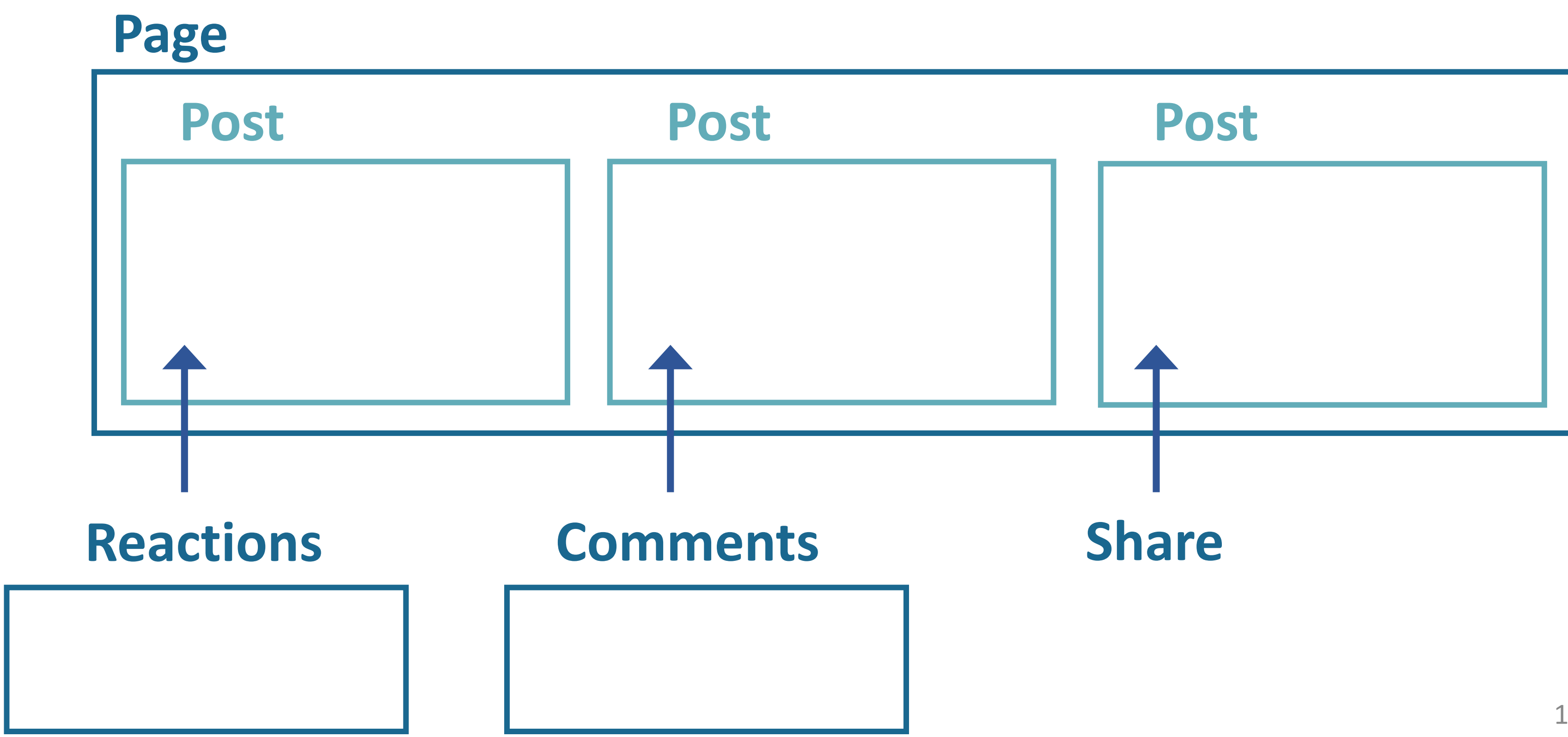
Data Extraction: (by README)

1. Find all the pages ever mentioned Donald Trump and Hillary Clinton in August 2016.
2. Calculate the total number of likes, comments, and shares of candidate-related posts in these pages, and weight them by factors 1:7:14 (a weight suggested by social media consultant, see Calero (2013)), respectively. Changing the weight does not change the list too much.

Data Introduction

Only data related to fan pages are publicly available, which includes:

- Posts on fan pages
- Reactions to / comments of / public shares of these posts
- User id of those who do reactions, comments ~~and shares~~
- ~~Fan page likes other fan pages~~



Data Introduction

post data

1000-page

page_id	page_name	post_id
2.178595e+10	9GAG	21785951839_10155113971791840

post_type	post_name	post_message	post_caption	[illegible]
link	Official White House Photographer Reveals His ...	Obama is the coolest president in history. �� ...	9gag.com	https://external.xx.fbcdn.net/safe_image.php?d...

post_link	post_descrip[illegible]on	[illegible]
http://9gag.com/gag/ajqEV90?ref=fbp	Click to see the pic and write a comment...	1297326.0

post_likes	post_comments	post_shares	post_created_time_CT
1149630.0	20093.0	209506.0	2016-11-11 07:35:00+00:00

post_updated_time_CT	page_talking_about_count
2017-03-16 04:05:56+00:00	8425994.0

Data Introduction

page_id	page_name	post_id
2.178595e+10	9GAG	21785951839_10155113971791840

post_type	post_name	post_message	post_caption	post_picture
link	Official White House Photographer Reveals His ...	Obama is the coolest president in history. �� ...	9gag.com	https://external.xx.fbcdn.net /safe_image.php?d...

post_link	post_description	post_reactions
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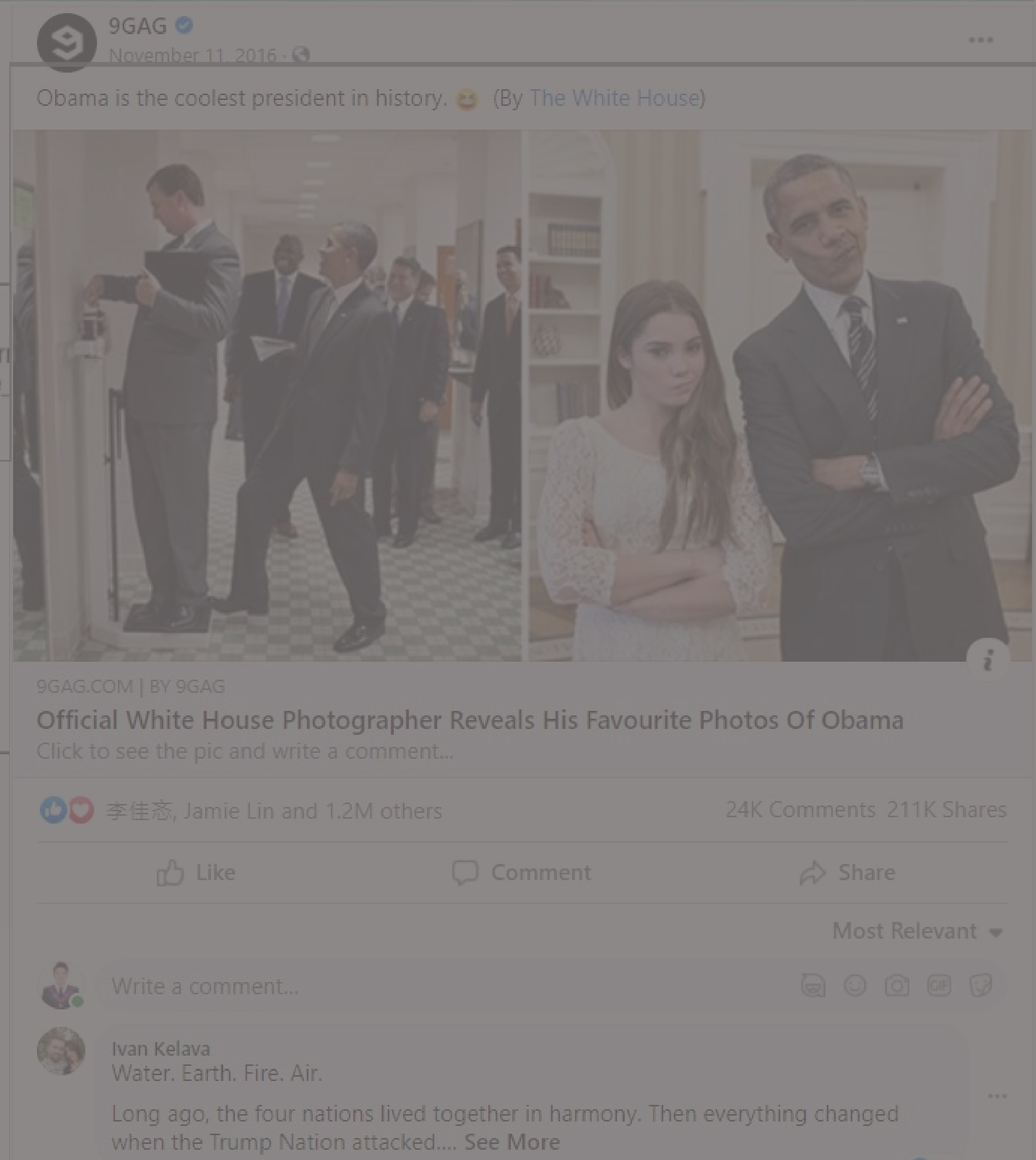
post_updated_time_CT	page_talking_about_count
2017-03-16 04:05:56+00:00	8425994.0

Data Introduction

post_type
link

	count	percentage
link	11235316	76.182%
photo	2099309	14.235%
video	1225049	8.307%
status	182016	1.234%
event	5692	0.039%
note	420	0.003%
music	102	0.001%
offer	41	0.000%



Data Introduction

post_type
link

	count	percentage
link	11235316	76.182%
photo	2099309	14.235%
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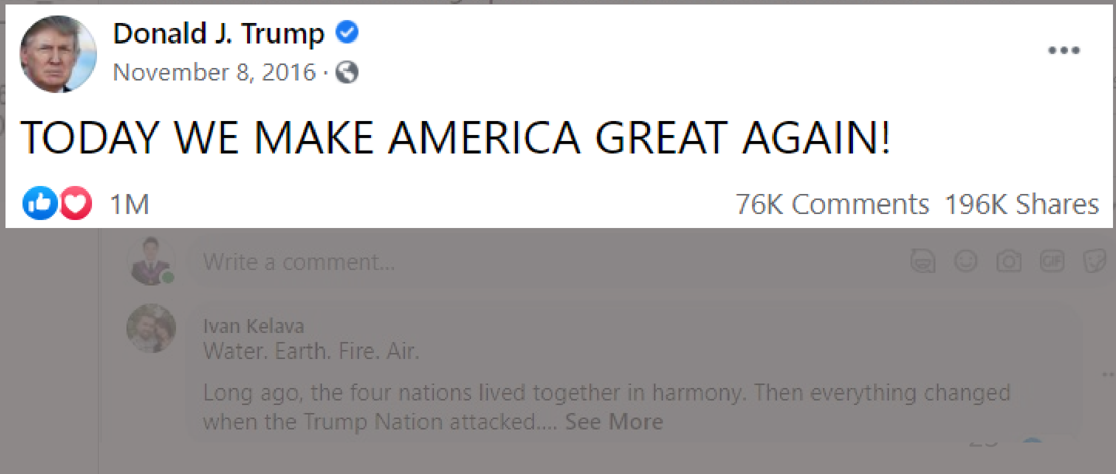

Data Introduction

page_id	page_name	post_id
2.178595e+10	9GAG	21785951839_10155113971791840

post_type	post_name	post_message	post_caption	post_picture
link	Official White House Photographer Reveals His ...	Obama is the coolest president in history. �� ...	9gag.com	https://external.xx.fbcdn.net/safe_image.php?d...

post_link	post_description	post_reactions
http://9gag.com/gag/ajqEV90?ref=fbp	Click to see the pic and write a comment...	1297326.0

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2017-03-16 04:05:56+00:00	8425994.0

Page

Data Introduction

page data

1000-page-info

page_id	page_name	post_id
2.178595e+10	9GAG	21785951839_10155113971791840

post_type	post_name	post_message	post_caption	p[illegible]
link	Official White House Photographer Reveals His ...	Obama is the coolest president in history. �� ...	9gag.com	https://external.xx.fbcdn.net/safe_image.php?d...

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post_updated_time_CT	page_talking_about_count
2017-03-16 04:05:56+00:00	8425994.0

Data Introduction

Data Introduction

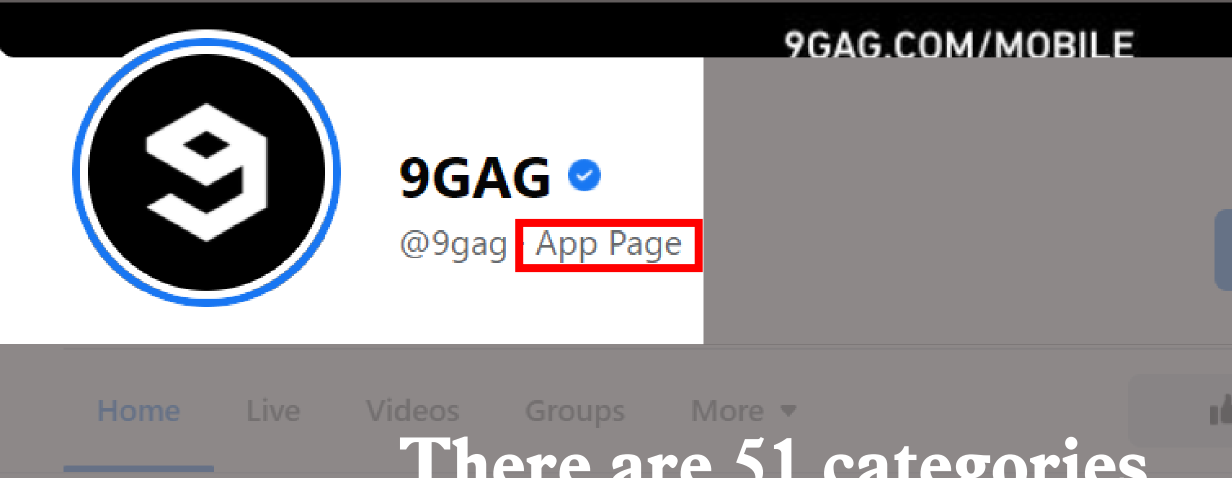
Page

1000-page-info

page_id	page_name	category	type	type_sub	type_issue	fan_count	talki
21785951839	9GAG	App Page	others	NaN	NaN	3215542	

page_url	total_like	total_comment	total_share	1:07:14	ran
https://www.facebook.com/9gag	13909	725	1555	4075.4	

	category
Media/News/Publishing	244
News/Media Website	159
Public Figure	90
Community	79
TV Channel	63
Non-Profit Organization	49
TV Show	43
Political Organization	38
Magazine	23
Politician	20
News Personality	15
Website	15
Musician/Band	14
Entertainment Website	13
Journalist	12
TV Network	12
Political Party	11
Society/Culture Website	11
Organization	10
Comedian	9
Entertainer	9
Author	7



There are 51 categories...

Data Introduction

Page

1000-page-info

type	type_sub	type_issue
others	NaN	NaN

	type
media	587
group	231
figure	138
others	44

	type_sub
website	303
NaN	275
tv	188
journalist	97
magazine	42
newspaper	42
politician	41
radio	12

	type_issue
NaN	952
gun	13
hispanic	10
LGBT	6
abortion	4
inequality	3
healthcare	3
jew	2
immigration	1
environment	1
jews	1
hispanics	1
muslim	1
muslims	1
black	1

Page

1000-page-info

page_id	page_name	category	type	type_sub	type_issue	fan_count	talking_about_count
21785951839	9GAG	App Page	others	NaN	NaN	32155423	11547502

page_url	total_like	total_comment	total_share	1:07:14	rank_1:7:14
http	[illegible]	725	1555	4075.4	760

type	type_sub	count	percentage
figure	journalist	97	9.700%
	politician	41	4.100%
group	NaN	231	23.100%
media	website	303	30.300%
	tv	188	18.800%
	magazine	42	4.200%
	newspaper	42	4.200%
	radio	12	1.200%
others	NaN	44	4.400%

Data Introduction

Page

1000-page-info

type	type_sub	type_issue
others	NaN	NaN

type	type_sub	count	percentage
figure	journalist	97	9.700%
	politician	41	4.100%
group	NaN	231	23.100%
media	website	303	30.300%
	tv	188	18.800%
	magazine	42	4.200%
	newspaper	42	4.200%
	radio	12	1.200%
others	NaN	44	4.400%

type	type_sub	type_issue	count	percentage
figure	journalist	NaN	97	13.379%
	politician	NaN	41	5.655%
media	magazine	NaN	40	5.517%
		LGBT	1	0.138%
		hispanic	1	0.138%
	newspaper	NaN	41	5.655%
		hispanic	1	0.138%
	radio	NaN	10	1.379%
		black	1	0.138%
		hispanics	1	0.138%
	tv	NaN	182	25.103%
		hispanic	4	0.552%
		muslim	1	0.138%
		muslims	1	0.138%
	website	NaN	294	40.552%
		hispanic	4	0.552%
		LGBT	3	0.414%
		gun	1	0.138%
		jews	1	0.138%

Data Introduction

page_id	page_name	post_id
2.178595e+10	9GAG	21785951839_10155113971791840

post_type	post_name	post_message	post_caption	post_picture
link	Official White House Photographer Reveals His ...	Obama is the coolest president in history. �� ...	9gag.com	https://external.xx.fbcdn.net/safe_image.php?d...

post_link	post_description	post_reactions
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post_likes	post_comments	post_shares	post_created_time_CT
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post_updated_time_CT	page_talking_about_count
2017-03-16 04:05:56+00:00	8425994.0

Comment

comment_message	post_id	comment_created_time
Waluigi he's not our president and I'm going t...	21785951839_10155113971791840	2016-11-11 13:49:48+00:00
Obama was the best president ������������gr vr...	21785951839_10155113971791840	2016-11-11 15:15:20+00:00
Great guy, so down to earth, shame he has to g...	21785951839_10155113971791840	2016-11-11 15:31:39+00:00
These are amazimg pictures! I think he is the ...	21785951839_10155113971791840	2016-11-11 15:43:10+00:00
Amanda, I just love this.	21785951839_10155113971791840	2016-11-11 17:31:11+00:00
He is on of kind god bless his life	21785951839_10155113971791840	2016-11-11 18:01:00+00:00
Best president of all time...	21785951839_10155113971791840	2016-11-11 19:55:25+00:00
Celine lookadit	21785951839_10155113971791840	2016-11-11 20:24:46+00:00
I think history will remember President Obama ...	21785951839_10155113971791840	2016-11-12 05:14:14+00:00
I think he's great. One of the last gentleman ...	21785951839_10155113971791840	2016-11-12 08:31:10+00:00
Amazing guy! Best president ever!	21785951839_10155113971791840	2016-11-12 09:07:24+00:00
That's only because I cannot be the president ...	21785951839_10155113971791840	2016-11-12 09:58:41+00:00

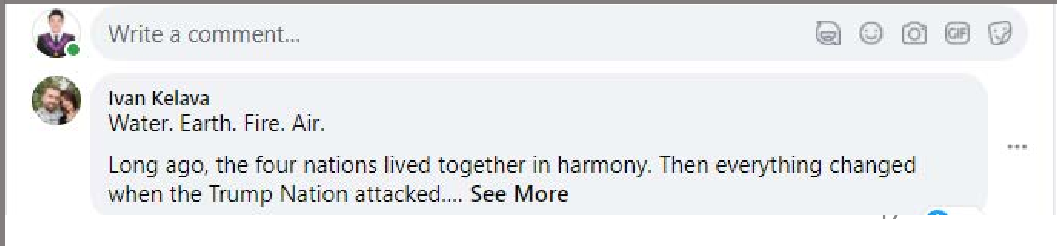
Includes:

- comments on posts
- (comments on comments)

There is no user_id. ☹

In this project, I would focus mainly on comment data.

Comment



Research Topic

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Data Preprocessing

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Data Preprocessing

Basic Preprocessing (for spacyTextBlob's input)

1. Drop completely duplicate rows
2. Add language labels (using Language Detection Model from fasttext)
3. Filter out non-English or empty comments; then, drop the language label column
4. Convert all words to lowercase (eg. Mr. Trump -> mr. trump)
5. Expand contractions (eg. yall're cool -> you all are cool)
6. Remove punctuations, links, newlines, tabs, and shrink consecutive spaces
7. Remove emojis
8. Remove stopwords (using nltk)
9. Lemmatize texts (using spacy)

   (eg. the cars are different colors -> the car be different color)
10. Pickle (Serialize) the result

Data Preprocessing

Basic Preprocessing (for Textual Data)

1. Drop completely duplicate rows
2. **Add language labels** (using Language Detection Model from fasttext)
3. **Filter out non-English or empty comments; then, drop the language label column**
4. Convert all words to lowercas
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9. Lemmatize texts (using spacy

   (eg. the cars are different col
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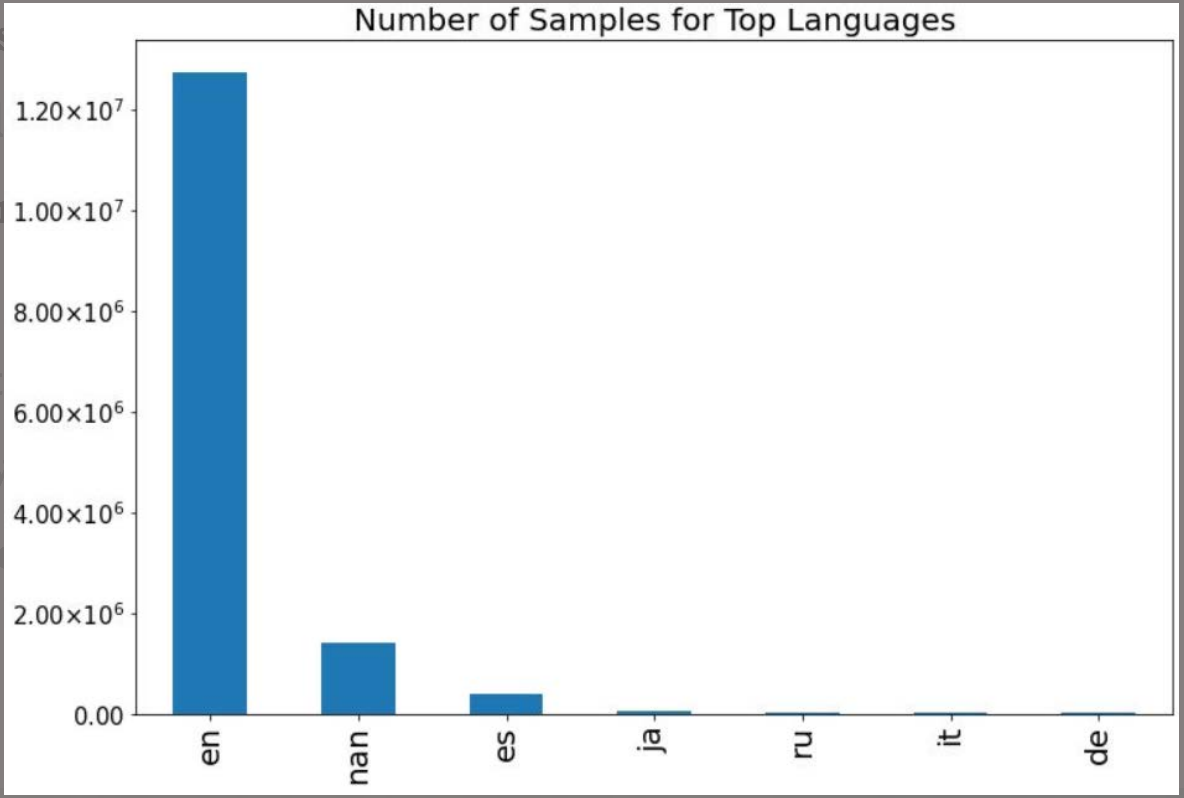


Data Preprocessing

```
"I'm": "I am",
"I'm'a": "I am about to",
"I'm'o": "I am going to",
"I've": "I have",
"I'll": "I will",
"I'll've": "I will have",
"I'd": "I would",
"I'd've": "I would have",
"Whatcha": "What are you",
"amn't": "am not",
⋮
```

```
"can't've": "can not have",
"could've": "could have",
"couldn't": "could not",
"couldn't've": "could not have",
"daren't": "dare not",
"daresn't": "dare not",
"dasn't": "dare not",
"didn't": "did not",
"didn’t": "did not",
"don't": "do not",
⋮
```

Basic Preprocessing (for Tex

1. Drop completely duplicate ro
2. Add language labels (using La
3. Filter out non-English or empty comments; then, drop the language label column
4. **Convert all words to lowercase** (eg. Mr. Trump -> mr. trump)
5. **Expand contractions** (eg. yall're cool -> you all are cool)
6. **Remove punctuations, links, newlines, tabs, and shrink consecutive spaces**
7. **Remove emojis**
8. Remove stopwords (using nltk)
9. Lemmatize texts (using spacy)

   (eg. the cars are different colors -> the car be different color)

```
"We're straining to be offended.\nMr. Trump says offensive things everyday.\n     This is a test 😍 👍. http://www.google.com"
```

↓

```
'we are straining to be offended mr trump says offensive things everyday this is a test '
```

Data Preprocessing

Basic Preprocessing (for Textual Data)

1. Drop completely duplicate rows
2. Add language labels (using Language Detection Model from fasttext)
3. Filter out non-English or empty comments; then, drop the language label column
4. Convert all words to lowercase (eg. Mr. Trump -> mr. trump)
5. Expand contractions (eg. yall're cool -> you all are cool)
6. Remove punctuations, links, newlines, tabs, and shrink consecutive spaces
7. Remove emojis
8. **Remove stopwords** (using nltk)
9. **Lemmatize texts** (using spacy)

   (eg. the cars are different colors -> the car be different color)

```
'we are straining to be offended mr trump says offensive things everyday this is a test '
```

↓

```
'strain offended mr trump say offensive thing everyday test'
```

10. Pickle (Serialize) the result

Data Preprocessing

Minimum Preprocessing

1. Drop completely duplicate rows

2. Add language labels

3. Filter out non-English or empty comments

Further Preprocessing

4. Convert all words to lowercase

5. Expand contractions

6. Remove punctuations, links, newlines, tabs, and shrink consecutive spaces

7. Remove emojis

8. Remove stopwords (using nltk)

9. Lemmatization

Data Preprocessing

Minimum Preprocessing

1. Drop completely duplicate rows
2. Add language labels
3. Filter out non-English or empty comments

Deep Learning Models (BERT)

Further Preprocessing

4. Convert all words to lowercase
5. Expand contractions
6. Remove punctuations, links, newlines, tabs, and shrink consecutive spaces
7. Remove emojis
8. Remove stopwords (using nltk)
9. Lemmatization

spacyTextBlob ML Model

Not introduced in depth in this presentation due to performance

To take a closer look, let's dive deeper

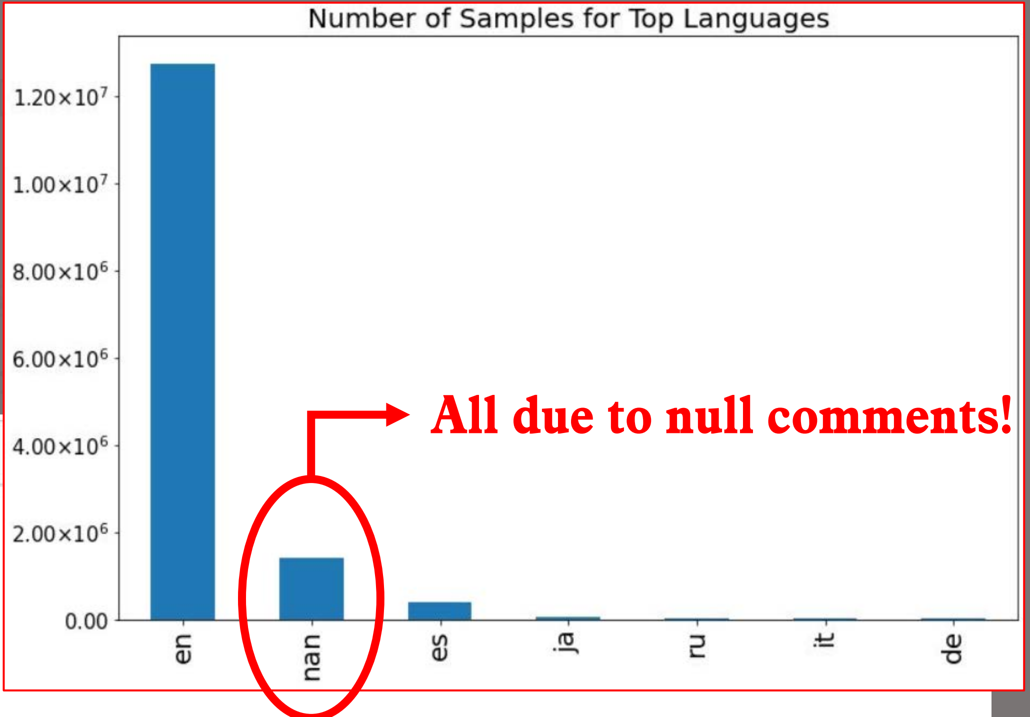
Data Preprocessing

Basic Preprocessing (for Textual Data)

1. **Drop completely duplicate rows**
2. **Add language labels** (using Language Detection Model from fasttext)
3. **Filter out non-English or empty comments; then, drop the language label column**
4. **Convert all words to lowercase** (eg. *Mr.* Trump -> mr. trump)
5. **Expand contractions and slangs** (eg. yall're cool -> you all are cool)
6. **Remove punctuations, links, newlines, tabs, and shrink consecutive spaces**
7. **Remove emojis**
8. **Remove stopwords** (using nltk)
9. **Lemmatize texts** (using spacy)
   (eg. the cars are different colors -> the car be different color)
10. **Pickle (Serialize) the result**

To take a closer look, let's dive deeper

About FB's fasttext
(language detection model)




```
comment.isna().sum()
```

```
comment_message        57872
post_id                    0
comment_created_time       0
language               57872
dtype: int64
```

```
# If language is null, then comment_message is null
comment.loc[comment['language'].isna(), ['comment_message', 'language']].isna().sum()
```

```
comment_message    57872
language           57872
dtype: int64
```

```
# If comment_message is null, then language is null
comment.loc[comment['comment_message'].isna(), ['comment_message', 'language']].isna().sum()
```

```
comment_message    57872
language           57872
dtype: int64
```

➔ countermeasure: Get rid of them!

About FB's fasttext (language detection model)

comment_message	language	comment_message_lower	lower2language
Amen	en	amen	ca
Brad Tronina	en	brad tronina	fr
Shazy Goni	en	shazy goni	it
NEVER!!!!!!!!! Dont give up cena plzzz	en	never!!!!!!!!! dont give up cena plzzz	fr
Aaron L. Johnson.	en	aaron l. johnson.	war
OH HELL YES!	en	oh hell yes!	de
GOD	en	god	sv
Deirdre	en	deirdre	pt
R I P ��	en	r i p ��	sv
Orlando	en	orlando	pt
Erika Correri	en	erika correri	pt
Kristen 'kMay' May	en	kristen 'kmay' may	de
Ian Long	en	ian long	pt
Sweet angel.	en	sweet angel.	no
Nancy La Ernie ��	en	nancy la ernie ��	fr

- Case-sensitive
- For those predicted English, becoming lowercase isn't favorable
- Contractions should be dealt with first

About FB's fasttext (language detection model)

comment_message	language	comment_message_lower	lower2language
BEAUTIFUL HEAD SHOT	ja	beautiful head shot	en
Lisa haha	de	lisa haha	en
POS	de	pos	en
Sara Ashley Castaneda	es	sara ashley castaneda	en
YOUR THE WORSE WISH WE COULD TAKE YOUR STATE F...	ja	your the worse wish we could take your state f...	en
TRUMP WILL BE IMPEACHED AS SOON AS HIS ASS HIT...	ja	trump will be impeached as soon as his ass hit...	en
SEEN!!!!!	da	seen!!!!!	en
EVERY TIME I HEAR THAT VOICE I GET DIZZY !!!	ja	every time i hear that voice i get dizzy !!!	en
Elisabeta Bačíkovic ��	sv	elisabeta bačíkovic ��	en
LOCK THEM ALL UP	ja	lock them all up	en
ENOUGH ALREADY! THE CREEP IS DELUSIONAL!	pt	enough already! the creep is delusional!	en
But ya	sw	but ya	en
DEFINITELY A FAMILY TRADITION!	ja	definitely a family tradition!	en
SPEAK-OUT NOW AGAINST THE COMING TYRANNY!	ja	speak-out now against the coming tyranny!	en
Bye	da	bye	en
BRAVO GIRL!	ja	bravo girl!	en
tWO BAD, BAD WOMEN!!	ja	two bad, bad women!!	en
CHUMPLY	zh	chumply	en
Home run!	id	home run!	en
Bye	da	bye	en

- For those predicted non-English, becoming lowercase IS favorable
- Mostly-uppercase texts are often misclassified (37.44% is upper case)
- Fasttext emphasizes "precision" more than "recall"

About FB's fasttext (language detection model)

Quick Summary:

In the cases of "Mismatch" ("original prediction" ≠ "lower-case prediction") :

1. **Most of those predicted English are in reality English!**

   → **But <u>were falsely predicted otherwise</u> after being transformed to lowercase.** 【Red Arrow】

2. **Most of those predicted non-English are in reality English!**

   → **And <u>were accurately predicted as English</u> after being transformed to lowercase.** 【Green Arrow】

About FB's fasttext (language detection model)

what I would see	Actually English	Actually Not English
Predicted English	what I want	what I don't want
Predicted Not English		

- Since I would filter out non-English comments, I would ONLY see those predicted English by FB' s fasttext
- The fact that fasttext emphasizes precision is GREAT for us
- To optimize the performance (so as to get as much TRUE English comments as possible), I wish the green arrows to happen.

About FB’s fasttext (language detection model)

what I would see	Actually English	Actually Not English
Predicted English	what I want	what I don’t want
Predicted Not English		

Lowercasing for the “mismatch” case: 48128

- To optimize the performance (so as to get as much TRUE English comments as possible), I wish the green arrows to happen.
- However, if I change all letters to lowercase, the green arrow and the red arrow both happen.
- I would preserve only the green arrow. Namely, changing those predicted non-English to lowercase, then run the fasttext model again.

About FB’s fasttext (language detection model)

Other (Failed) Attempts:

- **Punctuation Removal**
- **Punctuation Removal only for upper-/lower-case messages**

RECLAIM AMERICA! TRUMP / CARSON!!!!!	en	RECLAIM AMERICA TRUMP CARSON	ja
BENGHAZI! MURDER!	en	BENGHAZI MURDER	ru
BIG FUCKING BABIES.	en	BIG FUCKING BABIES	ja
TRUMP!	en	TRUMP	de
TRUMP LIES!	en	TRUMP LIES	fr
GOOD BYE!!!!!	en	GOOD BYE	ja
NEWS FLASH!!!!!!	en	NEWS FLASH	ja
EPISODE? DRUNK? DRUGGED?	en	EPISODE DRUNK DRUGGED	ja
QUE BUENA FOTO.	es	QUE BUENA FOTO	pt
FAKE FAKE FAKE AND SICK	en	FAKE FAKE FAKE AND SICK	ja
WTH???!!#	de	WTH	en
#VOTEFORTRUMP, #WOMENFORTRUMP, #TRUMP2016, #TE...	en	VOTEFORTRUMP WOMENFORTRUMP TRUMP2016 TEAMTRUM...	ja
STOP ALREADY !!!!	en	STOP ALREADY	ja
TRUMP 2016	en	TRUMP 2016	de
"AMEN"	pt	AMEN	it
YES !	ta	YES	en
WHATTTTTTT!!!!	en	WHATTTTTTT	eo
"LETS MAKE AMERICA GREAT AGAIN"	en	LETS MAKE AMERICA GREAT AGAIN	ja

Research Topic

Data Introduction

Data Preprocessing

Score Building

Analysis Results

Future Work

Procedure

Preliminary Data-Mining

- " Know your Data "
- We've roughly done that.

" Model-Mining " with Data

- " Know your Model ": Understand the limits/biases/tendencies that are inherent in the model (due to training data, or even human!). I proposed three ways.
  - Keyword Sanity Checks (for each model)
  - Score Distribution (across models)
  - Emojis & Emoticons

Data-Mining with Models

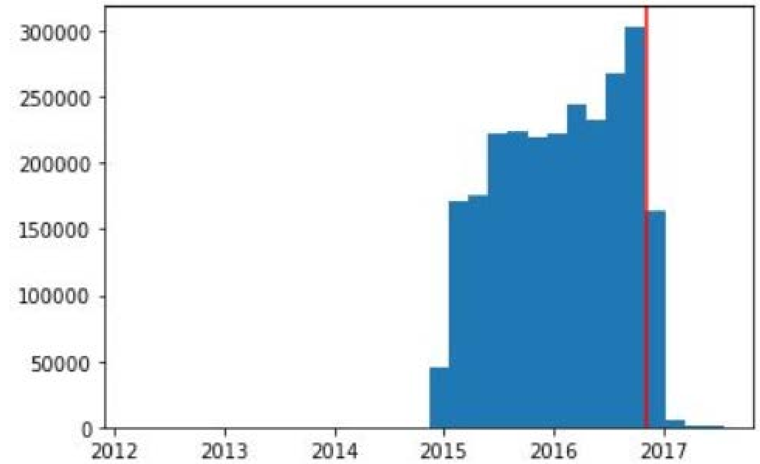
- Construction for Sentiment Score
- Validation for such Construction & Complete analysis

Sentiment Analysis on Comments

comment_message	post_id	comment_created_time
never like thought turkey even become extreme ...	198650096517_10154477788551518	2016-08-22 21:54:13+00:00
acceptable let get away year would change	519305544814653_898285223583348	2015-03-30 23:02:28+00:00
simple make black thug give gun crime murder d...	123624513983_10154497758328984	2016-07-08 23:59:07+00:00
anything well	7292655492_10153237963920493	2016-02-02 17:50:40+00:00
beautiful baby may rest eternal peace	149126144574_10154812315179575	2016-11-18 16:19:58+00:00

Exploratory Dataset

```
count                              2504216
mean      2016-01-24 11:49:14.871667456+00:00
min                 2012-03-09 02:46:06+00:00
25%                 2015-08-06 02:29:16+00:00
50%                 2016-02-06 05:04:28+00:00
75%                 2016-07-23 21:32:23+00:00
max                 2017-07-22 11:49:25+00:00
```



"Know Your Model"

	BERT	RoBERT	DistilBERT	XLNet
Size (millions)	**Base**: 110 **Large**: 340	**Base**: 110 **Large**: 340	**Base:** 66	**Base**: ~110 **Large**: ~340
Training Time	**Base**: 8 x V100 x 12 days* **Large:** 64 TPU Chips x 4 days (or 280 x V100 x 1 days*)	**Large:** 1024 x V100 x 1 day; 4-5 times more than BERT.	**Base**: 8 x V100 x 3.5 days; 4 times less than BERT.	**Large:** 512 TPU Chips x 2.5 days; 5 times more than BERT.
Performance	Outperforms state-of-the-art in Oct 2018	2-20% improvement over BERT	5% degradation from BERT	2-15% improvement over BERT
Data	16 GB BERT data (Books Corpus + Wikipedia). 3.3 Billion words.	160 GB (16 GB BERT data + 144 GB additional)	16 GB BERT data. 3.3 Billion words.	**Base**: 16 GB BERT data **Large**: 113 GB (16 GB BERT data + 97 GB additional). 33 Billion words.
Method	BERT (Bidirectional Transformer with MLM and NSP)	BERT without NSP**	BERT Distillation	Bidirectional Transformer with Permutation based modeling

Source: https://www.kdnuggets.com/2019/09/bert-roberta-distilbert-xlnet-one-use.html

Score Building

	BERT	RoBERT	DistilBERT	XLNet
Size (millions)	**Base**: 110 **Large**: 340	**Base**: 110 **Large**: 340	**Base**: 66	**Base**: ~110 **Large**: ~340
Training Time	**Base**: 8 x V100 x 12 days* **Large:** 64 TPU Chips x 4 days (or 280 x V100 x 1 days*)	**Large:** 1024 x V100 x 1 day; 4-5 times more than BERT.	**Base**: 8 x V100 x 3.5 days; 4 times less than BERT.	**Large:** 512 TPU Chips x 2.5 days; 5 times more than BERT.
Performance	Outperforms state-of-the-art in Oct 2018	2-20% improvement over BERT	5% degradation from BERT	2-15% improvement over BERT
Data	16 GB BERT data (Books Corpus + Wikipedia). 3.3 Billion words.	160 GB (16 GB BERT data + 144 GB additional)	16 GB BERT data. 3.3 Billion words.	**Base**: 16 GB BERT data **Large**: 113 GB (16 GB BERT data + 97 GB additional). 33 Billion words.
Method	BERT (Bidirectional Transformer with MLM and NSP)	BERT without NSP**	BERT Distillation	Bidirectional Transformer with Permutation based modeling

Source: https://www.kdnuggets.com/2019/09/bert-roberta-distilbert-xlnet-one-use.html

Score Building

Model	Returns
spacytextblob - baseline	Polarity(-1 ~ +1), Subjectivity (0 ~ 1)
DistilBERT (finetuned on SST-2)	POSITIVE, NEGATIVE
BERT-base-multilingual-uncased (finetuned on product reviews)	1 star, 2 stars, 3 stars, 4 stars, 5 stars
BERT-base-uncased-emotion (finetuned on emotion dataset ~ 8.11MB)	sadness, joy, love, anger, fear, surprise
RoBERTa-large (finetuned on 15 data sets, including reviews, tweets)	POSITIVE, NEGATIVE
RoBERTa-base (finetuned on TweetEval benchmark ~58M tweets)	NEGATIVE, NEUTRAL, POSTIVE

Score Building

Model	Training Data
spacytextblob - baseline	2000 Movie Reviews
DistilBERT (finetuned on SST-2)	BookCorpus (11,038 books, ~ 74M sentences and 1G words)
	English Wikipedia (6,330,642 articles, ~18.6 G words)
BERT-base-multilingual-uncased (finetuned on product reviews)	Same as above
BERT-base-uncased-emotion (finetuned on emotion dataset ~ 8.11MB)	Same as above
RoBERTa-large (finetuned on 15 data sets, including reviews, tweets)	BookCorpus, English Wikipedia, CC-News, OpenWebText, Stories (~160 GB texts)
RoBERTa-base (finetuned on TweetEval benchmark)	~58M tweets

Score Building

Model	Accuracy
spacytextblob - baseline	56% on 1.6 million tweets (test_size=0.2)
DistilBERT (finetuned on SST-2)	91.3% on the dev set
BERT-base-multilingual-uncased (finetuned on product reviews)	67% (Exact Match) , 5000 held-out 95% (Off-by-one) , 5000 held-out
BERT-base-uncased-emotion (finetuned on emotion dataset ~ 20k records)	94.05% , 2000 test set
RoBERTa-large (finetuned on 15 data sets, including reviews, tweets)	93.2% on average (leave-one-out 14:1)
RoBERTa-base (finetuned on TweetEval benchmark)	72.6% for the sentiment task 65.2% for all seven tasks

Quick Test: Tricky Problems for spacytextblob

```
sentiment_score('It should have been better.')

It should have been better.

   distilBERT: NEGATIVE: 0.9993190765380859
RoBERTa-large: NEGATIVE: 0.9976003766059875
RoBERTa-tweet:  NEUTRAL: 0.5068300366401672

    BERT_star:  3 stars: 0.5845696330070496
                2 stars: 0.3204025328159332

 BERT_emotion:
                sadness: 0.13417424261569977
                    joy: 0.7985766530036926
                   love: 0.006028416566550732
                  anger: 0.05297849327325821
                   fear: 0.004903731867671013
               surprise: 0.0033384431153535843
```

Negative comments containing only positive words.

Most BERT models are able to handle them correctly.

```
I love his charisma but I hate his policies.

    distilBERT: NEGATIVE: 0.997506856918335
 RoBERTa-large: NEGATIVE: 0.9993733167648315
 RoBERTa-tweet:  NEGATIVE: 0.5355085730552673

     BERT_star:  3 stars: 0.43239906430244446
                 2 stars: 0.2154700607061386

  BERT_emotion:
                 sadness: 0.0037230639718472958
                     joy: 0.0007427089149132371
                    love: 0.00046253454638645053
                   anger: 0.9940525889396667
                    fear: 0.000747219193726778
                surprise: 0.00027186755323782563
```

```
I am happy that you are angry.

    distilBERT: POSITIVE: 0.9976312518119812
 RoBERTa-large: POSITIVE: 0.9979450702667236
 RoBERTa-tweet:  POSITIVE: 0.599236249923706

     BERT_star:  5 stars: 0.6437188982963562
                 4 stars: 0.2716260850429535

  BERT_emotion:
                 sadness: 0.0024523830506950617
                     joy: 0.010998108424246311
                    love: 0.0008390203583985567
                   anger: 0.9837892055511475
                    fear: 0.0011402983218431473
                surprise: 0.0007809720700606704
```

```
I hate his policies but I love his charisma.

    distilBERT: POSITIVE: 0.9997598528862
 RoBERTa-large: POSITIVE: 0.9972110986709595
 RoBERTa-tweet:  NEGATIVE: 0.4327501654624939

     BERT_star:  4 stars: 0.4284682273864746
                 5 stars: 0.28129449486732483

  BERT_emotion:
                 sadness: 0.006067375652492046
                     joy: 0.09167621284723282
                    love: 0.008227312006056309
                   anger: 0.8918558359146118
                    fear: 0.0009415088570676744
                surprise: 0.0012318018125370145
```

```
I am angry that you are happy.

    distilBERT: NEGATIVE: 0.9902612566947937
 RoBERTa-large: NEGATIVE: 0.998938262462616
 RoBERTa-tweet:  NEGATIVE: 0.7087507247924805

     BERT_star:  5 stars: 0.5313980579376221
                 4 stars: 0.23201106488704681

  BERT_emotion:
                 sadness: 0.001180061837658286
                     joy: 0.008976660668849945
                    love: 0.0009814432123675942
                   anger: 0.9869871735572815
                    fear: 0.0010897686006501317
                surprise: 0.0007848881068639457
```

```
I love his charisma but I hate his policies.

    distilBERT: NEGATIVE: 0.997506856918335
 RoBERTa-large: NEGATIVE: 0.9993733167648315
 RoBERTa-tweet:  NEGATIVE: 0.5355085730552673

     BERT_star:  3 stars: 0.43239906430244446
                 2 stars: 0.2154700607061386

  BERT_emotion:
                 sadness: 0.0037230639718472958
                     joy: 0.0007427089149132371
                    love: 0.00046253454638645053
                   anger: 0.9940525889396667
                    fear: 0.000747219193726778
                surprise: 0.00027186755323782563
```

```
I am happy that you are angry.

    distilBERT: POSITIVE: 0.9976312518119812
 RoBERTa-large: POSITIVE: 0.9979450702667236
 RoBERTa-tweet:  POSITIVE: 0.599236249923706

     BERT_star:  5 stars: 0.6437188982963562
                 4 stars: 0.2716260850429535

  BERT_emotion:
                 sadness: 0.0024523830506950617
                     joy: 0.0109981084246311
                    love: 0.0008390203583985567
                   anger: 0.983789205511475
                    fear: 0.0011402983218431473
                surprise: 0.0007809720700606704
```

```
I hate his policies but I love his charisma.

    distilBERT: POSITIVE: 0.9997598528862
 RoBERTa-large: POSITIVE: 0.9972110986709595
 RoBERTa-tweet:  NEGATIVE: 0.4327501654624939

     BERT_star:  4 stars: 0.4284682273864746
                 5 stars: 0.2812944948673248З

  BERT_emotion:
                 sadness: 0.006067375652492046
                     joy: 0.09167621284723282
                    love: 0.008227312006056309
                   anger: 0.8918558359146118
                    fear: 0.0009415088570676744
                surprise: 0.0012318018125370145
```

```
I am angry that you are happy.

    distilBERT: NEGATIVE: 0.9902612566947937
 RoBERTa-large: NEGATIVE: 0.99893826246261б
 RoBERTa-tweet:  NEGATIVE: 0.7087507247924805

     BERT_star:  5 stars: 0.5313980579376221
                 4 stars: 0.2320110648870468l

  BERT_emotion:
                 sadness: 0.0011800618376582 86
                     joy: 0.0089766606688 49945
                    love: 0.0009814432123675942
                   anger: 0.9869871735572815
                    fear: 0.0010897686006501317
                surprise: 0.0007848881068639457
```

Most BERT models are able to encode contextual semantics in a sentence.

But no model is perfect…

Score Building

Problems with BERT models (transformers)

```
sentiment_score('Trump')
```

Trump (133682)

```
   distilBERT: POSITIVE: 0.9725903868675232
RoBERTa-large: POSITIVE: 0.9692159295082092
RoBERTa-tweet:  LABEL_1: 0.584307074546814

    BERT_star:  5 st[illegible]565
                4 st[illegible]825

 BERT_emotion:
                sadness: 0.09577899426221848
                    joy: 0.3048216700553894
                   love: 0.012770570814609528
                  anger: 0.5034168362617493
                   fear: 0.07124734669923782
               surprise: 0.011964641511440277
```

```
sentiment_score('Hillary')
```

Hillary (62515)

```
   distilBERT: POSITIVE: 0.997885525226593
RoBERTa-large: NEGATIVE: 0.991580605506897
RoBERTa-tweet:  LABEL_1[illegible]0.5108434557914734

    [illegible]s: 0.313565224091034
               [illegible]s: 0.2760293483734131

 BERT_emotion:
                sadness: 0.017226489260792732
                    joy: 0.03734379634261131
                   love: 0.003575555980205536
                  anger: 0.906836748123169
                   fear: 0.03291909396648407
               surprise: 0.002098318887874484
```

“Model-Mining”

"Model-Mining"

Keyword Sanity Checks

Problems with BERT models (transformers)

```
sentiment_score('Trump')
```

```
Trump (133682)

  distilBERT: POSITIVE: 0.9725903868675232
RoBERTa-large: POSITIVE: 0.9692159295082092
RoBERTa-tweet: LABEL_1: 0.584307074546814

   BERT_star: 5 stars: [illegible]
              4 stars: [illegible]

 BERT_emotion:
              sadness: [illegible]
                  joy: [illegible]
                 love: 0.012770570814609528
                anger: 0.5034168362617493
                 fear: 0.07124734669923782
             surprise: 0.011964641511440277
```

```
sentiment_score('Hillary')
```

```
Hillary (62515)

  distilBERT: POSITIVE: 0.997885525226593
RoBERTa-large: NEGATIVE: 0.99158060506897
RoBERTa-tweet: LABEL_1: 0.5108434557914734

   BERT_star: [illegible]: 0.313565224091034
              [illegible]: 0.2760293483734131

 BERT_emotion:
              sadness: 0.017226489260792732
                  joy: 0.03734379634261131
                 love: 0.003575555980205536
                anger: 0.906836748123169
                 fear: 0.03291909396648407
             surprise: 0.002098318887874484
```

Score Building

Problems with BERT models (transformers)

```
sentiment_score('Trump')
```

```
Trump  (133682)

    distilBERT: POSITIVE: 0.9725903868675232
RoBERTa-large: POSITIVE: 0.9692159295082092
RoBERTa-tweet:  LABEL_1: 0.584307074546814

     BERT_star:  5 stars: 0.47308531403541565
                 4 stars: 0.24837274849414825

  BERT_emotion:
                 sadness: 0.09577899426221848
                     joy: 0.3048216700553894
                    love: 0.012770570814609528
                   anger: 0.5034168362617493
                    fear: 0.07124734669923782
                surprise: 0.011964641511440277
```

```
sentiment_score('Hillary')
```

```
Hillary  (62515)

    distilBERT: POSITIVE: 0.997885525226593
RoBERTa-large: NEGATIVE: 0.991580605506897
RoBERTa-tweet:  LABEL_1: 0.5108434557914734

     BERT_star:  5 stars: 0.3135652244091034
                 4 stars: 0.2760293483734131

  BERT_emotion:
                 sadness: 0.017226489260792732
                     joy: 0.03734379634261131
                    love: 0.00357555980205536
                   anger: 0.906836748123169
                    fear: 0.03291909396648407
                surprise: 0.002098318887874484
```

Score Building

Problems with BERT models (transformers)

```
sentiment_score('Trump')
```

Trump (133682)

```
   distilBERT: POSITIVE: 0.9725903868675232
RoBERTa-large: POSITIVE: 0.9692159295082092
RoBERTa-tweet:  LABEL_1: 0.584307074546814

    BERT_star:  5 stars: 0.47308531403541565
                4 stars: 0.24837274849414825

 BERT_emotion:
               sadness: 0.09577899426221848
                   joy: 0.3048216700553894
                  love: 0.012770570814609528
                 anger: 0.5034168362617493
                  fear: 0.07124734669923782
              surprise: 0.011964641511440277
```

Trump fans (joy)

Hillary fans (anger)

```
sentiment_score('Hillary')
```

Hillary (62515)

```
   distilBERT: POSITIVE: 0.99788552226593
RoBERTa-large: NEGATIVE: 0.99158060506897
RoBERTa-tweet:  LABEL_1: 0.5108434557914734

    BERT_star:  5 stars: 0.3135652244091034
                4 stars: 0.2760293483734131

 BERT_emotion:
               sadness: 0.017226489260792732
                   joy: 0.03734379634261131
                  love: 0.00357555980205536
                 anger: 0.906836748123169
                  fear: 0.03291909396648407
              surprise: 0.002098318887874484
```

Trump fans (anger)

40 % difference

These three models seem to favor Trump more!

But things are getting more interesting with full names…

Score Building

Problems with BERT models (transformers)

```
sentiment_score('Donald Trump')
```

Donald Trump (14376)

```
   distilBERT: POSITIVE: 0.9968115091323853
RoBERTa-large: NEGATIVE: 0.5731404423713684
RoBERTa-tweet:  LABEL_1: 0.5287980437278748

    BERT_star:  5 stars: 0.3785494863986969
                4 stars: 0.2542939484119415 3

 BERT_emotion:
                sadness: 0.09323982149362564
                    joy: 0.25523635745048523
                   love: 0.009053708054125309
                  anger: 0.5888552665710449
                   fear: 0.045651838183403015
               surprise: 0.007962971925735474
```

```
sentiment_score('Hillary Clinton')
```

Hillary Clinton (10610)

```
   distilBERT: POSITIVE: 0.994881808757782
RoBERTa-large: POSITIVE: 0.861779212951660 2
RoBERTa-tweet:  LABEL_1: 0.692924261093139 6

    BERT_star:  5 stars: 0.3710388541221618 7
                4 stars: 0.287602990865707 4

 BERT_emotion:
                sadness: 0.09025482833385468
                    joy: 0.08369173854589462
                   love: 0.011154184117913246
                  anger: 0.770174324512481 7
                   fear: 0.041576992720365524
               surprise: 0.0031479541212320328
```

Score Building

Problems with BERT models (transformers)

```
sentiment_score('Donald Trump')
```

Donald Trump (14376)

```
    distilBERT: POSITIVE: 0.9968115091323853
RoBERTa-large: NEGATIVE: 0.5731404423713684
RoBERTa-tweet:  LABEL_1: 0.5287980437278748

     BERT_star:  5 stars: 0.3785494863986969
                 4 stars: 0.2542939484119415

  BERT_emotion:
                 sadness: 0.09323982149362564
                     joy: 0.2552363574504852
                    love: 0.009053708054125309
                   anger: 0.5888552665710449
                    fear: 0.045651838183403015
                surprise: 0.007962971925735474
```

Hillary fans

```
sentiment_score('Hillary Clinton')
```

Hillary Clinton (10610)

```
    distilBERT: POSITIVE: 0.994881808757782
RoBERTa-large: POSITIVE: 0.8617792129516602
RoBERTa-tweet:  LABEL_1: 0.6929242610931396

     BERT_star:  5 stars: 0.37103885412216187
                 4 stars: 0.2876029908657074

  BERT_emotion:
                 sadness: 0.09025482833385468
                     joy: 0.08369173854589462
                    love: 0.011154184117913246
                   anger: 0.7701743245124817
                    fear: 0.041576992720365524
                surprise: 0.0031479541212320328
```

Trump fans

18 % difference

Things flipped for RoBERTa-large!

BERT_star doesn't show preference anymore.

BERT_emotion is MUCH less biased!

Facts

- Models show preferences for Trump in general.
- Things flipped for RoBERTa-large in the case of "full names"

My Guess is that…

- Trump fans have a stronger online community.
- They love to express anger.
- However, they tend to use "short names" more often.
- Hillary fans, though weaker, tend to use "full names" more.
- Some models therefore pick up these biases "perfectly"

Score Building

Problems with BERT models (transformers)

```
sentiment_score('Republican Party')
```

```
Republican Party  (3364)

   distilBERT: POSITIVE: 0.9719760417938232
RoBERTa-large: NEGATIVE: 0.9907021522521973
RoBERTa-tweet:  LABEL_1: 0.7440347671508789

    BERT_star:  4 stars: 0.2642284333705902
                3 stars: 0.26280689239501953

 BERT_emotion:
               sadness: 0.051437657326459885
                   joy: 0.07962372899055481
                  love: 0.018300192430615425
                 anger: 0.775590360164623
                  fear: 0.06592267006635666
              surprise: 0.009125471115112305
```

```
sentiment_score('Democratic Party')
```

```
Democratic Party  (2351)

   distilBERT: POSITIVE: 0.9566918015480042
RoBERTa-large: NEGATIVE: 0.9798932075500488
RoBERTa-tweet:  LABEL_1: 0.754387363204956

    BERT_star:  3 stars: 0.27808520197868347
                4 stars: 0.269898146390149

 BERT_emotion:
               sadness: 0.08952565491199493
                   joy: 0.392833203077316
                  love: 0.019987786188721657
                 anger: 0.44837430119514465
                  fear: 0.04172710329294205
              surprise: 0.007551965303719044
```

Score Building

Problems with BERT models (transformers)

```
sentiment_score('Republican Party')
```

```
Republican Party (3364)

   distilBERT: POSITIVE: 0.9719760417938232
RoBERTa-large: NEGATIVE: 0.9907021522521973
RoBERTa-tweet:  LABEL_1: 0.7440347671508789

    BERT_star:  4 stars: 0.2642284333705902
                3 stars: 0.2628068923950195 3

 BERT_emotion:
                sadness: 0.05143765732645988 5
                    joy: 0.0796237289905548 1
                   love: 0.01830019243061542 5
Hillary supporters anger: 0.775590360164642 3
                   fear: 0.0659226700663566 6
               surprise: 0.00912547111511230 5
```

```
sentiment_score('Democratic Party')
```

```
Democratic Party (2351)

   distilBERT: POSITIVE: 0.9566918015480042
RoBERTa-large: NEGATIVE: 0.9798932075500488
RoBERTa-tweet:  LABEL_1: 0.7543877363204956

    BERT_star:  3 stars: 0.27808520197868347
                4 stars: 0.269898146390914 9

 BERT_emotion:
                sadness: 0.0895256549119949 3
Hillary supporters  joy: 0.392833203077316 3
                   love: 0.01998778618872165 7
Trump supporters  anger: 0.4483743011951446 5
                   fear: 0.0417271032929420 5
               surprise: 0.00755196530371904 4
```

Anger is shown more toward the Republican Party.

Less models exhibit biases or preferences.

Score Building

Problems with BERT models (transformers)

```
sentiment_score('Republicans')
```

```
Republicans (27632)

   distilBERT: POSITIVE: 0.7812759280204773
RoBERTa-large: NEGATIVE: 0.9946274161338806
RoBERTa-tweet:  LABEL_1: 0.7111724615097046

    BERT_star:  3 stars: 0.27862027287483215
                 1 star: 0.20595254004001617

  BERT_emotion:
                sadness: 0.13379821181297302
                    joy: 0.226376712322351
                   love: 0.023794466629624367
                  anger: 0.5194436311721802
                   fear: 0.08247973769903183
               surprise: 0.014107205905020237
```

```
sentiment_score('Democrats')
```

```
Democrats (27147)

   distilBERT: POSITIVE: 0.9105578660964966
RoBERTa-large: NEGATIVE: 0.996316909790391
RoBERTa-tweet:  LABEL_1: 0.603154420852661l

    BERT_star:  3 stars: 0.2681081295013428
                4 stars: 0.247552990913391l

  BERT_emotion:
                sadness: 0.14551712572574615
                    joy: 0.2647758424282074
                   love: 0.020851828157901764
                  anger: 0.539529621601l047
                   fear: 0.02431230992078781
               surprise: 0.005013232585042715
```

Score Building

Problems with BERT models (transformers)

```
sentiment_score('Republicans')
```

Republicans (27632)

```
   distilBERT: POSITIVE: 0.7812759280204773
RoBERTa-large: NEGATIVE: 0.9946274161338806
RoBERTa-tweet:  LABEL_1: 0.7111724615097046

    BERT_star:  3 stars: 0.27862027287483215
                 1 star: 0.20595254004001617
```

Hillary supporters

```
 BERT_emotion:
                sadness: 0.13379821181297302
                    joy: 0.226376712322351
                   love: 0.023794466629624367
                  anger: 0.5194436311721802
                   fear: 0.0824797376990318
               surprise: 0.014107205905020237
```

```
sentiment_score('Democrats')
```

Democrats (27147)

```
   distilBERT: POSITIVE: 0.9105578660964966
RoBERTa-large: NEGATIVE: 0.996316909790391
RoBERTa-tweet:  LABEL_1: 0.603154420852661

    BERT_star:  3 stars: 0.268108129501342
                4 stars: 0.247552990913391

 BERT_emotion:
                sadness: 0.14551712572574615
                    joy: 0.2647758424282074
                   love: 0.020851828157901764
                  anger: 0.539529621601104
                   fear: 0.024312309920787818
               surprise: 0.005013232585042715
```

Republicans has a lower star rate.

Less models exhibit biases or preferences.

Facts

- Anger is shown more toward the Republican Party.
- Republicans has a lower star rate.
- Less models exhibit biases or preferences.

My Guess is that…

- Hillary supporters level criticism more at the Republican Party than at Trump.
- Even so, they don't show as much anger as Trump supporters.
- "Trump/Hillary" provokes more emotions than "Republican/Democratic party "

Score Building

For better or worse, these models are still reliable in terms of sentiment analysis!

- **As more words are included, the biases will be mitigated and differences between them will even out.**

Score Building

For better or worse, these models are still reliable in terms of sentiment analysis!

- **As more words are included, the biases will be mitigated and differences between them will even out.**

```
sentiment_score('#gotrump')

#GoTrump

   distilBERT: POSITIVE: 0.8377019762992859
RoBERTa-large: POSITIVE: 0.998569905757904
RoBERTa-tweet:  NEUTRAL: 0.5993925333023071

    BERT_star:   1 star: 0.32074394822120667
                2 stars: 0.20401939749717712

 BERT_emotion:
                sadness: 0.008891078643500805
                    joy: 0.5073965191841125
                   love: 0.011058000847697258
                  anger: 0.4676983058452606
                   fear: 0.002409894717857241 6
               surprise: 0.0025462396442890167
```

```
sentiment_score('#gohillary')

#gohillary

   distilBERT: NEGATIVE: 0.910306036472320 6
RoBERTa-large: POSITIVE: 0.94978320598602 3
RoBERTa-tweet:  NEUTRAL: 0.64025002717971 8

    BERT_star:   1 star: 0.2494648993015289 3
                3 stars: 0.2097745537757873 5

 BERT_emotion:
                sadness: 0.015515195205807686
                    joy: 0.1092054247856140 1
                   love: 0.0032404744997620583
                  anger: 0.842630386352539 1
                   fear: 0.026823310181498528
               surprise: 0.0025852704420685 77
```

Score Building

For better or worse, these models are still reliable in terms of sentiment analysis!

As more words are included, the biases will be mitigated and differences between them will even out.

```
sentiment_score('We will vote for you! #gotrump')

We will vote for you! #gotrump

  distilBERT: POSITIVE: 0.9986934661865234
RoBERTa-large: POSITIVE: 0.9980786442756653
RoBERTa-tweet:  POSITVE: 0.6127783060073853

   BERT_star:  5 stars: 0.4745408296585083
               4 stars: 0.18664398789405823

 BERT_emotion:
               sadness: 0.0026922193355858326
                   joy: 0.9549510478973389
                  love: 0.010346263647079468
                 anger: 0.030505357310175896
                  fear: 0.0005179055151152961
              surprise: 0.0009872176451608539
```

```
sentiment_score('We will vote for you! #gohillary')

We will vote for you! #gohillary

  distilBERT: POSITIVE: 0.998278677463531 5
RoBERTa-large: POSITIVE: 0.9986332058906555
RoBERTa-tweet:  POSITVE: 0.8715099096298218

   BERT_star:  5 stars: 0.5570440888404846
               4 stars: 0.2187049388885498

 BERT_emotion:
               sadness: 0.005750871729105711
                   joy: 0.886862874031066 9
                  love: 0.01299843005836 01
                 anger: 0.09092111140489578
                  fear: 0.0015296215424314141
              surprise: 0.0019370005466 04395
```

Score Building

For better or worse, these models are still reliable in terms of sentiment analysis!

As more words are included, the biases will be mitigated and differences between them will even out.

```
sentiment_score('VoteForTrump')

VoteForTrump

   distilBERT: NEGATIVE: 0.8530213236808777
RoBERTa-large: POSITIVE: 0.9985228180885315
RoBERTa-tweet:  NEUTRAL: 0.5549483895301819

    BERT_star:   1 star: 0.2626546621322632
                3 stars: 0.2417004108428955

 BERT_emotion:
                sadness: 0.012041224166750908
                    joy: 0.10489775240421295
                   love: 0.009046209044754505
                  anger: 0.8592172861099243
                   fear: 0.011024881154298782
               surprise: 0.0037726890295743942
```

```
sentiment_score('Vote For Trump')

Vote For Trump

   distilBERT: POSITIVE: 0.9965157508850098
RoBERTa-large: POSITIVE: 0.9986465573310852
RoBERTa-tweet:  NEUTRAL: 0.6238986849784851

    BERT_star:  5 stars: 0.3185446560382843
                4 stars: 0.23902350664138794

 BERT_emotion:
                sadness: 0.02138894982635975
                    joy: 0.6888414025306702
                   love: 0.011685918085277708
                  anger: 0.2581046223640442
                   fear: 0.016510898247361183
               surprise: 0.0034682280384004116
```

Single-word comments is a problem.

Score Building

For better or worse, these models are still reliable in terms of sentiment analysis!

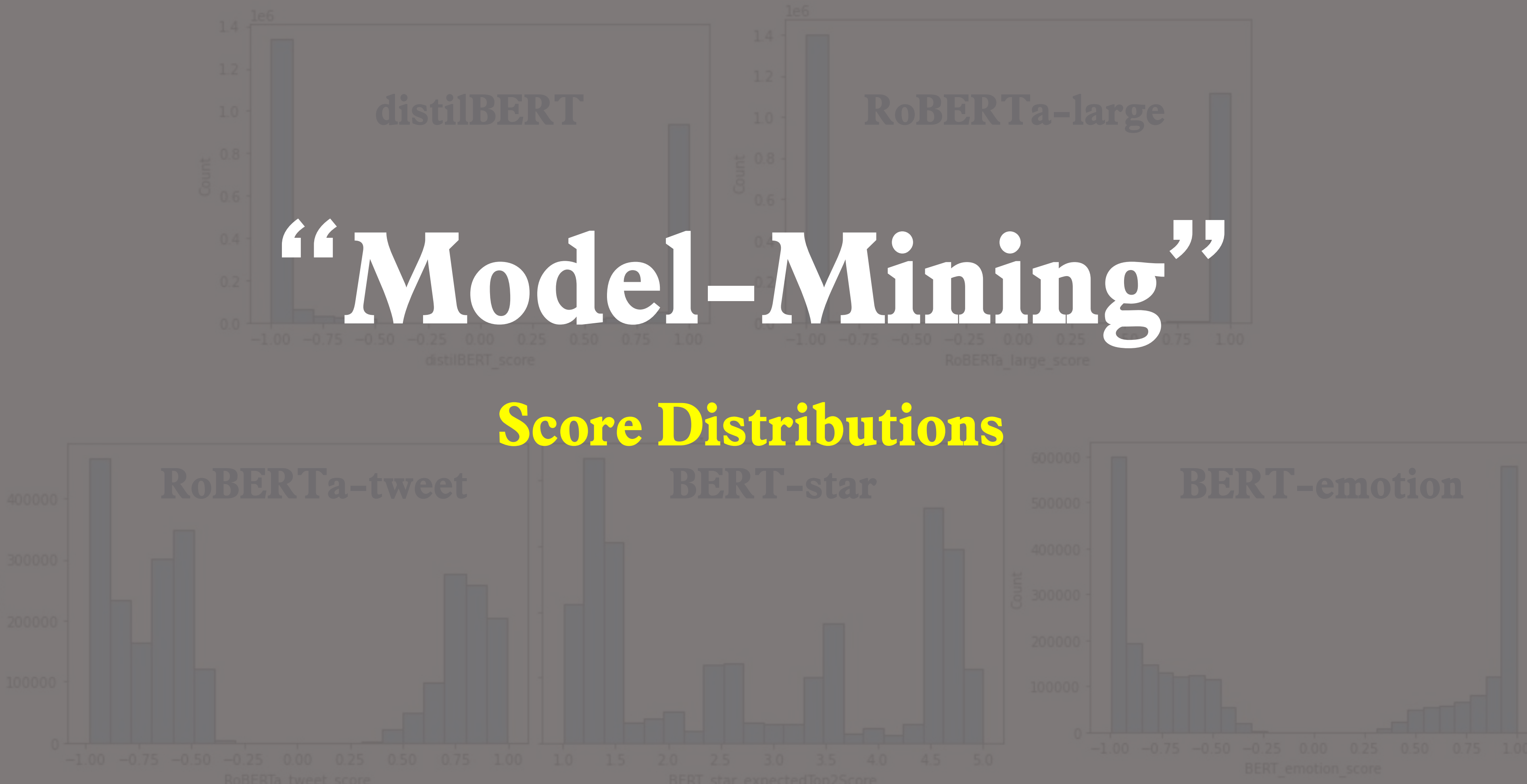
As more words are included, the biases will be mitigated and differences between them will even out.

```
sentiment_score('VoteForTrump')

VoteForTrump

    dis[illegible]
RoBERTa-large: POSITIVE: 0.9985228180885315
RoBERTa-tweet:  NEUTRAL: 0.5549483895[illegible]819

    BERT_star:    1 star: 0.2626546621322632
                  3 sta[illegible]

 BERT_emotion:
                sadness: 0.012041224166750908
                    joy: 0.10489775240421295
                   love: 0.009046209044754505
                  anger: 0.8592172861099243
                   fear: 0.011024881154298782
               surprise: 0.0037726890295743942
```

```
sentiment_score('Vote For Trump')

Vote For Trump

[illegible]0098
RoBERTa-large: POSITIVE: 0.[illegible]0852
RoBERTa-tweet:  NEUTRAL: 0.62[illegible]784851

    BERT_star:   5 stars: 0.3185446560382843
                 [illegible]: 0.23902350664138794

 BERT_emotion:
                sadness: 0.02138894982635975
                    joy: 0.6888414025306702
                   love: 0.01168591808527708
                  anger: 0.2581046223640442
                   fear: 0.016510898247361183
               surprise: 0.0034682280384004116
```

Single-word comments that includes a key word create noises and had better be filtered out for model accuracy and reliability.

Score Distributions



“Model-Mining”

Score Distributions

Score Building

Score distributions should be roughly the same

- Each model might have its preference/pattern for assigning scores, e.g. more toward the ends or more uniformly distributed.
- However, for the same data, there is only one correct answer (though unknown).
- Therefore, score distributions should vary too much across models.

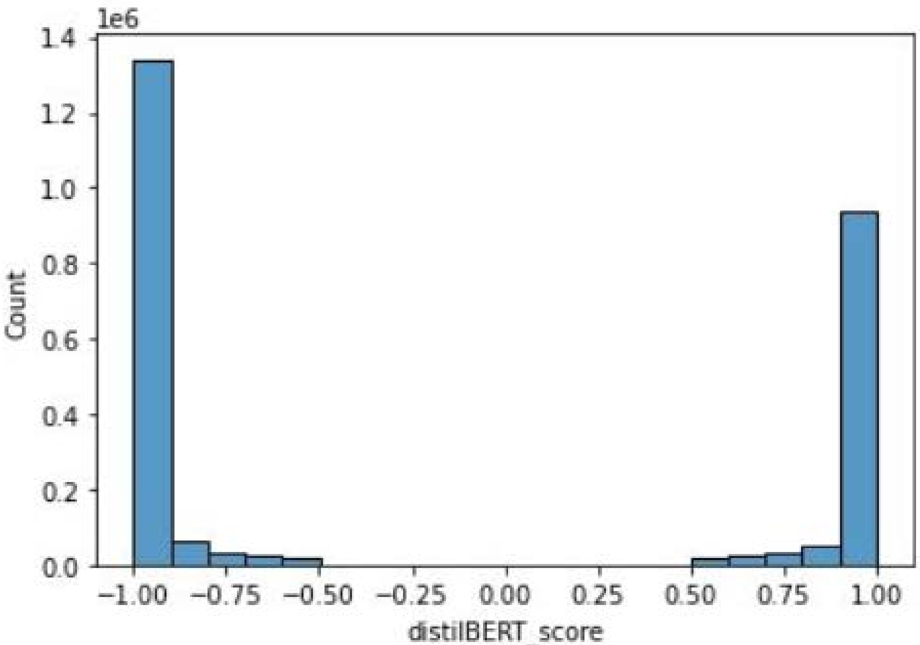
Compare distributions and Construct reasonable sentiment score.

- **Graphical Method**
  - Plot the score distributions out visually, and construct scores.
- **Mathematical Method**
  - Calculate the Wasserstein distance between every two distributions

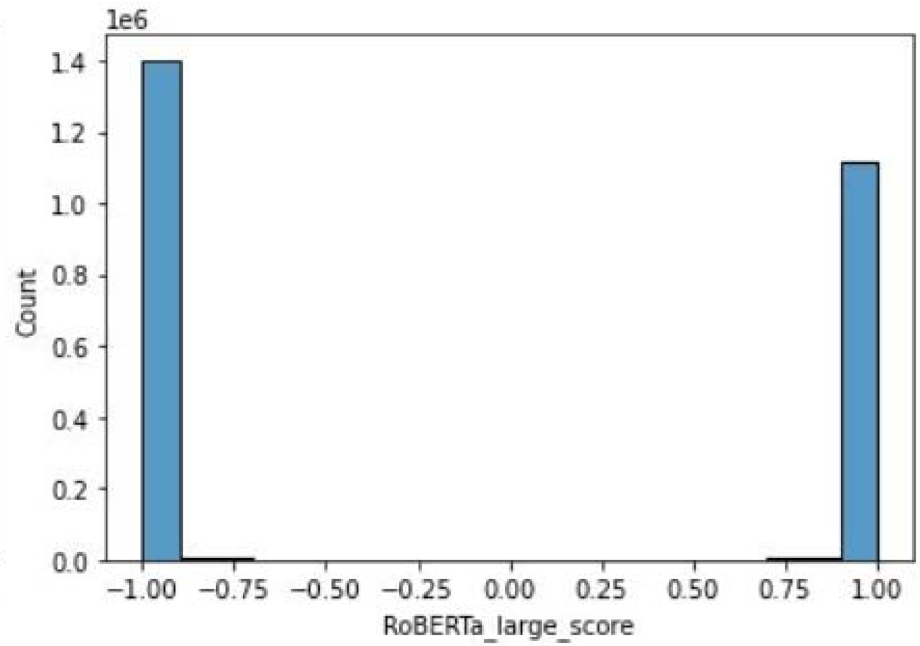
Score Building

Graphical Method

distilBERT



RoBERTa-large



These two models tend to assign extreme scores.

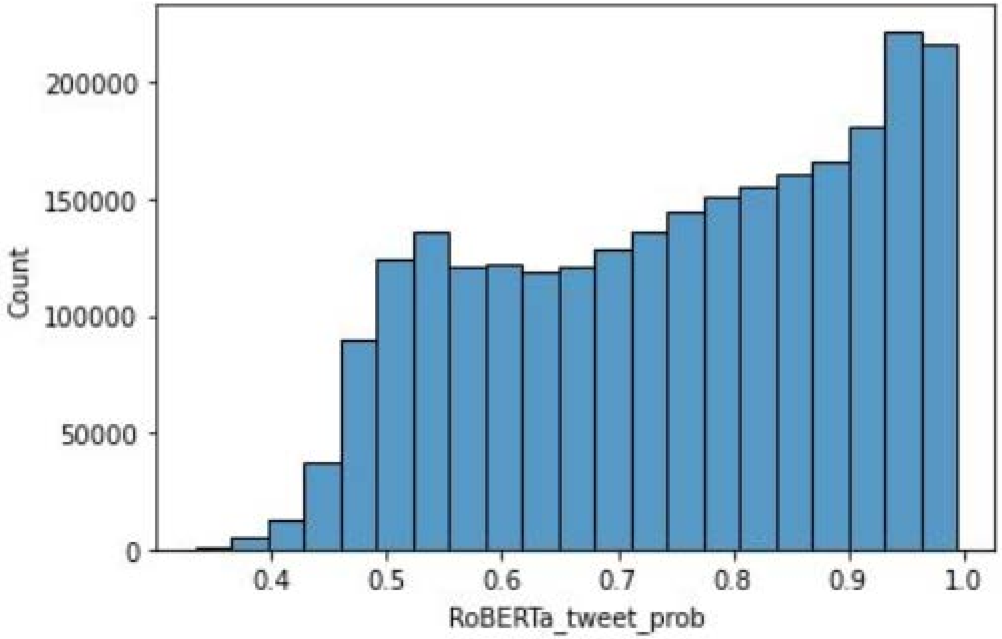
NEGATIVE comments are more than POSITIVE comments.

They look almost the same.

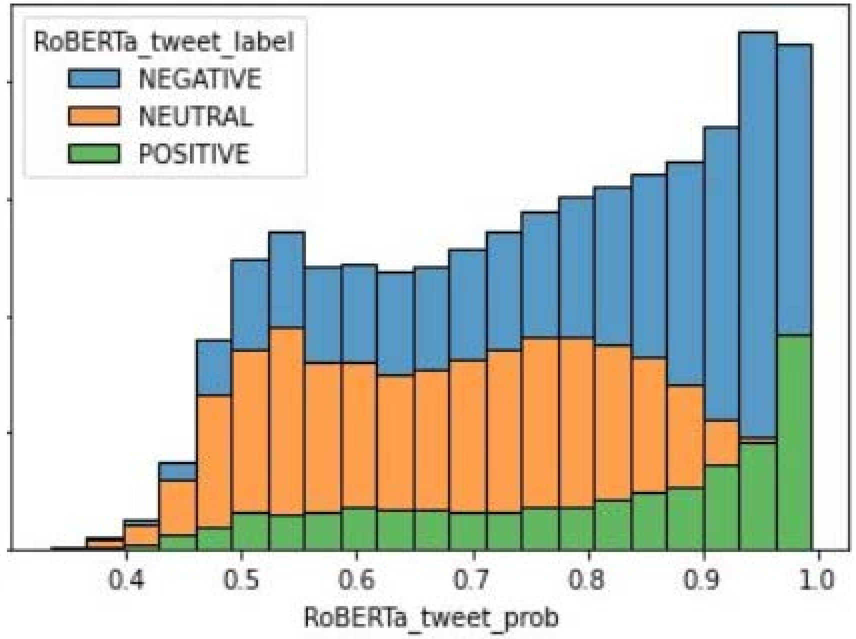
Score Building

Graphical Method

RoBERTa-tweet



RoBERTa-tweet by labels

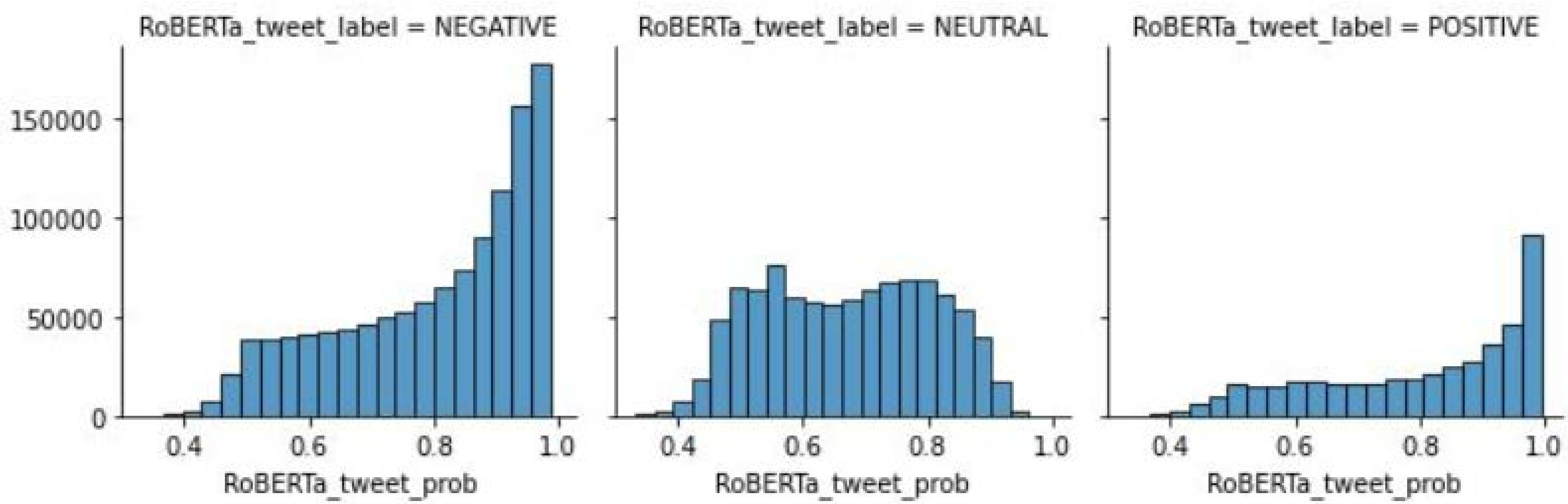


The difficulty is that there isn't a straightforward way to deal with NEUTRAL.

Score Building

Graphical Method

RoBERTa-tweet by labels



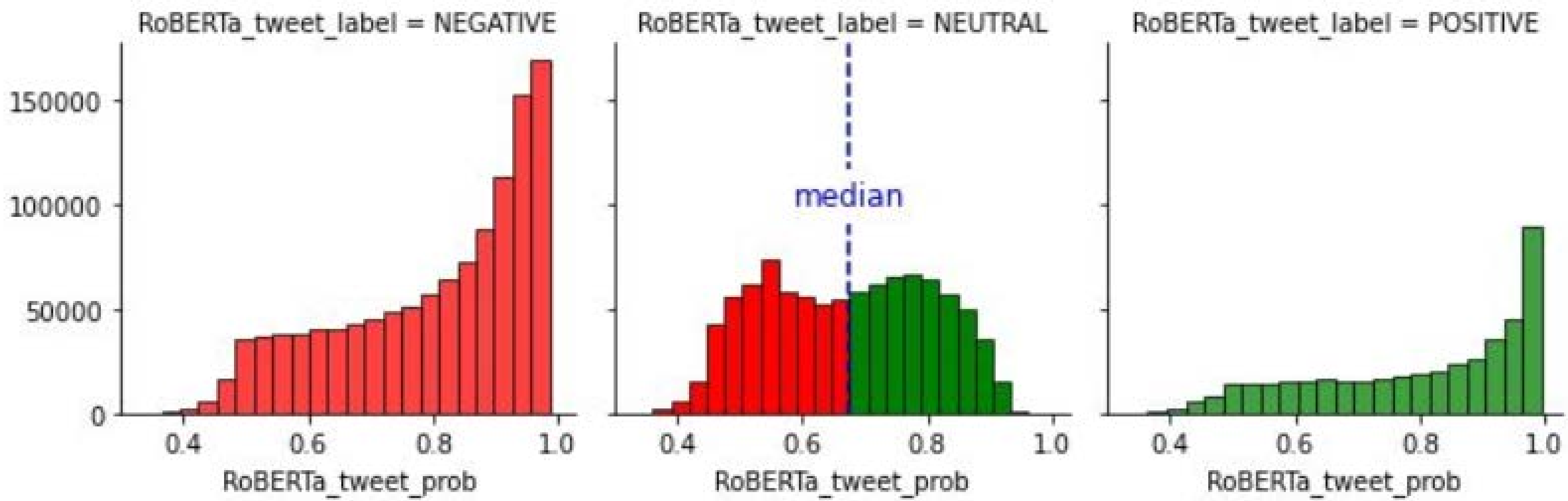
We still can see that NEGATIVE comments are more than POSITIVE ones. It tends to assign extreme scores, but not to the degree of the previous two.

As for NEUTRAL comments, we can see that the model wasn't as confident about giving this label as the other two.

Score Building

Graphical Method

RoBERTa-tweet by labels

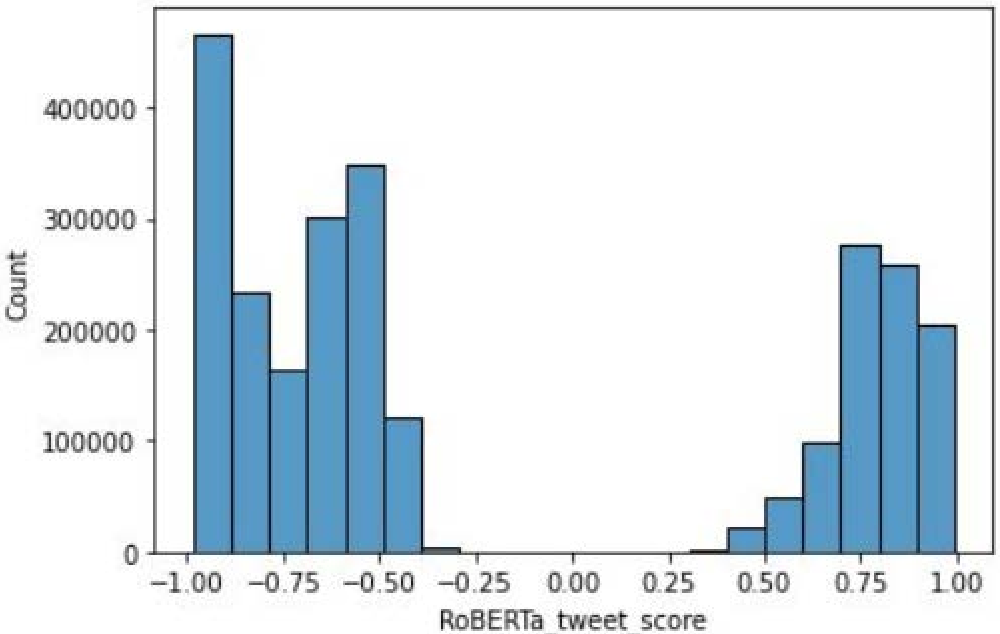


One way to enable comparability is to split NEUTRAL comments by half, and assign the labels accordingly.

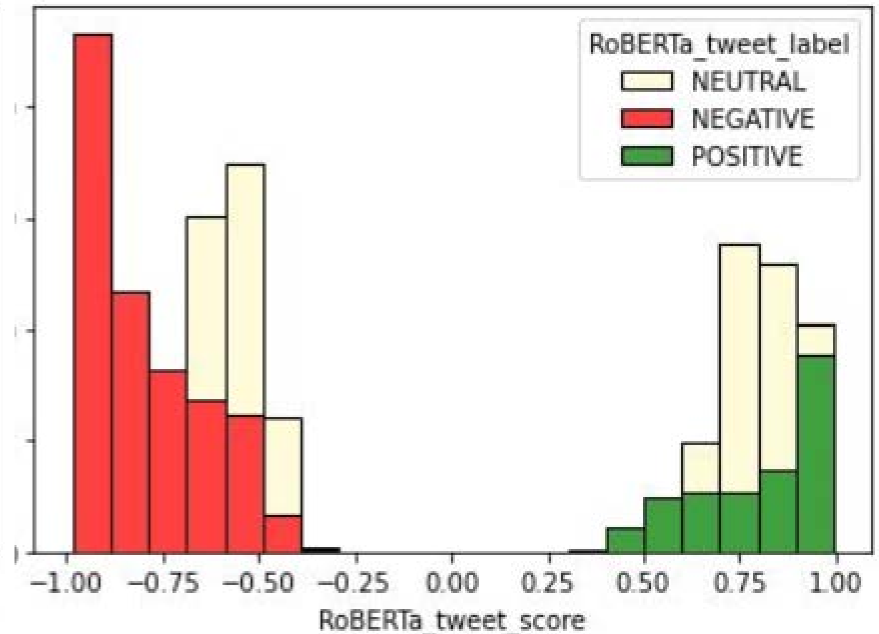
Score Building

Graphical Method

RoBERTa-tweet



RoBERTa-tweet by labels

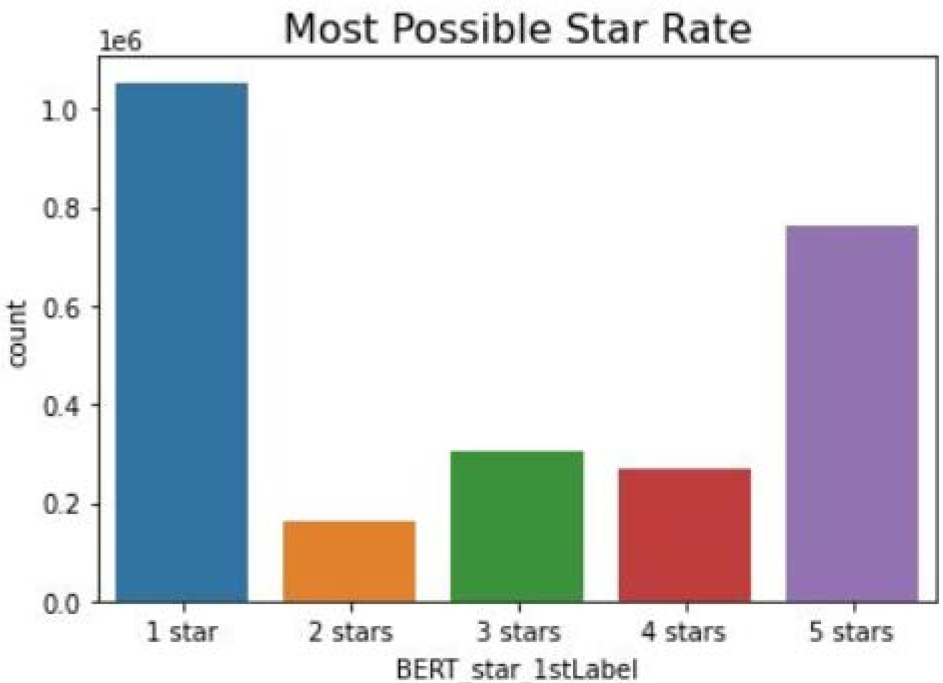


We can see that the distribution is more even, compared to the previous ones.

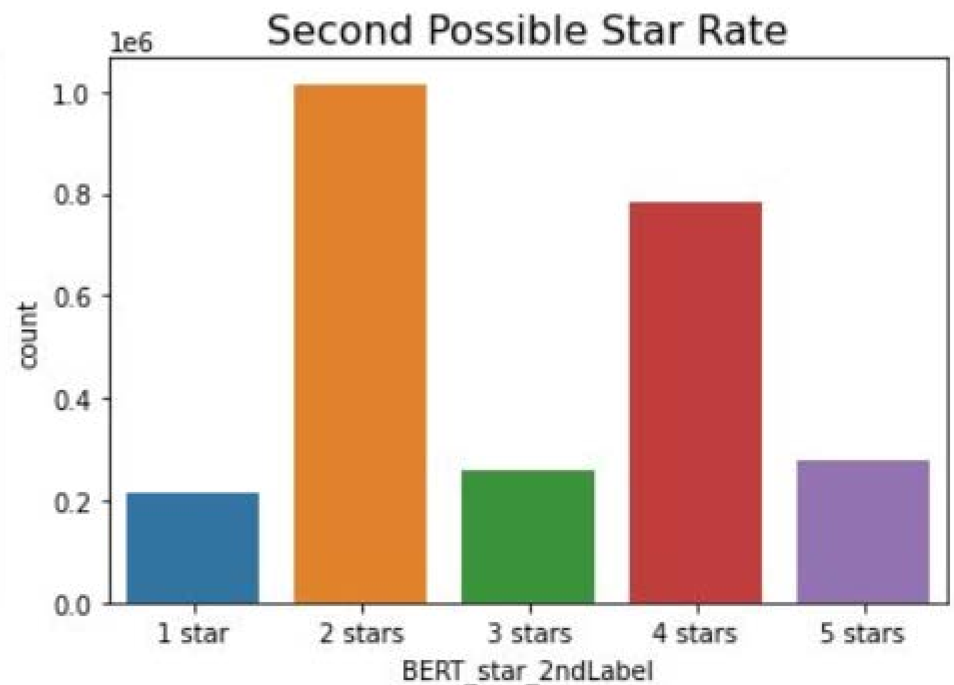
Score Building

Graphical Method

BERT-star



BERT-star

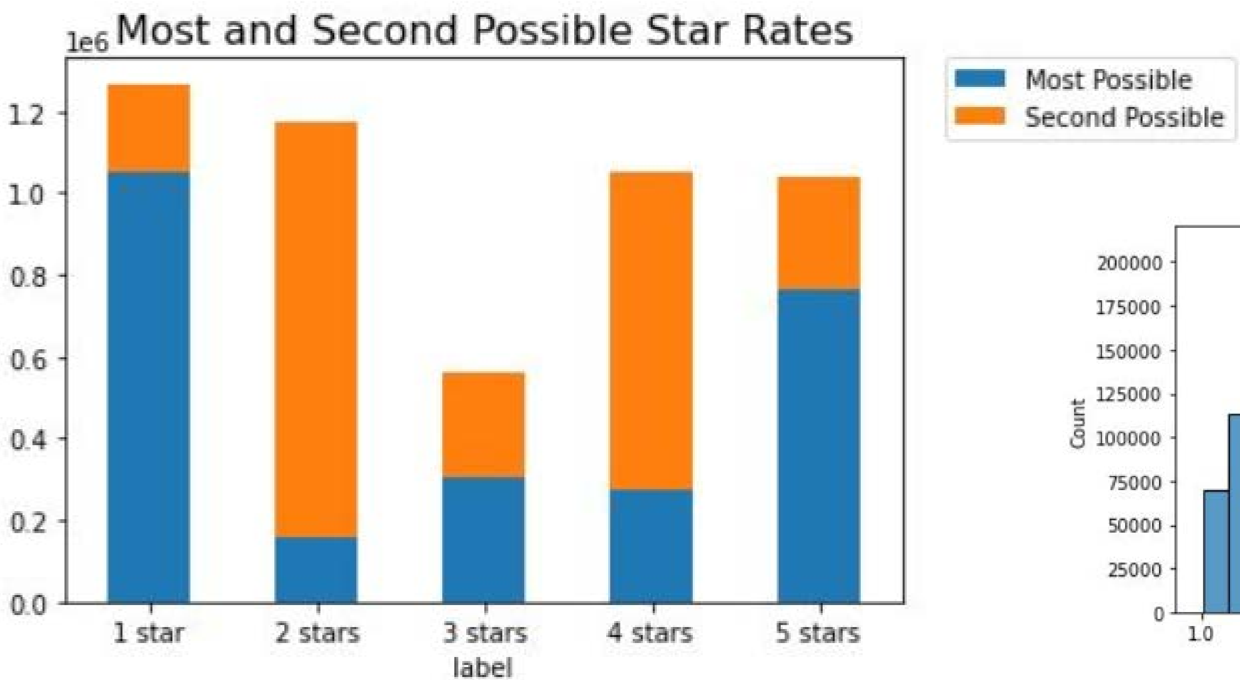


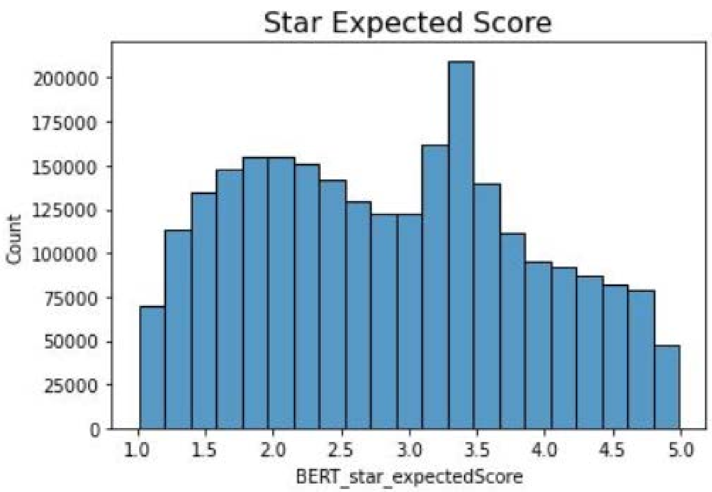
We can see that it tends to assign extreme scores, too.

Score Building

Graphical Method

BERT-star





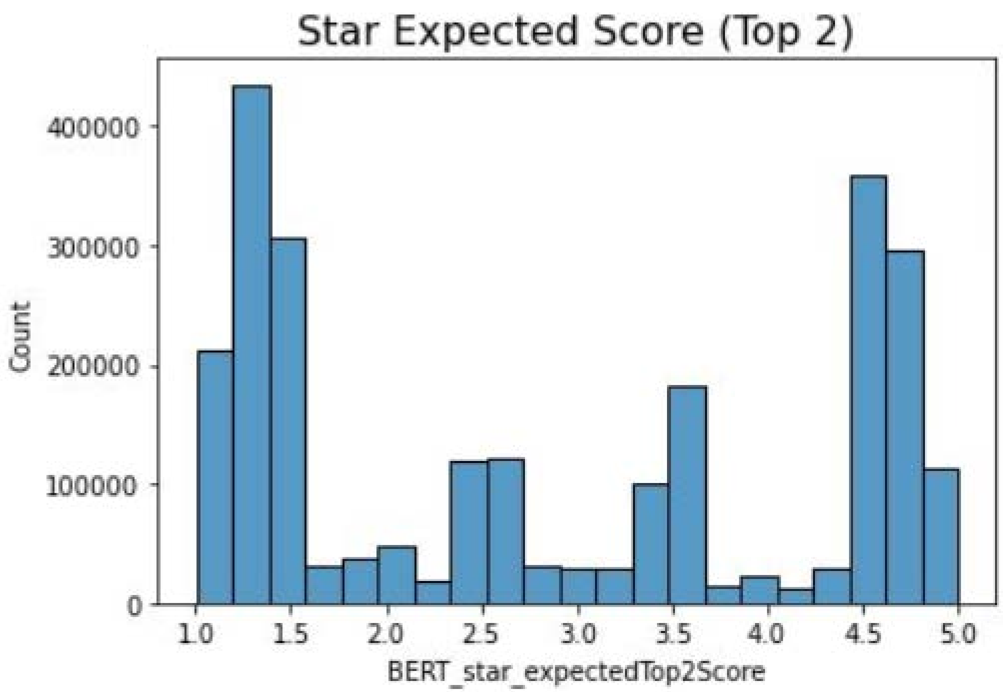
For any comment, we have the corresponding probabilities for each star rate.

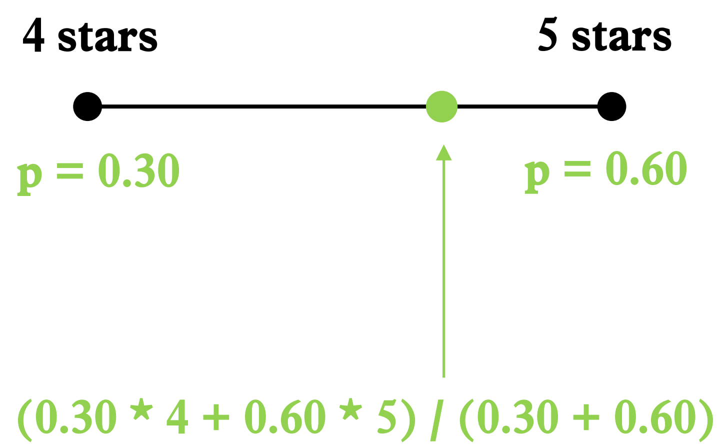
This allows us to compute expectation of star rates, but the distribution is weird.

Score Building

Graphical Method

BERT-star

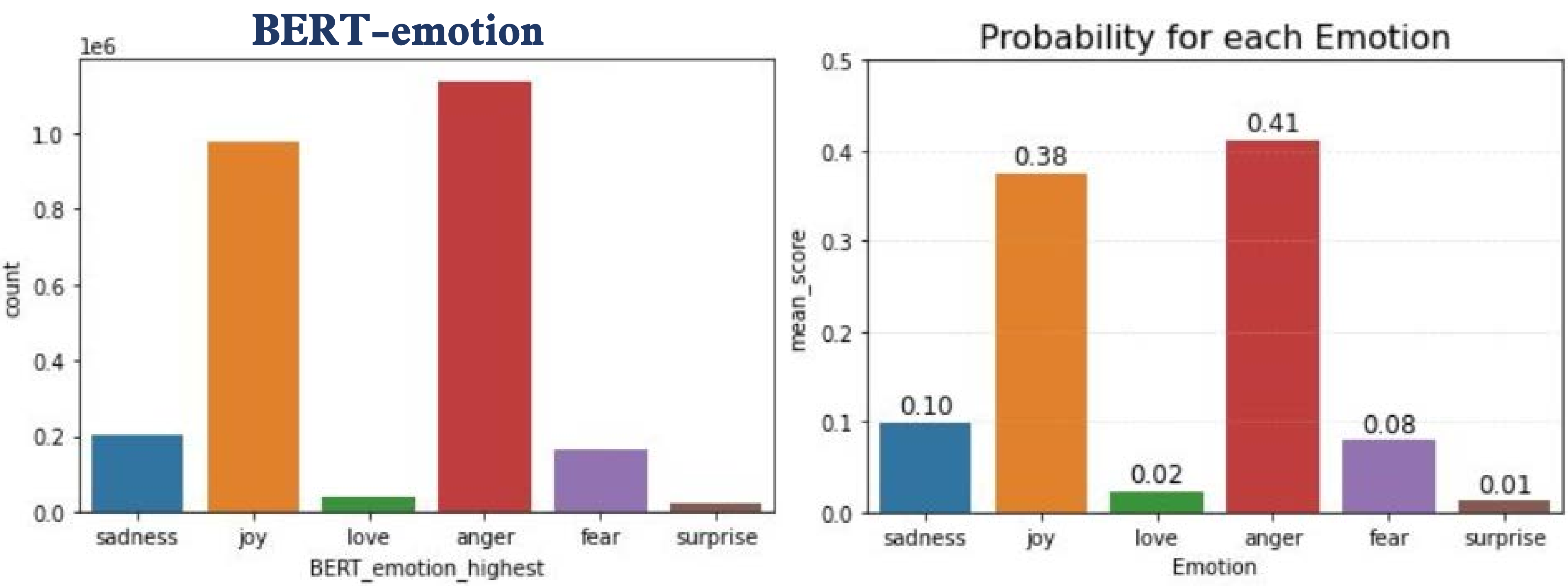




I figured that probabilities other than the top two was simply creating noise. Thus, I took the weighted average of only the top two star rate, where the weights are their probabilities normalized.

Score Building

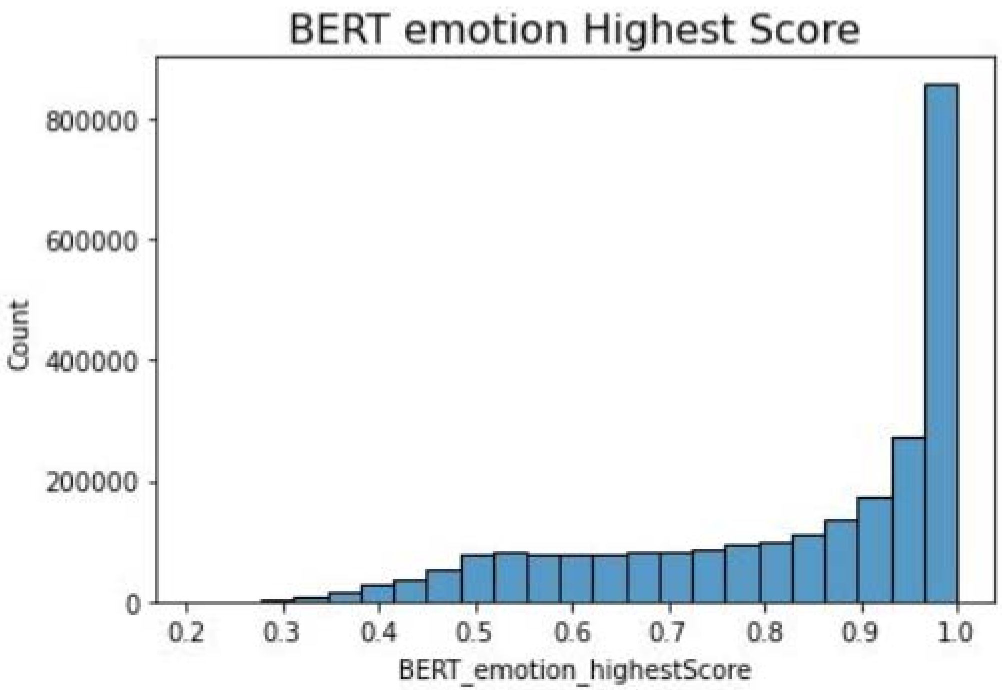
Graphical Method



Joy and Anger outnumber the other emotions by a long shot.

Score Building

Graphical Method

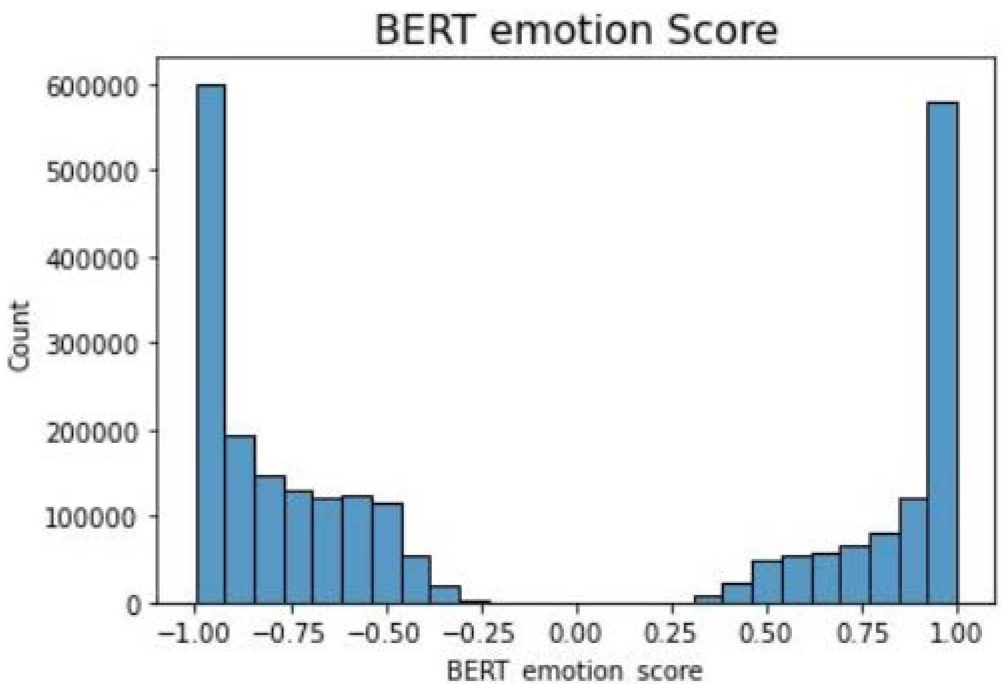


The model tends to assign extreme scores as well.

We face the issue of combining the results into one single score.

Score Building

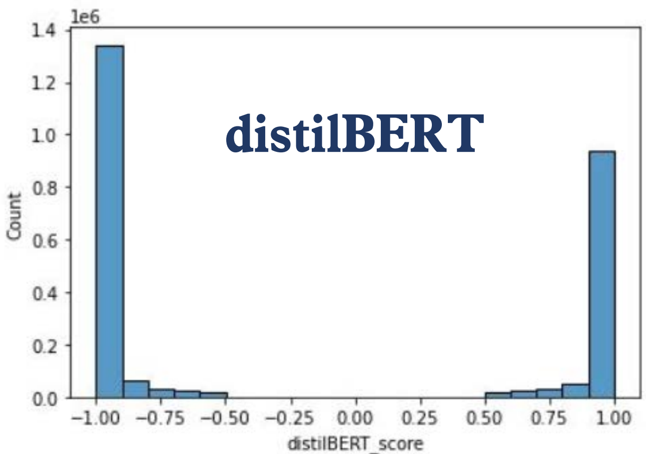
Graphical Method

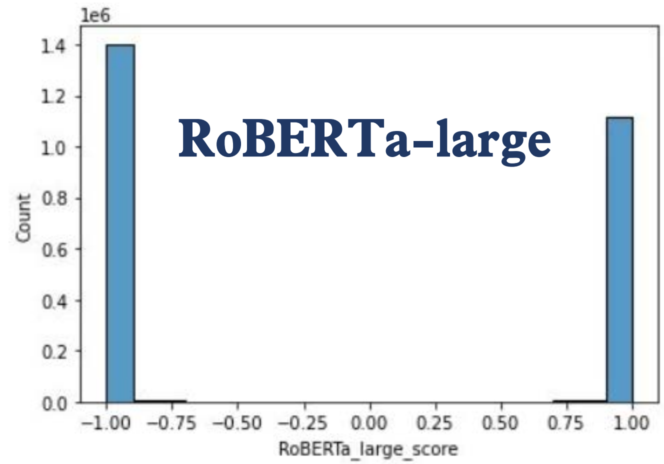


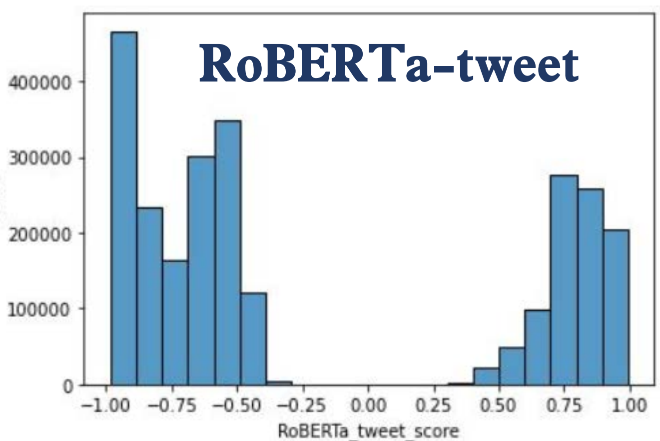
- **Joy, love, surprise → POSITIVE**
- **Anger, sadness, fear → NEGATIVE**

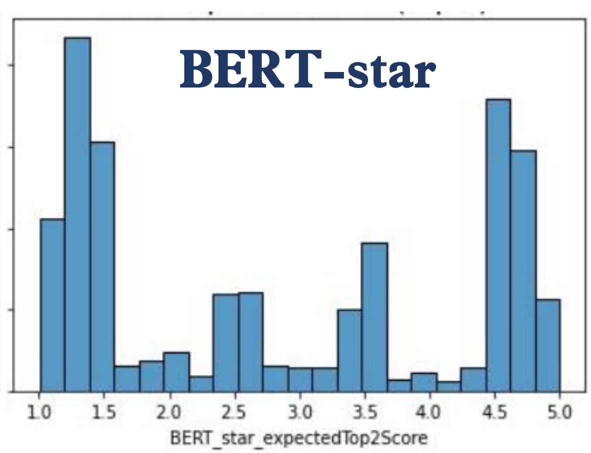
Score Building

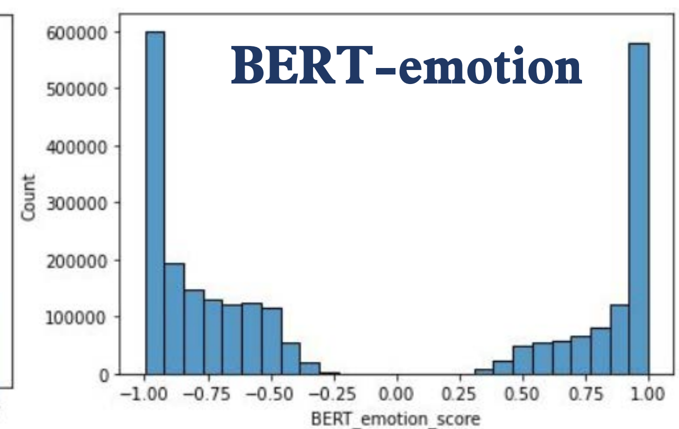
Score Distributions











Similar patterns have been found over and over again. It seems that the score distributions do not vary much across models. We need to quantify this.

Score Building

Mathematical Method

The mathematical tool here for quantifying the difference between distributions is "Wasserstein Distance", also known as "Earth Mover's Distance".

> **"Intuitively, if the distributions are interpreted as two different ways of piling up a certain amount of earth (dirt) over a region D, the Wasserstein Distance is the minimum cost of turning one pile into the other; where the cost is assumed to be the amount of dirt moved times the distance by which it is moved."**
>
> Source: https://en.wikipedia.org/wiki/Earth_mover%27s_distance

In the case of 1-D distributions, it can be proved that the Wasserstein Distance is equal to the area difference between the CDF of the two distributions.

Score Building

Mathematical Method

	distilBERT	RoBERTa_large	RoBERTa_tweet	BERT_star	BERT_emotion	mean_wdistance
distilBERT	0.000000	0.094798	0.235688	0.280457	0.146792	0.151547
RoBERTa_large	0.094798	0.000000	0.310408	0.298217	0.211318	0.182948
RoBERTa_tweet	0.235688	0.310408	0.000000	0.241955	0.121614	0.181933
BERT_star	0.280457	0.298217	0.241955	0.000000	0.176096	0.199345
BERT_emotion	0.146792	0.211318	0.121614	0.176096	0.000000	0.131164

First, standardization is applied to all sentiment scores because not all of their ranges are the same.

Then , the Wasserstein Distance is computed pairwise, which gives the above matrix.

The mean of each row is added to the end, representing the average difference from all other models.

Score Building

Mathematical Method

	distilBERT	RoBERTa_large	RoBERTa_tweet	BERT_star	BERT_emotion	mean_wdistance
distilBERT	0.000000	0.094798	0.235688	0.280457	0.146792	0.151547
RoBERTa_large	0.094798	0.000000	0.310408	0.298217	0.211318	0.182948
RoBERTa_tweet	0.235688	0.310408	0.000000	0.241955	0.121614	0.181933
BERT_star	0.280457	0.298217	0.241955	0.000000	0.176096	0.199345
BERT_emotion	0.146792	0.211318	0.121614	0.176096	0.000000	0.131164

The two “nearest” distributions are the scores of distilBERT and RoBERTa-large.

The “outlier” model is BERT-star, but on the whole, the differences are trivial. Now, it is safe to say that the score distributions do not vary much across models.

One interesting thing is that BERT-emotion has the lowest mean Wasserstein distance. It in some way functions as the center of all models.

Score Building

Mathematical Method

	distilBERT	RoBERTa_large	RoBERTa_tweet	BERT_star	BERT_emotion	mean_wdistance
distilBERT	0.000000	0.094798	0.235688	0.280457	0.146792	0.151547
RoBERTa_large	0.094798	0.000000	0.310408	0.298217	0.211318	0.182948
RoBERTa_tweet	0.235688	0.310408	0.000000	0.241955	0.121614	0.181933
BERT_star	0.280457	0.298217	[illegible]	0.000000	0.176096	0.199345
BERT_emotion	0.146792	0.211318	0.121614	0.176096	0.000000	0.131164

By means of score distributions, we are able to observe the difference between models and their behavior as they interact with our data.

> The two “m[illegible]RTa-large.

> The “outlier” model is BERT-star, but on the whole, the differences are trivial. Now, it is safe to say that the score distributions do not vary much across models.

> One interesting thing is that BERT-emotion has the lowest mean Wasserstein distance. It in some way serves as the center of all models.

“Model-Mining”

Emojis & Emoticons

Sentiment Analysis

Emojis and Emoticons are strong proxies for sentiment.

Emojis

Emoticons

:-)	Smiley Face
$_$	Greedy
=-O	Uh-oh
:-|	Indifferent
:/	Unsure
>:)	Evil Grin
:*)	Drunk
-	Dazed
:)	Smile
:o	Surprised
._.	Depressed

Score Building

Does Emojis & Emoticons matter?

```
SO HOW can people even wear fur, knowing it comes from creatures like these.  <3 :(

   distilBERT: NEGATIVE: 0.9914566278457642
RoBERTa-large: NEGATIVE: 0.9994542598724365
RoBERTa-tweet:  NEGATIVE: 0.9611835479736328

    BERT_star: 3 stars: 0.4916169047355652
               2 stars: 0.19454559683799744

 BERT_emotion:
               sadness: 0.019871590659022331
                   joy: 0.9143709540367126
                  love: 0.006086317356675863
                 anger: 0.04484333470463753
                  fear: 0.011959115043282509
              surprise: 0.0028685852885246277
```

Note that this is a sentence with mixed emotions.

This is a difficult sentiment classification task.

Score Building

Fix for Emojis & Emoticons

```
SO HOW can people even wear fur, knowing it comes from creatures like these.  Heart Frown sad angry or pouting

    distilBERT: NEGATIVE: 0.9985085129737854
 RoBERTa-large: NEGATIVE: 0.99943023920592
 RoBERTa-tweet:  NEGATIVE: 0.9445569515228271

     BERT_star:   1 star: 0.37004202604293823
                 2 stars: 0.36575841903686523

  BERT_emotion:
                sadness: 0.9841651320457458
                    joy: 0.0011369193671271205
                   love: 0.005048282444477081
                  anger: 0.008036556653678417
                   fear: 0.0013496528845280409
               surprise: 0.00026341085322220125
```

With the help of Emojis & Emoticons, we are able to classify the sentiment more accurately.

Score Building

Technical Issues with Emojis & Emoticons Conversion

```
To funny!♥

   distilBERT: POSITIVE: 0.9996313452720642
RoBERTa-large: POSITIVE: 0.9981774687767029
RoBERTa-tweet:  POSITIVE: 0.9687339663505554

    BERT_star:  5 stars: 0.45114848017692566
                4 stars: 0.266335666179657

 BERT_emotion:
               sadness: 0.0008376089972443879
                   joy: 0.008662187494337559
                  love: 0.006708914879709482
                 anger: 0.020311014726758003
                  fear: 0.004571969620883465
              surprise: 0.9589083194732666
```

```
:heart_suit:

To funny! :heart_suitEmbarrassed or blushing

   distilBERT: POSITIVE: 0.9970807433128357
RoBERTa-large: NEGATIVE: 0.9891810417175293
RoBERTa-tweet:  POSITIVE: 0.6707590818405151

    BERT_star:  2 stars: 0.28071123361587524
                 1 star: 0.2526819407939911

 BERT_emotion:
               sadness: 0.002065228996798396
                   joy: 0.05955982208251953
                  love: 0.2782672047615051
                 anger: 0.04505478963255882
                  fear: 0.034634482115507126
              surprise: 0.5804185271263123
```

- **Must convert Emojis first before converting Emoticons.**
- **Set the starting/ending delimiters to None, and remove the underscore.**

Otherwise, the result can be distorted.

Score Building

Technical Issues with Emojis & Emoticons Conversion

```
To funny! heart suit

   distilBERT: POSITIVE: 0.9998527765274048
RoBERTa-large: POSITIVE: 0.9897750616073608
RoBERTa-tweet:  POSITIVE: 0.8925580382347107

    BERT_star:  5 stars: 0.5201444625854492
                4 stars: 0.27984172105789185

 BERT_emotion:
                sadness: 0.0008076028316281736
                    joy: 0.008053800091147423
                   love: 0.007594647351652384
                  anger: 0.03504551947116852
                   fear: 0.006126851309090853
               surprise: 0.9423715472221375
```

- **Must convert Emojis first before converting Emoticons.**
- **Set the starting/ending delimiters to None, and remove the underscore.**

Otherwise, the result can be distorted.

Score Building

Technical Issues with Emojis & Emoticons Conversion

```
convert_emoticons('This is what he said: I am done')
'This is what he saiTongue sticking out cheeky playful or blowing a raspberry I am done'
```

There might be unexpected results where unreasonable emoticon patterns are matched.

```
convert_emoticons('This is what he said: I am done')
'This is what he said: I am done'
```

Therefore, I only consider emoticon patterns with a whitespace in front of them.

Research Topic

Data Introduction

Data Preprocessing

Score Building

Analysis Results

Future Work

Procedure

Preliminary Data-Mining

- " Know your Data "
- We've roughly done that.

" Model-Mining " with Data

- " Know your Model ": Understand the limits/biases/tendencies that are inherent in the model (due to training data, or even human!)
  - Keyword Sanity Checks (for each model)
  - Score Distribution (across models)
  - Emojis & Emoticons

Data-Mining with Models

- Construction for Sentiment Score
- Validation for such Construction & Complete analysis

Procedure

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- We’ve roughly done that.

“ Model-Mining ” with Data

- “ Know your Mod[illegible] [illegible]es that are inherent in the model (due to training data, or even human!)
  - Keyword Sanity Checks (for each model)
  - Score Distribution [illegible]
  - Emojis & Emoticons

Data-Mining with Models

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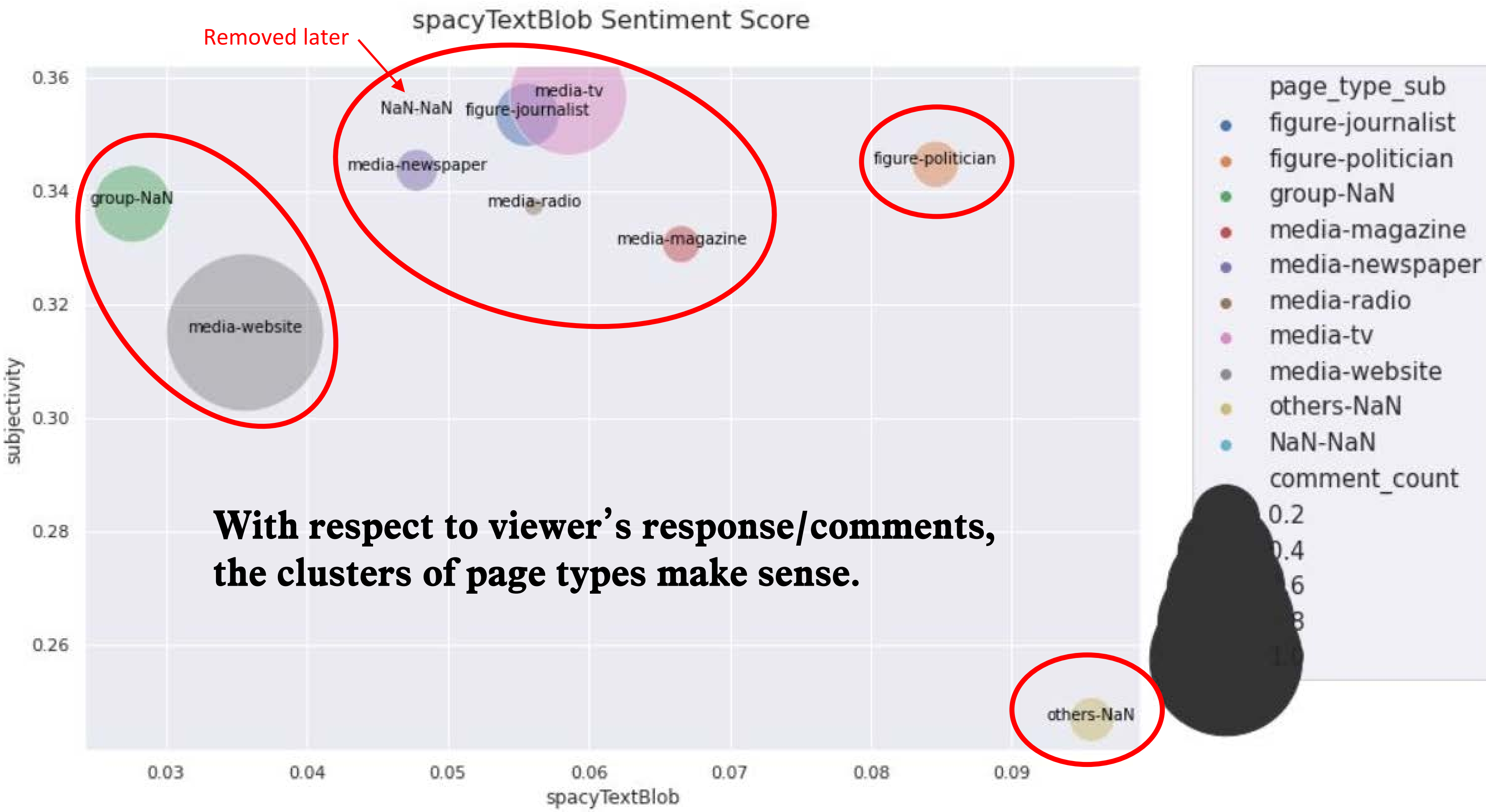
- Validation for such Construction & Complete analysis

“Data-Mining”

With Models

Results with spacyTextBlob from last time…

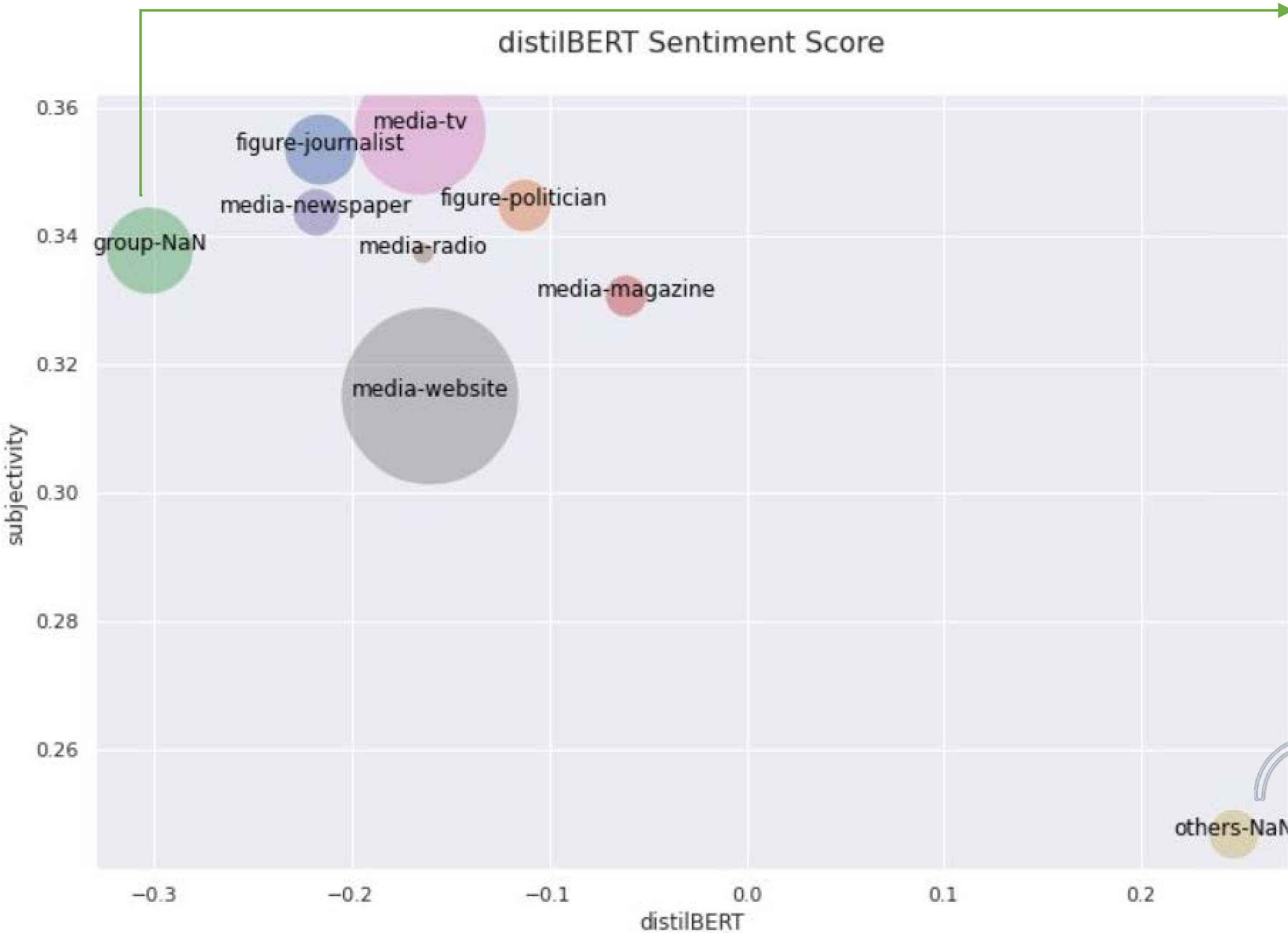


With respect to viewer's response/comments, the clusters of page types make sense.

Let's replace polarity with other sentiment scores!

Analysis Results

distilBERT

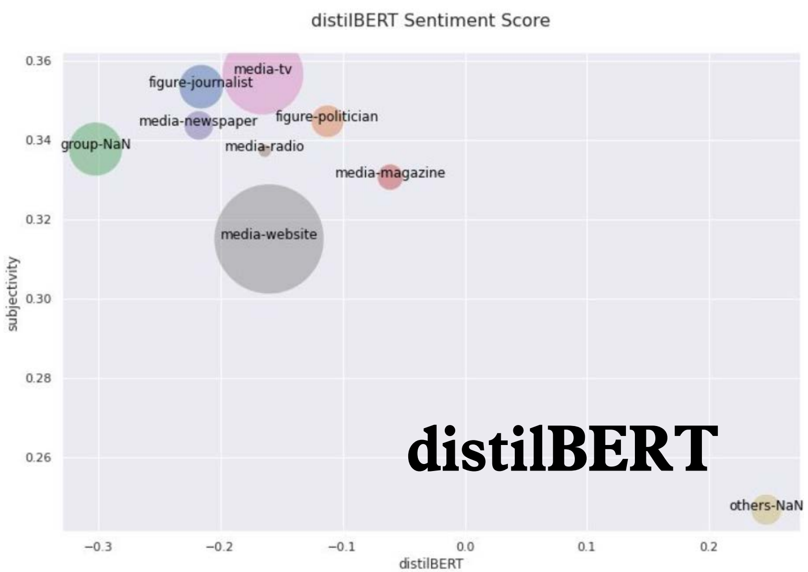


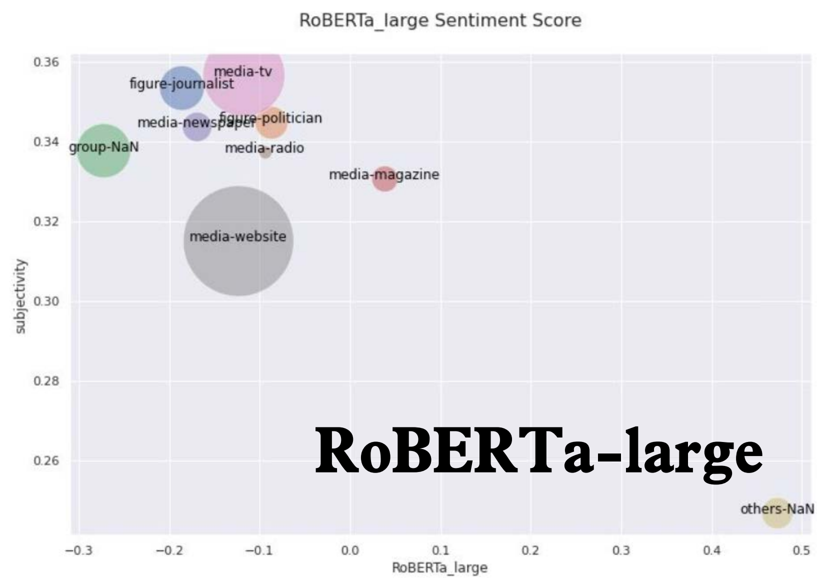
Community	74
Non-Profit Organization	43
Political Organization	37
Political Party	11
Organization	10
Society/Culture Website	7
Public Figure	6
Website	5
Media/News/Publishing	5
Cause	4
Community Organization	4
Politician	3
Comedian	3
Education	3
Just For Fun	2
Religious Organization	2
Education Website	2
Author	1
Magazine	1
Entertainer	1
Arts/Humanities Website	1
News Personality	1
Journalist	1
Entertainment Website	1
Non-Governmental Organization (NGO)	1
Government Website	1
Business Person	1

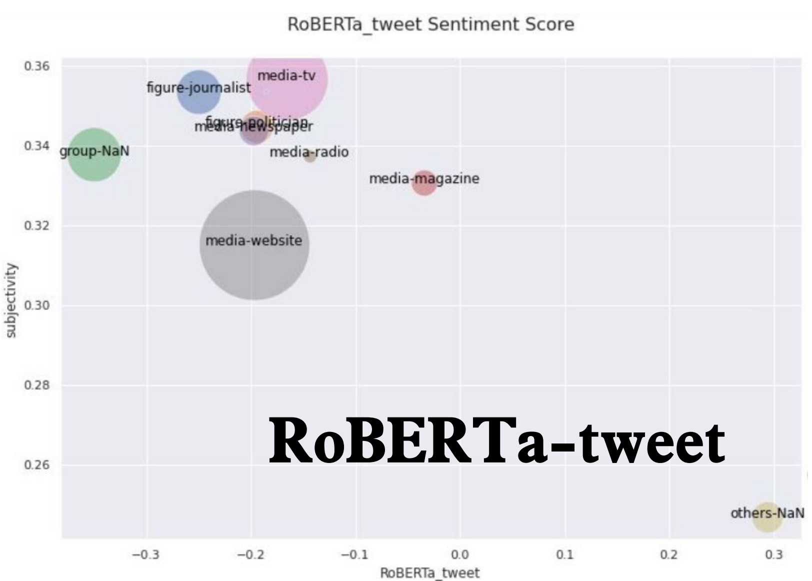
Musician/Band	14
Public Figure	6
Entertainment Website	5
Actor/Director	4
Entertainer	3
Comedian	2
Writer	1
Movie	1
Aerospace/Defense	1
Artist	1
Product/Service	1
News Personality	1
Arts/Humanities Website	1
Cause	1
Community	1
App Page	1

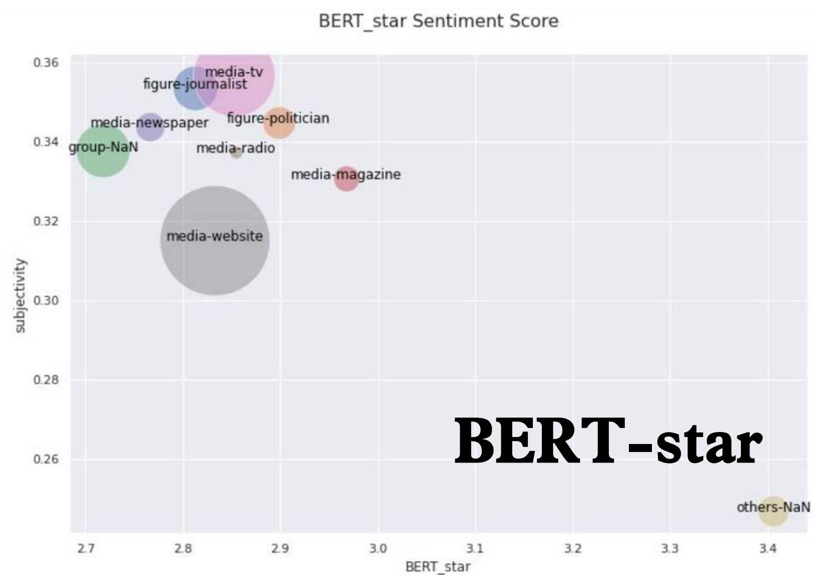
With distilBERT, the differences are not as obvious. This is, in fact, true to other models.

Analysis Results





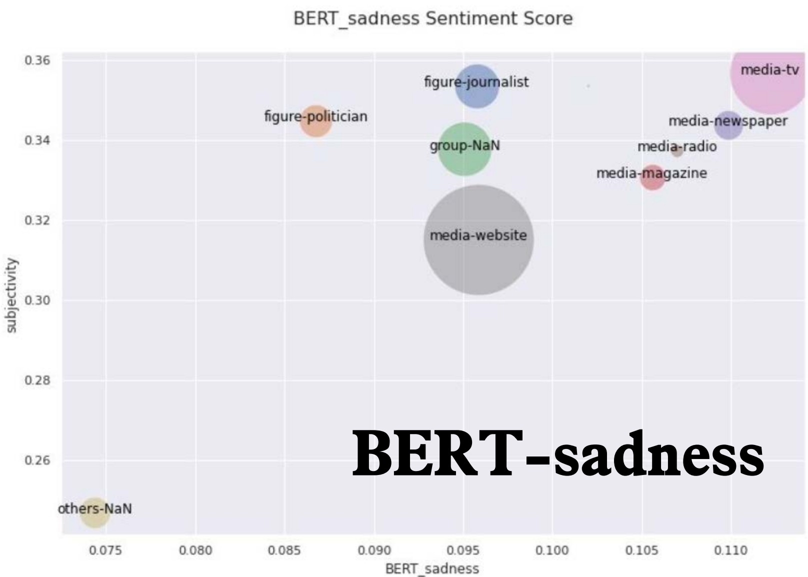


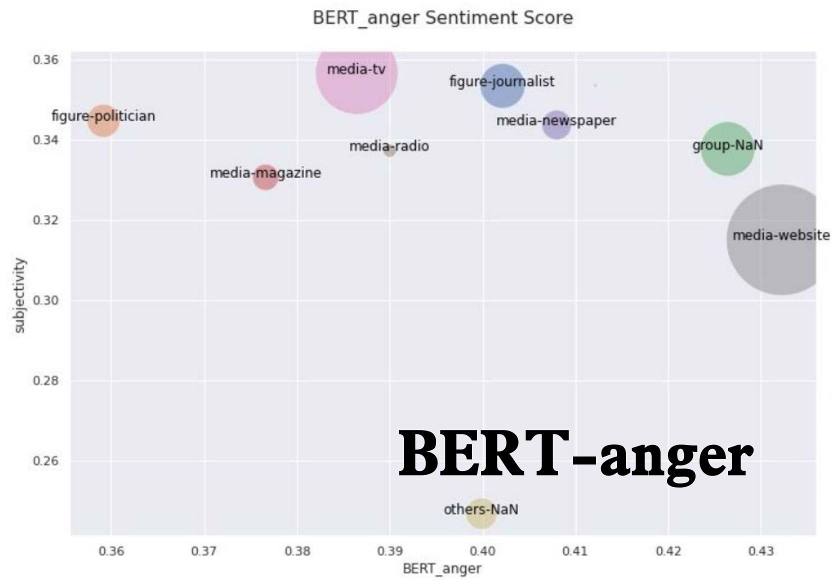


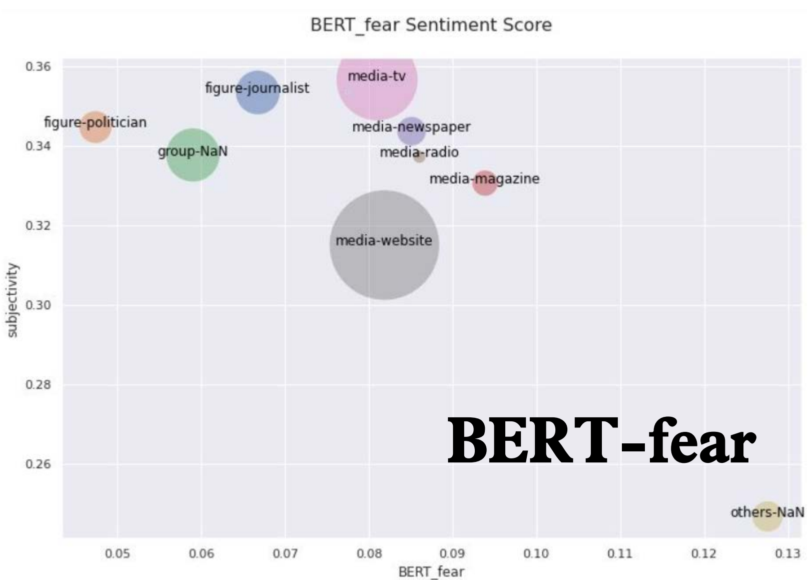
Analysis Results

The differences are minor.

Analysis Results



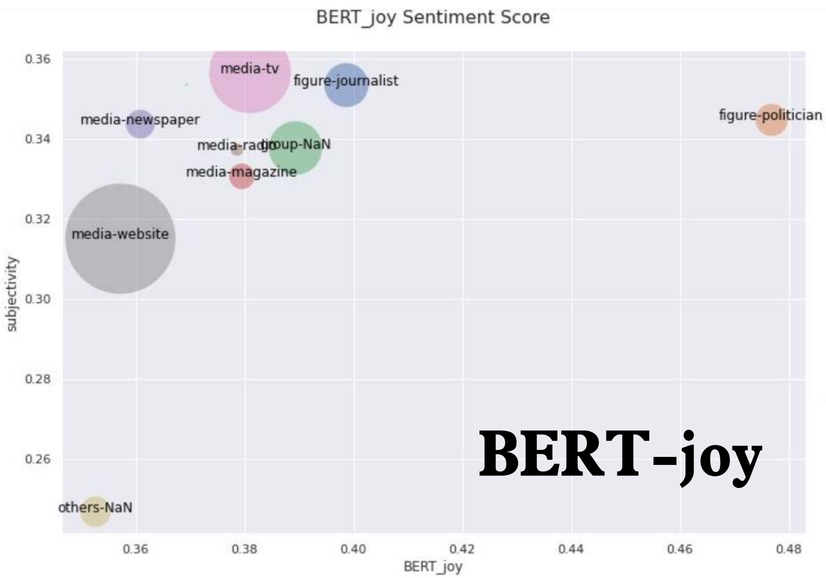


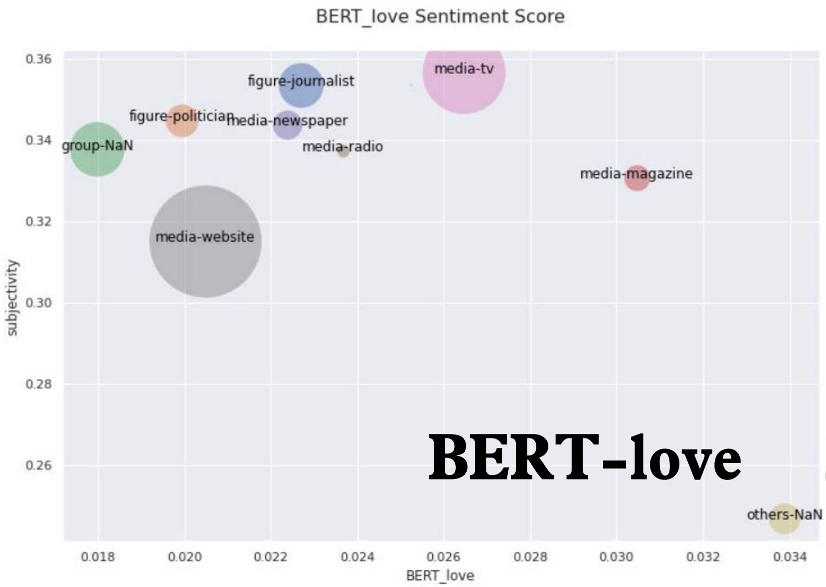


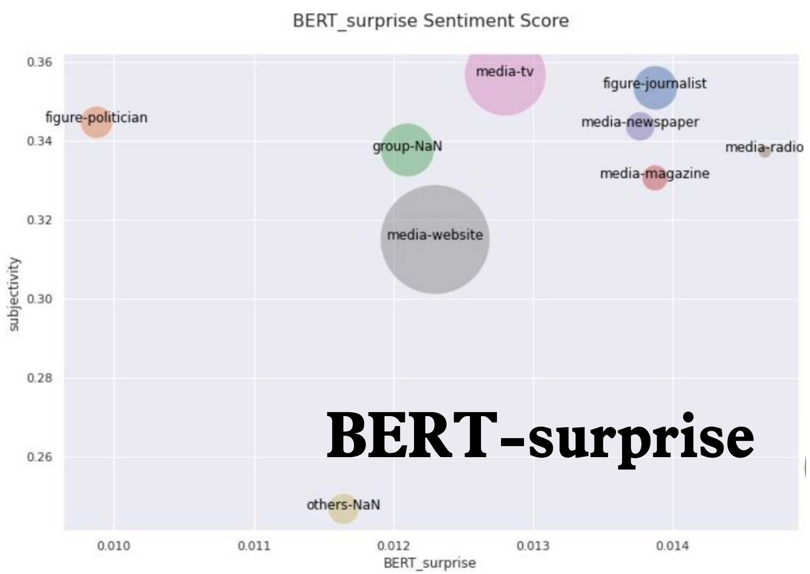
BERT-emotion Model

- Has a lot more to explore
- Captures different aspects of sentiment

Analysis Results







BERT-emotion Model

- **Has a lot more to explore**
- **Captures different aspects of sentiment**

Procedure

Preliminary Data-Mining

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- We've roughly done that.

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"Data-Mining" with Models

Construction for Sentiment Score

- "Know your Model": Understand the limits/biases/tendencies that are inherent in the model (due to training data, or even human!)
  - Score Distribution (across models)
  - Emojis & Emoticons

Data-Mining with Models

- Construction for Sentiment Score
- Validation for such Construction & Complete analysis

Construction for Sentiment Score

Pick one model

- Aspect-based Sentiment = sadness, joy, love, anger, fear, surprise

Combine multiple models

- Binary Sentiment labels = POSITIVE, NEGATIVE
- Continuous Sentiment Scores = [-1, +1]

Construction for Sentiment Score

Pick one model

- Aspect-based Sentiment = sadness, joy, love, anger, fear, surprise

Combine multiple models

- Binary Sentiment labels = POSITIVE, NEGATIVE
- Continuous Sentiment Scores = [-1, +1]

“ABC Scores”

Construction for Sentiment Score

Aspect-based Sentiment

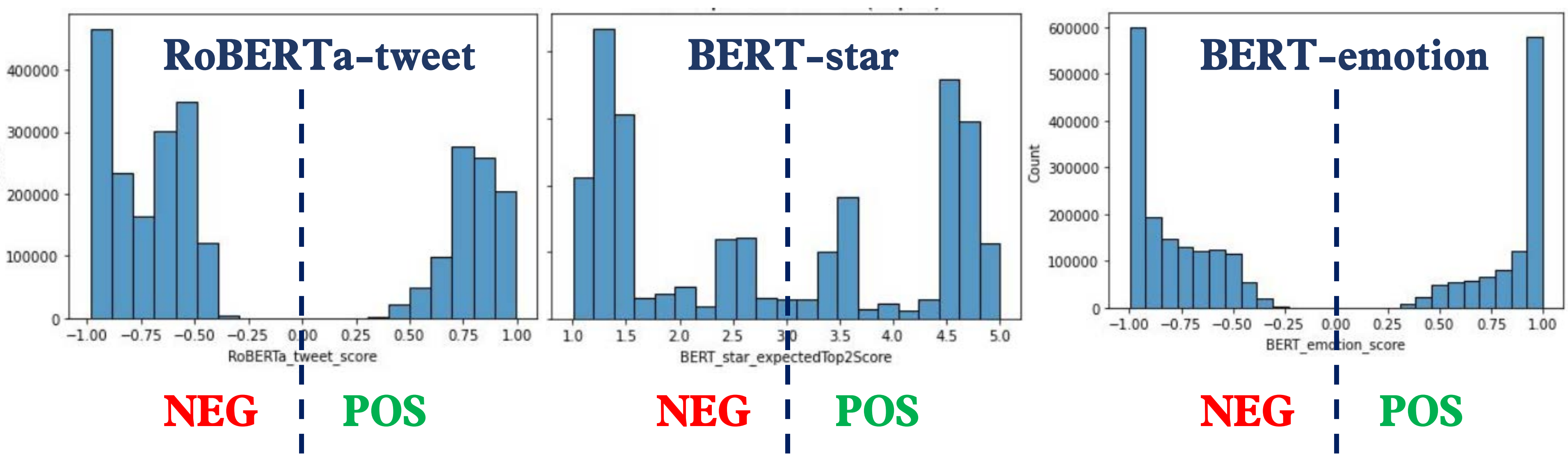
- Get the multi-class sentiments directly from BERT-emotion

	BERT_sadness	BERT_joy	BERT_love	BERT_anger	BERT_fear	BERT_surprise	BERT_emotion_highest
0	0.001692	0.034497	0.203237	0.750804	0.002372	0.007398	anger
1	0.028839	0.114509	0.003014	0.846426	0.005269	0.001943	anger
2	0.019148	0.506111	0.004474	0.462502	0.005904	0.001861	joy
3	0.033257	0.925305	0.003607	0.033050	0.003652	0.001128	joy
4	0.001002	0.935860	0.061434	0.000601	0.000400	0.000703	joy

Construction for Sentiment Score

Binary Sentiment labels

- Create Binary Labels for RoBERTa-tweet, BERT-star, BERT-emotion



- Then, take a majority vote out of the five models.

Construction for Sentiment Score

Binary Sentiment labels

distilBERT_label	RoBERTa_large_label	RoBERTa_tweet_binaryLabel	BERT_star_binaryLabel	BERT_emotion_binaryLabel	majority_vote
POSITIVE	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE
NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE
NEGATIVE	NEGATIVE	NEGATIVE	POSITIVE	POSITIVE	NEGATIVE
NEGATIVE	NEGATIVE	POSITIVE	POSITIVE	POSITIVE	POSITIVE
POSITIVE	POSITIVE	POSITIVE	POSITIVE	POSITIVE	POSITIVE

Majority Vote

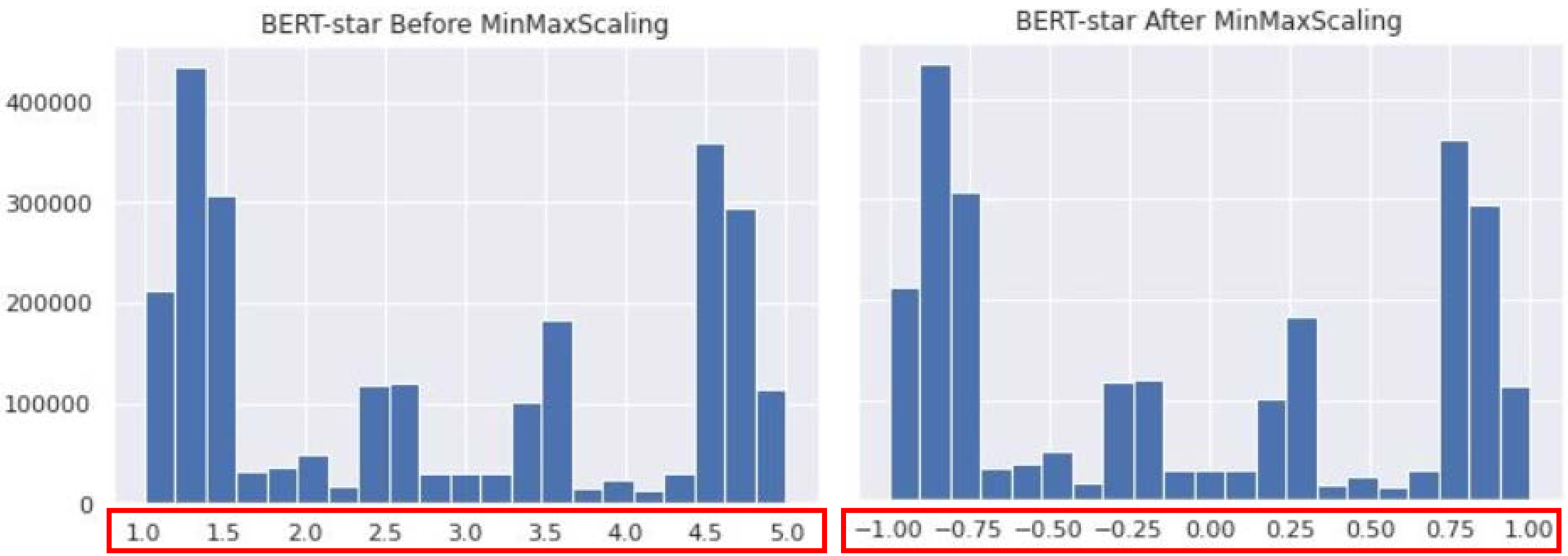
Result

	distilBERT_label	RoBERTa_large_label	RoBERTa_tweet_binaryLabel	BERT_star_binaryLabel	BERT_emotion_binaryLabel	majority_vote
NEGATIVE	1482475	1418657	1637680	1372605	1509082	1491074
POSITIVE	1065995	1129813	910790	1175865	1039388	1057396

Construction for Sentiment Score

Continuous Sentiment Scores

- **Min-max scale the sentiment score for BERT-star**



- **The range changes, but the distribution remains.**

Construction for Sentiment Score

Continuous Sentiment Scores

- **Selective Averaging**

distilBERT_score	RoBERTa_large_score	RoBERTa_tweet_score	BERT_star_scaledScore	BERT_emotion_score	majority_vote	selective_mean
0.990771	-0.998820	-0.964068	-0.727313	-0.750804	NEGATIVE	-0.860251
-0.998380	-0.999445	-0.926214	-0.287519	-0.846426	NEGATIVE	-0.811597
-0.999461	-0.994421	-0.829197	0.275097	0.506111	NEGATIVE	-0.941026
-0.948954	-0.773979	0.564369	0.583888	0.925305	POSITIVE	0.691187
0.999525	0.998621	0.953136	0.927033	0.935860	POSITIVE	0.962835

Selective Averaging **Result**

- **This gives us the magnitude of how positive of negative a text is.**

Validation for Sentiment Score

Human Labeling

- The best way to validate any sentiment score is to add labels/scores by human.
- However, this is expensive and we might not have budgets for it.

"Data-Mining" with Models

Validation for Sentiment Score

Validation for Sentiment Score

Human Labeling

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Validation for Sentiment Score

Human Labeling

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Designed Validation Tests

- The second best (and most realistic) way is to check by ourselves if the sentiment scores "make sense".
- Such sensibleness must be closely related to the research interest.
  - For example, if we're interested in whether comment sentiments are related to the US presidential election, we can aggregate sentiment scores of comments for each post.

Validation for Sentiment Score

Aspect-based Sentiment

	NEG	POS	POS	NEG	NEG	POS	
	BERT_sadness	BERT_joy	BERT_love	BERT_anger	BERT_fear	BERT_surprise	BERT_emotion_highest
page_name							
Donald J. Trump	0.074530	$\boxed{0.535005}$	0.019349	0.321067	0.04240	$\boxed{0.007648}$	joy
Hillary Clinton	$\boxed{0.087551}$	0.489037	$\boxed{0.021095}$	$\boxed{0.350155}$	$\boxed{0.04531}$	0.006852	joy

Trump wins

Hillary wins

Trump wins

This shows that Hillary was falling behind Trump, somewhat predictive of the US presidential result in 2016.

Analysis Results

Binary Sentiment Labels

		majority_vote
page_name	post_id	
Donald J. Trump	153080620724_10154994141850725	NEGATIVE
	153080620724_10154994200030725	POSITIVE
	153080620724_10154997068045725	POSITIVE
	153080620724_10155009354115725	POSITIVE
	153080620724_10155024375830725	POSITIVE
...	...	...
Hillary Clinton	889307941125736_999748683414994	NEGATIVE
	889307941125736_999824783407384	NEGATIVE
	889307941125736_999835160073013	NEGATIVE
	889307941125736_999865193403343	NEGATIVE
	889307941125736_999866820069847	POSITIVE

6534 rows × 1 columns

	pct
majority_vote	
NEGATIVE	55.40%
POSITIVE	44.60%

	pct
majority_vote	
NEGATIVE	68.60%
POSITIVE	31.40%

This shows that Hillary was falling behind Trump, somewhat predictive of the US presidential result in 2016.

Analysis Results

Continuous Sentiment Scores

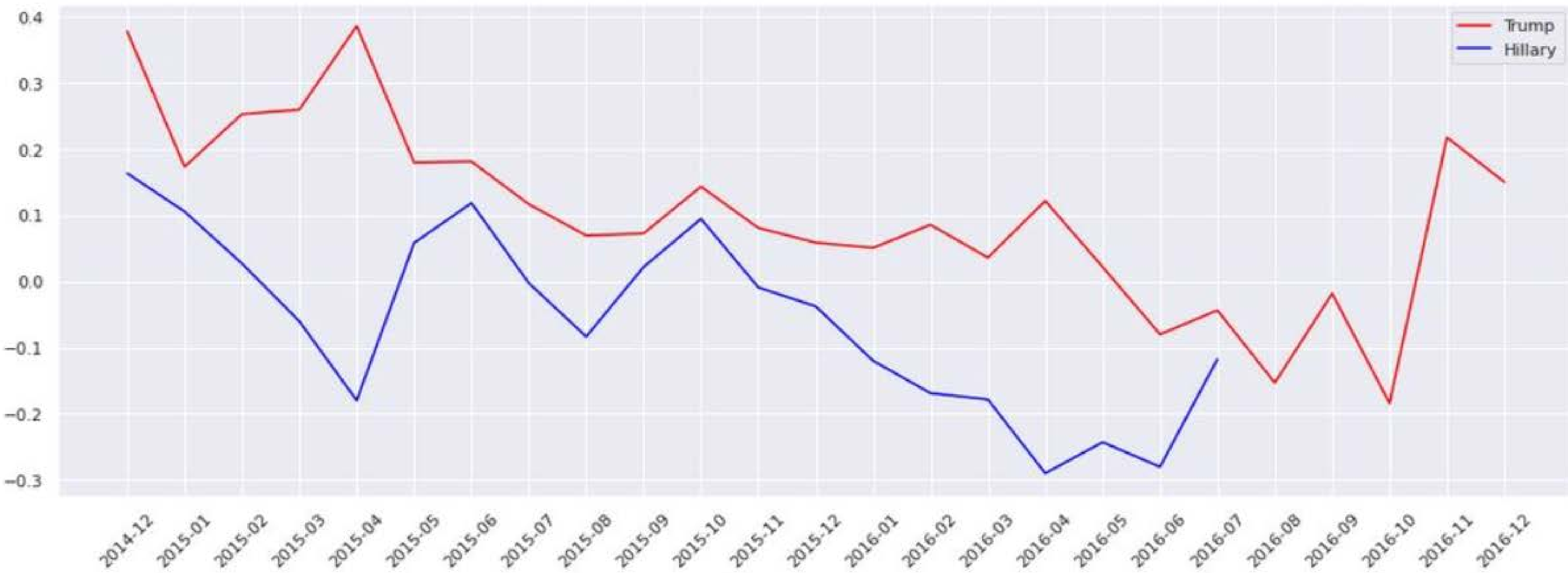
page_name	post_id	selective_mean
Donald J. Trump	153080620724_10154994141850725	-0.597309
	153080620724_10154994200030725	0.790403
	153080620724_10154997068045725	0.458304
	153080620724_10155009354115725	0.831108
	153080620724_10155024375830725	0.901359
...	...	...
Hillary Clinton	889307941125736_999748683414994	-0.861027
	889307941125736_999824783407384	-0.782836
	889307941125736_999835160073013	-0.913890
	889307941125736_999865193403343	-0.009094
	889307941125736_999866820069847	0.817181

page_name	selective_mean
Donald J. Trump	0.024271
Hillary Clinton	-0.139765

This shows that Hillary was falling behind Trump by 15%, somewhat predictive of the US presidential result in 2016.

Analysis Results

Continuous Sentiment Scores



This graph mimics a social listener software.

We can see that Hillary was losing. More on this in USFB_quick_results.pdf

Conclusion

The full recipe for constructing sentiment score

- **Preprocessing: Deal with Emojis & Emoticons**
- **Model:**
  - **Compare score distributions (graphically and mathematically)**
  - **Keyword sanity checks (few-word comments might be a problem)**
  - **Discard unsatisfactory models if needed**
- **Construction:**
  - **Aspect-based, Binary, Continuous Sentiment**
- **Validation:**
  - **Human Labeling (expensive; impractical)**
  - **Design Tests for Validation with regard to Research Interest (practical)**

Research Topic

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Future Work

Difficulties in Sentiment Analysis

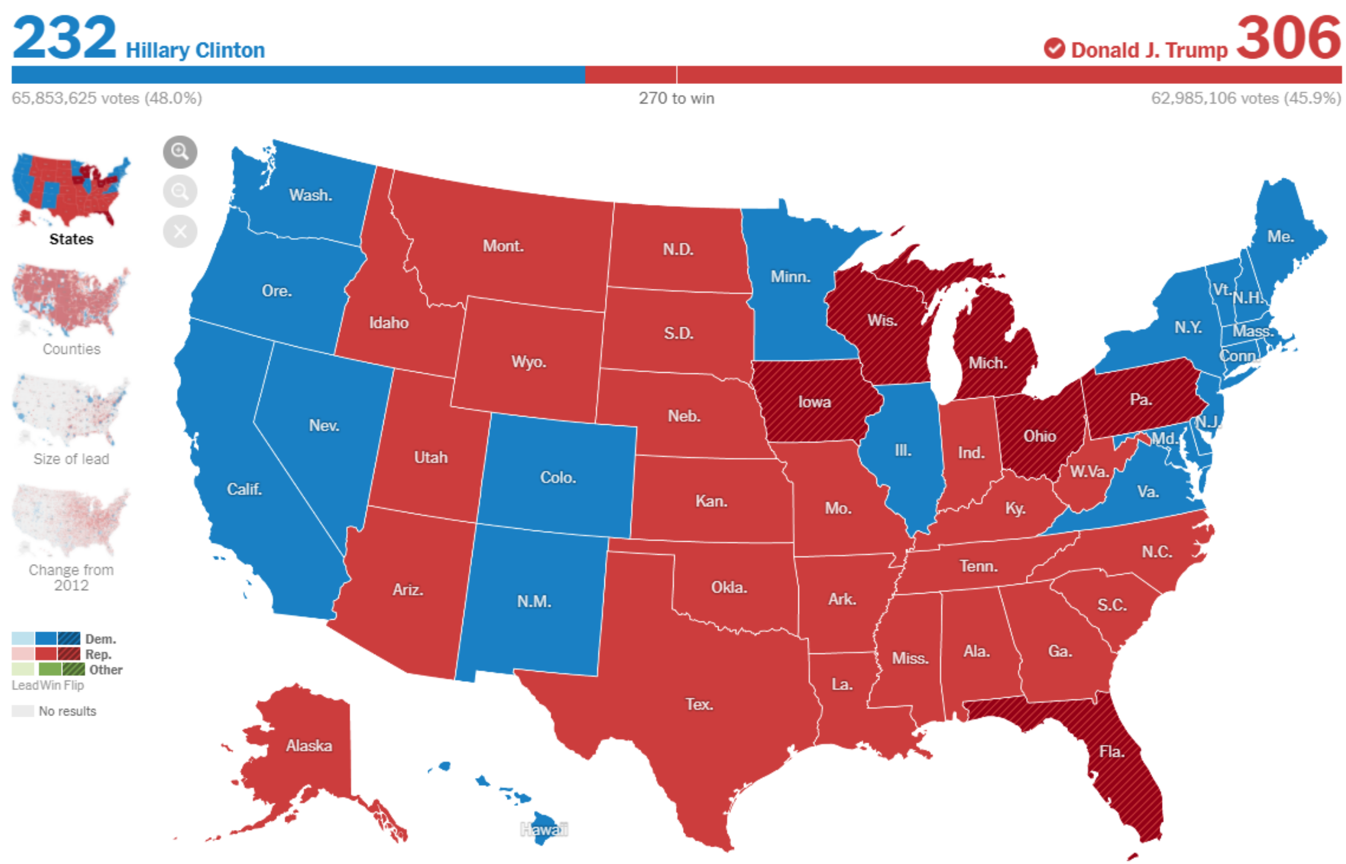
- **Ambiguity in Short Texts**
  - **"Damn what a night"** : positive or negative? Joy, surprise, sadness?
  - **"What the f*ck is going on?"** : fear, anger, sadness?
- **Texts with Mixed emotions**
  - **"So how can people wear fur, knowing it comes from such lovely creatures"**
    - love, anger, sadness, surprise?
  - **"I love his charisma. I hate his policies."**
    - Positive or negative?
- **Texts with Stances**
  - **"He is gay." ; " She is an atheist." ; "He is a Trump supporter."**
    - May vary a lot from person to person

Future Work

Other Cool Validations Ideas

Reconstruct this colored map using user_id and geographic features →

2016 US Presidential Election: Nov 8, 2016 (Tue)



Source: https://www.nytimes.com/elections/2016/results/president

THANKS

謝謝大家