

Sentiment Score Construction with Facebook Comments on US Politics

Presentation by Ching-Yao Lin (林璟耀)

執行摘要

Propose a Way to construct Sentiment Score with Social Media Comments

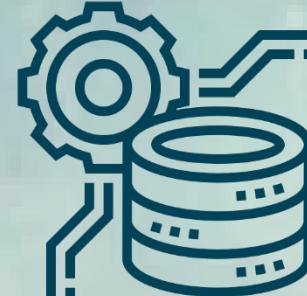
- Five SOTA deep learning models are adopted and combined for score construction
 - distilBERT, RoBERTa-large, RoBERTa-tweet, BERT-star, BERT-emotion
- Three types of sentiment score are constructed
 - Aspect-based Sentiment: scores on different emotions (within 0, 1)
 - Binary Sentiment Label: positive 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



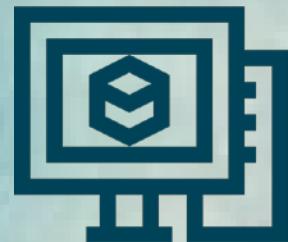
研究主題



資料介紹



資料前處理



模型建立



分析結果



未來方向



研究主題



資料介紹



資料前處理



模型建立



分析結果



未來方向

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

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

Data: Facebook Comments on US Politics

Models: BERT and its variants

研究主題

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](#)



研究主題



資料介紹



資料前處理



模型建立



分析結果



未來方向

資料介紹

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!

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)

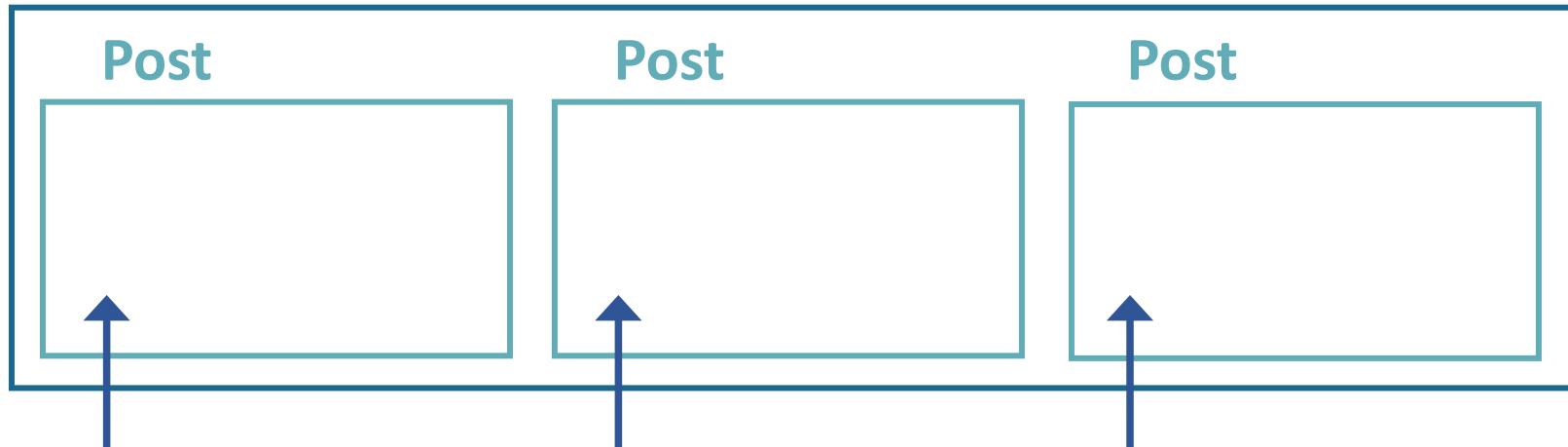
1. Find all the pages ever mentioned Donald Trump and Hillary Clinton in August 2016.
2. Calculate the total number of likes, comments, and shares of candidate-related posts in these pages, and weight them by factors 1:7:14 (a weight suggested by social media consultant, see Calero (2013)), respectively.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

資料介紹

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~~

Page



Reactions

Comments

Share

資料介紹

page_id	page_name	post_id	
2.178595e+10	9GAG	21785951839_10155113971791840	
post_type	post_message		post_caption
link	Official White House Photographer Reveals His ...	9gag.com	https://external.xx.fbcdn.net/safe_image.php?d...
post_link	post_descrip... tion	post... ptions	post... ptions
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		

post data

1000-page

9GAG  November 11, 2016 · 

Obama is the coolest president in history. 😊 (By The White House)



9GAG.COM | BY 9GAG

Official White House Photographer Reveals His Favourite Photos Of Obama

Click to see the pic and write a comment...

24K Comments 211K Shares

 李佳杰, Jamie Lin and 1.2M others

 Share

Most Relevant 

 Write a comment...

 Ivan Kelava

Water. Earth. Fire. Air.

Long ago, the four nations lived together in harmony. Then everything changed when the Trump Nation attacked.... See More



資料介紹

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...
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http://9gag.com/gag/ajqEV90?ref=fbp	Click to see the pic and write a comment...	1297326.0		
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9GAG  November 11, 2016 · [...](#)

Obama is the coolest president in history. 😊 (By [The White House](#))



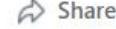
9GAG.COM | BY 9GAG

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 Like  Comment  Share

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2.178595e+10	9GAG	21785951839_10155113971791840																															
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link	Official White House Photographer Reveals His Favourite Photos Of Obama	Obama is the coolest president in history.  ...	9gag.com https://extern.../safe_																														
post_link	post_description	post_reactions																															
http://gag/ajqEV9	<table border="1"> <thead> <tr> <th></th> <th>count</th> <th>percentage</th> </tr> </thead> <tbody> <tr> <td></td><td>97326.0</td><td></td></tr> <tr> <td>link</td><td>11235316</td><td>76.182%</td></tr> <tr> <td>photo</td><td>2099309</td><td>14.235%</td></tr> <tr> <td>video</td><td>1225049</td><td>8.307%</td></tr> <tr> <td>status</td><td>182016</td><td>1.234%</td></tr> <tr> <td>event</td><td>5692</td><td>0.039%</td></tr> <tr> <td>note</td><td>420</td><td>0.003%</td></tr> <tr> <td>music</td><td>102</td><td>0.001%</td></tr> <tr> <td>offer</td><td>41</td><td>0.000%</td></tr> </tbody> </table>		count	percentage		97326.0		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%		
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Most Relevant 

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2.178595e+10	9GAG	21785951839_10155113971791840	
post_type	post_name	post_message	post_caption
link	Official White House Photographer Reveals His Favourite Photos Of Obama	Obama is the coolest president in history.  ...	9gag.com https://extern.../safe_
post_link	post_description	post_reactions	
http://gag/ajqEV9			
	count	percentage	
	97326.0		
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%	



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November 11, 2016 · 

Obama is the coolest president in history.  (By The White House)



9GAG.COM | BY 9GAG
Official White House Photographer Reveals His Favourite Photos Of Obama

...



Donald J. Trump 
November 8, 2016 · 

TODAY WE MAKE AMERICA GREAT AGAIN!

  1M

76K Comments 196K Shares

Write a comment...

Ivan Kelava
Water. Earth. Fire. Air.

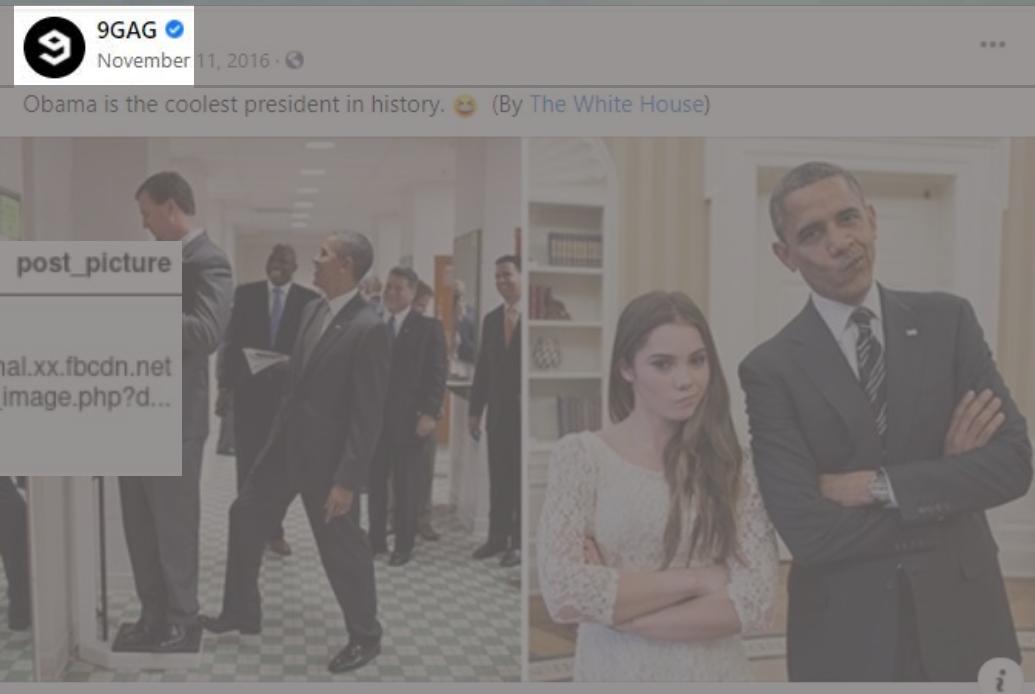
Long ago, the four nations lived together in harmony. Then everything changed when the Trump Nation attacked.... See More

...

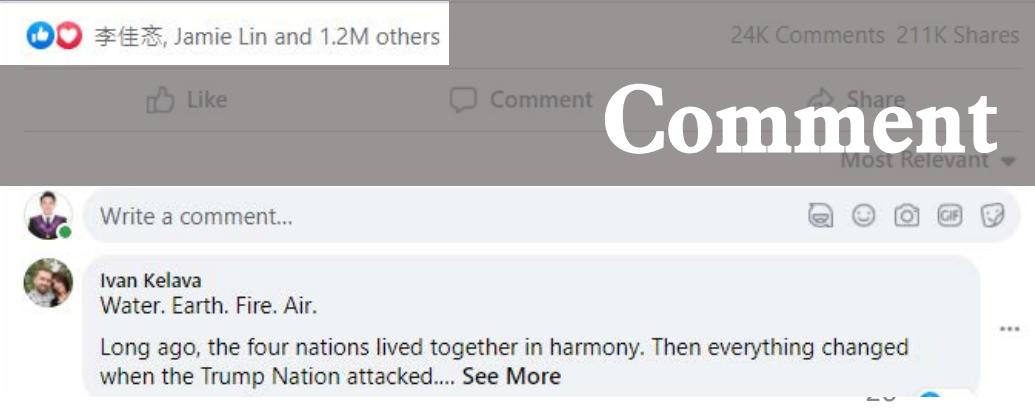
資料介紹

Page

page_id	page_name	post_id		
2.178595e+10	9GAG	21785951839_10155113971791840		
post_type	post_name	post_message	post_caption	post_picture
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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			



Reaction
G.COM | BY 9GAG
Click to see the pic and write a comment...



Comment
Most Relevant

資料介紹

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

page data

1000-page-info



9GAG 9GAG November 11, 2016

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Most Relevant

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More

Like

Message



...

資料介紹

Page

1000-page-info

page_id	page_name	category	type	type_sub	type_issue	fan_count	talki
21785951839	9GAG	App Page	others	Nan	Nan	3215547	
page_url			total_like	total_comment	total_share	1:07:14	ran
https://www.facebook.com/9gag			13909	725	1555	4075.4	



9GAG

@9gag App Page

9GAG.COM/MOBILE

Home Live Videos Groups More

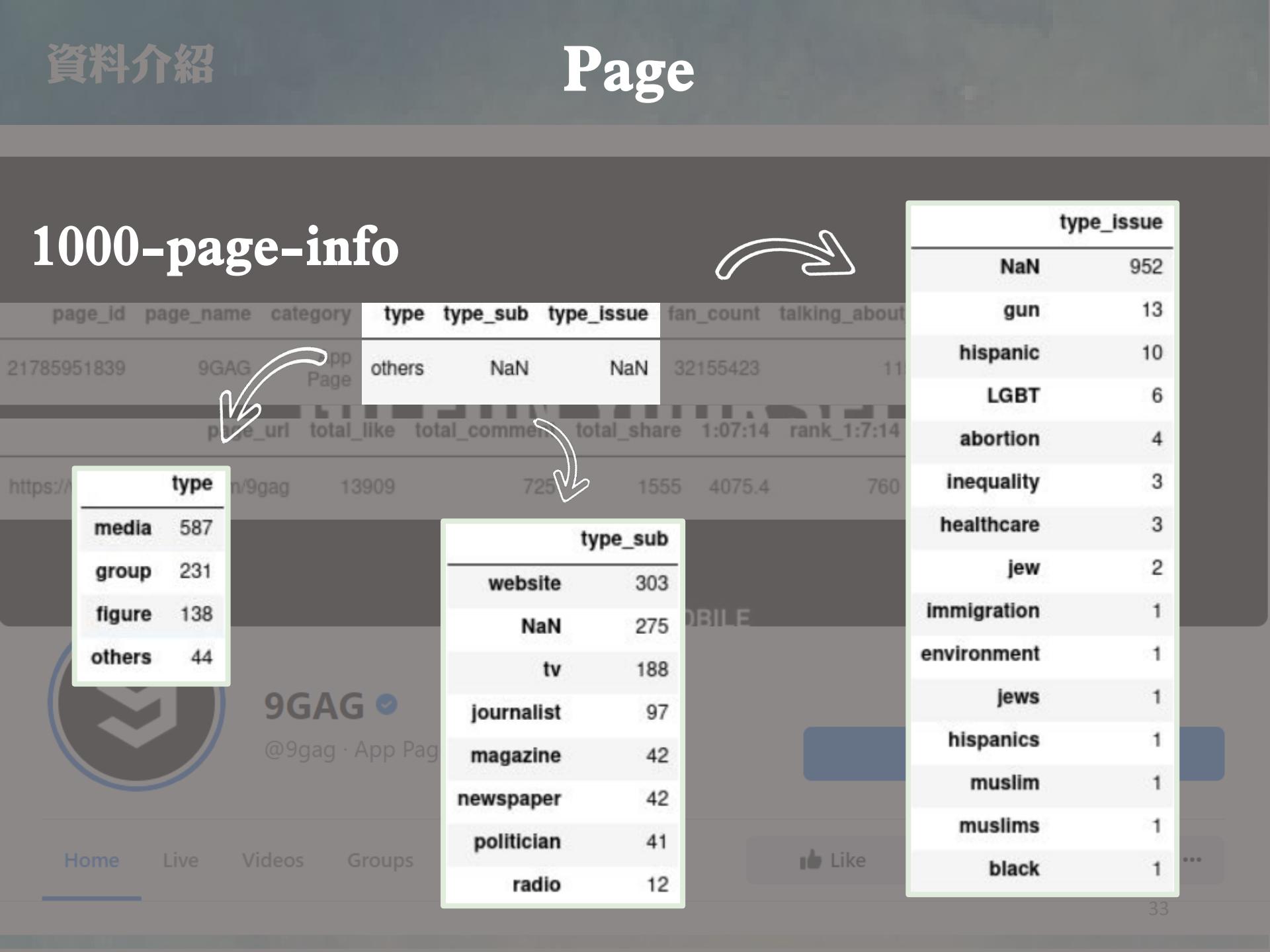
There are 51 categories...

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

資料介紹

Page

1000-page-info



The screenshot shows a table with the following columns: page_id, page_name, category, type, type_sub, type_issue, fan_count, talking_about, page_url, total_like, total_comments, total_share, 1:07:14, and rank_1:7:14. The 9GAG page is highlighted with a green box around the type, type_sub, and type_issue columns. A white arrow points from the 'type' column to a modal window. Another white arrow points from the 'type_sub' column to another modal window. A third white arrow points from the 'type_issue' column to a third modal window.

page_id	page_name	category	type	type_sub	type_issue	fan_count	talking_about	page_url	total_like	total_comments	total_share	1:07:14	rank_1:7:14
21785951839	9GAG	App Page	others	NaN	NaN	32155423	11	https://www.facebook.com/9gag	13909	725	1555	4075.4	760

type

media	587
group	231
figure	138
others	44

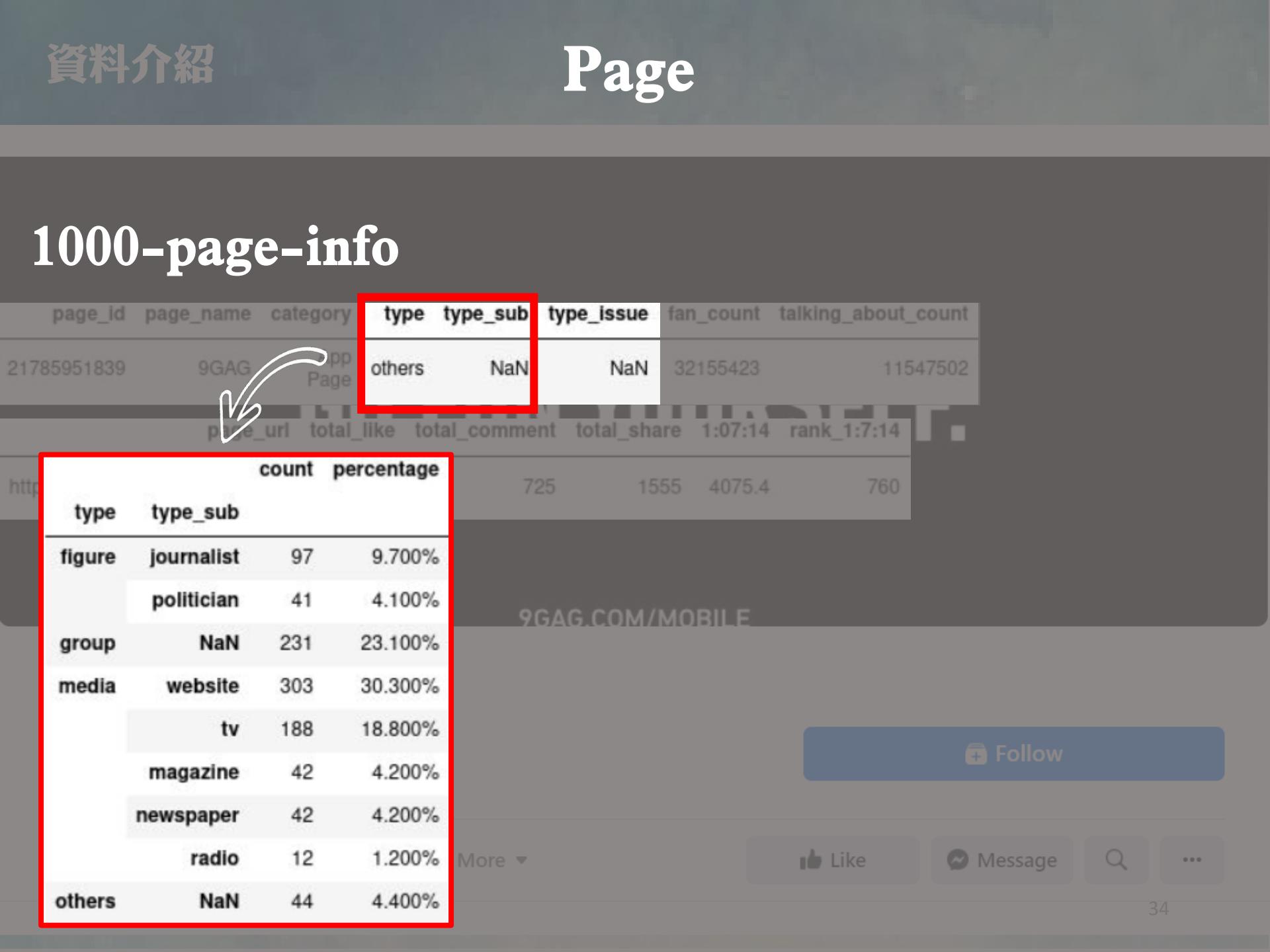
type_sub

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

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			count	percentage			
http://			725	15.55	4075.4	760	
type	type_sub						
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%				

資料介紹

Page

1000-page-info



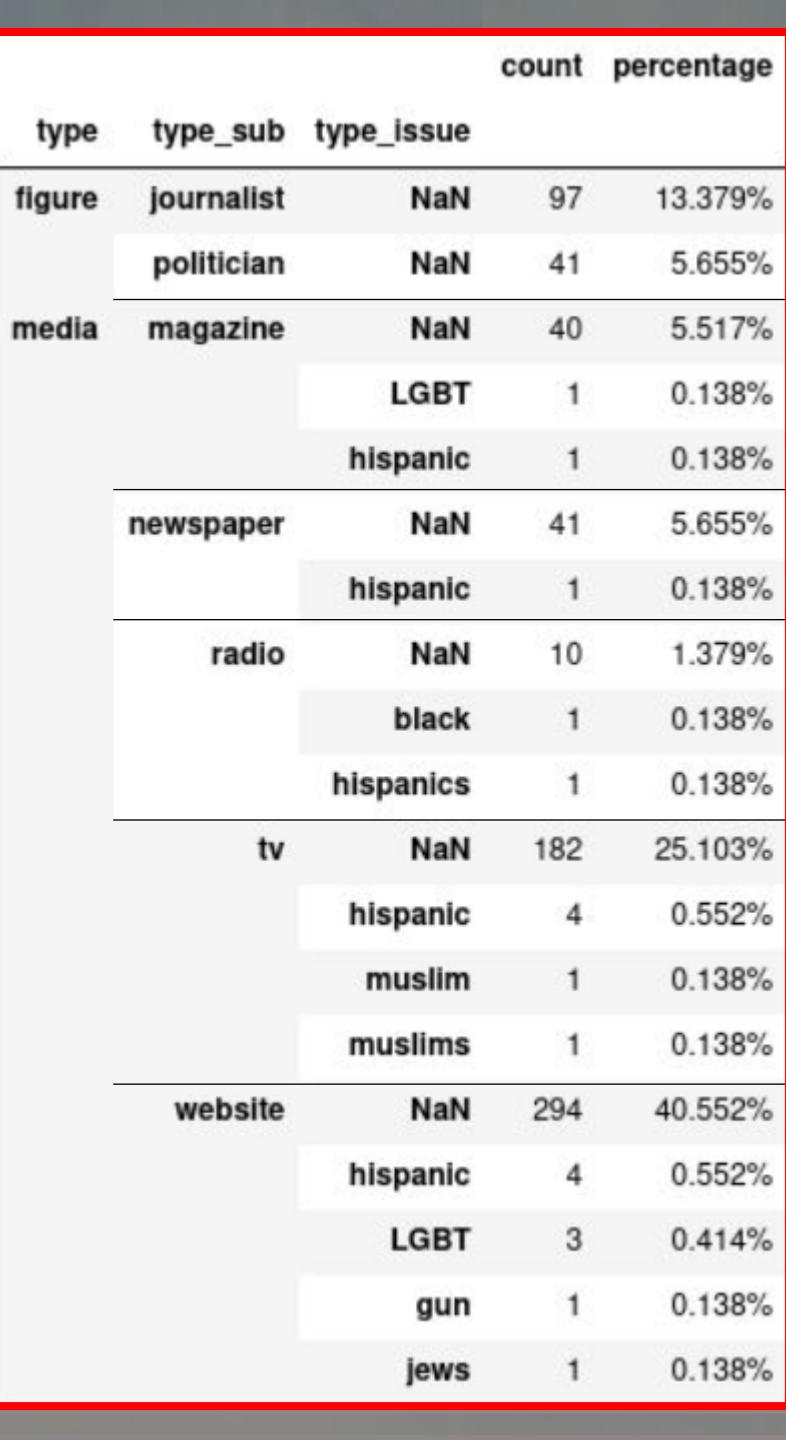
page_id page_name category type type_sub type_issue fan_count

page_id	page_name	category	type	type_sub	type_issue	fan_count
21785951839	9GAG	App Page	others	NaN	NaN	32155

http://9GAG.COM/MOBILE

		count	percentage
type	type_sub		
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%

More ▾



			count	percentage
type	type_sub	type_issue		
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%	

資料介紹

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			
post_likes	post_comments	post_shares	post_created_time_CT	<div style="display: flex; justify-content: space-between;"> <div style="flex: 1;"> <p>9GAG.COM BY 9GAG</p> <p>Official White House Photographer Reveals His Favourite Photos Of Obama</p> <p>Click to see the pic and write a comment...</p> </div> <div style="flex: 1; text-align: right;"> <p>24K Comments 211K Shares</p> </div> </div>	
1149630.0	20093.0	209506.0	2016-11-11 07:35:00+00:00	<div style="display: flex; justify-content: space-between;"> <div style="flex: 1;"> <p> 李佳杰, Jamie Lin and 1.2M others</p> <p> Like Comment Share</p> </div> <div style="flex: 1; text-align: right;"> <p>Most Relevant ▾</p> <h1>Comment</h1> </div> </div>	
post_updated_time_CT	page_talking_about_count	<div style="display: flex; justify-content: space-between;"> <div style="flex: 1;"> <p>2017-03-16 04:05:56+00:00</p> <p>8425994.0</p> </div> <div style="flex: 1;"> <p> Write a comment...</p> <p> Ivan Kelava</p> <p>Water. Earth. Fire. Air.</p> <p>Long ago, the four nations lived together in harmony. Then everything changed when the Trump Nation attacked.... See More</p> </div> <div style="flex: 1; text-align: right;"> <p> </p> </div> </div>			

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Most Relevant ▾

Comment

Write a comment...

Ivan Kelava

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	comment_message	post_id	comment_created_time
	Waluigi he's not our president and I'm going to ...	21785951839_10155113971791840	2016-11-11 13:49:48+00:00
Obama was the best president	Obama was the best president	21785951839_10155113971791840	2016-11-11 15:15:20+00:00
	Great guy, so down to earth, shame he has to go ...	21785951839_10155113971791840	2016-11-11 15:31:39+00:00
	These are amazing 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 one 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 ...	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 ...	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 ...	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.

Official White House Photographer Reveals His Favourite Photos Of Obama
Click to see the pic and write a comment...

 李佳恋, Jamie Lin and 1.2M others

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 Like

 Share

 Comment

Most Relevant ▾

Comment



Write a comment...



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研究主題



資料介紹



資料前處理



模型建立



分析結果



改進方向

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**

資料前處理

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

5. Expand contractions (eg. y'all)

6. Remove punctuations, links, etc.

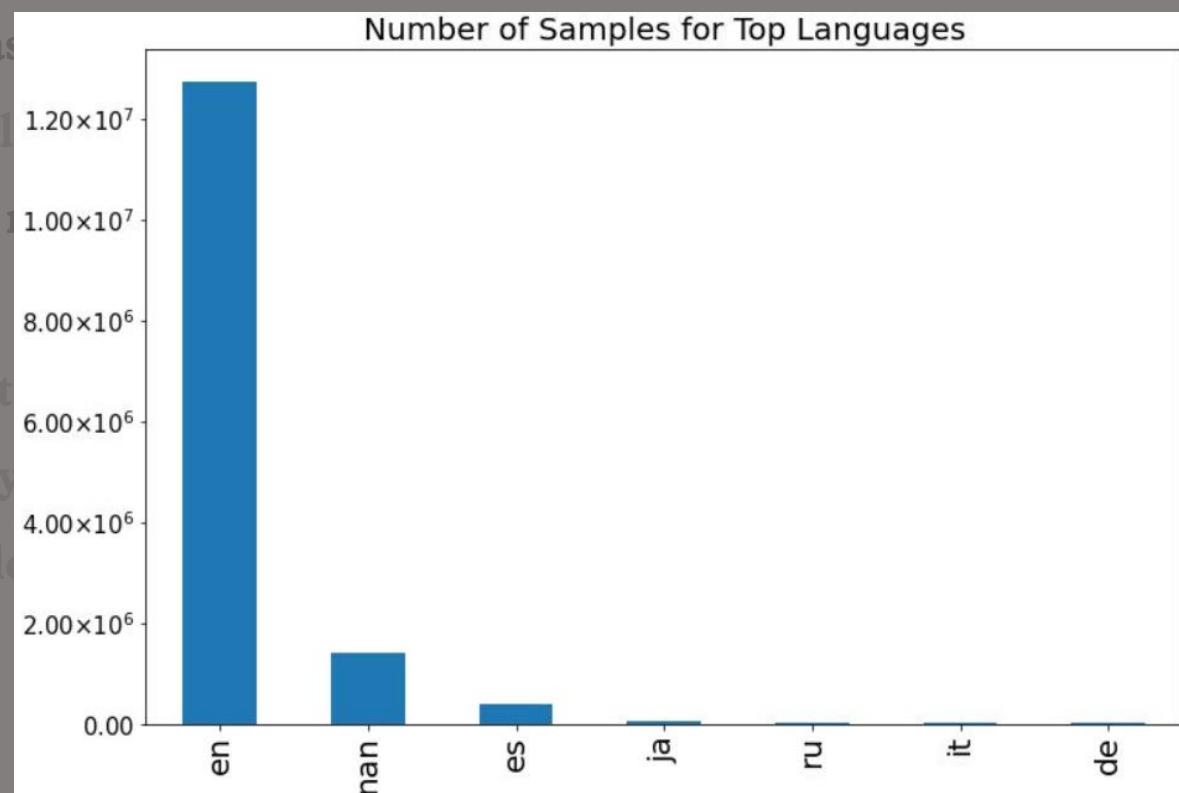
7. Remove emojis

8. Remove stopwords (using nltk)

9. Lemmatize texts (using spacy)

(eg. the cars are different colors)

10. Pickle (Serialize) the result



資料前處理

Basic Preprocessing (for Text)

1. Drop completely duplicate rows
2. Add language labels (using LanguageTool)
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)

"We're straining to be offended.\nMr. Trump says offensive things everyday.\n\n

This is a test 😊👍. <http://www.google.com>

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 '

"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",

資料前處理

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)

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

10. Pickle (Serialize) the result



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

Minimum Preprocessing

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

Further Preprocessing

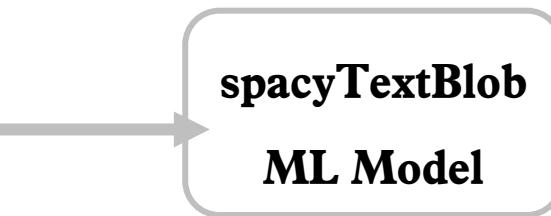
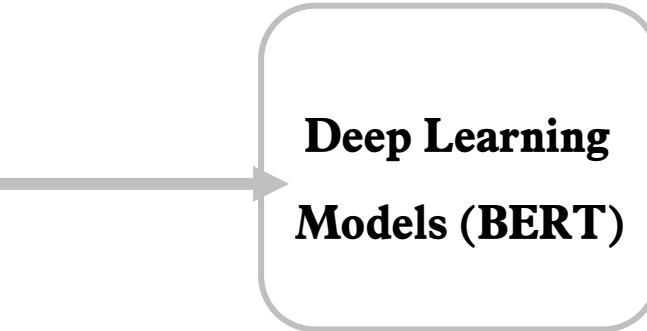
4. Convert all words to lowercase
5. Expand contractions
6. Remove punctuations, links, newlines, tabs, and shrink consecutive spaces
7. Remove emojis
8. Remove stopwords (using nltk)
9. Lemmatization

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



Not introduced in depth in this presentation due to performance

To take a closer look, let's dive deeper

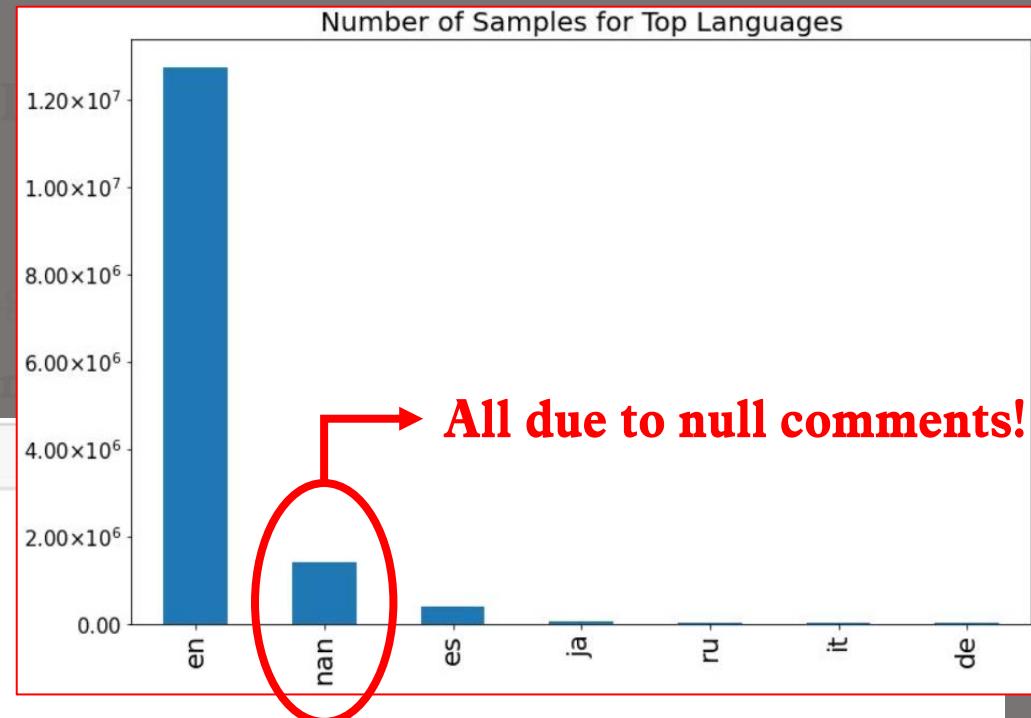
Basic Preprocessing (for Textual Data)

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

- Basic Preprocessing (for Textual Data)
1. Remove blank and null rows
 2. Add language labels (using Language Detection API)
 3. Filter out non-English or empty comments

```
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 Corrieri	en	erika corrieri	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

Basic Prep

1. Drop con

2. Add lang

3. Filter out

4. Convert a

5. Expand c

6. Remove p

7. Remove e

8. Remove s

9. Lemmatiz

el column

• Eg. Case-sensitive (different colors -> the car be different color)

• 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

Basic Pre

1. Drop c

2. Add lan

3. Filter o

4. Convers

5. Expand

6. Remove

7. Remove

8. Remove

9. Lemma

- 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”

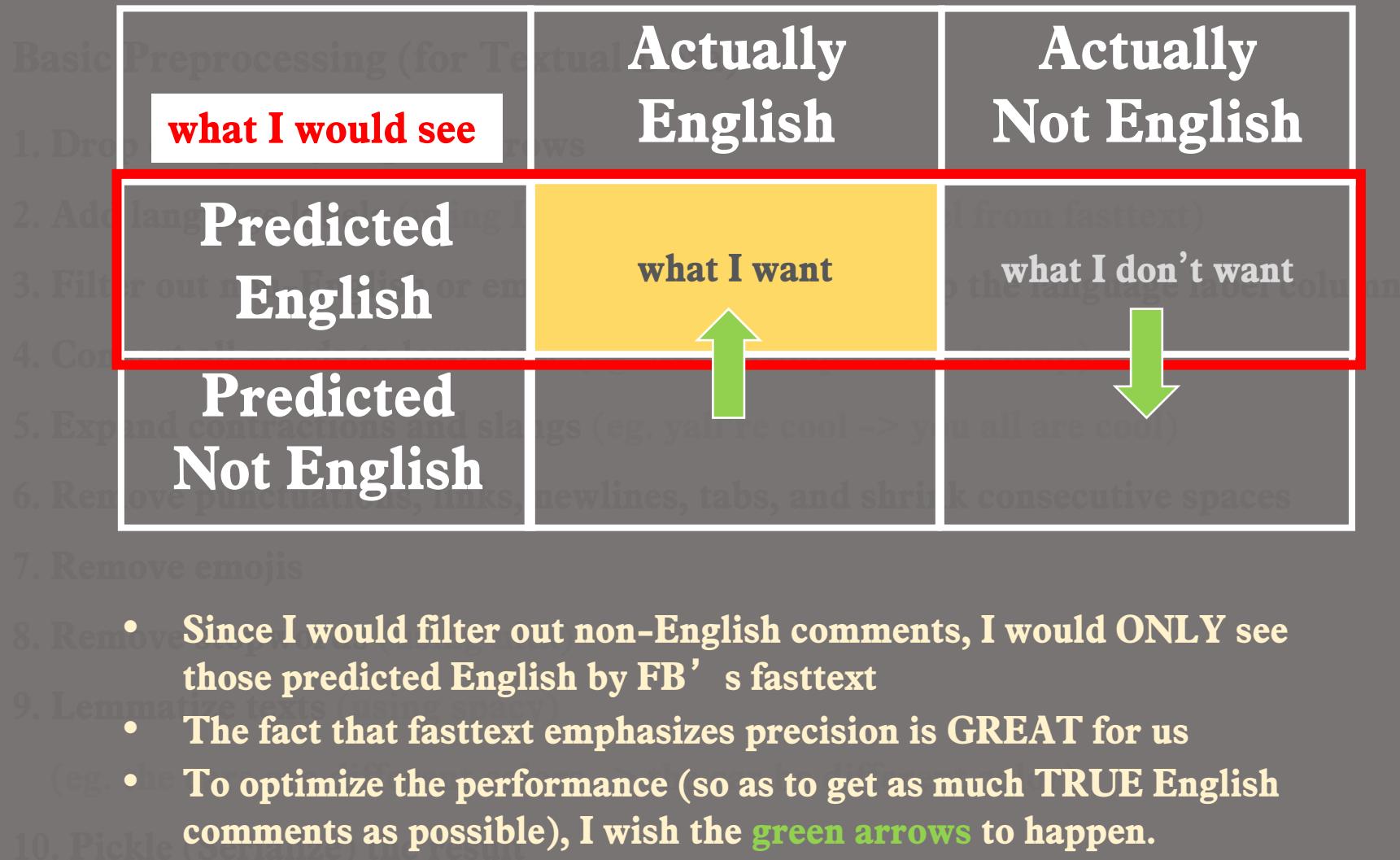
About FB's fasttext (language detection model)

Quick Summary:

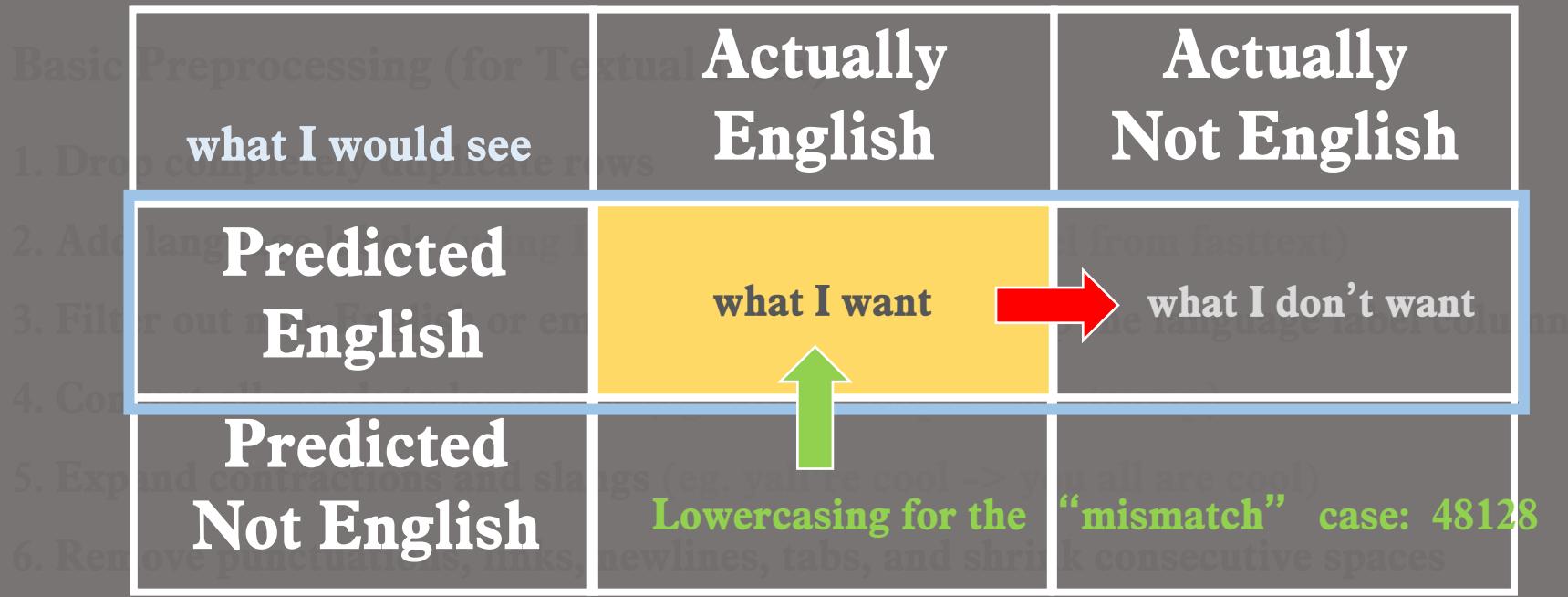
Basic Preprocessing (for Textual Data)

1. In the cases of “Mismatch” (“original prediction” \neq “lower-case prediction”) :
2. Add language labels (using Language Detection Model from fasttext)
3. Filter out non-English or empty comments; then, drop the language label column
 1. Most of those predicted English are in reality English!
4. Convert all words to lowercase (eg. Mr. Trump \rightarrow mr. trump)
→ But were falsely predicted otherwise after being transformed to
5. Expand contractions and slangs (e.g. you all are cool)
lowercase. **【 Red Arrow 】**
6. Remove punctuations, links, newlines, tabs, and shrink consecutive spaces
7. Most of those predicted non-English are in reality English!
8. → And were accurately predicted as English after being
9. Lemmatize texts (using NLTK)
transformed to lowercase. **【 Green Arrow 】**
(eg. the cars are different colors \rightarrow the car be different color)
10. Pickle (Serialize) the result

About FB's fasttext (language detection model)



About FB's fasttext (language detection model)



7. Remove emojis

8. Remove

- To optimize the performance (so as to get as much **TRUE** English comments as possible), I wish the green arrow to happen.

9. Lemmatize texts (using spacy)

- However, if I change all letters to lowercase, the green arrow and the red arrow both happen.

10. Pickle (Serialize) the result

- 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

1	RECLAIM AMERICA! TRUMP / CARSON!!!!	en	RECLAIM AMERICA TRUMP CARSON	ja
2	BENGHAZI! MURDER!	en	BENGHAZI MURDER	ru
3	BIG FUCKING BABIES.	en	BIG FUCKING BABIES	ja
4	TRUMP!	en	TRUMP	de
5	TRUMP LIES!	en	TRUMP LIES	fr
6	GOOD BYE!!!!	en	GOOD BYE	ja
7	NEWS FLASH!!!!!!	en	NEWS FLASH	ja
8	EPISODE? DRUNK? DRUGGED?	en	EPISODE DRUNK DRUGGED	ja
9	QUE BUENA FOTO.	es	QUE BUENA FOTO	pt
10	FAKE FAKE FAKE AND SICK	en	FAKE FAKE FAKE AND SICK	ja
11	WTH???!!#	de	WTH	en
12	#VOTEFORTRUMP, #WOMENFORTRUMP, #TRUMP2016, #TE...	en	VOTEFORTRUMP WOMENFORTRUMP TRUMP2016 TEAMTRUM...	ja
13	STOP ALREADY !!!	en	STOP ALREADY	ja
14	TRUMP 2016	en	TRUMP 2016	de
15	"AMEN"	pt	AMEN	it
16	YES !	ta	YES	en
17	WHATTTTTTT!!!!	en	WHATTTTTTT	eo
18	"LETS MAKE AMERICA GREAT AGAIN"	en	LETS MAKE AMERICA GREAT AGAIN	ja



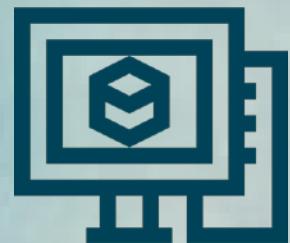
研究主題



資料介紹



資料前處理



模型建立



分析結果



未來方向

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

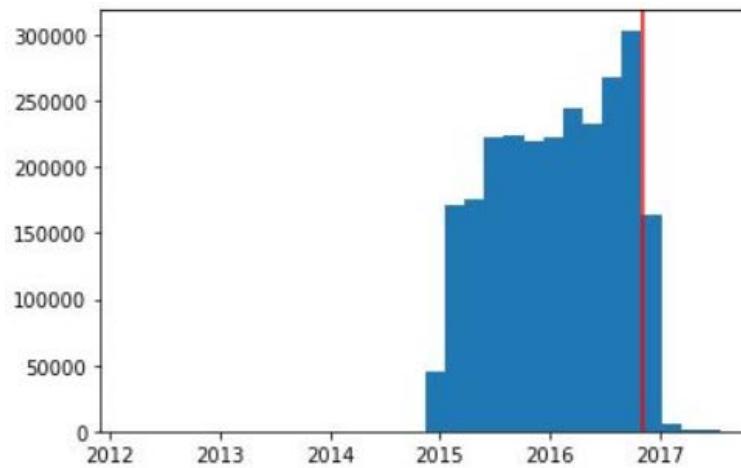
- Construction for Sentiment Score
- Validation for such Construction & Complete analysis

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



模型建立

	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 day**)	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

“Know Your Model”

模型建立

	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.
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Method	BERT (Bidirectional Transformer with MLM and NSP)	BERT without NSP**	BERT Distillation	Bidirectional Transformer with Permutation based modeling

模型建立

Model

spacytextblob - baseline

Returns

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

模型建立

Model

spacytextblob - baseline

DistilBERT (finetuned on SST-2)

BERT-base-multilingual-uncased
(finetuned on product reviews)

BERT-base-uncased-emotion (finetuned
on emotion dataset ~ 8.11MB)

RoBERTa-large (finetuned on 15 data
sets, including reviews, tweets)

RoBERTa-base (finetuned on TweetEval
benchmark)

Training Data

2000 Movie Reviews

BookCorpus (11,038 books, ~ 74M sentences
and 1G words)

English Wikipedia (6,330,642 articles,
~18.6 G words)

Same as above

Same as above

BookCorpus, English Wikipedia, CC-News,
OpenWebText, Stories (~160 GB texts)

~58M tweets

模型建立

Model

spacytextblob - baseline

Accuracy

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 94.05% , 2000 test set
on emotion dataset ~ 20k records)**

**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**

模型建立

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

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joy: 0.0007427089149132371
love: 0.00046253454638645053
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sadness: 0.006067375652492046
joy: 0.09167621284723282
love: 0.008227312006056309
anger: 0.8918558359146118 ✗
fear: 0.0009415088570676744
surprise: 0.0012318018125370145

I am happy that you are angry.

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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 ✗

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

But no model is perfect...

模型建立

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: 0.99444565  
4 stars: 0.9293723372337233
```

```
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_emotion:
```

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

“Model-Mining”

模型建立

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: 0.994456565  
4 stars: 0.929375375127825
```

```
BERT_emotion:
```

```
sadness: 0.0577809242621488  
joy: 0.504216700553894  
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_emotion:
```

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

“Model-Mining”

Keyword Sanity Checks

模型建立

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: 0.003575555980205536
anger: 0.906836748123169
fear: 0.03291909396648407
surprise: 0.002098318887874484

模型建立

Problems with BERT models (transformers)

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

Trump (133682)

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

Hillary (62515)

distilBERT: POSITIVE: 0.9725903868675232

distilBERT: POSITIVE: 0.997885525226593

RoBERTa-large: POSITIVE: 0.9692159295082092

RoBERTa-large: NEGATIVE: 0.991580605506897

RoBERTa-tweet: LABEL_1: 0.584307074546814

RoBERTa-tweet: LABEL_1: 0.5108434557914734

BERT_star: 5 stars: 0.47308531403541565
4 stars: 0.24837274849414825

BERT_star: 5 stars: 0.3135652244091034
4 stars: 0.2760293483734131

BERT_emotion:

Trump fans sadness: 0.09577899426221848
 joy: 0.3048216700553894
 love: 0.012770570814609528
Hillary fans anger: 0.5034168362617493
 fear: 0.07124734669923782
 surprise: 0.011964641511440277

BERT_emotion:

Trump fans sadness: 0.017226489260792732
 joy: 0.03734379634261131
 love: 0.003575555980205536
 anger: 0.906836748123169
 fear: 0.03291909396648407
 surprise: 0.002098318887874484

40 %
difference

These three models seem to favor Trump more!

But things are getting more interesting with full names...

模型建立

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: 0.25429394841194153

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: 0.8617792129516602
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

模型建立

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

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: 0.3785494863986969
4 stars: 0.25429394841194153

BERT_star: 5 stars: 0.37103885412216187
4 stars: 0.2876029908657074

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

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

18 %
difference

Things flipped for RoBERTa-large!

BERT_star doesn't show preference anymore.

BERT_emotion is MUCH less biased!

Facts

Problems with BERT models (transformers)

- 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”

BERT_star doesn't show preference anymore.

BERT_emotion is MUCH less biased!

模型建立

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

sentiment_score('Democratic Party')

Democratic Party (2351)

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

BERT_star: 4 stars: 0.2642284333705902
3 stars: 0.26280689239501953

BERT_star: 3 stars: 0.27808520197868347
4 stars: 0.2698981463909149

BERT_emotion:

sadness: 0.051437657326459885
joy: 0.07962372899055481
love: 0.018300192430615425
anger: 0.7755903601646423
fear: 0.06592267006635666
surprise: 0.009125471115112305

BERT_emotion:

sadness: 0.08952565491199493
joy: 0.3928332030773163
love: 0.019987786188721657
anger: 0.44837430119514465
fear: 0.04172710329294205
surprise: 0.007551965303719044

模型建立

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

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

Democratic Party (2351)

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

BERT_star: 4 stars: 0.2642284333705902
3 stars: 0.26280689239501953

BERT_star: 3 stars: 0.27808520197868347
4 stars: 0.2698981463909149

BERT_emotion:
sadness: 0.051437657326459885
joy: 0.07962372899055481
love: 0.018300192430615425

BERT_emotion:
sadness: 0.08952565491199493
Hillary supporters joy: 0.3928332030773163
love: 0.019987786188721657

Hillary supporters anger: 0.7755903601646423
fear: 0.06592267006635666
surprise: 0.009125471115112305

Trump supporters anger: 0.44837430119514465
fear: 0.04172710329294205
surprise: 0.007551965303719044

Anger is shown more toward the Republican Party.

Less models exhibit biases or preferences.

模型建立

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

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

Democrats (27147)

distilBERT: POSITIVE: 0.9105578660964966
RoBERTa-large: NEGATIVE: 0.9963169097900391
RoBERTa-tweet: LABEL_1: 0.6031544208526611

BERT_star: 3 stars: 0.27862027287483215
1 star: 0.20595254004001617

BERT_star: 3 stars: 0.2681081295013428
4 stars: 0.2475529909133911

BERT_emotion:

sadness: 0.13379821181297302
joy: 0.2263767123222351
love: 0.023794466629624367
anger: 0.5194436311721802
fear: 0.08247973769903183
surprise: 0.014107205905020237

BERT_emotion:

sadness: 0.14551712572574615
joy: 0.2647758424282074
love: 0.020851828157901764
anger: 0.5395296216011047
fear: 0.02431230992078781
surprise: 0.005013232585042715

模型建立

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

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

Democrats (27147)

distilBERT: POSITIVE: 0.9105578660964966
RoBERTa-large: NEGATIVE: 0.9963169097900391
RoBERTa-tweet: LABEL_1: 0.6031544208526611

BERT_star: 3 stars: 0.27862027287483215
1 star: 0.20595254004001617

BERT_star: 3 stars: 0.2681081295013428
4 stars: 0.2475529909133911

BERT_emotion: Hillary supporters

sadness: 0.13379821181297302
joy: 0.2263767123222351
love: 0.023794466629624367
anger: 0.5194436311721802
fear: 0.08247973769903183
surprise: 0.014107205905020237

BERT_emotion:

sadness: 0.14551712572574615
joy: 0.2647758424282074
love: 0.020851828157901764
anger: 0.5395296216011047
fear: 0.02431230992078781
surprise: 0.005013232585042715

Republicans has a lower star rate.

Less models exhibit biases or preferences.

Facts

Problems with BERT models (transformers)

- 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”

模型建立

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.

模型建立

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: 0.0024098947178572416
surprise: 0.0025462396442890167

```
sentiment_score('#gohillary')
```

#gohillary

distilBERT: NEGATIVE: 0.9103060364723206
RoBERTa-large: POSITIVE: 0.949783205986023
RoBERTa-tweet: NEUTRAL: 0.640250027179718

BERT_star: 1 star: 0.24946489930152893
3 stars: 0.20977455377578735

BERT_emotion:

sadness: 0.015515195205807686
joy: 0.10920542478561401
love: 0.0032404744997620583
anger: 0.8426303863525391
fear: 0.026823310181498528
surprise: 0.002585270442068577

模型建立

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

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

We will vote for you! #gohillary

distilBERT: POSITIVE: 0.9986934661865234

distilBERT: POSITIVE: 0.9982786774635315

RoBERTa-large: POSITIVE: 0.9980786442756653

RoBERTa-large: POSITIVE: 0.9986332058906555

RoBERTa-tweet: POSITVE: 0.6127783060073853

RoBERTa-tweet: POSITVE: 0.8715099096298218

BERT_star: 5 stars: 0.4745408296585083
4 stars: 0.18664398789405823

BERT_star: 5 stars: 0.5570440888404846
4 stars: 0.2187049388885498

BERT_emotion:
sadness: 0.0026922193355858326
joy: 0.9549510478973389
love: 0.010346263647079468
anger: 0.030505357310175896
fear: 0.000517905515152961
surprise: 0.0009872176451608539

BERT_emotion:
sadness: 0.005750871729105711
joy: 0.8868628740310669
love: 0.0129984300583601
anger: 0.09092111140489578
fear: 0.0015296215424314141
surprise: 0.001937000546604395

模型建立

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: 0.01168591808527708
anger: 0.2581046223640442
fear: 0.016510898247361183
surprise: 0.0034682280384004116

Single-word comments is a problem.

模型建立

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
```

```
sentiment_score ['Vote For Trump']
```

```
Vote For Trump
```

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

```
BERT_emotion:
```

```
    sadness: 0.012041224166750908
```

```
    joy: 0.10489775240421295
```

```
    love: 0.009046209044754505
```

```
    anger: 0.8592172861099243
```

```
    fear: 0.011024881154298782
```

```
    surprise: 0.0037726890295743942
```

```
BERT_emotion:
```

```
    sadness: 0.02138894982635975
```

```
    joy: 0.6888414025306702
```

```
    love: 0.01168591808527708
```

```
    anger: 0.2581046223640442
```

```
    fear: 0.016510898247361183
```

```
    surprise: 0.0034682280384004116
```

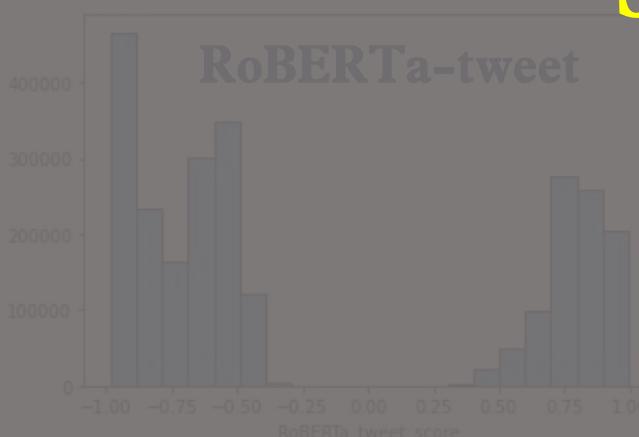
模型建立

Score Distributions



“Model-Mining”

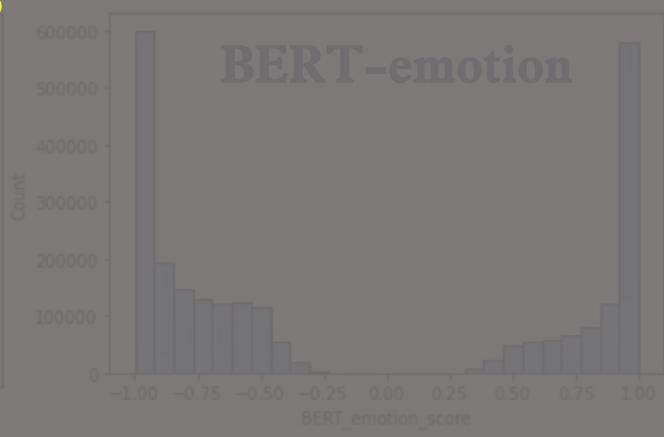
Score Distributions



BERT-star



BERT-emotion



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

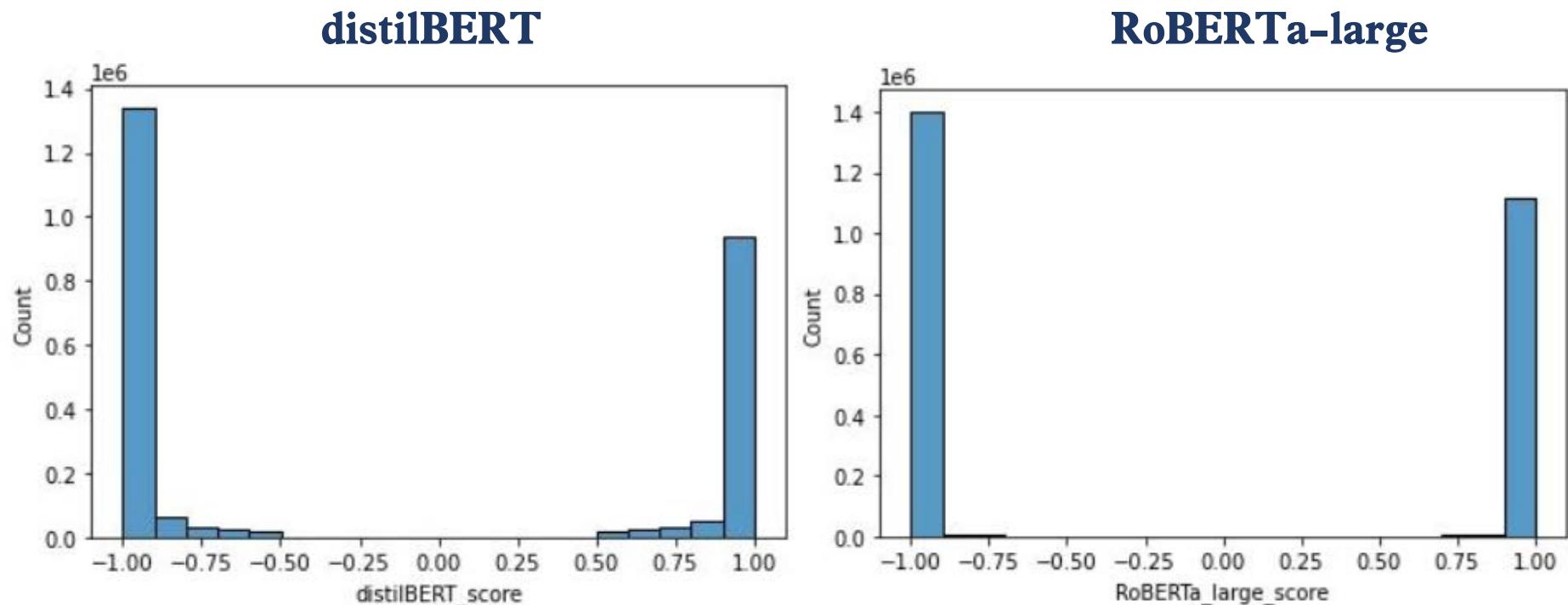
Plot the score distributions out visually, and construct scores.

Mathematical Method

Calculate the Wasserstein distance between every two distributions

模型建立

Graphical Method



These two models tend to assign extreme scores.

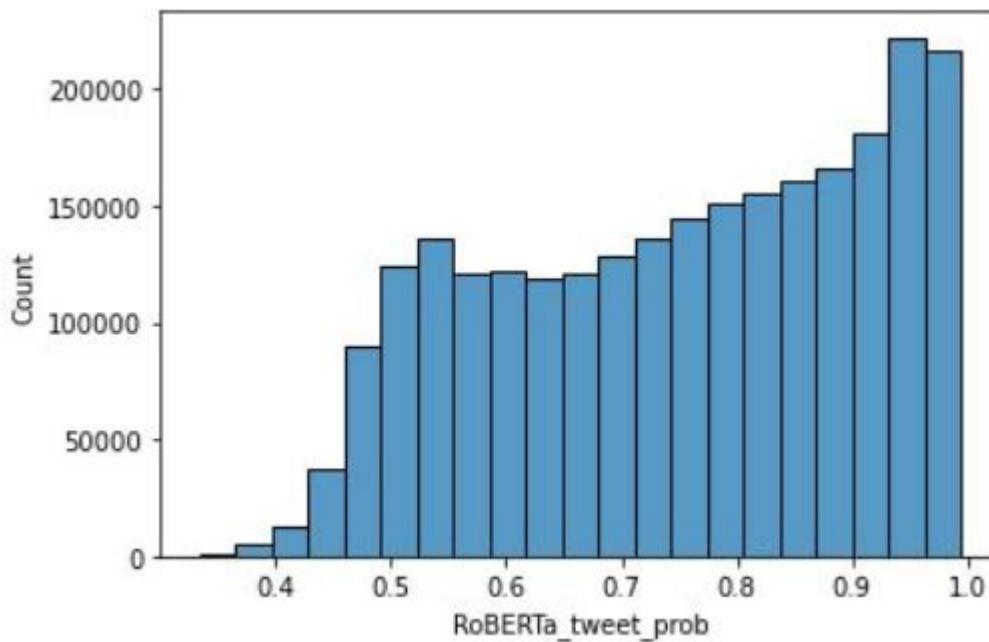
NEGATIVE comments are more than POSITIVE comments.

They look almost the same.

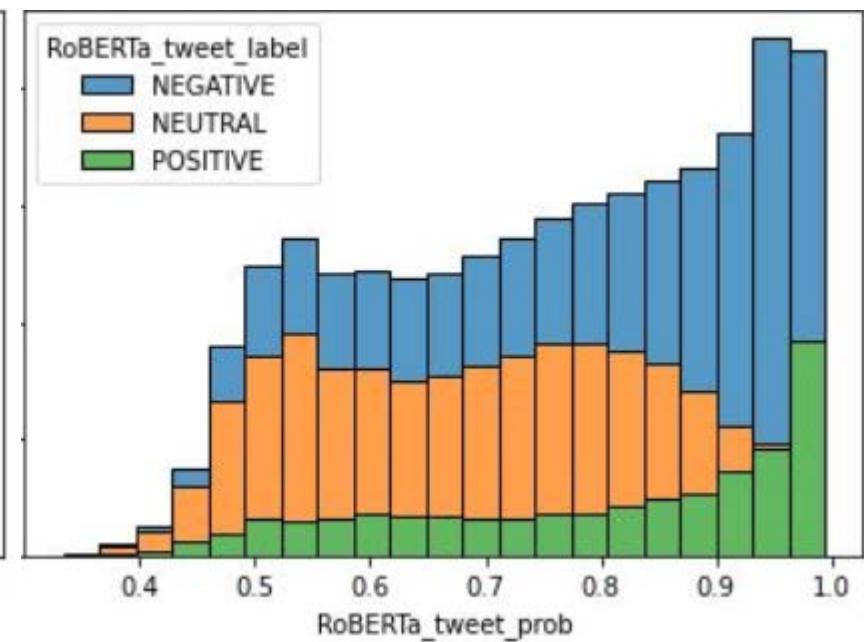
模型建立

Graphical Method

RoBERTa-tweet



RoBERTa-tweet by labels

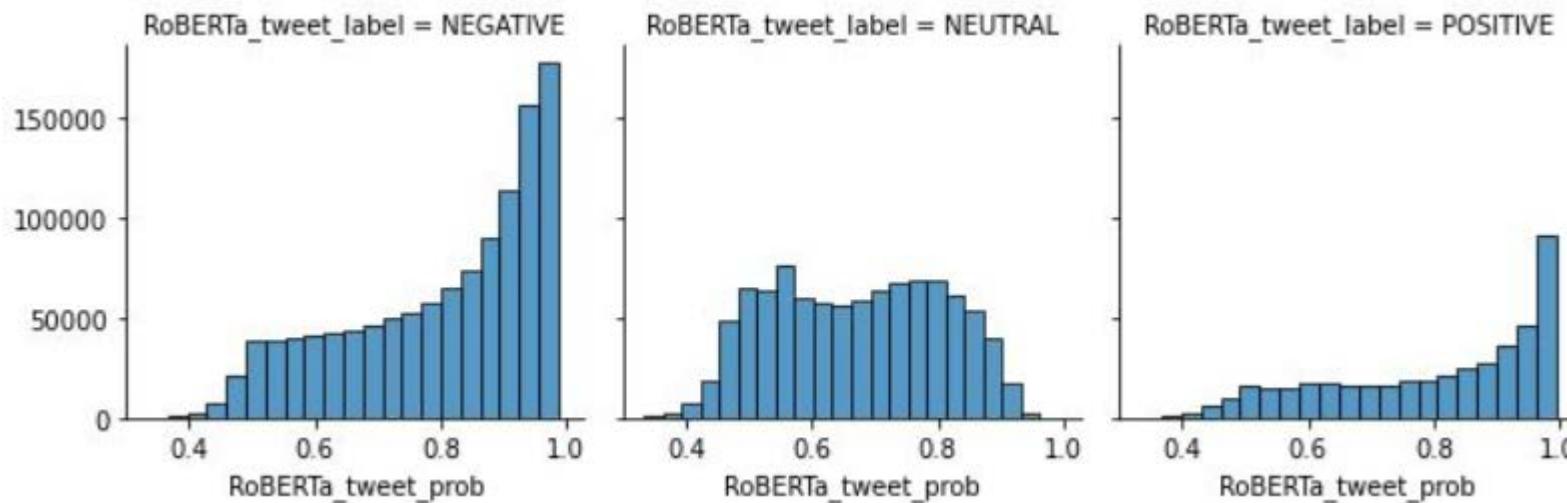


The difficulty is that there isn't a straightforward way to deal with NEUTRAL.

模型建立

Graphical Method

RoBERTa-tweet by labels

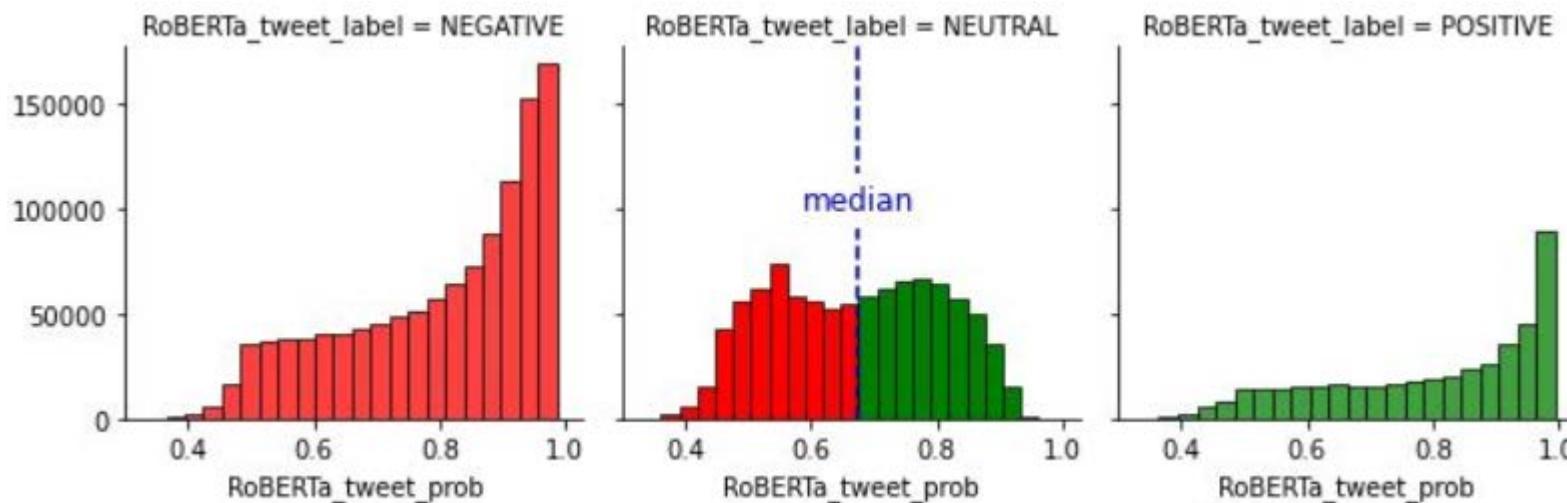


We still can see that **NEGATIVE** comments are more than **POSITIVE** ones. It tends to assign extreme scores, but not to the degree of the previous two. As for **NEUTRAL** comments, we can see that the model wasn't as confident about giving this label as the other two.

模型建立

Graphical Method

RoBERTa-tweet by labels

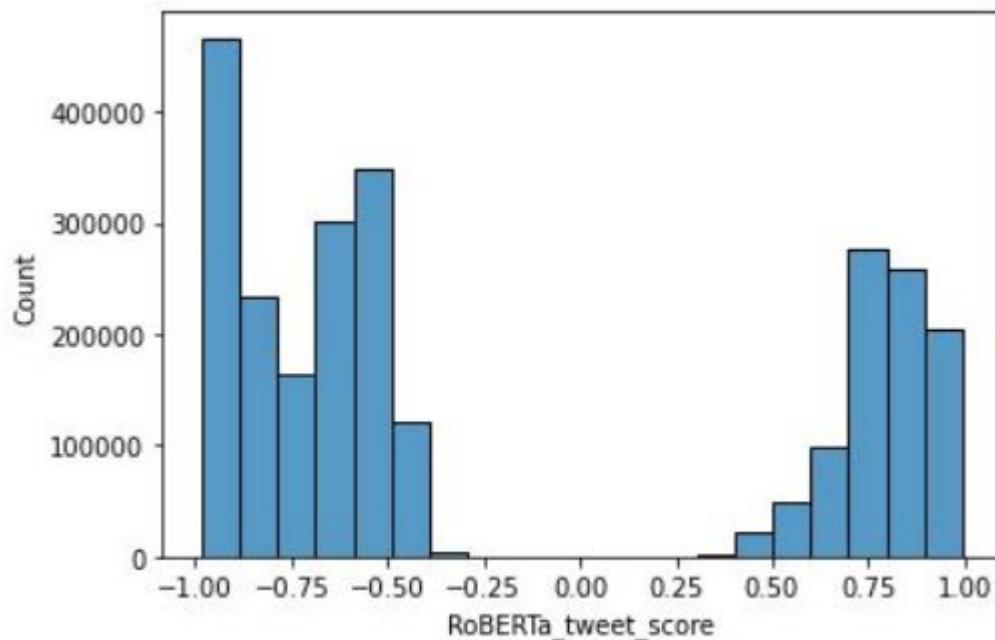


One way to enable comparability is to split NEUTRAL comments by half, and assign the labels accordingly.

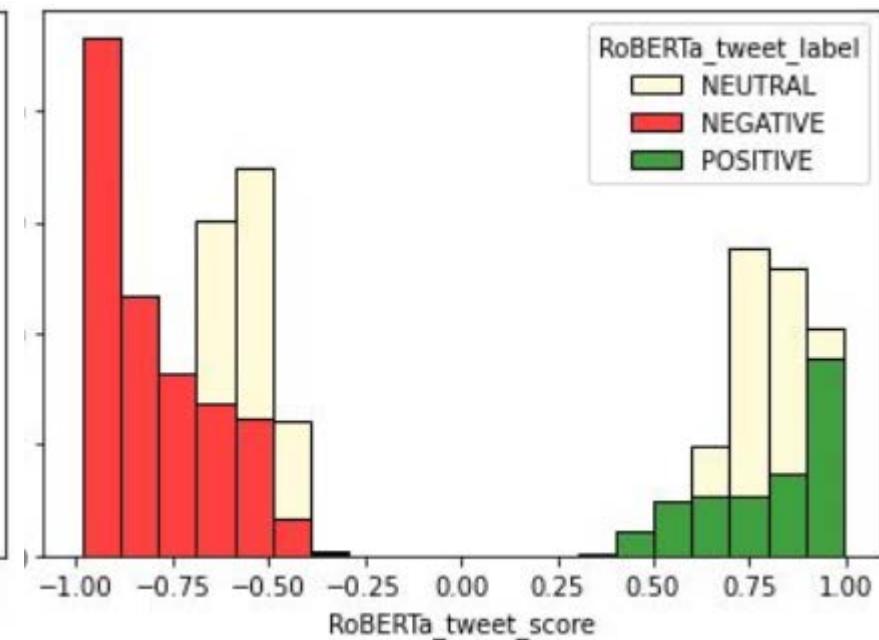
模型建立

Graphical Method

RoBERTa-tweet



RoBERTa-tweet by labels

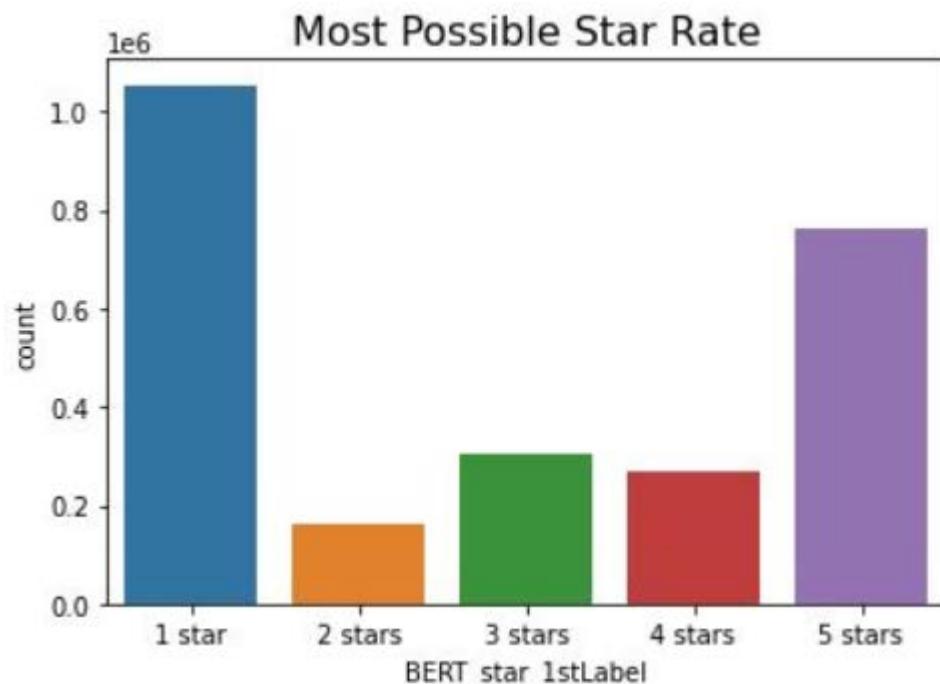


We can see that the distribution is more even, compared to the previous ones.

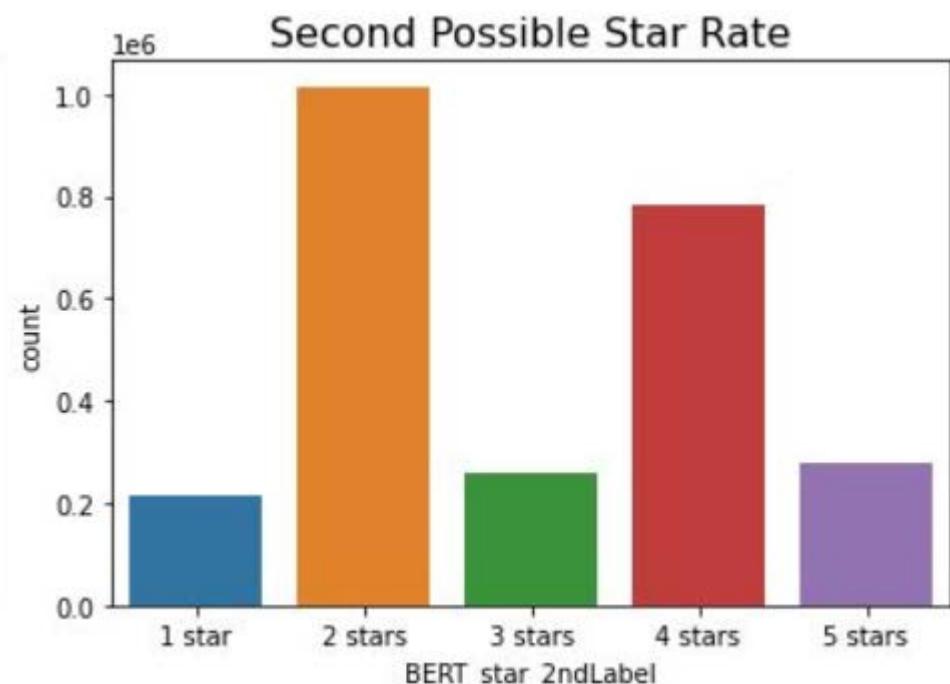
模型建立

Graphical Method

BERT-star



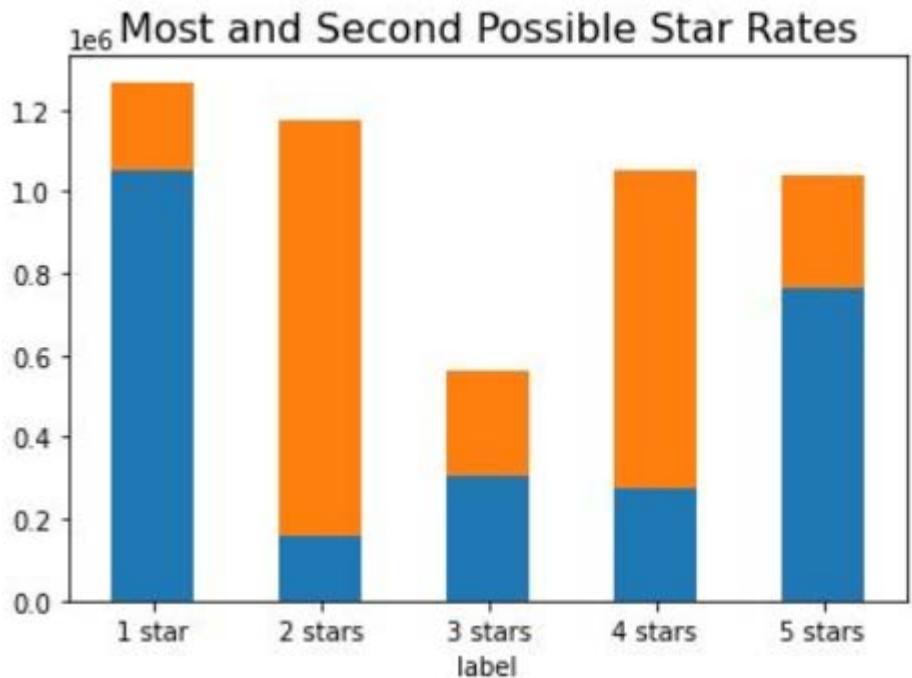
BERT-star



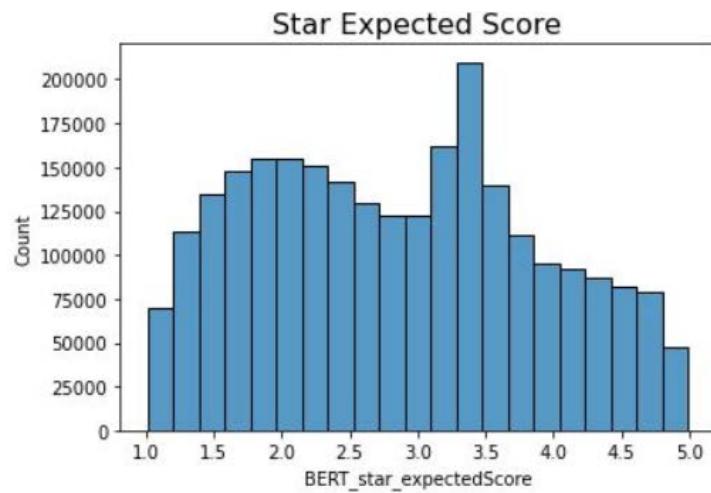
We can see that it tends to assign extreme scores, too.

Graphical Method

BERT-star



Most Possible
Second Possible

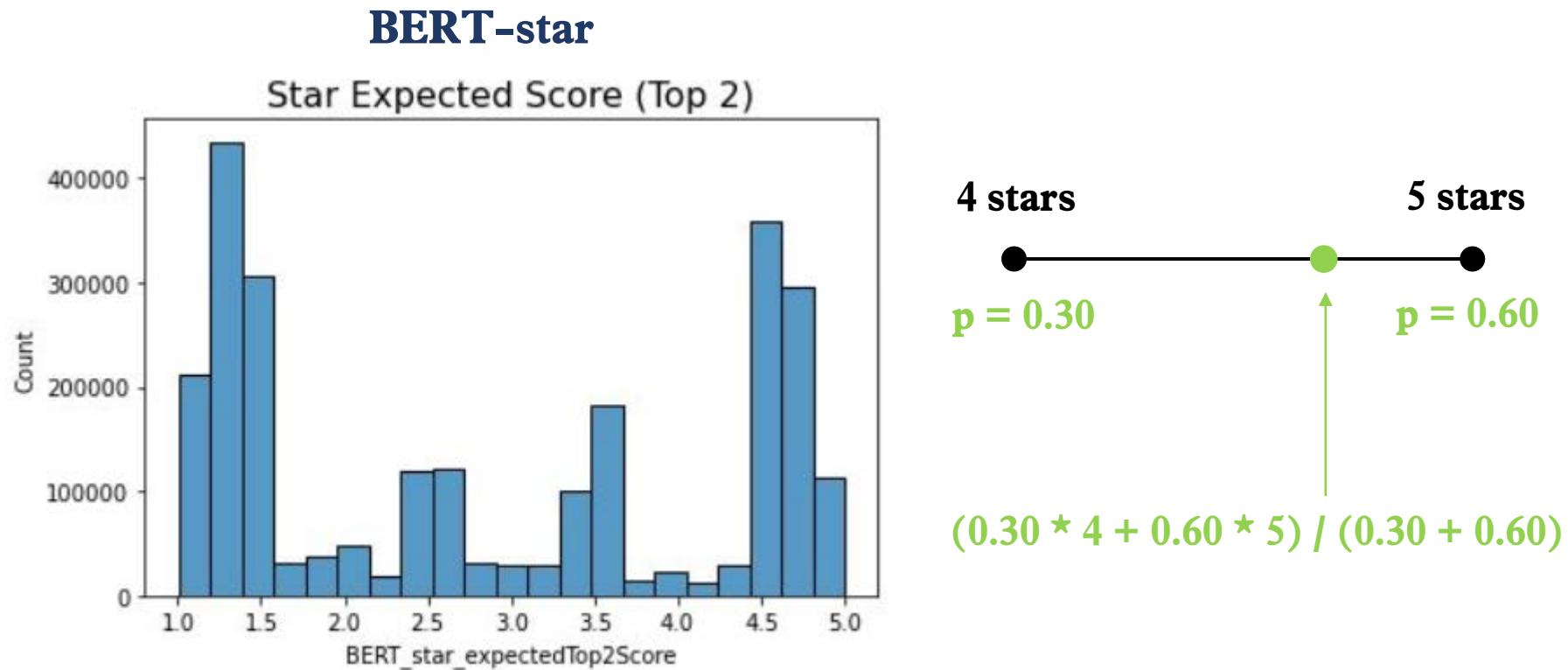


For any comment, we have the corresponding probabilities for each star rate.

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

模型建立

Graphical Method

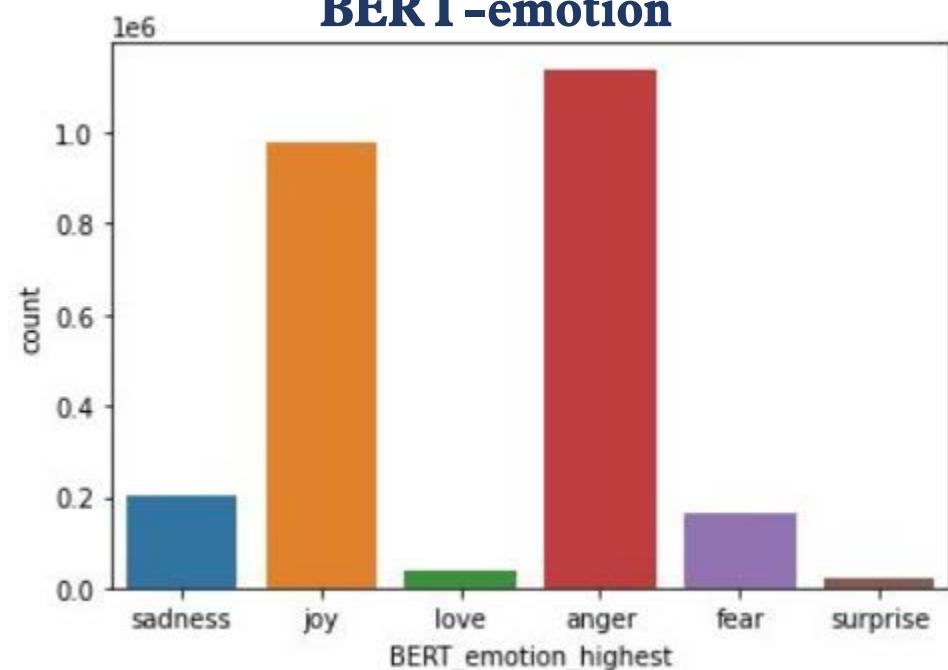


I figured that probabilities other than the top two was simply creating noise. Thus, I took the weighted average of only the top two star rate, where the weights are their probabilities normalized.

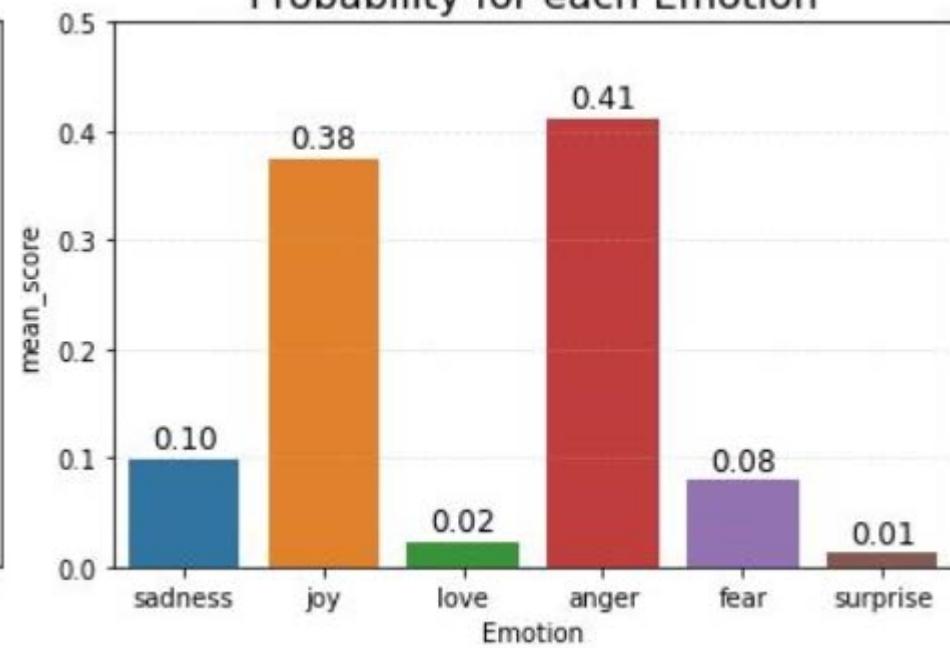
模型建立

Graphical Method

BERT-emotion



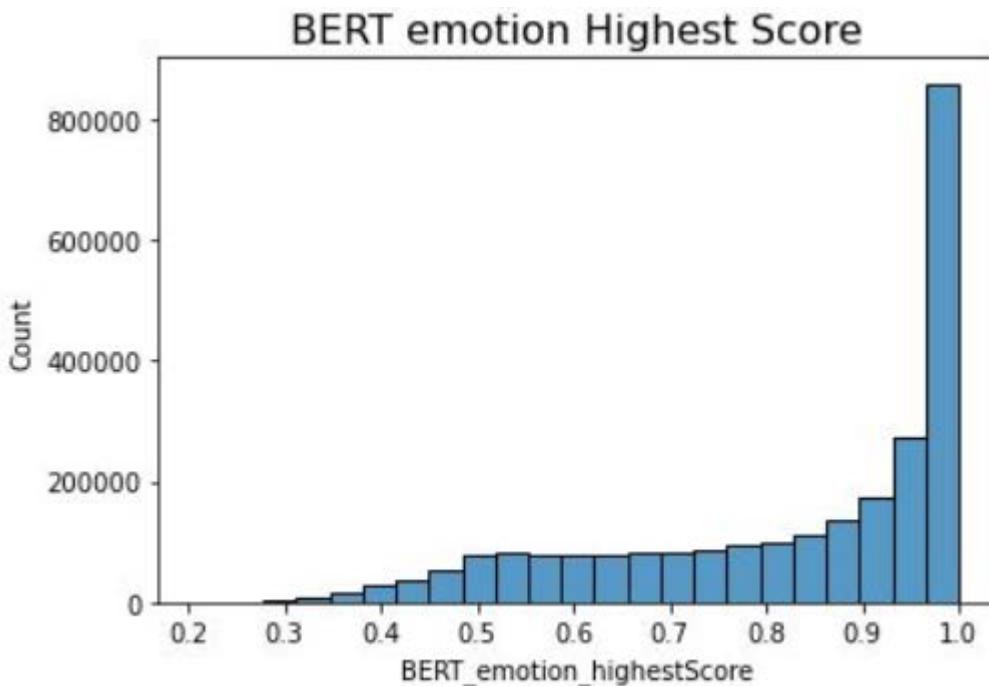
Probability for each Emotion



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

模型建立

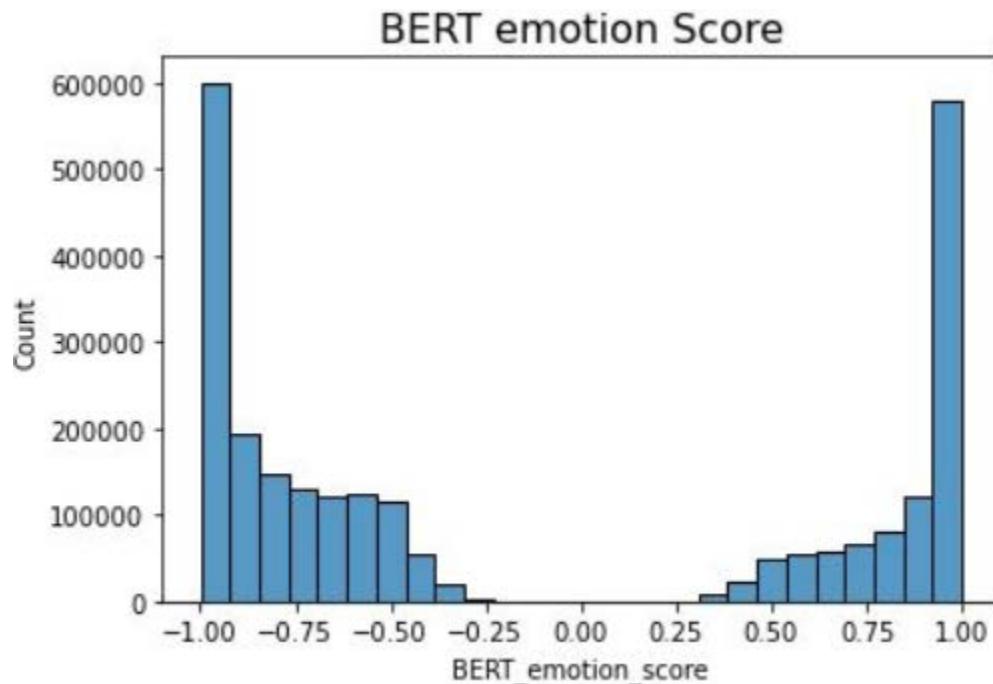
Graphical Method



The model tends to assign extreme scores as well.

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

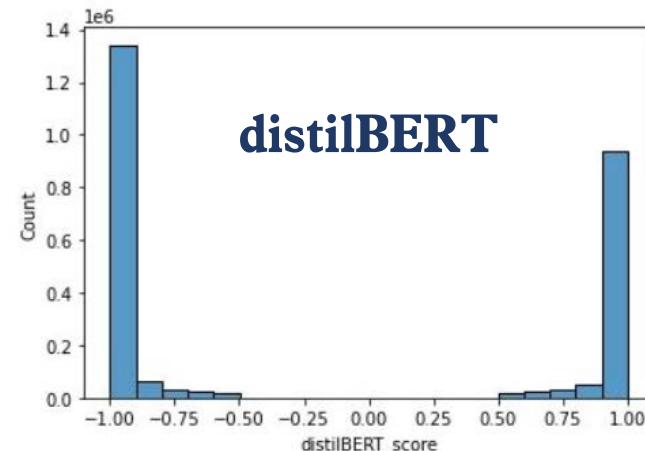
Graphical Method



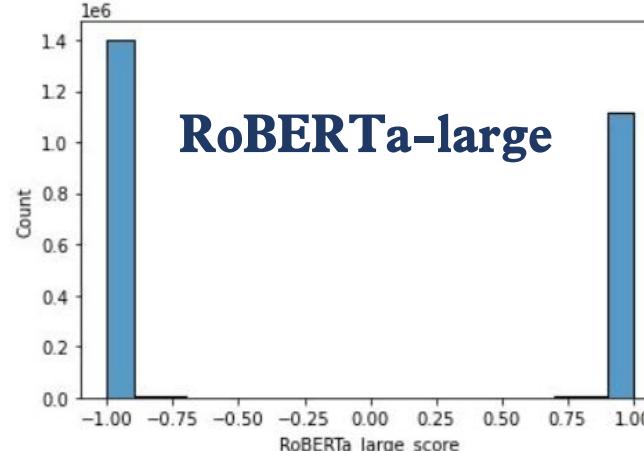
- Joy, love, surprise → **POSITIVE**
- Anger, sadness, fear → **NEGATIVE**

模型建立

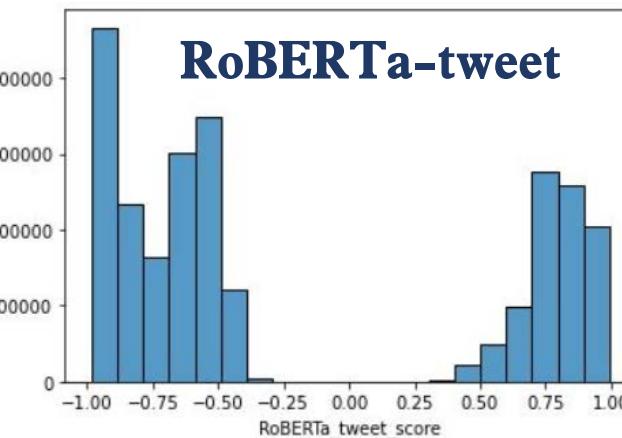
Score Distributions



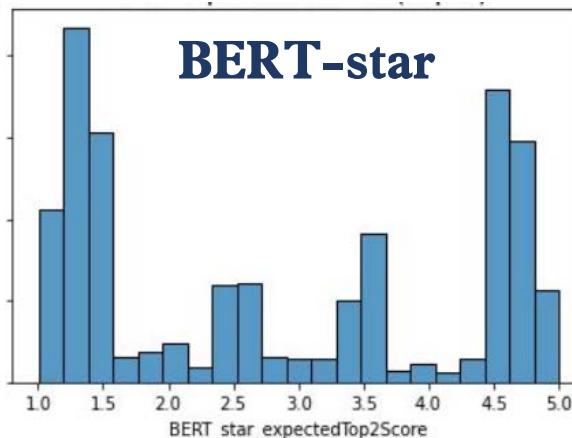
distilBERT



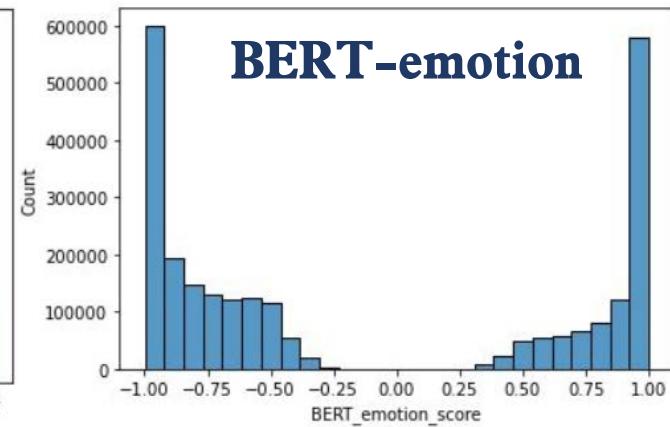
RoBERTa-large



RoBERTa-tweet



BERT-star



BERT-emotion

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.

模型建立

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.

模型建立

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.

模型建立

Mathematical Method

	distilBERT	RoBERTa_large	RoBERTa_tweet	BERT_star	BERT_emotion	mean_wdistance
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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.

Mathematical Method

	distilBERT	RoBERTa_large	RoBERTa_tweet	BERT_star	BERT_emotion	mean_wdistance
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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

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 “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

模型建立

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: 0.01987159065902233
  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.

模型建立

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: 0.999430239200592
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: 0.0002634108532220125

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

模型建立

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_suit Embarrassed 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.

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.

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'
```

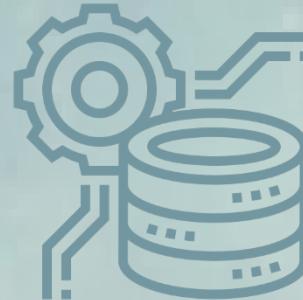
Therefore, I only consider emoticon patterns with a whitespace in front of them.



研究主題



資料介紹



資料前處理



模型建立



分析結果



未來方向

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

分析結果

Procedure

Preliminary Data-Mining

- “Know your Data”
- We've roughly done that.

“Model-Mining” with Data

- “Know your Model”
with Data
 - Keyword Sanity Checks (for each model)
 - Score Distribution (and its tail)
 - Emojis & Emoticons

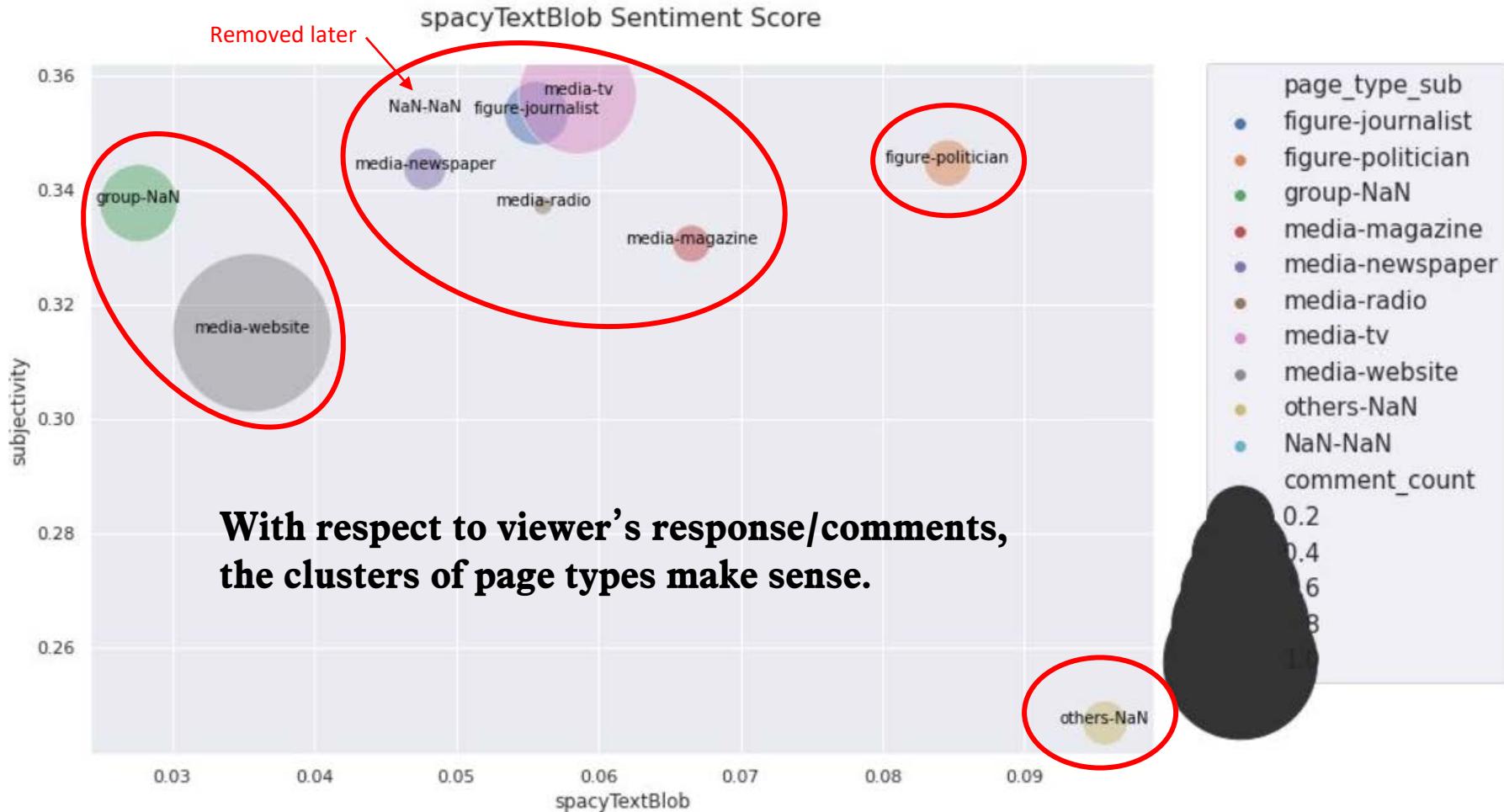
Data-Mining with Models

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

“Data-Mining” With Models

分析結果

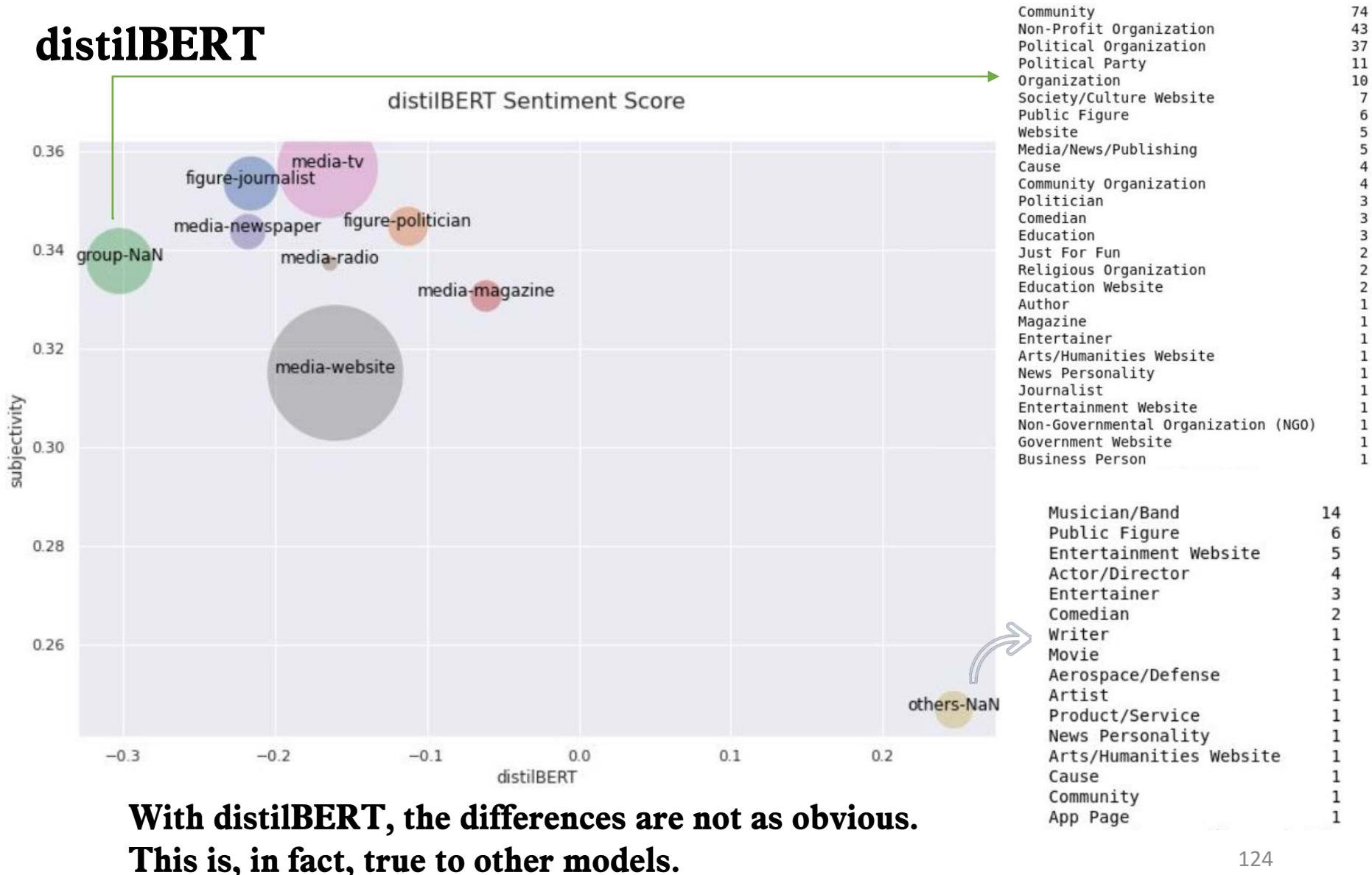
Results with spacyTextBlob from last time...



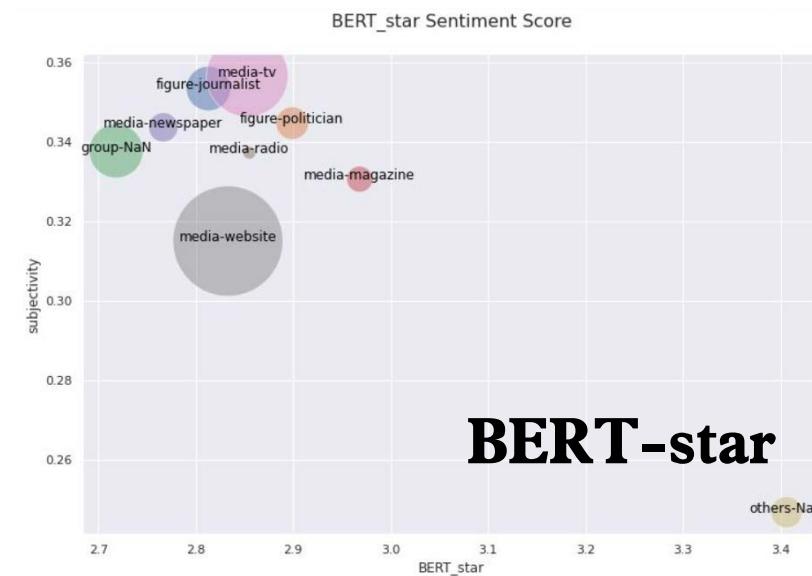
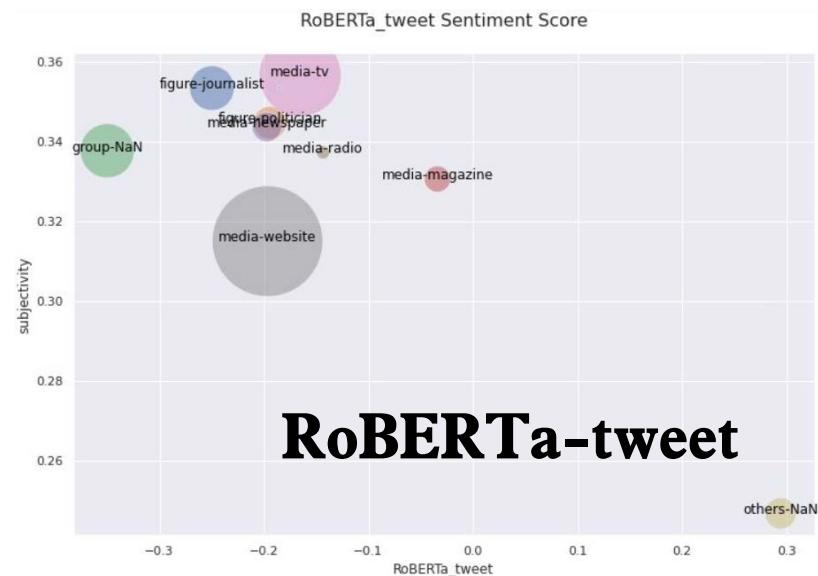
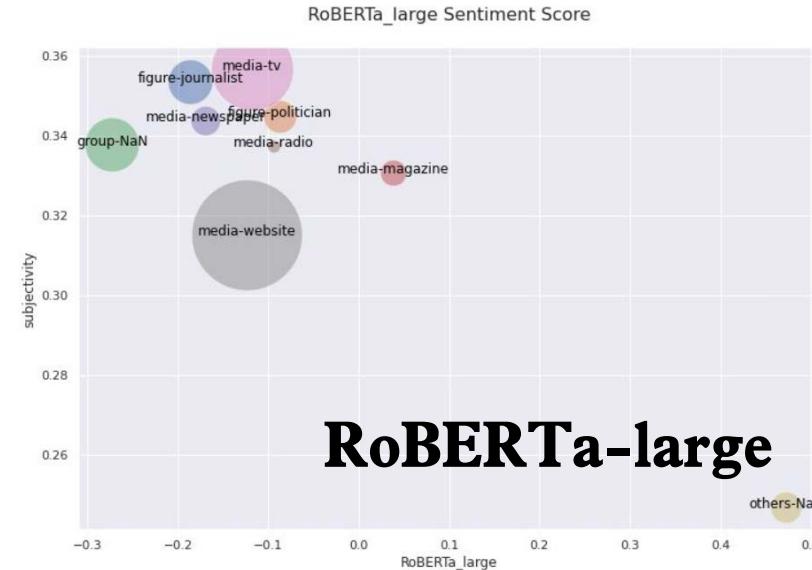
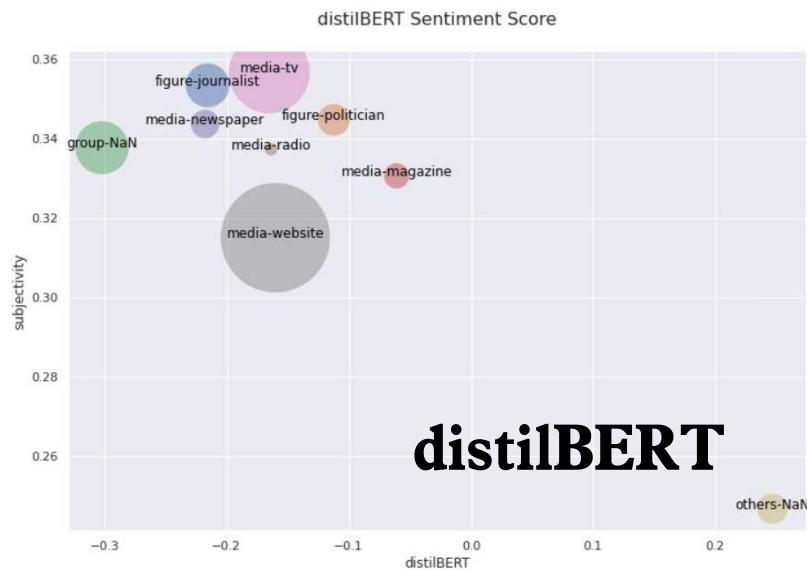
Let's replace polarity with other sentiment scores!

分析結果

distilBERT



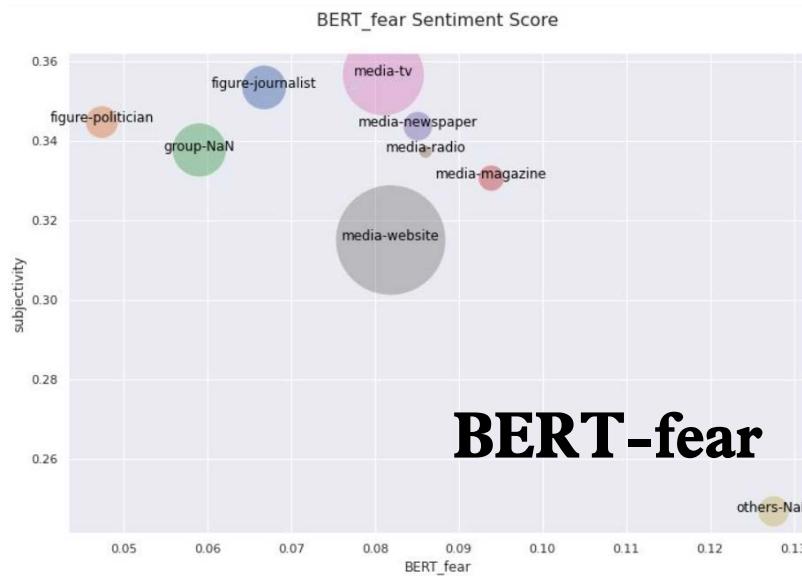
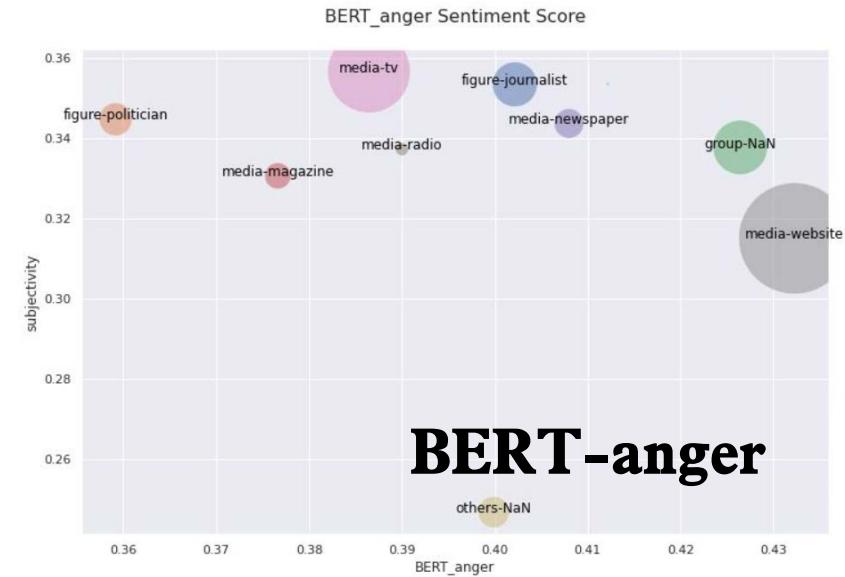
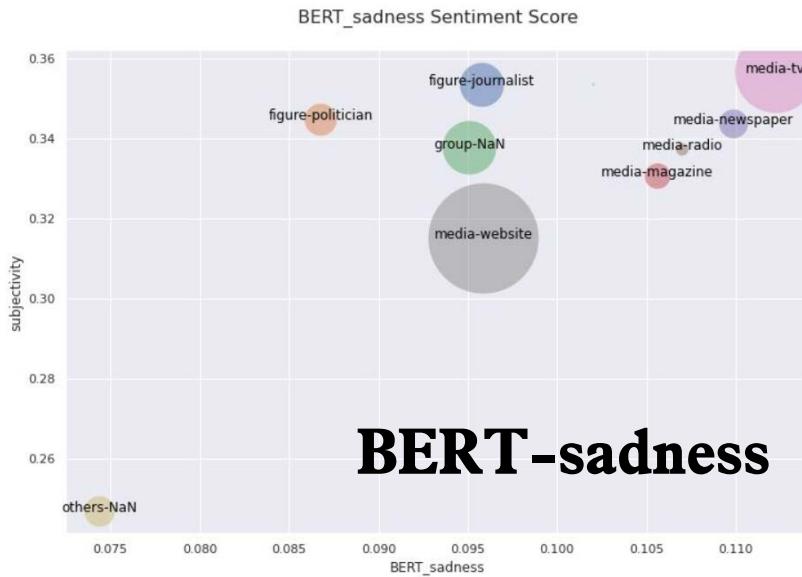
分析結果



分析結果



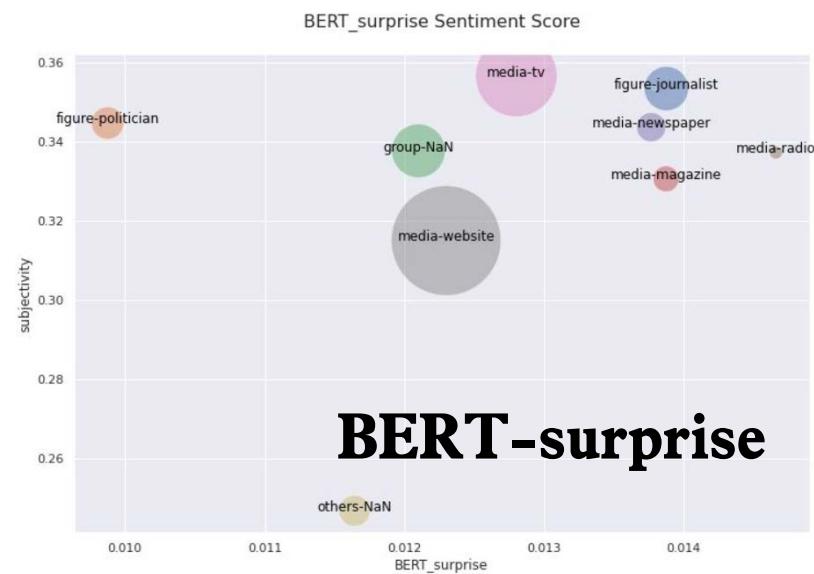
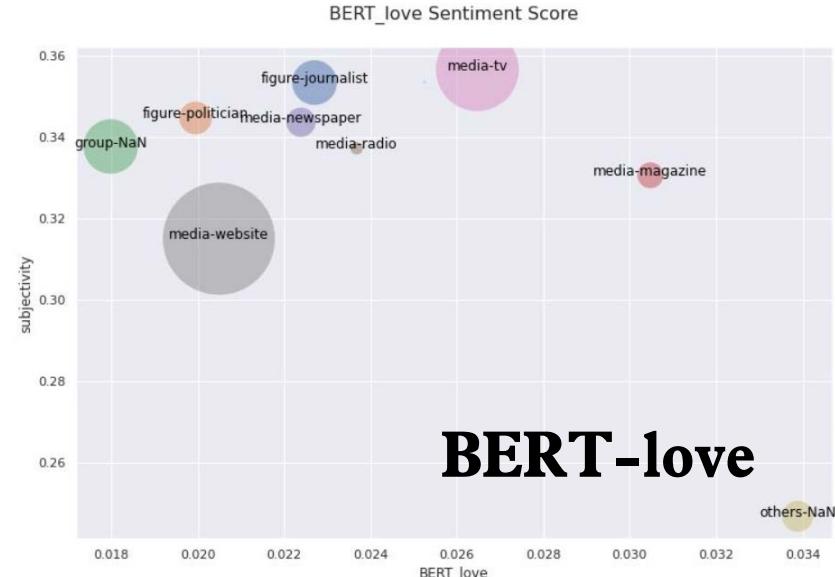
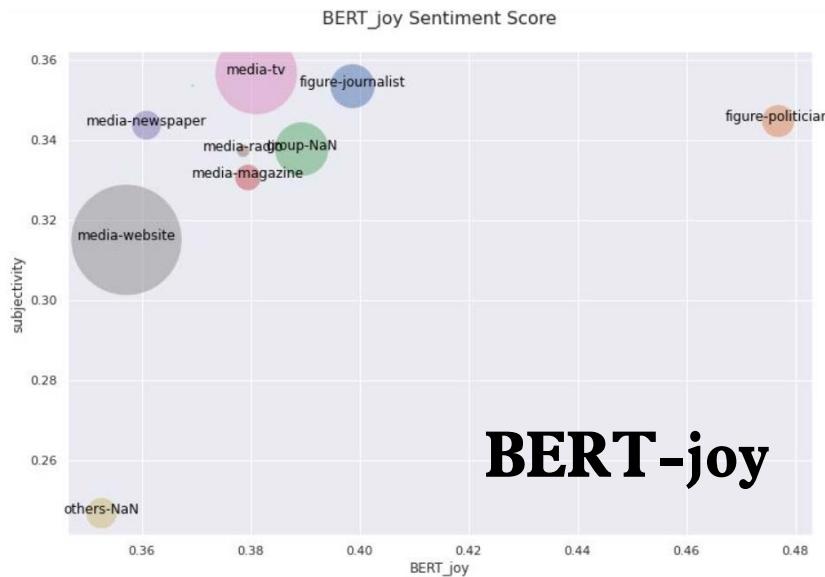
分析結果



BERT-emotion Model

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

分析結果



BERT-emotion Model

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

Procedure

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- “Know your Model”: Understand the flaws/biases/tendencies that are inherent in the model (due to training data, or even human!)

“Data-Mining” with Models

Construction for Sentiment Score

- 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

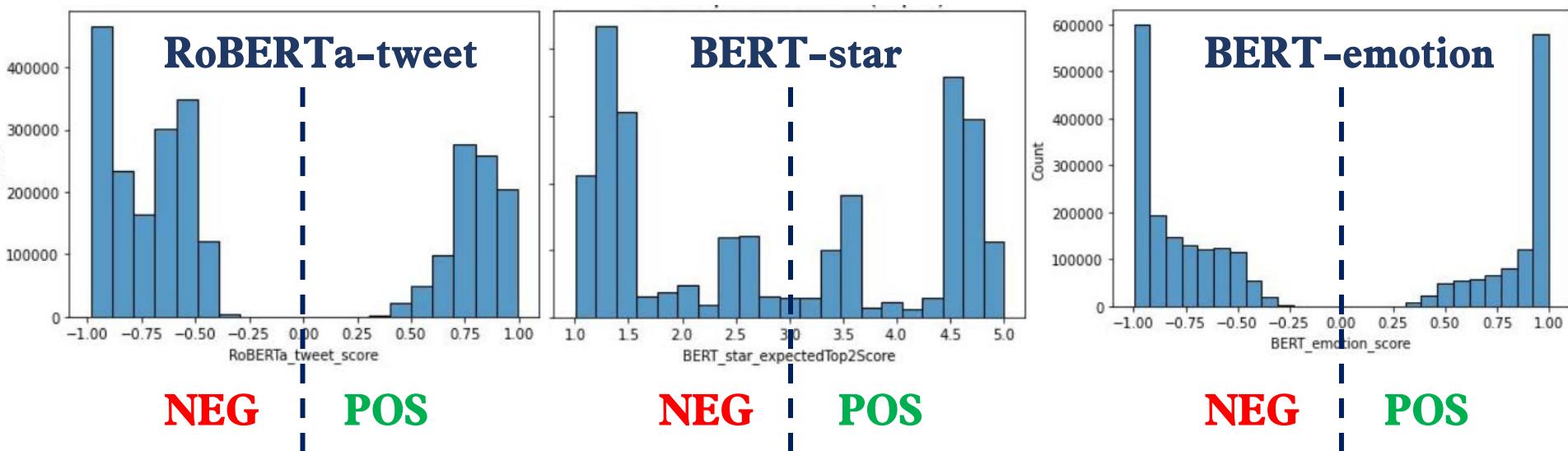
- Get the multi-class sentiments directly from BERT-emotion

	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

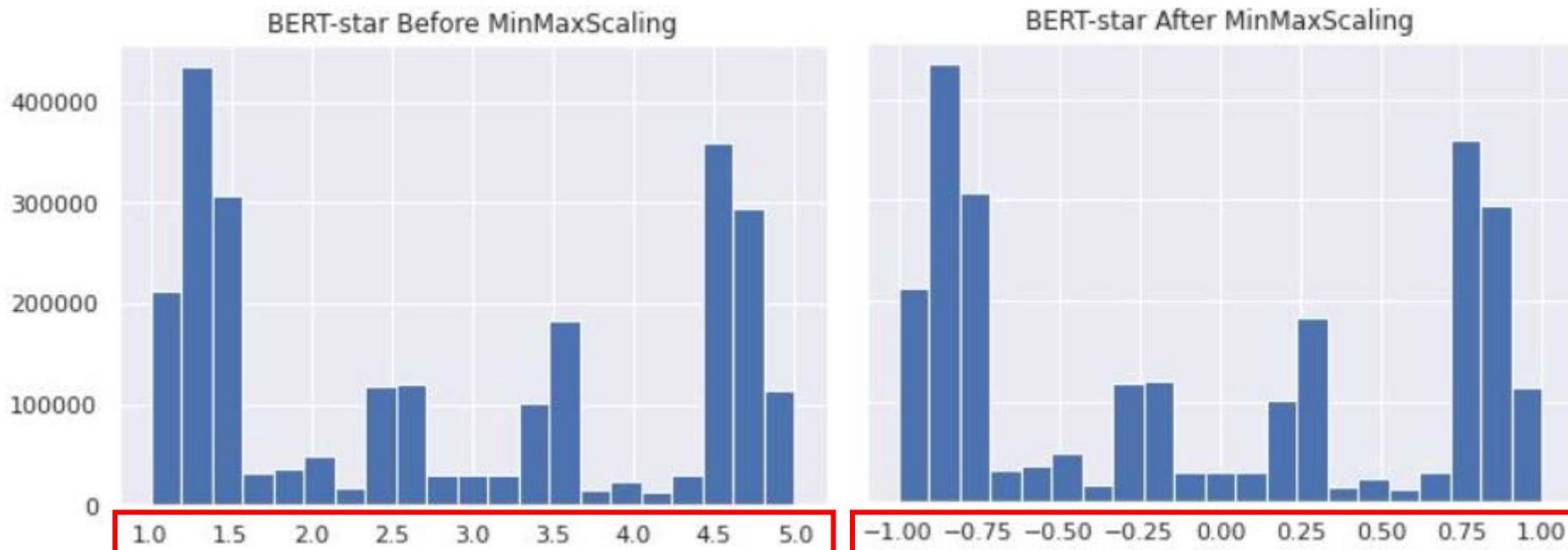
distilBERT_label	RoBERTa_large_label	RoBERTa_tweet_binaryLabel	BERT_star_binaryLabel	BERT_emotion_binaryLabel	majority_vote
POSITIVE	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE
NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE
NEGATIVE	NEGATIVE	NEGATIVE	POSITIVE	POSITIVE	NEGATIVE
NEGATIVE	NEGATIVE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

	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 or 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

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Validation for Sentiment Score

Human Labeling

- The best way to validate any sentiment score is to add labels/scores by human.
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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

page_name	NEG	POS	POS	NEG	NEG	POS	
	BERT_sadness	BERT_joy	BERT_love	BERT_anger	BERT_fear	BERT_surprise	BERT_emotion_highest
Donald J. Trump	0.074530	0.535005	0.019349	0.321067	0.04240	0.007648	joy
Hillary Clinton	0.087551	0.489037	0.021095	0.350155	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.

分析結果

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		
pct				
majority_vote				
NEGATIVE		55.40%		
POSITIVE		44.60%		
pct				
majority_vote				
NEGATIVE		68.60%		
POSITIVE		31.40%		

6534 rows × 1 columns

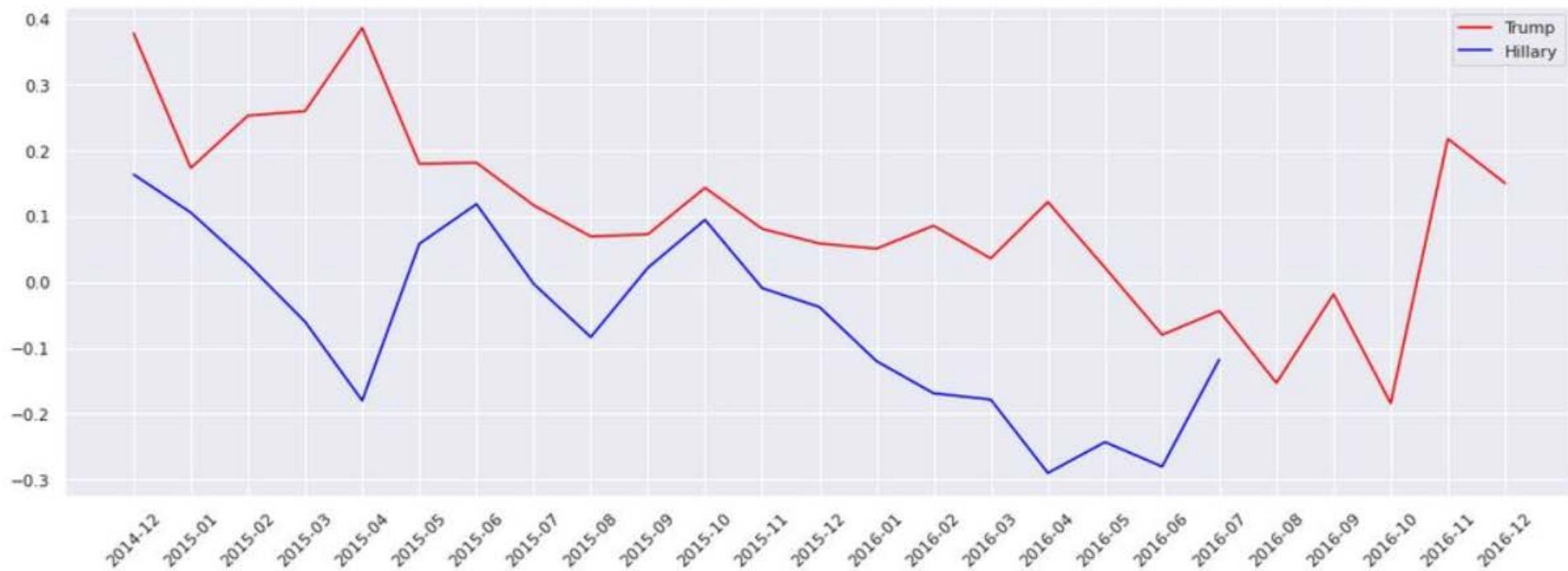
This shows that Hillary was falling behind Trump, somewhat predictive of the US presidential result in 2016.

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

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

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)



研究主題



資料介紹



資料前處理



模型建立



分析結果



未來方向

Difficulties in Sentiment Analysis

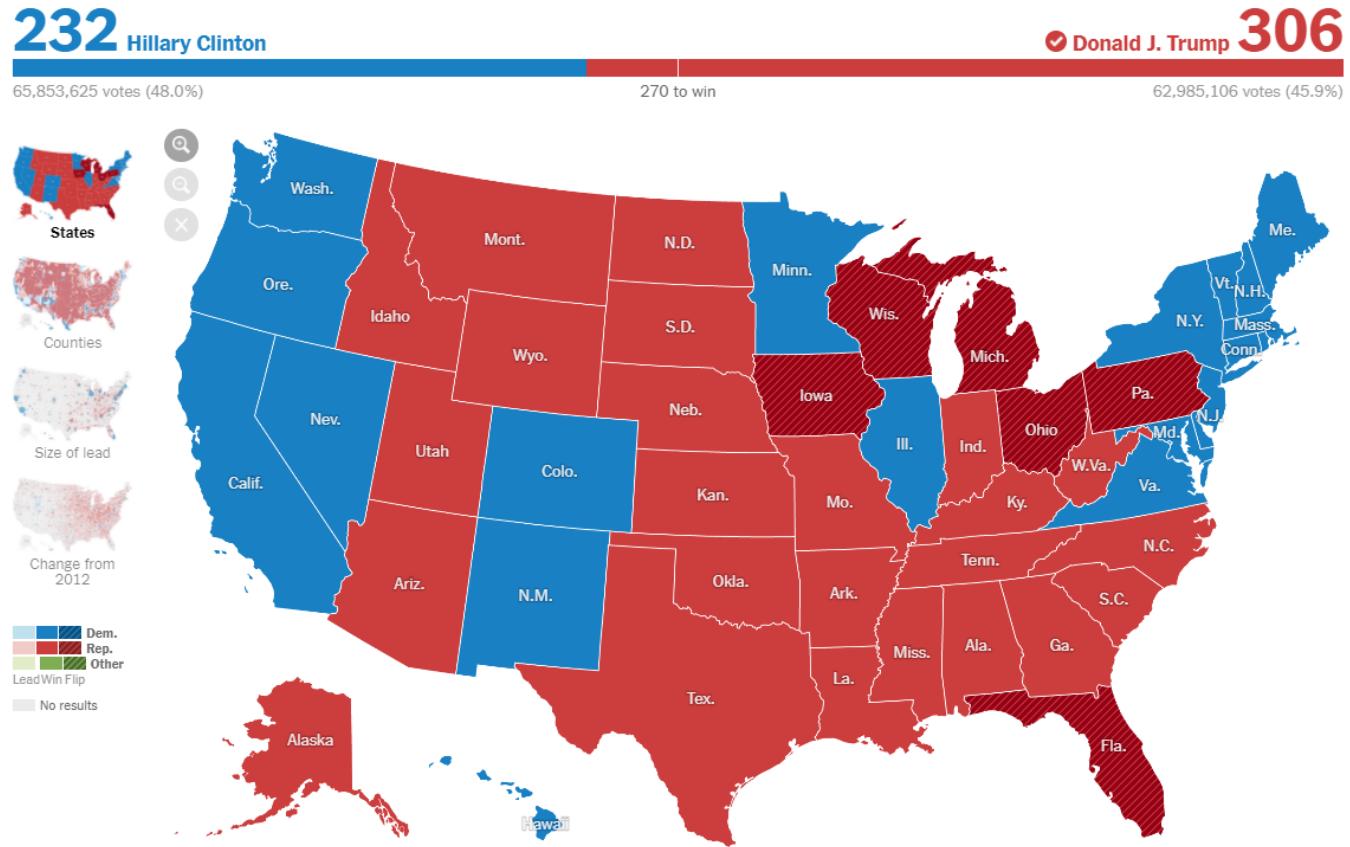
- **Ambiguity in Short Texts**
 - “**Damn what a night**” : positive or negative? Joy, surprise, sadness?
 - “**What the f*ck is going on?**” : fear, anger, sadness?
- **Texts with Mixed emotions**
 - “**So how can people wear fur, knowing it comes from such lovely creatures**”
 - love, anger, sadness, 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

Other Validations Ideas

Reconstruct this
colored map using
user_id and
geographic
features



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



THANKS

謝謝大家