Towards more accurate Language translation model using emotion analysis



Independent Study

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# Hello!

# I am Nayeon Kim

I am an MSCS student, taking Independent study under prof Lawrence Chung.

Research Interest: Natural Language Processing



#### **Emotion Analysis**

# What is the Emotion Analysis?

Analytical technique to determine the emotional meaning of sentences.

# Example:

Social Media Monitoring for Brand Emotion Analysis



#### **Sentiment Analysis**

## What is the Sentiment Analysis?

Analytical technique to determine the emotional meaning of sentences.

## Example:

Social Media Monitoring for Brand Sentiment Analysis - Repustate reference: https://www.differencebetween.com/difference-between-emotion-and-vs-sentiment/



#### **Emotion? Sentiment?**

#### What is the difference between Emotion and Sentiment?

- · Definition of Emotion and Sentiment:
  - · Emotions can be defined as complex psychological states.

#### towards something

· A sentiment can be defined as a mental attitude; a thought that has been influenced by emotion.

#### · Connection:

· Sentiments are the expression of emotions where they become tied to a social object.

#### · Dimension:

- · Emotions are mostly confined to the psychological dimensions.
- · Sentiments go a step further capturing the social dimension.

#### · Nature:

- · Emotions are very raw and natural.
- · Sentiments are highly organized.



## WHAT MAKES YOUR LIFE 100%?

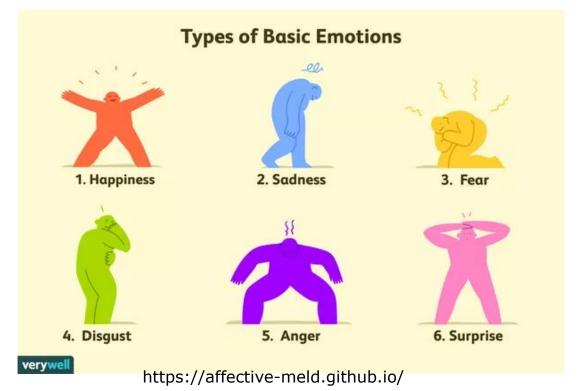
# Attitude is everything!

Let each letter of the alphabetic has a value equals to it sequence of the alphabetical order:

A B C D E F G H I J K L M N O P Q R S T U V W X Y Z 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26

		99	-	24	2200					5
1					S				=	82
					19					- 02
K	N	0	W	L	Ε	D	G	E	_	96
11	14	15	23	12	5	4	7	5		30
Н	Α	R	D		w	0	R	K		0.0
8	1	18	4		23	15	18	11		90
Α	Т	Т	1	Т	U	D	Ε			400
1	20	20	9	20	21	4	5			100







#### 1. Happiness

Happiness is often defined as a **pleasant emotional state** that is characterized by feelings of **contentment, joy, gratification, satisfaction, and well-being**.

- Facial expressions: such as smiling
- Body language: such as a relaxed stance
- Tone of voice: an upbeat, pleasant way of speaking



Sadness



#### 2. Sadness

Sadness is often defined as a **transient emotional state** characterized by feelings of **disappointment**, **grief**, **hopelessness**, **disinterest**, **and dampened** mood.

Crying, Dampened mood, Lethargy, Quietness, Withdrawal from others





#### 3. Fear

Fear is a powerful emotion about **survival**. when we face some danger situation, we go through fight or flight response.

- Facial expressions: such as widening the eyes and pulling back the chin
- **Body language**: attempts to hide or flea from the threat
- Tone of voice: such as rapid breathing and heartbeat





#### 4. Disgust

This sense of revulsion can originate from a number of things, including an unpleasant taste, sight, or smell. Poor hygiene, infection, blood, rot, and death can also trigger a disgust response.

- Facial expressions: turning away from the object of disgust
- Body language: such as vomiting or retching
- Tone of voice: such as wrinkling the nose and curling the upper lip



Trust (new basic emotion)



#### 5. Anger

Anger can be a particularly powerful emotion characterized by feelings of **hostility, agitation, frustration, and antagonism** towards others.

- Facial expressions: such as frowning or glaring such as frowning or glaring
- Body language: such as taking a strong stance or turning away
- Tone of voice: such as speaking gruffly or yelling



Fear



#### 6. Suprise

Surprise is usually quite brief and is characterized by a physiological startle response following something unexpected. This type of emotion **can be positive, negative, or neutral**.

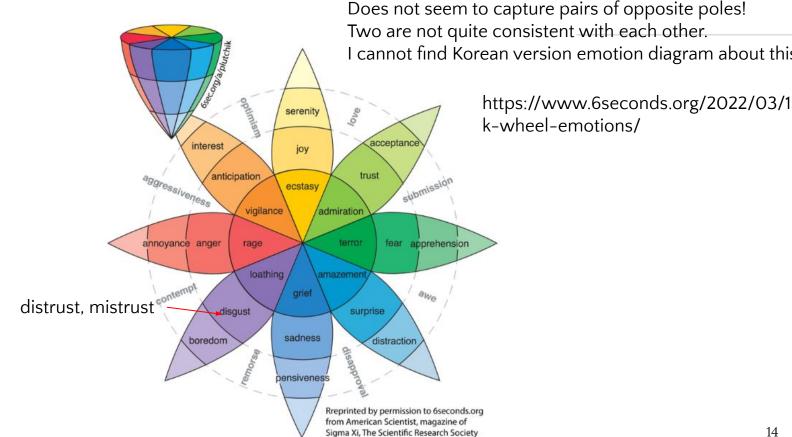
- Facial expressions: such as raising the brows, widening the eyes, and opening the mouth
- Body language: such as jumping back
- Tone of voice: such as yelling, screaming, or gasping



Anticipation (new basic emotion)

#### PLUTCHIK'S WHEEL OF EMOTIONS

NAME A FEELING & ENHANCE EMOTIONAL LITERACY





#### **Correct Google Translate**





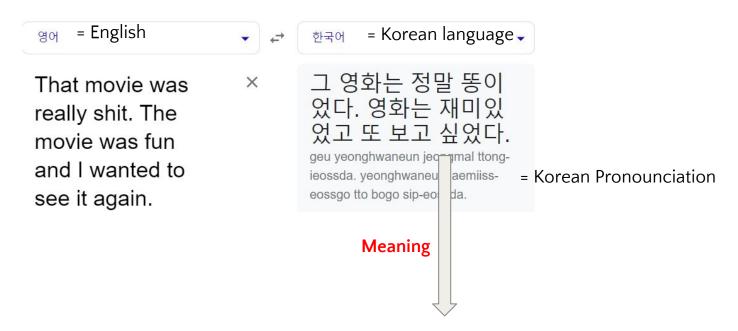
#### **Incorrect Google Translate**



That movie was legit. I want to see that movie again because it was fun."



#### **Incorrect Google Translate**



"That movie was shit. I want to see that movie again because it was fun."



#### **Incorrect Google Translate**

그 영화는 정말 개쩔었어. 그 영 화 재밌어서 또 한번 더 보고싶 어.

!=

그 영화는 정말 똥이 었다. 영화는 재미있 었고 또 보고 싶었다.

Incorrect!



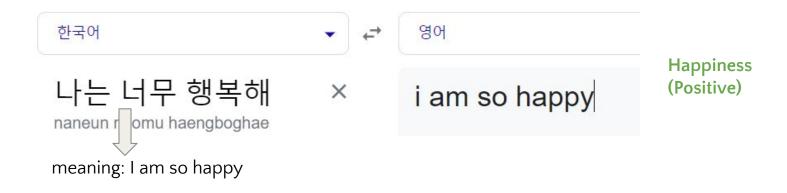
# Machine Learning Accuracy of Translation Result

		Actual		
		Positive	Negative	
cted	Positive	True Positive	False Positive	
Predicted	Negative	False Negative	True Negative	



#### **Example 1**

Happiness (Positive)

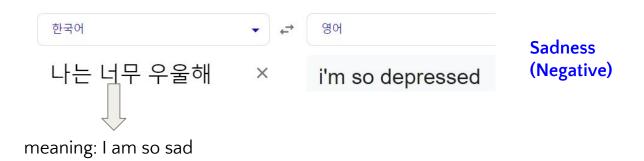




True Positive: Actual (korean)-> positive / Predict (English)-> positive

# Example 2

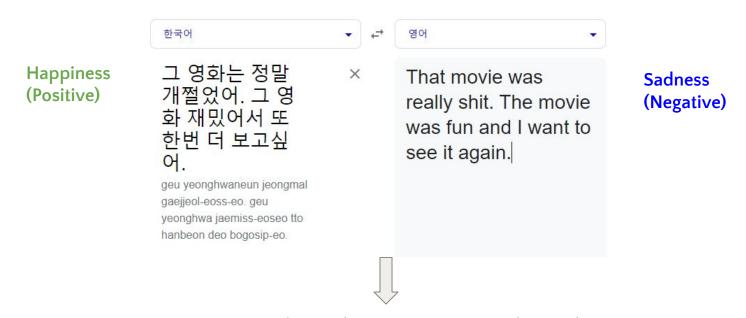






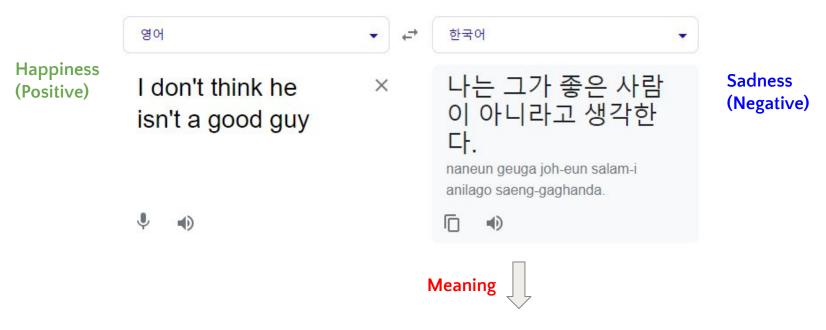
True Negative: Actual (korean)-> negative / Predict (English)-> negative





False Negative: Actual (korean)-> positive / Predict (English)-> negative

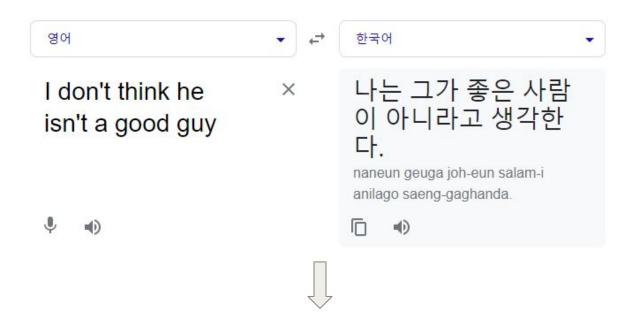




"I don't think he is a good guy"



## Example 4



False Negative: Actual (English)-> positive / Predict (Korean)-> negative



Google Translate users spotted an alarming mistake when entering the phrase "I am sad to see Hong Kong become part of China" into the multilingual machine translation service a few days ago (June 14th, 2019).

According to France 24, when the phrase was translated into both Traditional and Simplified Chinese, Google Translate changed the emotion 'sad' to 'happy', meaning the phrase had a completely different intent and meaning and instead read "I am happy to see Hong Kong become part of China".

False Positive: Actual (Chinese)-> Negative / Predict (English)-> Positive



# **Key Approach**

"Evaluate translation results through sentiment analysis model"



#### How? - Model's basic approach

Compare how much "similar" between source (Input sentence) and target (Output sentence) by using emotion analysis!

Cannot say that source and output are the "same"!

#### Why?

In reality, words in all languages cannot be matched one-to-one with 100% of the same meanings.

Because the cultural nuance is different and the number of words is different.

Joy, happiness, pleasant, delight => 행복, 즐거움, 기쁨



### Similar research paper

The Type of	Number	Number of	Positive	Negative	Sentiment	
the Analyzed	of	Negative	Percentage	Percentage	Score	
text	Positive Words	Words				
Arabic Lyrics	19	33	16%	%28	-0.1176	
My Translation	9	25	3%	9%	-0.0606	
Google Translation	10	19	5%	9%	-0.0437	
Arabic Lyrics	26	6	46%	11%	0.35088	
My Translation	20	3	19%	3%	0.16505	
Google Translation	13	3	14%	3%	0.10989	
Arabic Lyrics	23	38	17%	28%	-0.1087	
	the Analyzed text  Arabic Lyrics  My Translation  Google Translation  Arabic Lyrics  My Translation  Google Translation	the Analyzed text Of Positive Words  Arabic Lyrics 19  My Translation 9  Google 10  Translation 26  My Translation 20  Google 13  Translation 13	the Analyzed text         of Positive Words         Negative Words           Arabic Lyrics         19         33           My Translation         9         25           Google Translation         10         19           Arabic Lyrics         26         6           My Translation         20         3           Google Translation         13         3           Translation         3         3	the Analyzed text         of Positive Words         Negative Words         Percentage           Arabic Lyrics         19         33         16%           My Translation         9         25         3%           Google Translation         10         19         5%           Arabic Lyrics         26         6         46%           My Translation         20         3         19%           Google Translation         13         3         14%           Translation         14%         14%	the Analyzed text         of Positive Words         Negative Words         Percentage         Percentage           Arabic Lyrics         19         33         16%         %28           My Translation         9         25         3%         9%           Google Translation         10         19         5%         9%           Arabic Lyrics         26         6         46%         11%           My Translation         20         3         19%         3%           Google Translation         13         3         14%         3%           Translation         3%         3%         3%         3%	

https://era.library.ualberta.ca/items/55622b1e-bed3-4260-ad86-042408dff84d



#### **Translation Type: Syntactic**

Syntactic Translation: The literal translation that just translates the sequence of words by Ignoring the context or nuance of a sentence.

Ex)

Russian: дух бодр, но плоть немощна(=the spirit is willing, but the flesh is weak)

English: the vodka is strong but the meat is rotten

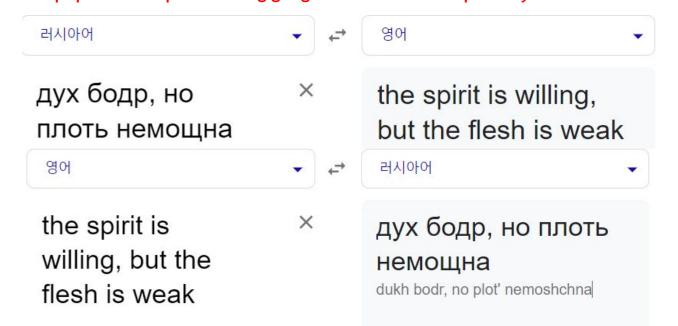


#### **Translation Type: Syntactic**

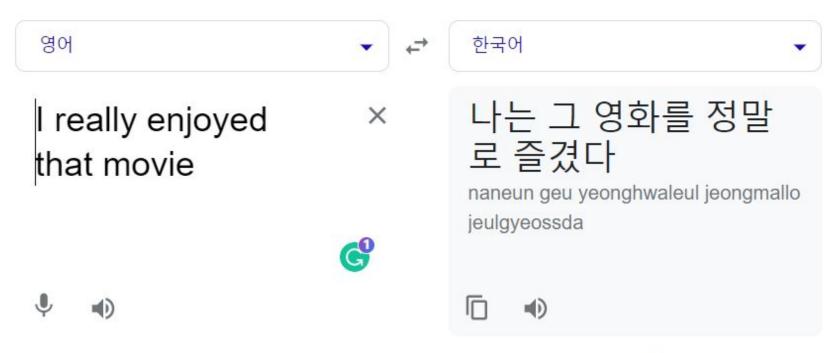
Russian: дух бодр, но плоть немощна(=the spirit is willing, but the flesh is weak)

English: the vodka is strong but the meat is rotten

This was the popular example of wrong google translation example of syntactic. But now it solved!



#### Another syntactic translation example





#### **Translation Type: Semantic**

Semantic: The translation that conveys the meaning of the phrase and sentence by considering context and nuance.

Ex)

#### 猿も木から落ちる(さるもきからおちる)

Syntactic translation: Even Monkeys Fall From Trees Semantic translation: Nobody's Perfect; To Err Is Human.



#### **Translation Type: Semantic**

Semantic: It means that the central concern of the translation is to convey the meaning of the phrase and sentence by considering context and nuance.

Ex)

#### 猿も木から落ちる(さるもきからおちる)

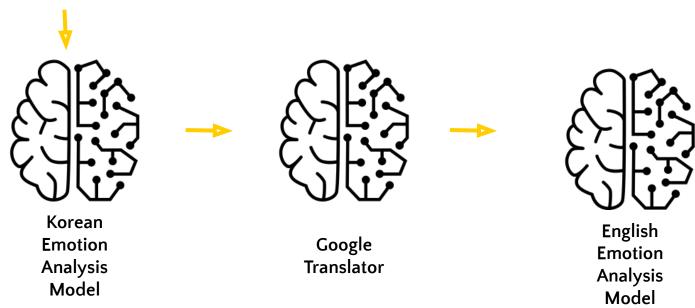
Syntactic translation: Even Monkeys Fall From Trees Semantic translation: Nobody's Perfect; To Err Is Human.

My Model: Emotion Translation!-> Goes beyond the traditional translation!



### Basic (idealiestic) system scenario

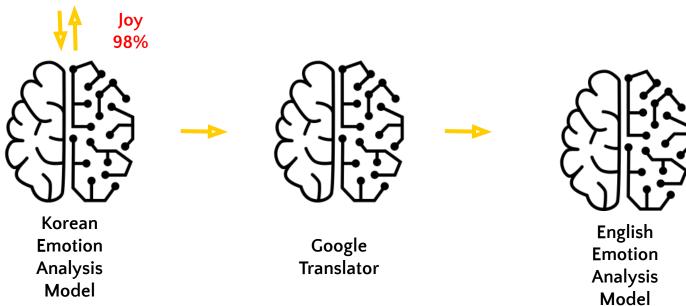
Input: 난 그영화 너무 재밌었어





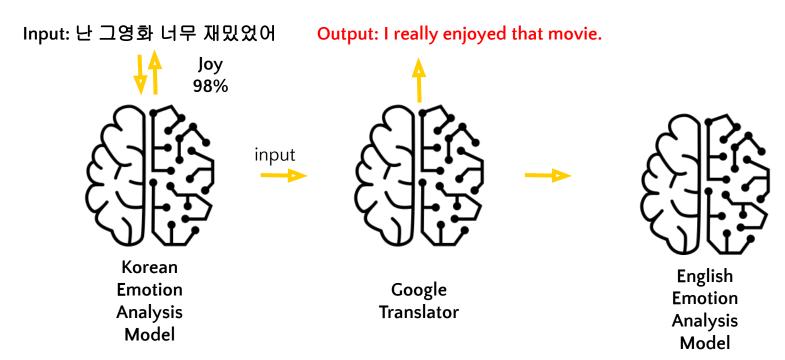
### Basic (idealiestic) system scenario

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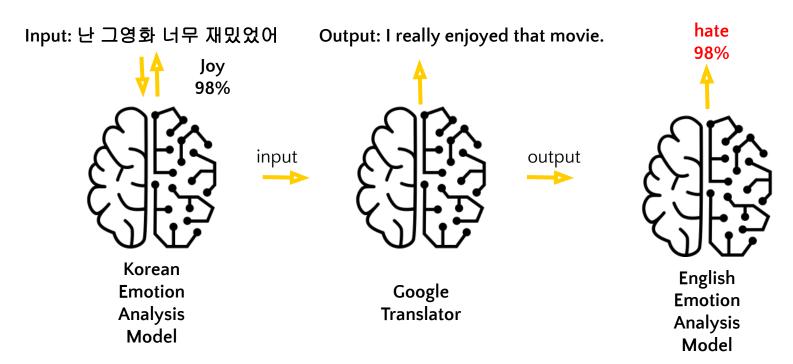


### Basic (idealiestic) system scenario



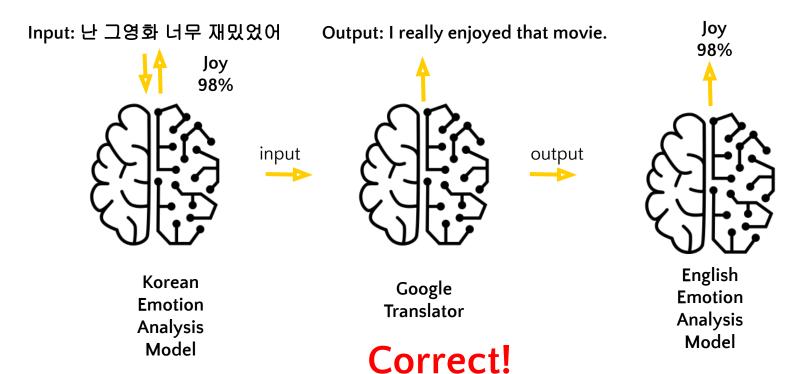


#### Basic (idealiestic) system scenario





### Basic (idealiestic) system scenario



#### Correct & Incorrect Judgement Criteria

**Delta = 20** 

#### **Correct:**

Input Emotion == Output Emotion
AND
|emotion % (input) - emotion % (output)| <= delta

#### **Incorrect:**

Input Emotion != Output Emotion

OR

|emotion % (input) - emotion% (output)| > delta

# Correct & Incorrect Judgement Example

**Delta = 20** 

#### **Correct:**

Input Emotion == Output Emotion &&

[emotion % (input) - emotion % (output)] <= delta

Input: 나는 정말 행복해 (happy 95%) Output: I am so happy (happy 90%) happy == happy && |95 - 90| = 5 <= 20(delta) => Correct!

# Correct & Incorrect Judgement Example

**Delta = 20** 

#### **Incorrect:**

Input Emotion != Output Emotion

OR

|emotion % (input) - emotion% (output)| > delta

Input: 그 영화 개쩔었어 (happy 95%) Output: The movie was shit (sad 90%) happy != happy => Incorrect!

# Correct & Incorrect Judgement Example

**Delta = 20** 

#### **Incorrect:**

Input Emotion != Output Emotion

OR

|emotion % (input) - emotion% (output)| > delta

Input: 그 영화 개쩔었어 (happy 95%)
Output: The movie was so good (happy 70%)
happy == happy ||
|70-95| = 25 > 20(delta) => Incorrect!

#### A model of the emotion detection process

From here, I will explain how to implement the Emotion Analysis model.

For the emotion analysis model, I used BERT. BERT is an pre-trained language model for natural language processing (NLP).

First, When given input to the Bert model, the model converts each word into a vector to help the computer understand the word. We call this tokken embedding.

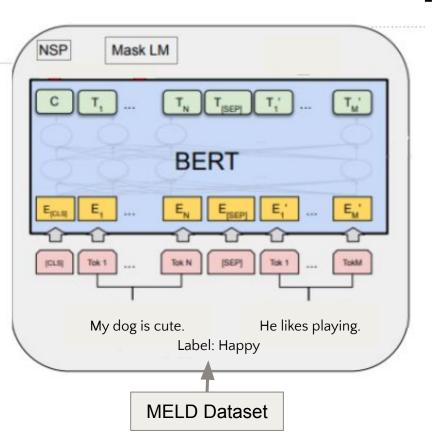
At this point, Input sentences has it's own emotion label. Thus, our model will learn this input by using MLM, NSP learning method in the training phase. These are the learning metric. So, to be precise, our model is a classification model that returns the corresponding emotion of the input sentence. Since this is the model training stage, there is no output.

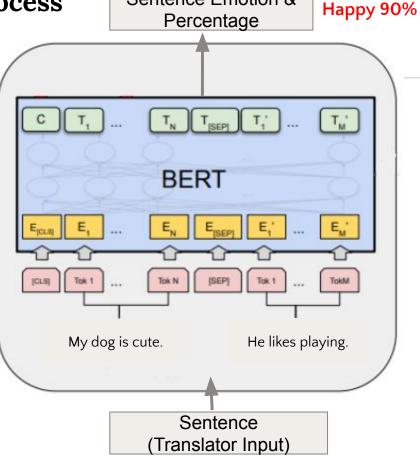
MLM is the learning method that randomly discarding tokens from the input and predict that tokens

NSP is the learning method that By giving two sentences and predicting the order, considering the relationship between sentences.

Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805 (2018). https://arxiv.org/abs/1810.04805

#### A model of the emotion detection process





Sentence Emotion &

Fine-tuning

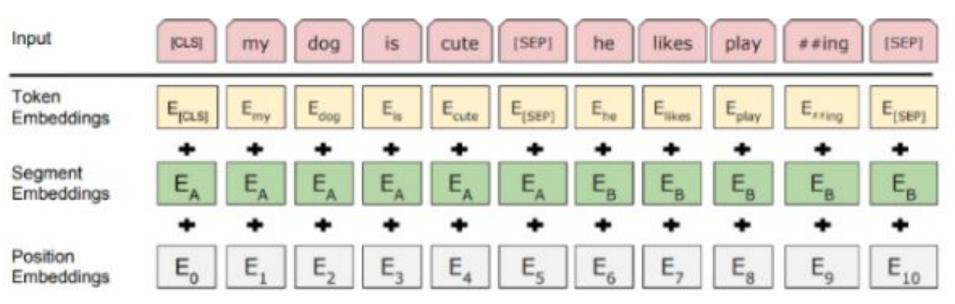
**Emotion Analysis** 

## What is embedding?

The entire process of converting natural language into a form (number, vector) that machines (computer) can understand



#### **Token Embedding**



## Input Example

My dog is cute. He likes playing.

[CLS], my, dog, is, cute, [SEP], he, likes, playing, [SEP]



#### BERT from an embedding point of view

- 1. Pretrained model. refined and embedded about 330 million words, and done semi-supervised learning. -> easily fine-tuned for other tasks
- 2. Better performance (**Accuracy**) than Word2Vec, GloVe, Fasttext (Old embedding methods)
- 3. Embedding performance of Bert is the best. (=**Bert preserves the semantic best!**)-> good performance in all natural language processing fields.

#### https://affective-meld.github.io/

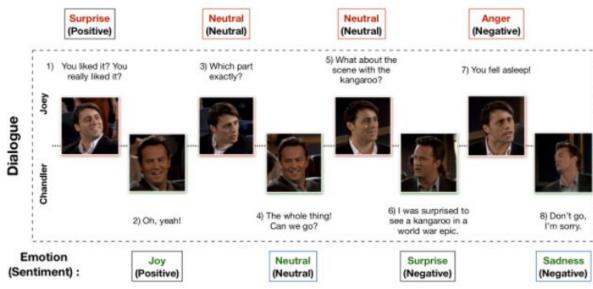


## **Pre-training Dataset**

MELD(Multimodal Emotion Lines Dataset):

Statistics	Train	Dev	Test
# of modality	{a,v,t}	{a,v,t}	{a,v,t}
# of unique words	10,643	2,384	4,361
Avg. utterance length	8.03	7.99	8.28
Max. utterance length	69	37	45
Avg. # of emotions per dialogue	3.30	3.35	3.24
# of dialogues	1039	114	280
# of utterances	9989	1109	2610
# of speakers	260	47	100
# of emotion shift	4003	427	1003
Avg. duration of an utterance	3.59s	3.59s	3.58s

#### Example dialogue





Originally, I wanted to use MELD dataset(previous slide), because with this dataset, I could analyze 6 types of emotion data rather than simply classifying only positive, negative, and neutral.

However, in order to classify the six emotions in the Korean emotion analysis model also, I need the dataset with the corresponding six emotion labels, but related data could not be found.

So, both the Korean and English datasets used the movie review dataset, and they were divided into two emotions: positive and negative.

Korean emotion analysis pre-training dataset: <a href="https://github.com/e9t/nsmc">https://github.com/e9t/nsmc</a>
English emotion analysis pre-training dataset: <a href="https://www.tensorflow.org/datasets/catalog/imdb\_reviews">https://www.tensorflow.org/datasets/catalog/imdb\_reviews</a>



# Demo of Emotion Analysis and decide translation result is correct or not

Code Link: <a href="https://github.com/developNY/AIM\_F21/blob/main/FinalModel.ipynb">https://github.com/developNY/AIM\_F21/blob/main/FinalModel.ipynb</a>

Language: Python IDE: Google CoLab

Package: Tensorflow, Transformer, SkLearn, GoogleTrans

#### How To Run:

- 1. Go to code link
- 2. Click "Open Colab"
- 3. Click "Runtime" > "Change Runtime as GPU" > "Execute All"
- 4. Waiting model training (it takes about more than 2h)
- 5. When the last cell will ask you type the korean language. Type korean (ex. 나는 행복하다)



#### **Bert Limitation**

It does not perform well for language models in certain fields (science, finance, etc.).

Why? words used, language characteristics are different of those fields.

And also emotion analysis is quite immature!



### **Emotion Analysis Limitation**

## **Challenges:**

- Sarcasm
- Emojis => Hard to analyze emotion!
- Idioms

# - Future Development

In this study, "Google Translate evaluated the accuracy of how much specific emotion data was preserved."

=> cannot judge that the translation result is correct.

Later, by adding other criteria to create a "translation result judgment model with accurate indicators" that can determine whether the translation result is correct or not.

# Lesson

- 1. As this semester was the first semester I started studying NLP, I was clumsy and couldn't do more in-depth research, but I got a better understanding of emotion analysis and machine translation.
- 2. It was my first time doing research, so I was also clumsy about research, but I learned about research methodology through other people's presentations and professors' feedback.

# Q&A



# Thanks!