Al Research Engineer Interview Presentation

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Presentation Structures

- Take-home Assignment
 - Sentiment Analysis (completed)
 - Image Classification (completed)
 - Named Entity Recognition (not complete)

Me x Wisesight

Take-home Assignment

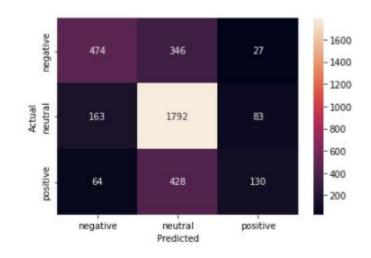
Sentiment Analysis API

Results

- Colab
- Docker

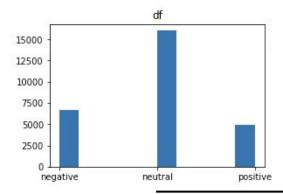
- Logistic Regression is the final model I deployed.
- The model has a high chance to correctly predict negative but not positive and neutral.
- positive texts are likely to be wrong predicted as neutral
- model has a bias toward neutral

Model	Val_Acc
LSTM_1	0.596
LSTM_2	0.61
RNN	0.549
Logistic Regression (ovr)	0.683



Exploring data





- This data contain text which is the mixture of Thai, English, emoji, etc.
- Informal language
- range from 1-508 words
- 3 classes total : 27504 texts

o positive: 4877

neutral : 15984

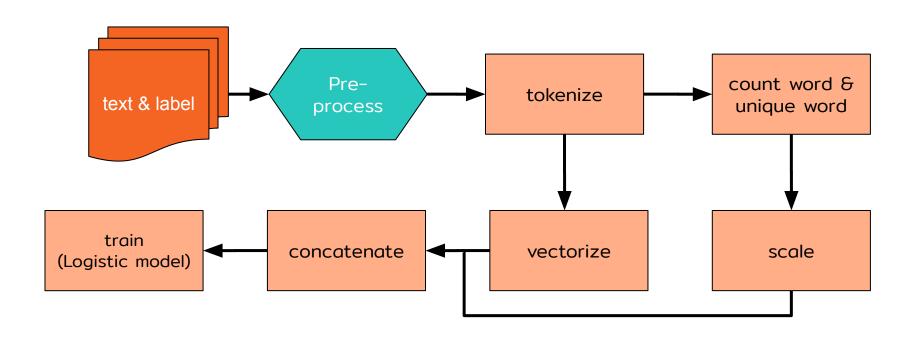
o negative: 6643

Pre-processing data

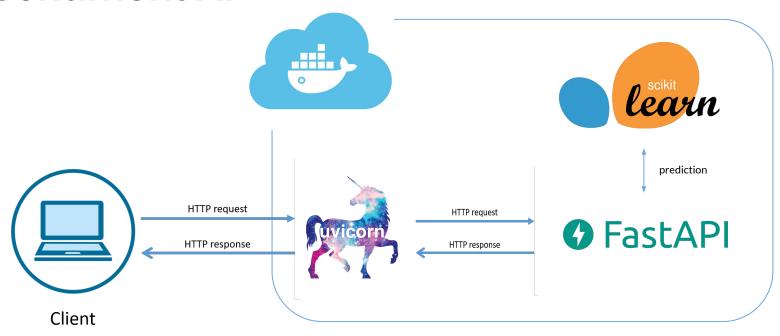
- tokenize text
- vectorize text
- count word and unique word
- scale wc and uwc
- concat vectorized text with scaled wc,uwc

texts	label	processed	wc	uwc
กูไปแก้โครงการที่ รร ตั้งแต่เมื่อวานละ ยังไม่ใ	neutral	กู ไป แก้ โครงการ ที่ รร ตั้งแต่ เมื่อวาน ละ ย	17	16
หิวบาบีก้อน	positive	หิว บาบี ก้อน	3	3
จัดปาย เสาร์นี้ 😂 🥹	positive	จัด ปา ย เสาร์ นี้ xxwrep 🥯	7	7
เช็ง 😔 เนื้อติดกะทะ🙉 #barbqplaza #wagyubeef	negative	เซ็ง <mark>ญ่เนื้</mark> อ ติด กะทะ <mark>ญ</mark> # barbqplaza # wagyubeef	10	9
ปล่อยตอก	neutral	ปล่อย ตอก	2	2

Data processing flow



Sentiment API



What you I have learned

- I found labeling really quite a bit matter. I believe some label should be different. But language is sentiment, so different person might have different feeling.
- FastAPI, I've never work with FastAPI before. It was a great experience
- I've tried to use deep learning (LSTM), but my models' performance were quite low and overfitting. I think it might take too much time tuning and training, so I tried to use supervised learning. Surprisingly, it has higher accuracy than deep learning models.
- I wasted a lot of time training deep learning model, so I might need to be caution.
- Might have to try the method that take less time and easier to implement first, before trying more complicate method.

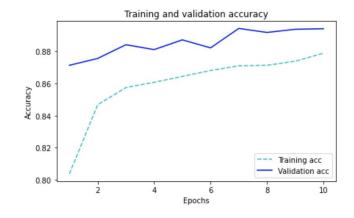
Image Classification

Result

- Colab
- Docker
 - o /api/classify
 - (document)/docs

- I use deep learning to train dataset
- use pre-trained model VGG16
- 3 classes classification (cats, dogs, others)
- Trained for 10 epoch, the train accuracy is 0.8788 and validation accuracy is 0.894
- From graph, the model seem underfitting, but the actual train acc and val acc is quite close.

Model	Val_Acc
CNN_1	0.847
CNN_2	0.84
RestNet50	0.625
VGG16	0.894



Exploring data

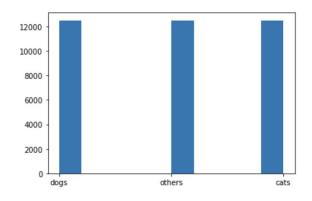
- I found the given dataset didn't come with label, and contain images of food, places etc.
- I decide to use open dataset for training.

Preprocessing

- create image data generator for augmentation
 - o rotate
 - rescale
 - resize
 - horizontal flip
 - height shift

• 3 classes : total 37500 images

cats: 12500dogs: 12500others: 12500



What you have learned

- From the training history, the accuracy tend to rise further, so I might have to train for more than 10 epoch.
- I want to try make validation accuracy has the value close to train accuracy more than it is right now.

Named Entity Recognition

Preprocessing

- Data contain 28055 texts (from sentiment dataset)
- split word, tag pos and name entities.
- Colab

pos	ner
[NN, VV, NN]	[0, 0, 0]
[NN, NN, AX, VV, VV, NN, NN, AV, VV, PS, PU, N	[B-PERSON, I-PERSON, O, O, O, O, O, O, O, O, O
[NU, PA]	[B-ORGANIZATION, I-ORGANIZATION]
[AV, VV, PS, NN, NN, NN, NN, PU, AX, NN, N	[O, O, O, B-LOCATION, I-LOCATION, I-LOCATION,
[VV, NN, NN, PU, AV, PU, NU, PU, CL, PU, NN, V	[O, O, O, O, O, O, B-TIME, I-TIME, I-TIME, O, \dots
[NN, NN, NN, NN, CC, VV, AV, VV, PU, NN, PU, N	[O,O,O,O,O,O,O,O,O,O,O,O,O,O,O]
[VV, NN, PA, PU, VV, NN, NN, CC, VV, AV, VV, P	[O, B-PERSON, I-PERSON, I-PERSON, I
[CC, AX, VV, VV, NN, PU, PS, NN, NN, PR, CC, V	[O, O, O, O, B-DATE, O, O, O, O, O, O, O, O, O
[NN, NG, VV, VV]	[B-LOCATION, O, O, O]
[PR, AX, VV, NN, NN, AV, VV, PU, NN, NN, VV, A	[O, O, O, O, B-LOCATION, O, O, O, O, O, O, O,
	[NN, VV, NN] [NN, NN, AX, VV, VV, NN, NN, AV, VV, PS, PU, N [NU, PA] [AV, VV, PS, NN, NN, NN, NN, NN, PU, AX, NN, N [VV, NN, NN, PU, AV, PU, NU, PU, CL, PU, NN, V [NN, NN, NN, NN, CC, VV, AV, VV, PU, NN, PU, N [VV, NN, PA, PU, VV, NN, NN, CC, VV, AV, VV, P [CC, AX, VV, VV, NN, PU, PS, NN, NN, PR, CC, V [NN, NG, VV, VV]

What you have learned

- I've never done NER before, so this is my first time learning about it, especially tagging.
- I spent too much time studying about tagging and tried several libraries,
 so I might need to work more on time management.
- I ended up with PyThaiNLP which I found very effective for Thai.

Me x Wisesight

I want to do this

While I was taking a shower, I came up with an idea to classify text to identify 'สามกีบ', 'สลิ่ม', 'IO' and 'neutral'. This might help filter out some text and message to display in some occasion.

Finished