Story Classification of Movie, Anime, Novel and Series in Traditional Chinese

***Abstract*—Our goal is to inference which story it is when giving a sentences describing the plot of story. It is too difficult to answer without limitation, so we see this problem as a classification problem giving the predefined choices and the model will return the probability of each choice. To deal with such classification problem of NLP domain, we introduce the BERT model [1] which is a very famous pre-trained model . And fine tuning the bert-base-chinese model to handle this task. We use web crawler in ptt movie to obtain the posts which is related to target movie and performing some process to obtain corpus with label. To evaluate the performance, the model should correctly classify the plot in wiki pedia inside the range of choices and predict "else" when giving the plot not in our choices. This may not be a good criterion because the posts written by other people might copy the plot in wiki pedia. To avoid the risk, when we pre-process the data we will mask out all the sentences which are entirely copied from the wiki pedia. In the end, we want to build a good model not only good at distinguish where the plots come from when describing it in different ways, but a model able to tell the sentences talking the same things. And also provide the other possible choices with given plots via probability.**

I. Introduction

Sometimes we will conjure some interesting plot or story, but we can't recall where did we see or when did we read it. So we are seeking a stable method to find what story it is. Currently, we usually turn to the help of search engines for example: Google, Edge, Firefox or more fancy tool like the AI agent based on GPT-3. But these method have a big fallacy when encountering such problems. They only identify with exactly same words if the sentences don't contain the "keyword" they can't perform well. However, the description of one story is very subjective which could vary by the choices of words decided by the writer. So, if your description is differ from other online resources, search engines are not able to return useful information. Thus, we want to develop a model/algorithm which can identify where this plot or story come from that not depending on the choices of words but the main idea or meaning behind sentences. In other word, current search engines are based on the "keyword" of sentences. We want to build another model to search/classify with the "content" of sentences.

(If you search the plot contain some keyword in English on Google, they may perform well. But it result not so well when search the plot in Traditional-Chinese without powerful keyword)

II. Related Knowledge

- 1.deep learning
- 2.neuron network
- 3.NLP
- 4.word embedding
- 5.self-attention layer
- 6.transformer
- 7.BERT
- 8.data augmentation
- 9.transfer learning

III. Related Work

This is basically a classification problem combined with some text understanding. Thus, other pre-trained model like ELMO [2], GPT [3], XLNet [4] can be used to solve this problem as well.Or maybe solving this problem in another angle.For example, Keyword extraction combined with search engine.If the keyword isn't power enough, replacing the keyword to other keywords with same meaning.Then, using searching engine to acquire the answer.For example,currently, Google are trying to replace the keyword-search to semantic-search [5] [6]

IV. Plan and Schedule

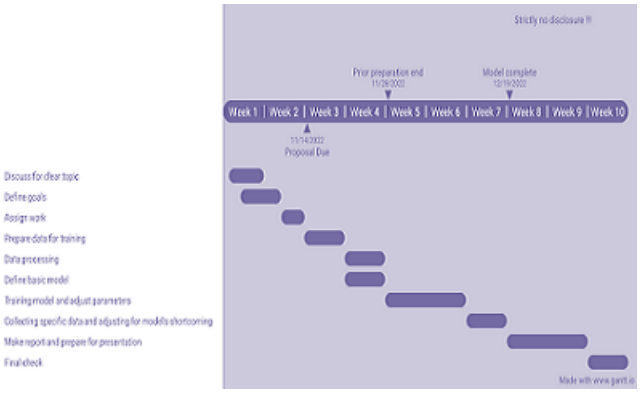

Fig. 1. gantt of schedule.

based model should be finished in 11/28 and complete finished in 12/19

V. Data used

1.Rough preprocess:just chunk the corpus when encounter / n, and clear all image(ex:http://imgur.....) and constrain the sentence length to (6˜80) Because our goal is to make the prediction model invariant to key word, so it's necessary to build a model that can output correct result without key-information(ex:name of character. So we try some tricks. See 4.).

2.Training Data: Use web crawler to collect the data variant to our predict-targets from PTT(https://www.ptt.cc/bbs/)So we just collect other people's posts with the title which mention our predict-targets.

3.Validation Data: Because we don't find systematical corpus to used, we Manually collect from many website and roughly scan the correctness while collecting the data.

(ex:https://zh.m.wikipedia.org/ https://baike.baidu.com/ and many other sites)

4.Mask Names:To mask character's name, which is related to POS (part-of-speach) and NER (named-entity-recognition) problems. We have tried two method. First,we use JIEBA model to do NER. Second, we try CKIP CoreNLP(which also based on BERT) provide by CKIP Lab resulting much better performance than JIEBA. (https://github.com/fxsjy/jieba) (https://github.com/ckiplab/ckipnlp)

VI. Experiment

0.Selection of Model:Pre-train model play an important role for NLP task. Currently,BERT, XLNet, ERNIE, PERT are some powerful and available choice. However, these model usually provided for simplified Chinese.The only choice for traditional Chinese we found is the BERT model provided by CKIPLab

(https://huggingface.co/ckiplab/bert-base-chinese?)

Because BERT is a powerful pre-train model, which has large capacity to accomodate training data.It's easy to reach low loss and 100 percent accuracy for training process.So, it's more crucial to take care of the generalization of model.Despite the build-in regularize technique in the BERT model.Here we introduce 1.Early stop 2.Drop out 3.Data augmentation 4.SAM

1.Early Stop:Maybe because the validation data isn't large enough, the result is a little bit noising, Here we just follow the basic algorithm, record the model with largest validation accuracy

2.Drop Out:Drop out is a common technique to regularize model. Though it's usually recommend to set drop out to 0.5, 0.5 might be too large for this problem that model cannot learn under this configuration. Through trial and error we think 0.1 to 0.4 might be an acceptable range for this problem and 0.25 usually perform relatively great.

3.Data Augmentation:Data augmentation usually used in image domain. Here we try to see if this technique can be applied to NLP domain.Because the name of character can be strongly connect to the target story, We try to block this information to train more robust model.Here we try two strategies see Fig.2. Fig.3. Fig.4. Strategy1: keep the character and plot information but anonymous, Strategy2:only keep plot information. Strategy2 performs slightly better, maybe because the strategy1 try to memorize the anonymous tokens which won't occur in validation and take relatively less attention to plot information.

4.SAM(Sharpness awareness minimization): This is a new technique introduced for regularization [7]. Based on the belief that convergence in flat area of training data will result in similar performance in testing data.We try to introduce this method into our project and increase around 3% accuracy for validation.And produce not-so-judgemental model which provides more information to the user.

5.Freeze Word Embedding:Word Embedding is a crucial part of this project, which provide similar hidden input to next layer for synonyms. However, the target specific tranfer learning might mess up the original semantic space from pre-train. So it's necessary to freeze the word embedding layer of pre-trained model, Which can improve 5% 10% accuracy of validation through out our experiment.

Note:Although we use val data as an indicator of performance but in final work we will put val data into training because they contain more precise information compared to train data. We believe the model will become better after apply valdata although we don't have data to prove it. So, the performance on validation data excluded might be seen as a lower bound of final model

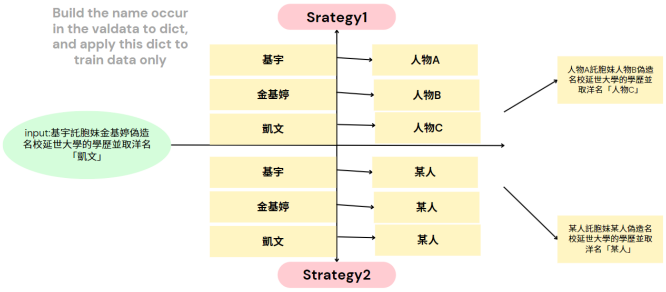

Fig. 2. replace strategy 1

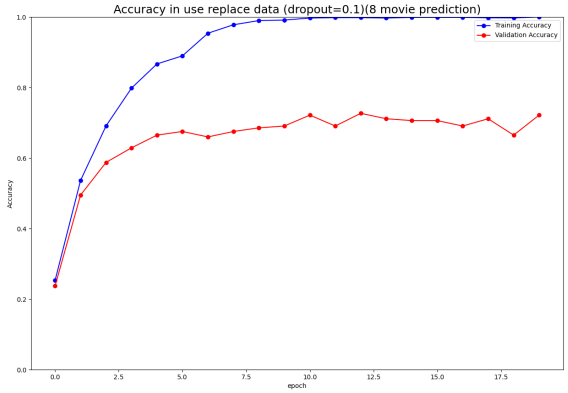

Fig. 3. replace strategy 1

VII. Results

We train five model for different task. Each of first four train with 8 different target, while last one is the combination of first three targets as illustrate in Fig.5. (Novel model use novel itself as training data and PTT posts as validation data, it's quite different from other so we don't include in total model) In the

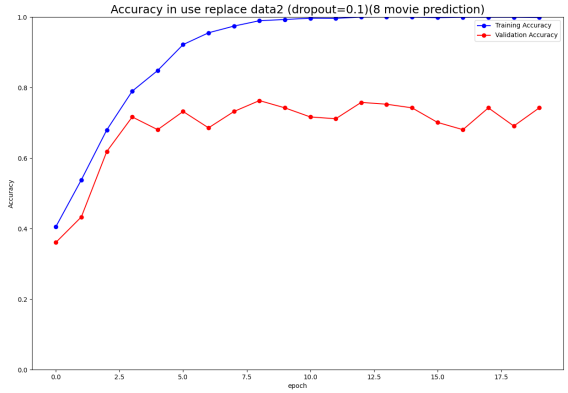

Fig. 4. replace strategy 2

MODEL TYPE	TARGETS' NUM	TRAIN ACC	VAL ACC
MOVIE	8	0.854	0.802
SERIES	8	0.812	0.442
NOVEL	8	0.957	0.751
ANIME	8	0.955	0.500
MOVIE+SERIES+ANIME	24	0.912	0.307

Fig. 5. model accuracy

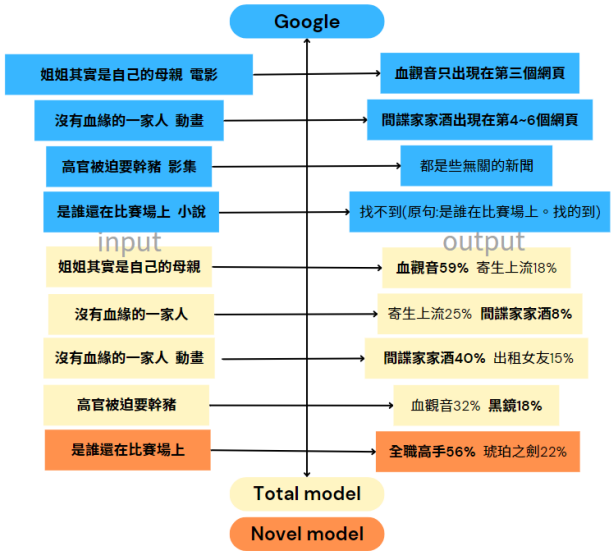

Fig. 6. input and output(SPOILER ALERT) (bold for ground Truth)

begin, we were wondering whether it work. Because the posts contain many unrelated content to the target and sometimes only a little part mention about our target.Surprisingly, in our first try, the movie task, it easily reach 70% accuracy of validation. Thus, we know this architecture might work. So we can proceed to dig into more detail to improve this model.

We use some manually create testing sentences to compared total model with search engine look Fig.6. We can see that although our model may fail sometime but it can still provide some information by giving possible choice.

However, we still face some problem. First, some targets are rarely pop out even we use some related test sentence. Maybe caused by the problem of unbalancing data.And this problem become more severe when training with different type of story.For example, series have times of content more than movies. However, due to the lack of indicator or proper criterion, we haven't find a good approach to handle this problem but only try to keep the training data balance by random delete. Second, synonymous problem. Although the model we use is an traditional-Chinese version of BERT. The word with same meaning still lead to different result(ex:"older sister" in Chinese there are two way to write)Maybe using BERT-wmm [8] can provide better result. But the current pre-train model is based on simplified Chinese.

VIII. Summary

1.Foresight: In the past time, we use the prediction of word to train the word embedding layer, and use the relation of sentences to train the BERT model. We hope this project can achieve the similar effect like training the text features extraction of NLP model

2.SAM For Smoothing:In the begin, we didn't include this method in our design. However, the model train with SAM resulting some smoothing effect.The model would provide more information by not-so-judgemental predictions (kind like the result of label smoothing). The convergence in flat area will reduce the probability of True answer but increase the probability of related answer. So, even the prediction fail, user still can get insight by the high-possibility choices.

3.Advantage:Although this architecture don't have dominant accuracy compared to the current search engine. It still have some advantage. Fist, it can provide more information to user. While giving rough description which appears in many story to the model,it will return some possible choice based on the plot. However,search engine usually give the most possible sometimes most popular answer and the website related to it. Second, memory-oriented. Human memory usually based on the Episodic memory which contain the full plot and scene. However, we often forced to subtract only some keyword of your memory to fit in search engines, many information loss in this stage. So, our model can facilitate full human memory

4.Ability to Combine:Because the emerge of ChatGPT, We think the GPT model have the ability to roughly create the testing data for our task. However, most of our target isn't included in ChatGPT, because it only train with the data before 2020 while most of our targets are new movie.

Here is our github repo(don't contain the pt file,but with the data and ipynb to train from scratch): https://github.com/BlueDyee/Story-classification

IX. References

References

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