Singlish Chatbot

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Abstract

Singlish is a unique form of language commonly used by average Singapore nationals. Its mix of different languages - English and the several ethnic languages - makes it a challenge for language model to understand and interpret. This project aims to develop a chatbot that understand Singlish and enable meaningful interactions with the older generation in Singapore who may not be well-versed with emerging technologies. The Singlish chatbot will be built using a transform-based attention model.

1 Introduction

The free communication between humans and machines is the ultimate objective of natural language processing (NLP) [1]. Multiple studies on NLP have agreed that the progress of information exchange between these two parties have been contributed heavily by chatbots [2]. According to [3], chatbots are defined as automated systems that aid users by responding to their queries. Several industrial sectors including advisory, service, and commercial have already employed the use of chatbots [4]. As proposed by [5], chatbots are required to have the following requirements such as having conversational capabilities to engage with the users rather than simply giving a yes or no response, responding with information that is semantically correct and meaningful for ease of understanding [6], and be trained on a specific domain of data [7] so that it can comprehend the specific terms and information. To satisfy the above requirements, the modelling of chatbots to consistently provide accurate responses to match the context of the users queries remains a challenge.

In our work, we aim to develop a chatbot with the ability to understand and converse in Singlish. A unique form of language commonly spoken by the average Singapore national, Singlish is a mix of different languages which borrows its vocabulary from English and the several ethnic languages found in Singapore. The purpose of developing these chatbots is to enable Singaporeans, especially those who are not fluent in English such as the older generation, to have meaningful interactions with these AI systems in their own language of familiarity. However, while our literature search may not have been exhaustive, we have not found any published study (in scientific journals) that has trained a chatbot to learn Singlish. To address this novel challenge, we have deployed a transformer-based attention model to learn this unique language.

An encoder-decoder model using Long Short Term Memory (LSTM) serves as the baseline. Such a model, also known as a sequence-to-sequence (seq2seq) model, is able to convert sequences from one domain to another. Hence, it is not only useful for machine translation tasks, but also text generation tasks. It is in this respect, that such a seq2seq model is designated as a base model on which other models will be compared.

2 Related Work

2.1 Singlish Datasets & Work

Singlish as a low resource English creole language is not entirely novel to the linguistic community. *Cambria et al.* in 2015 proposed using a combination of support vector machine and a custom algorithm incorporating n-gram Singlish sentic patterns and multilingual polarity sentic patterns for polarity sentiment analysis for Singlish text. They collected tweets on topics relevant to Singapore from Singaporean users on Twitter [8], constructing a Singlish-English polarity lexicon using Singlish terms extracted from these tweets. *Cambria et al.* later on added Singlish support into the SenticNet concept-level resource for sentiment analysis [9]. *Wang et al.* also created their own treebank for investigating dependency parsing of Singlish [10]. They crawled for Singlish posts from the *SG Talk Forum*[1], manually tagging and annotating the sentences under the Universal Dependencies scheme. This dataset was later used for later work done on studying transfer learning for Singlish universal dependency parsing and part-of-speech tagging [11], and also parsing Singlish with multingual cased BERT [12]. However, this dataset is not publically available. *Chen et al.* also collated a dataset of SMS messages from Singaporeans and students from the National University of Singapore, splitted into a Singaporean English corpus and a Mandarin Chinese corpus [13]. The Singaporean English corpus includes Singlish sentences but they are not specifically ordered according to coherent dialogues and only includes the sentences from the sender. However, it is still possible to artificially construct possible dialogue sessions by matching sentences within the corpus amongst each other.

2.2 Dialogue Generation

Approaches towards building chatbots or dialogue generation models can be mainly categorized into rule-based and data-driven approaches [14]. ELIZA [15] and PARRY [16] are instances of rule-based chatbots that uses pattern and transform rules for matching responses to prompt utterances. They are fast and easy to build compared to data-driven models but rules can become highly complex for performant chatbots. Data-driven models can be further information retrieval based and machine learning based models. Information retrieval based chatbots relies on information retrieval techniques such as using word-level vector space models and cosine distance for finding the most probably question-response pair [17]. Term Frequency-Inverse Document Frequency (TF-IDF) retrieval models have also been proposed [18, 19]. Meanwhile, machine learning approaches branch into neural networks based and reinforcement learning based. For the latter, it has been proposed that dialogue sessions be modeled as Markov Decision Processes (MDPs) [20] or Partially Observed Markov Decision Processes (POMDPs) [21, 22, 23, 24].

For this project, we will be focusing on neural network based approaches for building the Singlish chatbot. While the 2014 sequence-to-sequence (Seq2Seq) encoder-decoder architecture broke new grounds in word-level language modelling [25], modelling conversational dialogue presents greater challenges. Seq2Seq originally recurrent neural networks like Long Short-Term Memory (LSTM) [26] or gated recurrent units (GRU) [27]. With the introduction of the attention mechanism [28, 29], replacing the recurrent units with Transformers [30] pushed the boundaries even further and are used in the current state-of-the-art models like GPT [31, 32, 33], BERT [34] and BART [35]. While word-level language modelling for tasks like translation only require the model to predict the next word in context, sentence level dialogue modelling requires the model to predict subsequent words with relevance to the entire prompting sentence or historical dialogue. While a closed-domain expert system can sufficiently manage dialogue with a complex enough ruleset, open-domain dialogue modelling suffer from content or style inconsistencies [36, 37, 38], lack of long-term contextual information [39] and blandness [40, 41, 42]. Such problems are noted by Vinyals and Le when

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[1] http://sgtalk.com/

they trained their Seq2Seq architecture using LSTM for dialogue modelling [43]. Transformers being better than LSTMs and GRUs at modelling long-term dependency information generally lend themselves to modelling conversations, thus DialoGPT [44] seeked to extend GPT-2 [32] for the dialogue modelling task. *Wu et al.* used a pretrained BERT as the encoder and GPT as the decoder [45]. Alibaba used an attentive Seq2Seq model for both generating responses and reranking its own responses and responses generated from a information retrieval model [46]. Meena [47] investigated using the Evolved Transformer [48] as part of a Seq2Seq model on multi-turn open-domain dialogue modelling. *Mehri et al.* proposes masked context retrieval and inconsistency utterance identification as pretraining objectives for dialog context representation learning [49]. Most recently, DialogBERT [50] proposed a hierachical Transformer architecture and two novel training objectives, them being masked utterance regression and distributed utterance order ranking as additional loss terms, allowing the model to better capture dialogue coherence. They compared their model using BART, DialoGPT as baselines. They also used a RNN model and a Transformer model, both using *Mehri et al.* pre-training methods, in their baseline models. They evaluated the models using perplexity, BLEU-4 and NIST, noting that perplexity correlated with human judgment scores significantly [47].

3 Approach

3.1 Data Preparation

The data used was a collection of SMS messages. More details pertaining to the data can be found in Section 4.1.

We first normalise the data into a tabular dataframe. We clean the text component of the data by removing non-ascii characters, chinese characters and multiple spaces and newlines. Text with less than 3 words and originating from non-Singapore users are filtered out. This ensures the sufficient text length to capture patterns and limit the language to Singlish by Singaporeans respectively. Additionally, we employ stemming and lemmatisation techniques.

In preparing the sentences for training, we give every sentence a preceding number of sentences that served as context. Thus, the amount of context provided for each response is a parameter that could determine the performance of the model. In this demonstration, we have maintained a number of 7 pieces of context per response. The data preparation phase is slightly different for the seq2seq baseline model, where the sentences are arranged as a sequence of questions and responses, akin to a dialogue format. Every response in turn acts as a question, and vice versa. Due to the large memory needed for the model, we use only the first 32,000 pairs. Of these, 20% are used as a validation set.

3.2 Model

The DialoGPT model [44] is used for this project. Its architecture is based on the GPT-2 model [32], which is an upscaled GPT model - a large transformer-based language model. GPT-2 proved that transformer-based models trained on very large datasets are able to capture long-term dependencies in textual data. Hence, the DialoGPT extends GPT-2 to address the challenges of conversational neural response generation.

DialoGPT is a 12-layer transformer with layer normalization and byte pair encodings for the tokenizer. Multi-turn dialogue sessions are concatenated into long text with source at the beginning portion of the text and target at the end. It uses masked self-attention that does not peek into the tokens to its right.

4 Experiments

4.1 Data

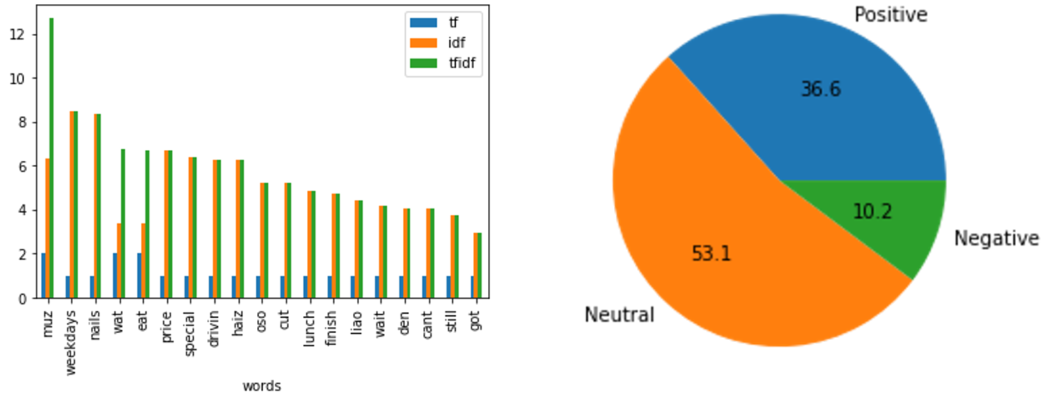
The dataset used in our work is the National University of Singapore SMS Corpus [13]. This dataset consists of 67093 SMS (Short Message Service) messages, with 35598 messages in Singapore English, and the remaining 31465 messages in Mandarin Chinese. These messages were collected from subjects participating in a research study, most of whom were Singaporeans attending the university. In our work, we will only be using the Singapore English (also known as Singlish) dataset to build our chatbot.

Before cleanup	Den only weekdays got special price... Haiz... Cant eat liao... Cut nails oso muz wait until i finish drivin wat, lunch still muz eat wat
After cleanup	Den only weekdays got special price Haiz Cant eat liao Cut nails oso muz wait until i finish drivin wat lunch still muz eat wat
Lowercase and removal of stop words and punctuation	den weekdays got special price haiz cant eat liao cut nails oso muz wait finish drivin wat lunch still muz eat wat

Table 1: Sample text data from Corpus

Our aim is to build a chatbot. The output, which is a proper conversational response, will be generated by the model based on the input sentence given by the user. Before using the dataset to train, pre-processing is carried out on the data. Firstly, simple clean up is performed such as removing non-ASCII characters, websites, newline, one-word characters, digits and extra white spaces. For the purpose of data analysis, the data is then converted to lowercase, with stop words and punctuation removed. Example:

TF-IDF is then carried out along with sentiment analysis.



(a) TF-IDF plot of a SMS text

(b) Pie chart of sentiment analysis of all SMS texts

Figure 1

4.2 Experimental Results using DialoGPT

Table 1 shows the hyper-parameters tested, where the first row are the hyper-parameters used for the base model. The best perplexity is given using the hyper-parameters at the third row from the bottom of the table. Unlisted values are identical to those of the base model.

Epochs	LR	Weight decay	Grad. Acc. Steps	Grad. clipping	Optimizer	Val set perp.
5	0.00005	0.0		1.0	AdamW	2.3525
				0.0		2.3525
				2.0		2.3526
			10			12.7012
			100			41.6984
		0.1				2.0938
		0.01				2.3219
	0.0001					491.9594
	0.001					1.3728
	0.01					536.3946
	0.1					984.6895
		0.1			SGD	292.5464
		0.1			SGD & 0.98 mom	158.8381
		0.1			Adamax	21.9244
	0.001	0.1				1.1459
3						5.5897
10						1.2026

Table 2: Hyper-parameters and Experimental Results

An example output of conversation with best perplexity score (1.1459):

» User: Oi, later meet bukit batok 6 Beng Bot: will be late think i ll eat dinner in school
» User: then liddat meet 8 at the arcade? Beng Bot: no rush going to be l
» User: wat u mean no rush, u the one who wanted to go arcade one leh Beng Bot: u there taking photo
» User: ya i taking photo your taiji meh Beng Bot: heee thanxoxo
» User: thank ur head ar, so how meet 8 at arcade isit Beng Bot: u went offline ar
» User: i as online as it gets liao bro Beng Bot: s ex la he said jus plan stay at e beach nothing else planned yet then u think need bring clothes chang
» User: of course lar, u want smelly smelly take mrt meh Beng Bot: haha okok gd gd luck 4r i got home le i use bd
» User:i thot u still at school?? Beng Bot: ya lor haha best is ben 2nd
» User: ben gonna smack u also if u dont tell us what time meet at the arcade Beng Bot: eh i ask my dad fetching me back to lot one then i take bus heh
» User: so isit got time to dinner or not Beng Bot: if u going ikea str wher

Table 3

Training with different pre-processed data set:

Epochs	lr	Weight decay	Gradient Acc. Steps	Gradient clipping	Optimizer
5	0.001	0.1	1	1.0	AdamW

When processing the data set, various methods were experimented on. One of the methods is to only use SMS texts of a certain word count. Another method is to use stemming and/or lemmatising. The results have shown that whether using stemming or lemmatising or both does not make much of a difference in perplexity. On the other hand, using a larger number of word count does improve perplexity. One thing to note is that the number of training examples are lesser when the word count required is higher. Therefore, the improvement in perplexity is likely due to the model overfitting due to smaller dataset. The following table shows the results:

For word_count > 3 (23482 training examples):

PorterStemmer	LancasterStemmer	WordNetLemmatizer	Validation set perplexity
Yes	No	Yes	1.1455
No	Yes	Yes	1.1512
Yes	No	No	1.1434
No	Yes	No	1.1470
No	No	Yes	1.1459

Table 4

For word_count > 6 (17192 training examples):

PorterStemmer	LancasterStemmer	WordNetLemmatizer	Validation set perplexity
Yes	No	Yes	1.0974
No	Yes	Yes	1.0985
Yes	No	No	1.0994
No	Yes	No	1.0982
No	No	Yes	1.0949

Table 5

For word_count > 10 (10926 training examples):

PorterStemmer	LancasterStemmer	WordNetLemmatizer	Validation set perplexity
Yes	No	Yes	1.0699
No	Yes	Yes	1.0702
Yes	No	No	1.0699
No	Yes	No	1.0702
No	No	Yes	1.0703

Table 6

Example output of conversation when word_count > 3:

» User: Oi, later meet bukit batok 6 Beng Bot: will be late think i ll eat dinner in school
» User: then liddat meet 8 at the arcade? Beng Bot: no rush going to be l
» User: wat u mean no rush, u the one who wanted to go arcade one leh Beng Bot: u there taking photo
» User: ya i taking photo your taiji meh Beng Bot: heee thanxoxo
» User: thank ur head ar, so how meet 8 at arcade isit Beng Bot: u went offline ar
» User: i as online as it gets liao bro Beng Bot: s ex la he said jus plan stay at e beach nothing else planned yet then u think need bring clothes chang

Table 7

Example output of conversation when word_count > 10:

» User: Oi, later meet bukit batok 6 Beng Bot: i is sleeping haha i just woke up p
» User: slp wut slp, wat time alr, dinner leh Beng Bot: dunno leh i random suggest suddenly all super on haha since u alsonot very interested in that movie and wq wanna watch also but gvpopcorn not nice
» User: ur stupid idea to watch one now u pangseh, bo steady leh Beng Bot: lol not bad arh but is hai ren one u won t like i tink lol okie night too
» User: ur stupid idea to watch one now u pangseh, bo steady leh Beng Bot: lol not bad arh but is hai ren one u won t like i tink lol okie night too
» User: u watch already U Still JIO US WATCH? ABIT guo fen ar dog Beng Bot: hey happy cny i don t know that s why was asking u all in email
» User: bro u high or what? dont come tok stupid with limpei leh Beng Bot: hee yes dearie dearest laogong sleep tighttight hold me tight mug mug
» User: muack ur head lar bye Beng Bot: hey i think got link just follow instruction only u need for

Table 8

During pre-processing, we can also choose to set the number of previous SMSes responses as replies for context. After experimenting with different values, we found out that using 7 previous replies gives the best perplexity score.

n number of previous replies	Validation set perplexity
7 (Base)	1.1459
3	4.9641
5	1.4063
9	1.6771

Comparing the DialoGPT model with the seq2seq model, we note that it has outperformed the seq2seq model. Keeping the data cleaning parameters similar, the perplexity of the seq2seq model is higher than the DialoGPT model, indicating a lower performance. The figures are summarized in the table below.

	DialoGPT	Seq2seq
Minimum Number of Word Count in SMS	3	3
Number of Previous Replies	7	1
Number of Epochs	5	5
Learning Rate	0.001	0.001
Optimizer	AdamW	Adamax
Perplexity Score	1.15	2.75

5 Analysis

It is important to choose the right hyper-parameters during training. Using a learning rate that is too small causes the model to learn too slowly while using a large gradient causes unstable training. Using more epochs improves the model but also increases training time. By using suitable parameters, we can train using less time and still achieve better results as shown in Table 2, where training for 5 epochs is able to give a better perplexity score than training for 10 epochs.

As mentioned in section 4.2, there is an improvement in perplexity when we use data sets that have word counts of less than 6 and 10 filtered out (Table 5 & 6). It has been pointed out that due to a smaller data set, there is a likely case of over-fitting. In general, using a large enough data set is vital to training a good model. Under the same section, using 7 previous replies as context for training gave the best perplexity. The reason 7 replies works better may be because it is the average length of SMS conversations. Using too little replies does not give the model enough context to work with. On the other hand, using too many decreases the accuracy of the context since the previous replies may belong to another conversation.

6 Conclusion

This project used the DialoGPT model for the construction of a Singlish Chatbot. From the example conversations shown in this report, it is clear that there are more work to be done. However, for start of conversation for word count more than 3 and more than 10, the first few replies by the chatbot seemed to make consist of common sense. Only at about 3rd or 4th turns, does the chatbot diverge from the conversation topic and stop speaking sense. This can be a good starting point for future works on building a Singlish-based chatbot.

The SMS Corpus used for this project encompasses the use of Singlish. However, it also included the use of short hand like LOL for "laugh out loud" and BTW for "by the way", which may not be relevant in the Singlish context where the focus is on Singlish words like "lah", "lor", "leh" etc. These short hands are a major factor when training the model. Another issue with managing such data is the standardisation of spelling. Using off-the-shelf lemmatizers like that in the Python NLTK package will not cover many of words unique to the Singlish language. Future work on creating a Singlish chatbot should focus on building up a proper conversational dataset that omits short hands. A customised lemmatizer should also be built from ground up so that the data can be processed properly in context.

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