CHATBOT FOR INTENT RECOGNITION

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INTENT RECOGNITION (IR)

- Intent recognition is sometimes called as intent classification which is the task of taking a written or spoken input, and classifying it based on what the user wants to achieve
- ☐ Intent recognition works through the process of providing examples of text alongside their intents to a machine learning (ML) model

APPLICATIONS: Chatbots, customer support, sales prospecting, etc.,



CHATBOTS USE IR?

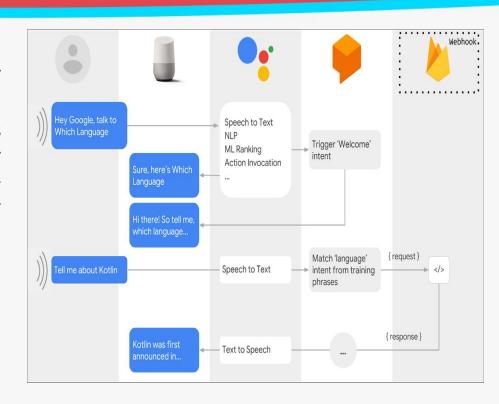
- Intent recognition is a critical feature in chatbot architecture that determines user's aim in starting any conversation
- NLP allows the chatbot to understand the user's message, and machine learning classification algorithms to classify the message based on the training data and deliver the correct response
- The chatbots' intent detection component helps to identify what general task or goal the user is trying to accomplish to handle the conversation with different strategies



GOOGLE & IR

- Google's Dialogflow Platform to design and integrate a conversational user interface
- When an end-user writes or says something, referred to as an end-user expression, Dialogflow matches the enduser expression to the best intent in your agent

Used by: Dominos, Malaysian Airlines, KLM Royal Dutch Airlines, Verizon, CNN, etc.,





DATASET

- ☐ Motivation NLU Benchmark (Few-Shot-Detection)
- ☐ Few-Shot-Intent-Detection is a repository designed for few-shot intent detection with/without Out-of-Scope (OOS) intents

Intents

out-of-domain OOS General out-of-scope queries which are not supported by the dialog systems

in-domain OOS

Queries which are more related to the in-scope intents, which makes the intent detection task more challenging



DATASET

- The scope of our dataset has been inherited from 'CLINC150' intent dataset
- Our purpose was to built a chatbot for intent recognition we have developed a custom-built dataset

Features of Dataset:

```
Intents - [{"intents":

| [{"tag": "greeting",
| "patterns": ["Hi", "How are you", "Is anyone there?", "Hello", "Good day"],
| "responses": ["Hello, thanks for visiting", "Good to see you again", "Hi there, how can I help?"],
| ]}}
```



MODELS

- **□**BERT
- □ DISTIL BERT
- **LSTM**



WHAT IS THE NEED FOR BERT?

- BERT uses bidirectional training
- ☐ It takes both the previous and next tokens into account simultaneously
- ☐ BERT applies the bidirectional training of Transformer to language modeling, learns the text representations





- ☐ Packages : Bert-for-tf2, BertModelLayer
- ☐ Pretrained model : uncased-bert-pretrained-model
- ☐ Tokenizer : FullTokenizer
- ☐ The pretrained bert model is embedded to the keras model with two dense layers and two dropout layers with value of 0.5 using the activation function of tanh and softmax





model.summary()

dense (Dense)

dense 1 (Dense)

dropout 1 (Dropout)

(None, 768)

(None, 768)

(None, 117)

590592

89973

0

Total params: 109,570,677 Trainable params: 109,570,677

Non-trainable params: 0

```
print("train acc", train_acc)
print("test acc", test_acc)

train acc [4.759221453693032, 0.07734807]
test acc [4.759221453693032, 0.07734807]
```

Accuracy is very poor

Reason: The training and test data of minimum 8000 entries respectively is required which was major drawback of our use case since it didn't had test set independently and was populated using train set itself



DISTILBERT

- ☐ Proposed to pre-train a smaller general-purpose language representation model
- ☐ It is the size of a BERT model reduced by 40%, while retaining 97% of its language understanding capabilities and being 60% faster
- Distil BERT is smaller, faster and lighter model is cheaper to pre-train and demonstrates its capabilities for on-device computations in a proof-of-concept experiment and a comparative on-device study



DISTILBERT

	BERT	RoBERTa	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.
Performance	Outperforms state-of- the-art in Oct 2018	2-20% improvement over BERT	3% 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



DISTILBERT

- ☐ For Distil BERT implementation we are making use of distil-bert-uncased model
- ☐ The data is tokenized by using the pattern column of the data, and building a tensor out of the padded input and sending it to the distil bert model
- ☐ The model's performance is measured by using the classification report from sklearn.metric package.

accuracy			0.32	37
macro avg	0.11	0.14	0.12	37
weighted avg	0.26	0.32	0.29	37





- ☐ Introduced to avoid the long-term dependency problem
- LSTMs efficiently improve performance by memorizing the relevant information that is important and finding the pattern
- ☐ In LSTM we can use a multiple word string to find out the class to which it belongs
- Use of appropriate layers of embedding and encoding in LSTM, will be able to find out the actual meaning in input string and will give the most accurate output class



GLOVE

- It is an unsupervised learning algorithm developed by researchers at Stanford University aiming to generate word embeddings by aggregating global word co-occurrence matrices from a given corpus
- ☐ The basic idea behind the Glove word embedding is to derive the relationship between the words from statistics





- Pretrained LSTM model is used
- ☐ GloVe: 6B.50d and 100d .txt
- ☐ Performed LSTM model building by embedding 1 dense layer with SoftMax activation function





Model: "model_1"		
Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 18)]	
embedding_1 (Embedding)	(None, 10, 50)	20008050
lstm_1 (LSTM)	(None, 18, 128)	91648
dropout_1 (Dropout)	(None, 18, 128)	
lstm_2 (LSTM)	(None, 128)	131584
dropout_2 (Dropout)	(None, 128)	8
dense_1 (Dense)	(None, 42)	5418
activation_1 (Activation)	(None, 42)	8
Total params: 20,228,700		
Trainable params: 228,658		
Non-trainable params: 20,800	, 850	
Model: "model"		

GloVe: 6B.50d

Accuracy: 0.90

Loss: 0.203

GloVe: 100d

Accuracy: 0.89

Loss: 0.2



WINNER

LSTM	<mark>0.904</mark>
BERT	0.077
DISTILBERT	0.32



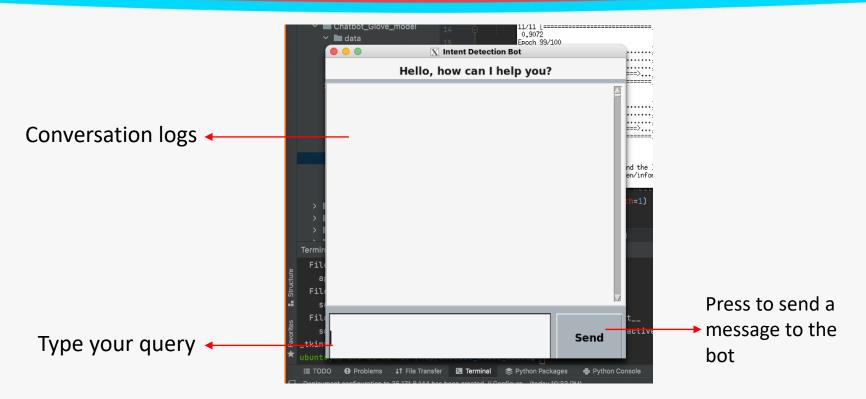


- ☐ Package : Tkinter
- To run the GUI, Xquartz has been used
- ☐ The GUI interacts with the user and retrieves the response using the best model

'LSTM'

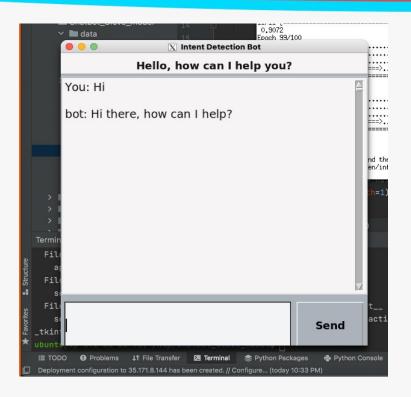


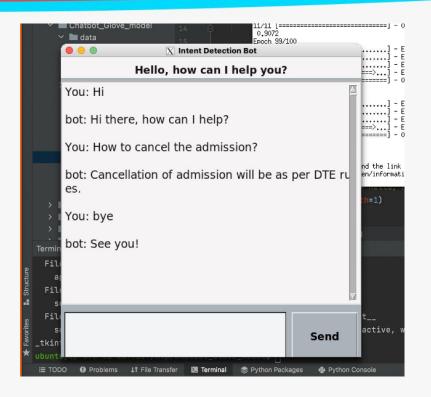
RESULTS





RESULTS







CONCLUSION & FUTURE SCOPE

- ☐ After making a comparison of all the model implementation we got to observe that LSTM is having the highest accuracy of 90%
- ☐ The further enhancements which can be done to this data is to increase the size of the train set and populate a test data
- ☐ Implementation of ConveRT A dual sentence encoder , it is effective, affordable, and quick to train also the size of the ConveRT model is less compared to the BERT model



REFERENCES

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- •https://github.com/sonos/nlu-benchmark/tree/master/2017-06-custom-intent-engines
- •https://github.com/huggingface/transformers
- •https://paperswithcode.com/task/intent-detection
- •https://www.sciencedirect.com/science/article/pii/S1877050918320374
- •https://analyticsindiamag.com/hands-on-guide-to-word-embeddings-using-glove/



PROJECT REPO

☐ The project implementation and codes can be found on the following repo:

https://github.com/Rehamanikandan/Final-Project-Group6