Outline

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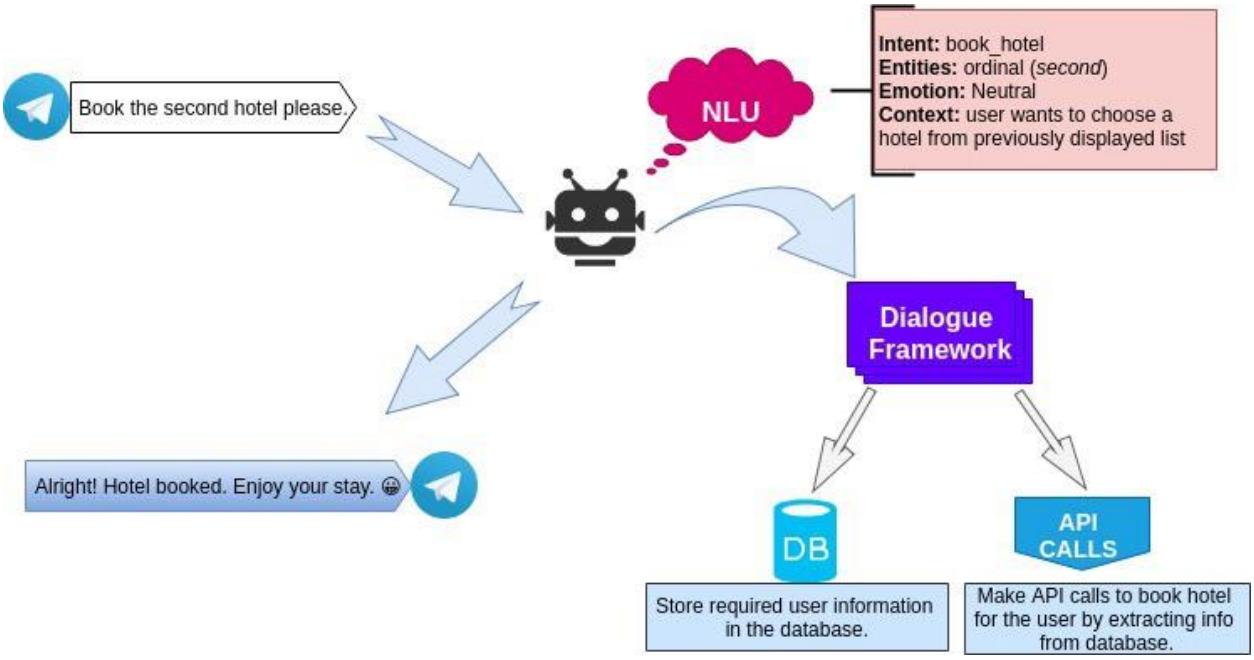
1. How does a Bot think?

For building any conversational agent, the most crucial part is understanding what the user is conveying. *Natural Language Understanding* (**NLU**) plays an important role in this aspect. After this, to actually build a bot, a *Dialogue Framework* needs to be chosen.



The flow of information through a Natural Language Understanding Engine and Dialog Framework

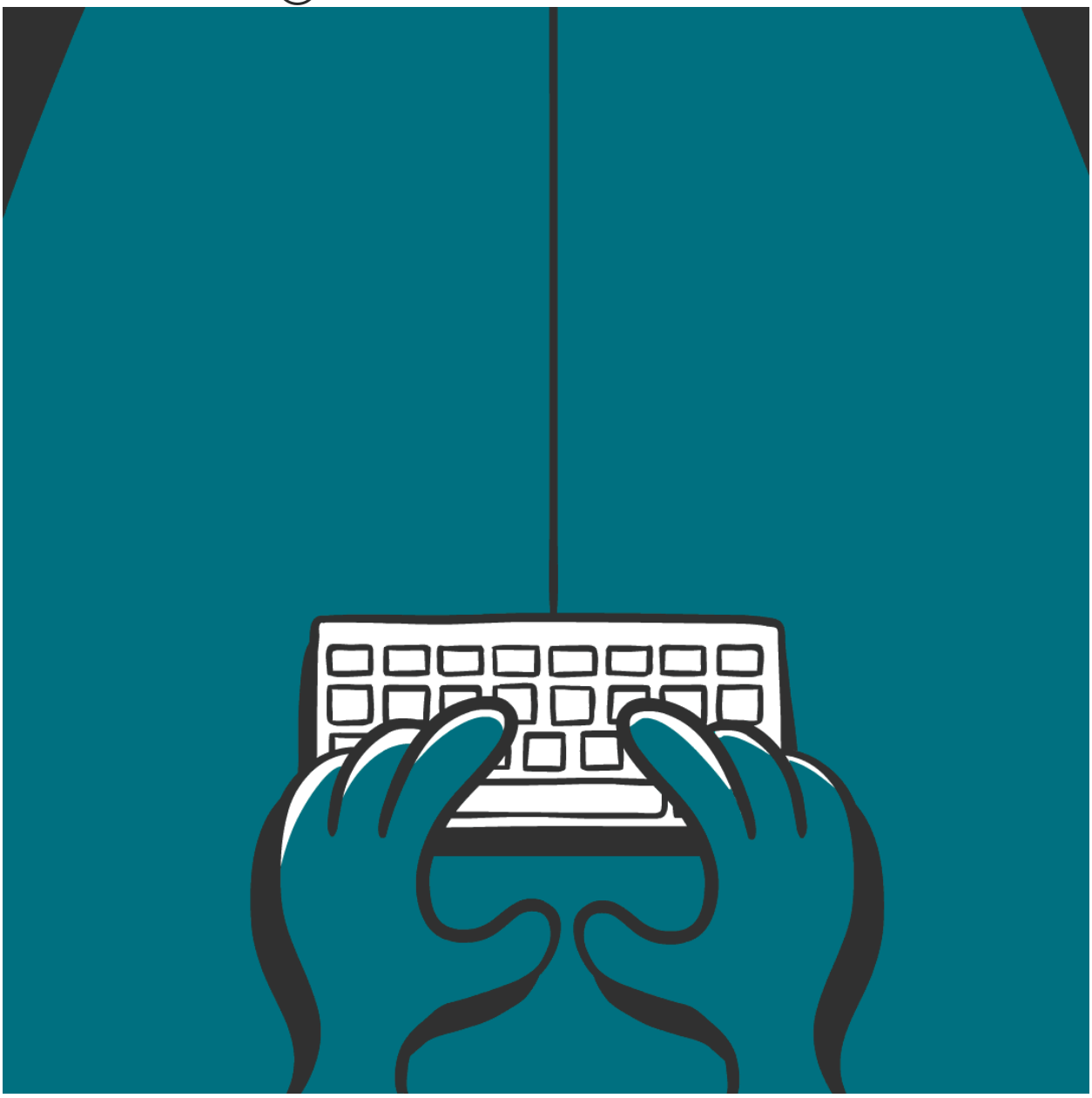
Whenever a user utters queries to our conversational agent, the first task is to classify the intention of the user utterance (*intent*) and alongside extract out important information present in the utterance (*entity*). A lot of additional tasks can be carried out in parallel, such as **emotion classification** (*to check the mood of the user*), **order request classification** and many more.

Once the conversational agent understands complete detail about the user utterance, it uses a Dialogue Framework to **predict the actions** to be carried out next. And then, that particular action is executed (may involve database fetch or API calls) to provide the desired response back to the user.

2. Domain Identification

Let us dive right into what we are eagerly waiting for…

Let's build a bot 😃



Highly caffeinated fingers ready to roll

We will start with a basic version of **Payment Bot** in **Hindi**.

The first step is to identify the domain of the bot. As discussed, two important aspects of NLU are *Intents* and *Entities*.

Intents are the different categories of utterances to classify what the user could mean while conversing with the bot.
Whereas, **Entities** are important information present in an utterance from user.

For example, let the user utterance be —

*“मुझे **दिल्ली** के लिए एक फ्लाइट बुक करनी है।”*

Clearly, the user intends to *book a flight* and also has provided the *destination* which is *Delhi*. Therefore, the following can be concluded.

***“intent”**: “book_flight”*
***“entities”**: {**“destination”** : “दिल्ली”}*

Let us narrow down our domain primarily focusing on a bot that can validate user’s mobile number, and show the current wallet balance. There are obviously some *general intents* needed for every domain.

General Intents	Domain Intents	Entities
greet	inform	mobile
bye	show_wallet_balance	otp
affirm		
deny		
thankyou		
restart		
revert		
repeat		

Building domain level understanding for Chatbot Development

At Saarthi.ai, we use our chatbot development platform to train the NLU models as per the required configurations. There is also a data tagging tool which facilitates multiple members in the Data Team to write intent utterances conveniently tagging the entities. But, since the work is at pre-release stage, let me explain using another commonly used open-source chatbot framework 'RasaNLU' , to walk you through the process of building a bot. We shall learn how to tweak some configurations in RasaNLU to make it perform better for our use case.

Installation

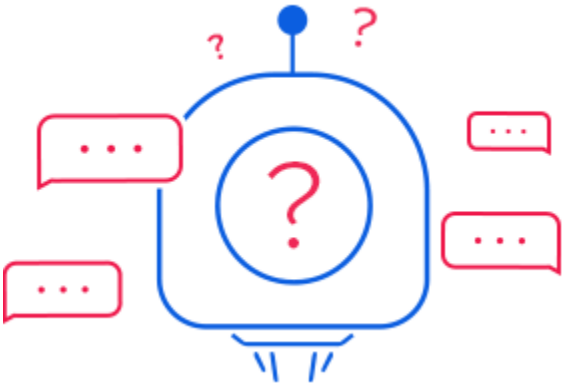
We will be installing RasaNLU open-source framework for NLU training.

First make sure, your system has Anaconda setup with the latest stable version.

```
## create a new conda environment
$ conda create -n rasanlu python==3.6.1
$ conda activate rasanlu$ git clone
https://github.com/RasaHQ/rasa_nlu.git
$ cd rasa_nlu
$ pip install -r requirements.txt
$ pip install -e .$ pip install rasa_nlu[spacy]
$ python -m spacy download en_core_web_md
$ python -m spacy link en_core_web_md en
$ pip install rasa_nlu[tensorflow]
```

Always prefer cloning the projects and installing from your local file system to make sure you can edit the source code according to your requirements.

3. Training Data for NLU



Preparing training data for your chatbot usecase

After the NLU domain is finalized, enters the cumbersome (as any developer might think 😒) task of preparing data for training the NLU. But, once the NLU server is up and running with acceptable accuracy for classification task, a huge hindrance is avoided 😀, which is usually coding the actions for the bot using any Dialogue Framework.

The training data needs to be prepared in Rasa format since we are using RasaNLU here. Markdown (md) format is shown as an example.

Please do have a look at training data format used in Rasa.

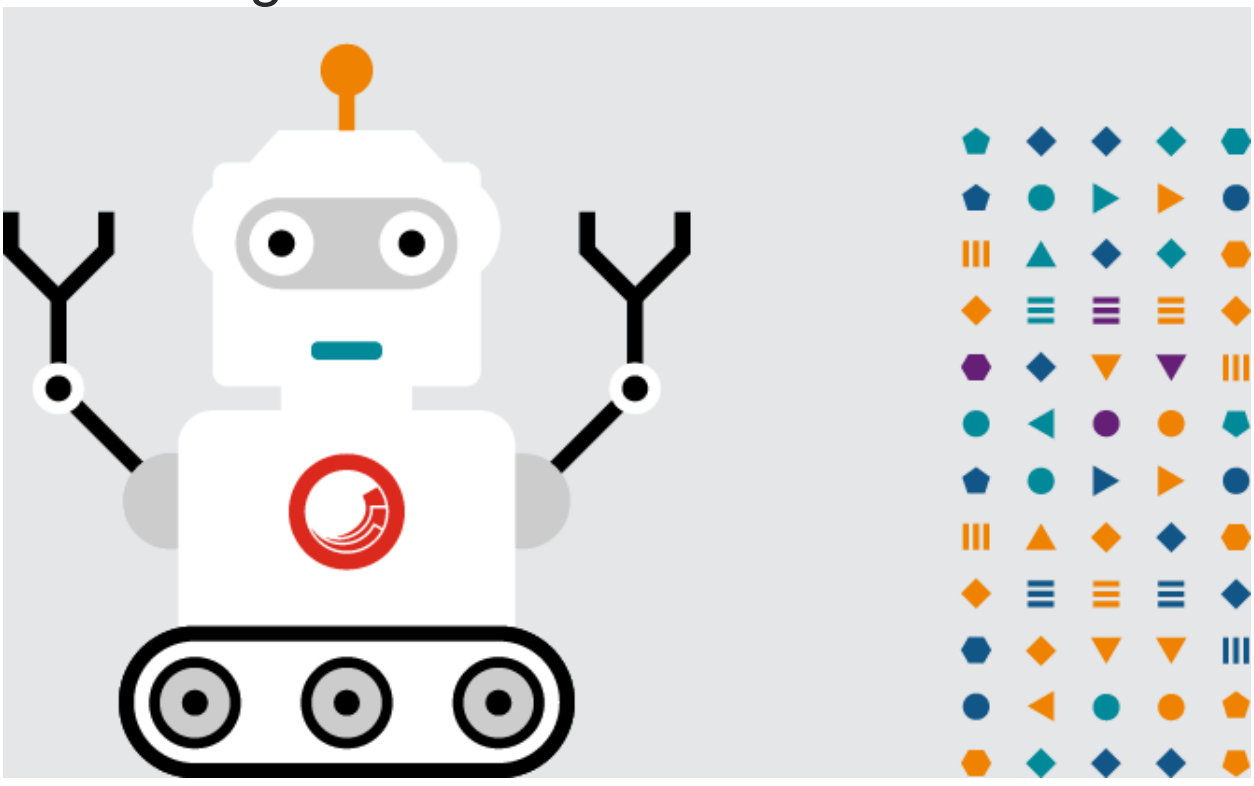
```
## intent:inform
- मेरा मोबाइल नंबर [9412312345](mobile) है
- [70014512345](mobile)
- ओ. टी. पी. [2343](otp)
...## intent:show_wallet_balance
- मेरा बैलेंस कितना है
- मेरे पैटीएम् वॉलेट में कितनी धनराशि है
...
```

While writing the utterances, it is a good practice to write them as an end-user of the bot.

Similarly, write the utterances for each intent present in the domain. Since we are going to use "*tensorflow embedding*" pipeline of Rasa, it is important to have **distinct utterances** of each intent in the final training data. Also, there must be at least **40 utterance examples** to make sure we have enough test data to evaluate our model.

With these points in mind, once the dataset is finalized, CONGRATS! 👏👏You have overcome the initial hurdle. Although there will be iterations on the NLU training data, for now you are all set to move towards training and evaluating the NLU.

4. Training and Evaluation



Time to check how conversant you are!

Before starting the training phase, there are few hacks that needs to be done in order to train on Hindi data.

Let us download a multi-language model from **Spacy**. Then link the short-form 'hi' (for Hindi) to this model. Make sure the NLU environment is activated and then use the following commands shown below.

```
$ python -m spacy download xx_ent_wiki_sm
$ python -m spacy link xx_ent_wiki_sm hi
```

We need to add a config file for training our Hindi dataset on RasaNLU. The configuration we are going to use is:

Save the above lines as 'config_tensorflow.yml'. Move the file into *rasa_nlu → sample_configs* directory where all the other predefined config files are saved.

Before we proceed towards training, have a look at the **token pattern** and **max_ngram**. *Token pattern* is regex defining tokens that are considered. The default regex by Rasa ignores words with single character, which might be a problem for languages apart from English. Hence, the token pattern is changed as shown above.

max_ngram defines the maximum number of consecutive words that can be considered together during featurization. Generally *max_ngram* performs well when set to 3. But there is

an option to evaluate each and every model and finding out the best model.

Now, it's time to **train** the NLU using this config file. But before that just one last step, separate out 10% of the utterances for each intent and create another test dataset for evaluation task.

```
$ python -m rasa_nlu.train \
         --config sample_configs/config_tensorflow.yml \
         --data <path to your training data file> \
         --path models \
         --fixed_model_name nlu \
         --project paytmbot --verbose
```

Once the model is successfully trained, let's **evaluate** our trained model.

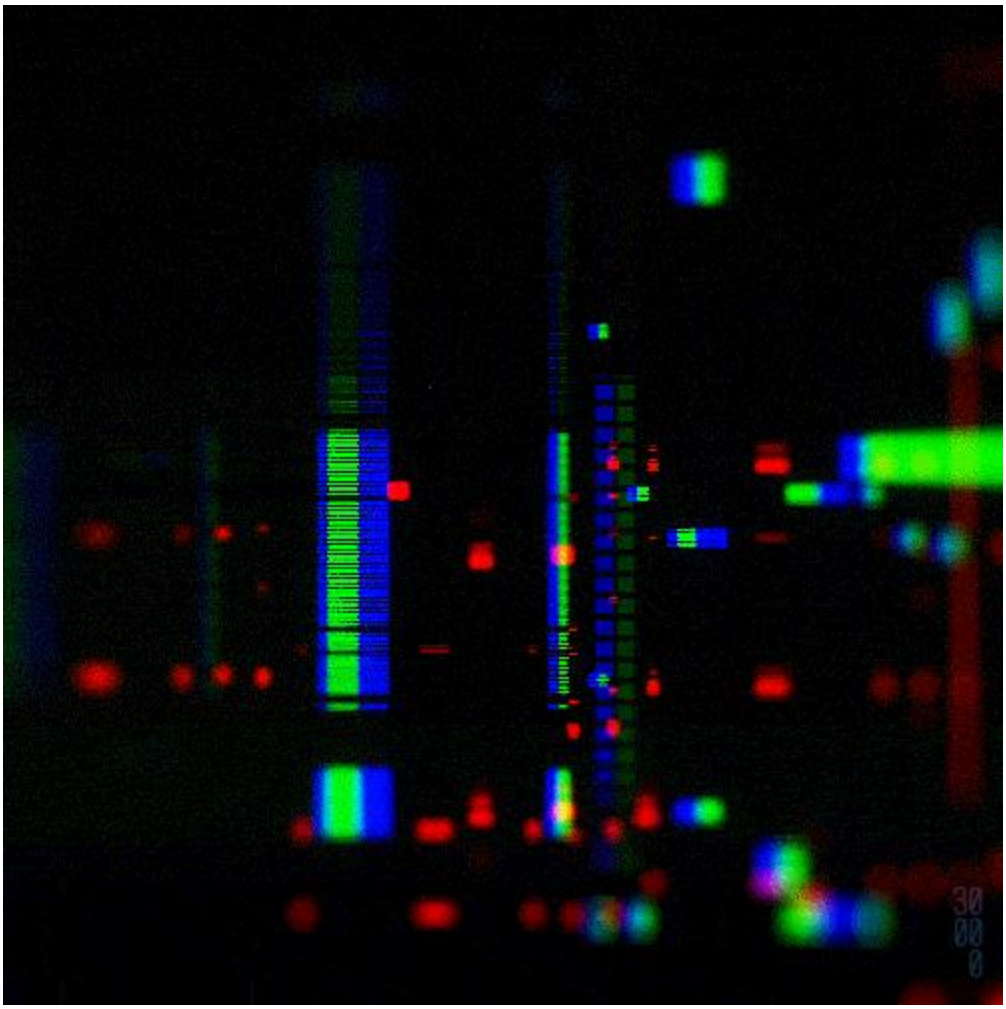
```
$ python -m rasa_nlu.evaluate \
         --data <path to test data set> \
         --model models/paytmbot/nlu
```

You might run into **TclError** because of the command line. Fix it using this link.

5. Setting up NLU server

Great! 😁

So, now we are almost done with our NLU. All we need is to run a **server** locally and test some of our own utterances.



Almost done now! Let’s get the server running.

```
$ python -m rasa_nlu.server -c sample_configs/config_tensorflow.yml
--path models --port <port number>
```

Open up the browser to check the NLU server.

```
localhost:<port
number>/parse?q=”<example_utterance>”&project=paytmbot&model=nlu
```

You can also use curl from terminal:

```
$ curl -XPOST localhost:<port no>/parse -d
'{"q":"<example_utterance>", "project":"paytmbot", "model":"nlu"}'
```