Football Dialogue Assistant

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In this project, I will try to build a dialogue system that will provide the information about football such as the league fixtures, team information, player statistic, ... The following is an example of conversation between user (label as \mathbf{U}) and the system (label as \mathbf{B})

```
U: Hi
B: Hello, How can I help you?
U: Tell me about Euro
B: There are 4 matches coming up:
   In 8th Finals:
   Croatia meet Spain on Jun 28 06:00PM;
   France meet Switzerland on Jun 28 09:00PM;
   England meet Germany on Jun 29 06:00PM;
   Sweden meet Ukraine on Jun 29 09:00PM;
U: top 2 players of the Euro now?
B: The following is 2 top player:
   1: Cristiano Ronaldo dos Santos Aveiro of Portugal with 5 goals.
   2: Romelu Lukaku Menama of Belgium with 3 goals.
U: How many goals did Ronaldo score at Euro?
B: At Euro Championship: total is 5; conceded is 0; assists is 1;
U: The next matches of England at Euro?
B: England will meet Germany at 8th Final of Euro Championship
   in Jun 29 06:00PM at home
U: The position of England?
B: England is participating UEFA Nations League,
   World Cup - Qualification Europe, and Euro Championship.
   Which league do you want to know about?
U: Euro Championship
B: In Euro Championship, England is at 1 position with 7 point
```

System Architecture

The Figure 1 show the architecture of dialogue system. There are three main components in the system:

- Google Assistant will interact with user. It converts user's speech to text (Automatic Speech Recognition) and converts text generated from Rasa to speech to respond to user (Text-to-Speech Synthesis).
- Rasa is main core component of system. It will generate information base on user's text input.
 - Spoken Language Understanding will receive text message and then extract the *intent* and entities from message
 - Dialogue Management will keep track of conversation state (stores concept values (entities and actions) into slots). It decide the next action based on state and user input (intent and entities) and update states (provide information to fill response). In this project, it will request Football News component to fill the information that user ask.

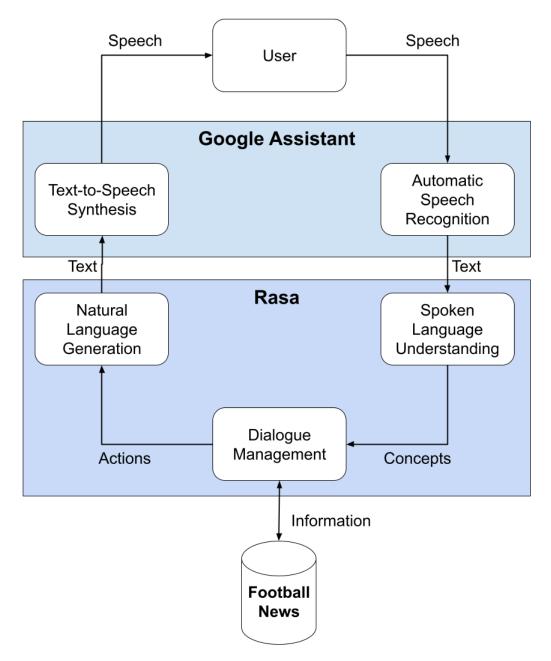


Figure 1: System Architecture

- Natural Language Generation will generate message to response to user.
- Football News will provide information such as league fixtures, player statistic, team information, ... to Dialogue Management. In this project, I will extract these information from API-FOOTBALL [1].

Implementation

Intents and Entities

To handle request from user, we need to classify the request to intents to understand type of request and then extract entities from intent to response suitable information. In this project, I will define six intents and five entities to handle utterance of user. Table 1 show the information of these intents and entities could be extracted from them.

Intent	Meaning	Entities	Examples
ask_league_info	request information of	league_name	Tell me about
	one specify league		[Euro](league_name)
ask_top_player	request information	league_name,	top
	about the players who	query_number	[2](query_number)
	score the most goals in		player of
	one specify league		[Euro](league_name)
ask_player_info	request information	query_type, PERSON,	number
	about statistic of	league_name	[goals](query_type)
	player such as number		of
	of goals, assists,		[Kai Havert](PERSON)
			at
			[euro](league_name)
ask_fixtures	request information	${\tt club_name},$	the fixtures of
	about fixtures of a club	league_name	[england](club_name)
	at one or all		at
	participated leagues		[euro](league_name)
ask_club_info	request the position of	${\tt club_name},$	update position of
	a club at one or all	league_name	[england](club_name)
	participated leagues		at
			[euro](league_name)
provide_league_info	specify which league	league_name	[euro](league_name)
	user want to know the		
	position of a club		

Table 1: Intent and entities

There are six corresponding custom actions to handle six intents classified from user's utterance. These actions will get extracted information from API-FOOTBALL that suitable with entities extracted from user's utterance. In detail:

- action_provide_league_info will handle intent ask_league_info. This action will get the fixtures of current round of entity league_name to response to user.
- action_top_player will handle intent ask_top_player. It will get top query_number scorers at league_name to return to user. If entity query_number is not provided, this action will return the information of the highest scorer.
- action_player_info will handle intent ask_player_info. It will get name of player from entity PERSON and return the query_type (goals, assists) statistic at league_name to user if it is specified otherwise return the information of query_type in all leagues that PERSON participates.
- action_fixtures will handle intent ask_fixtures. It will provide the next 5 matches of club_name at league_name if it is provided otherwise return the next 5 matches coming up at all league participated by club_name.

• action_club_info will handle intent ask_club_info. If user ask information in specified league which mean league_name entity is provided, this action will return the position of club_name at league_name. Otherwise, if league_name is not provided, this action will provide all leagues that club_name is participating and ask user chose one league_name or all. Then the action action_club_info_spec will provide the position information of club_name at league_name which is specified by user through provide_league_info intent.

Pipeline Configuration

Because league_name, club_name, query_type have known values, for example league_name may have values: Premier League, Euro Championship, ... club_name may have values: Chelsea, England, ... query_type is chosen from: goals, assists. I plan to use lookup tables from RegexEntityExtractor for extracting these entities. But in Rasa documentation, they recommend not use this extractor in combination with MitieEntityExtractor, in addition I cannot find the way to specify entity types will be applied by determined extractor. So, I will use RegexFeaturizer to use regexes matches (lookup tables) as additional signal for statistical extractor. Moreover RegexFeaturizer for entity extraction are currently only supported by the CRFEntityExtractor and the DIETClassifier components [2].

The player_name is a name of players. Therefore, to take advantage from pre-trained model, I will use dimension PERSON of SpacyEntityExtractor to extract player_name entity from user's utterance.

The query_number entity may have the different type such as a word four instead of a number 4. Therefore, I will use EntitySynonymMapper to recognize these cases.

Base on above observations, I will try three different pipeline configuration:

1. Using MITIE for intent classifier and entity extractor (which is called config_v1)

name: MitieNLP
 model: "data/total_word_feature_extractor.dat"
 name: MitieTokenizer
 name: MitieFeaturizer
 pooling: "mean"
 name: LexicalSyntacticFeaturizer
 name: MitieIntentClassifier

- name: MitieEntityExtractor - name: EntitySynonymMapper

2. Using DIETClassifier for intent classifier and combine SpacyEntityExtractor with DIETClassifier for entity extractor (which is called config_v2)

name: SpacyNLP
model: es_core_news_md
name: SpacyTokenizer
name: SpacyFeaturizer
name: LexicalSyntacticFeaturizer
name: DIETClassifier
batch_strategy: balance
intent_classification: True
entity_recognition: False
epochs: 500
constrain_similarities: true
name: ResponseSelector

epochs: 100

constrain_similarities: true
- name: SpacyEntityExtractor
 dimensions: ["PERSON"]
- name: RegexFeaturizer
- name: DIETClassifier
 batch_strategy: balance

intent_classification: False
entity_recognition: True

epochs: 100

- name: EntitySynonymMapper

3. Using MITIE for intent classifier and combine SpacyEntityExtractor with DIETClassifier for entity extractor (which is called config_v3)

- name: MitieNLP

model: "data/total_word_feature_extractor.dat"

- name: SpacyNLP

model: es_core_news_md
- name: MitieTokenizer
- name: MitieFeaturizer
pooling: "mean"

- name: LexicalSyntacticFeaturizer

name: MitieIntentClassifiername: SpacyEntityExtractor dimensions: ["PERSON"]

name: RegexFeaturizer
 name: DIETClassifier
 batch_strategy: balance
 intent_classification: False
 entity_recognition: True

epochs: 100

- name: EntitySynonymMapper

To evaluate of pipeline configurations, I will run each configuration above two times with different percentages of training data. The full comparison of results is found here. When running comparison in full dataset, the Figure 2 show the intent confusion matrix between config_v1 and config_v2, intent confusion matrix between config_v2 and config_v3 is shown in Figure 3. The entity extractor confusion matrix comparison between config_v1 and config_v2 is shown in Figure 4 and between config_v2 and config_v3 is shown in Figure 5.

From intent confusion matrix comparison between config_v1 and config_v2 (Figure 2), it is shown that the better result is achieved when apply MITIE for intent classification compare with DIETClassifier. For example, while all ask_fixtures intent is truly predicted in MITIE classifier, one utterance with ask_fixtures intent is predicted as ask_player_info in DIETClassifier. The wrong prediction also happen between ask_league_info and ask_fixtures in DIETClassifier.

From entity extractor confusion matrix comparison between config_v1 and config_v2 (Figure 4), because of take advantage of pre-trained SpacyEntityExtractor in PERSON entities, the config_v2 predicts truly while config_v1 mistakenly predict with league_name and no_entity.

Base on two observations above, I will chose config_v3 which is combined the advantage of MITIE for intent classifier and SpacyEntityExtractor for PERSON entity extractor, the other entities may be extracted from DIETClassifier. As shown in Figure 3 and Figure 5, the result of config_v3 will better than config_v2 in intent classifier because it use MITIE instead of DIETClassifier; and the result in entities extractor will be same because they both use SpacyEntityExtractor and DIETClassifier.

Conclusion

In this project, I have construct a simple dialogue system to provide some information about football. A system probably work but still simple. The number intent is limited (6 intent) so can serve limit request from user. Because of having to build data from scratch, the number of utterance for training is small.

For future work, I will build or find more data to train better model; build more intents to provide more information such as line-up, information related to a match such as confrontation history; build more complicated information such as instead of just provide position also provide the different point to

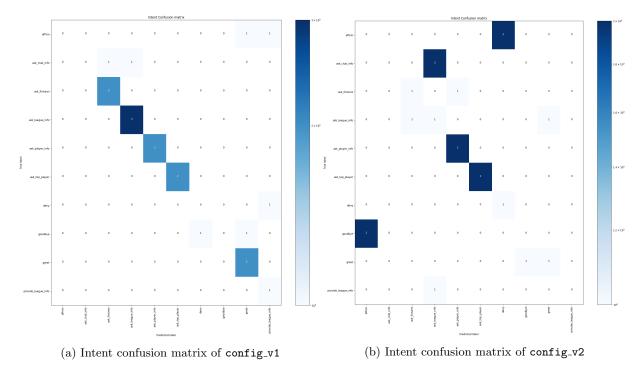


Figure 2: Intent confusion matrix comparison between config_v1 and config_v2

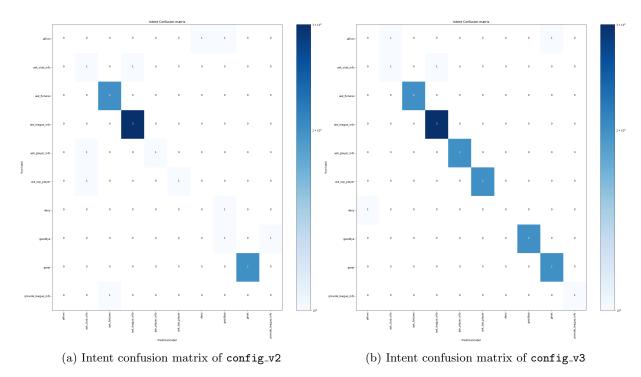


Figure 3: Intent confusion matrix comparison between config_v2 and config_v3

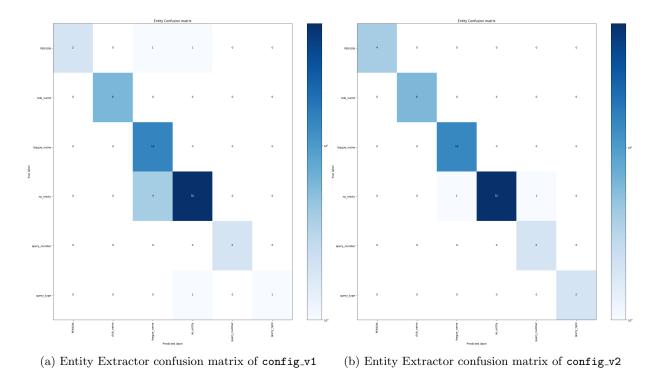


Figure 4: Entity Extractor confusion matrix comparison between config_v1 and config_v2

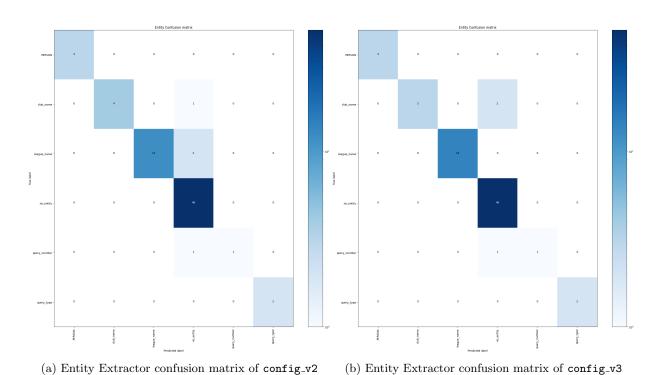


Figure 5: Entity Extractor confusion matrix comparison between config_v2 and config_v3

achieve a important position such as champion, top-4 or relegation position; and build more "intelligent" but such as automatically summary related information that user request from newspaper.

References

- [1] Api-football, https://rapidapi.com/api-sports/api/api-football/.
- [2] Rasa regex featurizer documentation, https://rasa.com/docs/rasa/components#regexfeaturizer.
- [3] Language understading systems lab, https://github.com/esrel/LUS.
- [4] Rasa documentation, https://rasa.com/docs/rasa/.