A Hybrid Solution to Learn Turn-Taking in Multi-Party Service-based Chat Groups

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Abstract
To predict the next most likely participant to interact in a multi-party conversation is a difficult problem. In a text-based chat group, the only information available is the sender, the content of the text and the dialogue history. In this paper we present our study on how these information can be used on the prediction task through a corpus and architecture that integrates turn-taking classifiers based on Maximum Likelihood Expectation (MLE), Convolutional Neural Networks (CNN) and Finite State Automata (FSA). The corpus is a synthetic adaptation of the Multi-Domain Wizard-of-Oz dataset (MultiWOZ) to a multiple travel service-based bots scenario with dialogue errors and was created to simulate user’s interaction and evaluate the architecture. We present experimental results which show that the CNN approach achieves better performance than the baseline with an accuracy of 92.34%, but the integrated solution with MLE, CNN and FSA achieves performance even better, with 95.65%.

1 Introduction
The multi-party turn-taking problem consists of determining the proper turn to interact in a conversation with more than two participants. Fundamentally, the goal is to predict which agent in the conversation is the most likely to speak next and, conversely, when an agent must wait before interacting. An agent can be either a person or a chatbot. That interaction can be a reply to the last interaction, a reply to an interaction in the past in the dialogue, or even an interruption. The two former are replies to existent turns, while the later is the creation of a new turn.

In this paper we present a hybrid architecture that has two components for controlling the dialogue of multiple travel service-based bots with an user. Previous works have implemented turn-taking controlling through a finite-state automata (FSA) based service which is called for every utterance exchanged in the group chat, by considering both the content and the history of interaction between participants [1][2][3]. This service is part of a platform called Ravel which enables the connection of several chatbots in a chat group with users. The rule-based system solves the turn-taking problem for an investment advisor scenario but it has limitations for scaling up the set of rules and the application to new domains since it is heavily dependent on expert’s knowledge.

Therefore, more recently [4], machine learning (ML) approaches which may provide a more scalable solution depending on the size of the dataset have also been applied to this problem. Given a finite set of possible agents that can speak, the learned models predict the most likely agent to speak next, assuming only one agent should speak at a time, and the information to predict that can include
only participant or both participant and content data. From the tested approaches, although the CNN modeling which considered both content and the agent information achieved the best performance, it requires a lot of data. While the MLE modeling requires less data but still was not as good as CNN. Therefore, there is a need for a hybrid approach.

To achieve that, we have then created a system which is an extension and instantiation of Ravel’s architecture. It integrates the MLE, CNN and FSA-based turn-taking classifiers in order to solve the task. To evaluate the system, we have adapted the multibotwoz corpus \[5\][4] to a multiple travel service-based bots scenario with dialogue errors in order to simulate the user’s interaction. We present experimental results which show that the integrated solution with MLE, CNN and FSA achieves performance even better (95.65% of accuracy) than the solution with only the CNN on the same dataset (92.34%).

2 Dataset

The Multi-Domain Wizard-of-Oz dataset (MultiWOZ)\[5\] is a fully-labeled collection of human-human written conversations spanning over multiple domains and topics. This dataset was not created considering that more than one bot would be in the conversation with the user. Rather, it was created considering a dyadic conversation between the user and a bot that can talk about multiple domains or topics, and the topics are actually service providers.

```
user  train bot  hotel bot  attraction bot  restaurant bot  travel bot  taxi bot
50    12       11       10       11       4         2
```

Figure 1: Bots Interactions Distribution

An adapted version of this corpus has been presented in \[4\]. The dialogues with only two topics or that contained topics which are present in small number of dialogues were filtered. The sender was then classified as one of the topic in order to determine the service provider. I.e., if the utterance was about booking a hotel room, even though there is no mention to the term "hotel" or "room", the sender was labeled as hotel bot. The resulted corpus was called the multibotwoz dataset and it contains only the following services: attractions, hotel, restaurant, taxi, train and travel bot, and ended up with 99,553 utterances in 6,138 dialogues with 4 agents on average in each dialogue.

\[1\]MultiWoZ dataset: https://www.repository.cam.ac.uk/handle/1810/280608
varying from 3 to 7 and 16 utterances exchanged on average in each dialogue (see Table 1). No bot interacts after another bot in the multibotwoz dataset, only after the user. Figures 1 and 2 present more details with the bots interaction ratio compared to the user interaction and the dialogue distribution per chat group size.

### 3 Turn-Taking Modeler

Based on the results on the comparison of ML modeling approaches as presented by [4], we have chosen the MLE and CNN. We therefore further describe them in this section along with the baseline.

#### 3.1 Baseline

We consider a baseline which we call **Repeat Last** to compare our proposed methods: this approach is based on a social rule often observed in multi-party human dialogues [6]: whenever an agent speaks, we might predict the next one as being the one that had spoken before. More formally, the Repeat Last baseline prediction works as following: let $A = \{ a_i | 1 \leq i \leq n \}$ be the set of agents in the dialogue, $n$ be the number of agents, and let $S = \{ s_t | 1 \leq t \leq T \}$ be the set of agents who sent an utterance in the dialogue up to a time $T$, where $s_t \in A$.

2Multibotwoz dataset: https://github.com/CognitiveHorizons/AIHN-publications
Whenever the speaker $s_t$ sends an utterance, the next agent selected to talk, denoted $s_{t+1}$, is the one who spoke at time $t-1$, i.e., $s_{t+1} = s_{t-1}$.

### 3.2 MLE and CNN Modeling

We make use of the one-hot encoding to convert the information of the agents to a feature vector, formalized as follows. Let $x$ be a vector and $x \in C^n$, a $n$-dimensional instance space with $n$ agents in the conversation and $a_i$ the $i$-th agent, where $1 \leq i \leq n$, and let $s_t$ be the agent who spoke at time $t$. The binary feature vector $x(t)$ at time $t$ of the dialog, can be defined as:

$$x(t) = [x_{t1}, x_{t2}, \ldots, x_{tn}]^T$$

$$x_{ti} = \begin{cases} 
1 & \text{if } a_i \text{ is the sender, i.e. } a_i = s_t \\
0 & \text{if } a_i \text{ is not the sender, i.e. } a_i \neq s_t 
\end{cases}$$

Therefore, in order to produce the input vector for our models, a linear transformation $T : C^n \rightarrow C^{W \times n}$ on $x(t)$ is performed by taking into account $x(t)$ until $x(t-W)$, where $W$ is the size of lookback window and $t > W$, as:

$$x'(t) = [x_{t1}, \ldots, x_{tn}, x_{t-W+1}, \ldots, x_{t-W+n}]^T$$

**A-MLE:** The A-MLE applies the Maximum Likelihood Estimation [7] after encoding only the information of the agents and by making use of the aforementioned one-hot encoding method. This learning method takes into account only the order in which the agents interact in the conversation. Therefore, transitions are learned by considering that the previous state is the last agent which sent an utterance and the next state is the following agent which sent an utterance. We modeled A-MLE considering a lookback window of size 2, which means the previous state contains information of the two last agents which sent an utterance. In this case, a $\theta$ transition from state $\pi - 1$ to $\pi$, is modeled as:

$$\theta : state(\pi - 1) = x'(t) \rightarrow state(\pi) = x(t + 1)$$

We then compute the MLE with smoothing to estimate the parameter for each $\theta(\pi) \in \Theta$ transition type. Therefore, for each corpus, we estimate $L$ for observed transitions as:

$$L(\theta|x'(t), x(t + 1)) = \frac{\text{count}(\theta, x'(t), x(t + 1)) + 1}{\text{count}(\theta, x'(t), x(t + 1)) + |\Pi|}$$

Where $\Pi$ is the set of states and $|\Pi|$ is the number of states in the set.

**AC-CNN:** the agent-and-content convolutional neural network (AC-CNN) modeler consists of a standard CNN modeling used for text classification adapted for the turn-taking task. Such adaptation consists of formatting the previous utterances and the name of the agent as a raw text, and defining the label as in the previous methods. More formally, let $s_{t-1}$ be the agent who spoke utterance $u_{t-1}$ at time $t - 1$, and $s_t$ the agent who spoke the last utterance $u_t$, to predict who will speak at time $t + 1$, we build the following raw text: $s_{t-1} \oplus u_{t-1} \oplus s_t \oplus u_t$, where $\oplus$ represents the concatenation of textual strings. That text is then used as input to the neural network.

The CNN’s architecture was designed with an embedding layer with 64 dimensions; dropout set to 0.2; convolutional layer with 64 filters with kernel size of 3 and stride equals to 1; 1D Global Max-pooling layer with pool size set to 5; another dropout set to 0.2; and 300-dimensional dense hidden layer.
The CNN model does not constraint with regard to waiting for a specific moment to start predicting, it follows a more classical batch-learning process. We considered a 70/30 train-test split, where 70% of subsequent dialogues are used for training and the remaining 30% for testing. In order to set meta-parameters for the models, cross-validation has been applied on the training set. The vocabulary is built with training and testing data, therefore, all words had WE and there were no words which where OOV. For both the embedding and the hidden layers in the AC-CNN models, Rectified-Linear-Units activation functions (Relu) are applied. For the training, we make use of the Adam optimizer, with 3 epochs for training and learning rate set to 0.001. Batch size is set to 5.

|       | A-MLE  | AC-CNN |
|-------|--------|--------|
| Accuracy | 84.39% | 92.34% |
| Disjoint Errors | 65.20% | 32.13% |

Table 2: Accuracy and Disjoint Errors.

Table 2 presents the accuracy and the percentage of disjoint errors between both A-MLE and AC-CNN modelers. Let $E_{A-MLE}$ be the set of errors achieved by A-MLE predictor, and $E_{AC-CNN}$ be the set of errors achieved by AC-CNN. The intersection between the sets ($E_{A-MLE} \cap E_{AC-CNN}$) was only 29.87% of the union of the sets ($E_{A-MLE} \cup E_{AC-CNN}$). The relative complement of $E_{AC-CNN}$ in $E_{A-MLE}$ ($E_{A-MLE} \setminus E_{AC-CNN}$) was 65.20% of $E_{A-MLE}$, while the relative complement of $E_{A-MLE}$ in $E_{AC-CNN}$ ($E_{AC-CNN} \setminus E_{A-MLE}$) was 32.13% of $E_{AC-CNN}$. Therefore, our proposed solution was defined with both classifiers with the goal to maximize the accuracy.

### 3.3 FSA-based Turn Taking

Ravel’s platform [2] is a MAS-based micro-services-driven architecture platform that enables the connection of conversational systems in a multi-bot environment. Ravel’s environment is mainly composed of an agent which is a Communication Hub (CH) that enables the message exchange between the chatbots which are agents; a Connector, which connects the agents to the CH; and a FSA-based Conversation Governance (CG) service to orchestrate the turn-taking. The CG service is implemented as an interpreter of a Domain Specific Language for Conversation Rules [3] (DSL-CR), which enables modeling, specification, and execution of multi-party turn-taking through deontic logic.

The Turn in the conversation is the exchange by one participant (agent or person) of one message which contains one or more utterances. It represents an event which can change the state of the conversation or the set of norms which are active in the conversation such as an utterance arrival. For a given turn in a conversation, the norms are defined as:

- **An obligation** requires the participant to pro-actively or reactively emit an utterance;
- **A permission** allows the participant to pro-actively or reactively emit an utterance;
- **A prohibition** forbids the participant to emit utterances, or states that they are not expected in that turn.

For each message that arrives, the GC service may use variables as $sender$, $last_sender$ and $receivers$, besides the participant roles, as dialogue context information to identify the members that can be eligible to receive the activated norms: the sender of the message, the sender of the message before the current and the agents which were mentioned in current message (if any), respectively.
4 The Proposed Hybrid Solution

In our hybrid solution we propose to model the output of the MLE and CNN classifiers into the finite state automata definition which is the input of the FSA-based (GC) service from Ravel, as illustrated in Figure 3.

![Figure 3: The Proposed Architecture Workflow](image)

More formally, the proposed solution prediction works as following: let $A = \{a_i|1 \leq i \leq n\}$ be the set of agents in the dialogue, $n$ be the number of agents, and let $S = \{s_t|1 \leq t \leq T\}$ be the set of agents who sent an utterance in the dialogue up to a time $T$, where $s_t \in A$.

Whenever the speaker $s_t$ sends an utterance, the next agent selected to talk, denoted $s_{t+1}$, is retrieved as:

$$s_{t+1} = \ell(x(t+1))|\ell \in L$$

(6)

$$\ell(x(t+1)) = \begin{cases} 
\ell(x_1(t+1)) & \text{if } C_1 \geq k_1 \\
\ell(x_2(t+1)) & \text{if } C_2 < k_1 \text{ and } C_2 \geq k_2 \\
\text{travel_bot} & \text{otherwise}
\end{cases}$$

(7)

Where $C_1$ and $C_2$ are the confidence scores for prediction using AC-CNN and A-MLE, respectively, and $k_1$ and $k_2$ are thresholds for each classifier.

The FSA-based Turn-Taking acts as a binary classifier by deciding, for a given input with sender, content (the utterance), i.e., $x'(t)$ and the predicted sender ($\ell(x(t+1))$), if the current sender can or cannot interact in that turn.

5 Experimental Results

In a live chat between humans and chatbots, it is not possible to determine when the bots tries to reply to the user’s utterance, hence nor the order. A bot that is not supposed to interact (for instance, because the user is requesting information about a train and not a taxi), should not have its response broadcasted in the group. Because of that, for our tests datasets, we have extended the multibotwoz corpus\(^3\) to include dialogue errors in order to simulate the interactions from bots that are not supposed to interact in a given turn and which try to do so (see Table 3). Therefore, for each correct answer of one bot to the previous sentence sent by the user, we added another answer from the other bots. And during the test phase, we randomly select an answer from all the replies. Therefore, only one reply should be expected, while the others no. Figure 4 illustrates the test scenario in relation to the training and the original corpus.

\(^3\)Multibotwoz Corpus with Dialogue Errors: https://github.com/CognitiveHorizons/AIHN-publications
Table 3: Multibotwoz Corpus with Dialogue Errors

| Metric                          | Value  |
|---------------------------------|--------|
| Nbr. of utterances              | 348,442|
| Nbr. of utterances per agent    | 49,778 |
| Nbr. of Dialogues               | 6,138  |
| Avg. nbr. of agents per Dialogue| 7      |
| Avg. nbr. of utterances per Dialogue| 56     |
| Avg. length of utterances (words)| 13     |

We designed two set of FSA rules: one for Scenario A and one for Scenario B. While Scenario A does not consider the output of the classifiers, Scenario B does and the set of rules for Scenario A is a subset of rules for Scenario B as described next. Below are the basic rules defined for Scenario A:

- **CR-A1**: The user has always **permission** to reply to any utterance sent.
- **CR-A2**: Whenever an utterance that mentions a participant in the conversation is sent, the mentioned participant has the **obligation** to reply and the other participants are prohibited.
- **CR-A3**: Whenever an utterance is sent from a participant with bot role without any mention, the sender and all other participants with bot role receive a **prohibition** to interact.
- **CR-A4**: Whenever an utterance is sent from a participant with user role without any mention, participants with bot role that try to interact after a reply is sent to that utterance receive a **prohibition**.

Scenario B extended Scenario A with the following rules:

- **CR-B1**: Whenever an utterance is sent from a participant with user role without any mention and any participant is expected to reply, the sender with bot role receives a **prohibition** to interact and participants with bot role that try to interact after a reply is sent to that utterance receive a **prohibition**.
- **CR-B2**: Whenever an utterance that is expected to be replied by the participant with user role is sent, the participant with the user role receives an **obligation** to reply and the other participants are prohibited.
- CR-B3: Whenever an utterance that is expected to be replied by the participant with bot role is sent, the participant with the bot role receives an obligation to reply and the other participants are prohibited.

As a result, Scenario A was implemented with the DSL-CR language through the specification of 6 norms and 3 transitions, while Scenario B was implemented by extending Scenario A. The conversation rule CR-B3 required 6 extra norms and 6 extra transitions (one for each service bot).

Scenario B rules were used in two experiments: B80 and B90. In the former, the threshold for the confidence score of both classifiers in Equation \( k_1 = k_2 = 0.8 \), while for the later, \( k_1 = k_2 = 0.9 \).

|               | Accuracy |
|---------------|----------|
| Baseline      | 0.8649   |
| A-MLE         | 0.8439   |
| **AC-CNN**    | **0.9234**|
| Scenario A    | 0.7600   |
| **Scenario B80** | **0.9565**|
| **Scenario B90** | **0.9174**|

Table 4: Accuracy.

Scenario B80 achieved the highest accuracy and the F1 score was 0.9240. With these results, we can conclude that both AC-CNN model and our model are better than Baseline (\( p\text{-value} < 0.01 \)), however our model is better than AC-CNN (\( p\text{-value} < 0.01 \)).

Through qualitative analysis, we observed that the majority of the errors with our solution was due to the mediation done by travel_bot. The AC-CNN was not able to learn the interaction of the mediation and we believe that might be because there are less data for these interactions and we could not design a rule which could be used by the FSA because it is hard to determine with a rule when the travel_bot will interact. We would need, for instance, at least two classifiers to help describing the interaction: a multi-topic classifier, i.e., a classifier that can classify more than one topic for a given utterance and a dialog act classifier in order to classify the ones that travel_bot uses to mediate.

6 Related Work

End-to-end data-driven dialogue systems have been built and evaluated [8] and some of them were built for multi-party dialogues. However, they were disentangled into dyadic dialogues before the modeling. The most closest work is [9], in which a model that encoded the context to predict the addressee and a response in multi-party conversation was proposed. However, their approach do not comprise a hybrid approach as ours, in which we model also interaction rules based on dialogue features and context. To the best of our knowledge, we have presented a novel work on this paper which integrates both machine learning with rules to address the turn taking problem.
Conclusions and Future Work

This paper presented a corpus and architecture that integrates turn-taking classifiers based on Maximum Likelihood Expectation (MLE), Convolutional Neural Networks (CNN) and Finite State Automata (FSA). The corpus is a synthect adaptation of the Multi-Domain Wizard-of-Oz dataset (MultiWOZ) to a multiple travel service-based bots scenario with dialogue errors and was created to simulate user’s interaction and evaluate the architecture. By simulating the user’s interaction from the multibotwoz corpus, our experiments show that our solution can improve the performance of the AC-CNN.

As future work, improvements can be done on the expressivity of the DSL-CR language in order to handle more dialogue context information. Furthermore, we plan to include online and reinforcement learning into the architecture, so a chatbot would be able to learn turn-taking during interaction, enabling a self-adaptive behavior on the turn-taking model.

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