Zero-shot Multi-Domain Dialog State Tracking Using Prescriptive Rules

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1. Motivation

- **Problem:** You have deployed a multi-label classification system based on Neural Networks, and now you would like the system to also predict a new label.
- **Standard solution:** annotate the dataset including the new label
- **Our solution:** incorporate prescriptive logical rules into the existing model.
- **Benefits:** avoid the expensive and time-consuming effort of annotating the data every time the prediction of a new label is required
- To our knowledge, this type of framework has not been applied to the fully-unsupervised problem of unseen-labels prediction.

Can we extend a system to **predict a new label without** any **additional data** and **without degrading the existing system**?

2. Multi-Domain Dialog State Tracker

A **Dialog State Tracker** predicts the **user's intent (state)** at any point of an ongoing conversation.

For example:

```
- User: Hi, can you help me find a place to eat on the north side?
  True State: {restaurant-area-north}
  System: Yes, we have 15 options, any preferences for price range?

- User: Yes, are there any expensive ones?
  True state: {restaurant-area-north, restaurant-pricerange-expensive}
  System: There are 2 expensive places, both Italian.
  ...
```

MultiWOZ 2.0 dataset [1]

- **9855 dialogues**
- **663 different domain-slot-value triplets**:
  - distributed across **27 slots** (food, area, price range, etc.) in **5 domains** (restaurant, hotel, attraction, train, taxi)

Multi-domain Neural Belief State Tracker [2]

Multi-layer networks with RNNs to model the user and system utterances, and the flow of the conversation.

3. Rules definition

R_1: **IF** the user said a word like expensive **AND** also a word like hotel **THEN** predict {hotel-pricerange-expensive}

R_2: **IF** the previous prediction contains {hotel-pricerange-expensive} **AND** the user did **NOT** said a word like moderate **AND** did **NOT** said a word like cheap **THEN** predict {hotel-pricerange-expensive}

Logical Operators

NOT $\neg X =_{def} 1 - X,$

AND $X \wedge Y =_{def} X \cdot Y,$

OR $X \vee Y =_{def} \neg(\neg X \wedge \neg Y) = X + Y - XY$

IMPLICATION $X \rightarrow Y =_{def} \neg(X \wedge \neg Y) = 1 - X(1 - Y)$

$$R_1 : (In_{thresh=c}(utt, \text{EXPENSIVE}) \wedge In_{thresh=c}(utt, \text{HOTEL})) \rightarrow Assert(b_t, \text{HOTEL-PRICERANGE-EXPENSIVE})$$

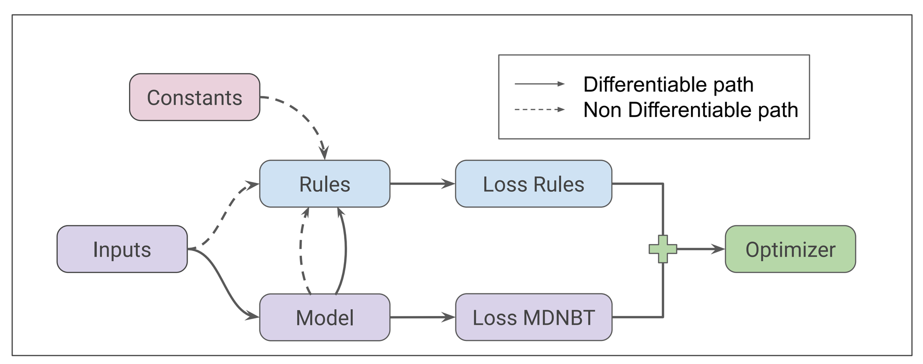
$$R_2 : Assert(b_{t-1}, \text{HOTEL-PRICERANGE-EXPENSIVE}) \wedge \neg(In_{thresh=c}(utt, \text{MODERATE}) \wedge \neg(In_{thresh=c}(utt, \text{CHEAP}) \rightarrow Assert(b_t, \text{HOTEL-PRICERANGE-EXPENSIVE})$$

4. Learning Mechanism

We use a simple posterior regularization approach to introduce the rules into the learning process

$$\mathcal{L}(\theta; \mathcal{D}; \mathcal{Y}; \mathcal{R}) = \mathcal{L}_{MDNBT}(\theta; \mathcal{D}; \mathcal{Y}) + w\ \mathcal{L}_{rules}(\theta; \mathcal{D}; \mathcal{R})$$

$$\mathcal{L}_{rules}(\theta; \mathcal{D}; \mathcal{R}) = \sum_{r \in \mathcal{R}} \mathcal{L}_r(\theta; \mathcal{D}) = \sum_{r \in \mathcal{R}} 1 - truthiness_r(\theta; \mathcal{D})$$



Antecedent and consequent learning in Implication

$$\Delta_r \theta = -\lambda \big(d_X(\mathcal{L}_r) d_\theta(X) + d_Y(\mathcal{L}_r) d_\theta(Y) \big)$$

$$\mathcal{L}_r = X(1 - Y) \quad \text{and} \quad \nabla(\mathcal{L}_r) = (1 - Y, -X)$$

For example if X=1 and Y=0 (the implication is not satisfied)

$$\Delta_r \theta = -\lambda\, d_\theta(X) + \lambda\, d_\theta(Y)$$

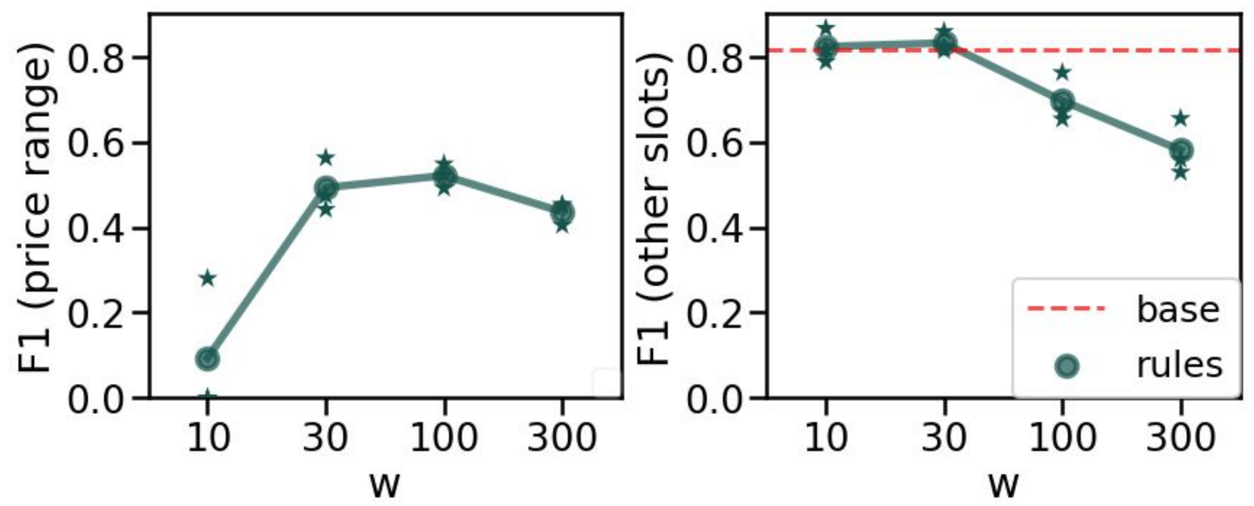
Thus, the network will update parameters in the direction of growth of Y and in the direction of decrease of X.

In rules of the form R_2 we avoid the learning through the antecedent by using non-derivable functions

5. Experiment

- We implemented rules of the form R_1 and R_2 for all the six possible combinations of domains (hotel and restaurant) and price ranges (cheap, moderate and expensive).
- We tested if this method allows the prediction of a new label by simulating an scenario in which we removed all existing annotations for the *price range* slot in the training set.
- We evaluated the performance of our model to predict the *price range* slot on the test set (which does have *price range* labels)
- For the remaining slots, we compared the performance of our rule-based model with a model trained in the same data and no rules. Here we tested if the addition of rules degrade the prediction capabilities over the rest of the labels
- In all evaluations, we used F1 score, measured by considering the correct and incorrect predictions in each slot of each domain.

6. Results



- There is a non-zero predictive capacity in the price range slot (left panel) for all rules-weight (w) values
- There is no performance degradation for the rest of the slots (right panel) for low rules-weight values (w =10, 30) (p-val>0.1). While values of w greater than 30 produce a notable decrease in the general performance (p-val = 0.06 and p-val= 0.004 respectively)

7. Discussion and Conclusions

- We show that it is possible to integrate rules into an existing system to allow the prediction of unseen labels (zero-shot learning) without degrading the predictive capabilities over the rest of the labels (as it is the case with w =30)
- It is necessary to pay special attention to the trade-off that is generated between learning the rules and the degradation of the system
- Our rules-based solution is independent of the neural network model and thus can be applied to any application (and neural network model) given the formulation of appropriate rules.

8. References

[1] Budzianowski, et al. "Multiwoz-a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling", EMNLP, 2018

[2] O. Ramadan, et al. "Large-scale multi-domain belief tracking with knowledge sharing", ACL, 2018