# A GENERALIZED RULE BASED TRACKER FOR DIALOGUE STATE TRACKING

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## ABSTRACT

Dialogue state tracking plays an important role in statistical dialogue management. Domain-independent rule-based approaches are attractive due to their efficiency, portability and interpretability. However, recent rule-based models are still not quite competitive to statistical tracking approaches. In this paper, a novel framework is proposed to formulate rule-based models in a general way. In the framework, a rule is considered as a special kind of polynomial function satisfying certain linear constraints. Under some particular definitions and assumptions, rule-based models can be seen as feasible solutions of an integer linear programming problem. Experiments showed that the proposed approach can not only achieve competitive performance compared to statistical approaches, but also have good generalisation ability. It is one of the only two entries that outperformed all the four baselines in the third Dialog State Tracking Challenge.

***Index Terms—*** Dialogue management, Dialogue state tracking, Rule-based model

## 1. INTRODUCTION

Dialogue state tracking plays an important role in dialogue management because it directly influences the choice of machine dialogue acts of the system to interact with users. However, inevitable automatic speech recognition and spoken language understanding (SLU) errors make it difficult to maintain the true dialogue state [1]. Hence, the distribution of dialogue states, also referred to as *belief state*, is usually tracked in state-of-the-art spoken dialogue systems. A well-founded theory for both dialogue state tracking and decision making has been offered by Partially observable Markov decision process (POMDP) framework [2–5]. Most earlier studies on state tracking in POMDP were devoted to generative models. In recent years, however, fundamental weaknesses of generative model was revealed by the results of [1]. In contrast, discriminative state tracking models were successfully used for spoken dialogue systems [6]. The results of the Dialog State Tracking Challenge (DSTC) [7] have further demonstrated the power of discriminative models.

Besides the change from generative models to discriminative models, there is another change which is from rule-based approaches to statistical approaches. Historically, most commercial systems have used hand-crafted rules for state tracking, selecting the SLU result with the highest confidence score so far and discarding alternatives [7, 8]. Conversely, statistical approaches compute a posterior distribution over multiple hypotheses for the dialogue state, and many competitive results are reported. Although there are more complicated rule-based approaches which can also compute scores for multiple hypotheses [9–11], in general, the performance of statistical approaches are shown superior in recent studies. Up to now, many discriminative statistical approaches including Maximum Entropy [12], Conditional Random Field [13], Deep Neural Network (DNN) [14], and Recurrent Neural Network [15] have been applied to dialogue state tracking and achieved large gains over conventional rule-based baselines.

This paper, however, proposes a new general framework to formulate rule-based models, which gets comparable or even better results than many statistical approaches. The general idea of the proposed approach is to depict rule-based models as a special kind of polynomial functions satisfying some linear constraints, referred to as *Markov Bayesian Polynomial* (MBP). Under certain assumptions, rule-based models can be seen as feasible solutions of an integer linear programming (ILP) problem, and generated. The models, i.e. the generated polynomial functions are then evaluated on training data to select the optimal model. Furthermore, as it is easy to generate various MBPs and model combination is usually effective [8, 12, 14–16], score averaging based combination is also investigated in this paper.

The DSTC provides a first common testbed in a standard format, along with a suite of evaluation metrics for dialogue state tracking [7]. To evaluate the effectiveness of the

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proposed approach, both the dataset from the second Dialog State Tracking Challenge (DSTC2) which is in restaurants domain [16], and the dataset from the third Dialog State Tracking Challenge (DSTC3) which is in tourists domain [17] are used. For both of the datasets, the dialogue state tracker receives SLU $N$-best hypotheses for each user turn, each hypothesis having a set of act-slot-value tuples with a confidence score. The dialogue state tracker is supposed to output a set of distributions for each of the three components of the dialogue state: *joint goals*, *method*, and *combined requested slots*. Note that it is possible that in some turn, some slots of the user's goal have not appeared in any SLU output. In such case, the labelled value is denoted as "the rest".

The rest of the paper is organized as follows. Section 2 presents the Markov Bayesian Polynomial framework. Section 3 describes rule generation in detail, followed by experiments in section 4. Finally, section 5 concludes the paper.

## 2. MARKOV BAYESIAN POLYNOMIAL

Due to space limitation, only the rule based approach for joint goals is described in detail in section 2 and 3. The approach for method and combined requested slots can be obtained with just slight modifications of the approach for joint goals.

### 2.1. Assumptions and definitions

**Definition 1.** For slot $s$, the $i$-th turn and value $v \neq$ "$the\ rest$", $p^+_{s,i}(v)$, $p^-_{s,i}(v)$, $\tilde{p}^+_{s,i}(v)$, $\tilde{p}^-_{s,i}(v)$, $b^r_{s,i}$, and $b_{s,i}(v)$, are defined as follows:

- $p^+_{s,i}(v)$ Summation of the scores of the SLU hypotheses informing or affirming that the value of slot $s$ is $v$.
- $p^-_{s,i}(v)$ Summation of the scores of the SLU hypotheses denying or negating that the value of slot $s$ is $v$.
- $\tilde{p}^+_{s,i}(v) = \sum_{v' \neq v} p^+_{s,i}(v') \quad v' \neq$ "$the\ rest$"
- $\tilde{p}^-_{s,i}(v) = \sum_{v' \neq v} p^-_{s,i}(v') \quad v' \neq$ "$the\ rest$"
- $b^r_{s,i}$ The belief of "the value of slot $s$ being '$the\ rest$' in the $i$-th turn" given by the rule-based model.
- $b_{s,i}(v)$ The belief of "the value of slot $s$ being $v$ in the $i$-th turn" given by the rule-based model.

Different slots are assumed to be independent for the proposed approach in this paper, so the belief of joint user goal $(s_1 = v_1, s_2 = v_2, \ldots)$ in the $i$-th turn is calculated by:

$$\prod_j \hat{b}_{s_j,i}(v_j) \tag{1}$$

where $j$ enumerates all slots and $\hat{b}_{s_j,i}(v_j) = b_{s_j,i}(v_j)$ if $v_j$ is not "$the\ rest$", otherwise $\hat{b}_{s_j,i}(v_j) = b^r_{s_j,i}$.

The proposed approach is assumed to be independent of slot, that is, different slots are assumed to use one common model. Based on that, the slot index $s$ will be omitted in the following text to keep the notation uncluttered.

Without loss of generality, in this paper, the score from SLU is assumed to have been mapped to $[0, 1]$; for each slot of each turn, the sum of all scores from SLU is 1; the belief given by the rule-based model is in $[0, 1]$; and the sum of all beliefs given by the rule-based model in one turn is 1. With these assumptions, the following inequalities hold:

$$0 \leq p^+_i(v) \leq 1 \tag{2}$$
$$0 \leq p^-_i(v) \leq 1 \tag{3}$$
$$0 \leq p^+_i(v) + p^-_i(v) + \tilde{p}^+_i(v) + \tilde{p}^-_i(v) \leq 1 \tag{4}$$
$$0 \leq b_i(v) \leq 1 \tag{5}$$
$$0 \leq b^r_i \leq 1 \tag{6}$$
$$b^r_i = 1 - \sum_{v'} b_i(v') \tag{7}$$

**Definition 2.** A *Bayesian polynomial* model is a general rule-based model, defined as a polynomial function $f$ to calculate $b_{i+1}(v)$ , which satisfies inequalities (5), (6), (7):

- If $i + 1 > 0$,

$$b_{i+1}(v) = f(\bigcup_{j \leq i} \{p^+_{j+1}(v), p^-_{j+1}(v), \tilde{p}^+_{j+1}(v), \tilde{p}^-_{j+1}(v), b^r_j, b_j(v)\}) \tag{8}$$

- Otherwise,

$$b_{i+1}(v) = 0 \tag{9}$$

**Definition 3.** A Bayesian Polynomial model is further called a *Markov Bayesian Polynomial* (MBP) model if for $i + 1 > 0$,

$$b_{i+1}(v) = f(p^+_{i+1}(v), p^-_{i+1}(v), \tilde{p}^+_{i+1}(v), \tilde{p}^-_{i+1}(v), b^r_i, b_i(v)) \tag{10}$$

**Definition 4.** A regular MBP model of order $k$ is an MBP model with polynomial order $k$ and all coefficients of $f$ is in $\{-1, 0, 1\}$.

In this paper, MBP, especially regular MBP is the focus.

### 2.2. Additional Constraints

Rule-based models that have good performance are supposed to be found in the space of the regular MBP. One direct way to check whether there exist good models in the space and (if exist) further pick out the good models is by enumerating all models in the space and testing them on the training data. However, the trivial search space of regular MBP of order $k$ is $3^{(k+1)(k+2)(k+3)(k+4)(k+5)(k+6)/720}$, so despite that the space of regular MBP is much smaller than that of definition 2 and 3, even for $k = 3$, the space is still too large to explore. It is notable that although the space is large, most of the models do not work well, so additional constraints from basic experience can be used to significantly reduce the number of bad models. Adding these constraints can be considered as applying prior knowledges.

- If neither positive nor negative information is collected, the belief should not change.

$$p_{i+1}^{+}(v) = 0 \wedge p_{i+1}^{-}(v) = 0 \wedge \tilde{p}_{i+1}^{+}(v) = 0 \wedge \\ \tilde{p}_{i+1}^{-}(v) = 0 \Rightarrow b_{i+1}(v) \equiv b_i(v) \tag{11}$$

  where here "$\wedge$" and "$\Rightarrow$" are used to denote logical conjunction and material implication respectively.

- If both ASR and SLU is perfectly correct, that is, 1 is assigned to all correct values and 0 to all incorrect values, then the model should always give the correct result. Considering the special case that there is only one value which is not "$the\ rest$", the following 3 constraints can be obtained.

$$p_i^{+}(v) = 1 \Rightarrow b_i(v) \geq 0.5 \tag{12}$$
$$p_i^{-}(v) = 1 \Rightarrow b_i(v) \leq 0.5 \tag{13}$$
$$p_i^{+}(v) = 0 \wedge \tilde{p}_i^{+}(v) = 1 \Rightarrow b_i(v) \leq 0.5 \tag{14}$$

- The belief should be unchanged or positively correlated with the positive scores from SLU.

$$\frac{\partial f(x_1, x_2, x_3, x_4, x_5, x_6)}{\partial x_1} \geq 0 \tag{15}$$

  where here the expression $f$ is corresponding to definition 3, and $x_1, x_2, \ldots, x_6$ are variables used to express the parameters of $f$.

- The belief should be unchanged or negatively correlated with the negative scores from SLU.

$$\frac{\partial f(x_1, x_2, x_3, x_4, x_5, x_6)}{\partial x_2} \leq 0 \tag{16}$$

- The belief should be unchanged or negatively correlated with the sum of the positive scores of the other values.

$$\frac{\partial f(x_1, x_2, x_3, x_4, x_5, x_6)}{\partial x_3} \leq 0 \tag{17}$$

- The belief should be unchanged or positively correlated with the sum of the negative scores of the other values.

$$\frac{\partial f(x_1, x_2, x_3, x_4, x_5, x_6)}{\partial x_4} \geq 0 \tag{18}$$

- The belief of the current turn should be unchanged or positively correlated with the belief of the last turn.

$$\frac{\partial f(x_1, x_2, x_3, x_4, x_5, x_6)}{\partial x_6} \geq 0 \tag{19}$$

The constraints help significantly reduce the search space. For example, with constraint (11), the trivial search space of regular MBP of order $k$ reduces to a $3^{(k+1)(k+2)/2}$-th of its former size (The proof is not provided due to space limitation). Different constraints contribute differently to the reduction of search space, and accurate analysis of search space reduction with joint constraints is left for future exploration. In later sections, $\mathcal{M}(k)$ is used to denote the space of the regular MBP of order $k$ with constraints (11) - (19).

## 3. RULE GENERATION AND SELECTION

Since $\mathcal{M}(k)$ with $k = 1$ or $k = 2$ is too small with few elements and $\mathcal{M}(k)$ with $k \geq 4$ is too large to enumerate all elements, $\mathcal{M}(3)$ is chosen as the suitable space to explore. However, although $\mathcal{M}(3)$ is not very large, it is still difficult to enumerate all elements directly because it is hard to check the exact constraints. The idea to solve that problem is to enumerate a superset of $\mathcal{M}(k)$ by relaxing the constraints. With the relaxation, the exact constraints are approximated by a number of easy-to-evaluate linear constraints. Superset generation is then formulated as a problem of calculating all feasible solutions of an ILP problem. Constraint relaxation is reasonable because the aim of enumerating elements is to provide candidates for optimal rule selection: on the one hand, no candidate will be lost if a superset is provided, on the other hand, over-generation provides chances to find better models. To simplify the presentation, the set consisting of all possible $(p_i^{+}(v), p_i^{-}(v), \tilde{p}_i^{+}(v), \tilde{p}_i^{-}(v), b_i^{r}, b_i(v))$ tuples is denoted by $\mathcal{X}$:

$$\mathcal{X} = \{(a_1, a_2, a_3, a_4, a_5, a_6) | 0 \leq a_1 \leq 1 \wedge 0 \leq a_2 \leq 1 \wedge \\ 0 \leq a_3 \leq 1 \wedge 0 \leq a_4 \leq 1 \wedge a_1 + a_2 + a_3 + a_4 \leq 1 \wedge \\ 0 \leq a_5 \leq 1 \wedge 0 \leq a_6 \leq 1 \wedge a_5 + a_6 \leq 1\} \tag{20}$$

The coefficients of a polynomial of $\mathcal{M}(3)$ is denoted by $w_{ijk}$:

$$f(a_1, a_2, a_3, a_4, a_5, a_6) = \sum_{0 \leq i \leq j \leq k \leq 6} w_{ijk} a_i a_j a_k \tag{21}$$

where $a_0 = 1$.

By definition 4, $w_{ijk}$ is integer and

$$-1 \leq w_{ijk} \leq 1 \tag{22}$$

The conversion from the exact constraints to the relaxed linear constraints is discussed in detail as below. For approximation purpose, two interval sequences, $T_5$ and $T_{10}$, need to be defined first:

$$T_5 = \{0, 0.2, 0.4, 0.6, 0.8, 1\}$$
$$T_{10} = \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$$

A number of theorems are then proved for the constraints approximation.

**Theorem 1.** If a rule satisfies constraints (5), (6), (7), then the rule satisfies the following sets of linear constraints:

$$\{0 \le f(\boldsymbol{a}) \le 1 | \boldsymbol{a} \in \mathcal{X}, a_i \in T_5\} \tag{23}$$

$$\begin{aligned}&\{0 \le f(\boldsymbol{a}) + f(\boldsymbol{b}) \le 1 | \boldsymbol{a}, \boldsymbol{b} \in \mathcal{X}, a_1 + a_3 = b_1 + b_3,\\ &a_2 + a_4 = b_2 + b_4, a_1 \le b_3, b_1 \le a_3, a_2 \le b_4, b_2 \le a_4,\\ &a_5 = b_5, a_5 + a_6 + b_6 = 1, a_i, b_i \in T_5\}\end{aligned} \tag{24}$$

*Proof.* The set of linear constraints (23) can be obtained by constraint (5). By combining constraint (6) and (7), it can be proved that $0 \le \sum_{v'} b_i(v') \le 1$. Thus the set of linear constraints (24) can be obtained by considering the special case that there are at least 2 values which are not "*the rest*". □

**Theorem 2.** A rule satisfies constraint (11) if and only if

$$\begin{aligned}w_{000} = w_{005} = w_{055} = w_{056} = w_{066} =\\ w_{555} = w_{556} = w_{566} = w_{666} = 0\end{aligned} \tag{25}$$

and

$$w_{006} = 1 \tag{26}$$

*Proof.* Suppose constraints (25) and (26) hold. Under the condition $p^+_{i+1}(v) = p^-_{i+1}(v) = \tilde{p}^+_{i+1}(v) = \tilde{p}^-_{i+1}(v) = 0$, then for all $v$, $(p^+_{i+1}(v) = p^-_{i+1}(v) = 0)$ by definition 1 and constraints (2)(3). Thus by definition 3 and equation (21)

$$\begin{aligned}b_{i+1}(v) \equiv\; & w_{000} + w_{005}b^r_i + w_{055}(b^r_i)^2 + w_{056}b^r_i b_i(v)\\ &+ w_{066}(b_i(v))^2 + w_{555}(b^r_i)^3 + w_{556}(b^r_i)^2 b_i(v)\\ &+ w_{566}b^r_i(b_i(v))^2 + w_{666}(b_i(v))^3 + w_{006}b_i(v)\\ \equiv\; & b_i(v)\end{aligned}$$

Therefore, constraint (11) holds. Reversely suppose constraint (11) holds, it is easy to check that under the condition that $p^+_{i+1}(v) = 0 \wedge p^-_{i+1}(v) = 0 \wedge \tilde{p}^+_{i+1}(v) = 0 \wedge \tilde{p}^-_{i+1}(v) = 0$, if at least one of constraint (25) or (26) does not hold, the identity "$b_{i+1}(v) \equiv b_i(v)$" does not hold. □

**Theorem 3.** If a rule satisfies constraints (12), (13), (14), then the rule satisfies the following set of linear constraints:

$$\{f(1, 0, 0, 0, a_5, 0) \ge 0.5 | a_5 \in T_{10}\} \tag{27}$$

$$\{f(0, 1, 0, 0, a_5, a_6) \le 0.5 | a_5, a_6 \in T_{10}, a_5 + a_6 = 1\} \tag{28}$$

$$\{f(0, 0, 1, 0, a_5, a_6) \le 0.5 | a_5, a_6 \in T_{10}, a_5 + a_6 = 1\} \tag{29}$$

*Proof.* The set of linear constraints (27) can be obtained by simply combining constraint (12) and definition 3. The derivations for the sets of linear constraints (28) and (29) are similar. □

**Theorem 4.** If a rule satisfies constraints (15), (16), (17), (18), (19), then the rule satisfies the following sets of linear constraints:

$$\begin{aligned}&\{f(\mathbf{a}) \ge f(\mathbf{b}) | \mathbf{a}, \mathbf{b} \in \mathcal{X}, a_i \in T_5, \forall i \ne 1 (a_i = b_i),\\ &a_1 = b_1 + 0.1\}\end{aligned} \tag{30}$$

$$\begin{aligned}&\{f(\mathbf{a}) \le f(\mathbf{b}) | \mathbf{a}, \mathbf{b} \in \mathcal{X}, a_i \in T_5, \forall i \ne 2 (a_i = b_i),\\ &a_2 = b_2 + 0.1\}\end{aligned} \tag{31}$$

$$\begin{aligned}&\{f(\mathbf{a}) \le f(\mathbf{b}) | \mathbf{a}, \mathbf{b} \in \mathcal{X}, a_i \in T_5, \forall i \ne 3 (a_i = b_i),\\ &a_3 = b_3 + 0.1\}\end{aligned} \tag{32}$$

$$\begin{aligned}&\{f(\mathbf{a}) \ge f(\mathbf{b}) | \mathbf{a}, \mathbf{b} \in \mathcal{X}, a_i \in T_5, \forall i \ne 4 (a_i = b_i),\\ &a_4 = b_4 + 0.1\}\end{aligned} \tag{33}$$

$$\begin{aligned}&\{f(\mathbf{a}) \ge f(\mathbf{b}) | \mathbf{a}, \mathbf{b} \in \mathcal{X}, a_i \in T_5, \forall i \ne 6 (a_i = b_i),\\ &a_6 = b_6 + 0.1\}\end{aligned} \tag{34}$$

*Proof.* The rule satisfies the set of linear constraints (30) is because constraint (15) indicates $f(x_1, x_2, x_3, x_4, x_5, x_6)$ is monotonically increasing with respect to $x_1$. The derivations for the other sets of linear constraints are similar. □

By theorem 1, 2, 3 and 4, it can be seen that the linear constraints (23) - (34) relax the constraints (5) - (7), (11) - (19). Therefore, the optimal MBP for joint goals can be described as the solution of the following integer programming (IP) problem:

$$\begin{aligned}&\textbf{maximize} && L(w_{001}, w_{002}, \ldots, w_{666})\\ &\textbf{subject to} && \mathit{constraints}\ (22) - (34)\\ &\textbf{and} && \forall 0 \le i \le j \le k \le 6\ (w_{ijk} \in \mathbb{Z})\end{aligned}$$

where $L(w_{001}, w_{002}, \ldots, w_{666})$ is the accuracy of the performance of MBP with coefficients $w_{001}, w_{002}, \ldots, w_{666}$ on the training dataset and development dataset of DSTC2 whose details are described in section 4.1. Here the optimal MBP is selected from a superset of $\mathcal{M}(3)$ (denoted by $\mathcal{S}$) which is a relatively small set of valid MBP described by linear constraints (22) - (34). Note that each element of $\mathcal{S}$ is corresponding to a rule-based model. In practice, it takes 2 steps to solve that IP problem. First, $\mathcal{S}$ can be obtained with some ILP solvers by calculating all feasible solutions of linear constraints (22) - (34), which can be regarded as a special kind of ILP problem whose objective function is to optimize a constant dummy variable. In this work, SCIP [18] was used for calculation of all feasible solutions. Next, every element of $\mathcal{S}$ is evaluated by $L(\cdot)$, and the element maximizing $L(\cdot)$, that is, the optimal rule for joint goals (denoted by $f^*_g$), is the solution of the IP problem.

The optimal rule for method denoted by $f^*_m$ and the optimal rule for combined requested slots denoted by $f^*_r$ can be obtained following similar steps with slightly modifying the definitions and constraints in section 2. $f^*$ is used to denote the combined rule which utilizes $f^*_g$, $f^*_m$, and $f^*_r$ for tracking joint goals, method, and combined requested slots respectively.

## 4. EXPERIMENT

### 4.1. Data description

Datasets of DSTC2 and DSTC3 are listed in table 1.

| Dataset | ASR | DM | Number of dialogues |
|---|---|---|---|
| dstc2_train | 0,1 | 0,1 | 1612 |
| dstc2_dev | | 0,1 | 506 |
| dstc2_test | | 2 | 1117 |
| dstc3_seed | 2,3 | 3,4,5,6 | 10 |
| dstc3_test | | 3,4,5,6 | 2265 |

**Table 1**. Speech recognisers (ASR), dialogue managers (DM) and the number of dialogues of different datasets. Different numbers in column ASR and DM indicate different speech recognisers and dialogue managers respectively.

Since our previous work showed the live semantic information was not good enough with some information lost [14], all experiments in this paper used the output from a new implemented semantic parser whose details are shown in [14] and [19] instead of the live SLU. The training dataset and the development dataset of DSTC2 are combined to form the dataset for optimal MBP model selection.

### 4.2. Performance

As recommended by DSTC2 and DSTC3, **Accuracy** measuring 1-best quality, **L2 norm** measuring probability calibration are selected as evaluation metrics in this paper. Moreover, schedule 2 and labelling scheme A [20] are employed. There are 4 baseline trackers provided by the DSTC organisers. They are the baseline tracker (Baseline), the focus tracker (Focus), the HWU tracker (HWU) and the HWU tracker with "original" flag set to (HWU+) respectively.

| | Goal | Method | Request |
|---|---|---|---|
| Baseline | 0.668 | 0.846 | 0.945 |
| Focus | 0.743 | 0.926 | 0.924 |
| HWU | 0.750 | 0.934 | 0.932 |
| HWU+ | 0.720 | 0.932 | 0.934 |
| DNN | 0.755 | 0.942 | 0.979 |
| $f^*$ | 0.760 | 0.934 | 0.979 |

**Table 2**. Accuracy of performance of $f^*$ compared with DNN and 4 baselines on the test dataset of DSTC2 (dstc2_test).

$f^*$ was tested on the test dataset of DSTC2 and the result is shown in table 2. It can be seen from the result that $f^*$ performs significantly better than all baselines of DSTC2[1], and has competitive performance compared to the DNN approach in our previous work [14].

$f^*$ was then tested on the test dataset of DSTC3, which tests the generalisation ability. It can be seen from table 3 that the proposed approach has better generalisation ability than the DNN approach.

[1]Test of significance shows it is at the 95% level that $f^*$ has higher accuracy of joint goals than that of all baselines except for HWU where more data is needed to claim the significance with 95% confidence.

| | | Goal | Method | Request |
|---|---|---|---|---|
| Accuracy | DNN | 0.583 | 0.968 | 0.945 |
| | $f^*$ | 0.606 | 0.968 | 0.945 |
| L2 | DNN | 0.583 | 0.053 | 0.091 |
| | $f^*$ | 0.561 | 0.091 | 0.090 |

**Table 3**. Performance of $f^*$ compared with DNN on the test dataset of DSTC3 (dstc3_test)

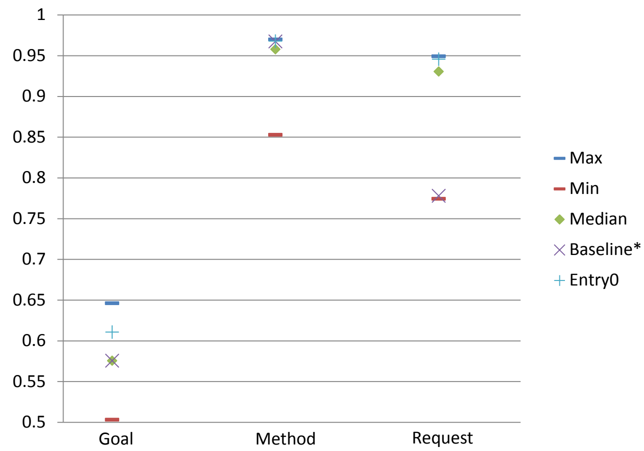


**Fig. 1**. Accuracy of performance among 28 trackers in DSTC3. Entry0 is the proposed approach with score averaging. Baseline* is the result of the best results from the 4 baselines in DSTC3.

As it is easy to generate various MBPs with the proposed approach, instead of only using the rule with the highest accuracy, for joint goals, score averaging was investigated and found to have better result than only using the rule with the highest accuracy. Therefore, the model submitted to DSTC3 was a model which used $f_m^*$ and $f_r^*$ for method and requested slots respectively and used a combined model which outputs the average score of the 5 rules with the highest accuracy in $\mathcal{M}(3)$ for joint goals. With score averaging, the accuracy for joint goal increases further from $f^*$'s $0.606$ to $0.610$ and it is found to be one of the only two entries that outperformed all the four baselines in DSTC3. The performance of the proposed approach with score averaging in DSTC3 is shown in figure 1[2].

## 5. CONCLUSION

This paper proposes a novel framework, referred to as *Markov Bayesian Polynomial* (MBP), to formulate rule-based models. Rule-based models are depicted as a special kind of polynomial functions satisfying some linear constraints. Experiments show the proposed approach not only has competitive

[2]For readers who are interested in performance of MBP with the original live SLU, the result is as follows: the accuracy of $f^*$ using the original live SLU for joint goals, method, and requested slots is $0.582$, $0.967$, $0.909$ respectively, while the result of bestline* in figure 1 is $0.575$, $0.967$, $0.778$.

performance, but also has relative good generalisation ability. Future work will further discuss the constraints for rule formulation, and explore applying MBP to a wide variety of domains. Furthermore, because our most recent result has suggested that polynomial functions with real coefficients have even better performance, the future work will also do some more research work on polynomial functions with real coefficients.

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