Abstract

We developed a machine learning approach that quantifies multiple aspects of the success or values in Customer Service contacts, at anytime during the interaction. Specifically, the value/reward function regarding to the turn-level behaviors across human agents, chatbots and other hybrid dialog systems is characterized by the incremental information and confidence gain between sentences, based on the token-level predictions from a multi-task neural network trained with only weak signals in dialog-level attributes/states. The resulting model, named Value Profiler, serves as a goal-oriented dialog manager that enhances conversations by regulating automated decisions with its reward and state predictions. It supports both real-time monitoring and scalable offline customer experience evaluation, for both bot- and human-handled contacts. We show how it improves Amazon customer service quality in several applications.

1. Background and Motivation

Customer Service (CS) contacts are commonly studied in the domain of task-oriented dialogs, where many typical tasks are clear and well-defined, e.g. movie and restaurant reservation. These simple tasks can be abstracted as different API calls, with slots to be filled with key entities extracted by Natural Language Understanding (NLU) and Dialog State Tracking (DST) from the conversation. The success of such a dialog is naturally defined as task completion, e.g. booking confirmed in the system. However, real life CS contacts for a company with various lines of products are complex, ambiguous and open-ended. In fact, many customer issues are manifests of failures in either functionality or reachability of the current system solutions. As a result, most CS contacts in real world are handled by human agents, with assistance from a dialog system, ranging from a simple call handler to full-fledged chatbots. The task diversity and complexity pose challenges in these hybrid systems for both dialog evaluation (assess the goodness of bot and agent behaviors) and imitation learning (train bots or design rules based on good agent behaviors).

We take the Amazon CS dialog system as an illustrative example for such hybrid systems, but the discussions are general to any goal-oriented dialog system with a similar data format. Amazon has a huge amount of CS contacts every day from world-wide via either phone calls, online chats or emails, and the level of scale and growth in the number of contacts demands automated solutions to customer issues in a timely and satisfactory manner. Amazon’s online CS text chat channel is available to customers on mobile apps and desktops. See Figure 1 for an overview. The hybrid dialog system is supported by a combination of rules, machine learning (ML) powered chatbots and human agents. Customers are first guided through a ‘workflow’ (WF) bot, consisting of a collection of designed dialog trees for related customer intents. Different WFs are triggered

Figure 1. Outline of the Amazon CS dialog interface for text chat. Left: components including WorkFlow (NLU+DST), Response Generator (neural text generation) and human agents. Right: user interface on Amazon mobile app.
by customers clicking preset buttons (e.g. questions about prime membership) and sometimes entering free texts to describe their needs. Certain contacts can be auto-resolved by related WFs, while others are routed to customer service human agents (CSA) with various skill sets. During the CSA session, a deep learning-based chatbot, Response Generator (RG; Lu et al., 2018), which is trained on historical contact transcripts, recommends a list of text responses for CSAs to choose from and edit, in order to save typing and increase efficiency.

Such hybrid systems have drawbacks in each of the components. (1) There lacks a comprehensive and quantitative understanding about the success or progress of the complex conversation during the customer-agent interaction. Although CSAs had proper training, their responses are not necessarily optimal. Most importantly, there is no data-driven attribution to actions: what can we do to actually improve our service? (2) Rule-based dialog systems (WF) require significant human efforts in design and do not scale beyond top few cases. (3) Dialog generators (RG) learn how to respond by imitating the most probable past human (CSA) behavior. Intuitively, dull phrases that do not carry information are prevalent in conversations under any situation, so they are ‘safe bets’ for the model to predict. This leads to a preference to generate conversation fillers (Thanks; A moment please; Sure) instead of conversation drivers (I have processed your refund; May I know the reason of the return). The three problems share a common solution: the ability to compute and understand at scale the values of any conversation turn and the overall quality.

For evaluating complex dialogs, human annotation is the gold standard but not scalable. Most automatic metrics for text generation, e.g. BLEU, Perplexity, and the recent developed embedding-based ones like BERTScore (Zhang et al., 2019) and MoverScore (Zhao et al., 2019), are surrogates of text likelihood or similarity, neither measuring the impact of dialog, nor indicating how to best influence it. In contrast, business metrics focus on the final impact, not the text itself. For example, metrics for contact quality may include no-recontact, whether the customer calls back in 24 hours, hows-my-driving, a yes-no survey sent after a contact, and agent-handling-time. However, the signals from these metrics are noisy, partial (e.g. no-recontact or short handling-time could be a result of customer frustration) and confounded (e.g. hows-my-driving survey, if ever responded, reflects customer’s sentiment, not necessarily the quality of service). These metrics are also sparse signals at dialog-level and not directly relevant to turn-level actions - the latter is the key to automatic opportunity seeking and optimization.

For the propensity to generate repeated, dull texts (text degeneration) of likelihood-based models, it is an active research field with solution proposals in either model training or decoding (Li et al., 2015; Holtzman et al., 2019; Welleck et al., 2019). Though for goal-oriented dialogs, if there exists a well-defined and strong indicator of success, e.g. booking confirmed, state-of-the-art methods can incorporate this reward signal into model training by Reinforcement Learning techniques, so that the text generator learns to maximize success (Zhao and Eskenazi, 2016; Dhingra et al., 2016; Kandasamy et al., 2017; Lipton et al., 2017; Zhou et al., 2017). However, as discussed, it is difficult to find such signals for complex dialogs like CS contacts. Therefore it is necessary to first design a business-aligned Value/Reward/Critic based on some weak but scalable signals, in order to train a Policy/Agent/Actor to make decisions that add most value.

Our contribution This work aims to attack the above challenges in separate components of a bot-human hybrid CS dialog system, with a single end-to-end solution. (1) In term of application, we present Value Profiler (VP), a multi-task neural network that reads customer contact conversation, assesses the situation and acts in real time to maximize the newly defined value/success, serving as a data-driven dialog manager to regulate natural language understanding/generation and dialog state tracking. (2) As for methodology, we propose a new formulation to evaluate goal-oriented dialog agent behaviors at scale and to design turn-level reward functions for bots, with the presence of only dialog-level attributes as weak signals.

In Section 2 we detail the Value Profiler model, and test its performance with experiments for different application areas in the Amazon customer service domain in Section 3. Additional related research work is reviewed in Section 4. Section 5 concludes the paper with future plans.

2. Method

The methodology is introduced in the following steps: (1) problem formulation - how to quantify the qualitative criteria of a successful CS contact, using the available datasets and a predictive model; (2) predictive model design details; (3) how to define the values based on the predictions and apply in practice.

2.1. Problem Formulation and Data

Without a single gold standard, we argue that a successful customer service contact is supported by the following aspects:

- the agent understands customer’s issue well
- the agent knows which action to take
- the contact outcome satisfies the customer
- the above process induces low costs
These criteria can be translated into some equivalent ones in statistics and ML terms, changing the subject from a human to a bot or model:

- a model predicts issues with high confidence
- a model predicts actions with high confidence
- a model predicts high $P$(no-re-contact)$^3$
- a model predicts low costs with confidence

This formulation translates the assessment of success criteria into a multi-task supervised learning problem (classification for issue/action/no-re-contact, regression for costs). The model is required to be calibrated, i.e. its outputs are proper probability distributions that faithfully reflect the underlying uncertainties within the data generation process, so that the model confidence measure is reliable. We defer the essential discussion of how to compute the level of model confidence and the value progress within the dialog to Section 2.3, and for now focus on this predictive model itself.

We briefly describe the high-level data structure need for the this formulation. Dialog texts need to contain all utterances from bot, customer and agent, with sensitive information removed. The issue could simply be a categorical variable, or has multiple layers of hierarchical tree structure, e.g. 3 layers from the most abstract level (e.g. digital and device), to the finest grain with more concrete cases (e.g. item received not expected). For the dataset used in this paper, the action labels are noisy and not turn-aligned so they are used also as a dialog-level outcome. Actions can be merged into some main categories (e.g. refund created) to avoid sparsity. Recontact within certain time should be well-defined. In this text we focus on the values in issue/action/recontact, and leave the cost aspect to future work.

In general, the required datasets are simply conversation texts and dialog-level outcomes, some of them we have a preference (no recontact, low costs), some of them we want to be as sure as possible (issue, action). A different goal-oriented dialog application could plug in its own available labels, e.g. dialog states slot values and the downstream impacts, and all discussions apply.

### 2.2. Value Profiler Predictive Model

Essentially, Value Profiler (VP) is a multi-task (predict issues, actions, recontact, etc.), token-level (predict at each token) sequential supervised learning model. See Figure 2 for illustration. The input to VP is the conversation history in the form of a sequence of tokens: $x_{t,i} = (x_{1,i}, \ldots, x_{t,i})$ where $i$ is dialog index and $t$ is token index. A causal-masked encoder $h(\cdot)$ then process the texts in a left-to-right manner, and outputs predictions at each token $\hat{y}_{t,i} = h(x_{t,i})$. The causal masking ensures the output at certain token only depends on the history, and any encoders with causal property can apply. In this paper, the pretrained transformer transformer GPT2 (Radford et al., 2019) is used and benchmarked with two common choices: LSTMs and dilated causal 1D CNNs (Oord et al., 2016).

For the three tasks, VP takes issue (or each leaf node of the issue tree) as a multi-class classification problems in the common softmax-cross-entropy setup. The action task is treated as a multi-label classification problem, consists of a set of binary classifications. This setup is a result of data structure: most dialogs have only a single intent, while multiple actions could be performed. Finally no-re-contact is simply another binary classification for customer satisfaction.

The prediction tasks are at token or sentence-level to enable dialog evaluation at any point, for any actions presented in the texts. Since all target signals are dialog-level, they are replicated along the sequence: $y_{t,i} = y_i$. This effectively trains all possible prediction scenarios within a conversation at the same time in a single sample (if length permits): $\hat{y}_{t,i} = h(x_{t,i})$ where $h$ is causal so $\hat{y}_{t-k,i}$ is generated only using the $x_{t-k,i}$ part of the input. The loss for the $i$th sample/dialog is defined as the sum of token-level losses: $\sum_i L(\hat{y}_{t,i}, y_i)$. This setup also naturally reflects the incremental elimination of uncertainty: at the beginning of the conversation/sequence, there is barely any information to predict the outcome, so the output probability should be around the population frequencies of classes in training samples. As conversation progresses, the output probability density will gradually grow sharper and concentrate towards the true label. This observation is essential to the value definition. Given the goal of value assessment, the predictions themselves are side-effects. However a well-tested high performance predictive model is not only beneficial to systems

$^3$Throughout this text, no-re-contact is used to measure customer satisfaction, for demonstration. Note hows-my-driving survey result is in exactly the same binary yes/no format so all discussion applies to it.
which can directly utilize its predictions (e.g. DST could be one of the tasks), but also more convincing for practitioners to rely on its value estimations.

2.3. Value Function

In Section 2.1 we discussed two kinds of tasks, one with a preferred outcome, the other requiring confidence in prediction. For the three tasks, no-recontact belongs to the former since we pursue a high probability for it, so the value for this aspect can be simply set as \( v_{(\text{no-recon})} = P(\text{no recontact}). \) For issues and actions, there is no preference on one class over the others. Even for the binary actions, there is no preference on act versus do nothing - many CS contacts end up to be purely informational or educational. For them, we care about how much information the model has gained during the conversation to yield confidence. We define this kind of general information gain and confidence value as the KL-divergence between the prediction and the non-informative distribution:

\[
V(p) := D_{\text{KL}}(p \parallel p_0) = H(p, p_0) - H(p)
\]

where \( p \) is the model’s predicted distribution, \( H(\cdot, \cdot) \) the cross-entropy function and \( H(\cdot) \) the entropy function. \( p_0 \) is the constant population empirical distribution of the target across all training samples, as the best guess in case there is no information provided at all at testing time. Intuitively, negative entropy \(-H(p)\) measures the confidence or sharpness in the prediction. The cross-entropy term measures the gap between the \( p \) and \( p_0 \), namely how far the prediction is from the non-informative one. In summary, high \( V(p) \) means the model has obtained abundant knowledge to make confident predictions.

Furthermore, for prediction \( p_t \) generated at the \( t \)th token in the dialog sequences, \( V(p_t) - V(p_{t-k}) \) captures the value change caused by the \( k \) tokens in between. This yields a powerful approach to evaluate the reward or importance of any sentences in the conversation\(^4\). In general, \( R(t) := V(p_{t+1}) - V(p_t) \) enables token- or sentence-level reward shaping for reinforcement learning agents, in the case that there is no strong reward signals but some relevant while indirect dialog-level attributes. The main idea is: even not directly goal-related, more knowledge and less uncertainty is always a better state for any solution-driven agents. Note for goal-oriented dialog, it is also desirable to achieve a high-level of confidence early, so the turn-level value series \( \{V(p_t)\}_t \) contain information to measure the conversation progress efficiency, as detailed in Section 3.3.

For human inspection, the multi-dimensional value vector \( \{v_{(\text{issue})}, v_{(\text{action})}, v_{(\text{no-recon})}\} \) is helpful to analyze and interpret the bot or agent behaviors (e.g. 'bot said this to increase no-recontact probability'). For automated solutions, the value vector has to be collapsed into a scalar, to enable ranking and optimization. We recommend weighting the different dimensions based on the application with domain knowledge. For demonstration, though the different dimensions in the value vector are not on the same scale, we define

\[
\Delta V := \sum_{k=0}^{N} \left[ D_{\text{KL}}(p_t \parallel p_{t-k}) \right]
\]

\(4\)The value gain \( \Delta V \) is chosen instead of \( D_{\text{KL}}(p_t \parallel p_{t-k}) \), for the sake of computation, storage and conceptual simplicity with the unified baseline \( p_0 \). KL divergence does not satisfy triangle inequality so using it to compare any token pairs would cause inconsistency.

### Table 1: Issue prediction accuracy improved by VP, with 95% confidence interval, for top intents.

| Last WF Intent     | Acc. improved % | 95% CI      |
|--------------------|-----------------|-------------|
| account            | 78.13%          | [73.26, 82.69] |
| delivered-not-received | -0.03%       | [-0.06, 0.01] |
| item-delivered     | 1.72%           | [1.34, 2.07] |
| item-in-transit    | 2.51%           | [2.17, 2.87] |
| item-not-received  | -0.02%          | [-0.05, 0.01] |
| live-help-request  | 3.50%           | [3.24, 3.78] |
| order-related      | 6.18%           | [5.55, 6.76] |
| prime              | 59.00%          | [55.66, 62.37] |
| return-refund-status| -1.97%         | [-2.44, -1.5] |
| returns-refunds    | -0.65%          | [-1.59, 0.39] |
| start-return       | 0.02%           | [-0.02, 0.07] |
| unknown-charge     | 8.77%           | [8.15, 9.41] |
| wms                | 0.72%           | [0.44, 1.01] |
| all-other-intents  | 3.01%           | [2.69, 3.33] |
| TOTAL              | 3.76%           | [3.64, 3.88] |
the collapsed value as a simple weighted average:
\[
v = \alpha v^{\text{issue}} + \beta v^{\text{action}} + v^{\text{no-recon}}
\]

where \(\alpha\) and \(\beta\) are normalizing constants to be set empirically, so that the scales of value contribution are similar across the tasks\(^3\). Finally, although the cost aspect is not covered, the general regression variant of value definition is briefly discussed in Appendix A for completeness.

### 3. Applications

We assess the performance of Value Profiler on an Amazon Customer Service Contacts dataset for three general applications. 1.6MM text chat contacts (sensitive fields removed) for US marketplace are sampled with the corresponding targets described in Section 2.1, and split 90/10 into training and testing set. For quantitative evaluation, we investigate how VP can benefit rule-based dialog trees as well as state-of-the-art dialog generators (WF and RG; discussed in Section 1) by comparing metrics with or without VP’s input in carefully designed offline, and small scale online studies\(^4\). For qualitative evaluation, we show that the value estimates align with human judgments, by sampling non-cherry-picking random examples as test sets.

#### Model Details

The scrubbed transcript of each contact is tokenized by the GPT2 tokenizer (Byte-Pair Encoding) into a variable-length list of tokens. For training, a mini-batch of 32 samples is generated, each being a contact with 512 tokens. Contact shorter than 512 tokens are padded on the right, and those longer are randomly (different for each epoch) sub-sequenced into 512 tokens. The mini-batch goes into the causal encoder, the encoder outputs token-level embeddings, followed by a weight-shared hidden layer of size 128 with ReLU activation. Finally the model outputs the softmax or sigmoid probabilities for each class in each task. The targets are replicated across all tokens, and linked to the outputs with a cross-entropy loss. For the pre-trained GPT2 encoder, we use the Tensorflow implementation from Wolf et al., 2019 and fine-tune for 3 epochs; for CNN/RNN encoder, the model is trained from scratch with 100 epochs. Adam optimizer with learning rate 0.0001 is used for fine-tuning and 0.001 for full training. The output values are collapsed as described in the previous section then normalized. To stabilize variance, sentence-level value is computed as the moving average of 7 token-level values centered at the last token of the sentence if evaluating offline, or 4 preceding token-level values if predicting online. The model architecture and training setting is intended to be a bare minimal implementation for the functionality without hyperparameter tuning.

#### 3.1. Prediction Accuracy

In this application we show VP has high accuracy in the predictive tasks, as a piece of evidence to support our trust in its value estimation. VP predicts the contact issue, the resolving actions and recontact status, all of them can influence dialog management decisions. There is no existing benchmark for recontact and action prediction for this dataset, but the WF system has an NLU component and outputs intent predictions. We design the following experiment to compare the VP issue (intent) prediction against the whole WF dialog system, including the NLU component and other deterministic routing rules. We sample 68111 contacts with issue codes filled by CSAs after the contact, and examine the issue prediction by VP at the last WF sentence, right before CSA joins, against the issue code as the ground truth. The benchmark is set to be the actual last WF visited in this contact. The idea is that, the last WF (with its intent label) indicates the best guess from the whole WF system back then about the customer issue, and the VP prediction at the same time is a fair competitor, both compared to the final label by CSA.

Accuracy comparison is shown in Table 1, grouped by some major intents and VP is better in most cases. The accuracy advantage mainly comes from the most ambiguous intents (live-help-request, order-related) and those with confusing topics (unknown charge, account, prime). Though without previous benchmarks on this dataset, the metrics of action and recontact predictions are considered as reasonable: depending on predicting at which point during the conversation, the accuracy for no-recontact prediction is from 72% (non-informative) to 83% (after reading all 512 tokens); across action types, the action prediction precision at the end of the contact is from 58% to 94%, and recall from 42% to 92%. For reference, many actions have 99%+ negative labels. Error analysis was conducted with a random sample of size 20 from each task where the prediction and label disagrees. By human evaluation, VP predictions for 78.3% (47 out of 60) of these ‘wrong’ cases are in fact more or equally appropriate compared to the label. This means all above metrics are underestimates, and implies potential applications in label imputation and correction. Calibration analysis (not shown) indicates that for most tasks except few issue categories, the output distribution is well calibrated. Volatility analysis based on five replicated experiments with random seeds show the accuracy fluctuations are within 1%. The CNN/LSTM benchmarks are both 10%+ worse than GPT2 for all tasks thus not further investigated. See Appendix C for detailed volatility and CNN/LSTM results.

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\(^3\)Another candidate could be using the sum of empirical quantiles of all different values. This would be better in terms of a uniform normalization, while also being more risky in overlooking certain patterns.

\(^4\)Larger scale online tests are scheduled.
Table 2: 10 from the 60 samples comparing the original top-1 response from RG with the re-ranked top-1 after adding VP signals. Contexts are not shown. Human evaluation on the actual winner and the reason are listed, with the CSA's previous choice marked as italic.

| ID | Winner | Reason       | Model   | Top 1 Recommendation                      |
|----|--------|--------------|---------|------------------------------------------|
| 1  | VP     | informative  | RG      | Sure.                                    |
|    |        |              | VP      | Refund issued successfully.               |
| 2  | VP     | informative  | RG      | Sorry to hear that the item was damaged. |
|    |        |              | VP      | In this case, I can process the refund for you. |
| 3  | VP     | follows context | RG | Are you able to print your own label? |
|    |        |              | VP      | I’ve successfully created a return label for you. |
| 4  | VP     | follows context | RG | Anything else needs to be taken care of? |
|    |        |              | VP      | Replacement successful.                   |
| 5  | VP     | saved 2 turns          | RG      | Great!                                   |
|    |        |              | VP      | …you prefer refund in original payment method or gift card? |
| 6  | RG     | question repeats      | RG      | I have issued a refund in original payment method method… |
|    |        |              | VP      | Quick question: a refund in gift card or original payment… |
| 7  | RG     | offer too early      | RG      | Yes.                                     |
|    |        |              | VP      | Refund to original payment method or gift card? |
| 8  | both   | same meaning       | RG      | Refund to original payment method or gift card? |
|    |        |              | VP      | Quick question: a refund in gift card or original payment… |
| 9  | both   | clarification      | RG      | May I know the date, amount and last 4 digits of the card… |
|    |        |              | VP      | Let me check it for you.                  |
| 10 | both   | non-informative    | RG      | Thanks for understanding.                 |
|    |        |              | VP      | You’re welcome.                           |

3.2. Reward Signals for Text Generation

There are various ways that VP can inject the reward signals into any dialog generator: (1) post-process the recommendation list (i.e. beam search or retrieval results) and re-rank by the estimated rewards of each suggestion; (2) pre-process to assign sample weights to the text generator’s training set by the estimated reward of target sentences; (3) Off-line Reinforcement Learning: VP serves as a static critic to provide rewards to the text generator training through policy gradient. In this text we demonstrate the first two approaches for their simplicity in integration with an existing dialog generator, and leave (3) to future work.

Re-Ranking We sampled a separate set of 47078 contacts, from some previous online experiments where CSAs were asked to read through the suggestions from the text generator (RG), until spotting the first applicable response then select it. Top 4 suggestions from RG are gathered, each with a score. This score is either a negative log-likelihood or a retrieval matching score, depending on the two types of RG model (see Lu et al., 2018 for details). We gather scores from RG and reward estimates from VP for each list, normalize both into [0, 1], then take the average as the ensemble score representing both the likelihood and the value of a response. The agent’s turn acceptance rate (TAR-1; percentage of top-1 recommendations from RG gets accepted/chosen by CSAs) is considered as the gold standard to assess RG performance. Note it is not fair to use the TAR-1 computed from the VP-influenced ranking and CSA’s choice back then, because this is an offline dataset and the perception bias caused by the original ranking would dominate. Instead, we draw a random sample of size 30 from each of the two sets: (A) CSA accepted RG’s top-1 but VP has a different top-1; (B) CSA did not accept RG’s top-1 but VP re-ranks their choice as top-1. Through this small scale human evaluation, the behavior difference between the two models is analyzed below, with some examples from this analysis listed in Table 2. Results: 19 out of 30 (63%) in set A and 11 out of 30 (36%) in set B are contacts that both top-1 suggestion are acceptable or have the same meaning; note the percentage difference indicates the bias towards the original ranking. In the remaining 11 contacts in set A, RG response is indeed better than VP in 7 of them, all due to VP responses hurrying to a solution that is either too early or out of context; for the other 4 contacts, VP responses are more appropriate. In the remaining 19 contacts in set B, VP response is indeed better than RG for all of them, because RG’s original response was either non-informative or out of contexts. This agrees with our expectation.

Training Weights A separate small-scale Japanese marketplace online A/B experiment is conducted to compare RG
Apart from automation-related applications, Value Profiler (control) and the same RG trained with VP induced sample weights (treatment). The weights are estimated target rewards, normalized to [0, 1]. 4 suggestions are generated by each model for a test set of 500 contacts and sent to Japanese annotators to choose from. Results: treatment improves (% relative to control; with bootstrap 90% Confidence Interval) MRR (mean reciprocal rank) by 4.04% (-1.6% ~ 9.61%) and TAR-1 by 8.64% (-3.29% ~ 20.39%). Statistical insignificance should come from limited sample size and noisy annotation, as the CIs are pretty wide. A larger size study is planned. Error analysis showed similar qualitative result as the re-ranking.

3.3. High Value Sentences and Dialogs for Contact Understanding

Apart from automation-related applications, Value Profiler enables scalable CS contacts understanding and evaluation, to minimize the effort in contact reading by specialists or sending contact survey with sparse response. VP automatically quantifies the conversation progress, and labels different aspects of the contact up to word-level granularity. For any part of the conversation, VP can quantify its contribution to the multi-aspect success: reducing recontacts, acquiring information, and reducing costs. This contribution could be positive, negative or insignificant. In Table 3, some randomly sampled sentences are listed, representing top positive, negative and near-zero reward for each aspect. Extracting high-value sentences not only provides insights and highlights of the contact, but also can assist the design of dialog system actions: if uncertainties are observed in some aspect, the system can select a question that historically results in huge information gain in the subsequent turn regarding to that aspect. We leave this as future work.

To evaluate whole dialog quality, we need more than turn-level rewards. As shown in the upper part of Figure 2, the ideal value progress starts from zero (non-informative), quickly climbs up (acquire/provide information) and saturates at a high level (resolved and satisfied). To quantify this intuition, we propose to evaluate dialog quality by comparing its value progress curve (value vs #turns) with the quantile curves of reference coordinated. For all the value curves from a subset of contacts, the quantile curves are defined as the connected point-wise empirical quantiles for each turn. For example, the P90 quantile curve consists of \( \hat{v}_t^{(0.9)} \) for each \( t \), so that \( P(v_{i,t} \leq \hat{v}_t^{(0.9)}) = 0.9 \) across the all samples. This can be interpreted as the P90 curve is higher than 90% of the contact curves. This quantile comparison yields a relative criteria to define high/low-value contacts and quantify its progress. In Figure 3, the value curves of 300 random contacts are plotted against the P10/P50/P90 quantile curves calculated from 30000 random contacts. The orange curve is a random sample drawn between the P50 and P90, so its quality is above median. The transcript of this example (with customer turns masked) can be found in Appendix B: the CSA approached the issue politely, proactively and timely. Other examples below the P50 curve (not shown) contains long-winded conversations, some of them showing customers trapped in WF loops. The quantile curve not only provides an automatic metric to evaluate historical contact quality and compare dialog models or human agents performance, it can also make online decisions when a conversation with a bot is trapped in the low-value area for too long. VP would consider it as a bot failure, and promptly suggest a CSA to take over and ensure customer experience.

4. Related Work

Information Gain used in RL and Dialog Information gain as a signal in Reinforcement Learning is not new, but mostly used as a ‘curiosity’ measure for exploration-exploitation in the next-state prediction tasks (Burda et al., 2018; Shyam et al., 2019). Peyrard, 2019 introduced some information-theoretic framework to evaluate the importance in text summarization. In the task-oriented dialog domain, Yu et al, 2019 and Shakla et al, 2019 uses information gain to select which question to ask. Our work differs in combining multi-aspect reward signals in a much more ambiguous CS dialog setting, and provides a richer set of evaluation methods for both bot and human conversation progresses.

Reward Design for Text Generation Using RL tricks to complement Maximum Likelihood learning for sequence generation has been well investigated. Ranzato et al., 2015 and Bahdanau et al., 2016 applied respectively REINFORCE and actor-critic approach to incorporate whole-sequence rewards into seq2seq training. The reward signal they used is BLEU and ROUGE, which are simple text statistics to compute on any text generation tasks but not far from likelihood. Yu et al., 2016 and Lin et al., 2017 used adversarial training with discriminator or ranker loss as reward signals for policy gradients. Li et al., 2016 designed a couple of heuristic rewards specifically for dialog generation, all based on certain transformations of context log probabilities within the texts. On the other end of spectrum, reward signals external to texts can be obtained much more expensively by either dedicated human labeling (Kandasamy et al., 2017; Liu et al., 2018), or by restricting to specific dialog applications with well-defined strong signals such as successful API calls for online reservation (Zhao and Eskenazi, 2016; Dhihgra et al., 2016). Zhou et al., 2017 is the closest to our work and their reward design is based on both BLEU scores and errors in predicting turn-level action API call slots. However, turn-aligned signals are still required. Also the prediction error is not available at test time, so real-time evaluation and monitoring is impossible. The value profiler reward design differs from above, by using
Table 3: Sampled sentences with top positive, negative and near-zero rewards ($\Delta v$) for different aspects. The reward numbers are scaled and the customer turns have been rephrased.

| Value    | Tier     | $\Delta v$ | Sentence (A: agent, B: bot, C: customer) |
|----------|----------|------------|------------------------------------------|
| action   | positive | 0.263      | C: I forgot my password, so I cannot change it |
| action   | positive | 0.248      | A: I will go ahead and cancel the order for stuck shipment. Okay? |
| action   | negative | -0.112     | A: I see you have been refunded for this item |
| issue    | positive | 0.684      | C: I want to cancel my amazon music subscription, immediately |
| issue    | positive | 0.537      | C: ...I can’t post reviews about some products that I’ve purchased |
| issue    | negative | -0.213     | C: No, that’s all |
| recontact| positive | 0.625      | C: It is too late for a phone call. I can do another chat tomorrow... |
| recontact| positive | 0.416      | C: I prefer online chat, since english is my second language. |
| recontact| negative | -0.472     | A: Let me connect you to the carrier, may I have your phone number? |
| total    | positive | 0.542      | A: I’ll escalate to the carrier..rescheduling the delivery at the earliest.. |
| total    | positive | 0.508      | B: Looks like this item should have been delivered by Thu, Feb 14. |
| total    | zero     | 0.001      | A: Yes, I can check the details. |
| total    | zero     | 0.001      | C: An item I ordered |
| total    | negative | -0.485     | A: To resolve the issue, I need to connect you to our specialist team |

Figure 3. Turn-level Value progress curve distribution. Each light blue solid line shows 1 of 300 random chats; the three blue dashed lines are the P10/P50/P90 curves computed based on 30000 random chats. A random high-value (above P50) sample is highlighted in orange. See Appendix B for the transcript of the sample.

5. Conclusion and Future Work

We presented Value Profiler, a deep learning model that profiles the multi-dimensional success of goal-oriented conversations, trained by only weak dialog-level signals. The dialog evaluation from VP can help contact understanding and bot/agent performance assessment. For injecting reward signals into text generation, we showed that the simple and practical pre- or post-processing methods result in improvements, however training with policy gradient methods is a formal choice to be investigated. The dialog generation task can also be added to the task list for joint optimization, leading to an end-to-end value-oriented conversational agent.

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### Appendix A Value for a Regression Task

For customer service contact evaluation, the cost aspect needs to be modeled as a regression task. Lower costs is desirable so negative predicted cost could be naively defined as the value directly. But there is also the uncertainty side of the story, since a poor estimate of cost with high volatility would invalidate the cost estimation number. Entropy for continuous distributions is comparatively difficult to compute, and depends on the choice of parametric distributions in a neural net. Therefore, we recommend adding a non-parametric quantile regression task. Let the model outputs two quantile estimates (e.g. P10 \( \hat{y}^{(0.1)} \) and P90 \( \hat{y}^{(0.9)} \)) of the numeric target (e.g. cost \( y \) in dollars). Assume the model is calibrated (i.e. P90 prediction does cover the true costs 90% of the time: \( P(y \leq \hat{y}^{(0.9)}) = 0.9 \)), then the length of the prediction interval \( [\hat{y}^{(0.1)}, \hat{y}^{(0.9)}] \) can be used to assess the confidence or sharpness of the model prediction. Prediction interval length is a general confidence measure for any numeric attributes. For the particular cost case (lower the better), a negative quantile estimate itself (e.g. P90) could be directly used as the value, considering both low-cost (effect-size) and high-confidence (significance).

### Appendix B An Example High Value Contact

See Figure 4 for the transcript of the highlighted contact in Figure 3.

### Appendix C Alternative Encoders and Volatility Results

See Table 4 for result metrics of LSTM/CNN encoders and volatility analysis.
Table 4: A lite comparison of different encoders and random seeds. All losses are cross entropy on test set. Accuracy for recontact and issue is computed at the 256th token (half way), and scaled by dividing that of the CNN model. Action metric difference is small due to the highly skewed distribution. The three GPT2 models shown are only fine-tuned for one epoch, while the final model has 3 epochs and is more stable (not shown).

| Encoder    | total loss | recon loss | issue loss | action loss | recon acc. | issue acc. |
|------------|------------|------------|------------|-------------|------------|------------|
| CNN        | 5.235      | 0.791      | 2.522      | 0.0461      | 1.000      | 1.000      |
| LSTM       | 5.381      | 0.788      | 2.586      | 0.0445      | 0.994      | 0.992      |
| GPT2 seed1 | 4.411      | 0.615      | 2.315      | 0.0421      | 1.178      | 1.152      |
| GPT2 seed2 | 4.448      | 0.612      | 2.343      | 0.0437      | 1.191      | 1.148      |
| GPT2 seed3 | 4.382      | 0.607      | 2.311      | 0.0428      | 1.203      | 1.168      |

Figure 4. The transcript of the orange example contact value curve in Figure 3. Customer utterances are masked. The value jumps at highly informative turns where the customer provides key information and the CSA maintained the high value by solving the issue politely, proactively and timely.