Data Distillation for Controlling Specificity in Dialogue Generation

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Abstract

People speak at different levels of specificity in different situations. A conversational agent should have this ability and know when to be specific and when to be general.

We propose an approach that gives a neural network–based conversational agent this ability. Our approach involves alternating between data distillation and model training: removing training examples that are closest to the responses most commonly produced by the model trained from the last round and then retrain the model on the remaining dataset. Dialogue generation models trained with different degrees of data distillation manifest different levels of specificity.

We then train a reinforcement learning system for selecting among this pool of generation models, to choose the best level of specificity for a given input. Compared to the original generative model trained without distillation, the proposed system is capable of generating more interesting and higher-quality responses, in addition to appropriately adjusting specificity depending on the context.

Our research constitutes a specific case of a broader approach involving training multiple subsystems from a single dataset distinguished by differences in a specific property one wishes to model. We show that from such a set of subsystems, one can use reinforcement learning to build a system that tailors its output to different input contexts at test time.

1 Introduction

People use different levels of specificity in their language depending on many factors about the context of a conversation: one’s interlocutor, one’s mood, how familiar one is with the topic discussed, how well one understands the other’s utterances, and so forth all influence the decision to respond with generics or specifics. A good dialogue agent should have a similar ability to vary the level of specificity of the responses it generates in an input-dependent way.

When humans speak, we can imagine that each has a series of language models in his mind, each of which is able to generate a sensible response, but which differ in specificity. One picks the appropriate model according to the current situation (whether one understands the input utterance, whether one is interested in the topic, etc.) and generates a dialogue utterance using the selected model. Motivated by this line of thinking, we ask whether a conversational agent could consider a pool of dialogue models that vary in language specificity and pick the best one for producing a response to any given input.

One seemingly straightforward approach would be to split the training data by language specificity and train separate generation models on each split. However, this requires classifying data by text specificity, a problem which poses significant challenges. Language specificity has been historically studied for noun phrases, and a few specificity-indicative features have been identified, such as singular terms, negations, or actual/non-actual moods (ENC, 1991; Lyons, 1995). However, there is no generally agreed criterion for defining the level of specificity of an arbitrary unit of natural language, let alone automatically generating sequences to have different levels of specificity.

In this paper, we propose an iterative data distillation approach for addressing this issue.2

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1 Depending on their knowledge, interlocutors, mood, etc.

2 The model is inspired by the concept of distillation in...
The proposed system operates as follows: a neural sequence-to-sequence generation (SEQ2SEQ) model is first trained and used to generate (decode) responses to inputs in a dataset. A list of the most common responses is constructed, and training examples with outputs that are semantically close to these common responses are removed (distilled). This process is then repeated by training another SEQ2SEQ model (from scratch) on the remaining data, decoding using the trained model, collecting generic responses and distilling more data. As the process iterates, responses that are generic are gradually distilled, and the trained models gradually increase in specificity.

At the end of the entire data distillation process, we are presented with a pool of generation models, all of which are able to produce sensible responses to input messages but differ in degree of specificity. This pool of models is analogous to specificity-varying models in a human’s mind. When presented with an input dialogue message, the dialogue system needs to pick one model out of the pool, Which model to choose depends on how well the bot understands the input message, how knowledgeable it is regarding the topic discussed, etc. To imbue the agent with this ability, we use reinforcement learning to train a model to pick the an appropriate level of specificity by selecting one of pre-trained generative models from the pool.

Experimental results show that models trained from different rounds of data distillation exhibit a clear spectrum of specificity. Models trained in early rounds of data distillation yield better responses. We also show that the reinforcement learning model is able to choose levels of specificity that are appropriate for a variety of inputs.

Our research constitutes a specific case of a broader approach involving training multiple subsystems from a single dataset distinguished by differences in a specific property one wishes to model (here, specificity), especially when this property is hard to model in a supervised learning setting. We show that from such a set of subsystems, one can use reinforcement learning to build a system that tailors its output to different input contexts at test time.

### 2 Related Work

#### Generic responses in open-domain dialogue

End-to-end dialogue systems (Ritter et al., 2011; Serban et al., 2016c; Vinyals and Le, 2015; Serban et al., 2016d,a; Asghar et al., 2016; Mei et al., 2016), tend to generate highly generic and commonplace responses (Sordoni et al., 2015; Mou et al., 2016). The goal of controlling output specificity is closely related to recent attempts to address this issue. Li et al. (2016a) propose using mutual information as an alternative training objective function in place of maximum likelihood, in which an N-best list generated by \( p(t|s) \) is reranked by the backward probability \( p(s|t) \).

The aim of this work is more general: instead of attempting to always avoid generic responses, our goal is to provide the system with the flexibility to generate responses at different levels of specificity. Blindly avoiding generating generic responses does not reflect how humans speak: we do not say dull, generic things like *I don’t know what you are talking about*, to communicate that we indeed do not understand part of the conversation, or to dismiss something as incorrect or nonsensical. A good dialogue system should have the ability to decide when to say generic things and when not to.

#### Data manipulation

The idea of training with data distillation is inspired by a variety of work in the active learning and subdata selection literature, the key idea of which is to select a subset of a large dataset to train a classifier with minimal performance loss, for when the training dataset is extremely large or training is extremely time-intensive (Wei et al., 2015; Zheng et al., 2014; Prasad et al., 2014; Ghahramani, 2013; Iyer and Bilmes, 2013). The proposed system differs from these subdata selection methods in both goals and implementation: we combine a series of models trained on different subsets of data, with the goal of increasing model performance rather than preserving the model’s performance while reducing the size of the training data.

The system we propose is also related to data manipulation strategies such as boosting (Breiman, 1996b), a type of ensemble method (Dietterich, 2002; Zhou et al., 2002; Krogh et al., 1995) that uses subsets of the original data to produce a series of models and then “boosts” their performance by combining them together; and bagging (Breiman, 1996a), which generates additional data for training using the original dataset to produce multisets.
of the same size as the original data, decreasing training variance.

3 Data Distillation

In the section, we describe the proposed data distillation model in detail. We use OpenSubtitles (Tiedemann, 2009) as our training dataset.4

3.1 Distilling common responses

We first use the following simple example to illustrate the core idea of our system: consider a model that predicts a multinomial distribution over an output variable (e.g., which fruit to choose). The probability of picking apple is 0.3, orange 0.25, blueberry 0.15, blackberry 0.15, and raspberry 0.15. Outputs that are generic are usually highly probable, since the high diversity of specific outputs results in each having smaller probability mass. We thus treat apple as the most generic fruit, and the various berries as more specific. Maximum likelihood estimation at test time will lead the model to always choose apple, since it has the largest probability. Observing that apple is the most common output, we will remove all apples from the training set and retrain the model, which will pick orange this time, since it has the greatest probability after apples are removed. We then remove oranges and repeat the process. With successive iterations of this distillation process, we will gradually obtain models that produce more specific outputs.

In the context of dialogue response generation, our approach works as follows: for each iteration, we first train a SEQ2SEQ model using attention (Bahdanau et al., 2014; Luong et al., 2015) on the original training set. Next, we use the trained model to decode responses to a number of input examples. We decode only a subset of the training set, 1 million responses in total. One could also use a held-out dataset for decoding, but the source of input messages is fairly unimportant in identifying the most frequent responses. We use greedy decoding (beam search with beam size 1). We then collect the most common responses in a list, denoted by $L$. A response is considered generic if its frequency of occurrence exceeds a threshold,

4OpenSubtitles is a large, noisy, open-domain dataset of lines from movie scripts. The noise in the dataset is largely due to the lack of speaker labels for lines of the subtitles. Following Vinyals et al. (2015), we train our models to predict the current line given the preceding ones, assuming that each line constitutes a full speaker turn and that consecutive turns belong to the same conversation. Both assumptions are occasionally untrue but yield reasonable results.

Algorithm 1: A brief summary of the proposed data distillation algorithm.

which is empirically set to 100 in this work. We then compare each response in the training data to each highly frequent response from the list $L$ and assign a relevance score $R(e)$ to each training example $e$ based on the cosine similarity between $e$ and the sequence most similar to it in $L$:}

$$R(e) = \max_{e' \in L} \cos(e, e')$$

(1)

We use the encoder part of the trained encoder-decoder model to map these sequences to vector representations, which are used to compute the cosine similarity. In this way, sentences that are semantically similar to frequent responses are assigned high relevance scores.5 We then remove (distill) examples from the training data with the highest relevance scores6 and retrain a new SEQ2SEQ model on the data that remains. An outline of the distillation algorithm is shown in Algorithm 1.

3.2 Choosing a specificity model

The data distillation process produces a pool of SEQ2SEQ models, each trained on the dataset remaining after a different data distillation round. When presented with an input message at test time, the system has to decide which generation model from the pool to use to decode a response to the input. We repeat the data distillation process 8 times, which means we have 8 models in the pool to choose from.7 The system should have the ability to choose different models in response to properties

5Other options include skip-thought vectors (Kiros et al., 2015) and bag-of-word representations. We find using the trained encoder works decently well.

6The amount to remove is empirically set to 8–10%.

7It requires two Tesla K-40 GPUs to fit the 8 models in memory.
of different inputs. For example, a good dialogue system should give concrete responses when asked things that it is sure about, but generic ones when the input message is difficult to understand.

We use reinforcement learning to train a model to make this choice. Given an input message \( X \) from a held-out dataset, we parameterize the action of choosing the generative model with index \( i \) from the pool \( G = \{ g_i \} \) of SEQS2SEQ models trained with data distillation as a policy network \( \pi(g_i | X) \), which produces a distribution over \(|G|\) classes. To compute the distribution, we first map the input message \( X \) to a vector representation \( h_X \) using an LSTM and then map \( h_X \) to a policy distribution over different \( g_i \in G \) using a softmax function:

\[
\pi(g_i | X) = \frac{\exp(h^T_X \cdot h_{g_i})}{\sum_{j=1}^{\left| G \right|} \exp(h^T_X \cdot h_{g_j})} \tag{2}
\]

where \( h_{g_i} \) is an output vector for each model \( g_i \) that is randomly initialized and then trained. Given an action, namely a choice of a generative model \( g_i \), we start decoding given the input message \( X \) using that model. Decoding generates an output response \( y \), which yields a reward \( R(y) \) evaluating response quality according to some metric. The reward signal \( R(y) \) is used to train the policy network.

We use the REINFORCE algorithm (Williams, 1992), a kind of policy gradient method, to find the optimal policy by maximizing the expected reward \( E_{\pi(g_i | X)}[R(y)] \). The expectation is approximated by sampling from \( \pi \) and the gradient is computed using the likelihood ratio (Aleksandrov et al., 1968):

\[
\nabla E(\theta) \approx [R(y) - b] \nabla \log \pi(g_i | X)) \tag{3}
\]

where \( b \) denotes a baseline value. 

### Adversarial evaluation for reward calculation

One remaining question is how to assign a reward \( R \) to a generated response \( y \) given the input \( X \), which boils down to the fundamental question of how to evaluate the general quality of a generated response. Dialogue quality is traditionally evaluated (Sordoni et al., 2015, e.g.) using word-overlap metrics such as BLEU and METEOR scores used for machine translation, which have recently been found to correlate poorly with human evaluations (Liu et al., 2016). Recent work has begun using more flexible and reliable evaluation metrics; automatic prediction of human ratings (Lowe et al., 2016) is one such metric, but this approach requires a large amount of human labeling effort to train a prediction model.

We employ adversarial evaluation (Li et al., 2016c; Anjuli and Oriol, 2016) for reward calculation. The idea of adversarial evaluation, first proposed by Bowman et al. (2015), is to train a discriminator (or evaluator) function to labels dialogues as machine-generated (negative) or human-generated (positive), a binary classification task. For our system, we use positive examples taken directly from training dialogues, while negative examples are decoded using generative models from different rounds of data distillation. To be specific, for each input message, we randomly sample a SEQS2SEQ model from the pool to decode a response to the input and use the response as a negative example. The evaluator is a hierarchical neural model (Serban et al., 2016b): dialogue utterances (i.e., source messages and responses) are first mapped to vector representations using an LSTM. Another LSTM is applied to the sequence of utterance representations to produce a dialogue representation, which is then fed to a binary classifier.

Given a pre-trained evaluator \( D \), an input source \( X \) and a machine generated target \( y \) decoded by the chosen generative model, the reward \( R \) used to update the policy \( \pi \) is the probability that the evaluator \( D \) assigns to labeling \( y \) as a human-generated response. The policy update influences the choice of generative model for decoding the current input \( X \). We refer readers to (Li et al., 2016c) for more details about the adversarial evaluation.

### 3.3 Stochastic Greedy Sampling

Language specificity also relates to language diversity. Utterances with lower levels of diversity are usually generic because generic responses are usually generic in the same way. Modeling diversity also provides an indirect way to handle the issue of specificity.

Moreover, there is a degree of randomness in human language production: in the real world, if we ask a person the same question twice, even with the same environment and surroundings, it is unlikely that the person will give the same answer both times. Sampling from the distribution not only better mimic the way humans generate tokens, but also provides a way to handle the issue of language specificity.

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8The baseline value is estimated using another neural model. We refer the readers to Ranzato et al. (2015) and Zaremba and Sutskever (2015) for more details.
One simple solution is to sample directly from the distribution \( p(y|x) \) in all cases. However, we observe that sampling leads to incoherent, ungrammatical, or even irrelevant responses. We expect there to be a sweet spot on the spectrum of randomness, between full sampling on one end and greedy or beam search on the other.\(^9\)

We propose a straightforward algorithm called Stochastic Greedy Sampling, in which instead of sampling from the full distribution over all candidate tokens, the model only samples from the few (e.g., 5) words with the highest probability. The model provides with both the flexibility of incorporating randomness and the rigidity of adhering to a pre-trained generation model at the same time.

Again, we use Adversarial Evaluation for comparing purposes. We report AdverSuc and machine-vs-random proposed by Anjuli and Oriol (2016). machine-vs-random denotes the the accuracy of distinguishing between machine-generated responses and randomly sampled responses using a machine evaluator, trained in a way similar to the evaluator in AdverSuc. Table 1 presents results for AdverSuc and machine-vs-random results for greedy decoding, pure sampling and the proposed stochastic greedy model. As can be seen, sampling all the time obtains the best score for AdverSuc, but also extremely low score for machine-vs-random accuracy, which indicates the inferiority of the always sampling strategy. The proposed stochastic greedy model perform better than always taking greedy actions as in greedy. This indicates that properly combining greedy search and sampling will potentially lead to better results.

| Model         | AdverSuc | machine-vs-random |
|---------------|----------|-------------------|
| greedy        | 0.042    | 0.935             |
| pure sampling | 0.384    | 0.642             |
| stochastic greedy | 0.058   | 0.933             |

Table 1: Adversarial evaluation results for different greedy vs. sampling decoding strategies.

4 Experimental Results

In this section, we present the results of experiments.

\(^9\)Since greedy decoding has been shown to generate higher-quality responses than beam search in dialogue response generation (Li et al., 2016a), we focus on greedy decoding. However, all algorithms can be easily adapted to use beam-search decoding.

| iter | data size | ppl | oracle-ppl | div-1 | div-2 |
|------|-----------|-----|------------|-------|-------|
| 1    | 45.2M     | 33.2| 33.2       | 0.65% | 1.57% |
| 2    | 40.6M     | 33.3| 32.3       | 0.92% | 2.81% |
| 3    | 35.7M     | 33.7| 31.6       | 1.18% | 3.22% |
| 4    | 32.7M     | 34.3| 31.2       | 1.44% | 3.60% |
| 5    | 30.1M     | 35.0| 30.8       | 1.87% | 3.94% |
| 6    | 27.9M     | 35.5| 30.7       | 2.21% | 4.32% |
| 7    | 25.5M     | 36.7| 30.5       | 2.72% | 4.65% |
| 8    | 22.8M     | 37.2| 30.3       | 3.10% | 5.01% |

Table 2: Training set size (examples) after data distillation in each iteration and perplexity (ppl) and n-gram diversity scores (dis-n) of the trained generative models on the development set.

4.1 Comparing generative models from different iterations

It is interesting to first compare the generative models and the remaining training data from each of the 8 rounds of data distillation. We use Iter+N to denote the generation model trained on the dataset after N repetitions of data distillation.

Perplexity and diversity The size of the training dataset after each round of data distillation and the perplexity of the corresponding trained models on the full development set is shown in the first two columns of Table 2. Perplexity increases for models trained with more data distillation (as expected, since distillation removes opportunities for the model to learn to produce the most common outputs).

However, we expect models trained with distillation to complement the model trained on the entire dataset by better modeling more specific outputs. To quantify the potential of the pool of generation models to complement each other when used in different contexts, we also report oracle perplexity (“oracle-ppl”) as a function of the number of iterations \( K \): for each example, we identify the generation model (out of Iter1 through IterK) that assigns the highest probability to the true output. Oracle perplexity is the perplexity computed using these maximal probabilities, instead of the probabilities assigned by any one model. This is equivalent to the perplexity of a model with an RL policy network that chooses perfectly every time. We expect to find that oracle perplexity on the development set decreases when adding the models trained in the first few rounds of data distillation, after which it levels off. This confirms that there are benefits to be had from choosing smartly among the different models.
Table 3: Most frequent responses generated using greedy search at the end of 1–4 rounds of data distillation. “Count” indicates the number of occurrences of a response in 1 million decoded outputs.

| Count | Response                                      | Count | Response                                      |
|-------|-----------------------------------------------|-------|-----------------------------------------------|
| 145575| i don ’t know what you are talking about.     | 54227| i ’m not in the mood.                        |
| 84435 | i ’m not going to let you go.                 | 29559| i ’m sorry about the way i acted.            |
| 36032 | i ’m sorry i didn ’t mean to offend you.      | 22987| you ’re not in the mood.                     |
| 23890 | i ’m not so sure.                             | 21392| i ’m gonna take a look at the new york times.|
| 19405 | i don ’t know what to say.                    | 20380| i ’ll be there in a minute.                  |
| 16888 | i ’m not going to let you go!                 | 14736| i ’m gonna take a look at this.              |
| 16948 | that ’s a good idea.                          | 13753| i ’ll get the money.                        |
| 12782 | i don ’t know what to do.                     | 13013| i ’m gonna take a shower.                   |
| 11840 | i ’m not going to be able to do that.         | 11746| i ’m in the middle of a war.                |
| 11604 | i ’m sorry i can ’t help you.                  | 10130| you ’re not getting any sleep.              |
| 11254 | i ’m sure you ’re right.                      | 9966 | i ’m gonna take a look at the other side.    |
| 9474  | you don ’t know what you are saying.          | 9644 | i ’m sorry about the way you did.            |
| 9471  | i ’m not going to tell you.                   | 9169 | i ’ve been doing a lot of things.            |
| 8905  | i ’m not sure i can do it.                    | 7837 | you ’re a dead man.                         |
| 7905  | i have no idea.                               | 5320 | i was just getting a little tired of it.     |
| 41139 | i ’m not an idiot.                            | 30378| i ’m not from around here.                  |
| 34738 | i ’m not an expert on this.                   | 26705| i ’m not from the future.                   |
| 20252 | i ’m sorry but i ’m not an expert on this.    | 9923 | i was just talking to my wife.              |
| 16275 | i ’ve got some bad news for you.              | 9012 | i ’m not doing this.                        |
| 16081 | i ’ll get you a new suit.                     | 8573 | you ’re a goddamn liar.                     |
| 13007 | i ’m not an idiot !                           | 7424 | i ’ll be on the way.                        |
| 11254 | i ’m gonna make a big deal out of this.       | 6919 | i ’m sorry ma ’am.                          |
| 6532  | i ’m just an ordinary man.                    | 5546 | i ’m going back to the hotel.               |
| 5724  | i ’m not an expert on the police.             | 4569 | i ’ll be on my way.                         |
| 5604  | i ’m not an expert on the subject.            | 4555 | i ’m not staying here.                      |
| 5168  | i ’m not your enemy !                         | 4416 | you ’re a goddamn genius.                   |
| 4963  | i ’m not an expert on the law.                | 4184 | i ’m a little tired.                        |
| 4454  | i ’m gonna need some more help with this.     | 4183 | i ’m gonna take a look at this.             |
| 4342  | i was just about to get my hands on the wall | 4103 | he ’s a bit of a jerk.                      |
| 3969  | i can ’t believe you ’re still alive.         | 3819 | he ’s a bit of a pain in the ass.           |

Table 2 also shows a measure of the diversity of generated responses, namely, the number of distinct unigrams (“div-1”) and bigrams (“div-2”) in generated responses as a fraction of the total generated tokens, as described in (Li et al., 2016a). As can be seen, as the data distillation process proceeds and more generic responses are distilled, the system generates increasingly diverse responses.

**Distilled responses** The highest-frequency responses from different rounds of data distillation are shown in Table 3. Top responses are more generic for models trained in earlier iterations. In iteration 1, the top responses are broadly generic statements of uncertainty (“I don’t know”, “I am not sure”) or agreement (“i think you are right” or “that’s a good idea”), but the meanings of frequent responses start diverging as the distillation algorithm proceeds. The number of the occurrences of the top frequent responses from different iterations also validates this point, with the number gradually decreasing.

Table 4 presents sampled outputs from the generation models trained after different rounds of the distillation. Responses from Iter1 are usually generic but safe, mostly i don’t know what to do/what you are talking about and that’s a good idea. As the amount of distilled data increases, the corresponding model generates increasingly concrete responses but has a greater risk of outputting confusing or irrelevant responses.

### 4.2 Choosing the correct model for decoding

Next, we present results from the proposed reinforcement learning model and analyze how it decides which model to pick from the pool.

The distribution over different models used to decode input messages in the development set is shown in Figure 1. As can be seen, the RL model chooses to decode using the model trained on the entire dataset (i.e., Iter1) for 16 percent of all inputs. The models trained after 2, 3 and 4 rounds are responsible for decoding responses to approximately half of the inputs.

**Human evaluation** For human evaluation, we follow protocols defined in Li et al. (2016b), employing crowdsourced judges to evaluate a random
| Input | Output | RL model choice |
|-------|--------|-----------------|
| Iter1: i’m sorry i didn’t hear you. | Iter1 | Iter2: i’d better hear you. |
| Iter5: i can’t help you. | Iter2 | Iter2: i’m sorry to hear you. |
| Iter5: i’m not going to do that. | Iter3 | Iter2: you know i’m a real looker. |
| Iter5: i’m gonna make you some of your own kind of girl. | Iter4 | Iter2: ‘re in a big house! |
| Iter5: you know i can tell when she is a little bit ... ... but she’s not very good. | Iter5 | Iter2: i’m sure she’ll have a good time with the rest of the crew. |
| Iter5: i didn’t even see you go back there. | Iter6 | Iter2: i don’t know what you are doing about. |
| Iter5: i was just wondering if you could help me out. | Iter6 | Iter2: i don’t know what to do. |
| Iter5: he’s been a long time since he got here. | Iter6 | Iter2: the zone is the only place where the people are. |
| Iter5: maybe his eyes were too big for his stomach. | Iter6 | Iter2: it’s a little early in the morning for me. |
| Iter5: i think he was a good kid. | Iter6 | Iter2: i’m sorry about the delay. |
| Iter5: i think he was a good kid. | Iter6 | Iter2: i’m glad that’s your name and all. |
| Iter5: the rest of the crew are also on their way home. | Iter6 | Iter2: don’t talk to me that way man. |
| Iter5: i’m not leaving until tomorrow. | Iter6 | Iter2: i’m not a human being. |
| Iter5: i’m never heard of any of these. | Iter6 | Iter2: you’re not an idiot anymore. |
| Iter5: i’m not going to be able to see her. | Iter6 | Iter2: you’re in no position to talk like that. |
| Iter5: i’m not going to be able to see her. | Iter6 | Iter2: you’re not a good guy. |
| Iter5: i’m not going to be able to see her. | Iter6 | Iter2: well it’s not that simple. |
| Iter5: i’m not going to be able to see her. | Iter6 | Iter2: the explosion was caused by a meteor disturbance. |

Table 4: Sample of outputs generated by models from different rounds (1,2,5,7) of data distillation, along with the model that the proposed reinforcement learning (RL) algorithm chooses to decode the response. Responses chosen by the RL model are in Bold.

Sample of 200 items. We present labelers with an input message and the generated outputs from three models, Iter1, Iter2, and RL, and ask them to rank the three outputs by quality. Note that the outputs from the RL model can be the same as those from Iter1 or Iter2 if the RL model chooses that particular model (Iter1 or Iter2) for decoding. In these cases, a tie is automatically recorded. Figure 2 shows the proportions of the outputs ranked first by the human labelers. As can be seen, the reinforcement learning model performs best 60 percent of the time, followed by Iter2, which wins 37 percent
Iter1 Iter2 Iter3 Iter4 Iter5 Iter6 Iter7 Iter8
RL model choice
0
5
10
15
20
25
30% of examples

Figure 1: Distribution of the iteration used by the RL model to decode responses (dev set).

Figure 2: The proportions of outputs from different models ranked first in the human evaluation. Note that the sum is larger than 100 percent due to ties.

| pairs            | win | lose | tie |
|------------------|-----|------|-----|
| RL vs. Iter2     | 51  | 29   | 20  |
| RL vs. Iter1     | 64  | 28   | 8   |
| Iter2 vs. Iter1  | 62  | 38   | -   |

Table 5: Pairwise human judgments between the reinforcement learning model (RL) and the first two distillation models (Iter1 and Iter2).

Table 6: Adversarial success and machine-vs-random accuracy for Iter1 which always generating response using the model trained on the full set, random which randomly samples a model for generation, and the proposed model.

Adversarial evaluation

| model        | AdverSuc | machine-vs-random |
|--------------|----------|-------------------|
| Iter1 (standard) | 0.058    | 0.933             |
| random       | 0.056    | 0.940             |
| RL           | 0.088    | 0.944             |

Adversarial success and machine-vs-random accuracy. We refer readers to Li et al. (2016c) for more details. We observe that the RL model performs better than always using the model trained on the full dataset (Iter1) or choosing a distillation model at random (as one would expect, since the RL model is trained to optimize adversarial success).

Analyzing results

Table 4 shows example choices made of the RL model in response to different inputs. When input messages are vague and hard to reply to, the RL model usually picks Iter1, which in turn outputs safe responses like “that’s great” or “i don’t know what you are talking about”. The RL model has a tendency to pick models from the latter stages of distillation training if all of the generation models from the different iterations of distillation are able to output meaningful responses, since models from the later stages output produce more diverse and interesting outputs. We also observe a high correlation between the number of unknown words in the source sentence and the choice to use Iter1.

5 Conclusion

In this paper, we investigate the language specificity issue in dialogue generation. We propose a data distillation method, which trains a series of generation models that exhibit different levels of specificity and uses a reinforcement learning model to choose the model best suited for decoding depending on the dialogue context.

The success of the proposed system confirms the importance of data processing in training a successful open-domain dialogue system. We anticipate that strategies resembling the one we propose can be used more generally for controlling properties of dialogue generation other than specificity, by training several models on different subsets of a single dataset that differ in the desired property, and choosing among these to produce outputs that tailor the quality of interest to the situation at hand.
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