ConQX: Semantic Expansion of Spoken Queries for Intent Detection based on Conditioned Text Generation

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Abstract

Intent detection of spoken queries is a challenging task due to their noisy structure and short length. To provide additional information regarding the query and enhance the performance of intent detection, we propose a method for semantic expansion of spoken queries, called ConQX, which utilizes the text generation ability of an auto-regressive language model, GPT-2. To avoid off-topic text generation, we condition the input query to a structured context with prompt mining. We then apply zero-shot, one-shot, and few-shot learning. We lastly use the expanded queries to fine-tune BERT and RoBERTa for intent detection. The experimental results show that the performance of intent detection can be improved by our semantic expansion method.

1 Introduction

In human-to-machine conversational agents, such as Amazon Alexa and Google Home, intent detection aims to identify user intents that determine the command to be executed. Spoken query, also called as utterance, can be classified into a set of pre-defined user intents (Tur et al., 2010). Intent detection is a challenging task due to the noisy, informal, and limited structure of spoken queries. Detection models may suffer from the problems of sparsity, ambiguity, and limited vocabulary. Recent state-of-the-art language models, such as GPT-2 (Radford et al., 2019) and GPT-3 (Brown et al., 2020) based on the Transformer architecture (Vaswani et al., 2017), incorporate domain-independent large corpora in training. They have the capability of coherent text generation when the task is prompted in natural language. The clarification of short spoken queries can be done by generating coherent and semantically related text. For instance, the given query “what is amzn worth” is expanded to “what is amzn worth what is Amazon’s stock worth” that clarifies stock worth, as well as solving the ambiguity in amzn.

Transformer-based text generation does not always produce meaningful text segments (Shao et al., 2017a). For instance, the given query without conditioning “has my card application processed yet?” is expanded to “has my card application processed yet? If you are not yet with us” that gets a trivial text segment given in italic. The reason would be that the model does not know the context of card application, such as banking or membership card. However, the input can be conditioned with a better prompt “[I am a bank customer], has my card application processed yet?” that gets additional context as bank customer. The input would then be expanded to a non-trivial text segment in the context of bank cards.

In order to solve the problems regarding the noisy and limited structure of spoken queries, we propose a novel method, called ConQX, for semantic expansion of spoken queries with conditioned text generation. The method name refers to Conditioned spoken Query eXpansion. Specifically, we employ a Transformer-based language model, namely GPT-2, to generate semantically related text segments. We condition the input query to set up a structured context for generating text segments. For conditioning, we mine useful prompts that provides structured context, as we call prompt mining. We then append the generated text segments to existing spoken queries, and fine-tune state-of-the-art language models, namely BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), for the downstream task of intent detection.

Conditioned expansion aims to describe the task to the model in natural language and provide a number of ground truth demonstrations of the task at inference time. To exploit conditioned expansion, we examine zero-shot, one-shot, and few-shot learning (Brown et al., 2020).

Traditional semantic expansion methods rely on keyword-based expansion, which utilizes proximity in a semantic space regardless of contextual
coherence (Roy et al., 2016). However, the models using contextual word embeddings, such as BERT, are shown to benefit from natural language queries that keep the grammar structure and word relations (Padaki et al., 2020; Dai and Callan, 2019). Transformer-based text generation can output more coherent natural language queries, compared to keyword-based expansion (Radford et al., 2019) that mostly adapts to improve the performance of retrieval algorithms (Claveau, 2020).

The language model can be adapted to the downstream task with natural language prompts to achieve competitive performance. The design of an input prompt is important, since different writings of the task can affect the performance significantly (Jiang et al., 2020). Although there are some efforts for the automation and standardization of prompt generation (Jiang et al., 2020; Gao et al., 2020), they do not consider long text generation tasks, as in the case of semantic expansion. We employ prompt mining on a set of manually generated conditioning prompts and experiment with zero-shot, one-shot, and few-shot learning to further adapt the language model to the task of semantic expansion.

2 Conditioned Query Expansion

Given a set of spoken queries and input prompts, we use a pre-trained Transformer-based language model, GPT-2 (Radford et al., 2019), to generate coherent text. A spoken query is placed in manually generated natural language prompts that are determined with prompt mining, and given as input to GPT-2 with zero/one/few-shot mining. The generated text segment is appended to the end of the original query to obtain the expanded query. BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) are then fine-tuned for the task of intent detection.

2.1 Text Generation

Our method for semantic expansion is based on language modeling (Bengio et al., 2003), formulated in Equation 1, where \( q \) is a spoken query and \( p(q) \) is the maximum likelihood probability of document estimation based on a sequence of tokens.

\[
p(q) = \prod_{i=1}^{n} p(s_i|s_1, \ldots, s_{i-1})
\]

ConQX employs the conditional probability of estimating semantic expansion, \( q' \), given the original query within the context of the input prompt,

\[
p(q'|q) = p(s_{n+1}, \ldots, s_{n+k}|s_1, \ldots, s_n),
\]

where \( q \) has the length of \( n \) tokens, and \( q' \) has \( k \) tokens. The likelihood is estimated by an auto-regressive language model that considers the distributions of previously generated tokens for next token prediction.

There are several methods to utilize autoregressive text generation. Greedy search predicts the next token that has the highest probability of occurrence. However, greedy search does not generate coherent text due to repetitive results (Shao et al., 2017a). We apply top-k sampling that (Fan et al., 2018) predicts the next token from the most likely \( k \) tokens to provide coherent and diverse text.

2.2 Zero/One/Few-shot Learning

Pre-trained language models are trained over large and domain-independent corpora. When used for a downstream task, such as semantic expansion in our case, they need conditioning to deduce the task and generate contextually related text. Zero-shot expansion aims to achieve this conditioning by inserting spoken queries into input prompts that contain natural language descriptions of the task without any demonstrations of the desired output.

In one-shot expansion, the input prompt contains a ground-truth demonstration of the semantic expansion task. The language model is expected to infer the semantic expansion task more easily, compared to zero-shot expansion. Lastly, few-shot learning provides a number of true demonstrations to increase the performance of task inference.

Figure 1 shows an example spoken query for semantic expansion with zero/one/few-shot learning. The ability of task inference is known to be available in the large models in terms of the number of parameters, such as GPT-3 (Brown et al., 2020); but also observed in smaller models, such as GPT-2 (Schick and Schütze, 2020).

2.3 Prompt Mining

Determination of the proper input prompt for conditioning the language model can be achieved through prompt mining. The prompts provide additional context for the task inference of the language model. We manually generate a set of prompts that differ in text length, formality of the language, syntactic structure, and context. We apply empirical evaluation on the prompts, such that the classification performance is used to select a prompt after 10-fold leave-one-out cross-validation. We provide a subset of these prompts in Table 1.
In conversational search, spoken queries are generally short and need to be expanded. For example, “has my credit card application processed yet?” is hard to process and can lead to poor quality results. The query may be rewritten as: “what is my credit card application status?”

We provide a short prompt (the first), as well as a longer one (the second) that aims to exploit the ability of Transformer to model long-term dependencies with the Attention mechanism. The third prompt introduces a syntactic structure to condition the model, imitating a dialog. The fourth prompt is written in a more formal language, while the others in a daily language. The last one has additional context information as banking. Note that some of the prompts end with a quotation mark that enforces the language model to generate an example language; while the others generate expansions in the form of sentence completions.

### Table 2: The details of the datasets used in this study.

| Details         | Banking | CLINC | SNIPS |
|-----------------|---------|-------|-------|
| Train samples   | 10,003  | 18,000| 13,084|
| Test samples    | 3,080   | 4,500 | 700   |
| Number of intents | 77     | 150   | 7     |
| Avg. length (tokens) | 12.27  | 9.38  | 11.24 |

### 3 Experiments

#### 3.1 Datasets

We use three publicly available datasets for intent detection; namely Banking, CLINC, and SNIPS. Banking (Casanueva et al., 2020) has 77 intents about banking, which is challenging due to subtle differences among classes. CLINC (Larson et al., 2019) is a balanced dataset with 150 intents. SNIPS (Coucke et al., 2018) is another balanced dataset covering seven intents. The details of the datasets are given in Table 2. We apply no preprocessing.

#### 3.2 Experimental Design

Query expansion is conducted on NVIDIA 2080Ti GPU with 12 GB memory; BERT fine-tuning uses the same infrastructure as well. Query expansion takes approximately an hour to complete in the 10-fold setting. The details of the compared methods are given as follows.

- **Without expansion**: As a baseline method, we fine-tune BERT-base (Devlin et al., 2019) and RoBERTa-base (Liu et al., 2019) with default
Table 3: Comparison of ConQX with the baselines for intent detection in terms of the weighted F1 score. The means of 10-fold cross-validation are reported. The bold score is the highest. • indicates statistically significant improvement at a 95% interval in pairwise comparisons between the highest method and baselines marked with ◦.

| Expansion Method | Banking | CLINC | SNIPS |
|------------------|---------|-------|-------|
| Without expansion | BERT 0.908 ◦ 0.923 | RoBERTa 0.959 0.964 | BERT 0.974 0.979 |
| Bag-of-words (kNN) | BERT 0.909 ◦ 0.922 | RoBERTa 0.953 ◦ 0.957 ◦ | RoBERTa 0.969 ◦ 0.972 ◦ |
| Transformer (GPT-2) | 0.912 0.923 | 0.954 0.964 | 0.976 0.981 |
| ConQX (zero-shot) | 0.920 • 0.928 | 0.960 • 0.965 ◦ | 0.978 • 0.983 ◦ |
| ConQX (one-shot) | 0.920 • 0.928 | 0.959 0.961 | 0.983 • 0.981 |
| ConQX (few-shot) | 0.916 0.925 | 0.962 ◦ 0.962 | 0.981 0.976 |

parameters by Huggingface (Wolf et al., 2019), but without expansion.  
• Bag-of-words (kNN): As a baseline expansion method, we consider that the expanded words are independent (bag-of-words), and use GloVe (Pennington et al., 2014) word embeddings. We sample $k=1$ nearest neighbor of each input token in the embedding space, and append them to the input, using scikit-learn (Pedregosa et al., 2011).  
• Transformer (GPT-2): As a baseline expansion method, GPT2-large with 774M parameters by Huggingface (Wolf et al., 2019) is used for text generation, given the original query with no input prompt (Radford et al., 2019). The number of generated tokens is approximated to the number of input tokens.  
• ConQX (zero-shot): Our semantic expansion method with zero-shot learning. Both train and test instances are expanded, and fine-tuning is done using the expanded queries. For top-k sampling in GPT-2, we experiment $k \in (10, 50, 100)$, and select empirically by F1 score on the test set.  
• ConQX (one-shot): Our method with one-shot learning. A single true demonstration of semantic expansion is provided.  
• ConQX (few-shot): Our method with few-shot learning. Multiple true demonstrations of semantic expansion are provided (we use four demonstrations for the sake of efficiency).  

We report the weighted average F1 score for intent detection with leave-one-out 10-fold cross validation. We use scikit-learn (Pedregosa et al., 2011) for evaluation metrics. Any improvements over the baselines are statistically validated by the two-tailed paired t-test at a 95% interval.

3.3 Experimental Results

We compare the effectiveness of baselines and our method for intent detection in Table 3. The results show that ConQX improves the effectiveness of intent detection in all datasets, compared to all baselines. Although, the gap between baselines and ConQX is not too wide, we show that the differences are statistically significant in some cases. We show that conditioned text generation is a promising approach for semantic expansion of spoken queries, and its performance can be improved by additional prompt mining. ConQX with zero/one-shot learning lead to better improvement in most cases, showing that hand-crafted true demonstrations could cause noise in few-shot learning, i.e. prompt mining can generate better demonstrations. GPT-2 without conditioned text generation does not always improve effectiveness, showing the need of conditioned text generation. kNN-based expansion also deteriorates effectiveness in some cases, possibly due to the fact that the neighbor words do not clarify the context of short queries.

We analyze prompts differing in length, formality of language, and syntactic structure using punctuation. Longer prompts tend to result in more coherent and informative expansions. However, depending on the dataset and classifier, shorter prompts may be more suitable. The role of different prompts are application-dependent, formally written prompts are favored by formal domains such as banking. Syntactic structures, such as quotation marks, make irrelevant text filtered out and result in less noisy expansions.

4 Conclusion and Future Work

We propose conditioned query expansion using Transformer-based language models. We show that the performance is increased in all datasets from different domains, with proper selection of parameters (zero/one/few-shot and prompts). ConQX is thereby a promising method for similar tasks that can benefit from semantic expansion.

Future work would have more observations on other models and sampling strategies, such as beam
search (Shao et al., 2017b). We improve the performance with hand-crafted prompts, but prompt mining and prompt engineering are novel research areas. We plan to focus on tuning parameters, such as zero/one/few-shot learning and a systematic way to generate prompts (Jiang et al., 2020).

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