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Schema-Guided Paradigm for Zero-Shot Dialog

This paper is about developing a mechanism which can help to adapt to new unseen domains and tasks using a schema guided paradigm where the task-specific dialog policy is explicitly provided to the model. The authors introduced Schema Attention Model (SAM) and improved schema representations for the STAR corpus which obtains significant improvement in zero-shot settings.

Introduction

- Task-oriented dialog systems aim to satisfy user goals pertaining to certain tasks.
- Neural models for such dialog have become dominant because they can learn complex patterns using data-driven approaches.
- Resulting models struggle to generalize on unseen dialog tasks and domains.
- This is a long-standing question: *How can a dialog system be extended to handle a new task (e.g., hotel booking), without collecting additional data?*
- Zero-shot generalization using the schema-guided paradigm.
- Large scale pre-training leads to progress in domain adaptation across different areas in NLP.
- Generalization in end-to-end task-oriented dialog is difficult in zero-shot settings because of dialog policy.
- Traditional end-to-end dialog system must perform 3 different tasks:
    - Understand the dialog history and identify any relevant user intents or slots.
    - Decide on the appropriate system action, according to a task- specific dialog policy.
    - Generate a natural language utterance corresponding to the system action.
- An E2E dialog model trained on several tasks, will implicitly learn the dialog policies from the data.
- This is difficult for generalization to a new task in a zero-shot setting; it has no knowledge of the dialog policy for the new task.
- To address this, authors introduce schema-guided paradigms.
    - Explicitly provide the task-specific dialog policies to the model in the form of a schema graph.
- This schema graph defines the system’s behaviour for a specific task and thus while transferring to a new task, a new schema task is explicitly provided to the model.
- Thus, the model learns/interprets the dialog history and aligns it with the schema graph.
- STAR dataset used as a baseline, which is extended for task: *next action prediction*.
    - Developed SAM to perform the said task for 24 tasks in the STAR dataset.
    - The model obtained +22 F1 score improvement over the baseline approach in zero-shot settings.

Related Work

Zero-Shot Dialog

- Different approaches:
    - Chen et al. (2016) present an approach for learning embeddings for unseen intents.
    - Bapna et al. (2017) show how to leverage slot names and descriptions implicitly to align slots across domains.
    - Wu et al. (2019) use slot names, in combination with a generative model for state tracking.
    - Shah et al. (2019) leverage examples for zero-shot slot filling.
    - The advent of large-scale pre-training allows language understanding across different domains eg: Rastogi et al. (2020a) uses BERT for state tracking with domain specific API.
    - Action matching framework by Zhao and Eskenazi (2018).
    - Model-agnostic meta learning by Qian and Yu (2019).
    - Both of the above are not suitable for the STAR dataset as they rely on additional annotations.

- Still zero-shot generalization is in language understanding not in adaptation of end-to-end dialog systems.
    - Mosig et al. (2020) presented STAR, a corpus consisting of 24 different dialog tasks, and several baseline models for zero-shot adaptation on STAR.
    - This paper uses the said dataset and outperforms the baseline using **schema-guided paradigm.**

Schema-Guided Paradigm [SGP]

- Similar technique:
    - Plan-based dialog systems decouple the task-specific dialog policy from the task-agnostic components of the system. [Ferguson and Allen, 1998; Rich and Sidner, 1998; Bohus and Rudnicky, 2009; Bohus and Rudnicky, 2009]
- SGP aims to disentangle the dialog policy in neural, data-driven dialog systems.
- Different Approaches:
    - Shi et al., 2019; Qiu et al., 2020; Xu et al., 2020; Hu et al., 2019 - enhance generation for open- domain dialog (Qiu et al., 2020; Hu et al., 2019.
- According to authors, these techniques haven't been implemented in either generation in task- oriented dialog nor in zero-shot settings

Task Definition

- Authors address the problem of transferring dialog models to unseen tasks and domains as such there is a tradeoff between adaptation of non-neural based systems and the performance of neural models.

STAR Dataset

- For studying transfer learning
- 24 different tasks - 13 different domains and 3 different types of dialogs:
  - (1) happy single-task dialogs
  - (2) unhappy single-task dialogs
  - (3) multi-task dialogs
- Amazon Mechanical Turk (AMT) workers were used for data collection.
- Flow charts with defined tasks provided to the workers to reduce variance.
- Mosig et al. (2020) incorporate a suggestions module to further minimize variance.
- Objective of *Next Action Prediction by Mosig et al. (2020):*
  - Predict the correct system action conditioned on the dialog history.

Zero Shot Setting

- Two types of transfer learning experiments:
  - Task-Transfer:
    - Train on n-1 tasks and test on the other one task for all tasks individually.
  - Domain-Transfer:
    - Train on n-1 domains and test on the other one domain for all domains individually.

Methods

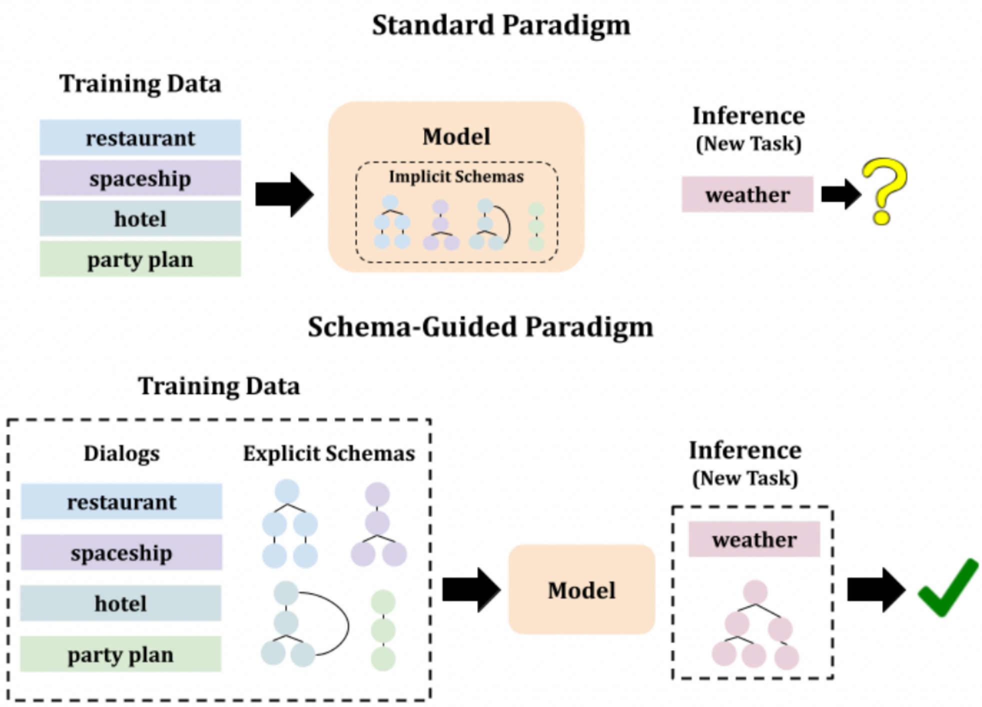
- SAM is used for both the experiments.

Baseline

- BERT as a encoder is used to get model representations from dialog history and then probabilistic distributions over the actions are calculated.

Schema-Guided Paradigm

- Two tasks:
  - (1) interpret the dialog context and identify the relevant intents and slots.
  - (2) learn the task-specific dialog policies for the different tasks in the training data.



- As shown in the figure, the schema-guided paradigm consists of the representation of the schema graph, and a neural model which interprets the dialog context and aligns it to the schema graph.

Schema Representation

- Task-specific dialog policy.
- The baseline schema-graph by Mosig et al. (2020) fails as it only provides system-utterance, and thus the authors further extend it by providing user-utterances as well.
- Properties of Schema Graph:
  - System actions are deterministic.
  - One-to-One mapping between system actions and system responses.

Schema Attention Model

- Extends baseline by doing the following:
  - (1) Leveraging a stronger attention mechanism.
  - (2) Improving the training algorithm.
  - (3) Removing the linear classification layer which is detrimental to zero-shot performance.
- Role:
  - Understand the dialog history and align it to the schema representation.
- Main Objective:
  - Predict the node in the schema graph that best corresponds to the dialog context.

- How it is achieved: Probability distribution over the nodes corresponding to user utterances and database responses using attention mechanisms.
- *For more detail on how it is done read this section the paper.*
- The difference between Mosig et al. (2020) and this paper for the said objective:
    - SGM of Mosig et al. (2020) uses sentence level representations while, SAM uses word-level attention both using the same BERT-base model.
- Why word-level attention vectors:
    - Can handle multiple user information.
    - Can handle spelling errors in the user utterances.
    - Attention helps in more generalization as it computes only over the schema graph.
- Also, modify the training algorithm to have in-domain negative samples which result in the model learning to identify fine-grained relationships.

Results

Standard Experiments

- Models are trained and tested on the same tasks. [80%-20% split].
- Not much performance improvement was observed as the model is intended for a zero-shot learning environment but still a good upper bound is developed.

Zero-Shot Transfer Experiments

- Task Transfer and Domain Transfer:
    - +22 F1 score improvement in task transfer
    - +24 F1 score improvement in domain transfer
- Why: Improved schema representations and model architecture.
- Also, authors experimented by adding schema with user utterances to BERT+s which improved it's F1 score with a +15 score which proves that the baseline is compromised with only system utterances.
- Several experiments are done by introducing each technique one by one with the SAM model which all make the performance of the model better than the baseline.
- All of these experiments show that not only are they able to perform better transfer learning than baseline models, they are performing zero-shot generalization over vastly dissimilar domains of the STAR corpus.

Conclusion

- This paper shows strong strides towards zero-shot generalization for task and domain transfer in dialog systems using schema guided paradigm.
- Dialog Policy is the crux of the said task.
- So, authors provide dialog policy in schema graph format.
- Also, SAM is introduced in this paper improving the said schema graphs for the STAR corpus in the zero-shot settings with a +22 F1 score.
- Further Work: Improve Schema representations, Improve model architecture and Extending to other problems [response generation].