Generalized Zero Shot Learning for Intent Classification and Slot Filling

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Content

Introduction to DST

Nowadays many services implement in their works dialogue system because it helps to provide services at any time of the day without additional labour costs. DST is a Core component in today's task-oriented dialogue systems, maintains a user's intentional states through the course of a dialogue.

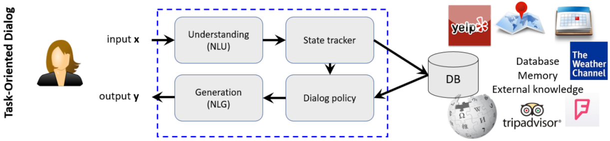


Figure: Dialogue system

Introduction to DST

During the dialogue, we recognize the user intends. And fill the appropriate slot.
For different services, we have different intends and slots.
So if we include new service we need to provide train dialogues and train again system.

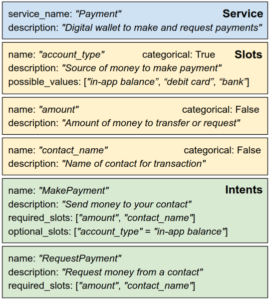


Figure: Example of shema dialogue system.

GZSL

Generalized Zero-shot learning aims to recognize objects whose class may not have been seen during training.
For classes, we have some description. So GZSL methods trying to extract knowledge between class description and class example.

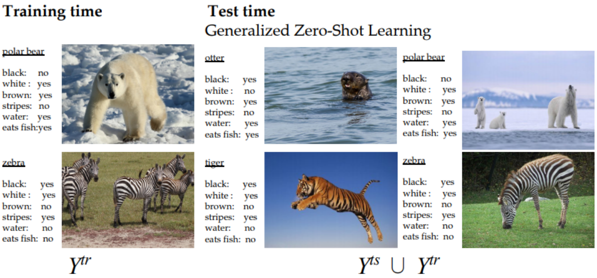


Figure: Flow visualisation[1]

[1] B. Schiele Y. Xian C. H. Lampert and Z. Akata. "Zero-Shot Learning - A Comprehensive Evaluation of the Good, the Bad and the Ugly". In: (2018). URL:

Our command creating a tool for Zero-shot task. Using this system you can perform zls task or evaluate your architecture on wild used datasets.

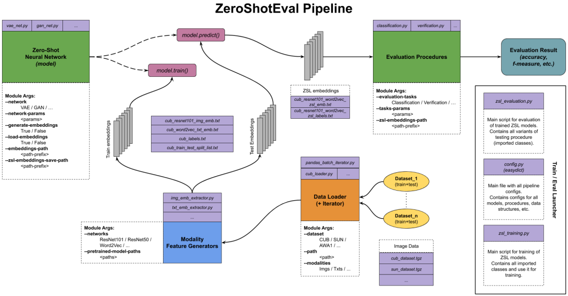


Figure: Strurcure of Zero-shot eval system[2]

[2] https://github.com/ZSLresearch-team/ZeroShotEval.

GZSL Nets

There's a lot of different approaches to perform GZSL task.
In ZeroShortEval inplement 2 nets: CADA-VAE and CLSWGAN.
CADA-VAE: based on Variation auto encoder.[3]
CLSWGAN: based on GAN[4]
for input to this nets, we take picture embedding(resnet-101) and class embedding. output: ZSL-embedding.
Also, there are Bayesian networks, knowledge graph etc.

[3] S. Sinha T. Darrell Z. Akata E. Schonfeld S. Ebrahimi. "Generalized Zero- and Few-Shot Learning via Aligned Variational Autoencoders". In: (2019). URL: https://arxiv.org/pdf/1812.01784.pdf.

[4] B. Schiele Z. Akata Y. Xian T. Lorenz. "Feature Generating Networks for Zero-Shot Learning". In: (2018). URL: https://arxiv.org/pdf/1712.00981v2.pdf.

GZSL to DST

Tasks: filing new slots which weren't in the training set.
Classification new intend which wasn't in the train set. combination of this task if we want to implement new services, which wasn't in a train set
Also, GZLS in NLP is text classification, performing tasks in different languages etc
Using GZSL we can easily implement our dialogue system to new services without training.

BERT approaches

Using BERT is a popular architecture for many NLP tasks. There are o lot of works in DST with BERT. For example in this work with architecture similar to this work..[5]

$[h_0, \ldots, h_T] = BERT([e_1, \ldots, e_T]); y_i = softmax(Wh_i + b);$

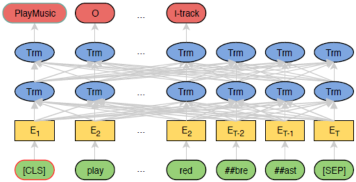


Figure: A high-level view of the observed model. The input query is "play the song little robin redbreast".

[5]W. Wang Q. Chen Z. Zhuo. "BERT for Joint Intent Classification and Slot Filling". In: (2019). URL: https://arxiv.org/pdf/1902.10909.pdf.

BERT approach

Models	Snips			ATIS		
	Intent	Slot	Sent	Intent	Slot	Sent
Joint BERT	**98.6**	**97.0**	**92.8**	97.5	**96.1**	88.2
Joint BERT + CRF	98.4	96.7	92.6	**97.9**	96.0	**88.6**

Figure: Shows the model performance as slot filling F1, intent classification accuracy, and sentence-level semantic frame accuracy on the Snips and ATIS datasets.

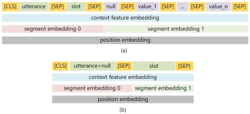
This approach has similar to BERT-dst work..[6]

[6] I. Lane G.-L. Chao. "BERT-DST: Scalable End-to-End Dialogue State Tracking with Bidirectional Encoder Representations from Transformer". In: (2019). URL: https://arxiv.org/pdf/1907.03040.pdf.

Schema-Guided Zero-Shot Dialogue State Tracking

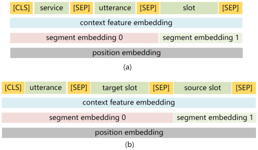
Another paper.[7] also uses BERT, but modify input for it and another interesting feature.

- slot prediction: predict slot (categorial or free-form)
- In-domain slot transfer: transfer slot from the earlier utterance in current service.
- Cross-domain slot transfer: transfer slot from the earlier utterance in other services.



BERT input representation in the *slot prediction* module: a) for categorial slot value prediction, and b) for free-form slot value prediction or requested slot prediction.

Figure



BERT input representation in the *slot transfer prediction* module: a) for in-domain slot transfer prediction, and b) for cross-domain slot transfer prediction.

Figure

[7] J.-C. Gu Q. Liue Y.-P. Ruan Z.-H. Ling. "Fine-Tuning BERT for Schema-Guided

Schema-Guided Zero-Shot Dialogue State Tracking continue

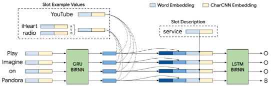
All BERT output put into the linear layer with softmax activation. scores and receive score. The score thresholds are set to 0.8, 0.5, 0.9, 0.85, and 0.9 for the categorical slot, free-form slot, requested slot, in-domain slot transfer, and cross-domain slot transfer prediction respectively.

	Active Intent Acc.	Requested Slot F1	Average Goal Acc.	Joint Goal Acc.
	SGP-DST			
All APIs	0.9529	0.9839	0.9387	0.8001
Seen APIs	0.9571	0.9845	0.9659	0.8831
Unseen APIs	0.9476	0.9832	0.9027	0.6923
	SGP-DST without in-domain slot transfer			
All APIs	0.9529	0.9839	0.8100	0.4975
Seen APIs	0.9571	0.9845	0.8362	0.5416
Unseen APIs	0.9476	0.9832	0.7753	0.4400
	SGP-DST without cross-domain slot transfer			
All APIs	0.9529	0.9839	0.8406	0.6361
Seen APIs	0.9571	0.9845	0.8748	0.7106
Unseen APIs	0.9476	0.9832	0.7954	0.5393
	SGP-DST without in&cross-domain slot transfer			
All APIs	0.9529	0.9839	0.7048	0.3940
Seen APIs	0.9571	0.9845	0.7353	0.4170
Unseen APIs	0.9476	0.9832	0.6644	0.3640

Figure

BiRNN

Another approach based on biLSTM nets. Common schema is concatenating slot description to utterance for example in this work



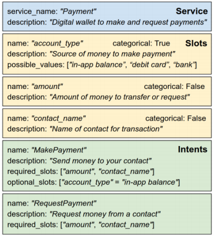
Figure

Also, there are a lot of other architects.

Capsule networks, CONVOLUTIONAL DEEP STRUCTURED SEMANTIC MODELS, based on XML model etc.

Datasets

During literature reviews next datasets is frequent occurrence: DSTC 23, SNIPS.
Also occure: XSchema, MultiWOZ 2.1., ect
Also some special Dataset DSTC-8 (SGP-DST).[8] Special new dataset for



Example schema for a digital wallet service.

Figure

[8] S. Sunkara R. Gupta P. Khaitan A. Rastogi X. Zang. "Schema-Guided Dialogue State Tracking Task at DSTC8". In: (2020). URL: https://arxiv.org/pdf/2002.01359.pdf

Metrics

1. Active Intent Accuracy: The fraction of user turns for which the active intent has been correctly predicted.
2. Requested Slot F1: The macro-averaged F1 score for requested slots over all eligible turns. Turns with no requested slots in ground truth and predictions are skipped.
3. Average Goal Accuracy: For each turn, we predict a single value for each slot present in the dialogue state. This is the average accuracy of predicting the value of a slot correctly.
4. Joint Goal Accuracy: This is the average accuracy of predicting all slot assignments for a given service in a turn correctly.
   Also Harmonic mean between seen and unseen classes.[9]

[9] Y. Xian and Akata., "Zero-Shot Learning - A Comprehensive Evaluation of the Good, the Bad and the Ugly".

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