Novel Slot Detection Trong Hệ Thống Đối Thoại Hướng Nhiệm Vụ

GVHD: ThS. Nguyễn Văn Kiệt

Sinh Viên: Trần Triệu Vũ - 19522539
Võ Minh Trí - 19522396
Phạm Đức Thể - 19522253

Khoa Khoa học và Kỹ thuật thông tin
Bộ môn Khoa học dữ liệu

CONTENTS

Introduction

What is Slot filling?

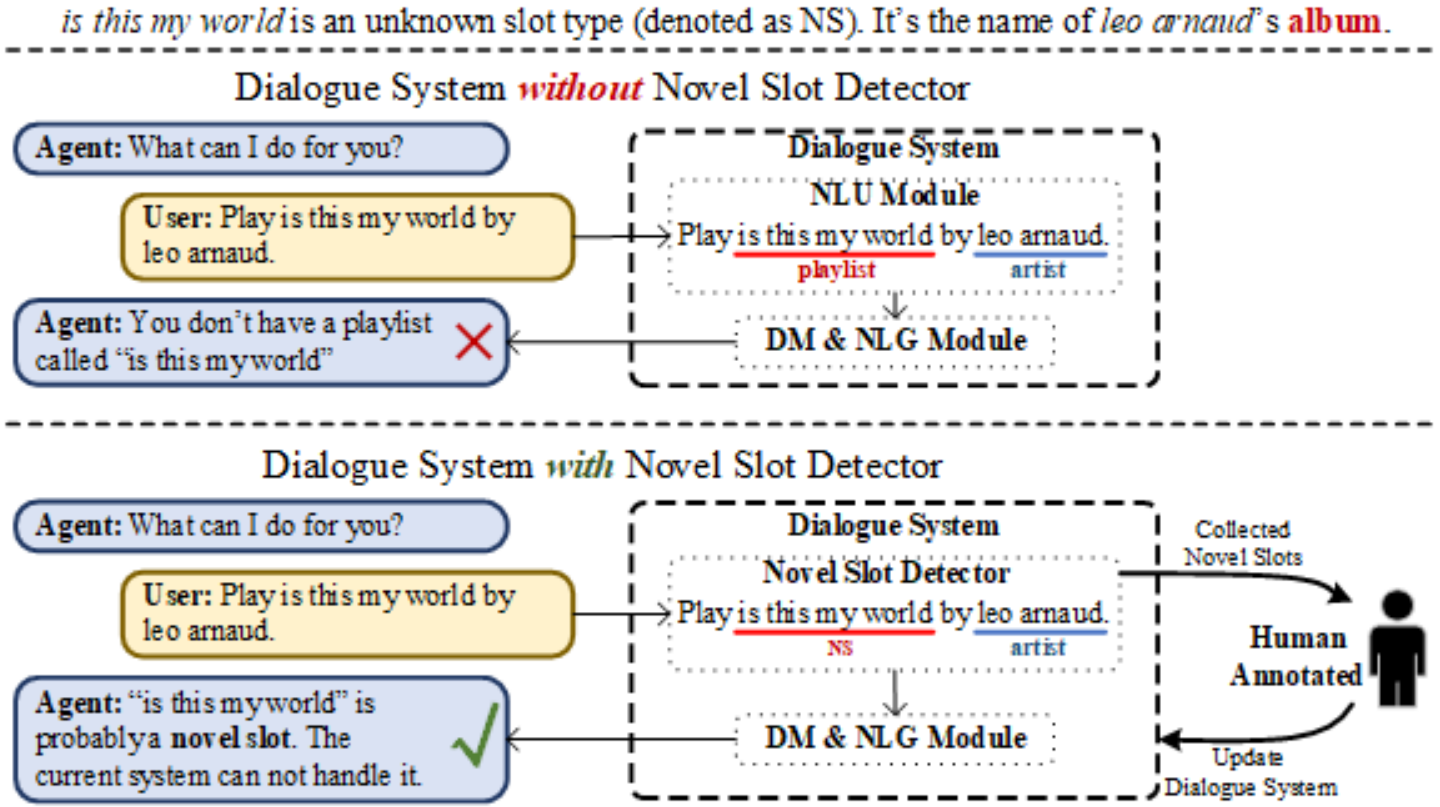
- Slot filling plays a vital role to understand user queries in personal assistants such as Alexa (Amazon), Siri (Apple), Google Assistant (Google), etc.
- It aims at identifying a sequence of tokens and extracting semantic constituents from the user queries.
- Given a large scale pre-collected training corpus, existing neural-based models have been actively applied to slot filling and achieved promising results.

Introduction

What is Novel Slot Detection?

- A reliable slot filling model should not only predict the pre-defined slots but also detect potential unknown slot types to know what it doesn't know, which we call Novel Slot Detection (NSD).
- Novel Slot (NS) as new slot types that are not included in the pre-defined slot set.
- NSD aims to discover potential new or out-of-domain (OOD) entity types to strengthen the capability of a dialogue system based on in-domain (IND) pre-collected training data.

Input/output



An example of Novel Slot Detection in the task-oriented dialogue system.

Dataset

Dataset	train utterances	dev utterances	test utterance
Snips	13,084	700	700
ATIS	4,478	500	893

Dataset

- Random select part of slot types in 2 dataset as unknown slots { 5% / 15% / 30% }
- For OOD intent detection, we just need to remove these sentences in training and validation set. However, for Novel Slot Detection, a sentence perhaps contains both in-domain slots and unknown slots, which is nontrivial for tackling unknown slots at the token level.

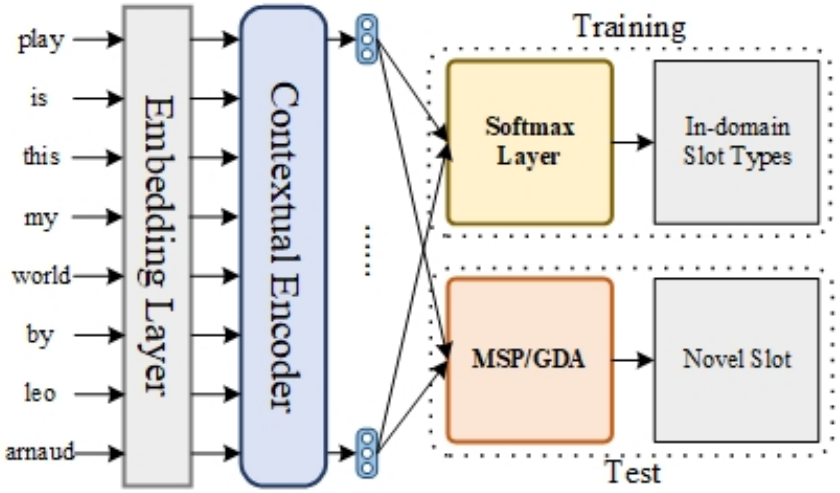
Dataset

Therefore, they propose three different processing strategies as follows:

Replace	Mask	Remove
Label the unknown slot values with all *O* in the training set while the original values remain unchanged.	Label the unknown slot values with all *O* and mask these slot values with a special token *MASK*.	All the sentences containing unknown slots are removed.

Original Utterance		play	**is**	**this**	**my**	**world**	by	leo	arnaud
Original Slot Filling Labels		O	**B-album**	**I-album**	**I-album**	**I-album**	O	B-artist	I-artist
Strategy	**Replace**	play	**is**	**this**	**my**	**world**	by	leo	arnaud
		O	**O**	**O**	**O**	**O**	O	B-artist	I-artist
	Mask	play	**MASK**	**MASK**	**MASK**	**MASK**	by	leo	arnaud
		O	**O**	**O**	**O**	**O**	O	B-artist	I-artist
	Remove	-	-	-	-	-	-	-	-
		-	-	-	-	-	-	-	-

Model



Overall Framework

- In the training stage, we either train a multiple-class classifier or binary classifier using different training objective. We use public BERT-large embedding layer and BiLSTM-CRF for token level feature extraction. Then, in the test stage, we use the typical neural multiple classifier to predict the in-domain slot labels.
- Meanwhile, we use the detection algorithm, MSP or GDA to figure out novel slot tokens. Finally, we override the slot token labels which are detected as NS.

Model

Training objective:

In-domain slot	
Multiple classifier	Binary classifier
Refers to the traditional slot filling objective setting	Non-O or O

Model

Training objective: in test stage

In-domain slot	Novel slot detection		
Multiple classifier	Multiple classifier	Binary classifier	Multiple + Binary

Multiple + Binary: the token = “NS” only both classifiers predict it as NS.

Model

Detection algorithm:

Maximum Softmax Probability	Gaussian Discriminant Analysis
The maximum falls below the threshold, the token will be predicted to be a NS token	Is a generative distancebased classifier for out-of-domain detection with Euclidean space.

Model

Distance strategy

- In original GDA, when the Minimum distance is greater than a certain threshold, it is predicted to be “ns”.
- Author propose a novel strategy named Difference, which uses the maximum distance minus the minimum distance, when the difference value of a target is less than a threshold, it is predicted as “ns”.

Experiment

pre-trained Bert-large-uncased	Layers = 24 hidden states = 1024 Heads = 16 336M parameters
BiLSTM	hidden size = 128
Optimizer: Adam	Lr = 2e-5
Dropout, batch size	Drop out = 0.5, batch size = 256
Early stopping	Patience = 10

Result

Our

Model			5%			15%			30%		
			IND	NSD		IND	NSD		IND	NSD	
detection method	objective	distance stragy	Span F1	Span F1	Token F1	Span F1	Span F1	Token F1	Span F1	Span F1	Token F1
GDA	multiple	minimum	92.33	28.27	58.09	85.21	18.46	42.11	87.32	17.21	42.14

Bảng V: Kết quả thực nghiệm trên Snips-NSD 5%, 15%, 30%.

Author's

Models			5%			15%			30%		
			IND	NSD		IND	NSD		IND	NSD	
detection method	objective	distance strategy	Span F1	Span F1	Token F1	Span F1	Span F1	Token F1	Span F1	Span F1	Token F1
MSP	binary	-	87.21	12.34	25.16	71.44	12.31	39.50	58.88	8.73	40.38
	multiple	-	88.05	14.04	30.50	79.71	20.97	40.02	78.52	25.26	46.91
	binary+multiple	-	89.59	23.58	37.55	83.72	24.70	45.32	79.08	30.66	52.10
GDA	binary	difference	87.95	23.83	35.83	83.65	22.06	43.99	78.72	32.50	44.13
	binary	minimum	61.29	10.36	17.08	49.11	16.91	31.10	48.07	15.56	33.78
	multiple	difference	**93.14**	29.73	45.99	90.07	31.96	53.02	85.56	36.16	54.55
	multiple	minimum	93.10	**31.67***	**46.97***	**90.18**	**32.19**	**53.75***	**86.26***	**38.64***	**55.24***

Table 5: IND and NSD results with different proportions (5%, 15% and 30%) of classes are treated as unknown slots on Snips-NSD. * indicates the significant improvement over all baselines ($p < 0.05$).

Models			5%			15%			30%		
			IND	NSD		IND	NSD		IND	NSD	
detection method	objective	distance strategy	Span F1	Span F1	Token F1	Span F1	Span F1	Token F1	Span F1	Span F1	Token F1
MSP	binary	-	92.04	19.73	29.63	91.74	23.40	33.89	80.49	21.88	39.17
	multiple	-	94.33	27.15	31.16	92.54	39.88	42.29	87.63	40.42	47.64
	binary+multiple	-	94.41	32.49	43.48	93.29	41.23	43.13	90.14	41.76	51.87
GDA	binary	difference	93.69	27.02	34.21	92.13	30.51	36.30	88.73	30.91	45.64
	binary	minimum	93.57	15.90	20.96	90.98	24.53	27.26	88.21	26.40	39.83
	multiple	difference	95.20	**47.78***	**51.54***	**93.92**	**50.92***	**52.24***	**92.02**	**51.26***	**56.59***
	multiple	minimum	**95.31***	41.74	45.91	93.88	43.78	46.18	91.67	45.44	52.37

Table 6: IND and NSD results with different proportions (5%, 15% and 30%) of classes are treated as unknown slots on ATIS-NSD. * indicates the significant improvement over all baselines ($p < 0.05$).

Analysis

- 1. Error.
  - Tag O.
  - Open Vocabulary Slot.
  - Simmilar Slots.
- 2. Challenges.
  - Function tokens.
  - Insufficient context.
  - Dependencies between slots.
  - Open vocabulary slots.

Conclusion

- Research about Novel Slot Detection.
- Experiment on Snips-NSD.
- Analysis the result, challenge and suggest development directions for future research.

Demo

Thanks for watching