

From sequence tagging to graph generation for Spoken Language Understanding

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Introduction

- Spoken Language Understanding (SLU) task : reduced to Intent detection and Slot filling
- Working on single Intent Corpora (ATIS, SNIPS)
- Using *flat* semantic annotation scheme with BIO encoding
 - ➔ It is not enough for structured semantic representations

[CLS]	AddToPlaylist
Add	O
another	O
song	B-music_item
to	O
the	O
Cita	B-playlist
Romántica	I-playlist
playlist	O

BIO annotation of SNIPS' sample

Introduction

- Can we go beyond the Intent/Slot paradigm when dealing with more **complex human-machine** interactions?
 - Multi-domain and Multi-Intents corpora
 - Conversational datasets
 - Dialog context
- Can we take advantage of seq2seq approach rather than sequence-tagging?
- What is the potential of graph generation method on SLU task ?

Objectives

- NLU task on Multi-domain and Multi-Intent dataset: MultiWOZ2.3
- Studying different strategies to project this semantic frames annotations:
 - **Sequence tagging approach**: flatten MultiWOZ semantic structure to fit the BIO representation
 - **ARMILU**: Abstract Representation for Multi-Intent spoken and natural Language Understanding
- Contextual NLU/SLU models

Related Work

- Seq2seq NLU/SLU models

- 1. Y. Feng, Y. Wang, and H. Li, “A sequence-to-sequence approach to dialogue state tracking,” 2021**

- Seq2seq approach for DST with a specification of the domain ontology (MultiWOZ)
 - ❖ Reduced the hallucination problem
 - ❖ limited to pre-defined schema
- Seq2seq approach for non contextual dataset (SNIPS, ATIS)
 - ❖ Producing only pointers to word spans in the current utterance
 - ❖ limited to flat SLU models with BIO encoding

Related Work

- Seq2seq NLU/SLU models

2. K. Raman, I. Naim, J. Chen, K. Hashimoto, K. Yalasangi, and K. Srinivasan, “Transforming sequence tagging into a seq2seq task,” 2022

- Several encoding for mixing words and semantic labels for seq2seq SLU model
 - ❖ Several benchmark corpora
 - ❖ No-contextual or multi-intent datasets
 - ❖ Flat BIO projection

ARMILU and State of the Art on SNIPS

K. Raman, I. Naim, J. Chen, K. Hashimoto, K. Yalasangi, and K. Srinivasan,
“Transforming sequence tagging into a seq2seq task,” 2022

Input	<extra_id_0> Add	<extra_id_1> Kent	<extra_id_2> James	<extra_id_3> to	<extra_id_4> the	<extra_id_5> Disney	<extra_id_6> soundtrack
Target	<extra_id_0> O	<extra_id_1> ARTIST	<extra_id_2> I-ARTIST	<extra_id_3> O	<extra_id_4> O	<extra_id_5> PLAYLIST	<extra_id_6> O

➤ Only flat BIO single Intent and non contextual SLU

Related Work

- Contextual NLU/SLU models:
 - **A. Gupta, P. Zhang, G. Lalwani, and D. Mona, “Casa-nlu: Context-aware self-attentive natural language understanding for task-oriented chatbots,” 2019**
 - Using the dialog context for predicting the current interpretation of a turn
 - Building a specific architecture with contextual representation based on a fixed window size made of the last n turns
 - Working on Machine-to-Machine Simulated Dialogue Corpus (M2M)

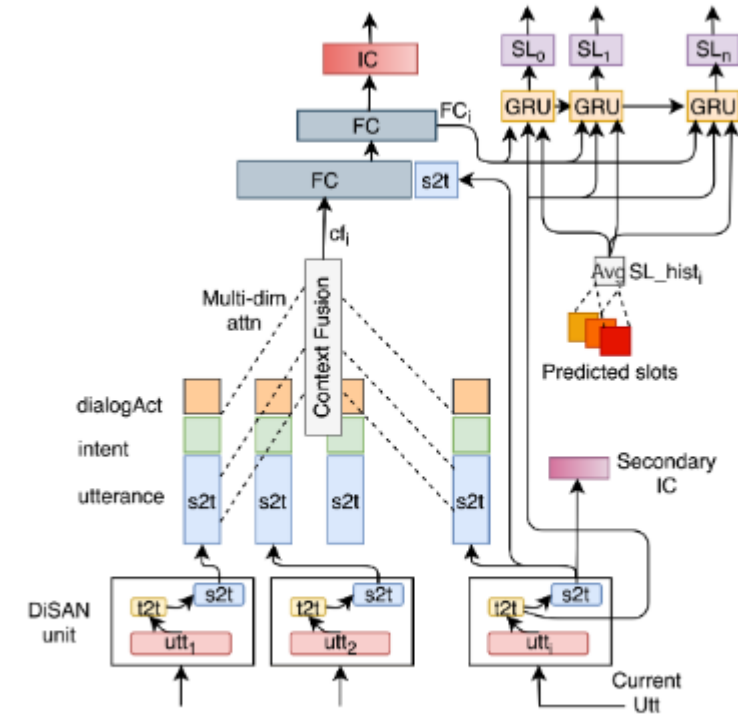


Figure 2: CASA-NLU model architecture for joint IC-SL

MultiWOZ2.3 dataset

- A large-scale multi-domain and multi-Intent English dataset
- Frequently used in Dialogue State Tracking, Dialog Policy and Dialog Generation tasks.
- Each dialog turn is associated with the current dialog state:
 - A set of **Intents** and **Slots** with **Values**

I need to make sure it's cheap and I need parking

❖ **Semantic Frame annotation**

❖ “**Hotel-Inform**”:[["**Parking**", “yes”], [“**Price**”, “**cheap**”, 6,6]]

- Intent : **Hotel-Inform**
- Slots: **Parking**, **Price**
- Value with span: “**cheap**”
- Value without span: “**yes**”

MultiWOZ2.3 dataset: utterance difficulties

Utterances	Semantic annotation
I need to make sure it's cheap and I need parking	"Hotel-Inform":[[["Parking", "yes"], ["Price", "cheap", 6,6]]]
I'll need the address for one that does have wifi please	"Hotel-Inform":[[["Internet", "yes"]], "Hotel-Request":[[["Addr", "?"]]]
Can I get the postcode for that and I also need to book a taxi to the Golden Wok	"Taxi-Inform": [{"Dest", "golden wok« , 17,18}], "Attraction-Request": [{"Post", "?"}]
The taxi should depart from parkside police station	"Police-Inform":[[["Name", "parkside police station"]], "Taxi-Inform":[[["Depart", "parkside police station"]]]
yes I do, I 'd like to make sure I arrive at the restaurant by the booked time	"Taxi-inform": [{"Depart", "old schools"}, {"Dest", "the restaurant", 12,13}]

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Can I get the postcode for that and I also need to book a taxi to the Golden Wok	"Taxi-Inform": [{"Property": "Dest", "Value": "golden wok", "Start": 17, "End": 18}], "Attraction-Request": [{"Property": "Post", "Value": "?"}]]
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The taxi should depart from parkside police station	" Police-Inform ":[[{"Property": " Name ", "Value": " <i>parkside police station</i> ", "Start": 5, "End": 7}], " Taxi-Inform ":[[{"Property": " Depart ", "Value": " <i>parkside police station</i> ", "Start": 5, "End": 7}]]
yes I do, I 'd like to make sure I arrive at the restaurant by the booked time	"Taxi-inform": [{"Property": "Depart", "Value": "old schools"}, {"Property": "Dest", "Value": "the restaurant", "Start": 12, "End": 13}]]

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MultiWOZ2.3 dataset

	Statistics
#Conversations	10438
#User utterances	71521
#domains	9
#Slots	28 (27 explicit + « none »)
#intents (Domain-Act)	32
#Domain-Act+Slot	131

- ❖ A large dataset:
 - 8438 conversations with 56775 utterances in Train
 - 1000 conversation with 7372 utterances in test
- ❖ 8 application domains (*Train, Taxi, Hotel, Restaurant, Attraction, Hospital, Bus, Police*) and the *General* domain for generic acts (*bye, Greet, Thank and Welcome*)

- ❖ Categorical slots with normalized values: *yes, no, dontcare, none* and ?
- ❖ Other different class of normalized values for periphrasis:
 - « *I don't want to pay for wifi* »
 - slot*value: Price***free**

Flat projection: Propositions

- “Convlab: Multi-domain end-to-end dialog system platform,” 2019

❖ Dealing with multi-intent annotations suitable for use with a BERT pretrained language model representation

❖ **Not fully consistent** with the original annotation

❖ Only categorical slots with the 5 class of normalized values in **CLS** level

❖ **Mono-label** in slot level

tokens	Our version	Convlab
[CLS]	Hotel-Inform Hotel-Inform+ Parking*yes	Hotel-Inform+ Parking*yes
make	O	O
sure	O	O
it	O	O
's	O	O
cheap	B-Hotel-Inform+ Price	B-Hotel- Inform+ Price
and	O	O
I	O	O
need	O	O
parking	O	O

tokens	Our version	Convlab
[CLS]	Police-Inform Taxi-Inform	O
the	O	O
taxi	O	O
should	O	O
depart	O	O
from	O	O
parkside	B-Police-Inform+Name B-Taxi-Inform+Depart	B-Taxi-Inform+Depart
police	I-Police-Inform+Name I-Taxi-Inform+Depart	I-Taxi-Inform+Depart
station	I-Police-Inform+Name I-Taxi-Inform+Depart	I-Taxi-Inform+Depart

Models' implementation

- **Transformer based sequence tagging + BIO flat encoding**

- 1. Multi-label BIO Model**

- mBERT finetuning on the NLU Task

- 2. Convlab-2** (Q. Zhu and al., “Convlab-2: An open-source toolkit for building, evaluating, and diagnosing dialogue systems,” 2020)

- BERTNLU: two MLP layers on top of BERT to predict jointly the intents (multi-label) and the slots (mono-label).

ARMILU: Abstract Representation for Multi-Intent SLU

- **ARMILU**

- Inspired by recent works in semantic analysis to predict the Abstract Meaning Representation (AMR) format (L. Banarescu and al., “Abstract Meaning Representation for Sembanking,” 2013)

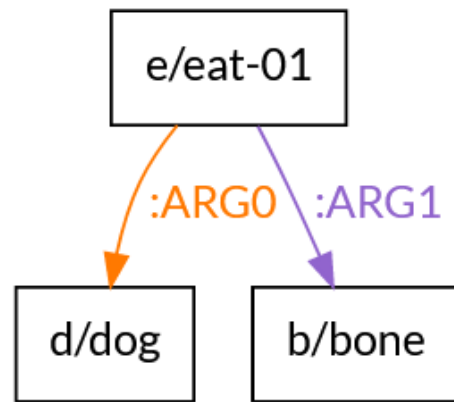
- **Transcription of AMR analysis to Penman formalism** (R. T. Kasper, “A flexible interface for linking applications to Penman’s sentence generator,” 1989)

- Producing a linear representation of a graph structure using parentheses and variables to express relations and concepts

AMR with Penman

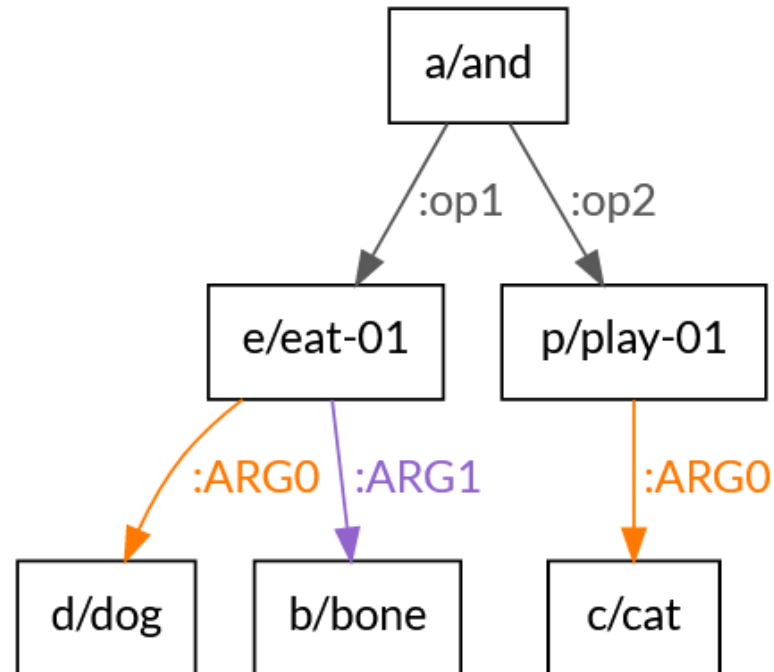
1: the dog is eating a bone

```
(e / eat-01  
  :ARG0 (d / dog)  
  :ARG1 (b / bone))
```



2: the dog is eating a bone and the cat is playing

```
(a / and  
  :op1 (e / eat-01  
    :ARG0 (d / dog)  
    :ARG1 (b / bone))  
  :op2 (p / play-01  
    :ARG0 (c / cat)))
```



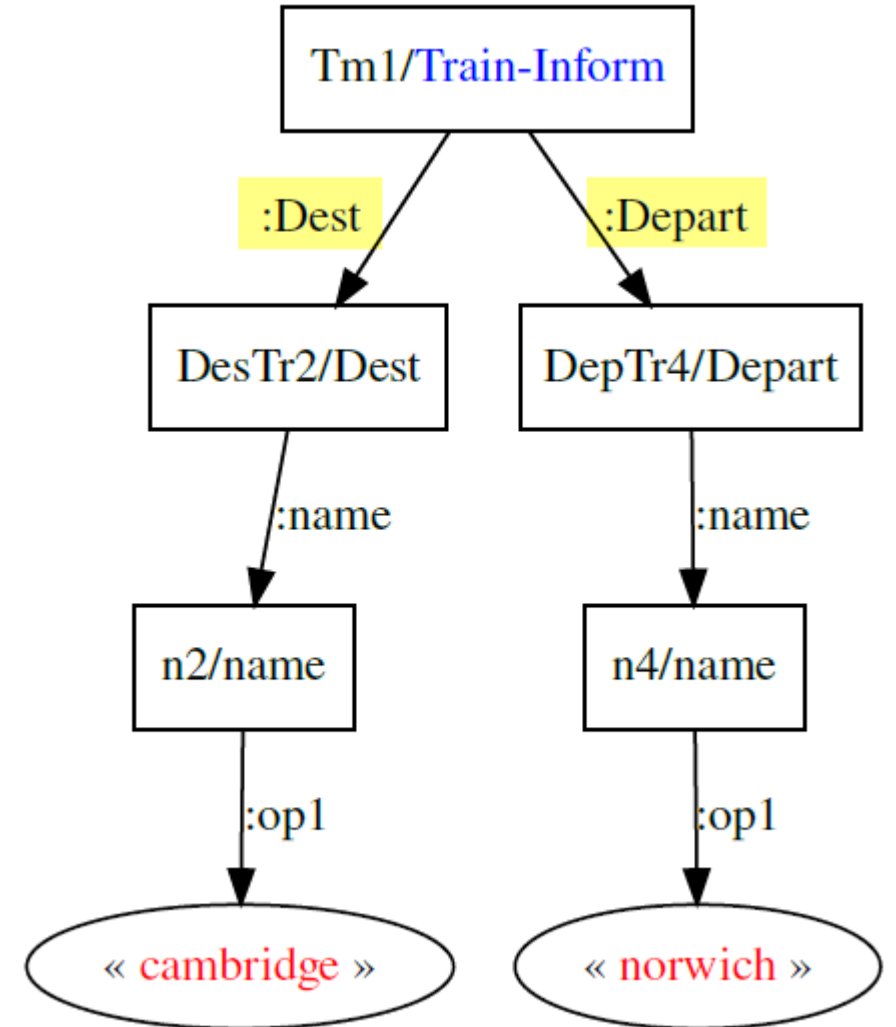
ARMILU: Mono-Intent

“I need train reservations from **norwich** to **cambridge**”

```
"dialog_act": {"Train-Inform":  
  [[":Dest", « cambridge", 7, 7], [":Depart",  
  "norwich", 5, 5]]}
```

Penman formalism

```
( Tm1 / Train-Inform  
  :Dest ( DesTr2 / Dest  
    :name ( n2 / name  
      :op1 "cambridge" ))  
  
  :Depart ( DepTr4 / Depart  
    :name ( n4 / name  
      :op1 "norwich" )))
```



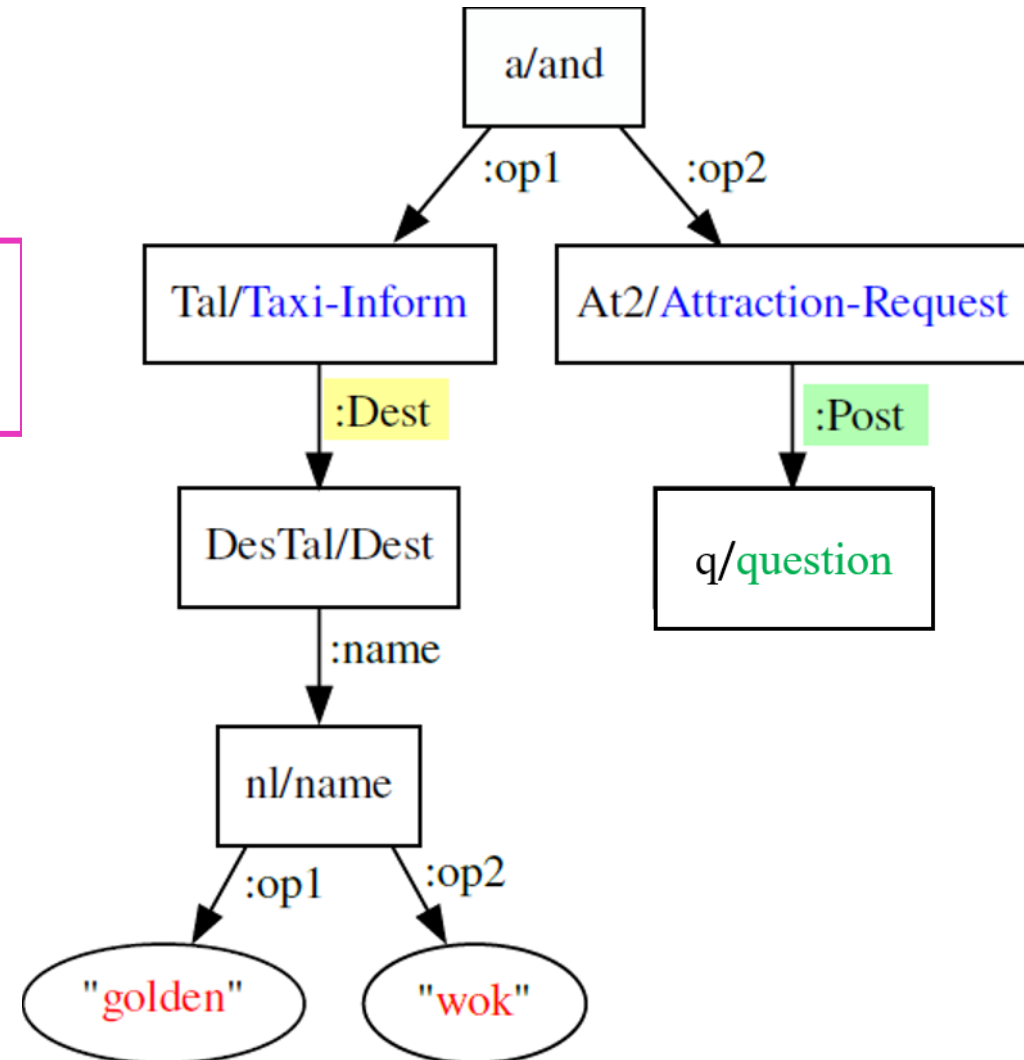
ARMILU: Multi-Intent

“Can I get the postcode for that I also need to book a taxi to the **golden wok**”

```
"dialog_act": {"Taxi-Inform": [{"Dest", "golden wok", 17, 18}], "Attraction-Request": [{"Post", "?"}]}
```

Penman formalism

```
(a / and
  :op1 (Ta1 / Taxi-Inform
    :Dest (DesTa1 / Dest
      :name (n1 / name
        :op1 "golden"
        :op2 "wok")))
  :op2 (At2 / Attraction-Request
    :Post (q / question)))
```



Models' implementation

- Abstract graph generation
 - Seq2seq model to generate directly the Penman linear representation
 - AMRlib library with the mt5 model
 - Specific module that guarantees graph consistency
 - Train from scratch

“Can I get the postcode for that I also need to book a taxi to the **golden wok**”

Penman formalism

```
(a / and
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        :op2 "wok"))))

:op2 (At2 / Attraction-Request
  :Post (q / question))
```

Context aware SLU

- Augmenting the input of the models with the previous turns (user and system)

- ❖ Multi-label flat BIO:

- [CLS] Ut_{t-2} Ut_{t-1} [SEP] Ut_t
- The context is labeled with O

- ❖ Convlab flat BIO:

- [CLS] Ut_{t-3} Ut_{t-2} Ut_{t-1} [SEP] Ut_t

- ❖ Generative model:

- [USER] Ut_{t-2} [SYS] Ut_{t-1} [SEP] Ut_t

Evaluation Method

- Comparable evaluations regardless of the projection approach:
 - Each system's output was projected to the formalism $Intent(Slot, Value)$
 - I need to make sure it's cheap and I need parking
 - ❖ **Semantic Frame annotation**
 - ❖ {“Hotel-Inform”:[["Parking", “yes”], [“Price”, “cheap”, 7,7]] }
 - ❖ **Formalism for evaluation**
 - ❖ [Hotel-Inform (Parking, yes), Hotel-Inform(Price, cheap)]
 - Compare the list of $Intent(Slot, Value)$ elements in reference and in the predictions of the various systems
- Metrics
 - **F1-score** at the $Intent$, $Slot$ and $Intent(Slot, Value)$ levels
 - Global accuracy evaluation: all the elements of utterances must be recognized

Results

Without Context	Multi-label BIO	Convlab BIO	ARMILU graph
<i>Intent F1</i>	91.5	91.9	92.0
<i>(Slot, Value) F1</i>	93.6	93.7	94.0
<i>Intent (Slot, Value) F1</i>	89.6	90.2	89.9
<i>Global accuracy</i>	81.0	81.6	82.3

With Context	Multi-label BIO	Convlab BIO	ARMILU graph
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<i>(Slot, Value) F1</i>	94.7	94.6	94.9
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<i>Global accuracy</i>	86.5	86.6	87.4

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- ❖ Comparable results for Intent and (Slot, Value) F-scores.
- ❖ Global accuracy is slightly higher for the ARMILU approach
 - Graph based approach is better at predicting semantic structures spanning the whole turn.

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➤ Better results with introducing the context in all levels for all systems

Contrastive Experiments: Different partitions of MultiWOZ

- Partitions according to several criteria related to potential difficulty levels
 - ❖ Utterances with negation marks (*not, n't*) vs utterance without negation marks
 - ❖ Utterances with implicit values (*dontcare, yes, no*), no value (*none*) and other *normalized values without span* vs all the others
 - ❖ Interrogative sentences (value *?*) vs no Interrogative values
 - ❖ Utterances with Multi-label (*Multi Intent+Slot*) vs Mono-label
 - ❖ First utterance of each conversation (*commands for the system*) vs the others (need *the context*)

Contrastive Experiments: Different partitions of MultiWOZ

	<i>Négation</i>		<i>Implicit values</i>		<i>Value « ? »</i>		<i>Multi-label</i>		<i>1st utterances</i>	
<i>nb of samples</i>	+ (470)	- (6902)	+ (574)	- (6798)	+ (1499)	- (5837)	+ (3417)	- (3667)	+ (1000)	- (6372)
<i>Multi-label BIO</i>	64.7	88.0	54.7	89.2	76.7	89.0	80.2	92.2	91.6	85.7
<i>ARMILU graph</i>	68.3	88.7	58.2	89.9	78.7	89.7	81.5	93.0	91.7	86.8

global accuracy

Contrastive Experiments: Different partitions of MultiWOZ

<i>nb of samples</i>	<i>Négation</i>		<i>Implicit values</i>		<i>Value « ? »</i>		<i>Multi-label</i>		<i>1st utterances</i>	
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- ARMILU projection model is better on all the potentially difficult configurations.
- Important improvements for implicit values and for utterances with negations.
- Abstract representations can help going beyond classical span based slot/value utterances.

Contrastive Experiments:

First utterances and proportion of span-based values

	<i>Négation</i>		<i>Implicit values</i>		<i>Value « ? »</i>		<i>Multi-label</i>		<i>1st utterances</i>	
<i>nb of samples</i>	+ (470)	- (6902)	+ (574)	- (6798)	+ (1499)	- (5837)	+ (3417)	- (3667)	+ (1000)	- (6372)
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<i>ARMILU graph</i>	68.3	88.7	58.2	89.9	78.7	89.7	81.5	93.0	91.7	86.8

- **88%** of slots with a span vs **60.8%**
- **1.4** slots per utterance on average vs **1.0**

➤ Predicting span-based values is challenging in a generative framework

Contrastive Experiments: SNIPS dataset

	Statistics
#User utterances	14 484
#intents	7
#Slots	39
#domains	7
#Domain-Act+Slot	53

- Mono-labels
- **100%** of slots with **explicit** span based values
- **2.6** slots per utterance on average

- Intents are transformed to domain-Intent:
 - Music-AddToPlaylist
- Projection to Penman formalism

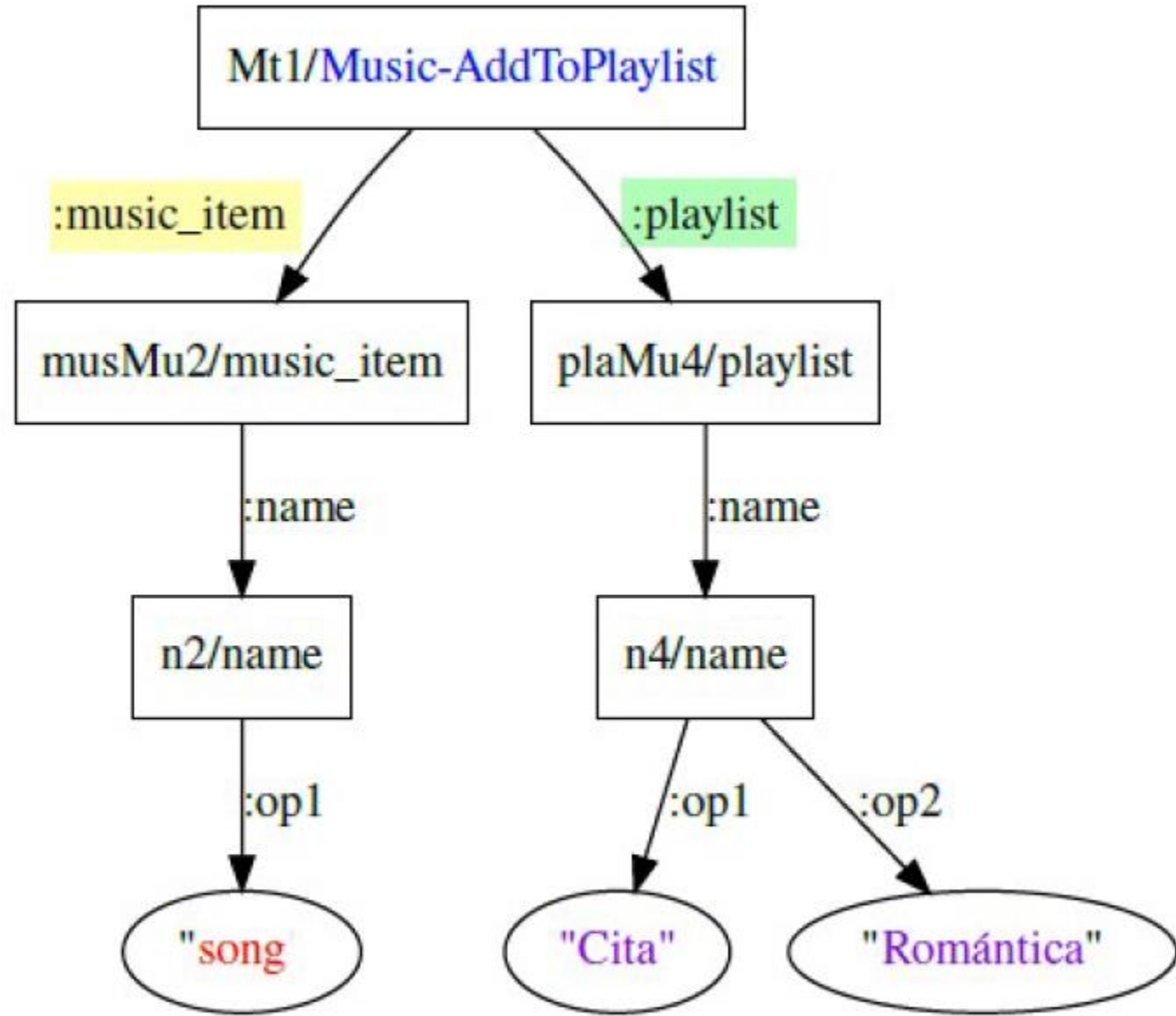
Contrastive Experiments: SNIPS dataset

Text: “Add another **song** to the **Cita Romántica** playlist”

(Mt1 / **Music-AddToPlaylist**

```
:music_item ( musMu2 / music_item  
  :name ( n2 / name  
    :op1 "song" ) )
```

```
:playlist ( plaMu4 / playlist  
  :name ( n4 / name  
    :op1 "Cita"  
    :op2 "Romántica" ) )
```



Contrastive Experiments: SNIPS dataset

- BIO encoding with sequence tagging remains more efficient on the overall.
- the lack of training corpus for some slot labels
- hallucinations occurring in slot values.
 - Text: Add *millie corretjer* to the rhythm playlist
 - Hyp: “*milie korrekter*”

	Multi-classification BIO	ARMILU graph
<i>Intent F1</i>	98.9	99.0
<i>(Slot, Value) F1</i>	96.3	95.3
<i>Intent (Slot, Value) F1</i>	96.2	95.1
<i>Global accuracy</i>	91.4	88.9

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➤ Only flat BIO single Intent and non contextual SLU

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	SOTA mBERT BIO	SOTA seq2seq BIO
<i>Perfect %</i>	86.57	90.1
<i>F1 CoNLL</i>	93.66	95.5

- **Perfect:** the % of times an example is parsed perfectly
- **F1 CoNLL :** slots + all the values are correct

ARMILU and State of the Art on SNIPS

K. Raman, I. Naim, J. Chen, K. Hashimoto, K. Yalasangi, and K. Srinivasan,
“Transforming sequence tagging into a seq2seq task,” 2022

	SOTA mBERT BIO	SOTA seq2seq BIO
<i>Perfect %</i>	86.57	90.1
<i>F1 CoNLL</i>	93.66	95.5

- Perfect: the % of times an example is parsed perfectly
- F1 CoNLL Micor: slots + all the values are correct

	mBERT BIO	ARMILU graph
<i>concept accuracy</i>	91.4	88.9
<i>F1 Micro concepts</i>	96.3	95.4

- Very close results in F1 level
- SOTA Seq2seq is better than ARMILU
 - less hallucination problems
 - Only **flat BIO single** Intent

Discussion

- New paradigm to project semantic annotations for SLU into an abstract graph and structured representation
- ARMILU exploits the Penman formalism also used for AMR
- Important improvements on more complex utterances thanks to the advantage of powerful seq2seq generative models
- More complex semantic annotations for dialogue
- Highly variable values remains challenging for the generative model

Perspectives

- Perform the module to handle corpora with slots of explicit based values
 - ATIS, DjingoSpeaker, etc.
- Ablation studies:
 - Flat BIO seq2seq models on dialog datasets
 - Generate directly the origin annotations
- Other learning methods like Zero/Few shot learning
 - New ontology
 - New domains/Intents
- AMR analysis for new semantic structures