From sequence tagging to graph generation for Spoken Language Understanding

Rim Abrougui, Géraldine Damnati, Johannes Heinecke, Frédéric Béchet

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**: **A**bstract **R**epresentation for **M**ulti-**I**ntent spoken and natural **L**anguage **U**nderstanding

- 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-contexual 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)

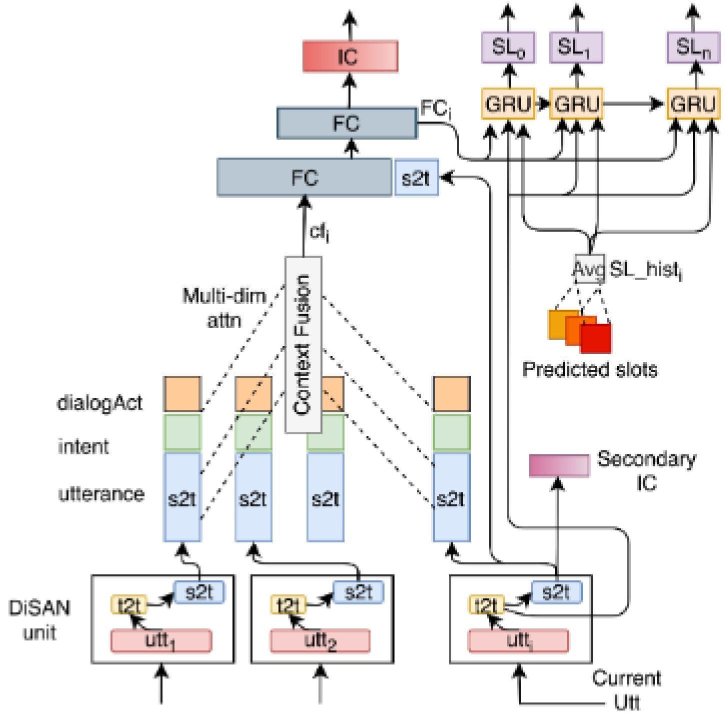


Figure 2: CASA-NLU model architecture for joint IC-SL

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]]

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]]

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]]

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]]

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*”, 5,7]], “**Taxi-Inform**”:[[“**Depart**”, “*parkside police station*”,5,7]]
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]]

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]]

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).

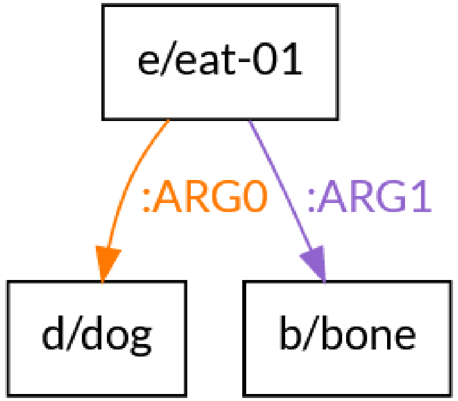
ARMILU: Abstract Representation for Multi-Intent SLU

- **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

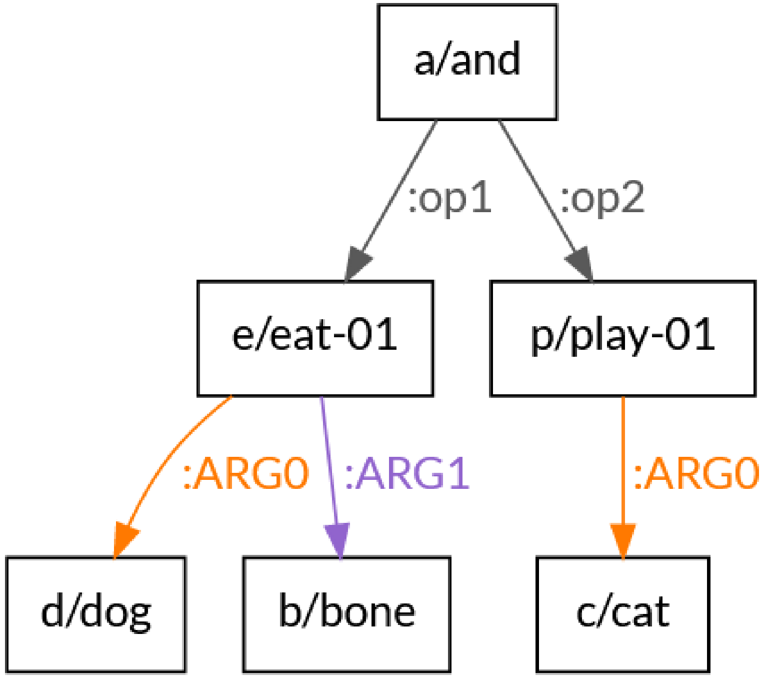
1: the dog is eating a bone

```
(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

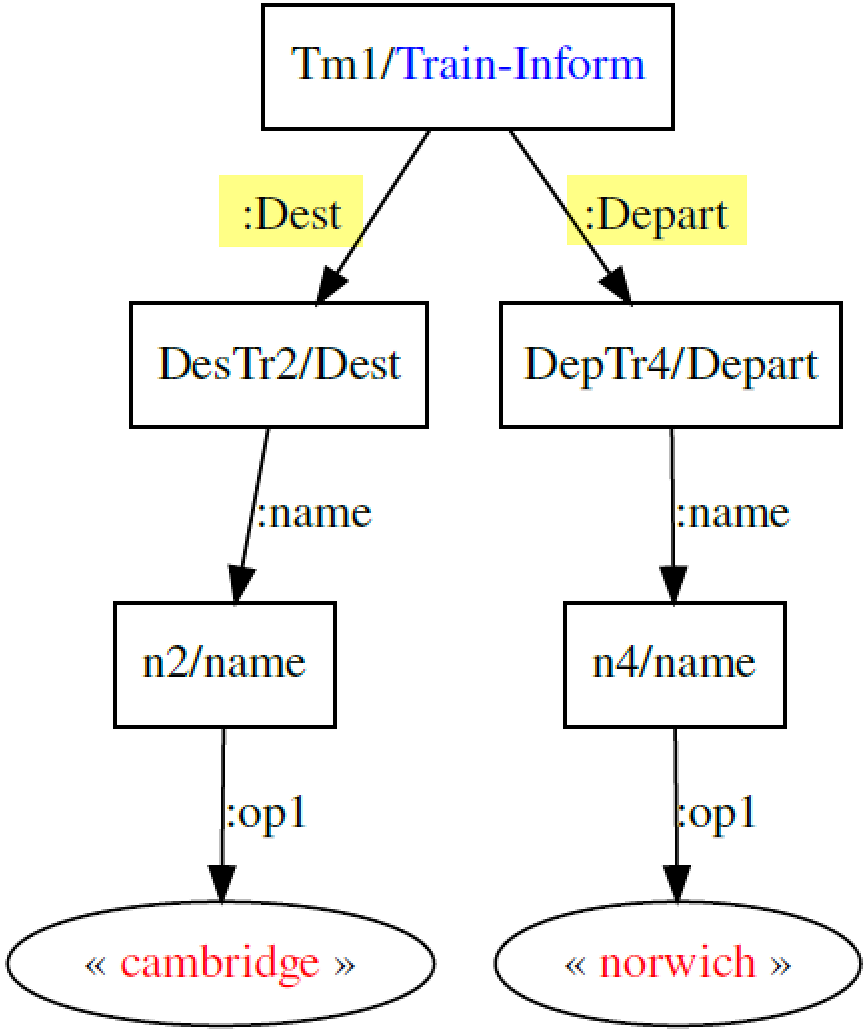
"I need train reservations from **norwich** to **cambridge**"

```
"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

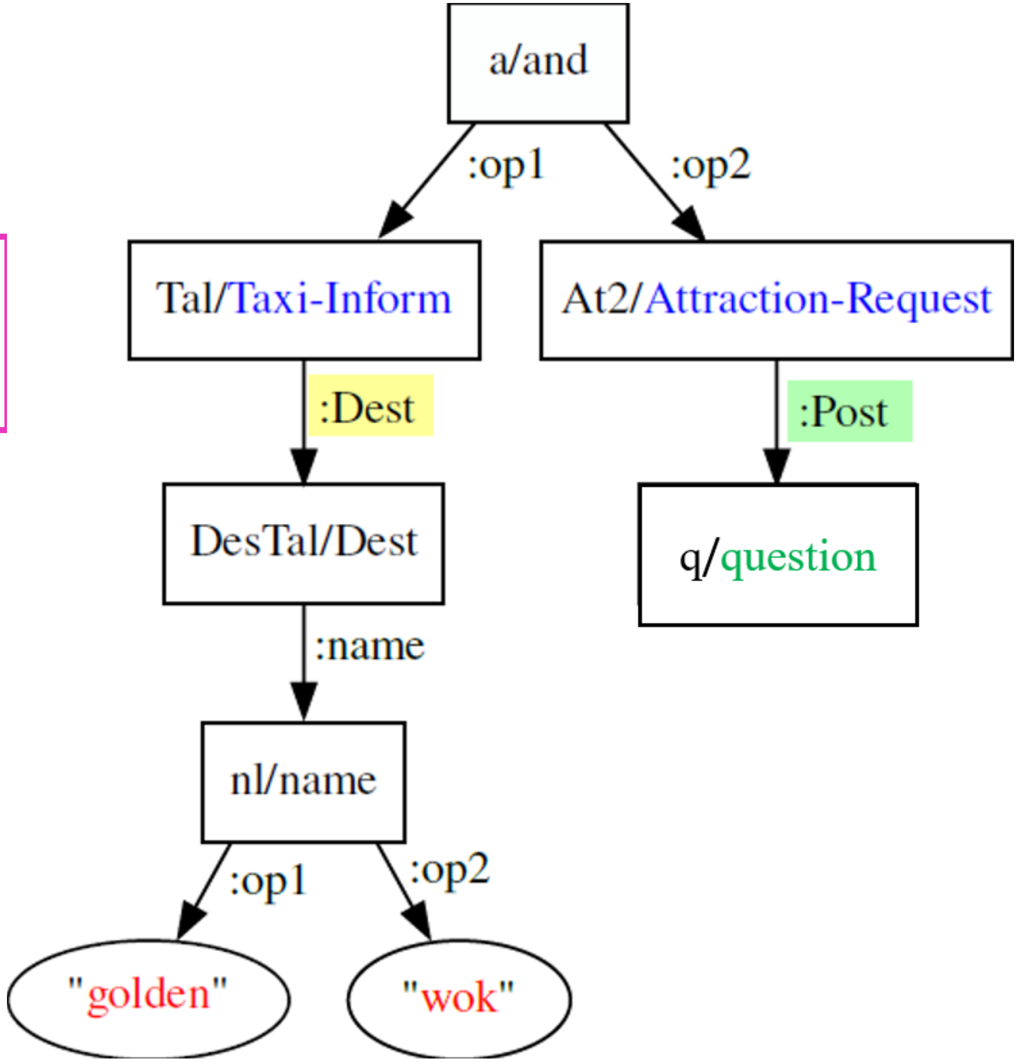
“Can I get the postcode for that I also need to book a taxi to the **golden wok**”


```
"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
    :op1 (Ta1 / Taxi-Inform
        :Dest (DesTa1 / Dest
            :name (n1 / name
                :op1 "golden"
                :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]` $\texttt{Utt}_{\texttt{t-2}}$ $\texttt{Utt}_{\texttt{t-1}}$ `[SEP]` $\texttt{Utt}_{\texttt{t}}$
    - The context is labeled with `O`
  - ❖ Convlab flat BIO:
    - `[CLS]` $\texttt{Utt}_{\texttt{t-3}}$ $\texttt{Utt}_{\texttt{t-2}}$ $\texttt{Utt}_{\texttt{t-1}}$ `[SEP]` $\texttt{Utt}_{\texttt{t}}$
  - ❖ Generative model:
    - `[USER]` $\texttt{Utt}_{\texttt{t-2}}$ `[SYS]` $\texttt{Utt}_{\texttt{t-1}}$ `[SEP]` $\texttt{Utt}_{\texttt{t}}$

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**
Intent F1	91.5	91.9	92.0
(Slot,Value) F1	93.6	93.7	94.0
Intent (Slot,Value) F1	89.6	90.2	89.9
Global accuracy	81.0	81.6	82.3

With Context	**Multi-label BIO**	**Convlab BIO**	**ARMILU graph**
Intent F1	95.6	95.5	95.9
(Slot,Value) F1	94.7	94.6	94.9
Intent (Slot,Value) F1	94.0	94.1	94.2
Global accuracy	86.5	86.6	87.4

Results

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

With Context	Multi-label BIO	Convlab BIO	ARMILU graph
Intent F1	95.6	95.5	95.9
(Slot, Value) F1	94.7	94.6	94.9
Intent (Slot, Value) F1	94.0	94.1	94.2
Global accuracy	86.5	86.6	87.4

- ❖ 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.

Results

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

With Context	**Multi-label BIO**	**Convlab BIO**	**ARMILU graph**
Intent F1	95.6	95.5	**95.9**
(Slot,Value) F1	94.7	94.6	**94.9**
Intent (Slot,Value) F1	**94.0**	**94.1**	**94.2**
Global accuracy	**86.5**	**86.6**	**87.4**

- 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

	Négation		*Implicit values*		*Value « ? »*		*Multi-label*		*1st utterances*	
nb of samples	+ (470)	- (6902)	+ (574)	- (6798)	+ (1499)	- (5837)	+ (3417)	- (3667)	+ (1000)	- (6372)
Multi-label BIO	64.7	88.0	54.7	89.2	76.7	89.0	80.2	92.2	91.6	85.7
ARMILU graph	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

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

- ➢ 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

	Négation		*Implicit values*		*Value « ? »*		*Multi-label*		*1st utterances*	
nb of samples	+ (470)	- (6902)	+ (574)	- (6798)	+ (1499)	- (5837)	+ (3417)	- (3667)	+ (1000)	- (6372)
Multi-label BIO	64.7	88.0	54.7	89.2	76.7	89.0	80.2	92.2	91.6	85.7
ARMILU graph	**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

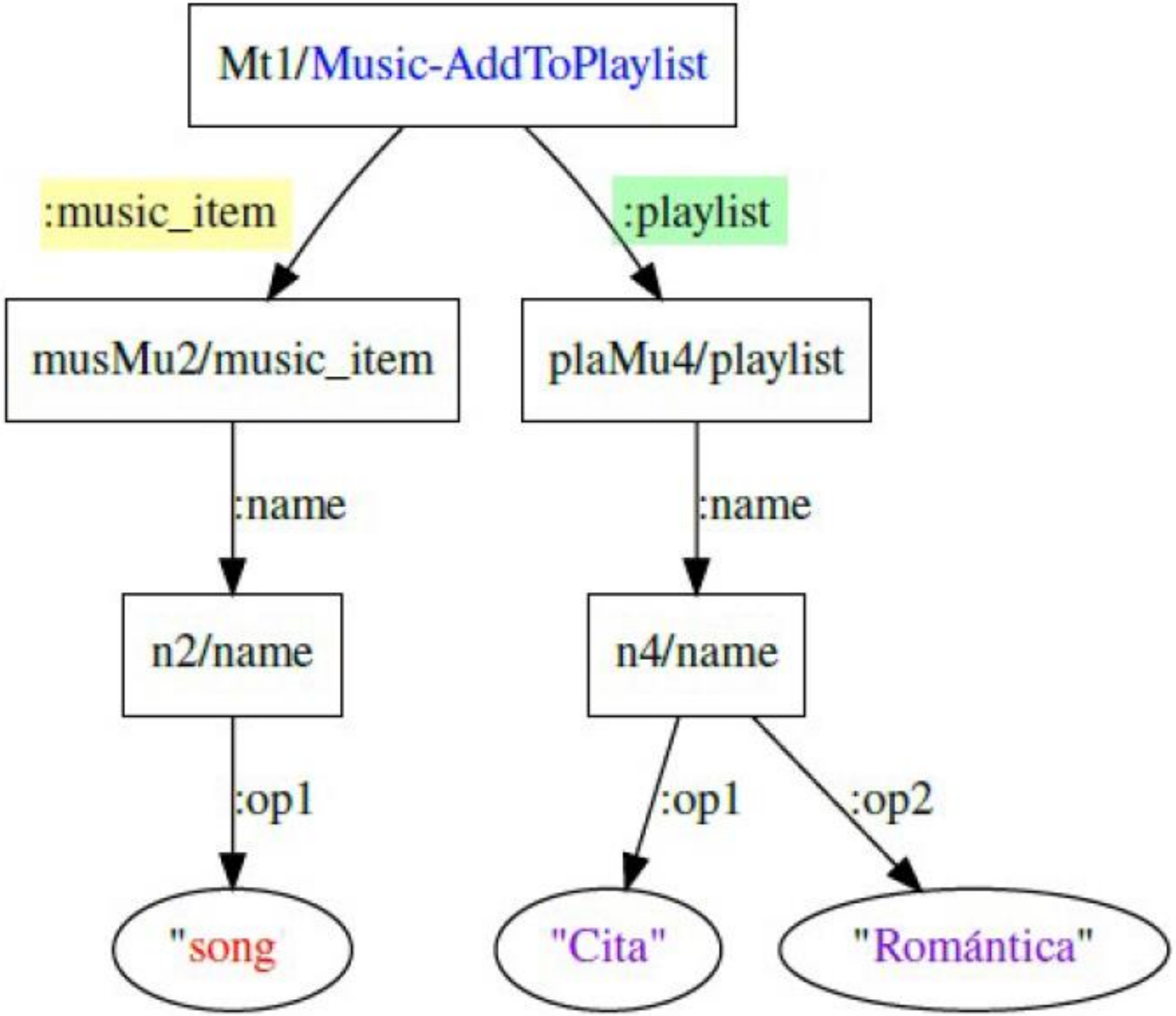
Contrastive Experiments: SNIPS dataset

Text: “Add another song to the Cita Rom´antica 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**
Intent F1	98.9	99.0
(Slot,Value) F1	**96.3**	95.3
Intent (Slot,Value) F1	**96.2**	95.1
Global accuracy	**91.4**	88.9

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

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
Perfect %	86.57	90.1
F1 CoNLL	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
Perfect %	86.57	**90.1**
F1 CoNLL	93.66	95.5

	mBERT BIO	ARMILU graph
concept accuracy	**91.4**	**88.9**
F1 Micro concepts	**96.3**	**95.4**

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

- 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