

# Intent Features for Rich Natural Language Understanding

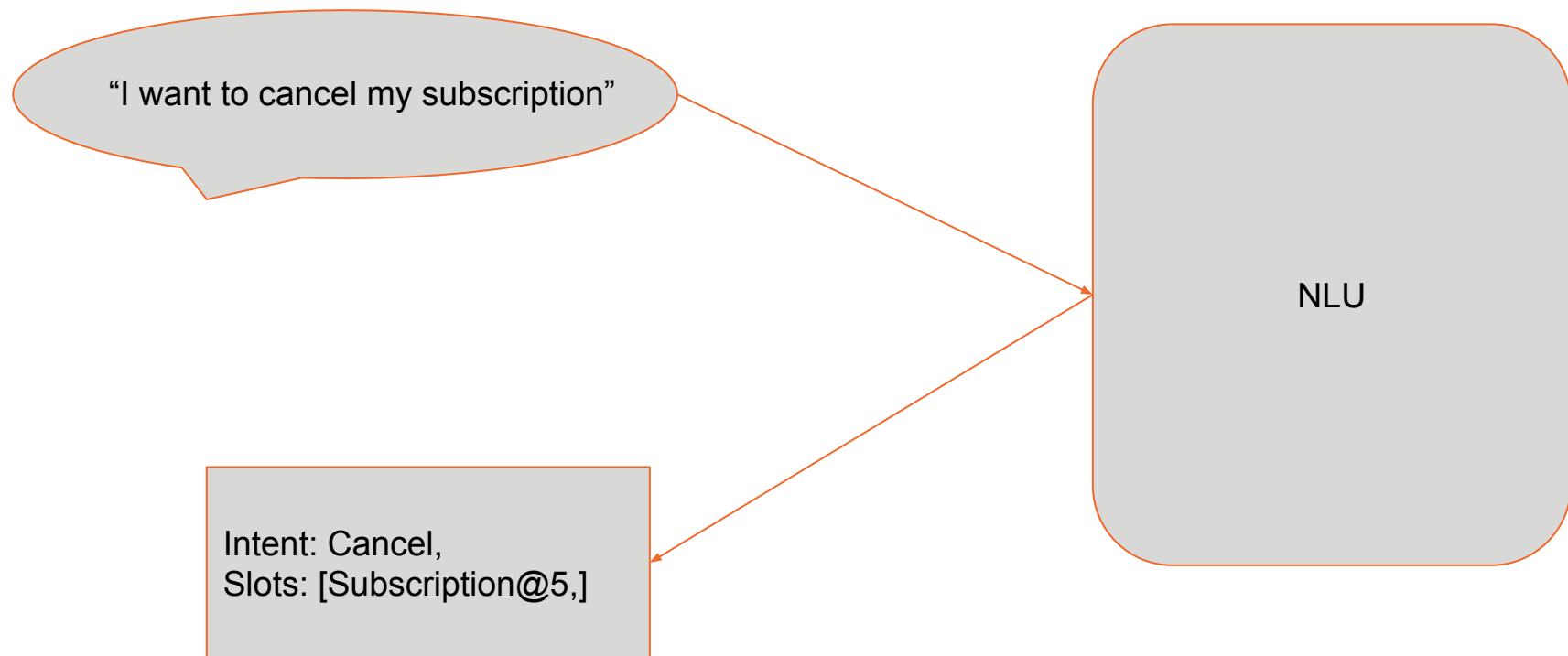
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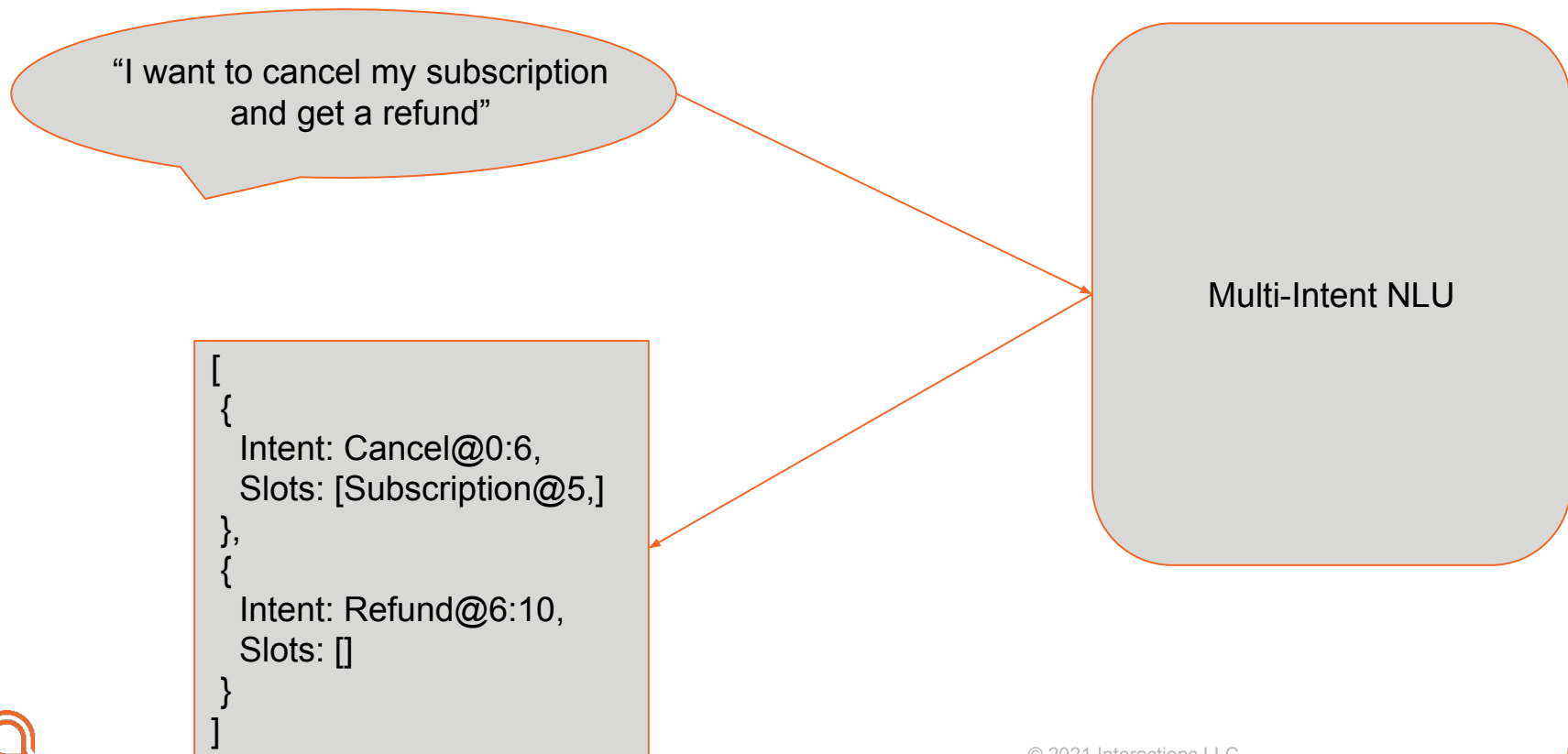


interactions

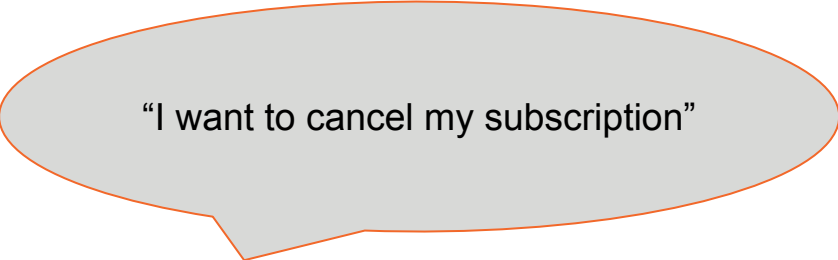
## Natural Language Understanding (NLU) in Dialogue Systems



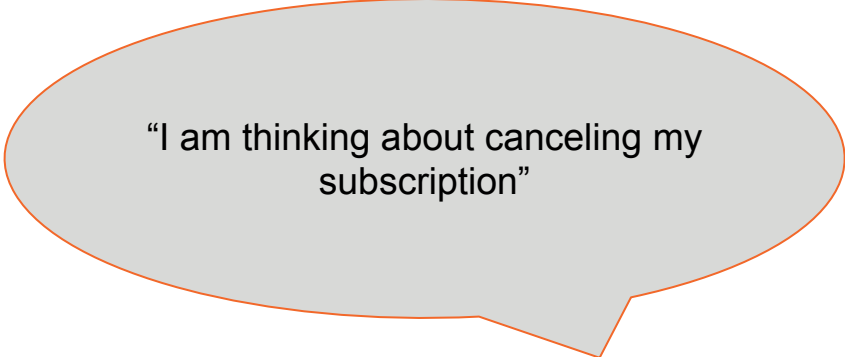
## Multi-Intent NLU in Dialogue Systems



## Similar, but Distinct, Situations

A light gray speech bubble with an orange outline, pointing towards the bottom left.

“I want to cancel my subscription”

A light gray speech bubble with an orange outline, pointing towards the bottom right.

“I am thinking about canceling my subscription”



## Possible Solution

One possible solution is splitting the intent space, creating different intents.

- `cancel`
- `think-cancel`

This has several problems

- Explosion of the intent space.
  - Hard to think about as dialogue designers
  - Hard to remember all while labeling
- Data Sparsity
  - Some versions of intents are much more rare
- Loss of compositionality
  - These are now different classes, you don't get to apply what you know about `cancel` to `think-cancel`



## Intent Features

Lets factor these differences out into another, general label:

- “I am thinking about canceling my subscription” -> cancel, modal-poss
- “I want to cancel my subscription” -> cancel, other



## Intent Features

- Communicative Functions
- Attribution
- Negation
- Tense
- Modality



## Communicative Features

- inform
- issue
- request-action
- request-confirm
- request-info





inform

“I am installing the program but it keeps saying I have an error”

“I am installing the program” -> install, inform



issue

“I am installing the program but it keeps saying I have an error”

“it keeps saying I have an error” -> general, issue



request-action

“I would like to install the program”



request-confirm

“Is the program installed”



request-info

“How do I install the program?”



## Attribution

- attr-cf
  - self
  - other
- attr-ev
  - self
  - other



## Attribution CF

Who is the primary source of information about the event



## Attribution Ev

Who is the cause of the action in the event.





## Attribution Example

Utterance	Attribution CF	Attribution Ev
I have paid \$70.00	self	self
I got an email confirming I paid \$70.00	other	self
I was charged \$70.00	self	other
I got an email confirming I was charged \$70.00	other	other



## Negation

- positive
- negative

“The program works on Android” -> compatibility, positive

“The program doesn’t work on the i-Phone” -> compatibility, negative



## Tense

- past
- present
- future



## Modality

- modal-poss
- modal-try
- other

“I’m trying to install the program” -> modal-try



## Intent Feature Annotation

Each utterance has multiple intent span annotated, each intent span in then annotated with intent features.

[I am trying to cancel /cancel/modal-try/present/...] and [get a refund /refund/other/present]



## Models for Intent Features

- BiLSTM-CRF
- BiLSTM-CRF with intent boundary features
- Span-level convolutional neural networks
- Global-Local model



## BiLSTM-CRF with and without Intent Boundaries

Surface	Intent	Modality	Intent-Boundaries
I	B-cancel	B-modal-try	B-intent
am	I-cancel	I-modal-try	I-intent
trying	I-cancel	I-modal-try	I-intent
to	I-cancel	I-modal-try	I-intent
cancel	E-cancel	E-modal-try	E-intent
and	0	0	0
get	B-refund	B-other	B-intent
a	I-refund	I-other	I-intent
refund	E-refund	E-other	E-intent



## Span-level Convolutional Neural Networks

A single multi-intent utterance

[I am trying to cancel /cancel/modal-try] and [get a refund /refund/other]

becomes two examples, without context

I am trying to cancel -> modal-try  
get a refund -> other





## Global-Local Model

A single multi-intent utterance

[I am trying to cancel /cancel/modal-try] and [get a refund /refund/other]

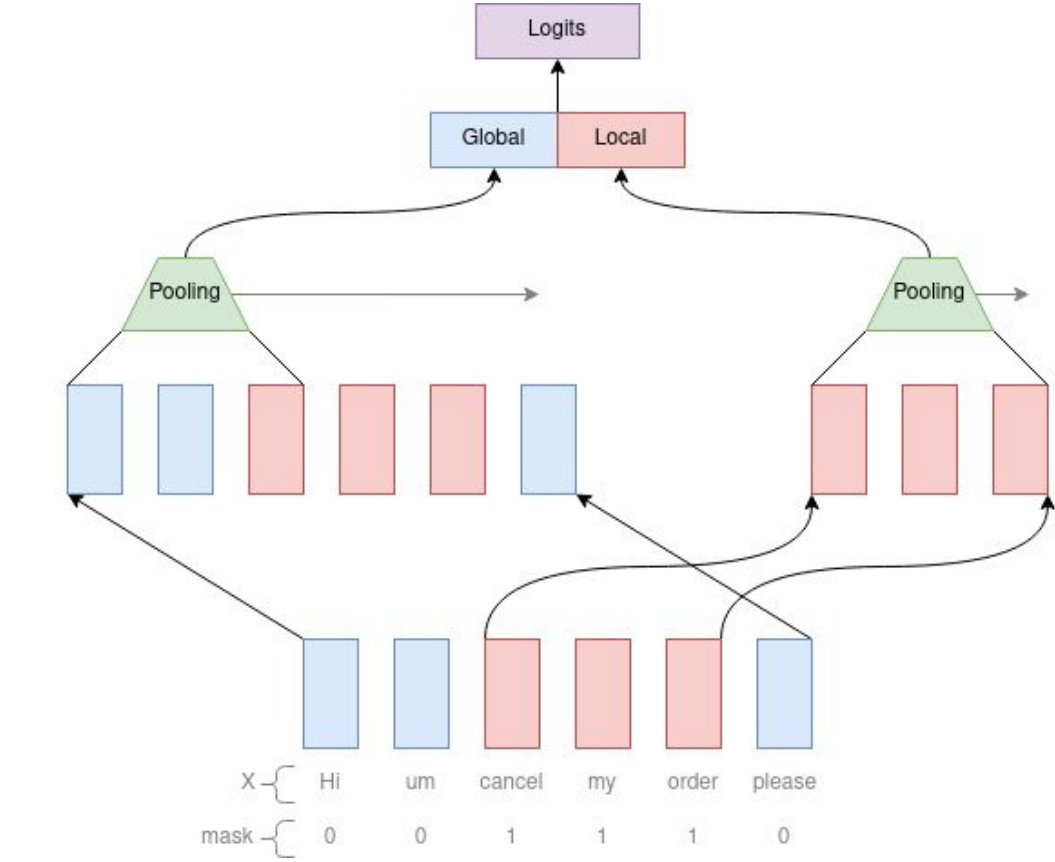
becomes two examples, that retain context

I am trying to cancel and get a refund -> modal-try  
1 1 1            1 1            0 0 0 0

I am trying to cancel and get a refund -> other  
0 0 0            0 0            0 1 1 1



Global-Local Model



## Results

Feature	BiLSTM-CRF	BiLSTM-CRF	Span-level	Global-Local
		Cascaded Tagger	Convolutional	
Attribution CF	78.63	91.90	95.37	<b>97.69</b>
Attribution EV	80.06	92.27	95.86	<b>98.16</b>
Communicative Function	69.07	89.22	90.12	<b>91.92</b>
Modality	79.31	92.61	96.60	<b>99.36</b>
Tense	73.49	86.01	89.31	<b>92.59</b>
Negation	78.47	94.45	95.86	<b>98.73</b>



## Ablations

Model	Attribution CF	Attribution Ev	CF	Modality	Tense	Negation
Global-Local	<b>97.69</b>	<b>98.16</b>	<b>91.91</b>	<b>99.36</b>	<b>92.59</b>	<b>98.73</b>
– Global Context	93.55	95.47	90.14	96.74	87.18	95.74
– Shared Embedding	97.65	96.63	91.43	98.34	90.17	96.36



## Conclusion

- Intent Features allow one to factor out small differences in situations, that need to be addressed, while keeping a general data-rich intent space.
  - Intent Features are being used in the NLU component of a production dialogue system
- The Global-Local model is an effective approach for classification of subsequences while including information from the whole sequence.



Thanks for watching!

Hopefully you'll be able to use intent features, or at least the global local model, somewhere!

- Twitter: <https://twitter.com/blester125>
- Site: <https://blester125.com/>
- Global Local Model Code: <https://github.com/blester125/global-local-model>

