NPFL099 Statistical Dialogue Systems

5. Language Understanding

http://ufal.cz/npfl099

Ondřej Dušek, Vojtěch Hudeček & Zdeněk Kasner

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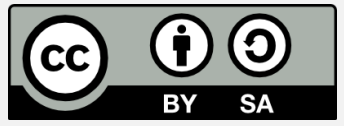
Charles University
Faculty of Mathematics and Physics
Institute of Formal and Applied Linguistics



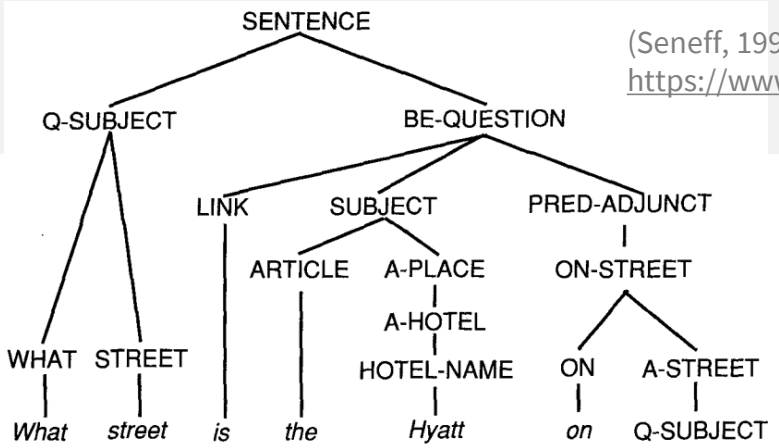
Natural Language Understanding

- **words → meaning**
  - whatever “meaning” is – can be different tasks
  - typically structured, explicit representation
- alternative names/close tasks:
  - **spoken language understanding**
  - **semantic decoding/parsing**
- integral part of dialogue systems, also explored elsewhere
  - stand-alone semantic parsers
  - other applications:
    - human-robot interaction
    - question answering
    - machine translation (not so much nowadays)

NLU Challenges

- non-grammaticality *find something cheap for kids should be allowed*
- disfluencies
  - hesitations – pauses, fillers, repetitions *uhm I want something in the west the west part of town*
  - fragments *uhm I'm looking for a cheap*
  - self-repairs (~6%!) *uhm find something uhm something cheap no I mean moderate*
- ASR errors *I'm looking for a for a chip Chinese rest or rant*
- synonymy *Chinese city centre*
  I've been wondering if you could find me a restaurant that has Chinese food close to the city centre please
- out-of-domain utterances *oh yeah I've heard about that place my son was there last month*

Semantic representations



(Seneff, 1992)
https://www.aclweb.org/anthology/J92-1004

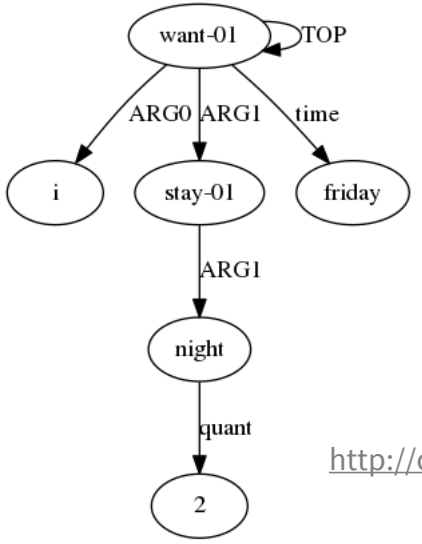
- syntax/semantic **trees**
  - typical for standalone semantic parsing
  - different variations
- **frames**
  - technically also trees, but smaller, more abstract
  - (mostly older) DSs, some standalone parsers
- **graphs** (AMR)
  - trees + co-reference
    (e.g. pronouns referring to the same object)
- **dialogue acts** = intent + slots & values
  - flat – no hierarchy
  - most DSs nowadays

inform(date=Friday, stay="2 nights")

oui l'hôtel don't le prix ne dépasse pas cent dix euros

response:	oui		
refLink:	co-ref.		
	singular		
BDObject:	hotel		
	room		
	payment:	amount	
		comparative:	less
		integer:	110
		unit:	euro

(Bonneau-Maynard et al., 2005)
https://www.isca-speech.org/archive/interspeech_2005/i05_3457.html



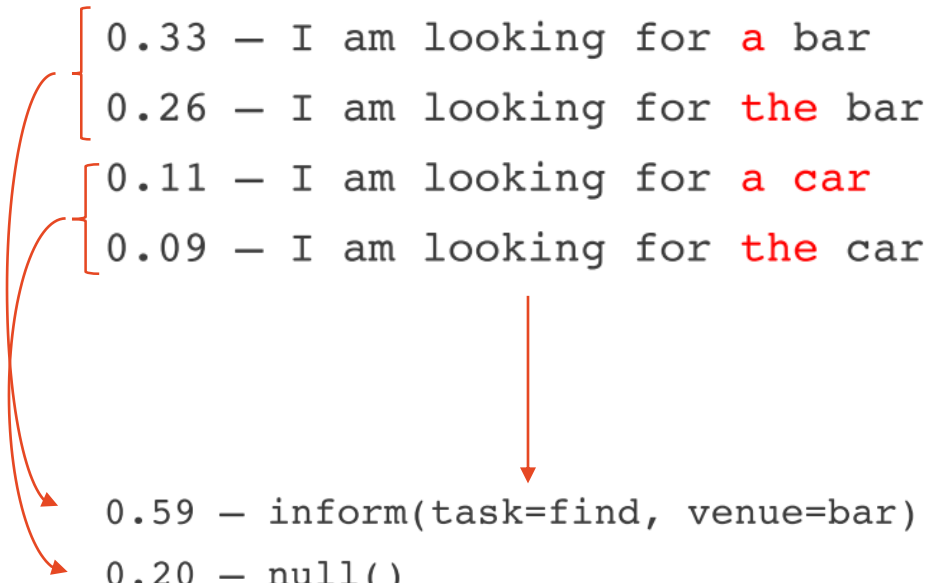
I want to stay 2 nights from Friday .

http://cohort.inf.ed.ac.uk/amreager.html

Handling ASR noise

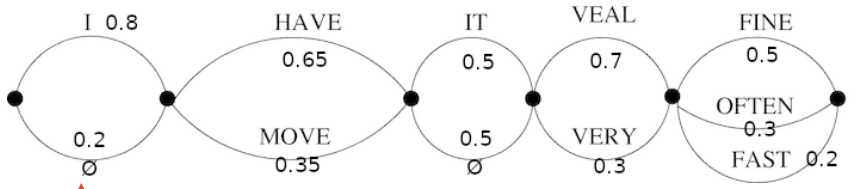
- ASR produces **multiple hypotheses**
- Combine & get resulting NLU hypotheses
  - NLU: $p(\text{DA}|\text{text})$
  - ASR: $p(\text{text}|\text{audio})$
  - we want $p(\text{DA}|\text{audio})$
- Easiest: **sum it up**

$$p(\text{DA}|\text{audio}) = \sum_{\text{texts}} P(\text{DA}|\text{text})P(\text{text}|\text{audio})$$



(from Filip Jurčíček's slides)

- Alternative: **confusion nets** with weighted words
  - a more concise way of showing the same thing

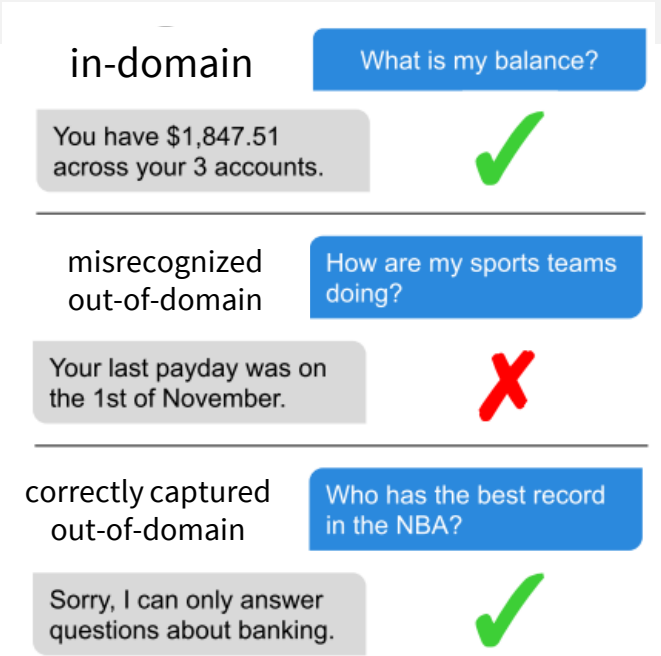


(skiping a word)

left-to-right: multiply probabilities

Handling out-of-domain queries

- Handcrafted: **no pattern matches** → out-of-domain
- Datasets – rarely taken into account!
- **Low confidence** on any intent → out-of-domain?
  - might work, but likely to fail (no explicit training for this)
- Out-of-domain data + **specific OOD intent**
  - adding OOD from a different dataset
    - problem: "out-of-domain" should be broad, not just some different domain
  - collecting out-of-domain data specifically
    - worker errors for in-domain
    - replies to specifically chosen irrelevant queries
  - always need to ensure that they don't match any intent randomly
  - not so many instances needed (expected to be rare)



(Larson et al., 2019)
http://arxiv.org/abs/1909.02027

NLU as classification

- using DAs – treating them as a **set of semantic concepts**
  - concepts:
    - intent
    - slot-value pair
  - binary classification: is concept Y contained in utterance X?
  - independent for each concept
- consistency problems
  - conflicting intents (e.g. *affirm* + *negate*)
  - conflicting values (e.g. *kids-allowed=yes* + *kids-allowed=no*)
  - need to be solved externally, e.g. based on classifier confidence

NER + delexicalization

- Approach:

1) **identify** slot values/named entities
2) **delexicalize** = replace them with placeholders (indicating entity type)
   - or add the NE tags as more features for classification

What is the phone number for Golden Dragon?
What is the phone number for <restaurant-name>?

I'm looking for a Japanese restaurant in Notting Hill.
I'm looking for a <food> restaurant in <area>.

- generally needed for NLU as classification
  - otherwise in-domain data is too sparse
  - this can vastly reduce the number of concepts to classify & classifiers

I need to leave after 12:00.
I need to leave after <time>.
*leave_at -> **leave_at***
*arrive_by -> **none***

Both can be <time>

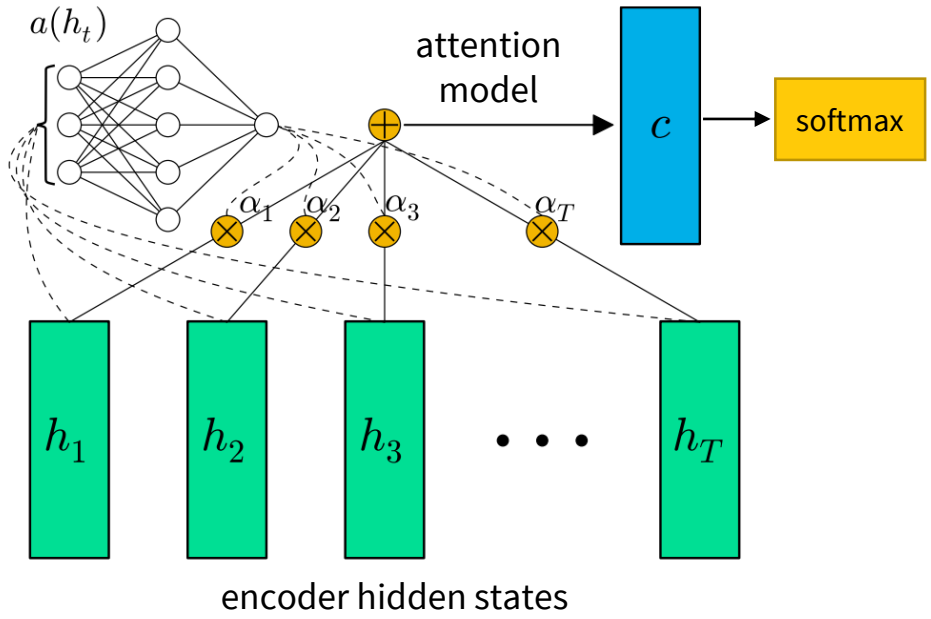
- NER is a problem on its own
  - but general-domain NER tools may need to be adapted
  - in-domain gazetteers, in-domain training data

NLU Classifier models

- note that data is usually scarce!
- **handcrafted / rules**
  - simple mapping: word/n-gram/regex match → concept
  - can work really well for a limited domain
  - no training data, no retraining needed (tweaking on the go)
- **linear classifiers**
  - logistic regression, SVM…
  - need handcrafted features
- **neural nets** (=our main focus today)

NN neural classifiers

- **intent** = **multi-class** (softmax)
- **slot** tagging = set of **binary classifiers** (logistic loss)
- using word embeddings (task-specific or pretrained)
  - no need for handcrafted features
  - still needs delexicalization (otherwise data too sparse)
- different architectures possible
  - bag-of-words feed-forward NN
  - RNN / CNN encoders + classification layers
  - attention-based



(Raffel & Ellis, 2016)
https://colinraffel.com/publications/iclr2016feed.pdf

Slot filling as sequence tagging

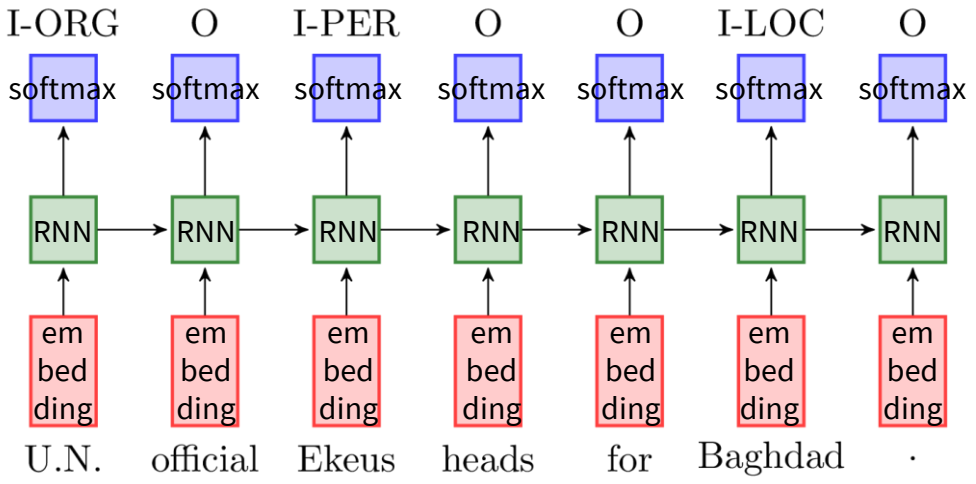
- get slot values directly – no need for delexicalization
  - each word classified
  - classes = slots & **IOB format** (inside-outside-beginning)
  - slot values taken from the text (where a slot is tagged)
  - NER-like approach

I	*need*	*a*	*flight*	*from*	*Boston*	*to*	*New*	*York*	*tomorrow*
O	**O**	**O**	**O**	**O**	**B-dept**	**O**	**B-arr**	**I-arr**	**B-date**

- rules + classifiers still work
  - keywords/regexes found at specific position
  - apply classifier to each word in the sentence left-to-right
- linear classifiers are still an option

Neural sequence tagging

- Basic neural architecture:
  RNN (LSTM/GRU) → softmax over hidden states
  - + some different model for intents (such as classification)
- Sequence tagging problem: overall consistency
  - slots found elsewhere in the sentence might influence what's classified now
  - may suffer from **label bias**
    - trained on gold data – single RNN step only
    - during inference, cell state is influenced by previous steps – danger of cascading errors
  - solution: **structured/sequence prediction**
    – conditional random fields (CRF)
    - can run CRF over NN outputs

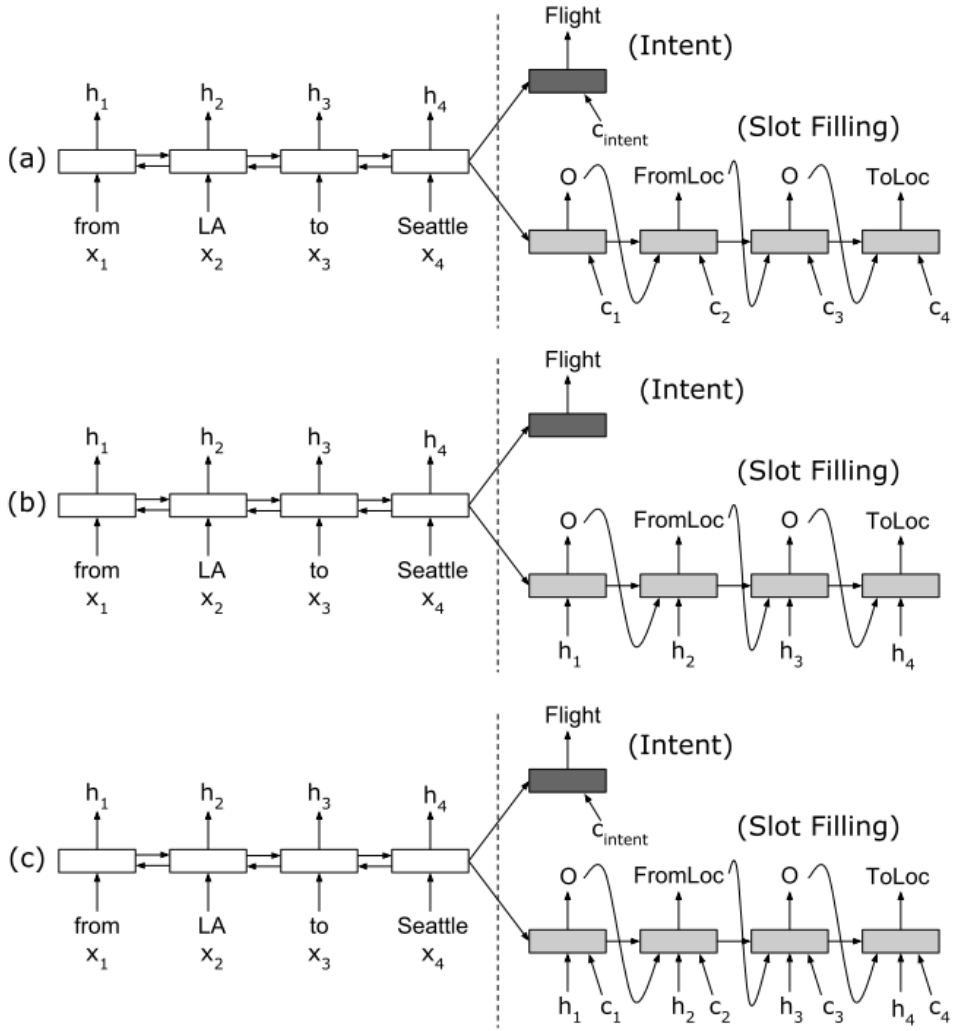


https://www.depends-on-the-definition.com/guide-sequence-tagging-neural-networks-python/

Joint Intent & Slots Model

(Liu & Lane, 2016)
http://arxiv.org/abs/1609.01454

- Same network for both tasks
- Bidirectional encoder
  - 2 encoders: left-to-right, right-to-left
  - "see everything before you start tagging"
- Decoder – tag word-by-word, inputs:
  - attention
  - input encoder hidden states ("aligned inputs")
  - both
- Intent classification:
  softmax over last encoder state
  - + specific intent context vector c_{intent}(attention)



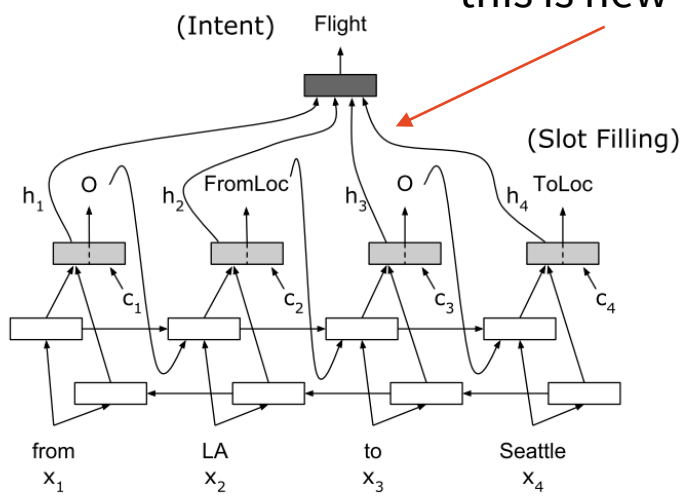
NN for Joint Intent & Slots

- Extended version:
  use slot tagging results in intent classification
  - Bidi encoder
  - Slots decoder with encoder states & attention
  - Intent decoder
    – attention over slots decoder states
- Training for both intent & slot detection improves results on ATIS flights data
  - this is multi-task training ☺
  - intent error lower (2% → 1.5%)
  - slot filling slightly better (F1 95.7% → 95.9%)
- Variant: treat **intent detection as slot tagging**
  - append <EOS> token & tag it with intent

5k instances
17 intents
~100 slots

(Liu & Lane, 2016)
http://arxiv.org/abs/1609.01454

this is new



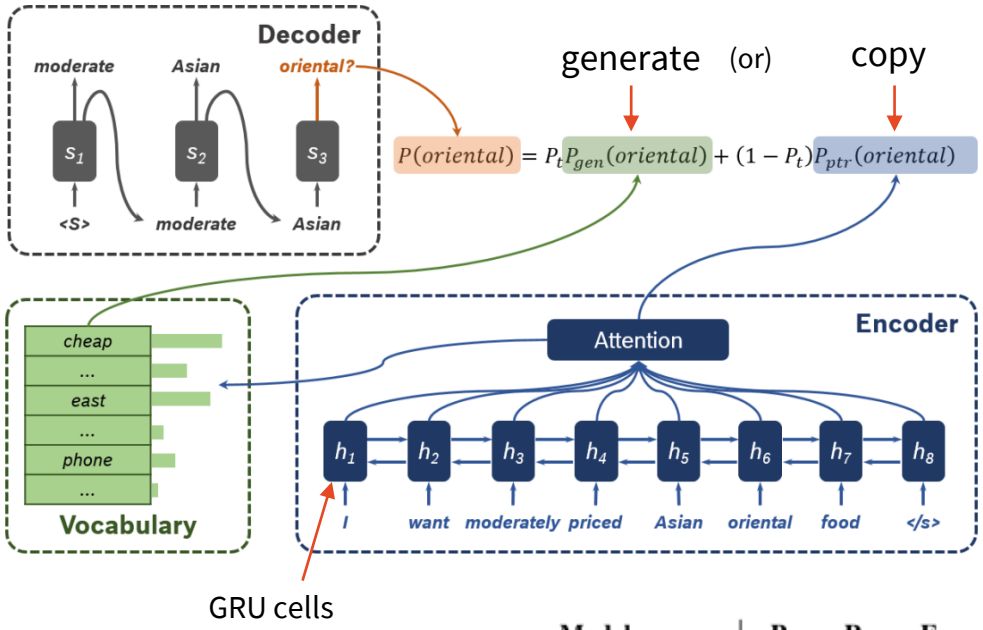
same as (c)
on previous slide

(Hakkani-Tür et al, 2016)
https://doi.org/10.21437/Interspeech.2016-402

Seq2seq-based NLU

(Zhao & Feng, 2018)
https://www.aclweb.org/anthology/P18-2068/

- seq2seq with **copy mechanism = pointer-generator net**
  - normal **seq2seq** with attention – generate output tokens (softmax over vocabulary)
  - **pointer net**: select tokens from input (attention over input tokens)
  - prediction = **weighted combination** of ⇀
- can work with out-of-vocabulary
  - e.g. previously unseen restaurant names
  - (but IOB tagging can, too)
- generating slots/values + intent
  - it's not slot tagging (doesn't need alignment)
    - **works for slots expressed implicitly or not as consecutive phrases**
  - treats intent as another slot to generate



Model	P	R	F
CNN	**93.5**	78.5	85.3
Seq2Seq w/ attention	87.5	82.7	85.0
Our model	89.0	**82.8**	**85.8**

DSTC2 results

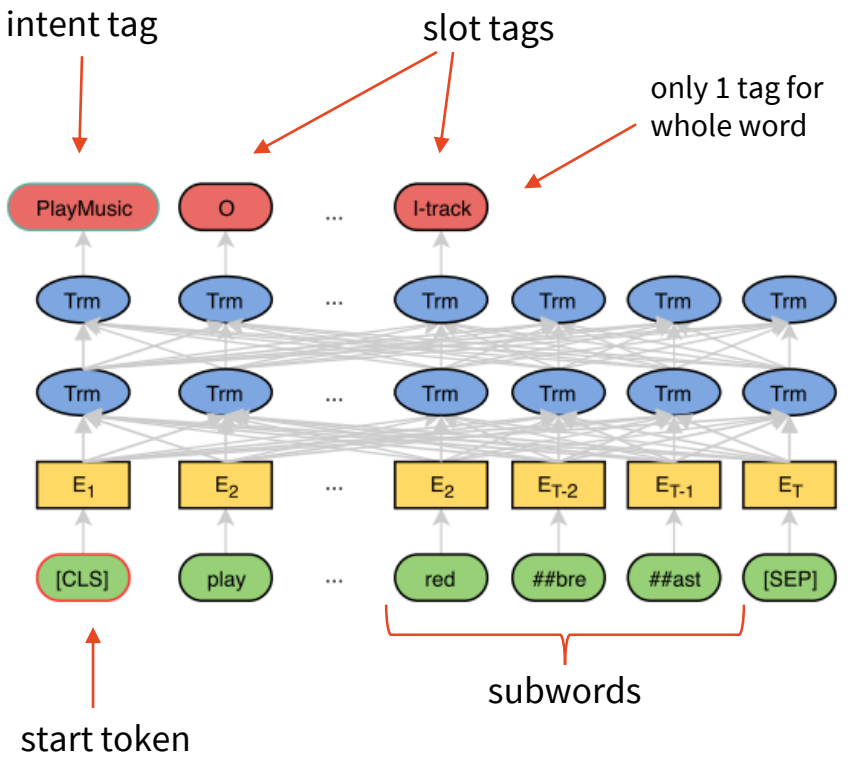
Can I bring my kids along to this restaurant?
I want a Chinese place with a takeaway option.

confirm(kids_friendly=yes)
inform(food=Chinese_takeaway)

BERT-based NLU

- slot tagging on top of pretrained BERT
  - standard **IOB approach**
  - just feed final hidden layers to **softmax over tags**
    - classify only at 1st subword in case of split words (don't want tag changes mid-word)
- special start token tagged with intent
- optional CRF on top of the tagger
  - for global sequence optimization

(Chen et al., 2019)
http://arxiv.org/abs/1902.10909



slightly different numbers, most probably a reimplementation →

Models	Snips			ATIS		
	Intent	Slot	Sent	Intent	Slot	Sent
RNN-LSTM (Hakkani-Tür et al., 2016)	96.9	87.3	73.2	92.6	94.3	80.7
Atten.-BiRNN (Liu and Lane, 2016)	96.7	87.8	74.1	91.1	94.2	78.9
Slot-Gated (Goo et al., 2018)	97.0	88.8	75.5	94.1	95.2	82.6
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**

accuracy

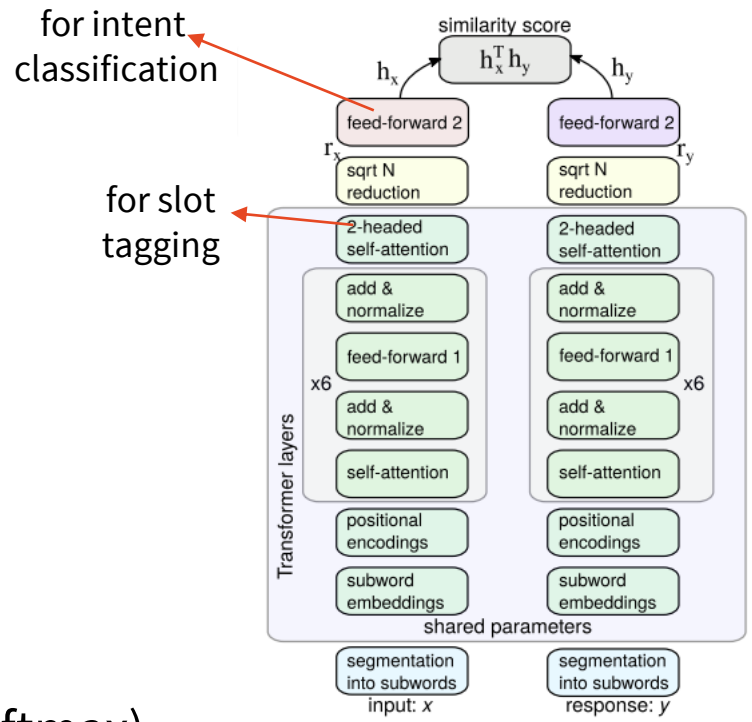
F1

% completely correct sentences

Dialogue Pretrained Models

(Henderson et al., 2020)
http://arxiv.org/abs/1911.03688

- Pretraining on dialogue tasks can do better (& smaller) than BERT
  - ConveRT: Transformer-based **dual encoder**
    - 2 Transformer encoders: context + response
      - optionally 3rd encoder with more context (concatenated turns)
    - feed forward + cosine similarity on top
  - training objective: **response selection**
    - response that actually happened = 1
    - random response from another dialogue = 0
  - trained on a large dialogue dataset (Reddit)
- can be used as a base to train models for:
  - **slot tagging** (top self-attention layer → CNN → CRF)
  - **intent classification** (top feed-forward → more feed-forward → softmax)
  - Transformer layers are fixed, not fine-tuned
  - works well for little training data (**few-shot**)

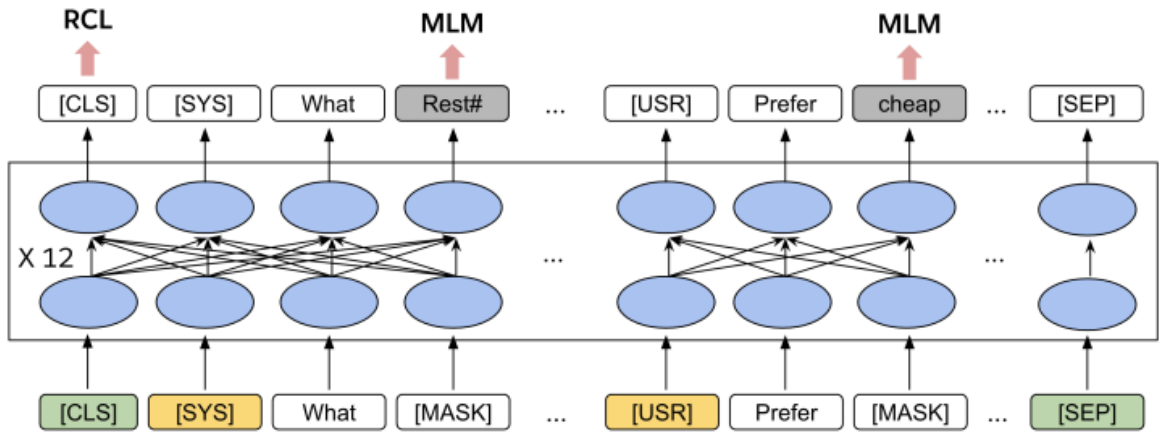


(Coope et al., 2020)
https://www.aclweb.org/anthology/2020.acl-main.11

(Casanueva et al., 2020)
https://www.aclweb.org/anthology/2020.nlp4convai-1.5

TOD-BERT

- pre-finetuning BERT on vast *task-oriented* dialogue data
  - basically combination of 2 previous
- BERT + add user/sys tokens + train for:
  - masked language modelling
  - response selection (dual encoder style)
    - over [CLS] tokens from whole batch
    - other examples in batch = negative
- result: “better dialogue BERT”
  - can be finetuned for various dialogue tasks
    - intent classification
    - slot tagging
  - good performance even “few-shot”
    - just 1 or 10 examples per class
    - bigger difference w. r. t. BERT

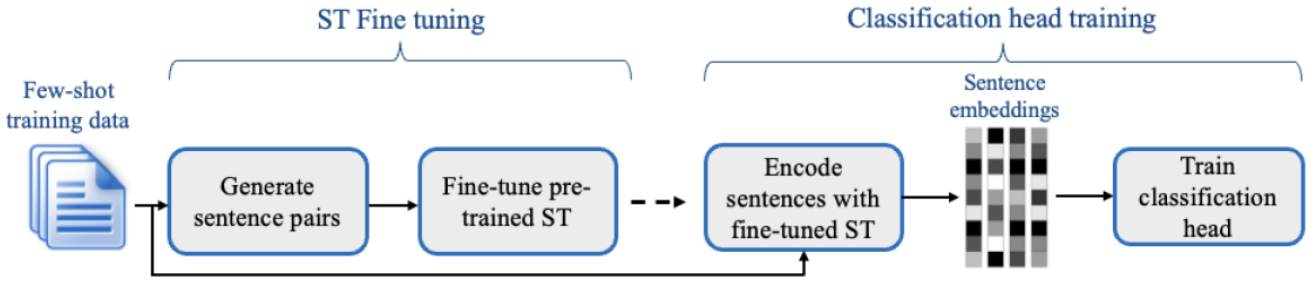


(Wu et al., 2020)
https://www.aclanthology.org/2020.emnlp-main.66

SETFIT: Sentence BERT + contrastive pre-finetuning

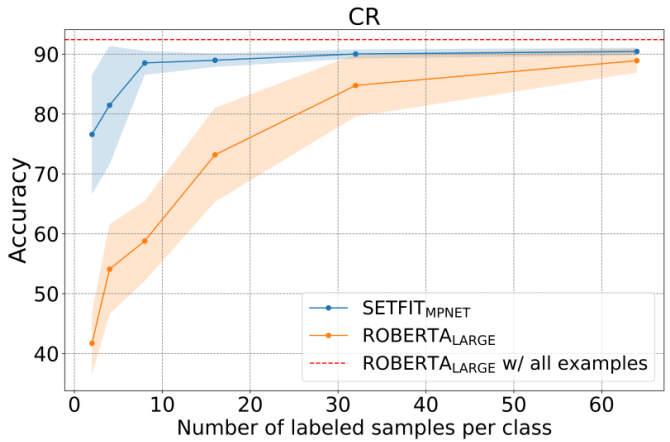
- Sentence Transformer (ST) = Transformer dual encoder
  - general, based on RoBERTa, produces sentence-level representations
  - trained for semantic similarity (NLI data)

(Reimers & Gurevych, 2019)
https://aclanthology.org/D19-1410/



(Tunstall et al., 2022)
http://arxiv.org/abs/2209.11055

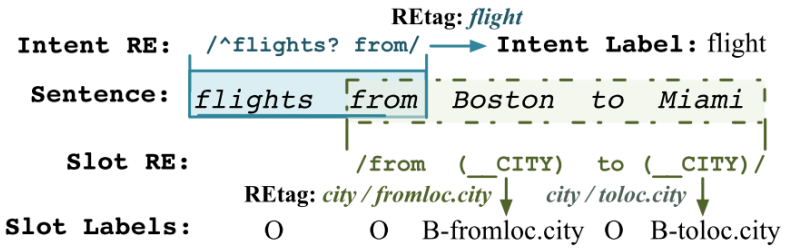
- Contrastive pre-finetuning:
  - 2 examples from same intent class = 1
  - 2 examples from random different intent classes = 0
- Intent classifier trained on top of the pre-finetuned model
- Good for low-data situations

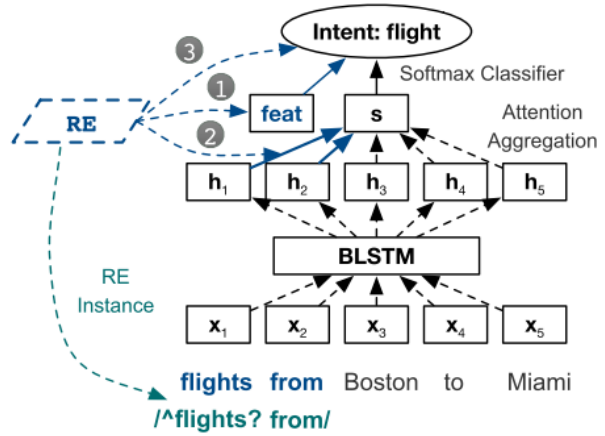


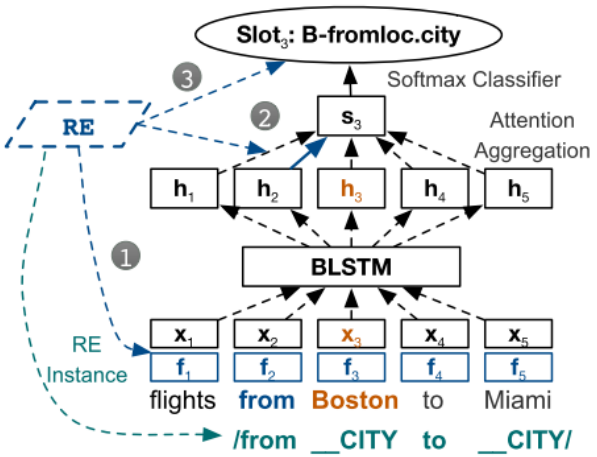
Regular Expressions & NNs for NLU

(Luo et al., 2018) http://arxiv.org/abs/1805.05588

- Regexes as manually specified features
  - **binary**: any matching sentence (for intents) + any word in a matching phrase (for slots)
    - **regexes meant to represent an intent/slot**
  - combination at different levels
    1) "input": aggregate word/sent + regex embeddings (at sentence level for intent, word level for slots)
    2) "network": per-label supervised attentions (log loss for regex matches)
    3) "output": alter final softmax (add weighted regex value)
- Good for limited amounts of data (few-shot)
  - works with 10-20 training examples per slot/intent
  - still improves a bit on full ATIS data →



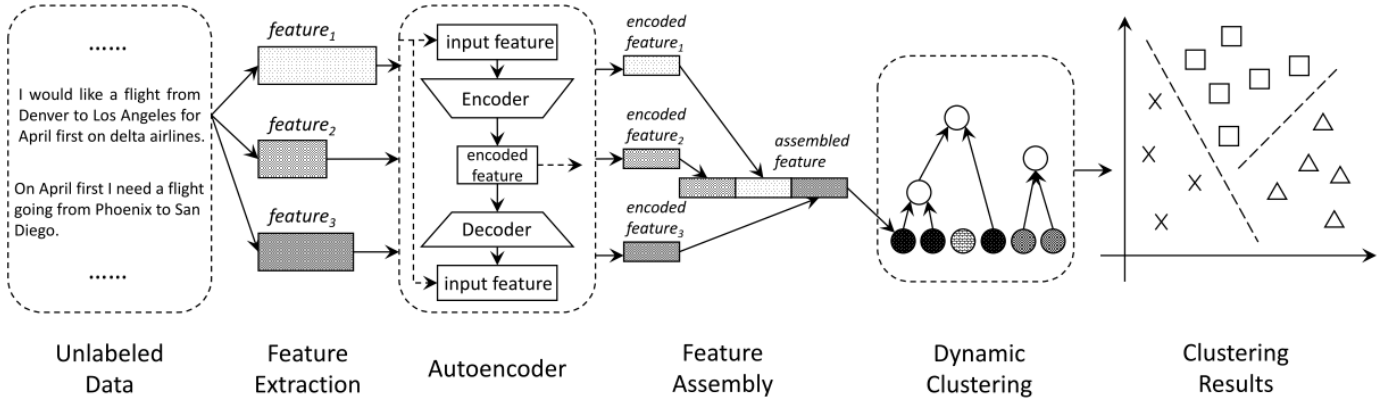




Model	Intent	Slot
	Macro-F1/Accuracy	Macro-F1/Micro-F1
Liu&Lane (2016)	- / 98.43	- / 95.98
no regex (BiLSTM)	92.50 / 98.77	85.01 / 95.47
(1) input	91.86 / 97.65	86.7 / 95.55
(3) output	92.48 / 98.77	86.94 / 95.42
(2) network	**96.20 / 98.99**	85.44 / 95.27

Unsupervised NLU

- **Clustering** intents & slots
- Features:
  - word embeddings
  - POS
  - word classes
  - topic modelling (biterm)
- Autoencoder to normalize # of dimensions for features
- Dynamic hierarchical clustering
  - decides # of clusters – stops if cluster distance exceeds threshold
- Slot clustering – word-level
  - over nouns, using intent clustering results



feature choice + AE seem to work quite well

ATIS

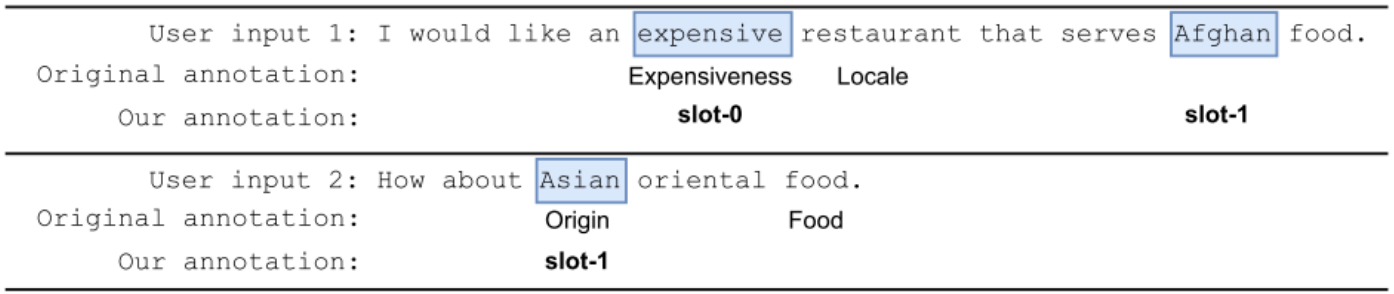
Models	Intent Labeling Acc (%)
topic model	25.4
CDSSM vector	20.7
glove embedding	25.6
auto-dialabel	**84.1**

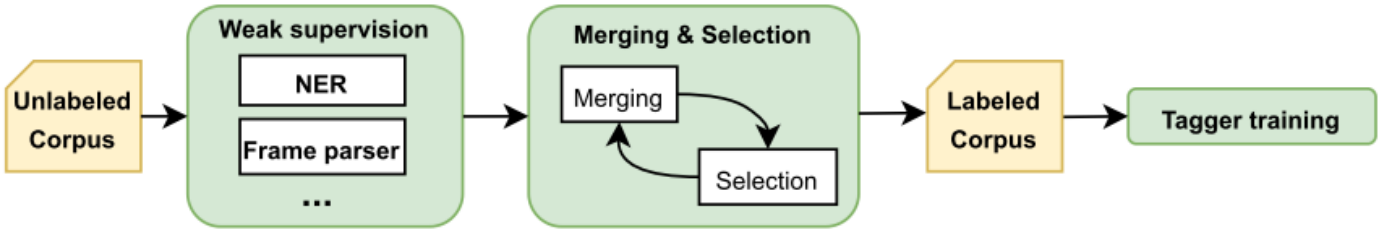
(Shi et al., 2018)
https://www.aclweb.org/anthology/D18-1072/

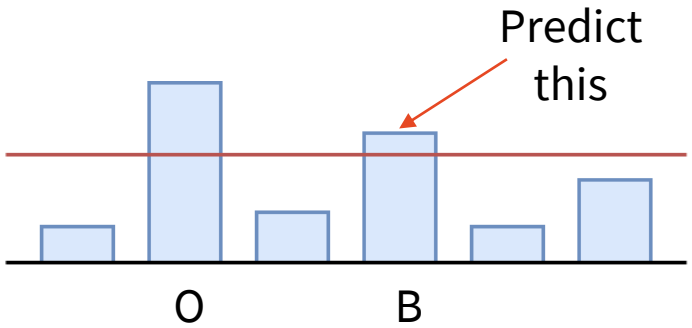
Weak Supervision from Semantic Frames

(Vojta's work)

- Finding relevant **slots** based on **generic (frame) parser output**
  - filter irrelevant candidates, merge similar ones & generalize better
- Iterative merging & selection
  - frequency, coherence, TextRank
  - w. r. t. to head verbs
- Training an LSTM tagger
  - standalone, based on merged annotation
  - 2nd option threshold to improve recall
- Promising, but not perfect
  - DB connection, interpretation of slots







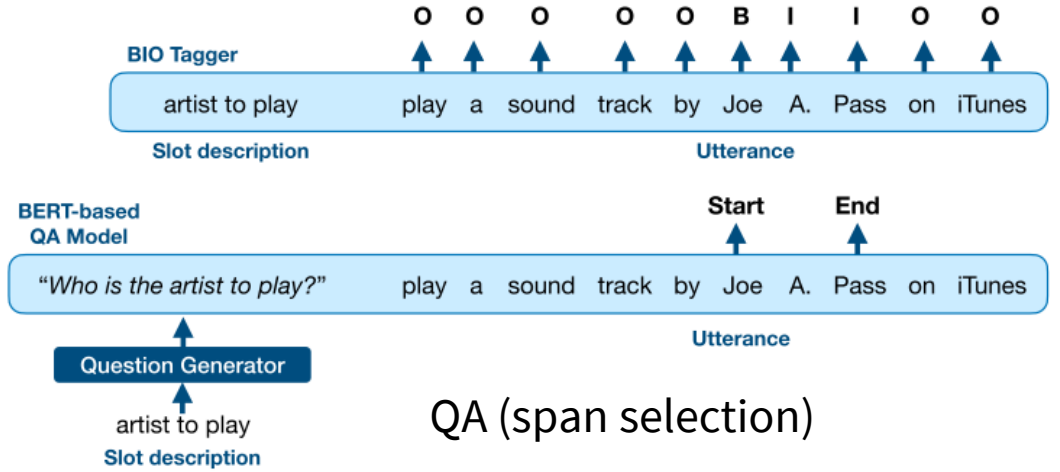
(Hudeček et al., 2021)
https://aclanthology.org/2021.acl-long.189

Weak supervision: QA-style NLU

- Zero-shot – just needs some slot descriptions
  - no in-domain training data needed
- Use a "question answering" BERT to do slot detection
  - generate questions from slot description – specifically ask for slots (rule-based)
  - QA model output = slot values
  - pretrained on other datasets (generate questions from ontology)
  - generalizes to unseen slots (though still far from perfect)

Slot	Raw Description	Our Question
playlist_owner	owner	who's the owner?
object_select	object select	which object to select?
best_rating	points in total	how many points in total?
num_book_people	number of people for booking	how many people for booking?

standard supervised slot tagger (for comparsion)



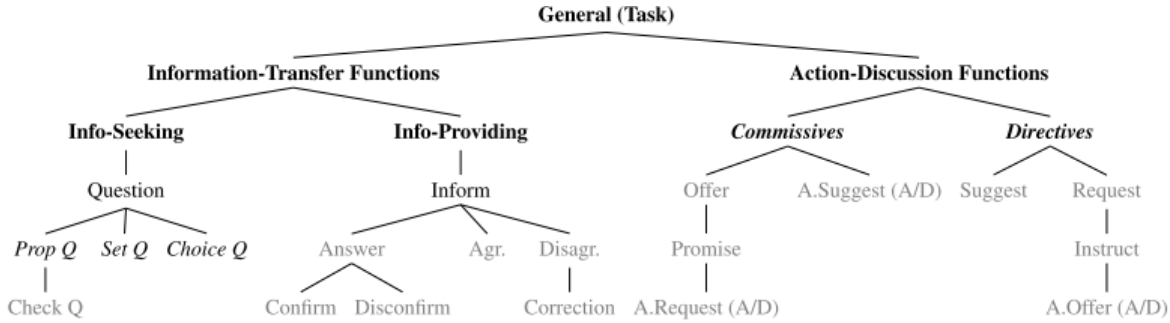
QA (span selection)

train: SNIPS, test: TOP	Zero-shot	Few-shot (20)	Few-shot (50)
Random NE	1.34	-	-
BERT seq tagging	8.82	37.60	42.73
BERT QA style	10.27	36.86	46.49
+ pretraining on other sets	12.35	39.78	47.91

(Du et al., 2021)
https://aclanthology.org/2021.acl-short.83

Universal Intents

- typically DAs are domain-dependent
- **ISO** 24617-2 DA tagging **standard**
  - pretty complex: **multiple dimensions**
    - Task, Social, Feedback…
  - DA types (intents) under each dimension



(Mezza et al, 2018) https://www.aclweb.org/anthology/C18-1300

- **Simpler approach** – non-hierarchical
  - **union** looking at different datasets
  - Mapping from datasets – manual/semi-automatic
    - mapping tuned on classifier performance
  - Intent tagging improved using multiple datasets/domains
    - generic intents only
  - Slots stay domain-specific

ack, affirm, bye, deny, inform, repeat, reqalts, request, restart, thank-you, user-confirm, sys-impl-confirm, sys-expl-confirm, sys-hi, user-hi, sys-negate, user-negate, sys-notify-failure, sys-notify-success, sys-offer

(Paul et al, 2019)
http://arxiv.org/abs/1907.03020

Summary

- NLU is mostly **intent classification** + **slot tagging**
- **Rules + simple methods work well** with limited domains
- Neural NLU:
  - **shapes**: CNN, LSTM, attention, seq2seq + pointer nets
  - **tasks**: classification, sequence tagging, sequence prediction, span selection
  - it helps to do joint intent + slots
  - pretrained LMs help (models are large though)
    - BERT, specific pretrained dialogue models
  - NNs can be combined with regexes/handcrafted features
    - helps with limited data
- Less/no supervision: pretrained LMs, generic parsers, clustering
  - helps with domain generalization

Thanks

Contact us:

https://ufaldsg.slack.com/
{odusek,hudecek,kasner}@ufal.mff.cuni.cz
Skype/Meet/Zoom (by agreement)

No labs today
Next week: lecture & labs

Get the slides here:

http://ufal.cz/npfl099

References/Inspiration/Further:

- mostly papers referenced from slides
- Milica Gašić's slides (Cambridge University): http://mi.eng.cam.ac.uk/~mg436/teaching.html
- Raymond Mooney's slides (University of Texas Austin): https://www.cs.utexas.edu/~mooney/ir-course/
- Filip Jurčíček's slides (Charles University): https://ufal.mff.cuni.cz/~jurcicek/NPFL099-SDS-2014LS/
- Hao Fang's slides (University of Washington): https://hao-fang.github.io/ee596_spr2018/syllabus.html
- Gokhan Tur & Renato De Mori (2011): Spoken Language Understanding