Dialogue Systems

NPFL123 Dialogové systémy

7. NLU with Neural Networks & Dialogue State Tracking

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2. 4. 2019

Neural networks

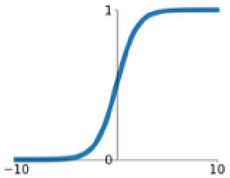
- Can be used for both classification & sequence models
- **Non-linear functions**, composed of basic building blocks
  - stacked into **layers**
- Layers are built of **activation functions**:
  - linear functions
  - nonlinearities – sigmoid, tanh, ReLU
  - softmax – probability estimates:

$$\mathrm{softmax}(\mathbf{x})_i = \frac{\exp(x_i)}{\sum_{j=1}^{|\mathbf{x}|} \exp(x_j)}$$

- Fully differentiable – training by gradient descent
  - gradients **backpropagated** from outputs to all parameters
  - (composite function differentiation)

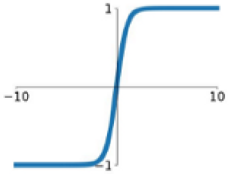
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



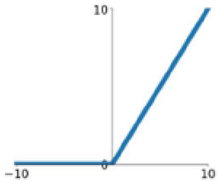
tanh

$\tanh(x)$



ReLU

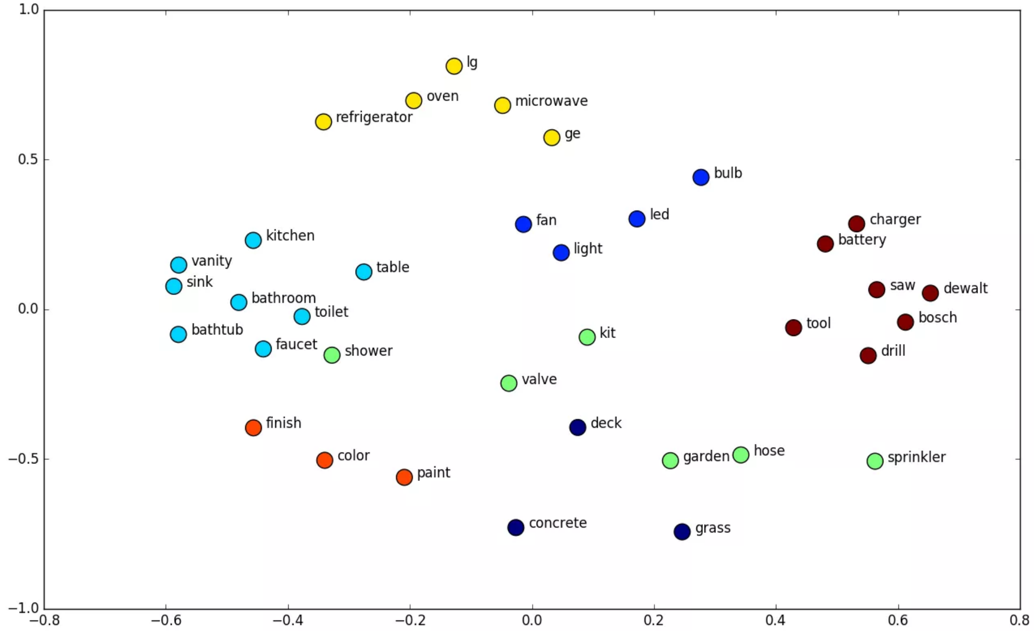
$\max(0, x)$



https://medium.com/@shrutijadon10104776/survey-on-activation-functions-for-deep-learning-9689331ba092

Neural networks – features

- You can use the same as for LR/SVM…
  - but it’s a lot of work to code them in
- **Word embeddings**
  - let the network learn features by itself
    - input is just words (vocabulary is numbered)
  - distributed word representation
    - each word = **vectors of floats**
  - part of network parameters – trained
    - a) random initialization
    - b) pretraining
  - network learns which words are used similarly
    - they end up having close embedding values
    - different embeddings for different tasks

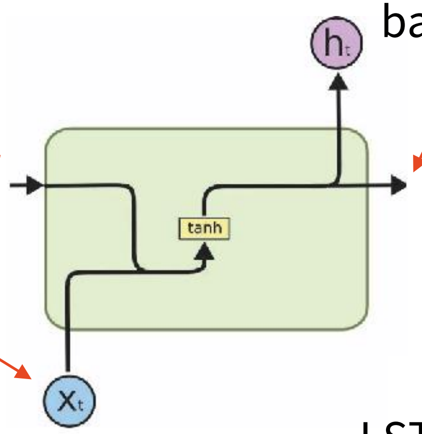


http://blog.kaggle.com/2016/05/18/home-depot-product-search-relevance-winners-interview-1st-place-alex-andreas-nurlan/

http://ruder.io/word-embeddings-2017/

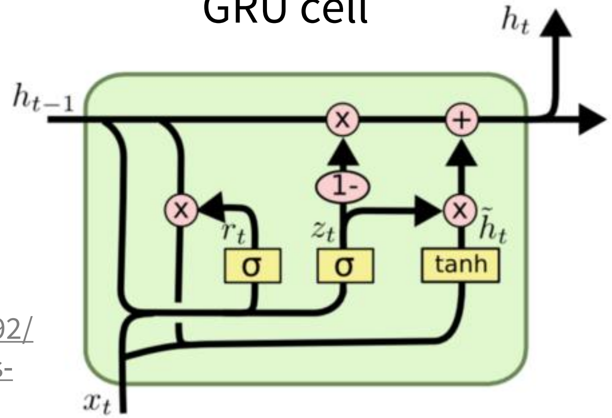
Recurrent Neural Networks

- Many identical layers with shared parameters (**cells**)
  - ~ the same layer is applied multiple times, taking its own outputs as input
    - ~ same number of layers as there are tokens
    - output = **hidden state** – fed to the next step
  - additional input – next token features
- Cell types
  - **basic RNN**: linear + tanh
    - problem: vanishing gradients
    - can't hold long recurrences
  - **GRU, LSTM**: more complex, to make backpropagation work better
    - "gates" to keep old values

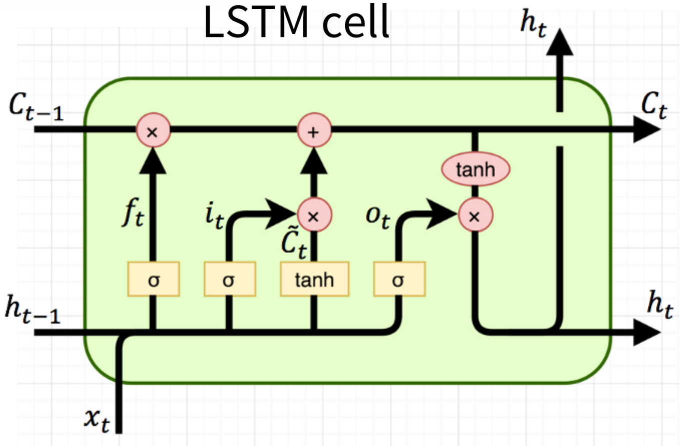


basic RNN cell

GRU cell



LSTM cell



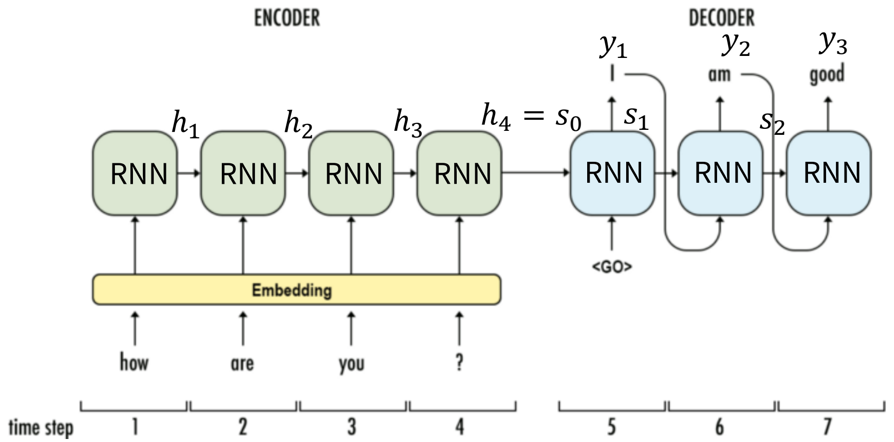
https://medium.com/@saurabh.rathor092/simple-rnn-vs-gru-vs-lstm-difference-lies-in-more-flexible-control-5f33e07b1e57

Encoder-Decoder Networks

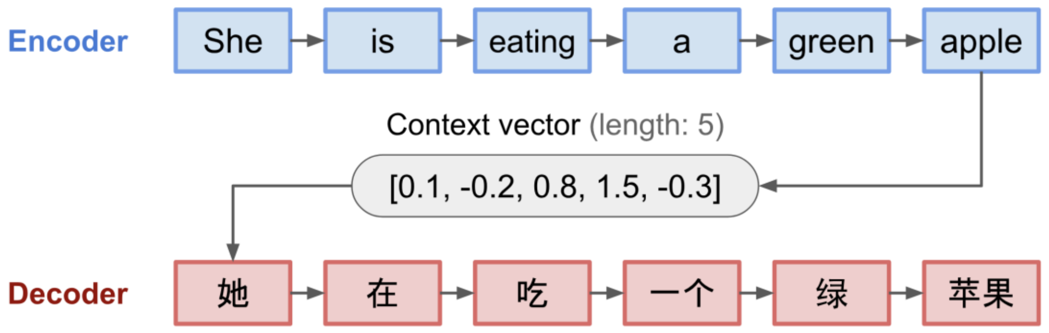
- Default RNN paradigm for sequences/structure prediction
  - **encoder** RNN: encodes the input token-by-token into **hidden states** h_t
    - next step: last hidden state + next token as input
  - **decoder** RNN: constructs the output token-by-token
    - initialized by last encoder hidden state
    - output: hidden state & softmax over output vocabulary + argmax
    - next step: last hidden state + last generated token as input
  - LSTM/GRU cells over vectors of ~ embedding size
  - MT, dialogue, parsing…
    - more complex structures linearized to sequences

$$\boldsymbol{h}_0 = \mathbf{0}$$
$$\boldsymbol{h}_t = \mathrm{cell}(\boldsymbol{x}_t, \boldsymbol{h}_{t-1})$$

$$\boldsymbol{s}_0 = \boldsymbol{h}_T$$
$$p(y_t | y_1, \dots y_{t-1}, \mathbf{x}) = \mathrm{softmax}(\boldsymbol{s}_t)$$
$$\boldsymbol{s}_t = \mathrm{cell}(\boldsymbol{y}_{t-1}, \boldsymbol{s}_{t-1})$$



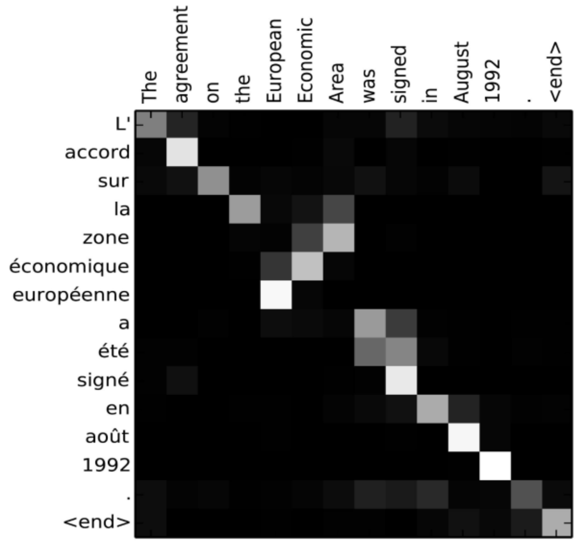
https://medium.com/syncedreview/a-brief-overview-of-attention-mechanism-13c578ba9129



https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html

Attention Models

- Encoder-decoder too crude for complex sequences
  - the whole input crammed into a fixed-size vector (last hidden state)
- **Attention** = "memory" of **all** encoder hidden states
  - weighted combination
  - re-weighted every decoder step
    → can focus on currently important part of input
  - fed into decoder inputs + decoder softmax layer



Attention Mechanism

attention value = **context vector**

t = decoder step

$1 \dots n$ = encoder steps

$$\boldsymbol{c}_t = \sum_{i=1}^{n} \alpha_{ti} \boldsymbol{h}_i$$

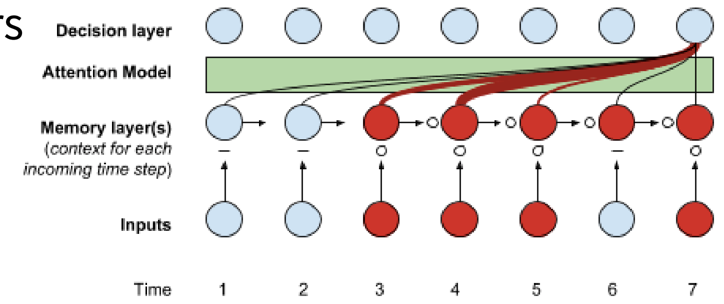
encoder hidden state

decoder state

trained parameters

attention weights
= **alignment model**

$$\alpha_{ti} = \mathrm{softmax}(\boldsymbol{v}_\alpha \cdot \tanh(\mathbf{W}_\alpha \cdot \boldsymbol{s}_{t-1} + \mathbf{U}_\alpha \cdot \boldsymbol{h}_i))$$

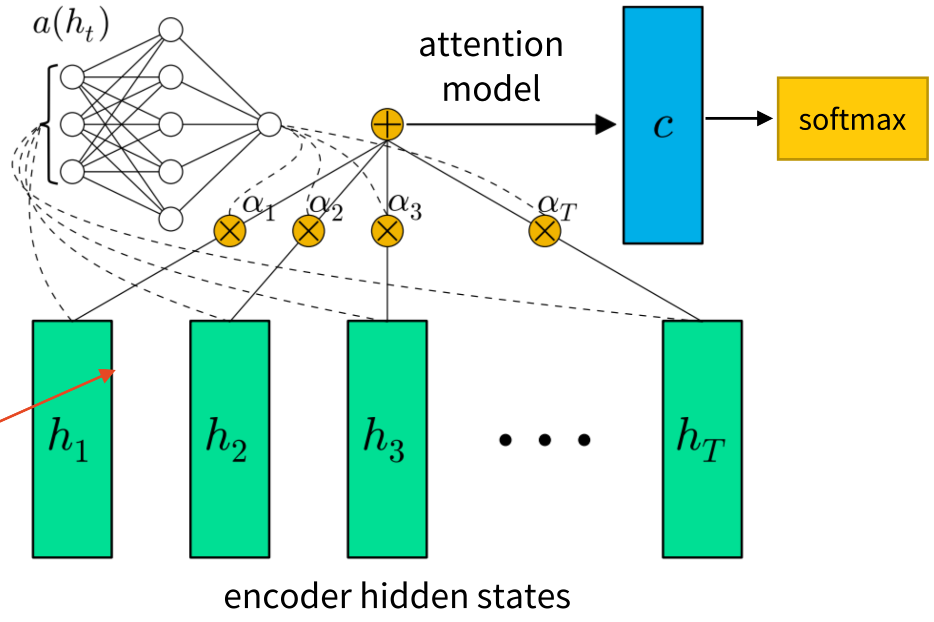


- **Self-attention** – over previous decoder steps

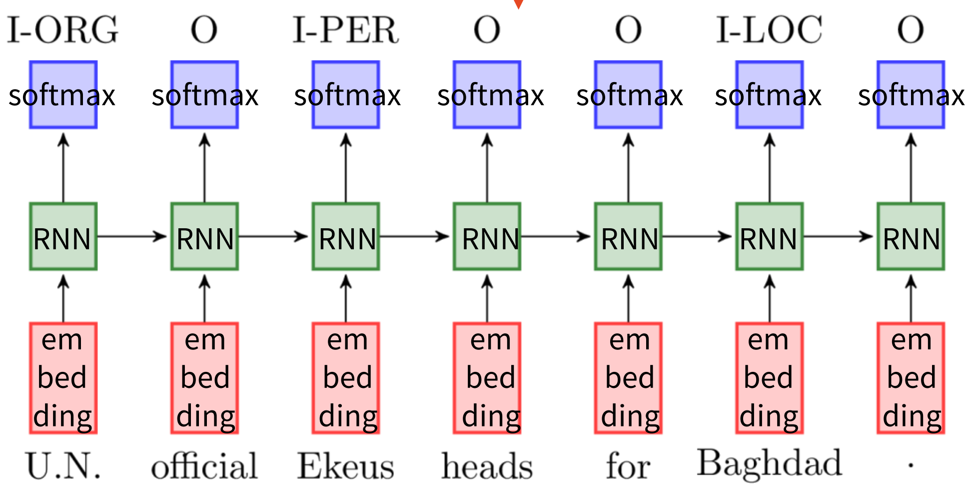
https://skymind.ai/wiki/attention-mechanism-memory-network

Neural NLU

- Various architectures possible
- Classification
  - feed-forward NN
  - RNN + attention weight → softmax
- Sequence tagging
  - RNN (LSTM/GRU) → softmax over hidden states
    - default version: label bias (like MEMM)
    - CRF over the RNN possible
- Still treats intent + slots independently



https://colinraffel.com/publications/iclr2016feed.pdf

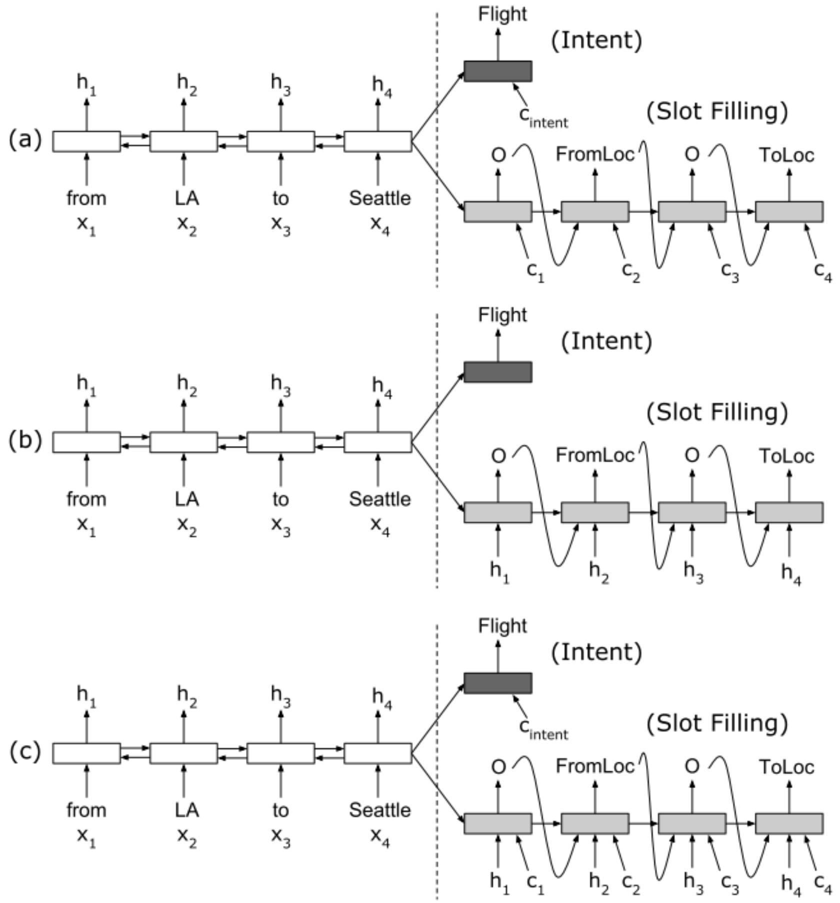


https://www.depends-on-the-definition.com/guide-sequence-tagging-neural-networks-python/

NN NLU – Joint Intent & Slots

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

- Same network for both tasks
- **Bidirectional encoder**
  - 2 encoders: left-to-right, right-to-left
  - concatenate hidden states
  - “see the whole sentence before you start tagging”
- Decoder – tag word-by-word, inputs:
  a) attention
  b) input encoder hidden states (“aligned inputs”)
  c) both
- Intent classification: softmax over last encoder state
  - + specific intent context vector (attention)



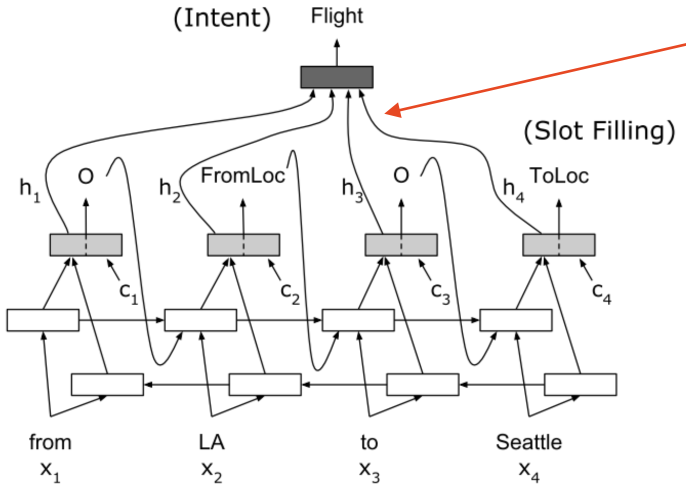
NN NLU – Joint Intent & Slots

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

- Extended version: use slot tagging in intent classification
  - Bidi encoder
  - Slots decoder with encoder states & attention
  - Intent decoder – attention over slots decoder states
- Works slightly better

this is new

same as (c)
on previous slide



Dialogue State Tracking

- Dialogue management consist of:
  - **State update** ← here we need DST
  - Action selection (later)
- **Dialogue State** needed to remember what was said in the past
  - tracking the dialogue progress
  - summary of the whole dialogue history
  - basis for action selection decisions

U: I'm looking for a restaurant in the city centre.
S: OK, what kind of food do you like?
U: Chinese.
✗ *S: What part of town do you have in mind?*
✗ *S: Sure, the Golden Dragon is a good Chinese restaurant. It is located in the west part of town.*
✓ *S: Sure, the Golden Dragon is a good Chinese restaurant. It is located in the city centre.*

Dialogue State Contents

- "All that is used when the system decides what to say next" (Henderson, 2015)
- **User goal**/preferences ~ NLU output
  - slots & values provided (search constraints)
  - information requested
- Past **system actions**
  - information provided
    - slots and values
    - list of venues offered
  - slots confirmed
  - slots requested
- **Other** semantic context
  - user/system utterance: bye, thank you, repeat, restart etc.

U: *Give me the address of the first one you talked about.*
U: *Is there any other place in this area?*

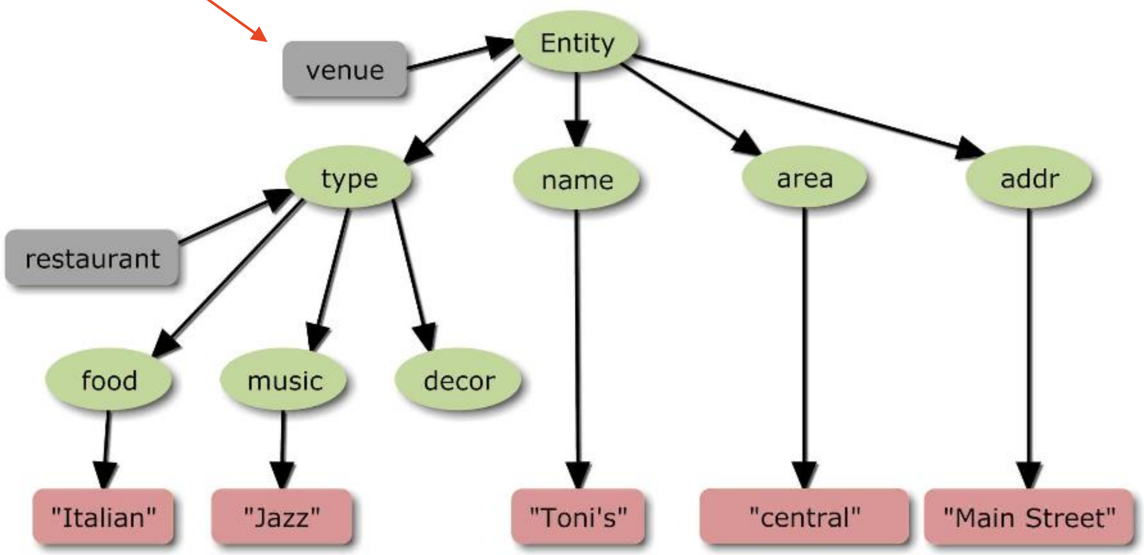
S: *OK, Chinese food. […]*

S: *What time would you like to leave?*

Ontology

- To describe possible states
- Defines all concepts in the system
  - List of slots
  - Possible range of values per slot
  - Possible actions per slot
    - requestable, informable etc.
  - Dependencies
    - some concepts only applicable
      for some values of parent concepts

"if entity=venue, then…"



entity = {venue, landmark}
venue.type = {restaurant, bar,…}

some slot names may need disambiguation
(venue type vs. landmark type)

food_type – only for type=restaurant
has_parking – only for type=hotel

http://mi.eng.cam.ac.uk/research/dialogue/papers/youn09.pdf

Problems with Dialogue State

- NLU is unreliable
  - takes unreliable ASR output
  - makes mistakes by itself – some utterances are ambiguous
  - output might conflict with ontology
- Possible solutions:
  - detect contradictions, ask for confirmation
  - ignore low-confidence NLU input
    - what's "low"?
    - what if we ignore 10x the same thing?
- Better solution: make the state probabilistic – **belief state**

ASR: 0.5 *I'm looking for an expensive hotel*
0.5 *I'm looking for inexpensive hotels*

NLU: 0.3 inform(type=restaurant, stars=5)

only hotels have stars!

Belief State

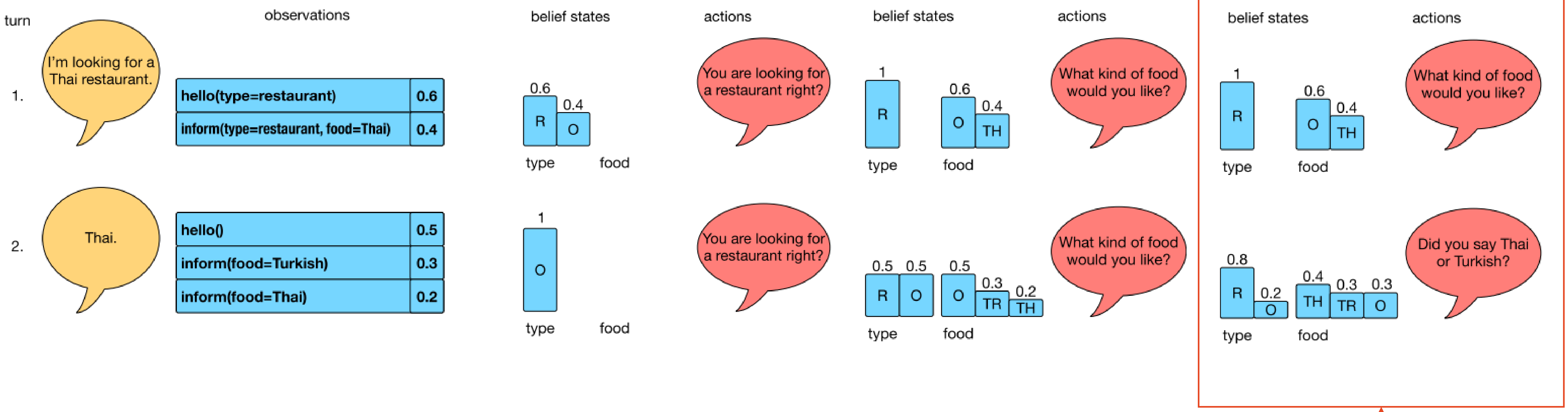
- Assume we don't know the true dialogue state
  - but we can estimate a probability distribution over all possible states
  - In practice: per-slot distributions
- More robust
  - accumulates probability mass over multiple turns
    - low confidence – if the user repeats it, we get it the 2nd time
  - accumulates probability over NLU n-best lists
- Plays well with probabilistic dialogue policies
  - but not only them – rule-based, too

Belief State

no probability accumulation (1-best, no state)

accumulating over NLU n-best list (still no state)

accumulating over NLU n-best + turns

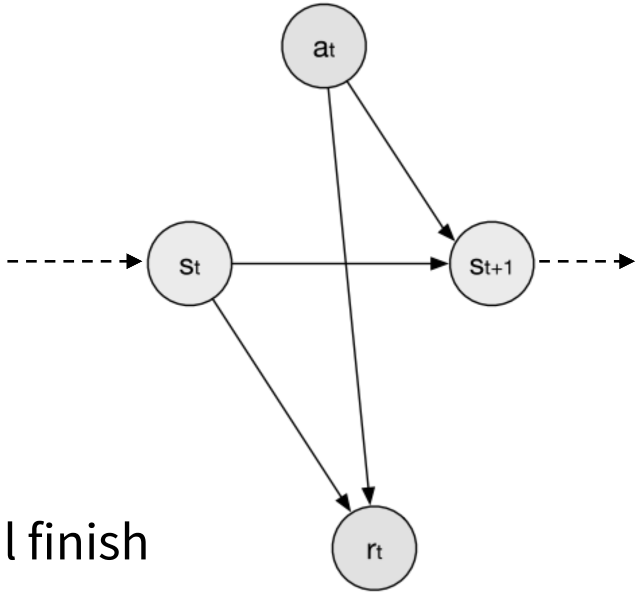


this is what we need (=belief state)

(from Milica Gašić's slides)

Dialogue as a Markov Decision Process

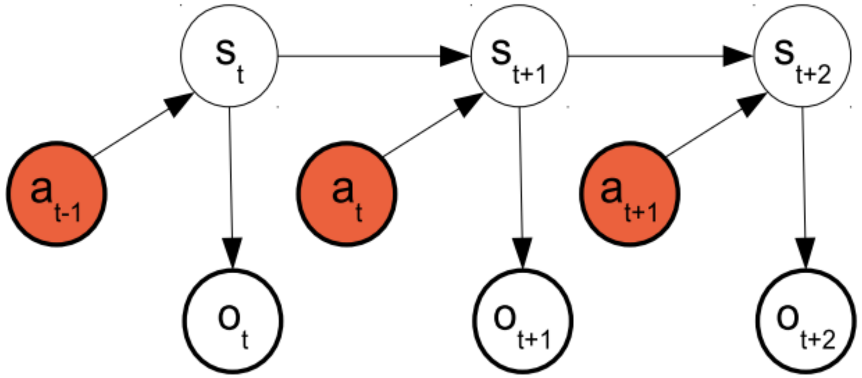
- MDP = probabilistic control process
  - model – Dynamic Bayesian Network
    - random variables & dependencies in a graph/network
    - "dynamic" = structure repeats over each time step t
  - s_t – dialogue **states** = what the user wants
  - a_t – **actions** = what the system says
  - r_t – **rewards** = measure of quality
    - typically slightly negative for each turn, high positive for successful finish
  - $p(s_{t+1}|s_t, a_t)$ – **transition probabilities**
- Markov property – state defines everything
- Problem: we're not sure about the dialogue state



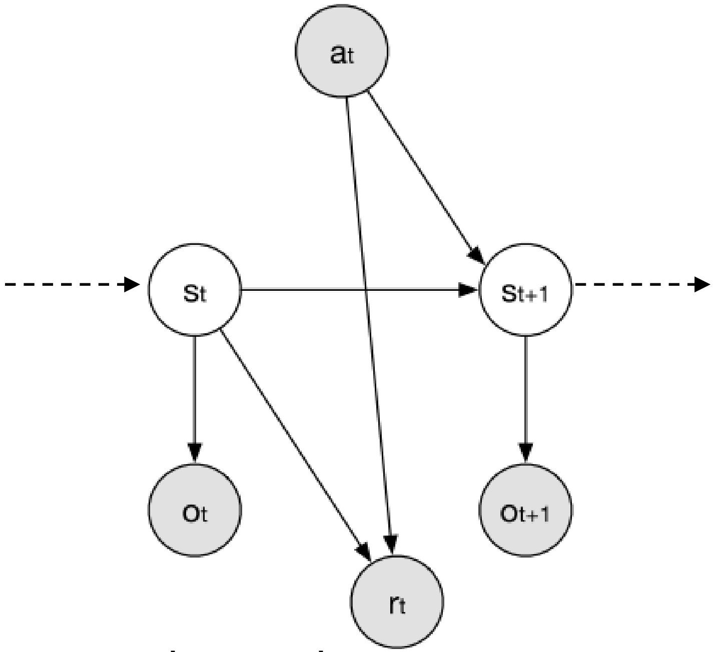
(from Milica Gašić's slides)

Partially Observable (PO)MDP

- Dialogue states are **not observable**
  - modelled probabilistically – belief state $b(s)$ is a prob. distribution over states
  - states (*what the user wants*) influence **observations** o_t (*what the system hears*)
- Still Markovian
  - $b'(s') = \frac{1}{Z} p(o|s') \sum_{s \in S} p(s'|s,a) b(s)$
  - $b(s)$ can be modelled by an HMM



(from Filip Jurčíček's slides)



grey = observed
white = unobserved

(from Milica Gašić's slides)

Digression:

Generative vs. Discriminative Models

What they learn:

- **Generative** – whole distribution $p(x, y)$
- **Discriminative** – just decision boundaries between classes ~ $p(y|x)$

To predict $p(y|x)$…

- **Generative models**
  1) Assume some functional form for $p(x), p(x|y)$
  2) Estimate parameters of $p(x), p(x|y)$ directly from training data
  3) Use Bayes rule to calculate $p(y|x)$
- **Discriminative models**
  1) Assume some functional form for $p(y|x)$
  2) Estimate parameters of $p(y|x)$ directly from training data

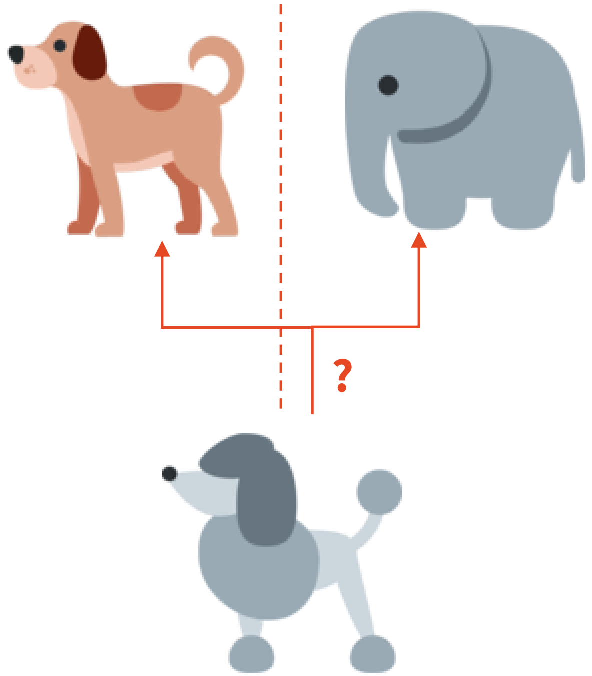
they get the same thing, but in different ways

https://medium.com/@mlengineer/generative-and-discriminative-models-af5637a66a3

Generative vs. Discriminative Models

Example: elephants vs. dogs http://cs229.stanford.edu/notes/cs229-notes2.pdf

- Discriminative:
  - establish decision boundary (~find distinctive features)
  - classification: just check on which side we are
- Generative
  - ~ 2 models – what elephants & dogs look like
  - classification: match against the two models



- Discriminative – typically better results
- Generative – might be more robust, more versatile
  - e.g. predicting the other way, actually generating likely (x, y)'s

Naïve Generative Belief Tracking
(= Belief Monitoring)

- Using the HMM model
  - estimate the transition & observation probabilities from data

$$b(s) = \frac{1}{Z} p(o_t | s_t) \sum_{s_{t-1} \in S} p(s_t | a_{t-1}, s_{t-1}) b(s_{t-1})$$

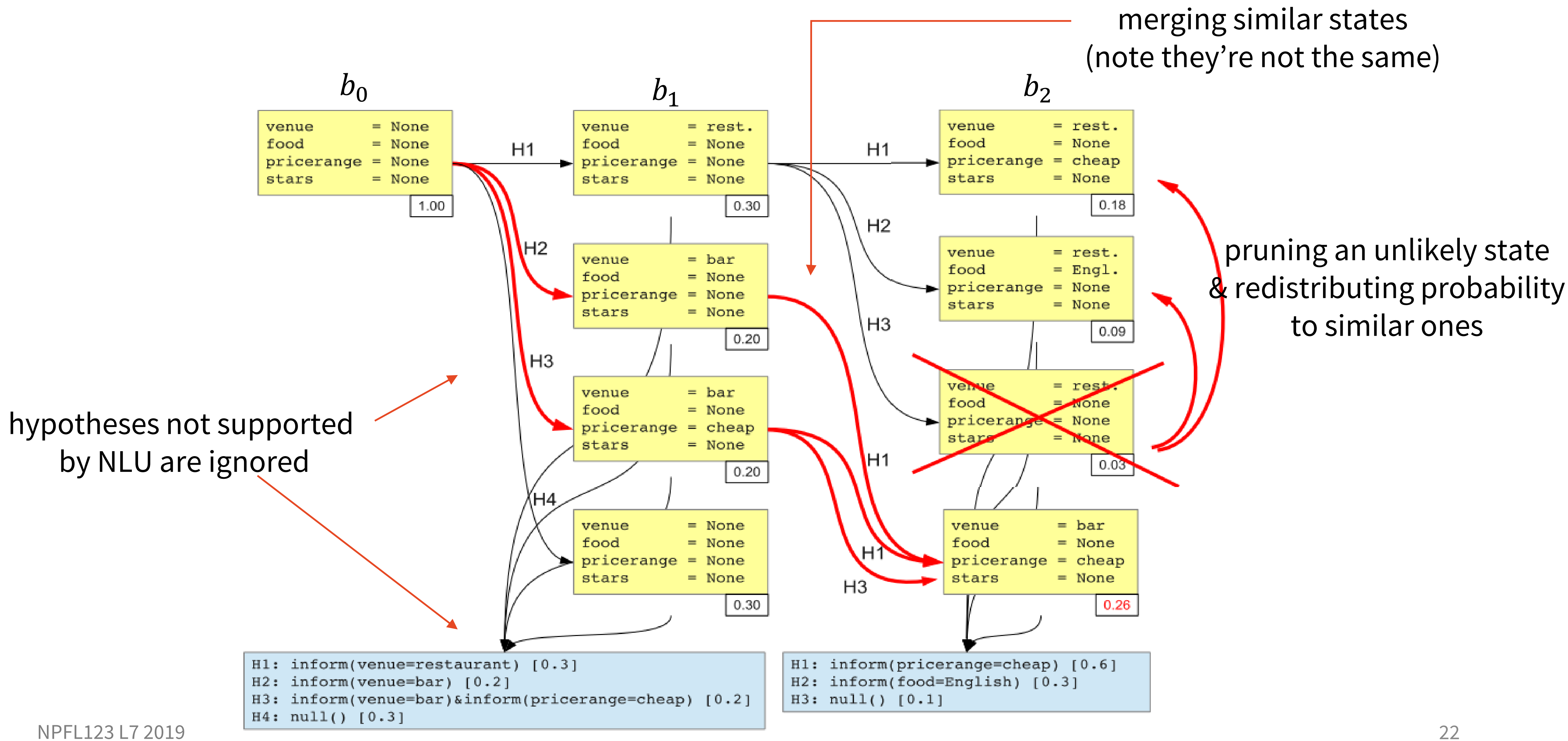
same as previous

- Problem: too many states
  - e.g. 10 slots, 10 values each → 10^{10} distinct states – intractable
- Solutions: pruning/beams, additional assumptions…
  - or different models altogether

Generative BT: Pruning/Beams

- Tricks to make the naïve model tractable:
  - only track/enumerate states supported by NLU
    - “other” = all equal, don’t even keep the rest in memory explicitly
  - just keep *n* most probable states (**beam**)
    - prune others & redistribute probability to similar states
  - merge similar states (e.g. same/similar slots, possibly different history)
    - along with probability mass
- Model parameters estimated from data
  - transition probabilities $p(s_{t+1}|s_t, a_t)$
  - observation probabilities $p(o_t|s_t)$
  - this is hard to do reliably, so they’re often set by hand

Generative BT: Pruning/Beams



(from Filip Jurčíček's slides)

Generative BT: Independence Assumptions

- **Partition the state** by assuming conditional independence
  - track parts of the state independently → reduce # of combinations
  - e.g. "each slot is independent":
    - state $\mathbf{s} = [s^1, \dots s^N]$, belief $b(\mathbf{s}_t) = \prod_i b(s_t^i)$
    - other partitions possible – speed/accuracy trade-off
- Slot partition:
  - $$b(s_t^i) = \sum_{s_{t-1}, o_t^i} p(s_t^i | a_{t-1}^i, s_{t-1}^i, o_t^i) b(s_{t-1}^i)$$
    $$= \sum_{s_{t-1}, o_t^i} \underbrace{p(s_t^i | a_{t-1}^i, s_{t-1}^i)}_{\text{transition probability}} \underbrace{p(o_t^i | s_t^i)}_{\text{observation probability}} \underbrace{b(s_{t-1}^i)}_{\text{last belief}}$$
- Further simplification: parameter tying

θ_T ~ rigidity (bias for keeping old values)

$$p(s_t^i | a_{t-1}^i, s_{t-1}^i) = \begin{cases} \theta_T \text{ if } s_t^i = s_{t-1}^i \\ \frac{1-\theta_T}{\#\text{values}^i - 1} \text{ otherwise} \end{cases}$$

$$p(o_t^i | s_t^i) = \begin{cases} \theta_O p(o_t^i) \text{ if } o_t^i = s_t^i \\ \frac{1-\theta_O}{\#\text{values}^i - 1} p(o_t^i) \text{ otherwise} \end{cases}$$

θ_O ~ confidence in NLU

$p(o_t^i)$ = NLU output

(Žilka et al., 2013; Marek, 2013)

Basic Discriminative Belief Tracker

- Based on the previous model
  - same slot independence assumption
- Actually simpler – "always trust the NLU"
  - this makes it parameter-free
  - …and kinda rule-based
  - but very fast, with reasonable performance

user silent about slot i

$$p(s_t^i | a_{t-1}^i, s_{t-1}^i, o_t^i) = \begin{cases} p(o_t^i) \text{ if } s_t^i = o_t^i \wedge o_t^i \neq \text{🤫} \\ p(o_t^i) \text{ if } s_t^i = s_{t-1}^i \wedge o_t^i = \text{🤫} \\ 0 \text{ otherwise} \end{cases}$$

update rule $$b(s_t^i) = \sum_{s_{t-1}^i, o_t^i} \underbrace{p(s_t^i | a_{t-1}^i, s_{t-1}^i, o_t^i)}_{\text{discriminative model}} b(s_{t-1}^i)$$

substitution

$$b(s_t^i) = \begin{cases} p(s_t^i = \text{🤫}) p(o_t^i = \text{🤫}) \text{ if } s_t^i = \text{🤫} \\ p(o_t^i = s_t^i) + p(o_t^i = \text{🤫}) p(s_t^i = s_{t-1}^i) \text{ otherwise} \end{cases}$$

the rule is now deterministic

(Žilka et al., 2013)

Discriminative Trackers

- Generative trackers – need many assumptions to be tractable
  - cannot exploit arbitrary features
  - … or they can, but not if we want to keep them tractable
  - often use handcrafted parameters
  - … may produce unreliable estimates http://ieeexplore.ieee.org/document/6424197/
- Discriminative trackers – can use any features from dialogue history
  - parameters estimated from data more easily
- General distinction
  - **static models** – encode whole history into features
  - **sequence models** – explicitly model dialogue as sequential

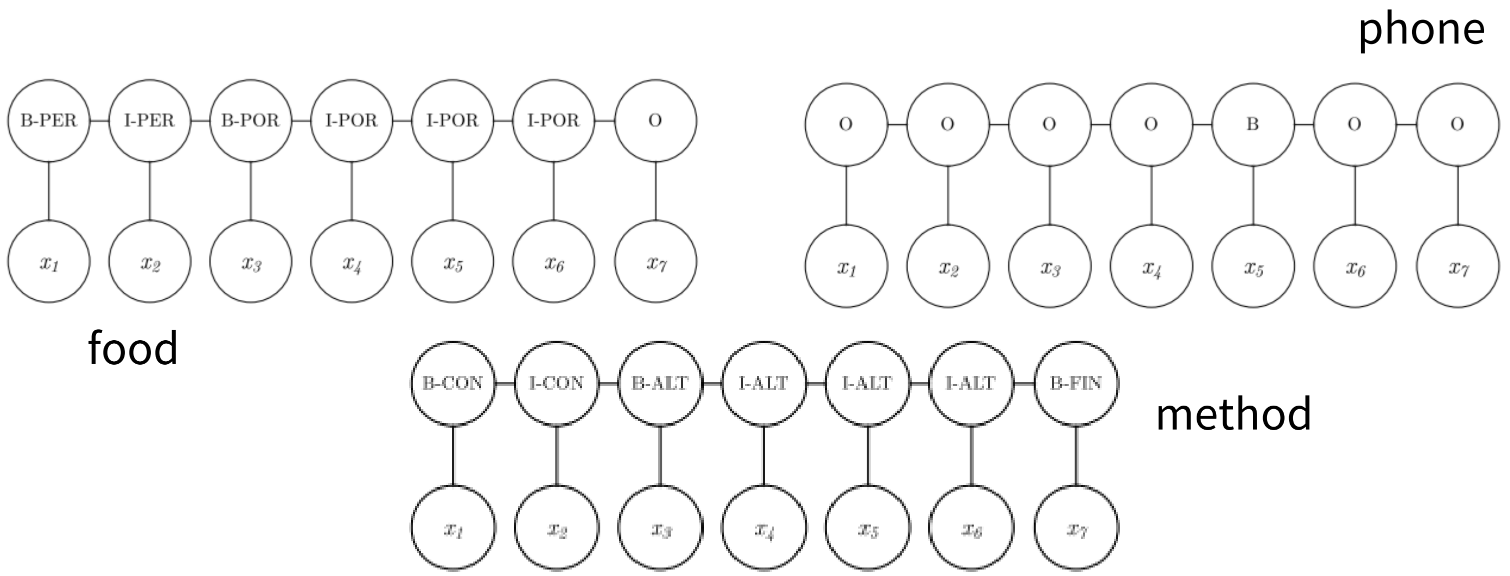
Static Discriminative Trackers

- Generally predict $p(s_t | o_1, a_1, \dots, a_{t-1}, o_t)$
  - any kind of classifier (SVM, LR…)
  - need fixed feature vector from $o_1, a_1, \dots, a_{t-1}, o_t$ (where t is arbitrary)
    - current turn, cumulative, sliding window
  - per-value features & tying weights– some values are too rare
- Global feature examples: https://www.aclweb.org/anthology/P13-1046
  - NLU n-best size, entropy, lengths (current turn, cumulative)
  - ASR scores
- Per-value v examples:
  - rank & score of hypo with v on current NLU n-best + diff vs. top-scoring hypo
  - # times v appeared so far, sum/average confidence of that
  - # negations/confirmations of v so far
  - reliability of NLU predicting v on held-out data

Sequence-Based Discriminative Trackers

- Dialogue as a sequence $p(s_1, \ldots s_t | o_1, \ldots o_t)$
- **CRF** models
  - similar features as previously – can be current-slot only (CRF will handle it)
  - feature value: NLU score for the given thing (e.g. DA type + slot + value)
  - target: per-slot BIO coding

	Utterance	Goals Food	Area
S_1	Hello, How may I help you?		
U_1	I need a Persian restaurant in the south part of town.	Persian	South
S_2	What kind of food would you like?		
U_2	Persian.	Persian	South
S_3	I'm sorry but there is no restaurant serving persian food		
U_3	How about Portuguese food?	Portuguese	South
S_4	Peking restaurant is a nice place in the south of town.		
U_4	Is that Portuguese?	Portuguese	South
S_5	Nandos is a nice place in the south of town serving tasty Portuguese food.		
U_5	Alright. Whats the phone number?	Portuguese	South
S_6	The phone number of nandos is 01223 327908 .		
U_6	And the address?	Portuguese	South
S_7	Sure, nandos is on Cambridge Leisure Park Clifton Way.		
U_7	Thank you good bye.		

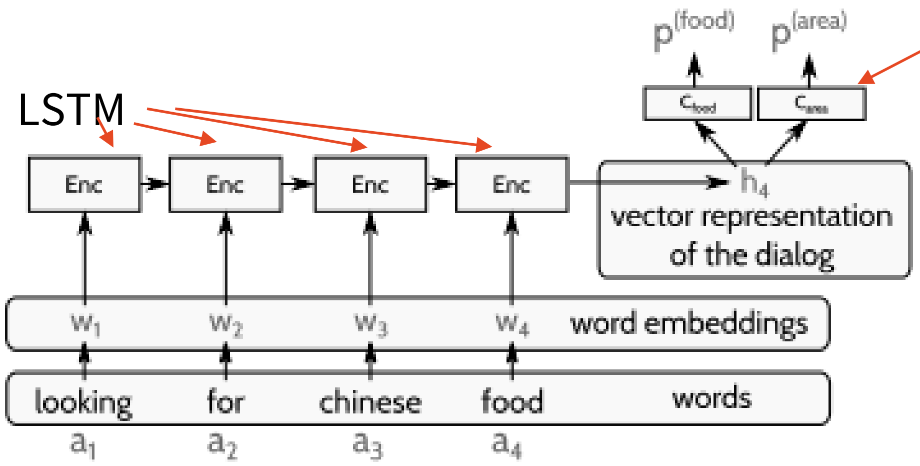


(Kim & Banchs, 2014) https://www.aclweb.org/anthology/W14-4345

Neural State Trackers

- Many different architectures
- Typically sequential, discriminative
- Typically **not** using NLU – directly ASR/words → belief
- Simple example: RNN over words + classification on hidden states
  - runs over the whole dialogue history (user utterances + system actions)

ReLU → softmax
(per slot)



(Žilka & Jurčíček, 2015)
https://dl.acm.org/citation.cfm?id=2955040
http://arxiv.org/abs/1507.03471

Neural State Trackers

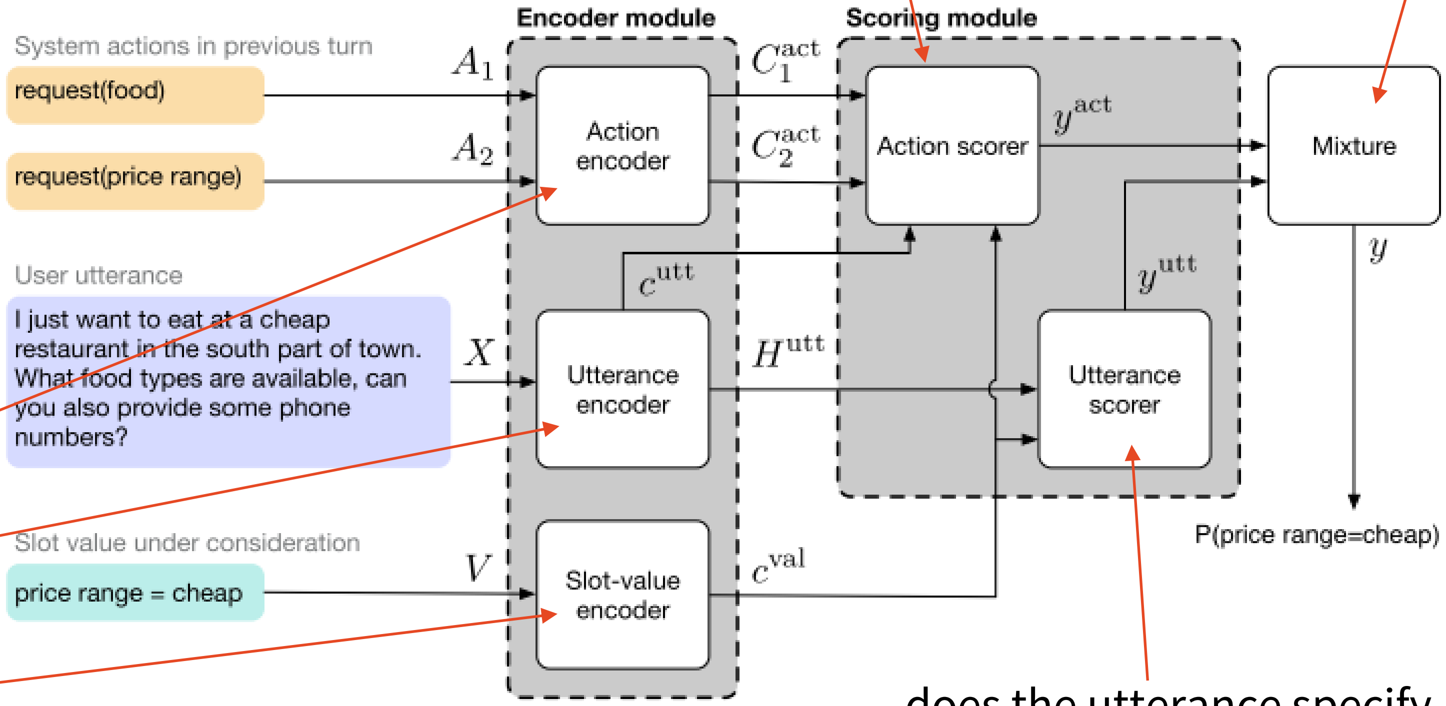
- More complex – better generalization across slots

(Zhong et al., 2018)
http://arxiv.org/abs/1805.09655

if utterance refers to previous system actions

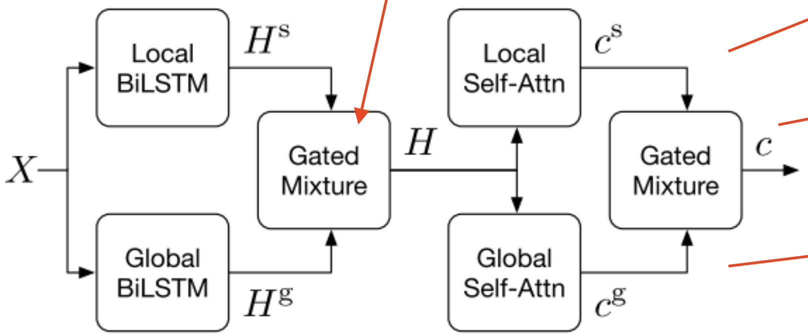
attention over prev. system actions w. r. t. current user utterance

weighted sum + sigmoid



β ·global + $(1-\beta)\cdot$ local

encoders shape:



local = per-slot, global = shared among slots

does the utterance specify this slot-value pair? attention over utterance w. r. t. slot-value pair

Summary

- Neural networks primer
  - embeddings
  - layers (sigmoid, tanh, ReLU)
  - recurrent networks (LSTM, GRU)
  - attention
- NN SLU examples
- Dialogue state, belief state
- Dialogue as (Partially observable) Markov Decision Process
- Generative belief trackers
- Discriminative belief trackers
- NN tracker examples

Thanks

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Labs tomorrow 9:00 SU1

Get these slides here:

http://ufal.cz/npfl123

References/Inspiration/Further:

- Filip Jurčíček's slides (Charles University): https://ufal.mff.cuni.cz/~jurcicek/NPFL099-SDS-2014LS/
- Milica Gašić's slides (Cambridge University): http://mi.eng.cam.ac.uk/~mg436/teaching.html
- Henderson (2015): Machine Learning for Dialog State Tracking: A Review https://ai.google/research/pubs/pub44018
- Žilka et al. (2013): Comparison of Bayesian Discriminative and Generative Models for Dialogue State Tracking https://aclweb.org/anthology/W13-4070 (+David Marek's MSc. thesis https://is.cuni.cz/webapps/zzp/detail/122733/)
- Liu & Lane (2016): Attention-Based Recurrent Neural Network Models for Joint Intent Detection and Slot Filling http://arxiv.org/abs/1609.01454
- Kim & Banchs (2014): Sequential Labeling for Tracking Dynamic Dialog States https://www.aclweb.org/anthology/W14-4345