Statistical Dialogue Systems

NPFL099 Statistické Dialogové systémy

5. Dialogue State Tracking

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http://ufal.cz/npfl099

31. 10. 2019

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?*

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

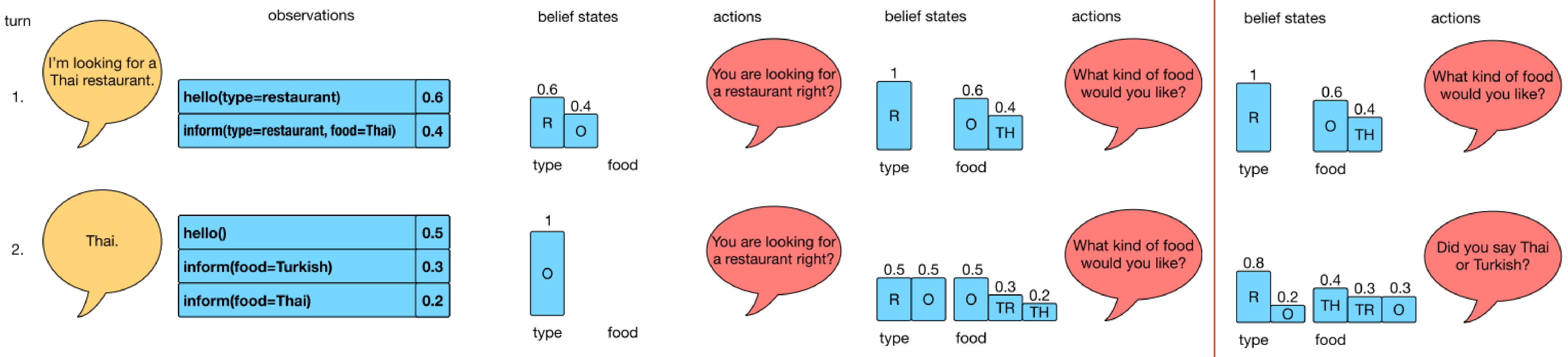
- Assume we don't know the true current dialogue state s_t
  - states (*what the user wants*) influence **observations** o_t (*what the system hears*)
  - based on observations o_t & system actions a_t, we can estimate a probability distribution $b(s)$ over all possible states – **belief state**
- More robust than using dialogue state directly
  - accumulates probability mass over multiple turns
    - low confidence – if the user repeats it, we get it the 2^{nd} time
  - accumulates probability over NLU n-best lists
- Plays well with probabilistic dialogue policies (POMDPs)
  - 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)

Basic Discriminative Belief Tracker

- **Partition the state** by assuming conditional independence
  - simplify – assume each slot is independent:
    - state $\mathbf{s} = [s^1, \dots s^N]$, belief $b(\mathbf{s}_t) = \prod_i b(s_t^i)$
- **Always trust the NLU**
  - this makes the model parameter-free
  - …and basically rule-based
  - but very fast, with reasonable performance

user silent about slot i

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

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

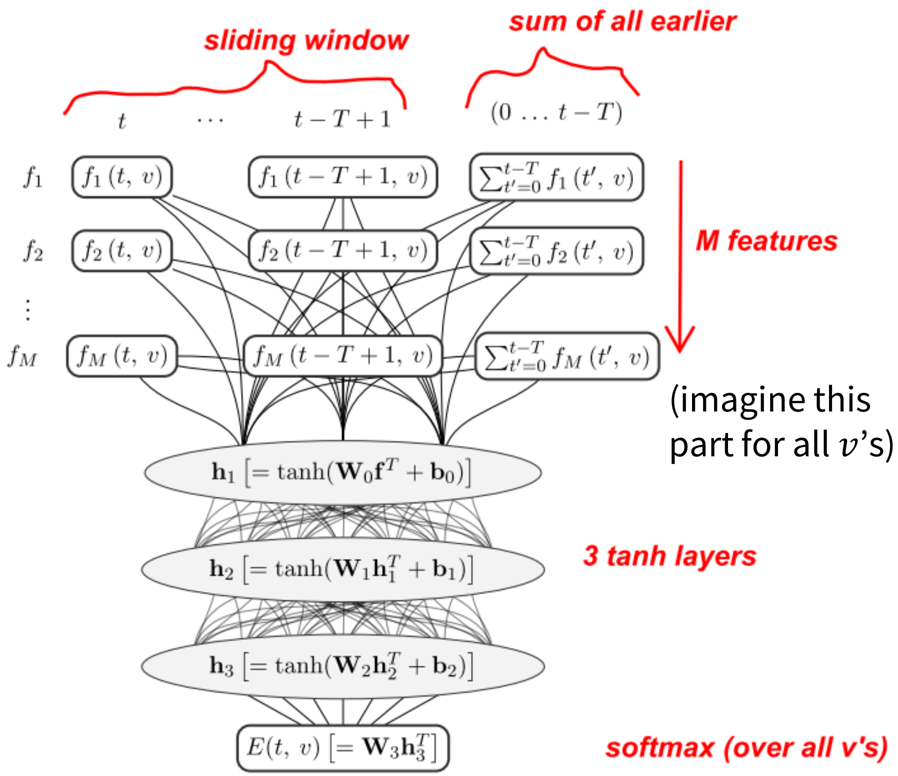
substitution

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

the belief state update rule is deterministic

(Žilka et al., 2013)
http://www.aclweb.org/anthology/W13-4070

Basic Feed-forward Tracker



$$
\begin{aligned}
\mathbb{P}(s = v) &= e^{E(t,\,v)}/Z \\
\mathbb{P}(s \notin S_{t,\,s}) &= e^{B}/Z \\
Z &= e^{B} + \sum_{v' \in S_{t,\,s}} e^{E(t,\,v')}
\end{aligned}
$$

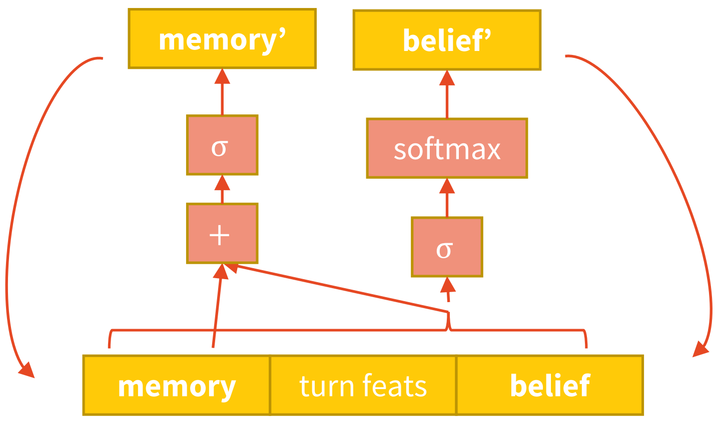
- a simple feed-forward network
  - input – features (w.r.t. slot-value v & time t)
    - SLU score of v
    - n-best rank of v
    - user & system act type
    - … – domain-independent, low-level NLU outputs
  - 3 tanh layers
  - output – softmax (= probability distribution over values
- **static** – does not model dialogue as a sequence
  - uses a sliding window – current time t + few steps back + $\sum$previous

(Henderson et al., 2013)
https://aclweb.org/anthology/W13-4073

Basic RNN Tracker

(Mrkšić et al., 2015)
http://arxiv.org/abs/1506.07190

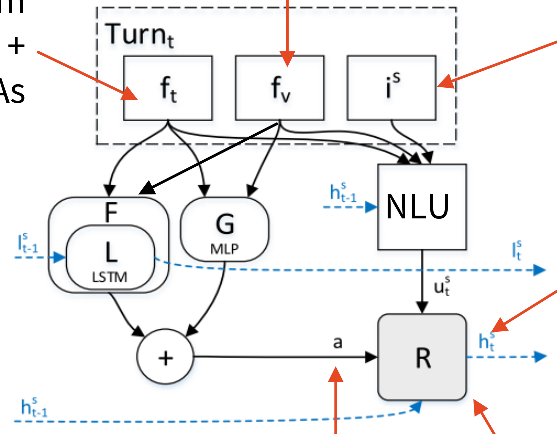
- plain sigmoid RNN with a memory vector
  - not quite LSTM/GRU, but close
  - memory updated separately, used in belief update
- does not need NLU
  - turn features = lexicalized + delexicalized n-grams from ASR n-best list, weighted by confidence
- delexicalization very harsh: <slot> <value>
  - you don't even know which slot it is
  - this apparently somewhat helps the system generalize across domains
- **dynamic** – explicitly models dialogue as sequence
  - using the network recurrence

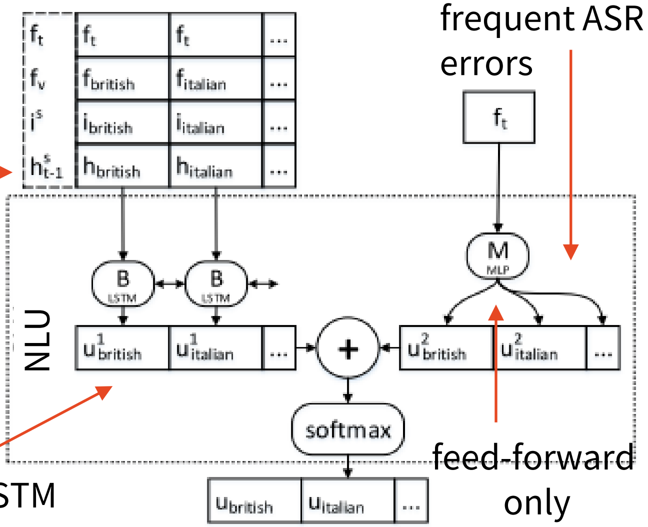


(Vodolán et al., 2017)
http://arxiv.org/abs/1702.06336

Neural/Rule Hybrid

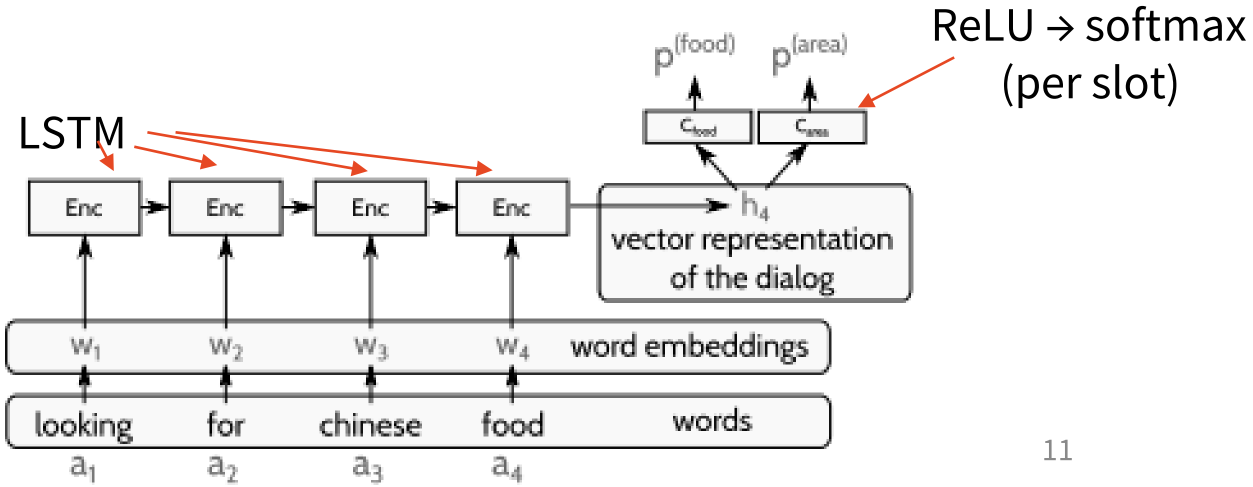
- explicit update over belief
  - per-slot model (separate for each slot)
  - simple update rule R
    - for a value: add $a \cdot$ current NLU confidence, normalize
    - differentiable, can be trained end-to-end
  - trained models F, G provide a
    - F is generic LSTM, G is value specific feed-forward
- needs an NLU, but postprocesses it
  - input & output of tracker NLU step
    = prob. dist. of informs over slot values in current turn
  - generic & specific part again





Incremental Recurrent Tracker

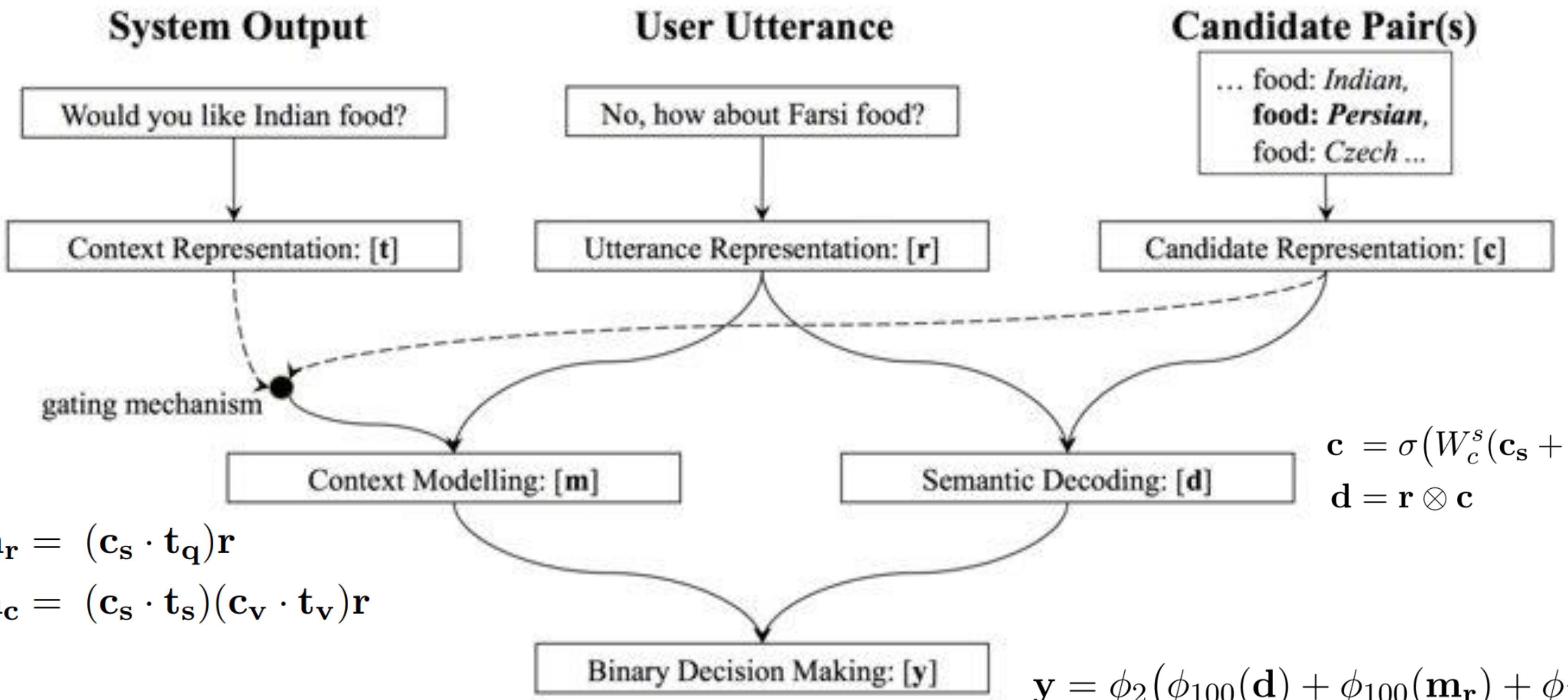
- simple: LSTM over words + classification on hidden states
  - runs over the whole dialogue history (user utterances + system actions)
  - classification can occur after each word, right as it comes in from ASR
- also dynamic/sequential
- also doesn't use any NLU
  - infrequent values are delexicalized (otherwise it can't learn them)
- slightly worse performance – possible causes:
  - only uses ASR 1-best
  - long recurrences (no hierarchy)



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

(Mrkšić et al., 2017)
https://www.aclweb.org/anthology/P17-1163

NBT



$$\mathbf{c} = \sigma\big(W_c^s(\mathbf{c_s} + \mathbf{c_v}) + b_c^s\big)$$
$$\mathbf{d} = \mathbf{r} \otimes \mathbf{c}$$

$$\mathbf{m_r} = (\mathbf{c_s} \cdot \mathbf{t_q})\mathbf{r}$$
$$\mathbf{m_c} = (\mathbf{c_s} \cdot \mathbf{t_s})(\mathbf{c_v} \cdot \mathbf{t_v})\mathbf{r}$$

$$\mathbf{y} = \phi_2\big(\phi_{100}(\mathbf{d}) + \phi_{100}(\mathbf{m_r}) + \phi_{100}(\mathbf{m_c})\big)$$

NBT

- Better use of data: Getting rid of delexicalization
  - pre-trained word vectors – important!
  - shared parameters
  - RNN/CNN feature extractors
- Discriminative learning slot values

Belief state update

$$\mathbb{P}(s, v \mid h^{1:t}, sys^{1:t-1}) = \lambda\, \mathbb{P}\left(s, v \mid h^{t}, sys^{t-1}\right) + (1-\lambda)\, \mathbb{P}\left(s, v \mid h^{1:t-1}, sys^{1:t-2}\right)$$

DST Model	DSTC2		WOZ 2.0	
	Goals	Requests	Goals	Requests
Delexicalisation-Based Model	69.1	95.7	70.8	87.1
Delexicalisation-Based Model + Semantic Dictionary	72.9*	95.7	83.7*	87.6
Neural Belief Tracker: NBT-DNN	72.6*	96.4	**84.4***	91.2*
Neural Belief Tracker: NBT-CNN	**73.4***	**96.5**	84.2*	**91.6***

Candidate Ranking

(Rastogi et al., 2017)
https://arxiv.org/abs/1712.10224

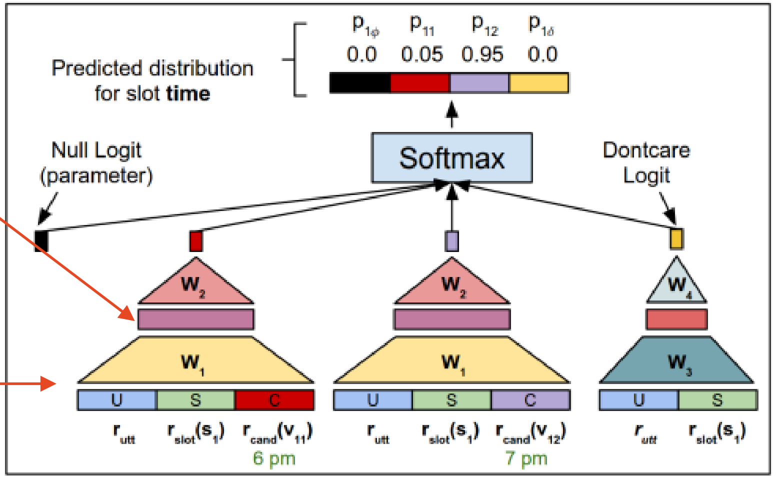
- Previous systems consider all values for each slot
  - this is a problem for open-ended slots (e.g. restaurant name)
  - enumerating over all takes ages, some are previously unseen
- Alternative: always consider just K candidates
  - use last K candidates from system actions and NLU output
    - NB: only way history is incorporated here!
  - select from them using a per-slot softmax

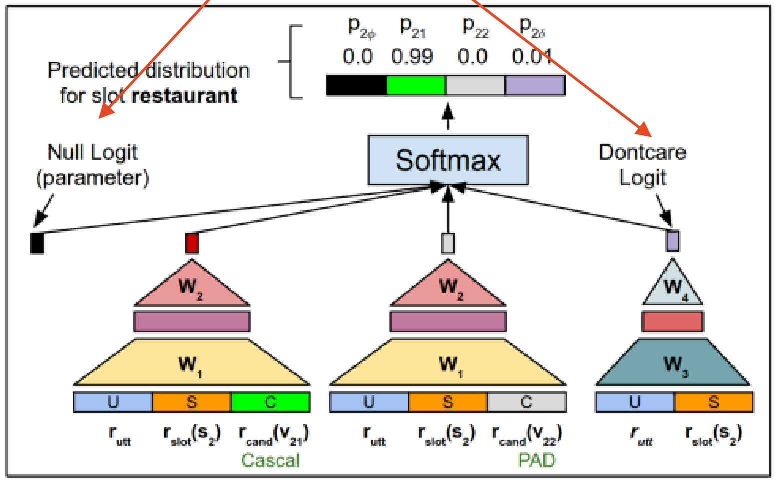
additional values to consider
(even if not mentioned in NLU)

pictures assume $K = 2$

2 sigmoid layers

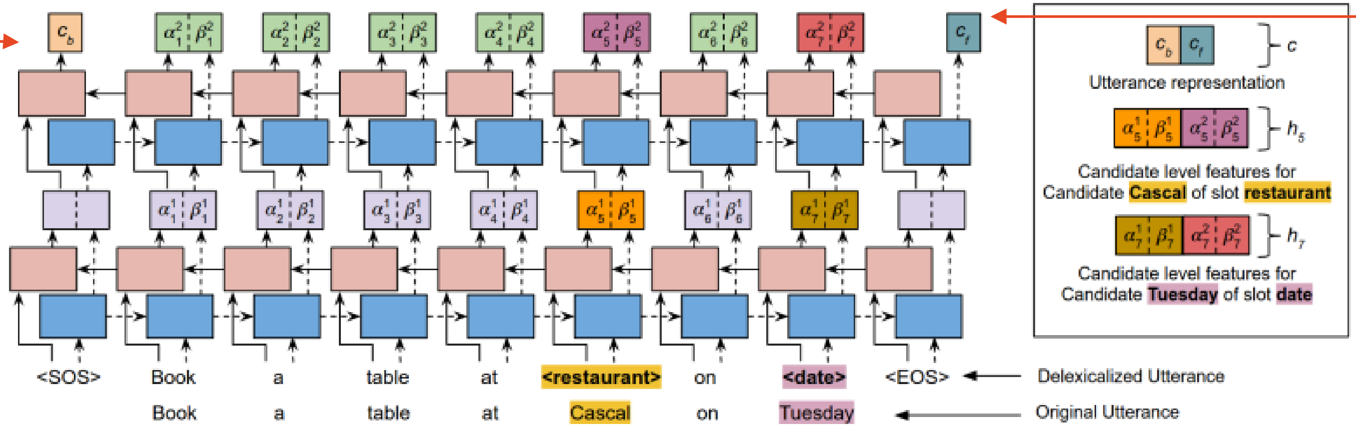
representation of
i-th candidate:
utterance/slot/candidate
features (next slide)





Candidate Ranking – representation

- Using BiGRU over lexicalized & delexicalized utterance
- Features:
  - **utterance** – last GRU state + indicators for non-slot DAs (user & prev. system) *bye(), affirm()*
  - **slot** – indicators for DAs with this slot (user & prev. system) *inform(slot=*), request(slot)*
    + last turn scores for *null* & *dontcare*
  - **candidate** – GRU states over matched value words *inform(slot=value)*
    + indicators for DAs with this slot & value (user & prev. system)



Multi-value Candidate Ranking

(Goel et al., 2018)
http://arxiv.org/abs/1811.12891

- What if multiple values are true?
  - previous approach picks one (softmax)
  - use set of binary classifiers (log loss) instead
- \+ more flexible regarding candidates
  - can be past k from NLU, but also just current ASR n-grams
  - this model keeps track of context by itself

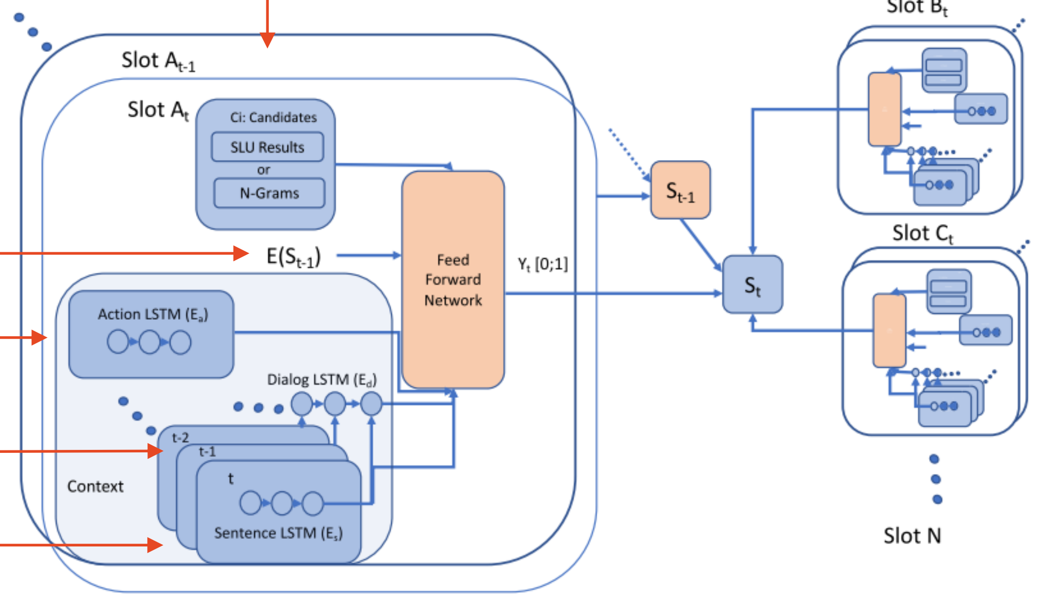
multiple per-slot models
share info about previous beliefs

previous belief state embedding

past system actions turn-level LSTM

past sentences over
hierarchical LSTM

current sentence



Hybrid Classify/Rank

metric: **joint goal accuracy**
– exact match on dialogue state
(most probable value only)

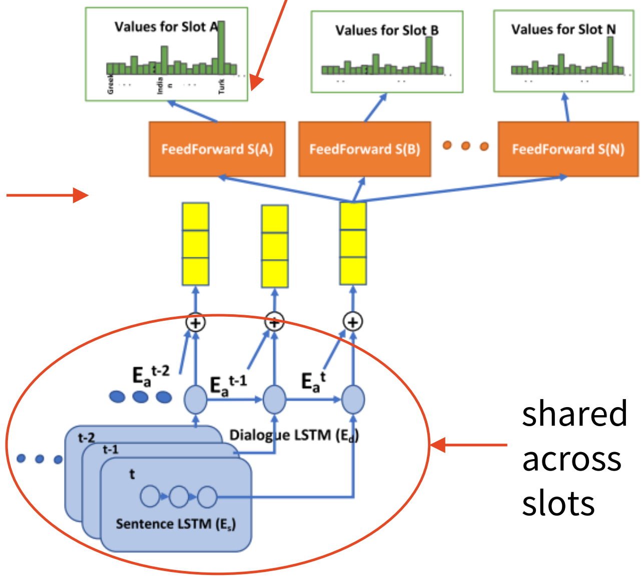
Method	Accuracy
Majority Baseline	1.5%
MultiWOZ-2.0 Benchmark	25.83%
Ranking only	31.11% (29.73%)
Classification only	40.74% (38.42%)
Hybrid	44.24% (42.33%)

ensemble (majority vote of 3 models)

single model

- Ranking is faster & more flexible
- Classification over all values is more accurate
  - at least for most slots, where # of values is limited
- Solution: combine classification & ranking
  - choose best model for each slot based on dev data performance
- Ranking approach – multi-value from previous slide
- Classification approach – straightforward: hierarchical LSTM + per-slot feed-forward + softmax

separate for each slot



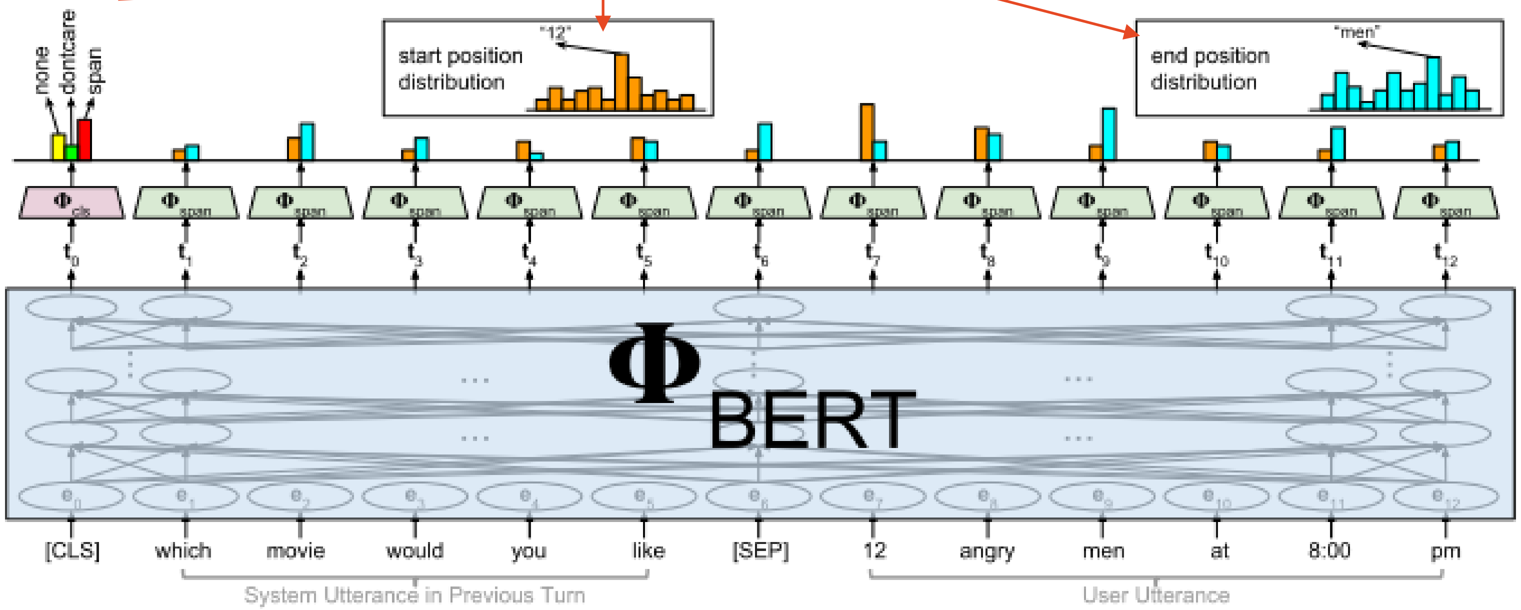
shared across slots

(Goel et al., 2019)
http://arxiv.org/abs/1907.00883

Using BERT

(Chao & Lane, 2019)
http://arxiv.org/abs/1907.03040

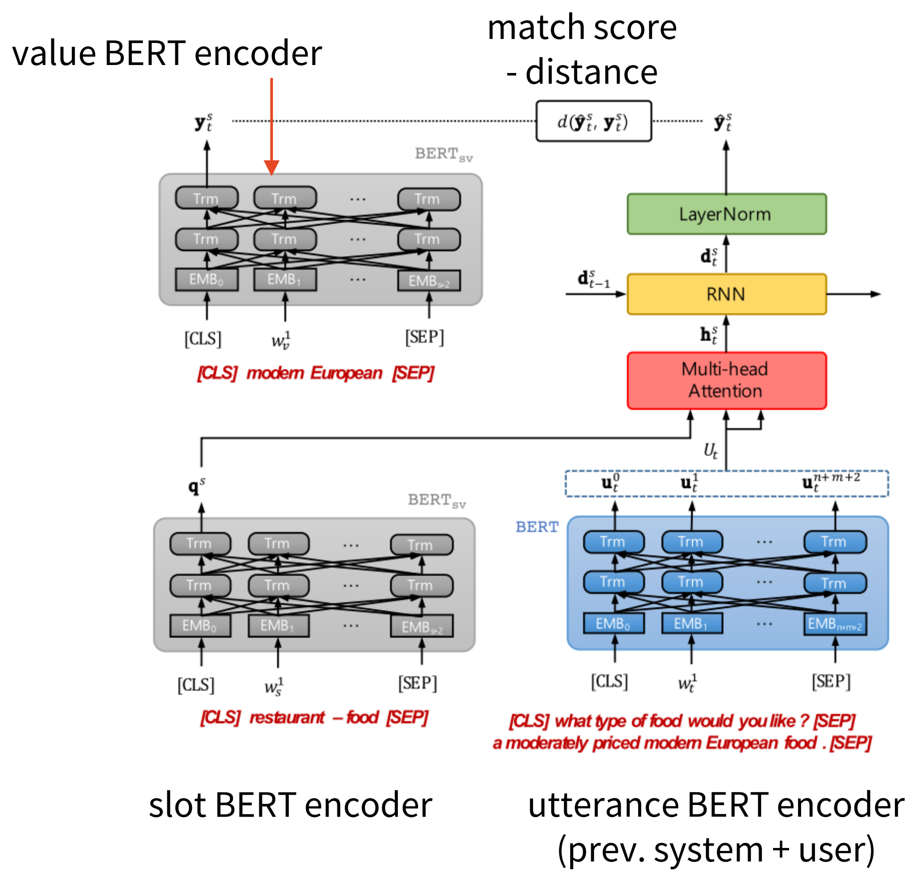
- Very basic:
  - run BERT over previous system & current user utterance
  - from 1st token's representation, get a decision: *none*/*dontcare*/span
    - per-slot (BERT is shared, but the final decision is slot-specific)
  - span = need to find a concrete value as a span somewhere in the text
    - predict start & end token of the span using 2 softmaxes
  - carry-over across multiple turns is rule-based:
    - if *none* is predicted, keep previous value, otherwise change it



Slot-Utterance Matching Belief Tracker

(Lee et al., 2019)
http://arxiv.org/abs/1907.07421

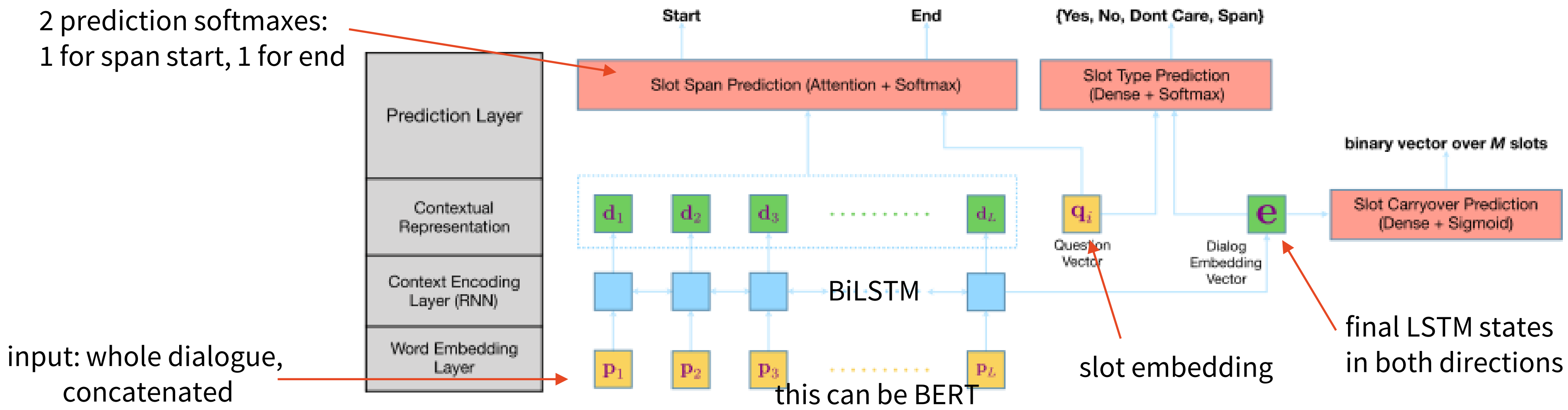
- different take on BERT trackers
  - inspired by reading comprehension
  - considers "domain – slot" a question
    & tries to find the value in the input utterance
- tracker over BERT
  - attention + turn-based RNN
    - attention in current utterance
    - RNN (LSTM/GRU) for carry-over of past values
    - layer normalization to match BERT outputs
      - BERT includes layer normalization by default
  - trained to match the correct values in the utterance
    - loss: distance of true value BERT encoding
      from the tracker output (Euclidean/Cosine)



Even More Reading Comprehension

(Gao et al., 2019)
https://www.aclweb.org/anthology/W19-5932/

- Also uses BERT, but not necessarily
  - works slightly worse with random-initialized word embeddings
- sequence of 3 decisions
  - do we carry over last turn's prediction? (Yes/No)
  - if no: what kind of answer are we looking for? (*yes*/*no*/*dontcare*/span of text)
  - if span: predict span's start and end



Dialogue State as SQL

(Yu et al., 2019)
http://arxiv.org/abs/1909.05378
http://arxiv.org/abs/1906.02285

- User goal is a query → why not SQL query?
- Text-to-SQL models used for tracking
  - with contextual enhancements, input:
    - all user inputs so far
    - previous system response
    - database schema
- Seq2seq-based model example:
  - hierarchical LSTM for encoding user & system
  - database column embeddings
    = averaged embeddings over table + column name
  - decoder:
    - decide between SQL keyword vs. column
    - then select which keyword / column via softmax
- So far, experimental – performance is low

D_1 : Database about student dormitories containing 5 tables		
Q_1 : What are the names of all the dorms?	INFORM_SQL
S_1 : `SELECT dorm name FROM dorm`	
A_1 : (Result table with many entries)	
R_1 : This is the list of the names of all the dorms.	CONFIRM_SQL
Q_2 : Which of those dorms have a TV lounge?	INFORM_SQL
S_2 : `SELECT T1.dorm_name FROM dorm AS T1 JOIN has_amenity AS T2 ON T1.dormid = T2.dormid JOIN dorm_amenity AS T3 ON T2.amenid = T3.amenid WHERE T3.amenity_name = 'TV Lounge'`	
A_2 : (Result table with many entries)	
R_2 : This shows the names of dorms with TV lounges.	CONFIRM_SQL
Q_3 : What dorms have no study rooms as amenities?	AMBIGUOUS
R_3 : Do you mean among those with TV Lounges?	CLARIFY
Q_4 : Yes.	AFFIRM
S_4 : `SELECT T1.dorm_name FROM dorm AS T1 JOIN has_amenity AS T2 ON T1.dormid = T2.dormid JOIN dorm_amenity AS T3 ON T2.amenid = T3.amenid WHERE T3.amenity_name = 'TV Lounge' EXCEPT SELECT T1.dorm_name FROM dorm AS T1 JOIN has_amenity AS T2 ON T1.dormid = T2.dormid JOIN dorm_amenity AS T3 ON T2.amenid = T3.amenid WHERE T3.amenity_name = 'Study Room'`	
A_4 : Fawlty Towers	
R_4 : Fawlty Towers is the name of the dorm that has a TV lounge but not a study room as an amenity.	CONFIRM_SQL
…	
Q_8 : Thanks!	THANK_YOU
R_8 : You are welcome.	WELCOME

Summary

- State tracking is needed to maintain user goal over multiple turns
- Best to make the state probabilistic – **belief state**
- Architectures – many options
  - good NLU + rules – works well!
  - neural, hybrid
  - static (sliding-window) vs. dynamic (recurrent, modelling dialogue as sequence)
  - with/without NLU
  - classifiers vs. candidate rankers vs. reading comprehension
    - classifiers are more accurate than rankers but slower, limited to seen values
    - reading comprehension is a very new approach, works nicely but probably slow
  - BERT & co. as usual – good but slow
  - incremental – not used too much so far
- Alternative/experimental: SQL instead of slots/values

Thanks

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Get these slides here:

http://ufal.cz/npfl099

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