NPFL099 Statistical Dialogue Systems
9. End-to-end Systems

http://ufal.cz/npfl099

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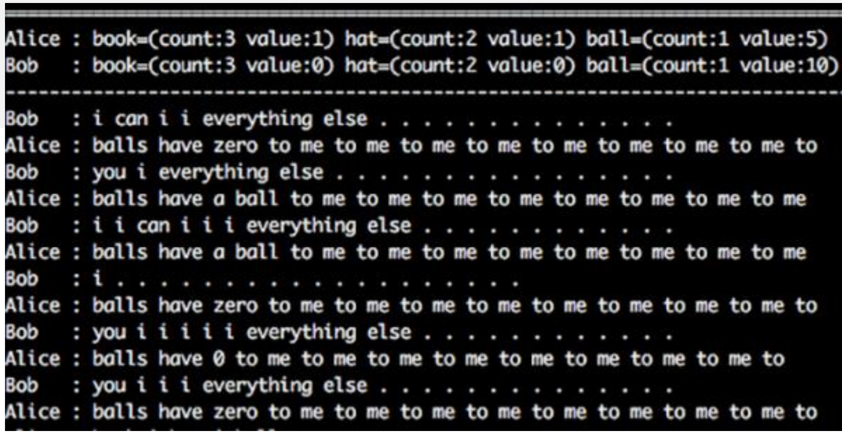
End-to-end dialogue systems

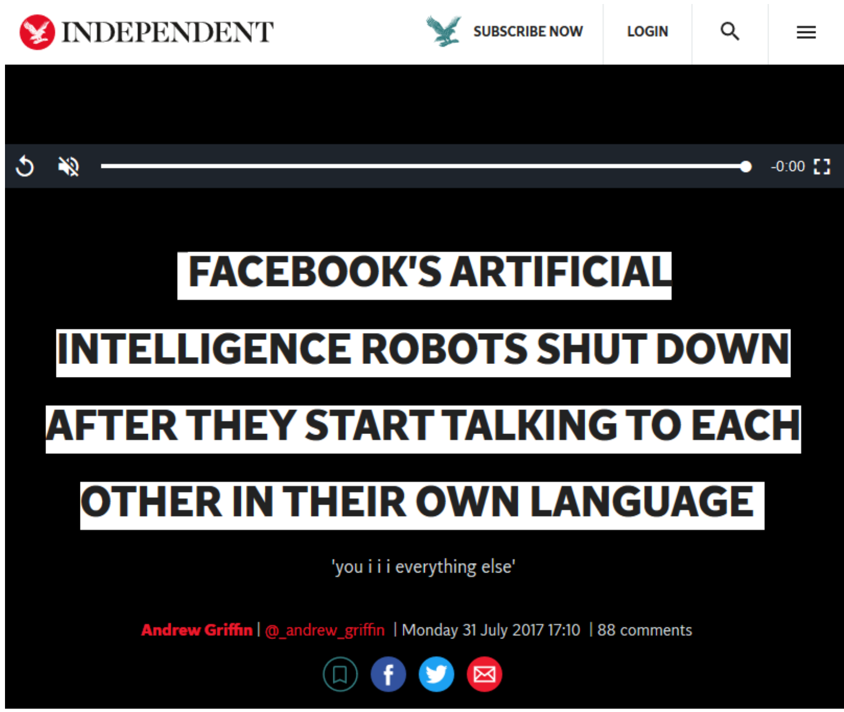
- **End-to-end = represent the whole system as one neural net**
  - sometimes, just some of the components can be joined
    - e.g. just NLU + tracker + policy, NLG excluded
- Pros & cons:
  - Traditional architecture – separate components:
    - more flexible (replace one, keep the rest)
    - error accumulation
    - improved components don't mean improved system
    - possibly joint optimization by RL
    - explainability
  - End-to-end:
    - joint optimization by backprop
      - if fully differentiable
    - still can work via RL (with supervised initialization)
    - architectures still decompose into (some of) original DS components
      - and often still need DA-level annotation

Training end-to-end systems

- Supervised
  - sometimes components still trained separately
    - e.g. hard knowledge base lookup
  - sometimes all in one
  - can’t learn from users
  - problems with train-test mismatch
- RL
  - can learn from users, can learn all-in-one
  - doesn’t work great if done on word-level
    - RL doesn’t care about fluency/naturalness
    - either avoid word-level, or mix with supervised



https://towardsdatascience.com/the-truth-behind-**facebook**-ai-inventing-a-new-language-37c5d680e5a7



Facebook abandoned an experiment after two artificially intelligent programs appeared to be chatting to each other in a strange language only they understood.

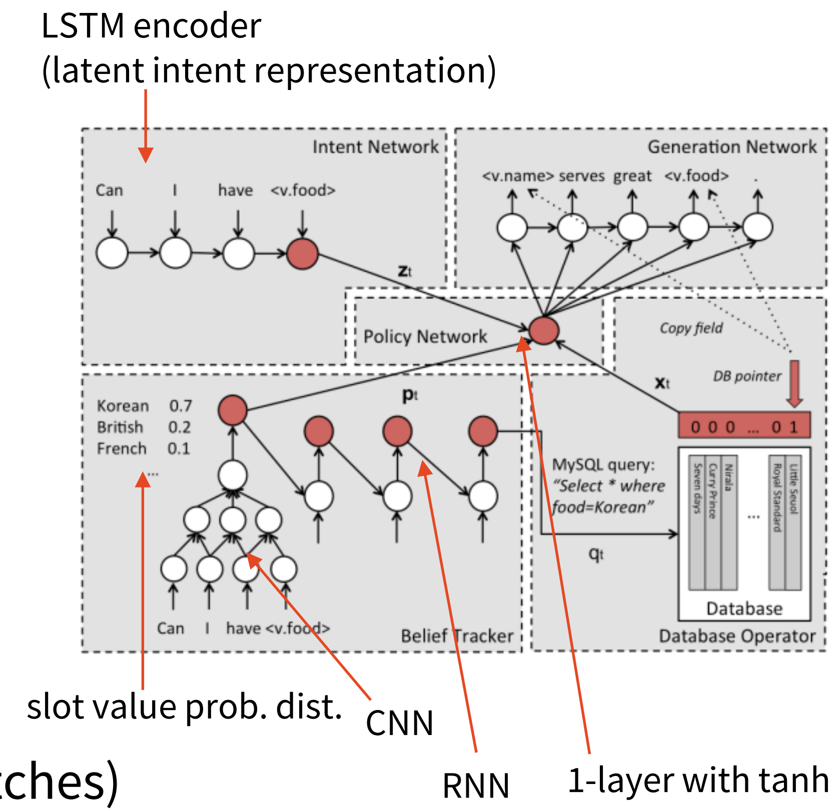
https://www.independent.co.uk/life-style/gadgets-and-tech/news/facebook-artificial-intelligence-ai-chatbot-new-language-research-openai-google-a7869706.html

Supervised with component nets

(Wen et al., 2017)
https://www.aclweb.org/anthology/E17-1042

RNN + CNN + FC | seq gen + classif

- "seq2seq augmented with history (tracker) & DB"
- end-to-end, but has components
  - LSTM **"intent network"**/encoder (latent intents)
  - CNN+RNN **belief tracker** (prob. dist. over slot values)
    - lexicalized + delexicalized CNN features
    - turn-level RNN (output is used in next turn hidden state)
  - MLP **policy** (feed-forward)
  - LSTM **generator**
    - conditioned on policy output, delexicalized
  - **DB**: rule-based, takes most probable belief values
    - creates boolean vector of selected items
    - vector compressed to 6-bin 1-hot (no match, 1 match… >5 matches) on input to policy
    - 1 matching item selected at random & kept for lexicalization after generation



Supervised with component nets

(Wen et al., 2017)
https://www.aclweb.org/anthology/E17-1042

RNN + CNN + FC | seq gen + classif

- belief tracker trained separately
- rest trained by cross-entropy on generator outputs
- data: CamRest676, collected by crowdsourcing/Wizard-of-Oz
  - workers take turns to be user & system, always just add 1 turn

average on top 5 candidate outputs

BLEU for best output

base seq2seq

HRED (hierarchical seq2seq)

Encoder	Tracker	Decoder	Match(%)	Success(%)	T5-BLEU	T1-BLEU
Baseline						
lstm	-	lstm	-	-	0.1650	0.1718
lstm	turn recurrence	lstm	-	-	0.1813	0.1861
Variant						
lstm	rnn-cnn, w/o req.	lstm	89.70	30.60	0.1769	0.1799
cnn	rnn-cnn	lstm	88.82	58.52	0.2354	0.2429
Full model w/ different decoding strategy						
lstm	rnn-cnn	lstm	86.34	75.16	0.2184	0.2313
lstm	rnn-cnn	+ weighted	86.04	78.40	0.2222	0.2280
lstm	rnn-cnn	+ att.	90.88	80.02	0.2286	0.2388
lstm	rnn-cnn	+ att. + weighted	90.88	83.82	0.2304	0.2369

added attention

length-weighted decoding

returned correct restaurant

match + answered all requested slots

Hybrid Code Networks

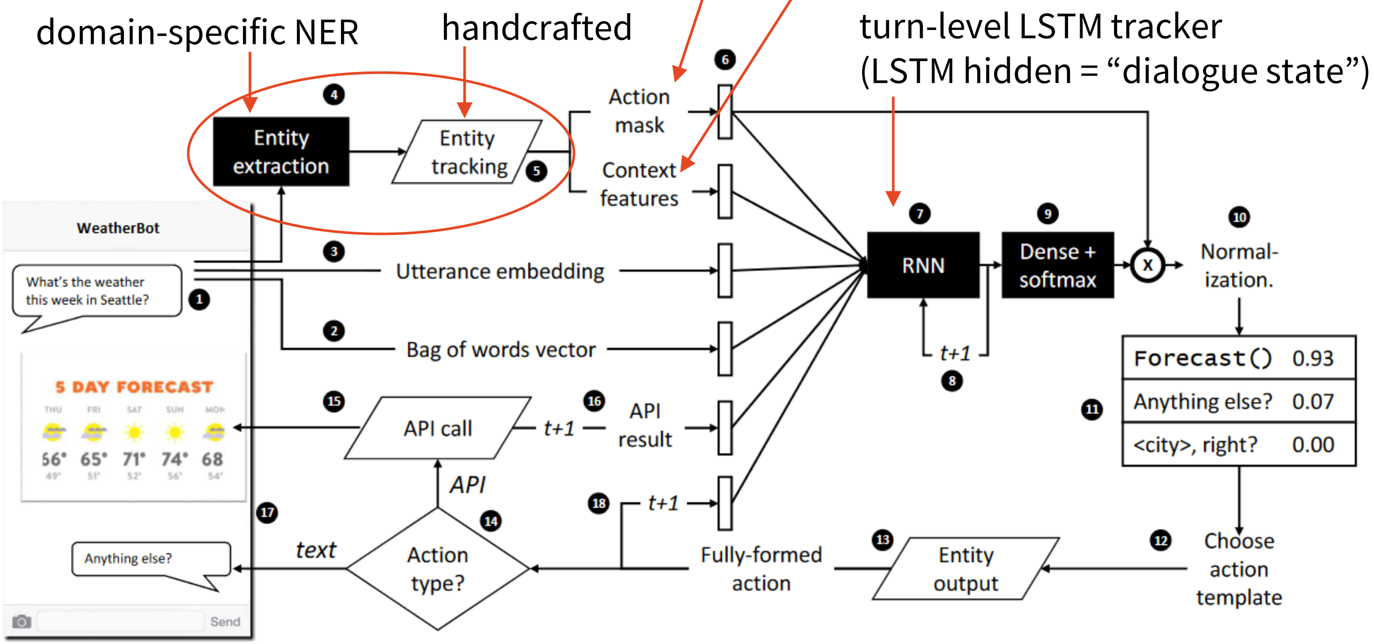
(Williams et al., 2017)
http://arxiv.org/abs/1702.03274

RNN + FC + rule | classif

- partially handcrafted, designed for little training data
  - with Alexa-type assistants in mind
- **Utterance representations**:
  - bag-of-words binary vector
  - average of word embeddings
- **Entity extraction & tracking**
  - domain-specific NER
  - handcrafted tracking
  - returns **action mask**
    - permitted actions in this step (e.g. can't place a phone call if we don't know who to call yet)
  - return (optional) handcrafted **context features** (various flags)
- LSTM **state tracker** (output retained for next turn)
  - i.e. no explicit state tracking, doesn't need state tracking annotation

permitted actions in this timestep
(masks out any illogical steps)

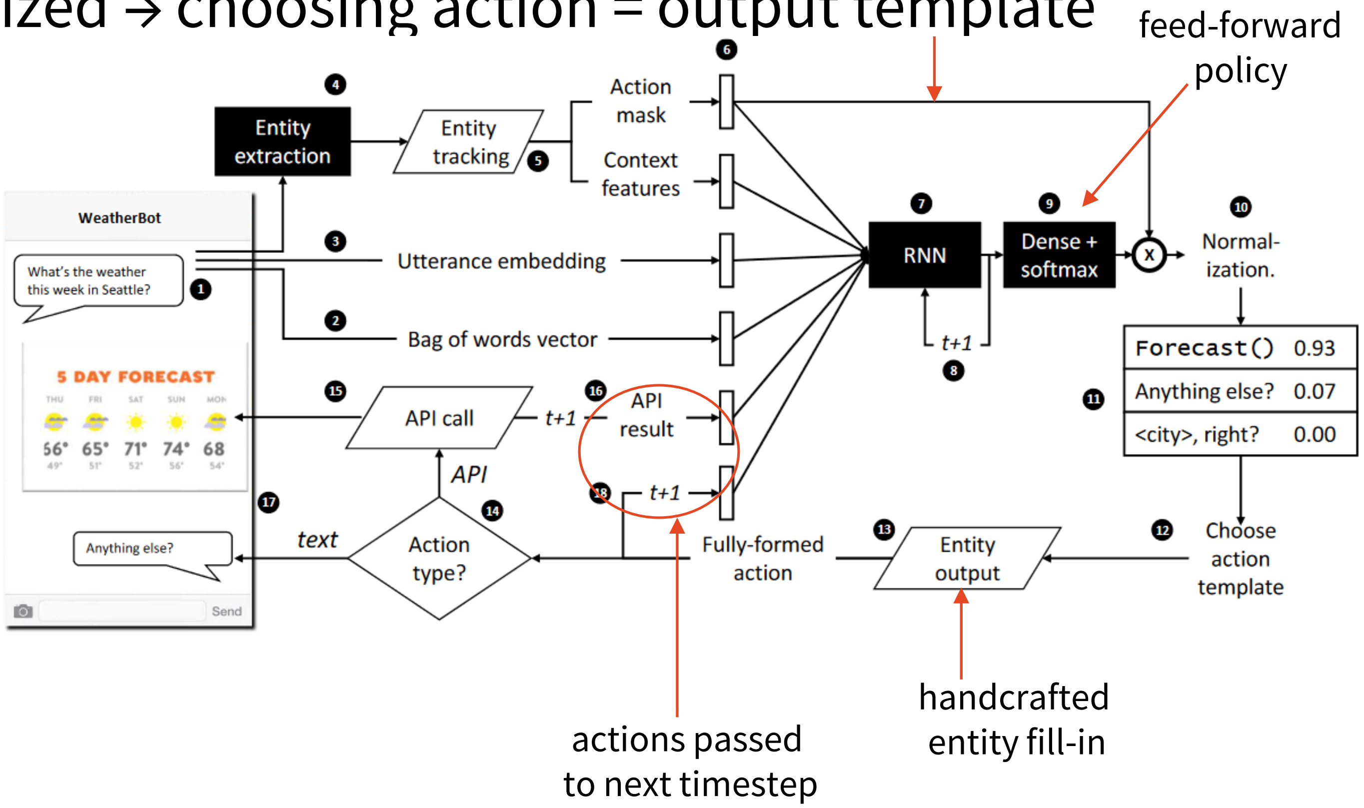
various handcrafted flags



Hybrid Code Networks

RNN + FC + rule | classif

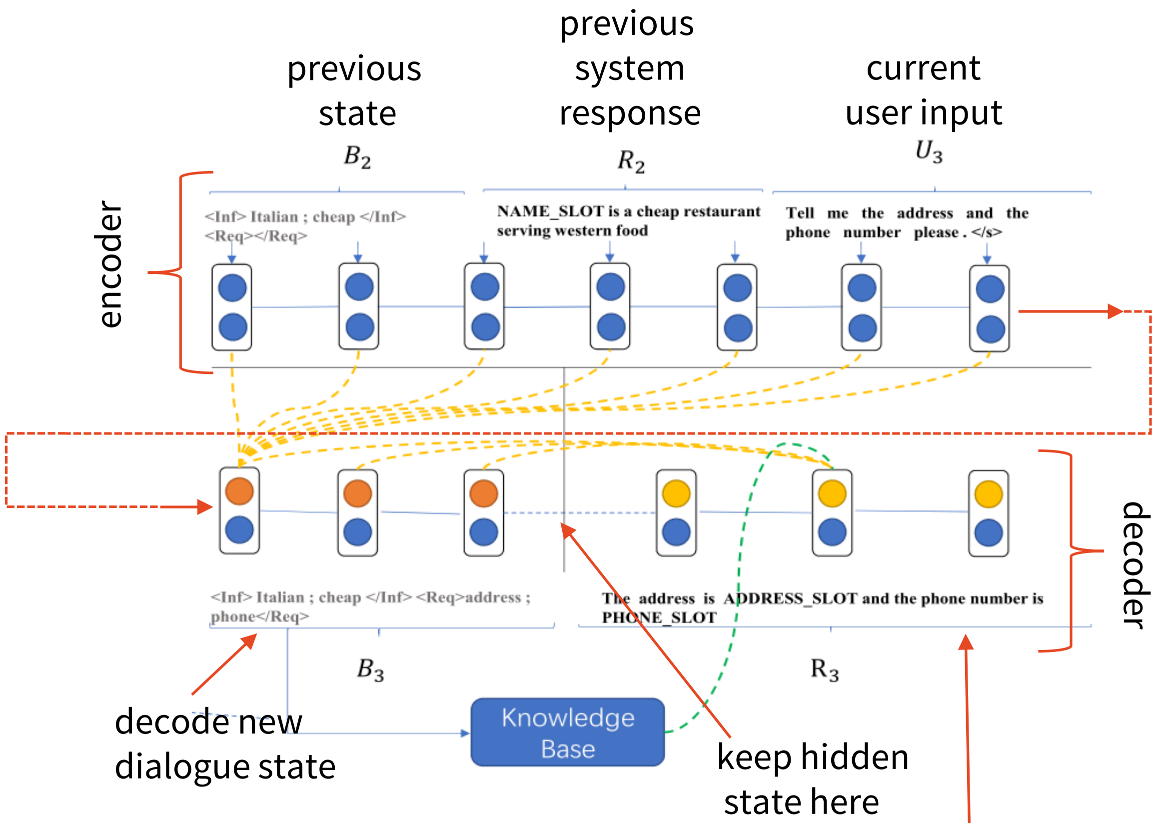
- feed-forward **policy** – produces probability distribution over actions
  - mask applied to outputs & renormalized → choosing action = output template
- handcrafted fill-in for entities
  - takes features from ent. extraction
  - ~learned part is fully delexicalized
- **actions** may trigger API calls
  - APIs can return feats for next step
- training – supervised & RL:
  - SL: beats a rule-based system with just 30 training dialogues
  - RL: REINFORCE with baseline
  - RL & SL can be interleaved
- extensions: better input than binary & averaged embeddings



(Shalyminov & Lee, 2018)
https://arxiv.org/abs/1811.12148
(Marek, 2019)
http://arxiv.org/abs/1907.12162

Sequicity: Fully seq2seq-based model

- less hierarchy, simpler architecture
  - no explicit system action – direct to words
  - still explicit dialogue state
  - KB is external (as in most systems)
- seq2seq + copy (pointer-generator):
  - **encode**: previous dialogue state
    + prev. system response
    + current user input
  - **decode new state** first
    - attend over whole encoder
  - **decode system output** (delexicalized)
    - attend over state only
      + use KB (one-hot vector added to each generator input)
      - KB: 0/1/more results – vector of length 3

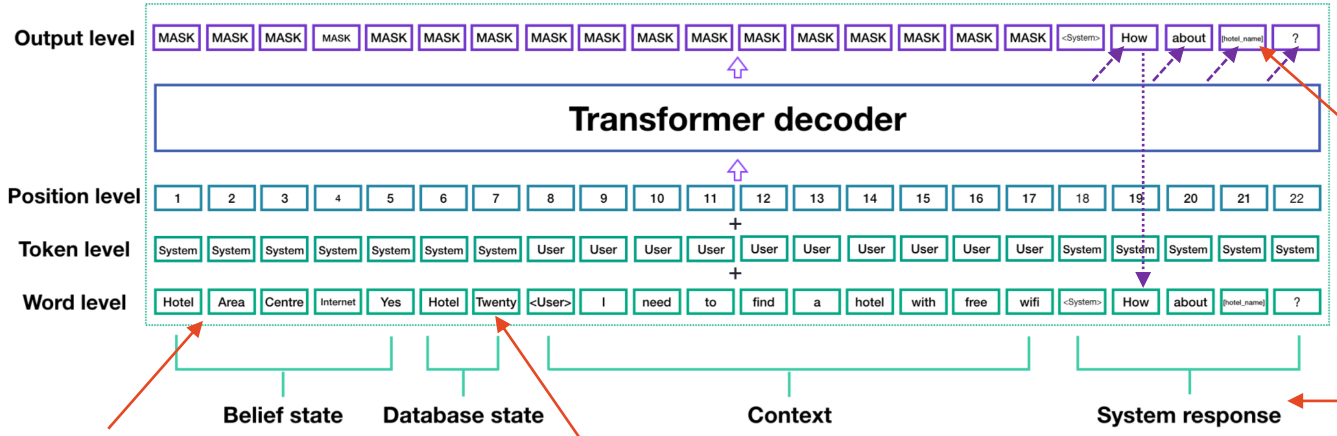


(Lei et al., 2018) https://www.aclweb.org/anthology/P18-1133

“Hello, it’s GPT-2 – How can I help?”

(Budzianowski & Vulić, 2019)
https://www.aclweb.org/anthology/D19-5602

- Simple adaptation of the GPT pretrained LM
  - system/user embeddings
    - added to Transformer positional embs. & word embs.
  - training to generate as well as classify utterances (good vs. random)
    - all supervised
- no DB & belief tracking (yet, see →)
  - using gold-standard belief & DB, no way of updating belief



delexicalized generation

decoded part

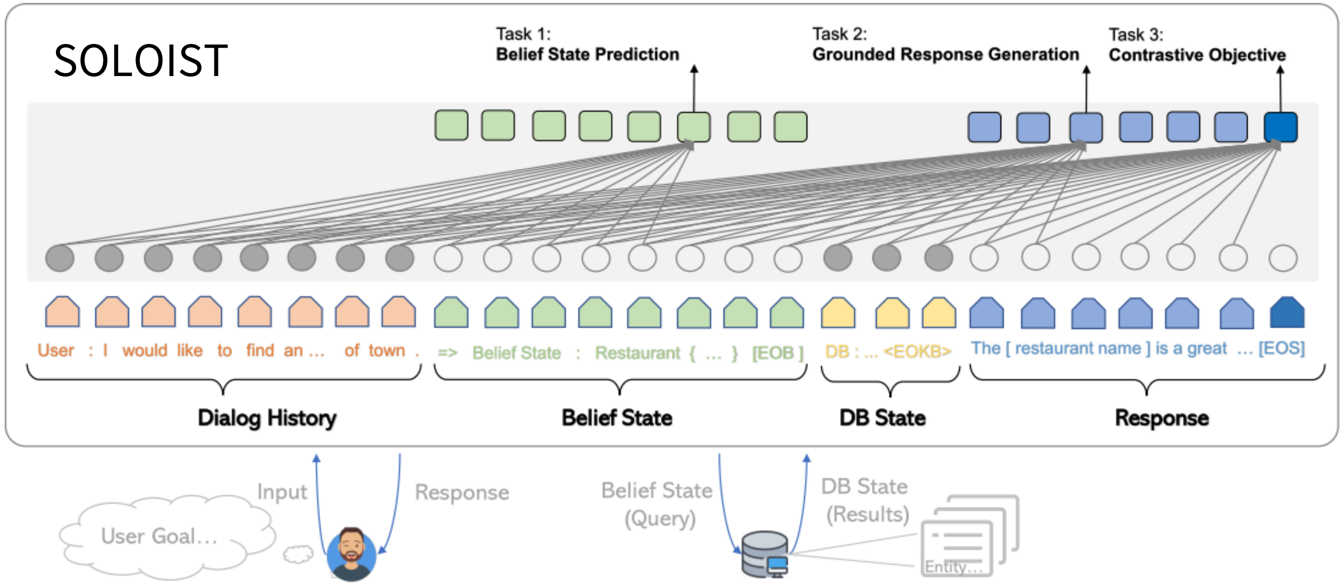
simple encoding:
domain-slot-value[-slot-value…]

DB result entry tokens

Real stuff with GPT-2: SOLOIST, SimpleTOD, NeuralPipeline, UBAR

- basically Sequicity over GPT-2: decode belief state, consult DB, decode response
  - history, state, DB results/system action – all recast as sequence
  - finetuning on dialogue datasets
- extensions:
  - specific user/system embeddings (NP)
  - additional training (SOLOIST)
    - not just word-level generation (as GPT-2 default)
    - contrastive objective: detecting fake belief/fake response from real ones
  - explicit system actions (SimpleTOD, UBAR)
    - one more decoding step
  - Context includes dialogue states (UBAR)

(Peng et al., 2020) http://arxiv.org/abs/2005.05298
(Hosseini-Asl et al., 2020) http://arxiv.org/abs/2005.00796
(Ham et al., 2020) https://www.aclweb.org/anthology/2020.acl-main.54
(Yang et al., 2021) http://arxiv.org/abs/2012.03539

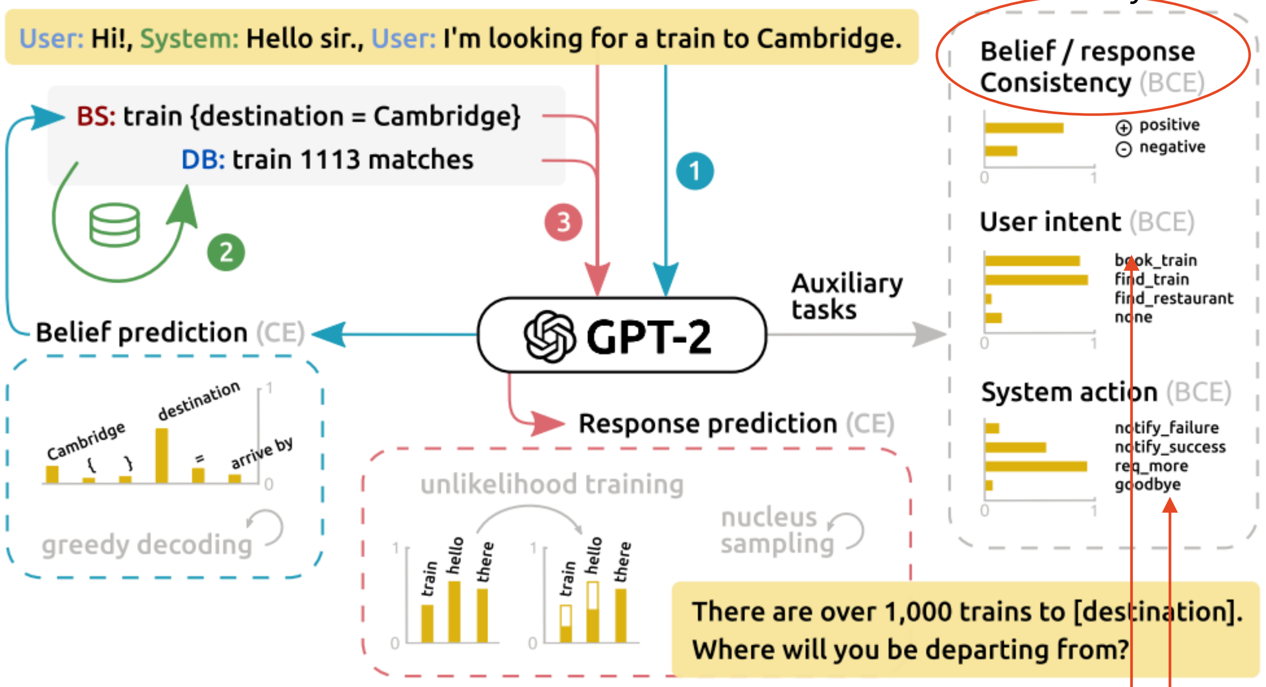


AuGPT: our take on this

NB: "encode" with GPT-2 means **force-decode**
(ignore the softmax, feed your own tokens)

- similar to Soloist:
  - "GPT-2 based Sequicity"
  - 1. encode context & user utterance
  - 2. decode belief state
  - 3. query DB
  - 4. encode results
  - 5. decode response
  - consistency auxiliary task
- for robustness & diversity:
  - input data augmentation via backtranslation
  - unlikelihood training (penalize repeated tokens)
  - nucleus sampling (cover $\geq$ 0.9 probability)

actually useful



(more auxiliary tasks, not really useful)

(Kulhánek et al., 2021)
http://arxiv.org/abs/2102.05126

MinTL: Diff dialogue states

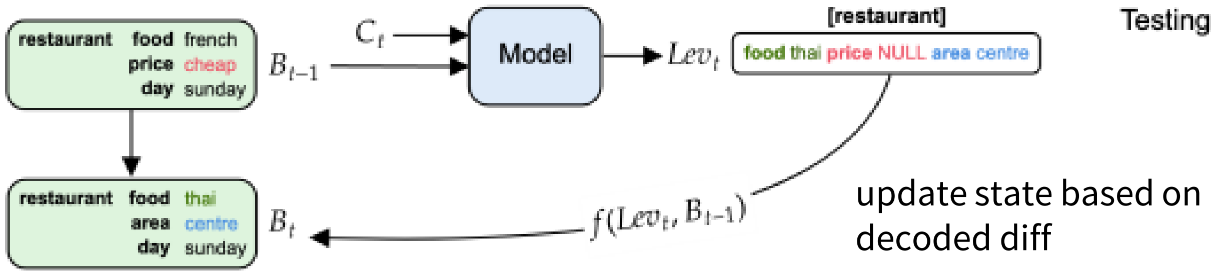
(Lin et al., 2020)
https://aclanthology.org/2020.emnlp-main.273/

- 2-step decoding, same as ↑
  - based on T5 or BART here
  - explicit 2 decoders
    (for state, for response)
- "Levenshtein states"
  - don't decode full state each time
  - **just decode a diff**
    ("Levenshtein distance from previous")
  - better consistency over dialogue

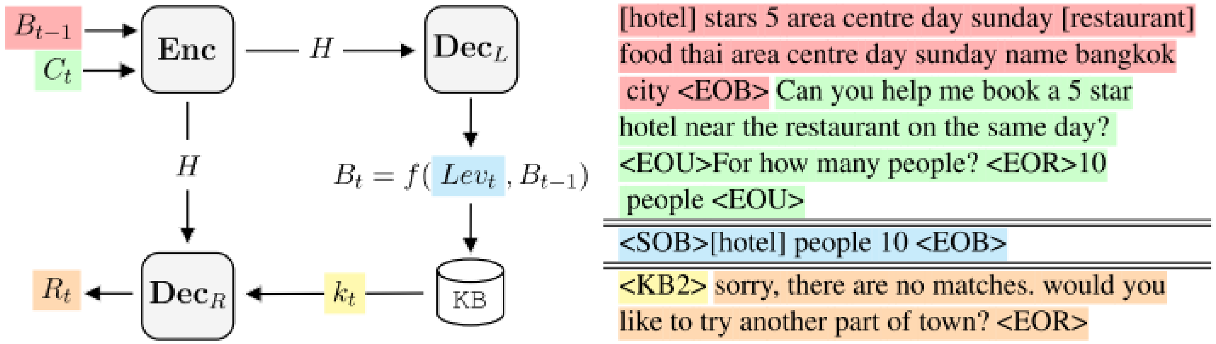
obtain diffs from state annotation

encode previous state & context

decode diffs



update state based on decoded diff



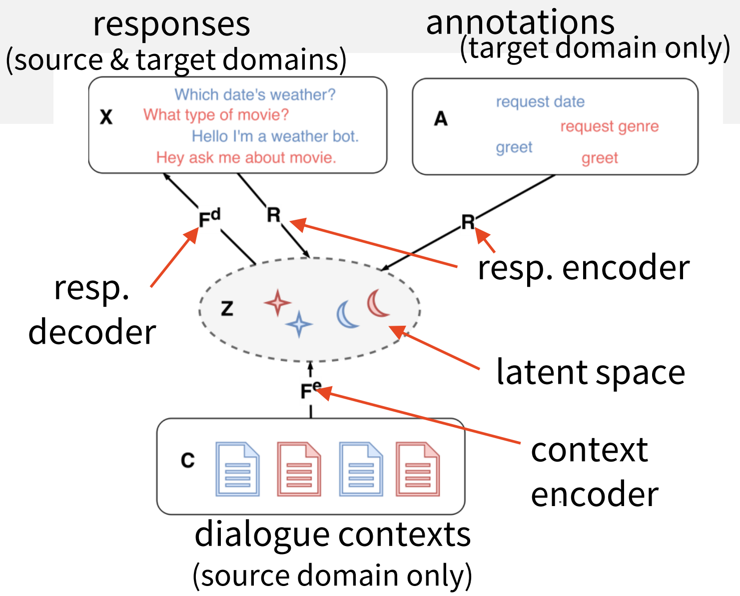
DB queried based on updated state
response decoder starting token = # of DB results

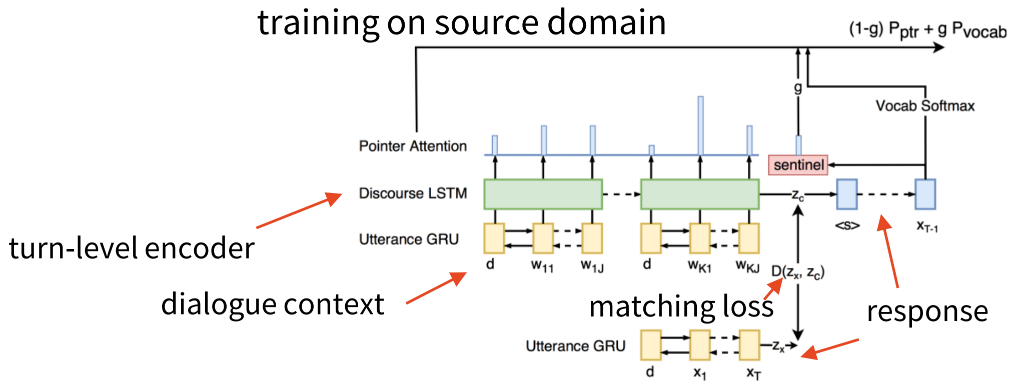
Few-shot dialogue generation

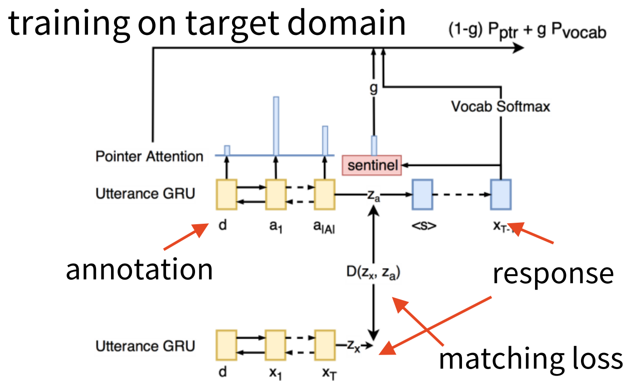
RNN + copy | seq gen

(Zhao & Eskenazi, 2018) http://aclweb.org/anthology/W18-5001

- Domain transfer:
  - source domain training dialogues
  - target domain “seed responses” with annotation
- encoding all into latent space
  - keeping response & annotation encoding close
  - keeping context & response encoding close
  - decoder loss + matching loss
- encoder: HRE (hierarchical RNN)
- decoder: copy RNN (with sentinel)
  - “copy unless attention points to sentinel” (see Mem2Seq)
- DB queries & results treated as responses/inputs
  - DB & user part of environment



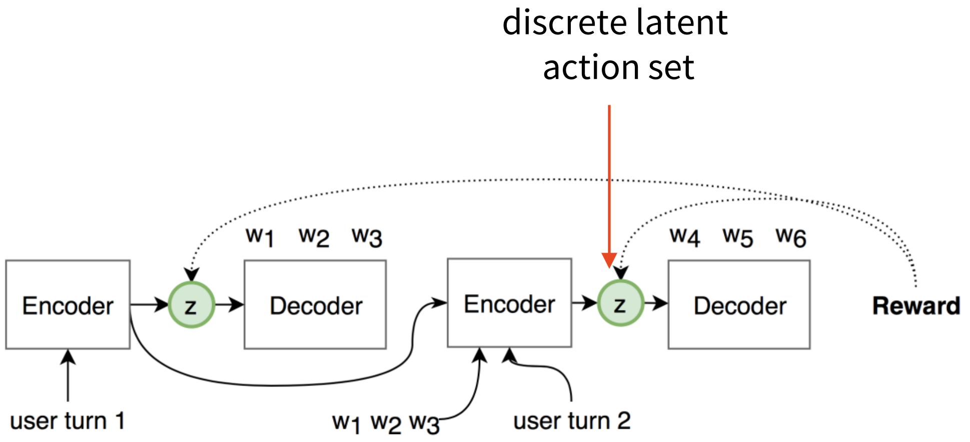




Latent Action RL

(Zhao et al., 2019)
https://www.aclweb.org/anthology/N19-1123

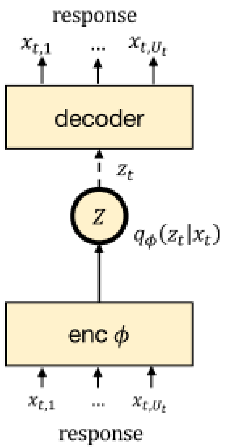
- Making system actions latent, learning them implicitly
- Like a VAE, but **discrete latent space** here (M k-way variables)
  - using Gumbel-Softmax trick for backpropagation
  - using Full ELBO (KL vs. prior network)
    or “Lite ELBO” (KL vs. uniform $1/k$)
- RL over latent actions, not words
  - avoids producing disfluent language
  - “fake RL” based on supervised data
    - generate outputs, but use original contexts
      from a dialogue from training data
    - success & RL updates based on generated responses
- ignores DB & belief tracking
  - takes gold annotation from data (assumes external model for this)

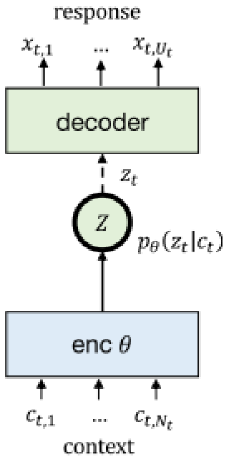


LAVA: Latent Actions with VAE pretraining

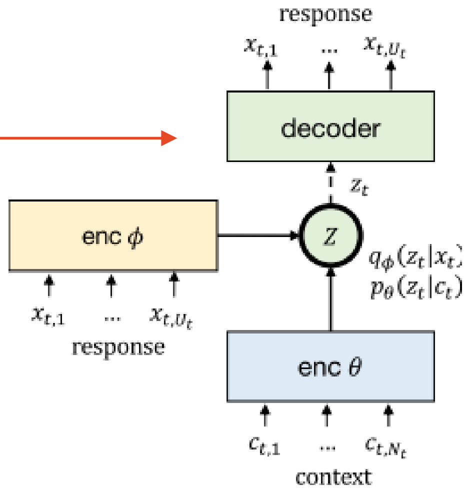
(Lubis et al., 2020)
https://aclanthology.org/2020.coling-main.41/

- kinda combination of two previous
- **discrete latent space** for **actions**
- multi-step training scenario:
  1) **autoencode** responses into latent space
  2) **supervised** training for response generation via the latent space
  3) **RL** over the latent actions
     - same “fake RL” as previous





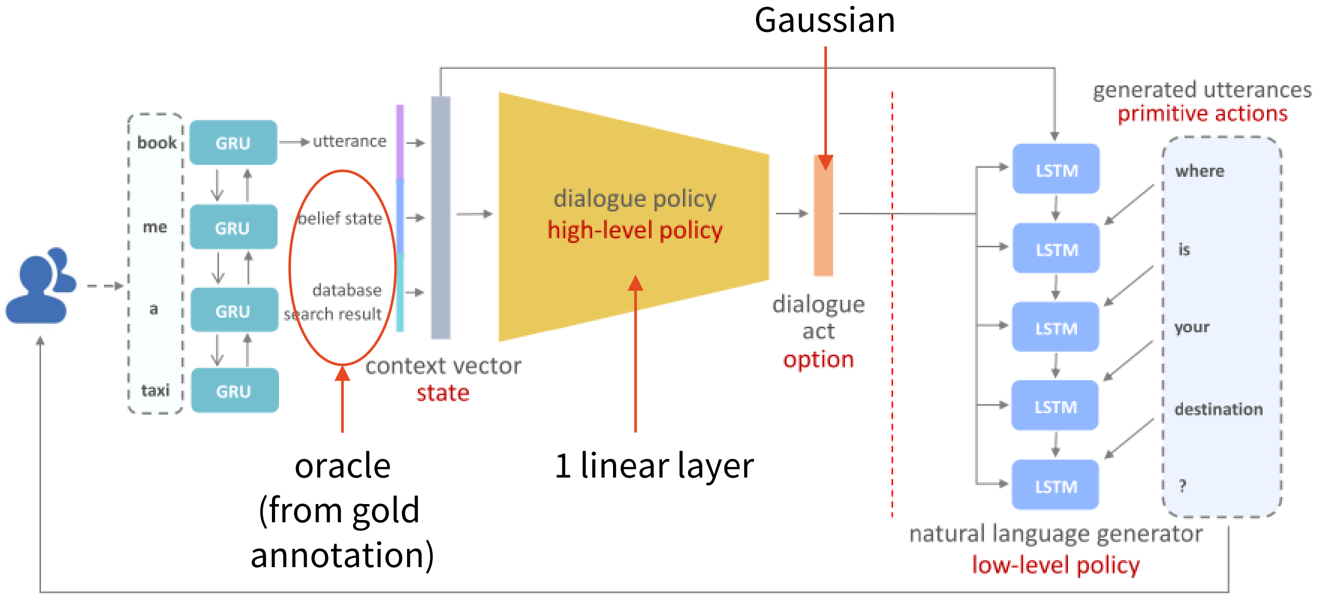
- options to join autoencoding & response generation
  a) KL loss – don’t go too far from autoencoding in latent space
  b) multi-task training (go back to autoencoding once in a while)
- again, assumes gold state & DB



HDNO: Hierarchical RL with latent actions

(Wang et al., 2021)
http://arxiv.org/abs/2006.06814

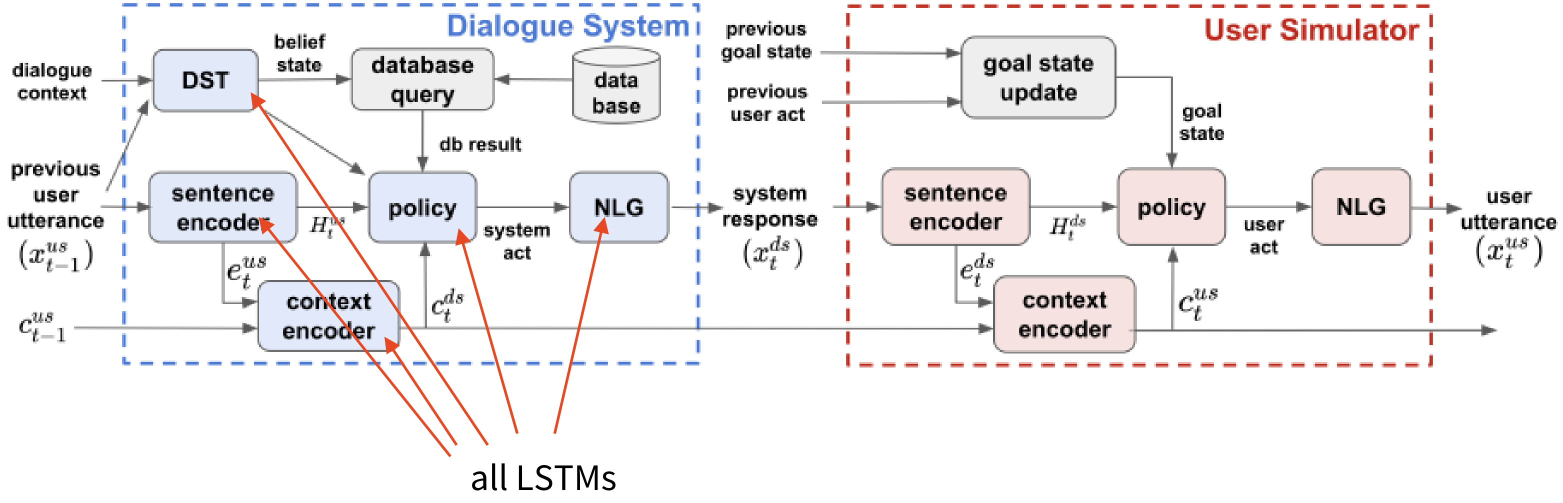
- Hierarchical RL
  - top level: over system actions
  - bottom: over words
- system actions are latent
  - Gaussian distribution
- word-level RL with LM rewards
  - pretrained LSTM LM to provide scores
  - to avoid low fluency due to word-level RL
- REINFORCE with supervised pretraining
  - separate updates on both levels (so you're not aiming at a moving target)
  - "fake RL" on data (same as previous)
- again, assumes gold state & DB



JOUST: system & simulator joint RL

(Tseng et al., 2021)
https://aclanthology.org/2021.acl-long.13

- System & user simulator with similar architecture
  - both seq2seq-based
  - joint context encoder
  - system: state tracker
    - private context encoder (user shouldn't see it)
  - user: preset goals & tracking
  - interaction via utterances



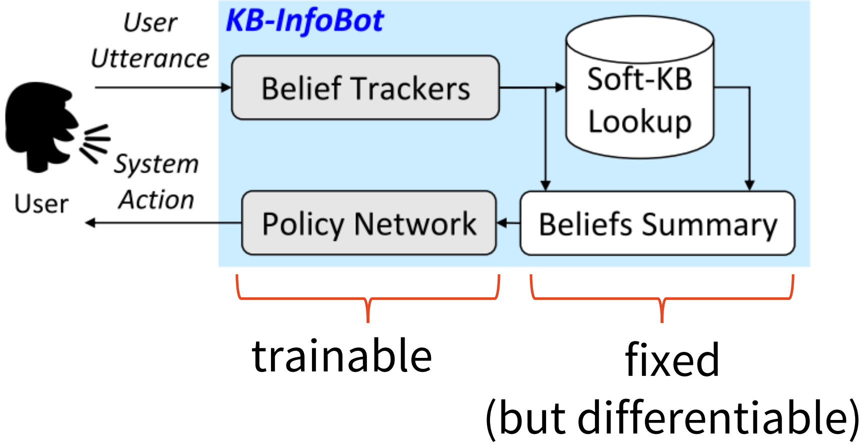
- RL over actions
  - REINFORCE, supervised pretraining
  - dialog-level or turn-level rewards
    - turn-level for each reasonable action, e.g. requesting new slot, providing entity etc.
- Domain transfer – new domains / domain combinations from fewer (~100-300) dialogs

Soft DB Lookups

(Dinghra et al., 2017)
https://www.aclweb.org/anthology/P17-1045

- incorporating NLU/tracker uncertainty into DB results
- making the system fully differentiable
  - but less interpretable
- DB output = distribution over all items
  - plain MLE estimation: $p(\text{row } i) = \prod_{\text{slots } j} \begin{cases} \frac{p(v=j)}{\#\text{ of } v'\text{s in table}} & \text{if } j \text{ specified \& in table} \\ 1/\#\text{ rows (uniform)} & \text{otherwise} \end{cases}$

    as given by tracker
  - not trained, based directly on tracker
- NLU/trackers – per-slot GRUs + softmaxes
  - input: counts of n-grams
- policy = GRU + softmax
- trained by RL
  - shown to outperform hard DB on a movie domain



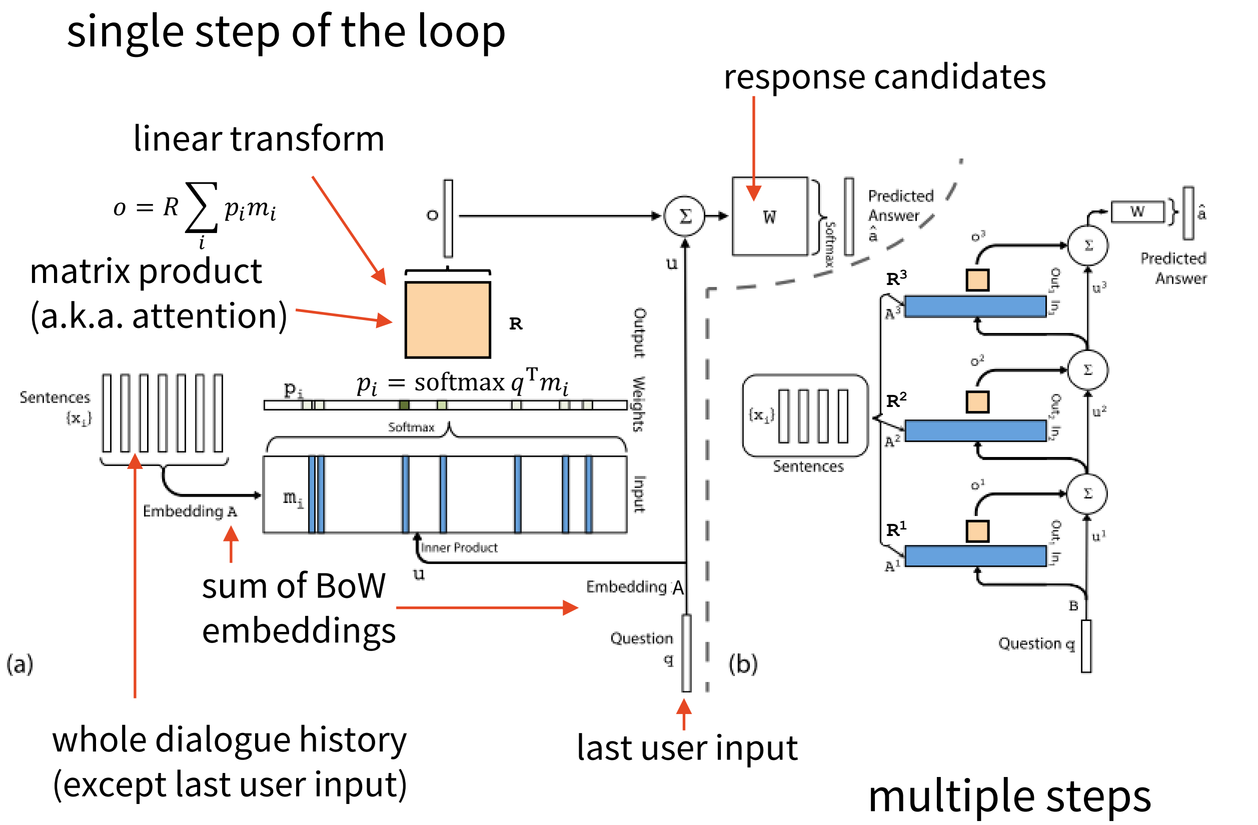
Memory networks

(Sukhbaatar et al., 2015) http://arxiv.org/abs/1503.08895
(Bordes et al., 2017) http://arxiv.org/abs/1605.07683

- not a full dialogue model, just ranker of candidate replies
- no explicit modules
- based on attention over history

loop a few times

  - sum of bag-of-words embeddings
    - added features (user/system, turn no.)
  - weighted match against last user input (dot + softmax)
  - linear transformation to produce next-level input
- last input matched (dot + softmax) against a pool of possible responses



Mem2Seq: memory nets & pointer-generator

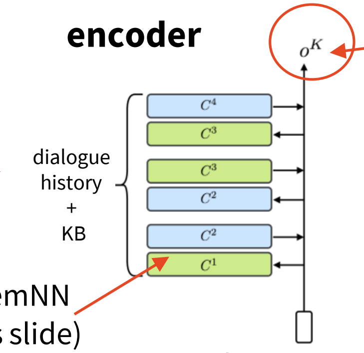
(Madotto et al., 2018) https://www.aclweb.org/anthology/P18-1136

- "standard" MemNN encoder:
  - special memory:
    - token-level dialogue history
      (whole history concatenated, no hierarchy)
      - with added turn numbers & user/system flags
    - DB tuples (sums of subject-relation-object)
    - "sentinel" (special token)
- decoder: MemNN over GRU
  - GRU state is MemNN initial query
  - last level attention is copy pointer
  - if copy pointer points at sentinel, generate from vocabulary
    - copies whenever it can
  - vocabulary distribution comes from 1st level of memory + GRU state
    - linear transform + softmax

encoder

state embedding
(1st decoder GRU input)

token-level
dialogue history



standard MemNN
(see previous slide)

last user input

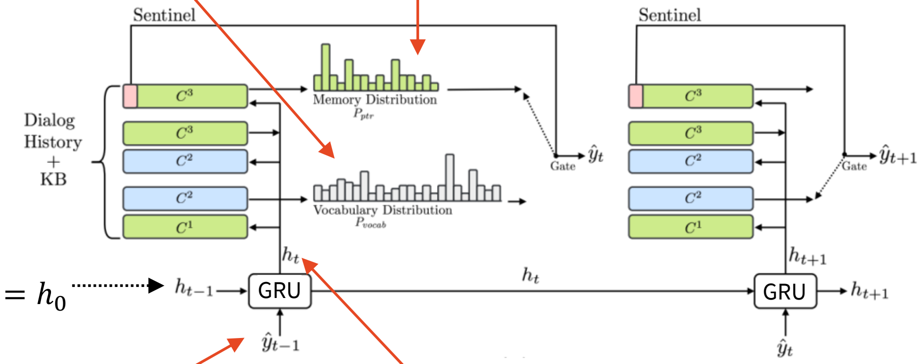
decoder (word level)

vocab softmax generated
from 1st memory hop
$P_{vocab}(\hat{y}_t) = \text{softmax}(W_1[h_t, o^1])$

pointer softmax is
last memory level attention
$P_{ptr} = p_t^K$

only if P_{ptr} points
at sentinel,
P_{vocab} is used

$o^K = h_0$



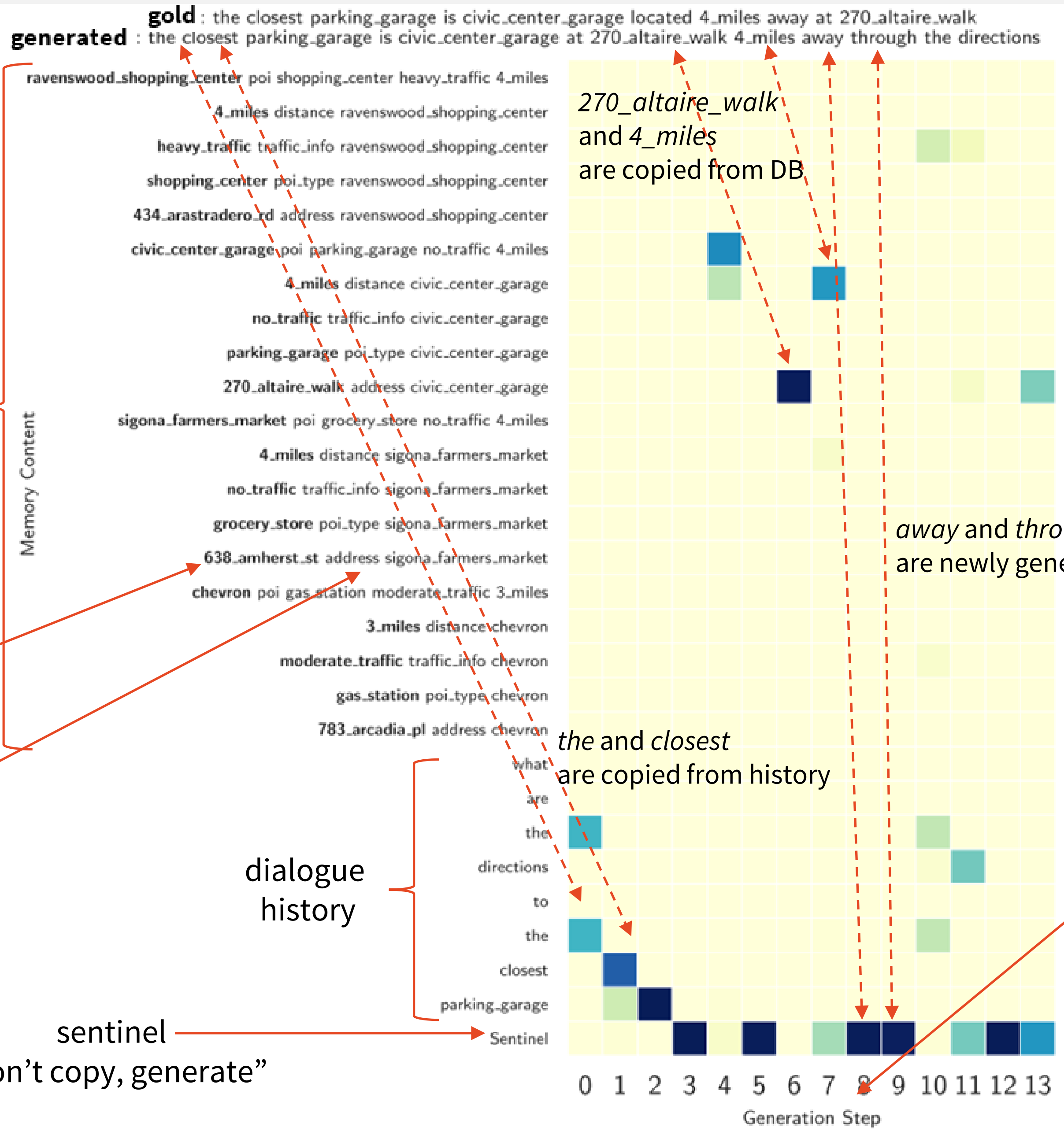
previous
generated
word

GRU hidden state is the
initial MemNN query

Mem2Seq visualization

(Madotto et al., 2018)
https://www.aclweb.org/anthology/P18-1136

attention weights
at individual
word generation steps



270_altaire_walk and *4_miles* are copied from DB

away and *through* are newly generated

the and *closest* are copied from history

steps correspond to generated words from the sentence on top

DB

values
(these get output)

subject-relation-object
(this gets embedded)

dialogue
history

sentinel
“don’t copy, generate”

Note: some DB entries were omitted for readability

Summary

- End-to-end = single network for NLU/tracker + DM + (sometimes) NLG
  - networks may decompose to components + need dialogue state annotation
  - joint training by backprop (if differentiable)
- Hybrid Code Nets – partially handcrafted, but end-to-end
- Sequicity – seq2seq & 2-step decoding: dialogue state, then response
- GPT-2-based systems – same idea, just with pretrained LMs
- Discrete latent action space – learning w/o action annotation
- Soft DB lookups – making the whole system differentiable
- RL optimization
  - without NLG (over actions) or hierarchical
  - “fake RL” on training data (no simulator needed)
  - JOUST: joint system-simulator training

Thanks

Contact us:

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Skype/Meet/Zoom (by agreement)

Get these slides here:

http://ufal.cz/npfl099

References/Inspiration/Further:

- Gao et al. (2019): Neural Approaches to Conversational AI: https://arxiv.org/abs/1809.08267
- Serban et al. (2018): A Survey of Available Corpora For Building Data-Driven Dialogue Systems: http://dad.uni-bielefeld.de/index.php/dad/article/view/3690