Neural Conversational AI

Ondřej Dušek

MLSS^N Summer School

30 June 2022

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

CC BY SA
unless otherwise stated

About

Ondřej

- Charles University, Prague
- ‘16-18 at Heriot-Watt Uni Edinburgh
- working mostly on language generation
- often in/with dialogue systems

This lecture

- relatively vague/high-level (focus on main ideas)
- focusing on what I work with (pretrained language models)
- trying to avoid digressions
- expecting you know NNs, but haven’t necessarily worked in NLP
- probably much more applied than other talks here
  - most of you probably know more about ML theory than I do
- slightly improvised (depending on timing, I might skip stuff)

Topics of Today

1. Intro: “Conversational AI” = “Dialogue Systems”
2. Transformer & pretrained language models
3. Neural models for dialogue system components
   - language understanding
   - state tracking
   - dialogue policy
4. End-to-end neural models
5. Evaluation metrics

1. Introduction

What's Conversational AI = Dialogue System?

- Definition: A *(spoken)* dialogue system is a **computer system designed to interact** with users **in** *(spoken)* **natural language**
  - Wide – covers lots of different cases
    - "smart speakers" / phone OS assistants
    - phone hotline systems (even tone-dial ones)
    - in-car systems
    - assistive technologies: therapy, elderly care, companions
    - entertainment: video game NPCs, chatbots

- DSs are cool:
  - ultimate natural interface: say what you want
  - lots of active research – far from solved
  - already used commercially

https://www.digitaltrends.com/mobile/5-things-you-need-to-know-about-microsofts-chinese-girlfriend-chatbot-xiaoice/

Real-life dialogue systems: virtual assistants

- Google, Amazon, Apple & others, Mycroft, Rhasspy: open-source
- Really good microphones
  - and not much else – listen for wake word, processing happens online
- Huge knowledge bases
  - combined with web search
- Lots of domains programmed in, but all by hand
  - integration with a lot of services (calendar, music, shopping, weather, news…)
  - you can add your own (with limitations)
- Can keep some context
- Conversational capabilities limited

https://www.lifehacker.com.au/2018/02/specs-showdown-google-home-vs-amazon-echo-vs-apple-homepod/

https://homealarmreport.com/smart-home/amazon-echo-vs-google-home/

Dialogue System Types

Task-oriented

- focused on completing a certain task/tasks
  - booking restaurants/flights, finding bus schedules, smart home…
- most actual DS in the wild
  - also our main focus in this course
- (typically) **single/multi domain**
  - talk about 1/more topics

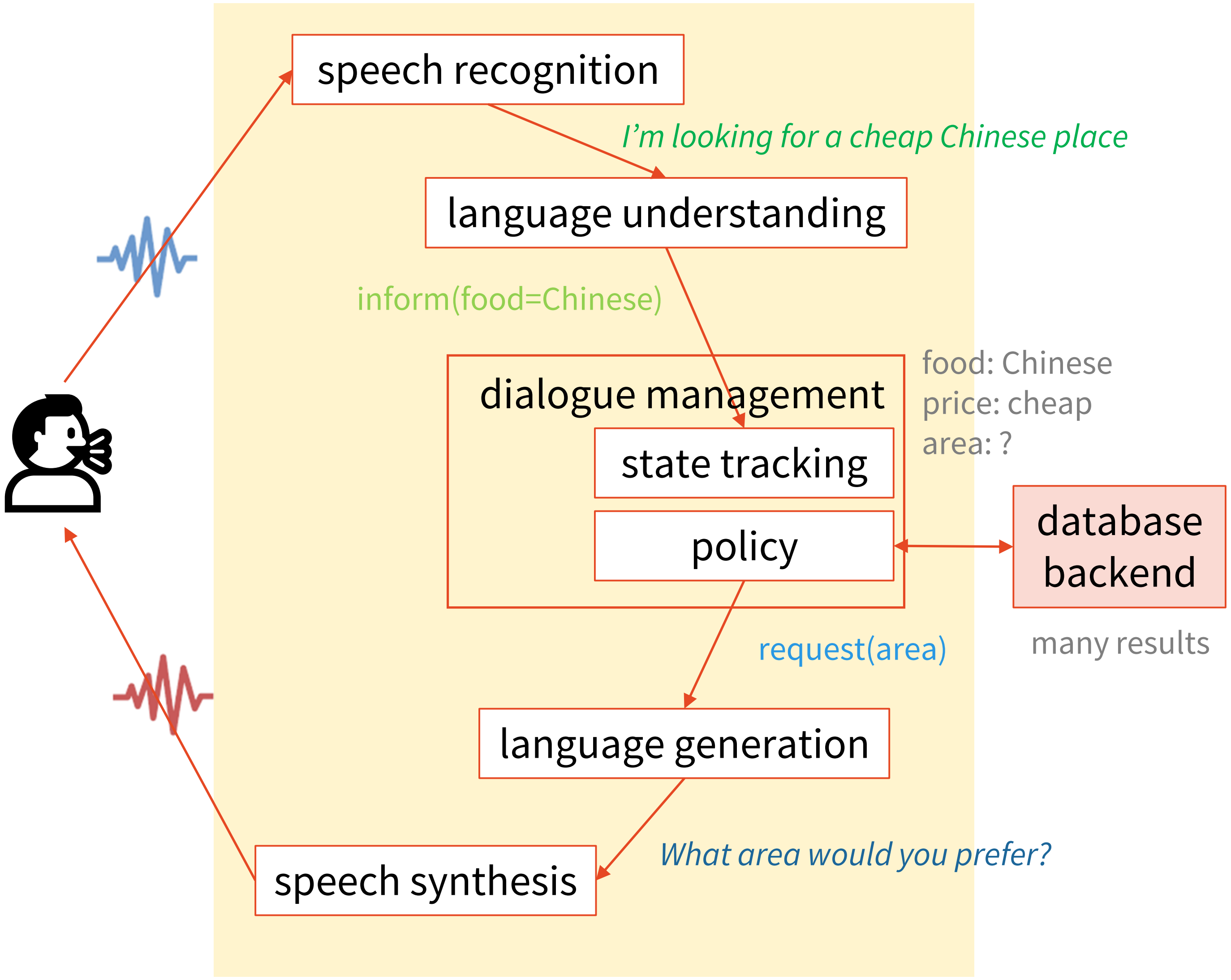
Non-task-oriented

- chitchat – social conversation, entertainment
  - persona, gaming the Turing test
- typically **open-domain** – talk about anything

Comm. Modes: voice / text / multimodal (face, graphics…)

Dialogue Systems Architecture

- traditional DS pipeline:
  - ASR: voice → text
  - **NLU: text → meaning**
  - **DM: meaning → reaction**
  - **NLG: reaction → text**
  - TTS: text → voice
- backend
  - needed for anything better than basic chit-chat
- text-based systems (here): NLU→DM→NLG



Task-oriented Dialogue Example

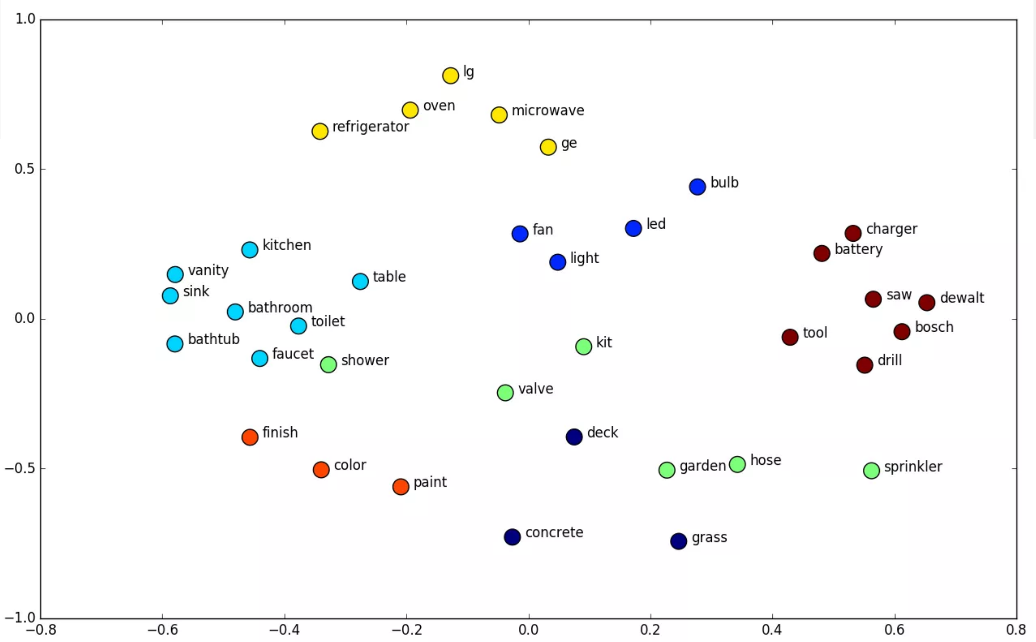
(Budzianowski et al., 2018)
https://aclanthology.org/D18-1547/

- MultiWOZ: benchmark for task-oriented dialogue in multiple domains
  - hotels, restaurants, attractions, trains, taxi, police, hospital
  - domains are connected (e.g. taxi from hotel to attraction)
  - 10k dialogues, extensive annotation (but noisy!)

1. user: I am looking for a train from Cambridge to London Kinks Cross.
   state: *{train {departure = cambridge, destination = london kings cross}}*
   DB: *{train (70) {…}}*
   system: There are **[count]** 70 trains departing from **[departure]** Cambridge to **[destination]** London Kings Cross. What day would you like to travel?
2. user: I would like to leave on Saturday after 18:45.
   state: *{train {day = saturday, departure = cambridge, destination = london kings cross, leave at = 18:45}}*
   DB: *{train (3) {arrive by = 19:51,21:51,23:51; id = TR0427,TR0925,TR4898; leave at = 19:00,21:00,23:00; … }}*
   system: **[id]** TR0427 leaves at **[leave_at]** 19:00 and arrives by **[arrive_by]** 19:51 . Would you like to book this train?
3. user: Yes, I would like to book it for eight people.
   system: I have booked it for you. Your reference number is **[reference]** 00000057. Is there anything else I can help you with?
4. user: I am also looking for an expensive restaurant in the centre.
   belief: *{restaurant {area = centre, price range = expensive} train {...}}*
   DB: *{restaurant (33) {area = centre (33); name=Curry Garden, ...; ...}, ...}*
   system: There are **[count]** 33 **[price_range]** expensive restaurants in the **[area]** centre. Is there a particular type of food you would like?

2. Transformer & Pretrained Models

Representing Language: Embeddings



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

- distributed representation
  - **each word = a vector of floats**
  - basically an easy conversion of 1-hot → numeric
  - a dictionary of trainable features
- part of network parameters – trained
  a) pretraining (optional)
  b) training for the target task
- the network learns which words are used similarly – for the given task
  - they end up having close embedding values
  - different embeddings for different tasks
- embedding size: ~100s-1000
- vocab size: ~50-100k

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

Subwords

- vocabulary is unlimited, embedding matrix isn't
  - + the bigger the embedding matrix, the slower your models
- Special **out-of-vocabulary token** *<unk>*
  - loses information, we don't want it on the output
- **Subwords:** groups of characters that
  - make shorter sequences than using individual characters
  - cover everything
  - 20-50k subwords for 1 language, ~250k subwords multilingual
- **Byte-pair Encoding** (=one way to get subwords)
  - start from individual characters
  - iteratively merge most frequent bigram, until you get desired # of subwords

f a s t _
f a s t e r _
t a l l _
t a l l e r _

→

fast er _
tall er _
s l o w er _
tall e s t _

(Sennrich et al., 2016) https://www.aclweb.org/anthology/P16-1162/

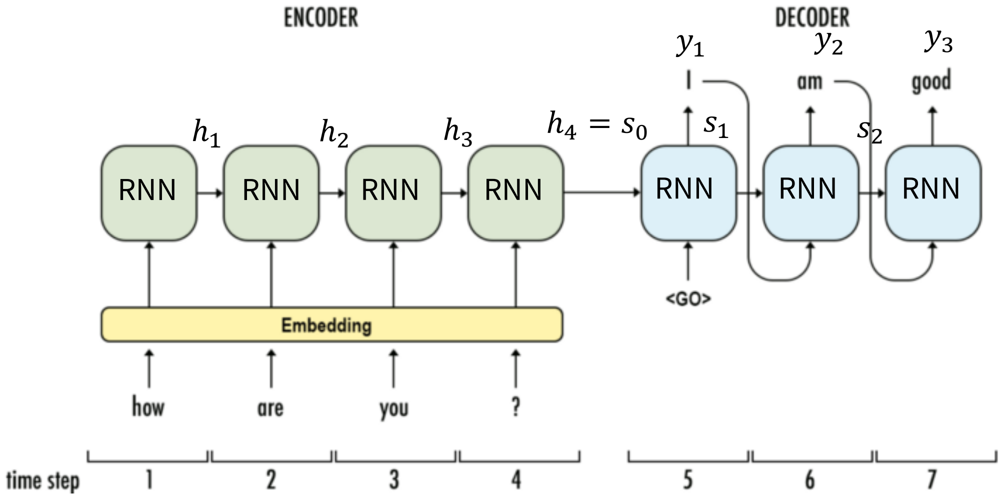
(Kudo, 2018) https://aclanthology.org/P18-1007

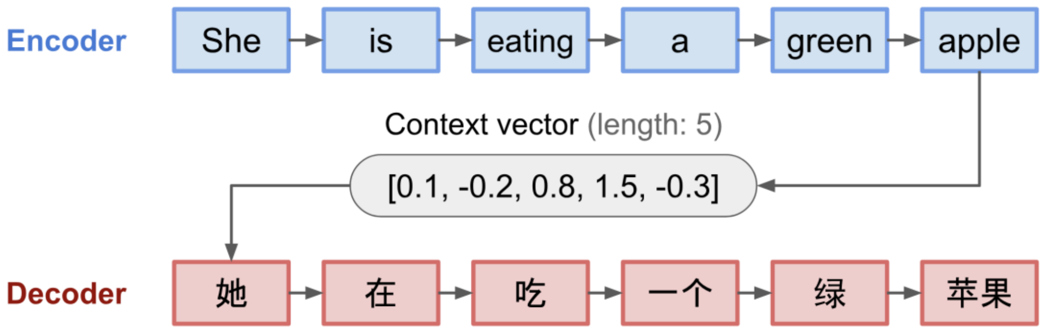
Encoder-Decoder Networks (Sequence-to-sequence)

- 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 **autoregressively**
    - 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=layers over vectors of ~ embedding size
  - used for many NLP tasks

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

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



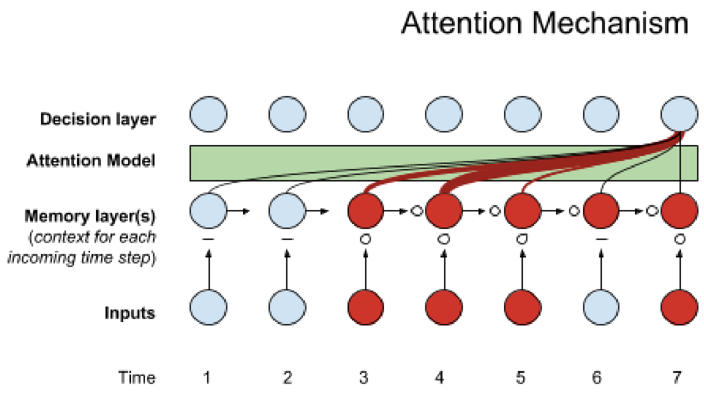


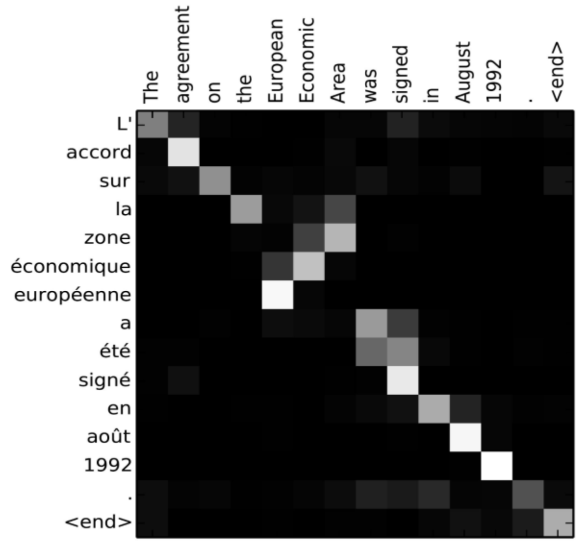
https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html

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

Attention

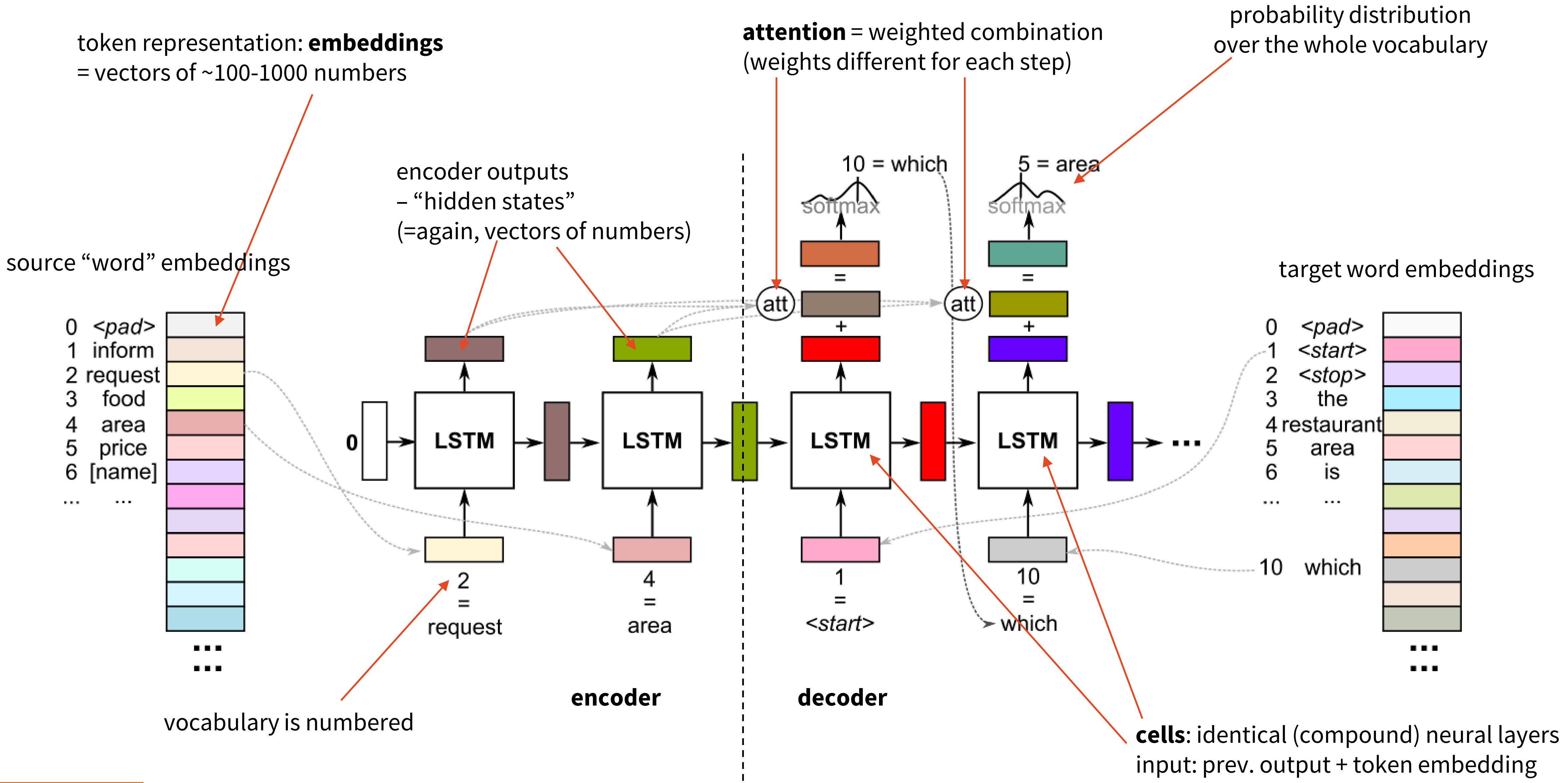
- Encoder-decoder is too crude for complex sequences
  - the whole input is crammed into a fixed-size vector (last hidden state)
- **Attention** = “memory” of **all encoder** hidden states
  - weighted combination, re-weighted for every decoder step
    → can focus on currently important part of input
  - fed into decoder inputs + decoder softmax layer
- **Self-attention** – over **previous decoder steps**
  - increases consistency when generating long sequences





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

Seq2seq RNNs with Attention

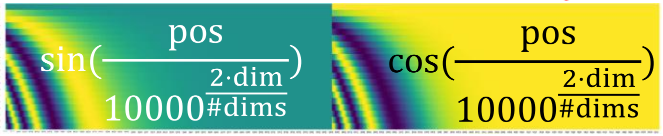


(Bahdanau et al., 2015) http://arxiv.org/abs/1409.0473

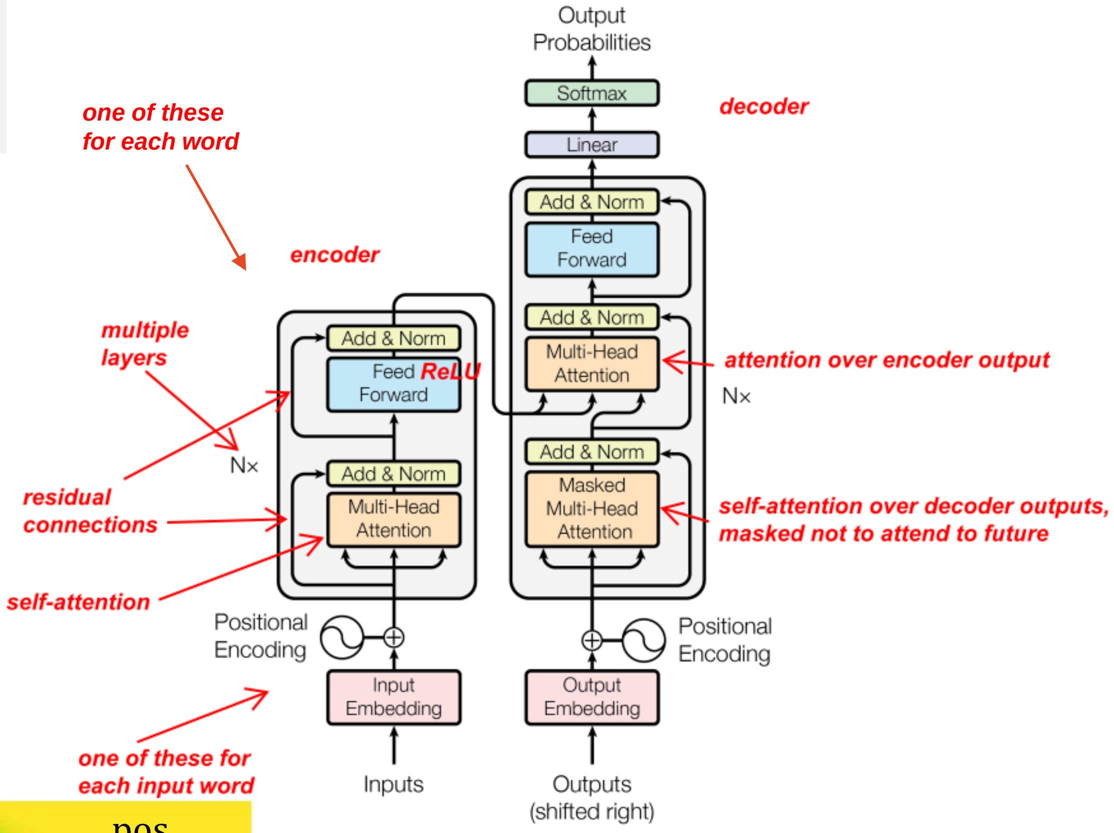
Transformer

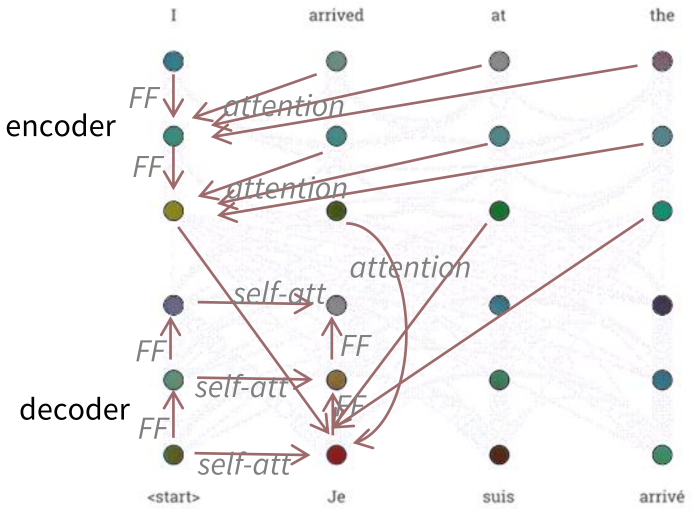
(Waswani et al., 2017)
https://arxiv.org/abs/1706.03762

- getting rid of recurrences
  - faster to train, allows bigger nets
  - replace everything with **attention** + **feed-forward** networks
  - ⇒ needs more layers
  - ⇒ needs to encode positions
- positional encoding
  - adding position-dependent patterns to the input



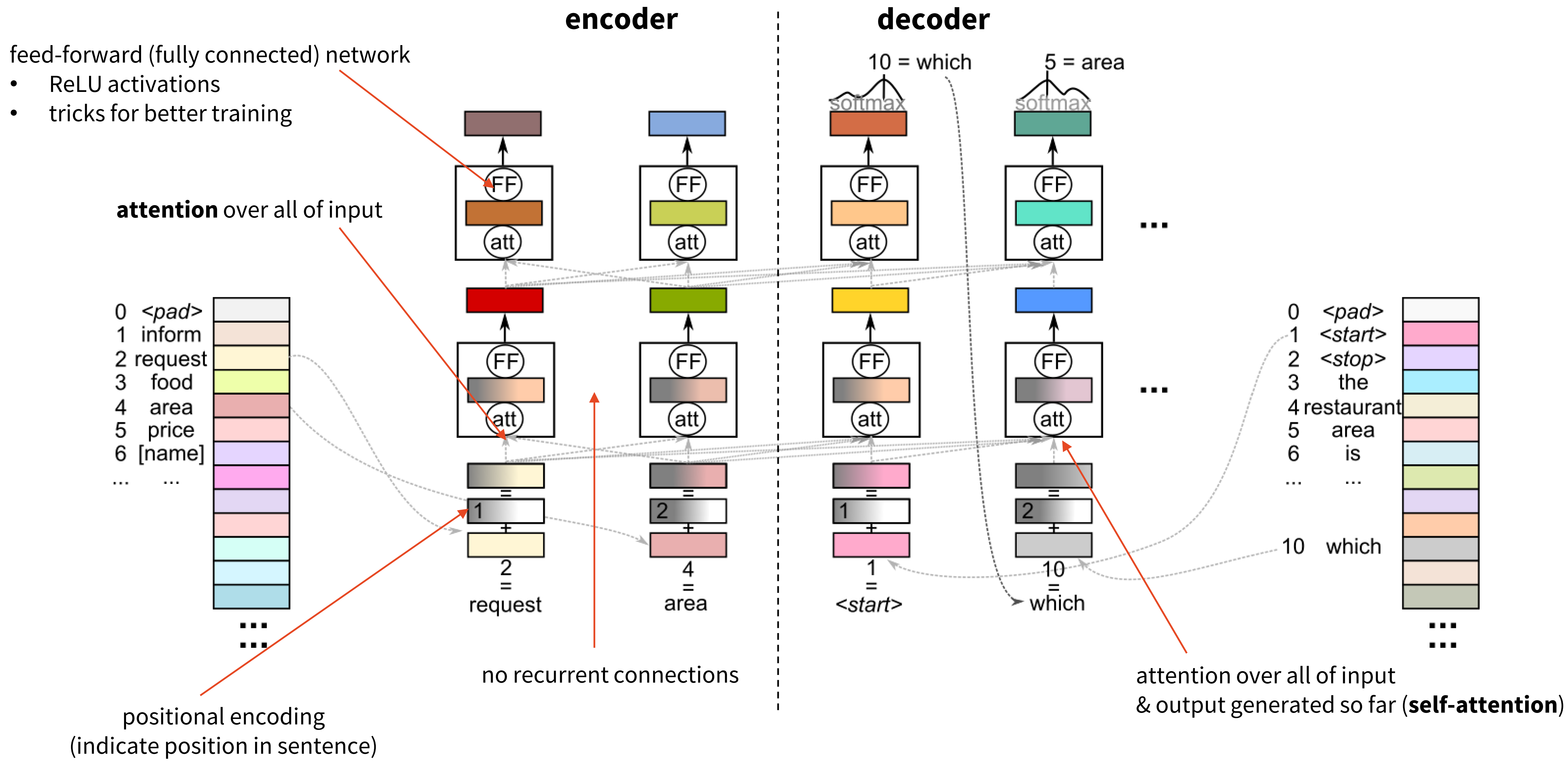
- attention – simple dot-product
  - scaled by $\frac{1}{\sqrt{\#\mathrm{dims}}}$ (so values don't get too big)
  - **more heads** (attentions in parallel) – focus on multiple inputs





http://jalammar.github.io/illustrated-transformer/ https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

Transformer



(Vaswani et al., 2017) http://arxiv.org/abs/1706.03762

Pretrained Language Models

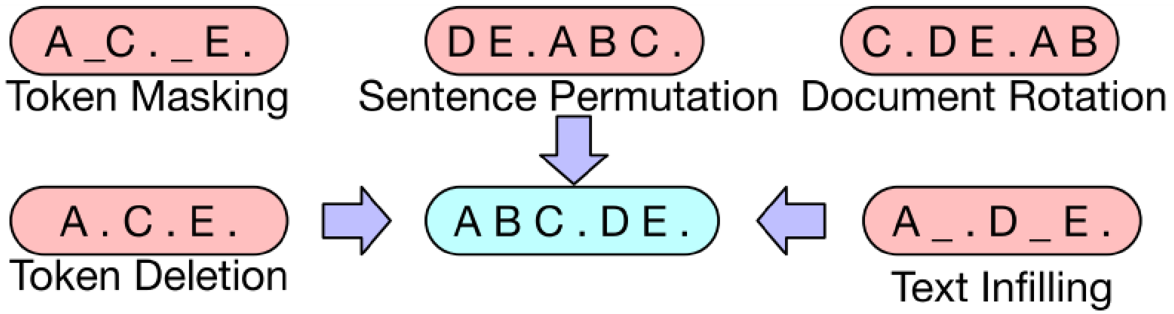
- Transformer Architecture
  - Encoder-only (= good for classification/token tagging)
  - Decoder-only (= good for generation)
  - Encoder-Decoder (= RNN seq2seq equivalent)
- **Self-supervised pretraining**
  - standard supervised training, but without annotation
    - naturally occurring labels
    - automatic labels ~ fix artificially corrupted data
  - typically simple language tasks (→)
  - used with huge amounts of data – many GBs of text (e.g. CommonCrawl)
  - models not useful for much, but **can be finetuned** for the target task
    - just train further, use data for target task

Pretrained Language Models

(Devlin et al., 2019)
https://www.aclweb.org/anthology/N19-1423
https://github.com/google-research/bert

(Rogers et al., 2020) http://arxiv.org/abs/2002.12327
(Liu et al., 2019) http://arxiv.org/abs/1907.11692

- Pretraining Tasks
    - Masked word prediction
    - Next-word prediction
    - Fixing corrupt sentences
    - Sentence order prediction



(Lewis et al., 2020) http://arxiv.org/abs/1910.13461
(Raffel et al., 2019) http://arxiv.org/abs/1910.10683

- Models
    - **BERT** encoder only, variants: multilingual, **RoBERTa** (optimized)
    - **GPT**(**-2**/**-3**/**-j**/**-neo**): decoder only, next-word prediction
    - **(m)BART, (m)T5**: encoder-decoder
    - **ByT5**: enc-dec, byte-level (instead of subwords)
- a lot of pretrained models released plug-and-play
    - you only need to finetune (and sometimes, not even that)

(Radford et al., 2019) https://openai.com/blog/better-language-models/
(Brown et al., 2020) http://arxiv.org/abs/2005.14165
(Xue et al., 2022) https://doi.org/10.1162/tacl_a_00461

https://github.com/huggingface/transformers

3. Component Models

Natural/Spoken Language understanding (NLU/SLU)

- **Words → meaning:** Extracting the meaning from user utterance
- **dialogue acts** (or other structured semantic representation):
  - act type/**intent** (*inform, request, confirm*)
  - **slot**/attribute (*price, time…*)
  - **value** (*11:34, cheap, city center…*)
  - typically intent classification + slot-value tagging
  - (other, more complex representations – e.g. trees, predicate logic)

inform(food=Chinese, price=cheap)
request(address)

- Specific steps:
  - **named entity resolution** (NER)
    - identifying task-relevant names (*London, Saturday*)
  - **coreference resolution**
    - (*"it"* –> *"the restaurant"*)

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*

NLU basics

- You can get far with keywords/regexes (for a limited domain)
- **Intent classification**
  - RNN: last hidden state
  - Transformers, PLMs: typically over 1st input element (start-of-sentence token)
- **Slot value detection**
  - classification (binary: *“is slot value X present?”*)
  - **slot tagging** – classify every token
    BIO/IOB scheme: beginning (+slot) – inside (+slot) – outside

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

- **Delexicalization**: replacing slot values by placeholders
  - essentially named entity recognition
  - essentially tagging, but typically done by dictionaries

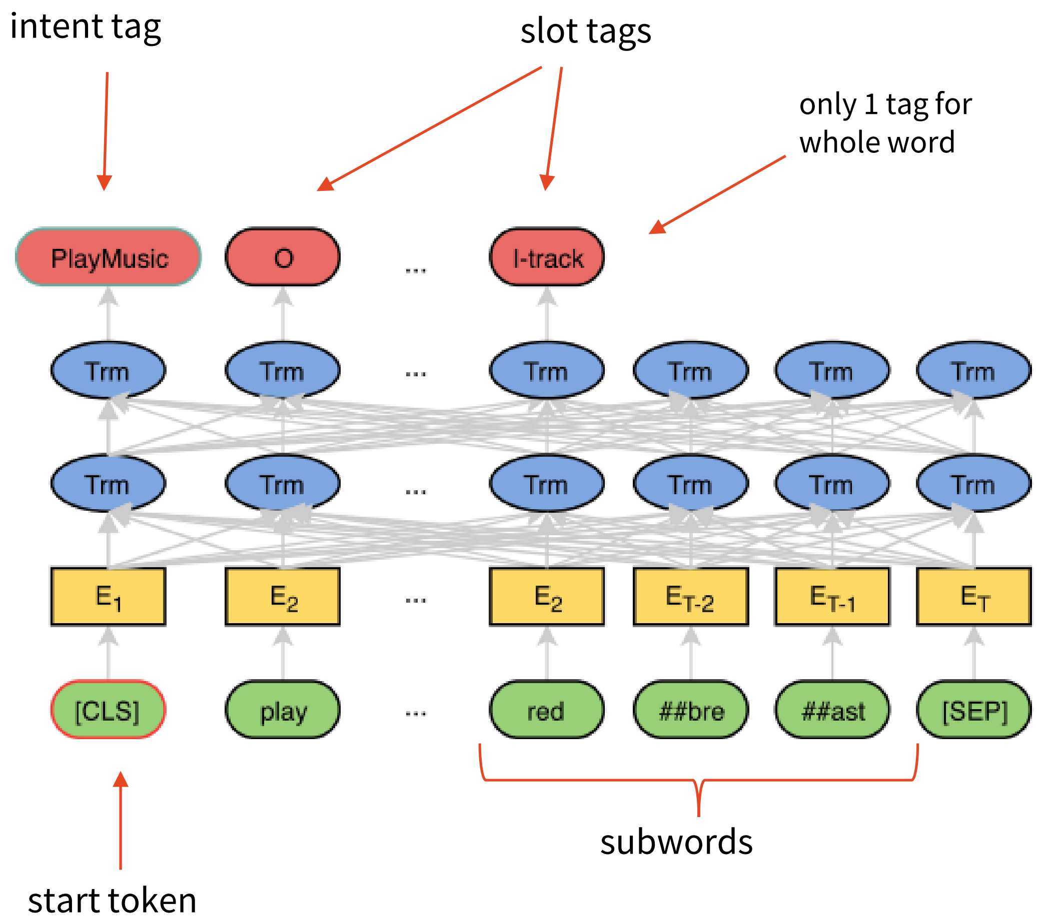
I’m looking for a Japanese restaurant in Notting Hill.
I’m looking for a <food> restaurant in <area>.

I need to leave after 12:00.
I need to leave after <time>.
(= not necessarily 1:1 with slots)

BERT-based NLU

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

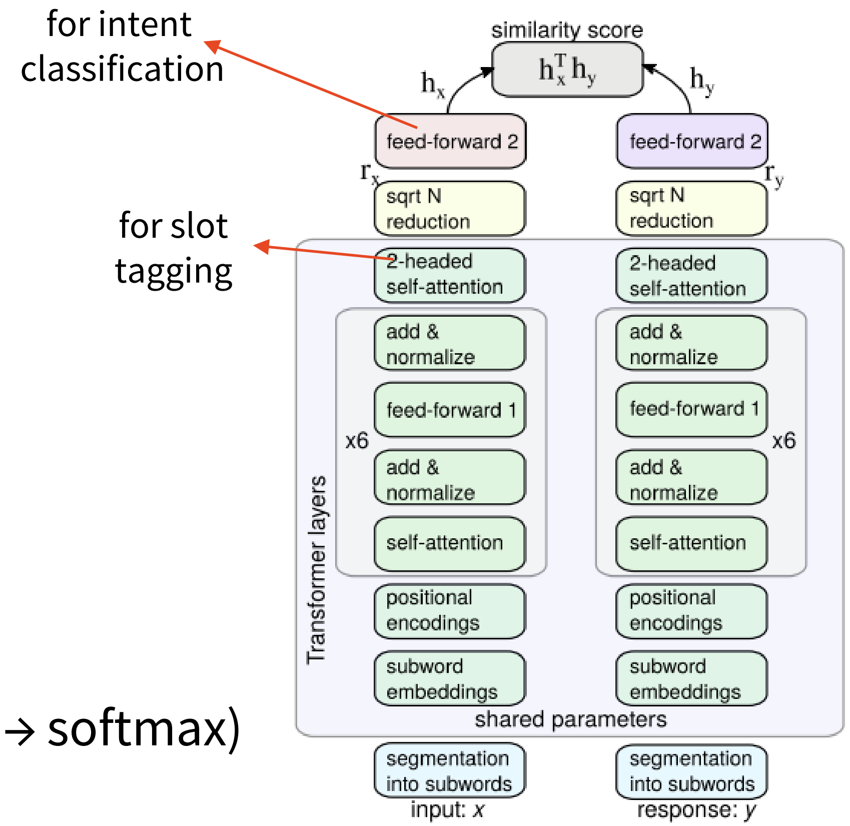
- combined intent-slot
- slot tagging on top of pretrained BERT
  - standard **IOB approach**
  - feed last BERT layers to **softmax over tags**
    - classify only at 1st subword in case of split words (don't want tag changes mid-word)
- special start token tagged with intent
  - again, softmax on top of last BERT layer
- finetune both tasks at once
  - essentially same task,
    just having different labels on the 1st token ☺



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
    - 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**)

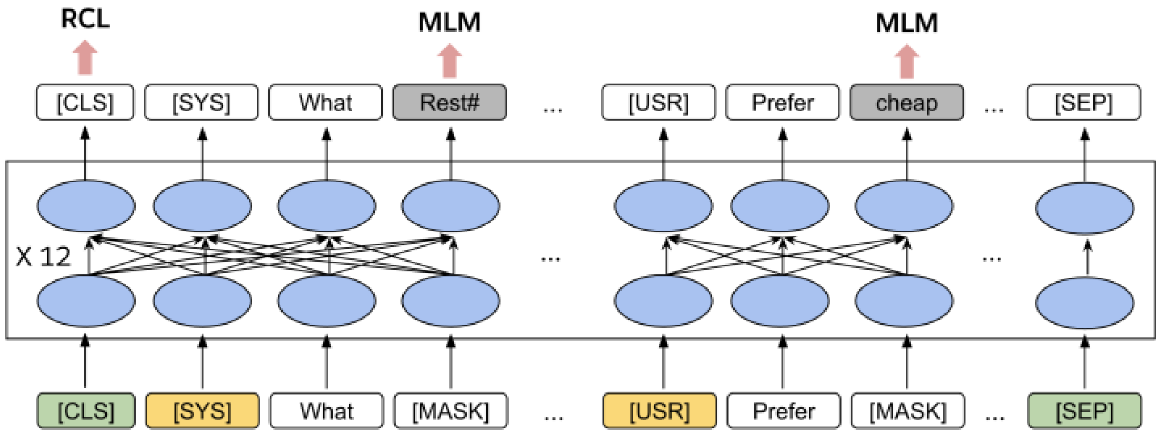


(Coope et al., 2020)
https://www.aclweb.org/anthology/2020.acl-main.11

(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 approaches
- **BERT + 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



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

Dialogue Manager (DM)

- Given NLU input & dialogue so far,
  responsible for **deciding on next action**
  - keeps track of what has been said in the dialogue
  - keeps track of user profile
  - interacts with backend (database, internet services)
- Dialogue so far = **dialogue history**, modelled by **dialogue state**
  - managed by **dialogue state tracker**
- System actions decided by **dialogue policy**

Dialogue state / State tracking

- Stores (a summary of) dialogue history
  - User requests + information they provided so far
  - Information requested & provided by the system
  - User preferences
- Implementation
  - **handcrafted** – e.g. replace value for slot with last-mentioned
    - good enough in some circumstances
  - **probabilistic (belief state)**
    – keep an estimate of per-slot preferences based on NLU
    - more robust, more complex
    - accumulates probability over time & n-best lists
    - → handles NLU/ASR errors
      – e.g. 3x same low-confidence input = prob. high enough to react

price: cheap
food: Chinese
area: riverside

price: 0.8 cheap
0.1 moderate
0.1 <null>

food: 0.7 Chinese
0.3 Vietnamese

area: 0.5 riverside
0.3 <null>
0.2 city center

Basic State/Belief Trackers

a) Always trust the NLU

for **null** value:

$\boldsymbol{p} = \mathbf{prev} \cdot \boldsymbol{p}($🤫$)$ ~ user didn't mention this slot

non-null value v:

$\boldsymbol{p} = \mathbf{prev} \cdot \boldsymbol{p}($🤫$) + \boldsymbol{p}(\boldsymbol{v})$

~ didn't mention = carry from previous

~ did mention = add new NLU probability

- basically rule-based (but good if NLU is good)

b) "NLU" over whole dialogue

- typically classification ("is slot value v present?")
  - option: limit to some candidates (from NLU/delexicalization), rank them
- may not need NLU, may be better, but slower

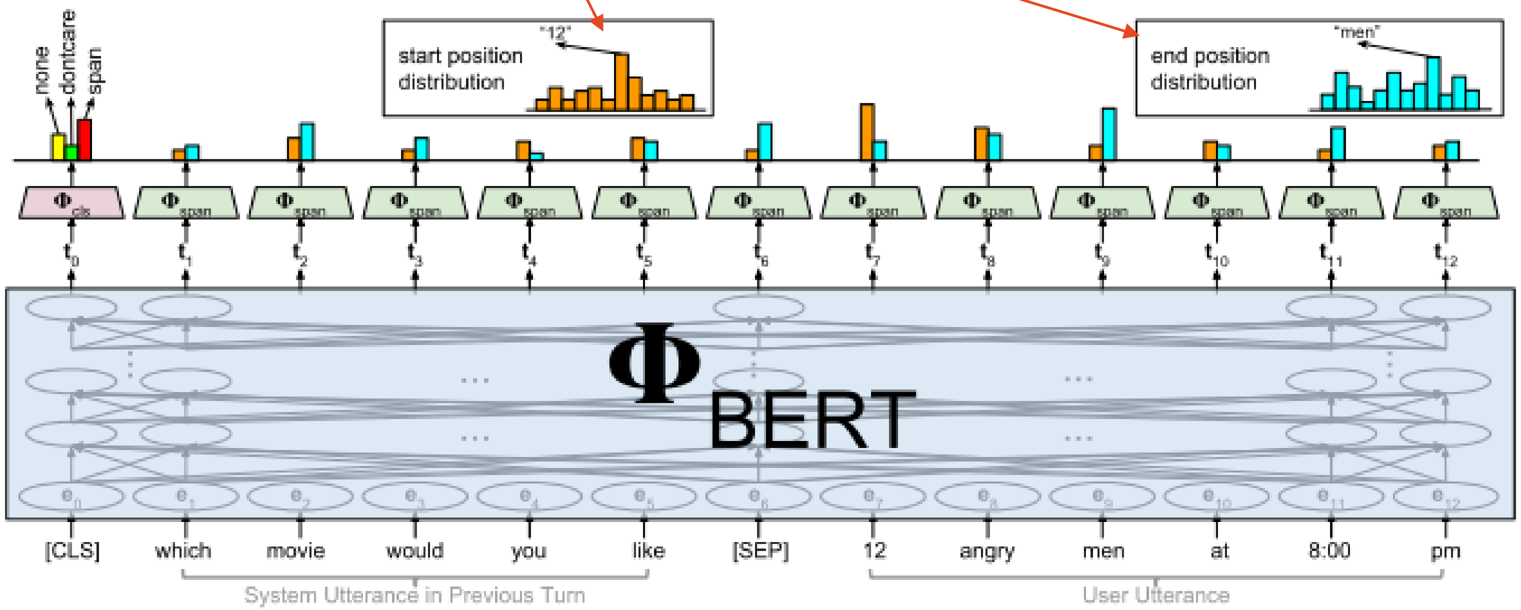
(Žilka et al., 2013)
http://www.aclweb.org/anthology/W13-4070

BERT & Span Selection

a.k.a. Span Tagging
(~question answering/reading comprehension)

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

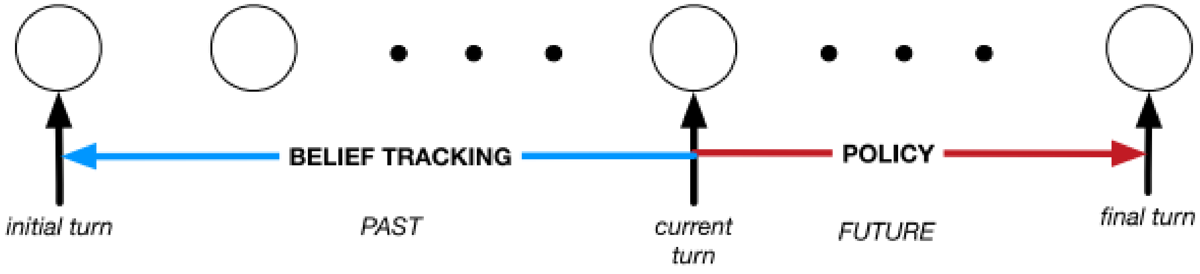
- BERT over previous system & current user utterance
- from 1st token's representation, get a **decision:** ***none*/*dontcare*/span**
  - per-slot (BERT is shared, but the final decision is slot-specific)
- span = need to find a concrete value as a span somewhere in the text
  - **predict start & end token** of the span using 2 softmaxes over tokens
- rule-based update:
  - if *none* is predicted, keep previous value
  - essentially similar to NLU & update rule



Break

Action Selection / Policy

- **Deciding what to do next**
  - **action** based on the current belief state
  - following a **policy** (strategy) towards an end **goal** (e.g. book a flight)
  - controlling the coherence & flow of the dialogue
  - actions: linguistic & non-linguistic (backend access)
  - actions represented by system dialogue acts



(from Milica Gašić's slides)

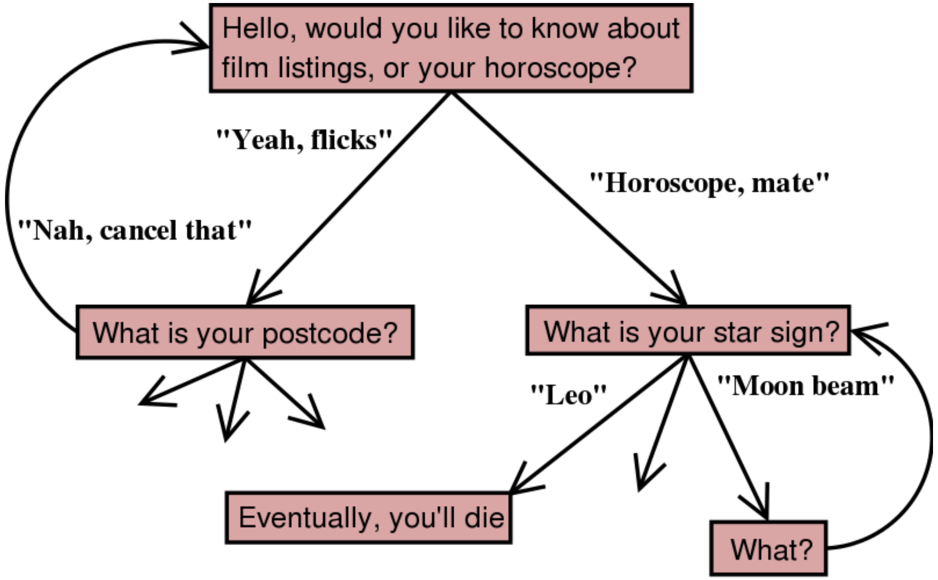
confirm(food=Chinese)

inform(name=Golden Dragon,
food=Chinese, price=cheap)

- DM/policy should:
  - manage uncertainty from belief state ← *Did you say Indian or Italian?*
  - recognize & follow dialogue structure ← follow convention, don't be repetitive
  - plan actions ahead towards the goal ← e.g. ask for all information you require

Action Selection Approaches

- Finite-state machines
  - simplest possible
  - dialogue state is machine state
- Frame-based/flowcharts (e.g. VoiceXML)
  - slot-filling + providing information – basic agenda
  - rule-based in essence
- Rule-based
  - any kind of rules (e.g. Python code)
- **Statistical**
  - typically trained with **reinforcement learning**



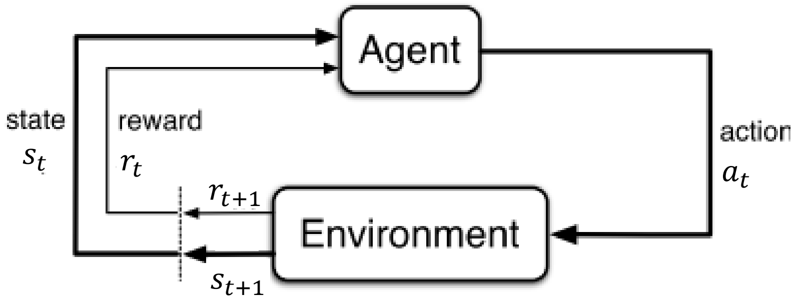

```
        elif fact['we_did_not_understand']:
            # NLG("Sorry, I did not understanc
            res_da = DialogueAct("notunderstoc
            res_da.extend(self.get_limited_cor
            dialogue_state["ludait"].reset()

        elif fact['user_wants_help']:
            # NLG("Pomoc.")
            res_da = DialogueAct("help()")
            dialogue_state["ludait"].reset()

        elif fact['user_thanked']:
            # NLG("Díky.")
            res_da = DialogueAct('inform(cordi
            dialogue_state["ludait"].reset()

        elif fact['user_wants_restart']:
```

Why Reinforcement Learning

- **Action selection ~ classification** → use supervised learning?
  - set of possible actions is known
  - belief state should provide all necessary features
- Yes, but…
  - You'd **need** sufficiently large **human-human data** – hard to get
    - human-machine would just mimic the original system
  - Dialogue is ambiguous & complex
    - there's **no single correct next action**– multiple options may be equally good
    - but datasets will only have one next action
    - **some paths will be unexplored** in data, but you may encounter them
  - DSs won't behave the same as people
    - ASR errors, limited NLU, limited environment model/actions
    - **DSs should behave differently** – make the best of what they have
  - supervised classification **doesn't plan ahead**
    - RL optimizes for the whole dialogue, not just the immediate action

Reinforcement learning: Definition

- MDP formalism: agent in an environment, **state-action-reward**



- RL = finding a **policy that maximizes long-term reward**
  - unlike supervised learning, we don't know if an action is good
  - immediate reward might be low while long-term reward high

return = accumulated long-term reward

$$R_t = \sum_{t=0}^{T} \gamma^t r_{t+1}$$

$\gamma \in [0,1]$ = **discount factor** (immediate vs. future reward trade-off)

- state transition is stochastic → maximize **expected return**

$$\mathbb{E}[R_t | \pi, s_0]$$

expected R_t if we start from state s_0 and follow policy π

Policy Gradients

- Train a **network to represent the policy** $\pi(a|s,\theta)$ – θ are parameters
- To optimize, we need a **performance metric**: $J(\theta) = V^{\pi_\theta}(s_0)$
  - expected return in starting state when following π_θ
  - we want to directly optimize this using gradient ascent
- **Policy Gradient Theorem**:
  - expresses $\nabla J(\theta)$ in terms of $\nabla\pi(a|s,\theta)$

$$\nabla J(\theta) \propto \sum_s \mu(s) \sum_a Q^\pi(s,a)\nabla\pi(a|s,\theta) = E_\pi\left[\sum_a Q^\pi(s,a)\nabla\pi(a|s,\theta)\right]$$

$\mu(s)$ is state probability under π – this is the same as expected value E_π

$Q^\pi(s,a)$ = "Q-function"
– value of taking action a in state s, then following policy π

(Sutton & Barto, 2018; p. 324ff)

REINFORCE: Monte Carlo Policy Gradients

- direct search for policy parameters by stochastic gradient ascent
  - looking to maximize performance $J(\boldsymbol{\theta}) = V^{\pi_\theta}(s_0)$
- choose learning rate α, initialize $\boldsymbol{\theta}$ arbitrarily
- loop forever:
  - generate an episode $s_0, a_0, r_1, \dots, s_{T-1}, a_{T-1}, r_T$, following $\pi(\cdot \mid \cdot, \boldsymbol{\theta})$
  - for each $t = 0,1 \dots T$: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha\gamma^t R_t \nabla \ln \pi(a_t | s_t, \boldsymbol{\theta})$

this will guarantee the right state distribution/frequency $\mu(s)$

returns $R_t = \sum_{i=t}^{T-1} \gamma^{i-t} r_{i+1}$

this is stochastic $\nabla J(\boldsymbol{\theta})$:
- from policy gradient theorem
- using single action sample a_t
- expressing Q^π as R_t (under E_π)
- using $\nabla \ln x = \frac{\nabla x}{x}$

variant – **advantage** instead of returns: discounting a **baseline** $b(s)$ (predicted by any model) $A_t = R_t - b(s_t)$ instead of R_t gives better performance

(Sutton & Barto, 2018; p. 327f)

Rewards in RL

- Typical setup – **handcrafted rewards**:
    - every turn: -1 (encourage fast dialogues)
    - successful dialogue: + 20
    - unsuccessful: - 10 (~center around 0)
- Problems:
  - domain knowledge needed to detect dialogue success
  - **need simulated and/or paid users** (known goal)
    - simulated = essentially another dialogue system
    - paid users = costly + often fail to follow pre-set goals
  - needs a lot of dialogues to train (1000s) → simulated users, supervised pretraining
- Solutions:
  - trained rewards
    - provided by a network, can be turn-level
  - corpus-based RL (supervised/RL hybrid)
    - follow dataset, just assign rewards like RL (→)

Natural Language Generation (NLG) / Response Generation

- Representing system dialogue act in natural language (text)
  - reverse NLU
- How to express things might depend on context
  - Goals: fluency, naturalness, avoid repetition (…)
- Traditional approach: **templates**
  - Fill in (=**lexicalize**) values into predefined templates (sentence skeletons)
  - Works well for limited domains

inform(name=Golden Dragon, food=Chinese, price=cheap)

+

<name> is a **<price>**-ly priced restaurant serving **<food>** food

=

Golden Dragon is a cheaply priced restaurant serving Chinese food.

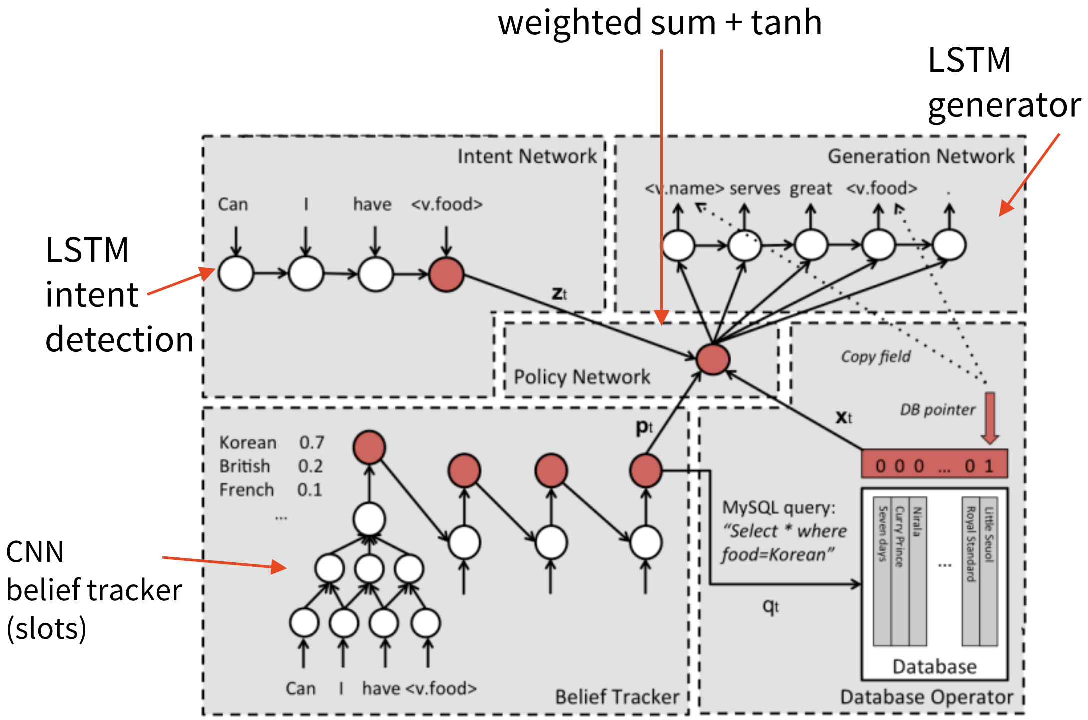
- Statistical approach: **seq2seq**/pretrained language models
  - input: system dialogue act, output: sentence (operation similar to →)

4. End-to-end models

Neural Conv AI

End-to-End Systems

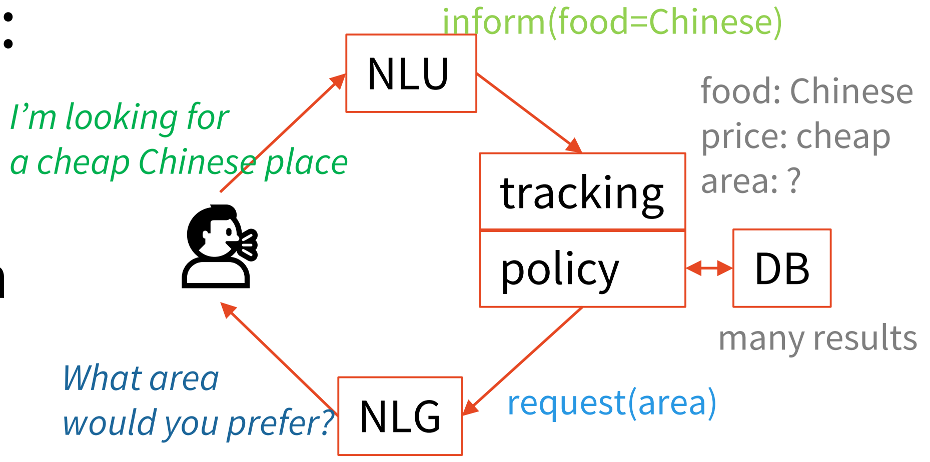
- experimental, research state-of-the-art
  - but not ready for practical deployment
- the whole system (NLU/DM/NLG) is a single neural network
  - joint training ("end-to-end")
  - more elegant
  - potentially easily retrainable
- typically still needs annotation
  - same as individual modules
  - can be less predictable
- connecting the database is a problem
  - typically this step is done separately



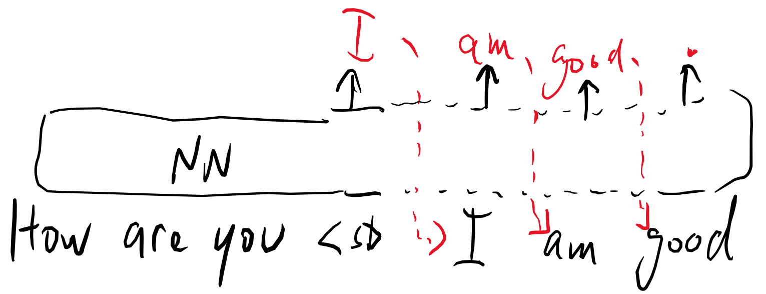
(Wen et al., 2017)
https://www.aclweb.org/anthology/E17-1042/

End-to-end vs. separate components

- 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
  - more explainable



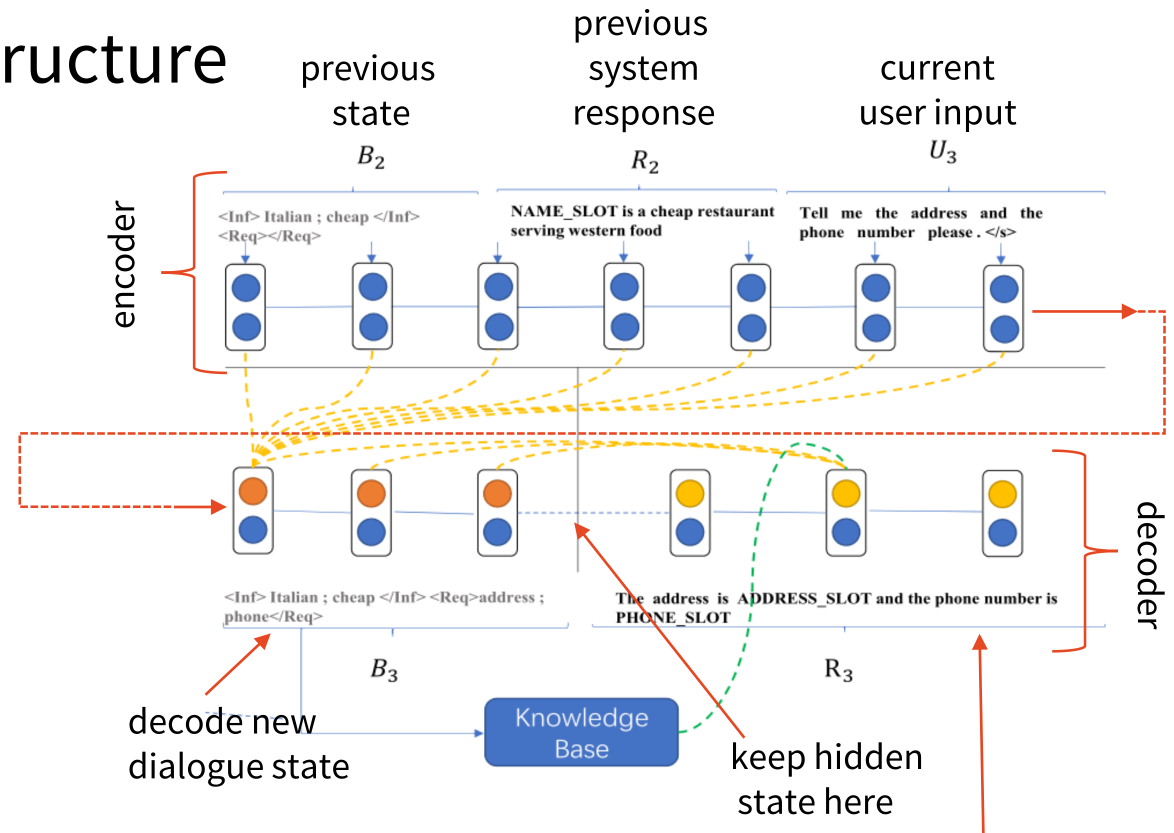
- End-to-end:
  - joint supervised optimization, RL still works
  - still needs DA-level annotation
  - typically needs a lot of data
  - less control of outputs: hallucination, dull/repetitive



Sequicity: Two-stage Copy Net

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

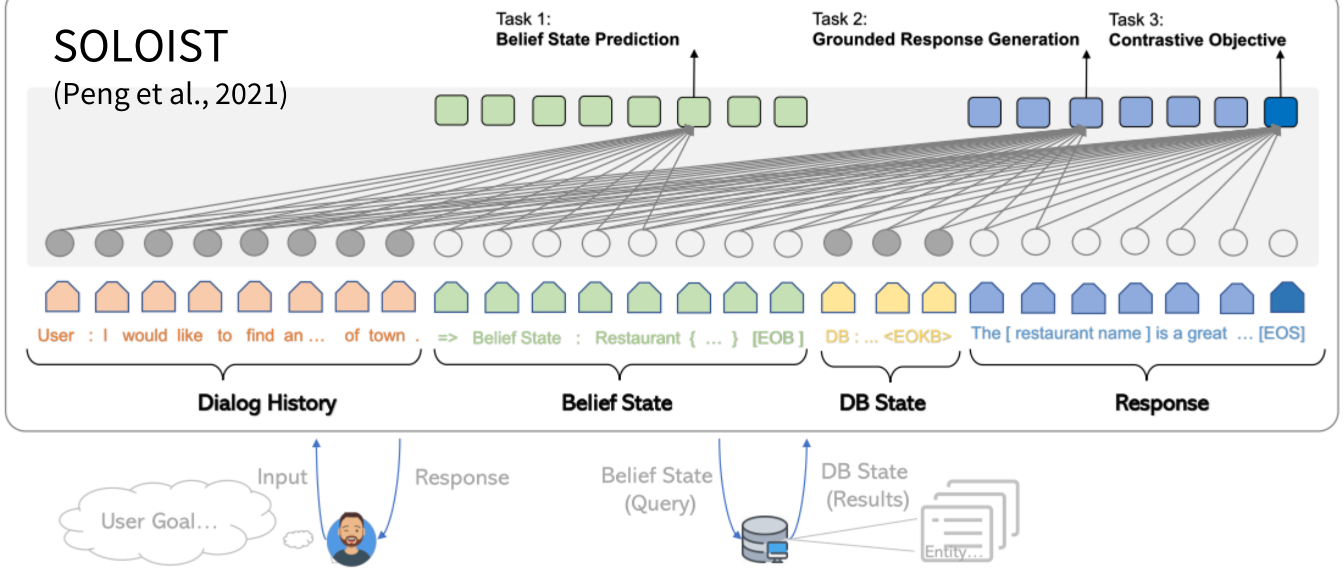
- fully **RNN/seq2seq**-based, not much structure
  - still explicit dialogue state
  - DB is external (as in most systems)
- operation:
  1) **encode**
     - previous dialogue state
     - prev. system response
     - current user input
  2) **decode new dialogue state** first
     - attend over whole encoder
  3) **decode system output** (delexicalized)
     - attend over state only
       + use DB output (one-hot vector added to each generator input)
       - DB: 0/1/more results – vector of length 3
  - **delexicalized** decoding: use placeholders (replaced based on full DB result)



End-to-end Dialogue with GPT-2

- Multiple recent DSs are based on GPT-2 (SOLOIST, UBAR, SimpleTOD, NeuralPipeline)
  - decoder-only PLM
- Similar to Sequicity, everything recast as sequence generation
  - dialogue context, belief state, database outputs represented as sequences
  - GPT-2 **prompting**: force-decode some input (ignore softmaxes, feed your tokens)
    - allows attention over it, conditions following text
    - essentially works like an encoder
- Multi-step operation:
  1) prompt with context & decode belief state
  2) query DB (external)
  3) prompt with DB output & decode response

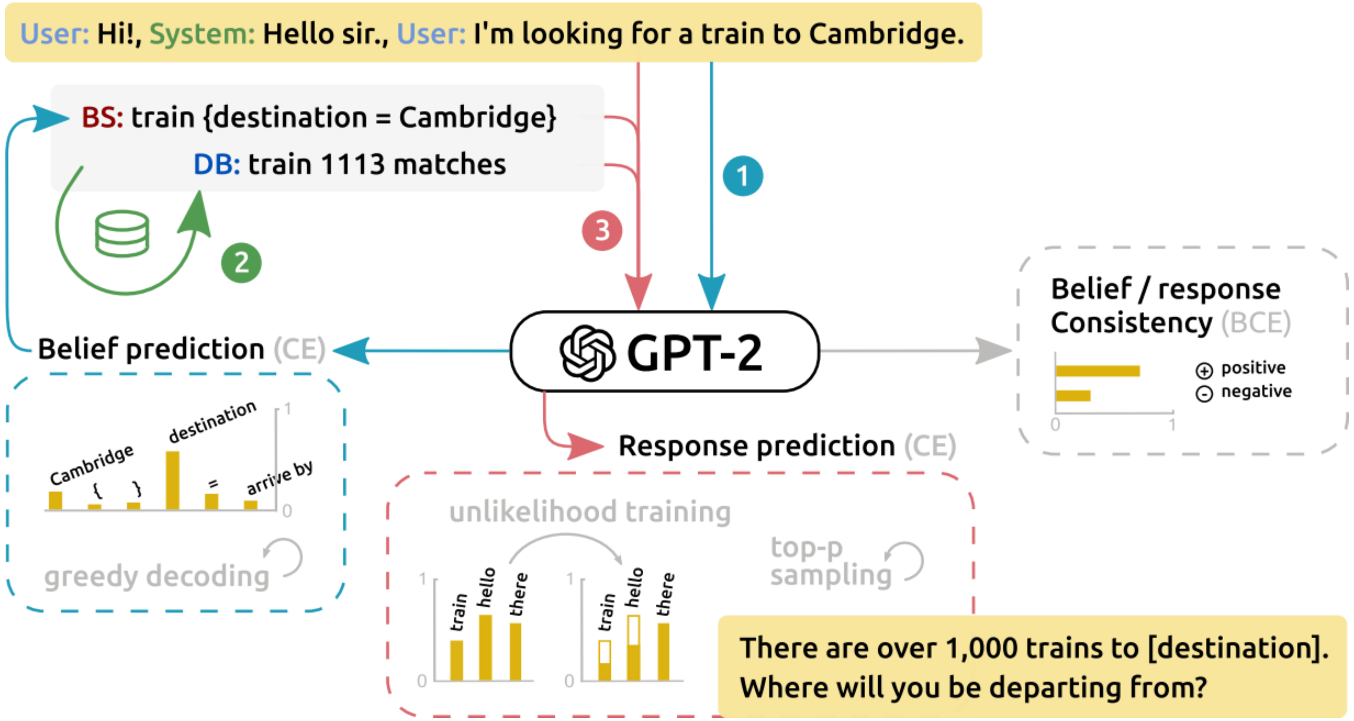
SOLOIST
(Peng et al., 2021)



AuGPT: Our take on this approach

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

- Same idea as ↑, multiple improvements
- Operation:
  1) context → belief state
     - prompt w. context & user utterance
     - greedy decoding of state
     - text-like belief state representation
  2) belief state → DB
     - text-like DB results
  3) DB → response
     - top-p sampling (diversity)
     - delexicalized (slot placeholders)
- Training:
  - belief/response prediction + consistency (Y/N)



Consistency task

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

- **Additional training task** – generating & classifying at the same time
  - additional classification layer on top of last decoder step logits
  - incurs additional loss, added to generation loss
- Aim: **robustness** – detecting problems
  - **½ data artificially corrupted** – state or target response don't fit context
  - prev. work: corrupted state sampled randomly
  - **AuGPT**: corrupted state sampled from the **same domain – harder!**

context	state	**response**	**consistent?**	
i want a cheap italian restaurant	*{ price range = cheap , food = Italian }*	ok which area ?	✓	
i want a cheap Italian restaurant	*{ price range = cheap , food = Italian }*	thanks, goodbye !	✗	bad response
i want a cheap italian restaurant	*{ destination = Cambridge , leave at = 19:00 }*	ok which area ?	✗	bad state
i want a cheap italian restaurant	*{ area = north , food = Chinese }*	ok which area ?	✗	bad state (same domain)

new in AuGPT

Further improvements

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

- **Data augmentation** via backtranslation (en → xx → en)
  - MT between English and 40 languages from the ELITR project (https://elitr.eu/)
  - we chose 10 best languages
  - user inputs chosen at random from **original & 10 backtranslated texts**
- **Data cleaning**
  - checking consistency of user goal with database
  - ~30% MultiWOZ data discarded
- **Unlikelihood loss** for output diversity
  - repeated tokens are penalized
- **Sampling** for output diversity

MinTL: Diff dialogue states

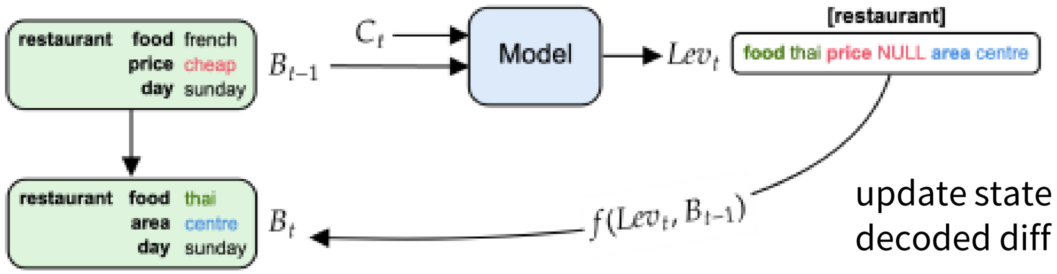
(Lin et al., 2020)
https://aclanthology.org/2020.emnlp-main.273/

- 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

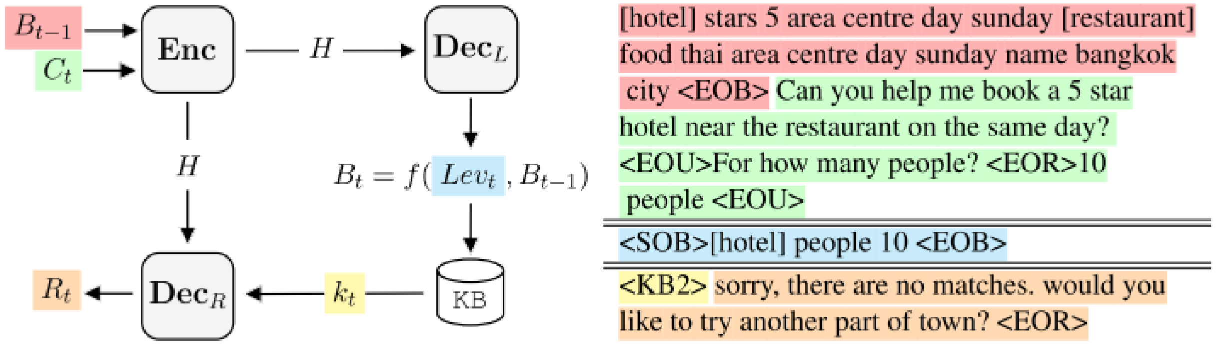
encode previous state & context

decode diffs



Testing

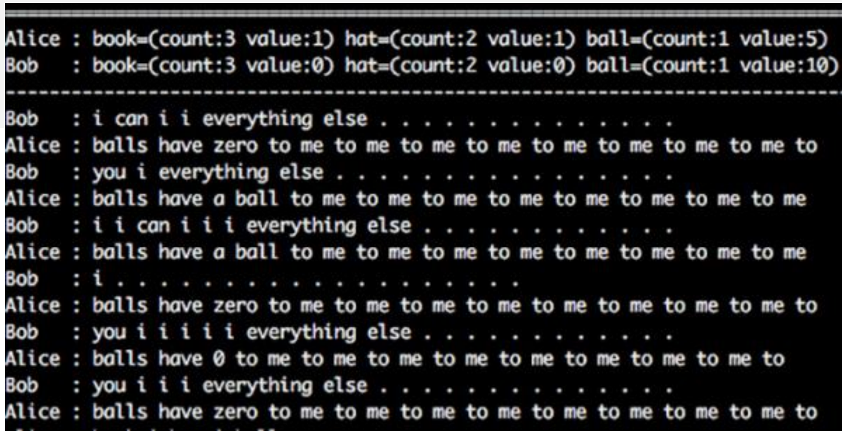
update state based on decoded diff



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

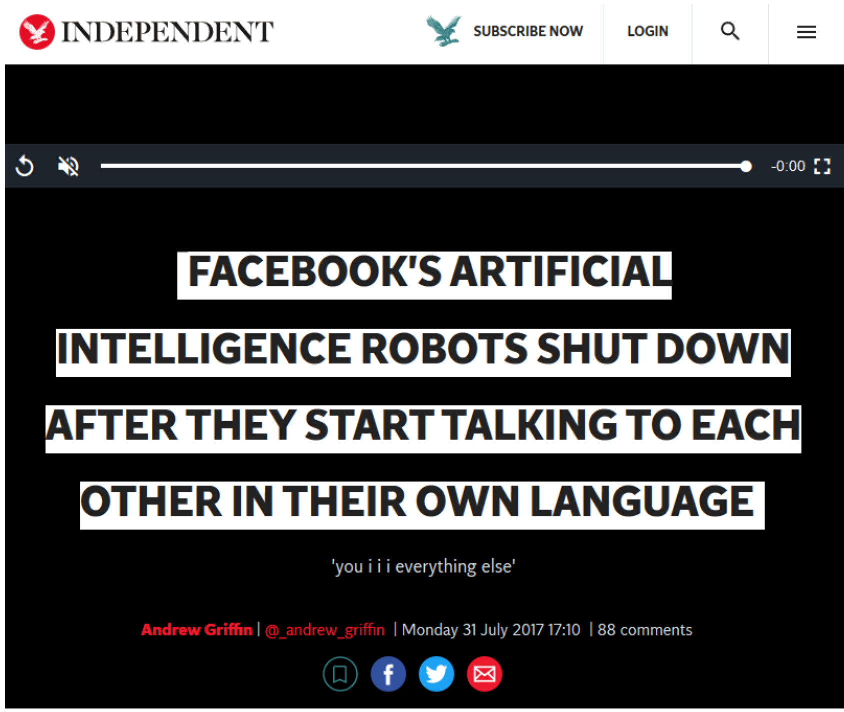
Training end-to-end systems: RL?

- 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



```
Alice : book=(count:3 value:1) hat=(count:2 value:1) ball=(count:1 value:5)
Bob   : book=(count:3 value:0) hat=(count:2 value:0) ball=(count:1 value:10)

Bob   : i can i i everything else . . . . . . . . . . . . . .
Alice : balls have zero to me to me to me to me to me to me to me to
Bob   : you i everything else . . . . . . . . . . . . . .
Alice : balls have a ball to me to me to me to me to me to me to me
Bob   : i i can i i i everything else . . . . . . . . . . . .
Alice : balls have a ball to me to me to me to me to me to me to me
Bob   : i . . . . . . . . . . . . . . . . . . .
Alice : balls have zero to me to me to me to me to me to me to me to
Bob   : you i i i i i everything else . . . . . . . . . . . .
Alice : balls have 0 to me to me to me to me to me to me to me to
Bob   : you i i i everything else . . . . . . . . . . . . . .
Alice : balls have zero to me to me to me to me to me to me to me to
```

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.

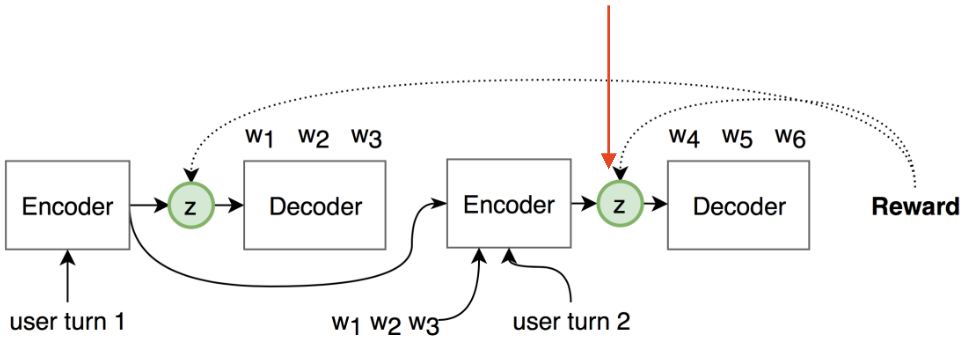
https://www.independent.co.uk/life-style/gadgets-and-tech/news/facebook-artificial-intelligence-ai-chatbot-new-language-research-openai-google-a7869706.html

Latent Action RL

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

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

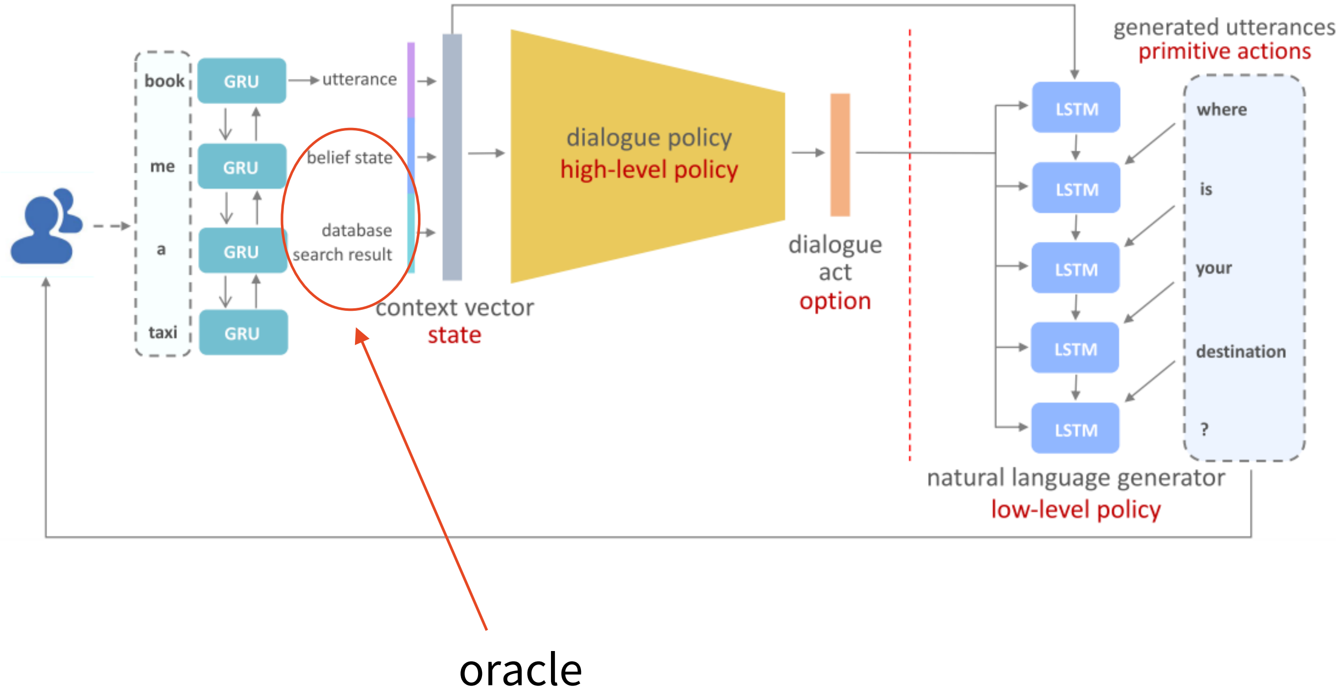
discrete latent action set



HDNO: Hierarchical RL End-to-end Dialogue

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

- Similar to (↑), but tries word-level RL
  - corpus-level RL
  - RNN architecture
  - dialogue state not tracked
- hierarchical RL:
  - **top level**: latent actions, like LARL
    - latent actions Gaussian here
    - standard reward based on success
  - **bottom level**: words
    - reward based on fluency
    - language model probability
  - both rewards weighted (word level much lower)
  - levels updated asynchronously



5. Evaluation

Corpus-based evaluation

(Nekvinda & Dušek, 2021)
https://aclanthology.org/2021.gem-1.4

- Task: take real dialogue history from corpus + **generate 1 response**
  - repeat over whole dialogue, collect responses
- Metrics:
  - **Inform rate** – last offered entity matches user constraints
  - **Success rate** – ↑ + system provided all requested information about it
  - **Joint goal accuracy** – % turns where all user constraints are captured correctly
  - **BLEU** – n-gram precision (matching sub-phrases of 1-4 words against reference)
- Problems:
  - really artificial setting, but easiest to use (just need test data)
  - Inf/Succ/JGA: matching the provided entities (more ways to do it)
  - BLEU: tokenization, measuring over delexicalized text

Simulator Evaluation

- **User Simulator** – works as a user, tries to follow goals
- **Dialogue-level** – good over 1 turn ≠ good over whole dialogue
  - especially for end-to-end systems, errors may accumulate over time
  - simulator is the only automatic way to assess this
- Main metric: **Success rate**: was the simulated user's goal reached?
  - i.e. did the system give a correct entity & all information
  - technically same as corpus-based, but now over real dialogues
- Problems:
  - the simulator needs to be built for a given domain
  - it's essentially another dialogue system (🐥x🥚)
  - simulator behavior will bias the evaluation

Human Evaluation

Metrics (objective – measuring):

- **Task success** (boolean): did the user get what they wanted?
  - (paid) testers with known goal → check if they found what they were supposed to
    - [warning] sometimes people go off script
  - basic check: did we provide any information at all?
- **Duration**: number of turns (fewer is better)

Metrics (subjective – questionnaries):

- **Success rate:** Did you get all the information you wanted?
  - typically different from objective measures!
- **Future use:** Would you use the system again?
- Component-specific questions

System	# calls	Subjective Success Rate	Objective Success Rate
HDC	627	82.30% (±2.99)	62.36% (±3.81)
NBC	573	84.47% (±2.97)	63.53% (±3.95)
NAC	588	89.63% (±2.46)	66.84% (±3.79)
NABC	566	90.28% (±2.44)	65.55% (±3.91)

(Jurčíček et al., 2012)
https://doi.org/10.1016/j.csl.2011.09.004

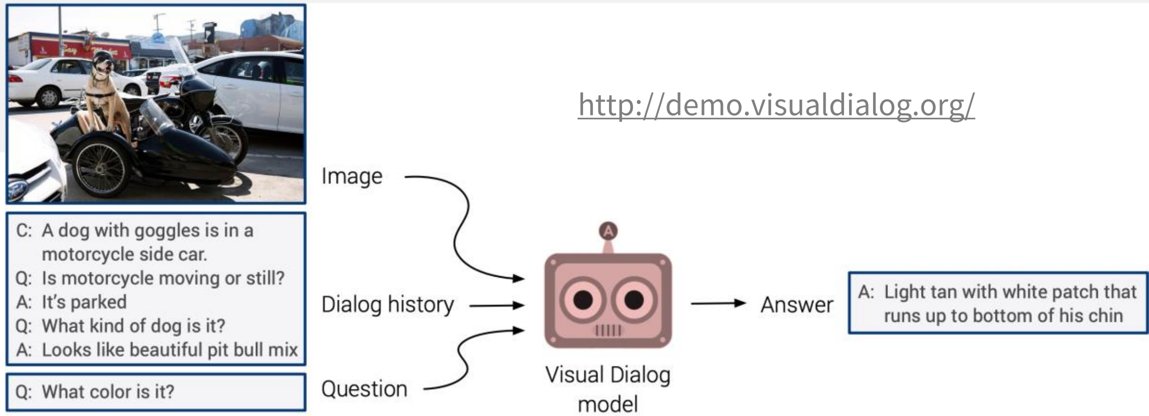
Final Remarks

Further Research Areas

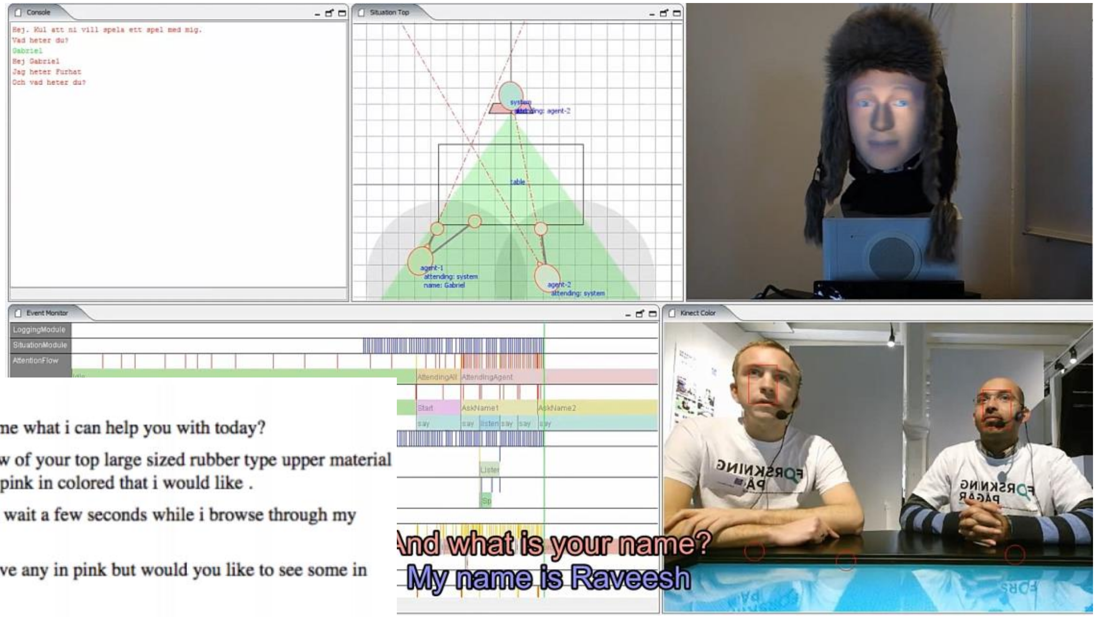
- Multi/open domains
  - reusability, domain transfer
  - training from little data
  - using less annotation
  - connecting task-oriented systems and chatbots
- Context dependency
  - understand/reply in context (grounding, speaker alignment)
- Incrementality
  - don’t wait for the whole sentence to start processing
- Evaluation
  - neural-net-based metrics

Multimodal/Visual Dialogue

- adding other modalities
- specific components
  - parallel to NLU
    - vision – image classification networks
    - face identification/tracking
  - parallel to NLG
    - mimics/gesture generation
    - gaze
    - image retrieval
  - vision – typically CNN
    - often off-the-shelf stuff
  - specific classifiers/rules



http://demo.visualdialog.org/



https://youtu.be/5fhjuGu3d0I?t=137

https://vimeo.com/248025147

(Agarwal et al., 2018)
http://aclweb.org/anthology/W18-6514

Thanks

Contact me:

MLSS^N Slack
in person till tomorrow
odusek@ufal.mff.cuni.cz

I’m looking for a postdoc
& will be looking for PhD students
(know someone?)
http://ufal.cz/ng-nlg/postdoc

Get the slides here:

http://ufal. cz/ondrej-dusek/bibliography (under “Talks”)

References/Inspiration/Further:

Apart from materials referred directly, these slides are based on slides and syllabi by:

- Pierre Lison (Oslo University): https://www.uio.no/studier/emner/matnat/ifi/INF5820/h14/timeplan/index.html
- Oliver Lemon & Verena Rieser (Heriot-Watt University): https://sites.google.com/site/olemon/conversational-agents
- Filip Jurčíček (Charles University): https://ufal.mff.cuni.cz/~jurcicek/NPFL099-SDS-2014LS/
- Milica Gašić (University of Cambridge): http://mi.eng.cam.ac.uk/~mg436/teaching.html
- David DeVault & David Traum (Uni. of Southern California): http://projects.ict.usc.edu/nld/cs599s13/schedule.php
- Luděk Bártek (Masaryk University Brno): https://is.muni.cz/el/1433/jaro2018/PA156/um/
- Gina-Anne Levow (University of Washington): https://courses.washington.edu/ling575/

Recommended Reading

Best:

- Jurafsky & Martin: Speech & Language processing. 3rd ed. draft 2021, Chap. 24 (+23, 25, 26) (https://web.stanford.edu/~jurafsky/slp3/) – relatively brief intro, good for rest of NLP too!
- McTear: Conversational AI. Morgan & Claypool 2021. (https://doi.org/10.2200/S01060ED1V01Y202010HLT048) – a bit more advanced & focused, pretty new
- Gao et al.: Neural Approaches to Conversational AI, 2019 (http://arxiv.org/abs/1809.08267) – more advanced, slightly outdated
- Sutton & Barto: Reinforcement Learning: An Introduction, 2018 (freely online) – specifically on RL, pretty advanced
- recent papers from the field (linked on individual slides)

Also good (but more outdated):

- McTear et al.: The Conversational Interface: Talking to Smart Devices. Springer 2016.
- Jokinen & McTear: Spoken dialogue systems. Morgan & Claypool 2010.
- Lemon & Pietquin: Data-Driven Methods for Adaptive Spoken Dialogue Systems. Springer 2012.
- Rieser & Lemon: Reinforcement learning for adaptive dialogue systems. Springer 2011.