NFPL099 Statistical Dialogue Systems
10. Chatbots/Open-Domain Systems

http://ufal.cz/npfl099

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5.12.2023

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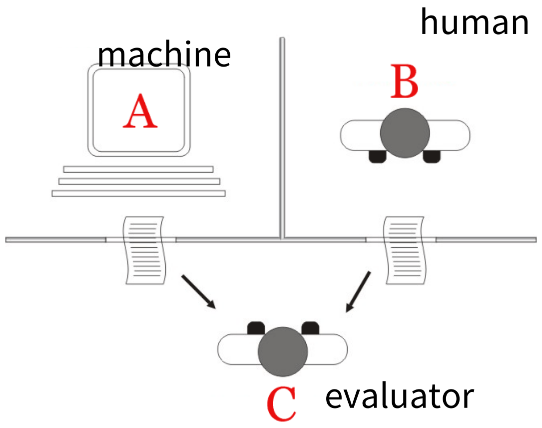
Chatbots / Chatterbots

(Skantze & Doğruöz, 2023)
https://aclanthology.org/2023.sigdial-1.57

- dialogue systems for **open-domain** dialogue – **chitchat**
  - i.e. "talk about anything", though this definition is problematic
    - we don't talk about anything with anyone, there's a lack of shared context (common ground)
    - definitions aren't unified across literature (may be more "social")
- mostly **non-task-oriented** (though this changes)
  - main goal: keep the user entertained
  - standard evaluation: conversation length, user engagement
- (somewhat) different architecture
  - mostly simpler, integrated – like end-to-end DS (i.e. no separate NLU/DM/NLG)
  - it's hard to have explicit NLU – no task to guide the meaning formalism
  - some of them don't need a DB connection (but some use it)
- beware: *any dialogue system* is called a "chatbot" nowadays
  - this lecture: only non-task-oriented / open-domain systems

Chatbot tests

- **Turing test** (1950)
  - evaluator & 2 conversations, with a machine & human, text-only
  - needs to tell which is which
  - does not concern what/if the machine thinks,
    only how it acts → can be (and is!) gamed



- **Loebner Prize** (1990-2019)
  - Turing test style, first topic-restricted 1995+ unrestricted
  - time-limited (currently 25 minutes for both conversations)
  - criticized as publicity stunt – hype but no real progress
- **Amazon Alexa Prize** (2017+, “Socialbot Grand Challenge”)
  - no pretending it’s human, just coherent & engaging conversation for 20 mins.
  - topic semi-restricted (“on popular topics”)
  - evaluator & 3 judges with stop-buttons
  - score: duration + 1-5 scale of “would talk again”

alexa prize

Chatbot history

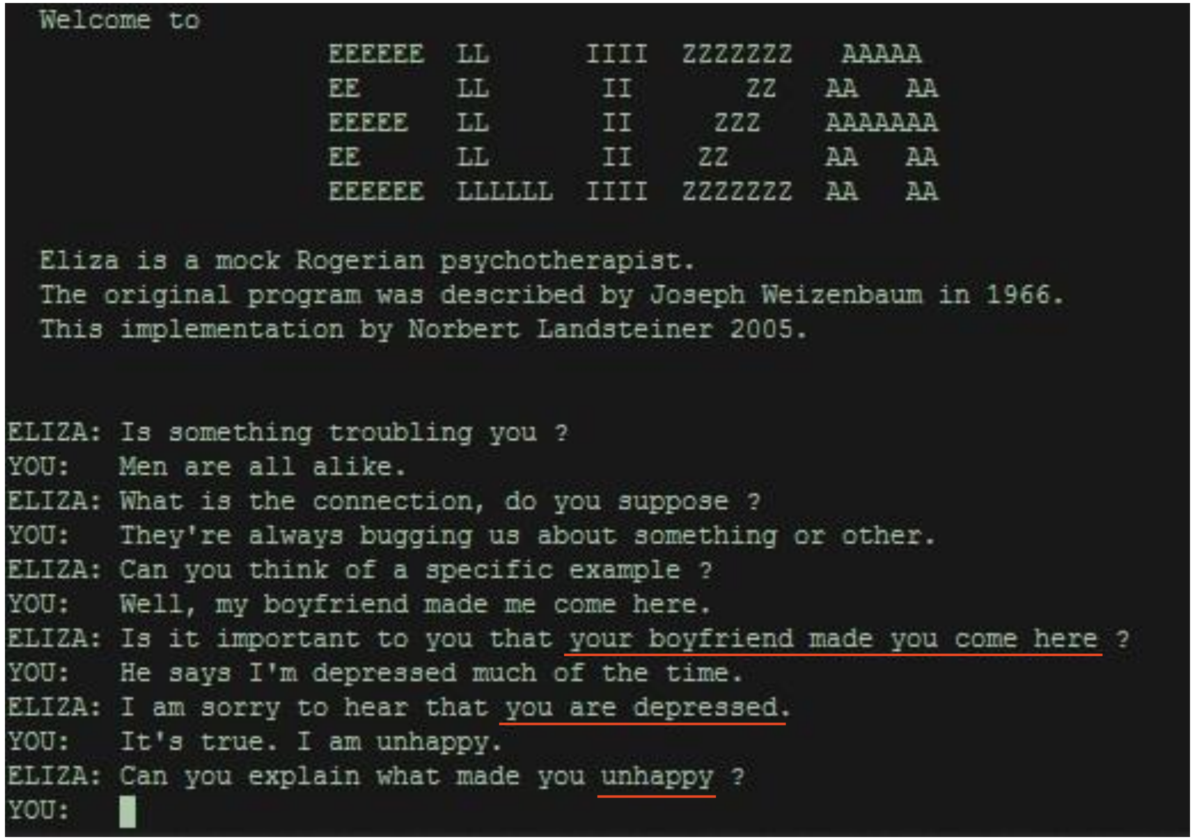
- natural communication – important part of general AI
  - concerned people even before modern computers (cf. Turing)
- 1st chatbot: **Eliza** (1966)
  - rule-based, simulates a therapist
- **Parry** (1972)
  - similar, simulates a person with paranoid schizophrenia
  - was able to fool psychotherapists in a Turing test
- Not much progress until end of 1990's – just better rules
  - research focused on task-oriented systems
- 1990's/2000's – retrieval-based systems
- 2015+ – huge surge of generative models

Chatbot basic architectures

- **Rule-based**
  - human-scripted, react to keywords/phrases in user input
  - very time-consuming to make, but still popular
    - chitchat by conversational assistants is typically rule-based
  - AIML – standard for keyword spotting rules (e.g. Pandorabots platform)
- **Data-driven**
  - **retrieval** – remember a corpus & get replies from there
    - “nearest neighbour” approaches
    - corpus can contain past conversations with users
    - chatbots differ in the sophistication of reply selection
  - **generative** – (typically) seq2seq-based models
    - trained typically on static corpora
    - (theoretically) able to handle unseen inputs, produce original replies
    - basic seq2seq architecture is weak (dull responses) → many extensions

Eliza (rule-based chatbots)

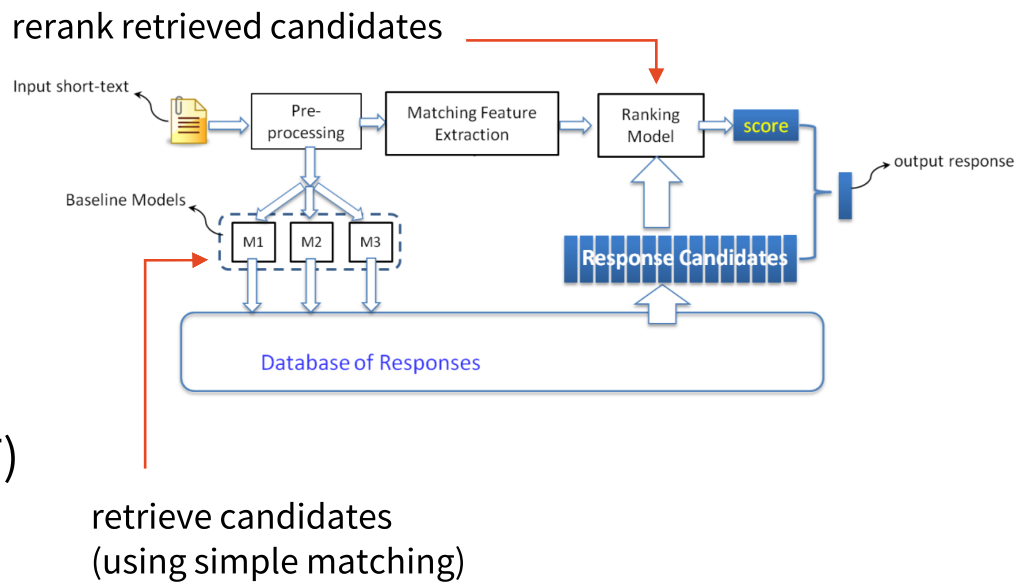
- very basic pattern-matching rules
  - minimal context
    (typically just the last utterance)
  - keyword-match rules & precedence
    - e.g. *alike* → *what is the connection*
  - fallbacks
    - *I see. <next question>*
    - *Please go on*
    - refer & respond to some previous utterance
- signalling understanding
  - repeating & reformulating user's phrasing
- it's all about the framing
  - it's easier to appear human as a therapist (or paranoid schizophrenic)



https://en.wikipedia.org/wiki/ELIZA

Retrieval-based chatbots

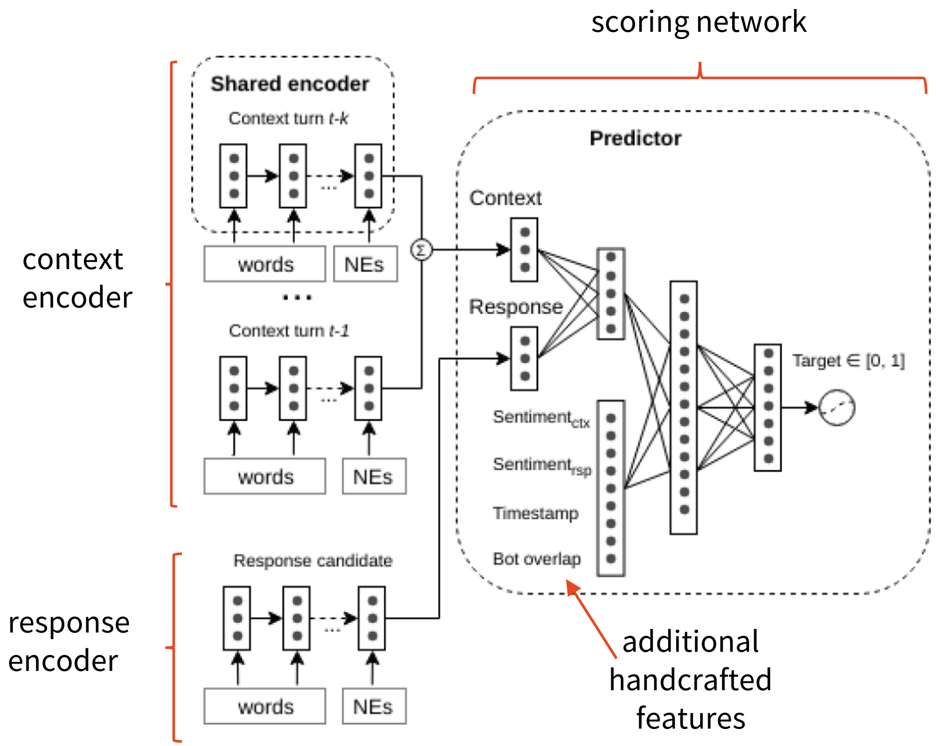
- remember a large corpus
  1) check for similar inputs in the corpus
  2) retrieve & rerank corresponding outputs
- needs 2 steps
  1) rough retrieval
     - needs to be fast to search the whole corpus (e.g. TF-IDF)
  2) more accurate reranking for candidates
     - most research focuses on this step
- problems:
  - can't produce unseen sentences
  - reply consistency isn't great
- solution:
  - use postprocessing, combine with rules (e.g. Cleverbot/Xiaoice bots)



(Wang et al., 2013)
https://aclweb.org/anthology/D13-1096

Ranking responses

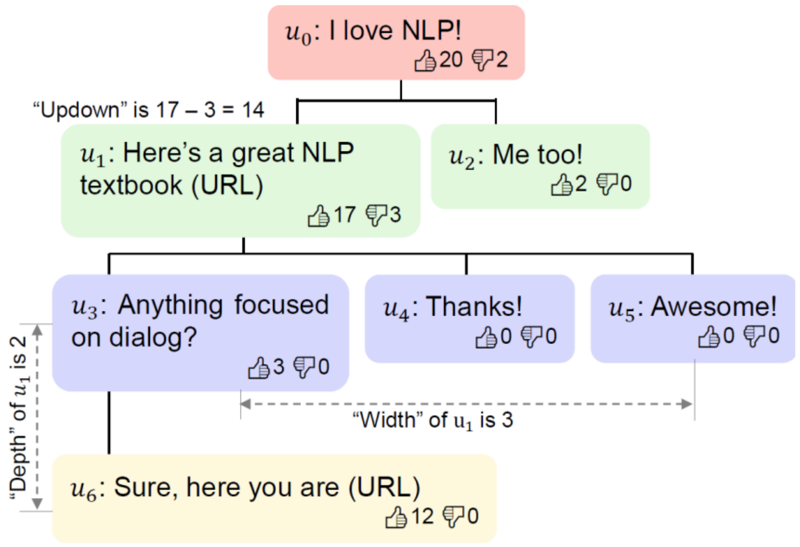
- Machine learning – **learning to rank**
  - **pointwise**: binary classifier
    - good=1, bad=0, ranking score = P(good)
  - **pairwise**: just learn to rank good > bad
    - incur loss for inversions
  - architecture – anything possible
    - typical neural: **dual encoder / Siamese network**
      - 2 RNNs, for context & response + fully connected
- training data problem:
  - datasets = positive examples only
    - but other responses might be good, too
  - need negative examples
    - manual annotation (expensive!)
    - random sampling (not very efficient)
    - smarter sampling (e.g., replies from “bad” dialogues where long = good & short = bad)



(Shalyminov et al., 2018)
https://www.aclweb.org/anthology/W18-5701

DialogRPT: Ranking with pretrained LMs

- GPT-2-based model (DialoGPT →)
- contrastive learning: feed 1 context + 2 responses, classify which is better
  - binary classification layer on top of last token
  - better than classify good/bad in isolation
- self-supervised data for ranking from Reddit
  - width = # of direct replies
  - depth = max. dialog length in subtree
  - updown = 👍 - 👎 votes



(Gao et al., 2020)
https://aclanthology.org/2020.emnlp-main.28/

Generative chatbots: RNNs

- Generic LSTM-based **Seq2seq** model
  - encode context / input, decode response
  - examples in the paper look great, but… (→)
    - the paper also reports some problems, but they're much more prevalent than it looked

U: *who is skywalker ?*
S: *he is a hero .*

U: *who is bill clinton ?*
S: *he 's a billionaire .*

U: *what is the purpose of life ?*
S: *to serve the greater good .*

U: *what is moral ?*
S: *what empowered humanity , what intellectual the essence is .*

Human: *who is skywalker ?*
Machine: *he is a hero .*
Human: *who is bill clinton ?*
Machine: *he 's a billionaire .*
Human: *is sky blue or black ?*
Machine: *blue .*
Human: *does a cat have a tail ?*
Machine: *yes .*
Human: *does a cat have a wing ?*
Machine: *no*
Human: *can a cat fly ?*
Machine: *no .*
Human: *how many legs does a cat have ?*
Machine: *four , i think .*
Human: *how many legs does a spider have ?*
Machine: *three , i think .*
Human: *how many legs does a centipede have ?*
Machine: *eight .*
Human: *what is the color of the sky ?*
Machine: *blue .*

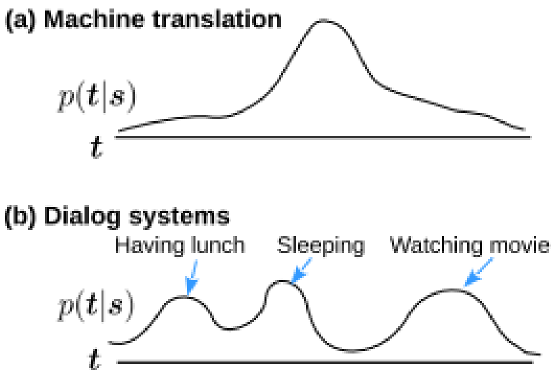
Human: *what is the color of water ?*
Machine: *water .*
Human: *what is the color of blood ?*
Machine: *it is the same as a black eye .*
Human: *what is the usual color of a leaf ?*
Machine: *it is a green one .*
Human: *what is the color of a yellow car ?*
Machine: *yellow .*
Human: *how much is two plus two ?*
Machine: *four .*
Human: *how much is ten minus two ?*
Machine: *seventy - two .*

(Vinyals & Le, 2015)
https://arxiv.org/abs/1506.05869

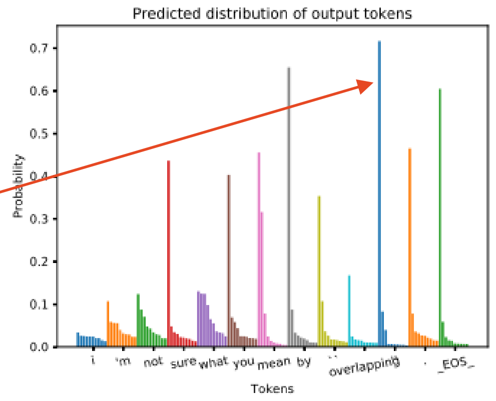
Seq2seq Chatbot Problems

- **generic/dull responses**
  - short, low-entropy, repetitive
  - problem: too many possible outputs given input
    - hard to train with MLE & use softmax – both prefer 1 option
    - models settle on safe replies, applicable to any context
    - they become over-confident (LM rules)
- **limited context**
  - encoding long contexts is slow & ineffective
  - contexts are too sparse to learn much
- **inconsistency**
  - ask the same question twice, get two different answers
  - no notion of own personality

(Wei et al., 2019)
https://arxiv.org/abs/1712.02250
https://ieeexplore.ieee.org/document/8682634



highest probs. grow



(Jiang & De Rijke, 2018)
https://www.aclweb.org/anthology/W18-5712

(Li et al., 2016)
https://www.aclweb.org/anthology/P16-1094

U: *How old are you?*
S: *16 and you?*
U: *What's your age?*
S: *18.*

U: *Where do you live now?*
S: *I live in Los Angeles.*
U: *In which city do you live now?*
S: *I live in Madrid.*
U: *In which country do you live now?*
S: *England, you?*

Improving diversity & coherence: MMI, HRED

- **Reranking**: MMI
  - avoid dull replies that work anywhere
  - instead of maximizing $P(Resp|Context)$, **maximize mutual information**
    - actually can be rewritten as a trade-off between $P(R|C)$ and $P(C|R)$
  - can't train it easily, so train normally & rerank beams afterwards

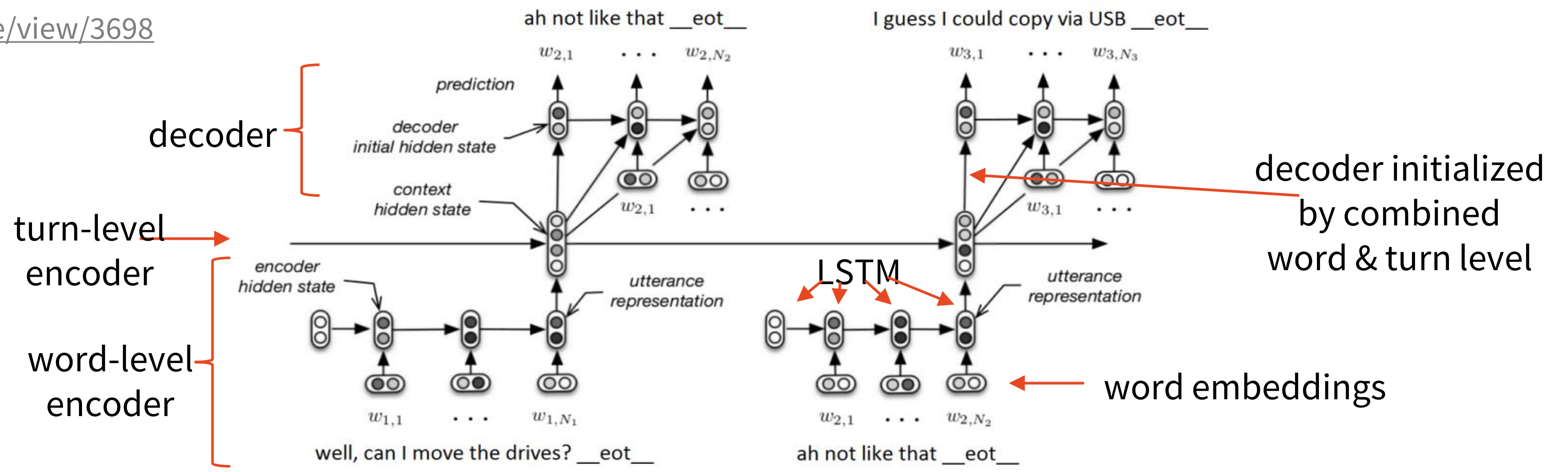
(Li et al., 2016)
https://www.aclweb.org/anthology/N16-1014

Input: what is your name?			
-0.91	I don't know.	...	
-0.92	I don't know!	-1.55	My name is Robert.
-0.92	I don't know, sir.	-1.58	My name is John.
-0.97	Oh, my god!	-1.59	My name's John.

$$\mathrm{MI} = \log \frac{P(R,C)}{P(R)P(C)}$$

- **Longer context**: HRED (Hierarchical Recurrent Encoder-Decoder)
  - 2nd, turn-level LSTM encoder, with word-level LSTM hidden state as input

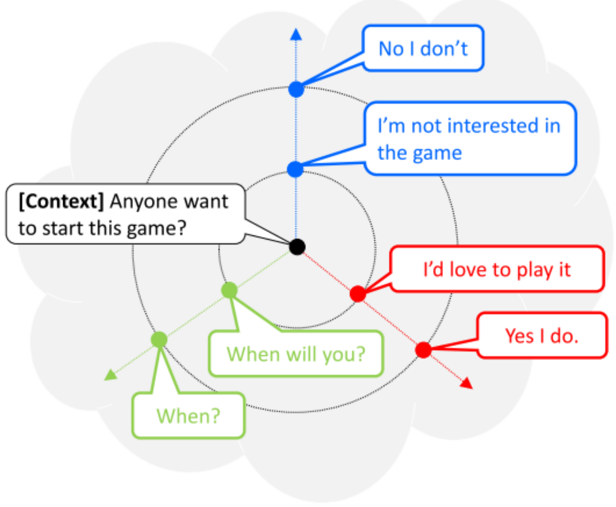
(Lowe et al., 2017)
http://dad.uni-bielefeld.de/index.php/dad/article/view/3698



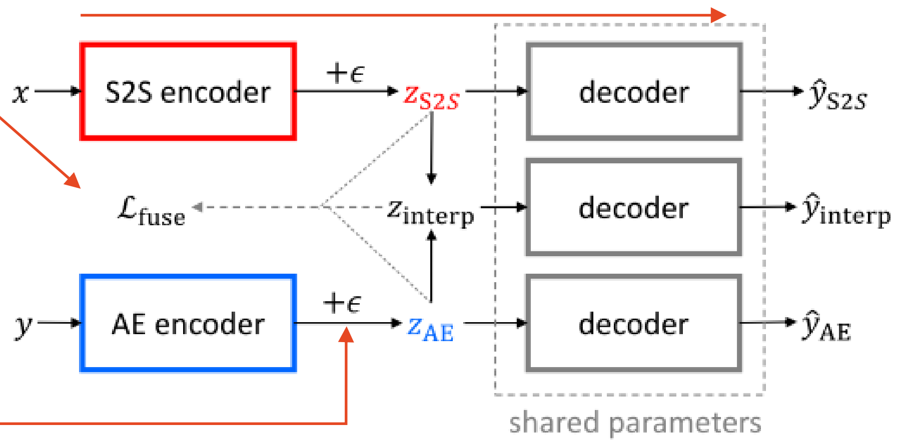
Improving diversity: VAE-style

- joining **next turn generation** & **autoencoding**
  - LSTM VAE-like model, shared latent space
  - multi-task learning
  - shared decoder
  - additional "fusion loss" enforcing the same encoding for both tasks
- inference: adding a little noise to encodings
  - to produce different outputs

latent space



response generation



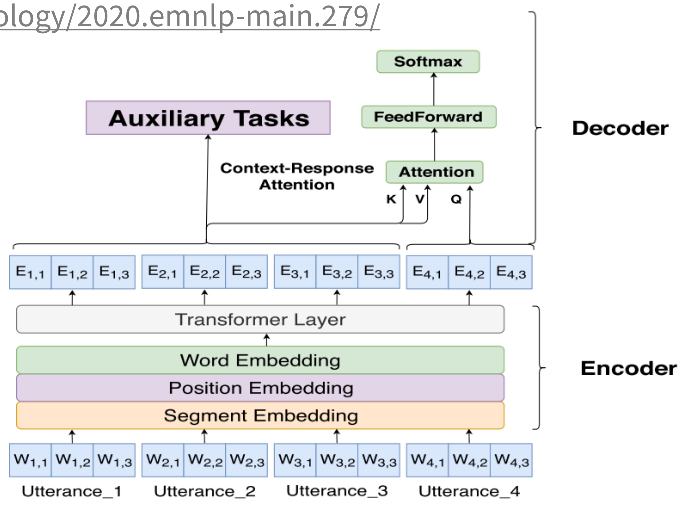
added noise

autoencoding

(Gao et al., 2019)
http://arxiv.org/abs/1902.11205

Improving coherence: Additional objectives

(Zhao et al., 2020)
https://www.aclweb.org/anthology/2020.emnlp-main.279/



- Transformer-based architectures
- **Denoising** (autoencoder): additional decoders
    - shuffled word order
    - masked words
    - masked utterance (mid-dialogue)
    - utterance order (GRU decoding order)

- **Unlikelihood** – demoting unlikely tokens
    - penalize set of tokens selected at each time step
    - repeating n-grams, too much high-freq. vocab…
    - weighted combination with regular MLE loss

(Li et al., 2020) https://www.aclweb.org/anthology/2020.acl-main.428

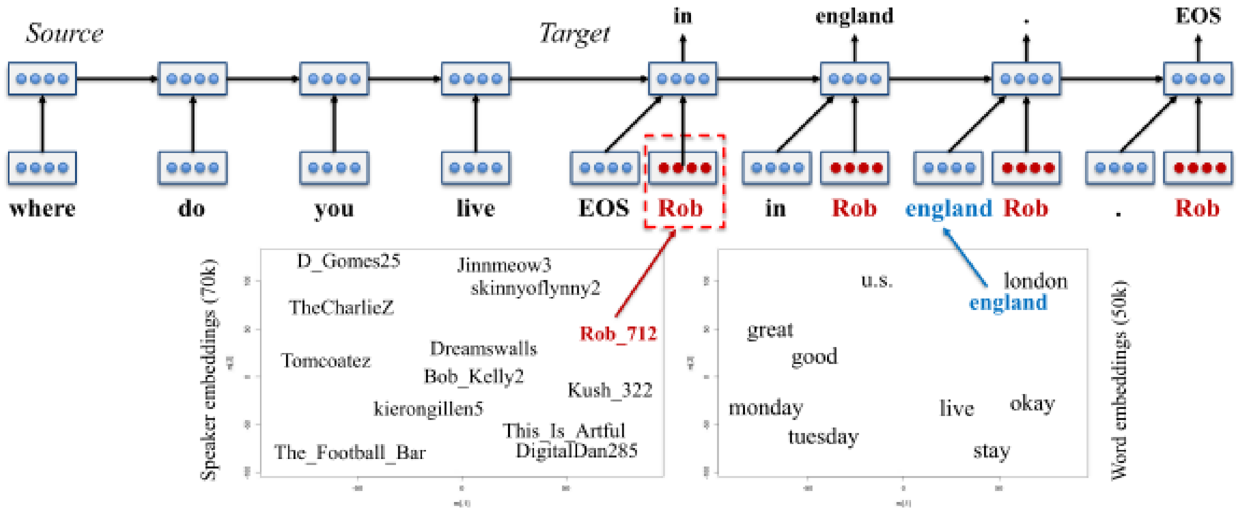
Chat-Specific Pretrained Language Models

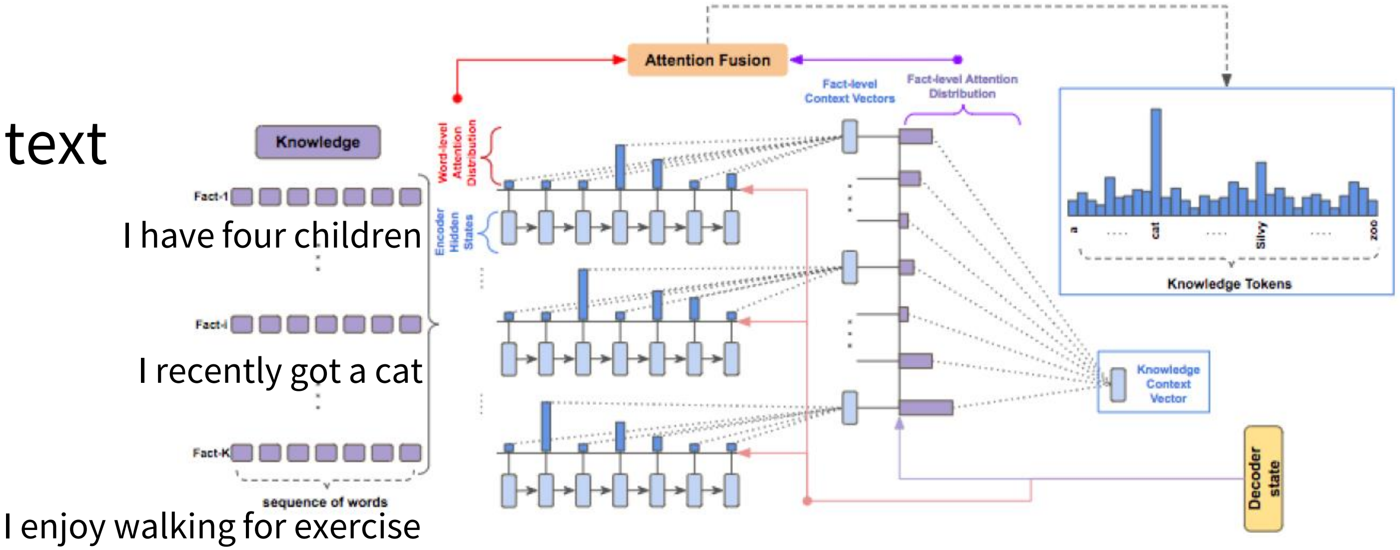
- **DialoGPT** – GPT-2 finetuned on Reddit (147M dialogues) (Zhang et al., 2020) https://www.aclweb.org/anthology/2020.acl-demos.30
  - no hierarchy, whole chat as a long text – next-word prediction
  - works better than seq2seq-based ones
- **Meena** (Adiwardana et al., 2020) https://arxiv.org/abs/2001.09977
  - “Evolved Transformer” architecture (Transformer + small changes automatically tuned)
  - encoder-decoder, huge, trained on 867M dialogues (next-word prediction)
  - rule-based postprocessing
  - evaluation: “making sense” & “being specific” – better on both
- **BlenderBot** (Roller et al., 2021) https://aclanthology.org/2021.eacl-main.24/
  - again, huge Transformers (but has a smaller version)
  - retrieval & generative versions
  - pretrained on Reddit, finetuned on a combination of specific dialogue datasets
  - constrained beam search (avoid too short replies), better than sampling

Consistent Personality

(Li et al., 2016)
https://www.aclweb.org/anthology/P16-1094

- improving consistency by modelling chatbot’s personality
- **Persona embeddings**
  - train speaker embeddings
  - use speaker + word embeddings in the decoder
  - needs lots of data
- **Persona copy-net**
  - add & attend to personal bio in context
    - chunks of text
  - copy-net or pretrained LMs





(Yavuz et al., 2019)
https://www.aclweb.org/anthology/W19-5917/

Personality in LLMs

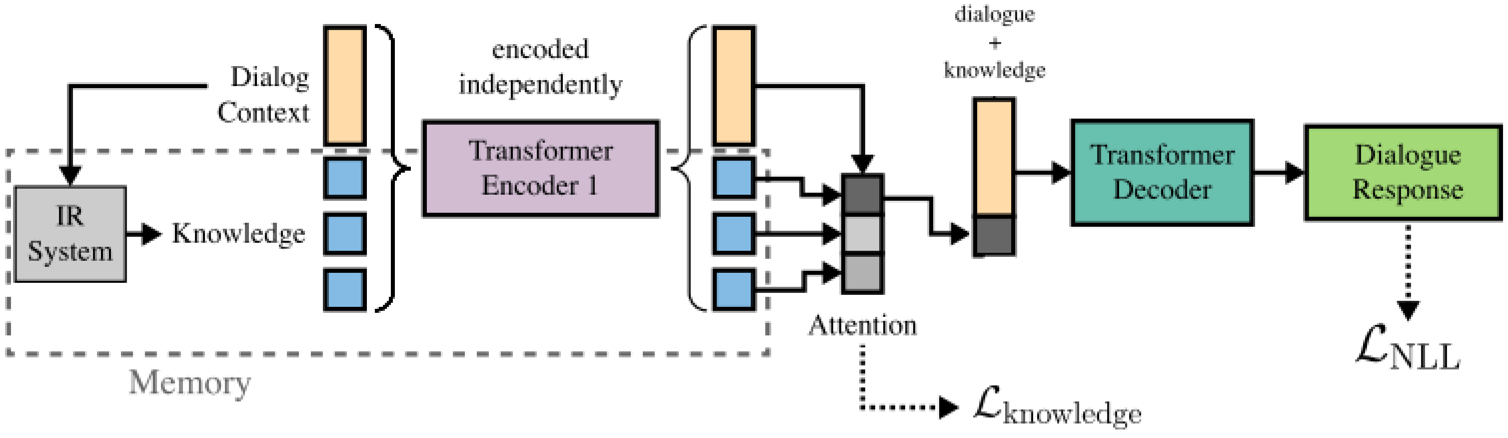
- LLM prompts often include “persona”
  - in their **system prompt / metaprompt / system message**
  - special prompt added before the actual conversation starts
  - ChatGPT: *You are a helpful assistant*
- Can include more details
  - personality, limitations, capabilities
  - behavior “guardrails” (*Avoid harmful or unethical content.*)
- Different personalities influence LM behavior & performance
  - adding a role help, esp. interpersonal & not too intimate (*friend, colleague*)
  - choosing the best role is tricky

(Zheng et al., 2023)
http://arxiv.org/abs/2311.10054

https://learn.microsoft.com/en-us/azure/ai-services/openai/concepts/system-message
https://www.promptingguide.ai/models/mistral-7b

Retrieval-augmented bots

- Combination of generation & retrieval
  1) **Retrieve** a candidate,
  2) **Edit** it using a seq2seq model to better match context
- Knowledge grounding
  - candidate = knowledge to be used in response
  - Wizard-of-Wikipedia
- Problem: right amount of copying
  - Don't ignore the retrieved
  - Don't copy it verbatim
  - Question of parameters, tradeoff, various hacks to achieve this
  - α-blending: replace retrieved with target with some probability, to promote copying

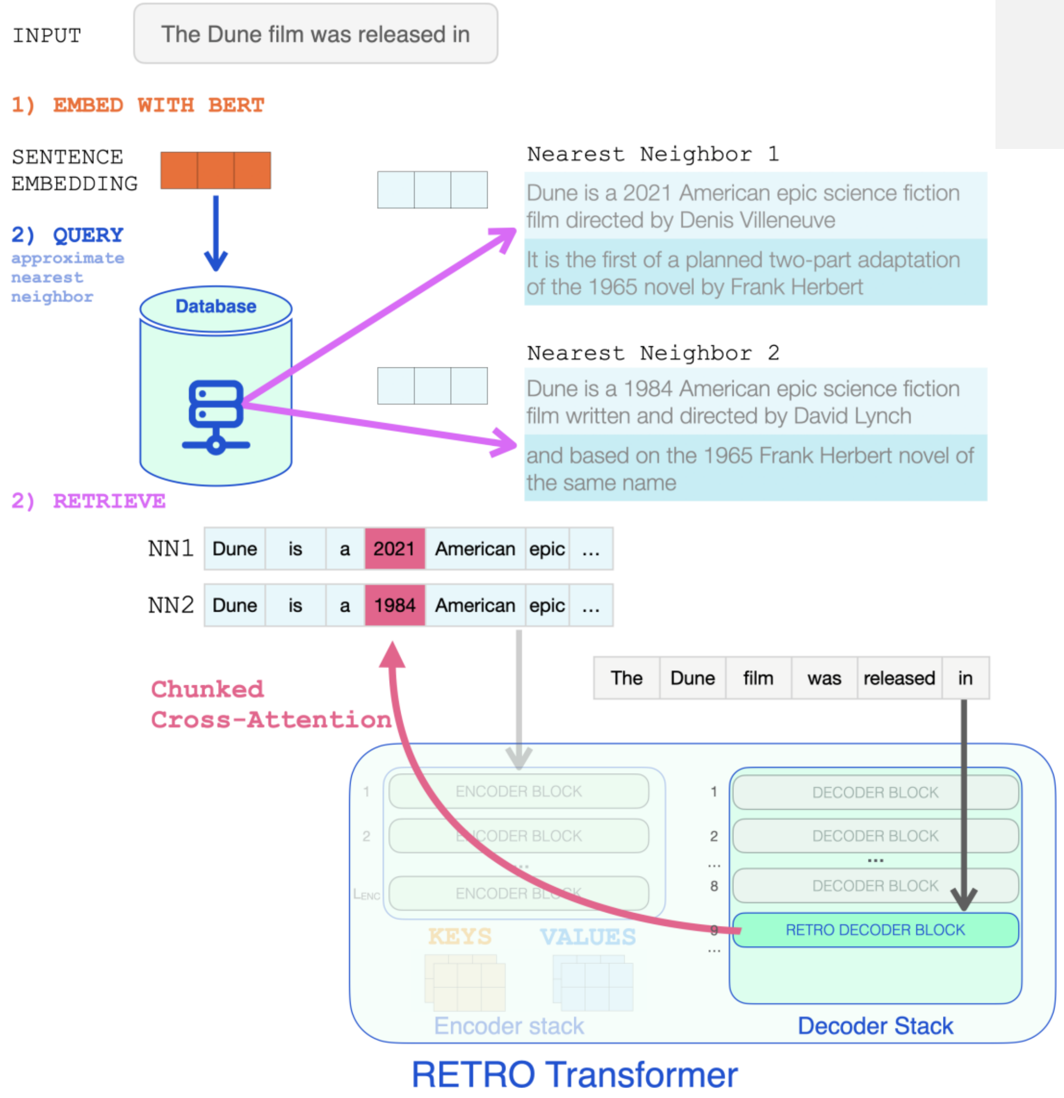


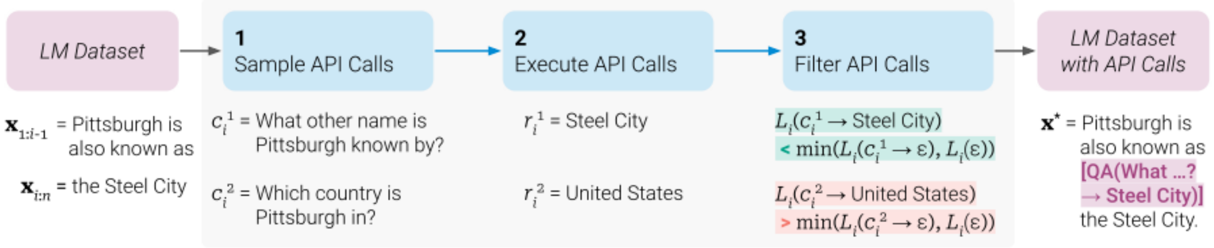
(Pandey et al., 2018) https://aclanthology.org/P18-1123/
(Weston et al., 2018) https://aclanthology.org/W18-5713/
(Dinan et al., 2019) https://arxiv.org/abs/1811.01241
(Xu et al., 2021) http://arxiv.org/abs/2107.07567

(Roller et al., 2021) https://aclanthology.org/2021.eacl-main.24

Retrieval Transformer / Toolformer

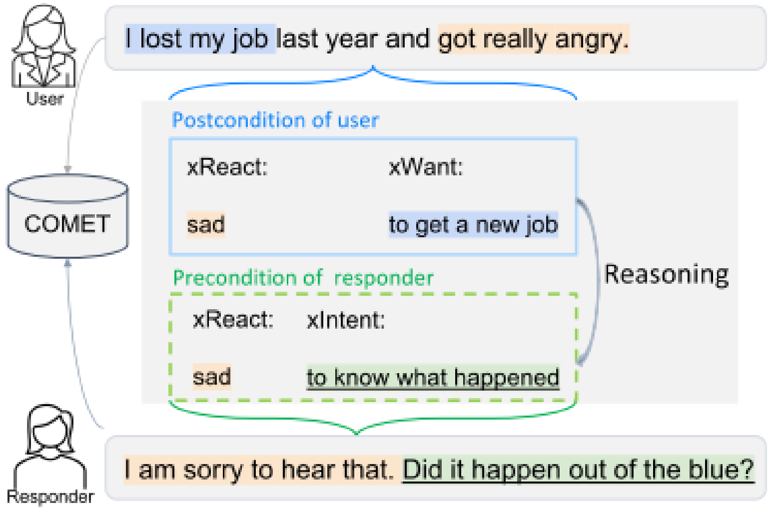
- Retrieval as you generate
  - conditioned on the already generated tokens
  - allows to feed in relevant factual info
- RETRO (Borgeaud et al., 2022) http://arxiv.org/abs/2112.04426 https://jalammar.github.io/illustrated-retrieval-transformer/
  - 2 nearest neighbor prefixes from DB
  - retrieved for each chunk = 4 tokens
  - retrieve, use in attention (via special layers)
- Toolformer (Schick et al., 2023) http://arxiv.org/abs/2302.04761
  - LM decodes special prefix + params for “tools” i.e. different API calls
  - finetuned on data with interleaved API calls
    - API calls sampled & filtered by loss reduction
  - QA, Wiki search, calc, calendar, MT





Reasoning via external model

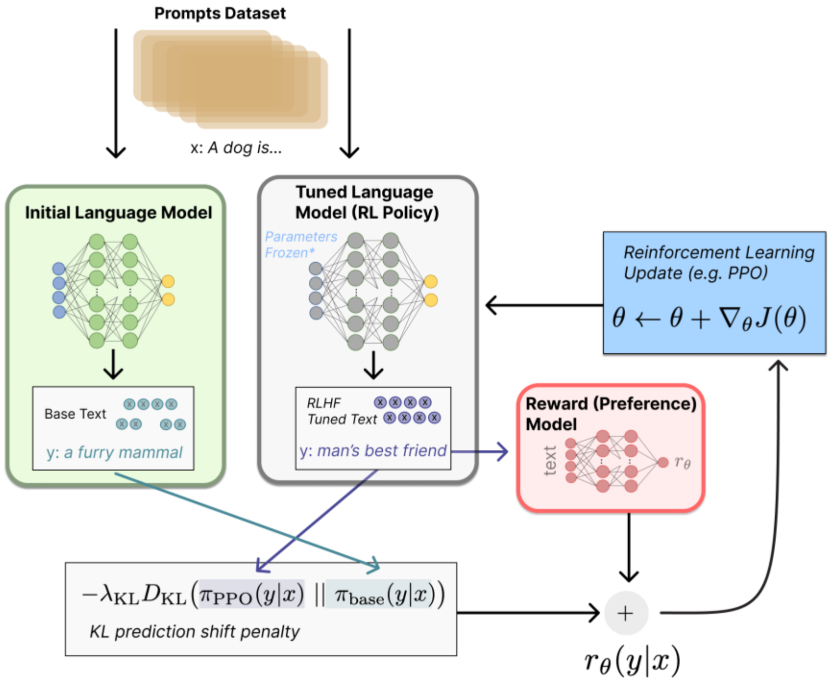
- COMET: pretrained commonsense model
  - inferring user/system emotion (xReact)
    + user desire (xWant) & system intent (xIntent)
  - user at runtime, system at training only
    (from ground truth data)
- system intent & emotion inferred at runtime
  - from user intent & emotion
  - using ChatGPT with specially crafted prompts
- ChatGPT / T5 conversation model
  - inferred intent & emotion inserted before reply



(Fu et al., 2023) https://aclanthology.org/2023.sigdial-1.60

Training from feedback

- **LaMDA**: LM + retrieval + “calculator” (Thoppilan et al., 2022) http://arxiv.org/abs/2201.08239
  - pretrained on dialogue
  - finetuned on annotated corrections of its own outputs
  - usage of retrieval & calculator annotated
  - generate multiple, filter (safety) & rerank
  - 2B/137B params versions
- **RLHF**: “standard” set by ChatGPT
  1) supervised finetuning
  2) evaluation/ranker model training
     - human annotations for model generation
  3) RL with proximal policy optimization
     - ranker model as reward
  - direct preference optimization: RL-free alternative

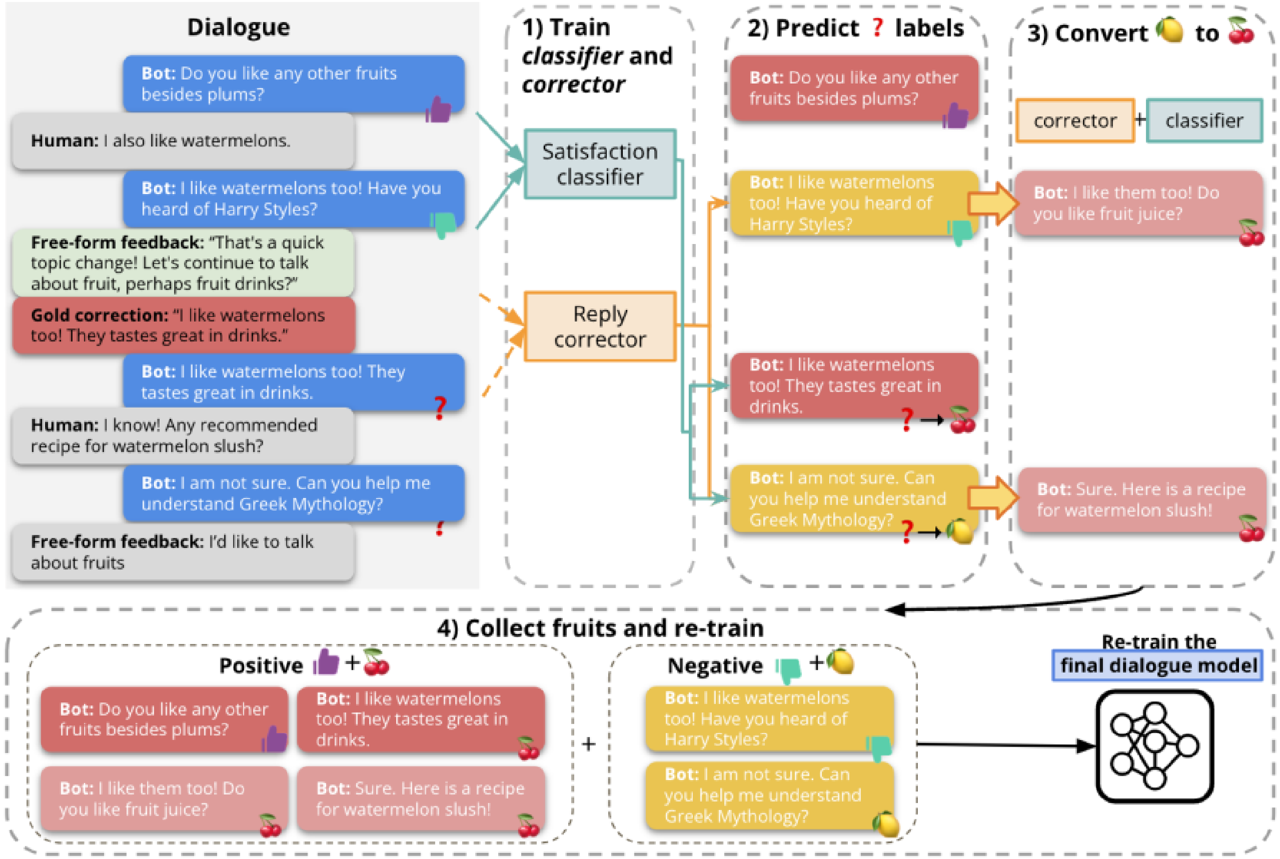


https://huggingface.co/blog/rlhf

(Ouyang et al., 2022) http://arxiv.org/abs/2203.02155
https://openai.com/blog/chatgpt/ , https://www.youtube.com/watch?v=0A8ljAkdFtg

Training from feedback

- JUICER
  - Get sparse user feedback & corrections
  - Label rest of the data
  - Train corrector LM
  - Convert bad → good replies
  - Retrain model on converted replies
- SYNDICOM
  - GPT-3 generated dialogues by rephrasing templates
  - GPT-3 error injection
  - Human feedback → corrector LM



(Shi et al., 2022) http://arxiv.org/abs/2210.15893 (Richardson et al., 2023) https://aclanthology.org/2023.sigdial-1.27

Hybrid / Ensemble Chatbots (a.k.a. most Alexa Prize Entries)

*if you want to retain some control

- Production SotA*: **combining all methods**
  - rule-based for sensitive/frequent/important questions
  - retrieval for jokes, trivia etc.
  - task-oriented-like systems for specific topics (handcrafted/specially trained)
    - news, weather etc.
  - seq2seq for everything else
- NLU is typically shared, with advanced NLP pipelines
  - NER is very important – can get relevant news & trivia
- Decision among bots
  - based on NLU topic detection
  - ranking multiple answers
  - profanity detection – censoring outputs

Sounding Board (Uni Washington, 2017 winner)

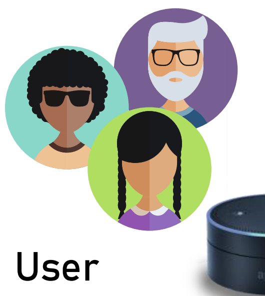
- full focus on content & user engagement
  - conversation itself is rather crude
    - menu-selections for conversation topics
  - tracking user sentiment
    - change topic if user doesn't like the current one
  - attempting at diversity & coherence
    - juggling different sub-bots
    - trying to continue on the same or related topic
  - explaining itself – conversation grounding
- tries to detect understanding errors
  - uses ASR n-best lists for NLU
  - 1st reaction: apologize & try to recover
  - 2nd reaction: change topic

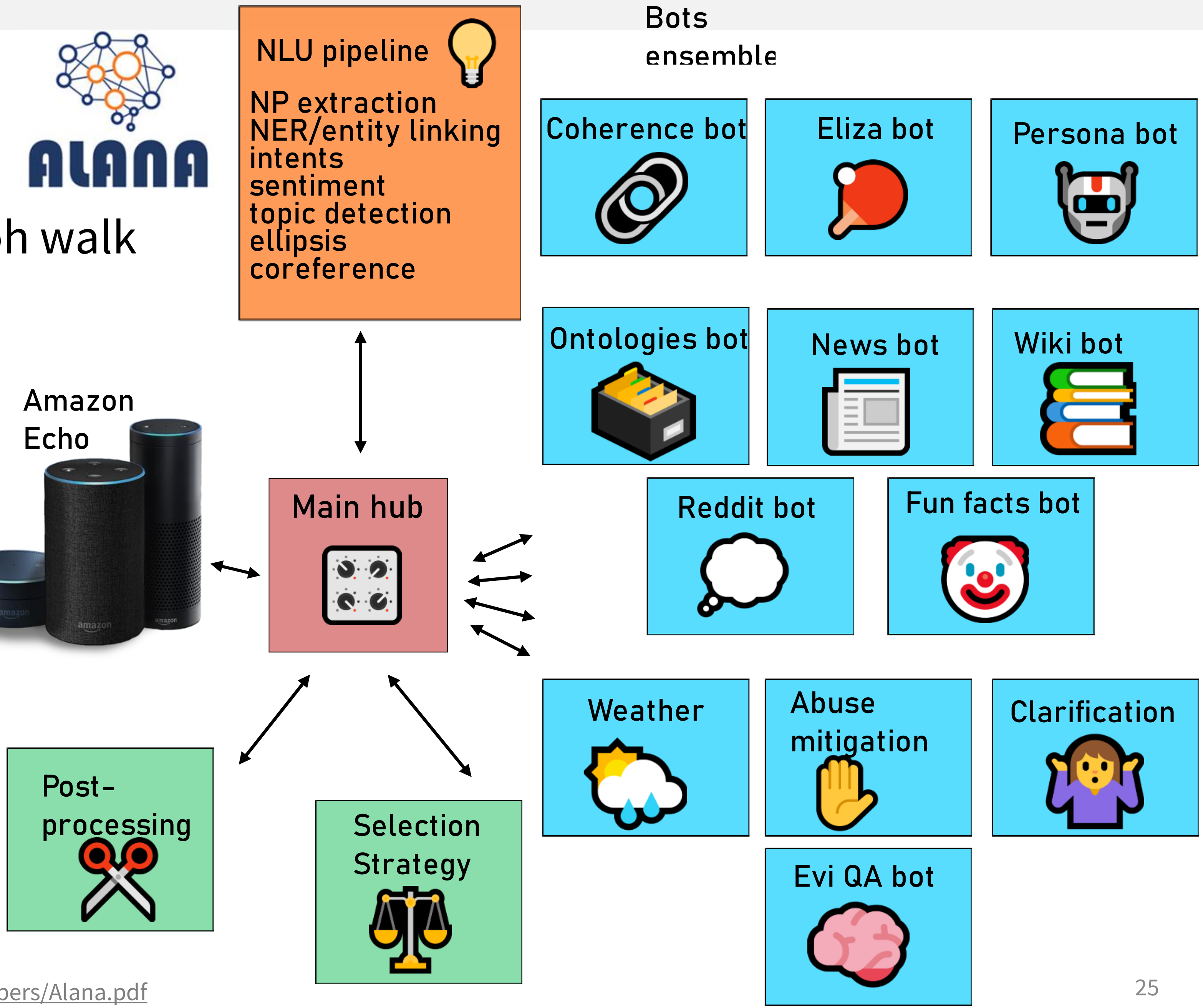
sub-bot:	Turn	User	Sounding Board
greeting	1	Let's chat	Hi! This is an Alexa Prize socialbot. How's your day?
negotiation	2	I'm five.	Glad to hear it! We could talk about robots, Batman, or Superman. Say "next", to chat about other things.
thoughts	3	Superman.	It looks like you wanna chat about Superman. I was high up in the cloud when I realized: If people don't recognize Clark Kent as Superman because of his glasses, does his eye doctor know his true identity?
facts	4	I guess so.	Did you know that Henry Cavill almost missed the call for the role of Superman cause he was playing "World of Warcraft"
movies	5	Really, I didn't know that.	Weird, right? Speaking of Superman, Did you see: Superman? It was released in 1997. It's a comedy.
movies	6	Yes, it was hilarious.	I'm glad you feel this is hilarious. Which part do you like best about this movie?
movies	7	The part when he met Lewis Leah.	Interesting. Meccartin and Raffi co-directed this film. The movie has a 6.3 out of 10 on IMDB. which seems pretty good! do you like the movie's director?

http://arxiv.org/abs/1804.10202
https://s3.amazonaws.com/alexaprize/2017/technical-article/soundingboard.pdf
https://sounding-board.github.io/

Alana (Heriot-Watt University, 2017 & 2018 3rd)

- Bots:
  - Rule-based chit-chat
  - Ontologies – knowledge graph walk
    - movies, music, sports, books
  - Retrieval
    - Reddit trivia
    - news
    - Wikipedia
    - fun facts
  - Specific services
- Bots compete for reply
  - priority list
  - bots can "lock"



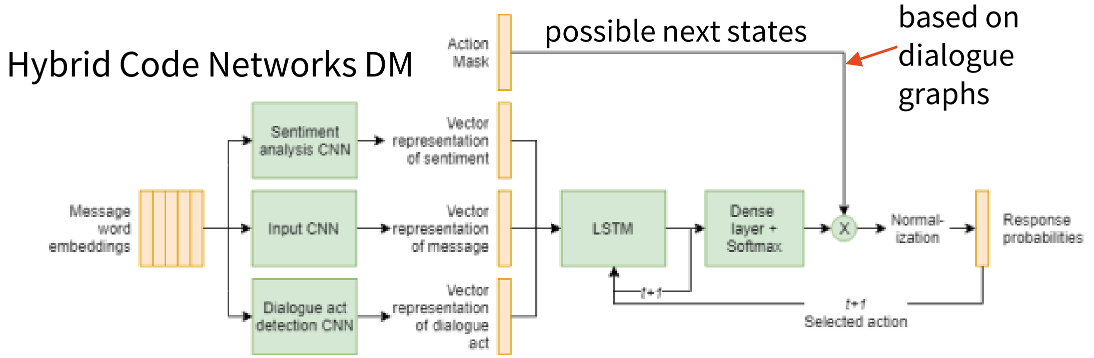


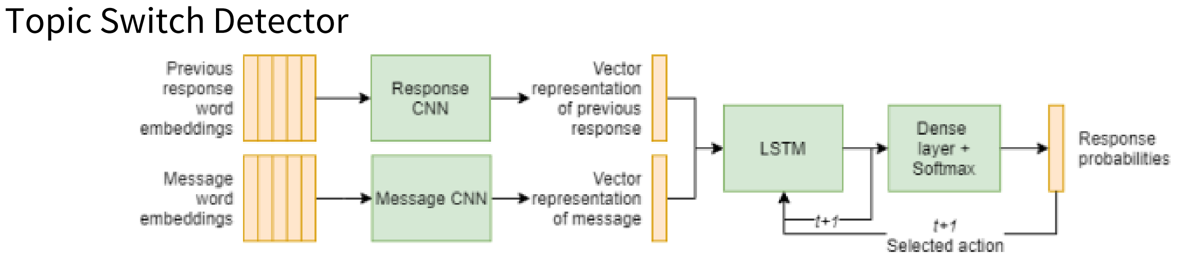
http://arxiv.org/abs/1712.07558
http://dex-microsites-prod.s3.amazonaws.com/alexaprize/2018/papers/Alana.pdf

Alquist (Czech Technical University, 2017&2018 2nd)

ALQUIST

- full NLU pipeline (similar to Alana)
- 2017 – handcrafted state machines
  - traversing sub-dialogue graphs
    - dividing for easier maintenance
  - well scripted
    - easy to break, but users play along
    - hand-added variation
- 2018 – adding machine learning
  - Hybrid Code Networks
    - RNN-based dialogue management
    - for each sub-dialogue/topic
  - topic switch detector
    - RNN-based architecture similar to HCN





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http://alexaprize.s3.amazonaws.com/2017/technical-article/alquist.pdf
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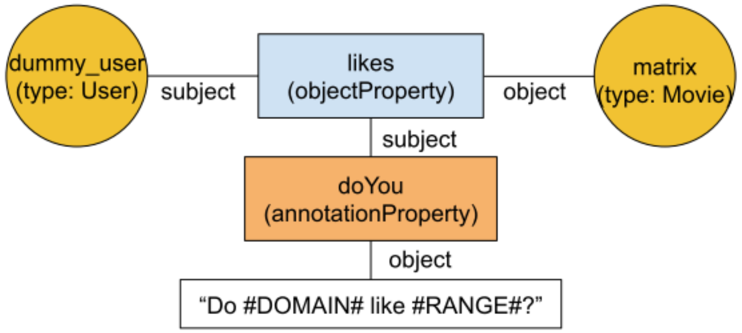
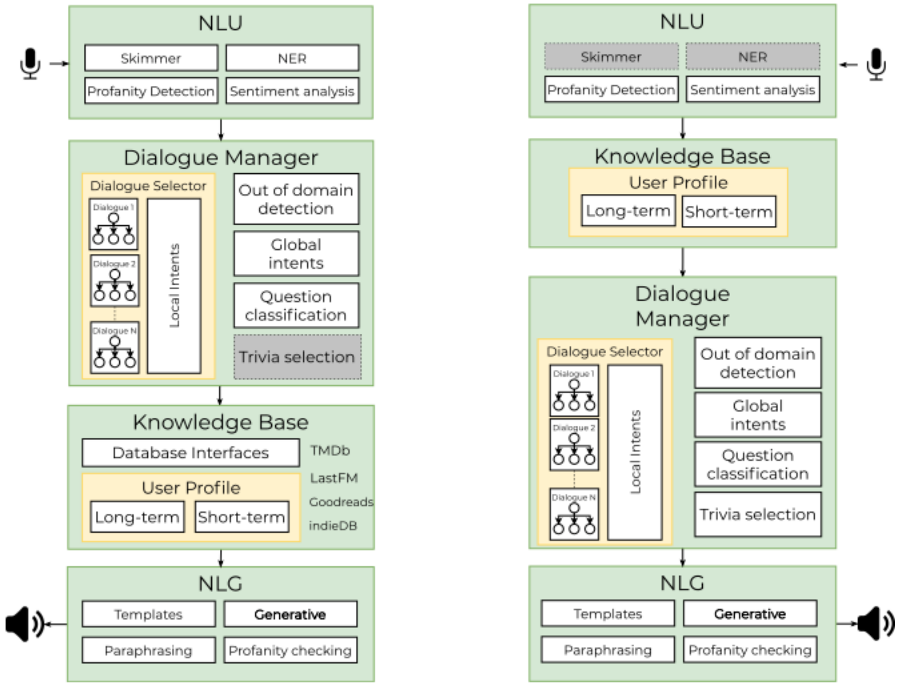
Alquist (Czech Technical University, 19/20 3rd, 20/21 1st)

(Pichl et al., 2020) https://arxiv.org/abs/2011.03261
(Konrád et al., 2021) https://arxiv.org/abs/2109.07968

- Knowledge graph: Wikidata + User + Bot model
  - RDF triples, partially delexicalized
  - allows building user profile + referencing it
- NLU – BERT-based segmenting (multiple intents)
  - produce responses to all, then select
- DM/NLG – response based on "adjacency pairs"
  - predefined input-response pairs/sub-graphs
  - transition depends on KG search
  - adding prompts (questions, fun facts etc.)
- Out-of-domain: detection & DialoGPT response
  - DialogRPT reranker
- Exploration vs. exploitation
  - first get to know user, then use this information





(a) Exploration flow

(b) Exploitation flow

Alexa Prize bottom line

- understanding is the bottleneck
  - ASR problems – chat-specific ASR improved things, but it's by far not perfect
  - vague concept of dialogue state, despite full NLP pipelines
    - result: typically very crude intents + list of named entities
  - recognizing multiple/fine-grained intents is a problem
- it's still more about social engineering than "AI"
  - a lot of strategies for not-understanding (switching topics, questions…)
- machine learning helps, but pure ML is not enough
  - lack of annotated data → often relatively simple methods
  - ML helps mainly in NLU, end-to-end seq2seq doesn't work well
- interesting content is crucial
  - the more handcrafted topics, the better
  - fluent NLG not so much (but prosody helps!)
- brutal variance in the evaluation – very subjective

Summary

- chatbots = **non-task oriented** systems
  - targets: **conversation length** & **user engagement**
  - impersonating a human – Turing test
- approaches:
  - **rule-based** – keyword spotting, scripting
  - **retrieval** – copy & paste from large databases
  - **generative** – seq2seq/transformer trained on corpora of dialogues
    - too many possible responses don't go well with MLE → safe, short, dull
    - many extensions: personality, coherence, diversity, retrieval-augmented, RLHF
  - **hybrid** – combining all of the above
- open-domain NLU is still an unsolved problem
  - despite that, many people enjoy conversations with chatbots
  - interesting content is crucial

Thanks

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Skype/Meet/Zoom (by agreement)

Labs in 10 mins
5th assignment

Get these slides here:

http://ufal.cz/npfl099

References/Inspiration/Further:

- Mainly individual papers referenced directly on slides
- Ram et al. (2018): Conversational AI: The Science Behind the Alexa Prize https://arxiv.org/abs/1801.03604
- Khatri et al. (2018): Advancing the State of the Art in Open Domain Dialog Systems through the Alexa Prize https://arxiv.org/abs/1812.10757
- Shum et al. (2018): From Eliza to XiaoIce: Challenges and Opportunities with Social Chatbots https://link.springer.com/article/10.1631/FITEE.1700826
- Vlahos (2018): Inside the Alexa Prize https://www.wired.com/story/inside-amazon-alexa-prize/
- Wikipedia: AIML Chatbot Cleverbot ELIZA Jabberwacky Loebner_Prize Mitsuku PARRY Turing_test Xiaoice Zo_(bot)