

NPFL123 Dialogue Systems
12. Chatbots
(non-task-oriented dialogue)

<https://ufal.cz/npfl123>

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18. 5. 2021



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unless otherwise stated

Chatbots / Chatterbots

- dialogue systems for **open-domain** dialogue / chitchat
- **non-task-oriented**
 - main goal: keep the user entertained
 - standard evaluation: conversation length, user engagement
- (more or less) different architecture
 - may have the same structure as task oriented (NLU → DM → NLG)
 - often simpler, integrated
 - it's hard to have explicit NLU for open domain
 - no task to guide a meaning formalism
 - some of them don't need a DB connection (but some use it)
- beware: anything is called chatbots nowadays
 - this lecture: only **chatterbots / non-task-oriented systems**

Chatbot tests

- **Turing test (1950)**

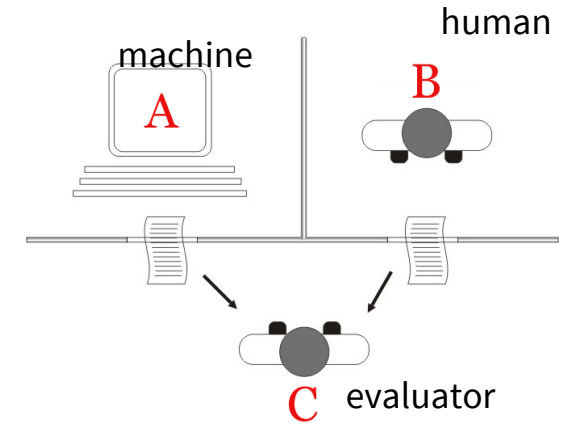
- evaluator & 2 conversations, with a machine & human, text-only
- needs to tell which is which
- does not concern what/if the machine thinks, only how it acts → can be (and is!) gamed

- **Loebner Prize (1990+)**

- Turing test style, first topic-restricted, 1995+ unrestricted
- time-limited (currently 25 minutes for both conversations)
- criticized as publicity stunt – creates hype but no real progress

- **Amazon Alexa Prize (2017+)**

- 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”

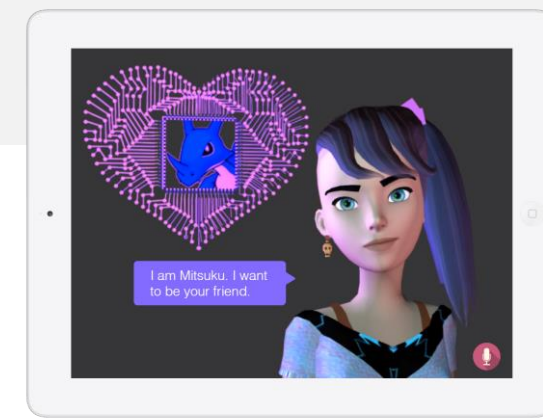


Chatbot history

- 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

Notable/hyped chatbots

- **Pandorabots/AIML** – framework for rule-based chatbots
 - A.L.I.C.E. bot – basic implementation, ~better Eliza
 - people can reuse & add their own personality
 - Mitsuku (2013+) – multiple times Loebner Prize winner
- **Jabberwacky/Cleverbot** (1997+)
 - attempts to learn from users
 - remembers & reuses past conversations (>100M)
 - also won Loebner Prize multiple times
- **Xiaolce** (2014+)
 - Microsoft-created, mainly Chinese (English: Tay/Zo, Japanese: Rinna)
 - on social networks (mainly Weibo)
 - also learns from users & reuses user inputs
 - partly rule-based, focus on emotions
 - a lot of people bonding with “her”



<https://home.pandorabots.com/home.html>



<https://www.cleverbot.com/>



<https://www.zo.ai/>
<https://www.facebook.com/zo/>

<https://youtu.be/z3jqlGT-kmg>
<http://nautil.us/issue/33/attraction/your-next-new-best-friend-might-be-a-robot>

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

- **Data-driven**

- **retrieval** – remember a corpus & get replies from there
 - “nearest neighbour” approaches
 - corpus can contain past conversations with users (Jaberwacky/XiaoIce)
 - 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)

```
Welcome to
EEEEEE LL      IIII ZZZZZZZ AAAAA
EE      LL      II      ZZ      AA  AA
EEEEEE LL      II      ZZZ      AAAAAAA
EE      LL      II      ZZ      AA  AA
EEEEEE LLLLLL IIII ZZZZZZZ AA  AA

Eliza is a mock Rogerian psychotherapist.
The original program was described by Joseph Weizenbaum in 1966.
This implementation by Norbert Landsteiner 2005.

ELIZA: Is something troubling you ?
YOU:   Men are all alike.
ELIZA: What is the connection, do you suppose ?
YOU:   They're always bugging us about something or other.
ELIZA: Can you think of a specific example ?
YOU:   Well, my boyfriend made me come here.
ELIZA: Is it important to you that your boyfriend made you come here ?
YOU:   He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.
YOU:   It's true. I am unhappy.
ELIZA: Can you explain what made you unhappy ?
YOU:   █
```

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

AIML (Pandorabots rules)

- XML-based markup language for chatbots
 - keyword spotting, not much smarter than Eliza
 - less powerful than regular expressions 😊
- main concepts:
 - **category** – basic unit of knowledge
 - groups patterns & templates
 - **pattern** – user input pattern (with wildcards)
 - **set** – lists of things of the same type
 - e.g. animals, musical instruments
 - can be used in patterns
 - **template** – response specification
 - allows multiple options
 - **srai** – symbolic reduction
 - used in patterns to redirect to another pattern
 - groups synonymous inputs
 - **variable** – can be set/retrieved in templates
 - e.g. remember user name

normalization is typically applied during preprocessing

```
<category><pattern>WHY DO NOT YOU ^</pattern>
<template><random>
<li>It's not something I've considered before.</li>
<li>Would you?</li>
<li>Is it fun, or dangerous?</li>
<li>I don't have an explanation for you.</li>
</random></template>
</category>
```

0/more words

multiple options chosen at random

```
<category><pattern>HOW DO YOU LIKE # EGGS #</pattern>
<template><srai>DIET</srai></template>
</category>
<category><pattern>YOU EAT *</pattern>
<template><srai>DIET</srai></template>
</category>
```

2 categories reduced via srai to the same pattern

0/more words (higher priority match)

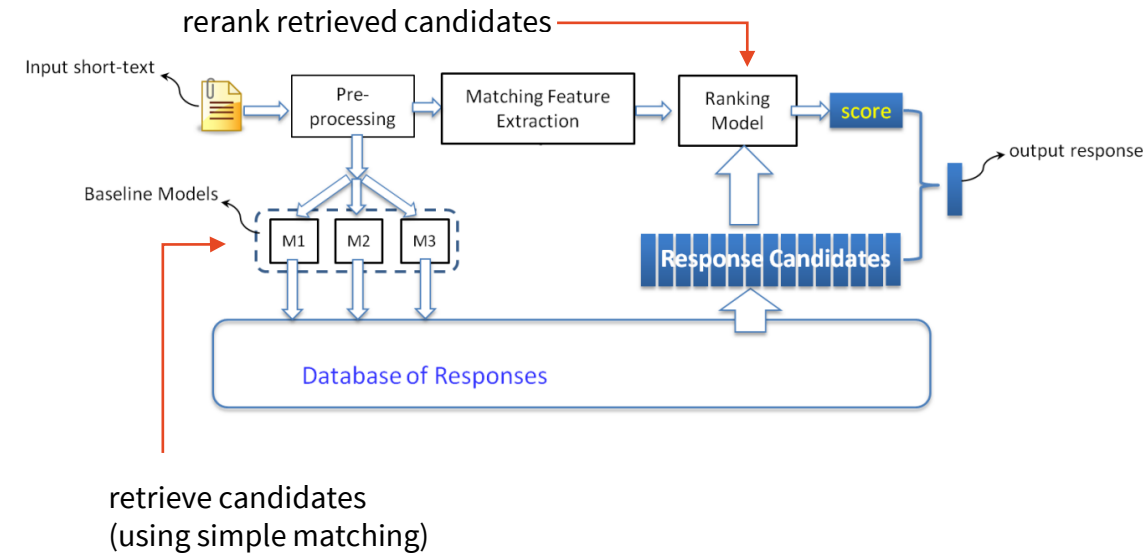
1/more words

```
<category><pattern>DIET</pattern>
<template>My diet consists mostly of <bot name="diet"/>.</template>
</category>
```

using a variable

Retrieval-based chatbots

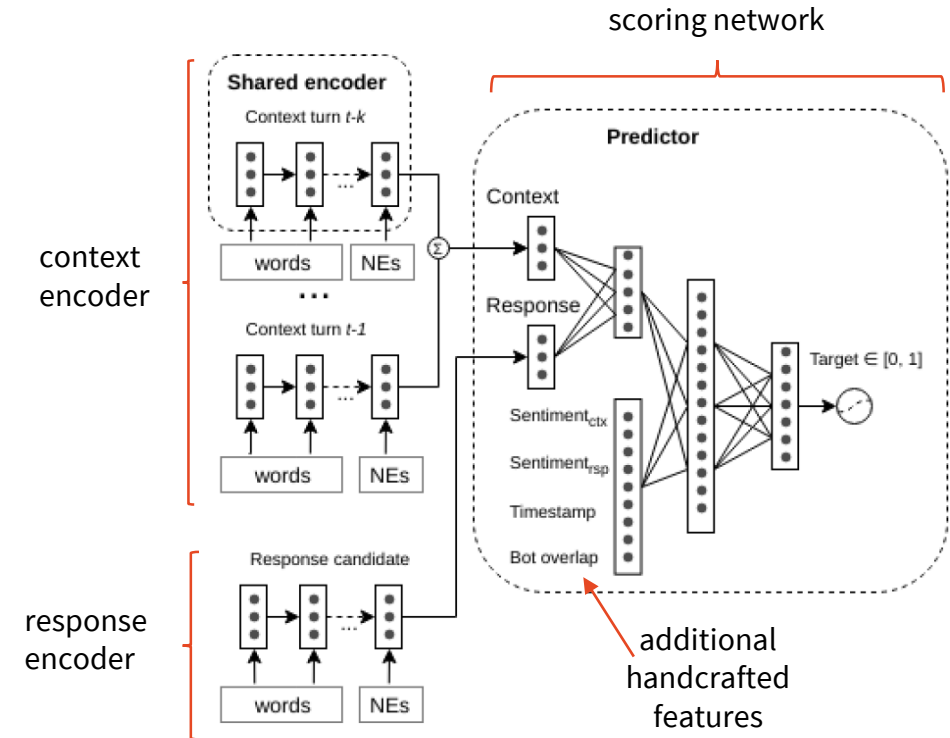
- remember a large corpus
 - 1) check for similar inputs in the corpus
 - 2) retrieve & rerank corresponding outputs
- needs 2 steps
 - 1) **rough retrieval**
 - needs to be fast to search the whole corpus
 - e.g. TF-IDF
 - 2) more accurate **reranking** for candidates
 - most research focuses on this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



(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 = $P(\text{good})$
 - **pairwise**: just learn to rank good > bad
 - incur loss for inversions
 - architecture – anything possible
 - typical neural: **dual encoder**
 - 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>

- Early generative approach – convert to **phrase-based MT**

- 1) **align phrases** in inputs & responses

- build **phrase table**

- 2) **build responses by covering input**

- cover each phrase in input with likely response phrase
 - order & select phrases according to a language model (n-gram LM)

- it's harder than MT

- possible responses are much more variable than possible translations

- using more sensitive phrase building (occurrence correlation)
 - discouraging input repetition (← would be vanilla MT behaviour)

- works, but...

- fluency is not ideal
 - limited context

U: *i want to go to a bonfire right about now.*

S: *that does sound fun bonfire i wan na go !*

U: *riding to the arc on my bike. Hopefully I won't melt into the pavement.*

S: *good luck on your bike ride arc*

U: *I really hate watching movies in the living room.*

S: *me too , what movies are you doing in room ?*

what	.	.	.	■	■
time	.	.	.	■	■
u	■
get	.	■	.	.	.
out	.	.	■	.	.
?
	i	get	off	at	s

Source	Target
rt [retweet]	thanks for the
potter	harry
ice	cream
how are you	you ?
good	morning
chuck	norris
watching	movie
i miss	miss you too
are you	i 'm
my birthday	happy birthday
wish me luck	good luck
how was	it was
miss you	i miss
swine	flu
i love you	love you too
how are	are you ?
did you	i did
jackson	michael
how are you	i 'm good
michael	mj

Using RNN LMs (still MT-inspired)

- Non-LSTM solution:

(Sordoni et al., 2015)
<https://www.aclweb.org/anthology/N15-1020>

- a) Vanilla **RNN LM, force-decode** input, decode response

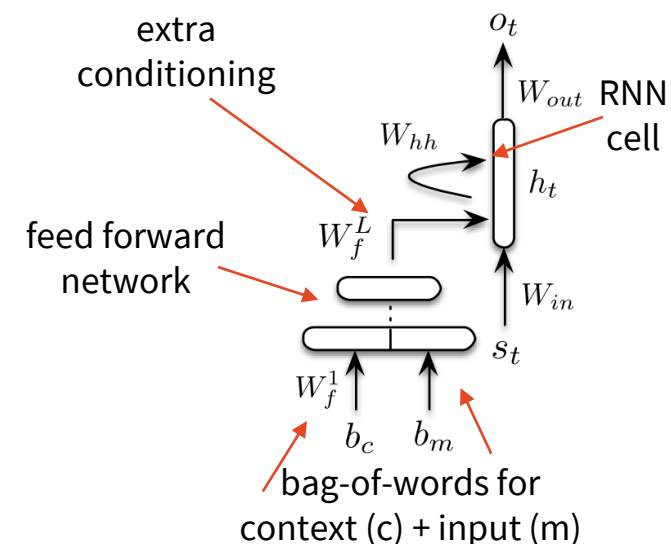
- problem: conditioned too loosely

- b) LM with **extra conditioning**

- encode input into a fixed vector (using bag-of-words + feed-forward)
 - inject it into each LM decode step
 - more fluent than phrase-based, problems with long replies
 - long replies get less fluent & wander off-topic

- Vanilla **Seq2seq** model

- encode input, decode response
 - sounds great, but... (→)



C[S]: *nothin much, and how's the book?!*
U: *its good but i'm only like halfway through cuz i don't feel like reading. i'm so bored ...*
S: *that's good! i have the book but i'm bored too.*

C[S]: *thanks. yeah i am good thanks! good, but angry!*
U: *sorry you're angry, been there, i hope it dies down.*
S: *i hope so too, i'm not angry!!*

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 .*

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

Seq2seq Chatbot Problems

- **generic/dull responses**

- short, low-entropy, repetitive
- see phrase-based model: too many possible outputs
 - 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

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

(Li et al., 2016)

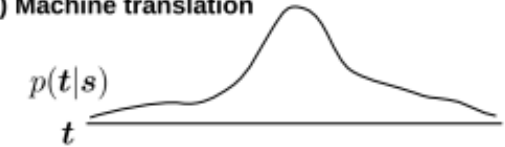
<https://www.aclweb.org/anthology/P16-1094>

(Wei et al., 2019)

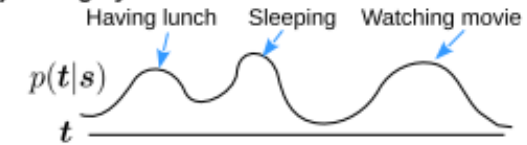
<https://arxiv.org/abs/1712.02250>

<https://ieeexplore.ieee.org/document/8682634>

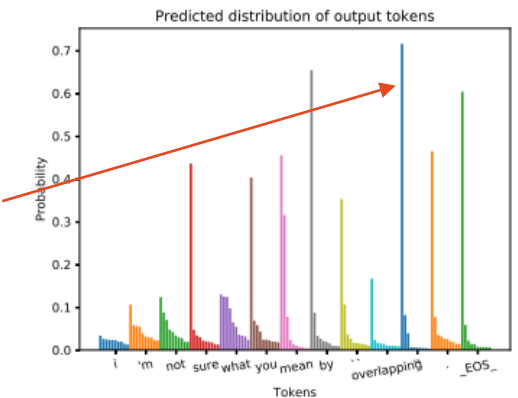
(a) Machine translation



(b) Dialog systems



highest probs. grow



(Jiang & De Rijke, 2018)

<https://www.aclweb.org/anthology/W18-5712>

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 upon Seq2seq

• Reranking

- avoid dull replies that work anywhere
- instead of maximizing $P(R|C)$, 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>

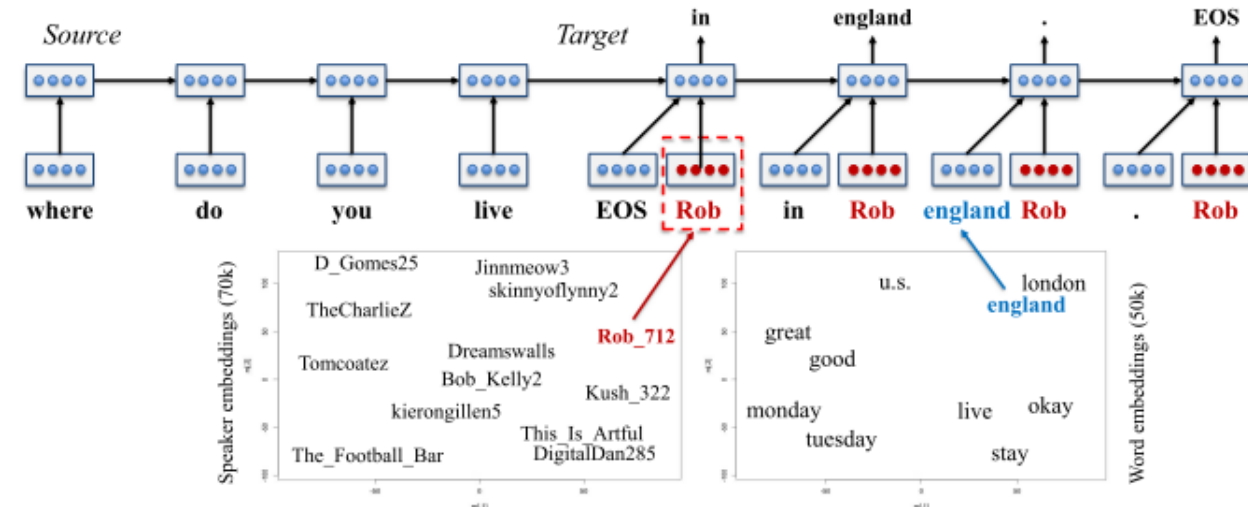
Input: what is your name?	
-0.91	I don't know. ...
-0.92	I don't know! -1.55 My name is Robert.
-0.92	I don't know, sir. -1.58 My name is John.
-0.97	Oh, my god! -1.59 My name's John.

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

C = context
 R = reply

• Persona extension

- improve consistency
- train speaker embeddings
 - this is a little data-picky
- use speaker + word embeddings in the decoder
 - can also be used in the encoder



(Li et al., 2016)

<https://www.aclweb.org/anthology/P16-1094>

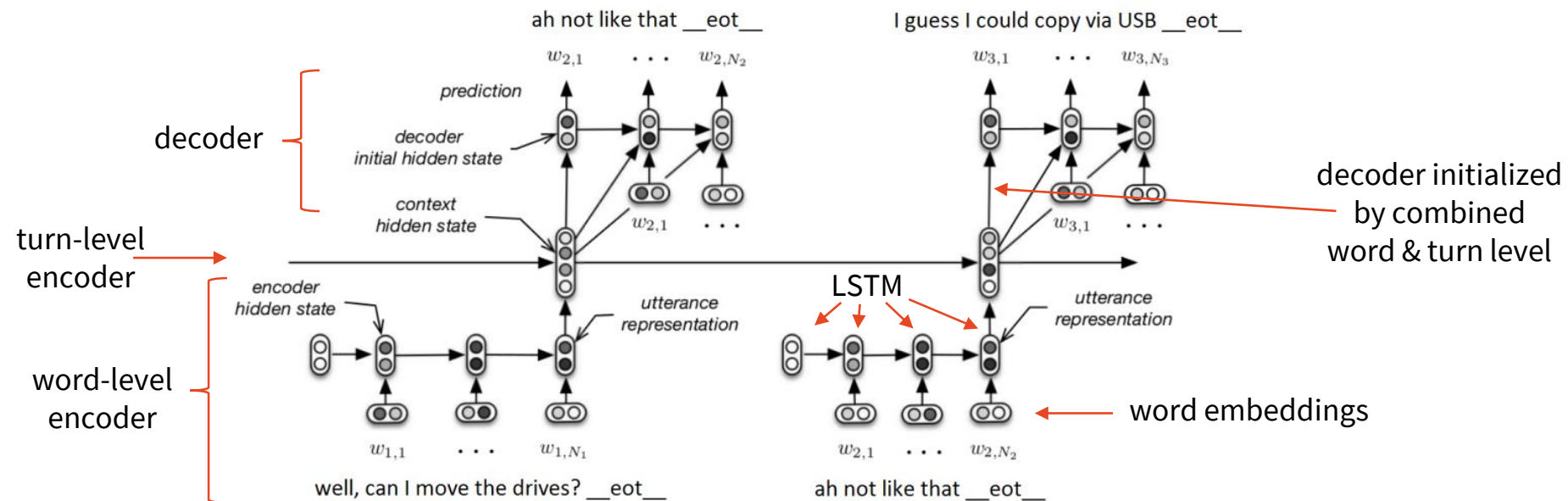
Improving upon Seq2seq

- **Hierarchical seq2seq** for longer context

(Lowe et al., 2017)

<http://dad.uni-bielefeld.de/index.php/dad/article/view/3698>

- HRED (Hierarchical Recurrent Encoder-Decoder)
- use a 2nd, turn-level LSTM encoder, word-level LSTM hidden state as input



- **Pretrained Transformer** models (TransferTransfo, DialoGPT)

(Wolf et al., 2018)

<https://arxiv.org/abs/1901.08149>

- large networks, trained on many dialogues

(Zhang et al., 2020)

<https://www.aclweb.org/anthology/2020.acl-demos.30>

- It's still an open (&active!) research topic!

Hybrid / Ensemble Chatbots (most Alexa Prize Entries)

- State-of-the-art today: **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 only as a backoff or not at all
- NLU is typically shared, with advanced NLP pipelines
 - NER is very important – can get relevant news & trivia
- Decision among bots
 - a) based on NLU topic detection
 - b) ranking multiple answers
 - profanity detection – censoring outputs

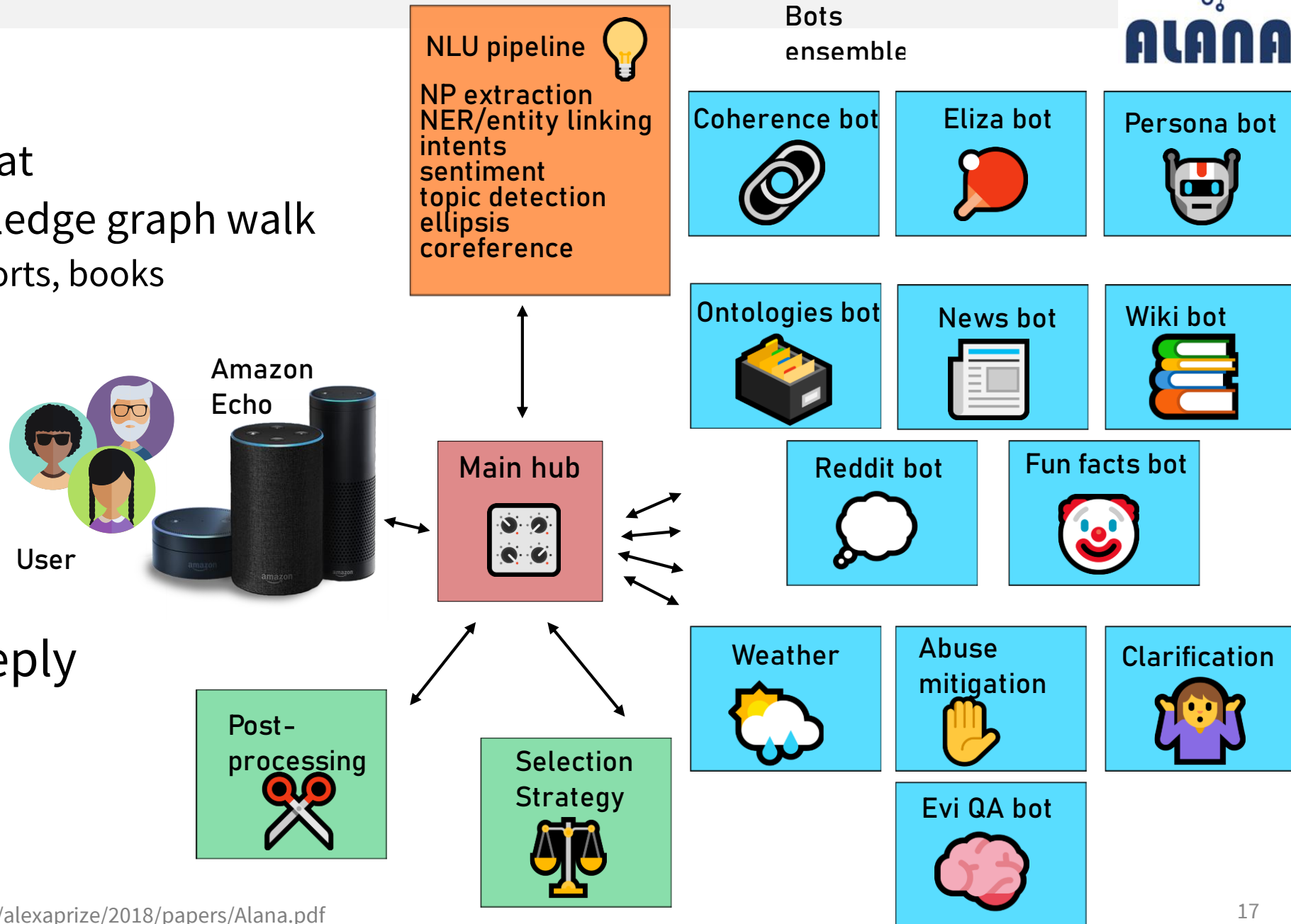


ALANA

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>

Alana Example dialogue

coherence: stay on topic
& ask further questions



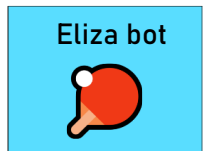
Alana: Welcome back then John. Since I remember that you like movies, [...] What movie are you looking forward to watching?

User: Vanilla Sky -> I'm looking forward to watching Vanilla Sky **[Ellipsis resolution]**



Alana: Oh I heard something interesting about Vanilla Sky. [... **Movie trivia**] Speaking of movies. What actors do you like? I like Leonardo DiCaprio [...]

User: Interesting



Alana: I just think the world is full of strange and unexpected things like that. So, talking about movies, What famous actor or actress would you like to meet? [...]

User: I want to talk about music



Alana: So, talking about music. Who is a singer that you like? I really like Taylor Swift [...]

User: Kendrick Lamar



Alana: Yes. One of my friends once told me something interesting about Kendrick Lamar. [... **Music trivia**] What's a band that you would like to see? [...]

User: any news about him -> any news about Kendrick Lamar **[Coreference resolution]**

Alana Example dialogue

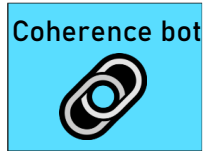
user model:
name + preferred topics



News bot

Alana: Hmm... about Kendrick Lamar, so John, I read a story with this headline [... **News headline**] Shall I say some more about this?

User: could we talk about something else



Coherence bot

Alana: So John, since I know you like books, what have you read recently? I am reading [...]

User: Let's talk about Tom Hardy



Clarification

Alana: Oh I know Tom Hardy. Do you mean Tom Hardy the English actor, screenwriter and producer or Thomas Hardy the English novelist and poet?

User: I mean the novelist



Ontologies bot

Alana: Yes. Some friends told me something interesting about Thomas Hardy. [... **Trivia**]

User: What do you know about pizza?

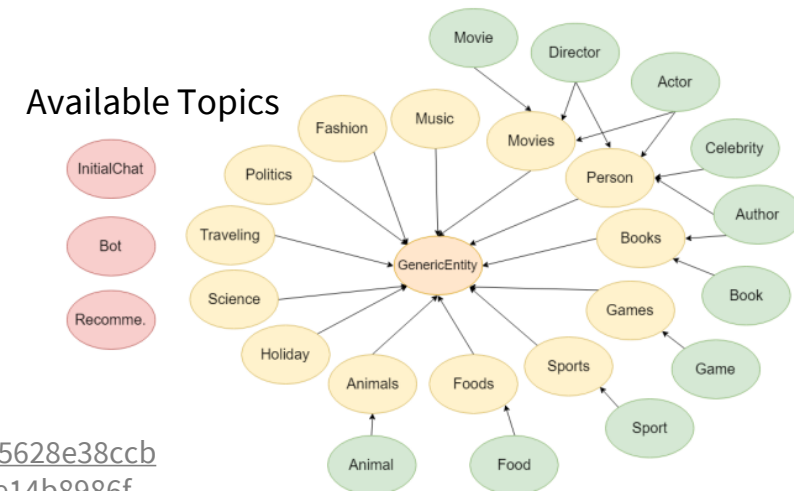
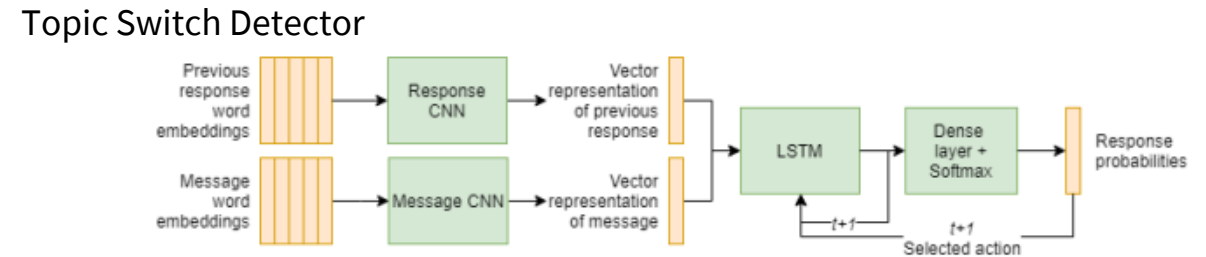
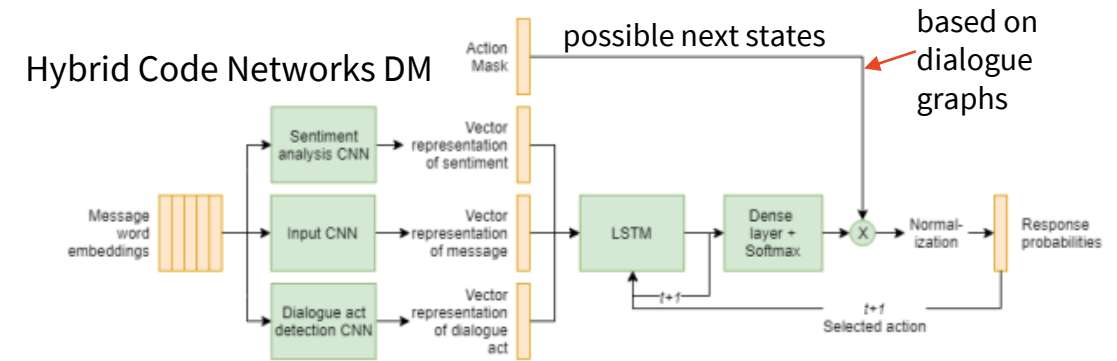


Reddit bot

Alana: I was thinking that whenever a pizza commercial has stretchy melty cheese, it looks good and appealing, but when it happens in real life it's annoying and messy.

bot personality

- 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



<http://alexaprize.s3.amazonaws.com/2017/technical-article/alquist.pdf>
<http://dex-microsites-prod.s3.amazonaws.com/alexaprize/2018/papers/Alquist.pdf>
<https://chatbotmagazine.com/13-lessons-we-have-to-learn-from-amazon-alexa-prize-965628e38ccb>
<https://towardsdatascience.com/11-more-lessons-we-have-to-learn-from-alexa-prize-94fe14b8986f>

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

Turn	User	Sounding Board
1	Let's chat	Hi! This is an Alexa Prize socialbot. How's your day?
2	I'm five.	Glad to hear it! We could talk about robots, Batman, or Superman. Say "next", to chat about other things.
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?
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"
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.
6	Yes, it was hilarious.	I'm glad you feel this is hilarious. Which part do you like best about this movie?
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?

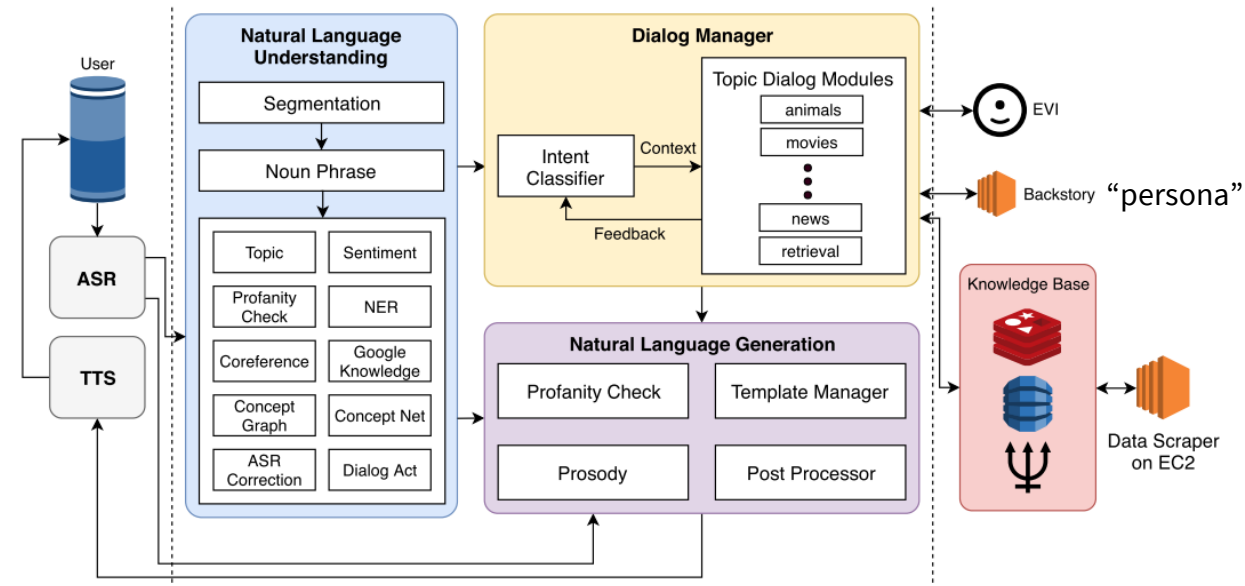
<http://arxiv.org/abs/1804.10202>

<https://s3.amazonaws.com/alexaprize/2017/technical-article/soundingboard.pdf>

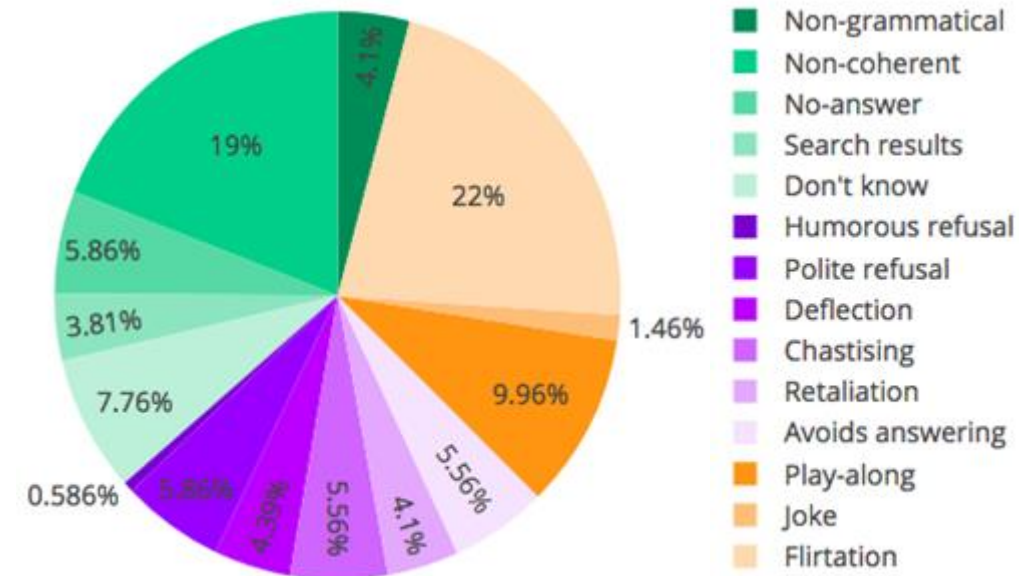
<https://sounding-board.github.io/>

Gunrock (UC Davis, 2018 winner)

- Improving ASR
 - error correction – KB fuzzy matching (allow for “typos”)
 - sentence segmentation (RNN-based)
- NLU – keyphrase extraction
 - focus on noun phrases
- Dialog manager – stack
 - return to previous topics
 - related topics
 - a lot of different topics with domain-specific KBs
 - games, psychology, travel...



- Ca. 4% of our 2017 data is sexually explicit
- Different harassment types:
 - comments on gender/sexuality
 - sexualized comments
 - sexualized insults
 - sexual requests & demands
- Chatbots/voice assistants' responses
 - various systems:
 - commercial (Alexa, Google...)
 - rule-based (Pandorabots, adult chatbots)
 - data-driven (seq2seq)
 - systems often present as women, have a woman's voice
 - responses often nonsense / play-along
 - conflict of interest for bot builders: be ethical vs. cater to abusive users



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
- 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
 - purely for user enjoyment
 - targets: **conversation length & user engagement**
 - impersonating a human – Turing test
- approaches
 - **rule-based** – keyword spotting, scripting
 - **retrieval** – copy & paste from large databases
 - **generative** – seq2seq etc. trained on corpora of dialogues
 - too many possible responses don't go well with MLE → safe, short, dull
 - **hybrid** – combining all of the above
 - typically mainly rule-based + retrieval, machine learning in NLU only
- open-domain NLU is still an unsolved problem
 - despite that, many people enjoy conversations with chatbots
 - interesting content is crucial

Thanks

Contact us:

<https://ufaldsg.slack.com/>
{odusek,hudecek}@ufal.mff.cuni.cz
Skype/Meet/Zoom (by agreement)

Get these slides here:

<http://ufal.cz/npfl123>

References/Inspiration/Further:

- 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 Xiaolce: 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 \(bot\)](#)

This is the Last Lecture

Next week:

Lab questions 9am

Exam

- Written test, 10 questions, 10 points each
 - 50%+ lab exercise points required
 - expected 1 hr, but you'll be given at least 2hrs (no pressure on time)
- Questions covering the 12 lectures
 - question pool coming soon
 - you'll need to write stuff on your own (not a-b-c-d, more like 2-3 sentences)
 - explanation of terms/concepts
 - no exact formulas needed (if needed, they might be provided)
 - but you should know the principles of how stuff works
 - relationships between concepts (“what’s the difference between X & Y”)
 - designing a dialogue system for a domain
 - focus on important stuff (mostly what’s mentioned in the summaries)
- Mark: 3:1 weighted exam-lab exercises
 - 60 % = pass (C), 73+% = B, 88+% = A