10. Chatbots
(non-task-oriented)

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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 – somewhat like end-to-end DS
  - 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* can be called chatbots nowadays
  - here: 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”
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)

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

**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>
```

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

```
<category><pattern>YOU EAT *</pattern>
<template><srai>DIET</template>
</category>
```

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

0/more words

0/more words (higher priority match)

1/more words

2 categories reduced via srai to the same pattern

multiple options chosen at random

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 (Xiaolce, 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(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
Inspiration from MT (Ritter et al., 2011)
http://www.aclweb.org/anthology/D11-1054

• 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 ?*
Using RNN LMs (still MT-inspired)

- Non-LSTM solution:
  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… (→)

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

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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: 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?

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


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

• **Reranking** (Li et al., 2016)
  
  - avoid dull replies that work anywhere
  - instead of maximizing $P(T|S)$, maximize mutual information
    - actually can be rewritten as a trade-off between $P(T|S)$ and $P(S|T)$
    - can’t train it easily, so train normally & rerank beams afterwards

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

(Lowe et al., 2017)

\[ \text{MI} = \log \frac{P(S,T)}{P(S)P(T)} \]

\[ \text{NPFL099 L10 2019} \]

\[ \text{14} \]
Diversity

- joining seq2seq (next turn generation) & autoencoding
  - multi-task learning
  - shared decoder
  - additional “fusion loss” enforcing same encoding for both tasks
- Inference: adding a little noise to produce different outputs

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

• **CVAE with a coherence measure**
  • GLoVe average embedding cosine similarity
  • training data: coherence of target response known
    • also good for data filtering
  • inference: set coherence very high: 0.95/1.0

• **GAN-style for consistent order**
  • detect if three turns are consecutive or not
    • given 1 ordered, 1 misordered triple from previous dialogue history
  • use in dialogue generation learning: good replies are easy to check for order
    • see if misorder is easy to detect with a generated reply
  • GAN: train generator to produce good replies (where misorder is easy to detect) train detector to detect misorder in real sentences, not in generated

(Xu et al., 2018)  
http://arxiv.org/abs/1809.06873
(Wu et al., 2019)  
http://arxiv.org/abs/1907.00448
Personality

• **Persona embeddings**
  - 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

• **Persona copy-net**
  - using a hierarchical pointer-generator net
  - context includes short personal bio

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

(Yavuz et al., 2019)
https://www.aclweb.org/anthology/W19-5917/
Hybrid / Ensemble Chatbots
a.k.a. 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 (2017 & 2018 3rd) (Heriot-Watt University)

- 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”

NLU pipeline
NP extraction
NER/entity linking
intents
sentiment
topic detection
ellipsis
coreference

Amazon Echo
Main hub
Selection Strategy
Post-processing

Coherence bot
Eliza bot
Persona bot

Ontologies bot
News bot
Wiki bot

Golf bot
Reddit bot
Fun facts bot

Weather
Abuse mitigation
Clarification

http://arxiv.org/abs/1712.07558
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]


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

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

Alana: So John, since I know you like books, what have you read recently? I am reading […]
User: Let's talk about Tom Hardy

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

Alana: Yes. Some friends told me something interesting about Thomas Hardy. [... Trivia]
User: What do you know about pizza?

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

- 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://alquistai.com/
https://chatbotsmagazine.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

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### 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. | Interesting, Mccarthy and Reiff 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?

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http://arxiv.org/abs/1804.10202
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…

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
  • 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
    • many extensions: personality, coherence, diversity
    • still doesn’t work very well
  • **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

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References/Inspiration/Further:
• Mainly individual papers referenced directly on slides
• Wikipedia: AIML Chatbot Cleverbot ELIZA Jabberwacky Loebner_Prize Mitsuku PARRY Turing_test Xiaoice Zo (bot)