Chatbot models, NLU & ASR

Pierre Lison

IN4080: Natural Language Processing (Fall 2020)

12.10.2020

Plan for today

- Obligatory assignment
- Chatbot models (cont'd)
- Natural Language Understanding (NLU) for dialogue systems
- Speech recognition

Plan for today

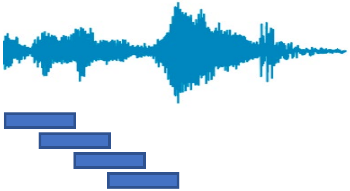
- **Obligatory assignment**
- Chatbot models (cont'd)
- Natural Language Understanding (NLU) for dialogue systems
- Speech recognition

Oblig 3

Three parts:

1. Chatbot trained on movie and TV subtitles

2. Silence detector in audio files



3. (Simulated) talking elevator

Oblig 3

- Deadline: November 6
  - Concrete delivery: **Jupyter notebook**
- Need to run version of Python with additional (Anaconda) packages
  - See obligatory assignment for details
- Computing the utterance embeddings in Part 1 requires some patience (or enough computational ressources)

Plan for today

- Obligatory assignment
- **Chatbot models (cont'd)**
- Natural Language Understanding (NLU) for dialogue systems
- Speech recognition

Chatbot models: recap

- Rule-based models:

```
if (some pattern match X on user input)
then respond Y to user
```

- IR models using cosine similarities between vectors

$$r = response\left(\underset{t \in C}{\operatorname{argmax}} \frac{q^T t}{||q|| ||t||}\right)$$

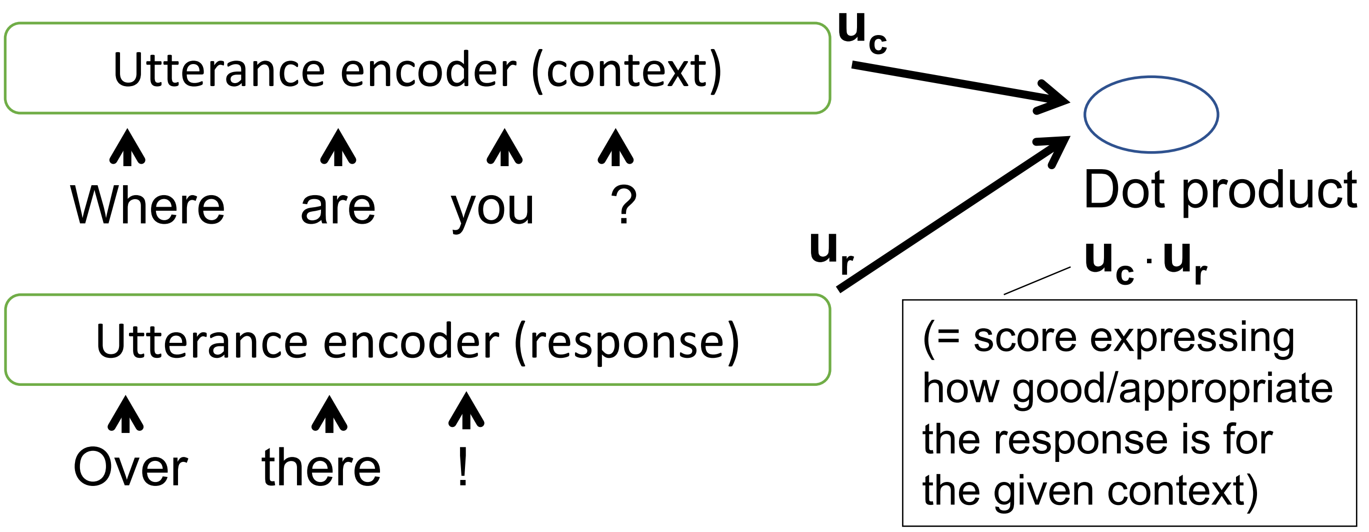
Where C is the set of utterances in dialogue corpus (in a vector representation)

and q is the user input (also in vector form)

Dual encoders

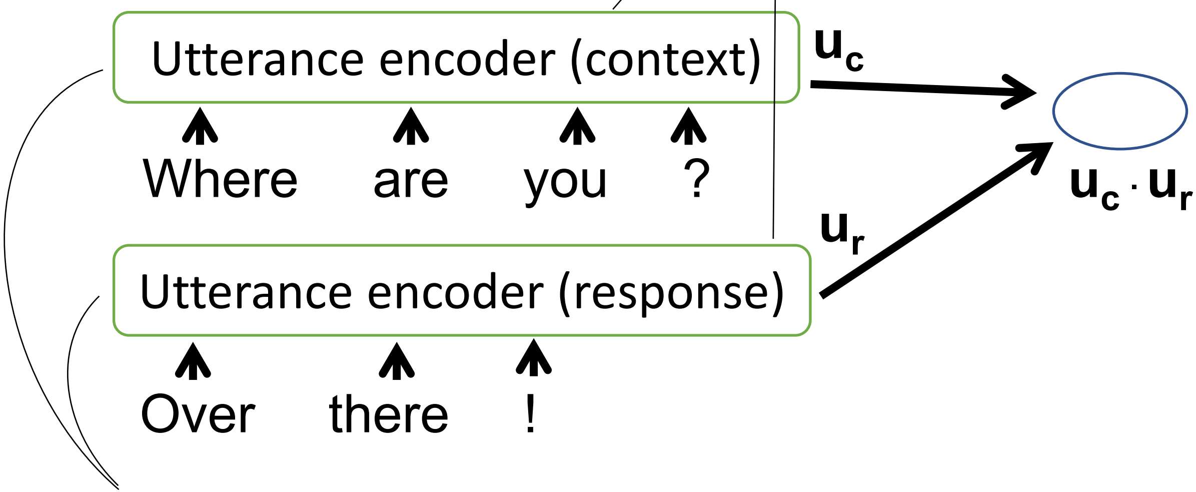
Another type of IR-based chatbots

- We compute here the dot product between the user input (called "*context*") and a possible *response*



Dual encoders

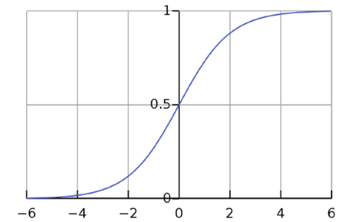
The encoders are typically deep neural networks, such as LSTMs or transformers

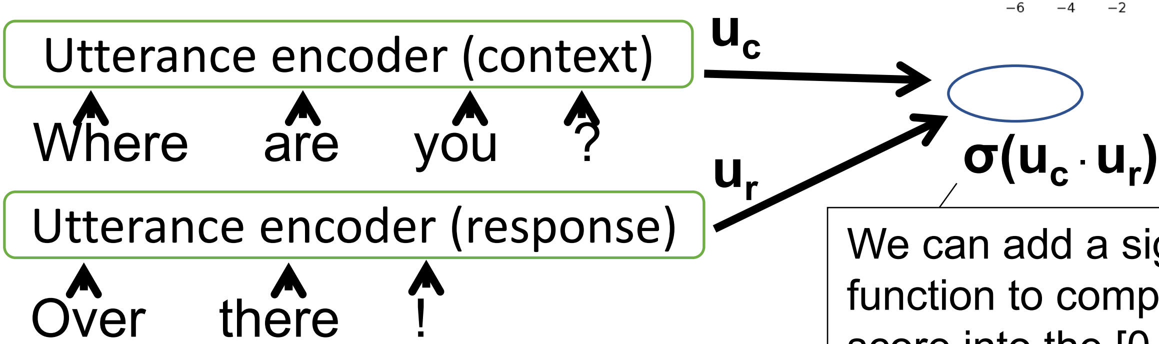


The two encoders often rely on a shared neural network, apart from a last transformation step that is specific for the context or response

Dual encoders

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



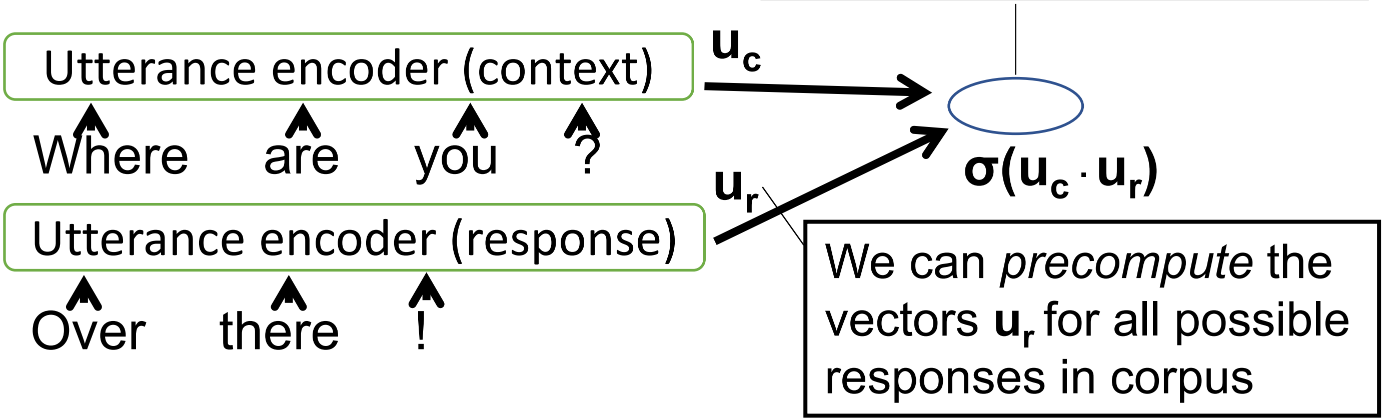


We can add a sigmoid function to compress the score into the [0,1] range

Dual encoders are trained with both *positive* and *negative* examples:

- *Positive* : actual consecutive pairs of utterances observed in the corpus → output=1
- *Negative*: random pairs of utterances → output=0

Dual encoders



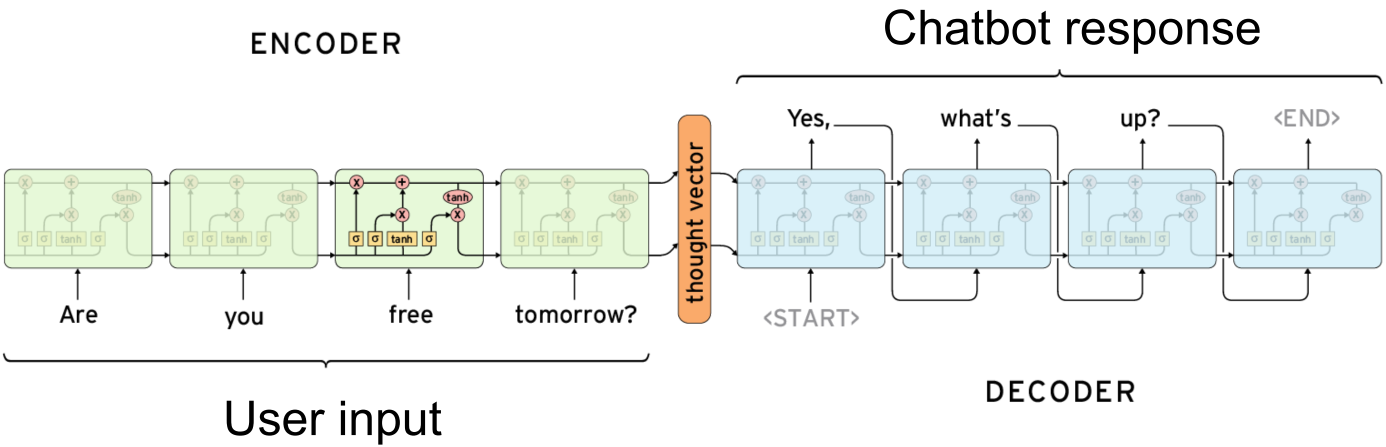
Given a new user input, we have to:

- Compute the context embeddings $\mathbf{u_c}$
- Compute its dot product with all responses
- Search for the response with max score

Seq2seq models

- Sequence-to-sequence models *generate* a response token-by-token
  - Akin to machine translation
  - Advantage: can generate «creative» responses not observed in the corpus
- Two steps:
  - First «encode» the input with e.g. an LSTM
  - Then «decode» the output token-by-token

Seq2seq models



NB: state-of-the-art seq2seq models use an attention mechanism (not shown here) above the recurrent layer

[Image borrowed from Deep Learning for Chatbots: Part 1]

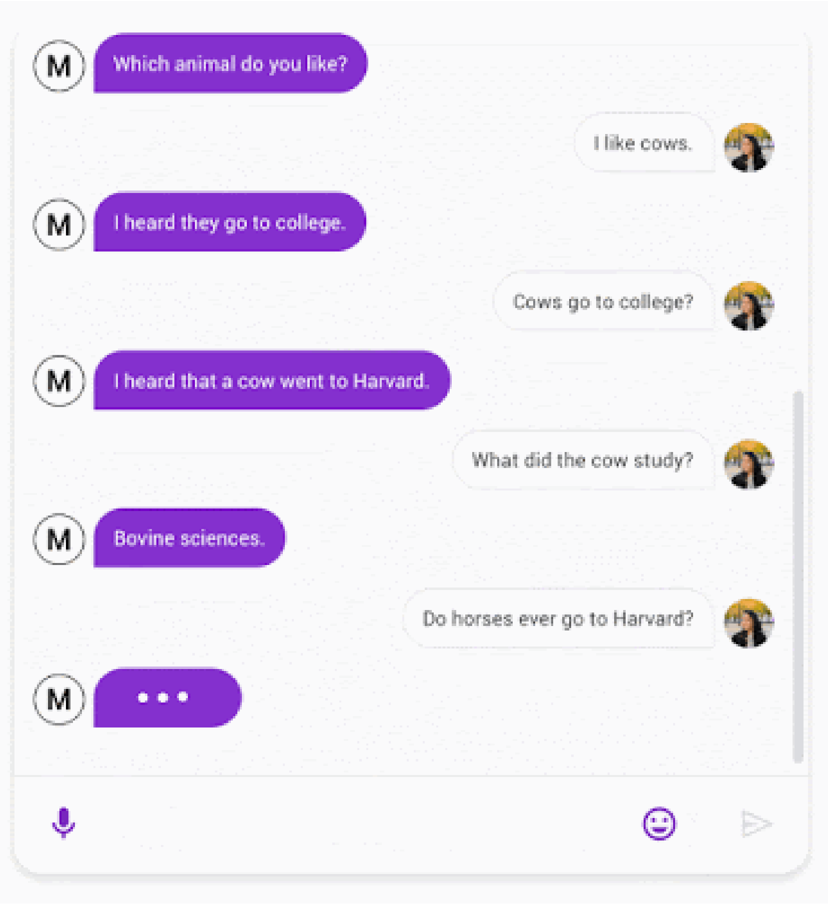
Seq2seq models

- Interesting models for dialogue research
- **But**:
  - Difficult to «control» (hard to know in advance what the system may generate)
  - Lack of diversity in the responses (often stick to generic answers: «I don't know» etc.)
  - Getting a seq2seq model that works reasonably well takes a lot of time (and tons of data)

[Li, Jiwei, et al. (2015) "A diversity-promoting objective function for neural conversation models.», ACL]

Example from Meena (Google)

2.6 billion parameters, trained on 341 GB of text (public domain social media conversations)



https://ai.googleblog.com/2020/01/towards-conversational-agent-that-can.html

Taking stock

- Rule-based chatbots

Pro: Fine-grained control on interaction

Con: Difficult to build, scale and maintain

- Corpus-based chatbots
  - IR approaches
  - Seq2seq

Pro: Easy to build, well-formed responses

Con: Can only repeat existing responses in corpus

Pro: Powerful model, can generate anything

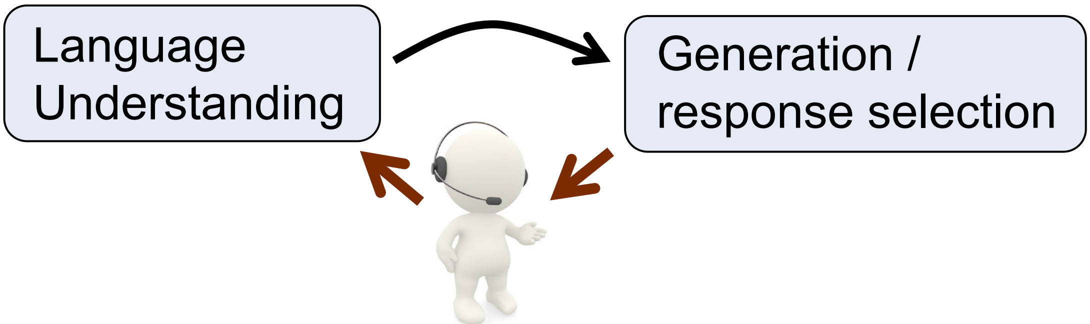
Con: Difficult to train, hard to control, needs lots of data

Corpus-based approaches seen so far often limited to chi-chat dialogues (for which we can easily crawl data)

Plan for today

- Obligatory assignment
- Chatbot models (cont'd)
- **Natural Language Understanding (NLU) for dialogue systems**
- Speech recognition

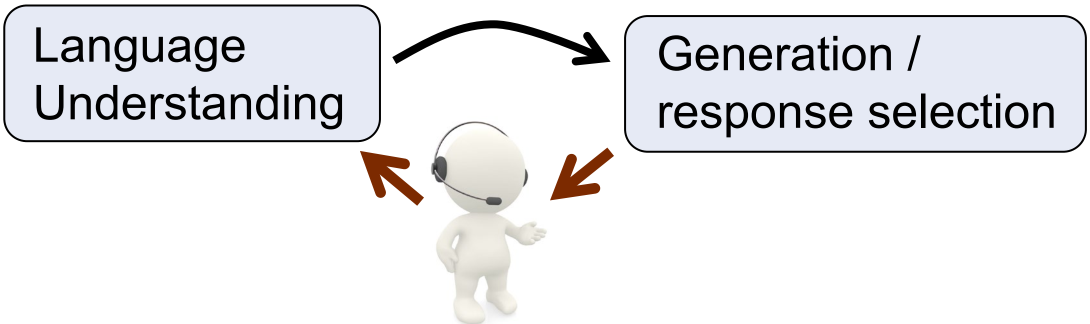
NLU-based chatbots



Can we build data-driven chatbots for task-specific interactions (not just chit-chat)?

- "Standard" case for commercial chatbots
- Typically: no available task-specific data

NLU-based chatbots

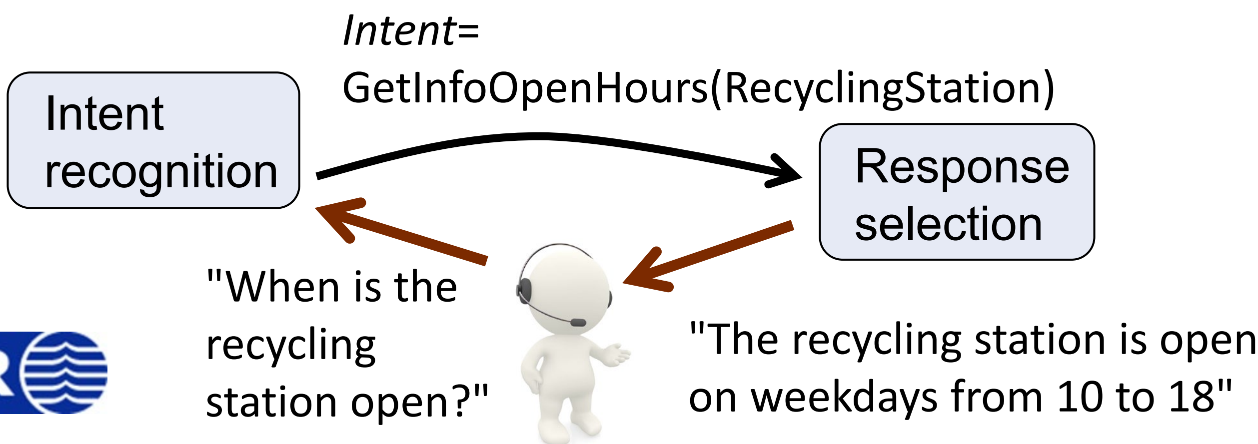


- Solution: NLU as a **classification task**
  - From a set of (predefined) possible **intents**
- Response selection generally handcrafted
  - Chatbot owners want to have full control over what the chatbot actually says

Intent recognition

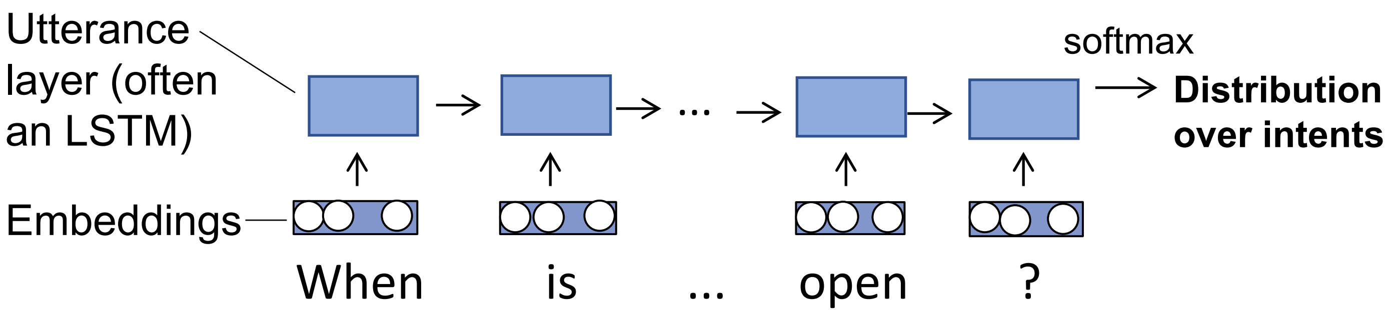
Goal: map user utterance to its most likely intent

- *Input*: sequence (of characters or tokens) + possibly preceding context
- *Output*: intent (what the user tries to accomplish)



Intent recognition

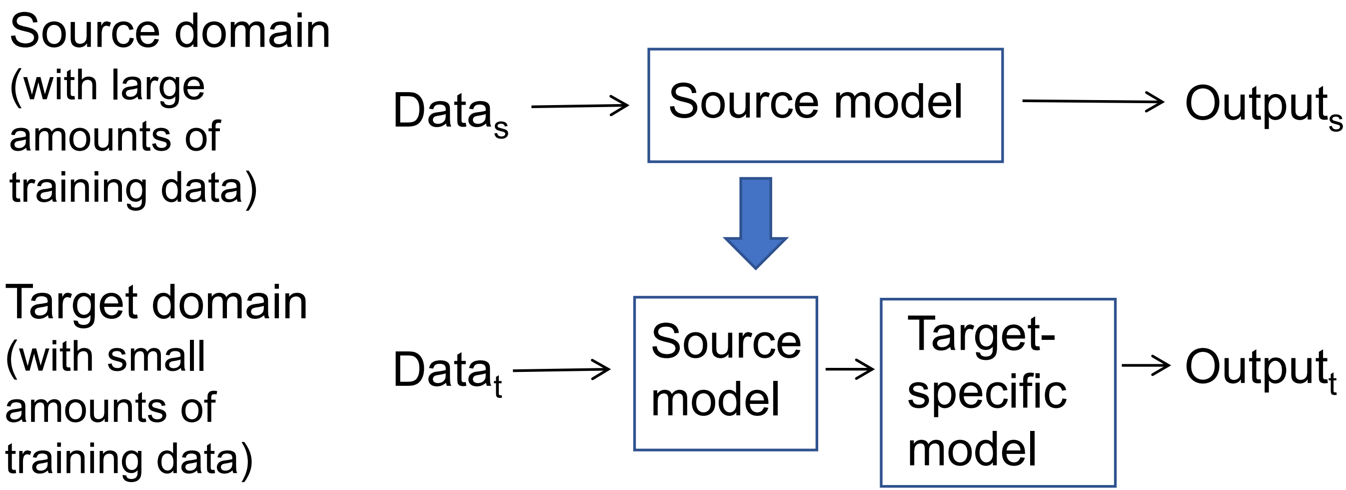
- ▶ Many possible machine learning models
  - ▪ Convolutional, recurrent, transformers, etc



- ▶ Must collect *training data*: user utterances (manually) annotated with intents
  - ▪ Often done by "chatbot trainers" in industry

Small amounts of data?

1. Use *transfer learning* to exploit models trained on related domains



Small amounts of data?

1. Use *transfer learning* to exploit models trained on related domains

2. Use *data augmentation* to generate new labelled utterances from existing ones

"**When** is the recycling station open?" → GetInfoOpenHours (RecyclingStation)

Replace with synonyms

"**At what time** is the recycling station open?" → GetInfoOpenHours (RecyclingStation)

Small amounts of data?

1. Use *transfer learning* to exploit models trained on related domains
2. Use *data augmentation* to generate more utterances from existing ones
3. Collect raw (unlabelled) utterances and use *weak supervision* to label those

[see e.g. Mallinar et al (2019), "Bootstrapping conversational agents with weak supervision", IAAI.]

Slot filling

- In addition to intents, we also sometimes need to detect specific entities ("slots"), such as mentions of places or times

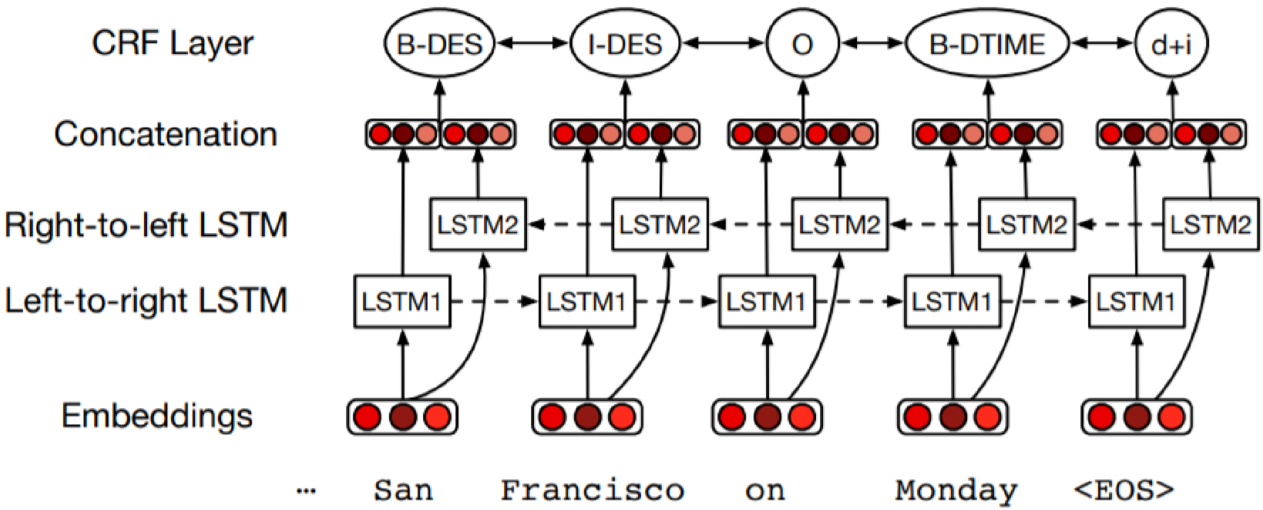
«Show me morning flights from Boston to San Francisco on Tuesday»

DOMAIN:	AIR-TRAVEL
INTENT:	SHOW-FLIGHTS
ORIGIN-CITY:	Boston
ORIGIN-DATE:	Tuesday
ORIGIN-TIME:	morning
DEST-CITY:	San Francisco

- Slots are domain-specific
  - And so are the ontologies listing all possible values for each slot

Slot filling

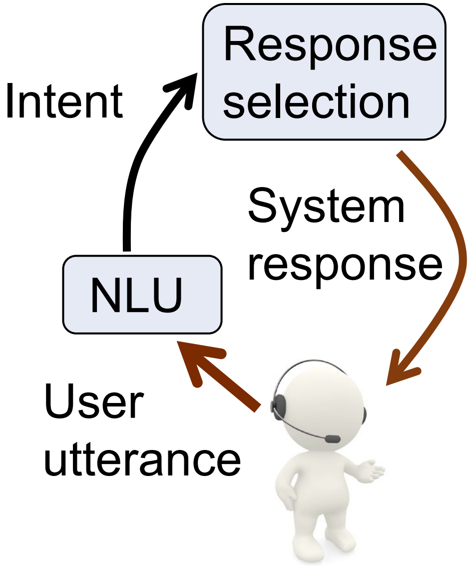
Can be framed as a *sequence labelling task* (as in NER), using e.g. **BIO** schemes



[illustration from D. Jurafsky]

Response selection

- Given an intent, how to create a response?
- In commercial systems, system responses are typically written by hand
  - Possibly in templated form, i.e. "{Place} is open from {Start-time} to {Close-time}"
- But data-driven generation methods also exists

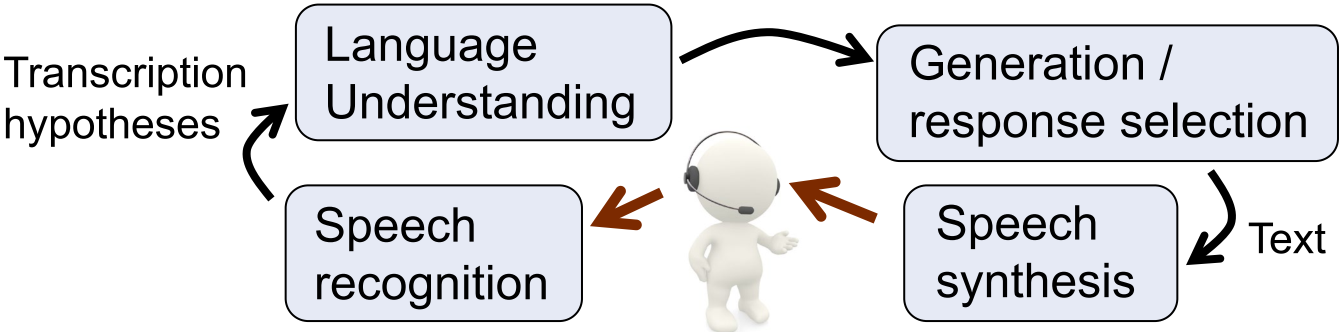


[see e.g. Garbacea & Mei (2020), "*Neural Language Generation: Formulation, Methods, and Evaluation*"]

Plan for today

- Obligatory assignment
- Chatbot models (cont'd)
- Natural Language Understanding (NLU) for dialogue systems
- **Speech recognition**

Spoken dialogue systems

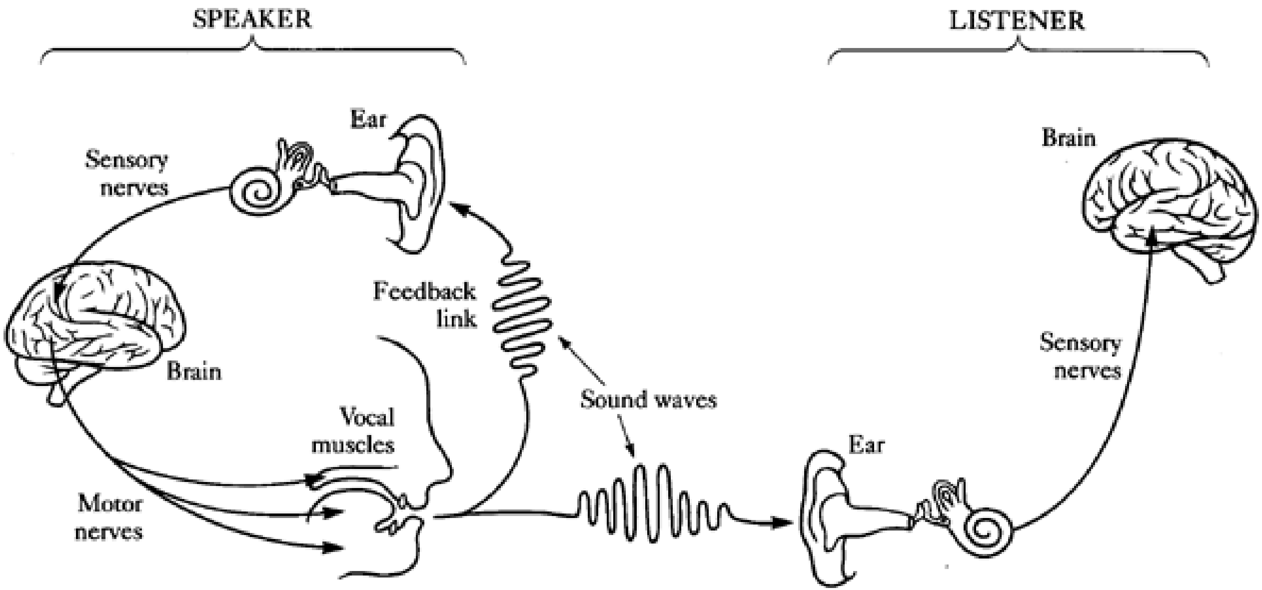


Spoken interfaces add a layer of complexity

- Need to handle uncertainties, ASR errors etc.
- Speech communicates more than just words (intonation, emotions in voice, etc.)
- Need to handle turn-taking

A difficult problem!

The speech chain



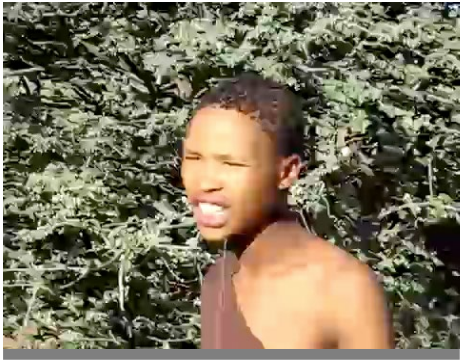
[Denes and Pinson (1993), «The speech chain»]

Speech production

- ► Sounds are *variations in air pressure*
- ► How are they produced?
  - An **air supply**: the *lungs* (we usually speak by breathing out)
  - A **sound source** setting the air in motion (e.g. vibrating) in ways relevant to speech production: the *larynx*, in which the *vocal folds* are located
  - A set of 3 **filters** modulating the sound: the *pharynx*, the *oral tract* (teeth, tongue, palate,lips, etc.) & the *nasal tract*

Speech production

Visualisation of the vocal tract via *magnetic resonance imaging* [MRI]:

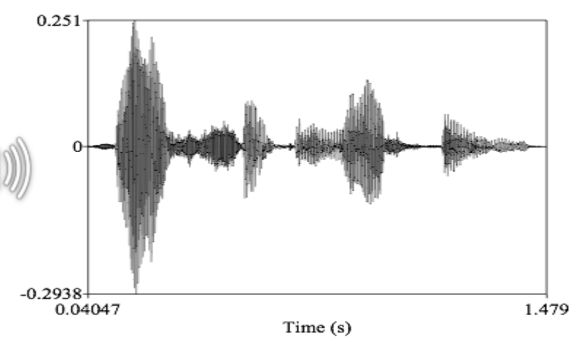


NB: A few languages also rely on sounds not produced by vibration of vocal folds, such as *click languages* (e.g. Khoisan family in south-east Africa):

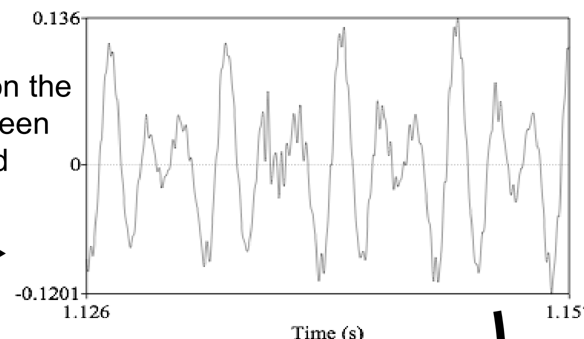
Speech perception

A (speech) sound is a variation of air pressure

- This variation originates from the speaker's speech organs
- We can plot a *wave* showing the changes in air pressure over time (zero value being the normal air pressure)



zoom on the part between 1.126 and 1.157 s.



About 4 cycles in the waveform, which means a frequency of about 4/0.03 ≈129 Hz

Important measures

1. The **fundamental frequency F_0**: lowest frequency of the sound wave, corresponding to the speed of vibration of the vocal folds (between 85-180 Hz for male voices and 165-255 Hz for female voices)

2. The **intensity**: the signal power normalised to the human auditory threshold, measured in **dB** (decibels):

$$\text{Intensity} = 10 \ \log_{10} \frac{\text{Power}}{P_0} = 10 \ \log_{10} \frac{1}{N P_0} \boxed{\sum_{i=1}^{N} y(t_i)^2}$$

Total energy of signal

for a sample of N time points $t_1, \ldots t_N$
P_0 is the human auditory threshold, = 2×10^{-5} Pa

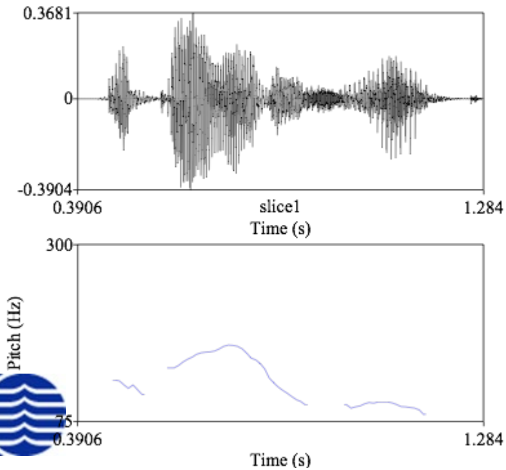
Note: dB scale is logarithmic, not linear!

Why are F_0 and the intensity important?

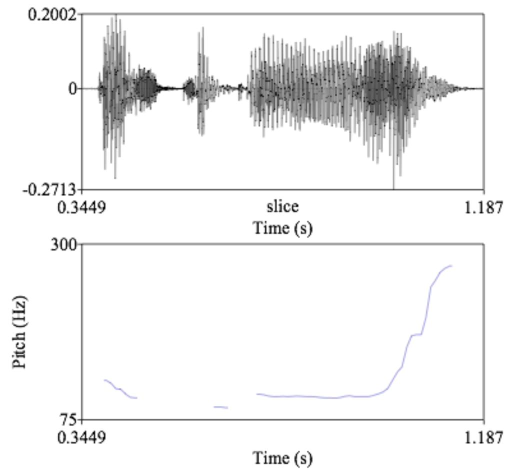
F_0 correlates with the *pitch* of the voice, and the pitch movement for an utterance will give us its *intonation*

Interrogative utterance
= rising intonation at the end

"The ball is red"



"Is the ball red?"

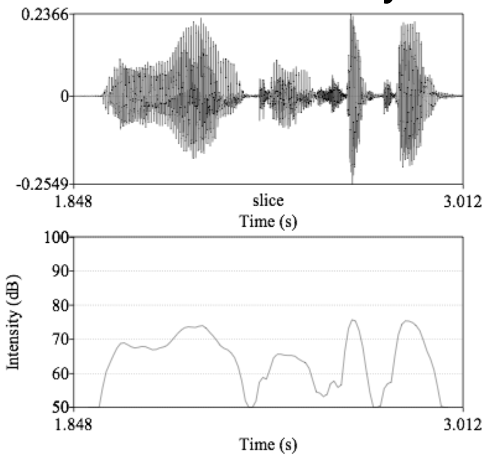


Why are F_0 and the intensity important?

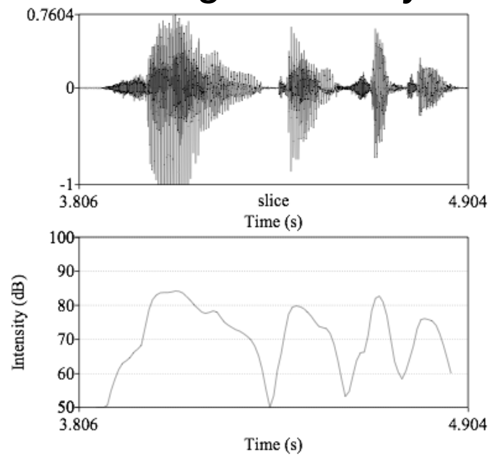
F_0 correlates with the *pitch* of the voice, and the pitch movement for an utterance will give us its *intonation*

The signal intensity corresponds to the *loudness* of the speech sound

low intensity

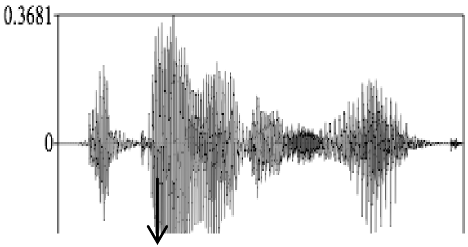


high intensity



The speech recognition task

Input: Audio data



Sequence **O** of acoustic observations (i.e. every 20 ms)

Output: Transcription

"The ball is red"

Goal: Map speech signal **O** into sequence of linguistic symbols $\widehat{\boldsymbol{W}}$ (words or characters):

$$\hat{W} = \underset{W}{\operatorname{argmax}} P(W|O)$$

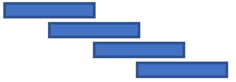
Why is ASR difficult?

- *Many sources of variation*: speaker voice (and style), accents, ambient noise, etc.

Why is ASR difficult?

- *Many sources of variation*: speaker voice (and style), accents, ambient noise, etc.
- Very long input sequences

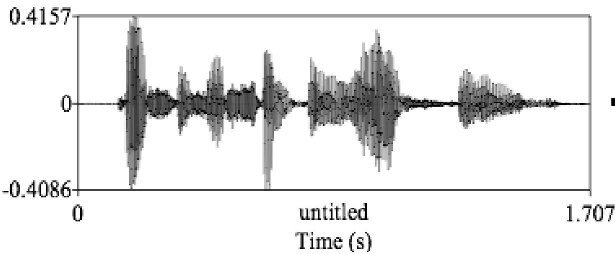
  - For audio frames lasting 20 ms. and offset of 10 ms. → 100 observations per sec. (each observation including many numerical features)

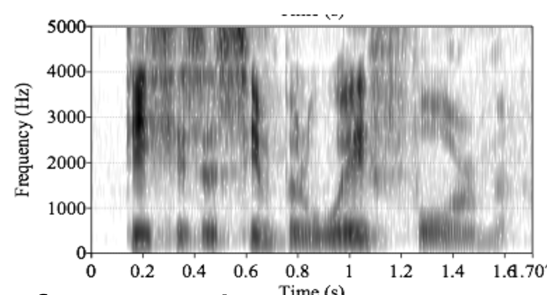


- But output sequence (e.g. phonemes, characters or tokens) much shorter and <u>*no explicit alignment between input and output*</u>

Preprocessing

- Most speech sounds cannot be distinguished from the raw waveform
- Better: convert the signal to a representation of the signal's *component frequencies*
    - Based on Fourier's transform





spectrogram showing which frequencies are most active at a given time

"Classical" model

Using Bayes' rule, we can rewrite Ŵ as:

$$\hat{W} = \underset{W}{\operatorname{argmax}} \frac{P(O|W)P(W)}{P(O)} \qquad \text{(Bayes)}$$

$$= \underset{W}{\operatorname{argmax}} P(O|W)P(W) \qquad \text{(P(O) constant for all W)}$$

Acoustic model

Language model

Determines the probability of the acoustic inputs O given the word sequence W

Determines the probability of the word sequence W

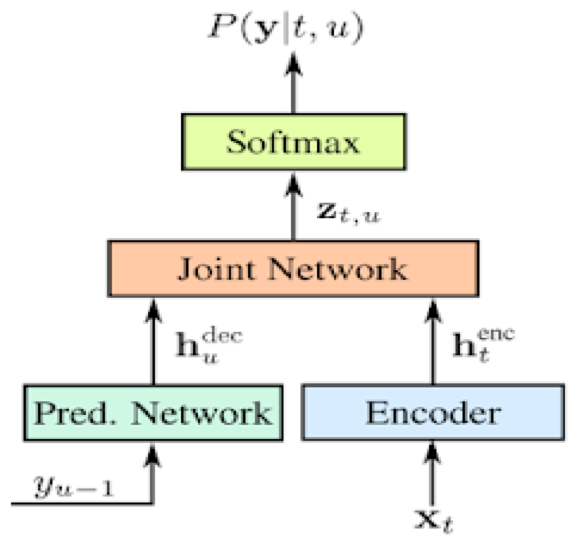
Neural ASR

- The best performing ASR are *deep, end-to-end neural architectures*
  - Less dependent on external ressources (such as pronunciation dictionaries)
  - Move from carefully handcrafted acoustic features to *learned* representations
- Too time demanding to review here
  - But they rely on the same building blocks as other NNs: convolutions, recurrence, (self-)attention, etc.

Neural ASR

https://ai.googleblog.com/2019/03/an-all-neural-on-device-speech.html

An example of a relatively simple neural model: Google's on-device ASR



- *Encoder maps* audio signal **x**t to hidden representations (with stacked LSTMs)
- *Prediction Network* is a language model
- Model then merges the two hidden representations and predicts outputs character-by-character

ASR Performance

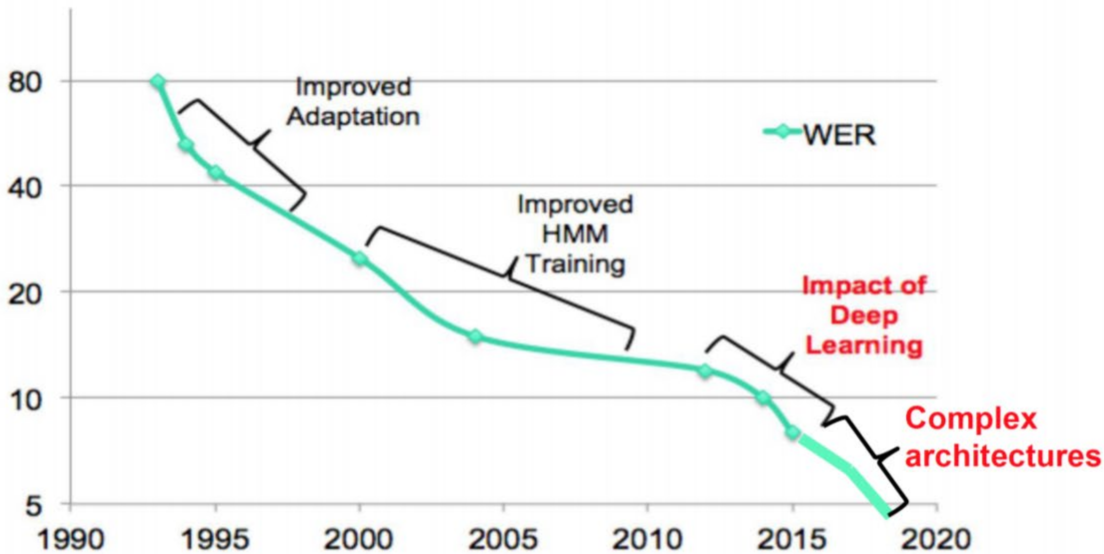


Figure: ASR Performance[1] on English Conversational Telephony (Switchboard)

[Figure from Bhuvana Ramabhadran's presentation at Interspeech 2018]

ASR evaluation

- Standard metric: **Word Error Rate**
  - Measures how much the utterance hypothesis h differs from the «gold standard» transcription t*
- = Minimum edit distance between h and t*, counting the number of word substitutions, insertions and deletions:

$$\text{Word Error Rate} = 100 \times \frac{\text{Insertions} + \text{Substitutions} + \text{Deletions}}{\text{Number of words in transcription}}$$

ASR evaluation

Gold standard Transcription	*yes can you now rotate this triangle*
ASR hypothesis	*yes can you not rotate this triangle there*

$$\text{WER} = 100 \times \frac{\text{1 Sub} + \text{1 Ins}}{7}$$

$$= 28.6\%$$

Gold standard Transcription	*there is five and*
ASR hypothesis	*the size and*

$$\text{WER} = 100 \times \frac{\text{2 Sub} + \text{1 Del}}{4}$$

$$= 75\%$$

Disfluencies

- Speakers construct their utterances «as they go», incrementally
  - Production leaves a *trace* in the speech stream
- Presence of multiple disfluencies
  - Pauses, fillers («øh», «um», «liksom»)
  - Repetitions («the the ball»)
  - Corrections («the ball err mug»)
  - Repairs («the bu/ ball»)

Disfluencies

Internal structure of a disfluency:

$$\text{Book a ticket } \underbrace{\text{to Boston}}_{\text{reparandum}} \; \underbrace{\text{uh I mean}}_{\text{interregnum}} \; \underbrace{\text{to Denver}}_{\text{repair}}$$

- reparandum: part of the utterance which is edited out
- interregnum: (optional) filler
- repair: part meant to replace the reparandum

[Shriberg (1994), «Preliminaries to a Theory of Speech Disfluencies», Ph.D thesis]

Some disfluencies

så gikk jeg e flytta vi til Nesøya da begynte jeg på barneskolen der
og så har jeg gått på Landøya ungdomsskole # som ligger ## rett over broa nesten # rett med Holmen

jeg gikk på Bryn e skole som lå rett ved der vi bodde den gangen e barneskole
videre på Hauger ungdomsskole

da hadde alle hele på skolen skulle liksom # spise julegrøt og det va- det var bare en mandel
og da var jeg som fikk den da ble skikkelig sånn " wow # jeg har fått den " ble så glad

[«*Norske talespråkskorpus - Oslo delen*» (NoTa), collected and annotated by the Tekstlaboratoriet]

Plan for today

- Obligatory assignment
- Chatbot models (cont'd)
- Natural Language Understanding (NLU)
- Speech recognition
- **Summary**

Summary

How to develop a chatbot:

- **Rule-based approaches**

Language Understanding

matched condition

Generation / response selection

= recognition of handcrafted patterns (e.g. regular expressions)

= handcrafted responses or templates to fill

Summary

How to develop a chatbot:

- Rule-based approaches
- **IR-based approaches**

Language Understanding

embedding

Generation / response selection

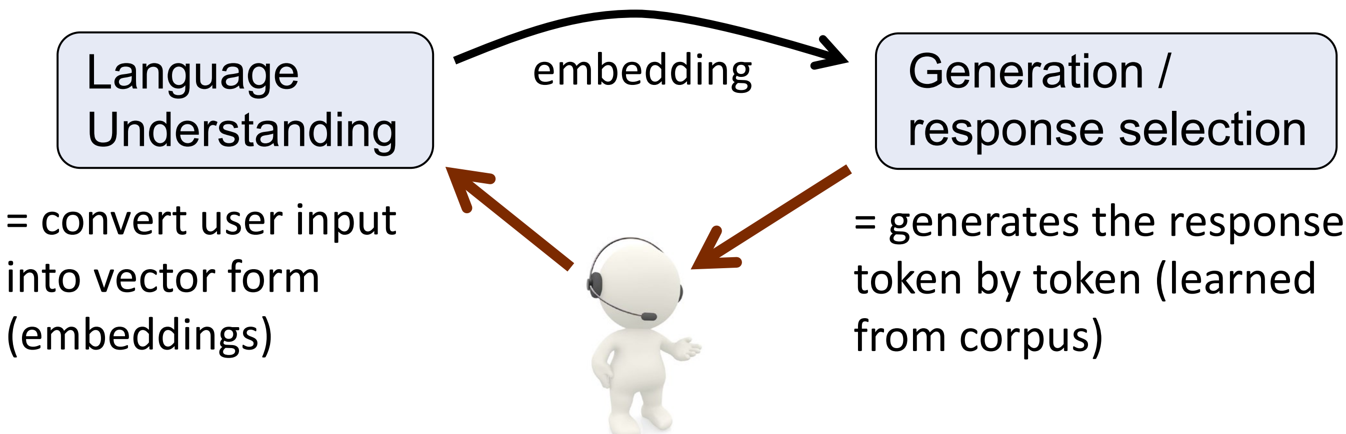
= convert user input into vector form (embeddings)

= select response from corpus that give maximum dot product

Summary

How to develop a chatbot:

- Rule-based approaches
- IR-based approaches
- **Seq-to-seq approaches**



Summary

How to develop a chatbot:

- Rule-based approaches
- IR-based approaches
- Seq-to-seq approaches
- **NLU-based approaches**

Often useful to rely on a combination of techniques – such as doing intent recognition using both rules and ML

Language Understanding

=map utterance to an intent + slots

Intent + slots

Generation / response selection

= handcrafted response or template to fill

Summary

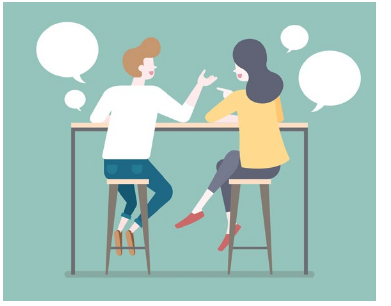
ASR: $\hat{W} = \underset{W}{\operatorname{argmax}} P(W|O)$

Acoustic observations
$O = o_1, o_2, o_3, \ldots, o_m$

Recognition hypothesis
$W = w_1, w_2, w_3, \ldots, w_n$

- Deep NNs have boosted ASR performance
  - But not yet a «solved problem»
  - (especially for ressource-poor languages and non-standard voices/acoustic environments)
  - *Word Error Rate metric* used for evaluation
- Disfluencies abound in spoken language

Next week



- Next week, we'll talk about *dialogue management* – that is, how do we control the flow of the interaction over time?
  - Including how to optimise dialogue policies using reinforcement learning
- And we will also talk about how to *design* and *evaluate* dialogue systems