NPFL123 Dialogue Systems
3. Data & Evaluation

https://ufal.cz/npfl123

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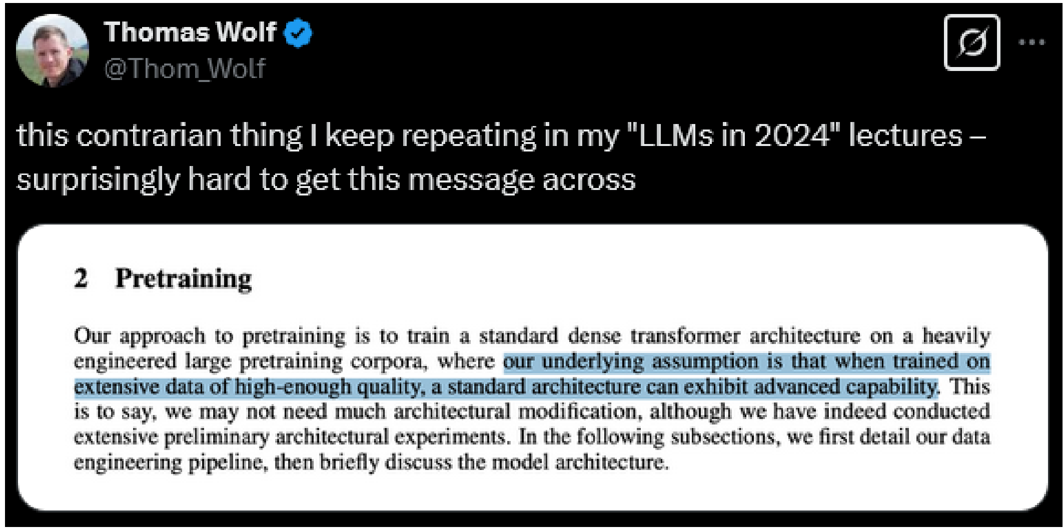
Before you build a dialogue system

Two significant questions, regardless of system architecture:

1) **What data** to base it on?
   - even if you handcraft, you need data
     - people behave differently
     - you can't enumerate all possible inputs off the top of your head
   - ASR can't be handcrafted – always needs data
2) **How to evaluate** it?
   - is my system actually helpful?
   - did recent changes improve/worsen it?
   - actually the same problem as data
     - you can't think of all possible ways to talk to your system



Thomas Wolf
@Thom_Wolf

this contrarian thing I keep repeating in my "LLMs in 2024" lectures – surprisingly hard to get this message across

2 Pretraining

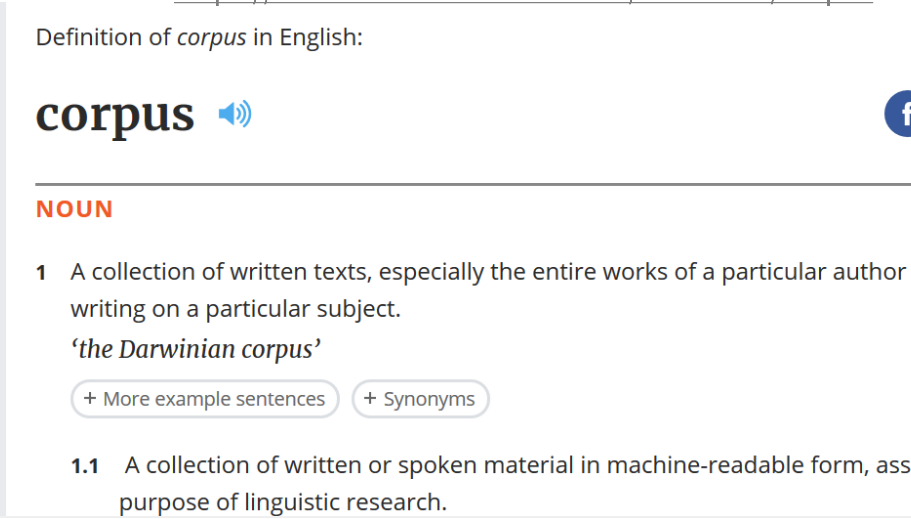
Our approach to pretraining is to train a standard dense transformer architecture on a heavily engineered large pretraining corpora, where our underlying assumption is that when trained on extensive data of high-enough quality, a standard architecture can exhibit advanced capability. This is to say, we may not need much architectural modification, although we have indeed conducted extensive preliminary architectural experiments. In the following subsections, we first detail our data engineering pipeline, then briefly discuss the model architecture.

https://twitter.com/Thom_Wolf/status/1766783830839406596

Data: Corpus (pl. Corpora)

- **Corpus** = **collection of** (linguistic) **data**
  - assuming access for automatic processing
  - used to train your system / inform yourself / evaluate
  - also called **dataset**
- Some of them are released openly
  - usage rights depend on a **license**
  - e.g. Creative Commons
    - BY (attribution) – SA (share alike) – NC (non-commercial) – ND (no derivatives)
- Useful for linguistic research/description, too

https://en.oxforddictionaries.com/definition/corpus



Definition of *corpus* in English:

corpus

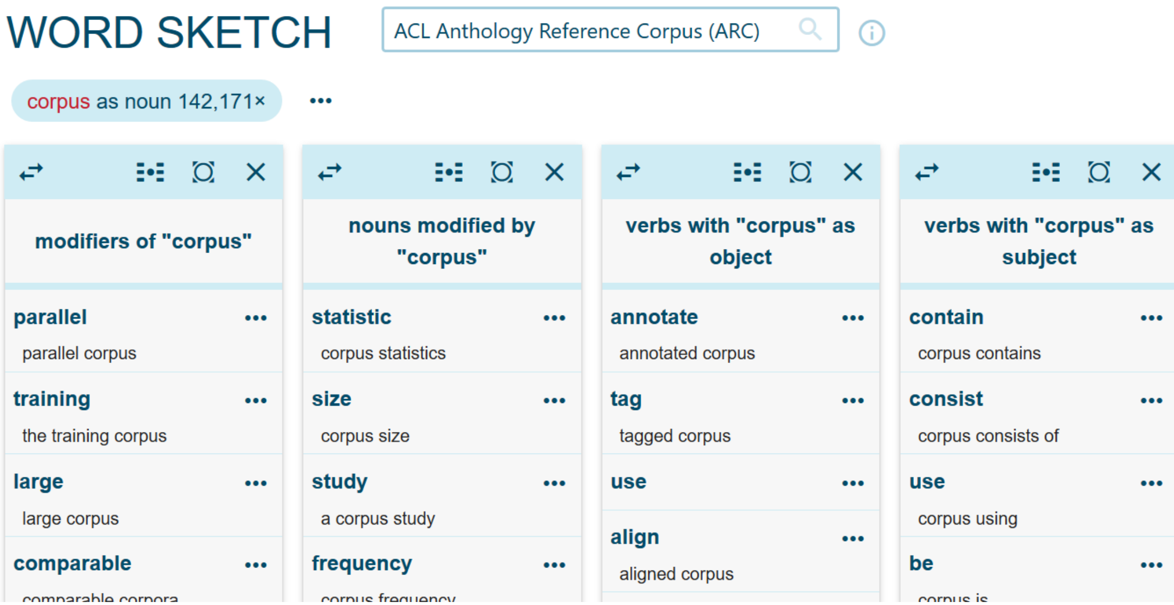
NOUN

1 A collection of written texts, especially the entire works of a particular author writing on a particular subject.

'the Darwinian corpus'

+ More example sentences + Synonyms

1.1 A collection of written or spoken material in machine-readable form, ass purpose of linguistic research.



WORD SKETCH ACL Anthology Reference Corpus (ARC)

corpus as noun 142,171×

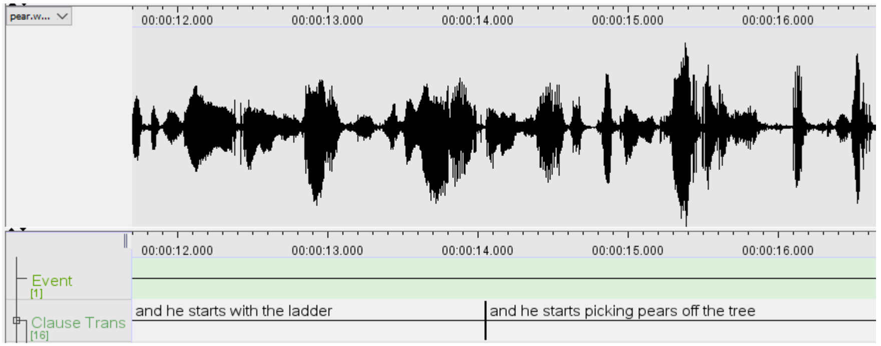
modifiers of "corpus"	nouns modified by "corpus"	verbs with "corpus" as object	verbs with "corpus" as subject
parallel parallel corpus	**statistic** corpus statistics	**annotate** annotated corpus	**contain** corpus contains
training the training corpus	**size** corpus size	**tag** tagged corpus	**consist** corpus consists of
large large corpus	**study** a corpus study	**use**	**use** corpus using
comparable comparable corpora	**frequency** corpus frequency	**align** aligned corpus	**be** corpus is

https://app.sketchengine.eu/#open

Dialogue Corpora/Dataset Types

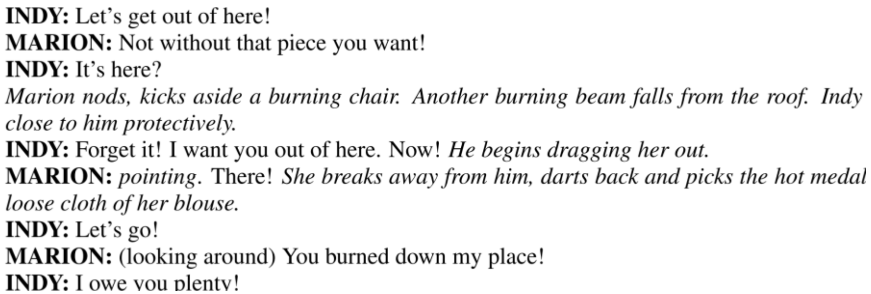
- **modality**: written / spoken / multimodal
- **data source**:
  - human-human conversations
    - real dialogues
    - scripted (e.g. movies)
  - human-machine (talking to a dialogue system)
  - automatically generated ("machine-machine")
- **domain**
  - closed/constrained/limited domain
  - multi-domain (more closed domains)
  - open domain (any topic, chitchat)

https://tla.mpi.nl/tools/tla-tools/elan/



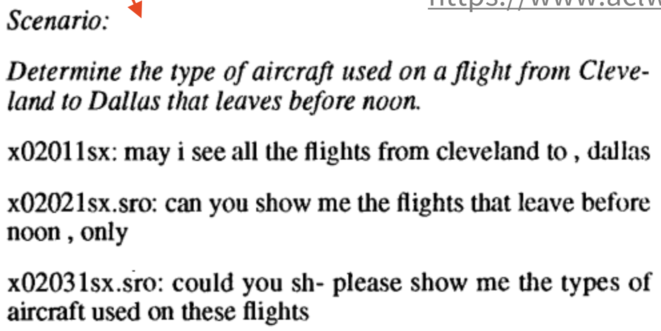
and he starts with the ladder

and he starts picking pears off the tree



INDY: Let's get out of here!
MARION: Not without that piece you want!
INDY: It's here?
Marion nods, kicks aside a burning chair. Another burning beam falls from the roof. Indy close to him protectively.
INDY: Forget it! I want you out of here. Now! *He begins dragging her out.*
MARION: *pointing*. There! *She breaks away from him, darts back and picks the hot medal loose cloth of her blouse.*
INDY: Let's go!
MARION: (looking around) You burned down my place!
INDY: I owe you plenty!

(Walker et al., 2012) https://www.aclweb.org/anthology/L12-1657/



Scenario:

Determine the type of aircraft used on a flight from Cleveland to Dallas that leaves before noon.

x02011sx: may i see all the flights from cleveland to , dallas

x02021sx.sro: can you show me the flights that leave before noon , only

x02031sx.sro: could you sh- please show me the types of aircraft used on these flights

(Dahl et al., 1994) https://www.aclweb.org/anthology/H94-1010/

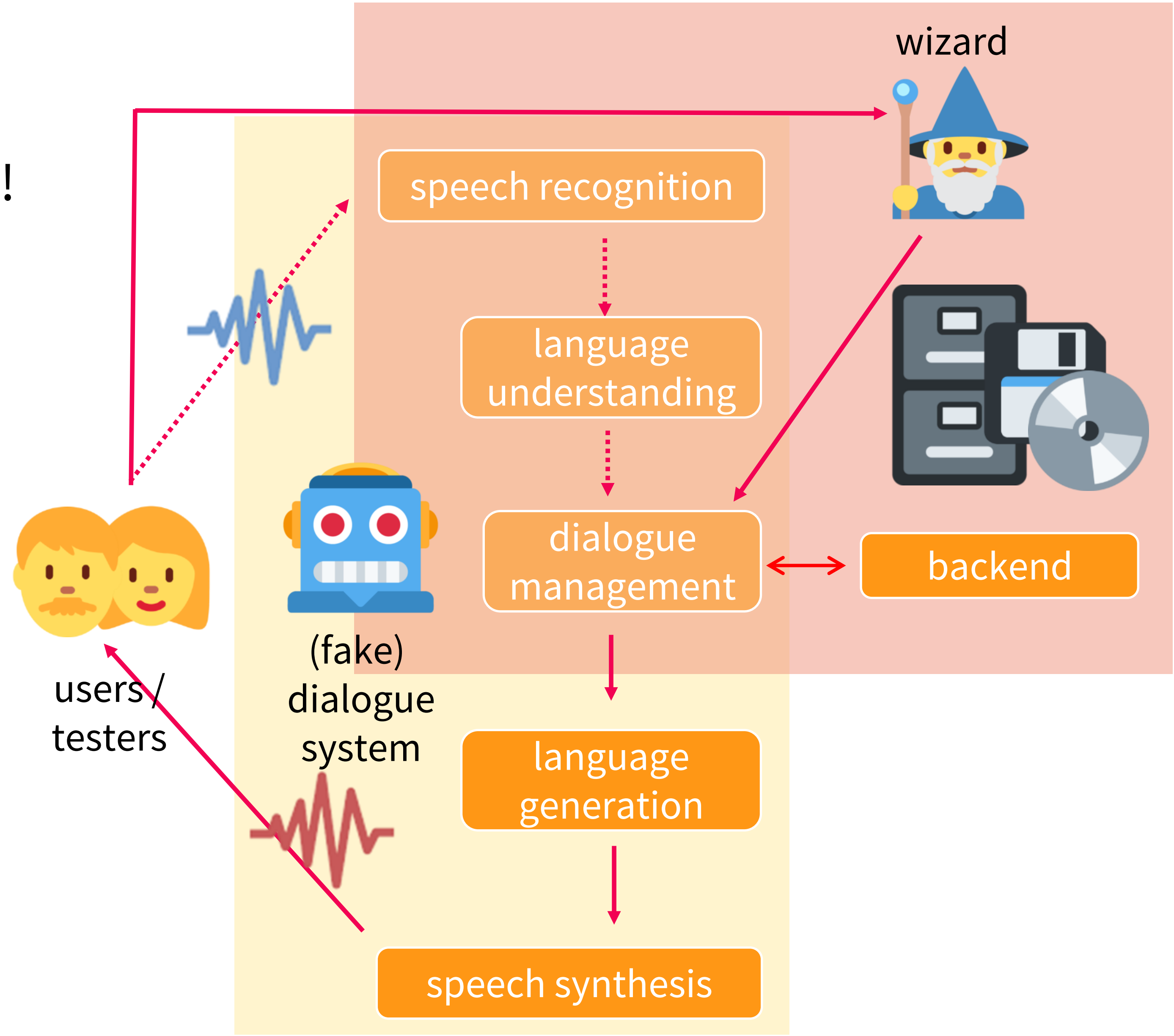
Dialogue Data Collection

Typical options:

- **in-house collection** using experts (or students)
    - safe, high-quality, but very expensive & time-consuming
    - free talk / scripting whole dialogues / **Wizard-of-Oz**(→)
- **web crawling**
    - fast & cheap, but typically not real dialogues
        - may not be fit for purpose
    - potentially unsafe (offensive stuff)
    - need to be careful about the licensing
- **crowdsourcing** (→)
    - compromise: employing (untrained) people over the web

Wizard-of-Oz (WoZ)

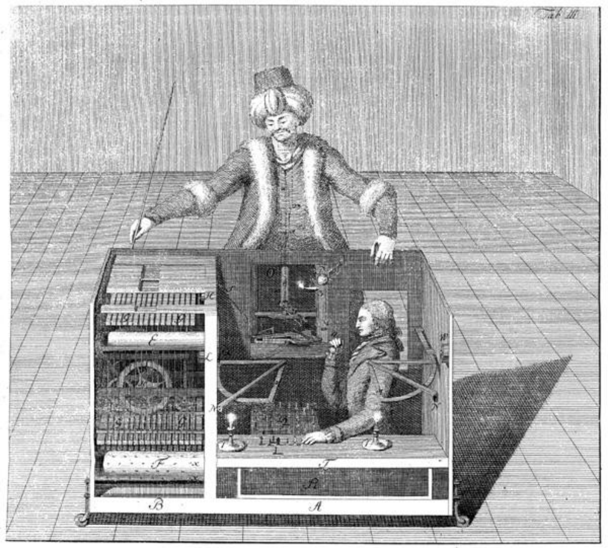
- for in-house data collection
  - also: to prototype/evaluate a system before implementing it!
- users believe they're talking to a system
  - different behaviour than when talking to a human
  - typically simpler
- system **in fact controlled by a human "wizard"** (=you)
  - typically selecting options (free typing too slow)

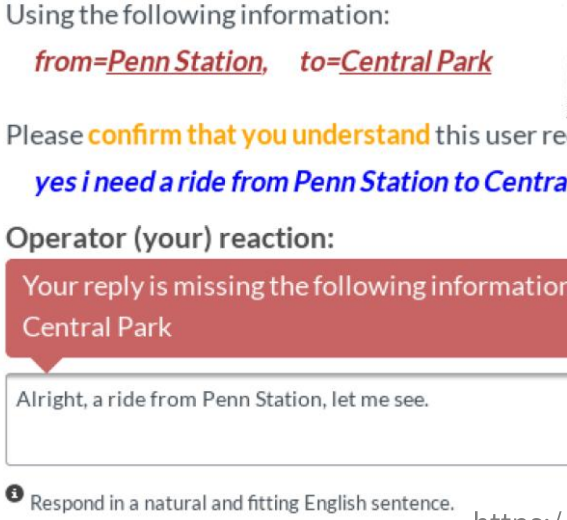


Crowdsourcing

- **hire people over the web**
  - create a webpage with your task
    - data collection / evaluation
  - no need for people to come to your lab
  - faster, larger scale, cheaper
- **platforms**/“marketplaces”
  - Amazon Mechanical Turk
  - Appen (formerly FigureEight/CrowdFlower)
  - Prolific
- problems
  - can’t be used in some situations (physical robots, high quality audio…)
  - **crowd workers tend to game the system** – noise/lower quality data
  - a lot of English speakers, but forget about e.g. Czechs

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





Using the following information:

from=Penn Station, to=Central Park

Please confirm that you understand this user request:

yes i need a ride from Penn Station to Central Park

Operator (your) reaction:

Your reply is missing the following information: Central Park

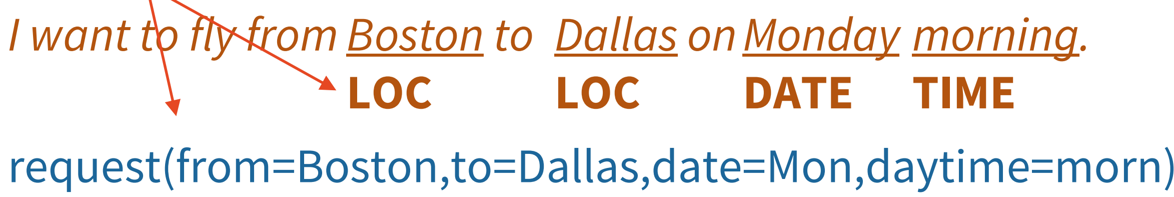
Alright, a ride from Penn Station, let me see.

Respond in a natural and fitting English sentence.

(Dušek & Jurčíček, 2016)
https://api.semanticscholar.org/CorpusID:15546788

Corpus Annotation

- more often than not, you’ll need more than just recordings
- **annotation** = labels, description added to the collected data:
  - **transcriptions** (textual representation of audio, for ASR&TTS)
  - **semantic annotation** such as dialogue acts (NLU)
  - **named entity** labelling (NLU)
  - other linguistic annotation: part-of-speech, syntax – typically not in DSs
- getting annotation
  - similar task as getting the data itself
  - DIY / hiring **experts**
  - **crowdsourcing**
  - (semi-)**automatic** annotation
    - use rules + manual fixes, annotate small dataset & use machine learning for the rest



I want to fly from Boston to Dallas on Monday morning.

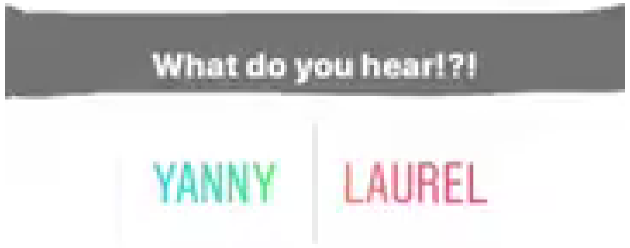
LOC LOC DATE TIME

request(from=Boston,to=Dallas,date=Mon,daytime=morn)

Inter-annotator Agreement (IAA)

- annotation is **inherently ambiguous**
  - people sometimes don’t even hear the same thing
  - let alone interpret the same semantics
- need to test if it’s reasonably **reliable** – **measuring IAA**
  - 2 or more people annotate/transcribe the same thing
  - need to account for agreement by chance
    - transcriptions – too many options (words) – no big deal
    - NER – just a few categories (e.g. 7) – may play a role
- typical measure: **Cohen’s Kappa** (0<κ<1)
  - for categorial annotation
  - 0.4 ~ fair, >0.7 ~ great

https://twitter.com/CloeCouture/status/996218489831473152
https://www.vox.com/2018/5/15/17357684/yanny-or-laurel-audio



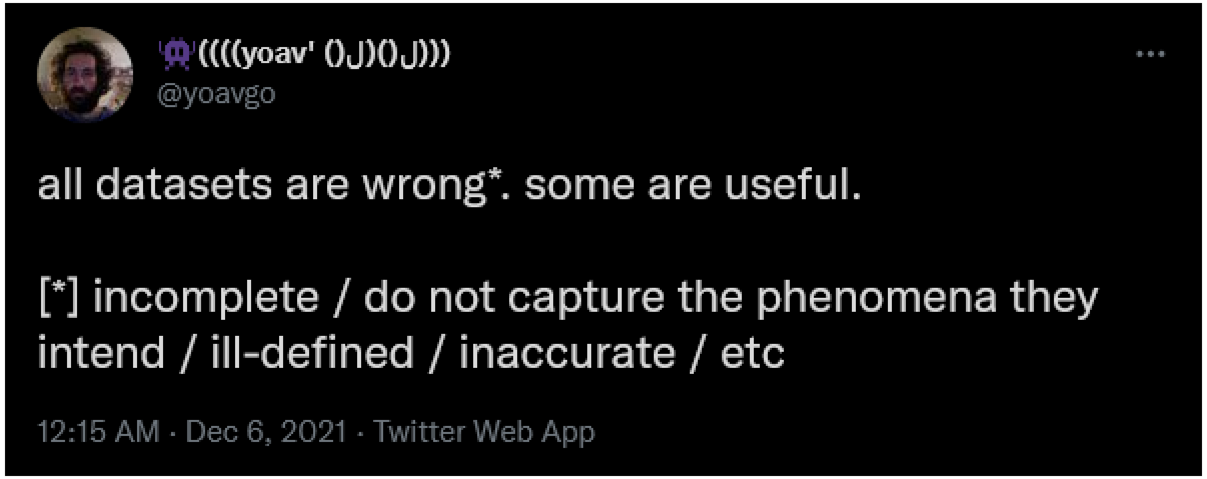
$$\kappa = \frac{\text{agreement} - \text{chance}}{1 - \text{chance}}$$

Corpus Size

- Size matters here
  - need enough examples for an accurate model
  - depends on what and how you’re modelling
- Speech – 10s-100s of hours minimum
  - pretrained LMs/audio LLMs: 100k-10M hrs
- NLU, DM, NLG
  - handcrafting – 10s-100s of dialogues may be OK to inform you
  - simple model/limited domain – 100s-1000s dialogues might be fine
  - open domain – sky’s the limit (LLMs: 1T+ tokens)
- TTS – single person, several hours at least
  - pretrained LMs: 10k+ hrs (multilingual)

Available Dialogue Datasets

- There’s a number of research datasets available
  - typically built as part of various research projects
  - license: some of them research-only, some completely free
- Drawbacks:
  - domain choice is rather limited
  - size is very often not enough – big AI firms have much more
  - vast majority is English only
  - few free datasets with audio
    - but there are non-dialogue ones (see http://www.openslr.org/)



👾((((yoav' ()J)()J)))
@yoavgo

all datasets are wrong*. some are useful.

[*] incomplete / do not capture the phenomena they intend / ill-defined / inaccurate / etc

12:15 AM · Dec 6, 2021 · Twitter Web App

https://mobile.twitter.com/yoavgo/status/1467633831465394181

Datasets: Human-Human Dialogues

- Spoken
  - **spontaneous**: phone calls
    - topic given (Switchboard), unrestricted (Callfriend)
  - **constrained**: specific tasks
    - *Walking around* – navigation, *DSTC4/5* – tourist guides
  - **scripted**: subtitles/movie scripts
    - *OpenSubtitles, Cornell Movies*
    - problems: swearing, lost visual context
- Written
  - **spontaneous**:
    - https://files.pushshift.io/
    - *Twitter* (closed API), *Reddit* (open) – large, messy
    - *DailyDialog* – language learning, cleaner + smaller
  - **constrained**: task-oriented
    - ***MultiWOZ*** – tourist info, very detailed annotation
    - *Ubuntu Dialogue, Schema-guided*…

Switchboard (Jurafsky et al., 1997)
https://web.stanford.edu/~jurafsky/ws97/manual.august1.html

[backchannel] B.22 utt1: *Uh-huh. /*
[statement, non-opinion] A.23 utt1: *I work off and on just temporarily and usually find friends to babysit, /*
[statement, non-opinion] A.23 utt2: *{C but } I don't envy anybody who's in that <laughter> situation to find day care. /*
[backchannel] B.24 utt1: *Yeah. /*

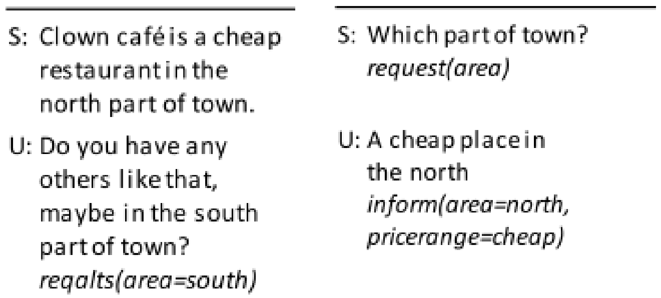
MultiWOZ (Budzianowski et al., 2018)
https://www.aclweb.org/anthology/D18-1547
https://github.com/budzianowski/multiwoz

{'train': {'semi': {'arriveBy': '21:15', 'day': 'sunday'}}}

I need a train leaving on a Sunday and arriving by 21:15.
Okay, I can help you with that. Where will you be traveling?
From London Kings Cross to Cambridge.
TR1681 will arrive at 20:08, would that work for you?
Yes, that sounds good. Please book a ticket on TR1681 for 6 people for me.
The booking was successful, your reference number is EAWIQ7HX. Is there anything else I can help you with?

Dialogue Datasets: Other types

- **Human-machine** (people talking with a system)
  - good for NLU & state tracking
  - no good for whole dialogue (=replicating the orig. system)
  - *DSTC1/2/3* – buses, restaurants
- **NLU** – individual turns only
  - good for NLU only, but easy to get (no system needed)
  - *Clinc* (many domains), *ATIS* (flights)
- **Synthetic dialogues** (machine-generated)
  - fake, but good for testing ability to learn
  - *bAbI* – restaurants, *SimDial* – any domain from description
- **NLG** – system action → text
  - needs special annotation/collection, mostly separate
  - *MultiWOZ* – has the annotation, *E2E NLG* – restaurants



S: Clown café is a cheap restaurant in the north part of town.

U: Do you have any others like that, maybe in the south part of town?
reqalts(area=south)

S: Which part of town?
request(area)

U: A cheap place in the north
inform(area=north, pricerange=cheap)

DSTC2 (Henderson et al., 2014)
https://www.aclweb.org/anthology/W14-4337/

Show	*flights*	*from*	*Boston*	*to*	*New*	*York*	*today*
O	O	O	**B-dept**	O	**B-arr**	**I-arr**	**B-date**

ATIS (Hemphill et al., 1990)
https://aclanthology.org/H90-1021/

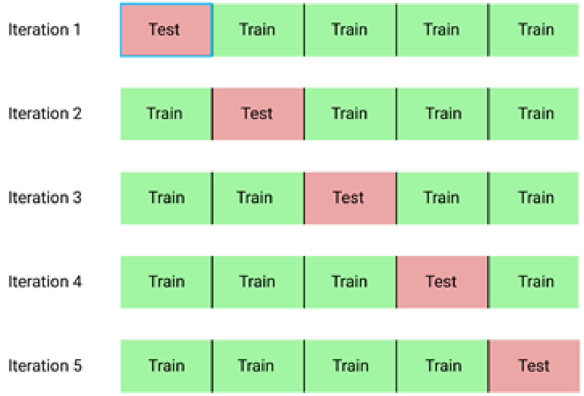
name[Loch Fyne], eatType[restaurant], food[Japanese], price[cheap], kid-friendly[yes]

Loch Fyne is a kid-friendly restaurant serving cheap Japanese food.

E2E NLG (Novikova et al., 2017)
https://www.aclweb.org/anthology/W17-5525/

Dataset Splits

- **Never evaluate on data you used for training**
  - memorizing training data would give you 100% accuracy
  - you want to know how well your model works **on new, unseen data**
  - also, never compare scores across datasets – seems obvious, but people do it
- Typical dataset split:
  - **training set** = to train your model
  - **development/validation set** = for evaluation during system development
    - this influences your design decisions, model parameter settings, etc.
  - **test/evaluation set** = only use for final evaluation
  - need sufficient sizes for all portions
- **Cross-validation** – when data is scarce:
  - split data into 5/10 equal portions,
    run 5/10x & test on different part each time



Iteration 1	Test	Train	Train	Train	Train
Iteration 2	Train	Test	Train	Train	Train
Iteration 3	Train	Train	Test	Train	Train
Iteration 4	Train	Train	Train	Test	Train
Iteration 5	Train	Train	Train	Train	Test

https://towardsdatascience.com/cross-validation-explained-evaluating-estimator-performance-e51e5430ff85

Dialogue System Evaluation

- Depends on dialogue system type / specific component
- Types:
  - **extrinsic** = how the system/component works in its intended purpose
    - x effect of the system on something outside itself, in the real world (i.e. user)
  - **intrinsic** = checks properties of systems/components in isolation, self-contained
  - **subjective** = asking users' opinions, e.g. questionnaires (~manual)
    - should be more people, so overall not so subjective ☺
    - x still not repeatable (different people will have different opinions)
  - **objective** = measuring properties directly from data (~automatic)
    - might or might not correlate with users' perception
- Evaluation discussed here is **quantitative**
  - i.e. measuring & processing numeric values
  - (*qualitative* ~ e.g. in-depth interviews, more used in social science)

Significance Testing

- Higher score is not enough to prove your model is better
  - Could it be just an accident?
- Need **significance tests** to actually prove it
  - Statistical tests, H_0 (**null hypothesis**) = “both models performed the same”
  - H_0 rejected with >95% confidence → pretty sure it’s not just an accident
  - more test data = more independent results → can get higher confidence (99+%)
- Various tests with various sensitivity and pre-conditions
  - Student’s *t*-test– assumes normal distribution of values
  - Mann-Whitney *U* test – any ordinal, same distribution
  - **Bootstrap resampling** – doesn’t assume anything
    1) randomly re-draw your test set (same size, some items 2x/more, some omitted)
    2) recompute scores on re-draw, repeat 1000x → obtain range of scores
    3) check if range overlap is less than 5% (1%...)

Getting the Subjects (for extrinsic evaluation)

- Can’t do without people
  - simulated user = another (simple) dialogue system
    - can help & give guidance sometimes, but it’s not the real thing – more for intrinsic
- In-house = ask people to come to your lab
  - students, friends/colleagues, hired people
  - expensive, time-consuming, doesn’t scale (difficult to get subjects)
- Crowdsourcing = hire people over the web
  - much cheaper, faster, scales (unless you want e.g. Czech)
  - not real users – mainly want to get their reward
- Real users = deploy your system and wait
  - best, but needs time & advertising & motivation
  - you can’t ask too many questions

Extrinsic – Task-Oriented (Objective)

https://research.aimultiple.com/chatbot-analytics/

How to measure:

1) **Record people** while interacting with your system
2) **Analyze the logs**

Metrics:

- **task success** / goal completion rate: did the user get what they wanted?
  - testers with agenda → check if they found what they were supposed to
    - [warning] sometimes people go off script
  - basic check: did we provide any information at all? (any bus/restaurant)
- **duration**: number of turns or time (fewer is better here)
- **retention rate** = % returning users over a time period
- **fallback rate** = % failed dialogues (+ confusion="not understood", reset, human takeover)
- # total/new/active users

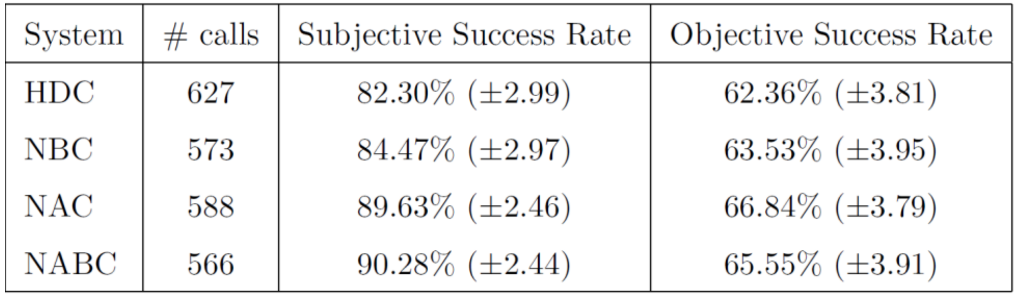
Extrinsic – Task-Oriented (Subjective)

- **Questionnaires** for users/testers
  - based on what information you need
- Question types
  - **Open-ended** – qualitative
  - **Yes/No** questions
  - **Likert scales** – agree … disagree (typically 3-7 points)
    - with a middle point (odd number) or forced choice (even number)
- Question guidelines:
  - easy to understand
  - not too many
  - neutral: not favouring/suggesting any of the replies

Extrinsic – Task-Oriented (Subjective)

Example questions:

- **Success rate:** Did you get all the information you wanted?
  - typically different from objective measures!
- **Future use:** Would you use the system again?
- **ASR/NLU**: Do you think the system understood you well?
- **NLG**: Were the system replies fluent/well-phrased?
- **TTS**: Was the system's speech natural?



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

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

Extrinsic – Non-Task-Oriented

Objective metrics:

- **Duration** – most common, easiest to get
  - longer = better here
- other (non-standard):
  - % returning users
  - checks for users swearing vs. thanking the system

Subjective:

- Future use + other same as task-oriented (except task success)
- **Likeability/Engagement**: Did you enjoy the conversation?

Intrinsic – ASR

- **Word error rate**
  - ASR output (hypothesis) compared to human-authored reference

$$\text{WER} = \frac{\#\text{substitutions} + \#\text{insertions} + \#\text{deletions}}{\text{reference length}}$$

  - ~ length-normalized edit distance (**Levenshtein distance**)
  - sometimes insertions & deletions are weighted 0.5x
  - can be >1
  - assumes one correct answer

true: I want a **restaurant**

ASR: want a **rest or rant**

WER = 1 + 2 + 1 / 4 = 1

Intrinsic – NLU

- Slot **Precision** & **Recall** & **F-measure** (F1)

(F1 is evenly balanced & default, other F variants favor *P* or *R*)

precision $$P = \frac{\#\text{correct slots}}{\#\text{detected slots}}$$ how much of the identified stuff is identified correctly

recall $$R = \frac{\#\text{correct slots}}{\#\text{true slots}}$$ how much of the true stuff is identified at all

F-measure $$F = \frac{2PR}{P + R}$$ harmonic mean – you want both *P* and *R* to be high (if one of them is low, the mean is low)

true: inform(name=Golden Dragon, food=Chinese)
NLU: inform(name=Golden Dragon, food=Czech, price=high)

$P = 1 / 3$
$R = 1 / 2$
$F = 0.2$

Intrinsic – NLU

- **Accuracy** (% correct) used for intent/act type
  - alternatively also **exact matches** on the whole semantic structure
    - easier, but ignores partial matches
- Again, one true answer assumed
- NLU on ASR outputs vs. human transcriptions
  - both options make sense, but measure different things!
  - intrinsic NLU errors vs. robustness to ASR noise

Intrinsic – Dialogue Manager

- Objective measures (task success rate, duration) can be measured with a **user simulator**
  - works on dialogue act level
  - responds to system actions
- Simulator implementation
  - **handcrafted** (rules + a bit of randomness)
    - **agenda-based** (goal: constraints, agenda: stack of pending DAs)
  - ***n*-gram** models over DA/dialogue turns + sampling from distribution
- Problem: simulator quality & implementation cost
  - the simulator is basically another dialogue system

Intrinsic – NLG

- No single correct answer here
  - many ways to say the same thing
- **Word-overlap** with reference text(s): **BLEU score**

(Papineni et al., 2002)
https://www.aclweb.org/anthology/P02-1040

range [0,1]
(percentage)

brevity penalty (1 if output longer than reference, goes to 0 if too short)

$$BLEU = BP \cdot \exp\left(\sum_{n=1}^{4} {}^{1}/_{4} \log\left(p_n\right)\right)$$

geometric mean

***n*-gram precision**:

$$p_n = \frac{\sum_u \#\ \text{matching n−grams in}\ u}{\sum_u \#\ \text{n−grams in}\ u}$$

- ***n*-gram** = span of adjacent *n* tokens
  - 1-gram (one word) = unigram, 2-gram (2 words) = bigram, 3-gram = trigram

Intrinsic – NLG

BLEU example:

output: ~~The Richmond~~ 's address ~~is 615 Balboa Street~~ . The phone ~~number is 4153798988 .~~

ref1: The number for Richmond is 4153798988 , the address is 615 Balboa .
~~ref2~~: The Richmond is located at 615 Balboa Street and their number is 4153798988 .

output: ~~What price~~ range would ~~you~~ like ~~?~~

ref1: What is your price range ?
~~ref2~~: What price are you looking for ?

matching unigrams: the (2x), Richmond, address, is (2x), 615, Balboa, Street, . (only 1x!), number, 4153798988, What, price, range, you, ?
p_1 = 17 / 22

matching bigrams: The Richmond, address is, is 615, 615 Balboa, Balboa Street, number is, is 4153798988, 4153798988 ., What price, price range
p_2 = 10 / 20

match for current segment, sum over the whole corpus

p_3 = 5 / 18, p_4 = 2 / 16, BP = 1, BLEU = 0.3403

- **BLEU is not very reliable** (people still use it anyway)
  - correlation with humans is questionable
  - never use for a single sentence, only over whole datasets

Intrinsic – NLG

Alternatives (not much):

- Other word-overlap metrics (NIST, METEOR, ROUGE …)
  - there are many, more complex, but frankly not much better
- **Slot error rate** – only for delexicalized NLG in task-oriented systems
  - delexicalized → generates placeholders for slot values
  - compare placeholders with slots in the input DA – WER-style

(Wen et al., 2015)
http://aclweb.org/anthology/D15-1199

output: The <hotel> ’s address is <addr> . The phone number is <phone> .
ref: The number for <hotel> is <phone> , the address is <addr> .

- **Diversity** – mainly for non-task-oriented
  - can our system produce different replies? (if it can’t, it’s boring)

$$D = \frac{\#\text{distinct } x}{\#\text{total } x}, \text{ where } x = \text{unigrams, bigrams, sentences}$$

Summary

- You **need data (corpus)** to build your systems
  - various sources: human-human, human-machine, generated
  - various domains
  - size matters
- Some models need **annotation** (e.g. dialogue acts)
  - annotation is hard, ambiguous – need to check **agreement**
- **Evaluation** needs to be done on a **test set**
  - **objective** (measurements) / **subjective** (asking humans)
  - **intrinsic** (component per se)
    - ASR: WER, NLU: slot F1 + intent accuracy, NLG: BLEU
  - **extrinsic** (in application)
    - objective: success rate, # turns; subjective: likeability, future use (…)
  - don’t forget to check **significance**
- Next week: NLU

Thanks

No labs this week!
(postponed)

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Get the slides here:

http://ufal.cz/npfl123

References/Inspiration/Further:

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

- Iulian V. Serban et al.'s Survey of corpora for dialogue systems (Dialogue & Discourse 9/1, 2018): https://breakend.github.io/DialogDatasets/
- Filip Jurčíček's slides (Charles University): https://ufal.mff.cuni.cz/~jurcicek/NPFL099-SDS-2014LS/
- Oliver Lemon & Arash Eshghi's slides (Heriot-Watt University): https://sites.google.com/site/olemon/conversational-agents
- Helen Hastie's slides (Heriot-Watt University): http://letsdiscussnips2016.weebly.com/schedule.html
- Wikipedia: Cohen's_kappa Levenshtein_distance Word_error_rate