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:

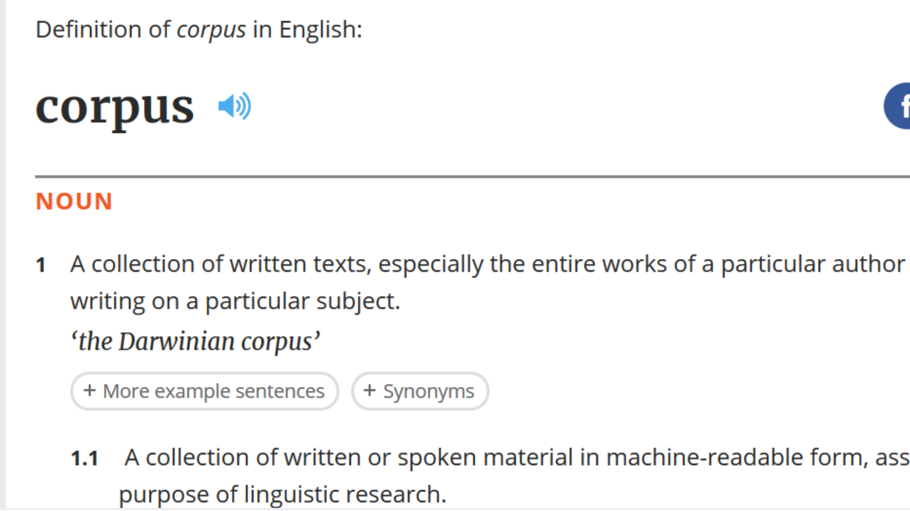
1) **What data** to base it on?
   - even if you handcraft, you need data
     - people behave differently
     - you can’t enumerate all possible inputs off the top of your head
   - ASR can’t be handcrafted – always needs data

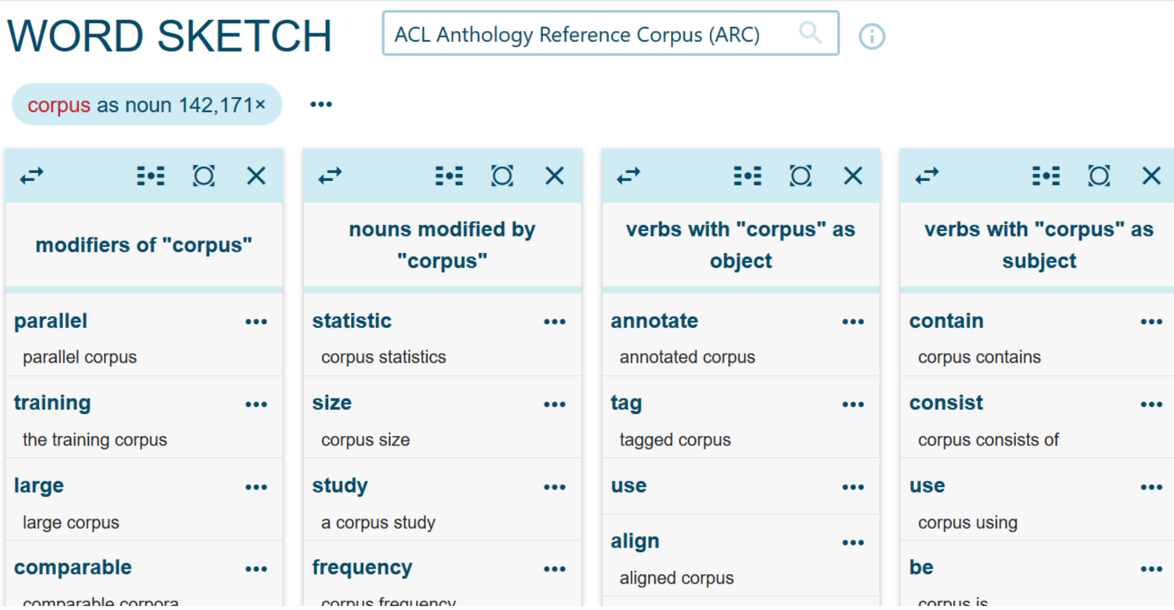
2) **How to evaluate** it?
   - is my system actually helpful?
   - did recent changes improve/worsen it?
   - actually the same problem as data
     - you can’t think of all possible ways to talk to your system

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



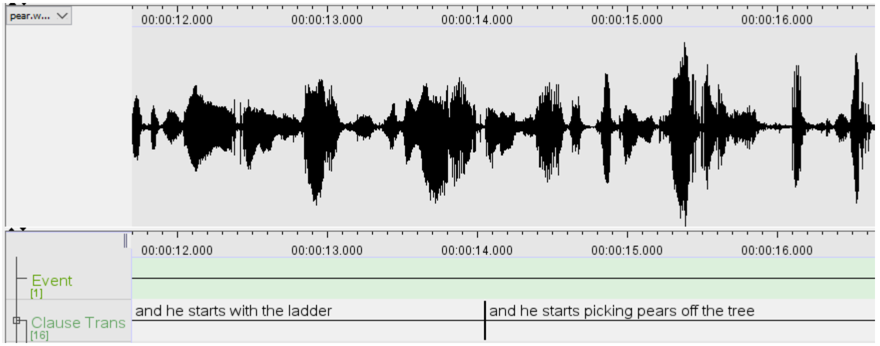


https://app.sketchengine.eu/#open

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/



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

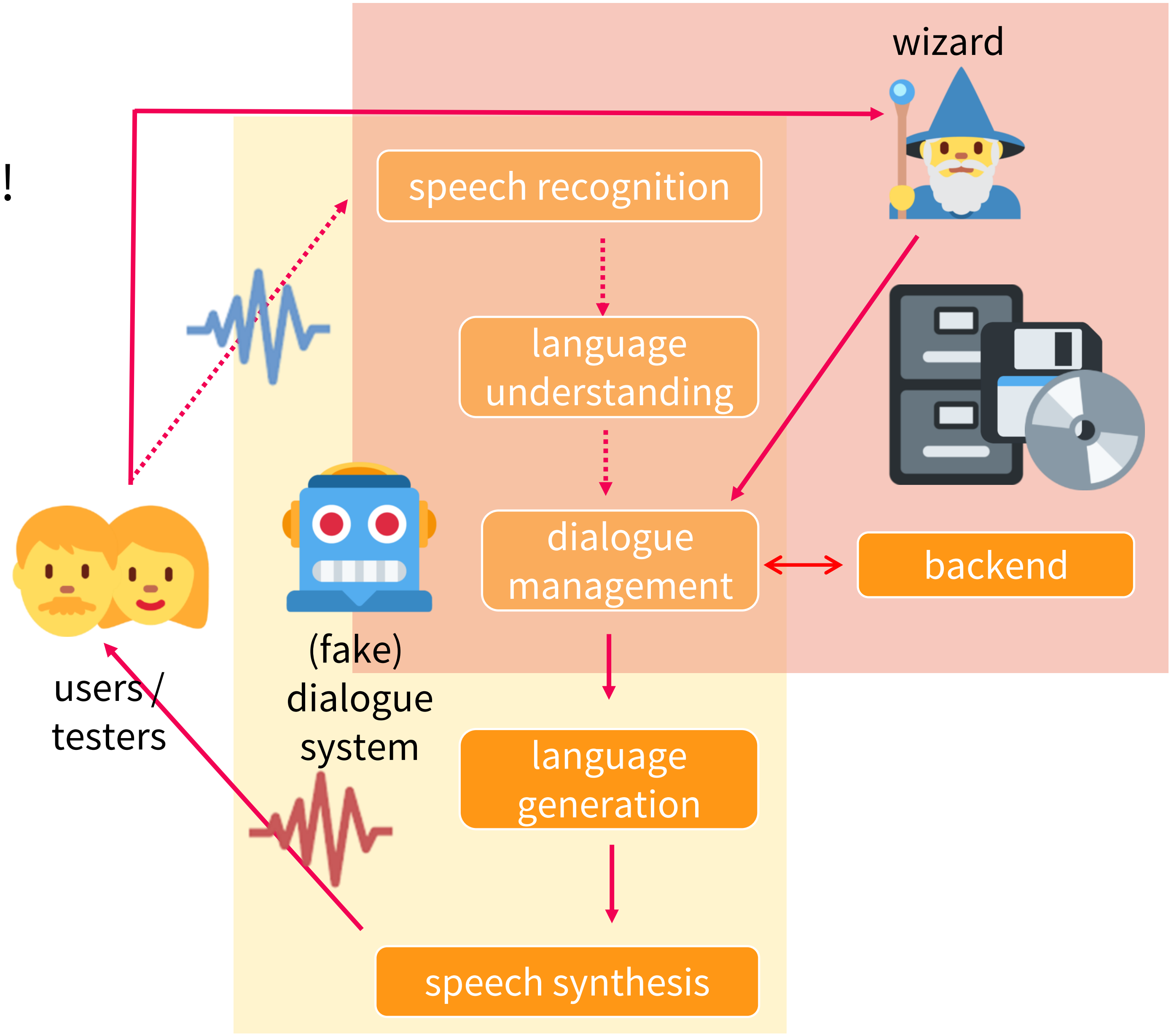
Typical options:

- **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

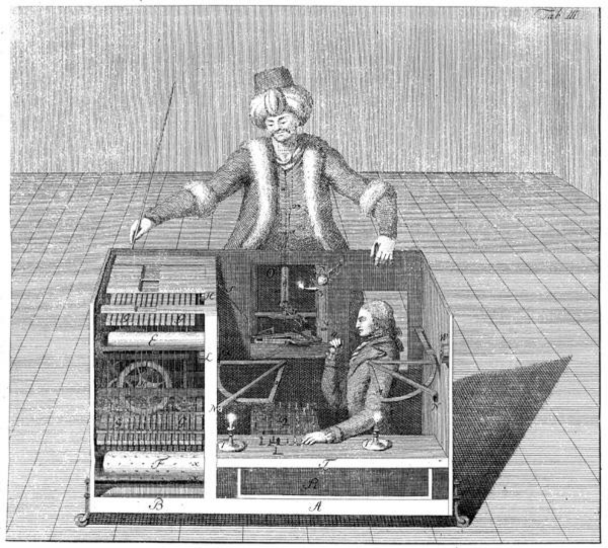
Wizard-of-Oz (WoZ)

- 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)

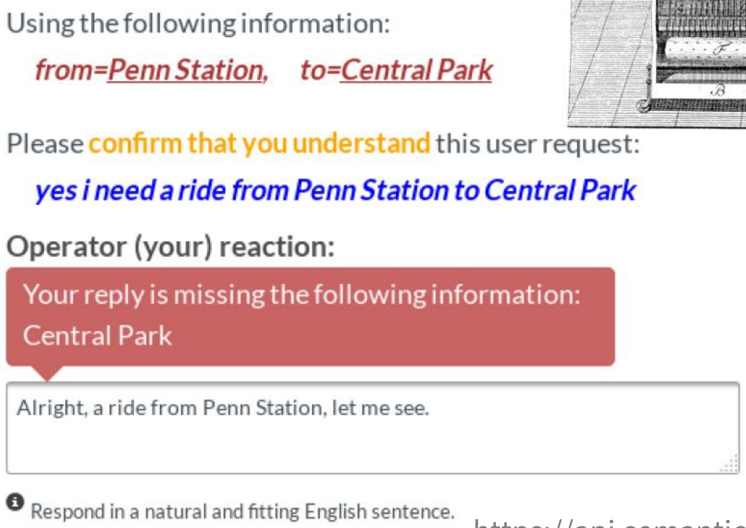


Crowdsourcing

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



- **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



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

- 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

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

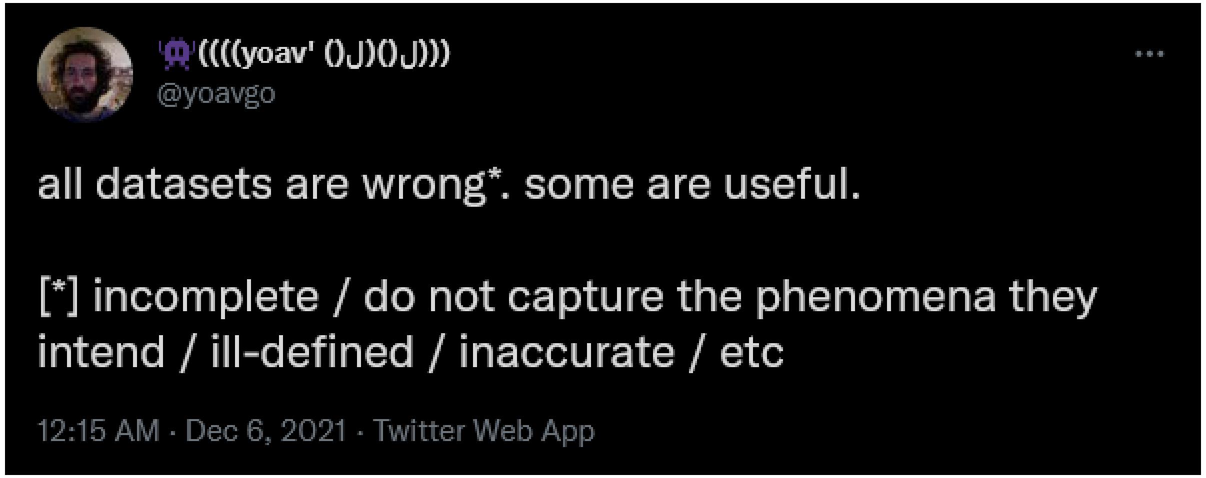
$$\kappa = \frac{\text{agreement} - \text{chance}}{1 - \text{chance}}$$

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
- 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
- TTS – single person, several hours at least

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/)



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/

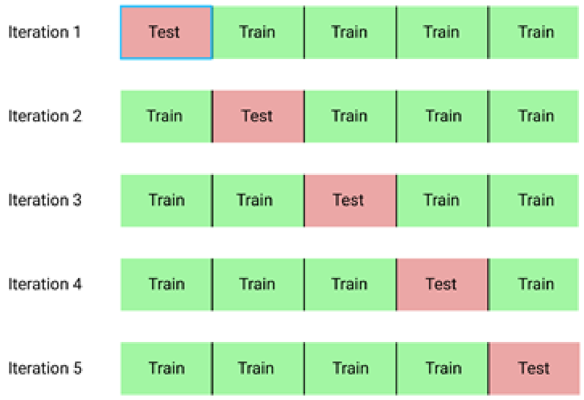
name [Loch Fyne], eatType[restaurant], food[Japanese], price[cheap], kid-friendly[yes]

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



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
    - 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 ☺
    - 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)

x

x

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)

How to measure:

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

Metrics:

- **Task success** (boolean): 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 (fewer is better here)
- Other: % returning users, % turns with null semantics …

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

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

match for current segment, sum over the whole corpus

- **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: linguistics of dialogue

Thanks

Contact us:

https://ufaldsg.slack.com/
odusek@ufal.mff.cuni.cz
Skype/Meet/Zoom (by agreement)

Labs in 10 mins

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