NPFL123 Dialogue Systems

2. 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

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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)

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**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

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**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 metal loose cloth of her blouse.
**INDY**: Let’s go!
**MARION**: (looking around) You burned down my place!
**INDY**: I owe you plenty!

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

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

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

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 ($0 < \kappa < 1$)
  - for categorial annotation
  - 0.4 ~ fair, >0.7 ~ great

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

https://twitter.com/CloeCouture/status/996218489831473152
https://www.vox.com/2018/5/15/17357684/yanny-or-laurel-audio
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**: [link]
    • *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…*

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Switchboard (Jurafsky et al., 1997)

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

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

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

| 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? inform(area=north, pricerange=cheap) |

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

Show flights from Boston to New York today

| O O O B-dept O B-arr I-arr B-date |

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

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

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

<table>
<thead>
<tr>
<th>System</th>
<th># calls</th>
<th>Subjective Success Rate</th>
<th>Objective Success Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>HDC</td>
<td>627</td>
<td>82.30% (±2.99)</td>
<td>62.36% (±3.81)</td>
</tr>
<tr>
<td>NBC</td>
<td>573</td>
<td>84.47% (±2.97)</td>
<td>63.53% (±3.95)</td>
</tr>
<tr>
<td>NAC</td>
<td>588</td>
<td>89.63% (±2.46)</td>
<td>66.84% (±3.79)</td>
</tr>
<tr>
<td>NABC</td>
<td>566</td>
<td>90.28% (±2.44)</td>
<td>65.55% (±3.91)</td>
</tr>
</tbody>
</table>

(Jurčiček 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?
• **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

\[
\text{WER} = 1 + 2 + 1 / 4 = 1
\]
Intrinsic – NLU

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

Precision

\[ P = \frac{\text{#correct slots}}{\text{#detected slots}} \]

Recall

\[ R = \frac{\text{#correct slots}}{\text{#true slots}} \]

F-measure

\[ F = \frac{2PR}{P + R} \]

how much of the identified stuff is identified correctly

how much of the true stuff is identified at all

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)

\[ P = \frac{1}{3} \]

\[ R = \frac{1}{2} \]

\[ F = 0.2 \]

(F1 is evenly balanced & default, other F variants favor \( P \) or \( R \))
• **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
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
• No single correct answer here
  • many ways to say the same thing

• **Word-overlap** with reference text(s): **BLEU score**

  \[
  \text{BLEU} = BP \cdot \exp \left( \sum_{n=1}^{4} \frac{1}{4} \log (p_n) \right)
  \]

  - **brevity penalty** (1 if output longer than reference, goes to 0 if too short)
  - **n-gram precision**: 
    \[
    p_n = \frac{\sum_u \text{# matching } n\text{-grams in } u}{\sum_u \text{# } n\text{-grams in } u}
    \]

• **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,

$p_2 = 10 / 20$

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

• **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
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

  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)

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

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

• 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

• (also, never compare scores across datasets)
  • seems obvious, but people do it
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%...)
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
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Skype/Meet/Zoom (by agreement)

Get the slides here:

http://ufal.cz/npfl123

References/Inspiration/Further:

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

- 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