Dialogue Systems
NPFL123 Dialogové systémy

3. Data & Evaluation

Ondřej Dušek & Vojtěch Hudeček & Jan Cuřín

http://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
  - 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
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
  - 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:sxo: can you show me the flights that leave before noon , only
- x02031sx:sxo: could you sh- please show me the types of aircraft used on these flights

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

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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 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/](https://www.aclweb.org/anthology/L12-1657/)

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

• 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.*

**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

\[
\kappa = \frac{\text{agreement} - \text{chance}}{1 - \text{chance}}
\]
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/)
Dialogue Datasets: Human-Machine

For NLU, state tracking, (possibly) DM:

- **Dialogue state tracking challenges (DSTC)**
  - real systems, single domain
  - DSTC1 Let’s go – bus information
  - DSTC2/3 Cambridge restaurants

- **Clinic** – 10 domains, 150 intents + out-of-scope
  - crowdsourcing, no real system involved

- **ATIS** – WoZ collection, flight booking (90’s)
  - manual annotation

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**DSTC1** – Let’s go (Williams et al. 2013)
[Link to paper](https://www.aclweb.org/anthology/W13-4065/)

**SYS**: East Pittsburgh Bus Schedules. Say a bus route, like 28X, or say I’m not sure.
**USR**: 61A
**SYS**: Okay, 61A. To change, say go back. Where are you leaving from?
**USR**: Downtown
**SYS**: Okay, downtown. You can always say go back. And where are you going to?

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**Clinic** (Larson et al., 2019)
[Link to paper](https://www.aclweb.org/anthology/D19-1131)

- can i travel to france as far as safety goes = `travel_alert`
- i need your help finding my lost phone = `find_phone`
- read me cat trivia = `fun_fact`
- what is the balance in my pnc account = `balance`

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**ATIS**
[Link to dataset](https://chsasank.github.io/spoken-language-understanding.html)

**DSTC2** – Restaurants (Henderson et al., 2014)
[Link to paper](https://www.aclweb.org/anthology/W14-4337/)

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**Show flights from Boston to New York today**

0 0 0 0 0 B-dept 0 B-arr I-arr 0 B-date
Datasets: Human-Human Spoken

Spontaneous:

• **Switchboard**
  - 260hr phone conversations
  - 2 people randomly connected to chat on a given topic
  - speech + transcription, but basic intent annotation also available

• **Callfriend**
  - phone conversations, just speech + transcription
  - friends calling each other
  - available for several languages

Switchboard: [http://compprag.christopherpotts.net/swda.html](http://compprag.christopherpotts.net/swda.html)

Callfriend: [https://ca.talkbank.org/access/CallFriend/](https://ca.talkbank.org/access/CallFriend/)
Datasets:
Human-Human Spoken

Constrained:
- **Walking around**
  - over-the-phone navigation
  - used to study dialogue alignment
- **Verbmobil**
  - business meetings EN–DE
- **DSTC4/5**
  - tourist-tour guide Skype conversations
- Many more (debates, games, emotions...)

Verbmobil  [https://www.phonetik.uni-muenchen.de/Bas/BasVM1eng.html](https://www.phonetik.uni-muenchen.de/Bas/BasVM1eng.html)

Datasets: Human-Human Spoken

Scripted:

• **OpenSubtitles (OST)**
  - movie subtitles from the web
  - 60 languages, 2.6bn sentences
    - parallel – used for translation, too
  - messy
    - turn annotation none or automatic

• **Cornell Movie Dialogs**
  - smaller, English-only
  - cleaner – extracted from movie scripts
    - lines paired with characters

• caveats: lots of swearing, missing visual context

OST – image from (Lison & Meena, 2016)
http://opus.nlpl.eu/OpenSubtitles2016.php

Blade Runner script
Datasets: Human-Human Written

- easier to get than spoken
  - caveats: specific language, may be offensive

Spontaneous:

- **Twitter**
  - need to mine it yourself (Twitter’s business model)
  - dialogues, with short replies and lot of data

- **Reddit**
  - huge dumps exist ([https://pushshift.io/](https://pushshift.io/) and elsewhere)
  - less dialogue-y (some posts are really long)

- **DailyDialog**
  - crawled from language learning sites
  - cleaner, non-offensive, annotated with emotion & intent
  - much smaller

https://www.reddit.com/r/ukpolitics/comments/as4bbr

A: I’m worried about something.
B: What’s that?
A: Well, I have to drive to school for a meeting this morning, and I’m going to end up getting stuck in rush-hour traffic.
B: That’s annoying, but nothing to worry about. Just breathe deeply when you feel yourself getting upset.

(Li et al., 2017)  
http://arxiv.org/abs/1710.03957  
http://yanran.li/dailydialog
Datasets: Human-Human Written

Constrained:

- **Ubuntu dialogue corpus**
  - >1M dialogues, from Ubuntu chat

- **MultiWOZ**
  - 10k dialogues, crowdsourced
  - multiple domains (hotels, restaurants, taxi…)
  - annotated

- **other**
  - Similar to MultiWOZ
    - assistant dialogues
  - **Taskmaster-1, MetalWOz, KVRET**
  - movie dialogues
  - Settlers of Catan
  - …

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Ubuntu Dialogue (Lowe et al., 2015)
http://aclweb.org/anthology/W15-4640
http://dataset.cs.mcgill.ca/ubuntu-corpus-1.0/

MultiWOZ (Budzianowski et al., 2018)
https://www.aclweb.org/anthology/D18-1547
http://dialogue.mi.eng.cam.ac.uk/index.php/corpus/

KVRET (Eric et al., 2017)
https://www.aclweb.org/anthology/W17-5506

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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: Machine Generated

- Still good for testing dialogue models
  - can the model learn a dataset of this complexity?
- Can be generated in any size
- Facebook **bAbI**
  - various tasks, mainly inference
  - auto-generated restaurant dialogues
- **SimDial**
  - auto-generating dialogues based on domain descriptions

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(Bordes et al., 2017)
https://research.fb.com/downloads/babi/

(Zhao & Eskenazi, 2018)
https://github.com/snakeztc/SimDial
NLG Datasets

• Specific – other datasets typically not usable
  • unless you want to generate directly, without explicit NLU & DM

• Cambridge RNNLG
  • restaurants, hotels, laptop, TVs (5-10k instances each)
  • crowdsourced, good for delexicalization (template style)

• E2E NLG data
  • restaurants, bigger (50k instances)
  • more complex, more messy
  • partially based on images to get more diversity

inform(type=restaurant;count='2';food=basque;kidsallowed=no;price range=moderate)
there are 2 restaurant -s where no child -s are allowed in the moderate price range and serving basque food

?request(near)
where would you like it to be near to

Loch Fyne is a kid-friendly restaurant serving cheap Japanese food.
Serving low cost Japanese style cuisine, Loch Fyne caters for everyone, including families with small children.

name [Loch Fyne], eatType[restaurant], food[Japanese], price[cheap], kid-friendly[yes]
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 mostly **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% (±3.70)</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., Comp. Speech & Language 2012
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**

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

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

  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)
  \[ P = \frac{1}{3} \]
  \[ R = \frac{1}{2} \]
  \[ F = 0.2 \]

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

(F1 is evenly balanced & default, other F variants favor \( P \) or \( R \))
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)
  • **n-gram** models over DA/dialogue turns + sampling from distribution
  • **agenda-based** (goal: constraints, agenda: stack of pending DAs)

• Problem: simulator 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**

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

- **Brevity penalty** (1 if output longer than reference, goes to 0 if too short)
- **N-gram precision**:
  \[
p_n = \frac{\sum_u \# \text{ matching } n-\text{grams in } u}{\sum_u \# n-\text{grams in } u}
\]
- **n-gram** = span of adjacent _n_ tokens
  • 1-gram (one word) = unigram, 2-gram (2 words) = bigram, 3-gram = trigram

range [0,1] (percentage)
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.

matching unigrams: the (2x), Richmond, address, is (2x), 615, Balboa, . (only 1x!), number, 4153798988
$p_1 = \frac{11}{15}$

matching bigrams: The Richmond, address is, is 615, 615 Balboa, Balboa Street, number is, is 4153798988, 4153798988.
$p_2 = \frac{8}{14}$
$p_3 = \frac{5}{13}$, $p_4 = \frac{2}{12}$, BP = 1, BLEU = 0.4048

• 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

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

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

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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: intro to assistants, question answering
Thanks

Contact us:

odusek@ufal.mff.cuni.cz
hudecek@ufal.mff.cuni.cz
or on Slack

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/
• 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