

# A Unifying View On Task-oriented Dialogue Annotation

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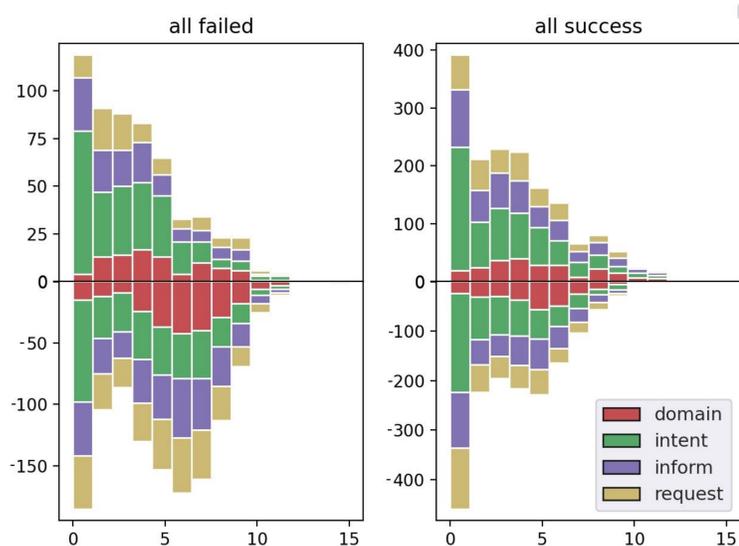
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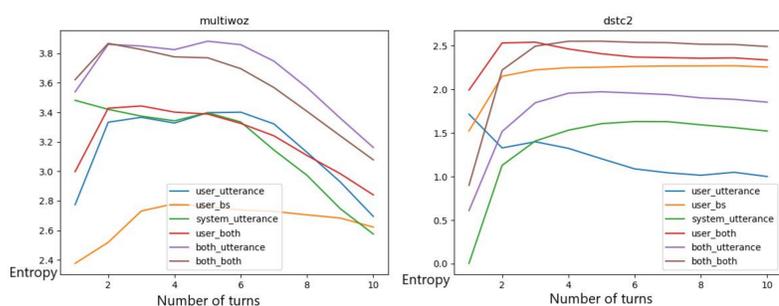
## Overview

- Unifying annotation & ontologies in 4 task-oriented dialogue datasets:
  - **MultiWOZ, SGD, DSTC2, CamRest**
  - → one of the largest annotated sets to date
- Data analysis and visualization
- Baseline model training and comparison

## Success/failure analysis



## Conditional entropy



## Analysis

- **3 dialogue phases** (based on conditional entropy)
  - information growth, stagnation, information deprecation
- **Human-human vs. human-machine** entropy evolution differs
- Most **dialogue failures** due to missing information
  - Recoverable
  - It is correlated with entropy evolution.
- **Best model** – trained on full data
  - SGD → better BLEU
  - MultiWOZ → better state tracking

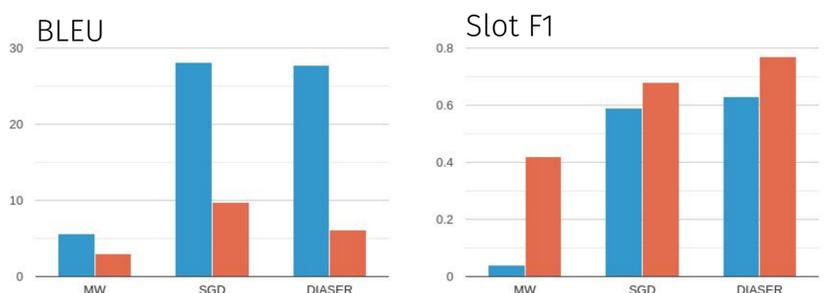
## Data Statistics

|                  | SGD   | MultiWOZ | DSTC2 | Camrest | Total |
|------------------|-------|----------|-------|---------|-------|
| Domains          | 18    | 7        | 1     | 1       | 19    |
| Slots            | 145   | 29       | 10    | 7       | 166   |
| Dialogues        | 22.8k | 10.4k    | 3.2k  | 700     | 37.1k |
| Avg. utt. length | 9.9   | 13.2     | 8.5   | 10.7    | 10.5  |
| Entropy          | 4.8   | 4.4      | 2.1   | 3.0     | 4.8   |

## Example

dialogue\_id: MUL0674.json, original\_dataset: multiwoz, ← origin IDs  
 domains: train, hotel  
 goal: hotel: { book: { day: thursday, people: 7, stay: 3 }  
 info: { name: aylesbray lodge guest house } ... ← dialogue goal descriptions  
 train: { book: { people: 7 }, info: { arriveBy ... }  
 message: You are looking for information in Cambridge. You are looking for a train. The train should arrive by ...  
 utterances: [  
 { ... actor: user ... I am looking for a train arriving by 21:45 and departing from cambridge. ... turn: 1, intent: train },  
 { ... actor: system ... What day are you making this trip, and where would you like to travel to? ... turn: 1, intent: train }, ← delexicalized versions  
 { actor: user,  
 utterance: Hi I would like to go to kings lynn on sunday please.  
 delex\_utterance: Hi I would like to go to [destination] on [day] please. ← consistent NLU & state format  
 nlu: Train-Inform(day=Sunday, destination=kings lynn)  
 state: train-day: Sunday, train-departure: cambridge,  
 train-destination: kings\_lynn, train-end\_time: 21:45 ← unified domain, intent, slot names  
 turn: 2, intent: train },  
 { actor: system,  
 utterance: Train TR1600 leaves Cambridge at 20:11 and arrives in Kings Lynn at 20:58. Would that work?  
 delex\_utterance: Train [train id] leaves [departure] at [leave at] and arrives in [destination] at [arrive by]. Would that work?  
 nlu: Train-Inform(arriveby=20:58, departure: Cambridge ...) &general-reqmore(),  
 turn: 2, ... ]

## Baseline results



## Joint-goal accuracy



- Train: 4 subcorpora mixes
- Eval.: SGD MW DIASER



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<https://github.com/ufal/diaser>

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