

# Counterfactual Learning from Human Proofreading Feedback for Semantic Parsing

Neural Information  
Processing Systems

Carolin Lawrence, Stefan Riezler  
Heidelberg University, Germany.

LBI  
Workshop

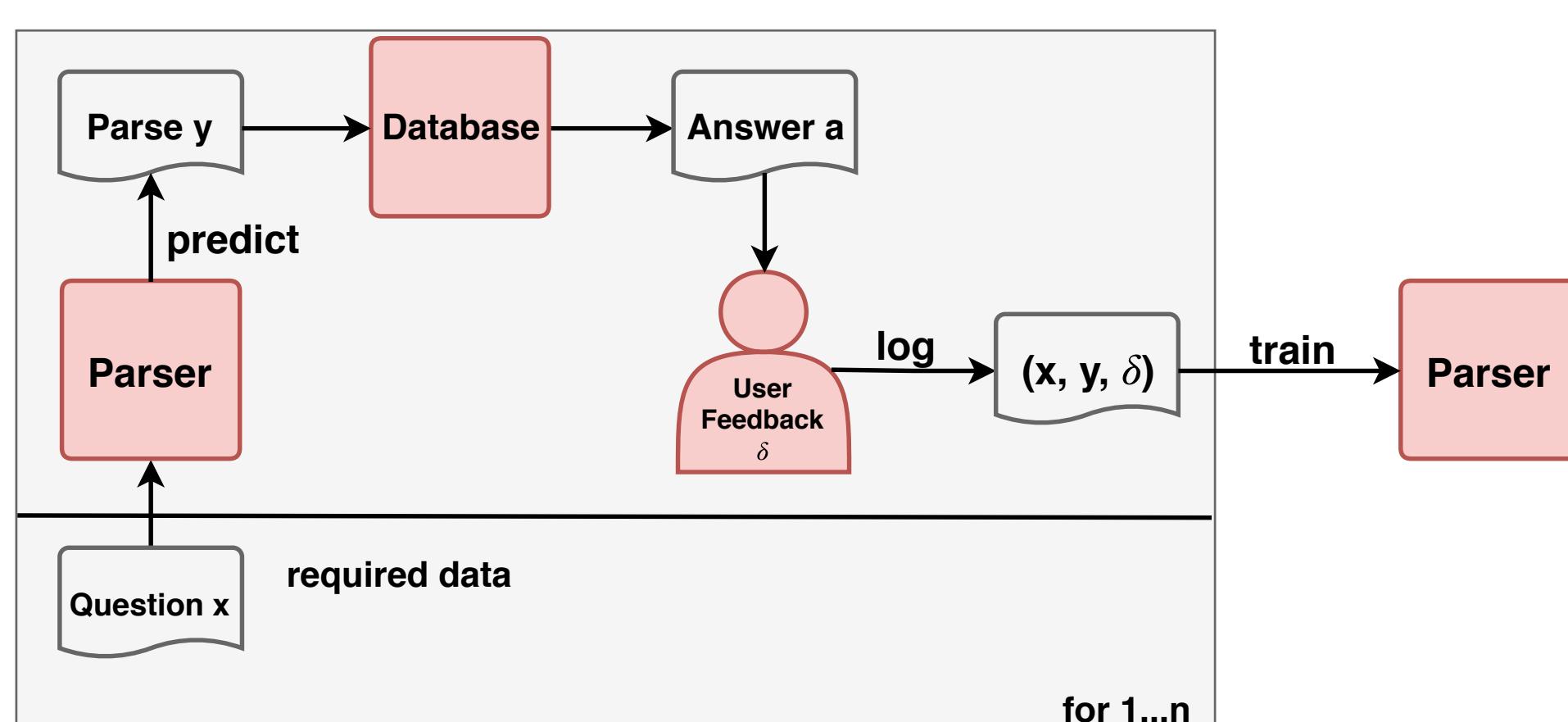
## Overview

Training a semantic parser typically requires either **question-parse** pairs or **question-answer** pairs. Both can be expensive to obtain.

How can we alleviate the need for these pairs?

How can we further improve deployed parsers?

→ **Collect feedback for model outputs from system-user interactions**



**Difficult** because

- No supervision: gold output is unknown
- Bandit: feedback for only one system output
- Bias: log  $\mathcal{D}$  is biased to the decisions of the deployed parser

**Solution:** Counterfactual Off-policy Reinforcement Learning (CL)  
Objectives

Collected log  $\mathcal{D}_{log} = \{(x_t, y_t, \delta_t)\}_{t=1}^n$  with

- $x_t$ : input
- $y_t$ : most likely output of deployed system  $\pi_0$
- $\delta_t \in [-1, 0]$ : loss (i.e. neg. reward) from user

**Deterministic Propensity Matching (DPM)**

- Minimize expected risk for a target policy  $\pi_w$

$$\hat{R}_{DPM}(\pi_w) = \frac{1}{n} \sum_{t=1}^n \delta_t \pi_w(y_t | x_t)$$

- Improve  $\pi_w$  using (stochastic) gradient descent

**Problem:** High variance

**Solution:** Multiplicative Control Variate - Reweighting (+R)

For random variables  $X$  and  $Y$ , with  $\bar{Y}$  the expectation of  $Y$ :

$$\mathbb{E}[X] \approx \mathbb{E}\left[\frac{X}{\bar{Y}}\right] \cdot \bar{Y}$$

→ RHS has lower variance if  $Y$  positively correlates with  $X$ .

$$\hat{R}_{DPM+R}(\pi_w) = \frac{\frac{1}{n} \sum_{t=1}^n \delta_t \pi_w(y_t | x_t)}{\frac{1}{n} \sum_{t=1}^n \pi_w(y_t | x_t)} \cdot 1$$

Reweight Sum R

- Reduces variance but introduces a bias of order  $O(\frac{1}{n})$  that decreases as  $n$  increases  
→  $n$  should be as large as possible

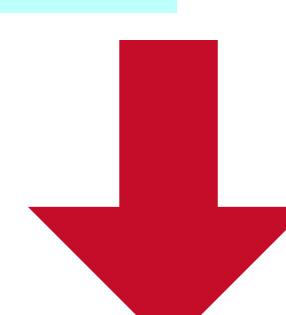
**Problem:** To train state-of-the-art neural networks, stochastic minibatch learning is employed and then  $n$  is too small.

## Task: NL Interface to OpenStreetMap (OSM)

- OSM: geographical database
- NLMAPS v2: 28,609 question-parse pairs
- Example question:  
*"How many hotels are there in Paris?"*
- Answer: 951
- Correctness of answers are difficult to judge  
→ judge parses by making them human-understandable
- Feedback collection setup:
  1. Transform a parse to a set of statements
  2. Humans judge the statements

## Automatically Transform a Parse

```
query(around(center(area(keyval('name','Paris')), nwr(keyval('name','Place de la République'))), search(nwr(keyval('amenity','parking'))), maxdist(WALKING_DIST)),qtype(findkey('name')))
```



Question #216: What are the names of cinemas that are within walking distance from the Place de la République in Paris?

|                 |                               | Information found in Question? |
|-----------------|-------------------------------|--------------------------------|
| Town            | Paris                         | Yes No                         |
| Reference Point | name : Place de la République | Yes No                         |
| POI(s)          | amenity : parking             | Yes No                         |
| Question Type   | What's the name               | Yes No                         |
| Proximity       | Around/Near                   | Yes No                         |
| Distance        | Walking distance              | Yes No                         |
|                 | Submit                        |                                |

Note: If no question type is specified, the default "Where" is correct.

**Solution:**  
**One-Step Late (+OSL) Reweighting**

Perform gradient descent updates & reweighting asynchronously:

- evaluate reweight sum  $R$  on the entire log of size  $n$  using past parameters  $w'$
- update using minibatches of size  $m$ ,  $m \ll n$
- periodically update  $R$

→ retains all desirable properties

$$\hat{R}_{DPM+OSL}(\pi_w) = \frac{\frac{1}{m} \sum_{t=1}^m \delta_t \pi_w(y_t | x_t)}{\frac{1}{n} \sum_{t=1}^n \pi_w(y_t | x_t)}$$

**Problem:**

Cannot learn from partially correct parses.

**Solution: Token-Level (+T) Feedback**

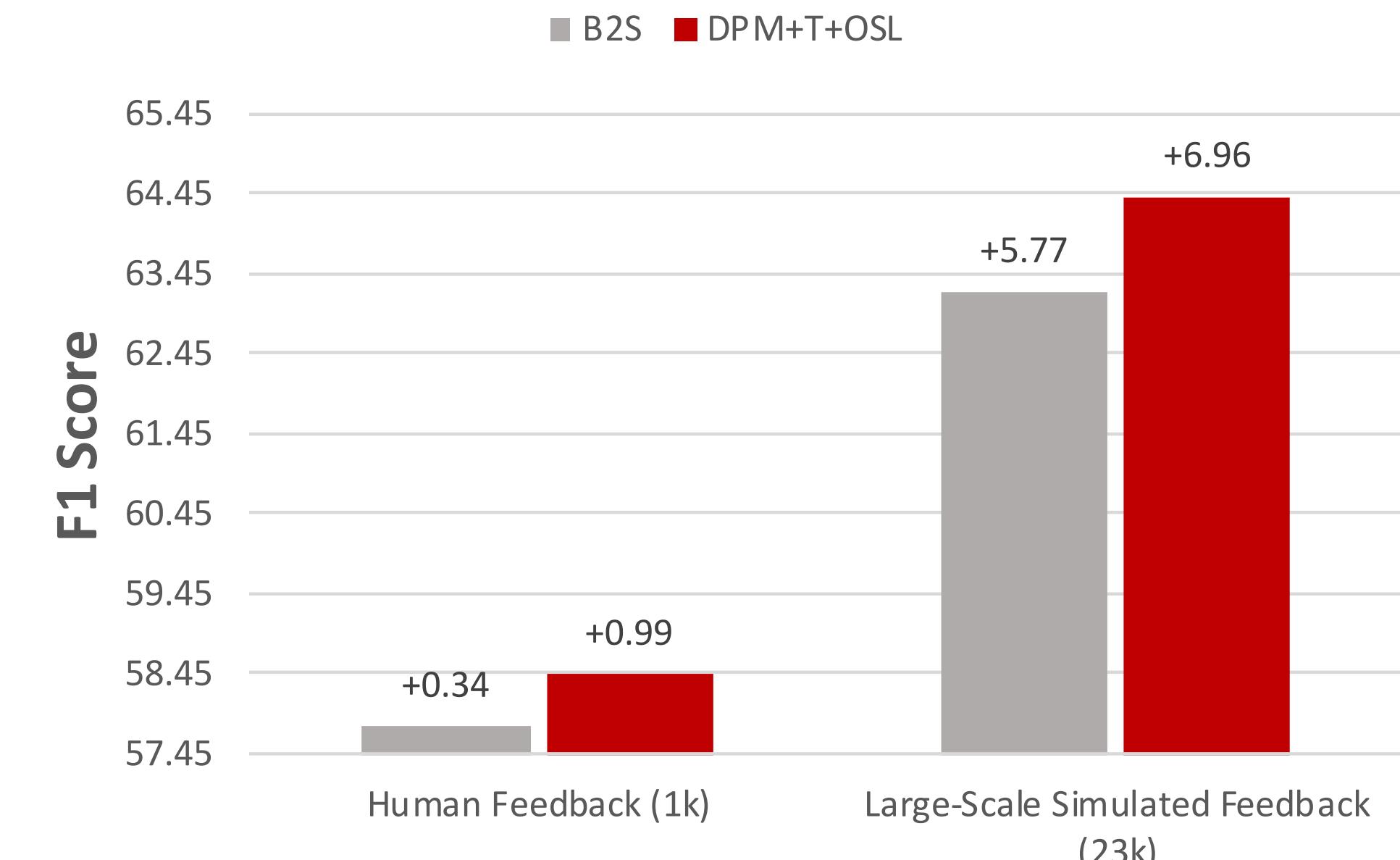
$$\hat{R}_{DPM+T}(\pi_w) = \frac{1}{n} \sum_{t=1}^n \left( \sum_{j=1}^{|y|} \delta_j \log \pi_w(y_j | x_t) \right)$$

$$\hat{R}_{DPM+T+OSL}(\pi_w) = \frac{\frac{1}{m} \sum_{t=1}^m \left( \sum_{j=1}^{|y|} \delta_j \log \pi_w(y_j | x_t) \right)}{\frac{1}{n} \sum_{t=1}^n \pi_w(y_t | x_t)}$$

## Experiments

- Sequence-to-Sequence neural network NEMATUS
- Deployed system: pre-trained on 2k question-parse pairs
- Feedback collection:
  1. Humans judged 1k system outputs
    - Average time to judge a parse: 16.4s
    - Most parses (>70%) judged in <10s
  2. Simulated feedback for 23k system outputs
    - Token-wise comparison to gold parse
- Bandit-to-Supervised conversion (B2S): all instances in log with reward 1 are used as supervised training

B2S in comparison to the best CL objective:



## Take Away

### Proofreading

- Parses are automatically transformed into a set of human-understandable statements
- One set is typically judged in 10 seconds or less by a non-expert user  
→ efficient alternative when the collection of question-parse or question-answer pairs is impossible or costly
- Feedback collection method enables blame assignment

### Counterfactual Learning

- CL can safely improve models offline
- We introduce two new CL objectives:
  - DPM+OSL: a reweighting objective applicable to stochastic gradient optimization
  - DPM+T: effectively leverages the collected token-level feedback
- The combination DPM+T+OSL significantly outperforms a bandit-to-supervised baseline
- Can be applied to other tasks as well, e.g. machine translation

### Future Work

Facilitate a dialogue with the user for a better user experience and to naturally encourage the collection of feedback.

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UNIVERSITÄT  
HEIDELBERG  
ZUKUNFT  
SEIT 1386