NLP LAB 2021 - VDA

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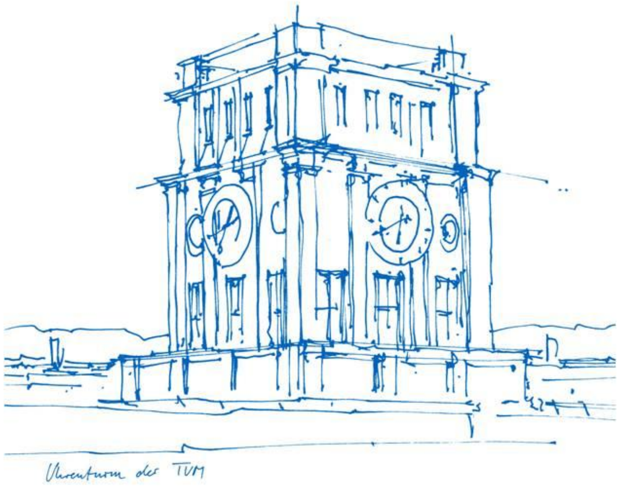
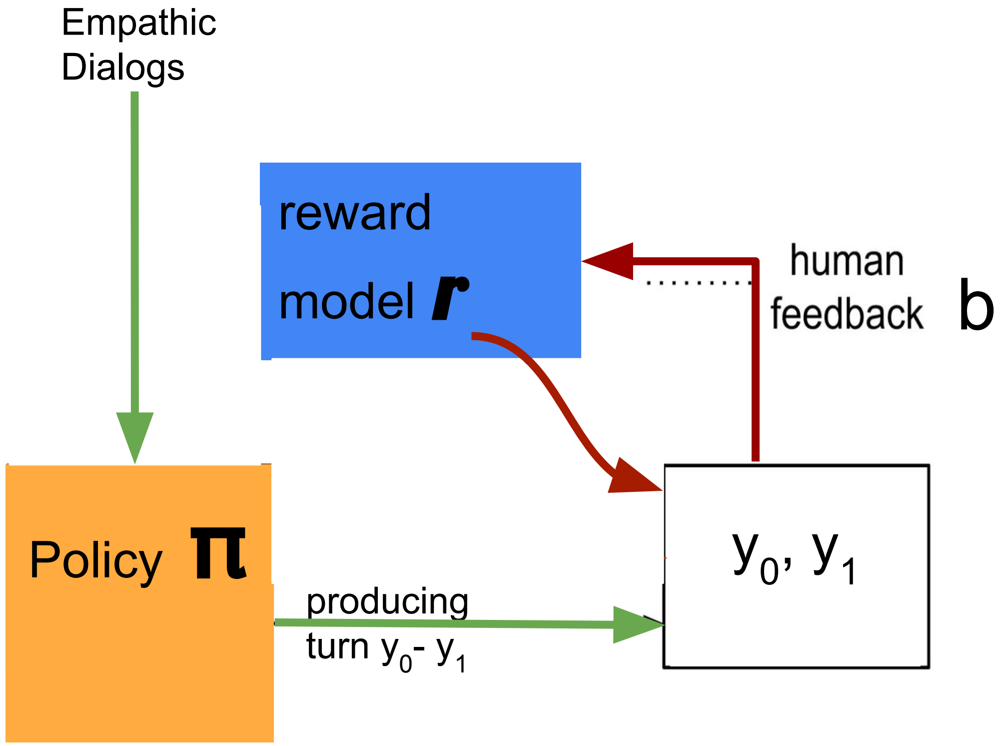


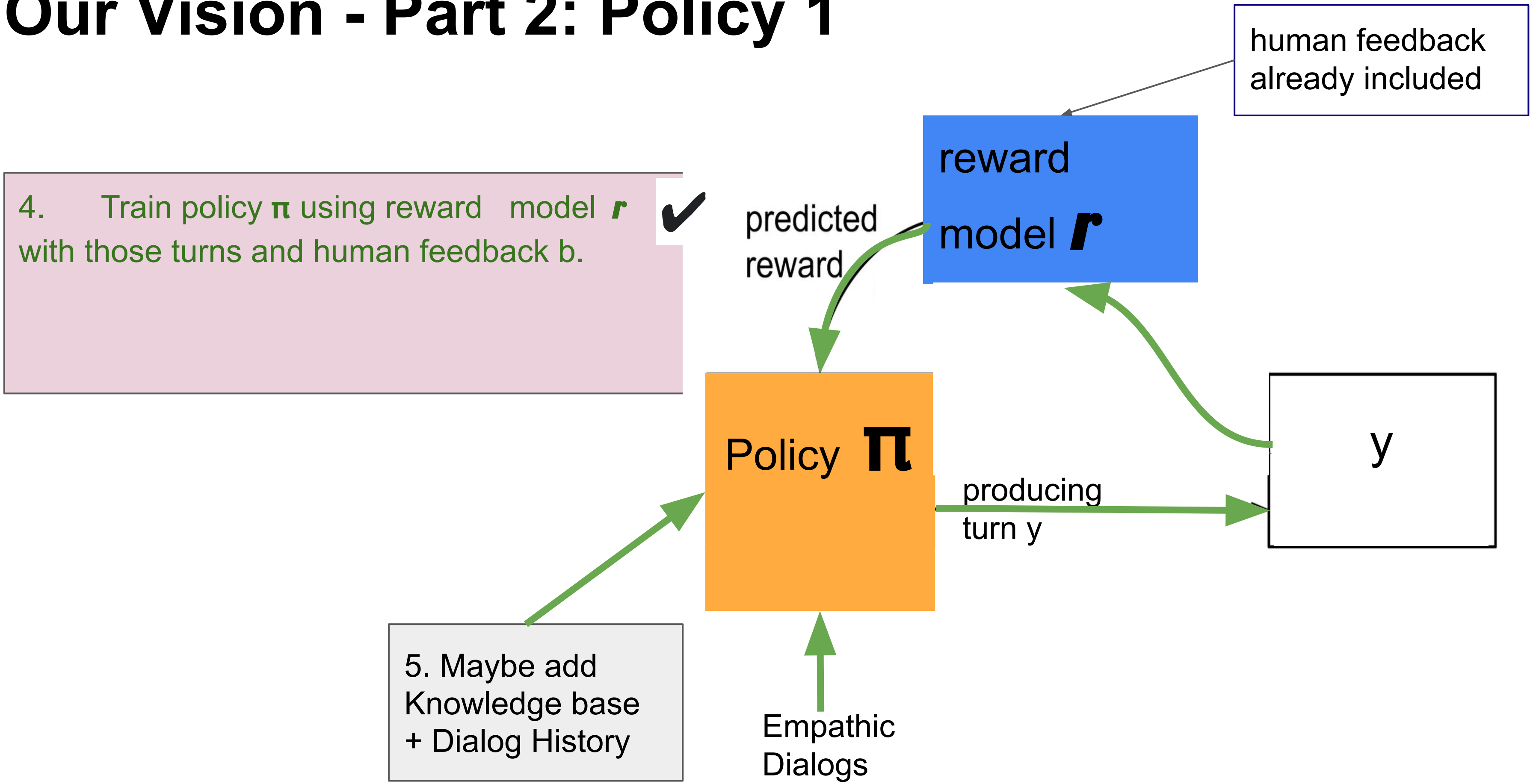
Our Vision - Part 1

1. Creating a Baseline: Fine-Tuning GPT-2 with Empathic Dialogues datasets
   a. Data Preprocessing (Encoding, Decoding & Importing Data) ✔
   b. Fine-Tuning to get π ✔
2. Producing turns y_0- y_1 to give human feedback on
   a. *With test/validation set of* ✔

      Empathic Dialogs dataset
3. Train reward model r with those turns and human feedback b ✔



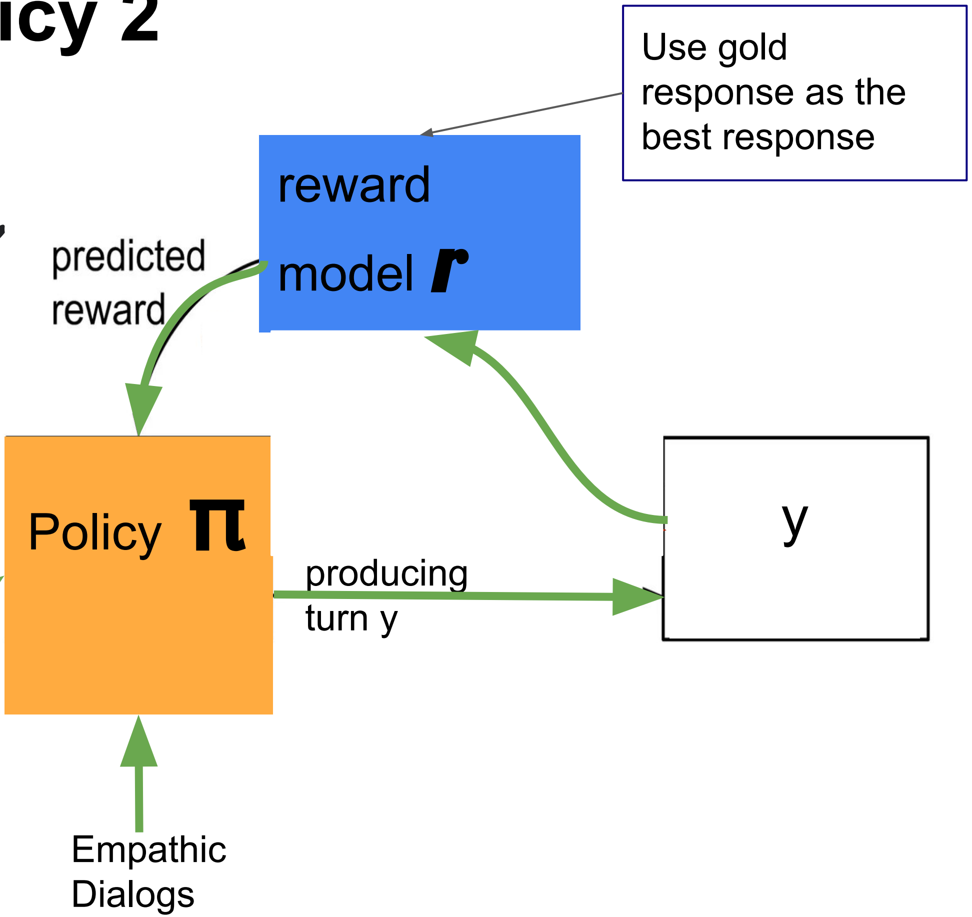
Our Vision - Part 2: Policy 1



Our Vision - Part 2: Policy 2

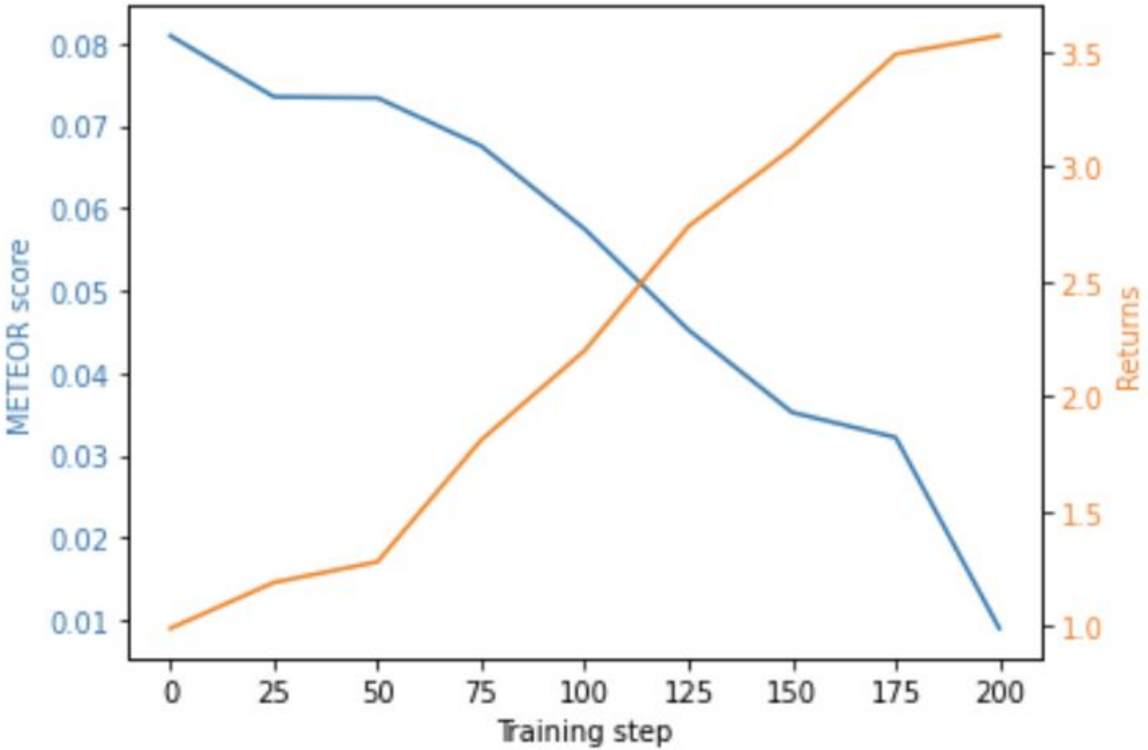
4. Train the reward model with validation s✔ gold responses as the best response.

5. Fine-tune the policy using above reward model.

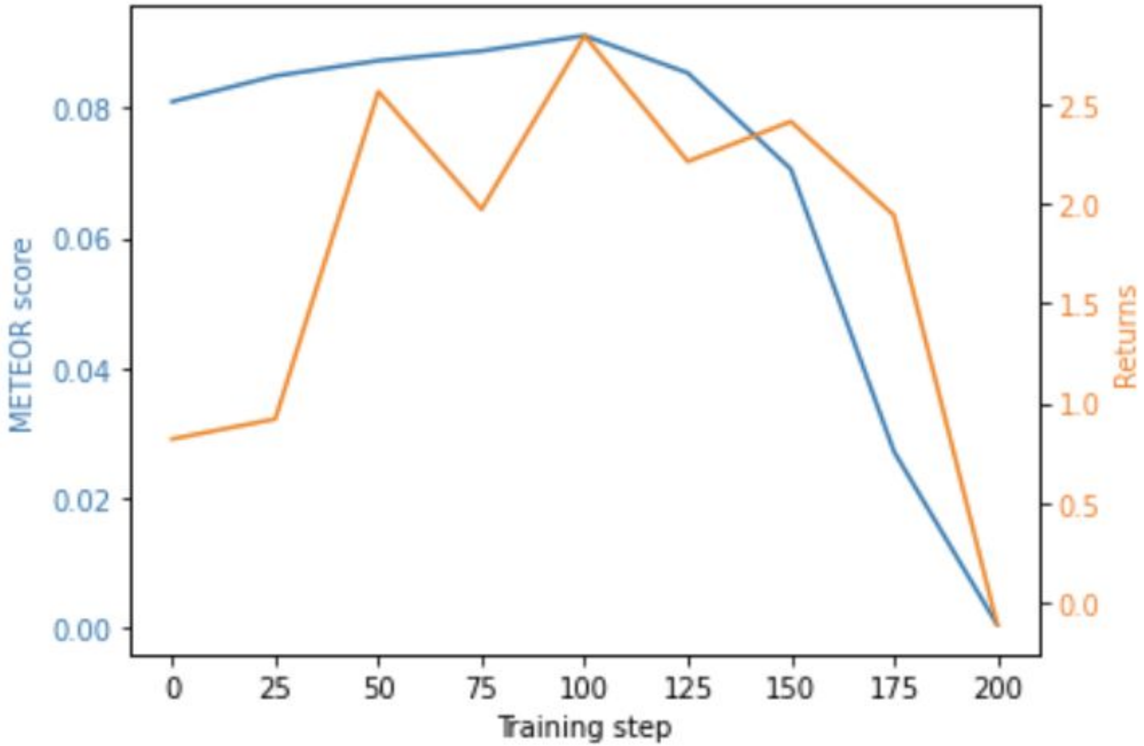


5. Maybe add Knowledge base + Dialog History

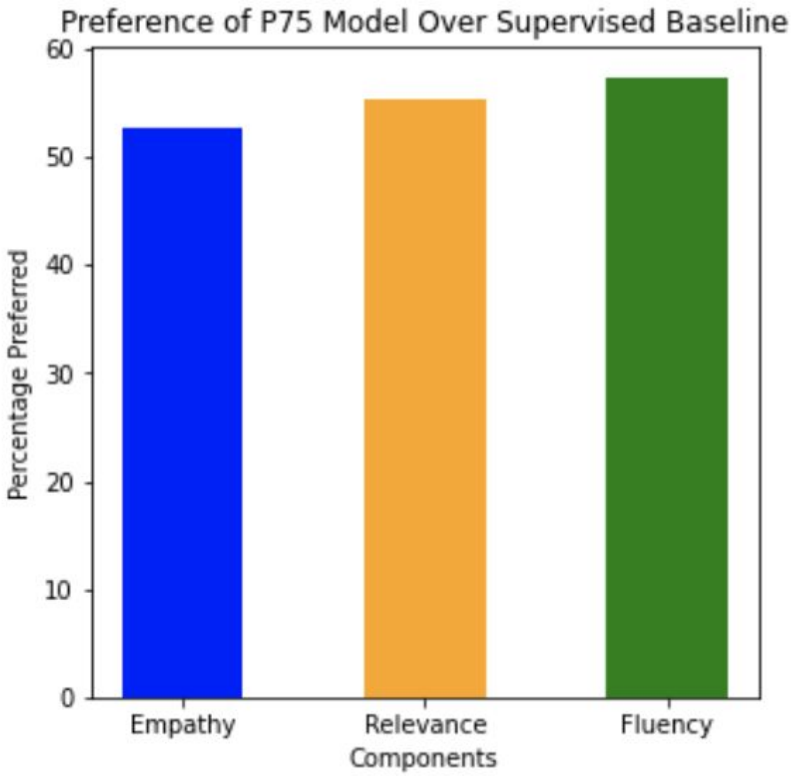
Results (Policy 1)



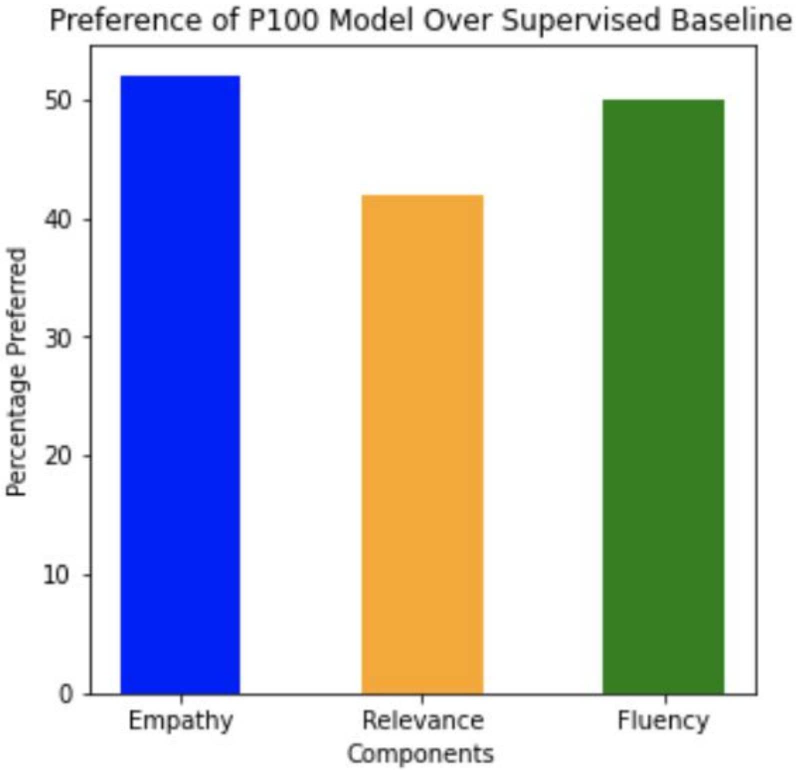
Results (Policy 2)



Human Evaluation (P75 vs Supervised Baseline)



Human Evaluation (P100 vs Supervised Baseline)



Perplexity Score

- **Perplexity =** normalised inverse probability of the test set
- high probability to the test set = model is **not surprised** to see it (it's not *perplexed* by it)
  -->has a good understanding of how the language works
  → Probability P high → Perplexity PP low → good model

- Perplexity=weighted branching factor
  -> PP=100 -> model has to pick between 100 words by guessing the new word → "perplex"

$$PP(W) = \sqrt[N]{\frac{1}{P(w_1, w_2, \ldots, w_N)}}$$

his is probably the most frequently seen definition of perplexity. In this

How does the code works?

Code

```
import nltk
from nltk.lm.preprocessing import padded_everygram_pipeline
from nltk.lm import MLE

train_sentences = ['an apple', 'an orange']
tokenized_text = [list(map(str.lower, nltk.tokenize.word_tokenize(sent)))
                for sent in train_sentences]
n = 1
train_data, padded_vocab = padded_everygram_pipeline(n, tokenized_text)
model = MLE(n)
model.fit(train_data, padded_vocab)

test_sentences = ['an apple', 'an ant']
tokenized_text = [list(map(str.lower, nltk.tokenize.word_tokenize(sent)))
                for sent in test_sentences]

test_data, _ = padded_everygram_pipeline(n, tokenized_text)
for test in test_data:
    print ("MLE Estimates:", [((ngram[-1], ngram[:-1]),model.score(ngram[-1], ngr

test_data, _ = padded_everygram_pipeline(n, tokenized_text)

for i, test in enumerate(test_data):
  print("PP({0}):{1}".format(test_sentences[i], model.perplexity(test)))
```

Example: Bigram model

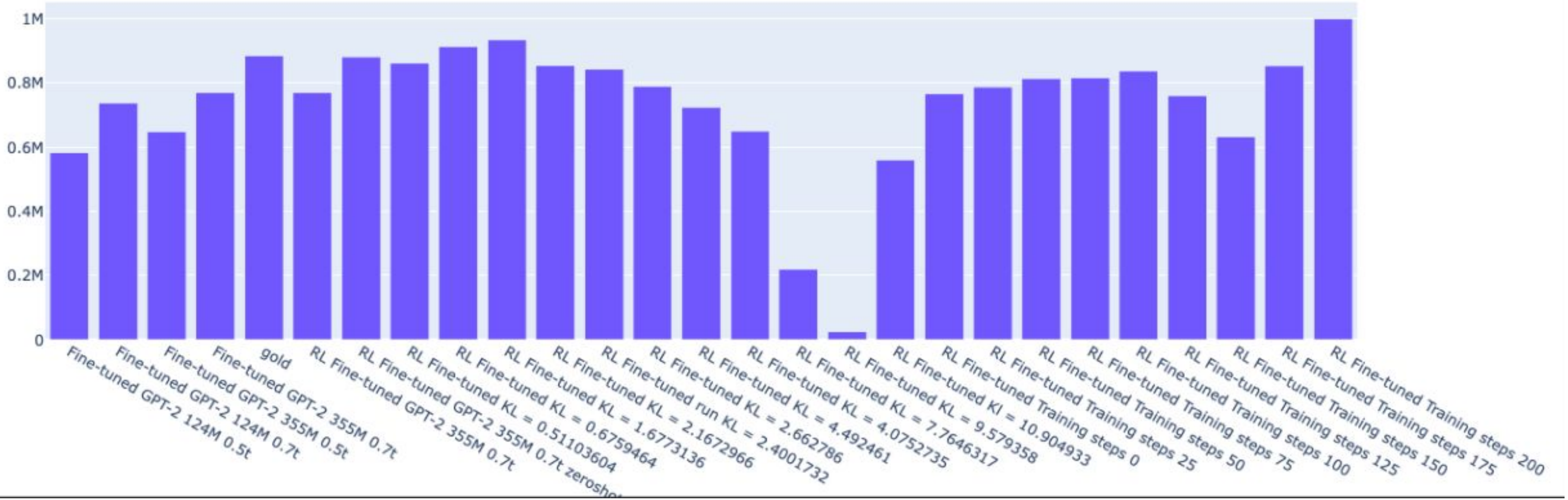
Train Data: "an apple", "an orange" Padded Train Data: "(s) an apple (/s)", "(s) an orange (/s)"
Vocabulary : (s), (/s) an, apple, orange, UNK

MLE estimates

p(w)	MLE estimate
p(an|s)	2/2 = 1
p(apple|an)	1/2 = 0.5
p(\s|apple)	1/1 = 1
p(ant|an)	0/1 = 0
p(\s|ant)	0

Perplexity Scores of our models

Gold model has the second best perplexity



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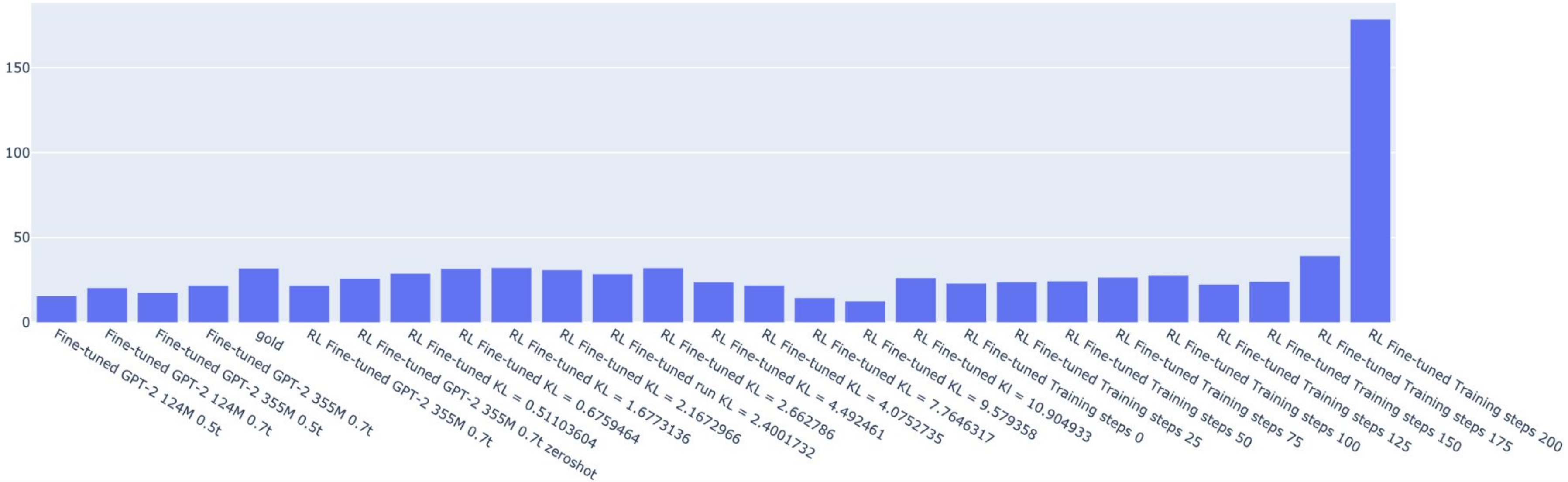
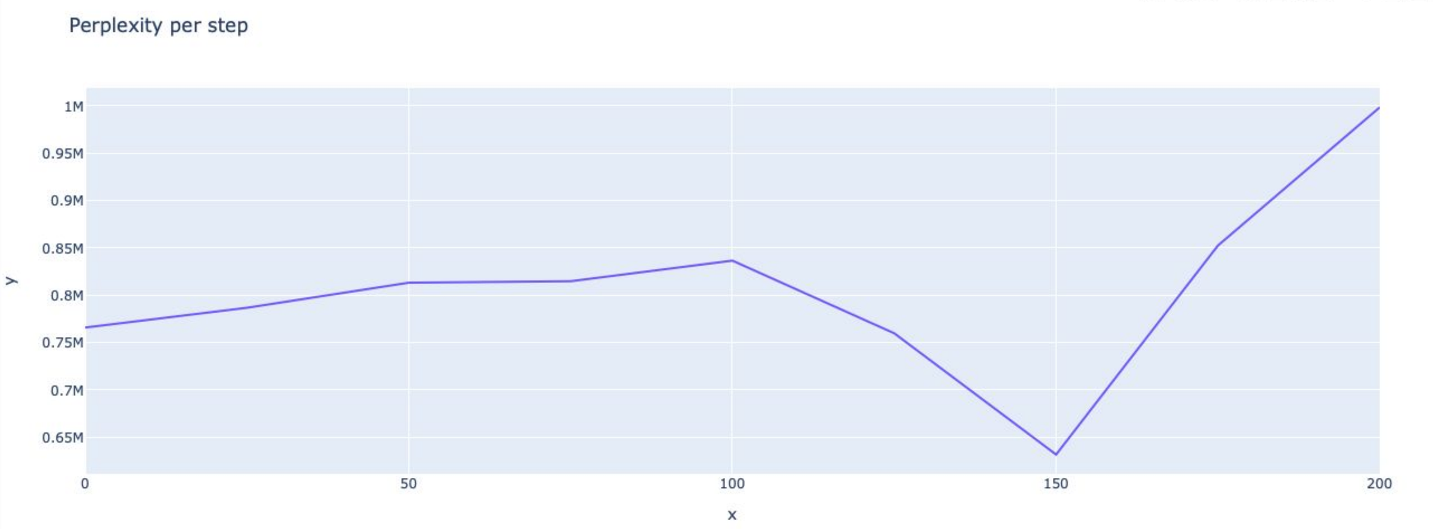


Perplexity vs. Training steps

- The more training steps the better the Perplexity score

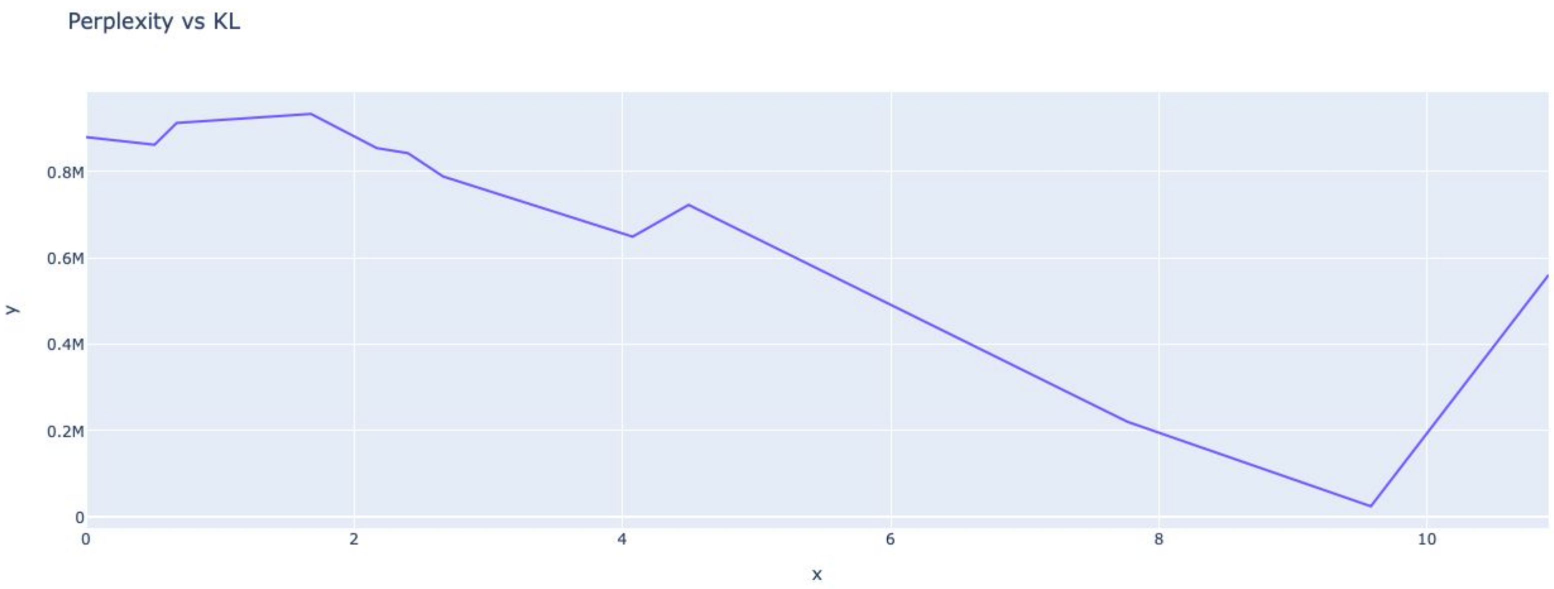
  → perplexity always better as in the original model except between 120-170 trainings

steps



Perplexity vs. KL

- Perplexity score decreases for higher KL



Questions

What to do with “unknown” words → perplextiy= inf / 1 / kick out?

Here we calculate how perplex the generated responses from the model are in comparison to the Empathic Dialogue Testset

→ Better to calculate just the perplexity of the model performance?

@Vivi

Evaluation Metrics - Florian

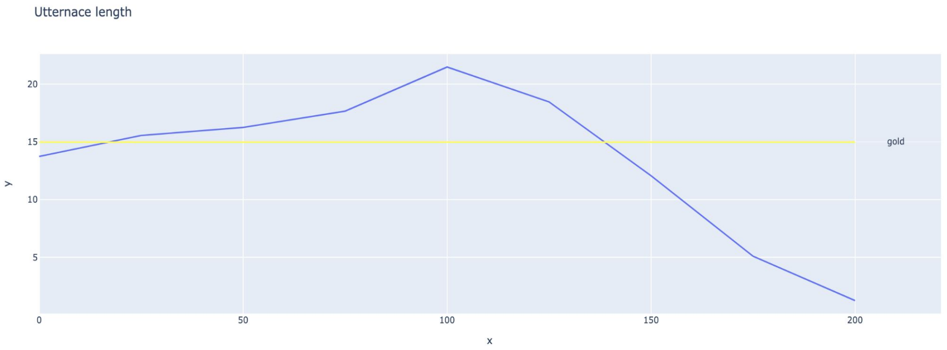
- **Utterance length**
- **Self repetition**
- **Utterance repetition**
- **Word repetition**
- **Conversation repetition**
- **Emotional reaction level**
- **Interpretation level**
- **Exploration level**

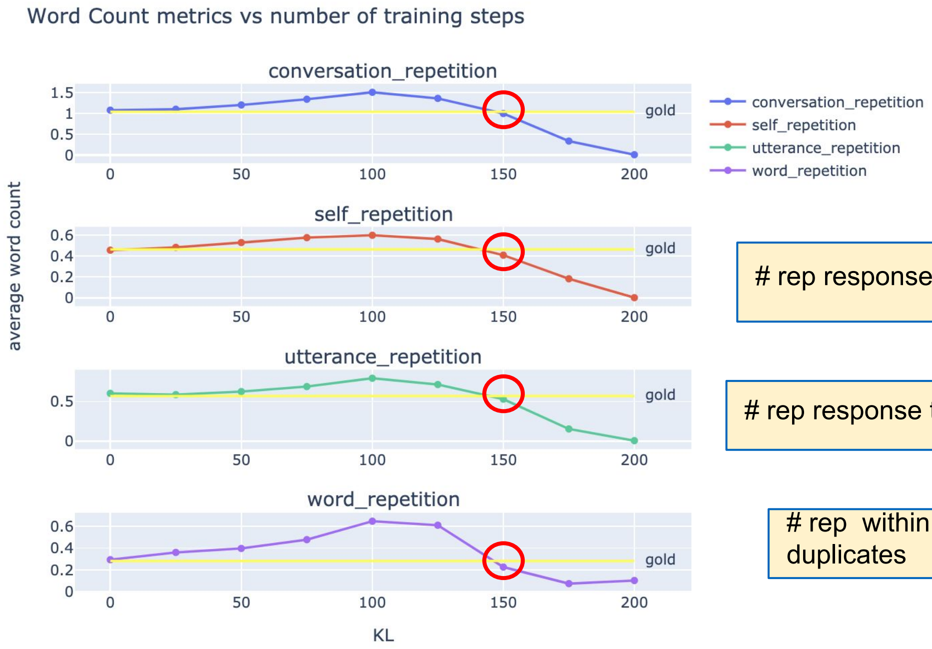
- **Question (1 else 0 -> avg)**
- **Question ration of all samples**
- **If gold is question ratio of sample questions**
- **If gold is no question ration of sample questions**

Metrics for policy-2

… trained based on the reward function

Word count metrics P2





rep response to whole context

rep response to prev own utterances

rep response to prev utterance

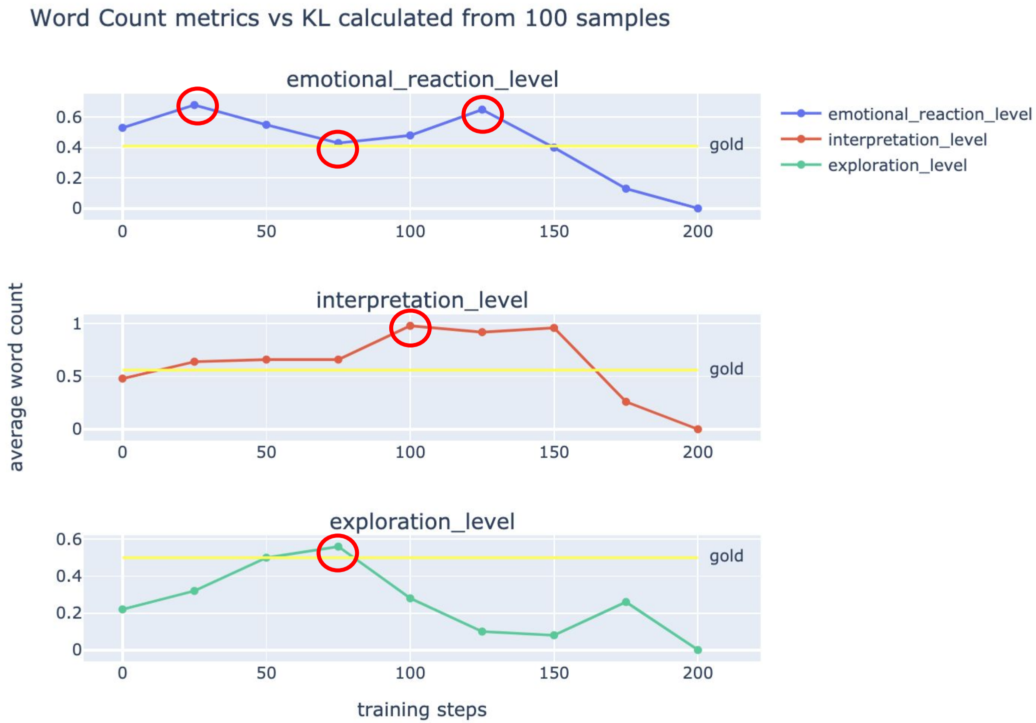
rep within current utterance/ duplicates

Best number of training steps: 150

Question metrics P2

Best number of training steps: 75

Empathy metrics P2

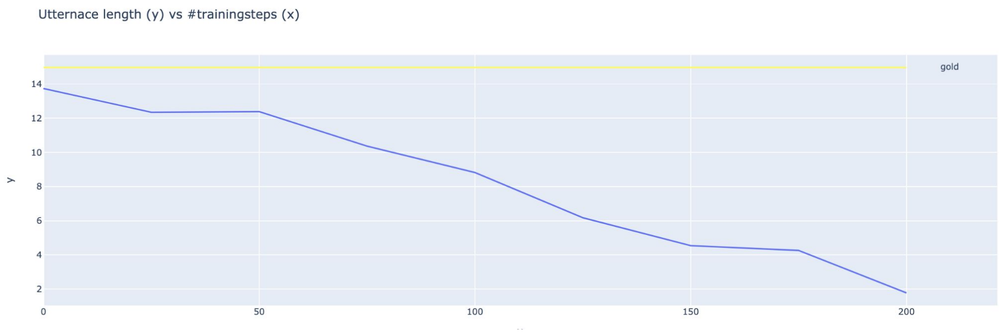


All metrics over the generated response from policy-2's model show that after traing step **75/100** the model reached it's best values!

Metrics for policy-1

… the model gets worse concerning every metric with higher training steps ....

Word count metrics P1



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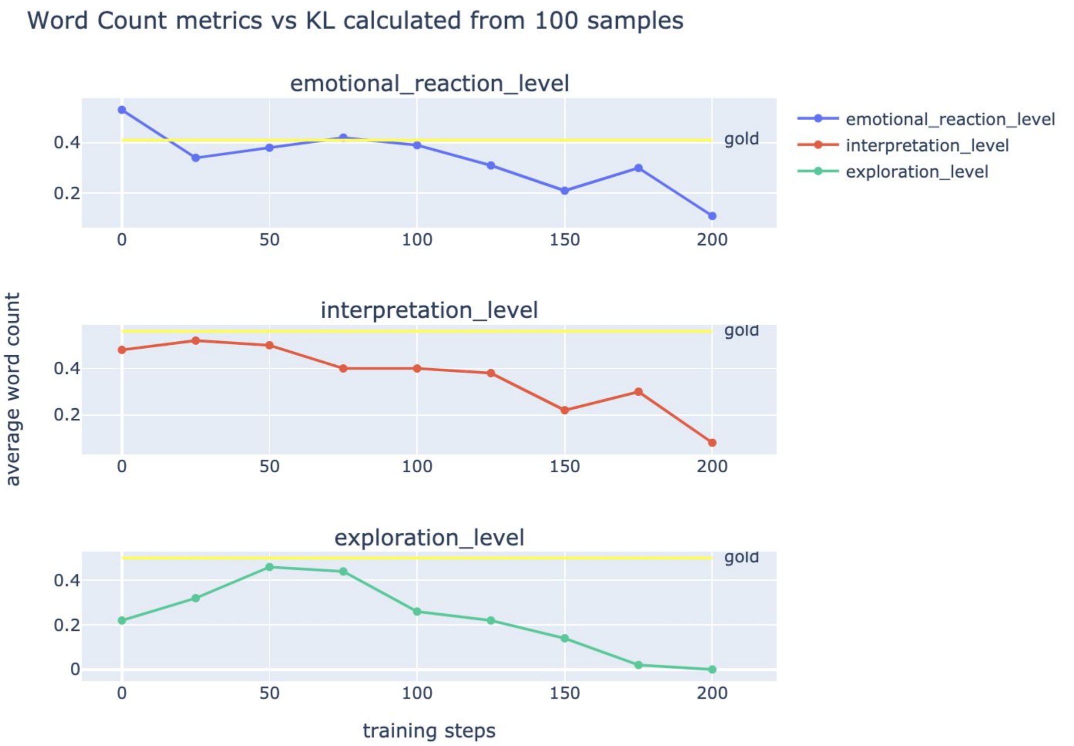
Question metrics P1

Empathy metrics P1



All metrics over the generated response from policy-1's model show that the model is getting worse on every way while training!