

NLP LAB 2021 - VDA

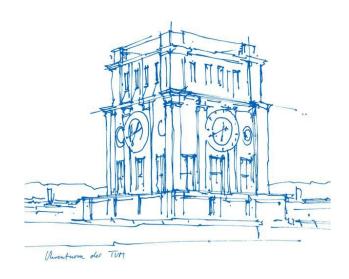
Ananta Bhattarai, Sophie Schoen, Viviane Rehor

Technische Universität München

Department of Informatics

Research Group Social Computing

Munich, June 22 2021



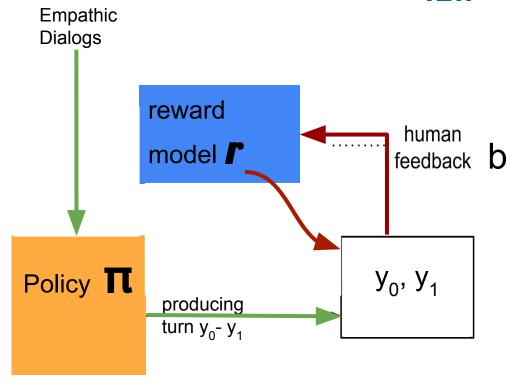


Our Vision - Part 1

- 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 y₀- y₁ 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**



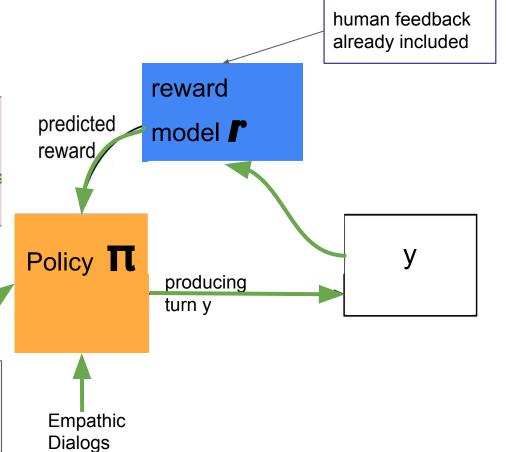


Our Vision - Part 2

- 4. Train policy π using reward model r with those turns and human feedback b
 - + Evaluate Model performance with metrics

5. Improve the idea with input from other papers

5. Maybe addKnowledge base+ Dialog History





Annotation Statistics

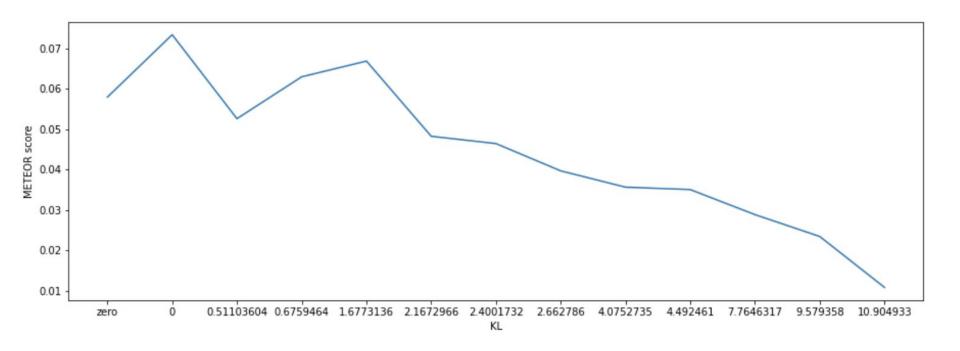
	Ananta		Vivi		Sophie	
	Agreement	Cohen Kappa	Agreement	Cohen Kappa	Agreement	Cohen Kappa
Ananta	-	-	68%	0.35	73%	0.45
Vivi	68%	0.35	-	-	73%	0.46
Sophie	73%	0.45	73%	0.46	-	-

All agreement: 57%

Average Cohen Kappa: 0.41

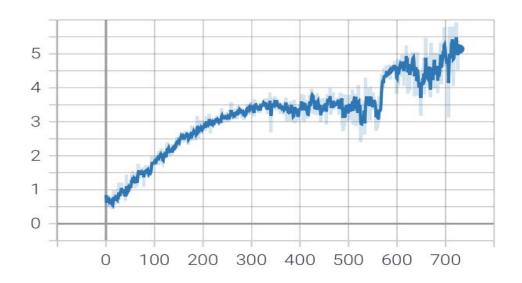


KL VS METEOR





KL vs Returns



Two possible reasons for high rewards even after over optimization:

- 1. Distributional shift of the samples that reward model hasn't seen while training.
- 2. Not enough training data to train reward model (2200 samples)



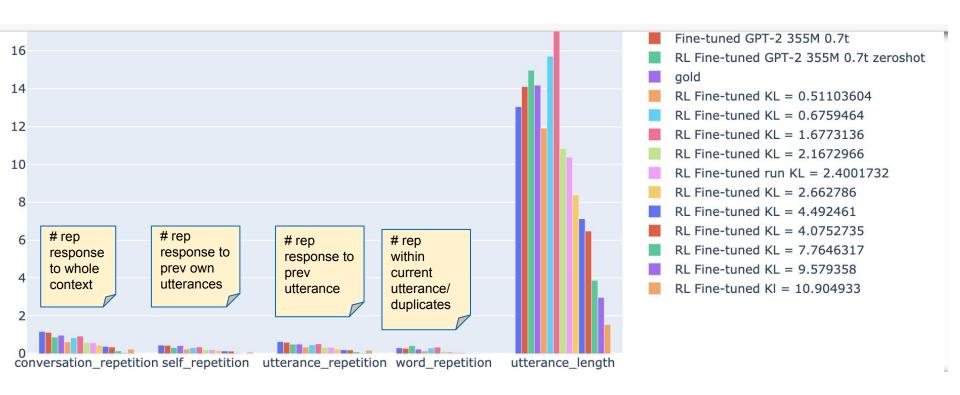
Evaluation Metrics - Florian

- Utterance length
- Self repetition
- Utterance repetition
- Word repetition
- Question
- Conversation repetition
- Emotional reaction level
- Interpretation level
- Exploration level
- QuestionVsGold (Monika's idea from last meeting)

- Deepmoji sentiment pos
- Deepmøji sentiment neg
- Deepmoji concrence
- Infersent coherence
- USE similarity
- Word2Vec coherence

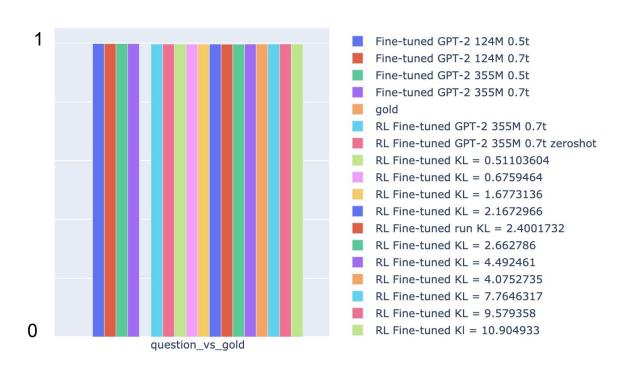


Word count metrics





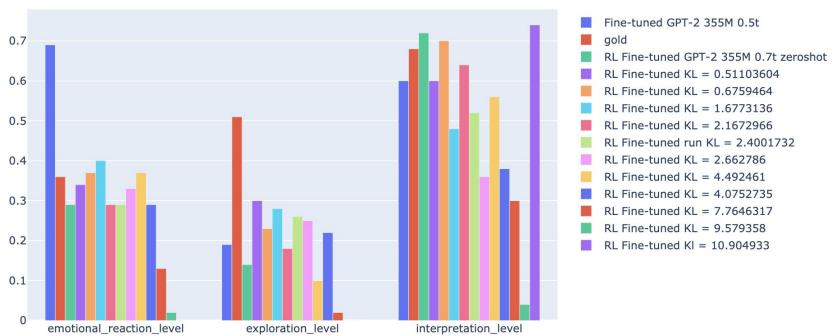
Question metric: Generated vs Gold utterance





Empathy metrics

=> Weird values => Ask Florian





- BLEU Score = Basis
 - judges translations on a per-word basis
 - measures MT **adequacy** by looking at word precision
 - measures MT fluency by calculating n-gram precisions
 - n-gram matching requires exact word matches
 - → better: METEOR Score



METEOR Score

- allows multiple reference translations
 - → addresses the problem of variability with flexibility in word matching
- Extra features to BLEU:
 - stemming
 - synonymy matching



3. NIST Score

- weights n-gram matches by their information gain & indirectly penalizes uninformative n-grams
 - ightarrow BLEU calculates n-gram precision by adding equal weight to each n-gram
 - → NIST also calculates how relevant a particular n-gram is
 - → More weight is given to n-grams that are considered less likely to occur

"Yes I made an interesting calculation"



4. TER Score

measures the number of edits required to change a system output into one of the references
→ evaluating the quality



Evaluating chatbots

Combine sensibleness and specificity in one metric: SSA (sensibleness and specificity average) ≈ human likeness

Human Evaluation setups:

- a) Static: benchmark models on a fixed set of multi-turn contexts to generate responses
- b) *Interactive*: allow humans to chat freely with chatbots

A: "I love tennis,"

B: "That's nice,"

→ not specific

A: "I love tennis,"

B: "Me too, I can't get enough of Roger Federer!"

→ specific



Automatic Evaluation

From Google Research: Towards a Human-like Open-Domain Chatbot

Automatic Perplexity metric

- correlates with human judgement of sensibleness and specificity (SSA metrics)
- seq2seq model outputs a probability distribution over possible next response tokens
- Correlation static sensibleness & specificity vs perplexity: R2=0.93
 - → perplexity= good automatic metric for measuring sensibleness and specificity



Perplexity Score

- good evaluation metric for chatbots
- With perplexity you are trying to evaluate the similarity between the token (in your case probably sentences) distribution generated by the model and the one in the test data.
- For instance, assuming you have



What are our best next steps?