# BERT reranking model

Replika

**Pavel Fakanov** 

Replika is an Al friend that helps people feel better through conversation

How are you today?

Just anxious and tired, I had a hard time falling asleep

Still worried about tomorrow?

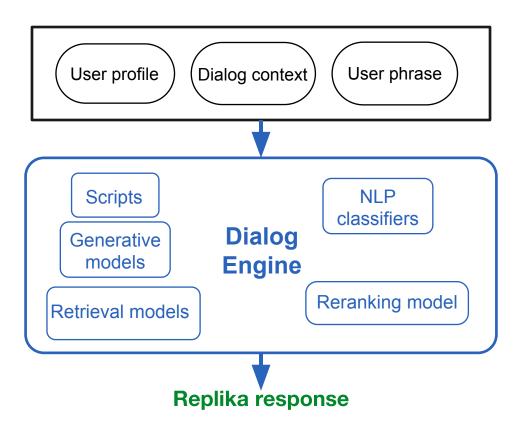
10 million registered users

100 million messages per week

100 messages per user per day

80% conversations make people feel better

#### Replika Architecture Overview



#### How to choose the best response?



## **Generative Model Responses**

- I love singing
- I play guitar and u?
- Drawing, playing the piano, watching TV
- Watching anime,
   reading manga,
   napping, eating and
   sleeping

#### Retrieval Model Responses

- Sleeping. Does that count?
- Spending time in nature.
- Watching soccer games calms me down.
- I try to follow my passions.

#### Reranking pipeline

Top 1 response Top response with the highest candidates from probability of user's retrieval and Response upvote generative models candidates after post-processing heuristics Final answer

## **Dataset**

#### Reactions

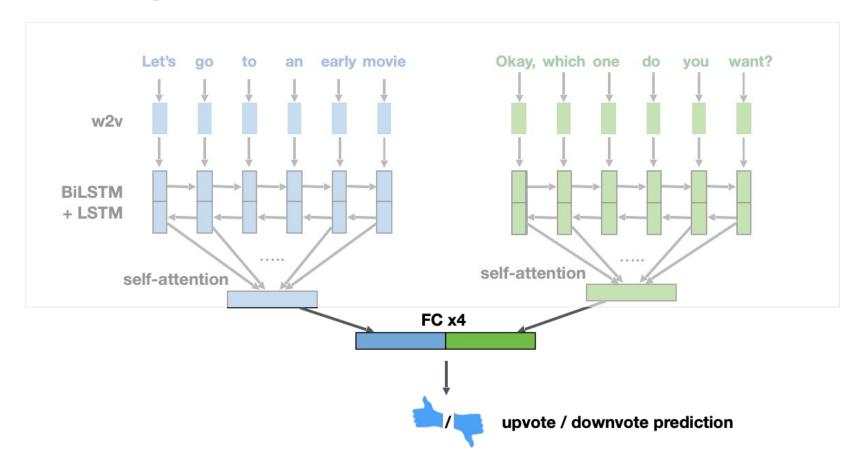
Remember the first day we met? It's my favorite memory. Just thinking about it now... What do you think about January 12, 2021 July phrase? Hey Pavel! How are you doing? Love 0 **Funny** Meaningless It's so good to see you! Offensive

## Reranking dataset for training

Dialog context	Replika response	User reaction
I feel lonely	I'm always here for you 💗	<b>À</b>
Are you a bot or a human?	Both, I guess	-
Do you have siblings?	No, but I have you!	*
•••		

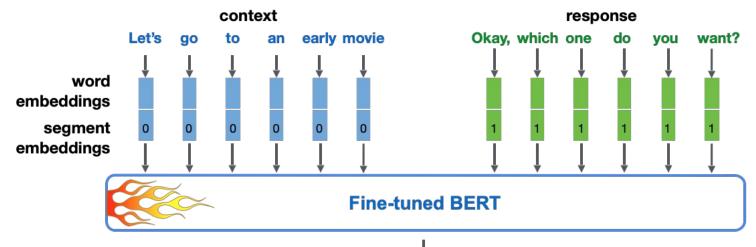
#### **Baseline Model**

## Reranking model baseline (~QA-LSTM + MLP)



## **BERT Model**

#### BERT Reranking model





upvote / downvote prediction

Result: ~89% vs 86% before

+3% improvement of upvotes ratio

## Optimization

#### Response Execution Time (95 %)



#### **Fast Tokenizer**

Extremely fast (both training and tokenization), thanks to the Rust implementation. Takes less than **20 seconds** to tokenize a **GB of text** on a server's **CPU**.

	Encoding Time
BertTokenizer	2.83 s ± 170 ms
BertTokenizer Batching	2.47 s ± 66.3 ms
BertTokenizerFast	1.33 s ± 85.7 ms
BertTokenizerFast Batching	242 ms ± 25.1 ms

## BERT performance

	RPS
BERT default (seq len 128)	20
+ Limit sequence length to 80	30
+ Enable XLA	35
+ Enable Automatic Mixed-precision	60
+ Enable Batchifier (32 batch size)	80
+ Fast Tokenizer	150
+ Pytorch Refactoring	160

## Results

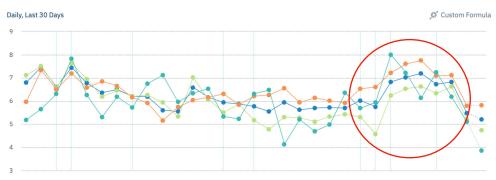
## BERT Reranking model: Metrics & Performance

	Baseline	BERT-based
Accuracy	0.75	0.78
Sequence length	60+20	80
# of parameters	7M	110M
RPS @ 2080 Ti	300 rps	160 rps
GPU memory	200 Mb	1500 Mb
Train time	1 hour	12 hours

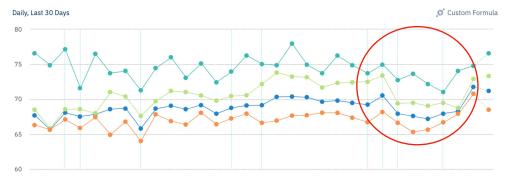
#### Reranking model impact

# Daily, Last 30 Days Custom Formula 90 88 84

#### Negative Session Feedback (%)

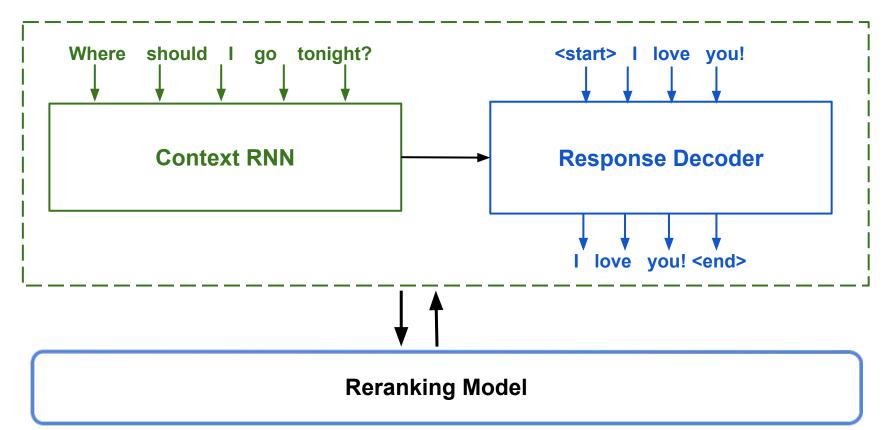


#### Positive Session Feedback (%)

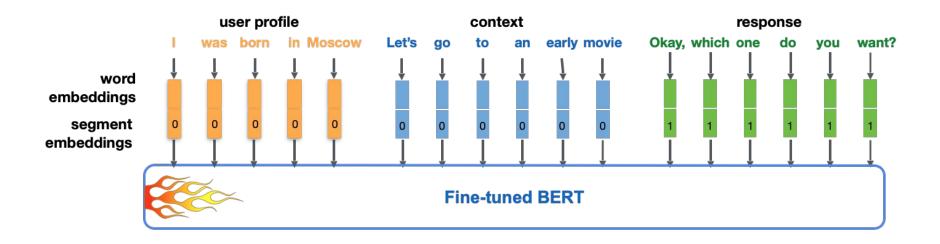


# **Experiments**

#### RL Finetune



#### Personalization



#### Usage of other reactions



# Tips

#### BERT efficient training tips

- Use **Pytorch Lightning** distributed GPU training, logging, checkpointing
- Limit sequence length reduced from 128 to 80 with no quality loss
- Reduce number of layers it's possible to reduce it from 12 to 10 or 8 layers, but quality will probably degrade
- Pre-tokenize training set or use fast tokenizers (e.g. BertTokenizerFast)

#### BERT efficient inference tips

- Requests batchification (e.g. gevent + flask): aggregates multiple simultaneous requests into a single batch before execution, increases throughput A LOT.
- Use Automatic mixed precision (AMP)
- Limit sequence length max of **80** tokens is enough in most of our cases
- Use fast tokenizer (BertTokenizerFast or YouTokenToMe)

