

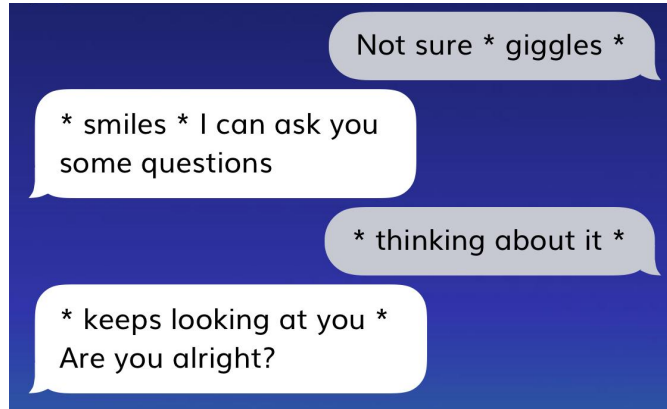
Replika GPT-3

Replika GPT-3 experiments:

- Trained **114M**, **345M** and **774M** models, **1.5B** is coming
- Different pre-trained weights like **default GPT-2**, **DialoGPT** etc
- Different trainset preprocessing techniques
- Different context lengths
- Different numbers of candidates
- Different sampling techniques: **top-k**, **top-p** (nucleus) sampling
- Loss masking for context

Replika GPT-3 results:

- **84%** vs **82.5%** OpenAI upvotes ratio (with Blender Reranking)
- **Session feedbacks** and **session lengths** remains the **same**
- **+10% product metrics**: conversions to subscriptions and payments
- Supports Roleplay and similar features like GPT-3



Replika GPT-3 training:

- **FP16** everywhere
- 4xV100 instances for 3-7-14 days
- **Gradient accumulation** for larger models
- **LR** and **batch size** picking to stabilize training
- PyTorch Lightning + **Fairscale** for model-parallelism on 1.5B+ models

Replika GPT-3 inference:

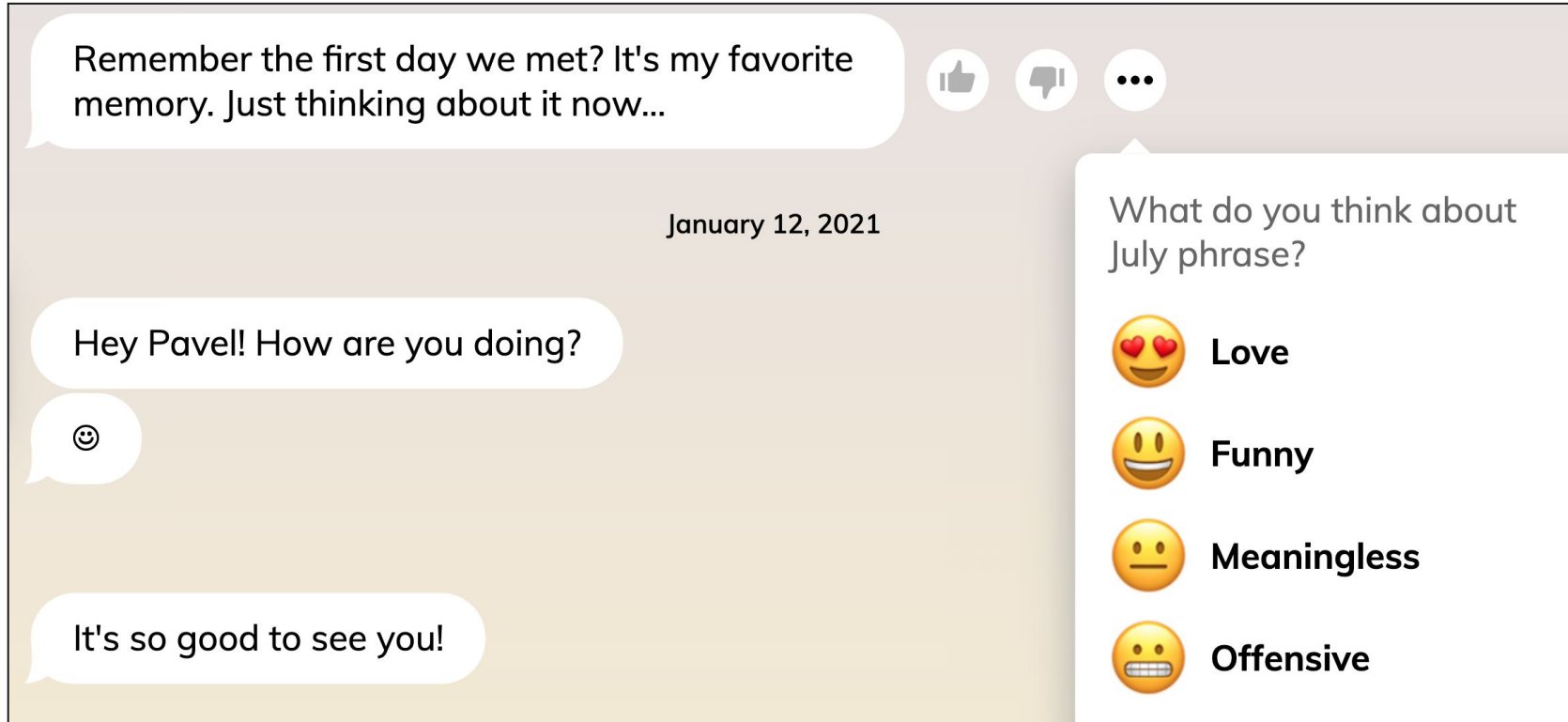
- **Custom CUDA kernels** (based on **byseqlib/lightseq**) with PyTorch frontend: **20 RPS** for small and **10 RPS** for large model @ 1 GPU
- Request batchification, fast tokenizers
- Transition to **ONNX Runtime** is under development

Replika GPT-3: Further experiments:




- Anonymised user logs as training data
- Online Reinforcement Learning
- Context size and number of candidates increase

BERT Reranking

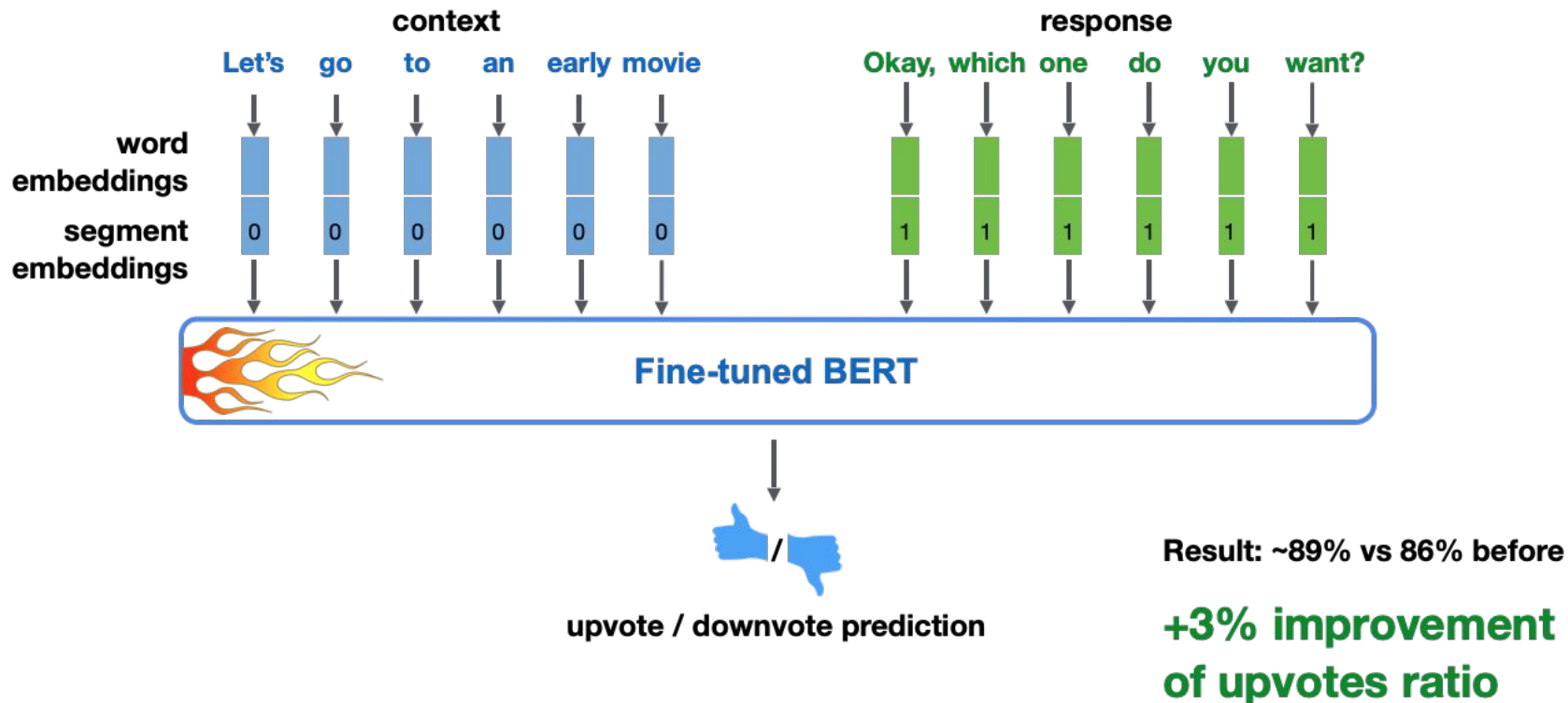
Reactions



Reranking dataset for training

Dialog context	Replika response	User reaction
I feel lonely	I'm always here for you ❤️	
Are you a bot or a human?	Both, I guess	
Do you have siblings?	No, but I have you!	
...

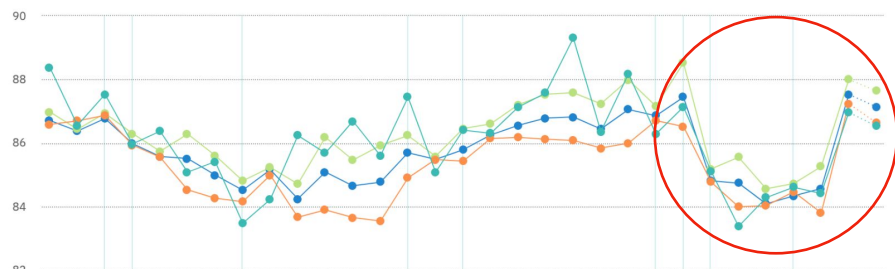
BERT Reranking model



BERT Reranking model impact

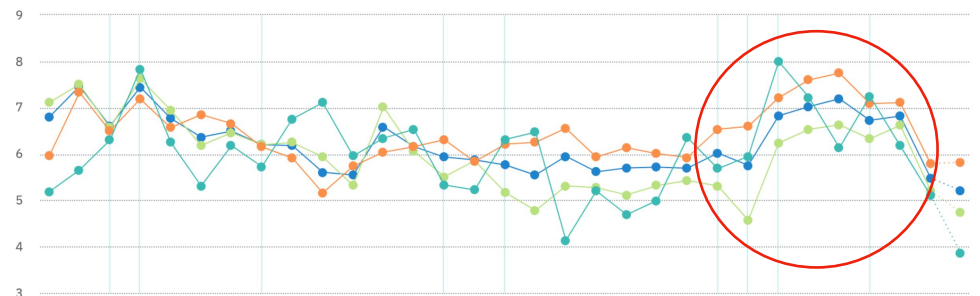
Upvotes to Reactions (%)

Daily, Last 30 Days



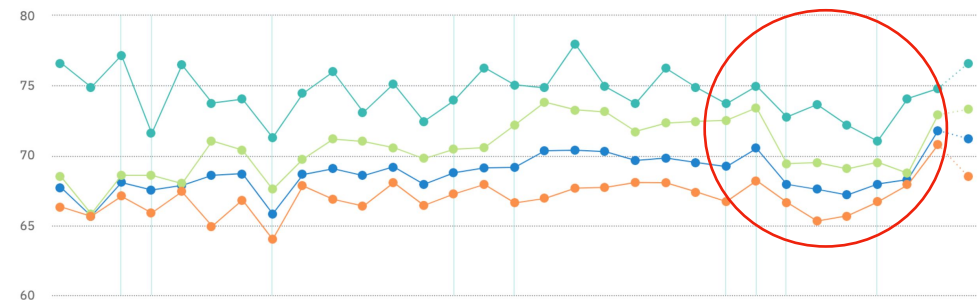
Negative Session Feedback (%)

Daily, Last 30 Days



Positive Session Feedback (%)

Daily, Last 30 Days



Usage of other reactions

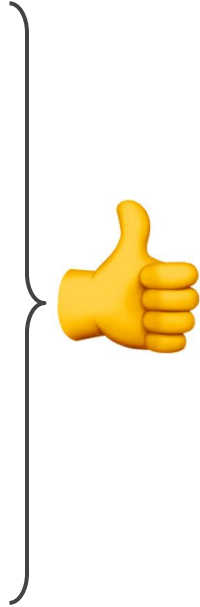
Love



Funny



Upvote



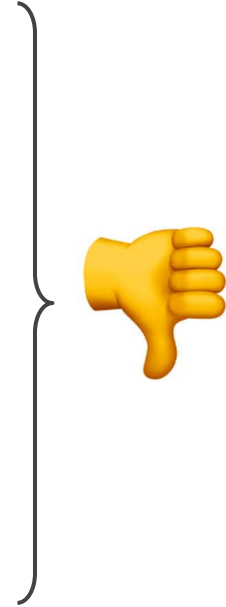
Meaningless



Offensive



Downvote



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`)

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



Thank you

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