Natural Language Processing

Episode 7 ‘2021

Model compression & acceleration

Yandex
Research

British Hedgehog
Preservation Society

Chapter 1: why should you care?

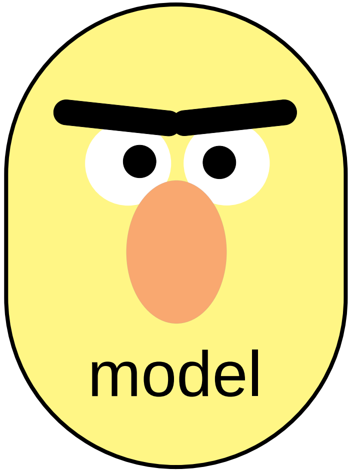
Case study: text classification

"I saw a cat"
"I f*** your mom"

▶ prepare batch ▶

$$\begin{pmatrix} 2 & 5 & 7 & 8 \\ 1 & 2 & 3 & 1 \\ 4 & 5 & 0 & 1 \end{pmatrix}$$

▶



▶

(0) Normal tweet
(1) Should ban

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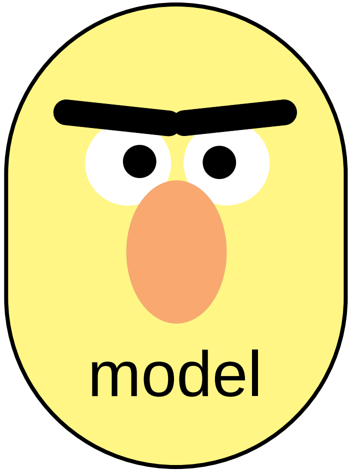

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Three kinds of efficiency:

Model Size
(mega)bytes

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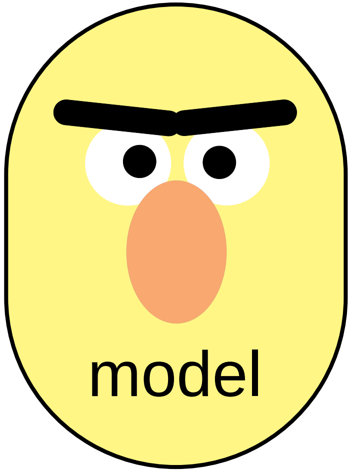

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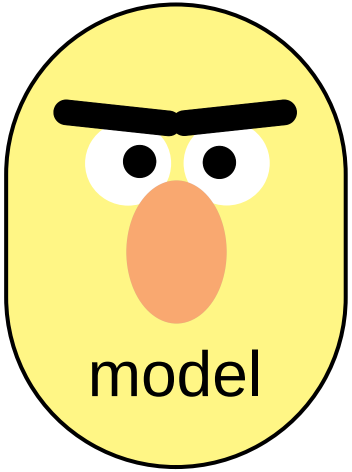

▶

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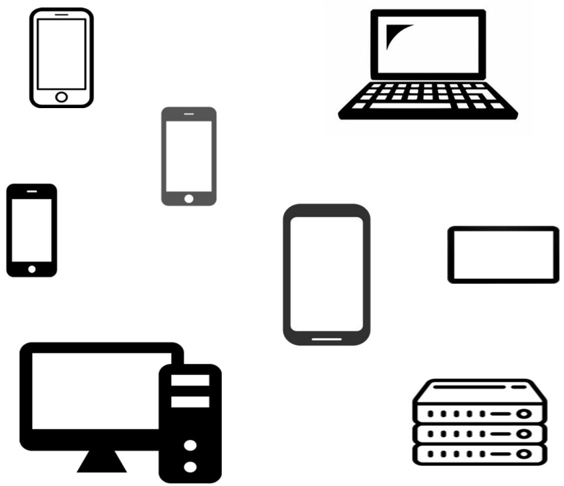
Three kinds of efficiency:

- **Model Size** (mega)bytes
- **Throughput** samples/second
- **Latency** ms@percentile

Scenario 1: inference server



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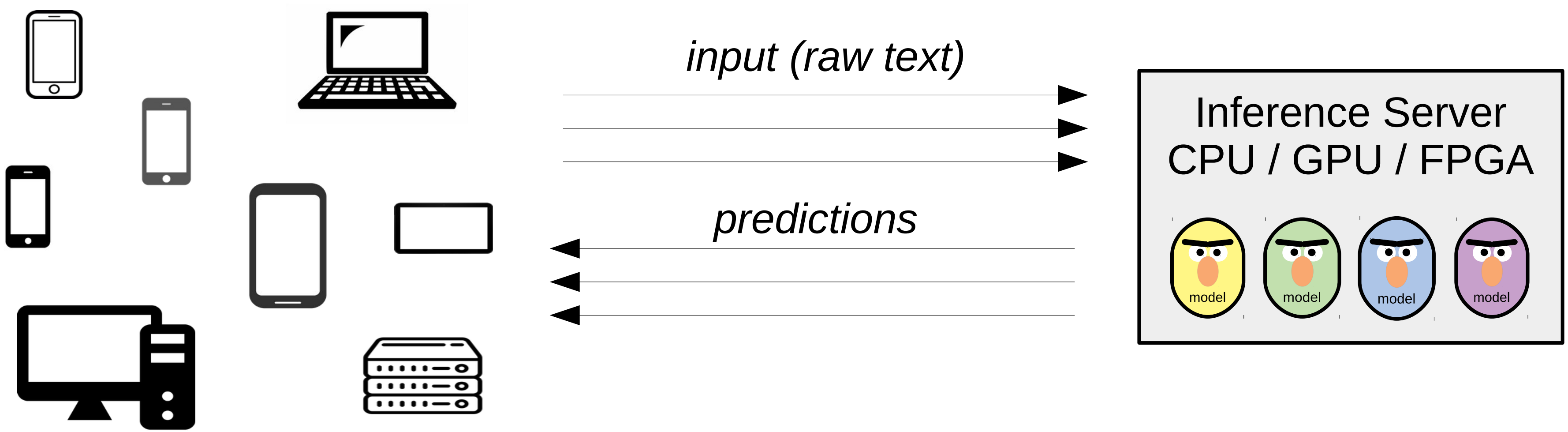

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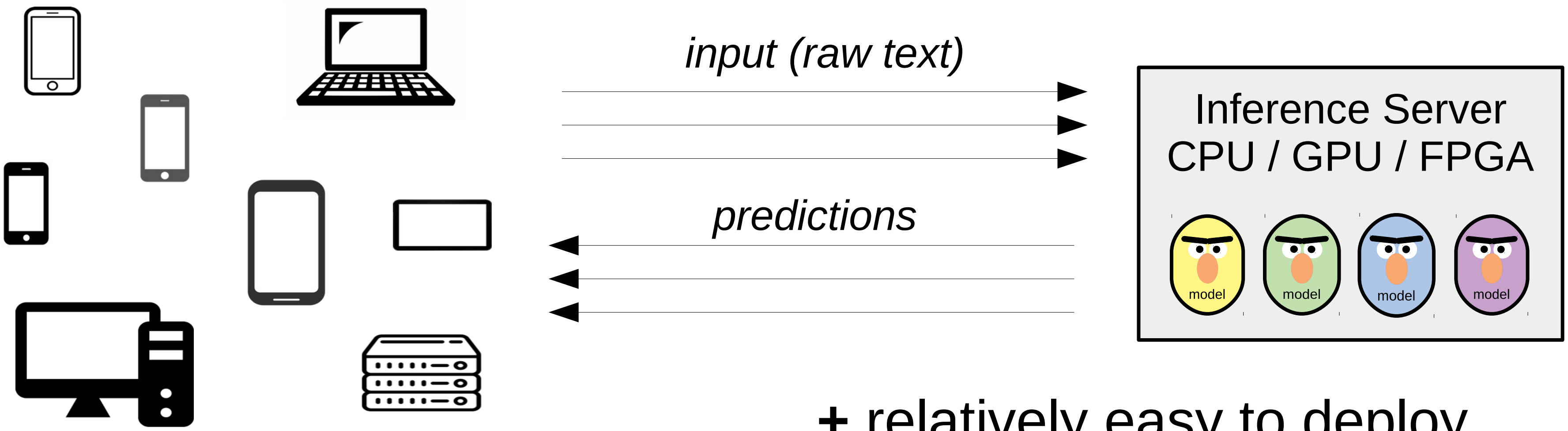
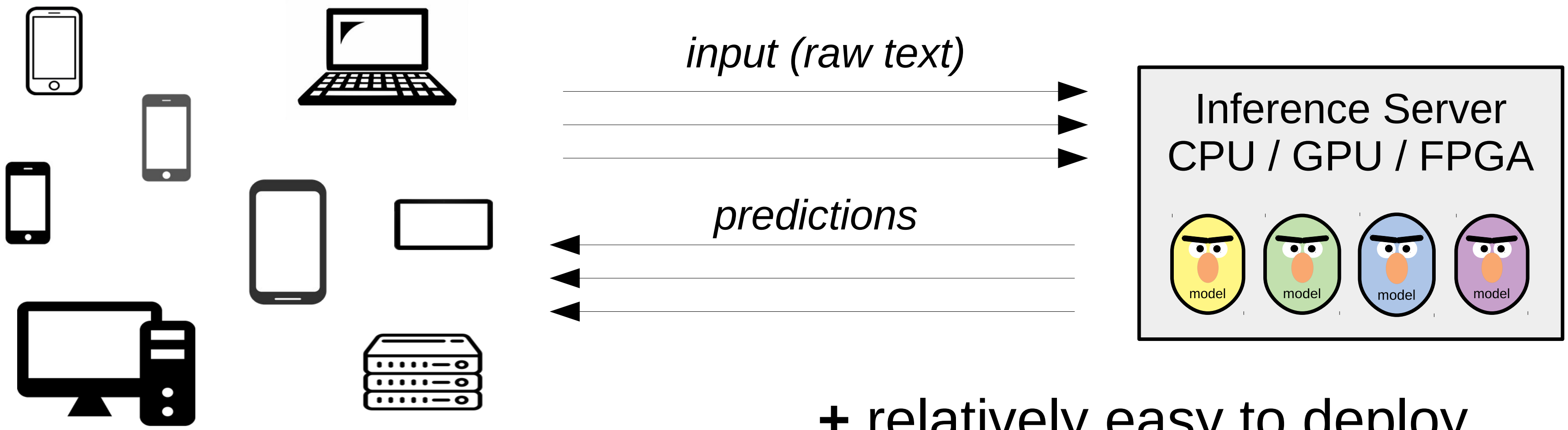


+ relatively easy to deploy
+ you control model & inference
+ clients don’t run compute

Scenario 1: inference server



+ relatively easy to deploy
+ you control model & inference
+ clients don’t run compute

– you pay for each inference
– clients can’t work offline
– network latency

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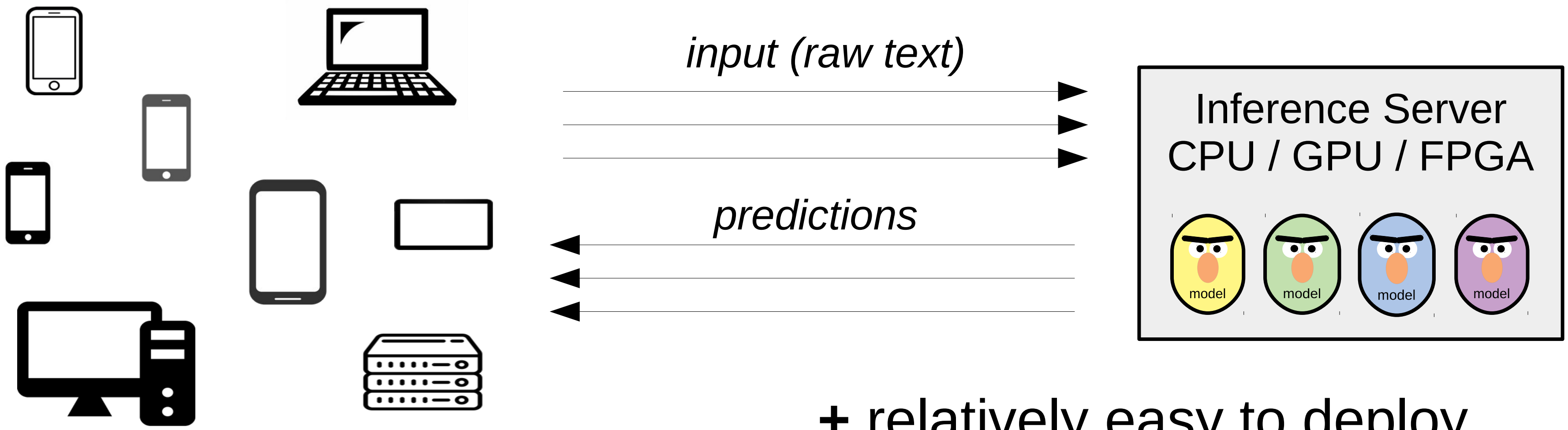

Which is the most important?

 ?  ?  ?

+ relatively easy to deploy
+ you control model & inference
+ clients don't run compute

– you pay for each inference
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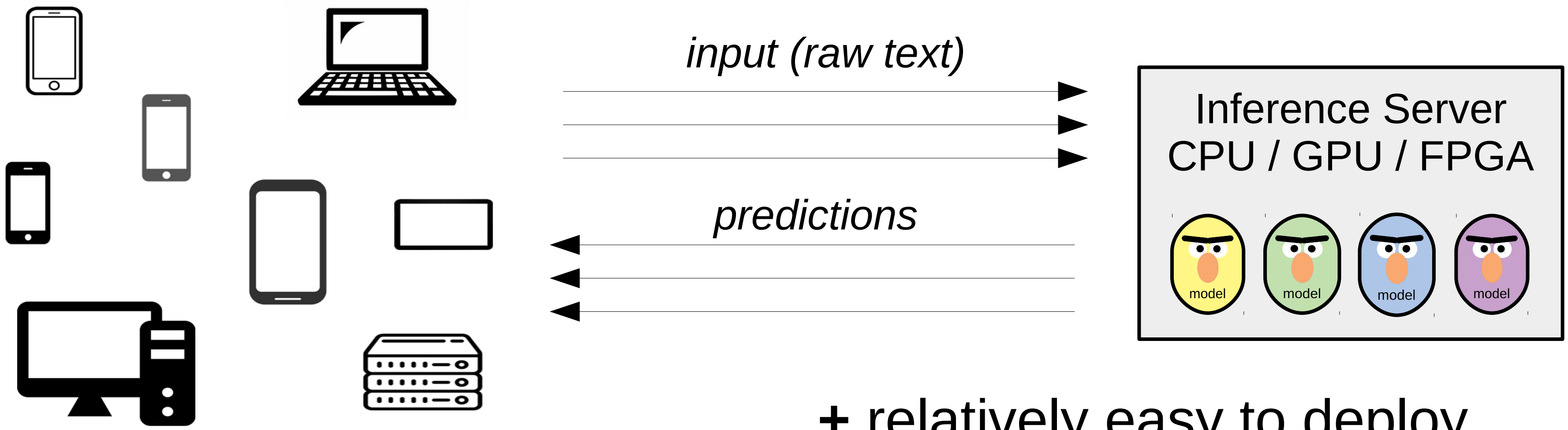
Scenario 1: inference server



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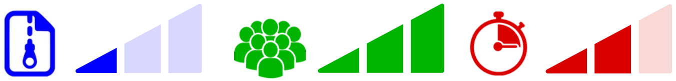
Priorities:



Note: smaller model = you can fit more models in the same memory

Scenario 1: inference server

- Group inputs into batches (e.g. by length)
  improves throughput at the cost of latency
- Multiple servers with load balancing
  improves throughput at the cost of your budget :)

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Popular frameworks:	priorities
TensorFlow Serving	efficiency $\ll$ developer time
TensorRT Inference Server (Triton)	efficiency $\approx$ developer time
 Custom model-dependent code	efficiency $\gg$ developer time

Scenario 2: local inference

Preload model onto a dedicated device, infer locally using that device

Typical use cases:

- Parallel speech recognition
- “Smart” cameras
- Autonomous drones
- Self-driving cars

Priorities:

Scenario 3: web/smartphone app

- Load model weights on the fly and infer locally
  - Model size is critical for both you and the user

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- Autonomous machine translation (tinyurl.com/yandex-translate-app)
- Pix2pix demo in a browser (https://affinelayer.com/pixsrv)

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Scenario 3: web/smartphone app

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- Priorities:

- Popular frameworks:

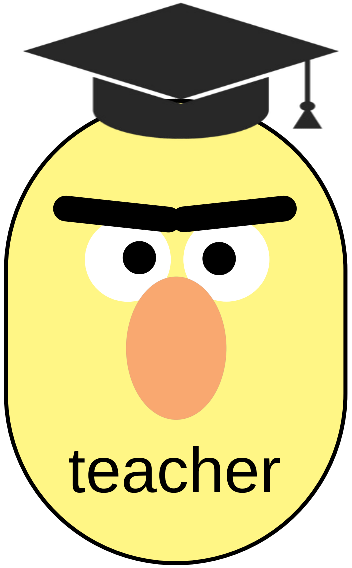
	Platform
TensorFlow.js	All modern browsers
CoreML	iOS devices
NNAPI	Android devices

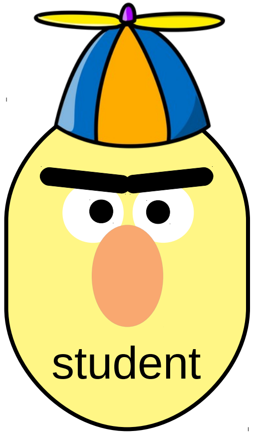
Chapter 2: how do I improve my model?

Compression by Distillation

Distillation…
Heard that word before?

Compression by Distillation

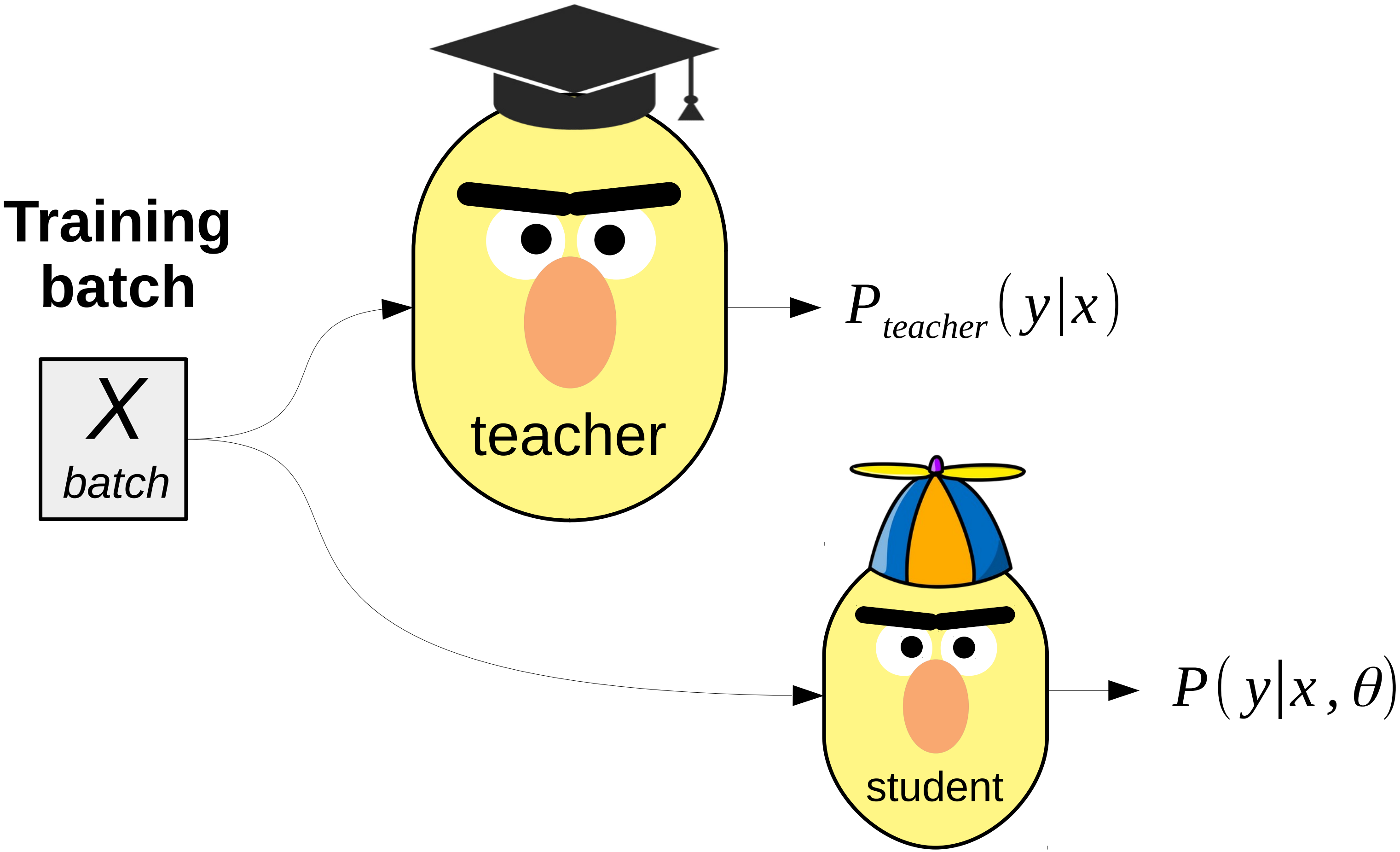




First, get the best performing model regardless of size

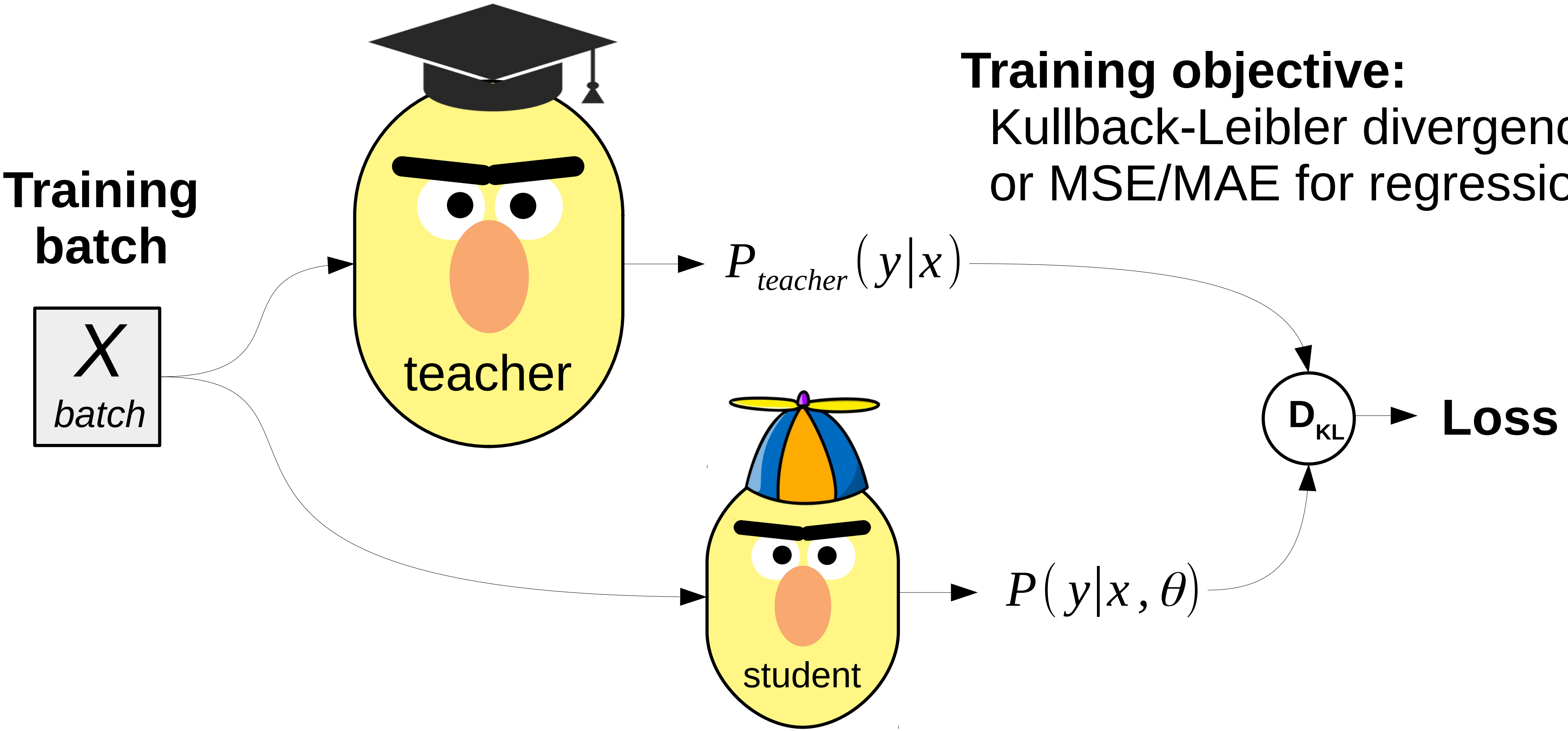
Then, train a more compact model to approximate it!

Compression by Distillation

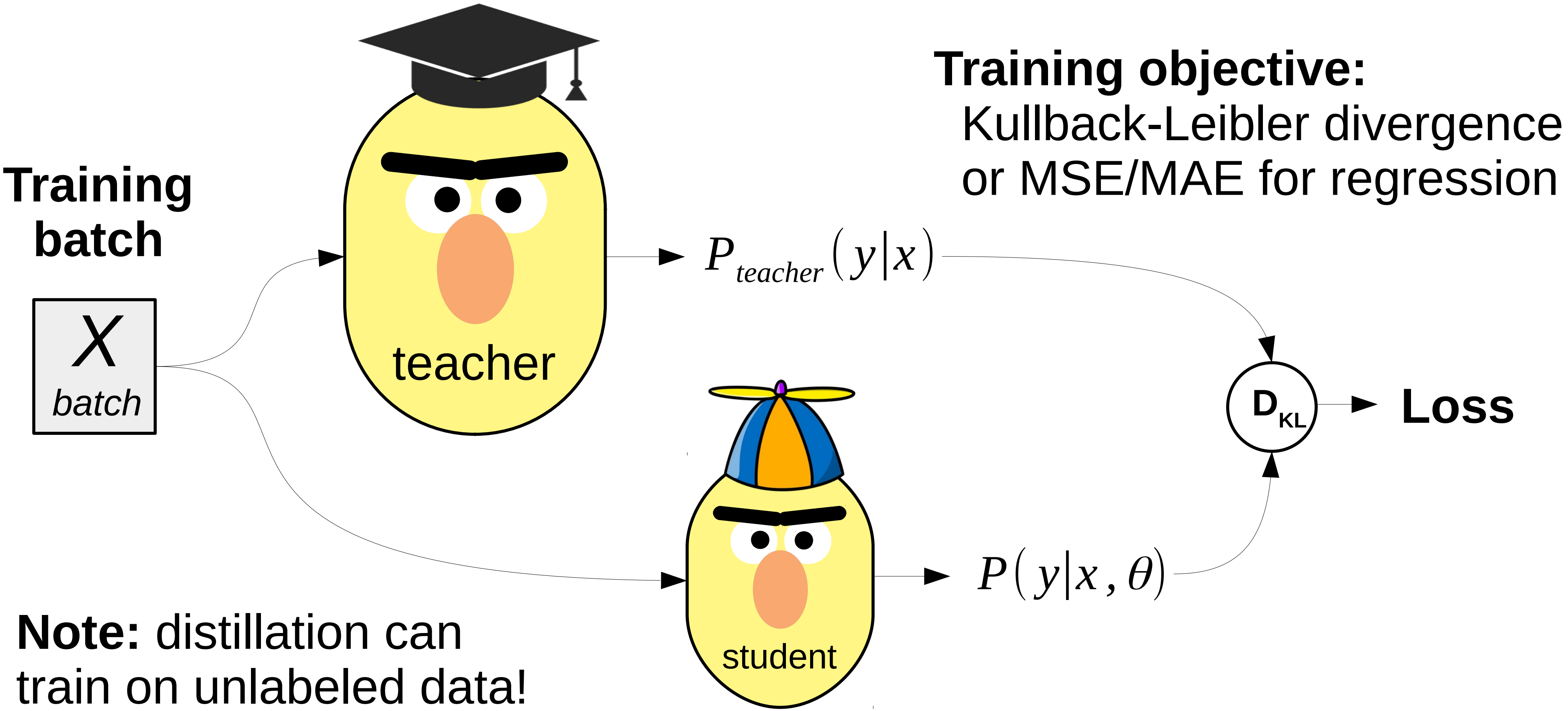


Compression by Distillation

Training objective:
Kullback-Leibler divergence
or MSE/MAE for regression



Compression by Distillation



Compression by Distillation

- Student architecture choices:
  Naïve: same but smaller, less layers / hidden units
  e.g. DistillBERT: https://arxiv.org/pdf/1910.01108.pdf

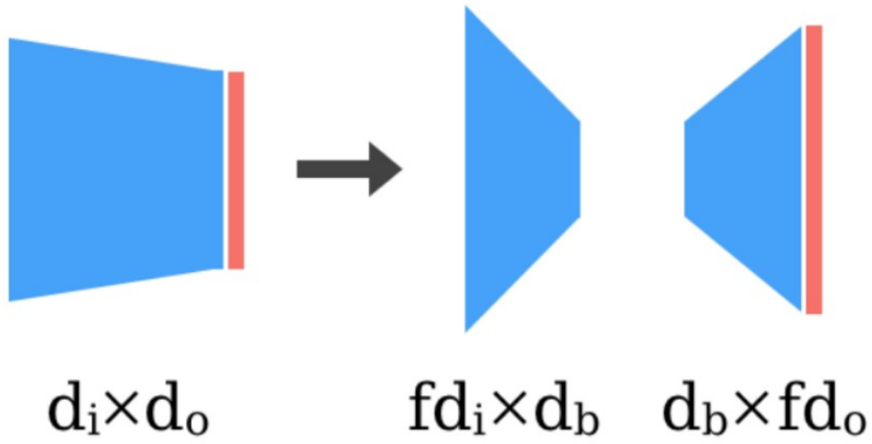
Same as BERT-base, but
with *half as many layers*
(and ≈1.5 times faster)

Model	# param. (Millions)	Inf. time (seconds)
ELMo	180	895
BERT-base	110	668
DistilBERT	66	410

Model	**Score**	CoLA	MNLI	MRPC	QNLI	QQP	RTE	SST-2	STS-B	WNLI
ELMo	68.7	44.1	68.6	76.6	71.1	86.2	53.4	91.5	70.4	56.3
BERT-base	79.5	56.3	86.7	88.6	91.8	89.6	69.3	92.7	89.0	53.5
DistilBERT	77.0	51.3	82.2	87.5	89.2	88.5	59.9	91.3	86.9	56.3

Compression by Distillation

- Student architecture choices:
  Naïve: same but smaller, less layers / hidden units
  Factorized: product of smaller matrices or tensors



Images: https://openreview.net/pdf?id=_zx8Oka09eF

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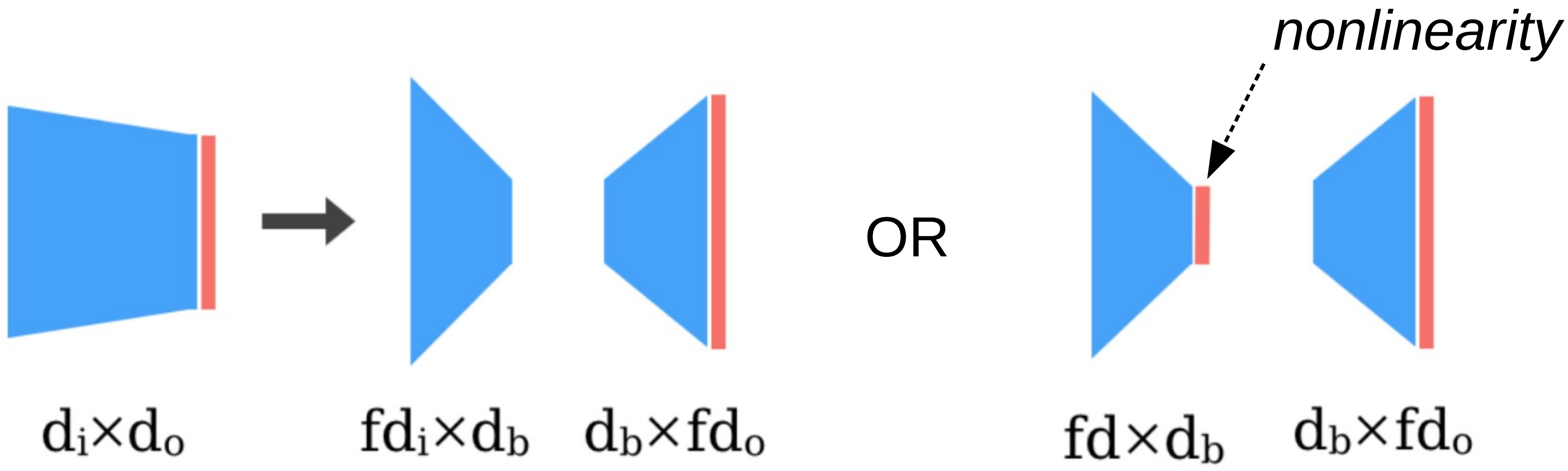

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Compression by Distillation

- Student architecture choices:
  Naïve: same but smaller, less layers / hidden units
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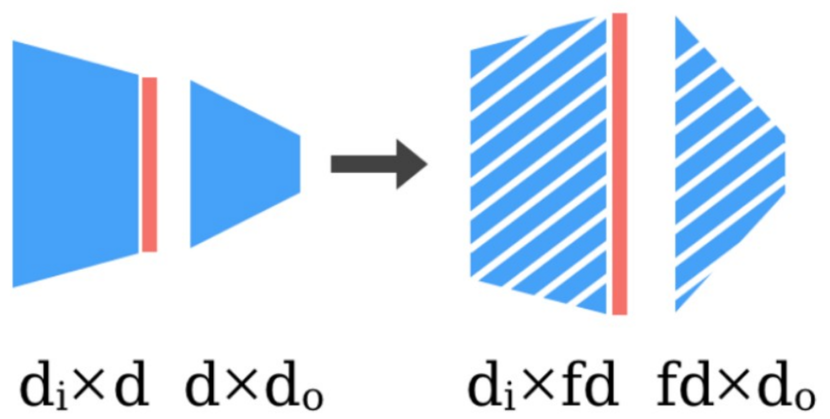
  Sparse: only a small (random) subset of weights are nonzero



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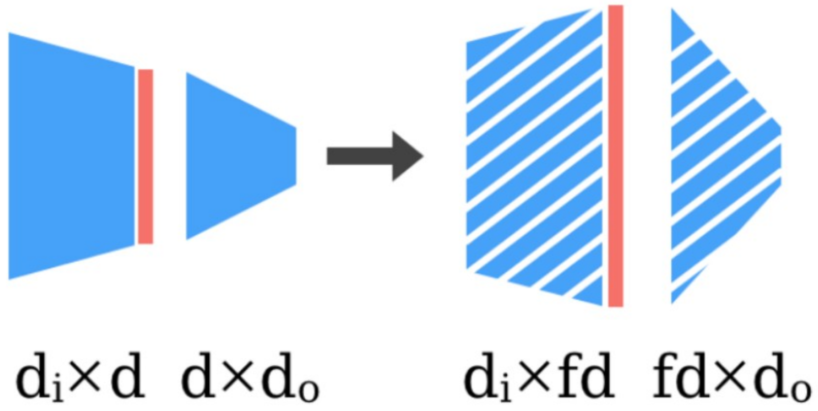

Q: how to store sparse weights?

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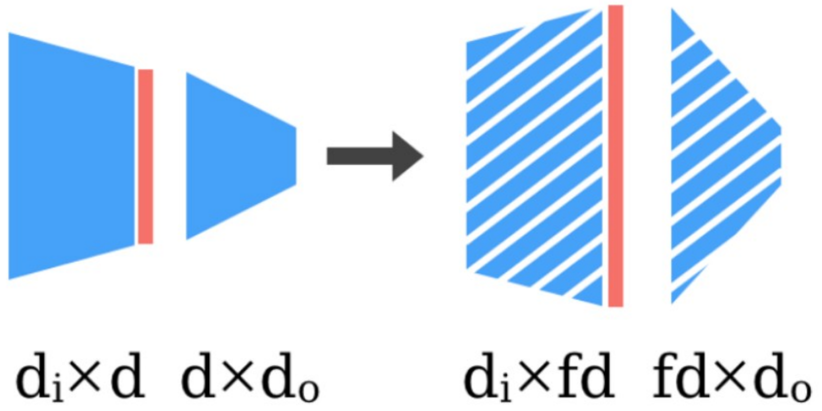

Storage: only store random seed and nonzero weights.

Compute: sparse matrix multiply

Images: https://openreview.net/pdf?id=_zx8Oka09eF

Compression by Distillation

- Student architecture choices:
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  Read more: https://openreview.net/pdf?id=_zx8Oka09eF
  Also: factorized embeddings https://arxiv.org/abs/1901.10787
  Also also: small-world sparse weights graphs for RNNs
  https://tinyurl.com/openai-blocksparse

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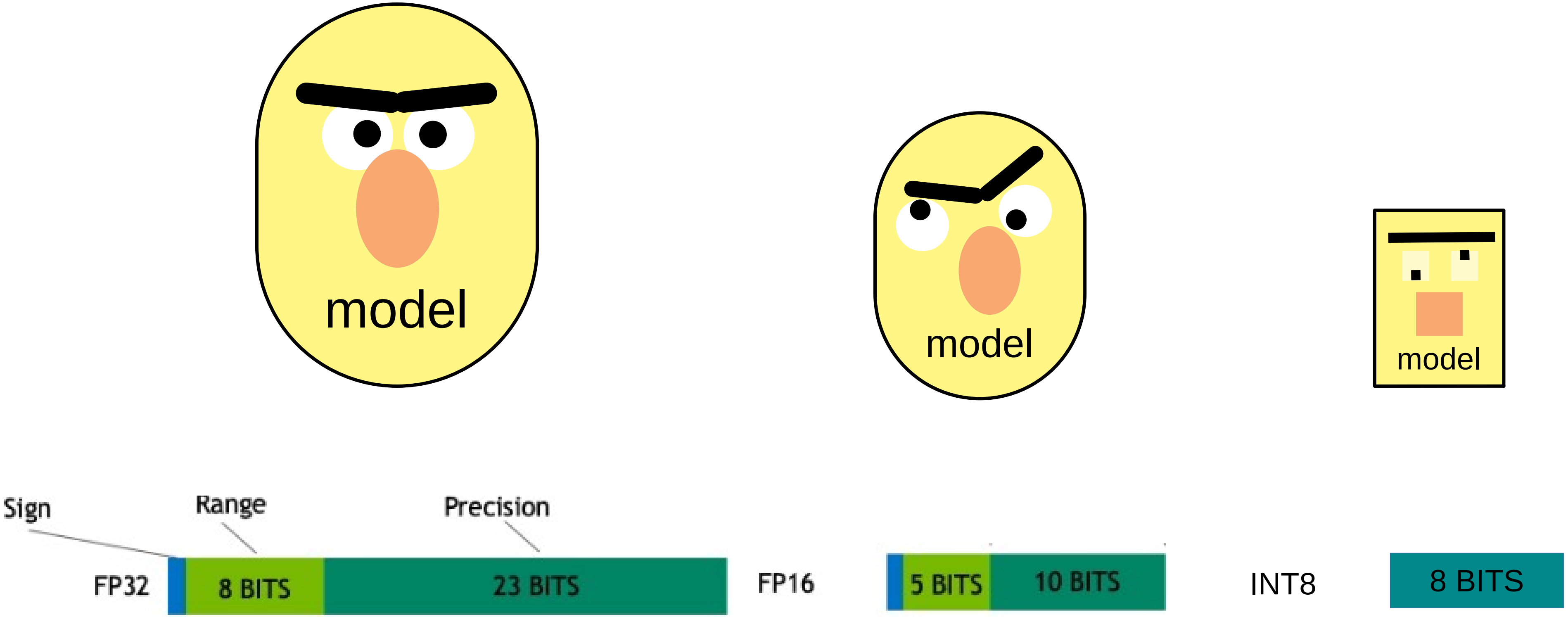
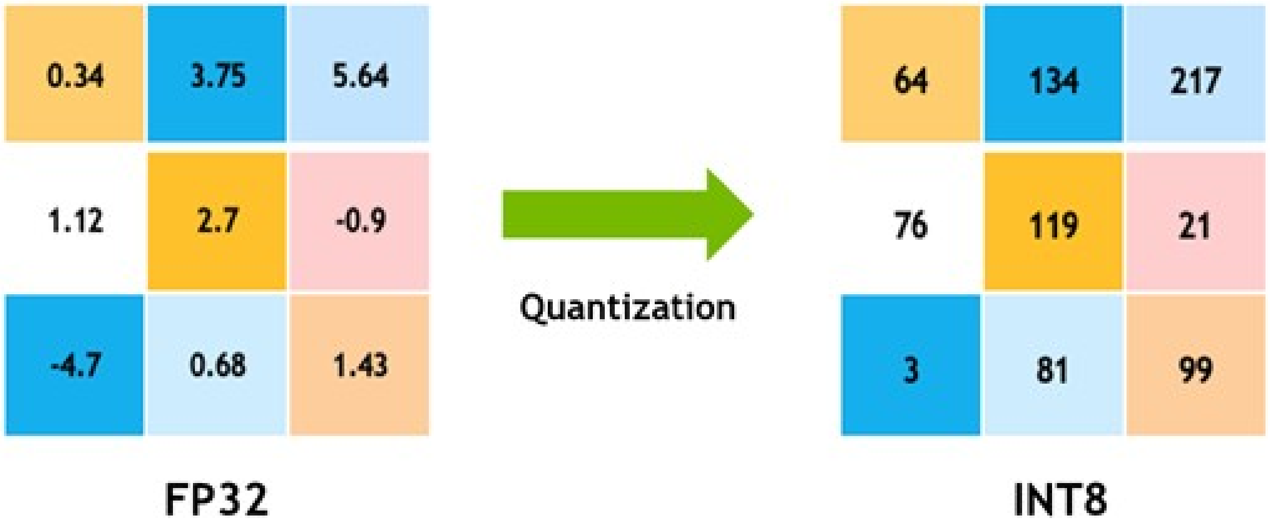
- More distillation tricks:

Ensemble distillation	https://arxiv.org/abs/1702.01802
Dropout distillation	http://proceedings.mlr.press/v48/bulo16.pdf
Co-distillation	https://arxiv.org/abs/1804.03235

Compression by quantization

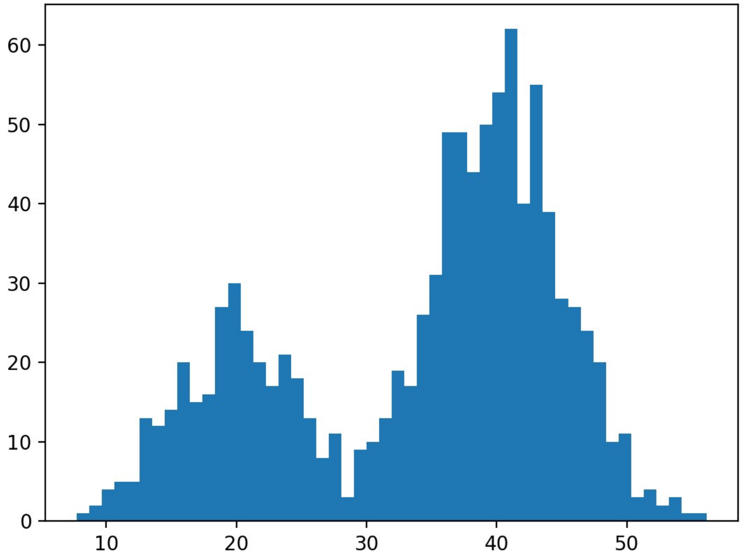


Linear quantization



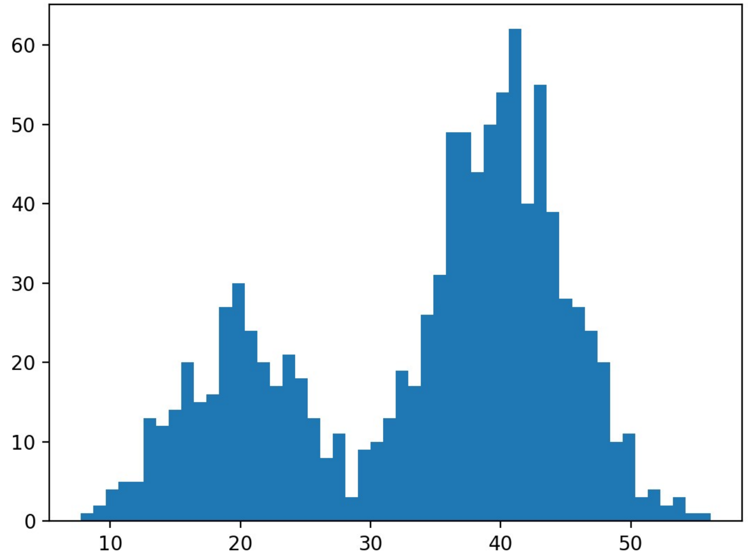
1) Scale inputs and parameters into uint8 range
2) Multiply in uint8, accumulate to int32
3) Un-scale multiplication results in float32

Non-linear quantization



Consider weights as a distribution

Non-linear quantization



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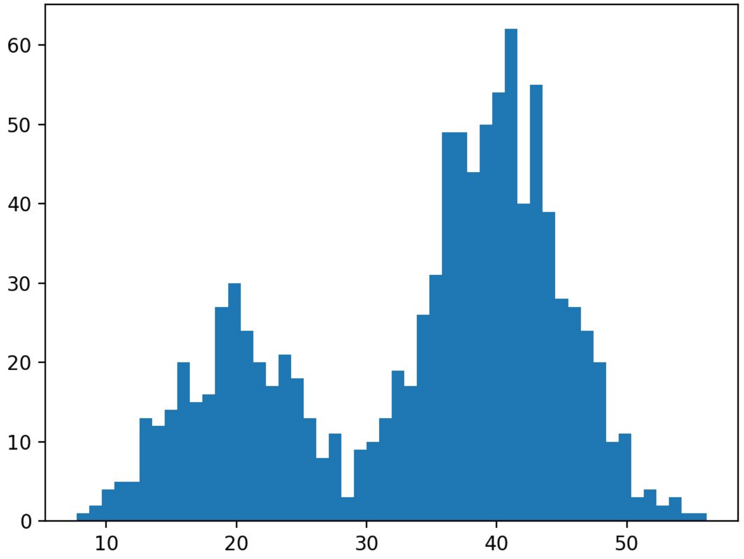

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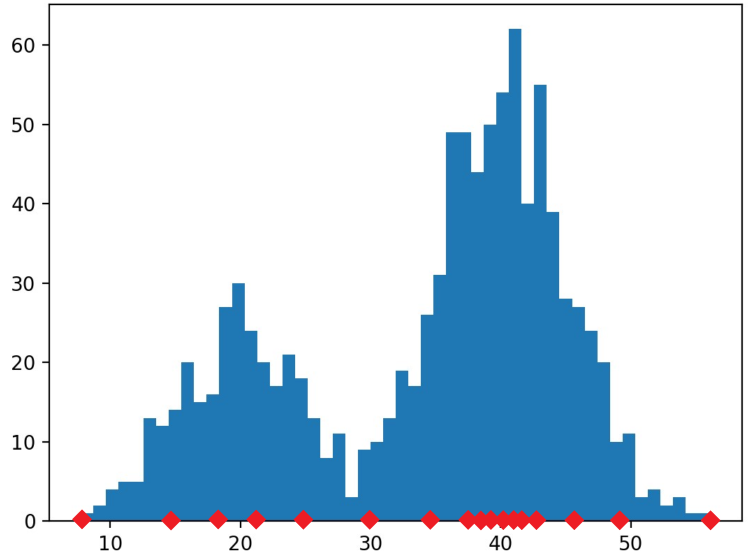
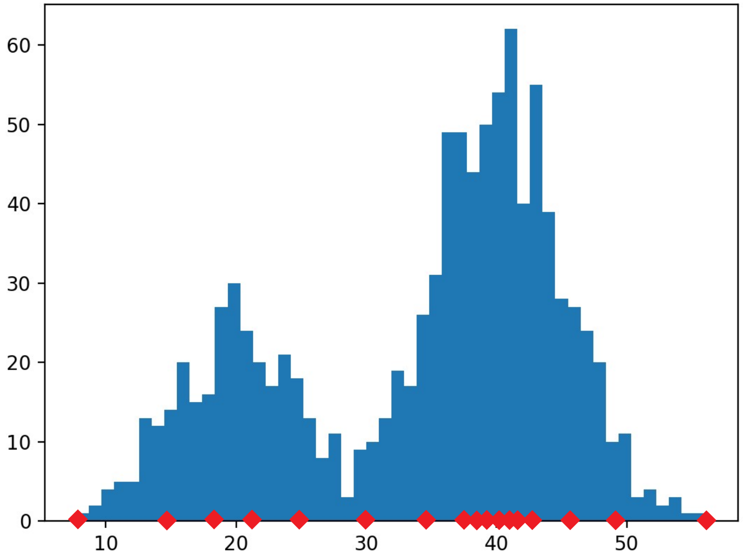


Compute a grid of percentiles

Non-linear quantization



percentiles (32-bit)

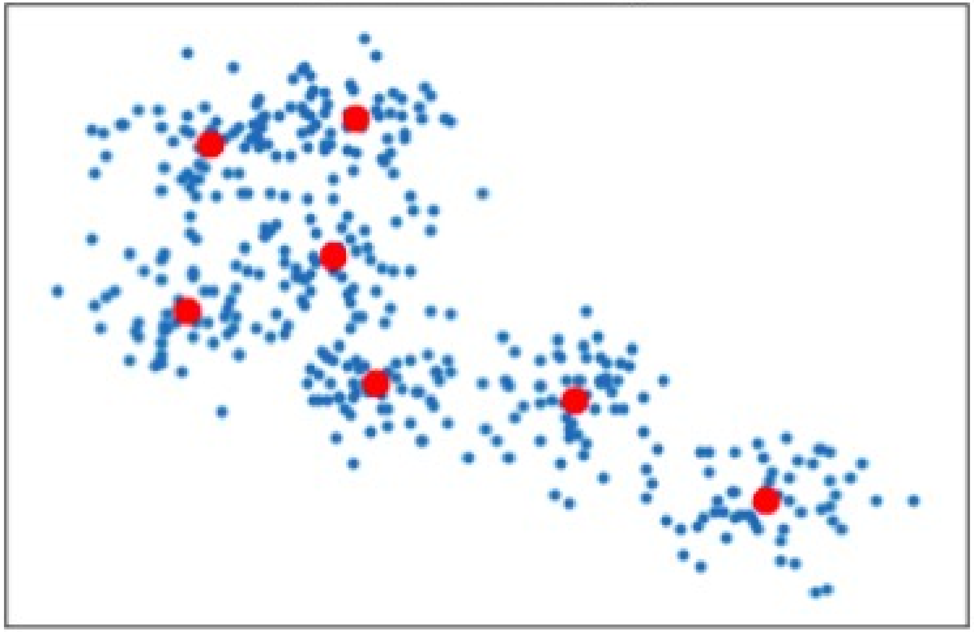
Index (4- or 8-bit) of nearest percentile for each weight

Store each weight as its nearest percentile

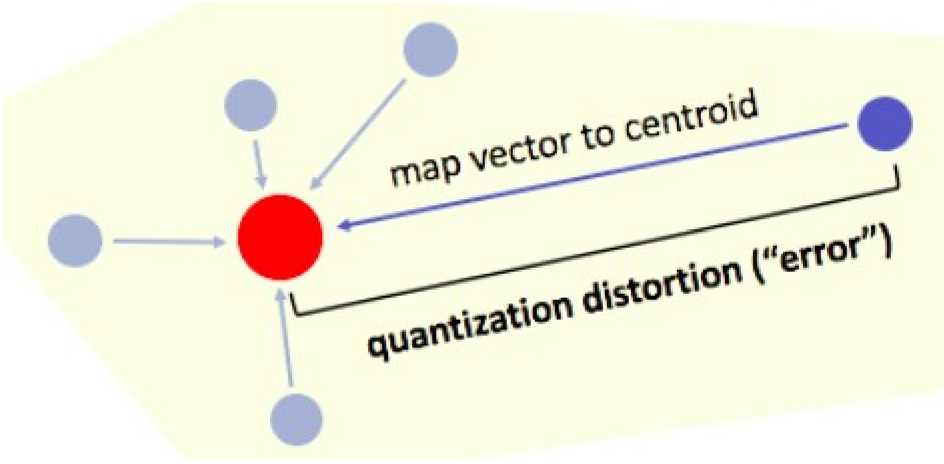
High-dimensional case

Quantize entire vectors as K-means

Quantization Example



quantizer = KMeans(n_clusters=7).fit(X)



Images: Jeremy Jordan

OPQ, AQ, LSQ

Product **Q**uantization

Split vectors into chunks, quantize each chunk separately

Orthogonal **P**roduct **Q**uantization

First run orthogonal transform, then product quantization

http://kaiminghe.com/publications/cvpr13opq.pdf

More:

Additive **Q**uantization https://tinyurl.com/babenko-aq-pdf

Local **S**earch **Q**uantization https://tinyurl.com/martinez-lsq-pdf

Images: Jeremy Jordan

Low-precision training!

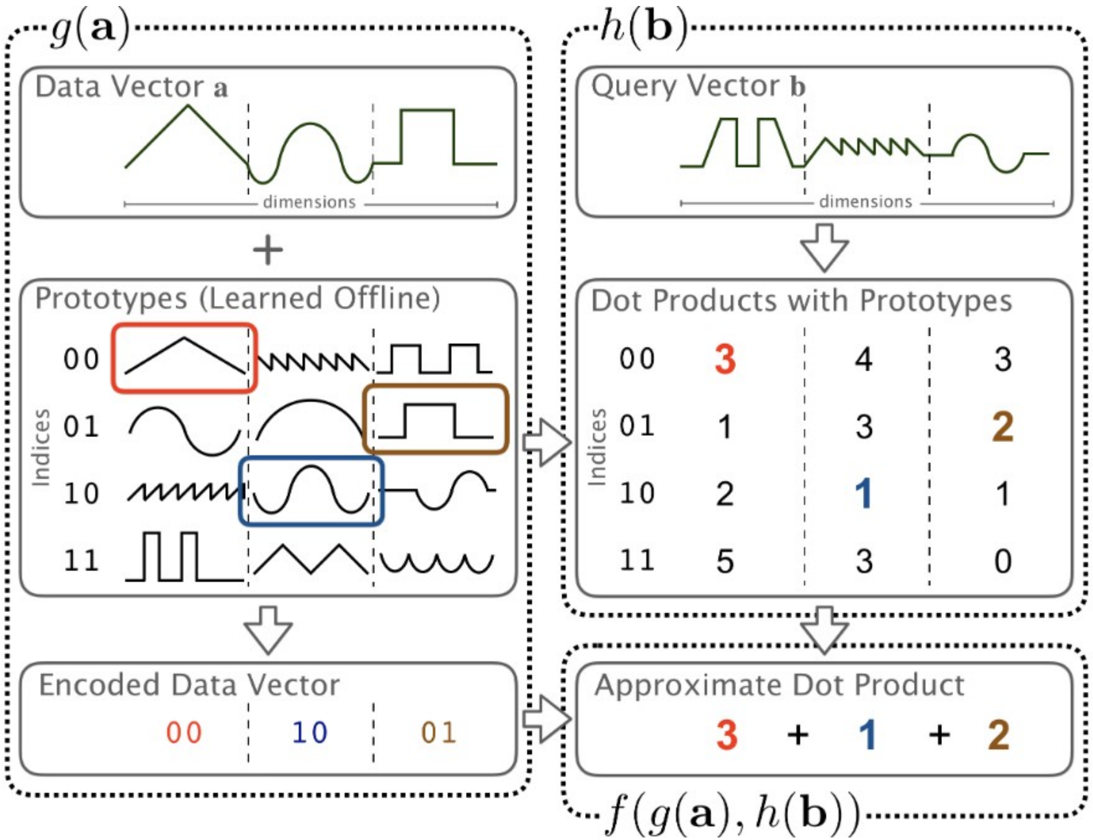
Training with 8-bit params:
https://arxiv.org/abs/1812.08011
https://arxiv.org/abs/1805.11046

Compressing gradients to 1 bit and beyond
https://arxiv.org/abs/2102.02888
https://arxiv.org/abs/1905.13727

Training with 8-bit optimizers:
https://www.youtube.com/watch?v=IxrlHAJtqKE
https://arxiv.org/abs/2110.02861

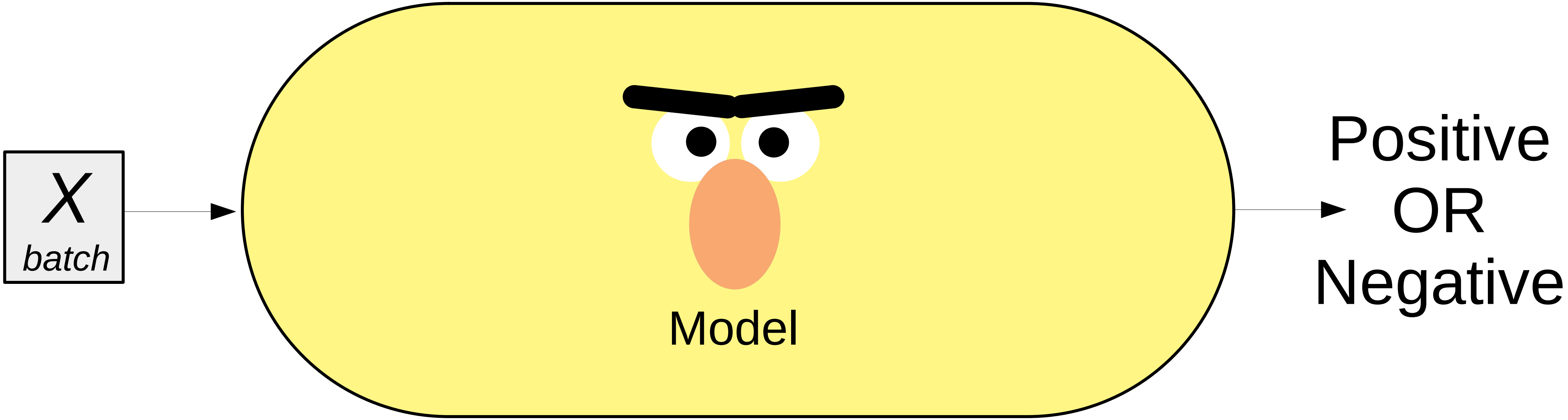
Quantization + pre-computation

Source: https://arxiv.org/abs/2106.10860



- product-quantize weights
- “quantize” inputs via LSH
- pre-compute dot products all inputs x all codes
- “multiply” by **looking up** pre-computed products

Acceleration by cascading



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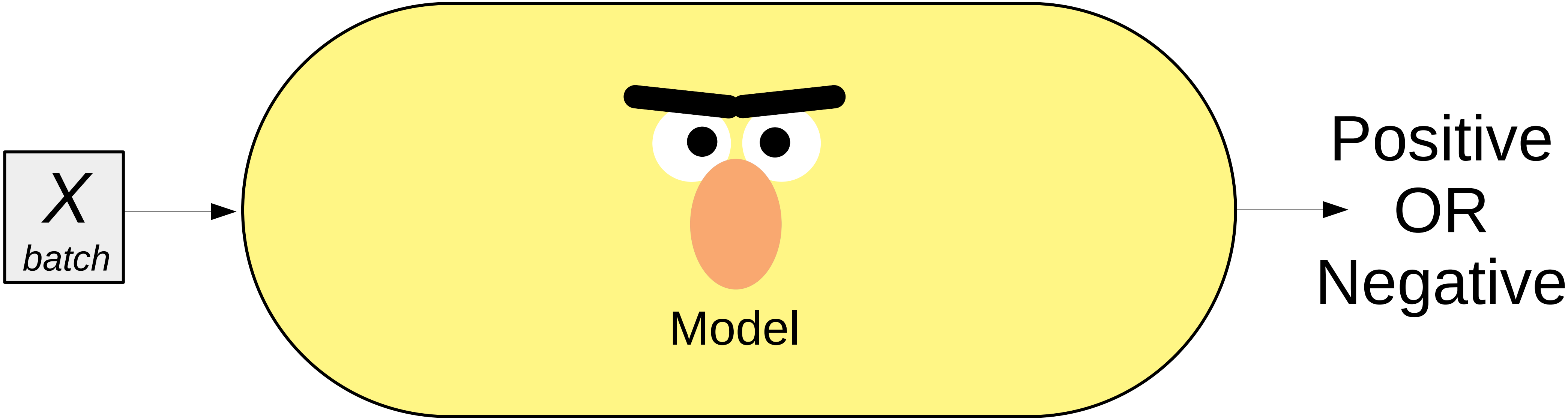
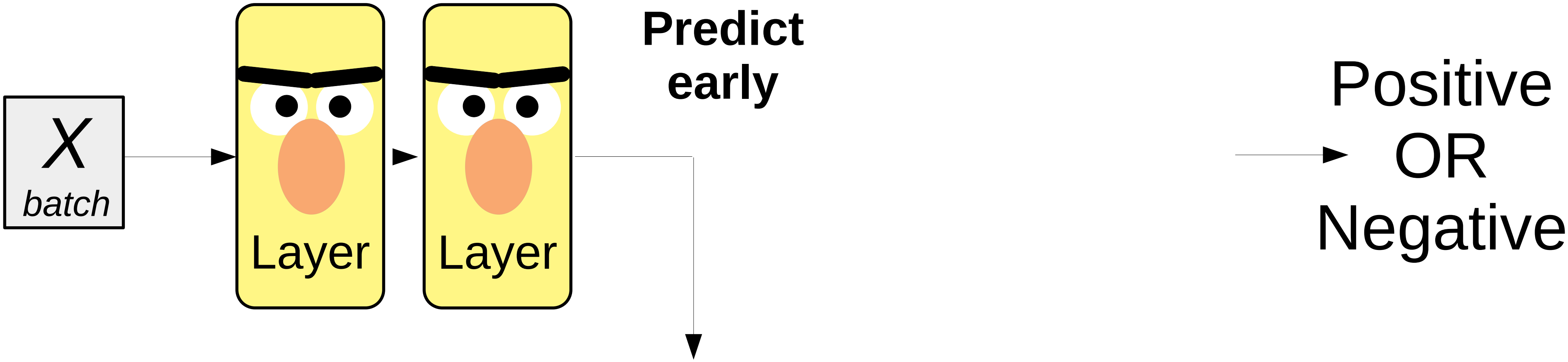


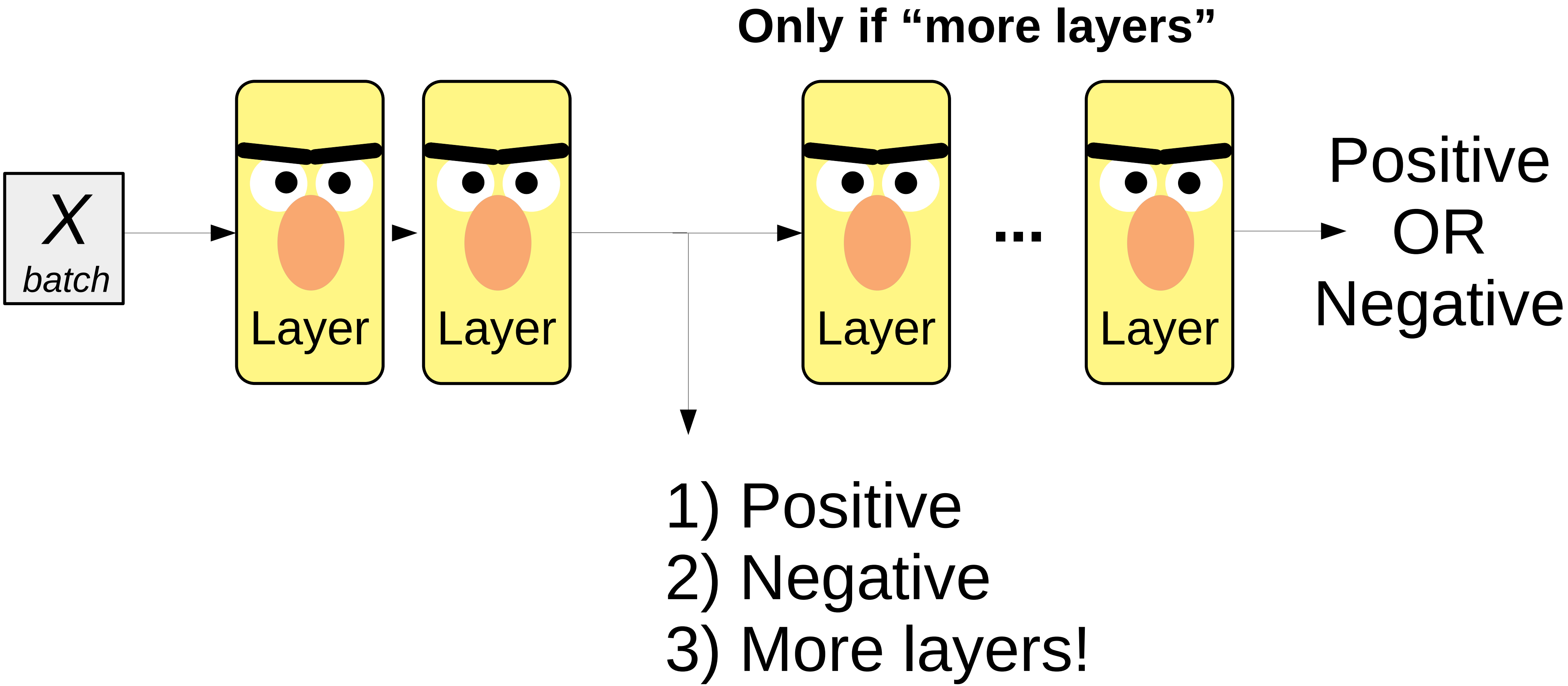
Do we really need every layer
all the time?

Acceleration by cascading

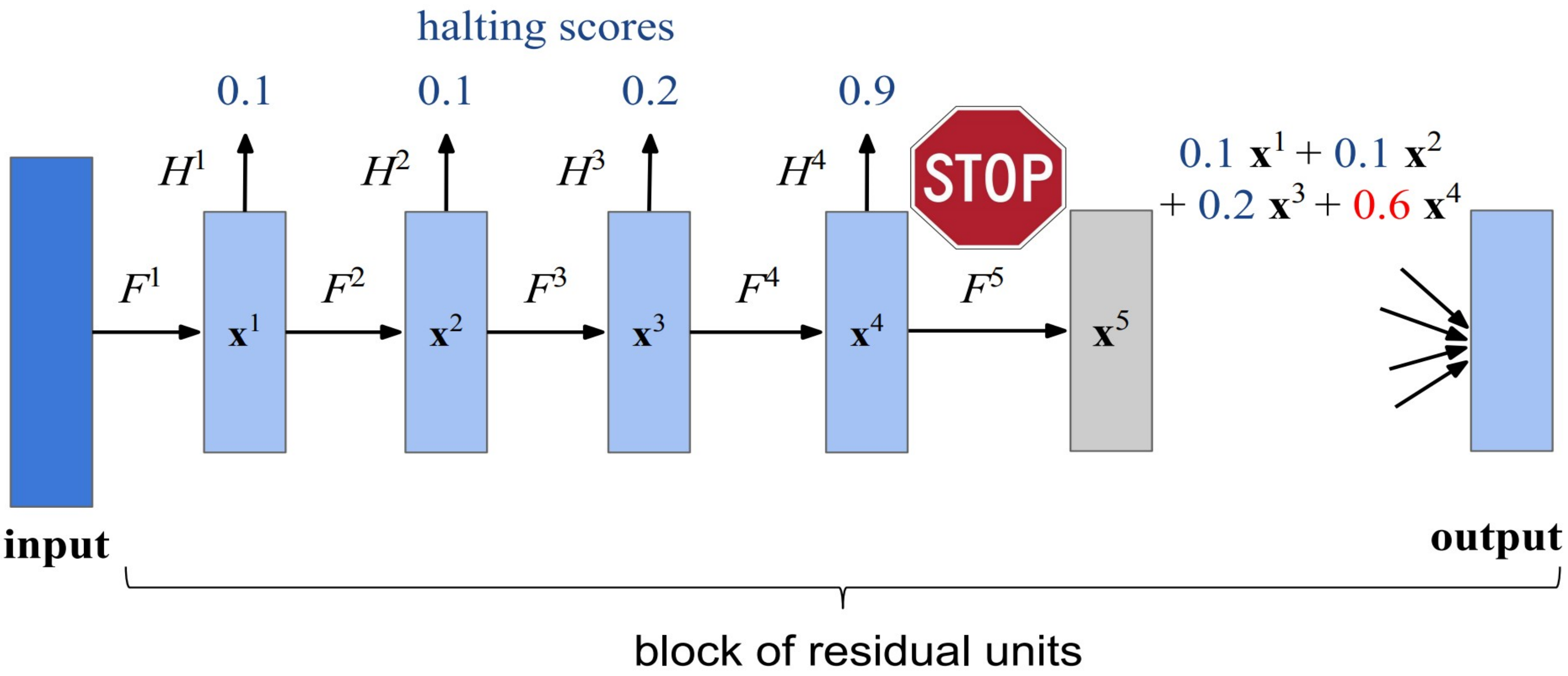


1) Positive
2) Negative
3) More layers!

Acceleration by cascading



Adaptive Computation Time



Origina ACTI (for RNN)
https://arxiv.org/abs/1603.08983

Spatial ACT (conv)
https://tinyurl.com/sact-pdf

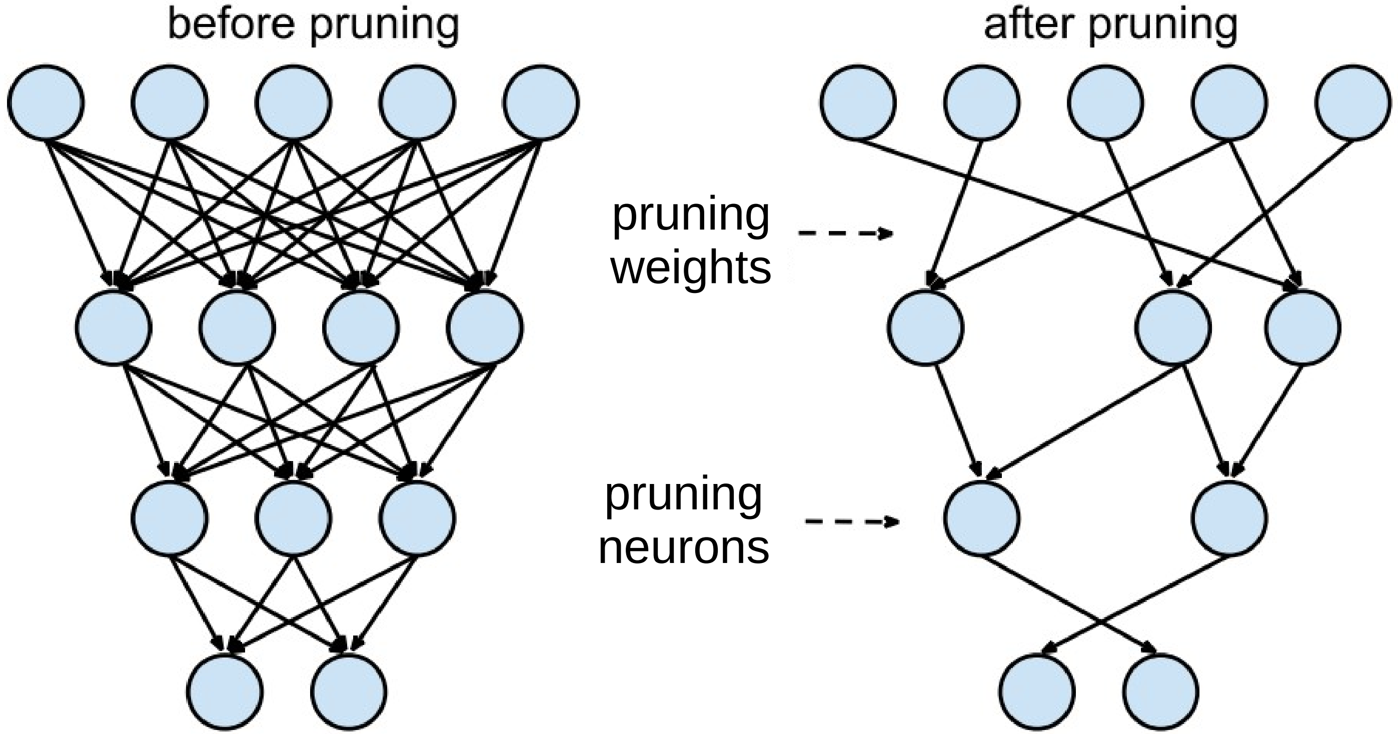
ACT Transformers
https://arxiv.org/abs/1807.03819

Compression by sparsification

Do we really need all D by D weights?

Compression by pruning

Do we really need all D by D weights?



Magnitude pruning

Drop ~5% smallest weights
from each layer every 1000 steps
(and keep training)

Reminds you of something?

Magnitude pruning

Drop ~5% smallest weights
from each layer every 1000 steps
(and keep training)

Reminds you of something?

See ML course, Optimal Brain Damage

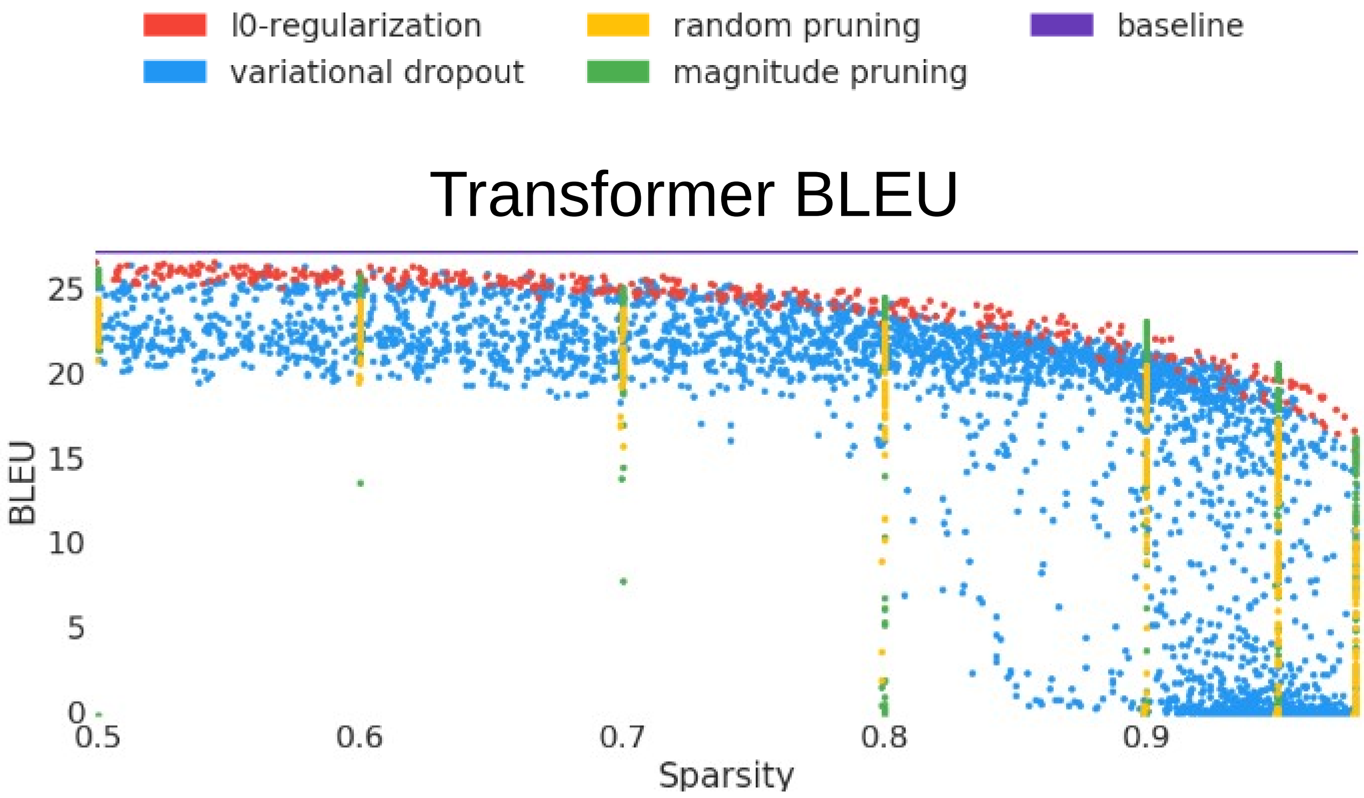
Pruning with L_0 regularization

Add a special regularizer that encourages dropping unnecessary weights

Whiteboard time!

Read more: https://arxiv.org/abs/1712.01312
Alternative: https://arxiv.org/abs/1701.05369

Which one works best?



Source https://arxiv.org/abs/1902.09574

Pruning with L_0 regularization

Add a special regularizer that encourages dropping unnecessary weights

Whiteboard time!

Pruning with L_0 regularization

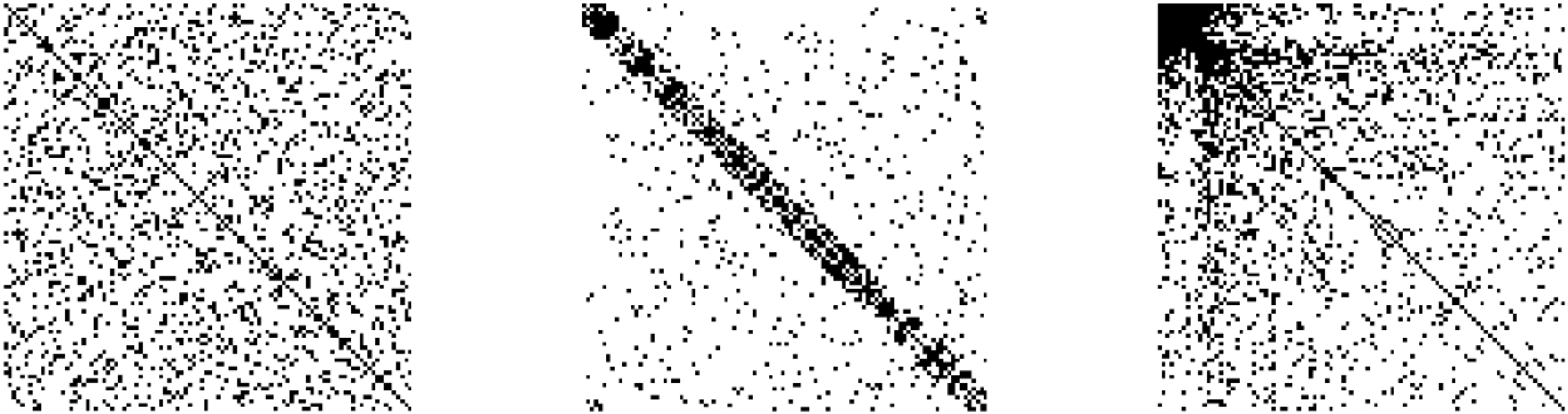
Add a special regularizer that encourages dropping unnecessary weights

Can prune
- individual weights
- Individual neurons
- attention heads
- entire layers!

$$\lambda = 0.01$$

Pruning heads: https://lena-voita.github.io/posts/acl19_heads.html

Sparse training



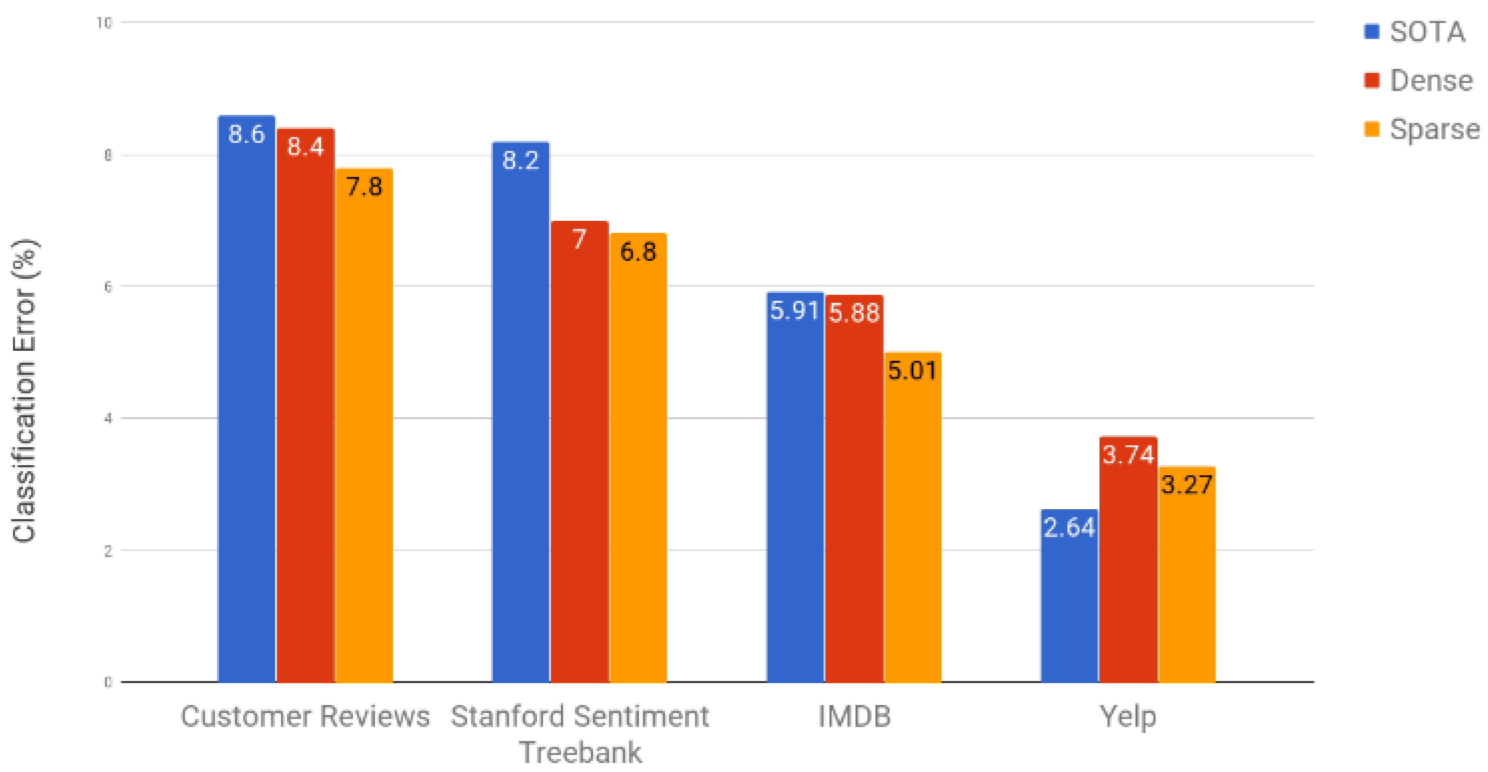
Random

1-Dimensional Watts-Strogatz

Barabasi-Albert

https://cdn.openai.com/blocksparse/blocksparsepaper.pdf

Sparse training



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What did we learn?