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DeepLearning.AI

High Performance Modeling

Welcome

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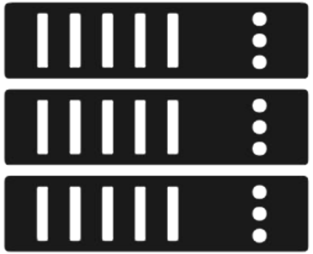
High Performance Modeling

Distributed Training

Rise in computational requirements

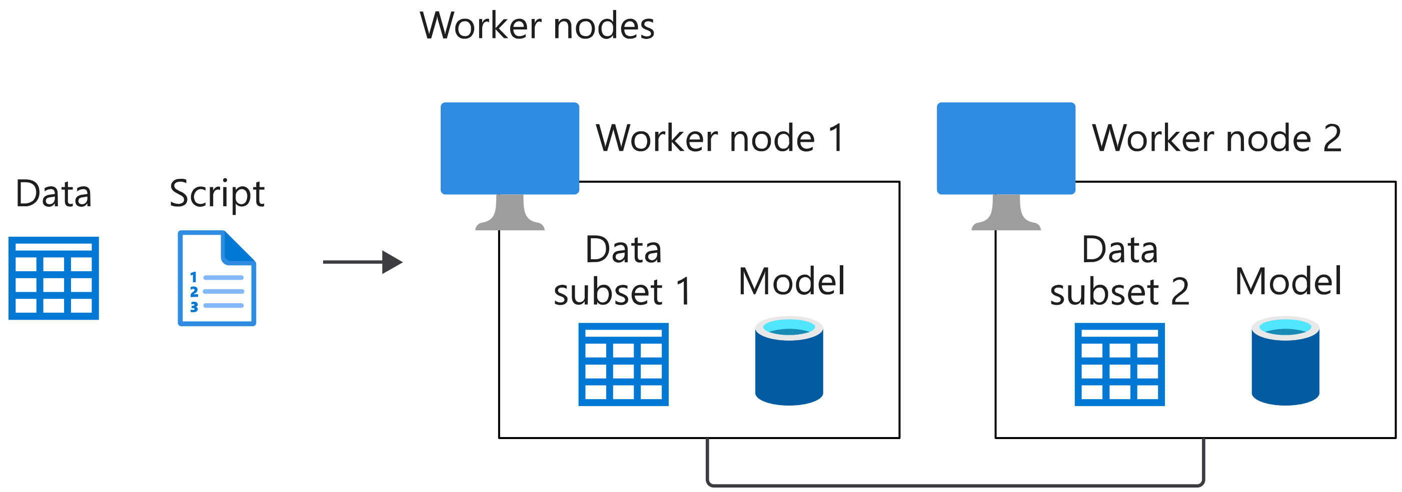
- At first, training models is quick and easy
- Training models becomes more time-consuming
  - With more data
  - With larger models
- Longer training -> More epochs -> Less efficient
- Use distributed training approaches



Types of distributed training

- **Data parallelism**: In data parallelism, models are replicated onto different accelerators (GPU/TPU) and data is split between them
- **Model parallelism**: When models are too large to fit on a single device then they can be divided into partitions, assigning different partitions to different accelerators

Data parallelism



Distributed training using data parallelism

Synchronous training

- All workers train and complete updates in sync
- Supported via all-reduce architecture

Asynchronous Training

- Each worker trains and completes updates separately
- Supported via parameter server architecture
- More efficient, but can result in lower accuracy and slower convergence

Making your models distribute-aware

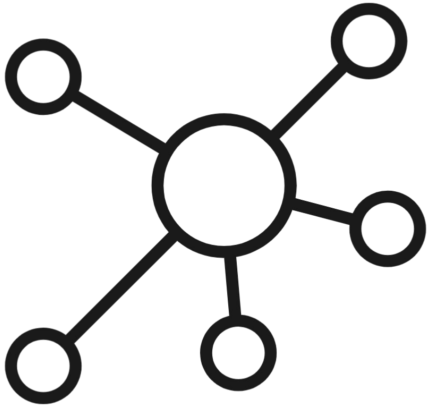
- If you want to distribute a model:
  - Supported in high-level APIs such as Keras/Estimators
  - For more control, you can use custom training loops

tf.distribute.Strategy

- Library in TensorFlow for running a computation in multiple devices
- Supports distribution strategies for high-level APIs like Keras and custom training loops
- Convenient to use with little or no code changes

Distribution Strategies supported by tf.distribute.Strategy

- **One Device Strategy**
- **Mirrored Strategy**
- **Parameter Server Strategy**
- Multi-Worker Mirrored Strategy
- Central Storage Strategy
- TPU Strategy



One Device Strategy

- Single device - no distribution
- Typical usage of this strategy is testing your code before switching to other strategies that actually distribute your code

Mirrored Strategy

- This strategy is typically used for training on one machine with multiple GPUs
    - Creates a replica per GPU <> Variables are mirrored
    - Weight updating is done using efficient cross-device communication algorithms (all-reduce algorithms)

Parameter Server Strategy

- Some machines are designated as workers and others as parameter servers
  - Parameter servers store variables so that workers can perform computations on them
- Implements asynchronous data parallelism by default

Fault tolerance

- Catastrophic failures in one worker would cause failure of distribution strategies.
- How to enable fault tolerance in case a worker dies?
  - By restoring training state upon restart from job failure
  - Keras implementation: BackupAndRestore callback

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High Performance Modeling

High-performance Ingestion

Why input pipelines?

Data at times can't fit into memory and sometimes, CPUs are under-utilized in compute intensive tasks like training a complex model

You should avoid these inefficiencies so that you can make the most of the hardware available → Use input pipelines

tf.data: TensorFlow Input Pipeline

Extract → Transform → Load

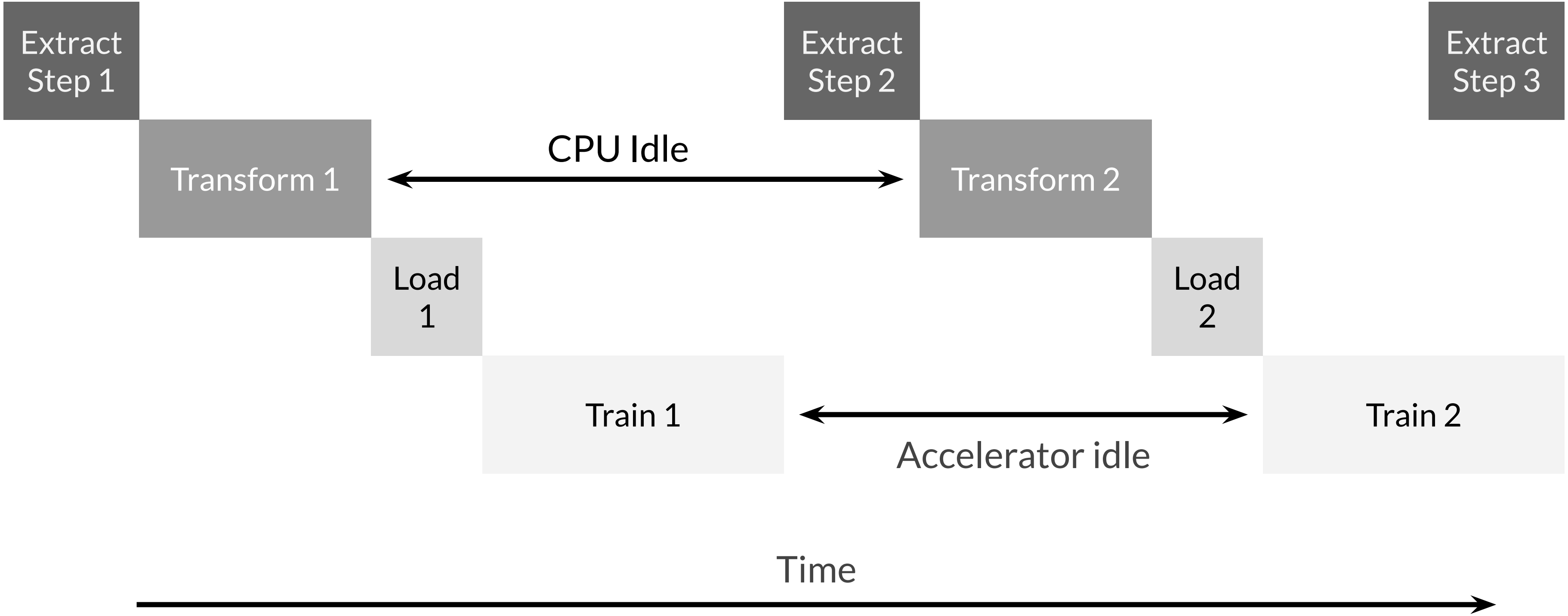
Local (HDD/SSD)

Remote (GCS/HDFS)

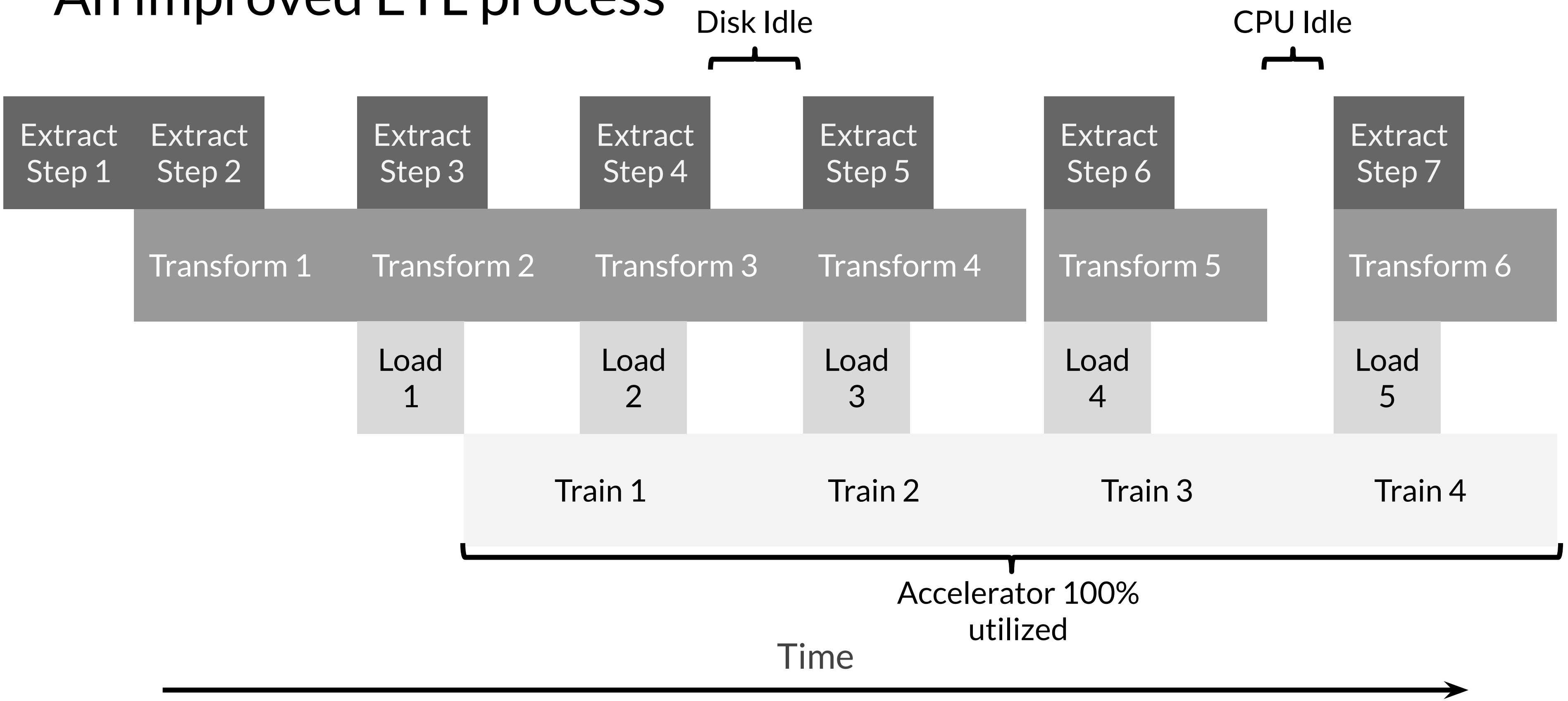
Shuffling & Batching
Decompression
Augmentation
Vectorization
. . .

Load **transformed data** to an **accelerator**

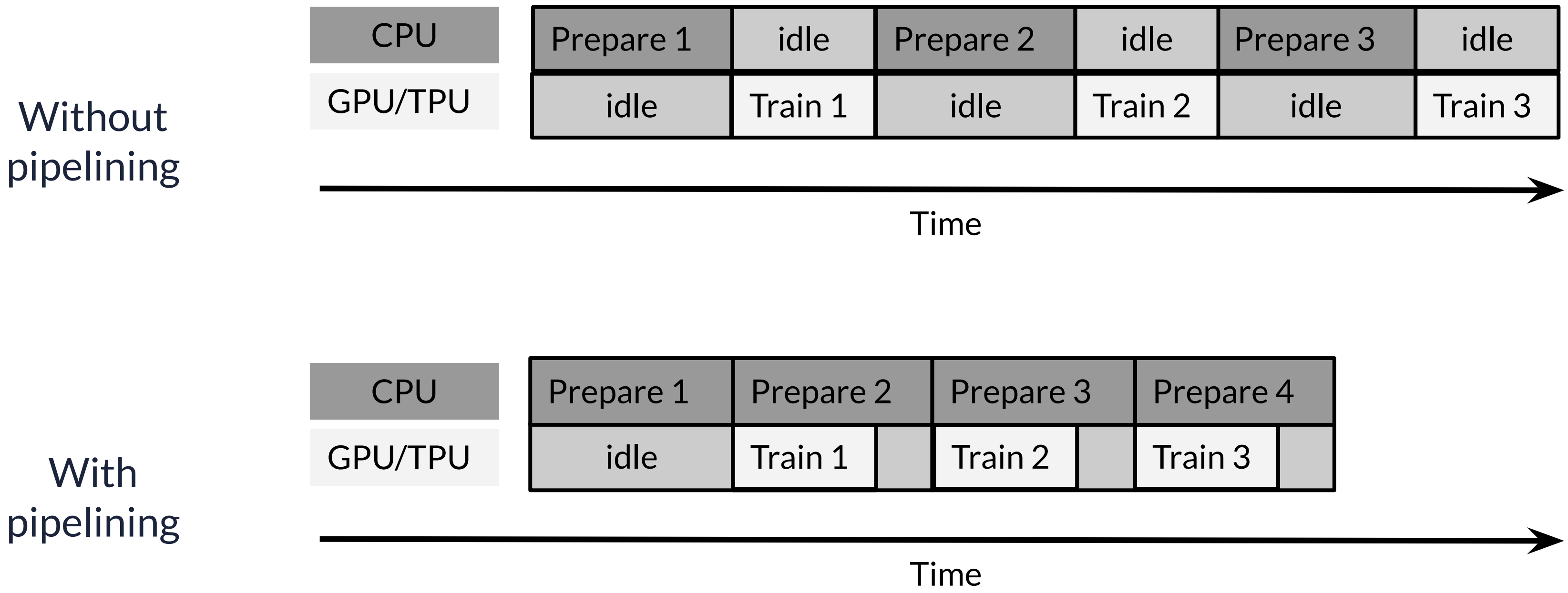
Inefficient ETL process



An improved ETL process



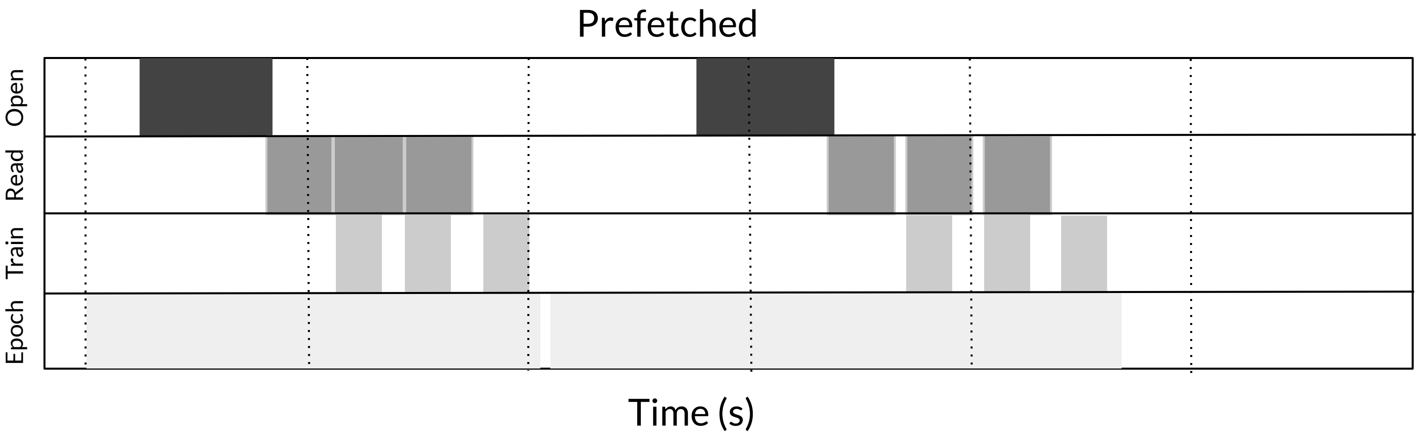
Pipelining


Without pipelining
CPU
GPU/TPU
Prepare 1
idle
Prepare 2
idle
Prepare 3
idle
idle
Train 1
idle
Train 2
idle
Train 3
Time
With pipelining
CPU
GPU/TPU
Prepare 1
Prepare 2
Prepare 3
Prepare 4
idle
Train 1
Train 2
Train 3
Time

How to optimize pipeline performance?

- Prefetching
- Parallelize data extraction and transformation
- Caching
- Reduce memory

Optimize with prefetching

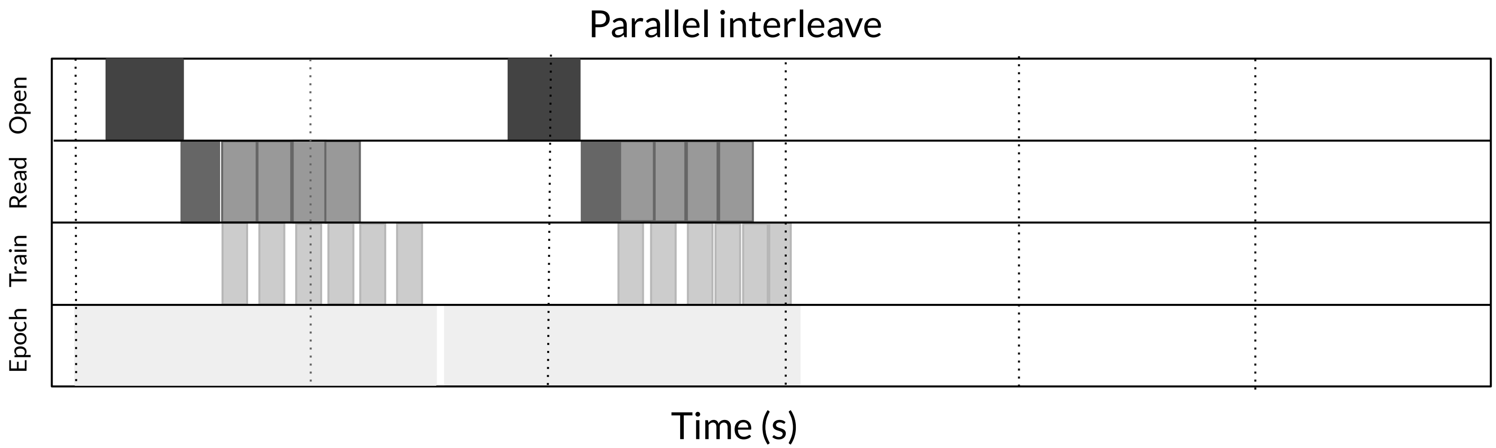



```
benchmark(
    ArtificialDataset()
    .prefetch(tf.data.experimental.AUTOTUNE)
)
```

Parallelize data extraction

- Time-to-first-byte: Prefer local storage as it takes significantly longer to read data from remote storage
- Read throughput: Maximize the aggregate bandwidth of remote storage by reading more files

Parallel interleave

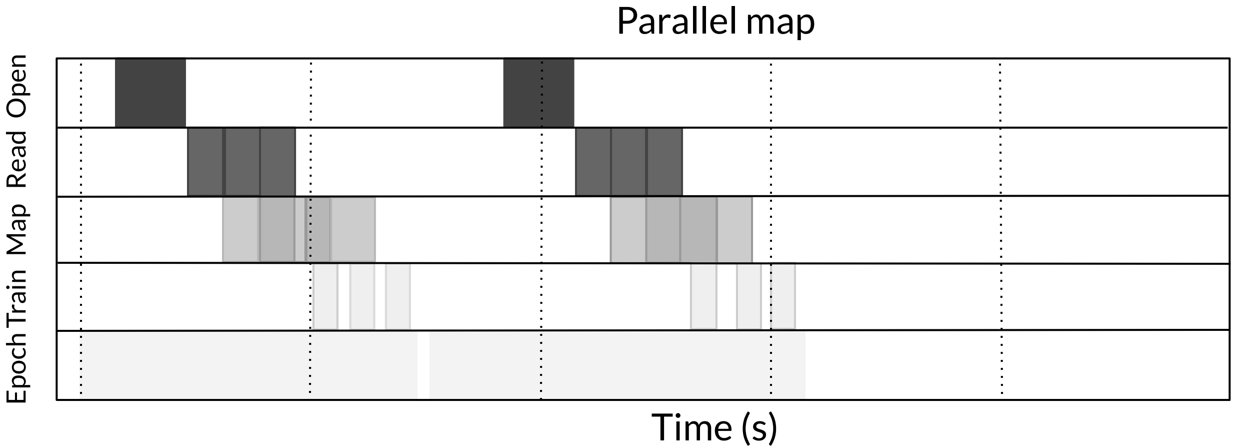



```
benchmark(
    tf.data.Dataset.range(2)
    .interleave(
        ArtificialDataset,
        num_parallel_calls=tf.data.experimental.AUTOTUNE
    )
)
```

Parallelize data transformation

- Post data loading, the inputs may need preprocessing
- Element-wise preprocessing can be parallelized across CPU cores
- The optimal value for the level of parallelism depends on:
  - Size and shape of training data
  - Cost of the mapping transformation
  - Load the CPU is experiencing currently
- With tf.data you can use AUTOTUNE to set parallelism automatically

Parallel mapping

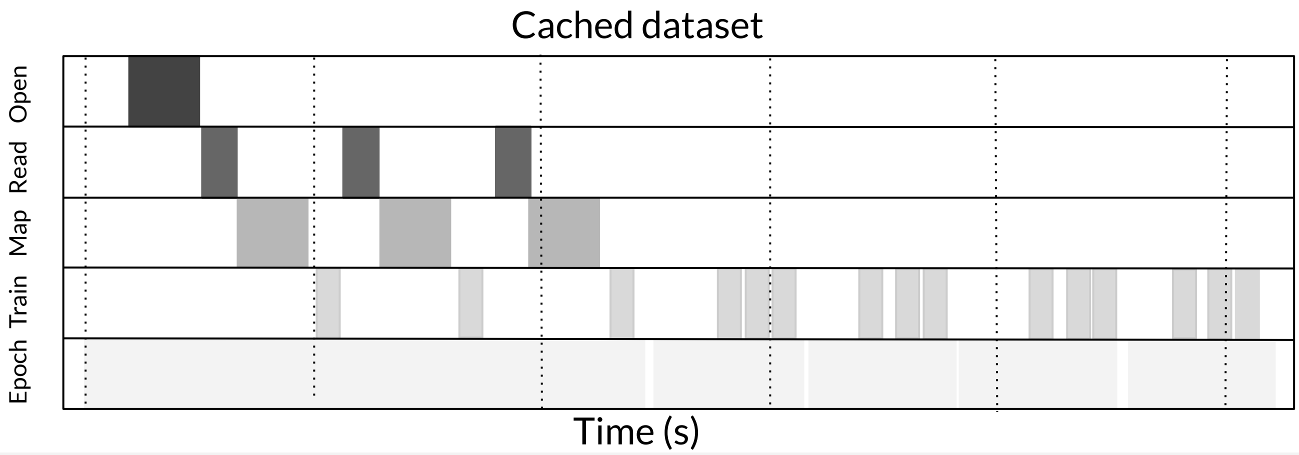



```
benchmark(
    ArtificialDataset()
    .map(
        mapped_function,
        num_parallel_calls=tf.data.AUTOTUNE
    )
)
```

Improve training time with caching

- In-memory: `tf.data.Dataset.cache()`
- Disk: `tf.data.Dataset.cache(filename=...)`

Caching




```
benchmark(
    ArtificialDataset().map(mapped_function).cache(),5
)
```

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High performance modeling

Training Large Models - The Rise of Giant Neural Nets and Parallelism

Rise of giant neural networks

- In 2014, the ImageNet winner was GoogleNet with *4 mil. parameters* and scoring a 74.8% top-1 accuracy
- In 2017, Squeeze-and-excitation networks achieved 82.7% top-1 accuracy with *145.8 mil. Parameters*

36 fold increase in the number of parameters in just 3 years!

Issues training larger networks

- GPU memory only increased by factor ~ 3
- Saturated the amount of memory available in Cloud TPUs
- Need for large-scale training of giant neural networks

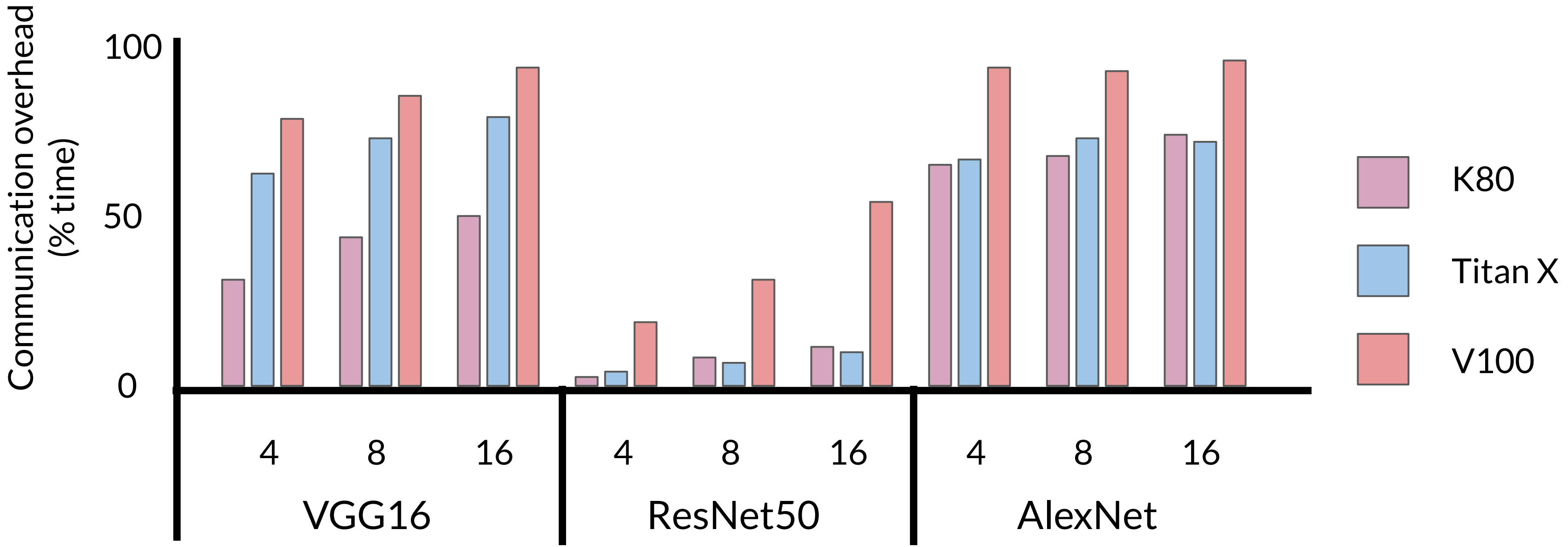
Overcoming memory constraints

- Strategy #1 - Gradient Accumulation
  - Split batches into mini-batches and only perform backprop after whole batch
- Strategy #2 - Memory swap
  - Copy activations between CPU and memory, back and forth

Parallelism revisited

- **Data parallelism**: In data parallelism, models are replicated onto different accelerators (GPU/TPU) and data is split between them
- **Model parallelism**: When models are too large to fit on a single device then they can be divided into partitions, assigning different partitions to different accelerators

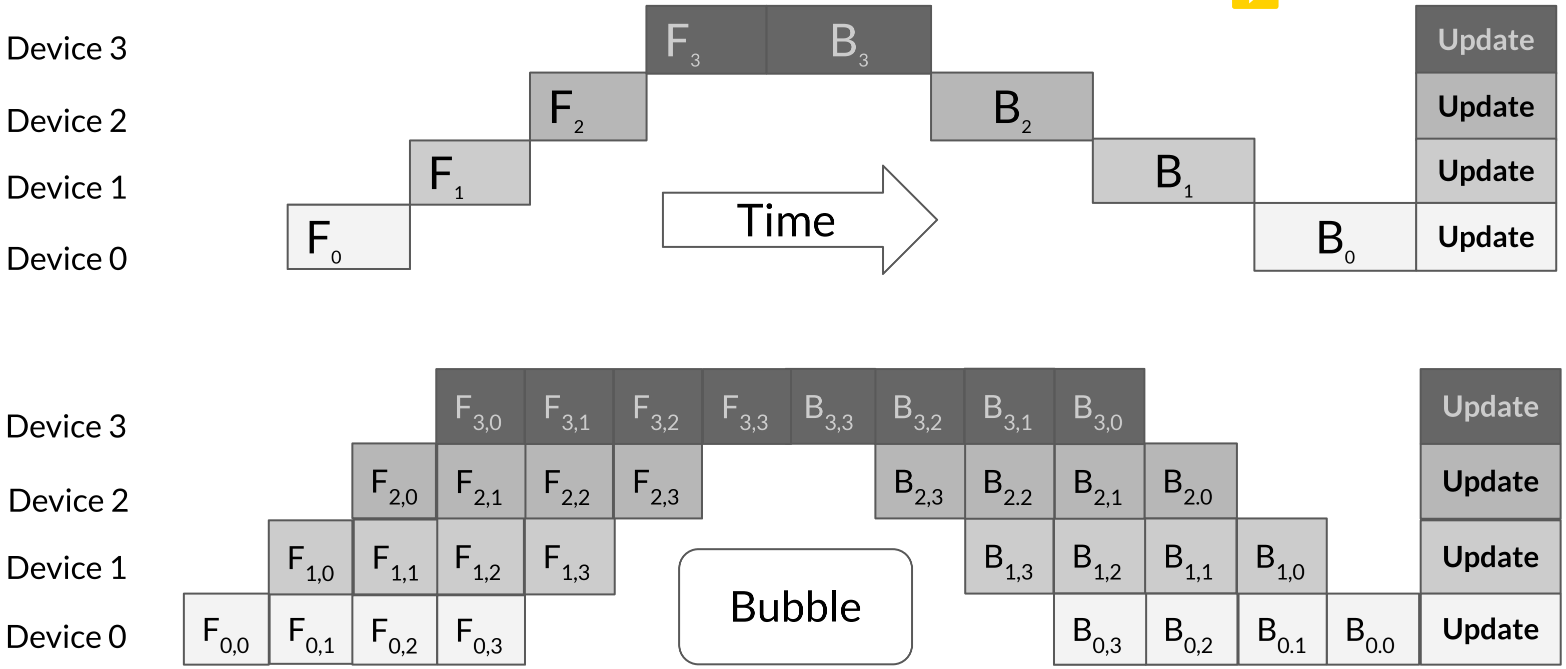
Challenges in data parallelism



Challenges keeping accelerators busy

- Accelerators have limited memory
- Model parallelism: large networks can be trained
    - But, accelerator compute capacity is underutilized
- Data parallelism: train same model with different input data
    - But, the maximum model size an accelerator can support is limited

Pipeline parallelism



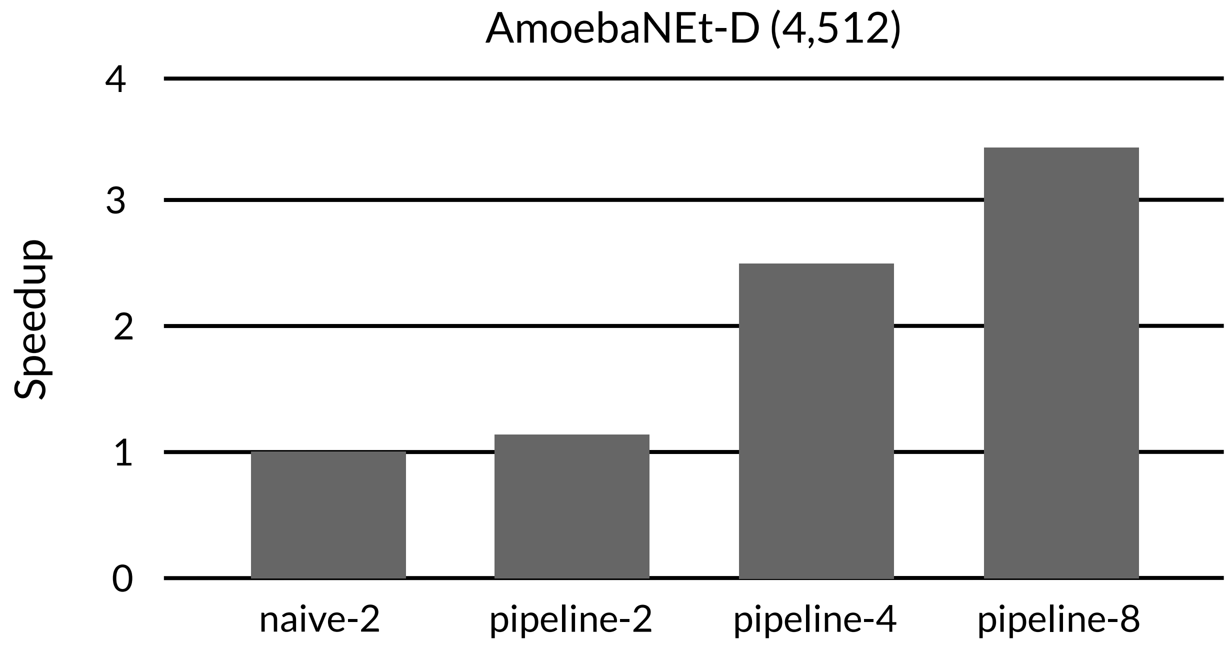
Pipeline parallelism

- Integrates both data and model parallelism:
    - Divide mini-batch data into micro-batches
    - Different workers work on different micro-batches in parallel
    - Allow ML models to have significantly more parameters

GPipe - Key features

- Open-source TensorFlow library (using Lingvo)
- Inserts communication primitives at the partition boundaries
- Automatic parallelism to reduce memory consumption
- Gradient accumulation across micro-batches, so that model quality is preserved
- Partitioning is heuristic-based

GPipe Results



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Knowledge Distillation

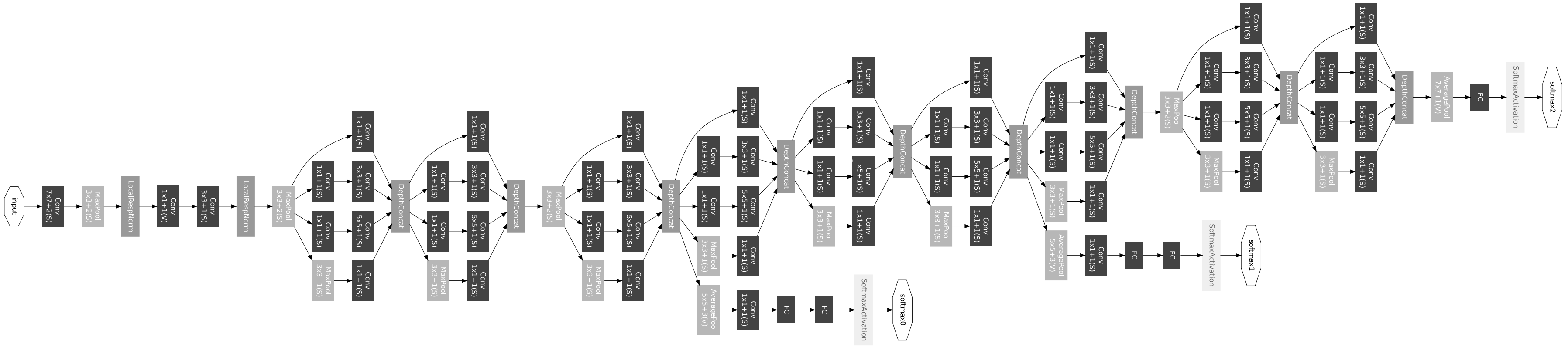
Teacher and Student Networks

Sophisticated models and their problems

- Larger sophisticated models become complex
- Complex models learn complex tasks
- Can we express this learning more efficiently?

Is it possible to ‘distill’ or concentrate this complexity into smaller networks?

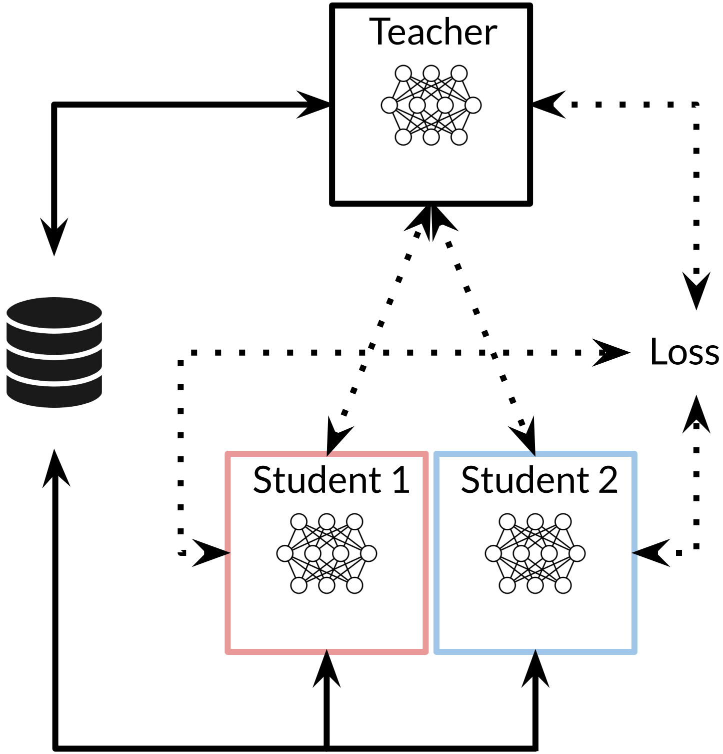
GoogLeNet


input
Conv 7x7+2(S)
MaxPool 3x3+2(S)
LocalRespNorm
Conv 1x1+1(V)
Conv 3x3+1(S)
LocalRespNorm
MaxPool 3x3+2(S)
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
DepthConcat
AveragePool 5x5+3(V)
FC
SoftmaxActivation
softmax0
softmax1
AveragePool 7x7+1(V)
softmax2

Knowledge distillation

- Duplicate the performance of a complex model in a simpler model

- Idea: Create a simple *'student'* model that learns from a complex *'teacher'* model



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Knowledge Distillation

Knowledge Distillation Techniques

Teacher and student

- Training objectives of the models vary
- Teacher (normal training)
  - maximizes the actual metric
- Student (knowledge transfer)
  - matches p-distribution of the teacher's predictions to form 'soft targets'
  - 'Soft targets' tell us about the knowledge learned by the teacher


Dark Knowledge

Transferring "dark knowledge" to the student

- Improve softness of the teacher's distribution with 'softmax temperature' (T)

- As T grows, you get more insight about which classes the teacher finds similar to the predicted one

$$p_i = \frac{\exp\left(\frac{z_i}{T}\right)}{\sum_j \exp\left(\frac{z_j}{T}\right)}$$

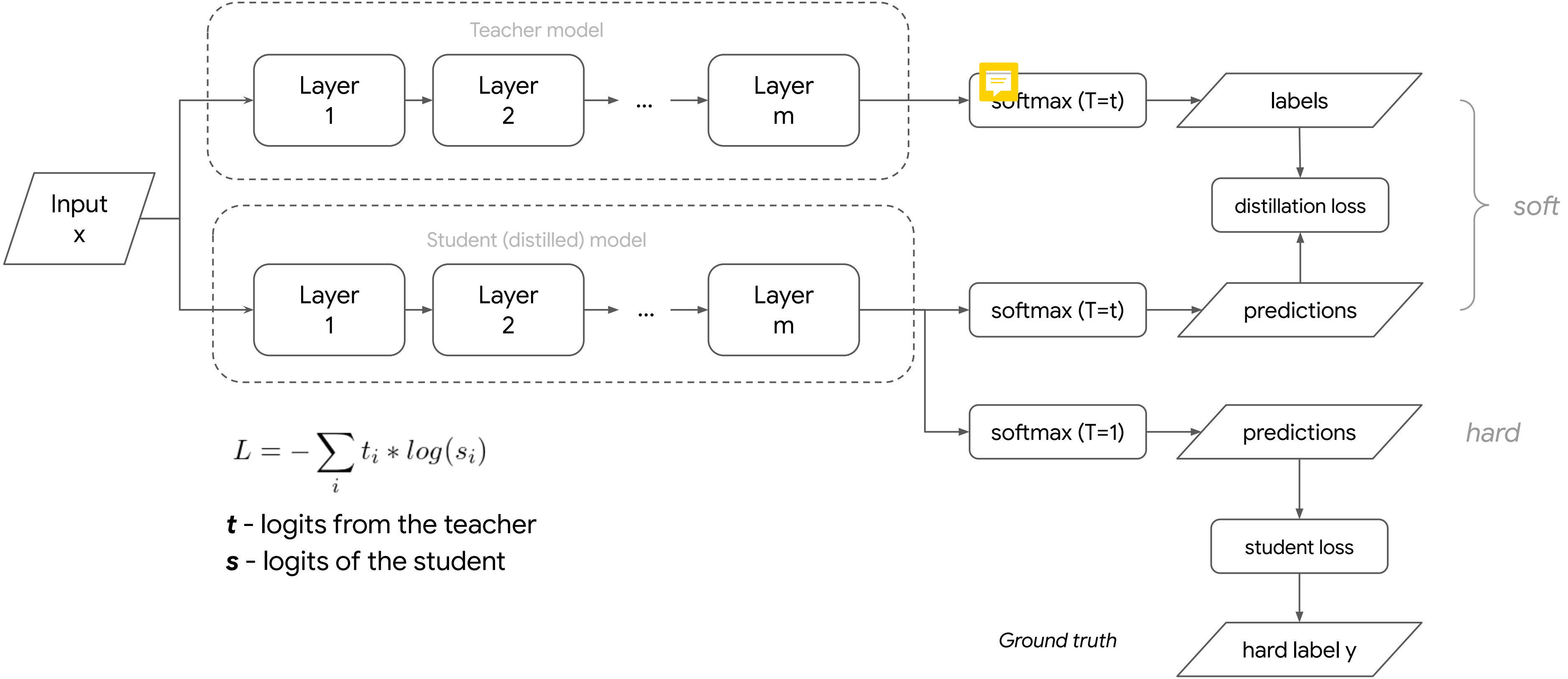
Techniques

- Approach #1: **Weigh objectives** (student and teacher) and combine during backprop
- Approach #2: **Compare distributions of the predictions** (student and teacher) using KL divergence

KL divergence

$$L = (1 - \alpha) L_H + \alpha L_{KL}$$

How knowledge transfer takes place



$$L = -\sum_i t_i * log(s_i)$$

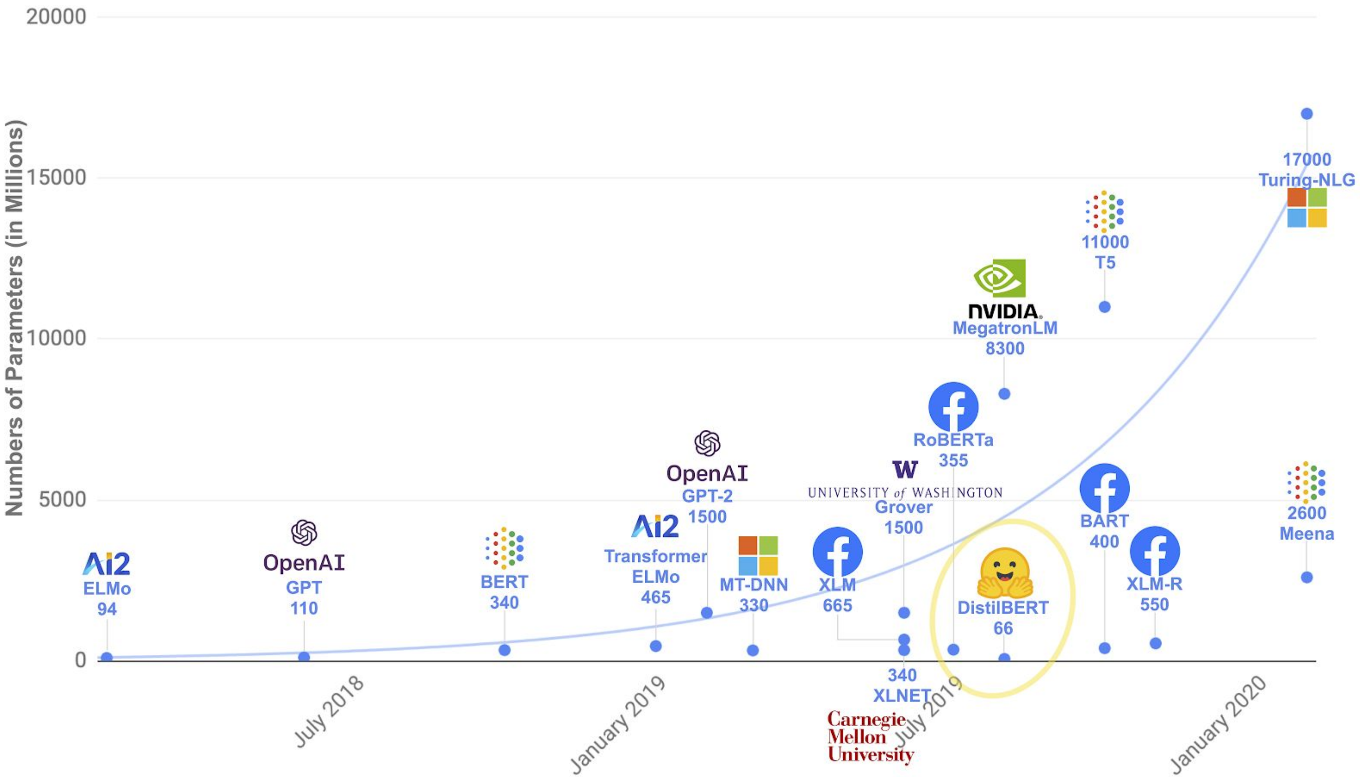
t - logits from the teacher

s - logits of the student

First quantitative results of distillation

Model	Accuracy	Word Error Rate (WER)
Baseline	58.9%	10.9%
10x Ensemble	61.1%	10.7%
Distilled Single Model	60.8%	10.7%

DistilBERT



20000
15000
10000
5000
0
Numbers of Parameters (in Millions)
ELMo
94
OpenAI
GPT
110
BERT
340
Transformer
ELMo
465
OpenAI
GPT-2
1500
MT-DNN
330
XLM
665
UNIVERSITY of WASHINGTON
Grover
1500
RoBERTa
355
340
XLNET
Carnegie
Mellon
University
DistilBERT
66
NVIDIA
MegatronLM
8300
11000
T5
BART
400
XLM-R
550
2600
Meena
17000
Turing-NLG
July 2018
January 2019
July 2019
January 2020

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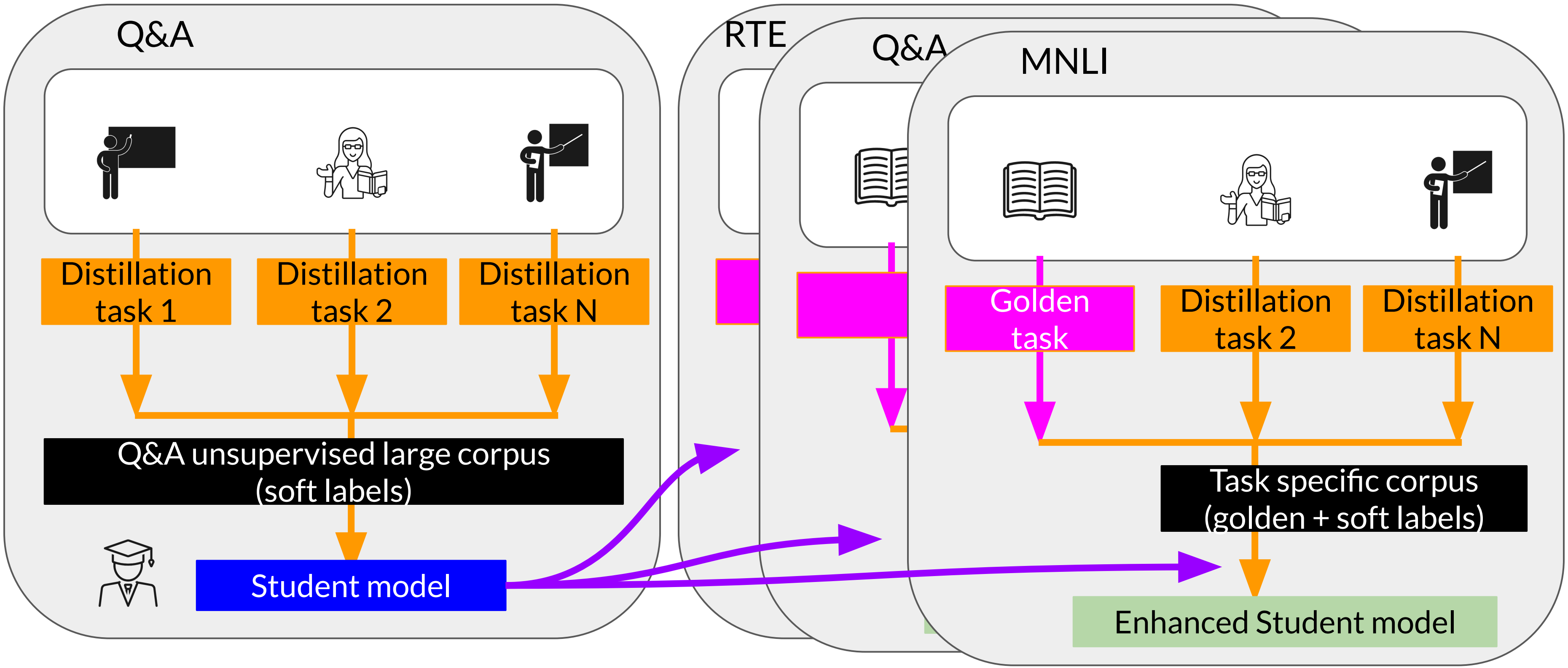
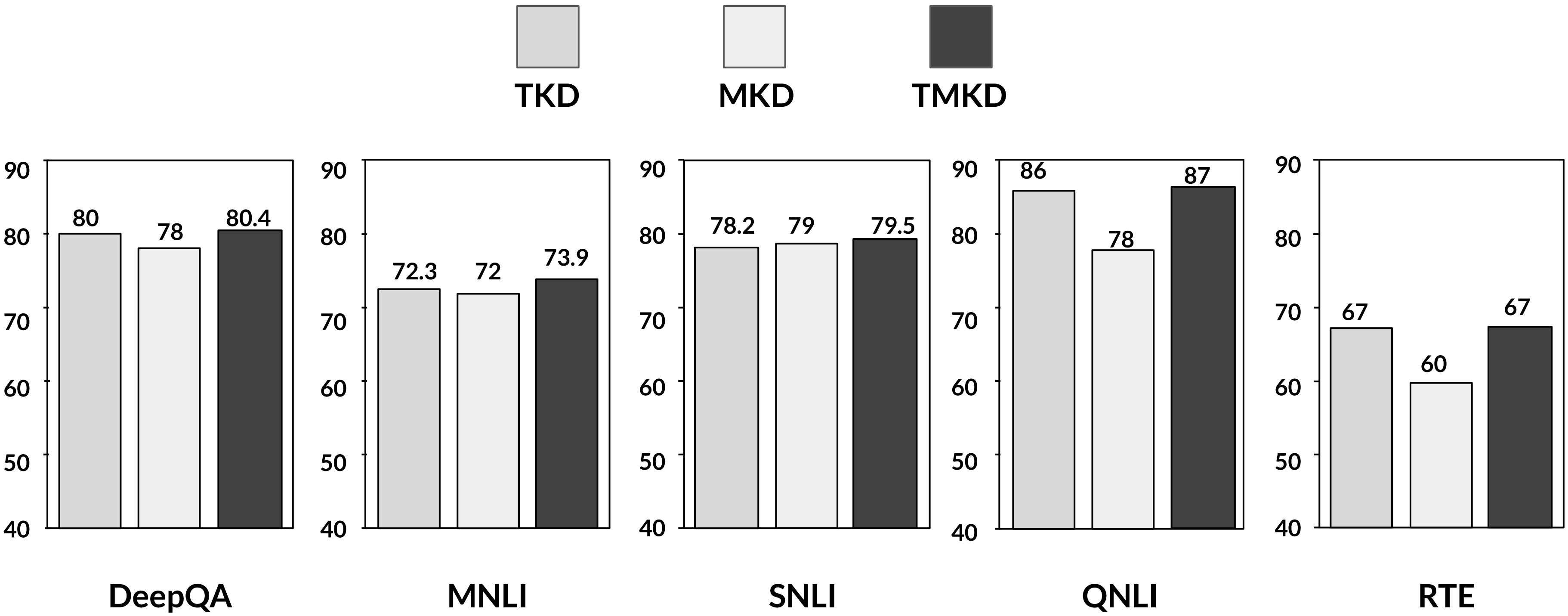
Knowledge Distillation

Case Study - How to Distill Knowledge for a Q&A Task

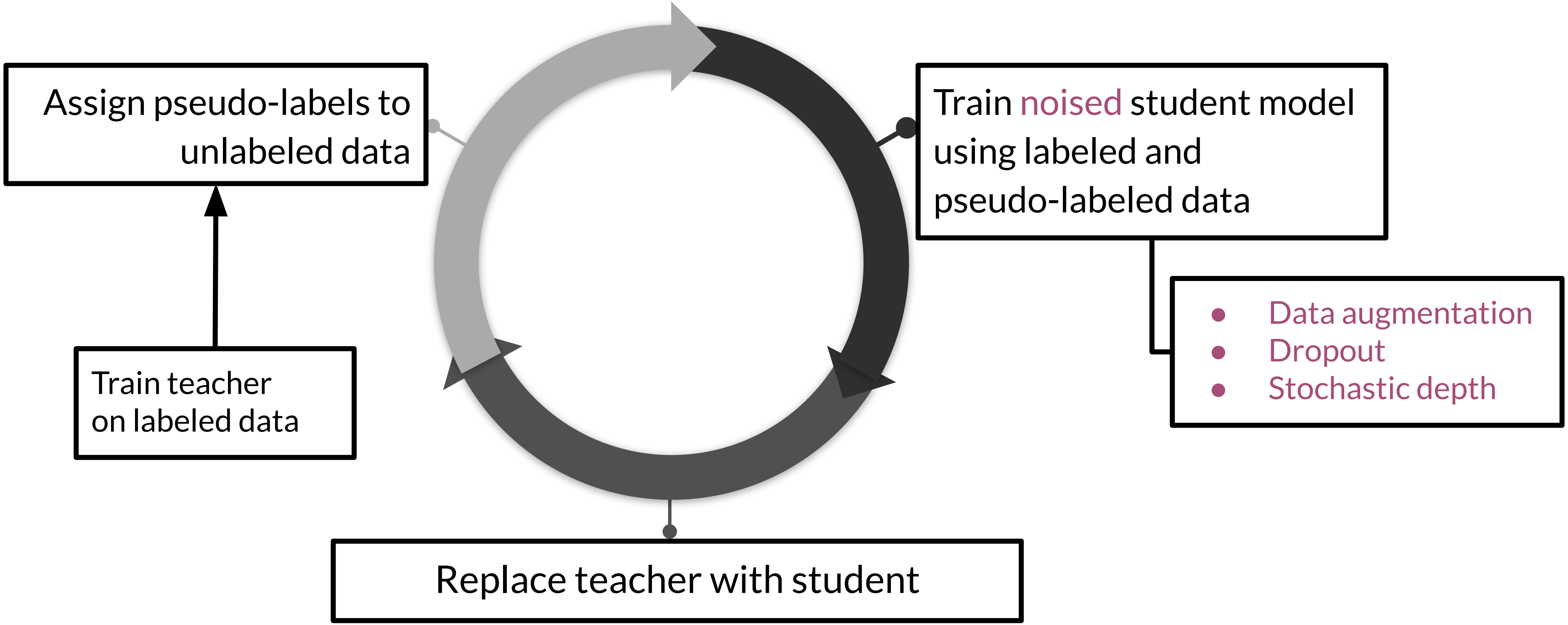
Two-stage multi-teacher distillation for Q & A



Impact of two-stage knowledge distillation



Make EfficientNets robust to noise with distillation



Results of noisy student training