Lecture 7: Data - TF Data, TF Records

AI-5

Productionizing AI (MLOps)

Pavlos Protopapas, Shivas Jayaram

Outline

- 1. Recap
- 2. Need for building efficient pipelines
- 3. TensorFlow Data
- 4. TensorFlow Records
- 5. Tutorial

Outline

1. Recap

2. Need for building efficient pipelines

Protopapas, Jayaram

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Recap: Motivation

The 3 components for better Deep Learning







Recap: Motivation

The 3 components for better Deep Learning



- Extraction
- Transformation
- Labeling
- Versioning
- Storage
- Processing
- Input to Training



- SOTA Models
- Transfer Learning
- Distillation
- Compression



- Scaling data processing
- GPU, TPU
- Multi GPU Server Training

Motivation: Data Size

Challenges:

- Medium datasets will not all fit in memory (RAM)
- Large datasets will not fit in disk (Hard drive)

Solution:

- Building data pipelines
 - Read data in batches which can fit in RAM
 - Feed data in batches to GPU
 - Read data from big data store in batches so not all data need to be present in local hard drive

Motivation: Data Size

Tools:

- Dask
- Google Cloud Storage (Big data store)
- TensorFlow Data
- TensorFlow Records

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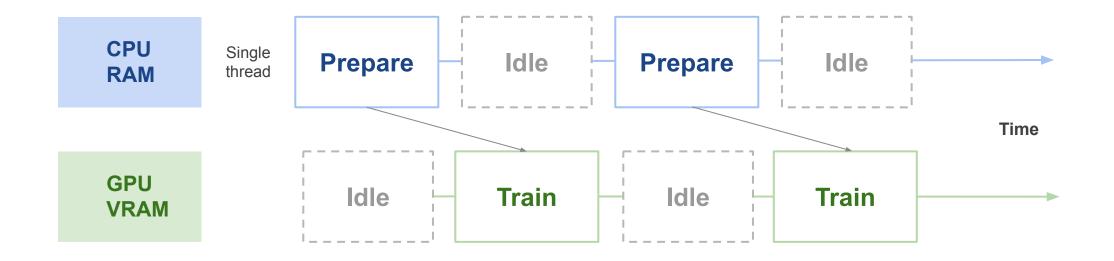
Why is training slow?

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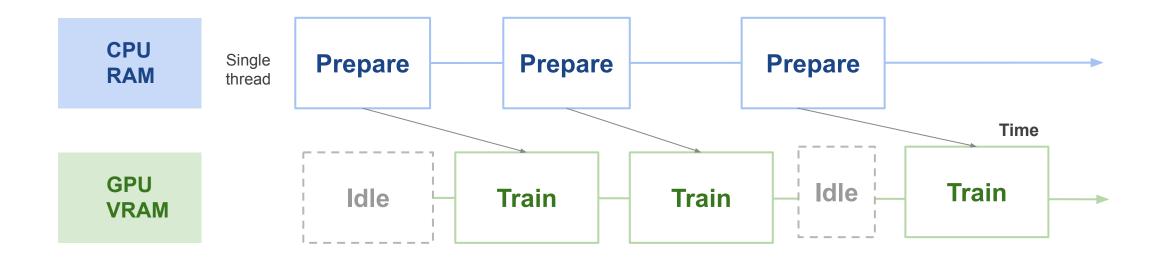
GPU Starvation

GPU Starvation:

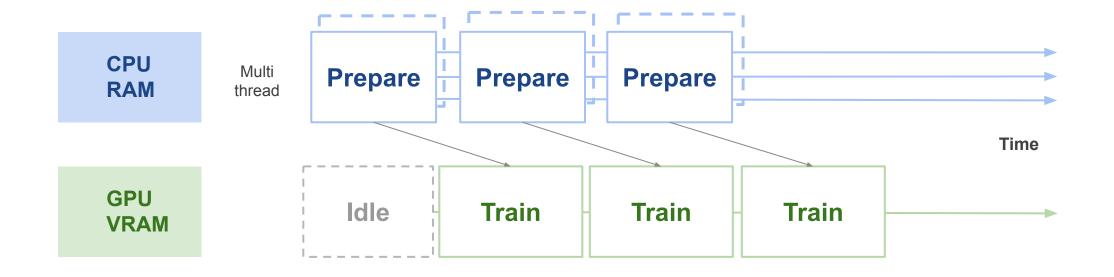
- Most times, data input to models take a long time
- Data process using CPU & RAM are the bottlenecks
- GPUs are expensive and not fully utilized



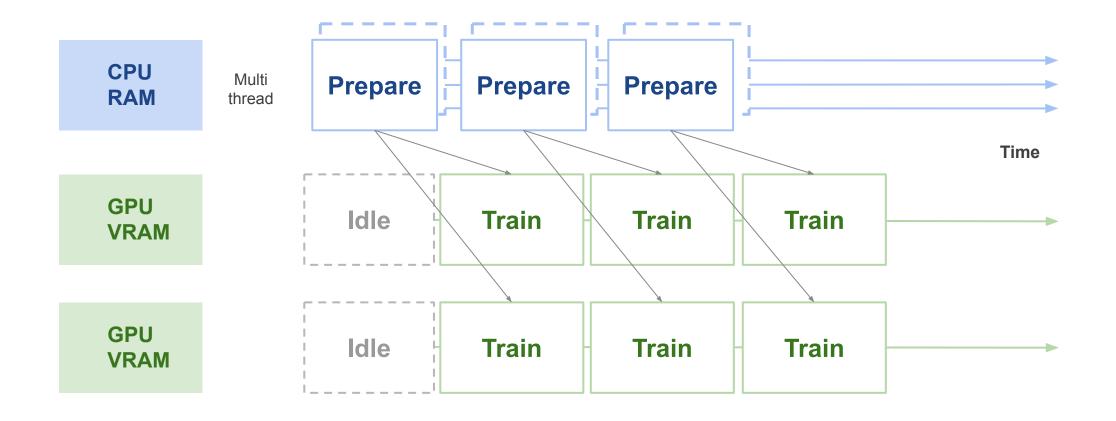
Single threaded CPU and single GPU working sequentially with NO prefetching



Single threaded CPU and single GPU working with prefetching



Multi threaded CPU and single GPU working with prefetching



Multi threaded CPU and multi GPU working with prefetching

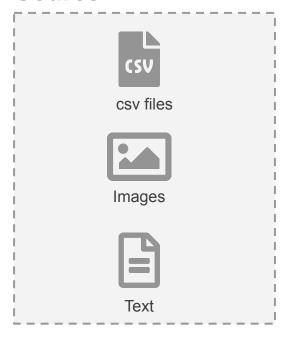
To build efficient pipelines we can use:

- TensorFlow Data
- TensorFlow Records

Outline

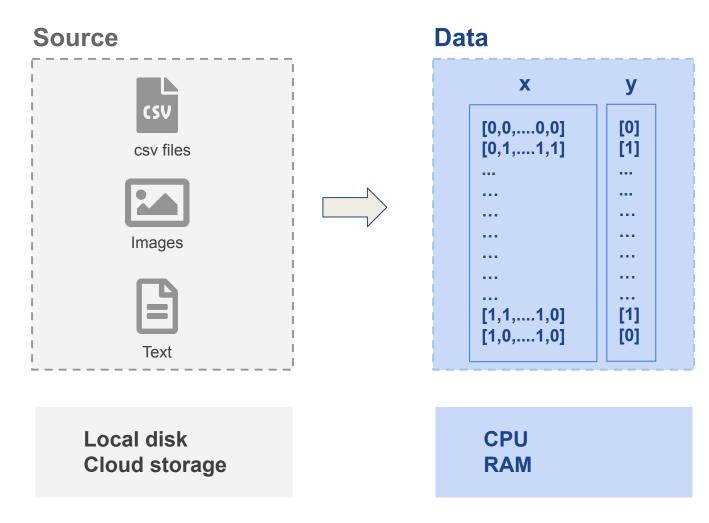
- 1. Recap
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Source



Local disk Cloud storage

Less than 2-4 GB

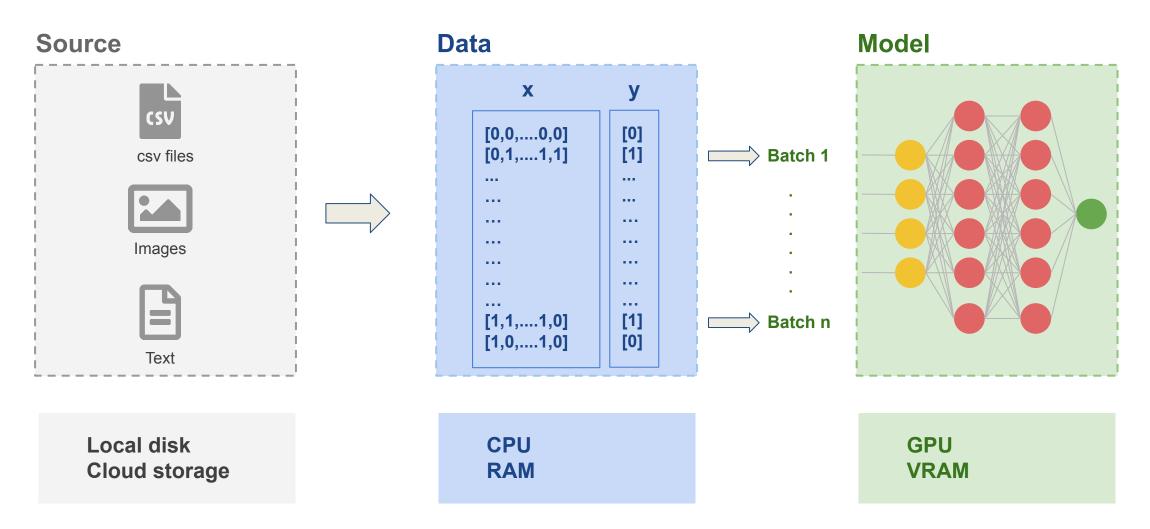


Less than 2-4 GB

All data loaded into memory

CS109 A/B scenario

Less than 2-4 GB



Al-5

Model trained in batches of data

All data loaded into memory

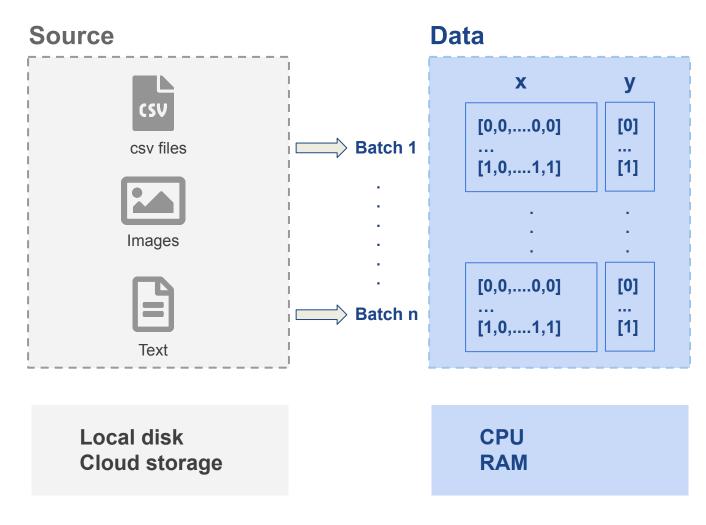
What do we do when our dataset size is greater than 5 GB?

Source



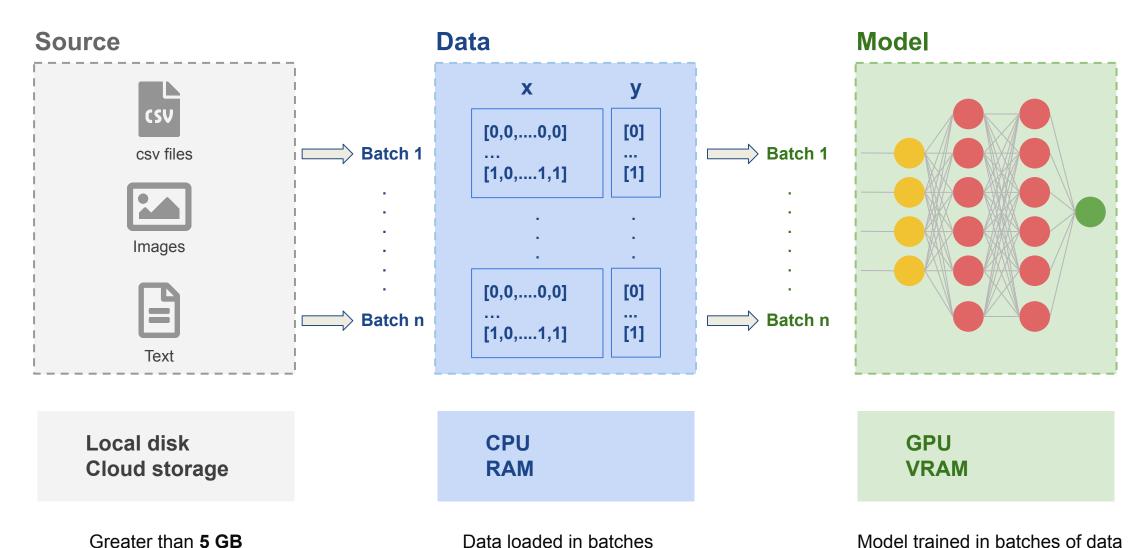
Local disk Cloud storage

Greater than 5 GB



Greater than 5 GB

Data loaded in batches



AI-5

So we need a way to efficiently:

- Extract data from various data sources
- Transform data for pre-processing/ augmentation
- Load data ahead of training in GPU

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- Extract data from various data sources
- Transform data for pre-processing/ augmentation
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TensorFlow Data to the rescue...

What is TensorFlow Data:

- TensorFlow makes building data pipelines easy using tf.data
- Build flexible and efficient data pipelines
- Read data in batches
- Parallelize data reads using CPU
- Does not load all data to memory and streams data to model
- Streams data from either local file system or distributed file systems

What you do:

- Create a Dataset object
- Specify where to get the data
- Describe how to transform it (Extract, process, augment)

tf.data takes care of:

- Multi threading
- Queuing
- Batching
- Prefetching
- Shuffling

All you need to do is:

```
# Create TF Dataset
train_data = tf.data.Dataset.from_tensor_slices((train_x, train_processed_y))
validation_data = tf.data.Dataset.from_tensor_slices((validate_x, validate_processed_y))
```

All you need to do is:

```
train_ds = tf.data.Dataset.from_tensor_slices(...)
```

```
train_ds = train_ds.shuffle()
train_ds = train_ds.map(<pre-process-function>)
train_ds = train_ds.batch()
train_ds = train_ds.prefetch()
```

Processing logic

All you need to do is:

```
train_ds = tf.data.Dataset.from_tensor_slices(...)
```

```
train_ds = train_ds.shuffle()
train_ds = train_ds.map(<pre-process-function>)
train_ds = train_ds.batch()
train_ds = train_ds.prefetch()
```

```
model.fit(train_ds,...)
```

Train

We can build data pipelines using a variety of operations

Extract

Read data:

- CSVs
- Images
- Text files
- Binary files
- SQL databases
- Google Big Query
- Local store
- Remote store

Transform

Prepare data:

- Clean
- Normalize
- Encode
- Embeddings
- Augment
- Shuffle
- Batch
- Repeat

Load

Pass data to Device:

- Training / Inference
- CPUs or GPUs or TPUs
- Parallelize
- Prefetch
- Cache

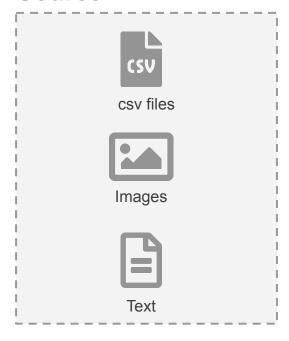
So in summary **tf.data** will help you:

- Work with large amounts of data
- Read from different data formats
- Perform complex transformations
- Build efficient data pipelines to reduce training time

Outline

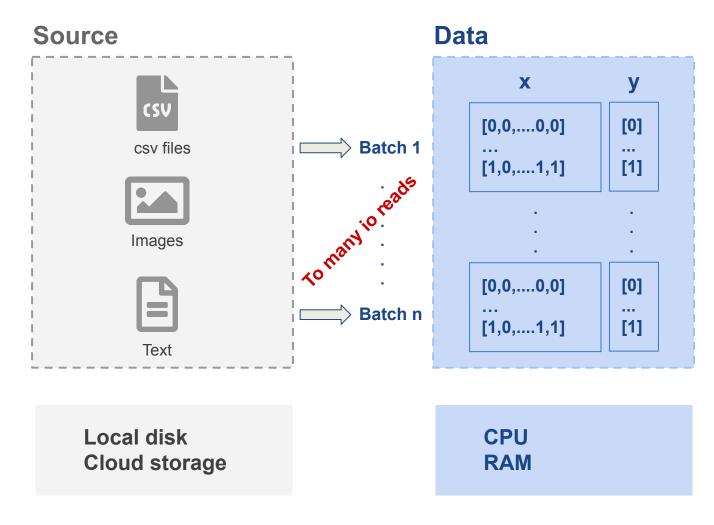
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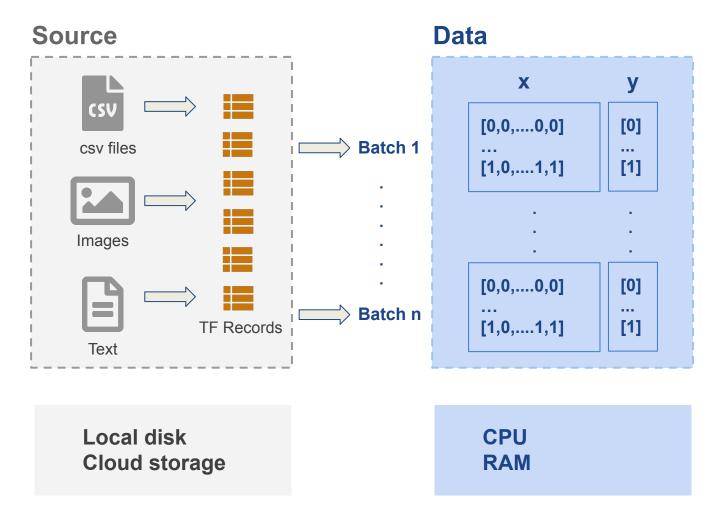
Local disk Cloud storage

Greater than 30 GB



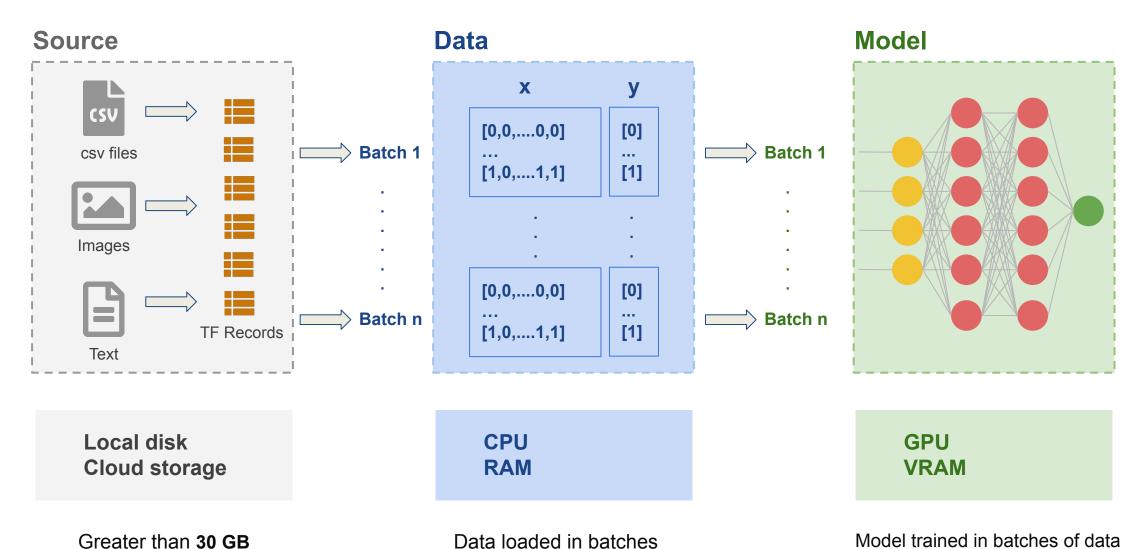
Greater than 30 GB

Data loaded in batches



Greater than 30 GB

Data loaded in batches



AI-5

TensorFlow Records

What are TensorFlow Records:

- TFRecord is TensorFlow's format for large amount of data
- It is a binary format defined using protocol buffers (protobuf)*
- Data is compressed and very efficient to read
- Use TFRecord when reading using tf.data is a bottleneck to training

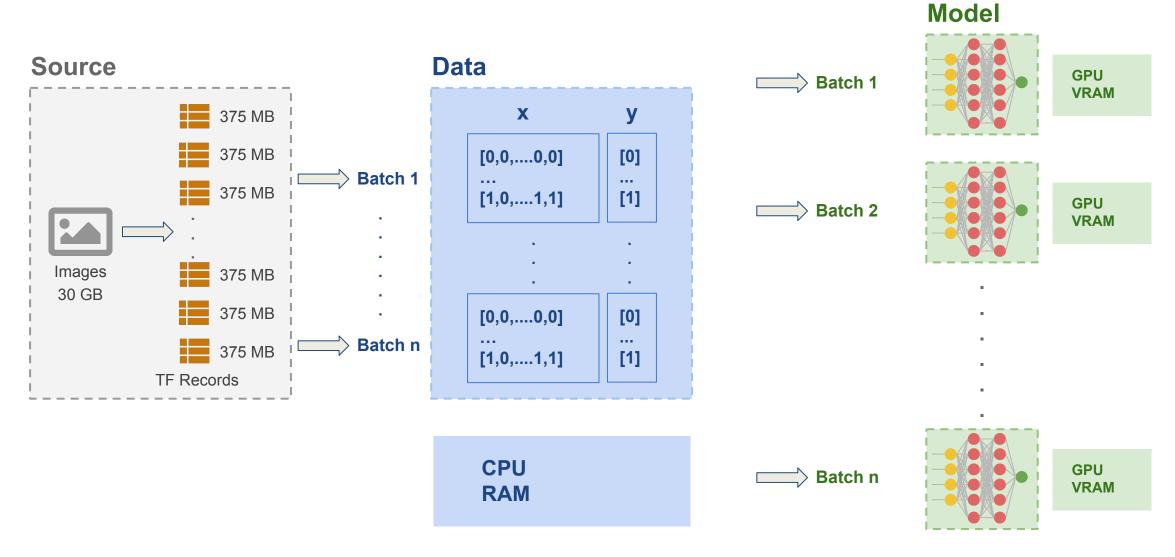
^{*}Protocol buffers are a portable, extensible, and efficient binary format developed and open sourced by Google

TensorFlow Records

Why use TFRecords:

- TFRecords is used to shard your data across multiple files
- Parallelize I/O reads across one or more training servers
- Each file size should be 10 MB to ideally > 100 MB
- For example if you have 30 GB of data and 8 training servers:
 - Number of shards = 10 * 8 = 80
 - Shard size = 30,000/(10*8) = 375MB

TensorFlow Records+Data

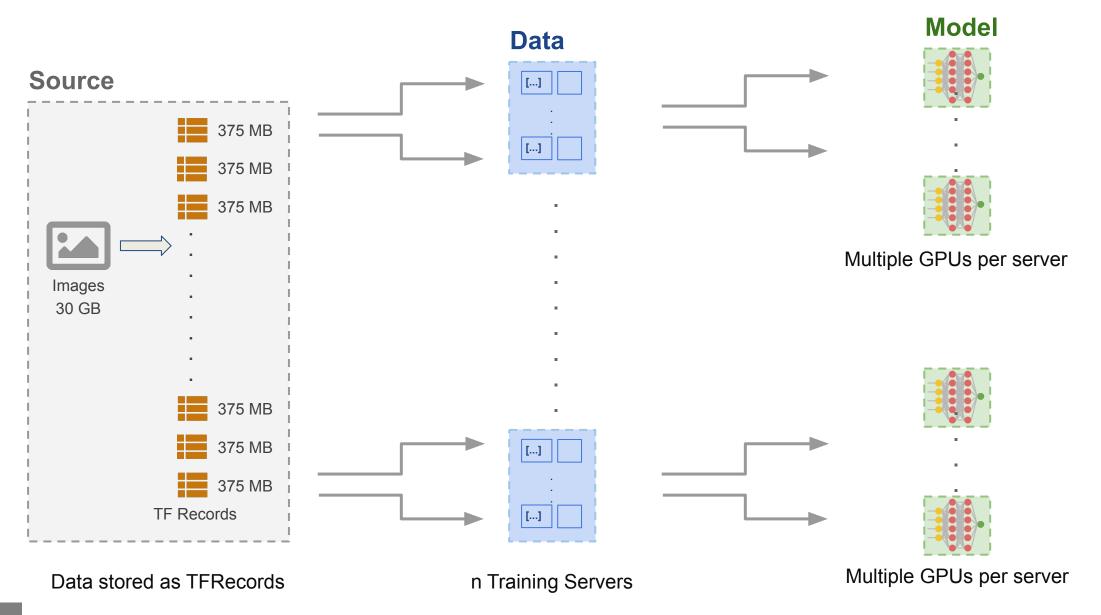


Data stored as TFRecords

1 Training Server

Model trained on multiple GPUs

TensorFlow Records+Data



TensorFlow Records

Creating TFRecords:

- TFRecords consists of files that are composed of a series of tf.Example messages
- tf.Example is a {"key": value} mapping where key is the feature name, and value is its binary representation
- For example to store image dataset, serialize all image attributes along with the label in a TFRecord file

```
"image": image.bytes(),
    "height": image.height,
    "width": image.width,
    "channel": image.channel,
    "label": label
}
```

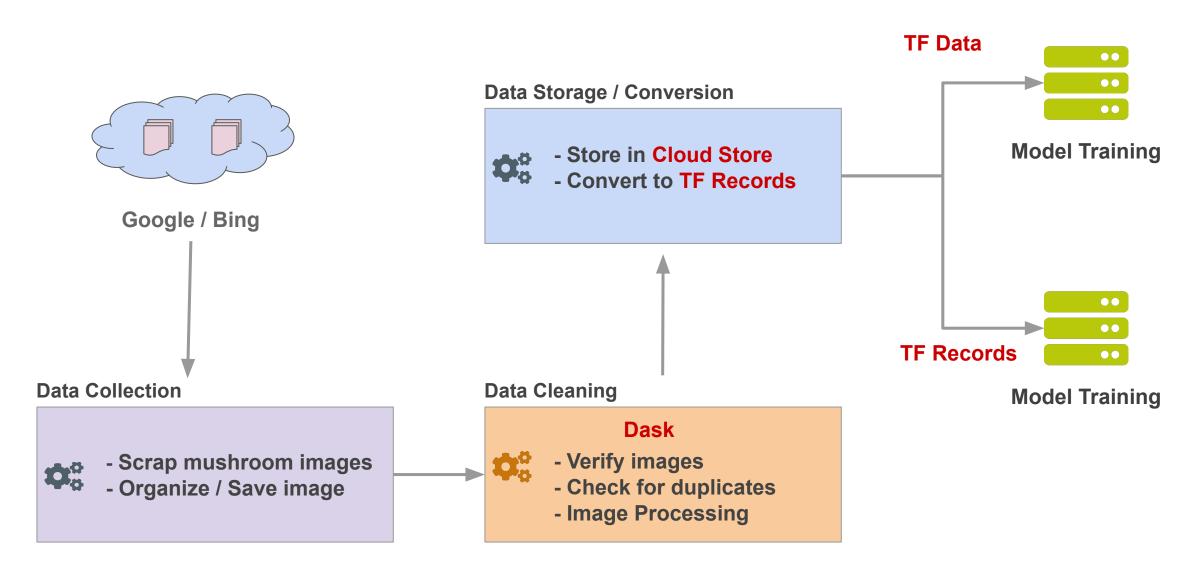
TensorFlow Records

Creating TFRecords:

```
"image": image.bytes(),
   "height": image.height,
   "width": image.width,
   "channel": image.channel,
   "label": label
}
```

The image is stored as binary and not using any compression format. So files can be read linearly as a sequence of bytes without a need to decode images. This saves time to read but using more disk space.

Putting it all together



Tutorial

Goals of the tutorial are

- Use tf.data APIs to build data pipelines for Deep Learning models
- Create TF Records and use them in your model training
 https://colab.research.google.com/drive/1InwuDS1INA_96sVA_J
 hNy025v64avF0A?usp=sharing

