Building data pipelines with

tf.data

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Agenda

- Why care about data pipelines?
- What is **tf.data**?
- How it is different from the existing options?
- Building data pipelines with tf.data
 - Simpler ones
 - More complex ones (w/ ImageDataGenerator)
- Performance comparisons

Acknowledgements

- The entire team at <u>PylmageSearch</u>
- Picsou Balthazar

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tf.data is a module by TensorFlow that:

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 - Simple
 - Reusable

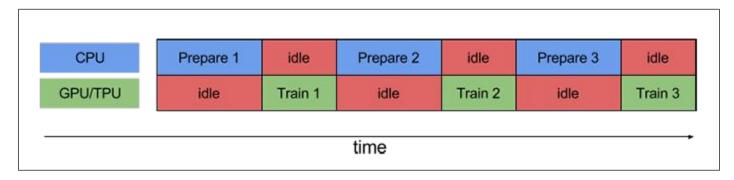
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 - For example, the data input pipelines for image and text can be completely different.
 - tf.data gives you programmable interfaces to aid your use cases.

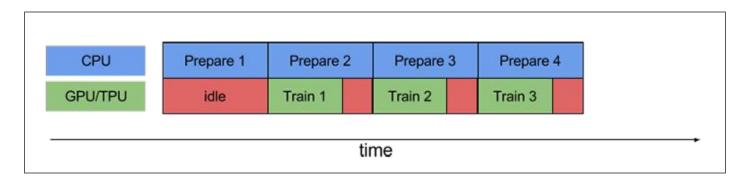
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Processes running without pipelines

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Processes running with pipelines

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- Efficient pipelining to reduce any additional time it takes to stream
 your data to the model ← tf.data.Dataset.prefetch()
- Parallelizable data transformation ←

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TLDR; parallelization made easier!



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Know more here: https://www.tensorflow.org/quide/data performance.

Enough talking! Show me some code!



• Use tf.data.Dataset.

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```
# FashionMNIST data along with images and labels
(train, test) = tf.keras.datasets.fashion_mnist.load_data()

# Create tf.data.Dataset!
X_train, y_train = train
train_dataset = tf.data.Dataset.from_tensor_slices((X_train, y_train))
X_test, y_test = test
test_dataset = tf.data.Dataset.from_tensor_slices((X_test, y_test))
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```

```
train_dataset
<TensorSliceDataset shapes: ((28, 28), ()), types: (tf.uint8, tf.uint8)>
```

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train_dataset = train_dataset.\
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train_dataset = train_dataset.\
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    repeat().\
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    prefetch(buffer_size=1000)

for (images, labels) in train_dataset.take(1):
    pass

print(images.shape) # TensorShape([256, 28, 28])
```

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```
model.fit(train_dataset,
    steps_per_epoch=len(X_train)//256,
    epochs=5,
    validation_data=test_dataset.batch(256)
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You can play with the notebook here: http://bit.ly/tfdata1



We will use the **Flowers dataset**.



• Initialize ImageDataGenerator with the augmentations.



Initialize ImageDataGenerator with the augmentations.

```
train aug = ImageDataGenerator(
   rotation range=30,
   zoom range=0.15,
   width shift range=0.2,
   height shift range=0.2,
   shear_range=0.15,
   horizontal_flip=True,
   fill mode="nearest")
```



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```
train_set = tf.data.Dataset.from_generator(
    lambda: train_aug.flow_from_directory(flowers,
            class mode="categorical",
            target size=(224, 224),
            color_mode="rgb",
            shuffle=True),
    output_types=(tf.float32, tf.float32),
    output_shapes=([None, 224, 224, 3], [None, 5])
```



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- And voila!



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You can play with the notebook here: http://bit.ly/tfdata2

In case you were wondering ...



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Data loading with tf.data:

```
1000 batches: 0.6213550567626953 s 412002.76269 Images/s
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Additionally, check out this blog post: http://bit.ly/tf-data-comp. It includes a comprehensive comparison on computation footprints.

Explore more about tf.data

- https://www.tensorflow.org/guide/data
- https://www.tensorflow.org/guide/data_performance
- PylmageSearch future blogs
- PylmageSearch's book <u>DL4CV</u> will be updated with tf.data in a future release
- Hands-On Machine Learning with Scikit-Learn, Keras, and <u>TensorFlow</u> (2nd ed.)

Slides available here: http://bit.ly/MLWeekend19

See you next time



Find me here: sayak.dev

Thank you very much:)



