TensorFlow v2.0 Cheat Sheet

TensorFlow™

TensorFlow is an open-source software library for high-performance numerical computation. Its flexible architecture enables to easily deploy computation across a variety of platforms (CPUs, GPUs, and TPUs), as well as mobile and edge devices, desktops, and clusters of servers. TensorFlow comes with strong support for machine learning and deep learning.

High-Level APIs for Deep Learning

Keras is a handy high-level API standard for deep learning models widely adopted for fast prototyping and state-of-the-art research. It was originally designed to run on top of different low-level computational frameworks and therefore the TensorFlow platform fully implements it.

The Sequential API is the most common way to define your neural network model. It corresponds to the mental image we use when thinking about deep learning: a sequence of layers.

```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models

# Load data set
mnist = datasets.mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
# Construct a neural network model
model = models.Sequential()
model.add(layers.Flatten(input_shape=(28, 28)))
model.add(layers.Dense(512, activation=tf.nn.relu))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(10, activation=tf.nn.softmax))
model.compile(optimizer='adam',
 loss='sparse_categorical_crossentropy',
 metrics=['accuracy'])

# Train and evaluate the model
model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```

The Functional API enables engineers to define complex topologies, including multi-input and multi-output models, as well as advanced models with shared layers and models with residual connections.

```
from tensorflow.keras.layers import Flatten, Dense,
Dropout from tensorflow.keras.models import Model

# Loading data set must be here <...>

inputs = tf.keras.Input(shape=(28, 28))
x = Flatten()(inputs)
x = Dense(512, activation='relu')(x)
x = Dropout(0.2)(x)
predictions = Dense(10, activation='softmax')(x)
model = Model(inputs=inputs, outputs=predictions)
# Compile, train and evaluate the model here <...>
```

A layer instance is called on a tensor and returns a tensor. An input tensor and output tensor can then be used to define a Model, which is compiled and trained just as a Sequential model. Models are callable by themselves and can be stacked the same way while reusing trained weights.

Transfer learning and fine-tuning of pretrained models saves your time if your data set does not differ significantly from the original one.

```
import tensorflow as tf
import tensorflow_datasets as tfds

dataset = tfds.load(name='tf_flowers', as_supervised=True)
NUMBER_OF_CLASSES_IN_DATASET = 5
IMG_SIZE = 160

def preprocess_example(image, label):
 image = tf.cast(image, tf.float32)
 image = (image / 127.5) - 1
 image = tf.image.resize(image, (IMG_SIZE, IMG_SIZE))
 return image, label

DATASET_SIZE = 3670
BATCH_SIZE = 32
train = dataset['train'].map(preprocess_example)
train_batches = train.shuffle(DATASET_SIZE).batch(BATCH_SIZE)
# Load MobileNetV2 model pretrained on ImageNet data
model = tf.keras.applications.MobileNetV2(
 input_shape=(IMG_SIZE, IMG_SIZE, 3),
 include_top=False, weights='imagenet', pooling='avg')
model.trainable = False

# Add a new layer for multiclass classification
new_output = tf.keras.layers.Dense(
 NUMBER_OF_CLASSES_IN_DATASET, activation='softmax')
new_model = tf.keras.Sequential([model, new_output])
new_model.compile(
 loss=tf.keras.losses.categorical_crossentropy,
 optimizer=tf.keras.optimizers.RMSprop(lr=1e-3),
 metrics=['accuracy'])

# Train the classification layer
new_model.fit(train_batches.repeat(), epochs=10,
 steps_per_epoch=DATASET_SIZE // BATCH_SIZE)
```

After the execution of the given transfer learning code, you can make MobileNetV2 layers trainable and perform fine-tuning of the resulting model to achieve better results.

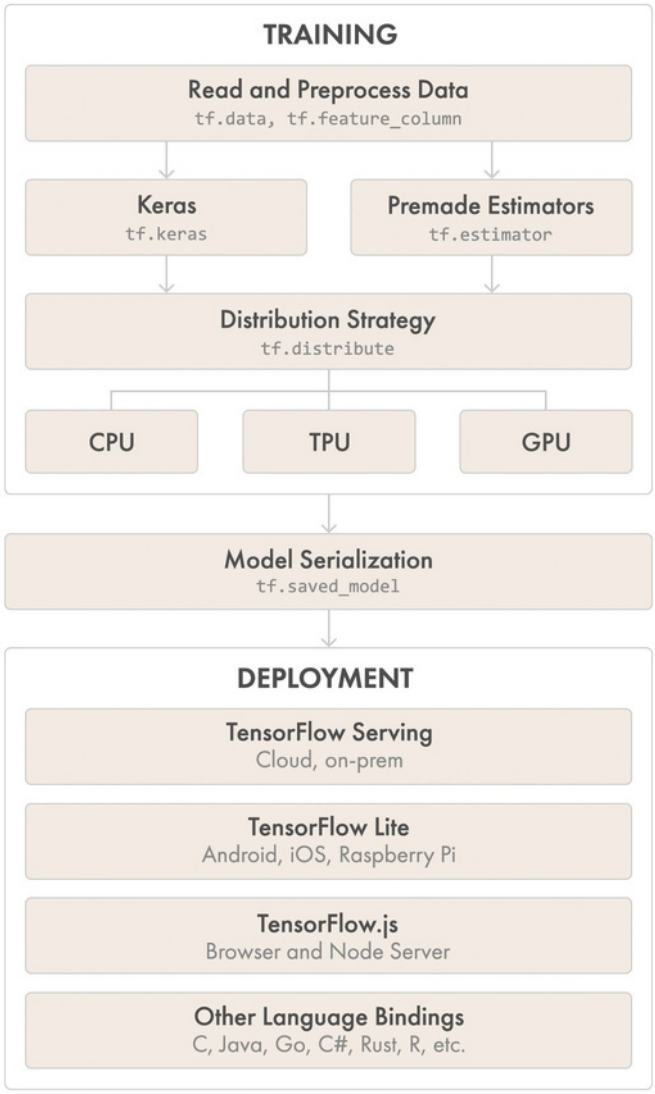
Jupyter Notebook

Jupyter Notebook is a web-based interactive computational environment for data science and scientific computing.

Google Colaboratory is a free notebook environment that requires no setup and runs entirely in the cloud. Use it for jump-starting a machine learning project.

A Reference Machine Learning Workflow

Here's a conceptual diagram and a workflow example:



01 Load the training data using pipelines created with tf.data. As an input, you can use either in-memory data (NumPy), or a local storage, or a remote persistent storage.

02 Build, train, and validate a model with tf.keras, or use premade estimators.

03 Run and debug with eager execution, then use tf.function for the benefits of graphs.

04 For large ML training tasks, use the Distribution Strategy API for deploying training on Kubernetes clusters within on-premises or cloud environments.

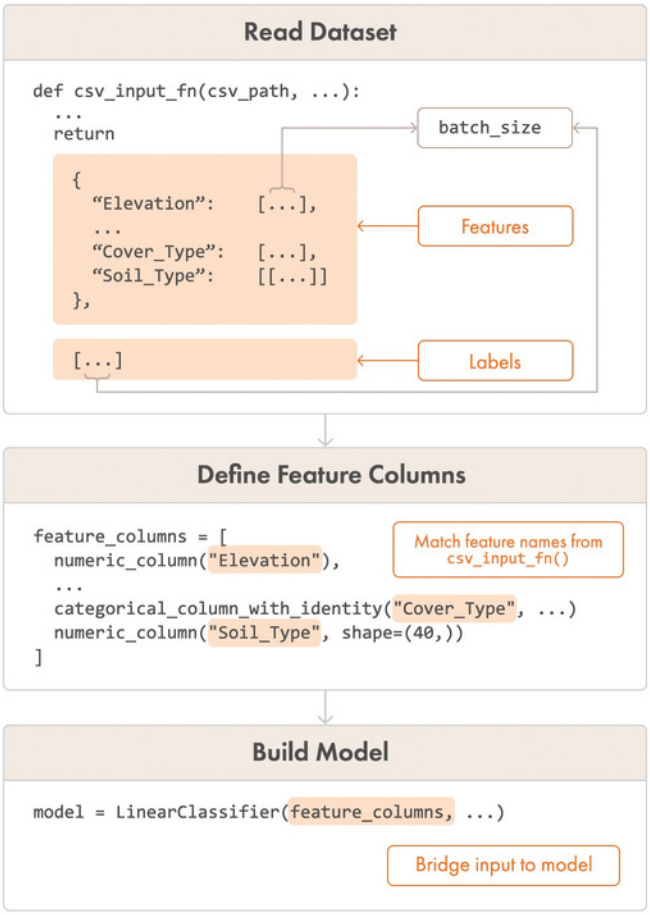
05 Export to SavedModel—an interchange format for TensorFlow Serving, TensorFlow Lite, TensorFlow.js, etc.

The tf.data API enables to build complex input pipelines from simple pieces. The pipeline aggregates data from a distributed file system, applies transformation to each object, and merges shuffled examples into training batches.

tf.data.Dataset represents a sequence of elements each containing one or more Tensor object(-s). This can be exemplified by a pair of tensors representing an image and a corresponding class label.

```
import tensorflow as tf

DATASET_URL = "https://archive.ics.uci.edu/ml/machine-" \
 "learning-databases/covtype/covtype.data.gz"
DATASET_SIZE = 387698
dataset_path = tf.keras.utils.get_file(
 fname=DATASET_URL.split('/')[-1], origin=DATASET_URL)

COLUMN_NAMES = [
 'Elevation', 'Aspect', 'Slope',
 'Horizontal_Distance_To_Hydrology',
 'Vertical_Distance_To_Hydrology',
 'Horizontal_Distance_To_Roadways',
 'Hillshade_9am', 'Hillshade_Noon', 'Hillshade_3pm',
 'Horizontal_Distance_To_Fire_Points', 'Soil_Type',
 'Cover_Type']

def _parse_line(line):

# Decode the line into values
 fields = tf.io.decode_csv(
 records=line, record_defaults=[0.0] * 54 + [0])

# Pack the result into a dictionary
 features = dict(zip(COLUMN_NAMES,
 fields[:10] + [tf.stack(fields[14:54])] + [fields[-1]]))

 # Extract one-hot encoded class label from the features
 class_label = tf.argmax(fields[10:14], axis=0)
 return features, class_label

def csv_input_fn(csv_path, test=False,
 batch_size=DATASET_SIZE // 1000):

# Create a dataset containing the csv lines
 dataset = tf.data.TextLineDataset(filenames=csv_path,
 compression_type='GZIP')
 # Parse each line
 dataset = dataset.map(_parse_line)

 # Shuffle, repeat, batch the examples for train and test
 dataset = dataset.shuffle(buffer_size=DATASET_SIZE,
 seed=42)

 TEST_SIZE = DATASET_SIZE // 10
 return dataset.take(TEST_SIZE).batch(TEST_SIZE) if test \
 else dataset.skip(TEST_SIZE).repeat().batch(batch_size)
```

Functions from the tf.feature_column namespace are used to put raw data into a TensorFlow data set. A feature column is a high-level configuration abstraction for ingesting and representing features. It does not contain any data but tells the model how to transform the raw data so that it matches the expectation. The exact feature column to choose depends on the feature type and the model type. The continuous feature type is handled by numeric_column and can be directly fed into a neural network or a linear model.



Categorical features can be ingested by functions with the "categorical_column_" prefix, but they need to be wrapped by `embedding_column` or `indicator_column` before being fed into Neural Network models. For linear models, indicator_column is an internal representation when categorical columns are passed in directly.

```
feature_columns = [tf.feature_column.numeric_column(name)
 for name in COLUMN_NAMES[:10]]

feature_columns.append(
 tf.feature_column.categorical_column_with_identity(
 'Cover_Type', num_buckets=8)
)
# Soil_type[1-40] is a tensor of length 40
feature_columns.append(
 tf.feature_column.numeric_column('Soil_Type', shape=(40,))
)
```

The Estimator API provides high-level encapsulation for best practices: model training, evaluation, prediction, and export for serving. The tf.estimator.Estimator subclass represents a complete model. Its object creates and manages tf.Graph and tf.Session for you. Premade estimators include Linear Classifier, DNN Classifier, and Gradient Boosted Trees. BaselineClassifier and BaselineRegressor will help to establish a simple model for sanity check during further model development.

```
# Build, train, and evaluate the estimator
model = tf.estimator.LinearClassifier(feature_columns,
 n_classes=4)
model.train(input_fn=lambda: csv_input_fn(dataset_path),
 steps=10000)
model.ev aluate(
 input_fn=lambda: csv_input_fn(dataset_path, test=True))
```

SavedModel contains a complete TF program and does not require the original model-building code to run, which makes it useful for deploying and sharing models.

```
# Export model to SavedModel
_builder = tf.estimator.export. \
 build_parsing_serving_input_receiver_fn
_spec_maker = tf.feature_column.make_parse_example_spec
serving_input_fn = _builder(_spec_maker(feature_columns))

export_path = model.export_saved_model(
 "/tmp/from_estimator/", serving_input_fn)
```

The following code sample shows how to load and use the saved model with Python.

```
# Import model from SavedModel
imported = tf.saved_model.load(export_path)

# Use imported model for prediction
def predict(new_object):
 example = tf.train.Example()

 # All regular continuous features
 for column in COLUMN_NAMES[:-2]:
 val = new_object[column]
 example.features.feature[column]. \
 float_list.value.extend([val])

 # One-hot encoded feature of 40 columns
 for val in new_object['Soil_Type']:
 example.features.feature['Soil_Type']. \
 float_list.value.extend([val])

 # Categorical column with ID
 example.features.feature['Cover_Type']. \
 int64_list.value.extend([new_object['Cover_Type']])

return imported.signatures['predict'](
 examples=tf.constant([example.SerializeToString()]))

predict({
 'Elevation': 2296, 'Aspect': 312, 'Slope': 27,
 'Horizontal_Distance_To_Hydrology': 256,
 'Horizontal_Distance_To_Fire_Points': 836,
 'Horizontal_Distance_To_Roadways': 1273,
 'Vertical_Distance_To_Hydrology': 145,
 'Hillshade_9am': 136, 'Hillshade_Noon': 208,
 'Hillshade_3pm': 206,
 'Soil_Type': [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
 'Cover_Type': 6})
```