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Btech CSE AIML B5

Neural Networks Lab 6

Installation

To install tensorflow in your linux system use the following commands.

sudo apt update

sudo apt install python3-dev python3-pip python3-venv

pip3 install --user --upgrade tensorflow

Tensors

TensorFlow operates on multidimensional arrays or *tensors* represented as `tf.Tensor` objects. Here is a two-dimensional tensor:

In [1]:
```python
import tensorflow as tf

x = tf.constant([[1., 2., 3.],
                 [4., 5., 6.]])

print(x)
print(x.shape)
print(x.dtype)
```

```
tf.Tensor(
[[1. 2. 3.]
 [4. 5. 6.]], shape=(2, 3), dtype=float32)
(2, 3)
<dtype: 'float32'>
```

The most important attributes of a `tf.Tensor` are its `shape` and `dtype` :

- `Tensor.shape` : tells you the size of the tensor along each of its axes.
- `Tensor.dtype` : tells you the type of all the elements in the tensor.

TensorFlow implements standard mathematical operations on tensors, as well as many operations specialized for machine learning.

For example:

In [2]:
```python
x + x
```

Out[2]:
```
<tf.Tensor: shape=(2, 3), dtype=float32, numpy=
array([[ 2.,  4.,  6.],
       [ 8., 10., 12.]], dtype=float32)>
```

In [3]:
```python
5 * x
```

Out[3]:
```
<tf.Tensor: shape=(2, 3), dtype=float32, numpy=
array([[ 5., 10., 15.],
       [20., 25., 30.]], dtype=float32)>
```

In [4]:
```
x @ tf.transpose(x)
```

Out[4]:
```
<tf.Tensor: shape=(2, 2), dtype=float32, numpy=
array([[14., 32.],
       [32., 77.]], dtype=float32)>
```

In [5]:
```
tf.concat([x, x, x], axis=0)
```

Out[5]:
```
<tf.Tensor: shape=(6, 3), dtype=float32, numpy=
array([[1., 2., 3.],
       [4., 5., 6.],
       [1., 2., 3.],
       [4., 5., 6.],
       [1., 2., 3.],
       [4., 5., 6.]], dtype=float32)>
```

In [6]:
```
tf.nn.softmax(x, axis=-1)
```

Out[6]:
```
<tf.Tensor: shape=(2, 3), dtype=float32, numpy=
array([[0.09003057, 0.24472848, 0.66524094],
       [0.09003057, 0.24472848, 0.66524094]], dtype=float32)>
```

In [7]:
```
tf.reduce_sum(x)
```

Out[7]:
```
<tf.Tensor: shape=(), dtype=float32, numpy=21.0>
```

Running large calculations on CPU can be slow. When properly configured, TensorFlow can use accelerator hardware like GPUs to execute operations very quickly.

In [8]:
```
if tf.config.list_physical_devices('GPU'):
  print("TensorFlow **IS** using the GPU")
else:
  print("TensorFlow **IS NOT** using the GPU")
```

```
TensorFlow **IS NOT** using the GPU
```

Variables

Normal `tf.Tensor` objects are immutable. To store model weights (or other mutable state) in TensorFlow use a `tf.Variable` .

In [9]:
```
var = tf.Variable([0.0, 0.0, 0.0])
```

In [10]:
```
var.assign([1, 2, 3])
```

Out[10]:
```
<tf.Variable 'UnreadVariable' shape=(3,) dtype=float32, numpy=array([1., 2., 3.], dtype=float32)>
```

In [11]:
```
var.assign_add([1, 1, 1])
```

Out[11]:
```
<tf.Variable 'UnreadVariable' shape=(3,) dtype=float32, numpy=array([2., 3., 4.], dtype=float32)>
```

Automatic differentiation

Gradient descent and related algorithms are a cornerstone of modern machine learning.

To enable this, TensorFlow implements automatic differentiation (autodiff), which uses calculus to compute gradients. Typically you'll use this to calculate the gradient of a model's *error* or *loss* with respect to its weights.

In [12]:
```
x = tf.Variable(1.0)

def f(x):
  y = x**2 + 2*x - 5
  return y
```

In [13]:
```
f(x)
```

Out[13]:
```
<tf.Tensor: shape=(), dtype=float32, numpy=-2.0>
```

At `x = 1.0`, `y = f(x) = (1**2 + 2*1 - 5) = -2`.

The derivative of `y` is `y' = f'(x) = (2*x + 2) = 4`. TensorFlow can calculate this automatically:

In [14]:
```
with tf.GradientTape() as tape:
  y = f(x)

g_x = tape.gradient(y, x)  # g(x) = dy/dx

g_x
```

Out[14]:
```
<tf.Tensor: shape=(), dtype=float32, numpy=4.0>
```

This simplified example only takes the derivative with respect to a single scalar (`x`), but TensorFlow can compute the gradient with respect to any number of non-scalar tensors simultaneously.

Graphs and tf.function

While you can use TensorFlow interactively like any Python library, TensorFlow also provides tools for:

- **Performance optimization**: to speed up training and inference.
- **Export**: so you can save your model when it's done training.

These require that you use `tf.function` to separate your pure-TensorFlow code from Python.

In [15]:
```
@tf.function
def my_func(x):
  print('Tracing.\n')
  return tf.reduce_sum(x)
```

The first time you run the `tf.function`, although it executes in Python, it captures a complete, optimized graph representing the TensorFlow computations done within the function.

In [16]:
```
x = tf.constant([1, 2, 3])
my_func(x)
```

```
Tracing.
```

Out[16]:
```
<tf.Tensor: shape=(), dtype=int32, numpy=6>
```

On subsequent calls TensorFlow only executes the optimized graph, skipping any non-TensorFlow steps. Below, note that `my_func` doesn't print *tracing* since `print` is a Python function, not a TensorFlow function.

In [17]:
```
x = tf.constant([10, 9, 8])
my_func(x)
```

Out[17]:
```
<tf.Tensor: shape=(), dtype=int32, numpy=27>
```

A graph may not be reusable for inputs with a different *signature* (`shape` and `dtype`), so a new graph is generated instead:

In [18]:
```
x = tf.constant([10.0, 9.1, 8.2], dtype=tf.float32)
my_func(x)
```

```
Tracing.
```

Out[18]:
```
<tf.Tensor: shape=(), dtype=float32, numpy=27.3>
```

Modules, layers, and models

`tf.Module` is a class for managing your `tf.Variable` objects, and the `tf.function` objects that operate on them. The `tf.Module` class is necessary to support two significant features:

1. You can save and restore the values of your variables using `tf.train.Checkpoint` . This is useful during training as it is quick to save and restore a model's state.
2. You can import and export the `tf.Variable` values *and* the `tf.function` graphs using `tf.saved_model` . This allows you to run your model independently of the Python program that created it.

Here is a complete example exporting a simple `tf.Module` object:

In [19]:
```
class MyModule(tf.Module):
  def __init__(self, value):
    self.weight = tf.Variable(value)

  @tf.function
  def multiply(self, x):
    return x * self.weight
```

In [20]:
```
mod = MyModule(3)
mod.multiply(tf.constant([1, 2, 3]))
```

Out[20]:
```
<tf.Tensor: shape=(3,), dtype=int32, numpy=array([3, 6, 9], dtype=int32)>
```

Save the `Module` :

In [21]:
```
save_path = './saved'
tf.saved_model.save(mod, save_path)
```

```
INFO:tensorflow:Assets written to: ./saved/assets
```

In [22]:
```
reloaded = tf.saved_model.load(save_path)
reloaded.multiply(tf.constant([1, 2, 3]))
```

Out[22]:
```
<tf.Tensor: shape=(3,), dtype=int32, numpy=array([3, 6, 9], dtype=int32)>
```

The `tf.keras.layers.Layer` and `tf.keras.Model` classes build on `tf.Module` providing additional functionality and convenience methods for building, training, and saving models. Some of these are demonstrated in the next section.

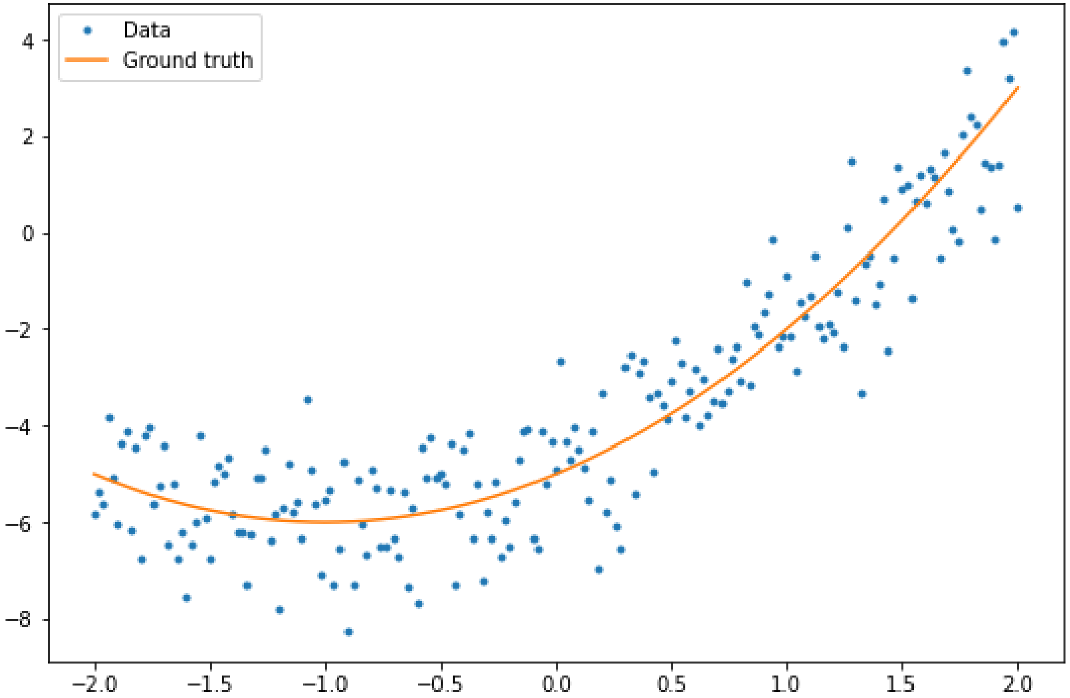
Training loops

Now put this all together to build a basic model and train it from scratch.

First, create some example data. This generates a cloud of points that loosely follows a quadratic curve:

In [23]:
```
import matplotlib
from matplotlib import pyplot as plt

matplotlib.rcParams['figure.figsize'] = [9, 6]
```

In [24]:
```
x = tf.linspace(-2, 2, 201)
x = tf.cast(x, tf.float32)

def f(x):
  y = x**2 + 2*x - 5
  return y

y = f(x) + tf.random.normal(shape=[201])

plt.plot(x.numpy(), y.numpy(), '.', label='Data')
plt.plot(x, f(x),  label='Ground truth')
plt.legend();
```



Create a model:

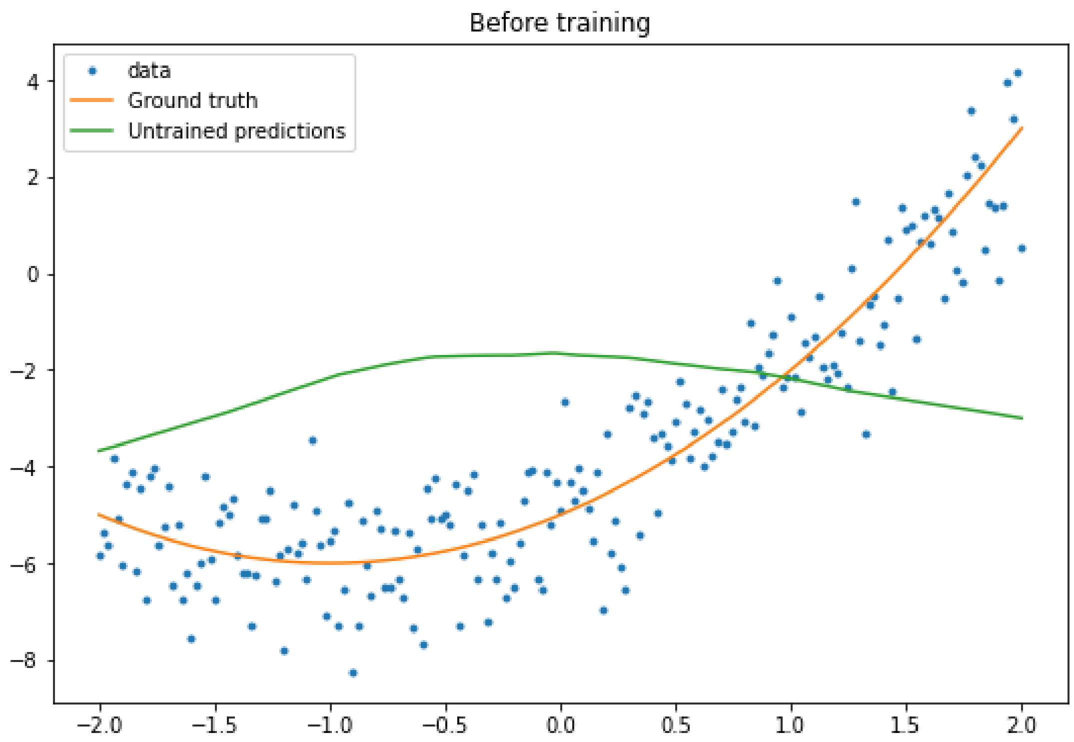
In [25]:

```
class Model(tf.keras.Model):
  def __init__(self, units):
    super().__init__()
    self.dense1 = tf.keras.layers.Dense(units=units,
                                        activation=tf.nn.relu,
                                        kernel_initializer=tf.random.normal,
                                        bias_initializer=tf.random.normal)
    self.dense2 = tf.keras.layers.Dense(1)

  def call(self, x, training=True):
    x = x[:, tf.newaxis]
    x = self.dense1(x)
    x = self.dense2(x)
    return tf.squeeze(x, axis=1)
```

In [26]:

```
model = Model(64)
```

In [27]:
```
plt.plot(x.numpy(), y.numpy(), '.', label='data')
plt.plot(x, f(x),  label='Ground truth')
plt.plot(x, model(x), label='Untrained predictions')
plt.title('Before training')
plt.legend();
```



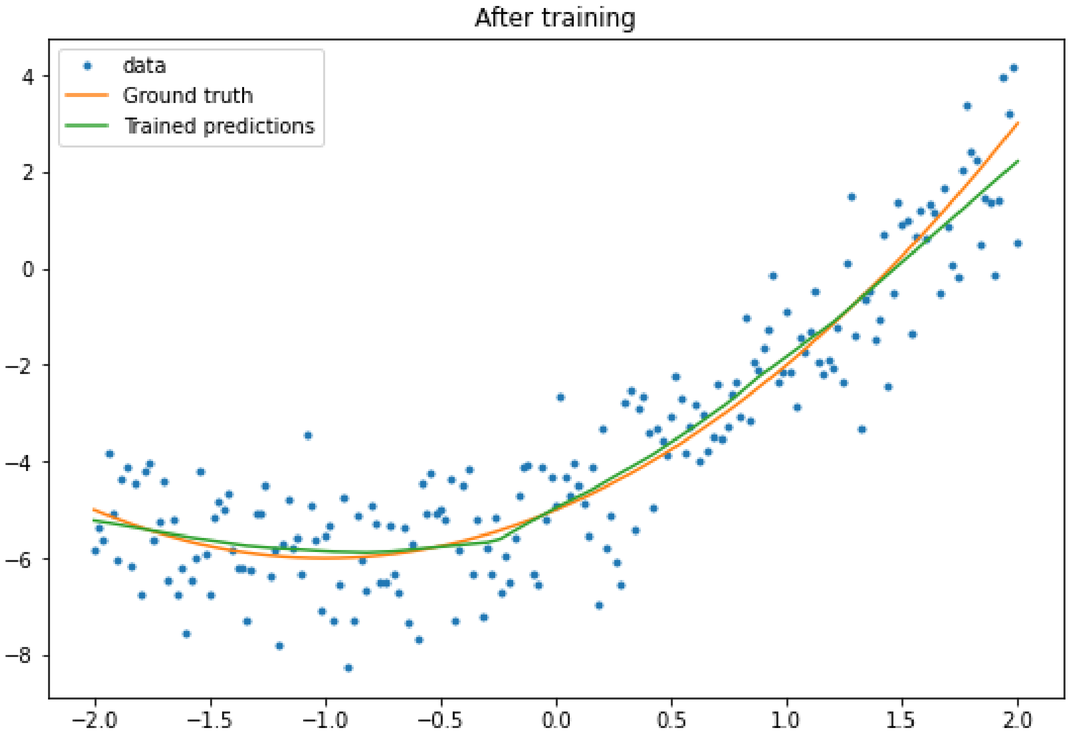
Write a basic training loop:

In [28]:

```
variables = model.variables

optimizer = tf.optimizers.SGD(learning_rate=0.01)

for step in range(1000):
  with tf.GradientTape() as tape:
    prediction = model(x)
    error = (y-prediction)**2
    mean_error = tf.reduce_mean(error)
  gradient = tape.gradient(mean_error, variables)
  optimizer.apply_gradients(zip(gradient, variables))

  if step % 100 == 0:
    print(f'Mean squared error: {mean_error.numpy():0.3f}')
```

```
Mean squared error: 10.085
Mean squared error: 1.083
Mean squared error: 1.077
Mean squared error: 1.074
Mean squared error: 1.071
Mean squared error: 1.068
Mean squared error: 1.066
Mean squared error: 1.065
Mean squared error: 1.064
Mean squared error: 1.062
```

In [29]:
```
plt.plot(x.numpy(),y.numpy(), '.', label="data")
plt.plot(x, f(x),  label='Ground truth')
plt.plot(x, model(x), label='Trained predictions')
plt.title('After training')
plt.legend();
```



That's working, but remember that implementations of common training utilities are available in the `tf.keras` module. So consider using those before writing your own. To start with, the `Model.compile` and `Model.fit` methods implement a training loop for you:

In [30]:
```
new_model = Model(64)
```

In [31]:

```
new_model.compile(
    loss=tf.keras.losses.MSE,
    optimizer=tf.optimizers.SGD(learning_rate=0.01))

history = new_model.fit(x, y,
                        epochs=100,
                        batch_size=32,
                        verbose=0)

model.save('./my_model')
```

```
INFO:tensorflow:Assets written to: ./my_model/assets
```

In [32]:

```
plt.plot(history.history['loss'])
plt.xlabel('Epoch')
plt.ylim([0, max(plt.ylim())])
plt.ylabel('Loss [Mean Squared Error]')
plt.title('Keras training progress');
```