In [ ]:

```
# Install TensorFlow
# !pip install -q tensorflow-gpu==2.0.0-beta1

try:
  %tensorflow_version 2.x  # Colab only.
except Exception:
  pass

import tensorflow as tf
print(tf.__version__)
```

```
`%tensorflow_version` only switches the major version: 1.x or 2.x.
You set: `2.x  # Colab only.`. This will be interpreted as: `2.x`.


TensorFlow 2.x selected.
2.2.0
```

In [ ]:

```
# Other imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [ ]:

```
# Get the data
!wget https://raw.githubusercontent.com/lazyprogrammer/machine_learning_examples/master/
```

```
--2020-06-18 16:14:29--  https://raw.githubusercontent.com/lazyprogrammer/machine_learni
ng_examples/master/tf2.0/moore.csv
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 151.101.0.133, 151.10
1.64.133, 151.101.128.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|151.101.0.133|:44
3... connected.
HTTP request sent, awaiting response... 200 OK
Length: 2302 (2.2K) [text/plain]
Saving to: ‘moore.csv’

moore.csv           100%[===================>]   2.25K  --.-KB/s    in 0s

2020-06-18 16:14:29 (37.1 MB/s) - ‘moore.csv’ saved [2302/2302]
```

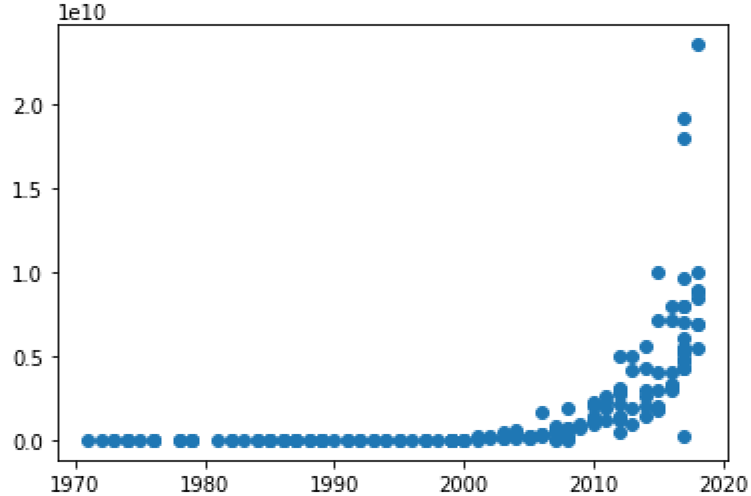
In [ ]:

```
# Load in the data
data = pd.read_csv('moore.csv', header=None).values
X = data[:,0].reshape(-1, 1) # make it a 2-D array of size N x D where D = 1
Y = data[:,1]
```

In [ ]:

```
# Plot the data - it is exponential!
plt.scatter(X, Y)
```

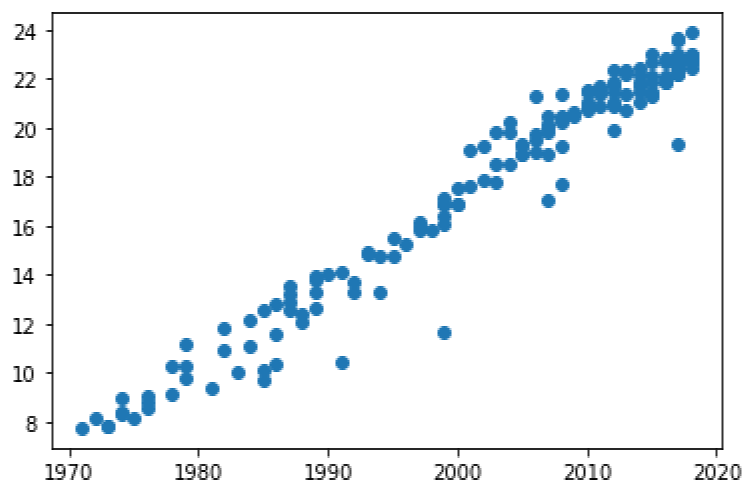
Out[ ]: `<matplotlib.collections.PathCollection at 0x7f0b9e493ac8>`



In [ ]:

```
# Since we want a linear model, let's take the log
Y = np.log(Y)
plt.scatter(X, Y)
# that's better
```

Out[ ]: <matplotlib.collections.PathCollection at 0x7f0b9b7eac18>



In [ ]:

```
# Let's also center the X data so the values are not too large
# We could scale it too but then we'd have to reverse the transformation later
X = X - X.mean()
```

In [ ]:

```
# Now create our Tensorflow model
model = tf.keras.models.Sequential([
  tf.keras.layers.Input(shape=(1,)),
  tf.keras.layers.Dense(1)
])

model.compile(optimizer=tf.keras.optimizers.SGD(0.001, 0.9), loss='mse')
# model.compile(optimizer='adam', loss='mse')


# learning rate scheduler
def schedule(epoch, lr):
  if epoch >= 50:
```

```
    return 0.0001
  return 0.001


scheduler = tf.keras.callbacks.LearningRateScheduler(schedule)


# Train the model
r = model.fit(X, Y, epochs=200, callbacks=[scheduler])
```

```
Epoch 1/200
6/6 [==============================] - 0s 2ms/step - loss: 564.7578 - lr: 0.0010
Epoch 2/200
6/6 [==============================] - 0s 1ms/step - loss: 416.5006 - lr: 0.0010
Epoch 3/200
6/6 [==============================] - 0s 1ms/step - loss: 435.8105 - lr: 0.0010
Epoch 4/200
6/6 [==============================] - 0s 1ms/step - loss: 291.5248 - lr: 0.0010
Epoch 5/200
6/6 [==============================] - 0s 1ms/step - loss: 309.7632 - lr: 0.0010
Epoch 6/200
6/6 [==============================] - 0s 1ms/step - loss: 173.2291 - lr: 0.0010
Epoch 7/200
6/6 [==============================] - 0s 1ms/step - loss: 122.9670 - lr: 0.0010
Epoch 8/200
6/6 [==============================] - 0s 1ms/step - loss: 88.1215 - lr: 0.0010
Epoch 9/200
6/6 [==============================] - 0s 1ms/step - loss: 51.1509 - lr: 0.0010
Epoch 10/200
6/6 [==============================] - 0s 1ms/step - loss: 39.1848 - lr: 0.0010
Epoch 11/200
6/6 [==============================] - 0s 1ms/step - loss: 50.0891 - lr: 0.0010
Epoch 12/200
6/6 [==============================] - 0s 1ms/step - loss: 57.7818 - lr: 0.0010
Epoch 13/200
6/6 [==============================] - 0s 1ms/step - loss: 46.9341 - lr: 0.0010
Epoch 14/200
6/6 [==============================] - 0s 1ms/step - loss: 43.3448 - lr: 0.0010
Epoch 15/200
6/6 [==============================] - 0s 1ms/step - loss: 28.4526 - lr: 0.0010
Epoch 16/200
6/6 [==============================] - 0s 1ms/step - loss: 15.1617 - lr: 0.0010
Epoch 17/200
6/6 [==============================] - 0s 2ms/step - loss: 6.5347 - lr: 0.0010
Epoch 18/200
6/6 [==============================] - 0s 2ms/step - loss: 5.3453 - lr: 0.0010
Epoch 19/200
6/6 [==============================] - 0s 2ms/step - loss: 13.6583 - lr: 0.0010
Epoch 20/200
6/6 [==============================] - 0s 1ms/step - loss: 13.0628 - lr: 0.0010
Epoch 21/200
6/6 [==============================] - 0s 2ms/step - loss: 6.2095 - lr: 0.0010
Epoch 22/200
6/6 [==============================] - 0s 1ms/step - loss: 2.2462 - lr: 0.0010
Epoch 23/200
6/6 [==============================] - 0s 1ms/step - loss: 1.5828 - lr: 0.0010
Epoch 24/200
6/6 [==============================] - 0s 1ms/step - loss: 1.2626 - lr: 0.0010
Epoch 25/200
6/6 [==============================] - 0s 1ms/step - loss: 1.1254 - lr: 0.0010
Epoch 26/200
6/6 [==============================] - 0s 2ms/step - loss: 1.4200 - lr: 0.0010
Epoch 27/200
6/6 [==============================] - 0s 1ms/step - loss: 1.8661 - lr: 0.0010
```

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Epoch 28/200
6/6 [==============================] - 0s 2ms/step - loss: 1.3886 - lr: 0.0010
Epoch 29/200
6/6 [==============================] - 0s 2ms/step - loss: 1.0745 - lr: 0.0010
Epoch 30/200
6/6 [==============================] - 0s 2ms/step - loss: 1.0018 - lr: 0.0010
Epoch 31/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9356 - lr: 0.0010
Epoch 32/200
6/6 [==============================] - 0s 1ms/step - loss: 1.0224 - lr: 0.0010
Epoch 33/200
6/6 [==============================] - 0s 1ms/step - loss: 1.1923 - lr: 0.0010
Epoch 34/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9860 - lr: 0.0010
Epoch 35/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9608 - lr: 0.0010
Epoch 36/200
6/6 [==============================] - 0s 1ms/step - loss: 1.0304 - lr: 0.0010
Epoch 37/200
6/6 [==============================] - 0s 2ms/step - loss: 1.2601 - lr: 0.0010
Epoch 38/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9664 - lr: 0.0010
Epoch 39/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9088 - lr: 0.0010
Epoch 40/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9199 - lr: 0.0010
Epoch 41/200
6/6 [==============================] - 0s 2ms/step - loss: 1.0986 - lr: 0.0010
Epoch 42/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9465 - lr: 0.0010
Epoch 43/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9290 - lr: 0.0010
Epoch 44/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9168 - lr: 0.0010
Epoch 45/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8770 - lr: 0.0010
Epoch 46/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9378 - lr: 0.0010
Epoch 47/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9742 - lr: 0.0010
Epoch 48/200
6/6 [==============================] - 0s 1ms/step - loss: 1.0062 - lr: 0.0010
Epoch 49/200
6/6 [==============================] - 0s 2ms/step - loss: 1.0642 - lr: 0.0010
Epoch 50/200
6/6 [==============================] - 0s 1ms/step - loss: 1.2359 - lr: 0.0010
Epoch 51/200
6/6 [==============================] - 0s 1ms/step - loss: 1.5608 - lr: 1.0000e-04
Epoch 52/200
6/6 [==============================] - 0s 1ms/step - loss: 1.4480 - lr: 1.0000e-04
Epoch 53/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9116 - lr: 1.0000e-04
Epoch 54/200
6/6 [==============================] - 0s 1ms/step - loss: 1.0805 - lr: 1.0000e-04
Epoch 55/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9856 - lr: 1.0000e-04
Epoch 56/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8962 - lr: 1.0000e-04
Epoch 57/200
6/6 [==============================] - 0s 3ms/step - loss: 0.8972 - lr: 1.0000e-04
Epoch 58/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8909 - lr: 1.0000e-04
Epoch 59/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9246 - lr: 1.0000e-04
Epoch 60/200
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6/6 [==============================] - 0s 1ms/step - loss: 0.9195 - lr: 1.0000e-04
Epoch 61/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8844 - lr: 1.0000e-04
Epoch 62/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8750 - lr: 1.0000e-04
Epoch 63/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8757 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8778 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8757 - lr: 1.0000e-04
Epoch 67/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8775 - lr: 1.0000e-04
Epoch 68/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8722 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8820 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8755 - lr: 1.0000e-04
Epoch 71/200
6/6 [==============================] - 0s 3ms/step - loss: 0.8759 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8742 - lr: 1.0000e-04
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Epoch 74/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8822 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8740 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8715 - lr: 1.0000e-04
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6/6 [==============================] - 0s 2ms/step - loss: 0.8746 - lr: 1.0000e-04
Epoch 80/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8734 - lr: 1.0000e-04
Epoch 81/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8754 - lr: 1.0000e-04
Epoch 82/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9202 - lr: 1.0000e-04
Epoch 83/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9127 - lr: 1.0000e-04
Epoch 84/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8801 - lr: 1.0000e-04
Epoch 85/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9101 - lr: 1.0000e-04
Epoch 86/200
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Epoch 87/200
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Epoch 88/200
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Epoch 89/200
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Epoch 91/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8835 - lr: 1.0000e-04
Epoch 92/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8738 - lr: 1.0000e-04
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Epoch 93/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8766 - lr: 1.0000e-04
Epoch 94/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8879 - lr: 1.0000e-04
Epoch 95/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8782 - lr: 1.0000e-04
Epoch 96/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8820 - lr: 1.0000e-04
Epoch 97/200
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Epoch 98/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8732 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8792 - lr: 1.0000e-04
Epoch 100/200
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Epoch 101/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8766 - lr: 1.0000e-04
Epoch 102/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8823 - lr: 1.0000e-04
Epoch 103/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8881 - lr: 1.0000e-04
Epoch 104/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8811 - lr: 1.0000e-04
Epoch 105/200
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Epoch 106/200
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6/6 [==============================] - 0s 2ms/step - loss: 0.8719 - lr: 1.0000e-04
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6/6 [==============================] - 0s 2ms/step - loss: 0.8730 - lr: 1.0000e-04
Epoch 109/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8898 - lr: 1.0000e-04
Epoch 110/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8772 - lr: 1.0000e-04
Epoch 111/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8751 - lr: 1.0000e-04
Epoch 112/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8814 - lr: 1.0000e-04
Epoch 113/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8745 - lr: 1.0000e-04
Epoch 114/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8742 - lr: 1.0000e-04
Epoch 115/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8779 - lr: 1.0000e-04
Epoch 116/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8807 - lr: 1.0000e-04
Epoch 117/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8740 - lr: 1.0000e-04
Epoch 118/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8724 - lr: 1.0000e-04
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6/6 [==============================] - 0s 2ms/step - loss: 0.8773 - lr: 1.0000e-04
Epoch 120/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8761 - lr: 1.0000e-04
Epoch 121/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8736 - lr: 1.0000e-04
Epoch 122/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8712 - lr: 1.0000e-04
Epoch 123/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8758 - lr: 1.0000e-04
Epoch 124/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8742 - lr: 1.0000e-04
Epoch 125/200
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6/6 [==============================] - 0s 1ms/step - loss: 0.8714 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8715 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8748 - lr: 1.0000e-04
Epoch 129/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8769 - lr: 1.0000e-04
Epoch 130/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8706 - lr: 1.0000e-04
Epoch 131/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8716 - lr: 1.0000e-04
Epoch 132/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8730 - lr: 1.0000e-04
Epoch 133/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8739 - lr: 1.0000e-04
Epoch 134/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8878 - lr: 1.0000e-04
Epoch 135/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8825 - lr: 1.0000e-04
Epoch 136/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8833 - lr: 1.0000e-04
Epoch 137/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9046 - lr: 1.0000e-04
Epoch 138/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8770 - lr: 1.0000e-04
Epoch 139/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8811 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8759 - lr: 1.0000e-04
Epoch 141/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8711 - lr: 1.0000e-04
Epoch 142/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8715 - lr: 1.0000e-04
Epoch 143/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8749 - lr: 1.0000e-04
Epoch 144/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8770 - lr: 1.0000e-04
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6/6 [==============================] - 0s 2ms/step - loss: 0.8729 - lr: 1.0000e-04
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6/6 [==============================] - 0s 2ms/step - loss: 0.8829 - lr: 1.0000e-04
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6/6 [==============================] - 0s 2ms/step - loss: 0.8759 - lr: 1.0000e-04
Epoch 149/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8953 - lr: 1.0000e-04
Epoch 150/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9202 - lr: 1.0000e-04
Epoch 151/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8893 - lr: 1.0000e-04
Epoch 152/200
6/6 [==============================] - 0s 3ms/step - loss: 0.8754 - lr: 1.0000e-04
Epoch 153/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8883 - lr: 1.0000e-04
Epoch 154/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8810 - lr: 1.0000e-04
Epoch 155/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9087 - lr: 1.0000e-04
Epoch 156/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8908 - lr: 1.0000e-04
Epoch 157/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8742 - lr: 1.0000e-04
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Epoch 158/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8722 - lr: 1.0000e-04
Epoch 159/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8697 - lr: 1.0000e-04
Epoch 160/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8768 - lr: 1.0000e-04
Epoch 161/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8773 - lr: 1.0000e-04
Epoch 162/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8770 - lr: 1.0000e-04
Epoch 163/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9014 - lr: 1.0000e-04
Epoch 164/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9614 - lr: 1.0000e-04
Epoch 165/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8981 - lr: 1.0000e-04
Epoch 166/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8774 - lr: 1.0000e-04
Epoch 167/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8831 - lr: 1.0000e-04
Epoch 168/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8719 - lr: 1.0000e-04
Epoch 169/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8717 - lr: 1.0000e-04
Epoch 170/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8751 - lr: 1.0000e-04
Epoch 171/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8804 - lr: 1.0000e-04
Epoch 172/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8728 - lr: 1.0000e-04
Epoch 173/200
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6/6 [==============================] - 0s 2ms/step - loss: 0.8736 - lr: 1.0000e-04
Epoch 176/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8843 - lr: 1.0000e-04
Epoch 177/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8807 - lr: 1.0000e-04
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6/6 [==============================] - 0s 1ms/step - loss: 0.8691 - lr: 1.0000e-04
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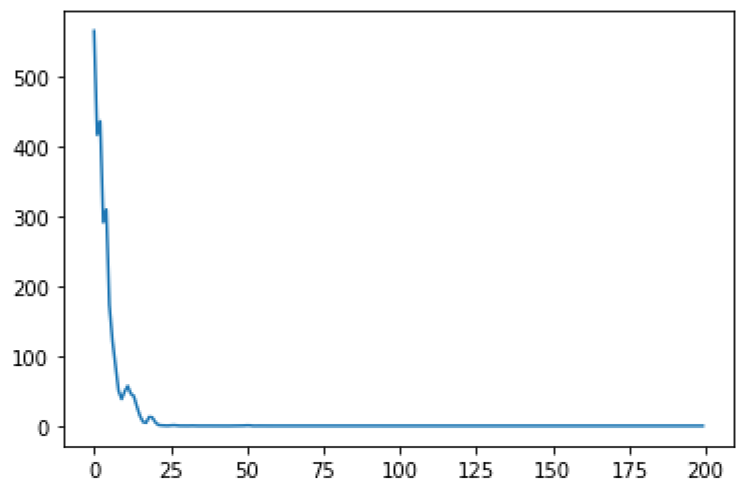
6/6 [==============================] - 0s 1ms/step - loss: 0.9173 - lr: 1.0000e-04
Epoch 180/200
6/6 [==============================] - 0s 2ms/step - loss: 0.9064 - lr: 1.0000e-04
Epoch 181/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8801 - lr: 1.0000e-04
Epoch 182/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8868 - lr: 1.0000e-04
Epoch 183/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8794 - lr: 1.0000e-04
Epoch 184/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8743 - lr: 1.0000e-04
Epoch 185/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8744 - lr: 1.0000e-04
Epoch 186/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8731 - lr: 1.0000e-04
Epoch 187/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8709 - lr: 1.0000e-04
Epoch 188/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8752 - lr: 1.0000e-04
Epoch 189/200
6/6 [==============================] - 0s 3ms/step - loss: 0.8969 - lr: 1.0000e-04
Epoch 190/200
```

```
6/6 [==============================] - 0s 1ms/step - loss: 0.8766 - lr: 1.0000e-04
Epoch 191/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8744 - lr: 1.0000e-04
Epoch 192/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8772 - lr: 1.0000e-04
Epoch 193/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9139 - lr: 1.0000e-04
Epoch 194/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9380 - lr: 1.0000e-04
Epoch 195/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8694 - lr: 1.0000e-04
Epoch 196/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8820 - lr: 1.0000e-04
Epoch 197/200
6/6 [==============================] - 0s 1ms/step - loss: 0.8696 - lr: 1.0000e-04
Epoch 198/200
6/6 [==============================] - 0s 2ms/step - loss: 0.8744 - lr: 1.0000e-04
Epoch 199/200
6/6 [==============================] - 0s 1ms/step - loss: 0.9066 - lr: 1.0000e-04
Epoch 200/200
6/6 [==============================] - 0s 3ms/step - loss: 0.8892 - lr: 1.0000e-04
```

In [ ]:

```python
# Plot the loss
plt.plot(r.history['loss'], label='loss')
```

Out[ ]: [<matplotlib.lines.Line2D at 0x7f0b923997f0>]



In [ ]:

```python
# Get the slope of the line
# The slope of the line is related to the doubling rate of transistor count
print(model.layers) # Note: there is only 1 layer, the "Input" layer doesn't count
print(model.layers[0].get_weights())
```

```
[<tensorflow.python.keras.layers.core.Dense object at 0x7f0b9e97eda0>]
[array([[0.3362535]], dtype=float32), array([17.74322], dtype=float32)]
```

In [ ]:

```python
# The slope of the line is:
a = model.layers[0].get_weights()[0][0,0]
```

Our original model for exponential growth is:

$$C = A_0 r^t$$

Where C is transistor the count and t is the year.

r is the rate of growth. For example, when t goes from 1 to 2, C increases by a factor of r. When t goes from 2 to 3, C increases by a factor of r again.

When we take the log of both sides, we get:

$$\log C = \log r * t + \log A_0$$

This is our linear equation:

$$\hat{y} = ax + b$$

Where:

$$\hat{y} = \log C$$

$$a = \log r$$

$$x = t$$

$$b = \log A_0$$

We are interested in r, because that's the rate of growth. Given our regression weights, we know that:

$$a = 0.34188038$$

so that:

$$r = e^{0.34188038} = 1.4076$$

To find the time it takes for transistor count to double, we simply need to find the amount of time it takes for C to increase to $2C$.

Let's call the original starting time t, to correspond with the initial transistor count C.

Let's call the end time t', to correspond with the final transistor count $2C$.

Then we also have:

$$2C = A_0 r^{t'}$$

Combine this with our original equation:

$$C = A_0 r^t$$

We get (by dividing the 2 equations):

$$2C/C = (A_0 r^{t'})/A_0 r^t$$

Which simplifies to:

$$2 = r^{(t'-t)}$$

Solve for $t' - t$:

$$t' - t = \frac{\log 2}{\log r} = \frac{\log 2}{a}$$

Important note! We haven't specified what the starting time t actually is, and we don't have to since we just proved that this holds for any t.

In [ ]:
```
print("Time to double:", np.log(2) / a)
```

```
Time to double: 2.0613828343145832
```

In [ ]:
```
# If you know the analytical solution
X = np.array(X).flatten()
Y = np.array(Y)
denominator = X.dot(X) - X.mean() * X.sum()
a = ( X.dot(Y) - Y.mean()*X.sum() ) / denominator
b = ( Y.mean() * X.dot(X) - X.mean() * X.dot(Y) ) / denominator
print(a, b)
print("Time to double:", np.log(2) / a)
```

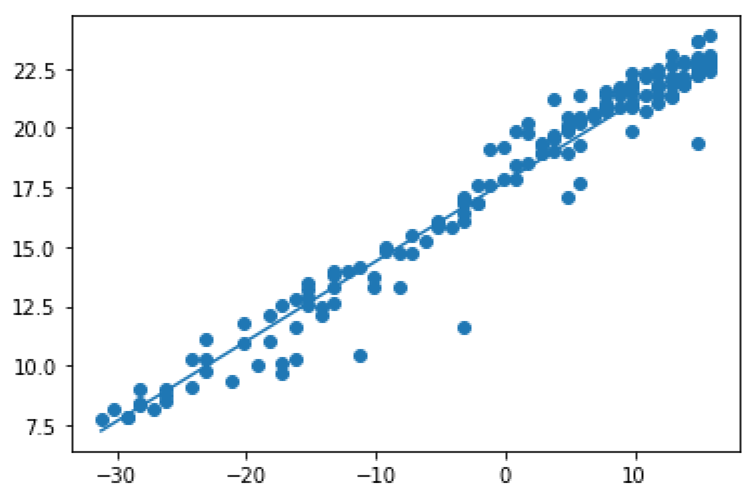
```
0.341682487387313 17.764939393631764
Time to double: 2.0286295205239204
```

Part 2: Making Predictions

This goes with the lecture "Making Predictions"

In [ ]:
```
# Make sure the line fits our data
Yhat = model.predict(X).flatten()
plt.scatter(X, Y)
plt.plot(X, Yhat)
```

Out[ ]:
```
[<matplotlib.lines.Line2D at 0x7f0b9236f4a8>]
```



In [ ]:
```
# Manual calculation

# Get the weights
w, b = model.layers[0].get_weights()
```

```python
# Reshape X because we flattened it again earlier
X = X.reshape(-1, 1)

# (N x 1) x (1 x 1) + (1) --> (N x 1)
Yhat2 = (X.dot(w) + b).flatten()

# Don't use == for floating points
np.allclose(Yhat, Yhat2)
```

Out[ ]: True