```
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Open in Colab

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

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
print(tf.__version__)
```

Saved successfully!

```
def plot_series(time, series, format="-", start=0, end=None):
    plt.plot(time[start:end], series[start:end], format)
    plt.xlabel("Time")
    plt.ylabel("Value")
    plt.grid(True)

def trend(time, slope=0):
    return slope * time

def seasonal_pattern(season_time):
    """Just an arbitrary pattern, you can change it if you wish"""
    return np.where(season_time < 0.4,
                    np.cos(season_time * 2 * np.pi),
                    1 / np.exp(3 * season_time))

def seasonality(time, period, amplitude=1, phase=0):
    """Repeats the same pattern at each period"""
    season_time = ((time + phase) % period) / period
    return amplitude * seasonal_pattern(season_time)
```

```
def noise(time, noise_level=1, seed=None):
    rnd = np.random.RandomState(seed)
    return rnd.randn(len(time)) * noise_level

time = np.arange(4 * 365 + 1, dtype="float32")
baseline = 10
series = trend(time, 0.1)
baseline = 10
amplitude = 20
slope = 0.09
noise_level = 5

# Create the series
series = baseline + trend(time, slope) + seasonality(time, period=365, amplitude=amplitude)
# Update with noise
series += noise(time, noise_level, seed=42)

split_time = 1000
time_train = time[:split_time]
x_train = series[:split_time]
time_valid = time[split_time:]
x_valid = series[split_time:]

window_size = 20
batch_size = 32
shuffle_buffer_size = 1000


plt.figure(figsize=(10, 6))
```

Saved successfully!

```
def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
  dataset = tf.data.Dataset.from_tensor_slices(series)
  dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
  dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
  dataset = dataset.shuffle(shuffle_buffer).map(lambda window: (window[:-1], window[-1]))
  dataset = dataset.batch(batch_size).prefetch(1)
  return dataset
```

```
dataset = windowed_dataset(x_train, window_size, batch_size, shuffle_buffer_size)

#everythings as same as before only that it's now a deep NN
model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(10, input_shape=[window_size], activation="relu"),
    tf.keras.layers.Dense(10, activation="relu"),
    tf.keras.layers.Dense(1)
])

#how do we know that this is an optimal learning rate?
model.compile(loss="mse", optimizer=tf.keras.optimizers.SGD(lr=1e-6, momentum=0.9))
model.fit(dataset,epochs=100,verbose=0)
```

```
<tensorflow.python.keras.callbacks.History at 0x7efcead56860>
```

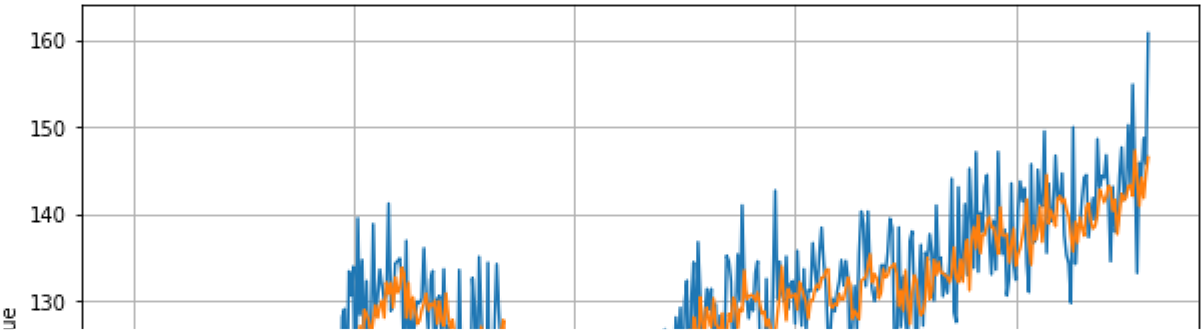
```
forecast = []
for time in range(len(series) - window_size):
                                       es[time:time + window_size][np.newaxis]))

forecast = forecast[split_time-window_size:]
results = np.array(forecast)[:, 0, 0]


plt.figure(figsize=(10, 6))

plot_series(time_valid, x_valid)
plot_series(time_valid, results)
```

Saved successfully!




```
tf.keras.metrics.mean_absolute_error(x_valid, results).numpy()
```

```
4.594142
```


```
dataset = windowed_dataset(x_train, window_size, batch_size, shuffle_buffer_size)


model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(10, input_shape=[window_size], activation="relu"),
    tf.keras.layers.Dense(10, activation="relu"),
    tf.keras.layers.Dense(1)
])

#the best way is to use the LearningRateScheduler which changes the learning rate
#each epoch
lr_schedule = tf.keras.callbacks.LearningRateScheduler(
    lambda epoch: 1e-8 * 10**(epoch / 20))
optimizer = tf.keras.optimizers.SGD(lr=1e-8, momentum=0.9)
model.compile(loss="mse", optimizer=optimizer)
                                          100, callbacks=[lr_schedule], verbose=0)


#draw the loss curve for all epochs and read the lr for the lowest cost
lrs = 1e-8 * (10 ** (np.arange(100) / 20))
plt.semilogx(lrs, history.history["loss"])
plt.axis([1e-8, 1e-3, 0, 300])
```

Saved successfully!

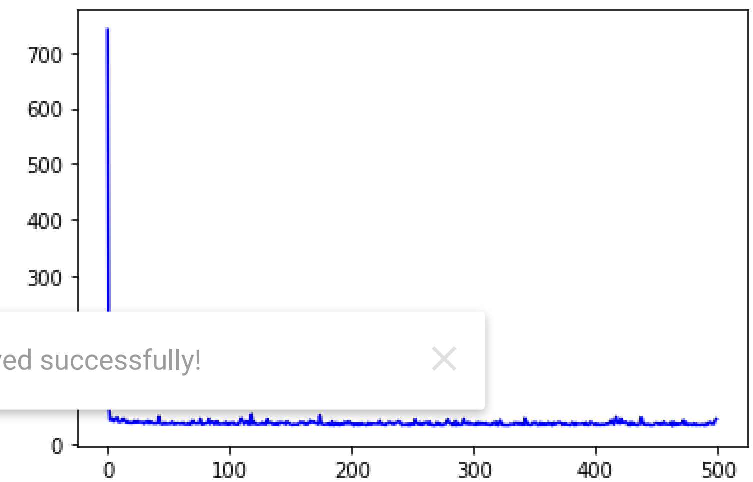
(1e-08, 0.001, 0.0, 300.0)

```
window_size = 30
dataset = windowed_dataset(x_train, window_size, batch_size, shuffle_buffer_size)

model = tf.keras.models.Sequential([
  tf.keras.layers.Dense(10, activation="relu", input_shape=[window_size]),
  tf.keras.layers.Dense(10, activation="relu"),
  tf.keras.layers.Dense(1)
])

#use the read lr as the lr
optimizer = tf.keras.optimizers.SGD(lr=8e-6, momentum=0.9)
model.compile(loss="mse", optimizer=optimizer)
history = model.fit(dataset, epochs=500, verbose=0)


loss = history.history['loss']
epochs = range(len(loss))
plt.plot(epochs, loss, 'b', label='Training Loss')
plt.show()
```

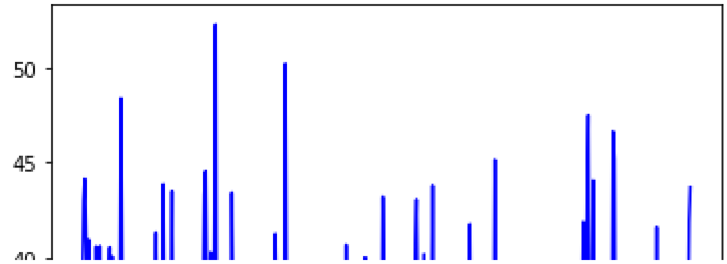


Saved successfully!

```
# Plot all but the first 10
loss = history.history['loss']
epochs = range(10, len(loss))
plot_loss = loss[10:]
print(plot_loss)
plt.plot(epochs, plot_loss, 'b', label='Training Loss')
plt.show()
```

Saved successfully!

```
[38.68077087402344, 38.62520217895508, 42.97085189819336, 44.14177703857422, 40.8681106
```

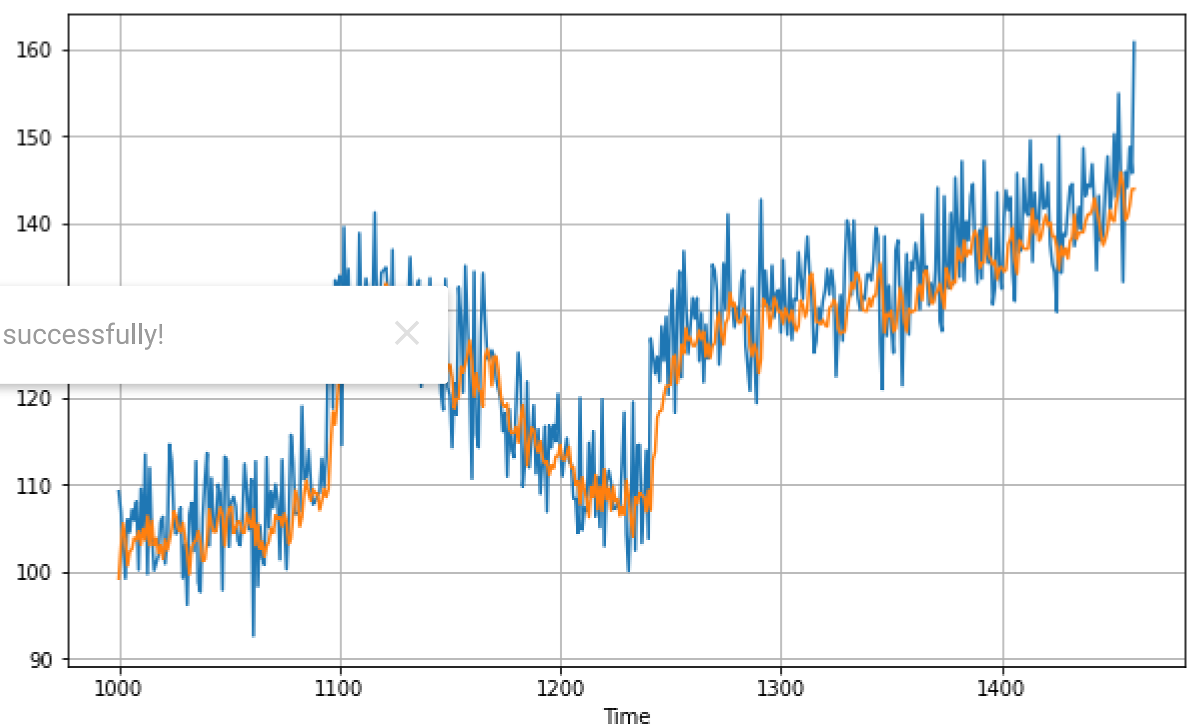



```
forecast = []
for time in range(len(series) - window_size):
  forecast.append(model.predict(series[time:time + window_size][np.newaxis]))

forecast = forecast[split_time-window_size:]
results = np.array(forecast)[:, 0, 0]


plt.figure(figsize=(10, 6))

plot_series(time_valid, x_valid)
plot_series(time_valid, results)
```




```
tf.keras.metrics.mean_absolute_error(x_valid, results).numpy()
```

```
4.7738533
```