

# RNN\_scratch

July 10, 2018

```
In [174]: import numpy as np
          import tensorflow as tf
          import matplotlib.pyplot as plt
          %matplotlib inline

In [3]: num_inputs = 2
        num_neurons = 3

In [4]: x0 = tf.placeholder(tf.float32, [None, num_inputs])
        x1 = tf.placeholder(tf.float32, [None, num_inputs])

In [5]: Wx = tf.random_normal(shape=[num_inputs, num_neurons])
        Wy = tf.random_normal(shape=[num_neurons, num_neurons])
        b = tf.zeros([1, num_neurons])

In [6]: # graphs
        y0 = tf.tanh(tf.matmul(x0, Wx) + b)
        # feedback + present
        y1 = tf.tanh(tf.matmul(y0, Wy) + tf.matmul(x1, Wx) + b)

In [7]: # initialize variables
        init = tf.global_variables_initializer()

In [8]: # create data
        # time stamp at t = 0
        x0_batch = np.array([ [0, 1], [2, 3], [4, 5] ])
        # time stamp at t = t + 1 = 1
        x1_batch = np.array([ [100, 101], [102, 103], [104, 105] ])

In [9]: with tf.Session() as sess:
        sess.run(init)

        y0_output_vals, y1_output_vals = sess.run([y0, y1],
            feed_dict = {x0:x0_batch, x1:x1_batch})

In [10]: y0_output_vals

Out[10]: array([[ 0.46511364, -0.921773   ,  0.9284943 ],
               [ 0.96557266, -0.9307549 ,  0.9783266 ],
               [ 0.9983207 , -0.93873835,  0.993547  ]], dtype=float32)
```

```
In [11]: y1_output_vals
```

```
Out[11]: array([[ 1.          , -0.99936646,  1.          ],
                [ 1.          , -0.9977223 ,  1.          ],
                [ 1.          , -0.99780226,  1.          ]], dtype=float32)
```

## 0.1 Vanishing Gradients

While backpropagating, in deeper networks, gradients get smaller and at some point, they stop changing significantly.

GRU and LSTM can be used to fix them (in RNN)

**Depends on activation function choice.**

Like **sigmoid**:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

It saturates both positive and negative values.

**Solution:**

Use **ReLU** (doesn't saturate positive values.) Problem: for -ve numbers, always 0.

**Solution:**

Use **Leaky ReLU**.

Others: **ELU** (Exponential Linear Unit)

**Another solution: Use Batch Normalization, Gradient Clipping** (cut off gradients to be b/w -1 and 1 : example)

## 0.2 Introduction to RNN using TF API

**Problem:** Time series. ( $\sin(t)$ ,  $t$  = time)

```
In [30]: import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [17]: class TimeSeriesData():
    def __init__(self, num_points, xmin, xmax):
        # creates data
        self.xmin = xmin
        self.xmax = xmax
        self.num_points = num_points
        self.resolution = (self.xmax - self.xmin)/(self.num_points)
        self.x_data = np.linspace(self.xmin, self.xmax, self.num_points)
        self.y_true = np.sin(self.x_data)

    def ret_true(self, x_series):
        return np.sin(x_series)

    def next_batch(self, batch_size, steps, return_batch_ts=False):
        # grab random starting point for each batch
```

```

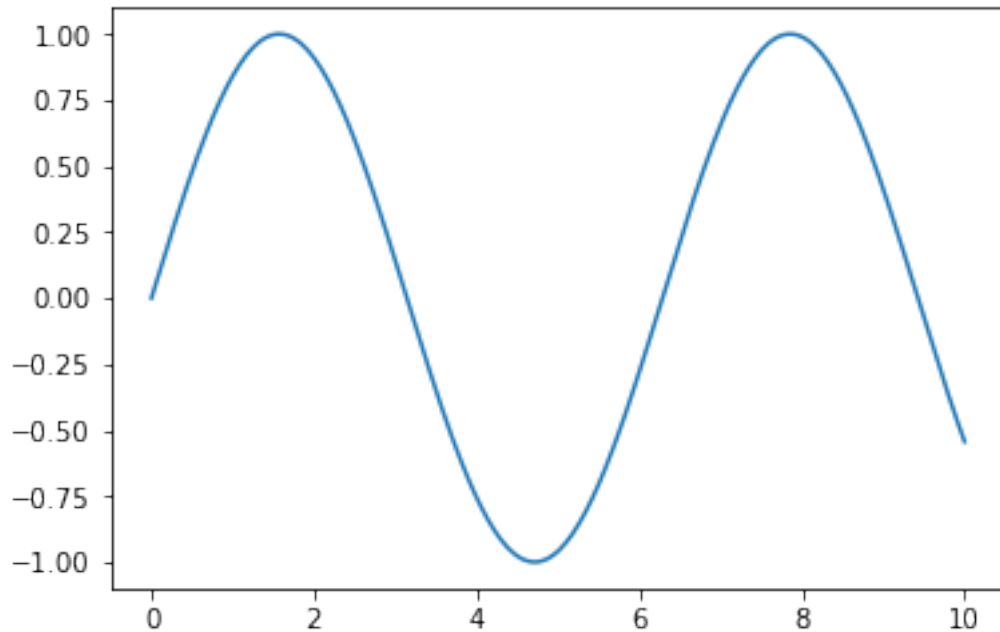
rand_start = np.random.rand(batch_size, 1)
# convert to be on time series
ts_start = rand_start * (self.xmax - self.xmin - \
                        (steps * self.resolution))
# create batch series : x axis
batch_ts = ts_start + np.arange(0.0, steps + 1) * \
self.resolution
# create y data for each x axis point
y_batch = np.sin(batch_ts)
# formatting for RNN
if return_batch_ts:
    return y_batch[:, :-1].reshape(-1, steps, 1), \
y_batch[:, 1:].reshape(-1, steps, 1), batch_ts
else:
    # returns at t = t and t = t + 1
    return y_batch[:, :-1].reshape(-1, steps, 1), \
y_batch[:, 1:].reshape(-1, steps, 1)

```

In [18]: ts\_data = TimeSeriesData(250, 0, 10)

In [20]: plt.plot(ts\_data.x\_data, ts\_data.y\_true)

Out[20]: [<matplotlib.lines.Line2D at 0x7f285e27d780>]



In [21]: num\_timesteps = 30 *# number of steps in each batch*

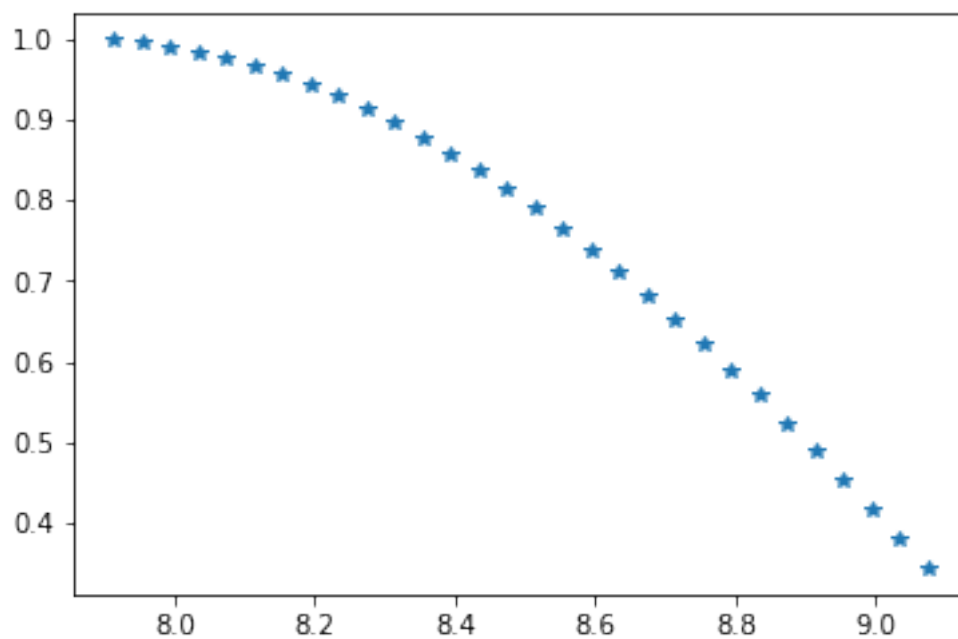
```
In [40]: def generateNextBatch(num_timesteps):
          y1, y2, ts = ts_data.next_batch(1, num_timesteps, True)
          return y1, y2, ts
```

```
In [28]: ts.shape
          # needs to be flattened
```

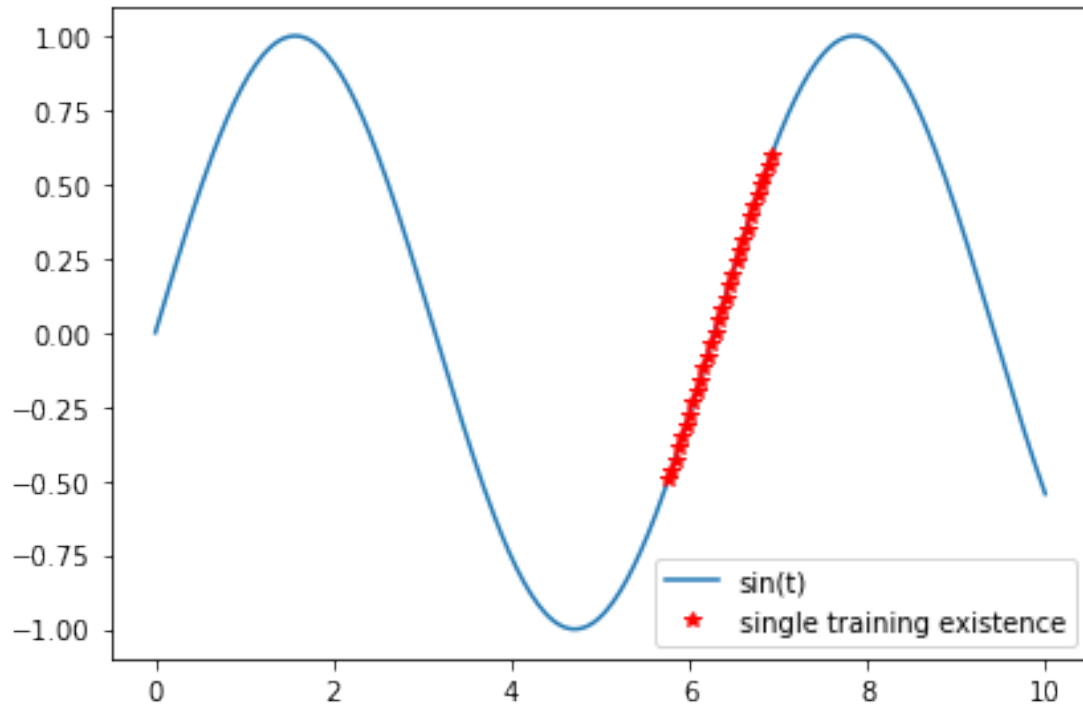
```
Out[28]: (1, 30, 1)
```

```
In [31]: plt.plot(ts.flatten()[1:], y2.flatten(), '*')
```

```
Out[31]: [<matplotlib.lines.Line2D at 0x7f285c74dcf8>]
```



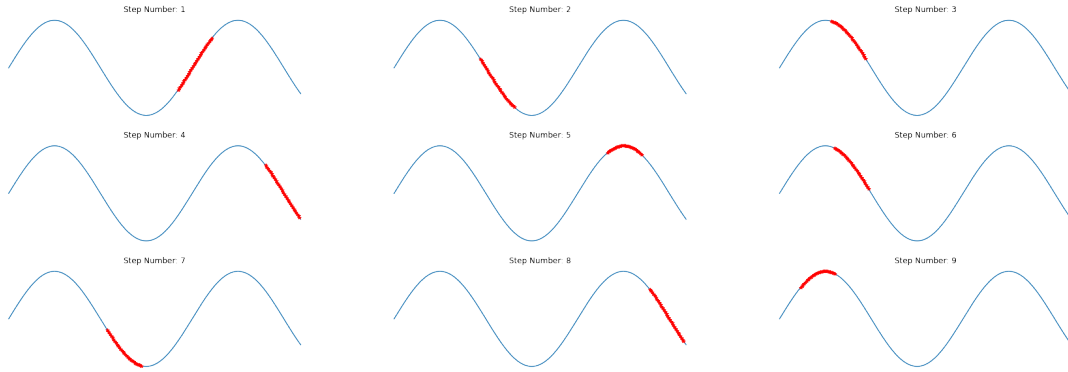
```
In [42]: y1, y2, ts = generateNextBatch(30)
          plt.plot(ts_data.x_data, ts_data.y_true, label='sin(t)')
          plt.plot(ts.flatten()[1:], y2.flatten(), '*', c = 'r', label='single training existence')
          plt.legend()
          plt.tight_layout()
```



```
In [76]: import math
```

```
plt.figure(figsize=[30,10])
num_cols = 3
num_images = 9
num_rows = math.ceil(num_images / num_cols)

for i in range(0, num_images):
    plt.subplot(num_rows, num_cols, i+1)
    plt.axis('off')
    y1, y2, ts = generateNextBatch(30)
    plt.plot(ts_data.x_data, ts_data.y_true, label='sin(t)')
    plt.plot(ts.flatten()[1:], y2.flatten(), '*', c = 'r', label='single training existence')
    plt.title("Step Number: " + str(i + 1))
```



```
In [56]: train_instance = np.linspace(5, 5 + ts_data.resolution * \
                                         (num_timesteps + 1), num_timesteps + 1)
```

```
In [57]: train_instance
```

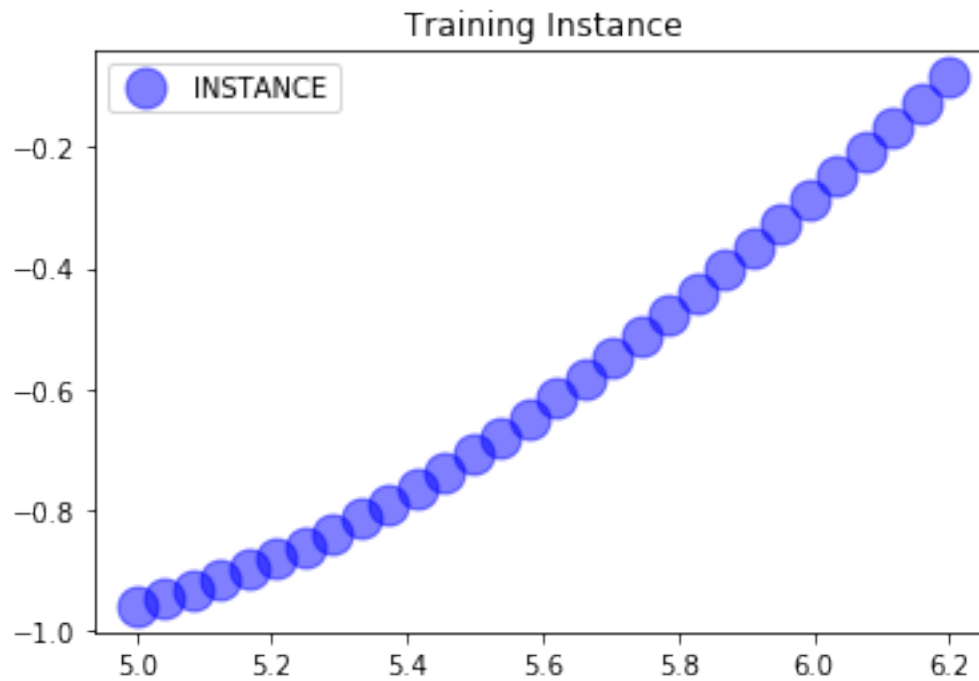
```
Out[57]: array([5.          , 5.04133333, 5.08266667, 5.124          , 5.16533333,
                5.20666667, 5.248          , 5.28933333, 5.33066667, 5.372          ,
                5.41333333, 5.45466667, 5.496          , 5.53733333, 5.57866667,
                5.62          , 5.66133333, 5.70266667, 5.744          , 5.78533333,
                5.82666667, 5.868          , 5.90933333, 5.95066667, 5.992          ,
                6.03333333, 6.07466667, 6.116          , 6.15733333, 6.19866667,
                6.24          ])
```

```
In [71]: plt.title('Training Instance')
```

```
plt.plot(train_instance[:-1], ts_data.ret_true(train_instance[:-1]),
         'bo', markerSize=15, alpha=0.5, label='INSTANCE')
```

```
plt.legend()
```

```
Out[71]: <matplotlib.legend.Legend at 0x7f282c417ac8>
```



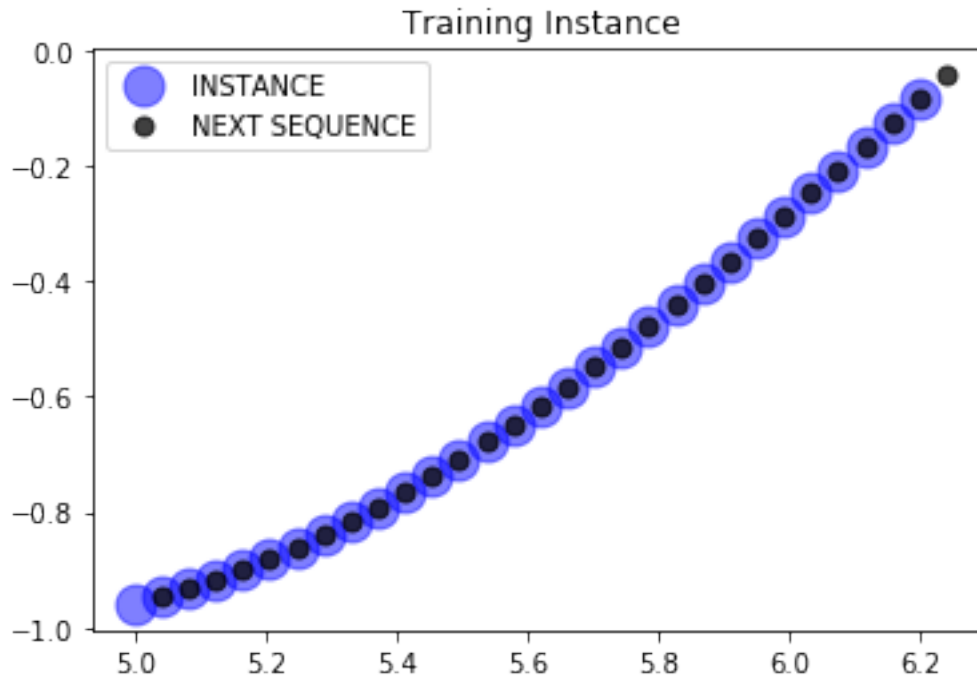
We want to predict one time step ahead of it. [Goal]

```
In [74]: plt.title('Training Instance')

plt.plot(train_instance[:-1], ts_data.ret_true(train_instance[:-1]),
         'bo', markerSize=15, alpha=0.5, label='INSTANCE')
# doing for next time step (1: )
plt.plot(train_instance[1:], ts_data.ret_true(train_instance[1:]),
         'ko', markerSize=7, alpha=0.75, label='NEXT SEQUENCE')

plt.legend()
```

```
Out[74]: <matplotlib.legend.Legend at 0x7f282d6b00b8>
```



Creating Model using Tensorflow

```
In [175]: # usually necessary when a graph has already been created
          # not needed here but worth it.
          tf.reset_default_graph()

In [176]: num_inputs = 1

In [177]: num_neurons = 100 # number of neurons in a layer

In [178]: num_outputs = 1

In [196]: lr = 0.001 # learning rate
          batch_size = 1
          num_train_iterations = 2000 # 2000 steps

In [180]: X = tf.placeholder(dtype=tf.float32, shape=[None, num_timesteps, \
                                                    num_inputs])

In [181]: Y = tf.placeholder(dtype=tf.float32, shape=[None, num_timesteps, \
                                                    num_outputs])

In [89]: # Recurrent Neural Network Cell Layer

In [182]: cell = tf.contrib.rnn.BasicRNNCell(num_units=num_neurons,
                                              activation=tf.nn.relu)

          # output projection wrapper
          cell = tf.contrib.rnn.OutputProjectionWrapper(cell, output_size=num_outputs)
```



```

In [183]: outputs, states = tf.nn.dynamic_rnn(cell, X, dtype=tf.float32)

In [184]: # MSE
          loss = tf.reduce_mean(tf.square(outputs - Y))

In [185]: # optimizer - adam
          optimizer = tf.train.AdamOptimizer(learning_rate=lr)

          # optimizer minimizes the loss calculated above
          train = optimizer.minimize(loss)

          # initialize all variables
          init = tf.global_variables_initializer()

In [97]: # if using gpu
          # uncomment the following line
          # gpu_options = tf.GPUOptions(per_process_gpu_memory_fraction = 0.85)

In [186]: saver = tf.train.Saver() # saves model

In [197]: with tf.Session() as sess:
          sess.run(init)

          for iteration in range(num_train_iterations):
              X_batch, Y_batch = ts_data.next_batch(batch_size, num_timesteps)

              sess.run(train, feed_dict = {X:X_batch, Y:Y_batch})

              if iteration % 100 == 0:
                  mse = loss.eval(feed_dict={X:X_batch, Y:Y_batch})
                  print(iteration, "\tMSE", mse)

          saver.save(sess, "./rnn_time_series_codealong")

0          MSE 0.54810894
100         MSE 0.20570844
200         MSE 0.0068678525
300         MSE 0.003448643
400         MSE 0.008003245
500         MSE 0.0062846127
600         MSE 6.705546e-05
700         MSE 0.016843755
800         MSE 0.00018747394
900         MSE 0.0028962297
1000        MSE 0.0023182756
1100        MSE 0.0018538045
1200        MSE 0.00010784715
1300        MSE 0.0142185
1400        MSE 0.0135010965

```

```

1500      MSE 0.0065394198
1600      MSE 0.008510323
1700      MSE 0.001088756
1800      MSE 0.01031712
1900      MSE 0.0007852756

```

```

In [198]: with tf.Session() as sess:
            saver.restore(sess, "./rnn_time_series_codealong")
            X_new = np.sin(np.array(train_instance[:-1].reshape(-1,
                                num_timesteps, num_inputs)))
            y_pred = sess.run(outputs, feed_dict={X:X_new})

```

```

INFO:tensorflow:Restoring parameters from ./rnn_time_series_codealong

```

### Testing Model

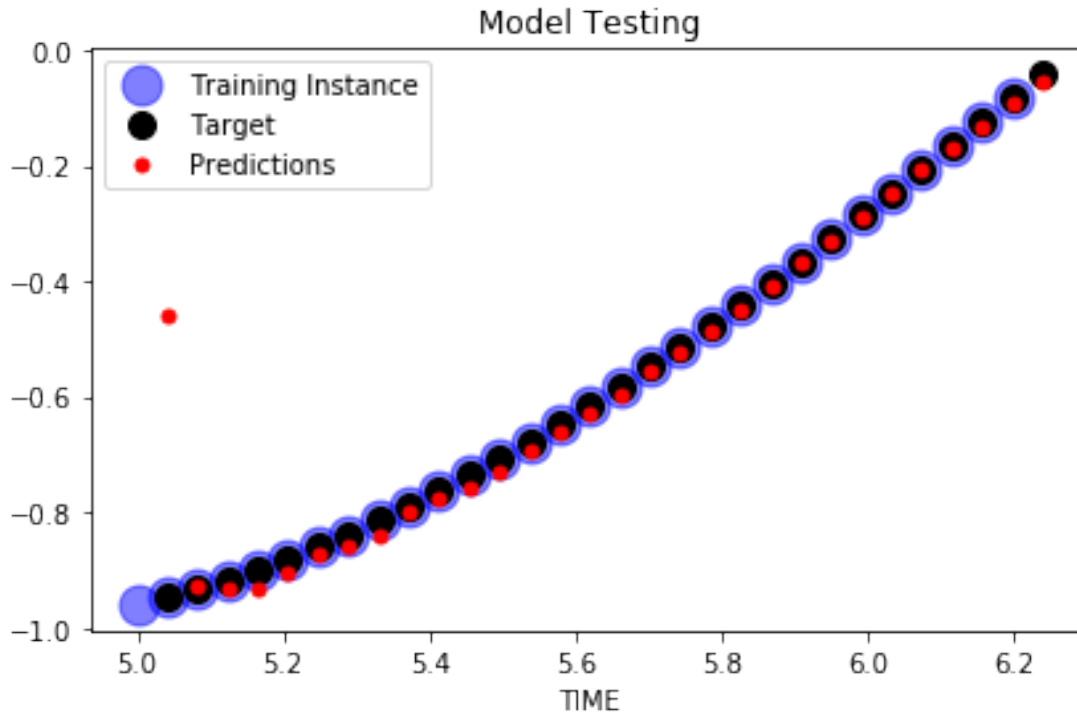
```

In [199]: plt.title("Model Testing")

            # training instance
            plt.plot(train_instance[:-1], np.sin(train_instance[:-1]),
                    "bo", markerSize=15, alpha=0.5, label="Training Instance")
            # ground truth values (np.sin(training instance))
            plt.plot(train_instance[1:], np.sin(train_instance[1:]),
                    "ko", markerSize=10, label="Target")
            # models prediction
            plt.plot(train_instance[1:], y_pred[0,:,0], 'r.',
                    markerSize=10, label='Predictions')

            plt.xlabel("TIME")
            plt.legend()
            plt.tight_layout()

```



```
In [190]: def testing_model(steps):
    batch_size = 1
    with tf.Session() as sess:
        sess.run(init)

        for iteration in range(steps):
            X_batch, Y_batch = ts_data.next_batch(batch_size, num_timesteps)

            sess.run(train, feed_dict = {X:X_batch, Y:Y_batch})

            if iteration % 100 == 0:
                mse = loss.eval(feed_dict={X:X_batch, Y:Y_batch})
                # print(iteration, "\tMSE", mse)

            saver.save(sess, "./rnn_time_series_codealong")

    with tf.Session() as sess:
        saver.restore(sess, "./rnn_time_series_codealong")
        X_new = np.sin(np.array(train_instance[:-1].reshape(-1,
            num_timesteps, num_inputs)))
        y_pred = sess.run(outputs, feed_dict={X:X_new})

    # plt.title("Model Testing")
```

```
    return y_pred
```

```
In [195]: # plt.figure(figsize=[100, 30])
```

```
num_cols = 1
num_images = 9
num_rows = math.ceil(num_images / num_cols)

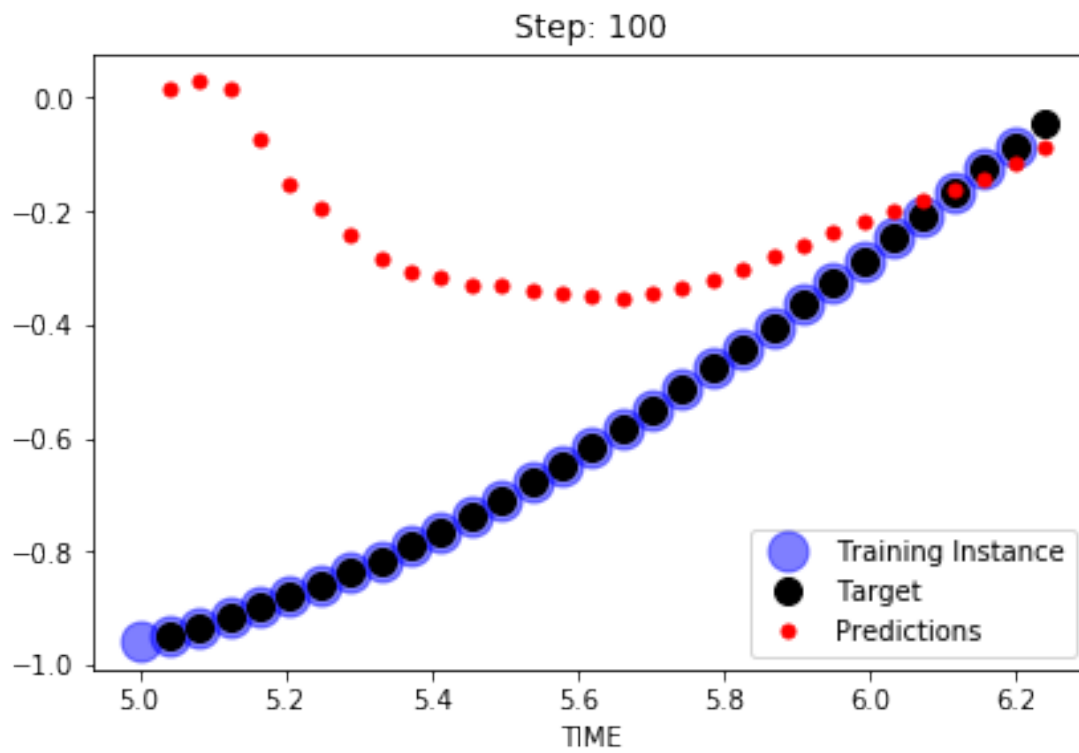
step = 100
i = 0
while(step <= 2000):
    # plt.subplot(num_rows, num_cols, i+1)

    y_pred = testing_model(step)

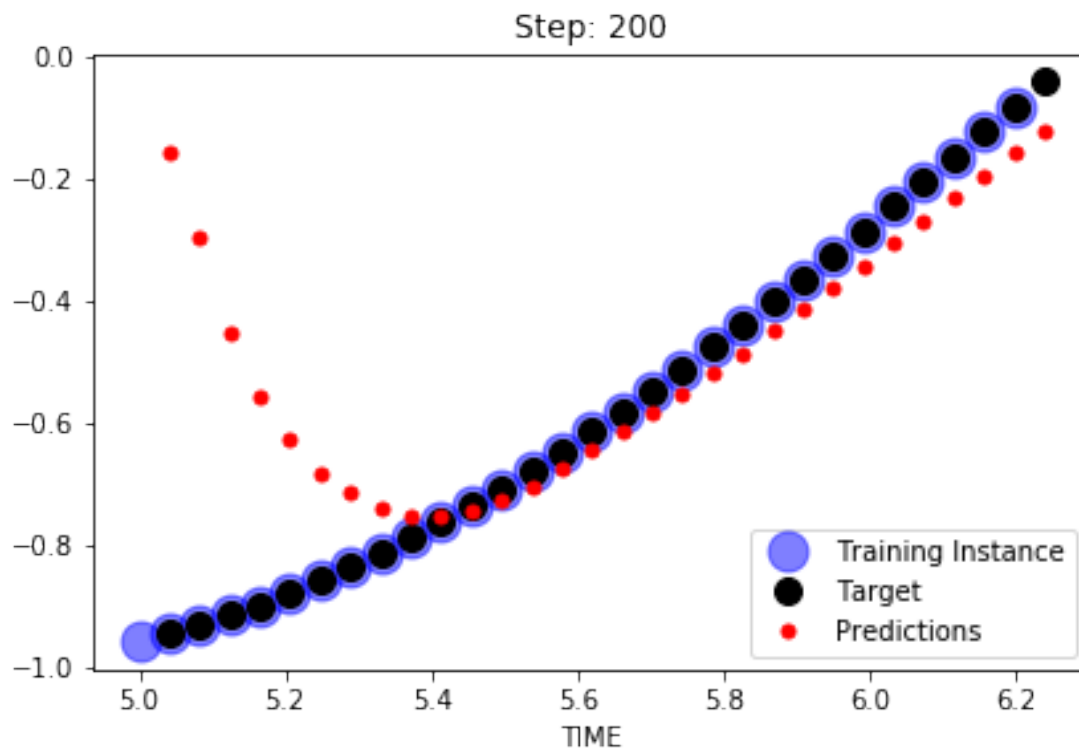
    #     print(y_pred.shape)
    print(step)
    # y1, y2, ts = generateNextBatch(30)
    plt.plot(train_instance[:-1], np.sin(train_instance[:-1]),
             "bo", markerSize=15, alpha=0.5, label="Training Instance")
    # ground truth values (np.sin(training instance))
    plt.plot(train_instance[1:], np.sin(train_instance[1:]),
             "ko", markerSize=10, label="Target")
    # models prediction
    plt.plot(train_instance[1:], y_pred[0,:,0], 'r.',
             markerSize=10, label='Predictions')

    plt.xlabel("TIME")
    plt.legend()
    plt.tight_layout()
    plt.title("Step: " + str(step))
    plt.show()
    step += 100
    i += 1
# training instance
```

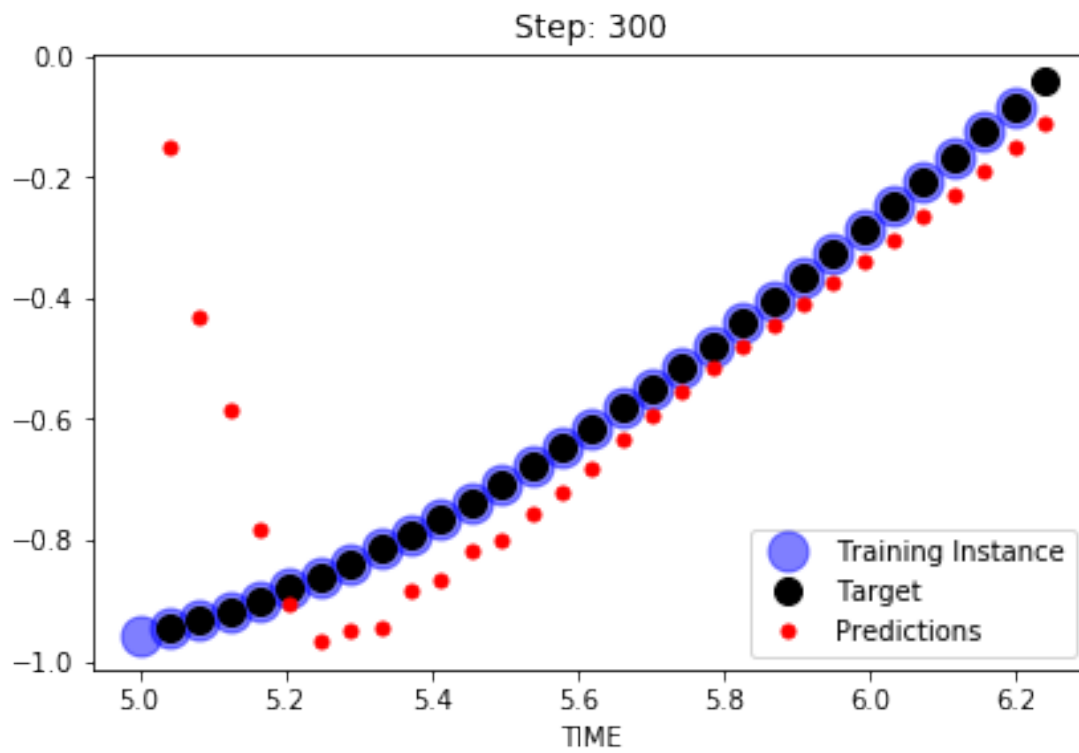
```
INFO:tensorflow:Restoring parameters from ./rnn_time_series_codealong
100
```



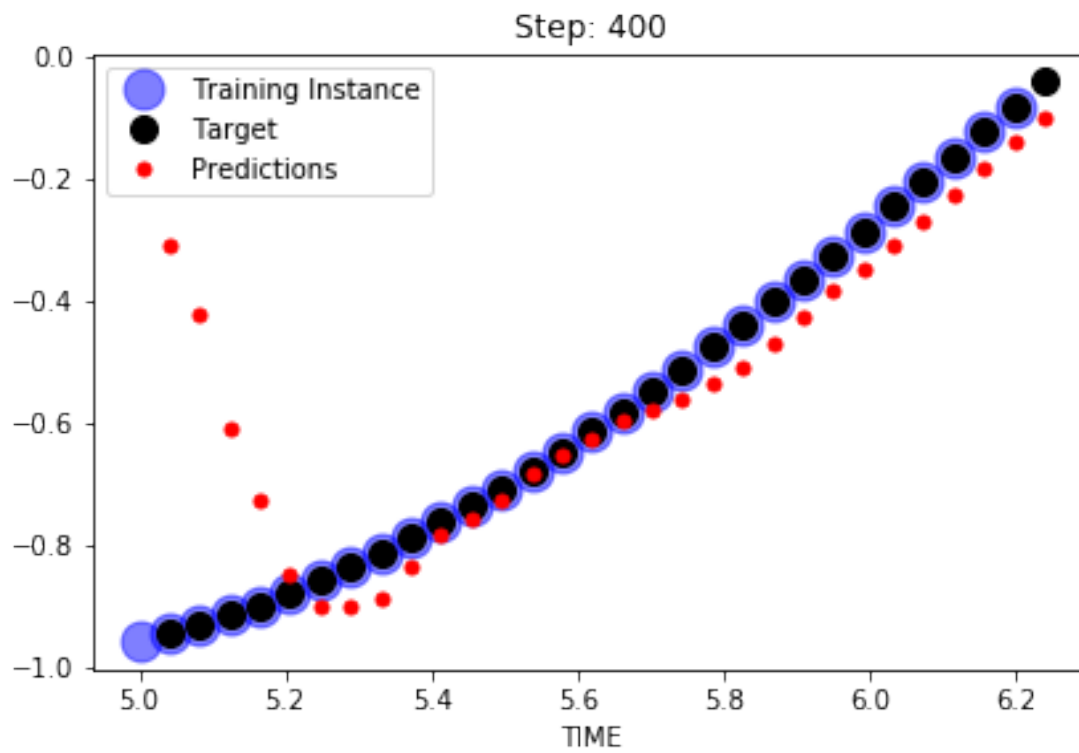
INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
200



INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
300

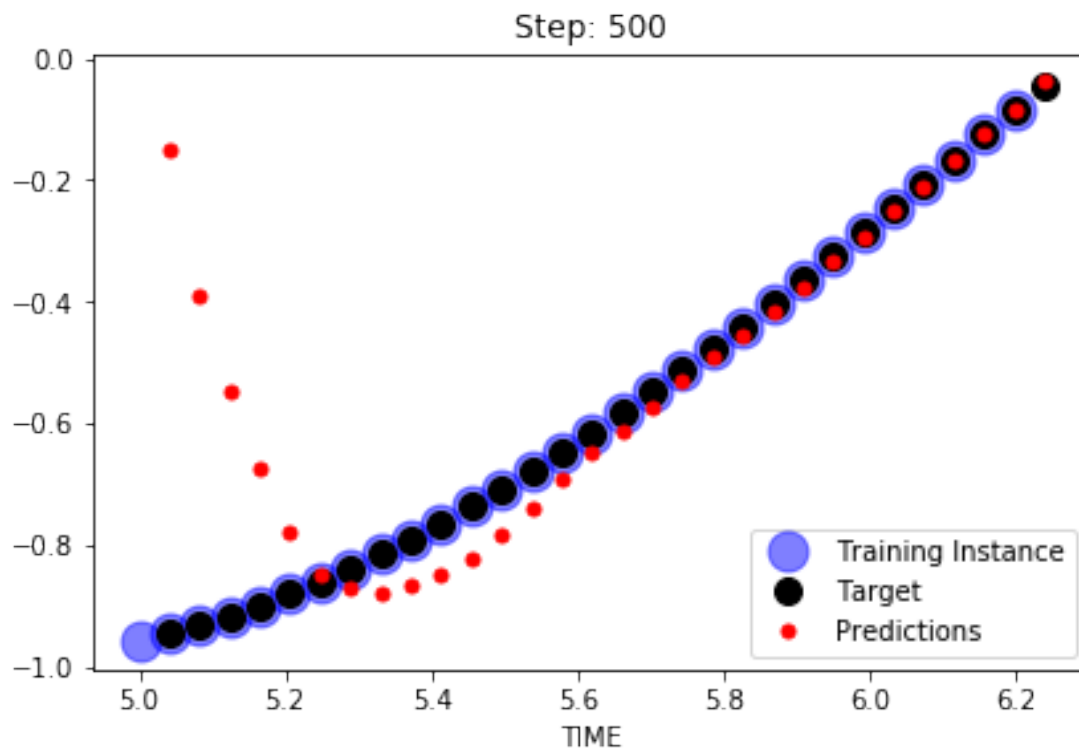


INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
400

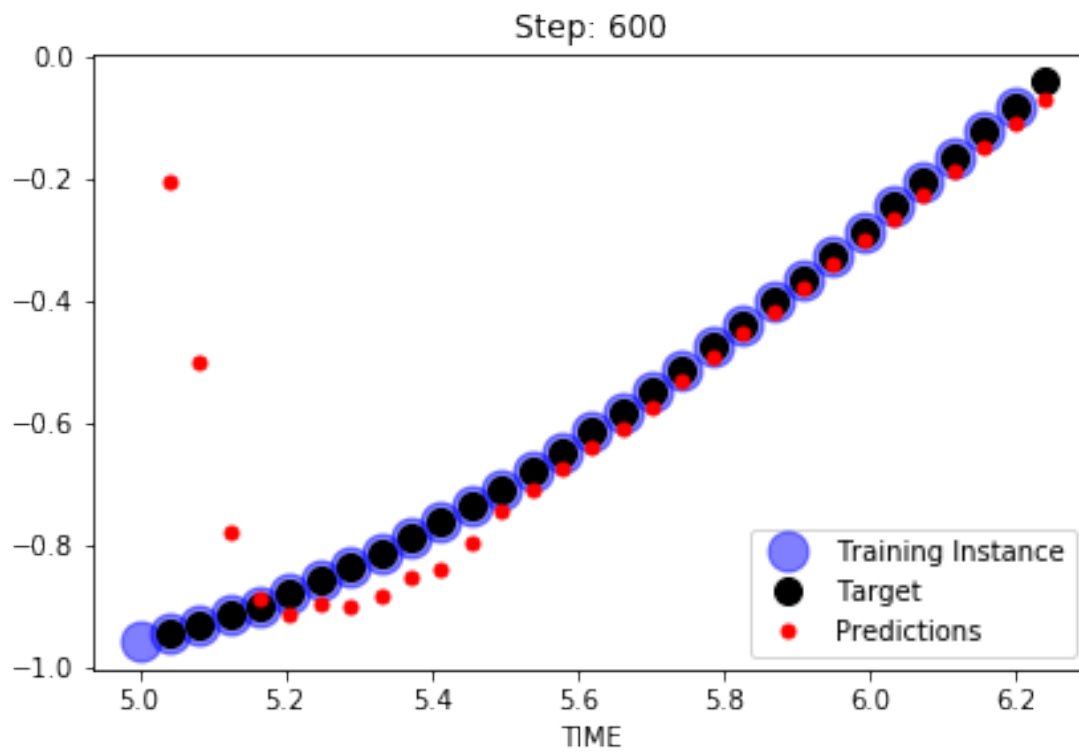


INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
500

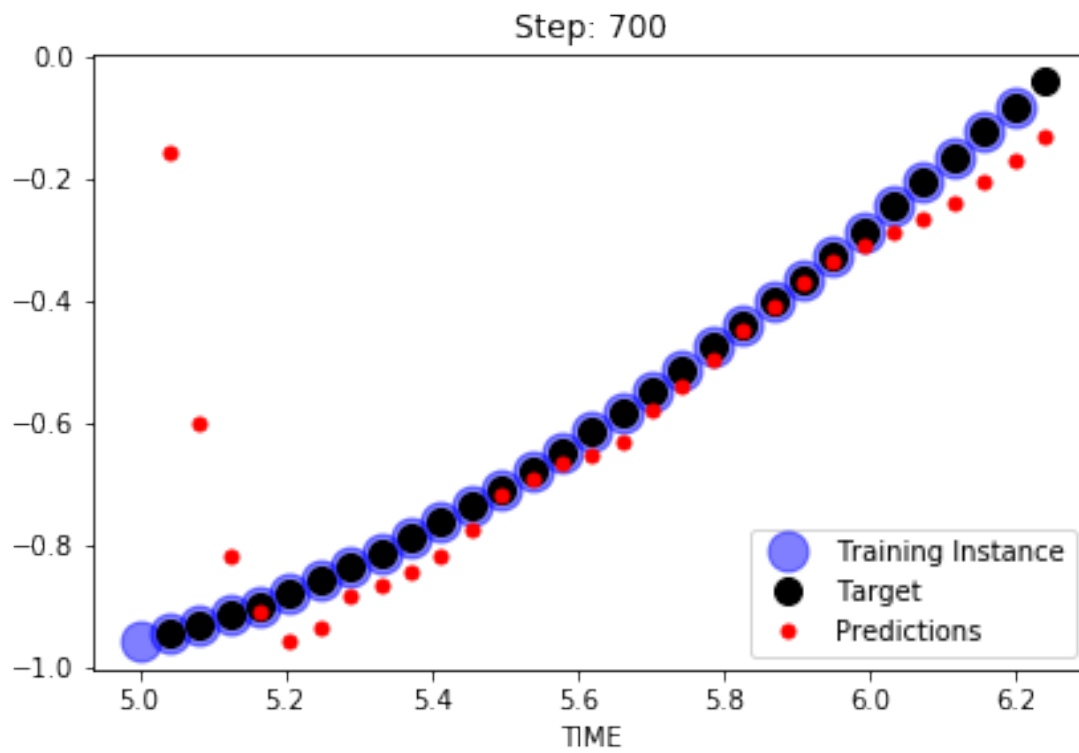




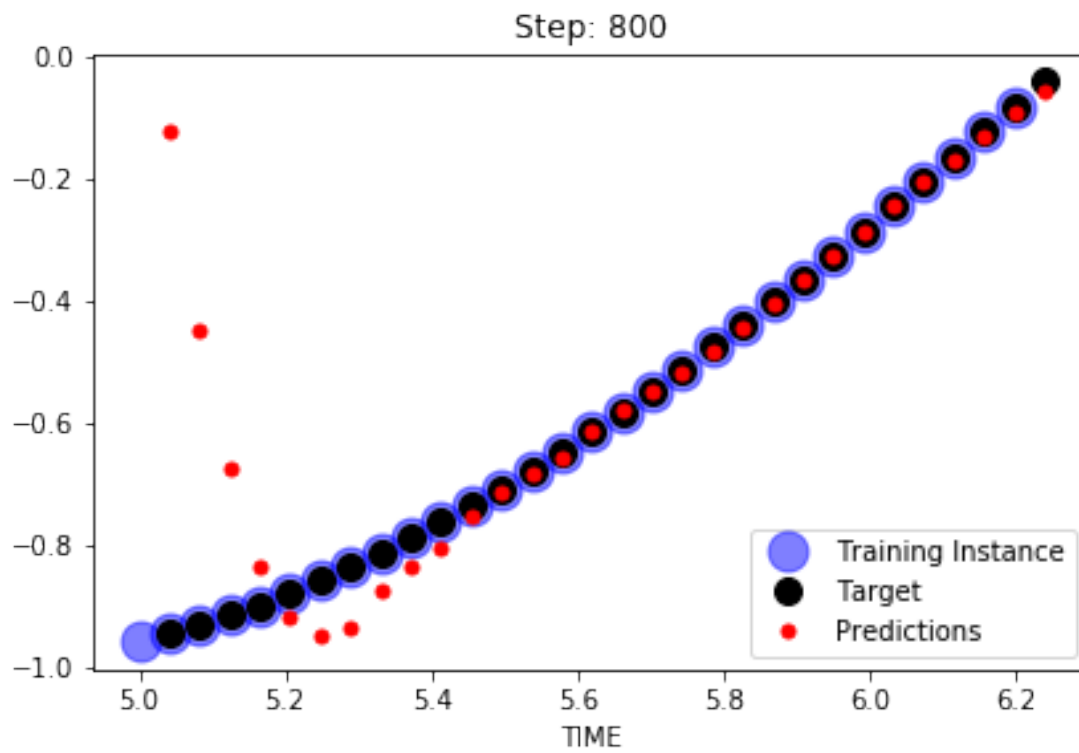
INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
600



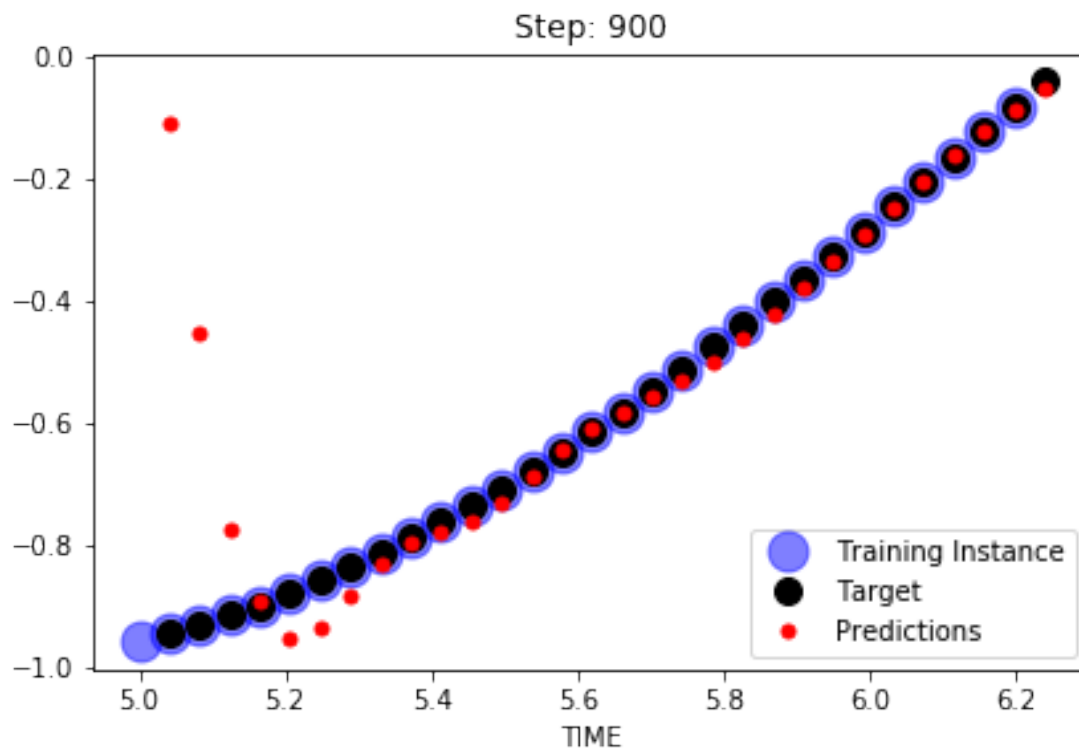
INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
700



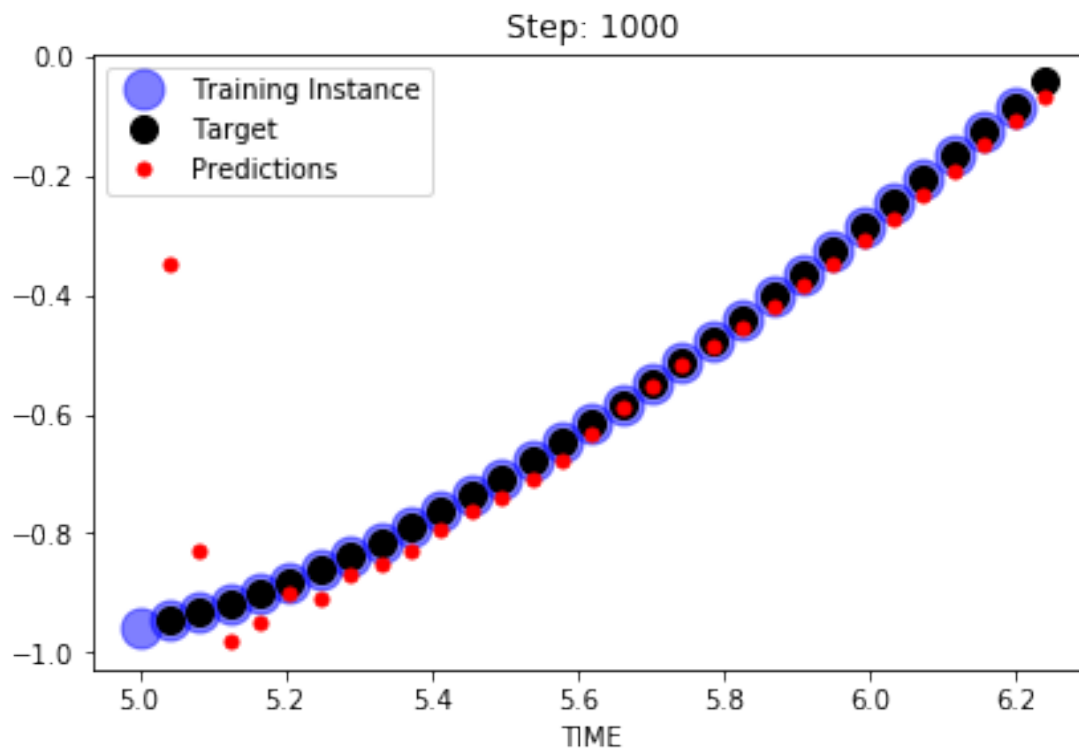
INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
800



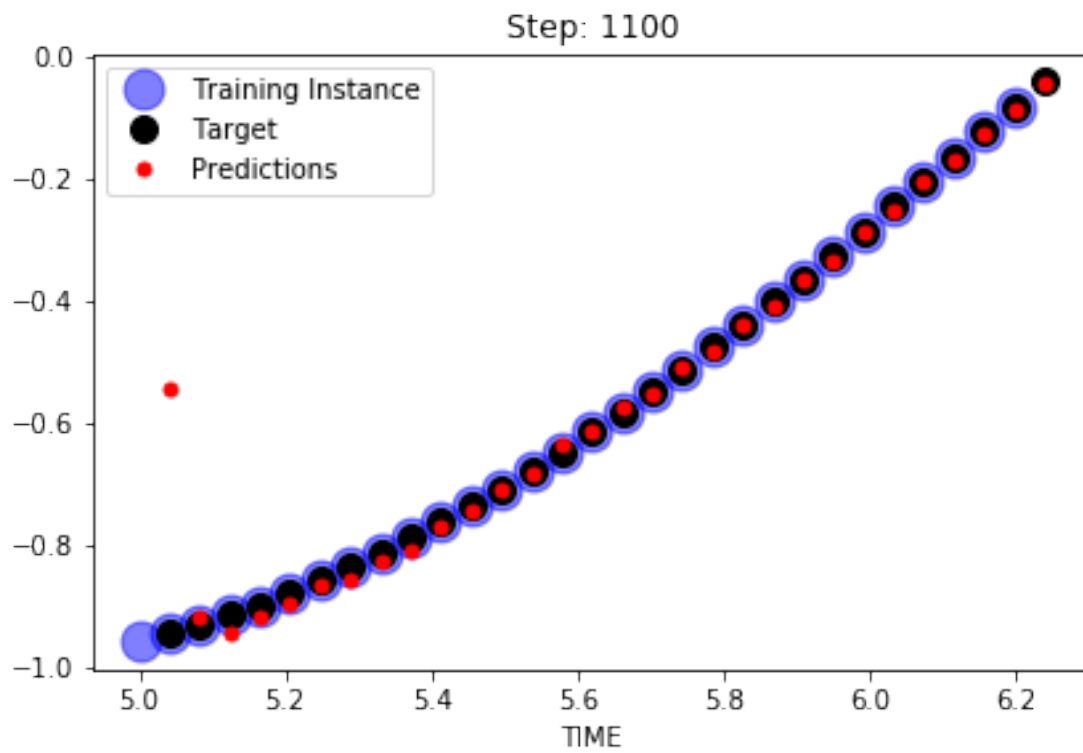
INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
900



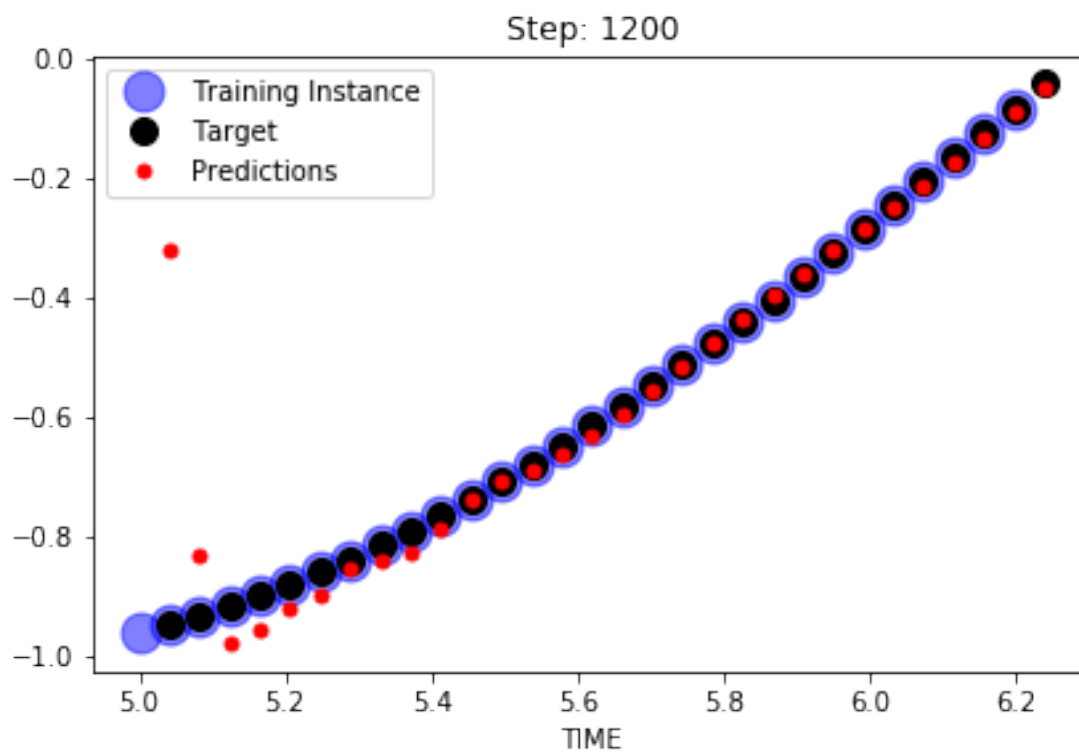
INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
1000



INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
1100

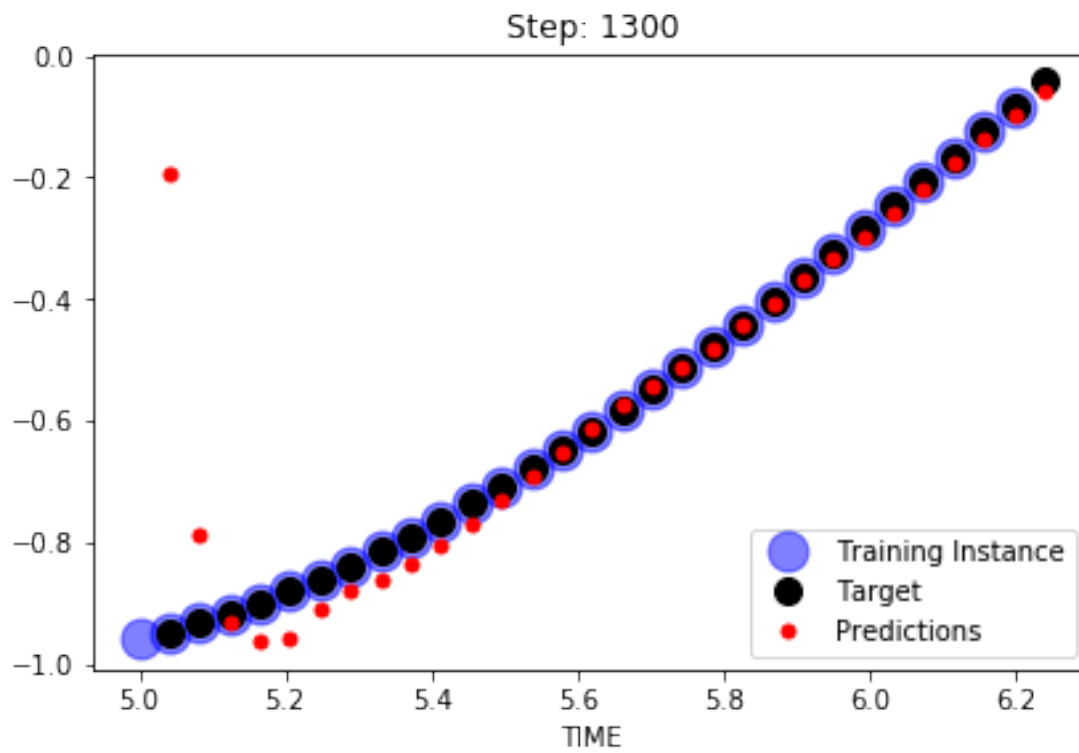


INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
1200

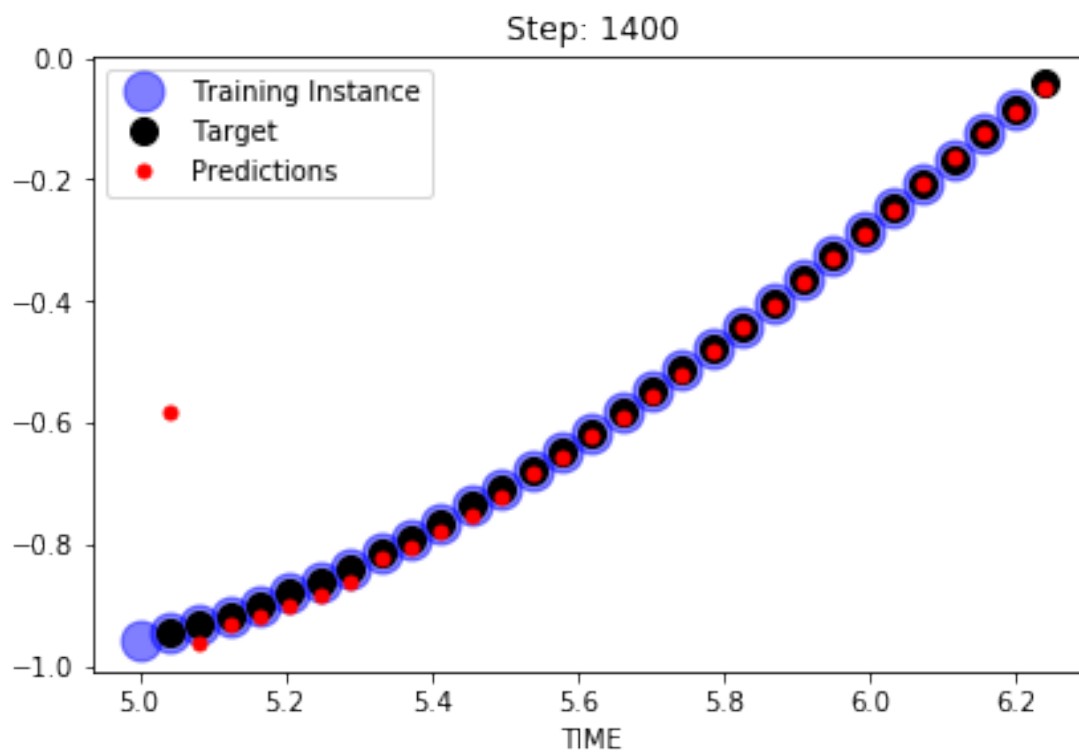


INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
1300

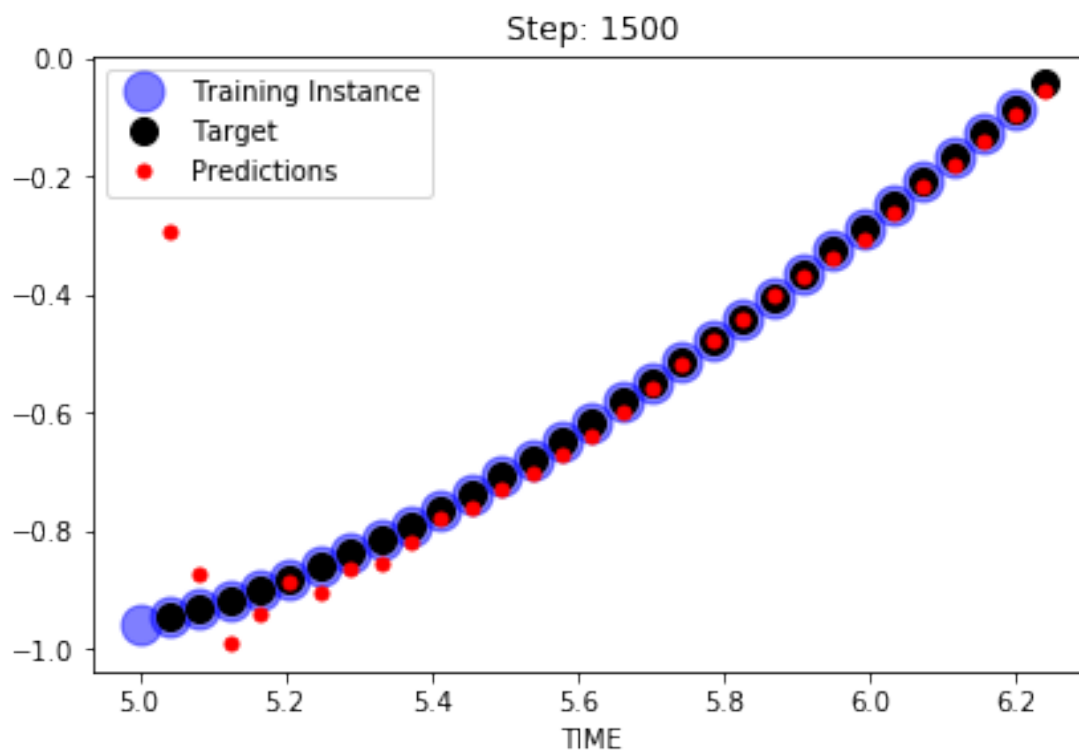




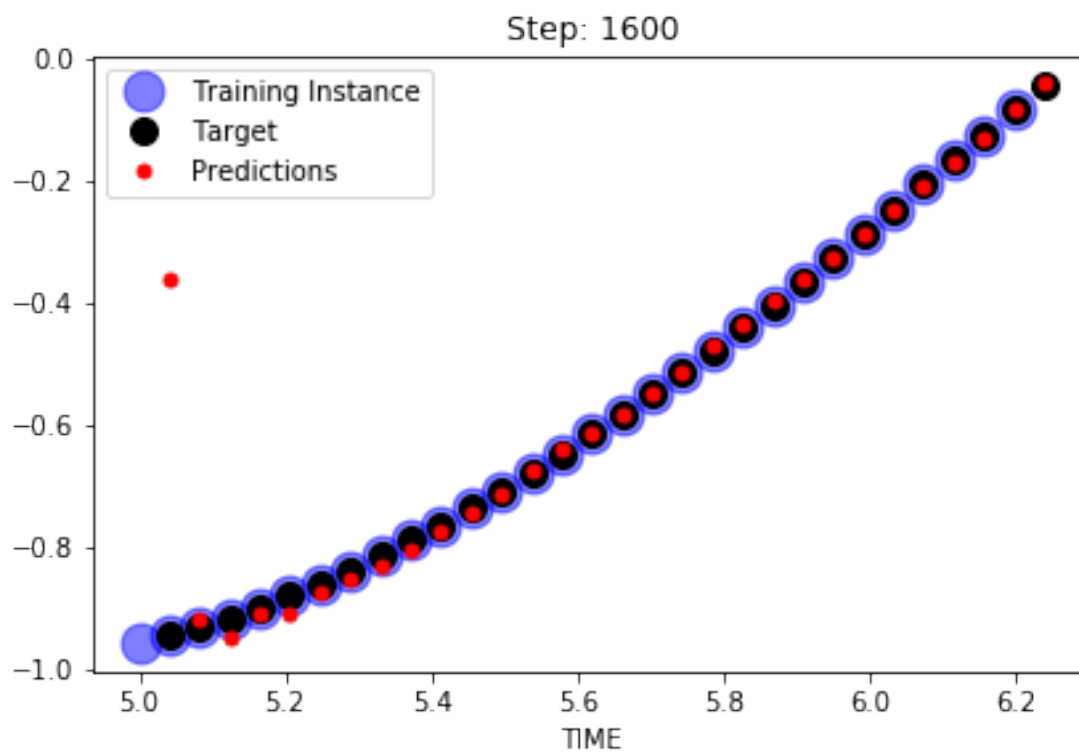
INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
1400



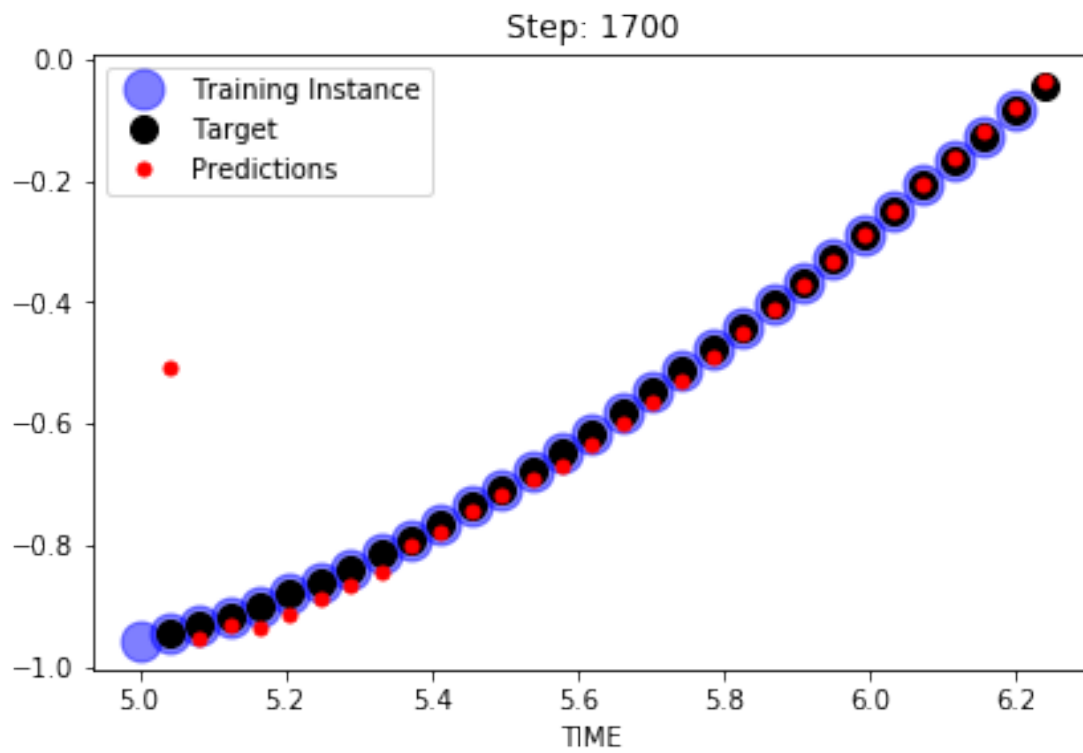
INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
1500



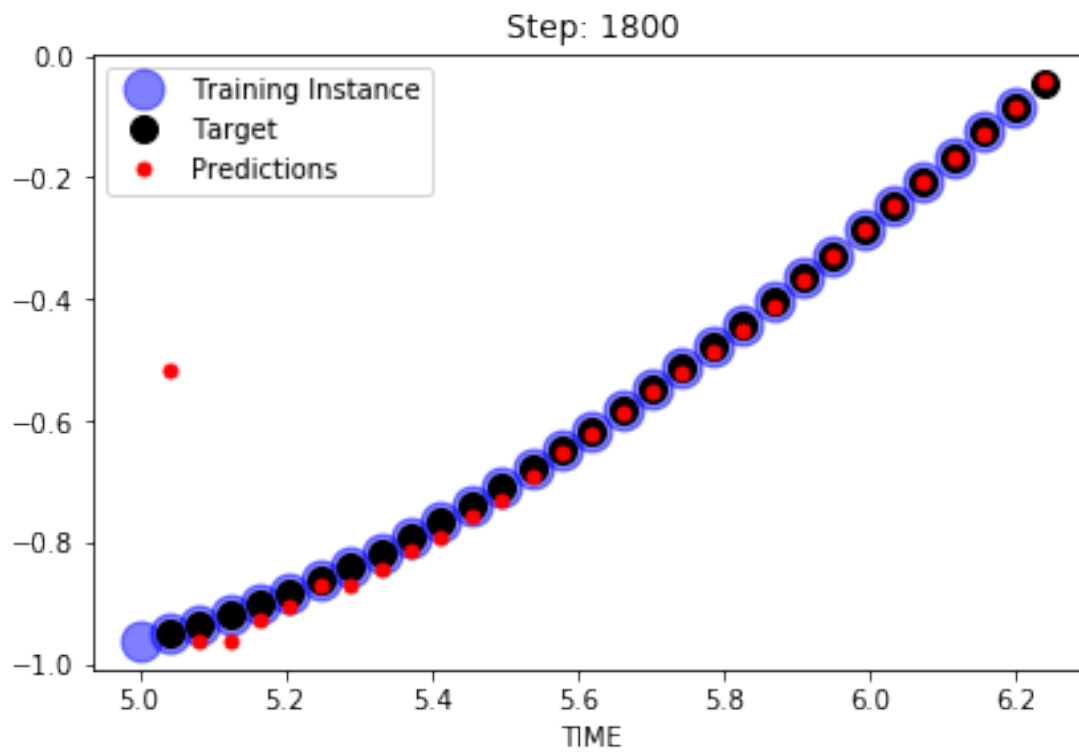
INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
1600



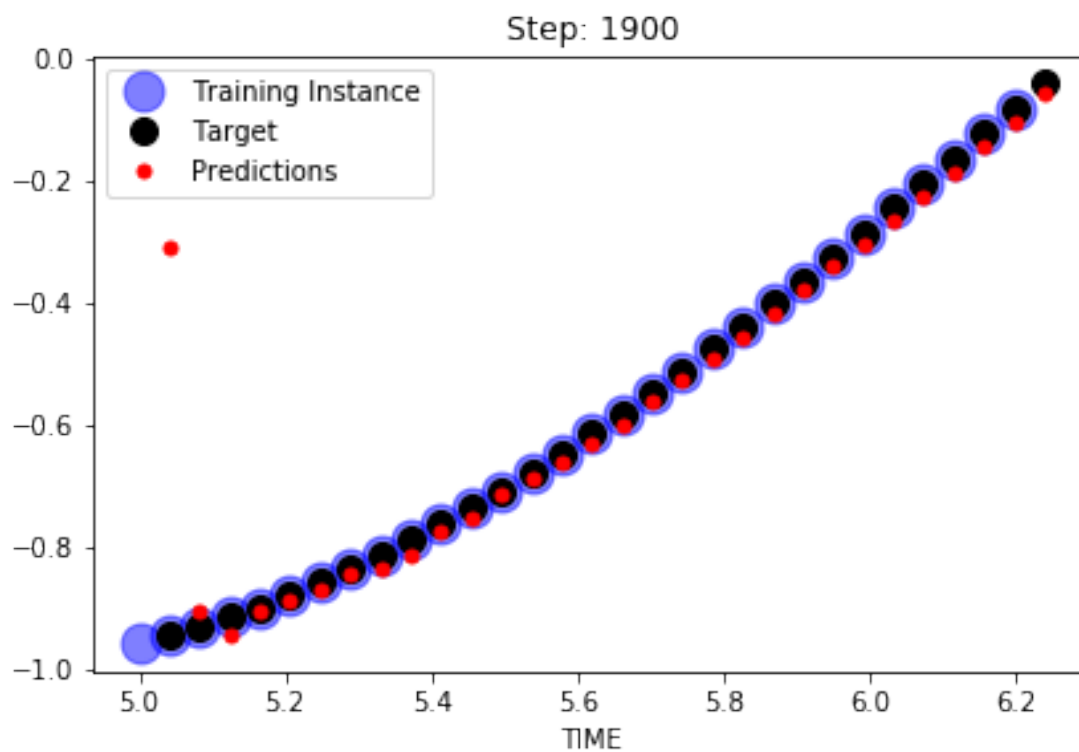
INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
1700



INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
1800



INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
1900



INFO:tensorflow:Restoring parameters from ./rnn\_time\_series\_codealong  
2000

