HDS5230 Deep learning with keras - HW14 - Miao Cai

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1 HDS 5230 Homework 14 - Deep learning with keras

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1.1 Libraries

```
In [1]: import os
        import pathlib
        import sys
        import numpy as np
        import pandas as pd
        import matplotlib
        import matplotlib.pyplot as plt
        import seaborn as sns
```

```
In [2]: import tensorflow as tf
```

```
In [3]: ## Enable inline plotting for graphics
        %matplotlib inline
        ## Set default figure size to be larger
        ## this may only work in matplotlib 2.0+!
        matplotlib.rcParams['figure.figsize'] = [10.0,6.0]
        ## Enable multiple outputs from jupyter cells
        from IPython.core.interactiveshell import InteractiveShell
        InteractiveShell.ast_node_interactivity = "all"
```

```
In [4]: ## Get Version information
        print(sys.version)
        print("Pandas version: {0}".format(pd.__version__))
        print("Matplotlib version: {0}".format(matplotlib.__version__))
        print("Numpy version: {0}".format(np.__version__))
        print("Tensorflow version: {0}".format(tf.__version__))
```

```
3.7.1 (default, Dec 14 2018, 13:28:58)
[Clang 4.0.1 (tags/RELEASE_401/final)]
Pandas version: 0.23.4
```

```
Matplotlib version: 3.0.2
Numpy version: 1.15.4
Tensorflow version: 1.13.1
```

1.2 Simulate a non-linear relationship

Simulate a non-linear relationship that would be hard to be modeled with linear modeling methods, such as `sin`, `cosin`, `inverse`, etc.

The following relationship should be modeled:

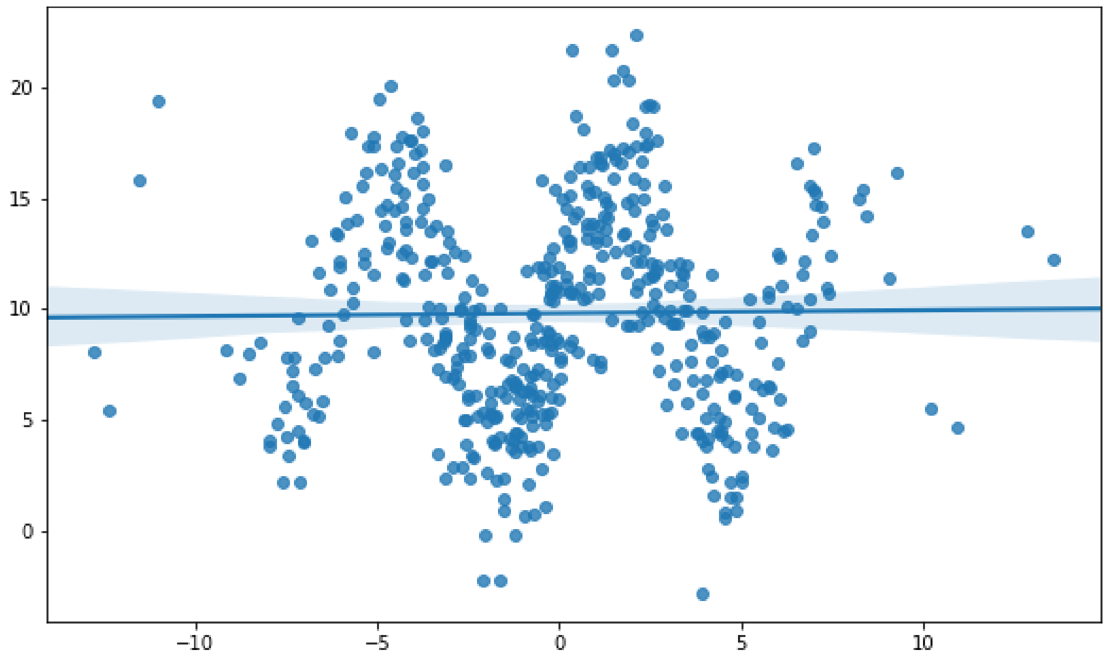
1. only have one input(`x`)
2. add some error into the model, then calculate `Y`
3. make a graph of `x` versus `y` with points to visualize the relationship

```
In [5]: import scipy.stats as ss
        np.random.seed(666)

        n = 500
        x = np.random.normal(loc=0,
                             scale=4,
                             size=n)
        ## simulate outcome
        error = \
            np.random.normal(loc=0,
                             scale=3,
                             size=n)
        ## map to outcome
        y = 10 + 5*np.sin(x) + error
```

```
In [6]: sns.regplot(x,y)
```

```
/Users/miaocai/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning:
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x1a34e870f0>
```



1.3 Fit a shallow neural network with one hidden layer

1. Be sure to standardize your input
2. You can start with a small number of epochs (300 ish)
3. Plot the history of the loss function across epochs
4. Plot the history of another metric that is not the loss function across epochs
5. Predict a new range of `X`'s as a line along with the original data as dots to understand how well your model fits

```
In [7]: from keras import models
        from keras import layers
        from keras import optimizers

        def build_model1():
            model = models.Sequential()
            model.add(layers.Dense(1,
                                   activation = 'linear',
                                   input_dim=1))
            model.compile(optimizer ='SGD',
                          loss = 'mse',
                          metrics = ['mae'])
            return model
```

```
Using TensorFlow backend.
```

```
In [8]: from sklearn import preprocessing
        trans_1 = preprocessing.StandardScaler().fit(x.reshape(-1, 1))
        x_scale = trans_1.transform(x.reshape(-1, 1))

        ## fit this model/architecture to my data
        regr = build_model1()
        regr.fit(x_scale, y, epochs = 300, verbose = 0)
```

```
WARNING:tensorflow:From /Users/miaocai/anaconda3/lib/python3.7/site-packages/tensorflow/python/
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From /Users/miaocai/anaconda3/lib/python3.7/site-packages/tensorflow/python/
Instructions for updating:
Use tf.cast instead.
```

```
Out[8]: <keras.callbacks.History at 0x1a351fc748>
```

```
In [9]: ## summarize model
        regr.summary()
```

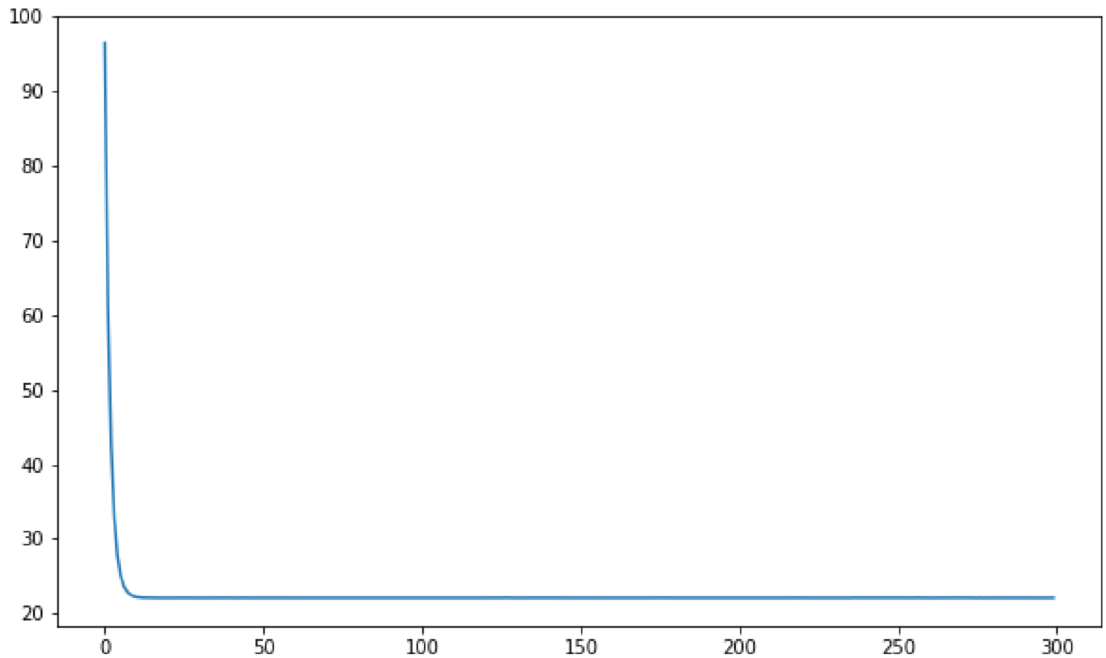
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 1)                 2
=================================================================
Total params: 2
Trainable params: 2
Non-trainable params: 0
_________________________________________________________________
```

```
In [10]: ## Retrieve the weights
         regr.get_weights()
```

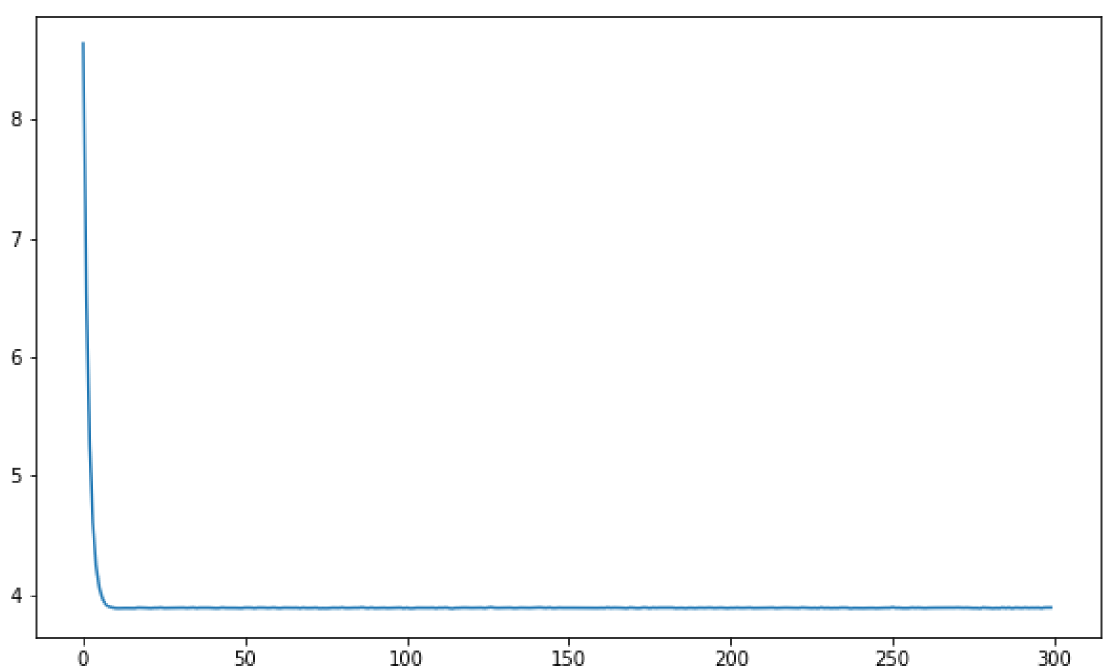
```
Out[10]: [array([[0.06326589]], dtype=float32), array([9.800141], dtype=float32)]
```

```
In [11]: ## plot the loss function per epoch
         plt.plot(regr.history.history['loss'])
```

```
Out[11]: [<matplotlib.lines.Line2D at 0x1a35d635f8>]
```



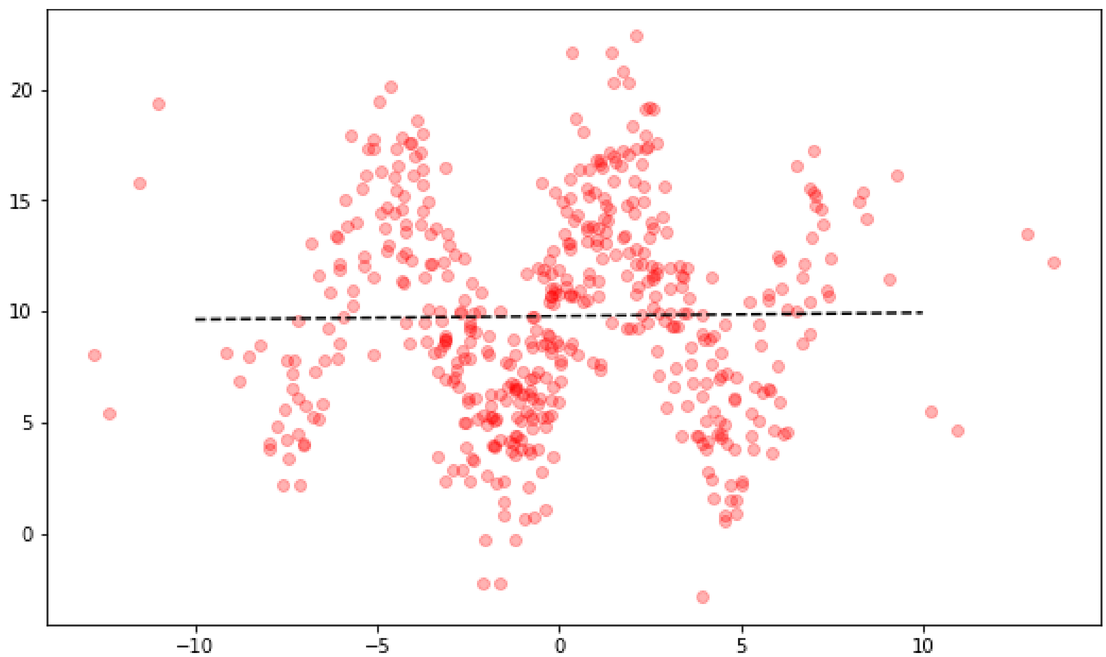

```
In [12]: ## plot a metric per epoch
         regr.metrics_names
         plt.plot(regr.history.history['mean_absolute_error'])

Out[12]: ['loss', 'mean_absolute_error']

Out[12]: [<matplotlib.lines.Line2D at 0x1a35dd59b0>]
```



```
In [13]: ## original data
         plt.plot(x, y,'ro',alpha=0.3)
         ## generate regular points along the range of x
         x2_range = np.linspace(-10,10,200)
         ## make predictions and plot
         plt.plot(x2_range,
                  regr.predict(trans_1.transform(x2_range.reshape(-1, 1))),
                  'k--')
```

```
Out[13]: [<matplotlib.lines.Line2D at 0x1a35fd7668>]
```

```
Out[13]: [<matplotlib.lines.Line2D at 0x1a35fd7ac8>]
```



Although the loss function and mean absolute error appear to be okay, the prediction plot turns out to be very bad.

1.4 Expand the neural network to more capacity

Different approaches: add layers (make it deeper), add more units per layer (make it wider), and more epochs

1. plot the history of the loss function and one more model metric across epochs
2. predict a new range of `X`'s as a line along with the original data as dots to understand how well your model fits.

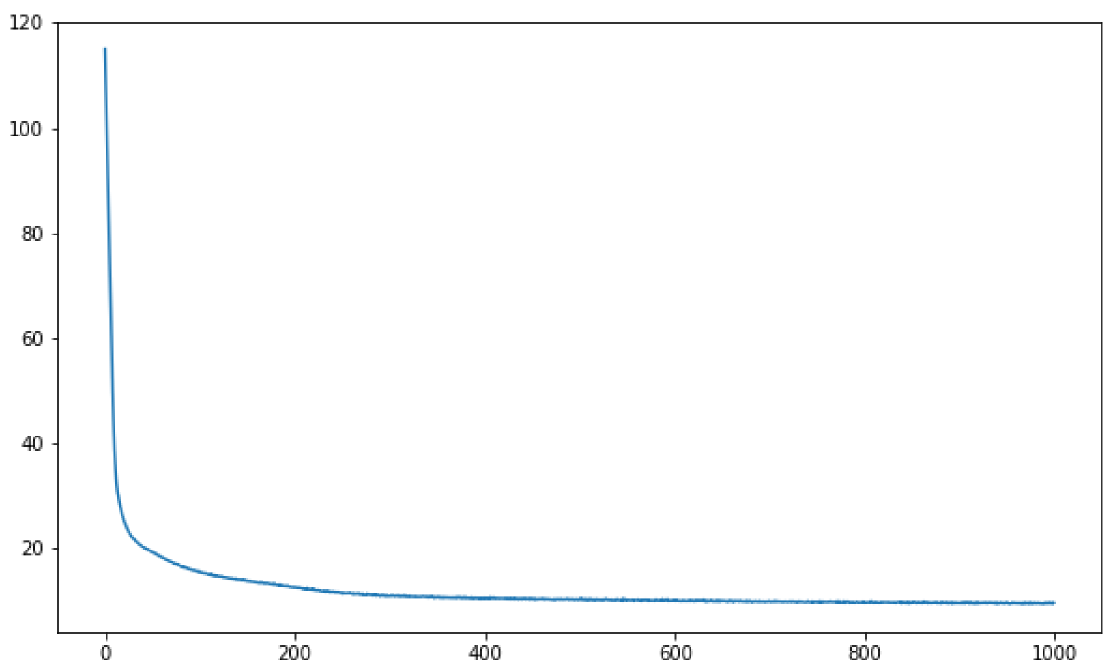
In [14]:
```
def build_model2():
    model = models.Sequential()
    model.add(layers.Dense(64,
                           activation = 'relu',
                           input_dim=1))
    model.add(layers.Dense(64,
                           activation = 'relu'))
    model.add(layers.Dense(1,
                           activation = 'linear'))
    model.compile(optimizer ='RMSprop',
                  loss = 'mse',
                  metrics = ['mae'])
    return model
```

In [15]:
```
## fit this model/architecture to my data
regr4 = build_model2()
regr4.fit(x_scale,
          y,
          epochs = 1000,
          batch_size = 64,
          verbose=0)
```

Out[15]:
```
<keras.callbacks.History at 0x1a36006c50>
```

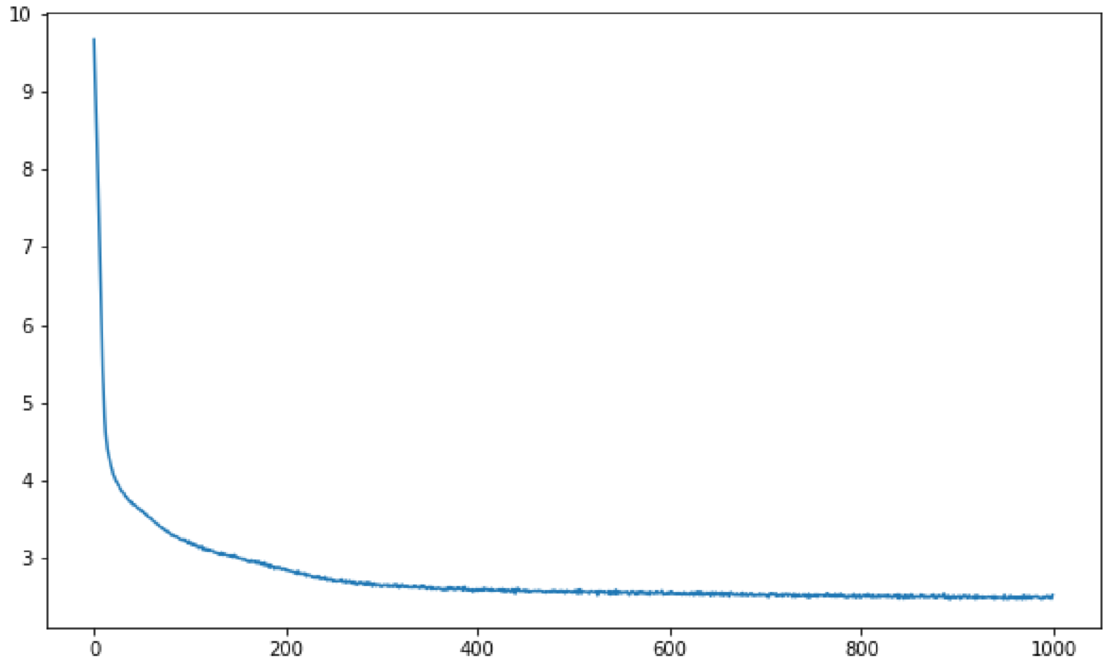
In [16]:
```
## plot the loss function
plt.plot(regr4.history.history['loss'])
```

Out[16]:
```
[<matplotlib.lines.Line2D at 0x1a36460d68>]
```



In [17]:
```
## plot the metrics
plt.plot(regr4.history.history['mean_absolute_error'])
```

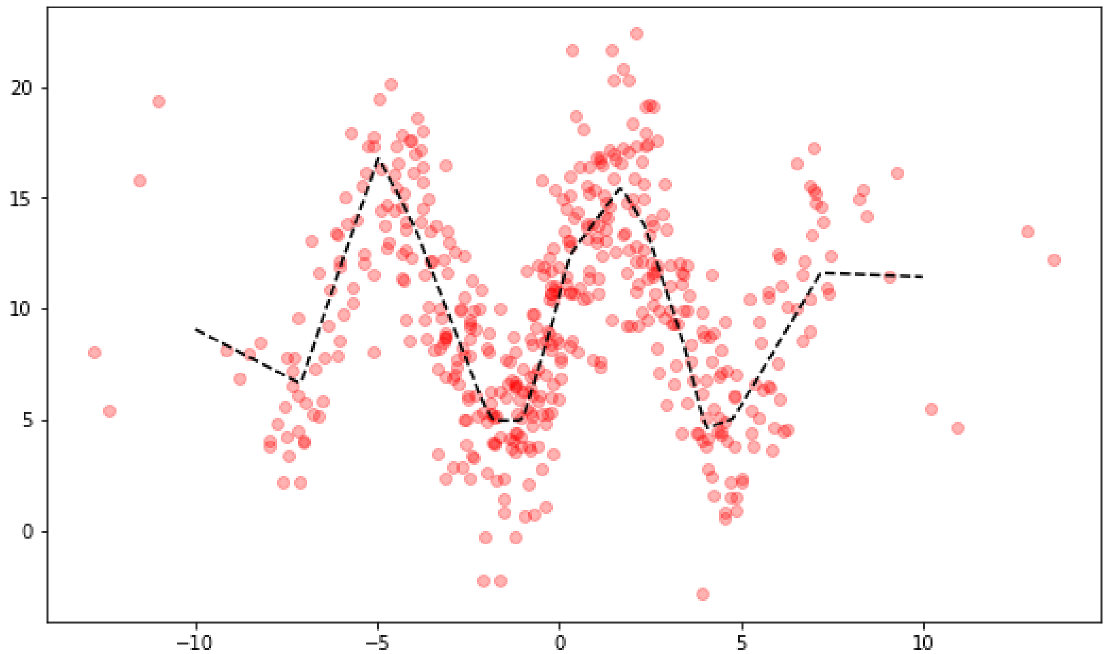
Out[17]: [<matplotlib.lines.Line2D at 0x1a36576898>]



In [18]:
```
## original data
plt.plot(x, y,'ro',alpha=0.3)
## generate regular points along the range of x
x2_range = np.linspace(-10,10,200)
## make predictions and plot
plt.plot(x2_range,
         regr4.predict(trans_1.transform(x2_range.reshape(-1, 1))),
         'k--')
```

Out[18]: [<matplotlib.lines.Line2D at 0x1a365ceb70>]

Out[18]: [<matplotlib.lines.Line2D at 0x1a365cef28>]



The prediction results seem reasonably well.