Heaton Research

Overview of Keras/TensorFlow Basic Operations

2017-07-22 (/2017/07/22/keras-getting-started.html)
ai (/categories/ai/)

I in the process of updating my deep learning course (https://sites.wustl.edu/jeffheaton/t81-558/) and books (http://www.aifh.org) to make use of Keras (https://keras.io/). This posting contains some of the basic examples that I put together. This post is not meant to be an introduction to neural networks in general. For such an introduction, refer to either my books (/book/) or this article (http://www.heatonresearch.com/content/non-mathematical-introduction-using-neural-networks).

I will expand on these examples greatly for both the book and course. The basic neural network operations that I needed were:

- Simple Regression
- Regression Early Stopping
- Simple Classification

About

Jeff Heaton, Ph.D. is a computer scientist, data scientist, and indie publisher. Heaton Research is the homepage for his projects and research.

Categories

- Classification Early Stopping
- Deep Neural Networks w/Dropout and Other Regularization
- Convolutional Neural Networks
- LSTM Neural Networks
- Loading/Saving Neural Networks

These are some of the most basic operations that I need to perform when working with a new neural network package. This provides me with a sort of Rosetta Stone for a new neural network package. Once I have these operations, I can more easily create additional examples that are more complex.

The first thing to check is what versions you have of the required packages:

```
import keras
import tensorflow as tf
import sys
import sklearn as sk
import pandas as pd

print("Tensor Flow Version: {}".format(tf.__version__)
print("Keras Version: {}".format(keras.__version__))
print()
print("Python {}".format(sys.version))
print('Pandas {}'.format(pd.__version__))
print('Scikit-Learn {}'.format(sk.__version__))
```

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```
Tensor Flow Version: 1.0.0
Keras Version: 2.0.6

Python 3.5.2 |Continuum Analytics, Inc.| (default, Jul
Pandas 0.19.2
Scikit-Learn 0.18.1
```

The following functions are from my set of helpful functions (https://github.com/jeffheaton/t81_558_deep_learning/blob/maste that I created for my class and use in many of my books (http://www.aifh.org):

```
import pandas as pd
from sklearn import preprocessing

# Encode text values to dummy variables(i.e. [1,0,0],[(
def encode_text_dummy(df, name):
    dummies = pd.get_dummies(df[name])
    for x in dummies.columns:
        dummy_name = "{}-{}".format(name, x)
        df[dummy_name] = dummies[x]
    df.drop(name, axis=1, inplace=True)

# Encode text values to indexes(i.e. [1],[2],[3] for re
def encode_text_index(df, name):
    le = preprocessing.LabelEncoder()
    df[name] = le.fit_transform(df[name])
    return le.classes_

```


Recents

```
# Convert all missing values in the specified column t
def missing_median(df, name):
    med = df[name].median()
    df[name] = df[name].fillna(med)

# Convert a Pandas dataframe to the x,y inputs that Te
def to_xy(df, target):
    result = []
    for x in df.columns:
        if x != target:
            result.append(x)

    # find out the type of the target column.  Is it r
    target_type = df[target].dtypes
    target_type = target_type[0] if hasattr(target_typ

    # Encode to int for classification, float otherwis
    if target_type in (np.int64, np.int32):
        # Classification
        dummies = pd.get_dummies(df[target])
        return df.as_matrix(result).astype(np.float32)
    else:
        # Regression
        return df.as_matrix(result).astype(np.float32)
```

Installing TensorFlow (/2017/09/14/install_tf.html)
Data Science Rosetta Stone: Classification in Python, R, MATLAB, SAS, & Julia (/2017/08/17/ds_rosetta_stone.html)

Simple Regression

Regression is where a neural network accepts several values (predictors) and produces a prediction that is numeric. In this simple example we attempt to predict the miles per gallon (MPG) of several cars based on characteristics of those cars. Several parameters and used below and described here.

- Losses Supported by Keras (https://keras.io/losses/)
  - Typically use **mean_squared_error** for regression (the square root of mean square error is root mean square error(RMSE)).
  - and for classification use: **binary_crossentropy** for 2 classes, **categorical_crossentropy** for more than 2 classes.
- kernel_initializer supported by Keras (https://keras.io/initializers/) - Species how the weights of are randomized.
- activation (https://keras.io/activations/) - Usually relu or softmax will be used.

```
nport Sequential
ore import Dense, Activation




 metrics

thubusercontent.com/jeffheaton/t81_558_deep_learning/master/c
tringIO(requests.get(url).content.decode('utf-8')),na_values=


place=True)
'horsepower')
")

)
 input_dim=x.shape[1], activation='relu'))
kernel_initializer='normal'))
'mean_squared_error', optimizer='adam')

se=2,epochs=100)
```

```
Epoch 1/100
0s - loss: 2240.8034
Epoch 2/100
0s - loss: 1469.8520
Epoch 3/100
0s - loss: 1038.2052
Epoch 4/100
0s - loss: 820.4976
Epoch 5/100

...

0s - loss: 560.3524
Epoch 99/100
0s - loss: 559.7951
Epoch 100/100
0s - loss: 559.2341
<keras.callbacks.History at 0x2263d8cc518>
```

Now that the neural network is trained, we will test how good it is and perform some sample predictions.

```
pred = model.predict(x)

# Measure RMSE error.  RMSE is common for regression.
score = np.sqrt(metrics.mean_squared_error(pred,y))
print("Final score (RMSE): {}".format(score))

# Sample predictions
for i in range(10):
    print("{}. Car name: {}, MPG: {}, predicted MPG: {}'
```

```
Final score (RMSE): 3.494112253189087
1. Car name: chevrolet chevelle malibu, MPG: [ 18.], pr
2. Car name: buick skylark 320, MPG: [ 15.], predicted
3. Car name: plymouth satellite, MPG: [ 18.], predicte
4. Car name: amc rebel sst, MPG: [ 16.], predicted MPG
5. Car name: ford torino, MPG: [ 17.], predicted MPG:
6. Car name: ford galaxie 500, MPG: [ 15.], predicted M
7. Car name: chevrolet impala, MPG: [ 14.], predicted M
8. Car name: plymouth fury iii, MPG: [ 14.], predicted
9. Car name: pontiac catalina, MPG: [ 14.], predicted M
10. Car name: amc ambassador dpl, MPG: [ 15.], predicte
```

Regression (Early Stop)

Early stopping sets aside a part of the data to be used to validate the neural
network. The neural network is trained with the training data and

validated
with the validation data. Once the error no longer improves on the validation
set, the training stops. This prevents the neural network from overfitting (https://en.wikipedia.org/wiki/Overfitting).

```
import pandas as pd
import io
import requests
import numpy as np
from sklearn import metrics
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.callbacks import EarlyStopping

url="https://raw.githubusercontent.com/jeffheaton/t81_5
df=pd.read_csv(io.StringIO(requests.get(url).content.de

cars = df['name']
df.drop('name',1,inplace=True)
missing_median(df, 'horsepower')
x,y = to_xy(df,"mpg")

# Split into train/test
x_train, x_test, y_train, y_test = train_test_split(
    x, y, test_size=0.25, random_state=45)

model = Sequential()
model.add(Dense(10, input_dim=x.shape[1], kernel_initia
model.add(Dense(1, kernel_initializer='normal'))
model.compile(loss='mean_squared_error', optimizer='ada

monitor = EarlyStopping(monitor='val_loss', min_delta=1

model.fit(x,y,validation_data=(x_test,y_test),callbacks
```

```
Train on 398 samples, validate on 100 samples
Epoch 1/1000
0s - loss: 374.7638 - val_loss: 179.2396
Epoch 2/1000
0s - loss: 199.9990 - val_loss: 169.4834
Epoch 3/1000
0s - loss: 197.9431 - val_loss: 153.8338
Epoch 4/1000
0s - loss: 187.7644 - val_loss: 152.2758
Epoch 5/1000
0s - loss: 185.5505 - val_loss: 149.9817

...

Epoch 179/1000
0s - loss: 10.3191 - val_loss: 8.2763
Epoch 180/1000
0s - loss: 10.0629 - val_loss: 8.3435
Epoch 181/1000
0s - loss: 10.7124 - val_loss: 8.4712
Epoch 182/1000
0s - loss: 10.6406 - val_loss: 8.4272
<keras.callbacks.History at 0x222a8ecd1d0>
```

Classification Model (Early Stop)

Early stopping can also be used with classification. Early stopping sets aside a part of the data to be used to validate the neural network. The neural network is trained with the training data and validated with the validation data. Once the error no longer improves on the validation set, the training stops. This prevents the neural network from overfitting (https://en.wikipedia.org/wiki/Overfitting).

```
import pandas as pd
import io
import requests
import numpy as np
from sklearn import metrics
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.callbacks import EarlyStopping

url="https://raw.githubusercontent.com/jeffheaton/t81_!
df=pd.read_csv(io.StringIO(requests.get(url).content.de

species = encode_text_index(df,"species")
x,y = to_xy(df,"species")

# Split into train/test
x_train, x_test, y_train, y_test = train_test_split(
    x, y, test_size=0.25, random_state=45)

model = Sequential()
model.add(Dense(10, input_dim=x.shape[1], kernel_initia
model.add(Dense(1, kernel_initializer='normal'))
model.add(Dense(y.shape[1],activation='softmax'))
model.compile(loss='categorical_crossentropy', optimize

monitor = EarlyStopping(monitor='val_loss', min_delta=1

model.fit(x,y,validation_data=(x_test,y_test),callbacks
```

```
Train on 150 samples, validate on 38 samples
Epoch 1/1000
0s - loss: 1.1095 - val_loss: 1.1143
Epoch 2/1000
0s - loss: 1.1065 - val_loss: 1.1096
Epoch 3/1000
0s - loss: 1.1041 - val_loss: 1.1057
Epoch 4/1000
0s - loss: 1.1020 - val_loss: 1.1038
Epoch 5/1000
0s - loss: 1.1011 - val_loss: 1.1017

...

Epoch 325/1000
0s - loss: 0.1758 - val_loss: 0.1320
Epoch 326/1000
0s - loss: 0.1755 - val_loss: 0.1332
Epoch 00325: early stopping
<keras.callbacks.History at 0x222a9242d68>
```

Show the predictions (raw, probability of each class.)

```
# Print out the raw predictions. Because there are 3 spe
# the probability that the flower is that type of iris.

np.set_printoptions(suppress=True)
pred = model.predict(x_test)
print(pred[0:10])
```

```
[[ 0.97540218  0.0245978   0.        ]
 [ 0.94149685  0.05850318  0.        ]
 [ 0.02133332  0.27963796  0.69902873]
 [ 0.94382465  0.05617536  0.        ]
 [ 0.95254719  0.04745276  0.        ]
 [ 0.95966363  0.04033642  0.        ]
 [ 0.94291645  0.05708356  0.        ]
 [ 0.00293462  0.06093681  0.93612856]
 [ 0.00873046  0.14257514  0.84869444]
 [ 0.00293431  0.0609317   0.93613404]]
```

```
# The to_xy function represented the input in the same w
# of iris.  This is the training data, we KNOW what type
# is 1.0 (hot)

print(y_test[0:10])
```

```
[[ 1.  0.  0.]
 [ 1.  0.  0.]
 [ 0.  0.  1.]
 [ 1.  0.  0.]
 [ 1.  0.  0.]
 [ 1.  0.  0.]
 [ 1.  0.  0.]
 [ 0.  0.  1.]
 [ 0.  0.  1.]
 [ 0.  0.  1.]]
```

```
from sklearn.metrics import log_loss

# Using the predictions (pred) and the known 1-hot encoc
# The lower a log loss the better.  The probabilities (p
# is of its prediction.  Log loss error pubishes the neu
# classifications.
print(log_loss(y_test,pred))
```

```
0.133210815783
```

```
# Usually the column (pred) with the highest prediction
# to convert the predictions to the expected iris specie
# for each row.

predict_classes = np.argmax(pred,axis=1)
expected_classes = np.argmax(y_test,axis=1)

print("Predictions: {}".format(predict_classes))
print("Expected: {}".format(expected_classes))
```

```

Predictions: [0 0 2 0 0 0 0 2 2 2 0 2 2 2 2 0 2 2 0 1 1
 0]
Expected: [0 0 2 0 0 0 0 2 2 2 0 2 2 2 2 0 2 2 0 1 1 1 2
 0]

```

```
# Of course it is very easy to turn these indexes back 

print(species[predict_classes[1:10]])
```

```
['Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-set
 'Iris-setosa' 'Iris-virginica' 'Iris-virginica' 'Iris-
```

```
from sklearn.metrics import accuracy_score

# Accuracy might be a more easily understood error metr
# what percent were correct?  The downside is it does n

correct = accuracy_score(expected_classes,predict_class
print("Accuracy: {}".format(correct))
```

```
Accuracy: 1.0
```

Deeper Networks

Keras makes it easy to add addition layers as shown here:

```
import pandas as pd
import io
import requests
import numpy as np
from sklearn import metrics
```

```
from keras.callbacks import EarlyStopping
from keras.layers import Dense, Dropout
from keras import regularizers

url="https://raw.githubusercontent.com/jeffheaton/t81_5
df=pd.read_csv(io.StringIO(requests.get(url).content.de

cars = df['name']
df.drop('name',1,inplace=True)
missing_median(df, 'horsepower')
x,y = to_xy(df,"mpg")

# Split into train/test
x_train, x_test, y_train, y_test = train_test_split(
    x, y, test_size=0.25, random_state=45)


model = Sequential()
model.add(Dense(50, input_dim=x.shape[1], kernel_initia
model.add(Dropout(0.2))
model.add(Dense(25, input_dim=x.shape[1], kernel_initia
model.add(Dense(10, input_dim=64,
                kernel_regularizer=regularizers.l2(0.01
                activity_regularizer=regularizers.l1(0
model.add(Dense(1, kernel_initializer='normal'))
model.compile(loss='mean_squared_error', optimizer='ada

monitor = EarlyStopping(monitor='val_loss', min_delta=1

model.fit(x,y,validation_data=(x_test,y_test),callbacks
pred = model.predict(x_test)

```

```
# Measure RMSE error.  RMSE is common for regression.
score = np.sqrt(metrics.mean_squared_error(pred,y_test
print("Final score (RMSE): {}".format(score))
```

```
Epoch 00064: early stopping
Final score (RMSE): 4.421816825866699
```

The Classic MNIST Dataset

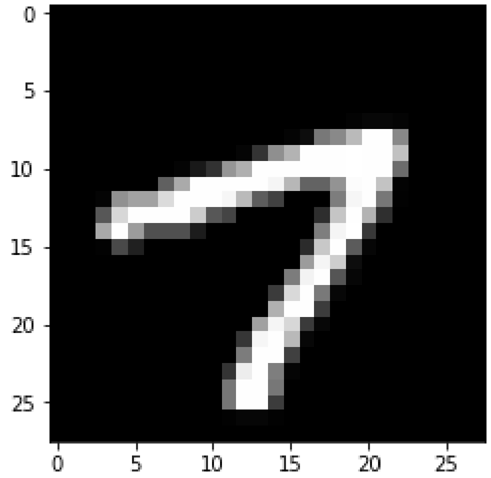
The next examples will use the MNIST digits dataset (http://yann.lecun.com/exdb/mnist/). The previous examples used CSV files to load training data. Most neural network frameworks, such as Keras, have common training sets built in. This makes it easy to run the example, but hard to abstract the example to your own data. Your on data are not likely built into Keras. However, the MNIST data is complex enough that it is beyond the scope of this article to discuss how to load it. We will use the MNIST data build into Keras.

```
from keras.datasets import mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data(

print("Shape of x_train: {}".format(x_train.shape))
print("Shape of y_train: {}".format(y_train.shape))
print()
print("Shape of x_test: {}".format(x_test.shape))
print("Shape of y_test: {}".format(y_test.shape))
```

```
Shape of x_train: (60000, 28, 28)
Shape of y_train: (60000,)

Shape of x_test: (10000, 28, 28)
Shape of y_test: (10000,)
```

```
# Display as image
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np

digit = 101 # Change to choose new digit

a = x_train[digit]
plt.imshow(a, cmap='gray', interpolation='nearest')
print("Image (#{}): Which is digit '{}'".format(digit,y
```

```
Image (#101): Which is digit '7'
```



Convolutional Neural Networks

Convolutional Neural Networks are specifically for images. They have been applied to other cases; however, use beyond images is somewhat rarer than with images.

```
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K

batch_size = 128
num_classes = 10
epochs = 12

# input image dimensions
```

```
img_rows, img_cols = 28, 28

if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_
    x_test = x_test.reshape(x_test.shape[0], 1, img_ro
    input_shape = (1, img_rows, img_cols)
else:
    x_train = x_train.reshape(x_train.shape[0], img_ro
    x_test = x_test.reshape(x_test.shape[0], img_rows,
    input_shape = (img_rows, img_cols, 1)

x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255
print('x_train shape:', x_train.shape)
print("Training samples: {}".format(x_train.shape[0]))
print("Test samples: {}".format(x_test.shape[0]))

# convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, num_clas
y_test = keras.utils.to_categorical(y_test, num_classe

model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=input_shape))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
```

```
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentro
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=2,
          validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss: {}'.format(score[0]))
print('Test accuracy: {}'.format(score[1]))
```

```
x_train shape: (60000, 28, 28, 1)
Training samples: 60000
Test samples: 10000
Train on 60000 samples, validate on 10000 samples
Epoch 1/12
271s - loss: 0.3435 - acc: 0.8950 - val_loss: 0.0817 -
Epoch 2/12
269s - loss: 0.1171 - acc: 0.9660 - val_loss: 0.0581 -
Epoch 3/12
458s - loss: 0.0885 - acc: 0.9742 - val_loss: 0.0453 -
Epoch 4/12
554s - loss: 0.0743 - acc: 0.9778 - val_loss: 0.0382 -
Epoch 5/12
261s - loss: 0.0642 - acc: 0.9810 - val_loss: 0.0346 -
Epoch 6/12
321s - loss: 0.0594 - acc: 0.9826 - val_loss: 0.0337 -
Epoch 7/12
309s - loss: 0.0515 - acc: 0.9846 - val_loss: 0.0335 -
Epoch 8/12
317s - loss: 0.0477 - acc: 0.9857 - val_loss: 0.0337 -
Epoch 9/12
308s - loss: 0.0448 - acc: 0.9870 - val_loss: 0.0330 -
Epoch 10/12
322s - loss: 0.0416 - acc: 0.9873 - val_loss: 0.0307 -
Epoch 11/12
326s - loss: 0.0394 - acc: 0.9879 - val_loss: 0.0300 -
Epoch 12/12
313s - loss: 0.0367 - acc: 0.9887 - val_loss: 0.0313 -
Test loss: 0.03131893762472173
Test accuracy: 0.9902
```

Long Short Term Memory (LSTM)

Long Short Term Memory is typically used for either time series or natural language processing (which can be thought of as a special case of natural language processing).

```
from keras.preprocessing import sequence
from keras.models import Sequential
from keras.layers import Dense, Embedding
from keras.layers import LSTM
from keras.datasets import imdb
import numpy as np

max_features = 4 # 0,1,2,3 (total of 4)
x = [
    [[0],[1],[1],[0],[0],[0]],
    [[0],[0],[0],[2],[2],[0]],
    [[0],[0],[0],[0],[3],[3]],
    [[0],[2],[2],[0],[0],[0]],
    [[0],[0],[3],[3],[0],[0]],
    [[0],[0],[0],[0],[1],[1]]
]
x = np.array(x,dtype=np.float32)
y = np.array([1,2,3,2,3,1],dtype=np.int32)

# Convert y2 to dummy variables
y2 = np.zeros((y.shape[0], max_features),dtype=np.floa
y2[np.arange(y.shape[0]), y] = 1.0
print(y2)

print('Build model...')
```

```
model = Sequential()
model.add(LSTM(128, dropout=0.2, recurrent_dropout=0.2,
model.add(Dense(4, activation='sigmoid'))

# try using different optimizers and different optimiz
model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])

print('Train...')
model.fit(x,y2,epochs=200)
pred = model.predict(x)
predict_classes = np.argmax(pred,axis=1)
print("Predicted classes: {}",predict_classes)
print("Expected classes: {}",predict_classes)
```

```
[[ 0.  1.  0.  0.]
 [ 0.  0.  1.  0.]
 [ 0.  0.  0.  1.]
 [ 0.  0.  1.  0.]
 [ 0.  0.  0.  1.]
 [ 0.  1.  0.  0.]]
Build model...


c:\users\jeffh\anaconda3\envs\tf-latest\lib\site-packa
c:\users\jeffh\anaconda3\envs\tf-latest\lib\site-packa


Train...
```

```
Epoch 1/200
6/6 [==============================] - 2s - loss: 0.70
Epoch 2/200
6/6 [==============================] - 0s - loss: 0.70
Epoch 3/200
6/6 [==============================] - 0s - loss: 0.68
Epoch 4/200
6/6 [==============================] - 0s - loss: 0.68
Epoch 5/200
6/6 [==============================] - 0s - loss: 0.67

...

Epoch 198/200
6/6 [==============================] - 0s - loss: 0.22
Epoch 199/200
6/6 [==============================] - 0s - loss: 0.29
Epoch 200/200
6/6 [==============================] - 0s - loss: 0.19
Predicted classes: {} [1 2 3 2 3 1]
Expected classes: {} [1 2 3 2 3 1]
```

Load/Save a Neural Network

It is very important to be able to load and save neural networks. This allows your neural network to be used each time without retraining.

```
import pandas as pd
import io
import requests
import numpy as np
from sklearn import metrics
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.models import load_model

url="https://raw.githubusercontent.com/jeffheaton/t81_!
df=pd.read_csv(io.StringIO(requests.get(url).content.de

cars = df['name']
df.drop('name',1,inplace=True)
missing_median(df, 'horsepower')
x,y = to_xy(df,"mpg")

model = Sequential()
model.add(Dense(10, input_dim=x.shape[1], kernel_initia
model.add(Dense(1, kernel_initializer='normal'))
model.compile(loss='mean_squared_error', optimizer='ada

model.fit(x,y,verbose=2,epochs=100)
```

```
Epoch 1/100
0s - loss: 188.3123
Epoch 2/100
0s - loss: 180.3333
Epoch 3/100
0s - loss: 177.1118
Epoch 4/100
0s - loss: 173.3682
Epoch 5/100
0s - loss: 167.0144

...

Epoch 98/100
0s - loss: 11.2297
Epoch 99/100
0s - loss: 11.0280
Epoch 100/100
0s - loss: 10.9314
```

```
pred = model.predict(x)

# Measure RMSE error.  RMSE is common for regression.
score = np.sqrt(metrics.mean_squared_error(pred,y))
print("Before save score (RMSE): {}".format(score))

# save neural network structure to JSON (no weights)
model_json = model.to_json()
with open("network.json", "w") as json_file:
    json_file.write(model_json)

# save neural network structure to YAML (no weights)
model_yaml = model.to_yaml()
with open("network.yaml", "w") as yaml_file:
    yaml_file.write(model_yaml)

# save entire network to HDF5 (save everything, sugges
model.save("network.h5")
```

```
Before save score (RMSE): 3.276093006134033
```

```
from keras.models import load_model

model2 = load_model('network.h5')

# Measure RMSE error.  RMSE is common for regression.
score = np.sqrt(metrics.mean_squared_error(pred,y))
print("After load score (RMSE): {}".format(score))
```