Lab 5

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In [7]:

```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib
import xgboost as xgb
from xgboost.sklearn import XGBClassifier
from xgboost.sklearn import XGBRegressor
import sklearn
from sklearn import model_selection
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.model_selection import StratifiedKFold
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import Imputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import StratifiedKFold
from sklearn.grid_search import GridSearchCV
import statsmodels.api as sm
from scipy import stats

import matplotlib.pyplot as plt
from scipy.stats import skew
from scipy.stats.stats import pearsonr


%config InlineBackend.figure_format = 'retina' #set 'png' here when working on notebook
%matplotlib inline
```

Q1

In [25]:

```
train = pd.read_csv("cs-training.csv")
test = pd.read_csv("cs-test.csv")
```

In [27]:

```
if (train.isnull() is True):
    print ("missing value")
else:
    print ("no missing value")

train.head()
```

```
no missing value
```

Out[27]:

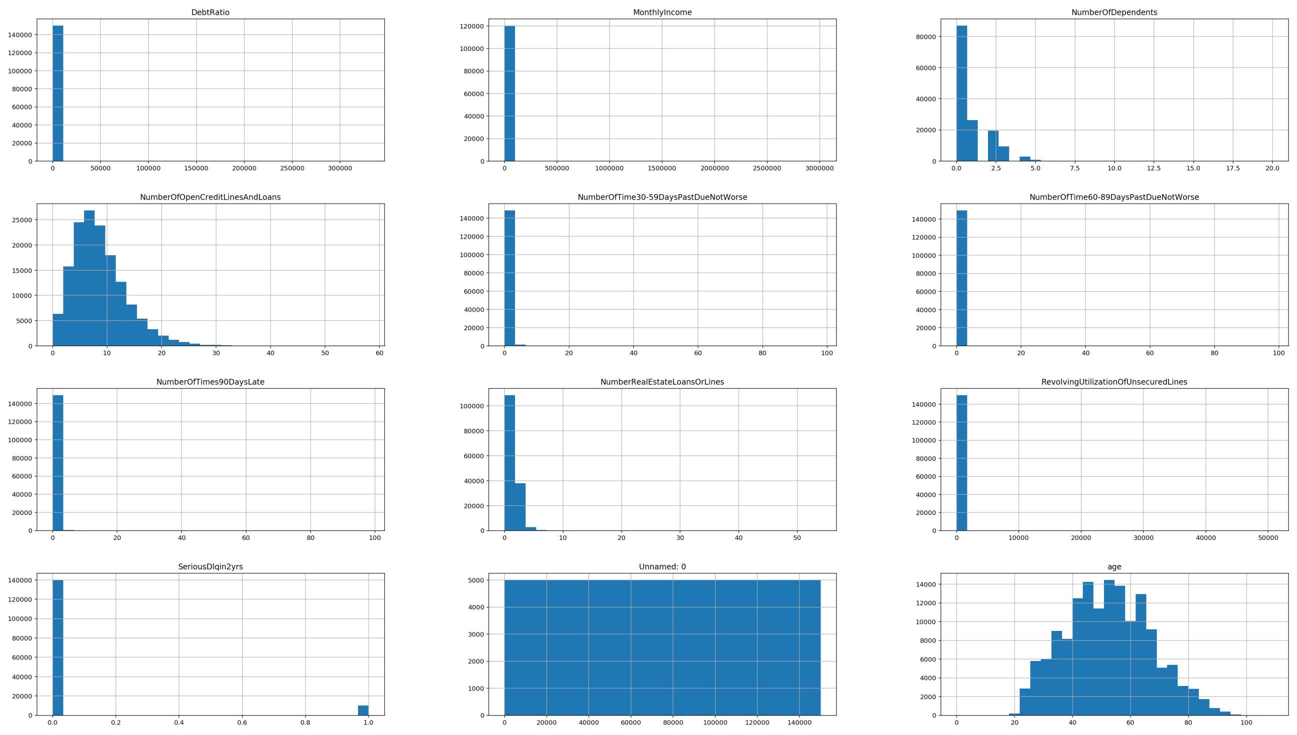
	Unnamed: 0	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio
0	1	1	0.766127	45	2	0.802982
1	2	0	0.957151	40	0	0.121876
2	3	0	0.658180	38	1	0.085113
3	4	0	0.233810	30	0	0.036050
4	5	0	0.907239	49	1	0.024926

In [9]:

```
#Display all histograms to see data distributions for each features
matplotlib.rcParams['figure.figsize'] = (35.0, 20.0)
train.hist(bins = 30, figsize = (35.0, 20.0))
```

Out[9]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x110ce13d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x110c17890>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x10a02bc90>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x10a0608d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x10a098690>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1113db750>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x111411910>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x111447ad0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x11147cc90>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x11167ae50>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1116bd050>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1116f4210>]], dtype=object)
```



1.0

In [54]:

```
train_df = pd.read_csv('cs-training.csv')
Y = train_df['SeriousDlqin2yrs'].values
X = train_df.drop(['SeriousDlqin2yrs', 'Unnamed: 0'], axis=1)
test_df = pd.read_csv('cs-test.csv')
test = test_df.drop(['Unnamed: 0','SeriousDlqin2yrs'], axis=1)
# A parameter grid for XGBoost
params = {
        'min_child_weight': [1, 5, 10],
        'gamma': [0.1, 0.2, 0.3, 0.4, 0.5],
        'subsample': [0.5, 0.7, 0.9],
        'colsample_bytree': [0.6, 0.8, 1.0],
        'max_depth': [4, 5, 6]
        }


xgb = XGBClassifier(learning_rate=0.1, n_estimators=1000, objective='binary:logistic',
                    silent=True, nthread=1)

folds = 4
param_comb = 6

skf = StratifiedKFold(n_splits=folds, shuffle = True, random_state = 1001)

random_search = RandomizedSearchCV(xgb, param_distributions=params, n_iter=param_comb, scoring='roc_auc', n_
jobs=4, cv=skf.split(X,Y), verbose=3, random_state=1001 )

random_search.fit(X, Y)

y_test = random_search.predict_proba(test)
results_df = pd.DataFrame(data={'Id':test_df['Unnamed: 0'], 'Probability':y_test[:,1]})
results_df.to_csv('xgbclassifier.csv', index=False)
```

```
Fitting 4 folds for each of 6 candidates, totalling 24 fits
[CV] subsample=0.9, colsample_bytree=1.0, max_depth=4, gamma=0.5, min_child_weight=5
[CV] subsample=0.9, colsample_bytree=1.0, max_depth=4, gamma=0.5, min_child_weight=5
[CV] subsample=0.9, colsample_bytree=1.0, max_depth=4, gamma=0.5, min_child_weight=5
[CV] subsample=0.9, colsample_bytree=1.0, max_depth=4, gamma=0.5, min_child_weight=5
[CV]  subsample=0.9, colsample_bytree=1.0, max_depth=4, gamma=0.5, min_child_weight=5, score=0.
855025526172, total= 1.7min
[CV]  subsample=0.9, colsample_bytree=1.0, max_depth=4, gamma=0.5, min_child_weight=5, score=0.
855865871952, total= 1.7min
[CV] subsample=0.5, colsample_bytree=0.8, max_depth=6, gamma=0.3, min_child_weight=1
[CV] subsample=0.5, colsample_bytree=0.8, max_depth=6, gamma=0.3, min_child_weight=1
[CV]  subsample=0.9, colsample_bytree=1.0, max_depth=4, gamma=0.5, min_child_weight=5, score=0.
862335806575, total= 1.7min
[CV] subsample=0.5, colsample_bytree=0.8, max_depth=6, gamma=0.3, min_child_weight=1
[CV]  subsample=0.9, colsample_bytree=1.0, max_depth=4, gamma=0.5, min_child_weight=5, score=0.
863319049627, total= 1.7min
[CV] subsample=0.5, colsample_bytree=0.8, max_depth=6, gamma=0.3, min_child_weight=1
[CV]  subsample=0.5, colsample_bytree=0.8, max_depth=6, gamma=0.3, min_child_weight=1, score=0.
837596479871, total= 2.1min
[CV] subsample=0.7, colsample_bytree=0.8, max_depth=6, gamma=0.2, min_child_weight=5
[CV]  subsample=0.5, colsample_bytree=0.8, max_depth=6, gamma=0.3, min_child_weight=1, score=0.
845069315995, total= 2.1min
[CV] subsample=0.7, colsample_bytree=0.8, max_depth=6, gamma=0.2, min_child_weight=5
[CV]  subsample=0.5, colsample_bytree=0.8, max_depth=6, gamma=0.3, min_child_weight=1, score=0.
840167015696, total= 2.1min
[CV] subsample=0.7, colsample_bytree=0.8, max_depth=6, gamma=0.2, min_child_weight=5
[CV]  subsample=0.5, colsample_bytree=0.8, max_depth=6, gamma=0.3, min_child_weight=1, score=0.
844031661195, total= 2.1min
[CV] subsample=0.7, colsample_bytree=0.8, max_depth=6, gamma=0.2, min_child_weight=5
[CV]  subsample=0.7, colsample_bytree=0.8, max_depth=6, gamma=0.2, min_child_weight=5, score=0.
850601878442, total= 2.4min
[CV] subsample=0.9, colsample_bytree=0.6, max_depth=6, gamma=0.5, min_child_weight=5
[CV]  subsample=0.7, colsample_bytree=0.8, max_depth=6, gamma=0.2, min_child_weight=5, score=0.
845303385418, total= 2.4min
[CV] subsample=0.9, colsample_bytree=0.6, max_depth=6, gamma=0.5, min_child_weight=5
[CV]  subsample=0.7, colsample_bytree=0.8, max_depth=6, gamma=0.2, min_child_weight=5, score=0.
844188310224, total= 2.4min
[CV] subsample=0.9, colsample_bytree=0.6, max_depth=6, gamma=0.5, min_child_weight=5
[CV]  subsample=0.7, colsample_bytree=0.8, max_depth=6, gamma=0.2, min_child_weight=5, score=0.
851680198085, total= 2.4min
[CV] subsample=0.9, colsample_bytree=0.6, max_depth=6, gamma=0.5, min_child_weight=5
[CV]  subsample=0.9, colsample_bytree=0.6, max_depth=6, gamma=0.5, min_child_weight=5, score=0.
848557085825, total= 2.0min
[CV] subsample=0.7, colsample_bytree=1.0, max_depth=5, gamma=0.2, min_child_weight=1
[CV]  subsample=0.9, colsample_bytree=0.6, max_depth=6, gamma=0.5, min_child_weight=5, score=0.
856837671262, total= 2.0min
[CV] subsample=0.7, colsample_bytree=1.0, max_depth=5, gamma=0.2, min_child_weight=1
[CV]  subsample=0.9, colsample_bytree=0.6, max_depth=6, gamma=0.5, min_child_weight=5, score=0.
849981325649, total= 2.0min
[CV] subsample=0.7, colsample_bytree=1.0, max_depth=5, gamma=0.2, min_child_weight=1
[CV]  subsample=0.9, colsample_bytree=0.6, max_depth=6, gamma=0.5, min_child_weight=5, score=0.
855209828877, total= 2.0min
[CV] subsample=0.7, colsample_bytree=1.0, max_depth=5, gamma=0.2, min_child_weight=1
[CV]  subsample=0.7, colsample_bytree=1.0, max_depth=5, gamma=0.2, min_child_weight=1, score=0.
847615981989, total= 2.3min
[CV] subsample=0.9, colsample_bytree=0.6, max_depth=5, gamma=0.3, min_child_weight=10
[CV]  subsample=0.7, colsample_bytree=1.0, max_depth=5, gamma=0.2, min_child_weight=1, score=0.
856154140416, total= 2.3min
[CV] subsample=0.9, colsample_bytree=0.6, max_depth=5, gamma=0.3, min_child_weight=10
[CV]  subsample=0.7, colsample_bytree=1.0, max_depth=5, gamma=0.2, min_child_weight=1, score=0.
84816048812, total= 2.3min
[CV] subsample=0.9, colsample_bytree=0.6, max_depth=5, gamma=0.3, min_child_weight=10
[CV]  subsample=0.7, colsample_bytree=1.0, max_depth=5, gamma=0.2, min_child_weight=1, score=0.
854891865387, total= 2.2min
[CV] subsample=0.9, colsample_bytree=0.6, max_depth=5, gamma=0.3, min_child_weight=10
[CV]  subsample=0.9, colsample_bytree=0.6, max_depth=5, gamma=0.3, min_child_weight=10, score=0
.852729525985, total= 1.5min
[CV]  subsample=0.9, colsample_bytree=0.6, max_depth=5, gamma=0.3, min_child_weight=10, score=0
.853641443667, total= 1.5min
[CV]  subsample=0.9, colsample_bytree=0.6, max_depth=5, gamma=0.3, min_child_weight=10, score=0
.861493316791, total= 1.5min
[CV]  subsample=0.9, colsample_bytree=0.6, max_depth=5, gamma=0.3, min_child_weight=10, score=0
.861299263615, total= 1.5min

[Parallel(n_jobs=4)]: Done  24 out of  24 | elapsed: 12.9min finished
```

Since we are classifying if someone is a high-risk individual, the XGBClassifier will be a good model that fits this problem. We ran a standard XGBClassifier with StratifiedKFold and submit the result to Kaggle, resulting a private score of 0.863163.

1.1

In [28]:

```
#Simple Model such as XGBClassifier
xgb = xgb.fit(X,Y)

#No extra on MonthlyIncome
preds_0 = xgb.predict_proba(test)[:,1]
print("Probability of delinquency with no extra MonthlyIncome is: %0.5f" %preds_0.mean())

#$1000 extra on MonthlyIncome
test.MonthlyIncome = test.MonthlyIncome + 1000
preds_1000 = xgb.predict_proba(test)[:,1]
print("Probability of delinquency with $1000 extra MonthlyIncome is: %0.5f" %preds_1000.mean())

#$2000 extra on MonthlyIncome
test.MonthlyIncome = test.MonthlyIncome + 1000
preds_2000 = xgb.predict_proba(test)[:,1]
print("Probability of delinquency with $2000 extra MonthlyIncome is: %0.5f" %preds_2000.mean())

#$3000 extra on MonthlyIncome
test.MonthlyIncome = test.MonthlyIncome + 1000
preds_3000 = xgb.predict_proba(test)[:,1]
print("Probability of delinquency with $3000 extra MonthlyIncome is: %0.5f" %preds_3000.mean())
```

```
Probability of delinquency with no extra MonthlyIncome is: 0.06236
Probability of delinquency with $1000 extra MonthlyIncome is: 0.06162
Probability of delinquency with $2000 extra MonthlyIncome is: 0.06102
Probability of delinquency with $3000 extra MonthlyIncome is: 0.06070
```

From the above result, we can see as the MonthlyIncome increases, the probability of delinquency decreases. Which make sense, higher income is a indication of financial stability, therefore lower the chance of delinquency.

1.2

In [5]:

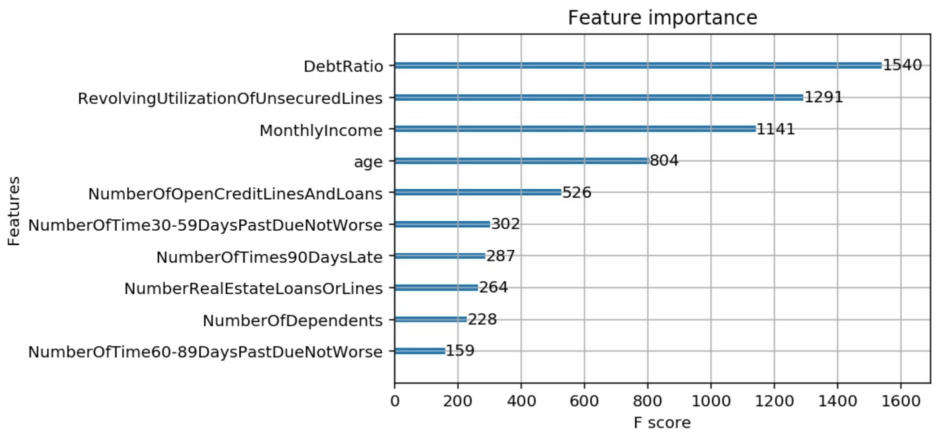
```
train_df = pd.read_csv('cs-training.csv')
Y = train_df['SeriousDlqin2yrs'].values
X = train_df.drop(['SeriousDlqin2yrs', 'Unnamed: 0'], axis=1)
test_df = pd.read_csv('cs-test.csv')
test = test_df.drop(['Unnamed: 0','SeriousDlqin2yrs'], axis=1)
# A parameter grid for XGBoost
params = {
        'min_child_weight': [1, 5, 10],
        'gamma': [0.1, 0.2, 0.3, 0.4, 0.5],
        'subsample': [0.5, 0.7, 0.9],
        'colsample_bytree': [0.6, 0.8, 1.0],
        'max_depth': [4, 5, 6]
        }


xgb_classi = XGBClassifier(learning_rate=0.1, n_estimators=1000, objective='binary:logistic',
                    silent=True, nthread=1)
xgb_classi = xgb_classi.fit(X,Y)
```

In [8]:

```
xgb.plot_importance(xgb_classi)
```

Out[8]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1125c3d50>
```



The most important variable in predicting delinquency is DebtRatio, because it has the highest F-score of 1540. The most important pair of variables would be DebtRatio and RevolvingUtilizationOfUnsecuredLines, they have the two highest F-scores.

1.3

In [13]:

```
#Seperate Under 40 years old and 40 or older

under40 = X[X['age'] < 40]
over40 = X[X['age'] >= 40]

#Predict Probability for both age group
preds_under40 = xgb_classi.predict_proba(under40)[:,1]
print("Probability of delinquency with for people under age 40 is: %0.5f" %preds_under40.mean())
preds_over40 = xgb_classi.predict_proba(over40)[:,1]
print("Probability of delinquency with for people who are 40 or older is: %0.5f" %preds_over40.mean())
```

```
Probability of delinquency with for people under age 40 is: 0.10521
Probability of delinquency with for people who are 40 or older is: 0.05643
```

Base on the probability showing above, our model will predict the people who are age under 40 will have about 5% higher chance of delinquency in 2 yrs compare to those who are 40 or older. And the percentage shows that the model does not discriminate against people of age 40 or older since they have lower probability for being classified as delinquency.

1.4

In [21]:

```
#Seperate group of people based on number dependents

#First Checked unique values in column NumberOfDependents
print train_df.NumberOfDependents.unique()

#Group them based on their number of dependents
depend_0 = X[X['NumberOfDependents'] == 0]
depend_1 = X[X['NumberOfDependents'] == 1]
depend_2 = X[X['NumberOfDependents'] == 2]
depend_3 = X[X['NumberOfDependents'] == 3]
depend_4 = X[X['NumberOfDependents'] == 4]
depend_5 = X[X['NumberOfDependents'] == 5]
depend_6 = X[X['NumberOfDependents'] == 6]
depend_7 = X[X['NumberOfDependents'] == 7]
depend_8 = X[X['NumberOfDependents'] == 8]
depend_9 = X[X['NumberOfDependents'] == 9]
depend_10 = X[X['NumberOfDependents'] == 10]
depend_13 = X[X['NumberOfDependents'] == 13]
depend_20 = X[X['NumberOfDependents'] == 20]
hasDepend = X[X['NumberOfDependents'] != 0]
#Predict probability of Delinquency
preds_depend_0 = xgb_classi.predict_proba(depend_0)[:,1]
print("Probability of delinquency with for people with 0 Dependent is: %0.5f" %preds_depend_0.mean())
preds_depend_1 = xgb_classi.predict_proba(depend_1)[:,1]
print("Probability of delinquency with for people with 1 Dependent is: %0.5f" %preds_depend_1.mean())
preds_depend_2 = xgb_classi.predict_proba(depend_2)[:,1]
print("Probability of delinquency with for people with 2 Dependent is: %0.5f" %preds_depend_2.mean())
preds_depend_3 = xgb_classi.predict_proba(depend_3)[:,1]
print("Probability of delinquency with for people with 3 Dependent is: %0.5f" %preds_depend_3.mean())
preds_depend_4 = xgb_classi.predict_proba(depend_4)[:,1]
print("Probability of delinquency with for people with 4 Dependent is: %0.5f" %preds_depend_4.mean())
preds_depend_5 = xgb_classi.predict_proba(depend_5)[:,1]
print("Probability of delinquency with for people with 5 Dependent is: %0.5f" %preds_depend_5.mean())
preds_depend_6 = xgb_classi.predict_proba(depend_6)[:,1]
print("Probability of delinquency with for people with 6 Dependent is: %0.5f" %preds_depend_6.mean())
preds_depend_7 = xgb_classi.predict_proba(depend_7)[:,1]
print("Probability of delinquency with for people with 7 Dependent is: %0.5f" %preds_depend_7.mean())
preds_depend_8 = xgb_classi.predict_proba(depend_8)[:,1]
print("Probability of delinquency with for people with 8 Dependent is: %0.5f" %preds_depend_8.mean())
preds_depend_9 = xgb_classi.predict_proba(depend_9)[:,1]
print("Probability of delinquency with for people with 9 Dependent is: %0.5f" %preds_depend_9.mean())
preds_depend_10 = xgb_classi.predict_proba(depend_10)[:,1]
print("Probability of delinquency with for people with 10 Dependent is: %0.5f" %preds_depend_10.mean())
preds_depend_13 = xgb_classi.predict_proba(depend_13)[:,1]
print("Probability of delinquency with for people with 13 Dependent is: %0.5f" %preds_depend_13.mean())
preds_depend_20 = xgb_classi.predict_proba(depend_20)[:,1]
print("Probability of delinquency with for people with 20 Dependent is: %0.5f" %preds_depend_20.mean())
preds_hasDepend = xgb_classi.predict_proba(hasDepend)[:,1]
print("Probability of delinquency with for people with any number of Dependents is: %0.5f" %preds_hasDepend.
mean())
```

```
[  2.   1.   0.  nan   3.   4.   5.   6.   8.   7.  20.  10.   9.  13.]
Probability of delinquency with for people with 0 Dependent is: 0.05863
Probability of delinquency with for people with 1 Dependent is: 0.07322
Probability of delinquency with for people with 2 Dependent is: 0.08180
Probability of delinquency with for people with 3 Dependent is: 0.08794
Probability of delinquency with for people with 4 Dependent is: 0.10283
Probability of delinquency with for people with 5 Dependent is: 0.09205
Probability of delinquency with for people with 6 Dependent is: 0.14287
Probability of delinquency with for people with 7 Dependent is: 0.10279
Probability of delinquency with for people with 8 Dependent is: 0.07035
Probability of delinquency with for people with 9 Dependent is: 0.01563
Probability of delinquency with for people with 10 Dependent is: 0.00863
Probability of delinquency with for people with 13 Dependent is: 0.24474
Probability of delinquency with for people with 20 Dependent is: 0.19226
Probability of delinquency with for people with any number of Dependents is: 0.07814
```

From the above probabilities for each group with different number of dependents, we can see a trend of higher probibility of delinquency when number of dependents is higher. But some cases like 4,8,10,20 do not prove the theory of increasing trend. This is probably due to low number of Ids that have 4,8,10 or 20 dependents, so the probility is not accurate. Therefore I group all the people that have dependents together, getting probibility of 0.07814, which is around 2% higher than the people who do not have dependents. The data shows people with no dependents is less likely to be classified with delinquency with people who have dependents. Next we will calculate the p-value to express confidency.

In [85]:

```
t,prob= stats.ttest_ind(preds_depend_0,preds_hasDepend, equal_var=False)
print("p-value is: ")
print(prob)
```

```
p-value is:
2.09589914066e-199
```

From the calculated p-value, we can see that the p-value is smaller than 0.05, which indicates strong evidence against the null hypothesis, so we reject the null hypothesis.

Q2

Q2.A

Let X be a uniform distribution between (−1,1).

Let Y=X^2.

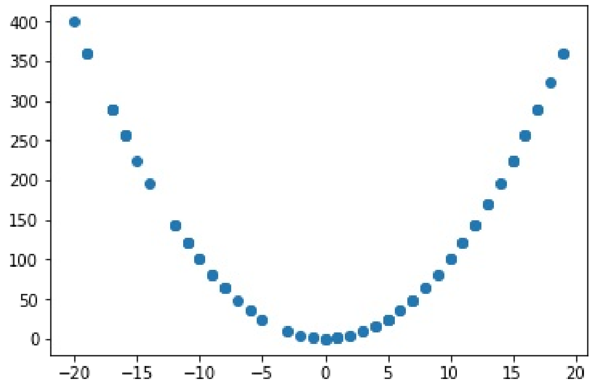
These two variables are uncorrelated but dependent. The covariance of X and Y is zero, and therefore both random variables are uncorrelated.

However, you can see the variable Y is clearly dependent on the values of X, so they are dependent.

Q2.B

In [68]:

```
##Part B

import numpy as np
import matplotlib.pyplot as plt
import random
import sklearn.linear_model

x = np.random.randint(-20,20,100)

z= np.random.randint(0,2,100)

y= (x**2)
x2= np.array(x)
z2=np.array(z)
y=np.array(y)

plt.scatter(x, y)
plt.show()

x=x.reshape(-1,1)
y=y.reshape(-1,1)

reg = LinearRegression()
reg.fit(x, y)
print(reg.coef_)
```



```
[[-0.64667709]]
```

Q3. a) Tensorflow/Keras tutorial

In [1]:

```
# TensorFlow and tf.keras
import tensorflow as tf
from tensorflow import keras

# Helper libraries
import numpy as np
import matplotlib.pyplot as plt

print(tf.__version__)
```

```
1.12.0
```

Import fashion MNIST dataset

In [2]:

```
fashion_mnist = keras.datasets.fashion_mnist

(train_images, train_labels), (test_images, test_labels) = fashion_mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-
idx1-ubyte.gz
32768/29515 [=================================] - 0s 2us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-
idx3-ubyte.gz
26427392/26421880 [==============================] - 5s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-i
dx1-ubyte.gz
8192/5148 [===============================================] - 0s 1us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-i
dx3-ubyte.gz
4423680/4422102 [==============================] - 2s 1us/step
```

Explore the features

In [3]:

```
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']
```

In [4]:

```
train_images.shape
```

Out[4]:

```
(60000, 28, 28)
```

In [6]:

```
len(train_labels)
```

Out[6]:

```
60000
```

In [7]:

```
train_labels
```

Out[7]:

```
array([9, 0, 0, ..., 3, 0, 5], dtype=uint8)
```

In [9]:

```
test_images.shape
```

Out[9]:

```
(10000, 28, 28)
```

In [10]:

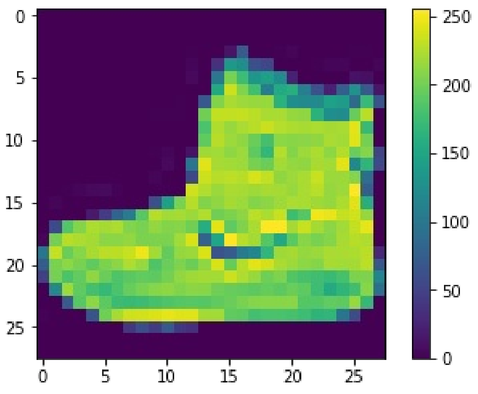
```
len(test_labels)
```

Out[10]:

```
10000
```

In [11]:

```
plt.figure()
plt.imshow(train_images[0])
plt.colorbar()
plt.grid(False)
```



rescale images before running through deep net

In [12]:

```
train_images = train_images / 255.0

test_images = test_images / 255.0
```

In [14]:

```
plt.figure(figsize=(10,10))
for i in range(25):
    plt.subplot(5,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(train_images[i], cmap=plt.cm.binary)
    plt.xlabel(class_names[train_labels[i]])
```

make deep net with three layers:

1) flatten image 2) fully connected layer with relu activation 3) fully connected layer with softmax activation (probabilities)

In [15]:

```
model = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation=tf.nn.relu),
    keras.layers.Dense(10, activation=tf.nn.softmax)
])
```

In [16]:

```
model.compile(optimizer=tf.train.AdamOptimizer(),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Train NN

In [17]:

```
model.fit(train_images, train_labels, epochs=5)
```

```
Epoch 1/5
60000/60000 [==============================] - 4s 60us/step - loss: 0.5032 - acc: 0.8241
Epoch 2/5
60000/60000 [==============================] - 4s 64us/step - loss: 0.3778 - acc: 0.8643
Epoch 3/5
60000/60000 [==============================] - 4s 64us/step - loss: 0.3395 - acc: 0.8779
Epoch 4/5
60000/60000 [==============================] - 3s 57us/step - loss: 0.3126 - acc: 0.8837
Epoch 5/5
60000/60000 [==============================] - 4s 61us/step - loss: 0.2948 - acc: 0.8903
```

Out[17]:

```
<tensorflow.python.keras.callbacks.History at 0x7f89d216dc18>
```

Test loss and accuracy (check for overfitting)

In [18]:

```
test_loss, test_acc = model.evaluate(test_images, test_labels)

print('Test accuracy:', test_acc)
```

```
10000/10000 [==============================] - 0s 30us/step
Test accuracy: 0.8752
```

running predictions

In [19]:

```
predictions = model.predict(test_images)
```

In [20]:

```
predictions[0]
```

Out[20]:

```
array([7.8977209e-06, 2.1013300e-05, 9.7989357e-07, 1.2041208e-05,
       1.6139153e-05, 7.4518453e-03, 9.0912608e-06, 5.5391472e-02,
       1.1348465e-04, 9.3697608e-01], dtype=float32)
```

In [21]:

```
np.argmax(predictions[0])
```

Out[21]:

```
9
```

In [22]:

```
test_labels[0]
```

Out[22]:

```
9
```

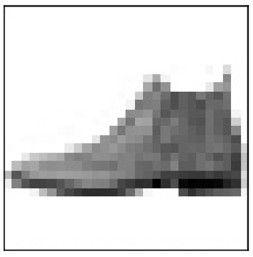
Look at full set of 10 channels

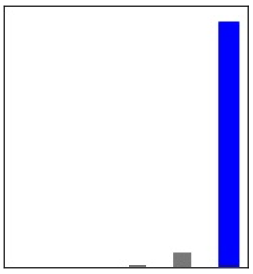
In [24]:

```
def plot_image(i, predictions_array, true_label, img):
  predictions_array, true_label, img = predictions_array[i], true_label[i], img[i]
  plt.grid(False)
  plt.xticks([])
  plt.yticks([])

  plt.imshow(img, cmap=plt.cm.binary)

  predicted_label = np.argmax(predictions_array)
  if predicted_label == true_label:
    color = 'blue'
  else:
    color = 'red'

  plt.xlabel("{} {:2.0f}% ({})".format(class_names[predicted_label],
                                100*np.max(predictions_array),
                                class_names[true_label]),
                                color=color)

def plot_value_array(i, predictions_array, true_label):
  predictions_array, true_label = predictions_array[i], true_label[i]
  plt.grid(False)
  plt.xticks([])
  plt.yticks([])
  thisplot = plt.bar(range(10), predictions_array, color="#777777")
  plt.ylim([0, 1])
  predicted_label = np.argmax(predictions_array)

  thisplot[predicted_label].set_color('red')
  thisplot[true_label].set_color('blue')
```

In [25]:

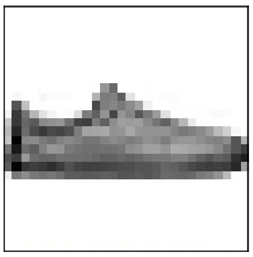
```
i = 0
plt.figure(figsize=(6,3))
plt.subplot(1,2,1)
plot_image(i, predictions, test_labels, test_images)
plt.subplot(1,2,2)
plot_value_array(i, predictions,  test_labels)
```

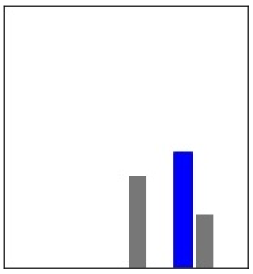

Ankle boot 94% (Ankle boot)



In [26]:

```
i = 12
plt.figure(figsize=(6,3))
plt.subplot(1,2,1)
plot_image(i, predictions, test_labels, test_images)
plt.subplot(1,2,2)
plot_value_array(i, predictions,  test_labels)
```

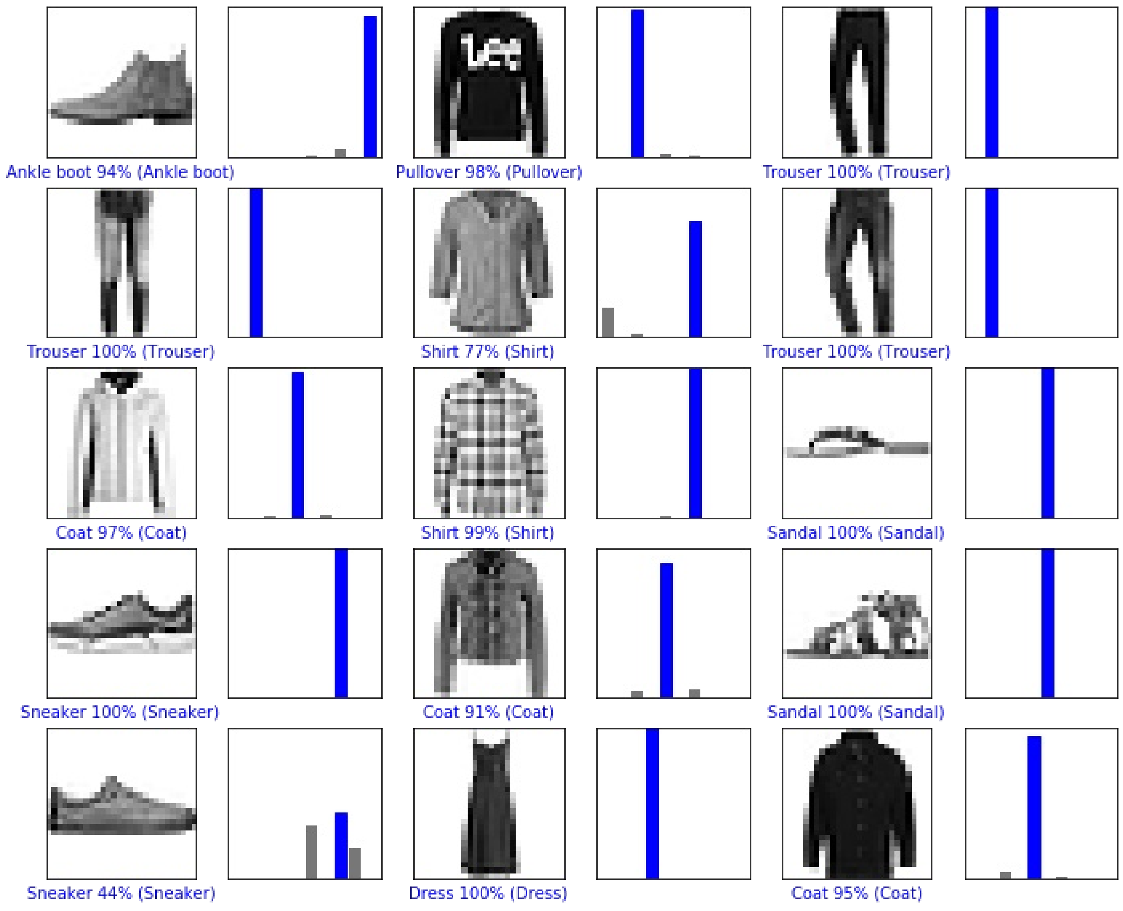

Sneaker 44% (Sneaker)



plot several images with their predictions

In [27]:

```
# Plot the first X test images, their predicted label, and the true label
# Color correct predictions in blue, incorrect predictions in red
num_rows = 5
num_cols = 3
num_images = num_rows*num_cols
plt.figure(figsize=(2*2*num_cols, 2*num_rows))
for i in range(num_images):
  plt.subplot(num_rows, 2*num_cols, 2*i+1)
  plot_image(i, predictions, test_labels, test_images)
  plt.subplot(num_rows, 2*num_cols, 2*i+2)
  plot_value_array(i, predictions, test_labels)
```



Use trained model to make prediction on single image

In [28]:

```
# Grab an image from the test dataset
img = test_images[0]

print(img.shape)
```

```
(28, 28)
```

In [29]:

```
# Add the image to a batch where it's the only member.
img = (np.expand_dims(img,0))

print(img.shape)
```

```
(1, 28, 28)
```

make prediction

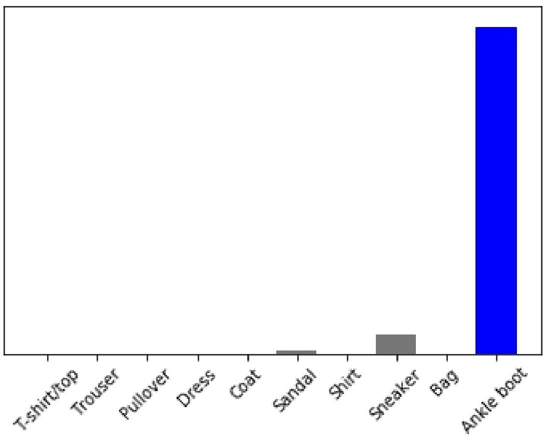
In [30]:

```
predictions_single = model.predict(img)

print(predictions_single)
```

```
[[7.8977364e-06 2.1013320e-05 9.7989459e-07 1.2041196e-05 1.6139122e-05
  7.4518523e-03 9.0912445e-06 5.5391464e-02 1.1348465e-04 9.3697608e-01]]
```

In [31]:

```
plot_value_array(0, predictions_single, test_labels)
_ = plt.xticks(range(10), class_names, rotation=45)
```



In [32]:

```
np.argmax(predictions_single[0])
```

Out[32]:

```
9
```

In [33]:

Q3 b) Image Transformation and prediction

Image Augmentation

In [91]:

```
# select 5 images and transform them
from keras.preprocessing.image import ImageDataGenerator
from keras.preprocessing.image import img_to_array

train_datagen = ImageDataGenerator(
    rotation_range=40,
    width_shift_range=0.5,
    height_shift_range=0.5,
    shear_range=0.5,
    zoom_range=0.5,
    horizontal_flip=True,
    fill_mode='nearest')
```

In [92]:

```
def transformer(img, train_datagen):
    tmp = img
    tmp = (np.expand_dims(tmp,3))
    tmp = (np.expand_dims(tmp,3))
    train_datagen.fit(tmp)
    return (train_datagen.random_transform(np.expand_dims(img,0), seed=None)).reshape(28,28)
```

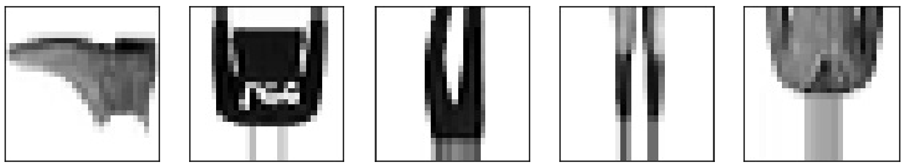
In [94]:

```
transformed = []

for i in range(5):
    transformed.append(transformer(test_images[i], train_datagen))
```

```
/home/daniel/Documents/Fall_2018/DSL/DataScienceLab/.env/lib/python3.5/site-packages/ipykernel_
launcher.py:4: DeprecationWarning: Both axis > a.ndim and axis < -a.ndim - 1 are deprecated and
 will raise an AxisError in the future.
  after removing the cwd from sys.path.
```

In [95]:

```
plt.figure(figsize=(10,10))
for i in range(5):
    plt.subplot(1,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(transformed[i], cmap=plt.cm.binary)
```



prediction on augmented images

In [99]:

```
test_images.shape
```

Out[99]:

```
(10000, 28, 28)
```

In [103]:

```
transformed = np.array(transformed)
transformed.shape
```

Out[103]:

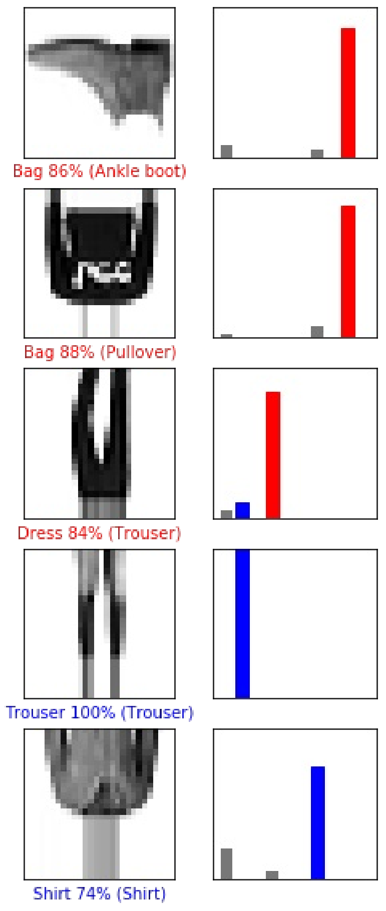
```
(5, 28, 28)
```

In [104]:

```
aug_preds = model.predict(transformed)
```

In [109]:

```
# Plot the 5 images, their predicted label, and the true label
# Color correct predictions in blue, incorrect predictions in red

num_rows = 5
num_cols = 1
num_images = num_rows*num_cols
plt.figure(figsize=(2*2*num_cols, 2*num_rows))
for i in range(num_images):
  plt.subplot(num_rows, 2*num_cols, 2*i+1)
  plot_image(i, aug_preds, test_labels, transformed)
  plt.subplot(num_rows, 2*num_cols, 2*i+2)
  plot_value_array(i, aug_preds, test_labels)
```



In [118]:

```
t_labels = [test_labels[i] for i in range(5)]
t_labels = np.array(t_labels)
t_labels.shape
```

Out[118]:

```
(5,)
```

Observations

In [119]:

```
test_loss, test_acc = model.evaluate(transformed, t_labels)

print('Test accuracy:', test_acc)
```

```
5/5 [==============================] - 0s 498us/step
Test accuracy: 0.4000000059604645
```

For this test, I modified images from the test set because these simulate images that our model has never seen before. If we wanted to improve our classifier, we would perform image augmentation (random transforms) on the training set, so that it will improve its performance on test images.

Q3. c) ImageNet

These are the images I have in my directory that I will run through the Inception classifier.

In [137]:

```
%%bash

cd ~/models/tutorials/image/imagenet
pwd
ls
```

```
/home/daniel/models/tutorials/image/imagenet
BUILD
classify_image.py
deadpool.jpeg
mouwser.jpeg
much_wow.jpeg
```

In [2]:

```
from matplotlib.pyplot import imshow
import numpy as np
from PIL import Image
```

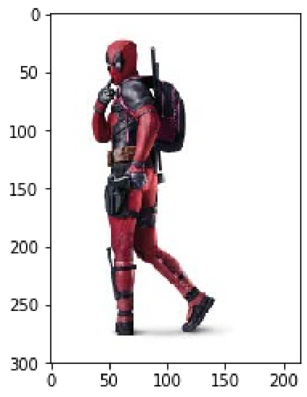
Deadpool Classification

In [155]:

```
deadpool = Image.open('/home/daniel/models/tutorials/image/imagenet/deadpool.jpg', 'r')
imshow(np.asarray(deadpool))
```

Out[155]:

```
<matplotlib.image.AxesImage at 0x7f89d51a7588>
```



In [156]:

```
%%bash

cd ~/models/tutorials/image/imagenet
python classify_image.py --image_file='deadpool.jpg'
```

```
cuirass (score = 0.18074)
breastplate, aegis, egis (score = 0.14944)
parachute, chute (score = 0.09794)
knee pad (score = 0.07775)
ski (score = 0.03096)
```

```
WARNING:tensorflow:From classify_image.py:141: FastGFile.__init__ (from tensorflow.python.platf
orm.gfile) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.gfile.GFile.
2018-11-25 22:26:28.422003: W tensorflow/core/framework/op_def_util.cc:355] Op BatchNormWithGlo
balNormalization is deprecated. It will cease to work in GraphDef version 9. Use tf.nn.batch_no
rmalization().
2018-11-25 22:26:28.562353: I tensorflow/core/platform/cpu_feature_guard.cc:141] Your CPU suppo
rts instructions that this TensorFlow binary was not compiled to use: AVX2 FMA
```

Looks like this classifier has no idea that this is deadpool.

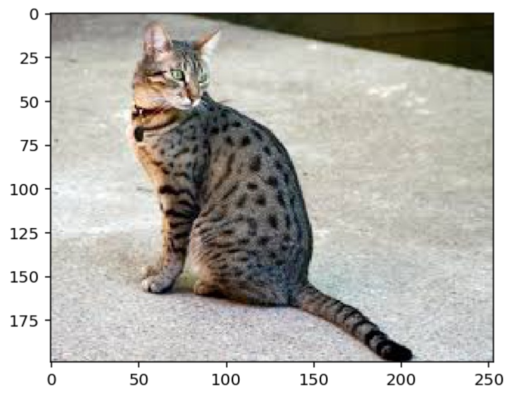
Cat Classification

In [11]:

```
mouwsers = Image.open('/home/daniel/mouwser.jpeg', 'r')
imshow(np.asarray(mouwsers))
```

Out[11]:

```
<matplotlib.image.AxesImage at 0x7f7b48e500f0>
```



In [158]:

```
%%bash

cd ~/models/tutorials/image/imagenet
python classify_image.py --image_file='mouwser.jpg'
```

```
Egyptian cat (score = 0.06883)
washbasin, handbasin, washbowl, lavabo, wash-hand basin (score = 0.05592)
Angora, Angora rabbit (score = 0.03440)
soap dispenser (score = 0.02485)
bath towel (score = 0.02154)
```

```
WARNING:tensorflow:From classify_image.py:141: FastGFile.__init__ (from tensorflow.python.platf
orm.gfile) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.gfile.GFile.
2018-11-25 22:27:39.316990: W tensorflow/core/framework/op_def_util.cc:355] Op BatchNormWithGlo
balNormalization is deprecated. It will cease to work in GraphDef version 9. Use tf.nn.batch_no
rmalization().
2018-11-25 22:27:39.447066: I tensorflow/core/platform/cpu_feature_guard.cc:141] Your CPU suppo
rts instructions that this TensorFlow binary was not compiled to use: AVX2 FMA
```

Highest score that the classifier gave is "Egyptian cat." Personally, I do not know if this cat is Egyptian, but it definitiely is a cat.

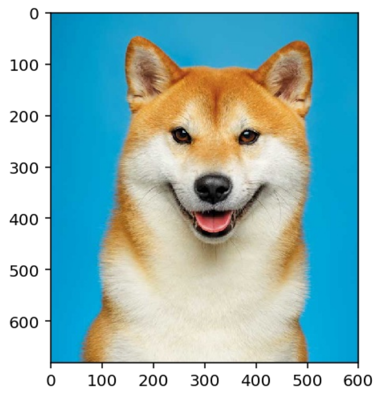
Dog Classification

In [10]:

```
much_wow = Image.open('/home/daniel/much_wow.jpg','r')
imshow(np.asarray(much_wow))
```

Out[10]:

```
<matplotlib.image.AxesImage at 0x7f7b48e873c8>
```



In [159]:

```
%%bash

cd ~/models/tutorials/image/imagenet
python classify_image.py --image_file='much_wow.jpg'
```

```
Pembroke, Pembroke Welsh corgi (score = 0.10619)
screen, CRT screen (score = 0.09168)
television, television system (score = 0.04612)
Norwegian elkhound, elkhound (score = 0.03515)
dingo, warrigal, warragal, Canis dingo (score = 0.02655)
```

```
WARNING:tensorflow:From classify_image.py:141: FastGFile.__init__ (from tensorflow.python.platf
orm.gfile) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.gfile.GFile.
2018-11-25 22:29:57.109948: W tensorflow/core/framework/op_def_util.cc:355] Op BatchNormWithGlo
balNormalization is deprecated. It will cease to work in GraphDef version 9. Use tf.nn.batch_no
rmalization().
2018-11-25 22:29:57.240810: I tensorflow/core/platform/cpu_feature_guard.cc:141] Your CPU suppo
rts instructions that this TensorFlow binary was not compiled to use: AVX2 FMA
```

Looks like the classifier's top guess is that this is a corgi. Indeed, the image is that of a dog. However, the classifier is almost as sure that the image is a dog, as it is sure that it is a TV.

Q4 -- Project Proposal

Prompt: Form the final project teams and make your project proposal. What datasets are you planning to use/collect? What are you planning to do with them?

The team for our final project will consist of the following four members:

- Beathan Andersen (bta383)
- Jerry Yang (jhy395)
- Zhaofeng Liang (zl4685)
- Daniel Diamont (dd28977)

Project: Homebrew and/or Commercial Beer Recipe Cluster Analysis Dataset: https://www.kaggle.com/jtrofe/beer-recipes (https://www.kaggle.com/jtrofe/beer-recipes)

Our objective is to perform analysis on metadata about homebrew and commercial beers to determine key factors that influence consumer ratings of said beers. We hope to scrape data off of beer review websites to augment the Kaggle Brewer's Friends Beer Recipes (https://www.kaggle.com/jtrofe/beer-recipes) dataset in order to obtain labeled data (e.g. style of beer, recipe, and consumer rating). We hope to collect enough data to cluster recipes and customers to gain insights as to the key factors that make beers more successful than others.

In [ ]:

```

```