DataExplore

November 4, 2018

0.1 Project Problem and Hypothesis

- This project is to verify Angela Duckworth's study on "Grit" and attempt to expand on it with other features present in their dataset (http://angeladuckworth.com/). I will also set out to verify current scientific assumptions of the differences between genders and big five personality traits.
  - On average, individuals who are gritty are more self-controlled, but the correlation between these two traits is not perfect: Some individuals are paragons of grit but not self-control, and some exceptionally well-regulated individuals are not especially gritty (Duckworth & Gross, 2014)
  - Feel free to take the test! (http://angeladuckworth.com/grit-scale/) My score was 3.3 (average).
- This dataset has many features and I have the opportunity to try different hypothesis. My main focus will be to predict a "grit" score from personality traits and demographic data.
  - Specifically, Duckworth mentioned on the Freakonomics Podcast, that the big five trait conscientiousness as an existing success factor, and I'd like to see how similar grit and this trait are.
  - We can test some widely accepted personality traits by gender as well.

0.2 Caveats and Wishes

- This data is reflects people that took this online personality test survey. It may be biased toward people who are interested in how gritty they are (potentially people who are already gritty).
- Only users who were willing to share their data for research purposes are present in the data.
- Some things that would make this dataset even better would be the 10 aspects of the big 5, IQ, some sort of success criteria, and political affiliation. Additionally, if all survey takers took the same test a year later, we could find more results.

Neuroticism	Agreeableness	Conscientiousness	Extroversion	Openness/Intellect
Volatility	Compassion	Industriousness	Enthusiasm	Openness
Withdrawal	Politeness	Orderliness	Assertiveness	Intellect

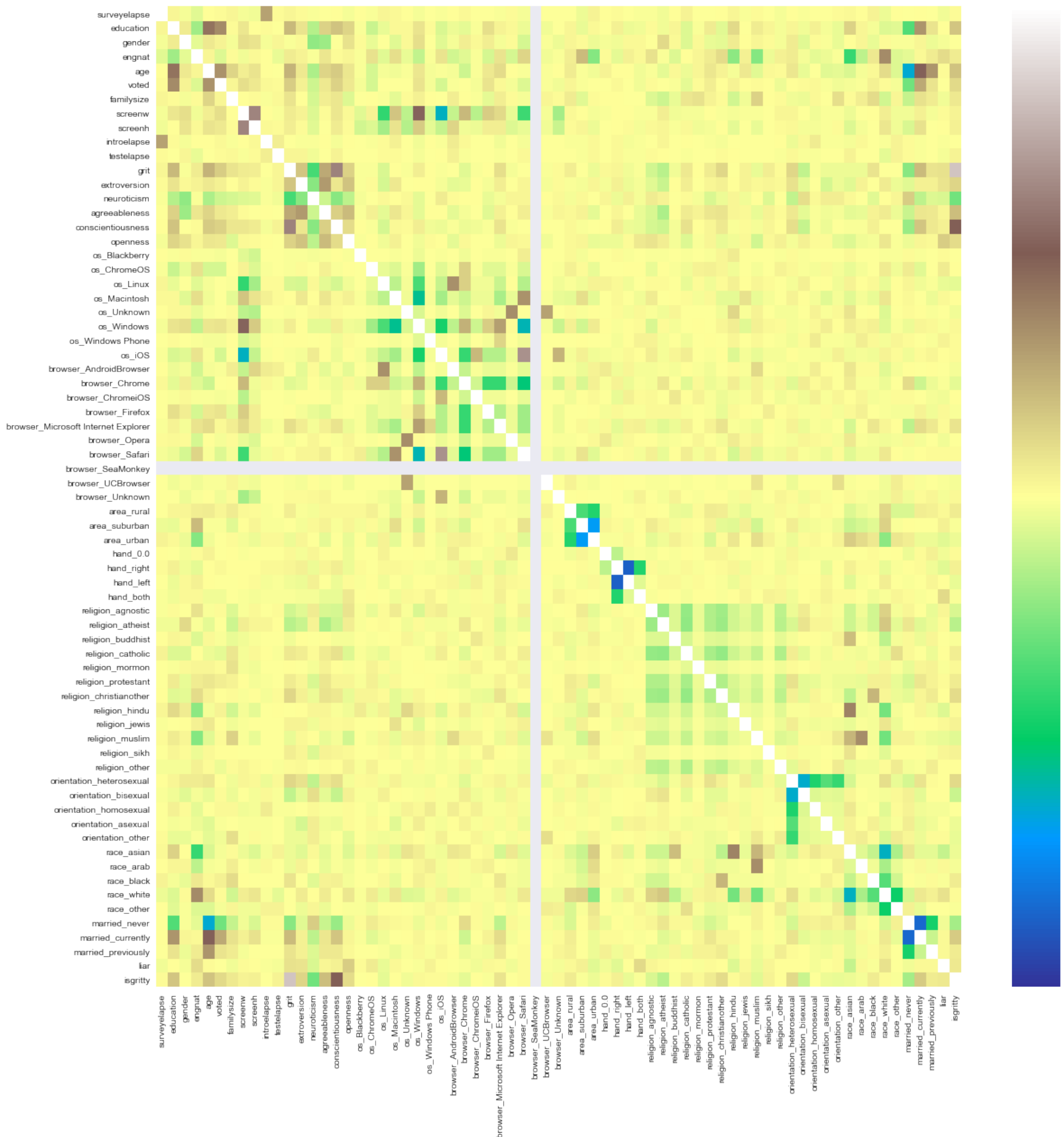
```
In [281]: import pandas as pd
          import seaborn as sns
          import numpy as np
          from matplotlib import pyplot as plt
          %matplotlib inline
```

0.3 Load the data and remove a test set

```
In [282]: full = pd.read_csv("../duckworth-grit-scale-data/cleanData.csv")

In [283]: len(full)

Out[283]: 3958

In [284]: del full['Unnamed: 0']

In [285]: full['isgritty'] = np.where(full['grit'] > 3.0, 1, 0)

In [290]: full['liar'] = full['liar'].astype(int)

In [322]: from random import shuffle
          n = len(full) #number of rows in your dataset
          indices = range(n)
          shuffle(indices)

          df = full.loc[indices[:3000]]
          dfTest = full.loc[indices[3000:]]
```

0.4 Generate a heatmap of all of the features in the dataset

```
In [292]: from matplotlib import pyplot

          dims = (20, 20)
          fig, ax = pyplot.subplots(figsize=dims)

          #cols = [c for c in df.columns if (c.lower()[:8] != 'country_' or \
          #         c == 'country_US') and 'os' not in c and 'screen' not in c and 'browser' no
          cols = [c for c in df.columns if (c.lower()[:8] != 'country_')]
          dfCorr=df[cols]

          corr = dfCorr.corr()
          #Pastel1 terrain
          sns.heatmap(ax=ax,data=corr,cmap="terrain")

Out[292]: <matplotlib.axes._subplots.AxesSubplot at 0x12b37b5d0>
```



0.4.1 There's so much to see here!

Who are gritty people?

- Married, educated, older voters who are conscientious and agreeable without being prone to emotional anxiety.
- Internet explorer users tend to be grittier.

Big 5 and gender

- The biggest differences in the big 5 personality traits and gender are opennes, neuroticism, and agreeableness.
- We'll take a closer look at agreeableness.

Validating the data

- Older people tend to be married, educated, voter who have developed “positive” big 5 traits
- iOS users have smaller screens and use the Safari browser. Windows users have larger screens and often use the Chrome browser.
- Hindu and Buddhist survey takers tended to be Asian
- Muslim survey takers tended to be Arabian.

The “liar” (confidence/invalid) column

- Whites lied more often, Asians were more honest
- If you say you write with both hands, you’re a liar
- Liars answer more positively about themselves

```
In [558]: df['grit'].describe()
```

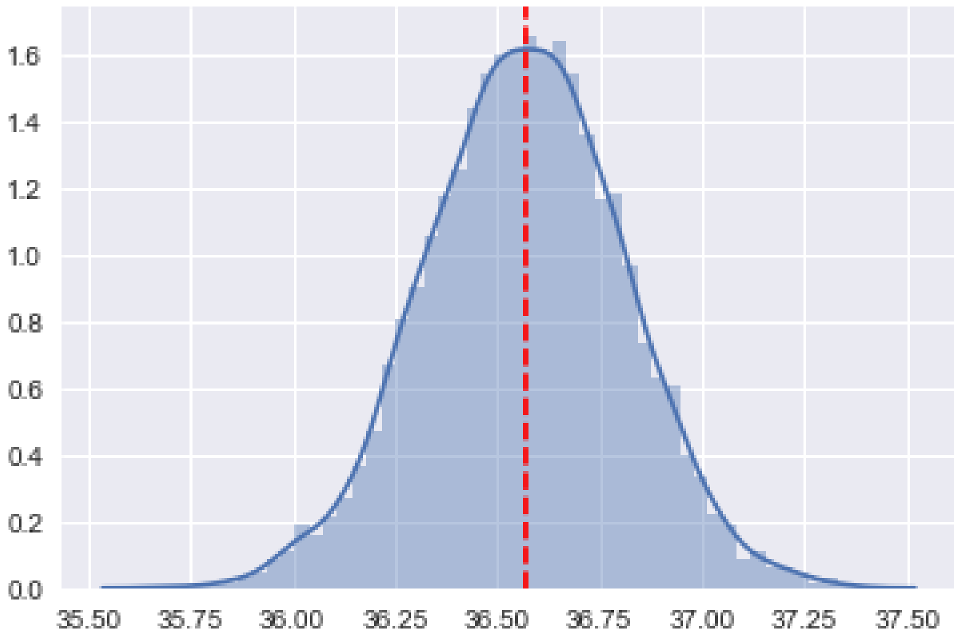
```
Out[558]: count    2211.000000
          mean        3.210274
          std         0.693705
          min         1.166667
          25%         2.666667
          50%         3.250000
          75%         3.750000
          max         5.000000
          Name: grit, dtype: float64
```

1 Differences in agreeableness by gender

Let’s bootstrap the mean from both groups and compare them to each other and the data in general.

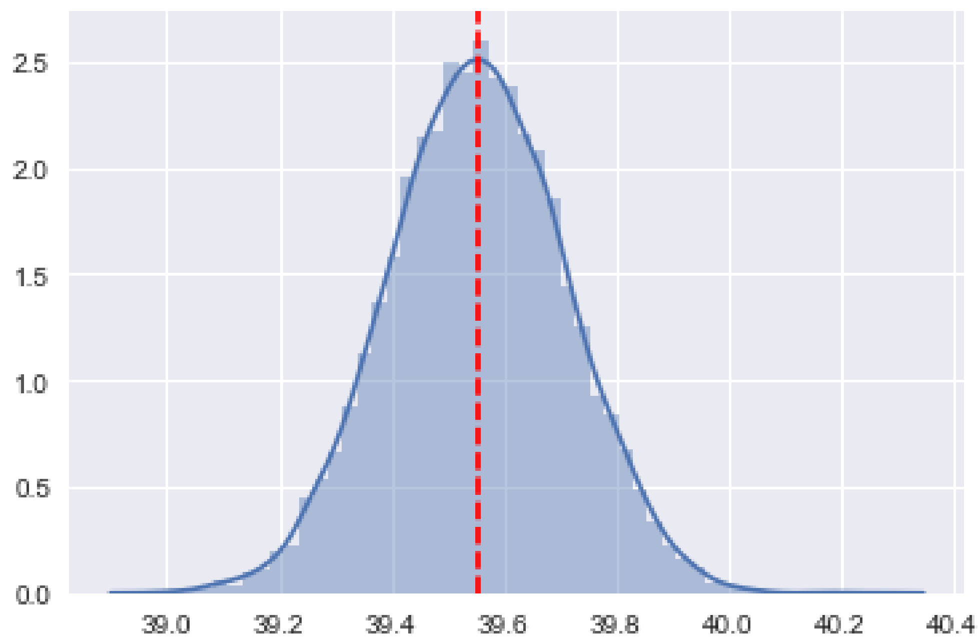
```
In [293]: def get_agree_means(df):
              menDf = df[df['gender'] == 1]
              sample_of_sample = [np.random.choice(menDf['agreeableness'],size=len(menDf),repla
              return np.mean(sample_of_sample)

          men_agree_means = [get_agree_means(df) for _ in range(10000)]
          fig, ax = plt.subplots()
          sns.distplot(men_agree_means)
          ax.axvline(np.mean(df[df['gender'] == 1]['agreeableness']),linestyle='--',color='red
```

```
Out[293]: <matplotlib.lines.Line2D at 0x1277198d0>
```




```
In [294]: def get_agree_means(df):
              menDf = df[df['gender'] == 0]
              sample_of_sample = [np.random.choice(menDf['agreeableness'],size=len(menDf),repla
              return np.mean(sample_of_sample)

          women_agree_means = [get_agree_means(df) for _ in range(10000)]
          fig, ax = plt.subplots()
          sns.distplot(women_agree_means)
          ax.axvline(np.mean(df[df['gender'] == 0]['agreeableness']),linestyle='--',color='red
```

```
Out[294]: <matplotlib.lines.Line2D at 0x12762ce10>
```



1.0.1 How confident are we that the means differ?

100% confident. There is no overlap in our male bootsrap samples and female bootstrap samples. We can keep this confidence up until about a difference of ~1.5

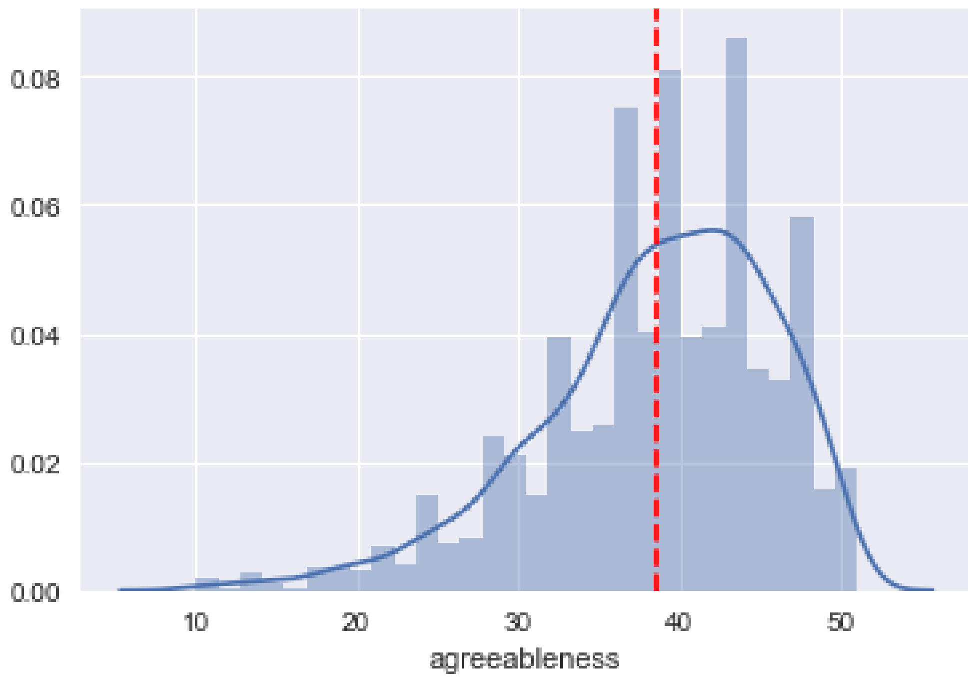
```
In [295]: count = 0
          men_max = np.max(men_agree_means)
          women_min = np.min(women_agree_means)
          print men_max
          print women_min
          print women_min - men_max
          for mean in women_agree_means:
              if mean < men_max:
                  count += 1
          print count
```

```
37.3986152324
38.978381096
1.57976586359
0
```

```
In [296]: print np.mean(df['agreeableness'])
          fig, ax = plt.subplots()
          sns.distplot(df['agreeableness'])
          ax.axvline(np.mean(df['agreeableness']),linestyle='--',color='red')
```

38.5476666667

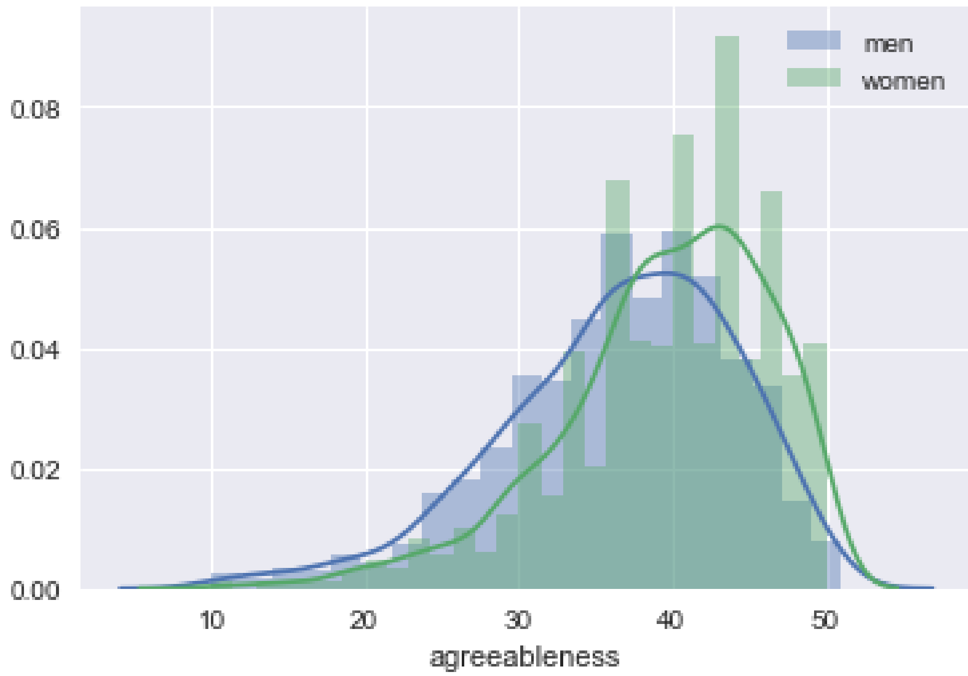
Out[296]: <matplotlib.lines.Line2D at 0x12a8e5850>



The mean of the bootsrap samples difference is just under a half of a standard deviation.

In [297]:
```
sns.distplot(df[df['gender'] == 1]['agreeableness'], label="men")
sns.distplot(df[df['gender'] == 0]['agreeableness'], label="women")

plt.legend()
```

Out[297]: <matplotlib.legend.Legend at 0x12b079910>



In [298]:
```
df['agreeableness'].describe()
```

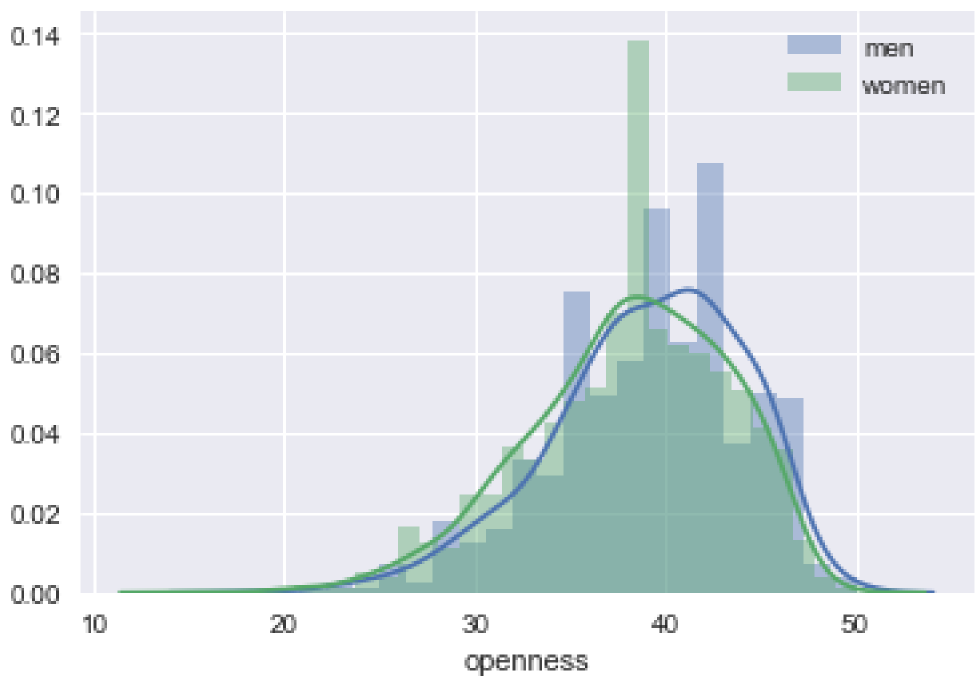
Out[298]:
```
count    3000.000000
mean       38.547667
std         7.307452
min        10.000000
25%        34.000000
50%        40.000000
75%        44.000000
max        51.000000
Name: agreeableness, dtype: float64
```

1.1 Differences in openness?

- Present, but not as drastic as agreeableness

In [299]:
```
sns.distplot(df[df['gender'] == 1]['openness'], label="men")
sns.distplot(df[df['gender'] == 0]['openness'], label="women")

plt.legend()
```

Out[299]:
```
<matplotlib.legend.Legend at 0x12b23ab10>
```



1.1.1 As suspected, grit is most highly correlated with conscientiousness:

```
In [300]: df['grit'].corr(df['conscientiousness'])
```

```
Out[300]: 0.61463512284440447
```

1.2 Train linear regression and decision tree models to describe the data

```
In [345]: indFeats = ['education','gender','age','voted','familysize','extroversion','neurotic
                      'agreeableness','conscientiousness','openness','married_never','married_cu
                      ]#'married_previously','liar'
```

```
In [559]: import numpy as np
          from sklearn import datasets, linear_model
          from sklearn.metrics import mean_squared_error, mean_absolute_error

          df = df[df['liar'] < 1]
          dfTest = dfTest[dfTest['liar'] < 1]

          # Create a features DF
          dfX = df[indFeats]
          df_test_X = dfTest[indFeats]

          # Create a label DF
          dfY = df['grit']
          df_test_Y = dfTest['grit']
```

```
In [353]: from sklearn.preprocessing import normalize
          data = normalize(dfX, axis=0, norm='max')
```

Linear regression with statsmodels (normalize to show feature importance):

```
In [546]: import statsmodels.api as sm

          model = sm.OLS(dfY,dfX)
          results = model.fit()
          print results.summary()
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               isgritty   R-squared:                       0.709
Model:                            OLS   Adj. R-squared:                  0.707
Method:                 Least Squares   F-statistic:                     446.4
Date:                Tue, 26 Sep 2017   Prob (F-statistic):               0.00
Time:                        11:12:27   Log-Likelihood:                -1185.7
No. Observations:                2211   AIC:                             2395.
Df Residuals:                    2199   BIC:                             2464.
Df Model:                          12
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
education             0.0286      0.011      2.556      0.011       0.007       0.051
gender               -0.0347      0.020     -1.770      0.077      -0.073       0.004
age                4.396e-05      0.001      0.051      0.959      -0.002       0.002
voted                -0.0039      0.021     -0.188      0.851      -0.045       0.037
familysize            0.0044      0.005      0.840      0.401      -0.006       0.015
extroversion          0.0016      0.001      1.518      0.129      -0.000       0.004
neuroticism          -0.0105      0.001    -10.992      0.000      -0.012      -0.009
agreeableness         0.0047      0.001      3.543      0.000       0.002       0.007
conscientiousness     0.0264      0.001     22.003      0.000       0.024       0.029
openness             -0.0038      0.002     -2.437      0.015      -0.007      -0.001
married_never        -0.1381      0.039     -3.578      0.000      -0.214      -0.062
married_currently    -0.0551      0.043     -1.293      0.196      -0.139       0.029
==============================================================================
Omnibus:                      669.048   Durbin-Watson:                   2.055
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              111.886
Skew:                          -0.161   Prob(JB):                     5.06e-25
Kurtosis:                       1.946   Cond. No.                         499.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Linear regression with sklearn:

```
In [550]: lm = linear_model.LinearRegression()
          lm.fit(dfX, dfY)

          dfPred = lm.predict(df_test_X)
```

1.3 With the LR model trained, let's look at the coefficients and visualize the results

```
In [560]: print indFeats
          # The coefficients
          print('Coefficients: ', lm.coef_)
          print('Intercept: ', lm.intercept_)
          # The mean squared error
          print("Mean squared error: %.2f" % mean_squared_error(np.array(df_test_Y),dfPred))
          print("Mean absolute error: %.2f" % mean_absolute_error(np.array(df_test_Y),dfPred))
```

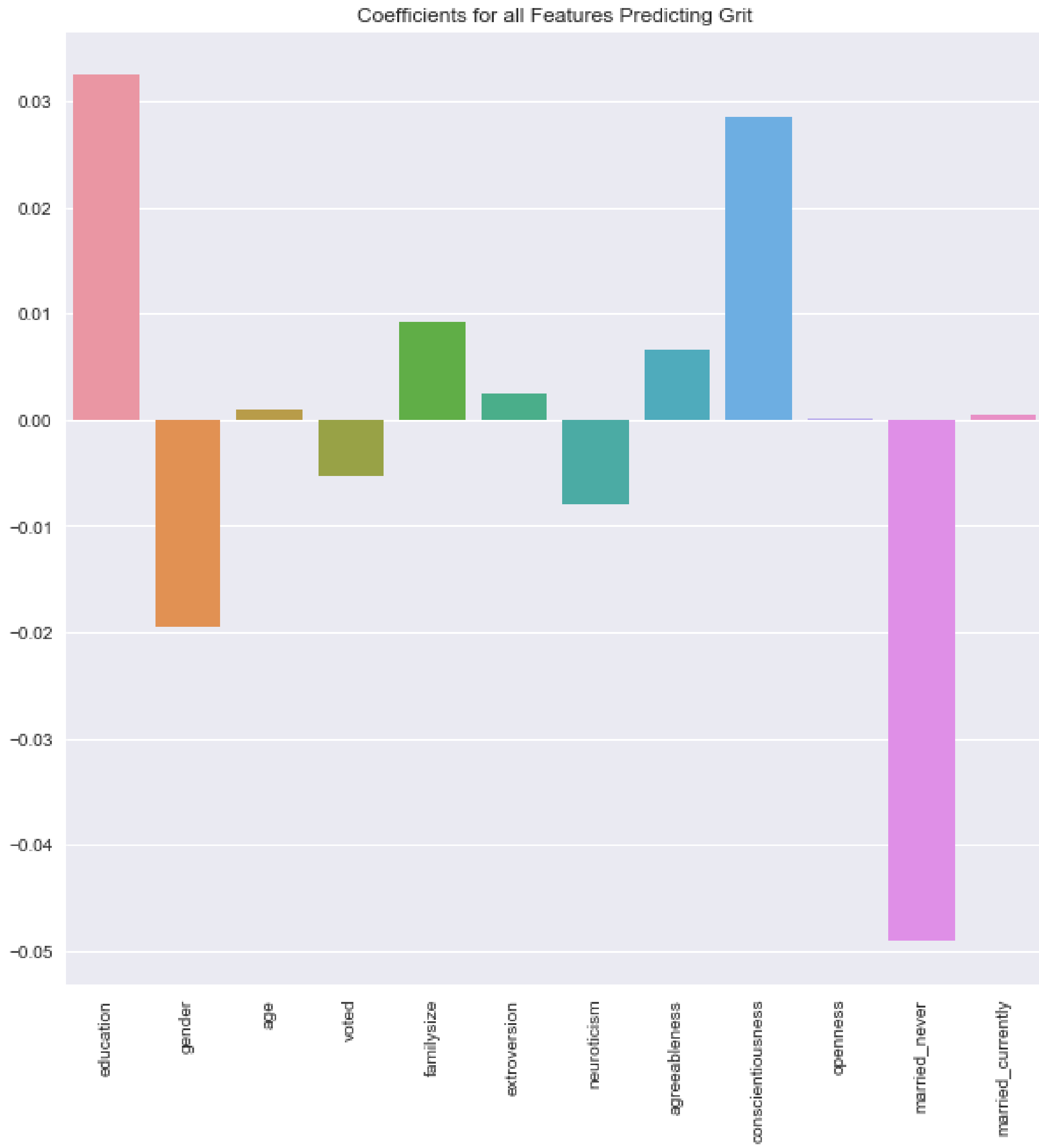
```
['education', 'gender', 'age', 'voted', 'familysize', 'extroversion', 'neuroticism', 'agreeable
('Coefficients: ', array([ 0.03245315, -0.01947561,  0.00098068, -0.00539197,  0.00915535,
        0.00239531, -0.00787071,  0.00653773,  0.02850376,  0.00017041,
       -0.04914387,  0.00048606]))
('Intercept: ', -0.53366561411052738)
Mean squared error: 7.15
Mean squared error: 2.62
```

Keep in mind, education is ordinal

- Less than high school
- High school
- University degree
- Graduate degree

Gender and "liar" appear to have a big affect, but keep in mind the range of conscientiousness is 10-50

```
In [552]: dims = (10, 10)
          fig, ax = pyplot.subplots(figsize=dims)
          sns.plt.title('Coefficients for all Features Predicting Grit')
          g = sns.barplot(ax=ax, x=indFeats, y=lm.coef_).set_xticklabels(rotation=90,labels=inc
```



1.4 Let's visualize predictions in terms of conscientiousness and another feature (neuroticism)

In [340]:
```
# Plot outputs
dims = (10, 10)
fig, ax = pyplot.subplots(figsize=dims)
plt.scatter(df_test_X['conscientiousness'],df_test_Y,color='green',alpha=.6)
plt.scatter(df_test_X['conscientiousness'],dfPred,color='blue',alpha=.4)

plt.title("Survey Takers' Grit by Conscientiousness (Predicted and Actual)")
```

```
plt.legend(["acutal","predicted"])

ax.set_xlabel('Conscientiousness')
ax.set_ylabel('Grit')

plt.show()
```


```
In [341]: # Plot outputs
dims = (10, 10)
fig, ax = pyplot.subplots(figsize=dims)
plt.scatter(df_test_X['neuroticism'],df_test_Y,color='green',alpha=.6)
plt.scatter(df_test_X['neuroticism'],dfPred,color='red',alpha=.4)
```

```
plt.title("Survey Takers' Grit by Neuroticism (Predicted and Actual)")
plt.legend(["acutal","predicted"])

ax.set_xlabel('Neuroticism')
ax.set_ylabel('Grit')

plt.show()
```

We can see that grit is highly correlated with conscientiousness. Our predictions vary only a little from the mean at each level of conscientiousness, while our predictions according to neuroticism have a much wider range.

1.5 Time to train and visualize a decision tree classifier

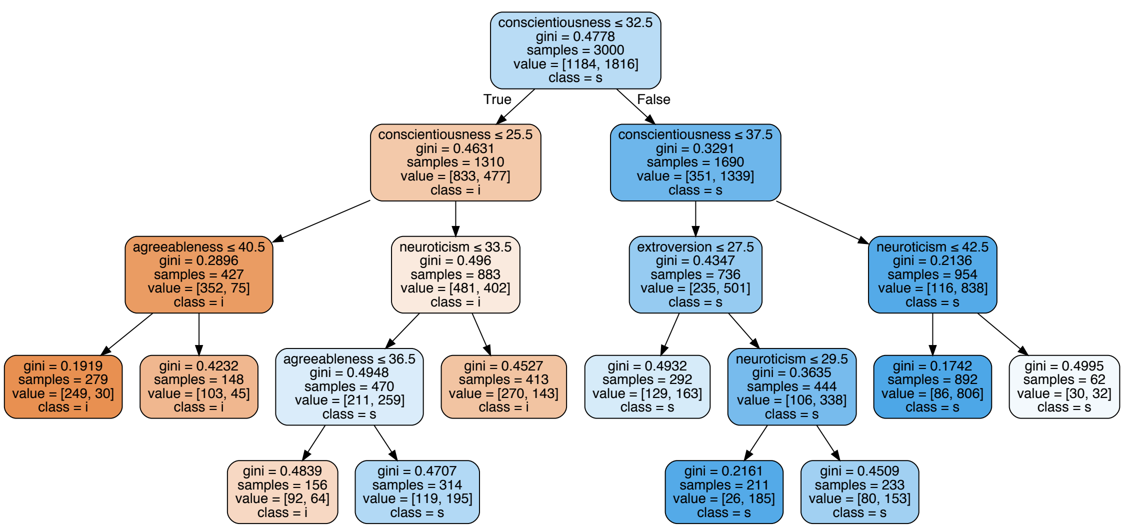
Something cool to keep in mind here is that the most important factors are personality traits. We could consider these as being an intrinsic cause for the other features as well

In [164]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score

dfY = df['isgritty']
dt = DecisionTreeClassifier(max_depth=5,max_leaf_nodes=10)
print cross_val_score(dt, dfX, dfY, cv=10)
mod = dt.fit(dfX,dfY,)
```

```
[ 0.70431894  0.77408638  0.71428571  0.66777409  0.73666667  0.76
  0.77257525  0.75585284  0.73913043  0.73578595]
```

In [165]:
```
from sklearn import tree
import graphviz

dot_data = tree.export_graphviz(mod, out_file=None,
                                feature_names=indFeats,
                                class_names='isgritty',
                                filled=True, rounded=True,
                                special_characters=True)
graph = graphviz.Source(dot_data)
graph
```

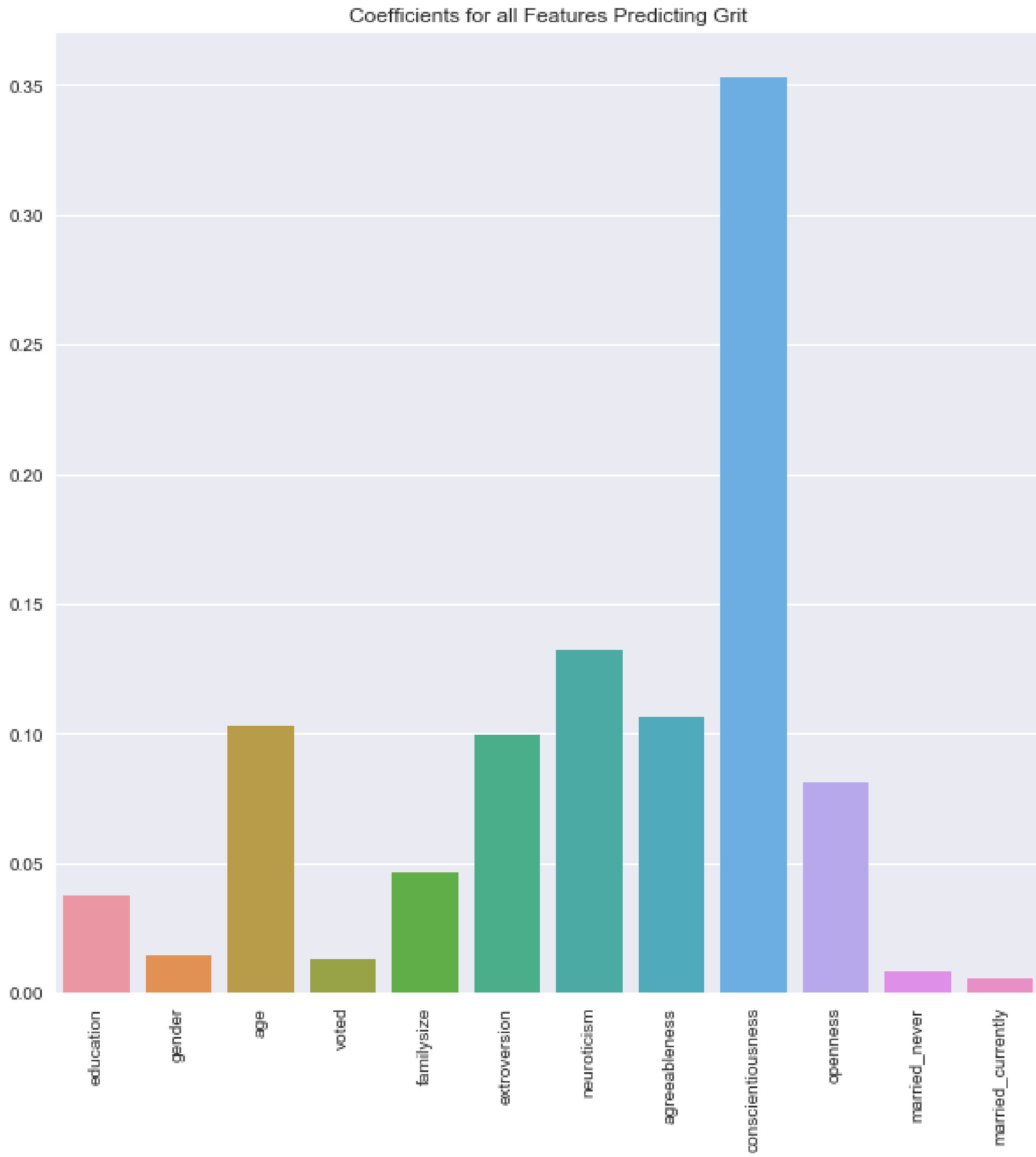
Out[165]:



1.6 If we train a random forest classifier, we see similar results in terms of which features are most important

In [554]:
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(max_depth=10,max_features=8,n_estimators=100)
rf.fit(dfX, dfY)

dims = (10, 10)
fig, ax = pyplot.subplots(figsize=dims)
sns.plt.title('Coefficients for all Features Predicting Grit')
g = sns.barplot(ax=ax, x=indFeats, y=rf.feature_importances_).set_xticklabels(rotatio

print indFeats
print rf.feature_importances_
```

```
['education', 'gender', 'age', 'voted', 'familysize', 'extroversion', 'neuroticism', 'agreeabl
[ 0.03738548  0.01415889  0.10278188  0.01332512  0.04623355  0.09959442
  0.13224122  0.10645969  0.35269368  0.08147232  0.00842247  0.00523129]
```



1.7 We have a good sense of our data and the factors that relate to grit now, so let's train a nueron and a nueral network to predict grit

```
In [564]: from numpy import exp, array, random, dot

          class Neuron():
              def __init__(self):
                  #random.seed(1988)
                  #start with random weights between -1 and 1
                  self.weights = 2.0 * random.random((12,1)) - 1.0
```

```
    #the sigmoid function is like the logistic function we used in logistic regressi
    #similarly, this allows for an output between 0 and 1
    #It looks like this is rarely used anymore in favor of the "RELU" function
    def __sigmoid(self, x):
        return 1 / (1 + np.exp(-x))

    #gradient of the sigmoid curve, this adjusts the severity of the error according
    def __sigmoid_derivative(self, x):
        return x * (1-x)

    def train(self, training_set_inputs, training_set_outputs, number_of_training_ite
        for iteration in xrange(number_of_training_iterations):
            #pass the training set through our neuron
            output = self.predict(training_set_inputs)

            #calculate the error
            error = training_set_outputs - output

            #multiply the error by the gradient of the sigmoid curve, then by the in
            adjustment = dot(training_set_inputs.T, error * self.__sigmoid_derivativ

            #adjust the weights
            self.weights += adjustment

            #print
            #print training_set_inputs.T

    def predict(self, inputs):
        #pass inputs through our neuron
        return self.__sigmoid(np.array(np.dot(inputs, self.weights),dtype=np.float32

#initialise a single neuron neural network
neuron = Neuron()

print 'random starting weights:'
print neuron.weights
print

#train the neural network using a training set.  do it 10,000 (or 600) times and mak
from sklearn.preprocessing import normalize
X = np.array(dfX.as_matrix(), dtype=float)
X = normalize(X, axis=0)#, norm='max')

dfY = df['isgritty']
Y = dfY.as_matrix().reshape(dfY.as_matrix().shape[0],-1)
neuron.train(X,Y,2000)
```

```
print 'new weights after training: '
print neuron.weights
```

```
random starting weights:
[[ 0.54230874]
 [ 0.15843374]
 [ 0.81331905]
 [ 0.51774819]
 [ 0.38414109]
 [ 0.97296606]
 [ 0.93687881]
 [-0.2758979 ]
 [-0.95800895]
 [-0.27431323]
 [-0.70229964]
 [ 0.34965651]]

new weights after training:
[[  13.58220469]
 [  -6.54035531]
 [  -2.76242087]
 [   0.45478189]
 [  -2.74036934]
 [   7.88566158]
 [-105.28036888]
 [  25.67214587]
 [ 193.3658723 ]
 [ -44.62970236]
 [ -58.51468447]
 [ -14.49317004]]
```

```
In [565]: print indFeats
          print('Coefficients: \n', lm.coef_)
```

```
['education', 'gender', 'age', 'voted', 'familysize', 'extroversion', 'neuroticism', 'agreeable
('Coefficients: \n', array([ 0.03245315, -0.01947561,  0.00098068, -0.00539197,  0.00915535,
        0.00239531, -0.00787071,  0.00653773,  0.02850376,  0.00017041,
       -0.04914387,  0.00048606]))
```

```
In [566]: from sklearn.metrics import accuracy_score
          #np.array(df_test_X.as_matrix(), dtype=float)
          X_test = normalize(np.array(df_test_X.as_matrix(), dtype=float), axis=0)#, norm='max
          Y_test = dfTest['isgritty']
          Y_test = Y_test.as_matrix().reshape(Y_test.as_matrix().shape[0],-1)

          print("Accuracy: %.2f"
                % accuracy_score(Y_test, np.round(neuron.predict(X_test))))
```

```
print("Accuracy: %.2f"
      % accuracy_score(Y,np.round(neuron.predict(X))))
```

```
Accuracy: 0.75
Accuracy: 0.73
```

This single neuron behaves similarly to logistic regression We can train a neural net to take into account feature interaction (This is a bit of overkill)

```
In [567]: from keras.models import Sequential
          from keras.layers import Dense
          from keras.layers import Dropout
```

```
In [571]: # create model
          model = Sequential()
          model.add(Dense(32,activation='relu',input_shape=(12,)))
          model.add(Dropout(0.3))
          model.add(Dense(16,activation='relu'))
          model.add(Dense(8,activation='relu'))
          model.add(Dense(4,activation='relu'))
          model.add(Dense(1,activation='sigmoid'))
          # Compile model
          model.compile(loss='binary_crossentropy', optimizer='rmsprop', metrics=['accuracy'])
```

```
In [578]: import datetime

          print datetime.datetime.now()
          # Fit the model
          model.fit(dfX.as_matrix(),dfY.as_matrix(), epochs=300, batch_size=200)
          print datetime.datetime.now()
```

```
2017-09-26 12:29:44.838318
Epoch 1/300
2211/2211 [==============================] - 0s - loss: 0.4954 - acc: 0.7463
Epoch 2/300
2211/2211 [==============================] - 0s - loss: 0.5089 - acc: 0.7390
Epoch 3/300
2211/2211 [==============================] - 0s - loss: 0.5026 - acc: 0.7368
Epoch 4/300
2211/2211 [==============================] - 0s - loss: 0.5047 - acc: 0.7413
Epoch 5/300
2211/2211 [==============================] - 0s - loss: 0.5073 - acc: 0.7390
Epoch 6/300
2211/2211 [==============================] - 0s - loss: 0.5100 - acc: 0.7399
Epoch 7/300
2211/2211 [==============================] - 0s - loss: 0.5039 - acc: 0.7508
Epoch 8/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5091 - acc: 0.7481
Epoch 9/300
2211/2211 [==============================] - 0s - loss: 0.5127 - acc: 0.7476
Epoch 10/300
2211/2211 [==============================] - 0s - loss: 0.5061 - acc: 0.7481
Epoch 11/300
2211/2211 [==============================] - 0s - loss: 0.5062 - acc: 0.7458
Epoch 12/300
2211/2211 [==============================] - 0s - loss: 0.5086 - acc: 0.7449
Epoch 13/300
2211/2211 [==============================] - 0s - loss: 0.4983 - acc: 0.7490
Epoch 14/300
2211/2211 [==============================] - 0s - loss: 0.5045 - acc: 0.7318
Epoch 15/300
2211/2211 [==============================] - 0s - loss: 0.5048 - acc: 0.7413
Epoch 16/300
2211/2211 [==============================] - 0s - loss: 0.5070 - acc: 0.7458
Epoch 17/300
2211/2211 [==============================] - 0s - loss: 0.5149 - acc: 0.7467
Epoch 18/300
2211/2211 [==============================] - 0s - loss: 0.5131 - acc: 0.7449
Epoch 19/300
2211/2211 [==============================] - 0s - loss: 0.5190 - acc: 0.7463
Epoch 20/300
2211/2211 [==============================] - 0s - loss: 0.5117 - acc: 0.7417
Epoch 21/300
2211/2211 [==============================] - 0s - loss: 0.5126 - acc: 0.7490
Epoch 22/300
2211/2211 [==============================] - 0s - loss: 0.5104 - acc: 0.7531
Epoch 23/300
2211/2211 [==============================] - 0s - loss: 0.5200 - acc: 0.7422
Epoch 24/300
2211/2211 [==============================] - 0s - loss: 0.5161 - acc: 0.7445
Epoch 25/300
2211/2211 [==============================] - 0s - loss: 0.5138 - acc: 0.7404
Epoch 26/300
2211/2211 [==============================] - 0s - loss: 0.5124 - acc: 0.7386
Epoch 27/300
2211/2211 [==============================] - 0s - loss: 0.5258 - acc: 0.7417
Epoch 28/300
2211/2211 [==============================] - 0s - loss: 0.5073 - acc: 0.7476
Epoch 29/300
2211/2211 [==============================] - 0s - loss: 0.5154 - acc: 0.7404
Epoch 30/300
2211/2211 [==============================] - 0s - loss: 0.5162 - acc: 0.7440
Epoch 31/300
2211/2211 [==============================] - 0s - loss: 0.5109 - acc: 0.7436
Epoch 32/300
```

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2211/2211 [==============================] - 0s - loss: 0.5214 - acc: 0.7368
Epoch 33/300
2211/2211 [==============================] - 0s - loss: 0.5169 - acc: 0.7377
Epoch 34/300
2211/2211 [==============================] - 0s - loss: 0.5214 - acc: 0.7399
Epoch 35/300
2211/2211 [==============================] - 0s - loss: 0.5116 - acc: 0.7350
Epoch 36/300
2211/2211 [==============================] - 0s - loss: 0.5322 - acc: 0.7463
Epoch 37/300
2211/2211 [==============================] - 0s - loss: 0.5315 - acc: 0.7404
Epoch 38/300
2211/2211 [==============================] - 0s - loss: 0.5039 - acc: 0.7445
Epoch 39/300
2211/2211 [==============================] - 0s - loss: 0.5283 - acc: 0.7408
Epoch 40/300
2211/2211 [==============================] - 0s - loss: 0.5177 - acc: 0.7467
Epoch 41/300
2211/2211 [==============================] - 0s - loss: 0.5101 - acc: 0.7413
Epoch 42/300
2211/2211 [==============================] - 0s - loss: 0.5212 - acc: 0.7395
Epoch 43/300
2211/2211 [==============================] - 0s - loss: 0.5200 - acc: 0.7318
Epoch 44/300
2211/2211 [==============================] - 0s - loss: 0.5165 - acc: 0.7413
Epoch 45/300
2211/2211 [==============================] - 0s - loss: 0.5244 - acc: 0.7499
Epoch 46/300
2211/2211 [==============================] - 0s - loss: 0.5249 - acc: 0.7408
Epoch 47/300
2211/2211 [==============================] - 0s - loss: 0.5215 - acc: 0.7553
Epoch 48/300
2211/2211 [==============================] - 0s - loss: 0.5131 - acc: 0.7485
Epoch 49/300
2211/2211 [==============================] - 0s - loss: 0.5241 - acc: 0.7481
Epoch 50/300
2211/2211 [==============================] - 0s - loss: 0.5197 - acc: 0.7345
Epoch 51/300
2211/2211 [==============================] - 0s - loss: 0.5272 - acc: 0.7449
Epoch 52/300
2211/2211 [==============================] - 0s - loss: 0.5219 - acc: 0.7386
Epoch 53/300
2211/2211 [==============================] - 0s - loss: 0.5215 - acc: 0.7449
Epoch 54/300
2211/2211 [==============================] - 0s - loss: 0.5262 - acc: 0.7372
Epoch 55/300
2211/2211 [==============================] - 0s - loss: 0.5193 - acc: 0.7467
Epoch 56/300
```

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2211/2211 [==============================] - 0s - loss: 0.5177 - acc: 0.7395
Epoch 57/300
2211/2211 [==============================] - 0s - loss: 0.5161 - acc: 0.7413
Epoch 58/300
2211/2211 [==============================] - 0s - loss: 0.5166 - acc: 0.7476
Epoch 59/300
2211/2211 [==============================] - 0s - loss: 0.5234 - acc: 0.7377
Epoch 60/300
2211/2211 [==============================] - 0s - loss: 0.5307 - acc: 0.7377
Epoch 61/300
2211/2211 [==============================] - 0s - loss: 0.5167 - acc: 0.7431
Epoch 62/300
2211/2211 [==============================] - 0s - loss: 0.5192 - acc: 0.7350
Epoch 63/300
2211/2211 [==============================] - 0s - loss: 0.5212 - acc: 0.7485
Epoch 64/300
2211/2211 [==============================] - 0s - loss: 0.5159 - acc: 0.7440
Epoch 65/300
2211/2211 [==============================] - 0s - loss: 0.5133 - acc: 0.7417
Epoch 66/300
2211/2211 [==============================] - 0s - loss: 0.5270 - acc: 0.7372
Epoch 67/300
2211/2211 [==============================] - 0s - loss: 0.5141 - acc: 0.7445
Epoch 68/300
2211/2211 [==============================] - 0s - loss: 0.5229 - acc: 0.7381
Epoch 69/300
2211/2211 [==============================] - 0s - loss: 0.5271 - acc: 0.7345
Epoch 70/300
2211/2211 [==============================] - 0s - loss: 0.5147 - acc: 0.7440
Epoch 71/300
2211/2211 [==============================] - 0s - loss: 0.5348 - acc: 0.7395
Epoch 72/300
2211/2211 [==============================] - 0s - loss: 0.5399 - acc: 0.7436
Epoch 73/300
2211/2211 [==============================] - 0s - loss: 0.5271 - acc: 0.7404
Epoch 74/300
2211/2211 [==============================] - 0s - loss: 0.5374 - acc: 0.7463
Epoch 75/300
2211/2211 [==============================] - 0s - loss: 0.5154 - acc: 0.7454
Epoch 76/300
2211/2211 [==============================] - 0s - loss: 0.5133 - acc: 0.7399
Epoch 77/300
2211/2211 [==============================] - 0s - loss: 0.5170 - acc: 0.7499
Epoch 78/300
2211/2211 [==============================] - 0s - loss: 0.5224 - acc: 0.7368
Epoch 79/300
2211/2211 [==============================] - 0s - loss: 0.5325 - acc: 0.7458
Epoch 80/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5336 - acc: 0.7327
Epoch 81/300
2211/2211 [==============================] - 0s - loss: 0.5146 - acc: 0.7454
Epoch 82/300
2211/2211 [==============================] - 0s - loss: 0.5191 - acc: 0.7368
Epoch 83/300
2211/2211 [==============================] - 0s - loss: 0.5302 - acc: 0.7390
Epoch 84/300
2211/2211 [==============================] - 0s - loss: 0.5133 - acc: 0.7427
Epoch 85/300
2211/2211 [==============================] - 0s - loss: 0.5265 - acc: 0.7422
Epoch 86/300
2211/2211 [==============================] - 0s - loss: 0.5356 - acc: 0.7395
Epoch 87/300
2211/2211 [==============================] - 0s - loss: 0.5336 - acc: 0.7463
Epoch 88/300
2211/2211 [==============================] - 0s - loss: 0.5234 - acc: 0.7381
Epoch 89/300
2211/2211 [==============================] - 0s - loss: 0.5237 - acc: 0.7386
Epoch 90/300
2211/2211 [==============================] - 0s - loss: 0.5288 - acc: 0.7427
Epoch 91/300
2211/2211 [==============================] - 0s - loss: 0.5279 - acc: 0.7381
Epoch 92/300
2211/2211 [==============================] - 0s - loss: 0.5298 - acc: 0.7503
Epoch 93/300
2211/2211 [==============================] - 0s - loss: 0.5210 - acc: 0.7467
Epoch 94/300
2211/2211 [==============================] - 0s - loss: 0.5173 - acc: 0.7436
Epoch 95/300
2211/2211 [==============================] - 0s - loss: 0.5337 - acc: 0.7463
Epoch 96/300
2211/2211 [==============================] - 0s - loss: 0.5266 - acc: 0.7476
Epoch 97/300
2211/2211 [==============================] - 0s - loss: 0.5306 - acc: 0.7458
Epoch 98/300
2211/2211 [==============================] - 0s - loss: 0.5305 - acc: 0.7377
Epoch 99/300
2211/2211 [==============================] - 0s - loss: 0.5264 - acc: 0.7381
Epoch 100/300
2211/2211 [==============================] - 0s - loss: 0.5301 - acc: 0.7350
Epoch 101/300
2211/2211 [==============================] - 0s - loss: 0.5201 - acc: 0.7458
Epoch 102/300
2211/2211 [==============================] - 0s - loss: 0.5435 - acc: 0.7359
Epoch 103/300
2211/2211 [==============================] - 0s - loss: 0.5105 - acc: 0.7413
Epoch 104/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5219 - acc: 0.7390
Epoch 105/300
2211/2211 [==============================] - 0s - loss: 0.5243 - acc: 0.7372
Epoch 106/300
2211/2211 [==============================] - 0s - loss: 0.5221 - acc: 0.7454
Epoch 107/300
2211/2211 [==============================] - 0s - loss: 0.5221 - acc: 0.7476
Epoch 108/300
2211/2211 [==============================] - 0s - loss: 0.5295 - acc: 0.7427
Epoch 109/300
2211/2211 [==============================] - 0s - loss: 0.5241 - acc: 0.7386
Epoch 110/300
2211/2211 [==============================] - 0s - loss: 0.5252 - acc: 0.7472
Epoch 111/300
2211/2211 [==============================] - 0s - loss: 0.5187 - acc: 0.7408
Epoch 112/300
2211/2211 [==============================] - 0s - loss: 0.5247 - acc: 0.7368
Epoch 113/300
2211/2211 [==============================] - 0s - loss: 0.5427 - acc: 0.7390
Epoch 114/300
2211/2211 [==============================] - 0s - loss: 0.5189 - acc: 0.7458
Epoch 115/300
2211/2211 [==============================] - 0s - loss: 0.5213 - acc: 0.7291
Epoch 116/300
2211/2211 [==============================] - 0s - loss: 0.5286 - acc: 0.7313
Epoch 117/300
2211/2211 [==============================] - 0s - loss: 0.5333 - acc: 0.7436
Epoch 118/300
2211/2211 [==============================] - 0s - loss: 0.5276 - acc: 0.7408
Epoch 119/300
2211/2211 [==============================] - 0s - loss: 0.5261 - acc: 0.7404
Epoch 120/300
2211/2211 [==============================] - 0s - loss: 0.5218 - acc: 0.7363
Epoch 121/300
2211/2211 [==============================] - 0s - loss: 0.5357 - acc: 0.7431
Epoch 122/300
2211/2211 [==============================] - 0s - loss: 0.5343 - acc: 0.7454
Epoch 123/300
2211/2211 [==============================] - 0s - loss: 0.5362 - acc: 0.7436
Epoch 124/300
2211/2211 [==============================] - 0s - loss: 0.5336 - acc: 0.7458
Epoch 125/300
2211/2211 [==============================] - 0s - loss: 0.5270 - acc: 0.7377
Epoch 126/300
2211/2211 [==============================] - 0s - loss: 0.5342 - acc: 0.7417
Epoch 127/300
2211/2211 [==============================] - 0s - loss: 0.5210 - acc: 0.7458
Epoch 128/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5397 - acc: 0.7436
Epoch 129/300
2211/2211 [==============================] - 0s - loss: 0.5313 - acc: 0.7404
Epoch 130/300
2211/2211 [==============================] - 0s - loss: 0.5212 - acc: 0.7463
Epoch 131/300
2211/2211 [==============================] - 0s - loss: 0.5206 - acc: 0.7404
Epoch 132/300
2211/2211 [==============================] - 0s - loss: 0.5257 - acc: 0.7422
Epoch 133/300
2211/2211 [==============================] - 0s - loss: 0.5337 - acc: 0.7363
Epoch 134/300
2211/2211 [==============================] - 0s - loss: 0.5090 - acc: 0.7381
Epoch 135/300
2211/2211 [==============================] - 0s - loss: 0.5129 - acc: 0.7440
Epoch 136/300
2211/2211 [==============================] - 0s - loss: 0.5280 - acc: 0.7395
Epoch 137/300
2211/2211 [==============================] - 0s - loss: 0.5195 - acc: 0.7377
Epoch 138/300
2211/2211 [==============================] - 0s - loss: 0.5418 - acc: 0.7372
Epoch 139/300
2211/2211 [==============================] - 0s - loss: 0.5476 - acc: 0.7227
Epoch 140/300
2211/2211 [==============================] - 0s - loss: 0.5237 - acc: 0.7408
Epoch 141/300
2211/2211 [==============================] - 0s - loss: 0.5484 - acc: 0.7417
Epoch 142/300
2211/2211 [==============================] - 0s - loss: 0.5301 - acc: 0.7368
Epoch 143/300
2211/2211 [==============================] - 0s - loss: 0.5231 - acc: 0.7363
Epoch 144/300
2211/2211 [==============================] - 0s - loss: 0.5268 - acc: 0.7458
Epoch 145/300
2211/2211 [==============================] - 0s - loss: 0.5166 - acc: 0.7458
Epoch 146/300
2211/2211 [==============================] - 0s - loss: 0.5198 - acc: 0.7350
Epoch 147/300
2211/2211 [==============================] - 0s - loss: 0.5152 - acc: 0.7422
Epoch 148/300
2211/2211 [==============================] - 0s - loss: 0.5264 - acc: 0.7381
Epoch 149/300
2211/2211 [==============================] - 0s - loss: 0.5112 - acc: 0.7463
Epoch 150/300
2211/2211 [==============================] - 0s - loss: 0.5227 - acc: 0.7322
Epoch 151/300
2211/2211 [==============================] - 0s - loss: 0.5158 - acc: 0.7436
Epoch 152/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5179 - acc: 0.7404
Epoch 153/300
2211/2211 [==============================] - 0s - loss: 0.5240 - acc: 0.7404
Epoch 154/300
2211/2211 [==============================] - 0s - loss: 0.5190 - acc: 0.7372
Epoch 155/300
2211/2211 [==============================] - 0s - loss: 0.5252 - acc: 0.7467
Epoch 156/300
2211/2211 [==============================] - 0s - loss: 0.5146 - acc: 0.7377
Epoch 157/300
2211/2211 [==============================] - 0s - loss: 0.5337 - acc: 0.7395
Epoch 158/300
2211/2211 [==============================] - 0s - loss: 0.5171 - acc: 0.7458
Epoch 159/300
2211/2211 [==============================] - 0s - loss: 0.5093 - acc: 0.7449
Epoch 160/300
2211/2211 [==============================] - 0s - loss: 0.5241 - acc: 0.7417
Epoch 161/300
2211/2211 [==============================] - 0s - loss: 0.5134 - acc: 0.7436
Epoch 162/300
2211/2211 [==============================] - 0s - loss: 0.5286 - acc: 0.7368
Epoch 163/300
2211/2211 [==============================] - 0s - loss: 0.5223 - acc: 0.7386
Epoch 164/300
2211/2211 [==============================] - 0s - loss: 0.5279 - acc: 0.7408
Epoch 165/300
2211/2211 [==============================] - 0s - loss: 0.5257 - acc: 0.7481
Epoch 166/300
2211/2211 [==============================] - 0s - loss: 0.5176 - acc: 0.7422
Epoch 167/300
2211/2211 [==============================] - 0s - loss: 0.5246 - acc: 0.7417
Epoch 168/300
2211/2211 [==============================] - 0s - loss: 0.5243 - acc: 0.7472
Epoch 169/300
2211/2211 [==============================] - 0s - loss: 0.5299 - acc: 0.7413
Epoch 170/300
2211/2211 [==============================] - 0s - loss: 0.5247 - acc: 0.7408
Epoch 171/300
2211/2211 [==============================] - 0s - loss: 0.5297 - acc: 0.7422
Epoch 172/300
2211/2211 [==============================] - 0s - loss: 0.5203 - acc: 0.7354
Epoch 173/300
2211/2211 [==============================] - 0s - loss: 0.5200 - acc: 0.7368
Epoch 174/300
2211/2211 [==============================] - 0s - loss: 0.5165 - acc: 0.7436
Epoch 175/300
2211/2211 [==============================] - 0s - loss: 0.5265 - acc: 0.7399
Epoch 176/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5277 - acc: 0.7368
Epoch 177/300
2211/2211 [==============================] - 0s - loss: 0.5233 - acc: 0.7427
Epoch 178/300
2211/2211 [==============================] - 0s - loss: 0.5193 - acc: 0.7395
Epoch 179/300
2211/2211 [==============================] - 0s - loss: 0.5158 - acc: 0.7399
Epoch 180/300
2211/2211 [==============================] - 0s - loss: 0.5257 - acc: 0.7363
Epoch 181/300
2211/2211 [==============================] - 0s - loss: 0.5166 - acc: 0.7427
Epoch 182/300
2211/2211 [==============================] - 0s - loss: 0.5233 - acc: 0.7368
Epoch 183/300
2211/2211 [==============================] - 0s - loss: 0.5162 - acc: 0.7454
Epoch 184/300
2211/2211 [==============================] - 0s - loss: 0.5138 - acc: 0.7440
Epoch 185/300
2211/2211 [==============================] - 0s - loss: 0.5154 - acc: 0.7404
Epoch 186/300
2211/2211 [==============================] - 0s - loss: 0.5215 - acc: 0.7454
Epoch 187/300
2211/2211 [==============================] - 0s - loss: 0.5283 - acc: 0.7445
Epoch 188/300
2211/2211 [==============================] - 0s - loss: 0.5064 - acc: 0.7336
Epoch 189/300
2211/2211 [==============================] - 0s - loss: 0.5211 - acc: 0.7458
Epoch 190/300
2211/2211 [==============================] - 0s - loss: 0.5245 - acc: 0.7399
Epoch 191/300
2211/2211 [==============================] - 0s - loss: 0.5270 - acc: 0.7404
Epoch 192/300
2211/2211 [==============================] - 0s - loss: 0.5232 - acc: 0.7399
Epoch 193/300
2211/2211 [==============================] - 0s - loss: 0.5220 - acc: 0.7363
Epoch 194/300
2211/2211 [==============================] - 0s - loss: 0.5271 - acc: 0.7408
Epoch 195/300
2211/2211 [==============================] - 0s - loss: 0.5232 - acc: 0.7445
Epoch 196/300
2211/2211 [==============================] - 0s - loss: 0.5482 - acc: 0.7422
Epoch 197/300
2211/2211 [==============================] - 0s - loss: 0.5107 - acc: 0.7395
Epoch 198/300
2211/2211 [==============================] - 0s - loss: 0.5379 - acc: 0.7395
Epoch 199/300
2211/2211 [==============================] - 0s - loss: 0.5371 - acc: 0.7386
Epoch 200/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5413 - acc: 0.7440
Epoch 201/300
2211/2211 [==============================] - 0s - loss: 0.5376 - acc: 0.7395
Epoch 202/300
2211/2211 [==============================] - 0s - loss: 0.5201 - acc: 0.7372
Epoch 203/300
2211/2211 [==============================] - 0s - loss: 0.5204 - acc: 0.7436
Epoch 204/300
2211/2211 [==============================] - 0s - loss: 0.5316 - acc: 0.7436
Epoch 205/300
2211/2211 [==============================] - 0s - loss: 0.5285 - acc: 0.7368
Epoch 206/300
2211/2211 [==============================] - 0s - loss: 0.5202 - acc: 0.7404
Epoch 207/300
2211/2211 [==============================] - 0s - loss: 0.5439 - acc: 0.7341
Epoch 208/300
2211/2211 [==============================] - 0s - loss: 0.5230 - acc: 0.7390
Epoch 209/300
2211/2211 [==============================] - 0s - loss: 0.5339 - acc: 0.7300
Epoch 210/300
2211/2211 [==============================] - 0s - loss: 0.5333 - acc: 0.7417
Epoch 211/300
2211/2211 [==============================] - 0s - loss: 0.5156 - acc: 0.7372
Epoch 212/300
2211/2211 [==============================] - 0s - loss: 0.5432 - acc: 0.7427
Epoch 213/300
2211/2211 [==============================] - 0s - loss: 0.5131 - acc: 0.7408
Epoch 214/300
2211/2211 [==============================] - 0s - loss: 0.5423 - acc: 0.7499
Epoch 215/300
2211/2211 [==============================] - 0s - loss: 0.5284 - acc: 0.7445
Epoch 216/300
2211/2211 [==============================] - 0s - loss: 0.5281 - acc: 0.7390
Epoch 217/300
2211/2211 [==============================] - 0s - loss: 0.5164 - acc: 0.7431
Epoch 218/300
2211/2211 [==============================] - 0s - loss: 0.5337 - acc: 0.7404
Epoch 219/300
2211/2211 [==============================] - 0s - loss: 0.5259 - acc: 0.7417
Epoch 220/300
2211/2211 [==============================] - 0s - loss: 0.5142 - acc: 0.7445
Epoch 221/300
2211/2211 [==============================] - 0s - loss: 0.5205 - acc: 0.7449
Epoch 222/300
2211/2211 [==============================] - 0s - loss: 0.5327 - acc: 0.7521
Epoch 223/300
2211/2211 [==============================] - 0s - loss: 0.5320 - acc: 0.7390
Epoch 224/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5203 - acc: 0.7368
Epoch 225/300
2211/2211 [==============================] - 0s - loss: 0.5202 - acc: 0.7390
Epoch 226/300
2211/2211 [==============================] - 0s - loss: 0.5160 - acc: 0.7413
Epoch 227/300
2211/2211 [==============================] - 0s - loss: 0.5360 - acc: 0.7395
Epoch 228/300
2211/2211 [==============================] - 0s - loss: 0.5182 - acc: 0.7431
Epoch 229/300
2211/2211 [==============================] - 0s - loss: 0.5221 - acc: 0.7427
Epoch 230/300
2211/2211 [==============================] - 0s - loss: 0.5160 - acc: 0.7399
Epoch 231/300
2211/2211 [==============================] - 0s - loss: 0.5135 - acc: 0.7399
Epoch 232/300
2211/2211 [==============================] - 0s - loss: 0.5235 - acc: 0.7413
Epoch 233/300
2211/2211 [==============================] - 0s - loss: 0.5100 - acc: 0.7377
Epoch 234/300
2211/2211 [==============================] - 0s - loss: 0.5304 - acc: 0.7313
Epoch 235/300
2211/2211 [==============================] - 0s - loss: 0.5229 - acc: 0.7422
Epoch 236/300
2211/2211 [==============================] - 0s - loss: 0.5173 - acc: 0.7431
Epoch 237/300
2211/2211 [==============================] - 0s - loss: 0.5193 - acc: 0.7390
Epoch 238/300
2211/2211 [==============================] - 0s - loss: 0.5305 - acc: 0.7404
Epoch 239/300
2211/2211 [==============================] - 0s - loss: 0.5303 - acc: 0.7359
Epoch 240/300
2211/2211 [==============================] - 0s - loss: 0.5269 - acc: 0.7417
Epoch 241/300
2211/2211 [==============================] - 0s - loss: 0.5218 - acc: 0.7436
Epoch 242/300
2211/2211 [==============================] - 0s - loss: 0.5393 - acc: 0.7390
Epoch 243/300
2211/2211 [==============================] - 0s - loss: 0.5186 - acc: 0.7413
Epoch 244/300
2211/2211 [==============================] - 0s - loss: 0.5168 - acc: 0.7440
Epoch 245/300
2211/2211 [==============================] - 0s - loss: 0.5485 - acc: 0.7363
Epoch 246/300
2211/2211 [==============================] - 0s - loss: 0.5259 - acc: 0.7422
Epoch 247/300
2211/2211 [==============================] - 0s - loss: 0.5136 - acc: 0.7395
Epoch 248/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5377 - acc: 0.7404
Epoch 249/300
2211/2211 [==============================] - 0s - loss: 0.5382 - acc: 0.7427
Epoch 250/300
2211/2211 [==============================] - 0s - loss: 0.5169 - acc: 0.7413
Epoch 251/300
2211/2211 [==============================] - 0s - loss: 0.5262 - acc: 0.7295
Epoch 252/300
2211/2211 [==============================] - 0s - loss: 0.5325 - acc: 0.7440
Epoch 253/300
2211/2211 [==============================] - 0s - loss: 0.5287 - acc: 0.7431
Epoch 254/300
2211/2211 [==============================] - 0s - loss: 0.5295 - acc: 0.7390
Epoch 255/300
2211/2211 [==============================] - 0s - loss: 0.5251 - acc: 0.7440
Epoch 256/300
2211/2211 [==============================] - 0s - loss: 0.5118 - acc: 0.7458
Epoch 257/300
2211/2211 [==============================] - 0s - loss: 0.5266 - acc: 0.7399
Epoch 258/300
2211/2211 [==============================] - 0s - loss: 0.5157 - acc: 0.7494
Epoch 259/300
2211/2211 [==============================] - 0s - loss: 0.5307 - acc: 0.7472
Epoch 260/300
2211/2211 [==============================] - 0s - loss: 0.5162 - acc: 0.7503
Epoch 261/300
2211/2211 [==============================] - 0s - loss: 0.5220 - acc: 0.7399
Epoch 262/300
2211/2211 [==============================] - 0s - loss: 0.5228 - acc: 0.7395
Epoch 263/300
2211/2211 [==============================] - 0s - loss: 0.5289 - acc: 0.7431
Epoch 264/300
2211/2211 [==============================] - 0s - loss: 0.5183 - acc: 0.7436
Epoch 265/300
2211/2211 [==============================] - 0s - loss: 0.5115 - acc: 0.7508
Epoch 266/300
2211/2211 [==============================] - 0s - loss: 0.5239 - acc: 0.7476
Epoch 267/300
2211/2211 [==============================] - 0s - loss: 0.5156 - acc: 0.7422
Epoch 268/300
2211/2211 [==============================] - 0s - loss: 0.5198 - acc: 0.7472
Epoch 269/300
2211/2211 [==============================] - 0s - loss: 0.5189 - acc: 0.7440
Epoch 270/300
2211/2211 [==============================] - 0s - loss: 0.5259 - acc: 0.7476
Epoch 271/300
2211/2211 [==============================] - 0s - loss: 0.5348 - acc: 0.7417
Epoch 272/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5296 - acc: 0.7449
Epoch 273/300
2211/2211 [==============================] - 0s - loss: 0.5357 - acc: 0.7422
Epoch 274/300
2211/2211 [==============================] - 0s - loss: 0.5290 - acc: 0.7377
Epoch 275/300
2211/2211 [==============================] - 0s - loss: 0.5191 - acc: 0.7413
Epoch 276/300
2211/2211 [==============================] - 0s - loss: 0.5269 - acc: 0.7499
Epoch 277/300
2211/2211 [==============================] - 0s - loss: 0.5095 - acc: 0.7485
Epoch 278/300
2211/2211 [==============================] - 0s - loss: 0.5154 - acc: 0.7535
Epoch 279/300
2211/2211 [==============================] - 0s - loss: 0.5217 - acc: 0.7377
Epoch 280/300
2211/2211 [==============================] - 0s - loss: 0.5190 - acc: 0.7431
Epoch 281/300
2211/2211 [==============================] - 0s - loss: 0.5256 - acc: 0.7363
Epoch 282/300
2211/2211 [==============================] - 0s - loss: 0.5268 - acc: 0.7422
Epoch 283/300
2211/2211 [==============================] - 0s - loss: 0.5245 - acc: 0.7345
Epoch 284/300
2211/2211 [==============================] - 0s - loss: 0.5382 - acc: 0.7445
Epoch 285/300
2211/2211 [==============================] - 0s - loss: 0.5170 - acc: 0.7436
Epoch 286/300
2211/2211 [==============================] - 0s - loss: 0.5321 - acc: 0.7449
Epoch 287/300
2211/2211 [==============================] - 0s - loss: 0.5273 - acc: 0.7408
Epoch 288/300
2211/2211 [==============================] - 0s - loss: 0.5283 - acc: 0.7440
Epoch 289/300
2211/2211 [==============================] - 0s - loss: 0.5342 - acc: 0.7445
Epoch 290/300
2211/2211 [==============================] - 0s - loss: 0.5355 - acc: 0.7499
Epoch 291/300
2211/2211 [==============================] - 0s - loss: 0.5173 - acc: 0.7399
Epoch 292/300
2211/2211 [==============================] - 0s - loss: 0.5285 - acc: 0.7345
Epoch 293/300
2211/2211 [==============================] - 0s - loss: 0.5492 - acc: 0.7427
Epoch 294/300
2211/2211 [==============================] - 0s - loss: 0.5328 - acc: 0.7386
Epoch 295/300
2211/2211 [==============================] - 0s - loss: 0.5242 - acc: 0.7381
Epoch 296/300
```

```
2211/2211 [==============================] - 0s - loss: 0.5259 - acc: 0.7413
Epoch 297/300
2211/2211 [==============================] - 0s - loss: 0.5220 - acc: 0.7440
Epoch 298/300
2211/2211 [==============================] - 0s - loss: 0.5214 - acc: 0.7485
Epoch 299/300
2211/2211 [==============================] - 0s - loss: 0.5266 - acc: 0.7467
Epoch 300/300
2211/2211 [==============================] - 0s - loss: 0.5277 - acc: 0.7490
2017-09-26 12:32:33.488392
```

```
In [580]: scores = model.evaluate(df_test_X.as_matrix(), dfTest['isgritty'].as_matrix())
          print("\n%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
 32/720 [>...] - ETA: 0s
acc: 75.56%
```

2 Conclusions

- Grit is highly correlated with conscientiousness (or conscientiousness is a great predictor of grit). It may be a redefinition of industriousness.
- A person's natural self (big 5 personality traits) is a better predictor of grit than other life outcomes.
- There are differences between some big 5 traits across demographics.
- For simple data sets, a single neuron can predict outcomes just as well as a neural network.

```
In [ ]:
```