CrimeDetection

May 2, 2018

1 Problem Description : Crime Detection Regression Analysis

```
In [1]: from keras.models import Sequential
        from keras.layers import Dense
        from keras.layers import LSTM
        from keras.layers import Dropout
        from keras.layers import Flatten,Input
        from keras import backend as K
        from keras.models import Model, load_model
        from sklearn.preprocessing import StandardScaler
        import matplotlib.pyplot as plt
        from sklearn.model_selection import KFold
        from scipy.spatial import distance
        from sklearn.decomposition import PCA
        from numpy import linalg as LA
        from keras.objectives import categorical_crossentropy
        from sklearn.metrics import roc_curve, auc
        import math
        from scipy.stats import pearsonr
        import copy
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import mean_squared_error, r2_score
        import itertools
        import csv
        from sklearn import metrics
        import tensorflow as tf
        import tensorflow.contrib.layers as tl
        import numpy as np
        import pandas as pd
        from sklearn import linear_model
        from sklearn.ensemble import RandomForestClassifier
        import seaborn as sb
        %matplotlib inline
```

```
/home/ramchalamkr/.local/lib/python2.7/site-packages/h5py/__init__.py:36: FutureWarning: Conve
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

1.1 Steps

1.2 1. Checking Data

In [2]:
```
X = pd.read_csv('crime_prep.csv',delimiter=',')
print X.shape
X[0:20]
```

```
(1994, 128)
```

Out[2]:

```
    target  v_cont_0  v_cat_0  v_cat_1                 v_cat_2  v_cat_3  \
0     0.20         8      NaN      NaN            Lakewoodcity        1
1     0.67        53      NaN      NaN            Tukwilacity         1
2     0.43        24      NaN      NaN            Aberdeentown        1
3     0.12        34      5.0  81440.0     Willingborotownship        1
4     0.03        42     95.0   6096.0       Bethlehemtownship        1
5     0.14         6      NaN      NaN       SouthPasadenacity        1
6     0.03        44      7.0  41500.0             Lincolntown        1
7     0.55         6      NaN      NaN               Selmacity        1
8     0.53        21      NaN      NaN          Hendersoncity         1
9     0.15        29      NaN      NaN             Claytoncity        1
10    0.24         6      NaN      NaN            DalyCitycity        1
11    0.08        36      NaN      NaN  RockvilleCentrevillage        1
12    0.06        25     21.0  44105.0             Needhamtown        1
13    0.09        55     87.0  30075.0          GrandChutetown        1
14    0.21         6      NaN      NaN          DanaPointcity         1
15    0.30        19    187.0  91370.0          FortDodgecity         1
16    0.49        36      1.0   1000.0             Albanycity         1
17    0.07        34     27.0  17650.0       Denvilletownship         1
18    0.15        18      NaN      NaN        Valparaisocity          1
19    0.03        42    129.0  66376.0      Rostravertownship         1

    v_cont_5  v_cont_6  v_cont_7  v_cont_8     ...      v_cont_117  \
0       0.19      0.33      0.02      0.90     ...            0.29
1       0.00      0.16      0.12      0.74     ...             NaN
2       0.00      0.42      0.49      0.56     ...             NaN
3       0.04      0.77      1.00      0.08     ...             NaN
4       0.01      0.55      0.02      0.95     ...             NaN
5       0.02      0.28      0.06      0.54     ...             NaN
6       0.01      0.39      0.00      0.98     ...             NaN
7       0.01      0.74      0.03      0.46     ...             NaN
8       0.03      0.34      0.20      0.84     ...             NaN
9       0.01      0.40      0.06      0.87     ...             NaN
10      0.13      0.71      0.15      0.07     ...             NaN
11      0.02      0.46      0.08      0.91     ...             NaN
12      0.03      0.47      0.01      0.96     ...             NaN
13      0.01      0.44      0.00      0.98     ...             NaN
14      0.04      0.36      0.01      0.85     ...             NaN
```

```
15      0.03      0.34      0.06      0.93     ...            NaN
16      0.15      0.31      0.40      0.63     ...           0.22
17      0.01      0.53      0.01      0.94     ...            NaN
18      0.02      0.47      0.01      0.97     ...            NaN
19      0.00      0.41      0.05      0.96     ...            NaN

    v_cont_118  v_cont_119  v_cont_120  v_cont_121  v_cont_122  v_cont_123  \
0         0.12        0.26        0.20        0.06        0.04        0.90
1         0.02        0.12        0.45         NaN         NaN         NaN
2         0.01        0.21        0.02         NaN         NaN         NaN
3         0.02        0.39        0.28         NaN         NaN         NaN
4         0.04        0.09        0.02         NaN         NaN         NaN
5         0.01        0.58        0.10         NaN         NaN         NaN
6         0.05        0.08        0.06         NaN         NaN         NaN
7         0.01        0.33        0.00         NaN         NaN         NaN
8         0.04        0.17        0.04         NaN         NaN         NaN
9         0.00        0.47        0.11         NaN         NaN         NaN
10        0.02        1.00        1.00         NaN         NaN         NaN
11        0.01        0.63        1.00         NaN         NaN         NaN
12        0.03        0.18        0.59         NaN         NaN         NaN
13        0.08        0.04        0.00         NaN         NaN         NaN
14        0.02        0.40        0.15         NaN         NaN         NaN
15        0.04        0.15        0.04         NaN         NaN         NaN
16        0.06        0.39        0.84        0.06        0.06        0.91
17        0.03        0.09        0.21         NaN         NaN         NaN
18        0.03        0.20        0.07         NaN         NaN         NaN
19        0.09        0.03        0.05         NaN         NaN         NaN

    v_cont_124  v_cont_125  v_cont_126
0          0.5        0.32        0.14
1          NaN        0.00         NaN
2          NaN        0.00         NaN
3          NaN        0.00         NaN
4          NaN        0.00         NaN
5          NaN        0.00         NaN
6          NaN        0.00         NaN
7          NaN        0.00         NaN
8          NaN        0.00         NaN
9          NaN        0.00         NaN
10         NaN        0.00         NaN
11         NaN        0.00         NaN
12         NaN        0.00         NaN
13         NaN        0.00         NaN
14         NaN        0.00         NaN
15         NaN        0.00         NaN
16         0.5        0.88        0.26
17         NaN        0.00         NaN
18         NaN        0.00         NaN
```

```
19          NaN        0.00         NaN

[20 rows x 128 columns]
```

1.3 2. Tidying the data

Missing data can either be filled with the means of the features or maybe 0 to ignore them or even other data imputation techniques to predict the missing values

In this case the mean of the features is taken for the missing values.

```
In [3]: print len(X['v_cat_2'].unique())
        X = X.fillna(X.mean())
        del X['v_cat_2']
        Y = X['target']
        del X['target']
        X.head()
```

```
1828
```

```
Out[3]:   v_cont_0    v_cat_0       v_cat_1  v_cat_3  v_cont_5  v_cont_6  v_cont_7  \
        0        8  58.826829  46188.336597        1      0.19      0.33      0.02
        1       53  58.826829  46188.336597        1      0.00      0.16      0.12
        2       24  58.826829  46188.336597        1      0.00      0.42      0.49
        3       34   5.000000  81440.000000        1      0.04      0.77      1.00
        4       42  95.000000   6096.000000        1      0.01      0.55      0.02

          v_cont_8  v_cont_9  v_cont_10    ...     v_cont_117  v_cont_118  \
        0     0.90      0.12       0.17    ...       0.290000        0.12
        1     0.74      0.45       0.07    ...       0.305987        0.02
        2     0.56      0.17       0.04    ...       0.305987        0.01
        3     0.08      0.12       0.10    ...       0.305987        0.02
        4     0.95      0.09       0.05    ...       0.305987        0.04

          v_cont_119  v_cont_120  v_cont_121  v_cont_122  v_cont_123  v_cont_124  \
        0       0.26        0.20    0.060000    0.040000    0.900000    0.500000
        1       0.12        0.45    0.163103    0.076708    0.698589    0.440439
        2       0.21        0.02    0.163103    0.076708    0.698589    0.440439
        3       0.39        0.28    0.163103    0.076708    0.698589    0.440439
        4       0.09        0.02    0.163103    0.076708    0.698589    0.440439

          v_cont_125  v_cont_126
        0       0.32    0.140000
        1       0.00    0.195078
        2       0.00    0.195078
        3       0.00    0.195078
        4       0.00    0.195078
```

```
[5 rows x 126 columns]
```

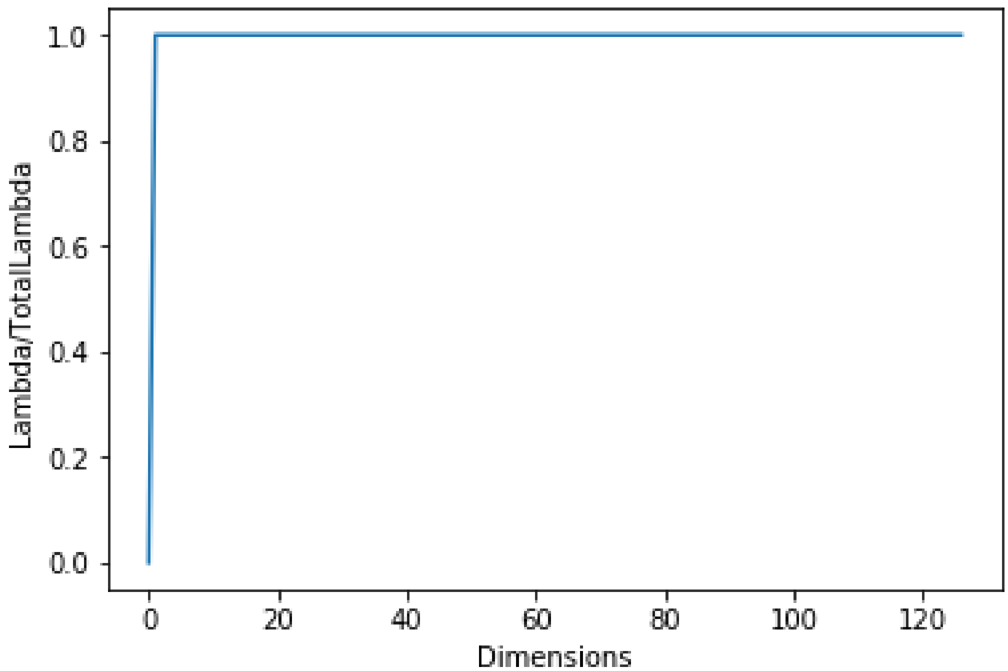
1.4 3. Exploratory Analysis

1.4.1 PCA

```
In [4]: print X.shape
        X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size = 0.3,random_state=42)

        Covariance = np.dot(X_train.T,X_train)
        print Covariance.shape

        Lambda, e = LA.eigh(Covariance)
        Lambda = Lambda.reshape(Lambda.shape[0],1)
        Lambda = sorted(Lambda,reverse=True)
        TotalLambda = np.sum(Lambda)
        LambdaProp = []
        for i in range(X_train.shape[1]):
            temp = np.sum(Lambda[0:i])*1.0/TotalLambda
            LambdaProp.append(temp)

        Dim = np.linspace(0, X_train.shape[1], X_train.shape[1])

        plt.plot(Dim,LambdaProp)
        plt.legend(bbox_to_anchor=(0., 1.02, 1., .102), loc=3,
                   ncol=2, mode="expand", borderaxespad=0.)
        plt.xlabel('Dimensions')
        plt.ylabel('Lambda/TotalLambda')
        plt.show()
```

```
(1994, 126)
(126, 126)
```

```
/home/ramchalamkr/.local/lib/python2.7/site-packages/matplotlib/axes/_axes.py:545: UserWarning
  warnings.warn("No labelled objects found. "
```




```
In [5]: X1 = X
        Y1 = Y

        for i in (range(1,100)):
            print i
            NewFeatureSet = np.dot(X1,e[:,126-i:126])
            print NewFeatureSet.shape
            X_train,X_test,Y_train,Y_test = train_test_split(NewFeatureSet,Y1,test_size = 0.2,
            #Normal Linear Regression
            regr = linear_model.LinearRegression(normalize = True)
            regr.fit(X_train,Y_train)
            Y_pred = regr.predict(X_test)
            Weights = regr.coef_
            print "RMSE %.2f" % math.sqrt(mean_squared_error(Y_test,Y_pred))
            print('Variance score: %.2f' % r2_score(Y_test, Y_pred))
```

```
1
(1994, 1)
RMSE 0.22
Variance score: -0.02
2
(1994, 2)
RMSE 0.22
Variance score: -0.02
3
```

```
(1994, 3)
RMSE 0.21
Variance score: 0.06
4
(1994, 4)
RMSE 0.21
Variance score: 0.07
5
(1994, 5)
RMSE 0.20
Variance score: 0.14
6
(1994, 6)
RMSE 0.15
Variance score: 0.52
7
(1994, 7)
RMSE 0.15
Variance score: 0.52
8
(1994, 8)
RMSE 0.15
Variance score: 0.54
9
(1994, 9)
RMSE 0.15
Variance score: 0.55
10
(1994, 10)
RMSE 0.14
Variance score: 0.59
11
(1994, 11)
RMSE 0.14
Variance score: 0.60
12
(1994, 12)
RMSE 0.14
Variance score: 0.62
13
(1994, 13)
RMSE 0.13
Variance score: 0.62
14
(1994, 14)
RMSE 0.13
Variance score: 0.62
15
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(1994, 15)
RMSE 0.13
Variance score: 0.63
16
(1994, 16)
RMSE 0.13
Variance score: 0.63
17
(1994, 17)
RMSE 0.13
Variance score: 0.63
18
(1994, 18)
RMSE 0.13
Variance score: 0.63
19
(1994, 19)
RMSE 0.13
Variance score: 0.64
20
(1994, 20)
RMSE 0.13
Variance score: 0.63
21
(1994, 21)
RMSE 0.13
Variance score: 0.63
22
(1994, 22)
RMSE 0.13
Variance score: 0.63
23
(1994, 23)
RMSE 0.13
Variance score: 0.63
24
(1994, 24)
RMSE 0.13
Variance score: 0.63
25
(1994, 25)
RMSE 0.13
Variance score: 0.63
26
(1994, 26)
RMSE 0.13
Variance score: 0.63
27
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(1994, 27)
RMSE 0.13
Variance score: 0.64
28
(1994, 28)
RMSE 0.13
Variance score: 0.64
29
(1994, 29)
RMSE 0.13
Variance score: 0.64
30
(1994, 30)
RMSE 0.13
Variance score: 0.64
31
(1994, 31)
RMSE 0.13
Variance score: 0.64
32
(1994, 32)
RMSE 0.13
Variance score: 0.64
33
(1994, 33)
RMSE 0.13
Variance score: 0.64
34
(1994, 34)
RMSE 0.13
Variance score: 0.64
35
(1994, 35)
RMSE 0.13
Variance score: 0.63
36
(1994, 36)
RMSE 0.13
Variance score: 0.63
37
(1994, 37)
RMSE 0.13
Variance score: 0.63
38
(1994, 38)
RMSE 0.13
Variance score: 0.64
39
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(1994, 39)
RMSE 0.13
Variance score: 0.63
40
(1994, 40)
RMSE 0.13
Variance score: 0.63
41
(1994, 41)
RMSE 0.13
Variance score: 0.63
42
(1994, 42)
RMSE 0.13
Variance score: 0.63
43
(1994, 43)
RMSE 0.13
Variance score: 0.63
44
(1994, 44)
RMSE 0.13
Variance score: 0.63
45
(1994, 45)
RMSE 0.13
Variance score: 0.64
46
(1994, 46)
RMSE 0.13
Variance score: 0.64
47
(1994, 47)
RMSE 0.13
Variance score: 0.64
48
(1994, 48)
RMSE 0.13
Variance score: 0.63
49
(1994, 49)
RMSE 0.13
Variance score: 0.63
50
(1994, 50)
RMSE 0.13
Variance score: 0.63
51
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(1994, 51)
RMSE 0.13
Variance score: 0.63
52
(1994, 52)
RMSE 0.13
Variance score: 0.63
53
(1994, 53)
RMSE 0.13
Variance score: 0.63
54
(1994, 54)
RMSE 0.13
Variance score: 0.63
55
(1994, 55)
RMSE 0.14
Variance score: 0.62
56
(1994, 56)
RMSE 0.14
Variance score: 0.62
57
(1994, 57)
RMSE 0.14
Variance score: 0.62
58
(1994, 58)
RMSE 0.14
Variance score: 0.62
59
(1994, 59)
RMSE 0.14
Variance score: 0.62
60
(1994, 60)
RMSE 0.14
Variance score: 0.62
61
(1994, 61)
RMSE 0.14
Variance score: 0.62
62
(1994, 62)
RMSE 0.14
Variance score: 0.62
63
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(1994, 63)
RMSE 0.14
Variance score: 0.62
64
(1994, 64)
RMSE 0.14
Variance score: 0.62
65
(1994, 65)
RMSE 0.14
Variance score: 0.62
66
(1994, 66)
RMSE 0.14
Variance score: 0.62
67
(1994, 67)
RMSE 0.14
Variance score: 0.62
68
(1994, 68)
RMSE 0.14
Variance score: 0.62
69
(1994, 69)
RMSE 0.14
Variance score: 0.62
70
(1994, 70)
RMSE 0.14
Variance score: 0.62
71
(1994, 71)
RMSE 0.14
Variance score: 0.62
72
(1994, 72)
RMSE 0.14
Variance score: 0.62
73
(1994, 73)
RMSE 0.14
Variance score: 0.61
74
(1994, 74)
RMSE 0.14
Variance score: 0.61
75
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(1994, 75)
RMSE 0.14
Variance score: 0.61
76
(1994, 76)
RMSE 0.14
Variance score: 0.61
77
(1994, 77)
RMSE 0.14
Variance score: 0.61
78
(1994, 78)
RMSE 0.14
Variance score: 0.61
79
(1994, 79)
RMSE 0.14
Variance score: 0.61
80
(1994, 80)
RMSE 0.14
Variance score: 0.61
81
(1994, 81)
RMSE 0.14
Variance score: 0.61
82
(1994, 82)
RMSE 0.14
Variance score: 0.61
83
(1994, 83)
RMSE 0.14
Variance score: 0.61
84
(1994, 84)
RMSE 0.14
Variance score: 0.61
85
(1994, 85)
RMSE 0.14
Variance score: 0.61
86
(1994, 86)
RMSE 0.14
Variance score: 0.61
87
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(1994, 87)
RMSE 0.14
Variance score: 0.61
88
(1994, 88)
RMSE 0.14
Variance score: 0.61
89
(1994, 89)
RMSE 0.14
Variance score: 0.61
90
(1994, 90)
RMSE 0.14
Variance score: 0.60
91
(1994, 91)
RMSE 0.14
Variance score: 0.61
92
(1994, 92)
RMSE 0.14
Variance score: 0.61
93
(1994, 93)
RMSE 0.14
Variance score: 0.61
94
(1994, 94)
RMSE 0.14
Variance score: 0.61
95
(1994, 95)
RMSE 0.14
Variance score: 0.61
96
(1994, 96)
RMSE 0.14
Variance score: 0.61
97
(1994, 97)
RMSE 0.14
Variance score: 0.61
98
(1994, 98)
RMSE 0.14
Variance score: 0.61
99
```
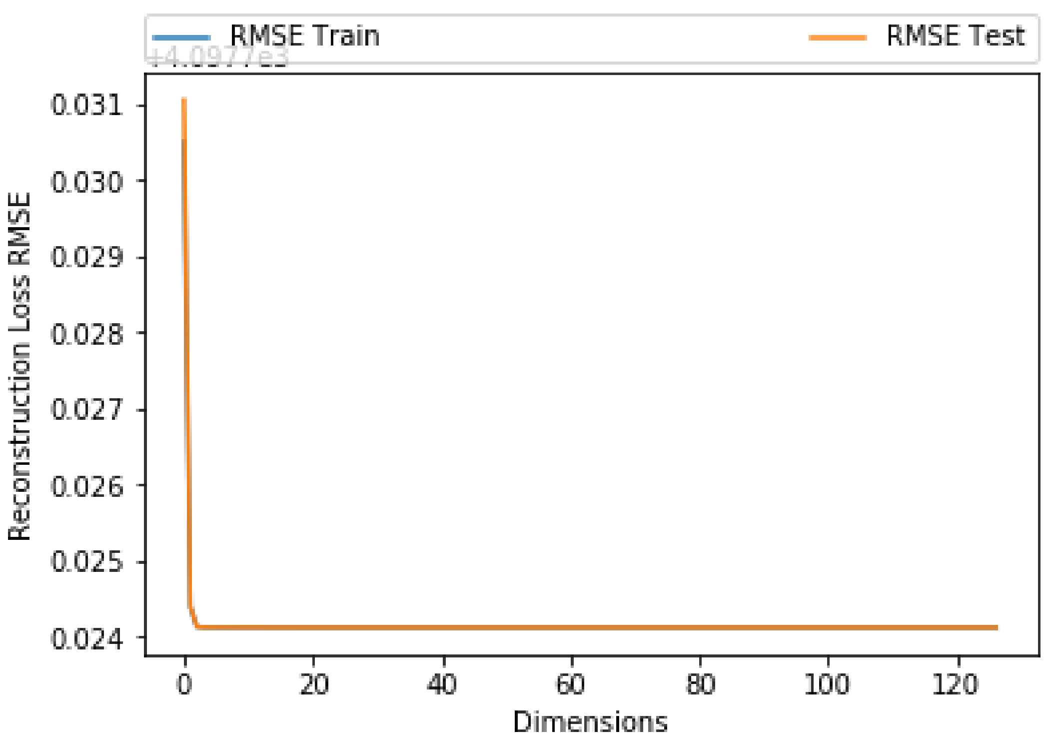

```
(1994, 99)
RMSE 0.14
Variance score: 0.62
```

```
In [6]: X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size = 0.3,random_state=42)
        RMSETrain =[]
        RMSETest =[]
        VarainceRatio = []
        Dim = np.linspace(0, X_train.shape[1], X_train.shape[1])
        for i in range(1,X_train.shape[1]+1):
            pca = PCA(n_components = i)
            pca.fit(X_train)
            VarainceRatio.append(pca.explained_variance_ratio_)
            X_trainhat = np.dot(pca.transform(X_train)[:,:i], pca.components_[:i,:])
            RMSETrain.append(math.sqrt(mean_squared_error(X_train,X_trainhat)))
            X_testhat = np.dot(pca.transform(X_test)[:,:i], pca.components_[:i,:])
            RMSETest.append(math.sqrt(mean_squared_error(X_test,X_testhat)))

        plt.plot(Dim,RMSETrain,label="RMSE Train")
        plt.plot(Dim,RMSETest,label="RMSE Test")
        plt.legend(bbox_to_anchor=(0., 1.02, 1., .102), loc=3,
                   ncol=2, mode="expand", borderaxespad=0.)
        plt.xlabel('Dimensions')
        plt.ylabel('Reconstruction Loss RMSE')
        plt.show()
```



```
In [7]: X1 = X
        Y1 = Y
        for i in range(1,15):
            pca = PCA(n_components = i)
            X_1 = pca.fit_transform(X1)
            #Varaince Ratio.append(pca.explained_variance_ratio_)
            print X_1
            print "no of componenets",i
            print "predict for transformed data"

            X_train,X_test,Y_train,Y_test = train_test_split(X_1,Y1,test_size = 0.2,random_sta
            #Normal Linear Regression
            regr = linear_model.LinearRegression(normalize = True)
            regr.fit(X_train,Y_train)
            Y_pred = regr.predict(X_test)
            Weights = regr.coef_
            print "RMSE %.2f" % math.sqrt(mean_squared_error(Y_test,Y_pred))
            print('Variance score: %.2f' % r2_score(Y_test, Y_pred))
```

```
[[ 5.51191613e-06]
 [ 1.20038458e-05]
 [ 6.20500714e-06]
 ...
 [ 3.38816276e+04]
 [ 2.64116337e+04]
 [-1.53519905e-05]]
no of componenets 1
predict for transformed data
RMSE 0.22
Variance score: -0.02
[[ 5.51191564e-06 -7.23694160e-01]
 [ 1.20038443e-05  8.50748193e-01]
 [ 6.20500640e-06 -1.62728214e-01]
 ...
 [ 3.38816276e+04 -7.07140111e+01]
 [ 2.64116337e+04 -5.77012878e+01]
 [-1.53519918e-05 -7.92744446e-01]]
no of componenets 2
predict for transformed data
RMSE 0.22
Variance score: -0.02
[[ 5.51191644e-06 -7.23694160e-01 -2.06611873e+01]
 [ 1.20038445e-05  8.50748193e-01  2.42899316e+01]
```

```
 [ 6.20500573e-06 -1.62728214e-01 -4.66962748e+00]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00]
 [-1.53519897e-05 -7.92744446e-01 -2.27055862e+01]]
no of componenets 3
predict for transformed data
RMSE 0.21
Variance score: 0.06
[[ 5.51191525e-06 -7.23694160e-01 -2.06611873e+01 -4.50141644e+00]
 [ 1.20038459e-05  8.50748193e-01  2.42899316e+01 -4.48189158e+00]
 [ 6.20500530e-06 -1.62728214e-01 -4.66962748e+00 -4.50471262e+00]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01  4.54755512e+00]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00  4.56160216e+00]
 [-1.53519899e-05 -7.92744446e-01 -2.27055862e+01  4.48857512e+00]]
no of componenets 4
predict for transformed data
RMSE 0.21
Variance score: 0.07
[[ 5.51191564e-06 -7.23694160e-01 -2.06611873e+01 -4.50141644e+00
  -4.03542918e-01]
 [ 1.20038448e-05  8.50748193e-01  2.42899316e+01 -4.48189158e+00
   3.42841940e-02]
 [ 6.20500562e-06 -1.62728214e-01 -4.66962748e+00 -4.50471262e+00
   5.13097023e-01]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01  4.54755512e+00
   9.31186120e-01]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00  4.56160216e+00
  -2.56492619e-01]
 [-1.53519896e-05 -7.92744446e-01 -2.27055862e+01  4.48857512e+00
   6.57593393e-01]]
no of componenets 5
predict for transformed data
RMSE 0.16
Variance score: 0.43
[[ 5.51191701e-06 -7.23694160e-01 -2.06611873e+01 -4.50141644e+00
  -4.03542918e-01 -6.64183045e-01]
 [ 1.20038478e-05  8.50748193e-01  2.42899316e+01 -4.48189158e+00
   3.42841939e-02  6.82017950e-01]
 [ 6.20500635e-06 -1.62728214e-01 -4.66962748e+00 -4.50471262e+00
   5.13097023e-01 -6.67107742e-01]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01  4.54755512e+00
   9.31186120e-01 -1.95816368e-01]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00  4.56160216e+00
  -2.56492619e-01  7.21579858e-01]
```

```
 [-1.53519905e-05 -7.92744446e-01 -2.27055862e+01  4.48857512e+00
   6.57593393e-01  1.66846282e+00]]
no of componenets 6
predict for transformed data
RMSE 0.15
Variance score: 0.51
[[ 5.51191629e-06 -7.23694160e-01 -2.06611873e+01 ... -4.03542918e-01
  -6.64183030e-01 -4.49741453e-01]
 [ 1.20038459e-05  8.50748193e-01  2.42899316e+01 ...  3.42841940e-02
   6.82017950e-01 -1.01855618e+00]
 [ 6.20500660e-06 -1.62728214e-01 -4.66962748e+00 ...  5.13097023e-01
  -6.67107736e-01  1.36876705e-01]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01 ...  9.31186120e-01
  -1.95816361e-01 -2.45860133e-01]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00 ... -2.56492619e-01
   7.21579859e-01 -4.45554921e-01]
 [-1.53519888e-05 -7.92744446e-01 -2.27055862e+01 ...  6.57593393e-01
   1.66846282e+00  7.00640209e-01]]
no of componenets 7
predict for transformed data
RMSE 0.15
Variance score: 0.51
[[ 5.51191435e-06 -7.23694160e-01 -2.06611873e+01 ... -6.64183030e-01
  -4.49741955e-01  1.64543813e-01]
 [ 1.20038436e-05  8.50748193e-01  2.42899316e+01 ...  6.82017952e-01
  -1.01855590e+00  2.55622705e-01]
 [ 6.20500272e-06 -1.62728214e-01 -4.66962748e+00 ... -6.67107733e-01
   1.36877578e-01  4.72453583e-03]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01 ... -1.95816368e-01
  -2.45861565e-01 -8.40040501e-01]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00 ...  7.21579856e-01
  -4.45555490e-01  4.79102300e-02]
 [-1.53519893e-05 -7.92744446e-01 -2.27055862e+01 ...  1.66846282e+00
   7.00639048e-01  2.00090598e-01]]
no of componenets 8
predict for transformed data
RMSE 0.15
Variance score: 0.55
[[ 5.51191561e-06 -7.23694160e-01 -2.06611873e+01 ... -4.49741544e-01
   1.64544130e-01 -5.35467325e-01]
 [ 1.20038453e-05  8.50748193e-01  2.42899316e+01 ... -1.01855589e+00
   2.55622807e-01 -1.86667889e-01]
 [ 6.20500443e-06 -1.62728214e-01 -4.66962748e+00 ...  1.36877719e-01
   4.72435652e-03 -6.58799790e-02]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01 ... -2.45861625e-01
```

```
  -8.40040513e-01 -1.22227719e-01]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00 ... -4.45555584e-01
   4.79102223e-02  3.32551821e-01]
 [-1.53519894e-05 -7.92744446e-01 -2.27055862e+01 ...  7.00639182e-01
   2.00091088e-01 -5.28195355e-01]]
no of componenets 9
predict for transformed data
RMSE 0.14
Variance score: 0.58
[[ 5.51191220e-06 -7.23694160e-01 -2.06611873e+01 ...  1.64544274e-01
  -5.35463693e-01 -4.28055285e-01]
 [ 1.20038439e-05  8.50748193e-01  2.42899316e+01 ...  2.55622869e-01
  -1.86667340e-01 -8.07341456e-01]
 [ 6.20500333e-06 -1.62728214e-01 -4.66962748e+00 ...  4.72436490e-03
  -6.58778322e-02  1.47154987e-01]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01 ... -8.40040604e-01
  -1.22230979e-01 -7.91918007e-02]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00 ...  4.79101612e-02
   3.32549723e-01 -1.27146167e-01]
 [-1.53519890e-05 -7.92744446e-01 -2.27055862e+01 ...  2.00091088e-01
  -5.28195516e-01 -3.40264107e-01]]
no of componenets 10
predict for transformed data
RMSE 0.14
Variance score: 0.61
[[ 5.51191562e-06 -7.23694160e-01 -2.06611873e+01 ... -5.35464047e-01
  -4.28052338e-01 -7.83355153e-02]
 [ 1.20038436e-05  8.50748193e-01  2.42899316e+01 ... -1.86666545e-01
  -8.07343513e-01 -3.19873660e-01]
 [ 6.20500591e-06 -1.62728214e-01 -4.66962748e+00 ... -6.58786116e-02
   1.47154751e-01 -5.46398241e-01]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01 ... -1.22230675e-01
  -7.91911538e-02  1.70014071e-01]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00 ...  3.32550029e-01
  -1.27146617e-01  6.20501380e-01]
 [-1.53519907e-05 -7.92744446e-01 -2.27055862e+01 ... -5.28195406e-01
  -3.40265790e-01  5.40280446e-03]]
no of componenets 11
predict for transformed data
RMSE 0.13
Variance score: 0.63
[[ 5.51191289e-06 -7.23694160e-01 -2.06611873e+01 ... -4.28058689e-01
  -7.83089047e-02  3.90496181e-02]
 [ 1.20038444e-05  8.50748193e-01  2.42899316e+01 ... -8.07342052e-01
  -3.19873323e-01 -6.76832123e-01]
 [ 6.20500425e-06 -1.62728214e-01 -4.66962748e+00 ...  1.47151702e-01
```

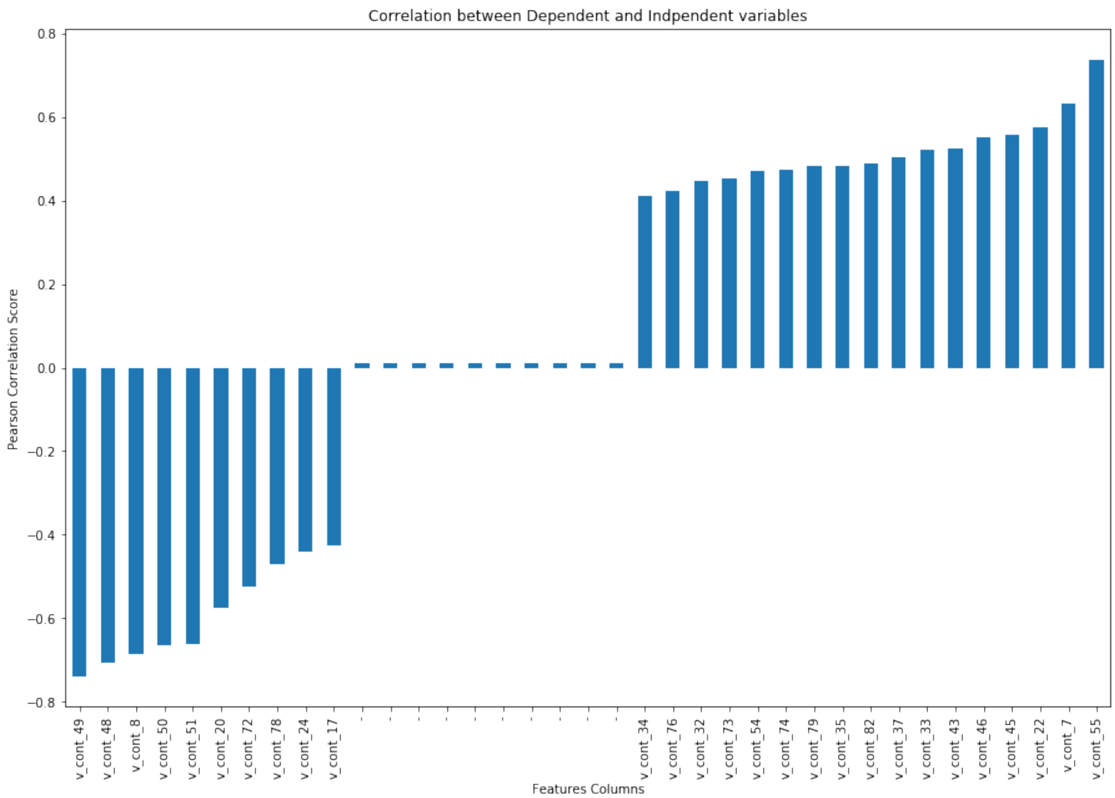
```
  -5.46383528e-01 -4.49723261e-01]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01 ... -7.91900477e-02
   1.70012838e-01  1.08975123e-01]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00 ... -1.27146121e-01
   6.20492273e-01 -1.40578877e-01]
 [-1.53519906e-05 -7.92744446e-01 -2.27055862e+01 ... -3.40265170e-01
   5.41788005e-03  2.77886535e-02]]
no of componenets 12
predict for transformed data
RMSE 0.13
Variance score: 0.63
[[ 5.51191646e-06 -7.23694160e-01 -2.06611873e+01 ... -7.81085678e-02
   3.90332255e-02  1.68625767e-01]
 [ 1.20038465e-05  8.50748193e-01  2.42899316e+01 ... -3.20561151e-01
  -6.76665215e-01 -2.88723340e-02]
 [ 6.20500441e-06 -1.62728214e-01 -4.66962748e+00 ... -5.46434800e-01
  -4.49417212e-01 -2.61362463e-02]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01 ...  1.71575975e-01
   1.08127559e-01  1.15700815e-01]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00 ...  6.21216815e-01
  -1.40958410e-01 -3.00472677e-02]
 [-1.53519911e-05 -7.92744446e-01 -2.27055862e+01 ...  5.75399630e-03
   2.77727729e-02  1.20431341e-01]]
no of componenets 13
predict for transformed data
RMSE 0.13
Variance score: 0.63
[[ 5.51191964e-06 -7.23694160e-01 -2.06611873e+01 ...  3.90025176e-02
   1.65470746e-01  9.18417955e-02]
 [ 1.20038474e-05  8.50748193e-01  2.42899316e+01 ... -6.76908334e-01
  -2.94303413e-02 -1.35019459e-01]
 [ 6.20500829e-06 -1.62728214e-01 -4.66962748e+00 ... -4.49522459e-01
  -2.52546924e-02  3.94281526e-01]
 ...
 [ 3.38816276e+04 -7.07140111e+01 -1.72278714e+01 ...  1.08835802e-01
   1.18866992e-01  4.23035986e-01]
 [ 2.64116337e+04 -5.77012878e+01 -1.68733318e+00 ... -1.40693348e-01
  -2.86039438e-02  4.96863259e-01]
 [-1.53519921e-05 -7.92744446e-01 -2.27055862e+01 ...  2.78717844e-02
   1.18346952e-01 -3.57631303e-02]]
no of componenets 14
predict for transformed data
RMSE 0.13
Variance score: 0.63
```

1.4.2 Feature engineering using Pearson's Coefficient

```
In [4]: X = (X - X.mean())
        Matrix = X.as_matrix()
        #print TrainX['ALSQM_Count']
        r=[]
        p=[]
        for i in range(X.shape[1]):
            t1,t2 = pearsonr(Matrix[:,i],Y)
            #print t1,i,
            r.append((t1,i,X.columns[i],t2))
        r.sort()
```

```
In [5]: frequencies = []
        labels =[]
        count=0
        for ind,x in enumerate(r):
            if(x[0]<-0.4 or x[0]>0.4):
                frequencies.append(x[0])
                labels.append(x[2])
            else:
                if count<10:
                    labels.append('-')
                    frequencies.append(0.01)
                    count+=1
        print len(frequencies)
        freq_series = pd.Series.from_array(frequencies)
        x_labels = range(len(freq_series))
        plt.figure(figsize=(15, 10))
        ax = freq_series.plot(kind='bar')
        ax.set_title('Correlation between Dependent and Indpendent variables')
        ax.set_xlabel('Features Columns')
        ax.set_ylabel('Pearson Correlation Score')
        rects = ax.patches
        ax.set_xticklabels(labels)
        plt.show()
```

```
37
```

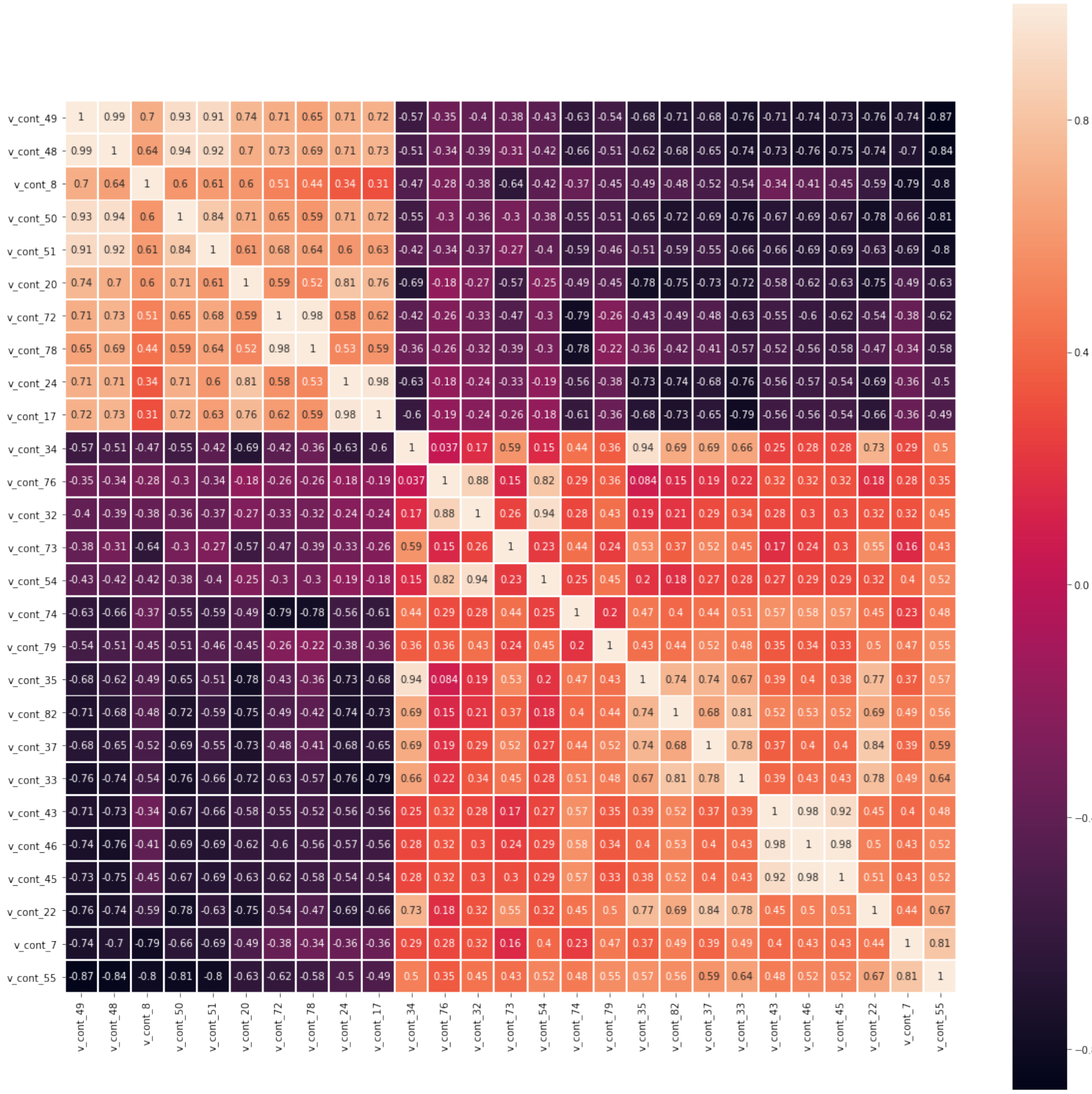


In [6]:
```
IndList =[]
for ind,x in enumerate(r):
    if(x[0]<-0.4 or x[0]>0.4):
        IndList.append(x[1])
CorrList =[]
CorrMatrix = np.zeros((len(IndList),len(IndList)))
Cols =[]
for i in range(len(IndList)):
    Cols.append(X.columns[IndList[i]])
    for j in range(len(IndList)):
        t1,t2 = pearsonr(Matrix[:,IndList[i]],Matrix[:,IndList[j]])
        CorrList.append((t1,IndList[i],X.columns[IndList[i]],IndList[j],X.columns[IndLi
        CorrMatrix[i][j] = t1
print CorrMatrix.shape
```

```
(27, 27)
```

In [7]:
```
fig, ax = plt.subplots(figsize=(20,20))
sb.heatmap(CorrMatrix,
        xticklabels=Cols,
        yticklabels=Cols,linewidths=1,annot=True, ax=ax,square =True)
```

```
plt.show()
```



1.5 4. Model Development and Performance

1.5.1 Linear Regression

```
In [8]: print IndList
        t=[]
        for i in IndList:
            t.append(X.columns[i])
        print t
        FinalTrainSet = np.zeros((len(IndList),Matrix.shape[0]))
```

```
for ind,i in enumerate(IndList):
    FinalTrainSet[ind] = (Matrix[:,i])
FinalTrainSet = FinalTrainSet.T
print FinalTrainSet.shape
print Y.shape

X_train,X_test,Y_train,Y_test = train_test_split(FinalTrainSet,Y,test_size = 0.3,randor
#Normal Linear Regression

regr = linear_model.LinearRegression(normalize = True)
regr.fit(X_train,Y_train)
Y_pred = regr.predict(X_test)
Weights = regr.coef_
print Weights
print "RMSE %.2f" % math.sqrt(mean_squared_error(Y_test,Y_pred))
print('Variance score: %.2f' % r2_score(Y_test, Y_pred))

# Linear Regression With Ridge regularisation
reg = linear_model.Ridge(alpha = 0.2,normalize = True)
reg.fit(X_train,Y_train)
Y_pred = reg.predict(X_test)
print "RMSE %.2f" % math.sqrt(mean_squared_error(Y_test,Y_pred))
print('Variance score: %.2f' % r2_score(Y_test, Y_pred))


# Linear Regression With Lasso regularisation
reg = linear_model.Lasso(alpha = 0.2,normalize = True)
reg.fit(X_train,Y_train)
Y_pred = reg.predict(X_test)
print "RMSE %.2f" % math.sqrt(mean_squared_error(Y_test,Y_pred))
print('Variance score: %.2f' % r2_score(Y_test, Y_pred))
```

```
[48, 47, 7, 49, 50, 19, 71, 77, 23, 16, 33, 75, 31, 72, 53, 73, 78, 34, 81, 36, 32, 42, 45, 44
['v_cont_49', 'v_cont_48', 'v_cont_8', 'v_cont_50', 'v_cont_51', 'v_cont_20', 'v_cont_72', 'v_
(1994, 27)
(1994,)
[-0.06986744 -0.20319033  0.00282052 -0.0764294  -0.00365693 -0.11640938
 -0.3154949   0.35358964  0.21298279 -0.04158515 -0.16352962  0.26255075
  0.12639153  0.2220687  -0.23364425  0.10495532  0.04729825  0.11573447
  0.02870576 -0.05019055 -0.06960878  0.4324694  -0.61741931  0.26619755
  0.05778619  0.19690957  0.16119416]
RMSE 0.13
Variance score: 0.64
RMSE 0.13
Variance score: 0.64
RMSE 0.22
Variance score: -0.01
```

1.5.2 Neural Nets

```
In [11]: X_train,X_test,Y_train,Y_test = train_test_split(FinalTrainSet,Y,test_size = 0.3,rand
         InputWidth = X_train.shape[1]
         K.clear_session()
         model = Sequential()
         model.add(Dense(128, input_shape = (InputWidth,), activation='relu'))
         model.add(Dropout(0.2))
         model.add(Dense(64, activation='relu'))
         model.add(Dropout(0.2))
         model.add(Dense(32, activation='relu'))
         model.add(Dropout(0.2))
         model.add(Dense(1, activation='relu'))
         #model.add(Dense(InputWidth, activation='relu'))
         print model.summary()
         # Compile model
         model.compile(loss='mean_squared_error', optimizer='sgd', metrics=['accuracy'])
         op = model.fit(X_train, Y_train, validation_data=(X_test, Y_test), nb_epoch=150, batc
         y_pred = model.predict(X_test)
         print "RMSE %.2f" % math.sqrt(mean_squared_error(Y_test,Y_pred))
         print('Variance score: %.2f' % r2_score(Y_test, Y_pred))
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 128)               3584
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                8256
_________________________________________________________________
dropout_2 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_3 (Dense)              (None, 32)                2080
_________________________________________________________________
dropout_3 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 33
=================================================================
Total params: 13,953
Trainable params: 13,953
Non-trainable params: 0
_________________________________________________________________
None
Train on 1395 samples, validate on 599 samples
Epoch 1/150
0s - loss: 0.1032 - acc: 0.0036 - val_loss: 0.0784 - val_acc: 0.0083
Epoch 2/150
0s - loss: 0.0814 - acc: 0.0036 - val_loss: 0.0539 - val_acc: 0.0083
```

```
Epoch 3/150
0s - loss: 0.0620 - acc: 0.0036 - val_loss: 0.0426 - val_acc: 0.0083
Epoch 4/150
0s - loss: 0.0529 - acc: 0.0036 - val_loss: 0.0375 - val_acc: 0.0083
Epoch 5/150
0s - loss: 0.0474 - acc: 0.0065 - val_loss: 0.0339 - val_acc: 0.0083
Epoch 6/150
0s - loss: 0.0436 - acc: 0.0079 - val_loss: 0.0312 - val_acc: 0.0100
Epoch 7/150
0s - loss: 0.0416 - acc: 0.0108 - val_loss: 0.0291 - val_acc: 0.0134
Epoch 8/150
0s - loss: 0.0392 - acc: 0.0093 - val_loss: 0.0275 - val_acc: 0.0134
Epoch 9/150
0s - loss: 0.0369 - acc: 0.0086 - val_loss: 0.0261 - val_acc: 0.0134
Epoch 10/150
0s - loss: 0.0343 - acc: 0.0129 - val_loss: 0.0249 - val_acc: 0.0150
Epoch 11/150
0s - loss: 0.0326 - acc: 0.0158 - val_loss: 0.0241 - val_acc: 0.0150
Epoch 12/150
0s - loss: 0.0345 - acc: 0.0172 - val_loss: 0.0235 - val_acc: 0.0167
Epoch 13/150
0s - loss: 0.0329 - acc: 0.0165 - val_loss: 0.0229 - val_acc: 0.0184
Epoch 14/150
0s - loss: 0.0305 - acc: 0.0158 - val_loss: 0.0224 - val_acc: 0.0184
Epoch 15/150
0s - loss: 0.0320 - acc: 0.0165 - val_loss: 0.0220 - val_acc: 0.0184
Epoch 16/150
0s - loss: 0.0320 - acc: 0.0172 - val_loss: 0.0217 - val_acc: 0.0184
Epoch 17/150
0s - loss: 0.0307 - acc: 0.0201 - val_loss: 0.0215 - val_acc: 0.0184
Epoch 18/150
0s - loss: 0.0281 - acc: 0.0201 - val_loss: 0.0213 - val_acc: 0.0184
Epoch 19/150
0s - loss: 0.0287 - acc: 0.0215 - val_loss: 0.0211 - val_acc: 0.0184
Epoch 20/150
0s - loss: 0.0289 - acc: 0.0222 - val_loss: 0.0209 - val_acc: 0.0200
Epoch 21/150
0s - loss: 0.0286 - acc: 0.0186 - val_loss: 0.0208 - val_acc: 0.0200
Epoch 22/150
0s - loss: 0.0288 - acc: 0.0208 - val_loss: 0.0207 - val_acc: 0.0200
Epoch 23/150
0s - loss: 0.0288 - acc: 0.0222 - val_loss: 0.0206 - val_acc: 0.0200
Epoch 24/150
0s - loss: 0.0285 - acc: 0.0208 - val_loss: 0.0205 - val_acc: 0.0200
Epoch 25/150
0s - loss: 0.0277 - acc: 0.0186 - val_loss: 0.0205 - val_acc: 0.0200
Epoch 26/150
0s - loss: 0.0297 - acc: 0.0201 - val_loss: 0.0204 - val_acc: 0.0200
```

```
Epoch 27/150
0s - loss: 0.0273 - acc: 0.0222 - val_loss: 0.0203 - val_acc: 0.0200
Epoch 28/150
0s - loss: 0.0300 - acc: 0.0186 - val_loss: 0.0203 - val_acc: 0.0200
Epoch 29/150
0s - loss: 0.0260 - acc: 0.0222 - val_loss: 0.0202 - val_acc: 0.0200
Epoch 30/150
0s - loss: 0.0279 - acc: 0.0201 - val_loss: 0.0202 - val_acc: 0.0200
Epoch 31/150
0s - loss: 0.0278 - acc: 0.0222 - val_loss: 0.0201 - val_acc: 0.0200
Epoch 32/150
0s - loss: 0.0293 - acc: 0.0194 - val_loss: 0.0201 - val_acc: 0.0200
Epoch 33/150
0s - loss: 0.0289 - acc: 0.0215 - val_loss: 0.0201 - val_acc: 0.0200
Epoch 34/150
0s - loss: 0.0281 - acc: 0.0222 - val_loss: 0.0200 - val_acc: 0.0200
Epoch 35/150
0s - loss: 0.0274 - acc: 0.0215 - val_loss: 0.0200 - val_acc: 0.0200
Epoch 36/150
0s - loss: 0.0269 - acc: 0.0222 - val_loss: 0.0199 - val_acc: 0.0200
Epoch 37/150
0s - loss: 0.0273 - acc: 0.0229 - val_loss: 0.0199 - val_acc: 0.0200
Epoch 38/150
0s - loss: 0.0275 - acc: 0.0222 - val_loss: 0.0199 - val_acc: 0.0200
Epoch 39/150
0s - loss: 0.0266 - acc: 0.0237 - val_loss: 0.0198 - val_acc: 0.0200
Epoch 40/150
0s - loss: 0.0270 - acc: 0.0208 - val_loss: 0.0198 - val_acc: 0.0200
Epoch 41/150
0s - loss: 0.0273 - acc: 0.0208 - val_loss: 0.0197 - val_acc: 0.0200
Epoch 42/150
0s - loss: 0.0278 - acc: 0.0215 - val_loss: 0.0197 - val_acc: 0.0200
Epoch 43/150
0s - loss: 0.0267 - acc: 0.0194 - val_loss: 0.0197 - val_acc: 0.0200
Epoch 44/150
0s - loss: 0.0265 - acc: 0.0215 - val_loss: 0.0197 - val_acc: 0.0200
Epoch 45/150
0s - loss: 0.0254 - acc: 0.0229 - val_loss: 0.0196 - val_acc: 0.0200
Epoch 46/150
0s - loss: 0.0271 - acc: 0.0186 - val_loss: 0.0196 - val_acc: 0.0200
Epoch 47/150
0s - loss: 0.0267 - acc: 0.0244 - val_loss: 0.0196 - val_acc: 0.0200
Epoch 48/150
0s - loss: 0.0277 - acc: 0.0229 - val_loss: 0.0195 - val_acc: 0.0200
Epoch 49/150
0s - loss: 0.0247 - acc: 0.0251 - val_loss: 0.0195 - val_acc: 0.0200
Epoch 50/150
0s - loss: 0.0264 - acc: 0.0222 - val_loss: 0.0195 - val_acc: 0.0200
```

```
Epoch 51/150
0s - loss: 0.0258 - acc: 0.0222 - val_loss: 0.0195 - val_acc: 0.0200
Epoch 52/150
0s - loss: 0.0264 - acc: 0.0229 - val_loss: 0.0194 - val_acc: 0.0200
Epoch 53/150
0s - loss: 0.0271 - acc: 0.0194 - val_loss: 0.0194 - val_acc: 0.0200
Epoch 54/150
0s - loss: 0.0266 - acc: 0.0215 - val_loss: 0.0194 - val_acc: 0.0200
Epoch 55/150
0s - loss: 0.0249 - acc: 0.0237 - val_loss: 0.0194 - val_acc: 0.0200
Epoch 56/150
0s - loss: 0.0272 - acc: 0.0201 - val_loss: 0.0194 - val_acc: 0.0200
Epoch 57/150
0s - loss: 0.0261 - acc: 0.0215 - val_loss: 0.0193 - val_acc: 0.0200
Epoch 58/150
0s - loss: 0.0261 - acc: 0.0201 - val_loss: 0.0193 - val_acc: 0.0200
Epoch 59/150
0s - loss: 0.0274 - acc: 0.0229 - val_loss: 0.0193 - val_acc: 0.0200
Epoch 60/150
0s - loss: 0.0254 - acc: 0.0237 - val_loss: 0.0193 - val_acc: 0.0200
Epoch 61/150
0s - loss: 0.0257 - acc: 0.0229 - val_loss: 0.0193 - val_acc: 0.0200
Epoch 62/150
0s - loss: 0.0266 - acc: 0.0208 - val_loss: 0.0192 - val_acc: 0.0200
Epoch 63/150
0s - loss: 0.0283 - acc: 0.0201 - val_loss: 0.0192 - val_acc: 0.0200
Epoch 64/150
0s - loss: 0.0262 - acc: 0.0215 - val_loss: 0.0192 - val_acc: 0.0200
Epoch 65/150
0s - loss: 0.0245 - acc: 0.0229 - val_loss: 0.0192 - val_acc: 0.0200
Epoch 66/150
0s - loss: 0.0275 - acc: 0.0215 - val_loss: 0.0192 - val_acc: 0.0200
Epoch 67/150
0s - loss: 0.0267 - acc: 0.0229 - val_loss: 0.0191 - val_acc: 0.0200
Epoch 68/150
0s - loss: 0.0258 - acc: 0.0215 - val_loss: 0.0191 - val_acc: 0.0200
Epoch 69/150
0s - loss: 0.0275 - acc: 0.0194 - val_loss: 0.0191 - val_acc: 0.0200
Epoch 70/150
0s - loss: 0.0264 - acc: 0.0222 - val_loss: 0.0191 - val_acc: 0.0200
Epoch 71/150
0s - loss: 0.0246 - acc: 0.0229 - val_loss: 0.0191 - val_acc: 0.0200
Epoch 72/150
0s - loss: 0.0252 - acc: 0.0237 - val_loss: 0.0191 - val_acc: 0.0200
Epoch 73/150
0s - loss: 0.0255 - acc: 0.0215 - val_loss: 0.0191 - val_acc: 0.0200
Epoch 74/150
0s - loss: 0.0255 - acc: 0.0222 - val_loss: 0.0191 - val_acc: 0.0200
```

```
Epoch 75/150
0s - loss: 0.0254 - acc: 0.0201 - val_loss: 0.0191 - val_acc: 0.0200
Epoch 76/150
0s - loss: 0.0267 - acc: 0.0222 - val_loss: 0.0190 - val_acc: 0.0200
Epoch 77/150
0s - loss: 0.0266 - acc: 0.0222 - val_loss: 0.0190 - val_acc: 0.0200
Epoch 78/150
0s - loss: 0.0255 - acc: 0.0222 - val_loss: 0.0190 - val_acc: 0.0200
Epoch 79/150
0s - loss: 0.0263 - acc: 0.0201 - val_loss: 0.0190 - val_acc: 0.0200
Epoch 80/150
0s - loss: 0.0263 - acc: 0.0215 - val_loss: 0.0190 - val_acc: 0.0200
Epoch 81/150
0s - loss: 0.0248 - acc: 0.0222 - val_loss: 0.0190 - val_acc: 0.0200
Epoch 82/150
0s - loss: 0.0251 - acc: 0.0251 - val_loss: 0.0189 - val_acc: 0.0200
Epoch 83/150
0s - loss: 0.0258 - acc: 0.0237 - val_loss: 0.0189 - val_acc: 0.0200
Epoch 84/150
0s - loss: 0.0253 - acc: 0.0237 - val_loss: 0.0189 - val_acc: 0.0200
Epoch 85/150
0s - loss: 0.0260 - acc: 0.0237 - val_loss: 0.0189 - val_acc: 0.0200
Epoch 86/150
0s - loss: 0.0248 - acc: 0.0237 - val_loss: 0.0189 - val_acc: 0.0200
Epoch 87/150
0s - loss: 0.0246 - acc: 0.0222 - val_loss: 0.0189 - val_acc: 0.0200
Epoch 88/150
0s - loss: 0.0261 - acc: 0.0229 - val_loss: 0.0189 - val_acc: 0.0200
Epoch 89/150
0s - loss: 0.0246 - acc: 0.0222 - val_loss: 0.0189 - val_acc: 0.0200
Epoch 90/150
0s - loss: 0.0242 - acc: 0.0237 - val_loss: 0.0188 - val_acc: 0.0200
Epoch 91/150
0s - loss: 0.0262 - acc: 0.0201 - val_loss: 0.0188 - val_acc: 0.0200
Epoch 92/150
0s - loss: 0.0255 - acc: 0.0229 - val_loss: 0.0188 - val_acc: 0.0200
Epoch 93/150
0s - loss: 0.0259 - acc: 0.0222 - val_loss: 0.0188 - val_acc: 0.0200
Epoch 94/150
0s - loss: 0.0250 - acc: 0.0215 - val_loss: 0.0188 - val_acc: 0.0200
Epoch 95/150
0s - loss: 0.0251 - acc: 0.0215 - val_loss: 0.0188 - val_acc: 0.0200
Epoch 96/150
0s - loss: 0.0253 - acc: 0.0237 - val_loss: 0.0188 - val_acc: 0.0200
Epoch 97/150
0s - loss: 0.0253 - acc: 0.0208 - val_loss: 0.0187 - val_acc: 0.0200
Epoch 98/150
0s - loss: 0.0236 - acc: 0.0244 - val_loss: 0.0187 - val_acc: 0.0200
```

```
Epoch 99/150
0s - loss: 0.0262 - acc: 0.0208 - val_loss: 0.0187 - val_acc: 0.0200
Epoch 100/150
0s - loss: 0.0257 - acc: 0.0201 - val_loss: 0.0187 - val_acc: 0.0200
Epoch 101/150
0s - loss: 0.0241 - acc: 0.0229 - val_loss: 0.0187 - val_acc: 0.0200
Epoch 102/150
0s - loss: 0.0251 - acc: 0.0229 - val_loss: 0.0187 - val_acc: 0.0200
Epoch 103/150
0s - loss: 0.0244 - acc: 0.0251 - val_loss: 0.0187 - val_acc: 0.0200
Epoch 104/150
0s - loss: 0.0249 - acc: 0.0251 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 105/150
0s - loss: 0.0246 - acc: 0.0208 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 106/150
0s - loss: 0.0251 - acc: 0.0237 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 107/150
0s - loss: 0.0251 - acc: 0.0222 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 108/150
0s - loss: 0.0243 - acc: 0.0237 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 109/150
0s - loss: 0.0240 - acc: 0.0244 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 110/150
0s - loss: 0.0245 - acc: 0.0244 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 111/150
0s - loss: 0.0237 - acc: 0.0237 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 112/150
0s - loss: 0.0244 - acc: 0.0229 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 113/150
0s - loss: 0.0254 - acc: 0.0208 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 114/150
0s - loss: 0.0248 - acc: 0.0222 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 115/150
0s - loss: 0.0261 - acc: 0.0222 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 116/150
0s - loss: 0.0233 - acc: 0.0222 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 117/150
0s - loss: 0.0243 - acc: 0.0237 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 118/150
0s - loss: 0.0246 - acc: 0.0222 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 119/150
0s - loss: 0.0247 - acc: 0.0222 - val_loss: 0.0186 - val_acc: 0.0200
Epoch 120/150
0s - loss: 0.0239 - acc: 0.0244 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 121/150
0s - loss: 0.0238 - acc: 0.0251 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 122/150
0s - loss: 0.0247 - acc: 0.0208 - val_loss: 0.0185 - val_acc: 0.0200
```

```
Epoch 123/150
0s - loss: 0.0247 - acc: 0.0251 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 124/150
0s - loss: 0.0244 - acc: 0.0258 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 125/150
0s - loss: 0.0252 - acc: 0.0215 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 126/150
0s - loss: 0.0249 - acc: 0.0222 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 127/150
0s - loss: 0.0247 - acc: 0.0244 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 128/150
0s - loss: 0.0248 - acc: 0.0215 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 129/150
0s - loss: 0.0231 - acc: 0.0251 - val_loss: 0.0185 - val_acc: 0.0200
Epoch 130/150
0s - loss: 0.0252 - acc: 0.0201 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 131/150
0s - loss: 0.0257 - acc: 0.0244 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 132/150
0s - loss: 0.0247 - acc: 0.0208 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 133/150
0s - loss: 0.0239 - acc: 0.0237 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 134/150
0s - loss: 0.0233 - acc: 0.0208 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 135/150
0s - loss: 0.0242 - acc: 0.0237 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 136/150
0s - loss: 0.0234 - acc: 0.0229 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 137/150
0s - loss: 0.0240 - acc: 0.0222 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 138/150
0s - loss: 0.0245 - acc: 0.0215 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 139/150
0s - loss: 0.0251 - acc: 0.0244 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 140/150
0s - loss: 0.0236 - acc: 0.0251 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 141/150
0s - loss: 0.0234 - acc: 0.0244 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 142/150
0s - loss: 0.0238 - acc: 0.0237 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 143/150
0s - loss: 0.0239 - acc: 0.0244 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 144/150
0s - loss: 0.0240 - acc: 0.0229 - val_loss: 0.0184 - val_acc: 0.0200
Epoch 145/150
0s - loss: 0.0248 - acc: 0.0201 - val_loss: 0.0183 - val_acc: 0.0200
Epoch 146/150
0s - loss: 0.0238 - acc: 0.0215 - val_loss: 0.0183 - val_acc: 0.0200
```

```
Epoch 147/150
0s - loss: 0.0234 - acc: 0.0229 - val_loss: 0.0183 - val_acc: 0.0200
Epoch 148/150
0s - loss: 0.0237 - acc: 0.0237 - val_loss: 0.0183 - val_acc: 0.0200
Epoch 149/150
0s - loss: 0.0235 - acc: 0.0237 - val_loss: 0.0183 - val_acc: 0.0200
Epoch 150/150
0s - loss: 0.0249 - acc: 0.0222 - val_loss: 0.0183 - val_acc: 0.0200
RMSE 0.22
Variance score: -0.01
```

FNN doesnt perform as well possibly due to the limited number of training samples.

In [12]:
```
HighCorrTuples =[]
LowCorrTuples=[]
Col =[]
ht ={}
CorrCopy = copy.deepcopy(CorrList)
for var in CorrCopy:
    if((var[0]>=0.8 or var[0]<=-0.8) and var[1]!=var[3]):
        if(var[1] not in ht or var[3] not in ht):
            print var
            ht[var[3]] =0
    else:
        LowCorrTuples.append(var)
print len(ht)
FinalFeatureSet =[]
print len(CorrCopy)
for index,var in enumerate(CorrCopy):
    if(not(var[1] in ht or var[3] in ht)):
        #print var
        FinalFeatureSet.append(var)
print len(CorrList)
print len(CorrCopy)
print len(FinalFeatureSet)
'''
assert(len(HighCorrTuples)+len(LowCorrTuples)==len(Corr))
UncorrelatedFeatureIndices=[]

for i in HighCorrTuples:
    UncorrelatedFeatureIndices.remove(i[1])
print len(UncorrelatedFeatureIndices)

for i in LowCorrTuples:
    if(i[1]!=i[3]):
        if(i[1] not in UncorrelatedFeatureIndices):
            UncorrelatedFeatureIndices.append(i[1])
```

```
            if(i[3] not in UncorrelatedFeatureIndices):
                UncorrelatedFeatureIndices.append(i[3])
    print len(UncorrelatedFeatureIndices)
    print UncorrelatedFeatureIndices

    '''
```

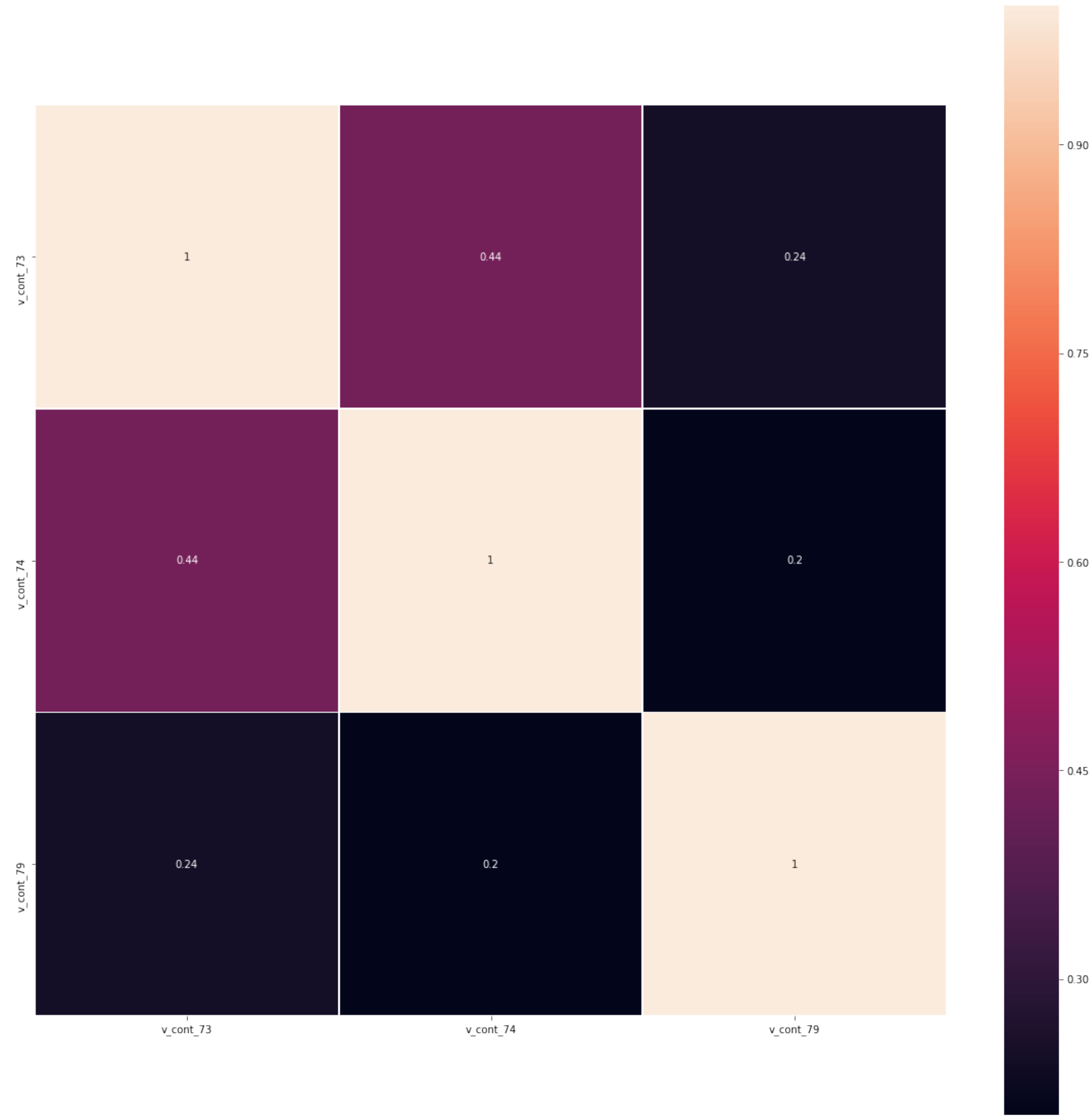
```
(0.985358028188035, 48, 'v_cont_49', 47, 'v_cont_48', 0.0)
(0.9311545163340417, 48, 'v_cont_49', 49, 'v_cont_50', 0.0)
(0.9076518065031174, 48, 'v_cont_49', 50, 'v_cont_51', 0.0)
(-0.8701983204454441, 48, 'v_cont_49', 54, 'v_cont_55', 0.0)
(0.985358028188035, 47, 'v_cont_48', 48, 'v_cont_49', 0.0)
(-0.8034519072989161, 7, 'v_cont_8', 54, 'v_cont_55', 0.0)
(0.8132433874202087, 19, 'v_cont_20', 23, 'v_cont_24', 0.0)
(0.981898517014815, 71, 'v_cont_72', 77, 'v_cont_78', 0.0)
(0.981898517014815, 77, 'v_cont_78', 71, 'v_cont_72', 0.0)
(0.8132433874202087, 23, 'v_cont_24', 19, 'v_cont_20', 0.0)
(0.9776158180285813, 23, 'v_cont_24', 16, 'v_cont_17', 0.0)
(0.9438503379649609, 33, 'v_cont_34', 34, 'v_cont_35', 0.0)
(0.8814456236410259, 75, 'v_cont_76', 31, 'v_cont_32', 0.0)
(0.8226685567453994, 75, 'v_cont_76', 53, 'v_cont_54', 0.0)
(0.8814456236410259, 31, 'v_cont_32', 75, 'v_cont_76', 0.0)
(0.9438503379649609, 34, 'v_cont_35', 33, 'v_cont_34', 0.0)
(0.8137998648445638, 81, 'v_cont_82', 32, 'v_cont_33', 0.0)
(0.8361952961320445, 36, 'v_cont_37', 21, 'v_cont_22', 0.0)
(0.8137998648445638, 32, 'v_cont_33', 81, 'v_cont_82', 0.0)
(0.9757255165940261, 42, 'v_cont_43', 45, 'v_cont_46', 0.0)
(0.9223946342691782, 42, 'v_cont_43', 44, 'v_cont_45', 0.0)
(0.9757255165940261, 45, 'v_cont_46', 42, 'v_cont_43', 0.0)
(0.8361952961320445, 21, 'v_cont_22', 36, 'v_cont_37', 0.0)
(0.8107003756835877, 6, 'v_cont_7', 54, 'v_cont_55', 0.0)
(-0.8034519072989161, 54, 'v_cont_55', 7, 'v_cont_8', 0.0)
(0.8107003756835877, 54, 'v_cont_55', 6, 'v_cont_7', 0.0)
24
729
729
729
9
```

```
Out[12]: '\nassert(len(HighCorrTuples)+len(LowCorrTuples)==len(Corr))\nUncorrelatedFeatureIndi
```

```
In [14]: Indfor ={}
         for ind,x in enumerate(FinalFeatureSet):
             if(x[1] not in Indfor):
                 Indfor[x[1]] = x[1]
         print len(Indfor)
         IndforCor =[]
```

```
for key,val in Indfor.items():
    IndforCor.append(val)
Cols=[]
FinalcorMatrix = np.zeros((len(Indfor),len(Indfor)))
for i in range(FinalcorMatrix.shape[0]):
    Cols.append(X.columns[IndforCor[i]])
    for j in range(FinalcorMatrix.shape[1]):
        t1,t2 = pearsonr(Matrix[:,IndforCor[i]],Matrix[:,IndforCor[j]])
        FinalcorMatrix[i][j] = t1

fig, ax = plt.subplots(figsize=(20,20))
sb.heatmap(FinalcorMatrix,
        xticklabels=Cols,
        yticklabels=Cols,linewidths=1,annot=True, ax=ax,square =True)

plt.show()
```

3




```
In [15]: print IndforCor
```

```
[72, 73, 78]
```

1.5.3 Linear regression on the remaining features

```
In [17]: FinalTrainSetForTrain = np.zeros((3,Matrix.shape[0]))
         for ind,k in enumerate(IndforCor):
             FinalTrainSetForTrain[ind] = (Matrix[:,k])
         FinalTrainSetForTrain = FinalTrainSetForTrain.T
         X_train,X_test,Y_train,Y_test = train_test_split(FinalTrainSetForTrain,Y,test_size = (
```

```python
#Normal Linear Regression

regr = linear_model.LinearRegression(normalize = True)
regr.fit(X_train,Y_train)
Y_pred = regr.predict(X_test)
Weights = regr.coef_
print "RMSE %.2f" % math.sqrt(mean_squared_error(Y_test,Y_pred))
print('Variance score: %.2f' % r2_score(Y_test, Y_pred))

# Linear Regression With Ridge regularisation
reg = linear_model.Ridge(alpha = 0.2,normalize = True)
reg.fit(X_train,Y_train)
Y_pred = reg.predict(X_test)
print "RMSE %.2f" % math.sqrt(mean_squared_error(Y_test,Y_pred))
print('Variance score: %.2f' % r2_score(Y_test, Y_pred))


# Linear Regression With Lasso regularisation
reg = linear_model.Lasso(alpha = 0.2,normalize = True)
reg.fit(X_train,Y_train)
Y_pred = reg.predict(X_test)
print "RMSE %.2f" % math.sqrt(mean_squared_error(Y_test,Y_pred))
print('Variance score: %.2f' % r2_score(Y_test, Y_pred))
```

```
RMSE 0.17
Variance score: 0.42
RMSE 0.17
Variance score: 0.42
RMSE 0.22
Variance score: -0.01
```