Fraud Detection in NYC Real Estate

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from pyod.utils.data import generate_data
# from pyod.models.knn import KNN   # kNN detector
from pyod.utils.data import evaluate_print
from pyod.utils.example import visualize
```

In [2]:

```
# read the dataframe
or_mydata = pd.read_csv('NY property data COMPLETE.csv')
or_mydata.shape

no_of_or_data = or_mydata.shape[0]
no_of_or_features = or_mydata.shape[1]
print('No of data points is: ',str(no_of_or_data))
print('No of features is ',str(no_of_or_features))
```

```
No of data points is:  1070994
No of features is  33
```

1. Feature Engineering

Create new features based on the ones in the original dataset

In [2]:

```
# read the dataframe
mydata = pd.read_csv('45_Variables.csv')
# mydata.shape

no_of_data = mydata.shape[0]
no_of_features = mydata.shape[1]
print('No of data points is: ',str(no_of_data))
print('No of features is ',str(no_of_features))
```

```
No of data points is:  1070994
No of features is  46
```

In [3]:

```
data_45 = mydata.drop(columns='Unnamed: 0')
data_45.head()
```

Out[3]:

	FULLVAL/LOTAREA_ZIP	FULLVAL/LOTAREA_ZIP3	FULLVAL/LOTAREA_TAXCLASS	FULLVAL/LO
0	0.126027	0.111252	0.189061	
1	124.901681	110.258630	187.372920	1
2	0.806334	0.711802	1.209632	
3	0.276320	0.243925	0.414526	
4	2.060754	1.819158	3.091467	

5 rows × 45 columns

In [4]:

```
npX_train = np.array(data_45.values)
npX_train.shape
```

Out[4]:

```
(1070994, 45)
```

2. Normalize Dataset

Normalize the dataset as a preprocessing step for dimensionality reduction

In [5]:

```
from sklearn import preprocessing
X_norm1 = preprocessing.scale(npX_train)
```

In [6]:

```
# verify the features are normalized
npX_train_norm = np.array(X_norm1)
# print('Normalized mean is: ',str(np.mean(npX_train_norm,axis=0)))
print('Normalized mean is: ',str(np.isclose(np.mean(npX_train_norm,axis=0),0)-1))
print('Normalized std is: ',str(np.std(npX_train_norm,axis=0)))
```

```
Normalized mean is:  [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0]
Normalized std is:  [1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

In [7]:

```
# output the normazized features to dataframe
X_1st_norm_df = pd.DataFrame(npX_train_norm,columns=data_45.columns)
# X_1st_norm_df.to_csv('Normalized_Data_45.csv')
X_1st_norm_df
```

Out[7]:

	FULLVAL/LOTAREA_ZIP	FULLVAL/LOTAREA_ZIP3	FULLVAL/LOTAREA_TAXCLASS	FULLV
0	-0.220109	-0.089338	-0.144911	
1	31.204520	10.982785	33.304014	
2	-0.048775	-0.028970	0.037460	
3	-0.182258	-0.076001	-0.104622	
4	0.267150	0.082343	0.373736	
...	...	...	...	
1070989	-0.204960	-0.054658	-0.131462	
1070990	-0.222187	-0.071508	-0.148816	
1070991	-0.226279	-0.075510	-0.152938	
1070992	-0.192667	-0.042634	-0.119079	
1070993	-0.160704	-0.011371	-0.086882	

1070994 rows × 45 columns

3. PCA dimension reduction

In [8]:

```
# this is for all PC's
from sklearn.decomposition import PCA
skt_all_pca_mod = PCA()
skt_all_pca_mod.fit_transform(X=npX_train_norm, y=None)
```

Out[8]:

```
array([[ 1.48027377e+00, -9.83675451e-01, -4.48044928e-02, ...,
         7.93374541e-03, -9.13088309e-03,  2.50234257e-02],
       [ 2.63401996e+01,  5.77771019e+01,  1.64094148e+01, ...,
        -2.39037209e-02,  1.42156194e-02, -4.01806990e-02],
       [ 8.76941240e-02,  2.83781759e-01, -6.19459039e-02, ...,
         3.87401536e-04,  3.32878694e-05, -2.63038322e-04],
       ...,
       [-1.69389181e-01, -2.76822823e-01, -6.83742732e-02, ...,
         1.66484394e-04,  9.18815094e-05,  1.62544701e-05],
       [-1.25363202e-01, -2.28012826e-01, -4.07846881e-02, ...,
         2.47088632e-04,  1.21895127e-04, -3.01498383e-05],
       [-1.15047539e-01, -1.45148934e-01, -2.81910652e-02, ...,
         1.43323163e-04,  9.20301118e-05, -3.87163619e-06]])
```

In [17]:

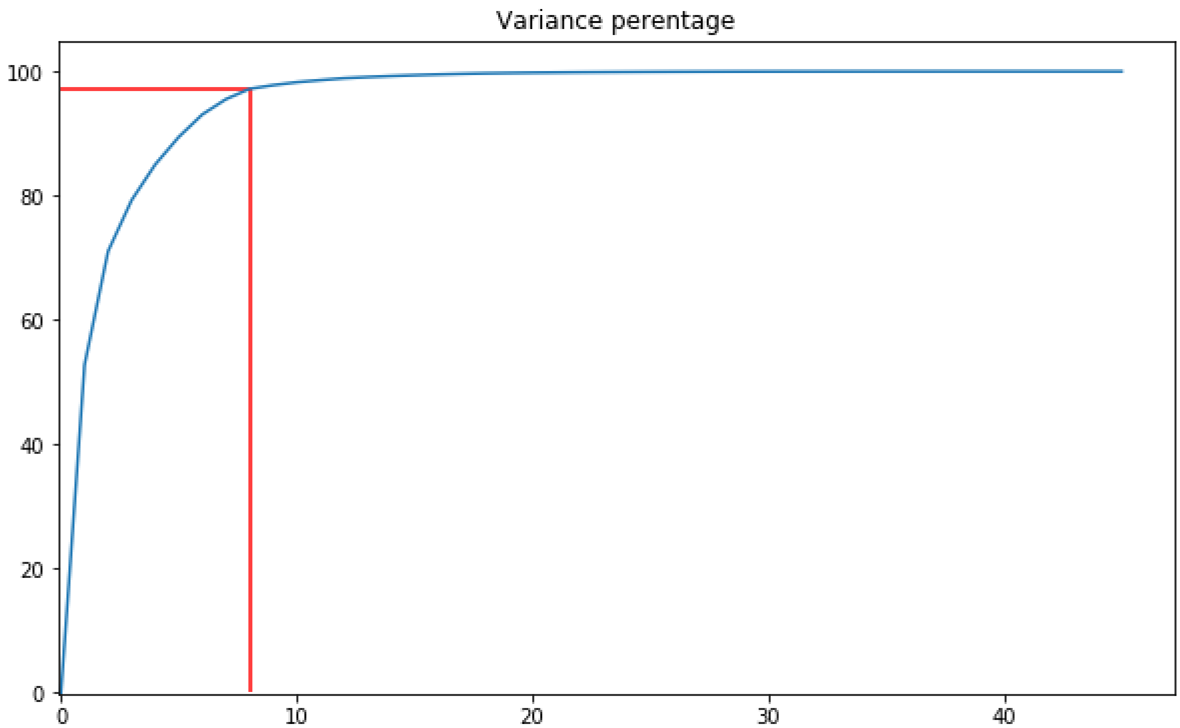
```
# The amount of variance explained by each of the selected components.
PCA_all_vecs = skt_all_pca_mod.explained_variance_ratio_
plot_pca_vecs = 8
print(skt_all_pca_mod.explained_variance_)
pca_plot_arr = np.zeros(len(PCA_all_vecs) + 1)
pca_plot_arr[1:] = np.cumsum(PCA_all_vecs)
#  = plt.subplots(1,1)
plt.figure(figsize=(10,6))

plt.plot(pca_plot_arr*100)
plt.title('Variance perentage')
# plt.axvline(x=8,c='r')
plt.vlines(x=plot_pca_vecs, ymin=0, ymax=pca_plot_arr[8]*100,color = 'r')
plt.hlines(y = pca_plot_arr[plot_pca_vecs]*100,xmin=0, xmax=plot_pca_vecs, color = 'r' )
plt.xlim(-0.1,)
plt.ylim(-0.1,)

# fig, ax = plt.subplots(1,1)
# p=ax.plot(x,y)
# ax.set_yticks(pca_plot_arr[plot_pca_vecs]*100)
# ax.set_yticklabels(pca_plot_arr[plot_pca_vecs]*100)

plt.show()
```

```
[2.37225461e+01 8.24597629e+00 3.70339908e+00 2.57895260e+00
 1.99774111e+00 1.62923907e+00 1.10447222e+00 7.46890879e-01
 2.67578840e-01 2.13390636e-01 1.50973942e-01 1.40090013e-01
 8.46317133e-02 7.35385845e-02 6.16854669e-02 5.40612909e-02
 4.52074834e-02 3.68129375e-02 2.38540471e-02 2.15472152e-02
 1.60928020e-02 1.43593705e-02 1.16679567e-02 9.98603211e-03
 9.29931404e-03 7.24548328e-03 5.93816885e-03 5.14184446e-03
 4.44342761e-03 3.00832302e-03 2.89125725e-03 1.79798841e-03
 1.64450847e-03 1.34267257e-03 8.76374149e-04 5.56254363e-04
 3.26484601e-04 2.59780307e-04 1.74972049e-04 1.51626875e-04
 9.32980690e-05 5.50485617e-05 4.92708676e-05 3.83005215e-05
 1.19714351e-05]
```

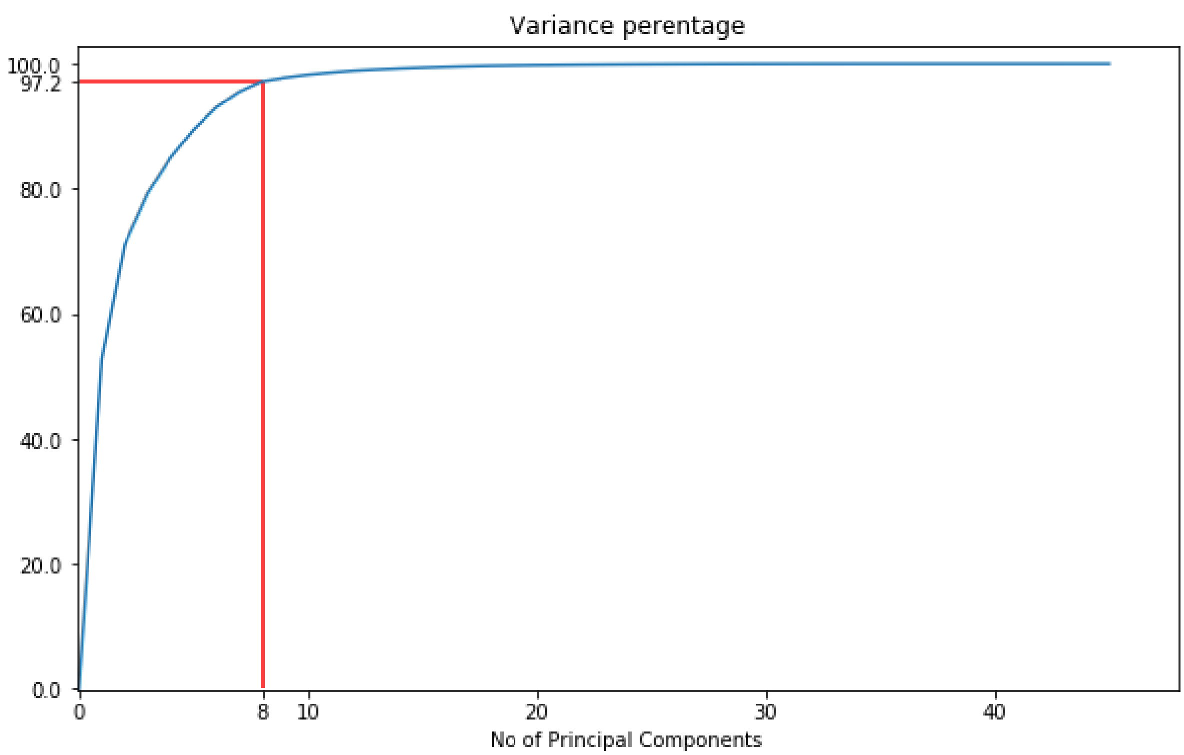


In [9]:

```
# The amount of variance explained by each of the selected components.
PCA_all_vecs = skt_all_pca_mod.explained_variance_ratio_
plot_pca_vecs = 8
pca_plot_arr = np.zeros(len(PCA_all_vecs) + 1)
pca_plot_arr[1:] = np.cumsum(PCA_all_vecs)
fig, ax = plt.subplots(1,1,figsize = (10,6))
p=plt.plot(pca_plot_arr*100)
plt.title('Variance perentage')
# plt.axvline(x=8,c='r')
plt.vlines(x=plot_pca_vecs, ymin=0, ymax=pca_plot_arr[8]*100,color = 'r')
plt.hlines(y = pca_plot_arr[plot_pca_vecs]*100,xmin=0, xmax=plot_pca_vecs, color = 'r' )
plt.xlim(-0.1,)
plt.ylim(-0.1,)

xt = ax.get_xticks()
xt=np.append(xt,plot_pca_vecs)
ax.set_xticks(xt)

yt = ax.get_yticks()
yt=np.append(yt,[pca_plot_arr[plot_pca_vecs]*100])
ax.set_yticks(yt)
# ax.set_yticklabels(100*pca_plot_arr[plot_pca_vecs])
plt.ylim([-0.1,103])
plt.xlim([-0.1,48])
plt.xlabel('No of Principal Components')
# plt.savefig('Figs/1_Var_vs_PC.png',dpi = 200)
plt.show()
```



In [12]:

```
# returns number of principal components until variance ratio is var_per (0.95)
var_per = 0.95
np.where(PCA_all_vecs.cumsum()>var_per)[0][0]
```

Out[12]:

```
6
```

In [226]:

```
pca_plot_arr[plot_pca_vecs]*100
```

Out[226]:

```
97.17594774388311
```

In [13]:

```
n_pca_comp = 8
skt_pca_mod = PCA(n_components=n_pca_comp)
# skt_pca_mod = PCA()
start_time = pd.datetime.now()
X_PCA_train = skt_pca_mod.fit_transform(X=npX_train_norm, y=None)
print('duration: ', pd.datetime.now() - start_time)
```

```
duration:  0:00:02.960314
```

In [14]:

```
# verify the dimensions of the reduced dimensions dataset
print('Dims of PCA set are',str(X_PCA_train.shape))
```

```
Dims of PCA set are (1070994, 8)
```

In [15]:

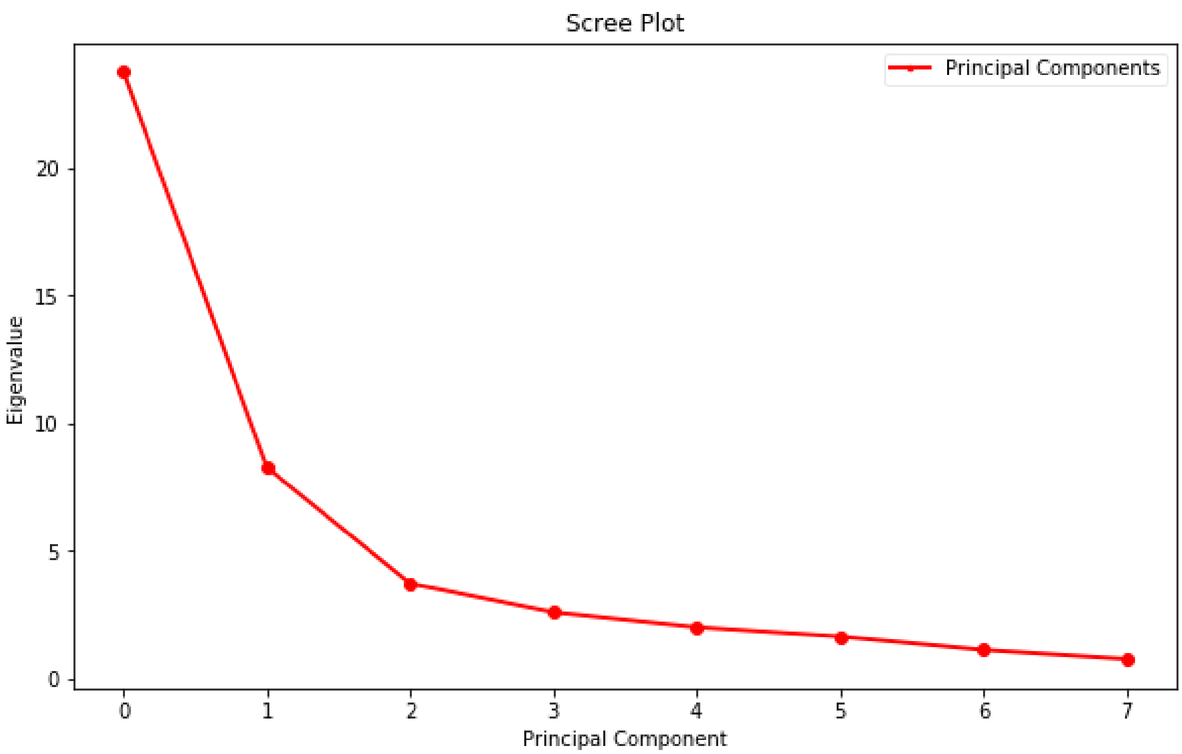
```
# The amount of variance explained by each of the selected components.
PCA_vecs_skt = skt_pca_mod.explained_variance_
PCA_vecs_skt
```

Out[15]:

```
array([23.72254606,  8.24597629,  3.70339908,  2.5789526 ,  1.99774111,
        1.62923907,  1.10447222,  0.74689088])
```

In [16]:

```
# plot the scree plot
fig = plt.figure(figsize=(10,6))
# sing_vals = np.arange(num_vars) + 1
plt.plot(np.arange(0,len(PCA_vecs_skt)), PCA_vecs_skt, 'ro-', linewidth=2)
plt.title('Scree Plot')
plt.xlabel('Principal Component')
plt.ylabel('Eigenvalue')
#I don't like the default legend so I typically make mine like below, e.g.
#with smaller fonts and a bit transparent so I do not cover up data, and make
#it moveable by the viewer in case upper-right is a bad place for it
leg = plt.legend(['Principal Components'], loc='best', borderpad=0.3,
                 shadow=False,
                 markerscale=0.4)
# plt.savefig('Figs/2_Scree_vs_PC.png',dpi = 200)
leg.get_frame().set_alpha(0.4)
plt.show()
```



4. Normalize the reduced dimension dataset

We normalize the output dataset from the PCA to use as input in the autoencoder.

In [15]:

```
X_pca_norm2 = preprocessing.scale(X_PCA_train)
# verify the normalizations
print('Normalized mean is: ',str(np.isclose(np.mean(X_pca_norm2,axis=0),0)-1))
print('Normalized std is: ',str(np.std(X_pca_norm2,axis=0)))
```

```
Normalized mean is:  [0 0 0 0 0 0 0 0]
Normalized std is:  [1. 1. 1. 1. 1. 1. 1. 1.]
```

5. Score 1

The 1st fraud score is the distance of each record of the normalized PCA dataset from the origin.

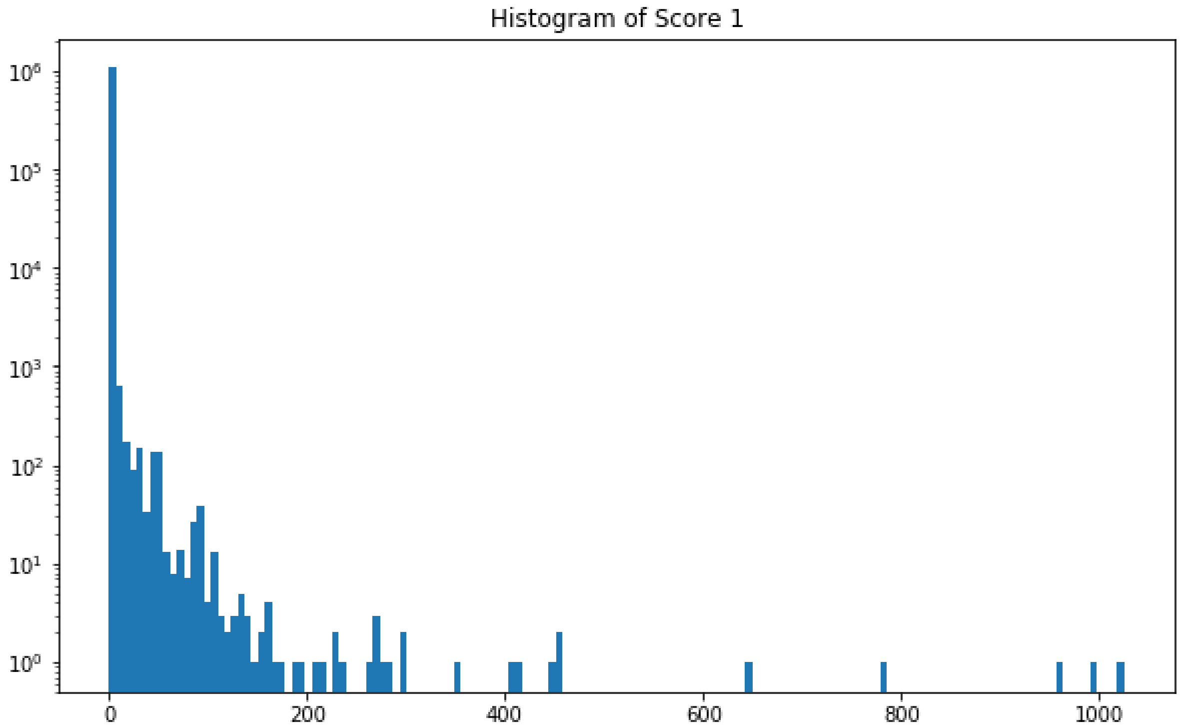
In [17]:

```
# aka take the lp-norm of each data point
from scipy.linalg import norm
# 2 for euclidean, 1 for manhattan, np.inf for infty norm (max) etc
# p = np.inf
# p = 1
p = 2
Scores_1 = norm(X_pca_norm2,ord = p,axis=1) # row-wise norm of X_pca_norm2
```

S1 histogram

In [19]:

```
# #normal histogram of S1
plt.figure(figsize=(10,6))
plt.hist(Scores_1, bins=150)
# plt.plot(Scores_1)
# plt.hist(Scores_1, bins=15)
titl_str = 'Histogram for Score 1 L-'+str(p)+' norm w/ PCA with '+str(n_pca_comp)+' PCs'
# plt.title(titl_str)
plt.title('Histogram of Score 1')
plt.yscale('log')
plt.show()
```



6. Score 2

We train an autoencoder on the PCA dataset. The autoencoder is written in Keras.

In [20]:

```
from keras.layers import Input, Dense
from keras.models import Model
# this is the size of our encoded representations
encoding_dim = 5 # number of hidden layer nodes

# this is our input placeholder
input_mat = Input(shape=(X_PCA_train.shape[1],))
# "encoded" is the encoded representation of the input
encoded = Dense(encoding_dim, activation='relu')(input_mat)
# "decoded" is the lossy reconstruction of the input
decoded = Dense(X_PCA_train.shape[1], activation='sigmoid')(encoded)
# this model maps an input to its reconstruction
autoencoder = Model(input_mat, decoded)
```

```
Using TensorFlow backend.
```

In [40]:

```
# load autoencoder and encoder models
# don't know how to make this work
# from keras.models import load_model
# encoder = load_model('autoencoder_5_nodes.h5')
# autoencoder = load_model('encoder_5_nodes.h5')
```

```
/home/thanos/miniconda3/envs/dev/lib/python3.6/site-packages/keras/engine/sav
ing.py:341: UserWarning: No training configuration found in save file: the mo
del was *not* compiled. Compile it manually.
  warnings.warn('No training configuration found in save file: '
```

In [21]:

```
# Let's also create a separate encoder model:

# this model maps an input to its encoded representation
encoder = Model(input_mat, encoded)
# As well as the decoder model:

# create a placeholder for an encoded (5-dimensional) input
encoded_input = Input(shape=(encoding_dim,))
# retrieve the last layer of the autoencoder model
decoder_layer = autoencoder.layers[-1]
# create the decoder model
decoder = Model(encoded_input, decoder_layer(encoded_input))

# autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')
autoencoder.compile(optimizer='adadelta', loss='mean_squared_error')
```

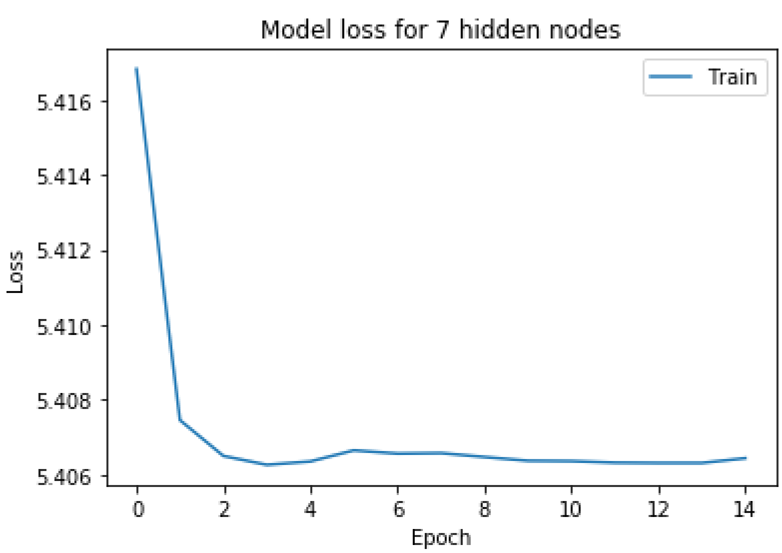
In [22]:

```
# fit the model
no_of_epochs = 5
start_time = pd.datetime.now()
history = autoencoder.fit(x=X_PCA_train, y=X_PCA_train, batch_size = None, epochs = no_of_
epochs, validation_split = 0)
print('duration: ', pd.datetime.now() - start_time)
```

```
Epoch 1/5
1070994/1070994 [==============================] - 33s 31us/step - loss: 5.41
73
Epoch 2/5
1070994/1070994 [==============================] - 32s 30us/step - loss: 5.40
81
Epoch 3/5
1070994/1070994 [==============================] - 32s 30us/step - loss: 5.40
75
Epoch 4/5
1070994/1070994 [==============================] - 32s 30us/step - loss: 5.40
78
Epoch 5/5
1070994/1070994 [==============================] - 32s 30us/step - loss: 5.40
77
duration:  0:02:41.322746
```

In [56]:

```
# Plot training & validation loss values
plt.plot(history.history['loss'])
# plt.plot(history.history['val_loss'])
plt.title('Model loss for '+str(encoding_dim)+' hidden nodes')
plt.ylabel('Loss')
plt.xlabel('Epoch')
# plt.legend(['Train', 'Test'], loc='upper left')
plt.legend(['Train'], loc='upper right')
plt.show()
```



Loss function per epoch on an autoencoder with 7 nodes in the middle layer

In [57]:

```
# save the model loss in dataframe
temp_df = pd.DataFrame.from_dict(history.history)
temp_df.columns = [str(encoding_dim)+' nodes']
# df_k_loss = df_k_loss.append(),ignore_index=False)
temp_df
```

Out[57]:

	7 nodes
0	5.416830
1	5.407450
2	5.406492
3	5.406254
4	5.406344
5	5.406641
6	5.406555
7	5.406568
8	5.406463
9	5.406362
10	5.406354
11	5.406311
12	5.406304
13	5.406304
14	5.406431

Loss function per epoch on an autoencoder with 3,4,5 & 7 nodes in the middle layer

In [58]:

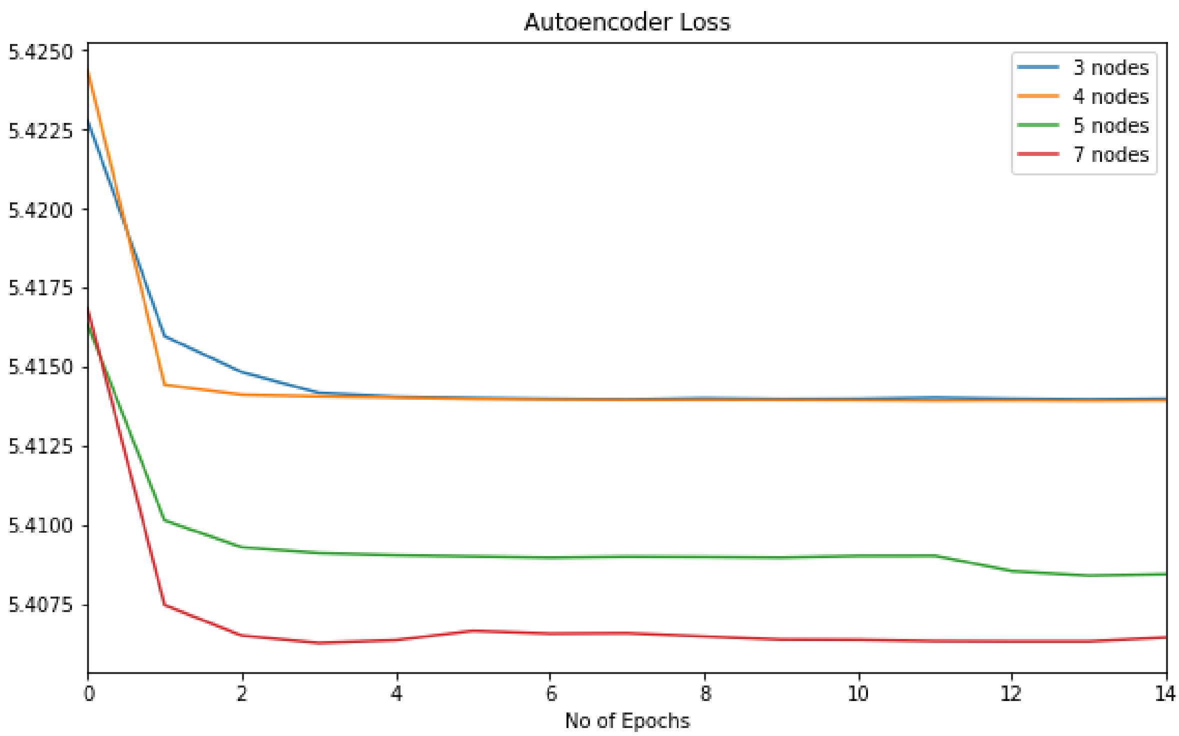
```
# combine the dataframes with loss history
# df_k_loss2 = pd.concat([df_k_loss2, temp_df], axis=1, sort=False)
# df_k_loss2
```

Out[58]:

	3 nodes	4 nodes	5 nodes	7 nodes
0	5.422779	5.424373	5.416325	5.416830
1	5.415954	5.414416	5.410127	5.407450
2	5.414820	5.414106	5.409283	5.406492
3	5.414163	5.414054	5.409096	5.406254
4	5.414044	5.414018	5.409030	5.406344
5	5.414004	5.413970	5.408993	5.406641
6	5.413978	5.413950	5.408955	5.406555
7	5.413959	5.413936	5.408985	5.406568
8	5.413996	5.413939	5.408976	5.406463
9	5.413971	5.413934	5.408957	5.406362
10	5.413978	5.413928	5.409008	5.406354
11	5.414015	5.413915	5.409011	5.406311
12	5.413980	5.413921	5.408529	5.406304
13	5.413958	5.413912	5.408385	5.406304
14	5.413979	5.413920	5.408432	5.406431

In [14]:

```
# df_k_loss2.to_csv('45_DS_losses.csv')
df_k_loss2 = pd.read_csv('45_DS_losses.csv')
df_k_loss2 = df_k_loss2.drop(columns = 'Unnamed: 0')
df_k_loss2
# plt.figure(figsize=(10,6))
df_k_loss2.plot(figsize=(10,6))
plt.title('Autoencoder Loss')
plt.xlabel('No of Epochs')
plt.savefig('Figs/4_Auto_enc_loss.png',dpi = 200)
```



Get the autoencoder output (decoder layer output)

In [23]:

```
# get autoencoder output (decoder layer output)
start_time = pd.datetime.now()
encoded_out = encoder.predict(X_PCA_train)
decoded_out = decoder.predict(encoded_out)
print('duration: ', pd.datetime.now() - start_time)
```

```
duration:  0:00:11.513360
```

In [24]:

```
print('Output layer shape is:',str(decoded_out.shape))
```

```
Output layer shape is: (1070994, 8)
```

6. Score 2

(b) The autoencoder fraud score is any measure of difference between the original input record and the autoencoder output record

In [25]:

```
# define the difference between input-output:
auto_enc_diff = X_PCA_train - decoded_out # input- output
```

In [26]:

```
# 2 for euclidean, 1 for manhattan, np.inf for infty norm (max) etc
# p = np.inf
# p = 1
# p = 2
Scores_2 = norm(auto_enc_diff,ord = p,axis=1) # row-wise norm of X_pca_norm2
print('Using ',str(p),'-norm')
```

```
Using  2 -norm
```

In [68]:

```
Scores_2.shape
```

Out[68]:

```
(1070994,)
```

In [28]:

```
saved_scores = pd.DataFrame({'Score 1': Scores_1, 'Score 2': Scores_2})
# saved_scores.to_csv('Scores/Scores_1_2.csv')
saved_scores.head()
```

Out[28]:

	Score 1	Score 2
0	1.943136	2.223851
1	27.296348	66.760675
2	0.247036	0.249262
3	0.185182	0.349862
4	26.047596	48.389204

In [ ]:

```
# histogram takes too long to run
# bins_2 = plot_2_hists(input_array=Scores_2,bin_num=10, norm_p=p, pca_no = n_pca_comp,sco
re_no=2)
```

7. Combine S_1 and S_2

Method 1 to combine scores: use the maximum of Score 1, Score 2 : $S_{F_1} = max\{S_1,S_2\}$

In [29]:

```
# define the combined score
Score_F = np.mean([Scores_1,Scores_2],axis= 0)
Score_F.shape
```

Out[29]:

```
(1070994,)
```

In [ ]:

```
# f_bins = plot_2_hists(input_array=Score_F,bin_num=10, norm_p=p, pca_no = n_pca_comp,scor
e_no='f')
```

In [30]:

```
# plt.plot(f_bins)
# plt.plot(bins_1)
# plt.plot(bins_2)
# plt.legend()
# plt.show()
```

In [30]:

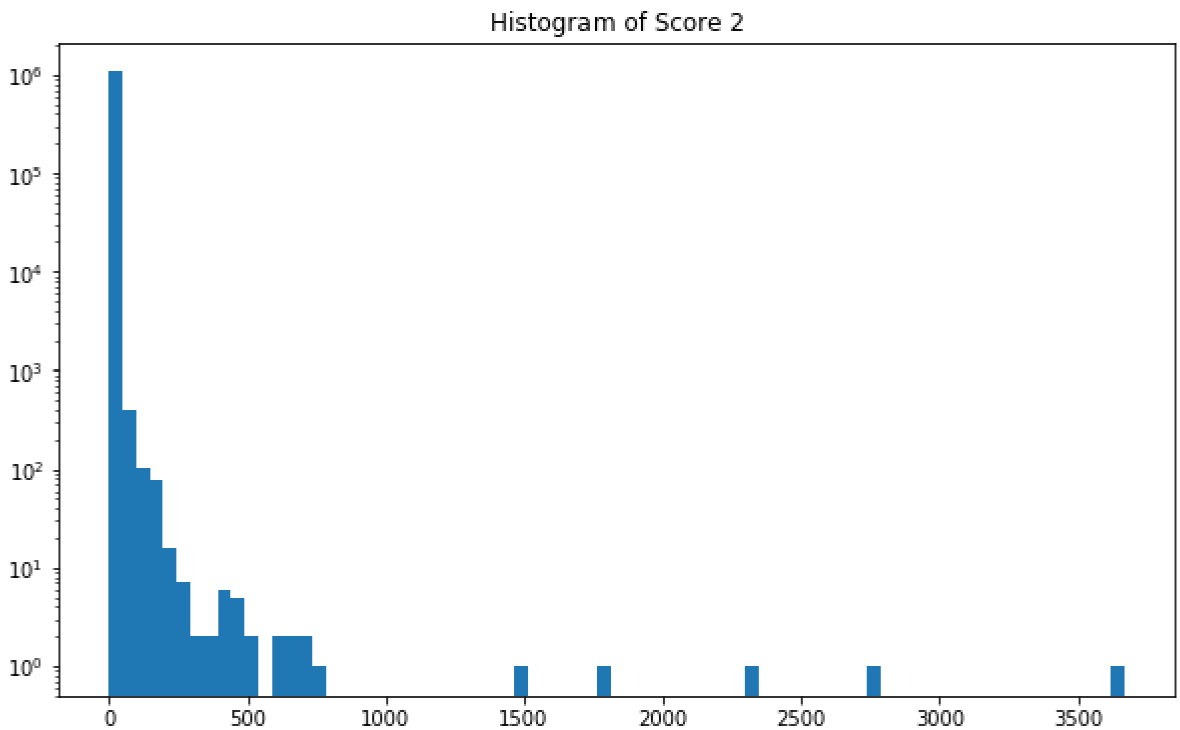
```
# define a dataframe with the scores
Scores_df = pd.DataFrame({'Score 1': Scores_1, 'Score 2': Scores_2,'F1. Score': Score_F})
Scores_df.head()
```

Out[30]:

	Score 1	Score 2	F1. Score
0	1.943136	2.223851	2.083494
1	27.296348	66.760675	47.028512
2	0.247036	0.249262	0.248149
3	0.185182	0.349862	0.267522
4	26.047596	48.389204	37.218400

In [34]:

```
# #normal histogram of S1\2
plt.figure(figsize=(10,6))
plt.hist(Scores_2, bins=75)
# plt.plot(Scores_1)
# plt.hist(Scores_1, bins=15)
titl_str = 'Histogram for Score 1 L-'+str(p)+' norm w/ PCA with '+str(n_pca_comp)+' PCs'
# plt.title(titl_str)
plt.title('Histogram of Score 2')
plt.yscale('log')
# plt.savefig('Figs/5_Hist_S2.png',dpi = 200)
plt.show()
```

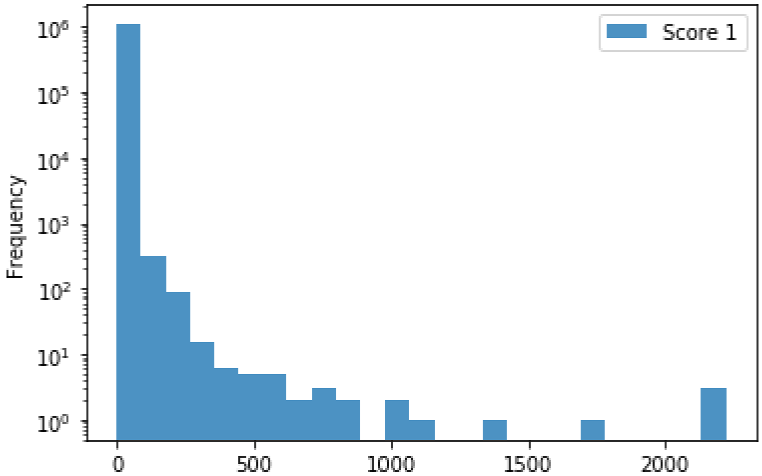


In [80]:

```
Scores_df[['Score 1']].plot.hist(bins=25, alpha=0.8)
plt.semilogy() #definetely need log scale
```

Out[80]:

```
[]
```



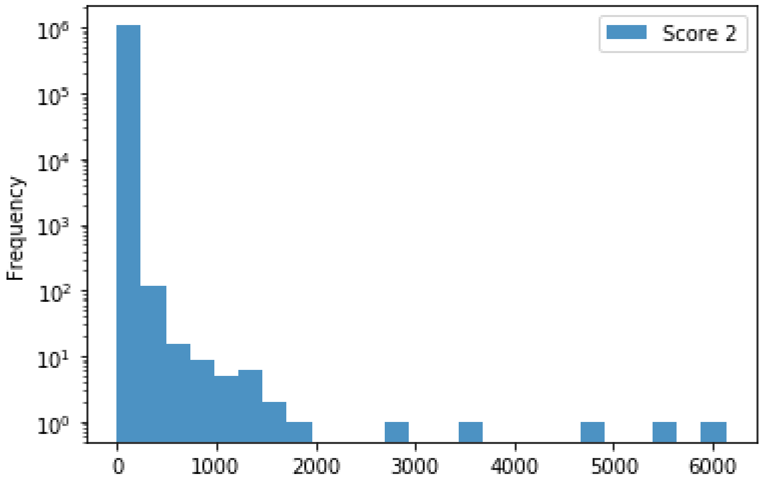
In [81]:

```
Scores_df[['Score 2']].plot.hist(bins=25, alpha=0.8)

plt.semilogy() #definetely need log scale
```

Out[81]:

```
[]
```



In [144]:

```
# quantile binning
quant_no_S1, quant_S1_bins = pd.qcut(Scores_df['Score 1'], 20,retbins=True)
quant_no_S1
# quant_S1_bins
```

Out[144]:

```
0          (0.979, 2222.01]
1          (0.979, 2222.01]
2            (0.457, 0.582]
3            (0.457, 0.582]
4          (0.979, 2222.01]
                 ...
1070989       (0.32, 0.364]
1070990      (0.364, 0.403]
1070991      (0.364, 0.403]
1070992       (0.32, 0.364]
1070993       (0.26, 0.286]
Name: Score 1, Length: 1070994, dtype: category
Categories (20, interval[float64]): [(0.033299999999999996, 0.115] < (0.115,
0.136] < (0.136, 0.153] < (0.153, 0.168] ... (0.443, 0.457] < (0.457, 0.582]
< (0.582, 0.979] < (0.979, 2222.01]]
```

In [160]:

```
Scores_df.sort_values('Score 1')
```

Out[160]:

	Score 1	Score 2	F1. Score
1053237	0.034299	0.109035	0.109035
1043972	0.035614	0.110784	0.110784
1043975	0.035673	0.111510	0.111510
1039547	0.035783	0.112608	0.112608
1039546	0.035783	0.112608	0.112608
...	...	...	...
565397	1355.859880	2829.537831	2829.537831
1067359	1750.441774	3572.760916	3572.760916
917941	2147.623007	4791.697885	4791.697885
565391	2206.991321	6130.698251	6130.698251
632815	2222.010440	5483.084146	5483.084146

1070994 rows × 3 columns

In [46]:

```
# Ordered_Scores_df = pd.DataFrame({'Rkd Score 1' : []})
Ordered_Scores_df = Scores_df[['Score 1']].sort_values('Score 1').rank()
Ordered_Scores_df.columns = ['Rkd Score 1']
Ordered_Scores_df['Rkd Score 2'] = Scores_df[['Score 2']].sort_values('Score 2').rank()
# Ordered_Scores_df.tail(20) # max 20 values
```

Method 2 to combine scores: use the harmonic mean of Score 1, Score 2 : $H_m(S_{N1},S_{N2}) = 2\frac{S_{N1}S_{N2}}{S_{N1}+S_{N2}}$

If both S_{N1},S_{N2} are large $H_m(S_{N1},S_{N2})$ is also large.

In [53]:

```
from scipy import stats

hmean_score_order = stats.hmean(np.abs(Ordered_Scores_df.values), axis = 1)
Hmean_scr_df_order = pd.DataFrame(hmean_score_order,columns=(['Ord Harm. Mean']))
Ordered_Scores_df['Ord Harm. Mean'] = Hmean_scr_df_order

indx_harm_mean = Ordered_Scores_df.tail(10).sort_values('Ord Harm. Mean').index
Ordered_Scores_df.tail(10).sort_values('Ord Harm. Mean')
print(indx_harm_mean)
```

```
Int64Index([585438, 248664, 565391, 750815, 556608, 917941, 1067359, 632815,
            565397, 585117],
           dtype='int64')
```

In [201]:

```
comp_no = 20 # compare the max comp_no elements of Score 1 with Score 2
# compare columns Rkd Score 1 with Rkd Score 2
# Ordered_Scores_df['Rkd Score 2'].tail(comp_no).isin(Ordered_Scores_df['Rkd Score 1'].tai
l(comp_no)).sum()
no_of_common_elements = Ordered_Scores_df['Rkd Score 1'].tail(comp_no).isin(Ordered_Scores
_df['Rkd Score 2'].tail(comp_no)).sum()
print('No of differences in max',str(comp_no),'elements in S1 & S2:',str(comp_no - no_of_c
ommon_elements))
```

```
No of differences in max 20 elements in S1 & S2: 2
```

In [54]:

```
Ordered_Scores_df.tail(10).sort_values('Ord Harm. Mean')
```

Out[54]:

	Rkd Score 1	Rkd Score 2	Ord Harm. Mean
585438	1070989.0	1070987.0	103149.663474
248664	1070987.0	1070985.0	186796.420500
565391	1070992.0	1070994.0	211807.089132
750815	1070986.0	1070983.0	300847.744968
556608	1070985.0	1070984.0	352613.277309
917941	1070993.0	1070992.0	361551.155576
1067359	1070991.0	1070991.0	439227.876649
632815	1070994.0	1070993.0	463259.757168
565397	1070990.0	1070990.0	513412.558457
585117	1070988.0	1070989.0	641526.441134

In [52]:

```
# get the max scores based on Final 1 score
no_max_outlier = 10
Scores_df.nlargest(n= no_max_outlier, columns='F1. Score')
```

Out[52]:

	Score 1	Score 2	F1. Score
565391	961.172323	3667.411127	2314.291725
632815	1024.715256	2786.823337	1905.769297
917941	993.183712	2319.966934	1656.575323
1067359	781.715697	1762.724790	1272.220244
565397	642.981784	1514.781114	1078.881449
585117	456.661563	739.117369	597.889466
585438	456.973945	687.535899	572.254922
248664	449.983153	649.753907	549.868530
556608	408.498685	627.846797	518.172741
750815	411.698256	612.750205	512.224231

In [62]:

```
hmean_score_S12 = stats.hmean(np.abs(Scores_df.values), axis = 1)
Scores_df['Score Harm. Mean'] = hmean_score_S12
# Scores_df.nlargest(n= no_max_outlier, columns='Score 1')
Scores_df = Scores_df.rename(columns={'F1. Score': 'Score Mean'})
Scores_df
```

Out[62]:

	Score 1	Score 2	Score Mean	Score Harm. Mean
0	1.943136	2.223851	2.083494	2.077180
1	27.296348	66.760675	47.028512	41.164962
2	0.247036	0.249262	0.248149	0.248146
3	0.185182	0.349862	0.267522	0.250075
4	26.047596	48.389204	37.218400	34.913984
...	...	...	...	...
1070989	0.148688	0.322358	0.235523	0.213167
1070990	0.178416	0.386676	0.282546	0.255748
1070991	0.174461	0.376243	0.275352	0.249552
1070992	0.153098	0.308313	0.230705	0.212619
1070993	0.113364	0.224461	0.168913	0.156279

1070994 rows × 4 columns

In [66]:

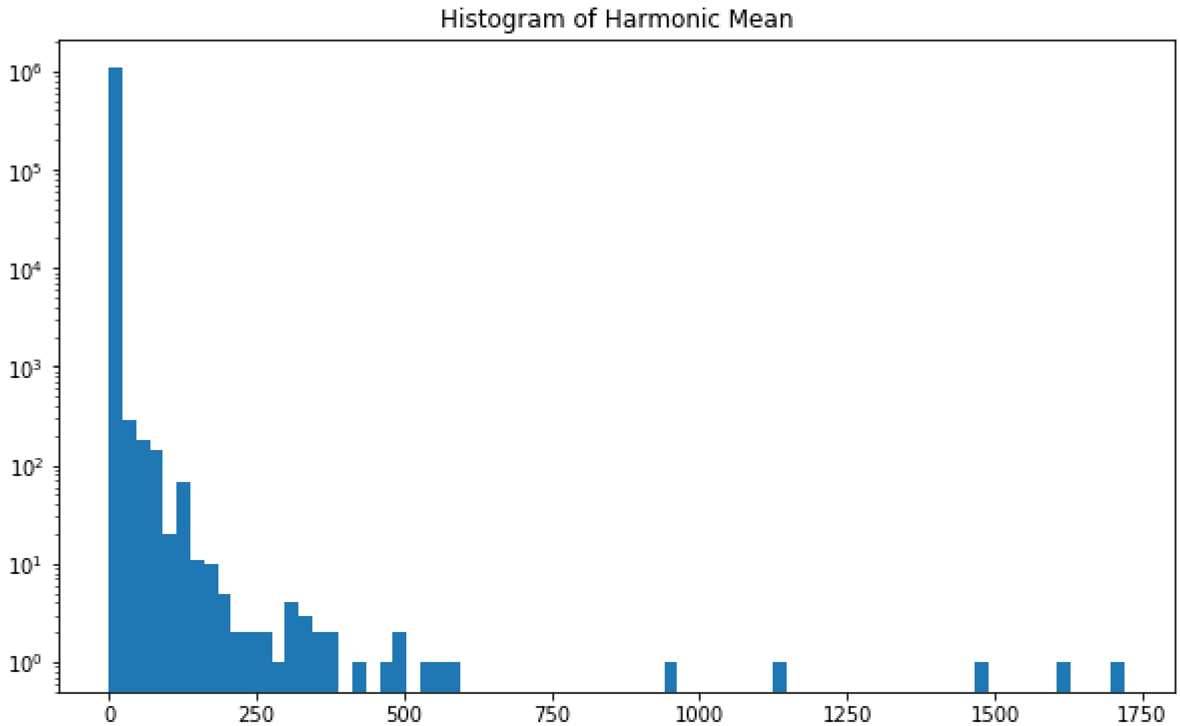
```
Hmean_ind = Scores_df.nlargest(n= no_max_outlier, columns='Score Harm. Mean').index
Scores_df.nlargest(n= no_max_outlier, columns='Score Harm. Mean')
```

Out[66]:

	Score 1	Score 2	Score Mean	Score Harm. Mean
565391	961.172323	3667.411127	2314.291725	1719.034453
632815	1024.715256	2786.823337	1905.769297	1613.393455
917941	993.183712	2319.966934	1656.575323	1469.465456
1067359	781.715697	1762.724790	1272.220244	1139.571525
565397	642.981784	1514.781114	1078.881449	954.714306
585117	456.661563	739.117369	597.889466	575.228306
585438	456.973945	687.535899	572.254922	556.560349
248664	449.983153	649.753907	549.868530	537.637667
556608	408.498685	627.846797	518.172741	502.462745
750815	411.698256	612.750205	512.224231	498.900771

In [103]:

```
# #normal histogram of S1\2
plt.figure(figsize=(10,6))
plt.hist(hmean_score_S12, bins=75)
# plt.plot(Scores_1)
# plt.hist(Scores_1, bins=15)
titl_str = 'Histogram for Score 1 L-'+str(p)+' norm w/ PCA with '+str(n_pca_comp)+' PCs'
# plt.title(titl_str)
plt.title('Histogram of Harmonic Mean')
plt.yscale('log')
plt.savefig('Figs/8_Hist_Hmean.png',dpi = 200)
plt.show()
```



In [ ]:

```
colors = np.where(norm_S_df['Label'] > 0.5, 'r', 'b')
start_time = pd.datetime.now()
norm_S_df.plot.scatter(x="Norm S1",y="Norm S2", s=60, c=colors)
# plt.legend(['Inliers','Outliers'])
plt.title('Ouliers')
```

In [68]:

```
# extract the index of the entries with biggest score
outl_index = Scores_df.nlargest(n= no_max_outlier, columns='Score Mean').index
```

8. Detect the outliers & result interpretation

In [75]:

```
# outliers on the 45 variable dataset
# fraud_rec_45df = X_1st_norm_df.loc[outl_index]
fraud_rec_45df = X_1st_norm_df.loc[Hmean_ind]
fraud_rec_45df
```

Out[75]:

	FULLVAL/LOTAREA_ZIP	FULLVAL/LOTAREA_ZIP3	FULLVAL/LOTAREA_TAXCLASS	FULLV
565391	400.712294	139.189591	282.511822	
632815	-0.020274	-0.081167	0.239653	
917941	1.573279	0.447074	0.450256	
1067359	644.121956	630.169433	648.924793	
565397	5.503866	1.898945	3.879238	
585117	-0.189811	-0.087311	-0.154963	
585438	0.264699	0.009469	0.018910	
248664	0.145267	-0.042419	-0.113330	
556608	102.587048	31.515977	63.987267	
750815	221.698916	19.111395	355.845855	

10 rows × 45 columns

In [163]:

```
pd.DataFrame(data_45.std()).transpose()
```

Out[163]:

	FULLVAL/LOTAREA_ZIP	FULLVAL/LOTAREA_ZIP3	FULLVAL/LOTAREA_TAXCLASS	FULLVAL/LO'
0	3.970634	9.948176	5.596112	'

1 rows × 45 columns

Final outlier records:

In [76]:

```
# outliers on the original dataset (transpose for readibility)
fraud_rec_df = or_mydata.loc[Hmean_ind]
fraud_rec_df.transpose()
```

Out[76]:

	565391	632815	917941	1067359	565397	585117	
Unnamed: 0	565391	632815	917941	1067359	565397	585117	
RECORD	565392	632816	917942	1067360	565398	585118	
BBLE	3085900700	4018420001	4142600001	5078530085	3085910100	4004200001	4
B	3	4	4	5	3	4	
BLOCK	8590	1842	14260	7853	8591	420	
LOT	700	1	1	85	100	1	
EASEMENT	NaN	NaN	NaN	NaN	NaN	NaN	
OWNER	U S GOVERNMENT OWNRD	864163 REALTY, LLC	LOGAN PROPERTY, INC.	NaN	DEPT OF GENERAL SERVI	NEW YORK CITY ECONOMI	
BLDGCL	V9	D9	T1	B2	V9	O3	
TAXCLASS	4	2	4	1	4	4	
LTFRONT	117	157	4910	1	466	298	
LTDEPTH	108	95	100	1	1009	402	
EXT	NaN	NaN	NaN	NaN	NaN	NaN	
STORIES	1	1	3	2	1	20	
FULLVAL	4.3263e+09	2.93e+06	3.7402e+08	836000	2.31088e+09	3.4434e+06	
AVLAND	1.94684e+09	1.3185e+06	1.79281e+09	28800	1.0399e+09	1.54953e+06	
AVTOT	1.94684e+09	1.3185e+06	4.66831e+09	50160	1.0399e+09	1.54953e+06	
EXLAND	1.94684e+09	0	1.79281e+09	0	1.0399e+09	0	
EXTOT	1.94684e+09	0	4.66831e+09	0	1.0399e+09	0	
EXCD1	2231	NaN	2198	NaN	2191	NaN	
STADDR	FLATBUSH AVENUE	86-55 BROADWAY	154-68 BROOKVILLE BOULEVARD	20 EMILY COURT	FLATBUSH AVENUE	28-10 QUEENS PLAZA SOUTH	
ZIP	11234	11373	11422	10307	11234	11101	
EXMPTCL	X1	NaN	X4	NaN	X1	X1	
BLDFRONT	20	1	20	36	20	1	
BLDDEPTH	40	1	28	45	40	1	
AVLAND2	8.48485e+08	1.2012e+06	1.64445e+09	NaN	4.35264e+08	1.58549e+06	
AVTOT2	8.48485e+08	1.2012e+06	4.50118e+09	NaN	4.35264e+08	1.58549e+06	
EXLAND2	8.48485e+08	NaN	1.64445e+09	NaN	4.35264e+08	NaN	
EXTOT2	8.48485e+08	NaN	4.50118e+09	NaN	4.35264e+08	NaN	
EXCD2	NaN	NaN	NaN	NaN	NaN	NaN	
PERIOD	FINAL	FINAL	FINAL	FINAL	FINAL	FINAL	

	565391	632815	917941	1067359	565397	585117
YEAR	2010/11	2010/11	2010/11	2010/11	2010/11	2010/11
VALTYPE	AC-TR	AC-TR	AC-TR	AC-TR	AC-TR	AC-TR

In [81]:

```
# scatter plot the outliers
no_max_outlier = 10
Scores_df['Label_Hm'] = np.zeros(norm_S_df.shape[0], dtype=int)
# outl_nomr_index = norm_S_df.nlargest(n= no_max_outlier, columns='Norm S1').index
Scores_df['Label_Hm'].loc[Hmean_ind] = 1
Scores_df
```

Out[81]:

	Score 1	Score 2	Score Mean	Score Harm. Mean	Label_Hm
0	1.943136	2.223851	2.083494	2.077180	0
1	27.296348	66.760675	47.028512	41.164962	0
2	0.247036	0.249262	0.248149	0.248146	0
3	0.185182	0.349862	0.267522	0.250075	0
4	26.047596	48.389204	37.218400	34.913984	0
...	...	...	...	...	...
1070989	0.148688	0.322358	0.235523	0.213167	0
1070990	0.178416	0.386676	0.282546	0.255748	0
1070991	0.174461	0.376243	0.275352	0.249552	0
1070992	0.153098	0.308313	0.230705	0.212619	0
1070993	0.113364	0.224461	0.168913	0.156279	0

1070994 rows × 5 columns

In [84]:

```
colors = np.where(Scores_df['Label_Hm'] > 0.5, 'r', 'b')
start_time = pd.datetime.now()
Scores_df.plot.scatter(x="Score 1",y="Score 2", s=60, c=colors,figsize=(10,6))
# plt.legend(['Inliers','Outliers'])
plt.title('Ouliers with Harmonic Mean')
plt.savefig('Figs/6_Scatter_w_Hmean.png',dpi = 200)
print('duration: ', pd.datetime.now() - start_time)
```

```
duration:  0:00:53.844018
```