In [2]:

```
import numpy as np
import pandas as pd
from scipy.stats import ks_2samp

from sklearn.cluster import DBSCAN
from sklearn import metrics
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import KFold
from sklearn.neighbors import NearestNeighbors

import time

import matplotlib.pyplot as plt
import seaborn as sns

import lightgbm as lgb
```

In [3]:

```
np.random.seed(0)
```

In [4]:

```
#### reading the data
data = pd.read_csv(r"creditcard.csv")
data.head()
```

Out[4]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533

5 rows × 31 columns

In [5]:

```
data.shape
```

Out[5]:

```
(284807, 31)
```

In [6]:

```
data.columns
```

Out[6]:

```
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V1
0',
       'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V2
0',
       'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount',
       'Class'],
      dtype='object')
```

In [7]:

```
data.tail()
```

Out[7]:

	Time	V1	V2	V3	V4	V5	V6	V7
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006

5 rows × 31 columns

In [8]:

```
numeric_cols = ['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',
                'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20',
                'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount']

len(numeric_cols)
```

Out[8]:

```
30
```

In [9]:

```
int(len(data)*0.1)
```

Out[9]:

```
28480
```

In [10]:

```
small_sub = data.sample(int(len(data)*0.1))
```

In [11]:

```
small_sub.shape
```

Out[11]:

```
(28480, 31)
```

In [13]:

```
for col in data.columns:
    print(col)
    print(ks_2samp(small_sub[col], data[col]))
    print("--"*30)
```

```
Time
KstestResult(statistic=0.0029919190446847654, pvalue=0.9740745041314022, s
tatistic_location=136676.0, statistic_sign=1)
----------------------------------------------------------
V1
KstestResult(statistic=0.005804036775663102, pvalue=0.3463241520019974, st
atistic_location=-0.343706800459705, statistic_sign=1)
----------------------------------------------------------
V2
KstestResult(statistic=0.007660723837112138, pvalue=0.09527423586587014, s
tatistic_location=0.313126416910685, statistic_sign=-1)
----------------------------------------------------------
V3
KstestResult(statistic=0.0052900466294482085, pvalue=0.4619251374159412, s
tatistic_location=0.134432811462959, statistic_sign=-1)
----------------------------------------------------------
V4
KstestResult(statistic=0.004426568383209872, pvalue=0.6889997784140736, st
atistic_location=-0.455511851586218, statistic_sign=1)
----------------------------------------------------------
V5
KstestResult(statistic=0.0062170396990305354, pvalue=0.2685028683215903, s
tatistic_location=-0.435803753951238, statistic_sign=-1)
----------------------------------------------------------
V6
KstestResult(statistic=0.0037645869775483343, pvalue=0.8551806160626388, s
tatistic_location=-0.170065103340078, statistic_sign=-1)
----------------------------------------------------------
V7
KstestResult(statistic=0.004830155187291629, pvalue=0.5799197639336293, st
atistic_location=-0.597927176560366, statistic_sign=1)
----------------------------------------------------------
V8
KstestResult(statistic=0.00350185065695785, pvalue=0.9075173407047937, sta
tistic_location=0.461458266563914, statistic_sign=-1)
----------------------------------------------------------
V9
KstestResult(statistic=0.00424924250398151, pvalue=0.7364257712548715, sta
tistic_location=0.171109831056042, statistic_sign=1)
----------------------------------------------------------
V10
KstestResult(statistic=0.006070709331724489, pvalue=0.2945000620443957, st
atistic_location=0.001424060861036, statistic_sign=1)
----------------------------------------------------------
V11
KstestResult(statistic=0.003940136570110997, pvalue=0.8147962075969885, st
atistic_location=-0.720089488245322, statistic_sign=-1)
----------------------------------------------------------
V12
KstestResult(statistic=0.003011238011445816, pvalue=0.9724375737666531, st
atistic_location=0.112813913375835, statistic_sign=-1)
----------------------------------------------------------
V13
KstestResult(statistic=0.005437818565326102, pvalue=0.4266829211298637, st
atistic_location=-0.873692191247653, statistic_sign=-1)
----------------------------------------------------------
V14
KstestResult(statistic=0.002120428645884076, pvalue=0.9998050806227521, st
atistic_location=-0.04462299317685, statistic_sign=-1)
----------------------------------------------------------
V15
```

```
KstestResult(statistic=0.004256234475244702, pvalue=0.7345788805383953, st
atistic_location=1.06015414826754, statistic_sign=1)
----------------------------------------------------------
V16
KstestResult(statistic=0.003327702811992961, pvalue=0.9357400163223406, st
atistic_location=-0.144777518154928, statistic_sign=1)
----------------------------------------------------------
V17
KstestResult(statistic=0.003876154374283014, pvalue=0.8299421140168017, st
atistic_location=0.671500801415856, statistic_sign=1)
----------------------------------------------------------
V18
KstestResult(statistic=0.00401433327726014, pvalue=0.7966964438046645, sta
tistic_location=-0.508599113954218, statistic_sign=-1)
----------------------------------------------------------
V19
KstestResult(statistic=0.0032678046700499452, pvalue=0.9441428997877089, s
tatistic_location=0.614757736783481, statistic_sign=1)
----------------------------------------------------------
V20
KstestResult(statistic=0.0038432685373019915, pvalue=0.8375437655501912, s
tatistic_location=0.691661301389519, statistic_sign=1)
----------------------------------------------------------
V21
KstestResult(statistic=0.006447583412784563, pvalue=0.23099756093972557, s
tatistic_location=-0.0536470802968275, statistic_sign=1)
----------------------------------------------------------
V22
KstestResult(statistic=0.00556976320510838, pvalue=0.3965430625230051, sta
tistic_location=-0.0570296868967611, statistic_sign=1)
----------------------------------------------------------
V23
KstestResult(statistic=0.002755544455435077, pvalue=0.9890725811110164, st
atistic_location=-0.228645820635454, statistic_sign=-1)
----------------------------------------------------------
V24
KstestResult(statistic=0.004860941731564067, pvalue=0.5717156667112646, st
atistic_location=-0.445255261647481, statistic_sign=1)
----------------------------------------------------------
V25
KstestResult(statistic=0.003490687469491882, pvalue=0.9094907553245156, st
atistic_location=0.148883137955471, statistic_sign=1)
----------------------------------------------------------
V26
KstestResult(statistic=0.003882198902248918, pvalue=0.8285309669564032, st
atistic_location=-0.399577825315102, statistic_sign=-1)
----------------------------------------------------------
V27
KstestResult(statistic=0.00607859351471729, pvalue=0.2930553986330019, sta
tistic_location=0.179105393822396, statistic_sign=-1)
----------------------------------------------------------
V28
KstestResult(statistic=0.004816755984330512, pvalue=0.5835000231749667, st
atistic_location=0.0029919614537601, statistic_sign=-1)
----------------------------------------------------------
Amount
KstestResult(statistic=0.005277414627480992, pvalue=0.46500675323188867, s
tatistic_location=148.74, statistic_sign=1)
----------------------------------------------------------
Class
KstestResult(statistic=0.00020369414466081537, pvalue=1.0, statistic_locat
```

```
ion=0, statistic_sign=-1)
-----------------------------------------------------------
```

This shows that the small_sub is representative of data

In [14]:

```
data.isnull().sum()
```

Out[14]:

```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

no missing values

In [15]:

```
sub = small_sub.copy()
```

In [16]:

```
sub = sub[numeric_cols]
sub.shape
```

Out[16]:

```
(28480, 30)
```

In [17]:

```
df_num = MinMaxScaler().fit_transform(sub)
pd.DataFrame(df_num).head()
```

Out[17]:

	0	1	2	3	4	5	6	7	8
0	0.728171	0.930566	0.747766	0.924522	0.223081	0.807006	0.213344	0.169347	0.606019
1	0.909992	0.929907	0.745482	0.928186	0.220646	0.806374	0.206467	0.168310	0.607205
2	0.882419	0.898292	0.684396	0.931694	0.285225	0.814791	0.195299	0.153363	0.616131
3	0.294691	0.876737	0.744165	0.953059	0.304048	0.785137	0.236605	0.164838	0.603369
4	0.115104	0.972107	0.718410	0.939569	0.242359	0.790376	0.208693	0.155711	0.607369

5 rows × 30 columns

In [18]:

```
pd.DataFrame(df_num).describe()
```

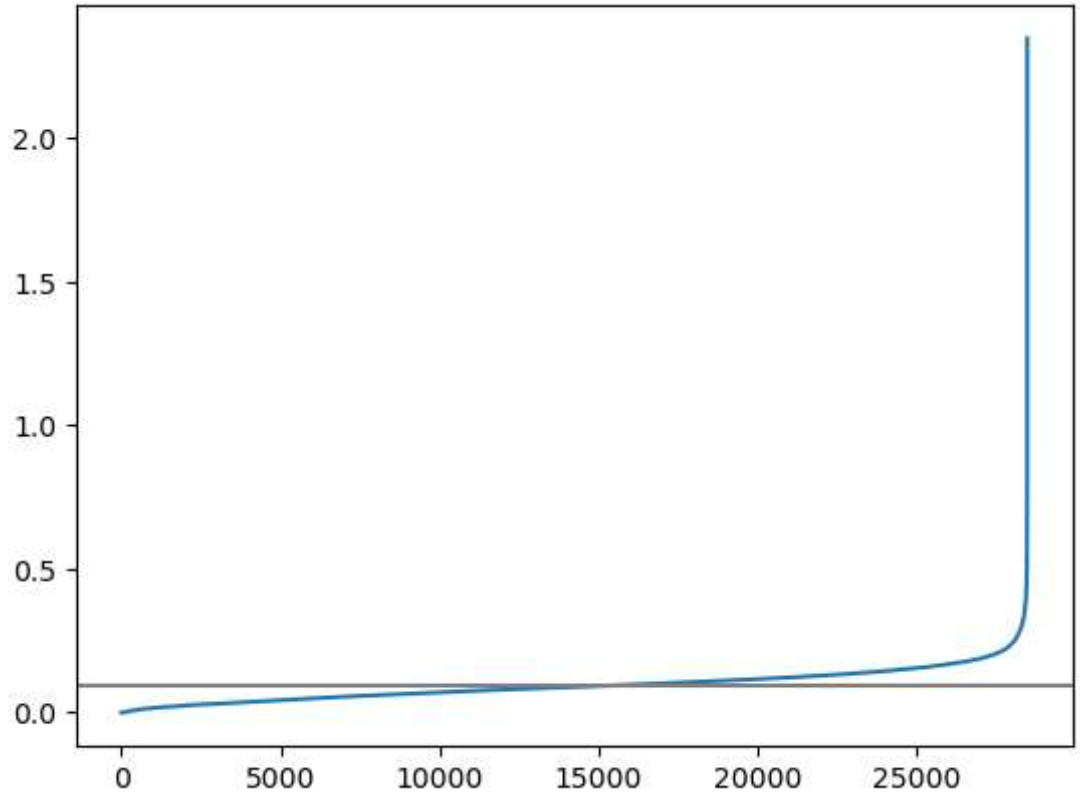
Out[18]:

	0	1	2	3	4	5
count	28480.000000	28480.000000	28480.000000	28480.000000	28480.000000	28480.000000
mean	0.547613	0.938296	0.728597	0.925471	0.252441	0.798242
std	0.274623	0.049329	0.029943	0.029529	0.069037	0.010597
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.312970	0.915725	0.717455	0.908733	0.211006	0.793374
50%	0.489541	0.938640	0.729857	0.929154	0.251270	0.797846
75%	0.804838	0.971381	0.743316	0.945071	0.288707	0.802548
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

8 rows × 30 columns

In [19]:

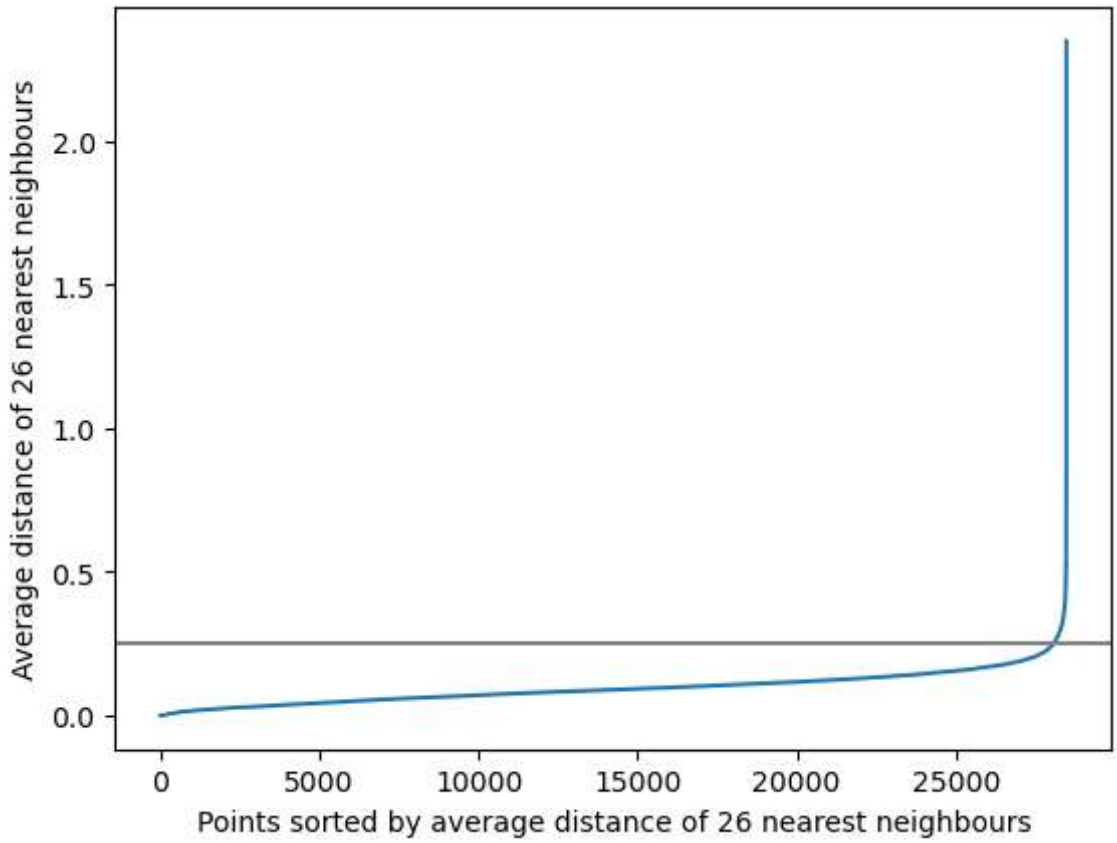
```
start_time = time.time()

neigh = NearestNeighbors(n_neighbors=60) ## 60 as it is double of number of numeric colu
nbrs = neigh.fit(df_num)
distances, indices = nbrs.kneighbors(df_num)

distances = np.sort(distances, axis=0)
distances = distances[:,1]
plt.plot(distances)
#plt.axhline(y =0.07,color='gray')
#plt.axhline(y =0.06,color='gray')
#plt.axhline(y =0.05,color='gray')
#plt.axhline(y =0.03,color='gray')
plt.axhline(y =0.095,color='gray')
plt.show()

end_time = time.time()
print("time taken for optimizing epsilon in dbscan is " , end_time - start_time , "secon
```




```
time taken for optimizing epsilon in dbscan is  1.9858295917510986 seconds
```

In [20]:

```
## little fancy line plot for distance ##
## axis description ##
plt.plot(distances)
plt.axhline(y =0.25,color='gray')
plt.xlabel("Points sorted by average distance of 26 nearest neighbours")
plt.ylabel("Average distance of 26 nearest neighbours")
plt.show()
```



Now applying DBSCAN eith these parameters

In [21]:

```
start_time = time.time()

db = DBSCAN(eps = 0.25, min_samples = 60).fit(df_num)

end_time = time.time()
print("time taken for this dbscan is " , end_time - start_time , "seconds")
```

```
time taken for this dbscan is  2.3602681159973145 seconds
```

In [22]:

```
labels = db.labels_
small_sub['labels'] = labels
```

In [23]:

```
small_sub['target'] = np.where(small_sub['labels']==0 , 0 , 1)
```

In [24]:

```
small_sub.head()
```

Out[24]:

	Time	V1	V2	V3	V4	V5	V6	V7
183484	125821.0	-0.323334	1.057455	-0.048341	-0.607204	1.259821	-0.091761	1.159101
255448	157235.0	-0.349718	0.932619	0.142992	-0.657071	1.169784	-0.733369	1.009985
244749	152471.0	-1.614711	-2.406570	0.326194	0.665520	2.369268	-1.775367	-1.139049
63919	50927.0	-2.477184	0.860613	1.441850	1.051019	-1.856621	2.078384	0.510828
11475	19899.0	1.338831	-0.547264	0.737389	-0.212383	-1.110039	-0.525744	-0.801403

5 rows × 33 columns

In [25]:

```
small_sub.labels.value_counts()
```

Out[25]:

```
 0    27538
-1      942
Name: labels, dtype: int64
```

In [26]:

```
small_sub.Class.value_counts()
```

Out[26]:

```
0    28425
1       55
Name: Class, dtype: int64
```

In [27]:

```
small_sub.target.value_counts()
```

Out[27]:

```
0    27538
1      942
Name: target, dtype: int64
```

In [28]:

```
pd.crosstab(small_sub.Class , small_sub.target)
```

Out[28]:

target	0	1
Class		
0	27531	894
1	7	48

In [29]:

```
small_sub.columns
```

Out[29]:

```
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V1
0',
       'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V2
0',
       'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount',
       'Class', 'labels', 'target'],
      dtype='object')
```

Now LightGBM training 5 folds

In [31]:

```
N = 5
kf = KFold(n_splits=N)
y_train = small_sub['target'].copy()
start = time.time()

features = [c for c in small_sub.columns if c not in ['Class','labels','target']]

param = {
    'bagging_freq': 5,
    'bagging_fraction': 0.2,
    #'boost_from_average':'false',
    'boost': 'gbdt',
    'feature_fraction': 0.7,
    'learning_rate': 0.05,
    'max_depth': -1,
    'metric':'auc',
    'min_data_in_leaf': 80,
    'min_sum_hessian_in_leaf': 10.0,
    'num_leaves': 31,
    #'num_threads': 8,
    #'tree_learner': 'serial',
    'objective': 'binary',
    #'reg_alpha': 0.1302650970728192,
    #'reg_lambda': 0.3603427518866501,
    'verbosity': 1
}
folds = KFold(n_splits=N)
oof = np.zeros(len(small_sub))

#predictions = np.zeros(len(X_test))

for fold_, (trn_idx, val_idx) in enumerate(folds.split(small_sub.values, y_train.values)
    print("Fold {}".format(fold_))
    trn_data = lgb.Dataset(small_sub.iloc[trn_idx][features], label=y_train.iloc[trn_idx
    val_data = lgb.Dataset(small_sub.iloc[val_idx][features], label=y_train.iloc[val_idx
    clf = lgb.train(param, trn_data, 100, valid_sets = [trn_data, val_data], verbose_eva
    oof[val_idx] = clf.predict(small_sub.iloc[val_idx][features], num_iteration=clf.best
    #predictions += clf.predict(X_test[features], num_iteration=clf.best_iteration) / fo

    feature_imp = pd.DataFrame(sorted(zip(clf.feature_importance(),features)), columns=[
    plt.figure(figsize=(12, 8))
    sns.barplot(x="Value", y="Feature", data=feature_imp.sort_values(by="Value", ascendi
    plt.title('LightGBM Features')
    plt.tight_layout()
    plt.show()
    #print(feature_imp.Feature[:20])
    #a[fold_] = feature_imp.Feature[-20:].tolist()


stop = time.time()
print("time taken for model run and predictions" , stop - start , "seconds")
```

```
Fold 0
[LightGBM] [Info] Number of positive: 750, number of negative: 22034
[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the overhe
ad of testing was 0.003056 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 7650
[LightGBM] [Info] Number of data points in the train set: 22784, number
of used features: 30
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.032918 -> initscore=-
3.380269
[LightGBM] [Info] Start training from score -3.380269
[LightGBM] [Warning] No further splits with positive gain, best gain: -
inf
Training until validation scores don't improve for 10 rounds
[LightGBM] [Warning] No further splits with positive gain, best gain: -
inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -
inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -
```

In [39]:

```
import numpy as np
import pandas as pd
from scipy.stats import ks_2samp

from sklearn.cluster import DBSCAN
from sklearn import metrics
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import KFold
from sklearn.neighbors import NearestNeighbors

import time
import gc

import matplotlib.pyplot as plt
import seaborn as sns

import lightgbm as lgb
```

In [40]:

```
def rep_sample(X, frac):
    X1 = X.sample(int(len(X)*frac))
    #df_one[~df_one.index.isin(df_two.index)]
    X2 = X[~X.index.isin(X1.index)]
    return(X1,X2)
```

In [41]:

```
def representative_check(X,X1):
    counter = 0
    for col in X.columns:
        if ks_2samp(X1[col], X[col]).pvalue > 0.05:
            counter = counter + 1
    if counter == X.shape[1]:
        print("Sample is representative")
    else: print("Sample is not representative, try sampling again")
```

In [42]:

```
def scale(X1):
    df_num = MinMaxScaler().fit_transform(X1)
    return(df_num)
```

In [43]:

```
def plot_optimal_eps(df_num):

    start_time = time.time()

    neigh = NearestNeighbors(n_neighbors=2*pd.DataFrame(df_num).shape[1])
    nbrs = neigh.fit(df_num)
    distances, indices = nbrs.kneighbors(df_num)
    distances = np.sort(distances, axis=0)
    distances = distances[:,1]

    plt.plot(distances)
    plt.xlabel("Points sorted by average distance of nearest neighbours")
    plt.ylabel("Average distance of "+str(2*pd.DataFrame(df_num).shape[1])+" nearest nei
    plt.show()

    end_time = time.time()

    print("time taken for optimizing epsilon in DBSCAN is " , end_time - start_time , "s
```

In [44]:

```
def pseudo_labels(df_num, opt_eps):

    start_time = time.time()

    db = DBSCAN(eps = opt_eps, min_samples = 2*X.shape[1]).fit(df_num)
    labels = db.labels_

    end_time = time.time()
    print("time taken for this dbscan is " , end_time - start_time , "seconds")

    return(labels)
```

In [45]:

```
def freq_labels(labels):
    unique, counts = np.unique(labels, return_counts=True)
    print (np.asarray((unique, counts)).T)
```

In [46]:

```
def create_train(X1,labels):
    X1["labels"] = labels
    X1['target'] = np.where(X1['labels']==0 , 0 , 1)
    del X1["labels"]
    gc.collect()
    return(X1)
```

In [47]:

```
param = {
    'bagging_fraction': 0.6,
    'boost': 'gbdt',
    'feature_fraction': 0.6,
    'learning_rate': 0.1,
    'max_depth': -1,
    'metric':'auc',
    'min_data_in_leaf': 40,
    'min_sum_hessian_in_leaf': 10.0,
    'num_leaves': 31,
    'objective': 'binary',
    'verbosity': 1
}
```

In [48]:

```
from sklearn.model_selection import GridSearchCV

def LightGBM_training(X1, N=5):
    y_train = X1['target'].copy()
    features = [c for c in X1.columns if c not in ['target']]

    # Define the hyperparameter grid
    param_grid = {
        'learning_rate': [0.05, 0.1, 0.2],
        'num_leaves': [20, 30, 40],
        'max_depth': [5, 10, 15],
        'bagging_fraction': [0.6, 0.8],
        'feature_fraction': [0.6, 0.8]
    }

    # Create a LGBMClassifier object
    lgbm = lgb.LGBMClassifier(boost='gbdt', metric='auc', objective='binary')

    # Use GridSearchCV to find the best hyperparameters
    grid_search = GridSearchCV(estimator=lgbm, param_grid=param_grid, cv=N, scoring='roc
    grid_search.fit(X1[features], y_train)

    # Print the best hyperparameters and their corresponding score
    print("Best hyperparameters: ", grid_search.best_params_)
    print("Best score: ", grid_search.best_score_)

    # Fit the model with the best hyperparameters
    clf = lgb.train({**param, **grid_search.best_params_}, lgb.Dataset(X1[features], lab

    # Get the feature importances
    feature_imp = pd.DataFrame(sorted(zip(clf.feature_importance(),features)), columns=[
    plt.figure(figsize=(12, 8))
    sns.barplot(x="Value", y="Feature", data=feature_imp.sort_values(by="Value", ascendi
    plt.title('LightGBM Features')
    plt.tight_layout()
    plt.show()

    return clf
```

In [49]:

```
X = pd.read_csv(r"creditcard.csv")
```

In [50]:

```
frac = 100000/(284807-100000)
frac
```

Out[50]:

```
0.5411050447223319
```

In [51]:

```
x1,x2 = rep_sample(X,frac)
```

In [52]:

```
representative_check(X,x1)
```

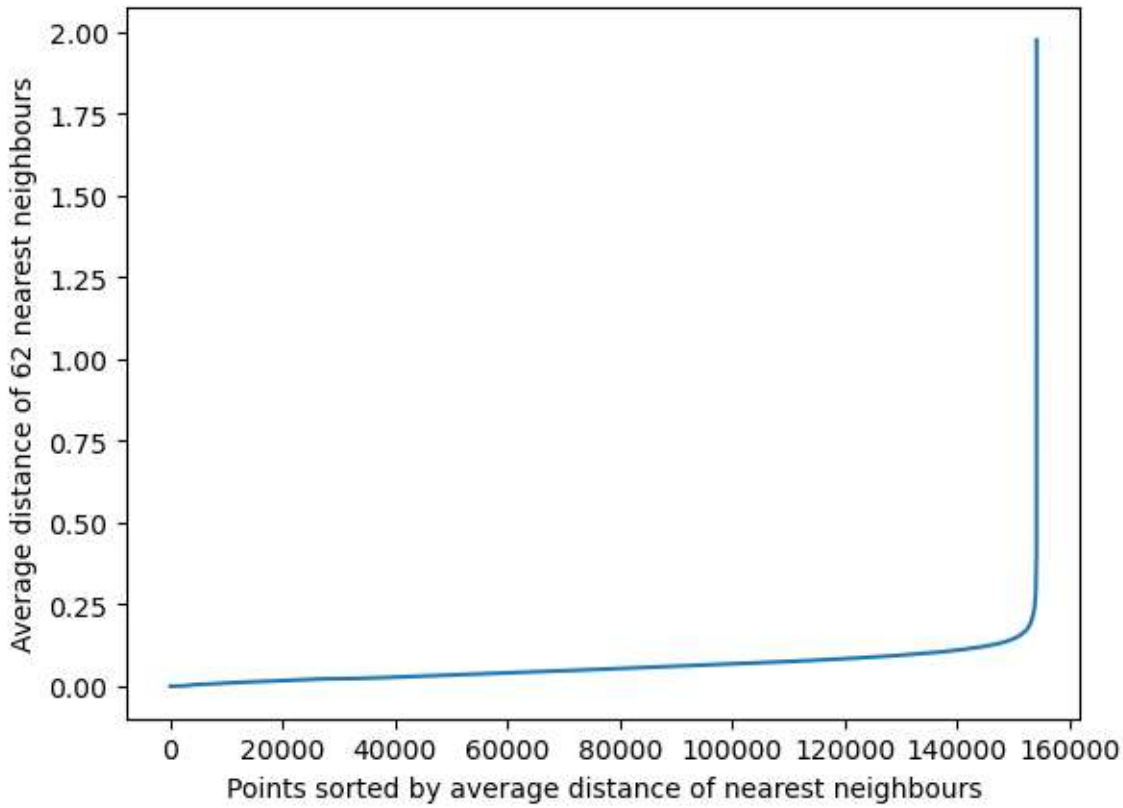
```
Sample is representative
```

In [53]:

```
df_num = scale(x1)
```

In [54]:

```
plot_optimal_eps(df_num)
```




```
time taken for optimizing epsilon in DBSCAN is  21.373374462127686 seconds
```

In [55]:

```
opt_esp = 0.2
```

In [58]:

```
labels = pseudo_labels(df_num,opt_esp)
```

```
time taken for this dbscan is  332.9945619106293 seconds
```

In [57]:

```
freq_labels(labels)
```

```
[[    -1   2594]
 [     0 151516]]
```

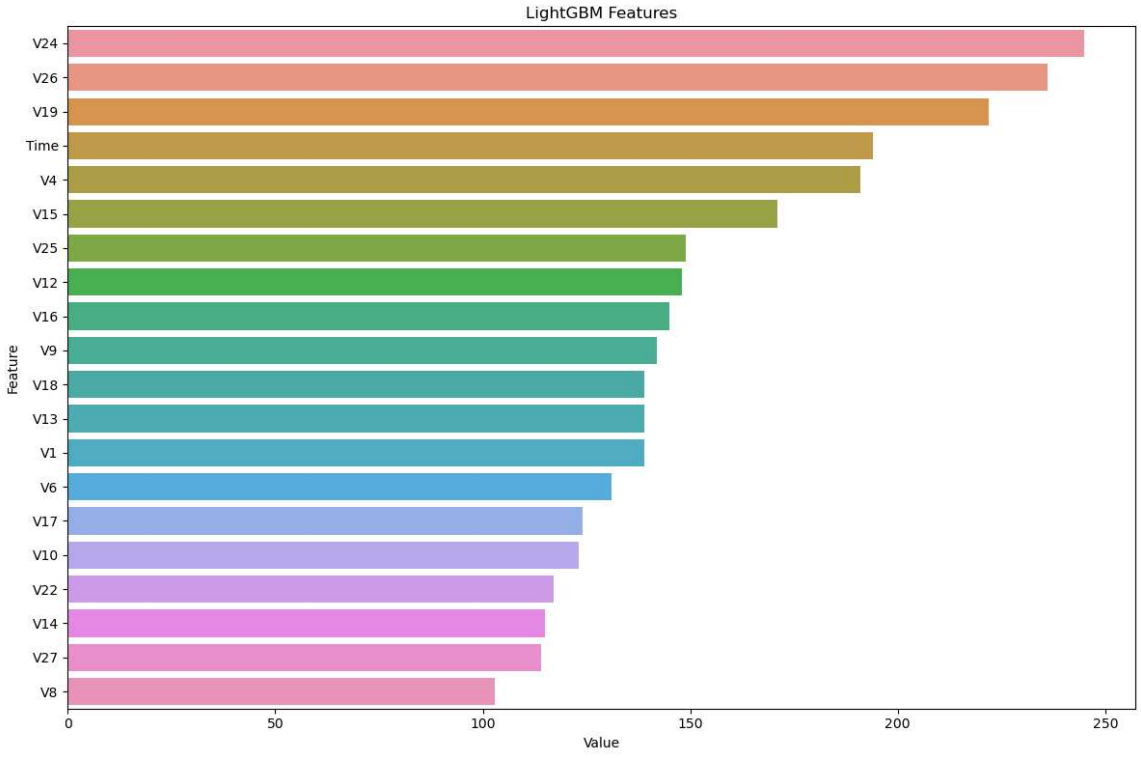
In [59]:

```
x1 = create_train(x1,labels)
```

In [60]:

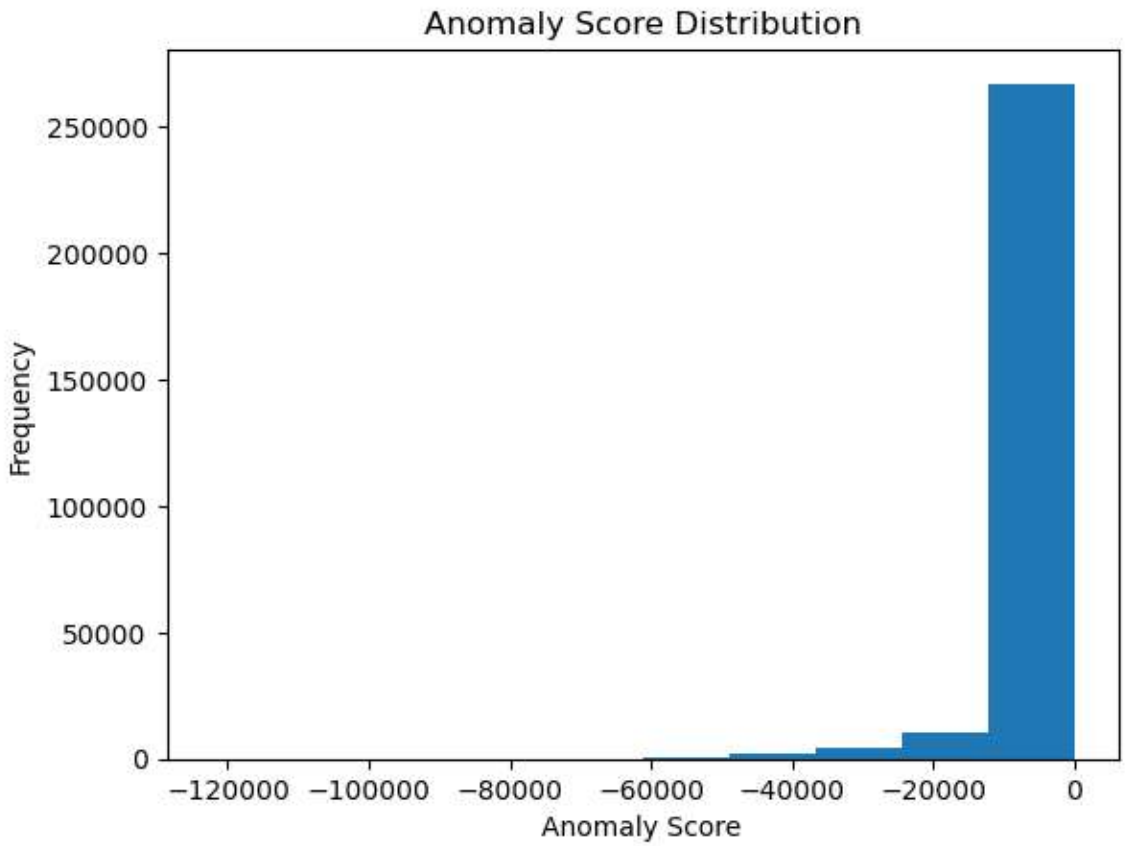
```
n = 5
clf = LightGBM_training(x1,5)
```

```
[LightGBM] [Warning] boosting is set with boosting_type=gbdt, will be over
ridden by boost=gbdt. Current value: boosting=gbdt
[LightGBM] [Warning] feature_fraction is set=0.8, colsample_bytree=1.0 wil
l be ignored. Current value: feature_fraction=0.8
[LightGBM] [Warning] bagging_fraction is set=0.6, subsample=1.0 will be ig
nored. Current value: bagging_fraction=0.6
Best hyperparameters:  {'bagging_fraction': 0.6, 'feature_fraction': 0.8,
'learning_rate': 0.1, 'max_depth': 15, 'num_leaves': 40}
Best score:  0.997686059831121
[LightGBM] [Info] Number of positive: 2594, number of negative: 151516
[LightGBM] [Warning] Auto-choosing col-wise multi-threading, the overhead
of testing was 0.015141 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 7652
[LightGBM] [Info] Number of data points in the train set: 154110, number o
f used features: 31
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.016832 -> initscore=-4.0
67490
[LightGBM] [Info] Start training from score -4.067490
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```



In [23]:

```
import matplotlib.pyplot as plt
from sklearn.mixture import GaussianMixture

# Create a Gaussian mixture model object
gmm = GaussianMixture(n_components=2, covariance_type='full', random_state=42)
gmm.fit(X)
# Compute the anomaly scores
log_prob = gmm.score_samples(X)
prob = np.exp(log_prob)
anomaly_scores = 1 - prob
plt.hist(anomaly_scores)
plt.title('Anomaly Score Distribution')
plt.xlabel('Anomaly Score')
plt.ylabel('Frequency')
plt.show()
```



In [19]:

In [ ]: