Fraud-Detection

June 25, 2019

1 Project - Credit Card Fraud Detection

Anonymized credit card transactions labeled as fraudulent or genuine
Photo by Ryan Born

1.1 Context

This is a Kaggle challenge organized by the 'Machine Learning Group - ULB' (Brussels, Belgium) 2 yrs ago.

It is important that credit card companies are able to recognize fraudulent credit card transactions so that customers are not charged for items that they did not purchase.

1.2 Goals

Identify fraudulent credit card transactions. Given the class imbalance ratio, we recommend measuring the accuracy using the Area Under the Precision-Recall Curve (AUPRC). Confusion matrix accuracy is not meaningful for unbalanced classification.

1.3 Acknowledgements

Please refer to the web page of the Kaggle challenge provided above

1.4 Libraries need

usual Python stack for Data Science

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        import os

In [2]: import warnings
        warnings.simplefilter(action='ignore', category=FutureWarning)

        pd.set_option('display.max_columns', 100)
```

```
In [3]: from sklearn.model_selection import train_test_split
        from sklearn.metrics import f1_score, classification_report, auc, precision_recall_curv
        from sklearn.preprocessing import StandardScaler
        from sklearn.decomposition import PCA
        from sklearn.manifold import TSNE

        from sklearn.model_selection import cross_val_score
        from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
        from sklearn.linear_model import LogisticRegression
        from sklearn.svm import SVC, LinearSVC
```

```
In [4]: import lightgbm as lgbm
        import xgboost as xgb
```

2 First Insight

2.1 Content

It is important that credit card companies are able to recognize fraudulent credit card transactions so that customers are not charged for items that they did not purchase.

```
In [7]: file_path = os.path.join('input', 'creditcardfraud', 'creditcard.csv')
```

```
In [8]: df = pd.read_csv(file_path)
        df.head()
```

```
Out[8]:    Time        V1        V2        V3        V4        V5        V6        V7  \
        0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
        1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
        2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
        3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
        4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

                 V8        V9       V10       V11       V12       V13       V14  \
        0  0.098698  0.363787  0.090794 -0.551600 -0.617801 -0.991390 -0.311169
        1  0.085102 -0.255425 -0.166974  1.612727  1.065235  0.489095 -0.143772
        2  0.247676 -1.514654  0.207643  0.624501  0.066084  0.717293 -0.165946
        3  0.377436 -1.387024 -0.054952 -0.226487  0.178228  0.507757 -0.287924
        4 -0.270533  0.817739  0.753074 -0.822843  0.538196  1.345852 -1.119670

                V15       V16       V17       V18       V19       V20       V21  \
        0  1.468177 -0.470401  0.207971  0.025791  0.403993  0.251412 -0.018307
        1  0.635558  0.463917 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775
        2  2.345865 -2.890083  1.109969 -0.121359 -2.261857  0.524980  0.247998
        3 -0.631418 -1.059647 -0.684093  1.965775 -1.232622 -0.208038 -0.108300
        4  0.175121 -0.451449 -0.237033 -0.038195  0.803487  0.408542 -0.009431

                V22       V23       V24       V25       V26       V27       V28  \
```

```
0  0.277838 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
1 -0.638672  0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724
2  0.771679  0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
3  0.005274 -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458
4  0.798278 -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153

   Amount  Class
0  149.62      0
1    2.69      0
2  378.66      0
3  123.50      0
4   69.99      0
```

In [9]: df.shape

Out[9]: (284807, 31)

In [10]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
Time      284807 non-null float64
V1        284807 non-null float64
V2        284807 non-null float64
V3        284807 non-null float64
V4        284807 non-null float64
V5        284807 non-null float64
V6        284807 non-null float64
V7        284807 non-null float64
V8        284807 non-null float64
V9        284807 non-null float64
V10       284807 non-null float64
V11       284807 non-null float64
V12       284807 non-null float64
V13       284807 non-null float64
V14       284807 non-null float64
V15       284807 non-null float64
V16       284807 non-null float64
V17       284807 non-null float64
V18       284807 non-null float64
V19       284807 non-null float64
V20       284807 non-null float64
V21       284807 non-null float64
V22       284807 non-null float64
V23       284807 non-null float64
V24       284807 non-null float64
V25       284807 non-null float64
V26       284807 non-null float64
```

```
V27        284807 non-null float64
V28        284807 non-null float64
Amount     284807 non-null float64
Class      284807 non-null int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

The datasets contains transactions made by credit cards in September 2013 by european cardholders. This dataset presents **transactions that occurred in two days**, where we have **492 frauds out of 284,807 transactions**. The dataset is **highly unbalanced**, the positive class (frauds) account for 0.172% of all transactions.

It contains only numerical input variables which are the **result of a PCA transformation**. Unfortunately, due to **confidentiality issues**, we cannot provide the original features and more background information about the data. Features V1, V2, ... V28 are the principal components obtained with PCA, the only features which have not been transformed with PCA are **'Time' and 'Amount'**. Feature 'Time' contains the **seconds elapsed between each transaction and the first transaction in the dataset**. The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-senstive learning. Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0 otherwise.

2.2 Cleaning the dataset

Not needed here except duplicated lines. There isn't any unrealistic values because all columns corresponds to real transactions.

```
In [11]: #df.isnull().sum()
```

```
In [12]: df.duplicated().sum()
```

```
Out[12]: 1081
```

The 1k duplicated lines are kept because values are scaled, and the functions could have probably rounded values... so theses might not be real duplicates

```
In [13]: #df = df.drop_duplicates()
         #df.shape
```

More infos here on how the Principal component analysis (PCA) works. If your learning algorithm is too slow because the input dimension is too high, then using PCA to speed it up can be a reasonable choice. This is probably the most common application of PCA. Another common application of PCA is for data visualization.

Here, the PCA has also been used to anonymize data.

```
In [14]: non_PCA_features = ['Time', 'Amount', 'Class']
         df[non_PCA_features].describe()
```

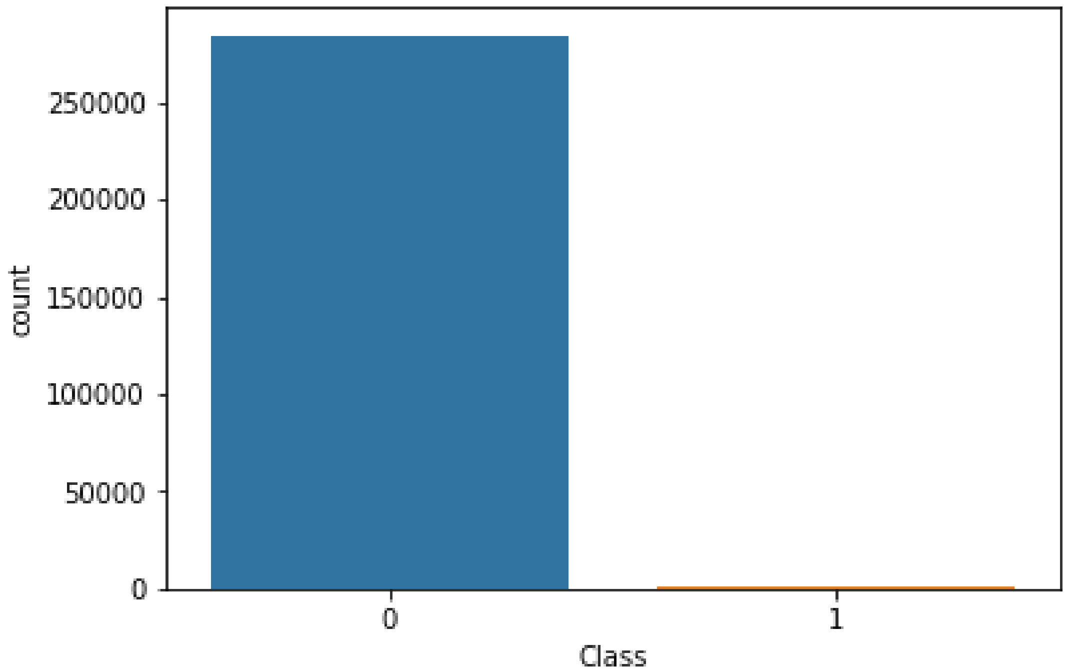
```
Out[14]:                  Time          Amount          Class
         count   284807.000000   284807.000000   284807.000000
```

```
mean     94813.859575      88.349619       0.001727
std      47488.145955     250.120109       0.041527
min          0.000000       0.000000       0.000000
25%      54201.500000       5.600000       0.000000
50%      84692.000000      22.000000       0.000000
75%     139320.500000      77.165000       0.000000
max     172792.000000   25691.160000       1.000000
```

3 Exploratory Data analysis

3.1 Target imbalanced

In [15]:
```
sns.countplot(x='Class', data=df)
plt.show()
```



In [16]:
```
ratio = df.Class.sum() / df.shape[0]
print(f'Percentage of class #1 : {ratio * 100 :.2f}% - Number of frauds is highly imba
```

```
Percentage of class #1 : 0.17% - Number of frauds is highly imbalanced !
```

3.2 Choosen metric

The goal is to identify fraudulent credit card transactions. Given the class imbalance ratio, it's recommended measuring the accuracy using the Area Under the Precision-Recall Curve (AUPRC). Confusion matrix accuracy is not meaningful for unbalanced classification.

See here the complete explanation of the metric, with an extract below:

It can be more flexible to predict probabilities of an observation belonging to each class in a classification problem rather than predicting classes directly.

This flexibility comes from the way that probabilities may be interpreted using different thresholds that allow the operator of the model to trade-off concerns in the errors made by the model, such as the number of false positives compared to the number of false negatives. This is required when using models where the cost of one error outweighs the cost of other types of errors.

Two diagnostic tools that help in the interpretation of probabilistic forecast for binary (two-class) classification predictive modeling problems are ROC Curves and Precision-Recall curves.

- ROC Curves summarize the trade-off between the true positive rate and false positive rate for a predictive model using different probability thresholds.
- Precision-Recall curves summarize the trade-off between the true positive rate and the positive predictive value for a predictive model using different probability thresholds.
- ROC curves are appropriate when the observations are balanced between each class, whereas **precision-recall curves are appropriate for imbalanced datasets**.

What Is a Precision-Recall Curve?

Precision is a ratio of the number of true positives divided by the sum of the true positives and false positives. It describes how good a model is at predicting the positive class. Precision is referred to as the positive predictive value.

Recall is calculated as the ratio of the number of true positives divided by the sum of the true positives and the false negatives. Recall is the same as sensitivity.

Reviewing both precision and recall is useful in cases where there is an imbalance in the observations between the two classes. Specifically, there are many examples of no event (class 0) and only a few examples of an event (class 1).

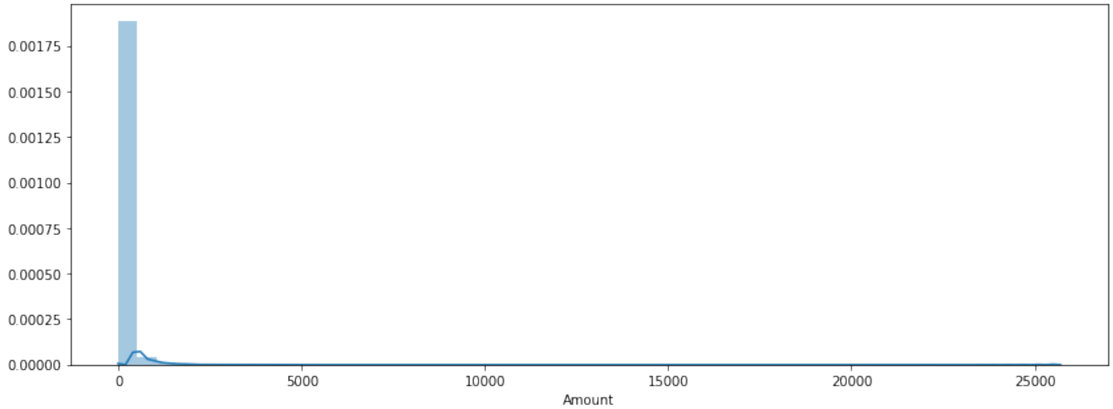
The reason for this is that typically the large number of class 0 examples means we are less interested in the skill of the model at predicting class 0 correctly, e.g. high true negatives

`Line Plot of Precision-Recall Curve`

- The curves of different models can be compared directly in general or for different thresholds.
- The area under the curve (AUC) can be used as a summary of the model skill. Area Under Curve: like the AUC, summarizes the integral or an approximation of the area under the precision-recall curve.

3.3 Distribution of the transaction amount

```
In [17]: plt.figure(figsize=(14, 5))
         sns.distplot(df['Amount'], label = 'Amount')
         plt.show()
```



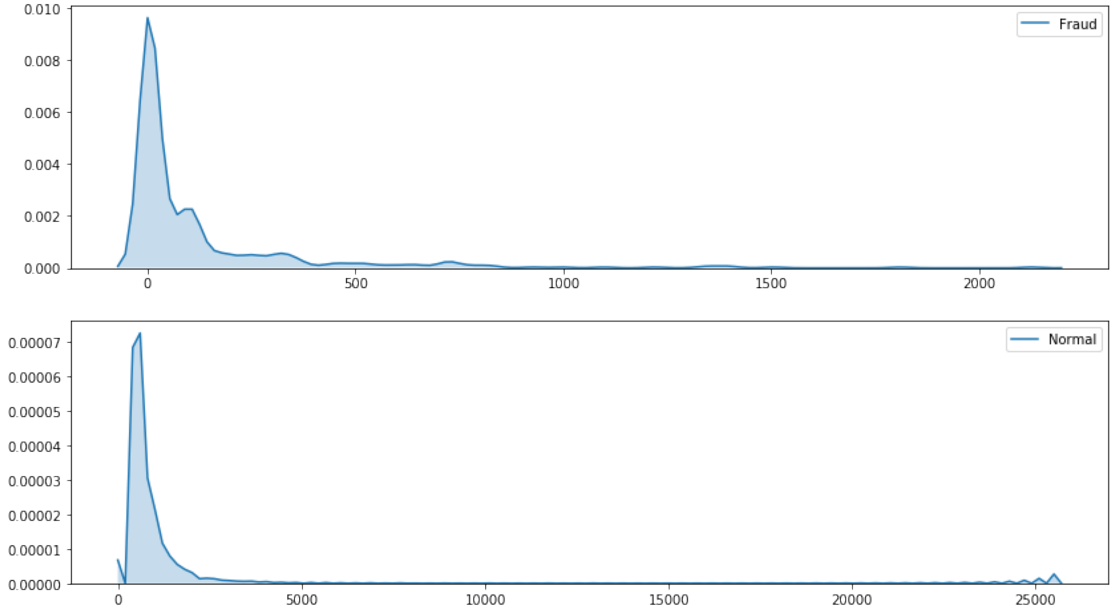

```
In [34]: print(f"Percentage of transactions' amount below 200 : {len(df[df.Amount < 200]) / le
```

```
Percentage of transactions' amount below 200 : 89.71%
```

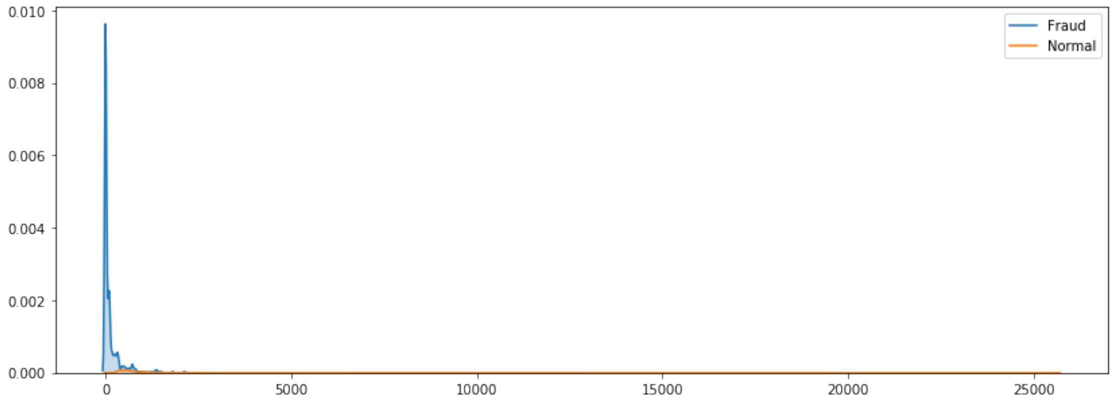
```
In [18]: print(f"Percentage of transactions' amount below 500 : {len(df[df.Amount < 500]) / le
```

```
Percentage of transactions' amount below 500 : 96.67%
```

```
In [20]: plt.figure(figsize=(14, 8))

         plt.subplot(2, 1, 1)
         sns.kdeplot(df.loc[df['Class'] == 1, 'Amount'], shade=True, label = 'Fraud')
         plt.subplot(2, 1, 2)
         sns.kdeplot(df.loc[df['Class'] == 0, 'Amount'], shade=True, label = 'Normal')
         plt.show()
```



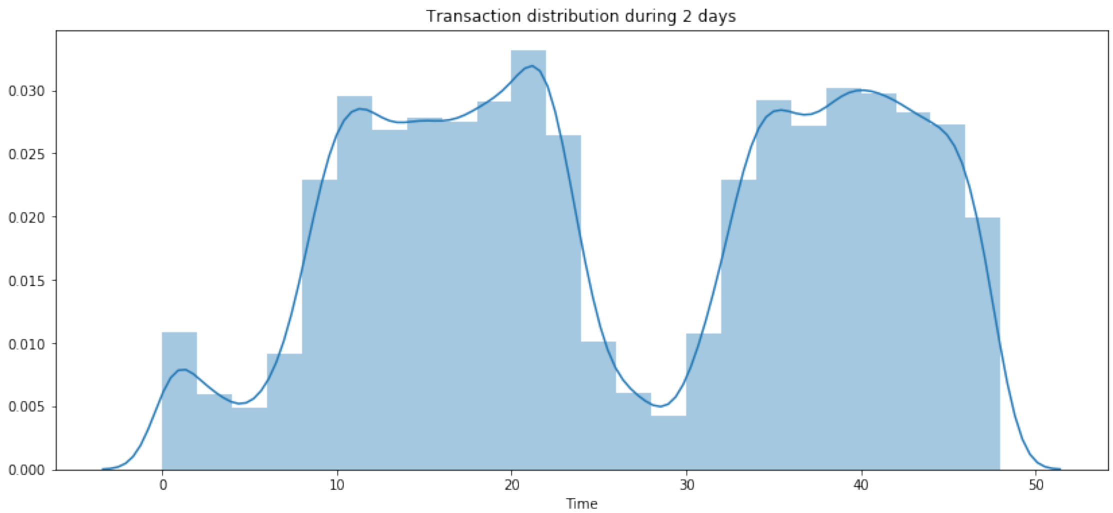
```
In [21]: plt.figure(figsize=(14, 5))

         sns.kdeplot(df.loc[df['Class'] == 1, 'Amount'], shade=True, label = 'Fraud')
         sns.kdeplot(df.loc[df['Class'] == 0, 'Amount'], shade=True, label = 'Normal')
         plt.show()
```



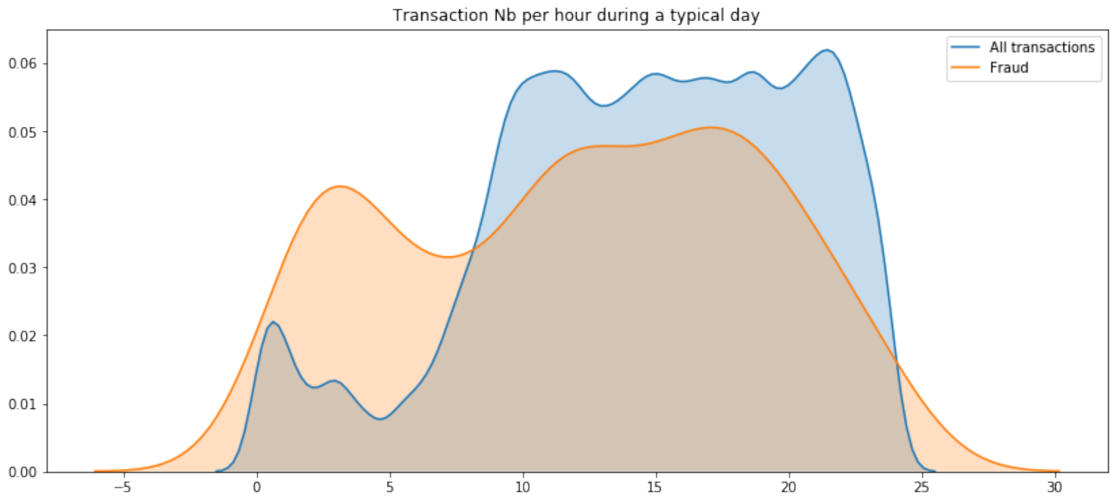
3.4 Values depending on time

```
In [22]: print(f'nb of days during when the data were collected : {df.Time.max() / (60 * 60 * 2

nb of days during when the data were collected : 2.00


In [23]: df['Hours'] = round((df['Time'] / (60 * 60)) % 24)
         df.Hours = df.Hours.astype(int)

In [24]: df['Days'] = round(df['Time'] / (60 * 60 * 24))
         df.Days = df.Days.astype(int)

In [25]: df.Days.value_counts()

Out[25]: 1    144825
         2     92576
         0     47406
         Name: Days, dtype: int64

In [26]: df.Class.sum()

Out[26]: 492
```

In [27]:
```
plt.figure(figsize=(14, 6))
sns.distplot((df['Time'] / (60 * 60)), label = 'All transactions', bins=24)
plt.title('Transaction distribution during 2 days')
plt.show()
```

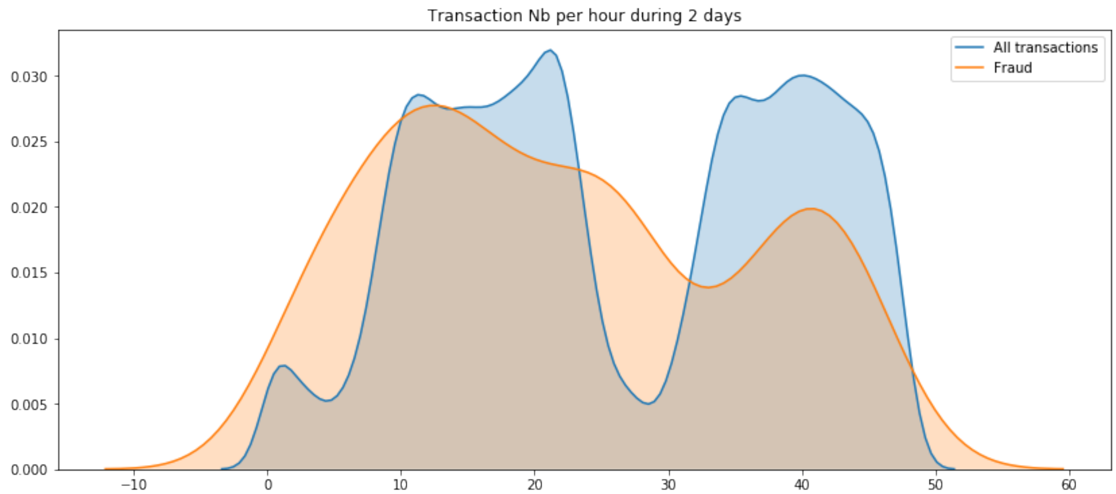


In [31]:
```
plt.figure(figsize=(14, 6))
sns.kdeplot((df['Time'] / (60 * 60)) % 24, label = 'All transactions', shade=True)
sns.kdeplot((df.loc[df['Class'] == 1, 'Time'] / (60 * 60)) % 24, label = 'Fraud', shad
plt.title('Transaction Nb per hour during a typical day')
plt.show()
```



In [30]:
```
plt.figure(figsize=(14, 6))
sns.kdeplot((df['Time'] / (60 * 60)), label = 'All transactions', shade=True)
```

```
sns.kdeplot((df.loc[df['Class'] == 1, 'Time'] / (60 * 60)), label = 'Fraud', shade=Tru
plt.title('Transaction Nb per hour during 2 days')
plt.show()
```

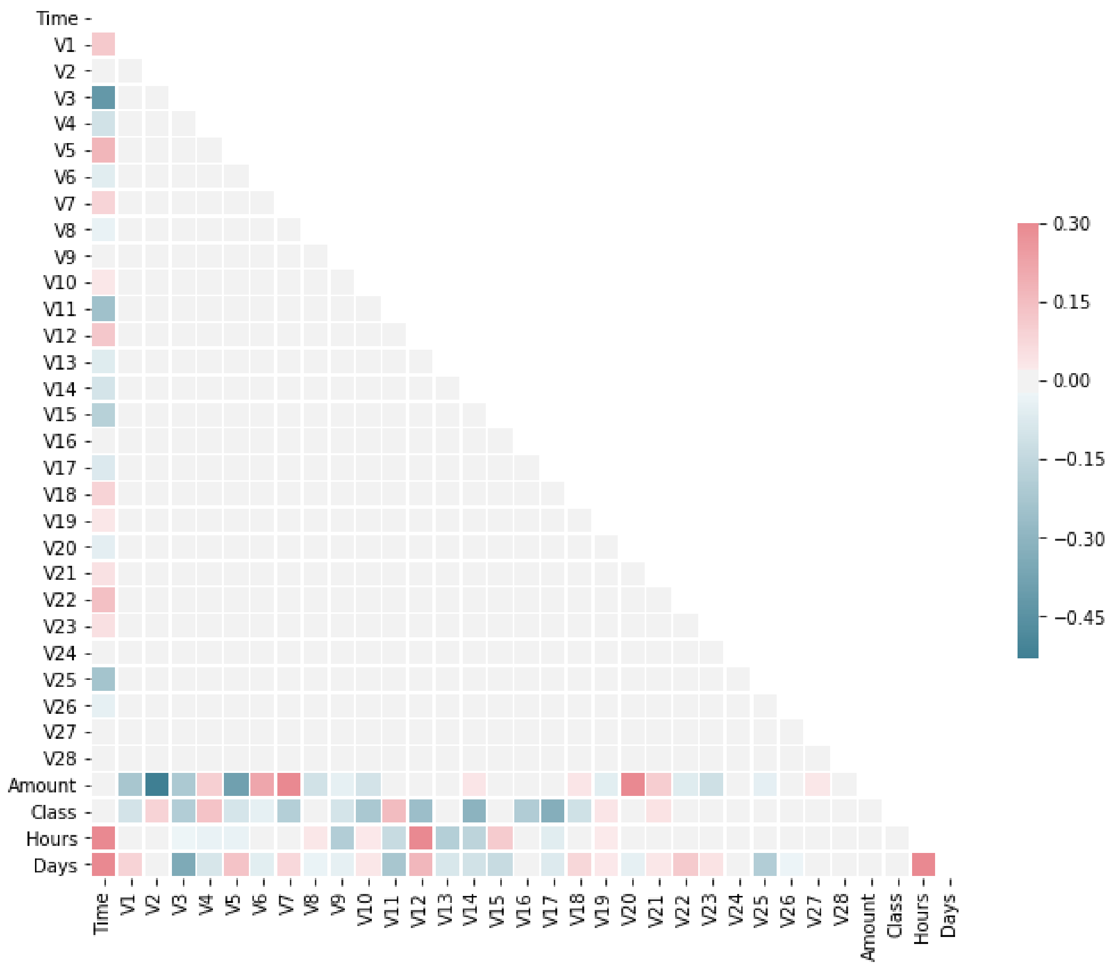


3.5 Correlations

In [32]:
```
corr = df.corr()
#corr
```

In [33]:
```
# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[33]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f069f03c668>
```



As expected there are not much correlations between features themselves because of the PCA. But we can see correlations between non PCA features in particular with the target. Nevertheless, there isn't any strong correlations.

3.6 Ploting the PCA in 2D

Here it could be interesting to redo a PCA in order to reduce the dimension number to 2 or 3 so that we can easily plot the data with T-SNE. In this way, we'll be able to see if class 1 is sparsed or grouped.

- If the class 1 points are not situated at the same place, a SMOTE will add other points at the wrong place among class 0, which is not interesting for us. In this case it's a better practice to do sub/over sampling.
- On the contrary, if the points of clas 1 are near each others, we can do a SMOTE.

First, the PCA is sensitive to different scales, so we've to centered the data and apply a standard scaler for instance.

In [35]:
```
pca_feat = ['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',
            'Hours']
y = df.Class
X_centered = df[pca_feat]
```

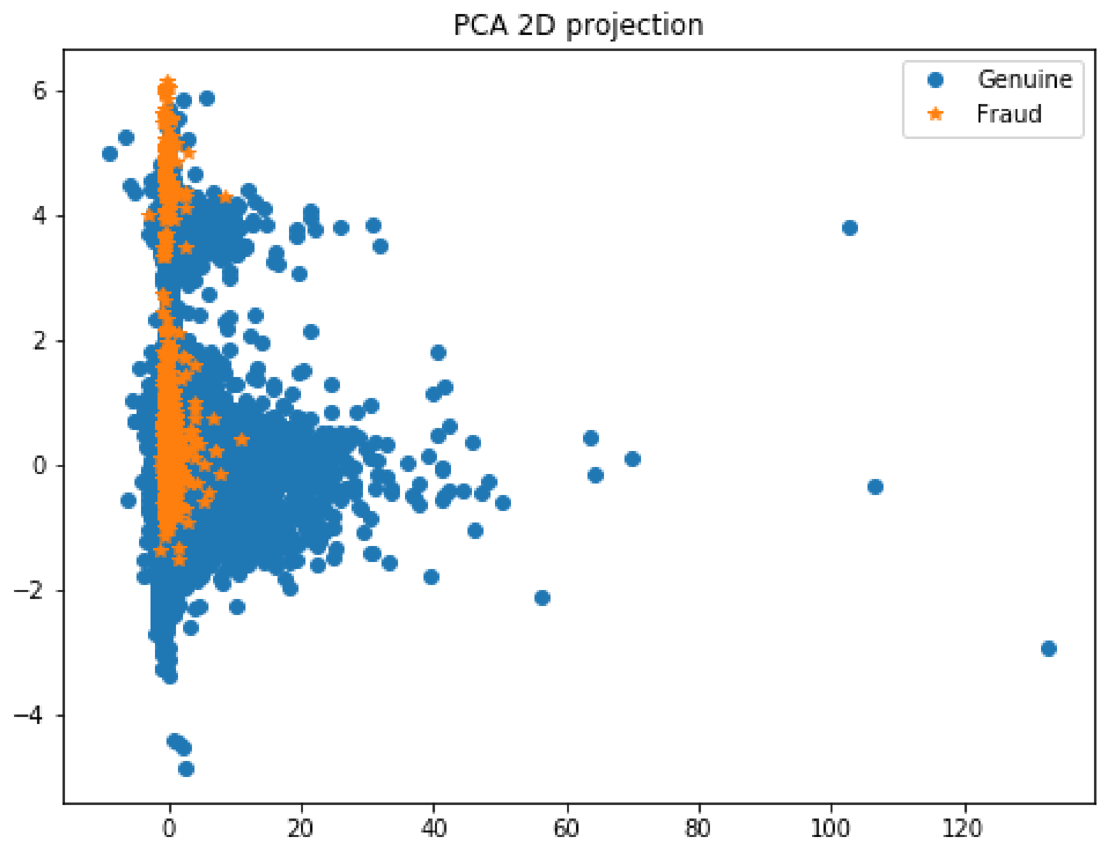
In [36]:
```
scaler = StandardScaler()
X_centered = scaler.fit_transform(X_centered)
```

```
/home/sunflowa/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:625: DataCon
  return self.partial_fit(X, y)
/home/sunflowa/anaconda3/lib/python3.7/site-packages/sklearn/base.py:462: DataConversionWarning
  return self.fit(X, **fit_params).transform(X)
```

In [37]:
```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_centered)
X_pca[:5]
```

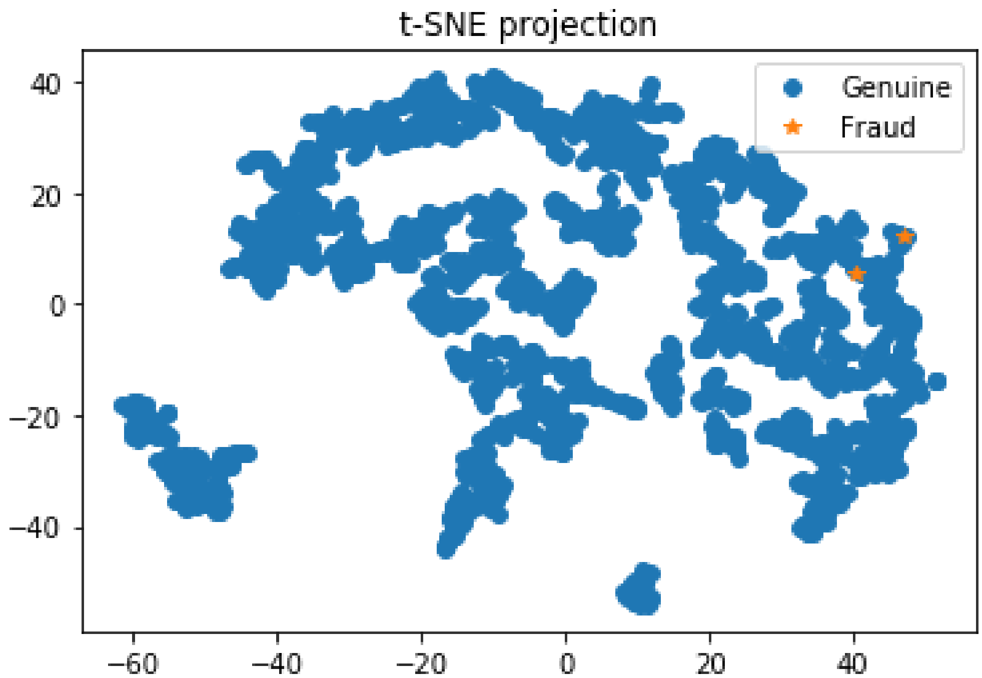
Out[37]:
```
array([[ 0.36387701,  1.55169943],
       [-0.42400152,  1.55246636],
       [ 1.82884782,  1.62882145],
       [ 0.26292935,  1.46965936],
       [-0.0220992 ,  1.66986345]])
```

In [38]:
```
# Then we plot the results of PCA
plt.figure(figsize=(8, 6))
plt.plot(X_pca[y == 0, 0], X_pca[y == 0, 1], 'o', label='Genuine')
plt.plot(X_pca[y == 1, 0], X_pca[y == 1, 1], '*', label='Fraud')
plt.legend(loc=0)
plt.title('PCA 2D projection')
plt.show()
```



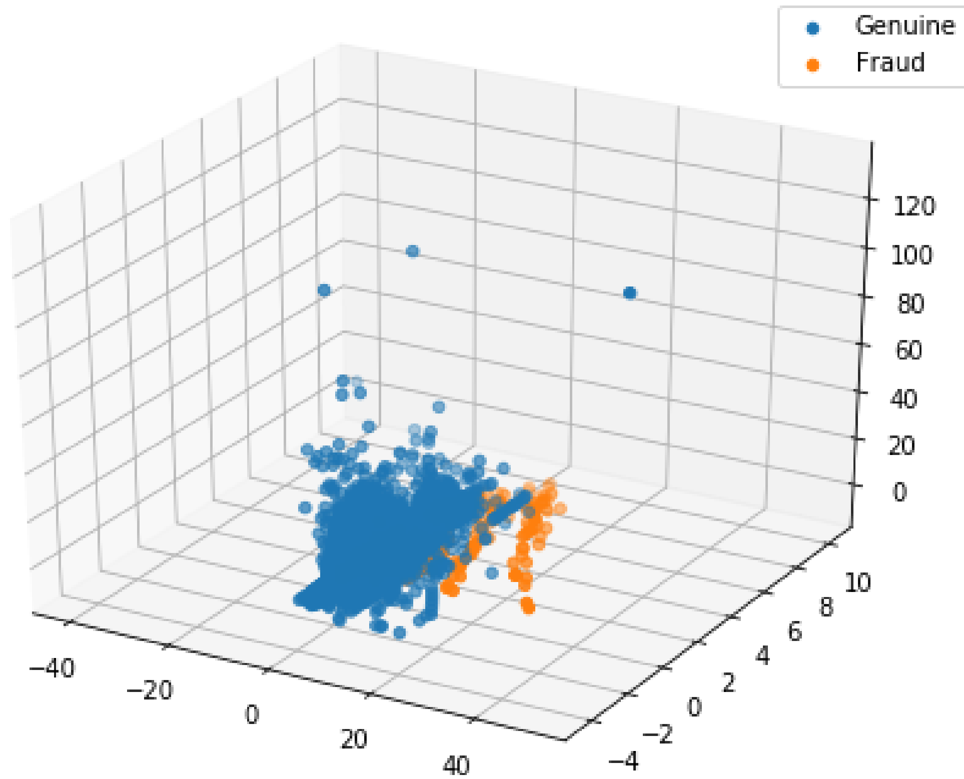
3.7 Plotting the TSNE in 2D - with a subsample

```
In [39]: from sklearn.utils import resample

         X_sub, y_sub = resample(X_pca, y, replace=False, n_samples=2000, random_state=0)

In [40]: tsne = TSNE(n_components=2)

         # Here we perform the t-SNE
         X_tsne = tsne.fit_transform(X_sub)

         # Then we plot the results of t-SNE
         plt.plot(X_tsne[y_sub == 0, 0], X_tsne[y_sub == 0, 1], 'o', label='Genuine')
         plt.plot(X_tsne[y_sub == 1, 0], X_tsne[y_sub == 1, 1], '*', label='Fraud')
         plt.legend(loc=0)
         plt.title('t-SNE projection')
         plt.show()
```



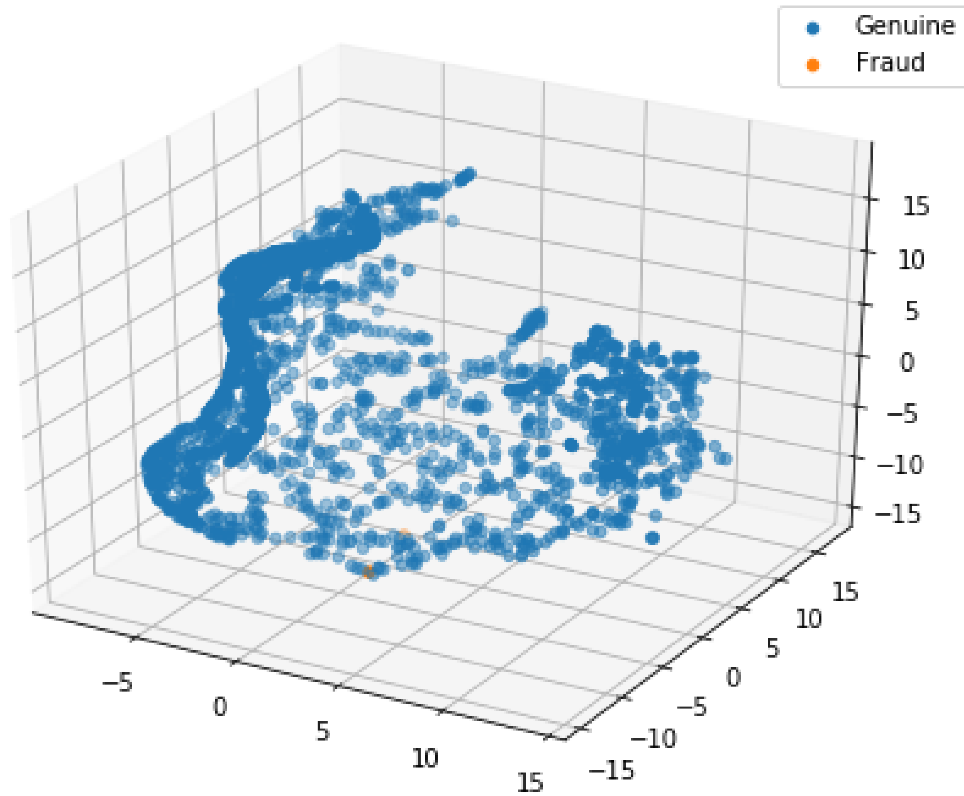
3.8 Ploting the PCA in 3D

```
In [41]: pca = PCA(n_components=3)
         X_pca = pca.fit_transform(X_centered)

In [42]: from mpl_toolkits.mplot3d import Axes3D

         fig = plt.figure(figsize=(8, 6))
         ax = fig.add_subplot(111, projection='3d')

         ax.scatter(X_pca[y == 0, 2], X_pca[y == 0, 1], X_pca[y == 0, 0], 'o', label='Genuine')
         ax.scatter(X_pca[y == 1, 2], X_pca[y == 1, 1], X_pca[y == 1, 0], '*', label='Fraud')

         plt.legend()
         plt.show()
```



3.9 Plotting the TSNE in 3D

```
In [43]: tsne = TSNE(n_components=3)
         X_tsne = tsne.fit_transform(X_sub)

         fig = plt.figure(figsize=(8, 6))
         ax = fig.add_subplot(111, projection='3d')

         ax.scatter(X_tsne[y_sub == 0, 0], X_tsne[y_sub == 0, 1], X_tsne[y_sub == 0, 2], 'o', l
         ax.scatter(X_tsne[y_sub == 1, 0], X_tsne[y_sub == 1, 1], X_tsne[y_sub == 1, 2], '*', l

         plt.legend()
         plt.show()
```



4 Data Preparation and Feature engineering

4.1 Features kept

At first glance, it seems not interesting to keep days as data are collected over 2 days only...and it's not relevant to keep the unchanged feature 'Time'.

```
In [44]: features_kept = ['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',
                  'Hours', 'Days']
```

```
In [45]: y = df['Class']
         X = df[features_kept]
```

4.2 Importance analysis

```
In [46]: rnd_clf = RandomForestClassifier(n_jobs=-1)
         rnd_clf.fit(X, y)
```

```
Out[46]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
```

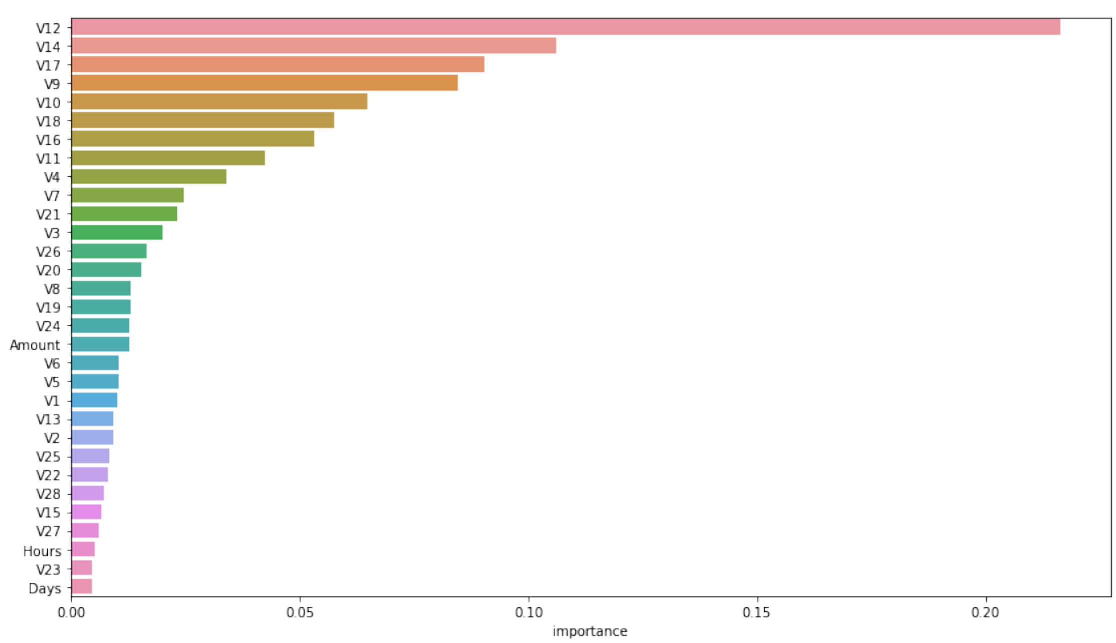
```
                    min_impurity_decrease=0.0, min_impurity_split=None,
                    min_samples_leaf=1, min_samples_split=2,
                    min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=-1,
                    oob_score=False, random_state=None, verbose=0,
                    warm_start=False)
```

In [48]:
```
feature_importances = pd.DataFrame(rnd_clf.feature_importances_, index = X.columns,
                                    columns=['importance']).sort_values('importance',
feature_importances[:10]
```

Out[48]:

	importance
V12	0.216463
V14	0.106220
V17	0.090474
V9	0.084557
V10	0.064671
V18	0.057420
V16	0.053249
V11	0.042484
V4	0.034072
V7	0.024718

In [49]:
```
plt.figure(figsize=(14, 8))
sns.barplot(x="importance", y=feature_importances.index, data=feature_importances)
plt.show()
```



4.3 Data transformation for models

```
In [50]: X = pd.get_dummies(data=X, columns=['Hours'], drop_first=True)

In [51]: X.head()

Out[51]:          V1        V2        V3        V4        V5        V6        V7  \
         0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
         1  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
         2 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
         3 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
         4 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

                 V8        V9       V10       V11       V12       V13       V14  \
         0  0.098698  0.363787  0.090794 -0.551600 -0.617801 -0.991390 -0.311169
         1  0.085102 -0.255425 -0.166974  1.612727  1.065235  0.489095 -0.143772
         2  0.247676 -1.514654  0.207643  0.624501  0.066084  0.717293 -0.165946
         3  0.377436 -1.387024 -0.054952 -0.226487  0.178228  0.507757 -0.287924
         4 -0.270533  0.817739  0.753074 -0.822843  0.538196  1.345852 -1.119670

                V15       V16       V17       V18       V19       V20       V21  \
         0  1.468177 -0.470401  0.207971  0.025791  0.403993  0.251412 -0.018307
         1  0.635558  0.463917 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775
         2  2.345865 -2.890083  1.109969 -0.121359 -2.261857  0.524980  0.247998
         3 -0.631418 -1.059647 -0.684093  1.965775 -1.232622 -0.208038 -0.108300
         4  0.175121 -0.451449 -0.237033 -0.038195  0.803487  0.408542 -0.009431

                V22       V23       V24       V25       V26       V27       V28  \
         0  0.277838 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
         1 -0.638672  0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724
         2  0.771679  0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
         3  0.005274 -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458
         4  0.798278 -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153

           Amount  Days  Hours_1  Hours_2  Hours_3  Hours_4  Hours_5  Hours_6  \
         0 149.62     0        0        0        0        0        0        0
         1   2.69     0        0        0        0        0        0        0
         2 378.66     0        0        0        0        0        0        0
         3 123.50     0        0        0        0        0        0        0
         4  69.99     0        0        0        0        0        0        0

           Hours_7  Hours_8  Hours_9  Hours_10  Hours_11  Hours_12  Hours_13  \
         0       0        0        0         0         0         0         0
         1       0        0        0         0         0         0         0
         2       0        0        0         0         0         0         0
         3       0        0        0         0         0         0         0
         4       0        0        0         0         0         0         0

           Hours_14  Hours_15  Hours_16  Hours_17  Hours_18  Hours_19  Hours_20  \
```

```
0         0         0         0         0         0         0         0
1         0         0         0         0         0         0         0
2         0         0         0         0         0         0         0
3         0         0         0         0         0         0         0
4         0         0         0         0         0         0         0

   Hours_21  Hours_22  Hours_23  Hours_24
0         0         0         0         0
1         0         0         0         0
2         0         0         0         0
3         0         0         0         0
4         0         0         0         0
```

In [52]:
```
scaler = StandardScaler()
X[['Amount', 'Days']] = scaler.fit_transform(X[['Amount', 'Days']])
```

```
/home/sunflowa/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:625: DataCon
  return self.partial_fit(X, y)
/home/sunflowa/anaconda3/lib/python3.7/site-packages/sklearn/base.py:462: DataConversionWarning
  return self.fit(X, **fit_params).transform(X)
```

In [53]:
```
X.drop(columns=['Days'])
X.head()
```

Out[53]:
```
         V1        V2        V3        V4        V5        V6        V7  \
0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9       V10       V11       V12       V13       V14  \
0  0.098698  0.363787  0.090794 -0.551600 -0.617801 -0.991390 -0.311169
1  0.085102 -0.255425 -0.166974  1.612727  1.065235  0.489095 -0.143772
2  0.247676 -1.514654  0.207643  0.624501  0.066084  0.717293 -0.165946
3  0.377436 -1.387024 -0.054952 -0.226487  0.178228  0.507757 -0.287924
4 -0.270533  0.817739  0.753074 -0.822843  0.538196  1.345852 -1.119670

        V15       V16       V17       V18       V19       V20       V21  \
0  1.468177 -0.470401  0.207971  0.025791  0.403993  0.251412 -0.018307
1  0.635558  0.463917 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775
2  2.345865 -2.890083  1.109969 -0.121359 -2.261857  0.524980  0.247998
3 -0.631418 -1.059647 -0.684093  1.965775 -1.232622 -0.208038 -0.108300
4  0.175121 -0.451449 -0.237033 -0.038195  0.803487  0.408542 -0.009431

        V22       V23       V24       V25       V26       V27       V28  \
0  0.277838 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
1 -0.638672  0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724
```

```
2  0.771679  0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
3  0.005274 -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458
4  0.798278 -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153

     Amount      Days  Hours_1  Hours_2  Hours_3  Hours_4  Hours_5  Hours_6  \
0  0.244964 -1.696601        0        0        0        0        0        0
1 -0.342475 -1.696601        0        0        0        0        0        0
2  1.160686 -1.696601        0        0        0        0        0        0
3  0.140534 -1.696601        0        0        0        0        0        0
4 -0.073403 -1.696601        0        0        0        0        0        0

   Hours_7  Hours_8  Hours_9  Hours_10  Hours_11  Hours_12  Hours_13  \
0        0        0        0         0         0         0         0
1        0        0        0         0         0         0         0
2        0        0        0         0         0         0         0
3        0        0        0         0         0         0         0
4        0        0        0         0         0         0         0

   Hours_14  Hours_15  Hours_16  Hours_17  Hours_18  Hours_19  Hours_20  \
0         0         0         0         0         0         0         0
1         0         0         0         0         0         0         0
2         0         0         0         0         0         0         0
3         0         0         0         0         0         0         0
4         0         0         0         0         0         0         0

   Hours_21  Hours_22  Hours_23  Hours_24
0         0         0         0         0
1         0         0         0         0
2         0         0         0         0
3         0         0         0         0
4         0         0         0         0
```

Let's split the data in a train and test set to evaluate models

In [90]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

5 Baselines with weighted classes but without resampling

5.1 Implamantation of the metric

In [55]:
```
# Just a test
model = RandomForestClassifier()
model.fit(X_train, y_train)

# predict probabilities
probs = model.predict_proba(X_test)

# keep probabilities for the positive outcome only
```

```
        probs = probs[:, 1]

        # calculate precision-recall curve
        precision, recall, thresholds = precision_recall_curve(y_test, probs)

        # calculate precision-recall AUC
        auc_score = auc(recall, precision)
        auc_score
```

Out[55]: 0.8753123564549905

```
In [56]: # f1_score binary by default
         def get_f1_scores(fitted_clf, model_name):
             y_train_pred, y_pred = fitted_clf.predict(X_train), fitted_clf.predict(X_test)
             print(model_name, ' :')
             print(f'Training F1 score = {f1_score(y_train, y_train_pred) * 100:.2f}% / Test F
             print(classification_report(y_test, y_pred))
```

```
In [57]: def get_auc_scores(fitted_clf, model_name):
             print(model_name, ' :')

             # get classes predictions for the classification report
             y_train_pred, y_pred = fitted_clf.predict(X_train), fitted_clf.predict(X_test)
             print(classification_report(y_test, y_pred), '\n') # target_names=y

             # computes probabilities keep the ones for the positive outcome only
             probs = fitted_clf.predict_proba(X_test)[:, 1]

             # calculate precision-recall curve
             precision, recall, thresholds = precision_recall_curve(y_test, probs)

             # calculate precision-recall AUC
             auc_score = auc(recall, precision)
             print(f'Area Under the Precision-Recall Curve (AUPRC) = {auc_score * 100 :.2f}%')
```

5.2 Randomforest without weighted classes

```
In [58]: model = RandomForestClassifier()
         model.fit(X_train, y_train)
         get_auc_scores(model, 'RandomForest not weighted')
```

```
RandomForest not weighted  :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56878
           1       0.87      0.82      0.85        84

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.94      0.91      0.92     56962
```

```
weighted avg       1.00      1.00      1.00     56962


Area Under the Precision-Recall Curve (AUPRC) = 88.65%
```

5.3 Randomforest with weighted classes

```
In [91]: y_train.sum(), len(y_train) - y_train.sum()
```

```
Out[91]: (398, 227447)
```

```
In [92]: model = RandomForestClassifier(class_weight={1:398, 0:227447})
         model.fit(X_train, y_train)
         get_auc_scores(model, 'RandomForest weighted')
```

```
RandomForest weighted  :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56868
           1       0.89      0.72      0.80        94

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.95      0.86      0.90     56962
weighted avg       1.00      1.00      1.00     56962


Area Under the Precision-Recall Curve (AUPRC) = 80.41%
```

We can see that the F1 score is the same but not the AUPRC (AUPRC = 88.65% without weighted classes and 85.16% with). This indicates that F1 score is definitvely not a better metrice than AUPRC.

5.4 LGBM without weights

```
In [63]: model = lgbm.LGBMClassifier(n_jobs = -1)
         model.fit(X_train, y_train)
         get_auc_scores(model, 'LGBM non weighted')
```

```
LGBM non weighted  :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56878
           1       0.15      0.35      0.21        84

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.58      0.67      0.61     56962
weighted avg       1.00      1.00      1.00     56962
```

```
Area Under the Precision-Recall Curve (AUPRC) = 20.58%
```

The results is disappointing...

5.5 LGBM with weights

```
In [93]: model = lgbm.LGBMClassifier(n_jobs = -1, class_weight={0:398, 1:227447})
         model.fit(X_train, y_train)
         get_auc_scores(model, 'LGBM weighted')
```

```
LGBM weighted   :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56868
           1       0.81      0.81      0.81        94

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.90      0.90      0.90     56962
weighted avg       1.00      1.00      1.00     56962


Area Under the Precision-Recall Curve (AUPRC) = 79.59%
```

That's better but not still less than the 1st random forrest clf.

5.6 XGB without ratio

```
In [66]: model = xgb.XGBClassifier(objective="binary:logistic")
         model.fit(X_train, y_train)
         get_auc_scores(model, 'XGB without ratio')
```

```
XGB without ratio   :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56878
           1       0.87      0.77      0.82        84

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.93      0.89      0.91     56962
weighted avg       1.00      1.00      1.00     56962


Area Under the Precision-Recall Curve (AUPRC) = 86.19%
```

5.7 XGB with ratio

```
In [94]: ratio = ((len(y_train) - y_train.sum()) - y_train.sum()) / y_train.sum()
         ratio

Out[94]: 570.4748743718593

In [95]: model = xgb.XGBClassifier(objective="binary:logistic", scale_pos_weight=ratio)
         model.fit(X_train, y_train)
         get_auc_scores(model, 'XGB with ratio')
```

```
XGB with ratio  :
              precision    recall  f1-score   support

           0       1.00      0.99      1.00     56868
           1       0.16      0.85      0.27        94

   micro avg       0.99      0.99      0.99     56962
   macro avg       0.58      0.92      0.63     56962
weighted avg       1.00      0.99      1.00     56962


Area Under the Precision-Recall Curve (AUPRC) = 70.62%
```

It seems that XGB doesn't work well with a ratio, the result is better without it.

6 Using the Synthetic Minority Over-sampling Technique

6.1 How SMOTe works

Brief description on SMOTe (Synthetic Minority Over-sampling Technique):
it creates synthetic observations of the minority class (bad loans) by:

- Finding the k-nearest-neighbors for minority class observations (finding similar observations)
- Randomly choosing one of the k-nearest-neighbors and using it to create a similar, but randomly tweaked, new observation.

More explanations can be found here
An other informative article

Oversampling is a well-known way to potentially improve models trained on imbalanced data. But it's important to remember that oversampling incorrectly can lead to thinking a model will generalize better than it actually does. Random forests are great because the model architecture reduces overfitting (see Brieman 2001 for a proof), but poor sampling practices can still lead to false conclusions about the quality of a model.

When the model is in production, it's predicting on unseen data. The main point of model validation is to estimate how the model will generalize to new data. If the decision to put a model into production is based on how it performs on a validation set, it's critical that oversampling is done correctly.

```
In [79]: # conda install -c conda-forge imbalanced-learn
         from imblearn.over_sampling import SMOTE
```

```
In [80]: X_train.shape, y_train.shape
```

```
Out[80]: ((227845, 54), (227845,))
```

The SMOTE is applied on the train set ONLY:

```
In [81]: sm = SMOTE(sampling_strategy='auto', k_neighbors=3, n_jobs=1, ratio=0.01)
         X_train, y_train = sm.fit_resample(X_train, y_train)
         X_train.shape, y_train.shape
```

```
Out[81]: ((229711, 54), (229711,))
```

```
In [85]: y_train.sum(), len(y_train) - y_train.sum()
```

```
Out[85]: (2274, 227437)
```

6.2 Randomforest

```
In [82]: model = RandomForestClassifier()
         model.fit(X_train, y_train)
         get_auc_scores(model, 'RandomForest with SMOTE')
```

```
RandomForest with SMOTE  :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56878
           1       0.89      0.83      0.86        84

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.94      0.92      0.93     56962
weighted avg       1.00      1.00      1.00     56962


Area Under the Precision-Recall Curve (AUPRC) = 88.21%
```

Result unchanged !

```
In [99]: model = RandomForestClassifier(class_weight={1:2274, 0:227437})
         model.fit(X_train, y_train)
         get_auc_scores(model, 'RandomForest weighted')
```

```
RandomForest weighted  :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56868
           1       0.93      0.67      0.78        94
```

```
   micro avg       1.00      1.00      1.00     56962
   macro avg       0.96      0.84      0.89     56962
weighted avg       1.00      1.00      1.00     56962


Area Under the Precision-Recall Curve (AUPRC) = 81.85%
```

6.3 LGBM

```
In [83]: model = lgbm.LGBMClassifier(n_jobs = -1)
         model.fit(X_train, y_train)
         get_auc_scores(model, 'LGBM with SMOTE')
```

```
LGBM with SMOTE  :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56878
           1       0.86      0.81      0.83        84

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.93      0.90      0.92     56962
weighted avg       1.00      1.00      1.00     56962


Area Under the Precision-Recall Curve (AUPRC) = 86.49%
```

That's really better, let's try with ratio

```
In [88]: model = lgbm.LGBMClassifier(n_jobs = -1, class_weight={0:2274, 1:227437})
         model.fit(X_train, y_train)
         get_auc_scores(model, 'LGBM with SMOTE and ratio')
```

```
LGBM with SMOTE and ratio  :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56878
           1       0.71      0.90      0.80        84

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.86      0.95      0.90     56962
weighted avg       1.00      1.00      1.00     56962


Area Under the Precision-Recall Curve (AUPRC) = 89.91%
```

That's the best result so far !

6.4 Logistic Regression

```
In [110]: lr = LogisticRegression(C=0.01, penalty='l1').fit(X_train, y_train)
          get_auc_scores(lr, 'Logistic Regression')
```

```
Logistic Regression  :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     56868
           1       0.88      0.47      0.61        94

   micro avg       1.00      1.00      1.00     56962
   macro avg       0.94      0.73      0.81     56962
weighted avg       1.00      1.00      1.00     56962


Area Under the Precision-Recall Curve (AUPRC) = 71.75%
```

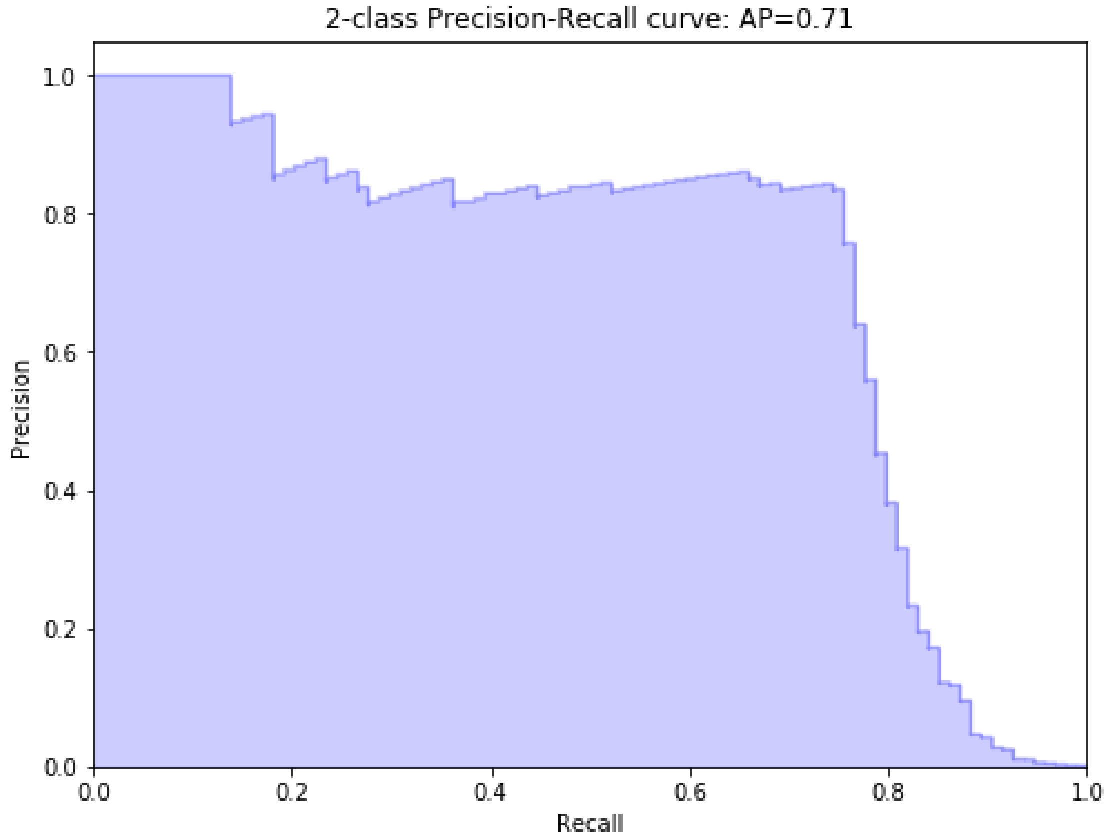
6.5 Precision-recall curve plot

```
In [96]: probs = model.predict_proba(X_test)[:, 1]
         precision, recall, thresholds = precision_recall_curve(y_test, probs)
```

```
In [97]: from inspect import signature
         from sklearn.metrics import average_precision_score

         average_precision = average_precision_score(y_test, probs)
         print('Average precision-recall score: {0:0.2f}'.format(average_precision))

         step_kwargs = ({'step': 'post'} if 'step' in signature(plt.fill_between).parameters el

         plt.figure(figsize=(8, 6))
         plt.step(recall, precision, color='b', alpha=0.2, where='post')
         plt.fill_between(recall, precision, alpha=0.2, color='b', **step_kwargs)

         plt.xlabel('Recall')
         plt.ylabel('Precision')
         plt.ylim([0.0, 1.05])
         plt.xlim([0.0, 1.0])
         plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(average_precision))
```

```
Average precision-recall score: 0.71
```

```
Out[97]: Text(0.5, 1.0, '2-class Precision-Recall curve: AP=0.71')
```



6.6 Models Scores Comparison

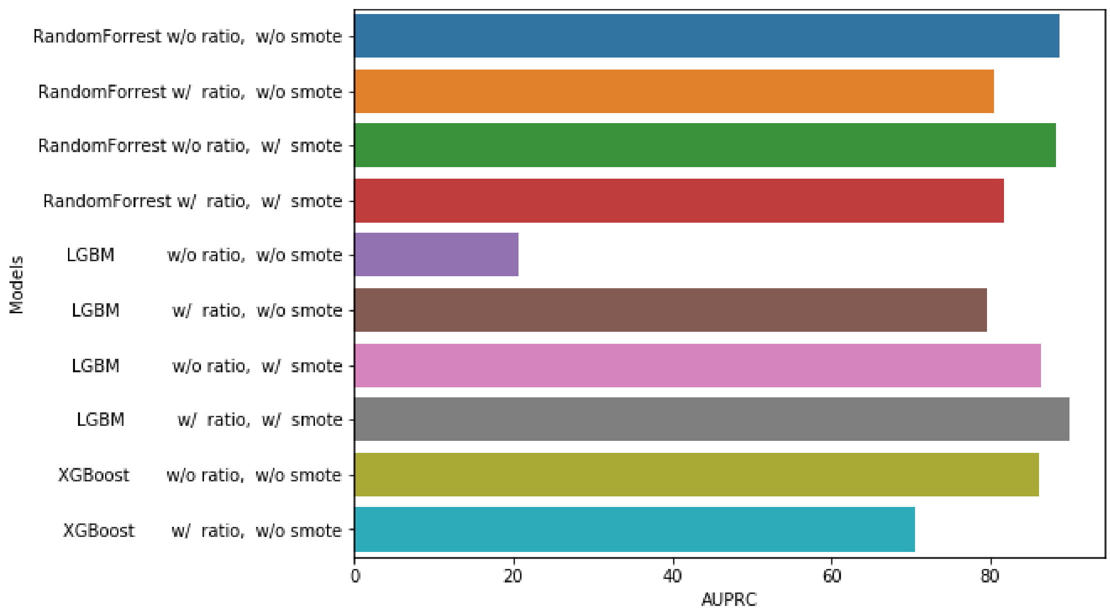
In [98]:
```
data = {'Country': ['Belgium',  'India',  'Brazil'],
    'Capital': ['Brussels',  'New Delhi',  'Brasilia'],
    'Population': [11190846, 1303171035, 207847528]}
test = pd.DataFrame(data,columns=['Country',  'Capital',  'Population'])
test
```

Out[98]:

	Country	Capital	Population
0	Belgium	Brussels	11190846
1	India	New Delhi	1303171035
2	Brazil	Brasilia	207847528

In [107]:
```
data = {'Models': ['RandomForrest w/o ratio,  w/o smote',
                   'RandomForrest w/  ratio,  w/o smote',
                   'RandomForrest w/o ratio,  w/  smote',
                   'RandomForrest w/  ratio,  w/  smote',
                   'LGBM          w/o ratio,  w/o smote',
                   'LGBM          w/  ratio,  w/o smote',
                   'LGBM          w/o ratio,  w/  smote',
                   'LGBM          w/  ratio,  w/  smote',
```

```
                    'XGBoost       w/o ratio,  w/o smote',
                    'XGBoost       w/  ratio,  w/o smote'],
    'AUPRC': [88.65, 80.41, 88.21, 81.85, 20.58, 79.59, 86.49, 89.91, 86.19, 70.62]}

scores_df = pd.DataFrame(data,columns=['Models',  'AUPRC'])

plt.figure(figsize=(8, 6))
sns.barplot(y="Models", x="AUPRC", data=scores_df)
plt.show()
```



7 Using anomalies detection models

for learning purposes :)

7.1 How LOF works under the hood

The LOF algorithm is an unsupervised outlier detection method which computes the local density deviation of a given data point with respect to its neighbors. It considers as outlier samples that have a substantially lower density than their neighbors.

The number of neighbors considered, (parameter n_neighbors) is typically chosen 1) greater than the minimum number of objects a cluster has to contain, so that other objects can be local outliers relative to this cluster, and 2) smaller than the maximum number of close by objects that can potentially be local outliers. In practice, such informations are generally not available, and taking n_neighbors=20 appears to work well in general.

7.2 Application

In [112]:
```
X_sub, y_sub = resample(X, y, replace=False, n_samples=2000, random_state=0)
```

In [113]:
```
X_sub.shape, y_sub.shape
```

Out[113]:
```
((2000, 54), (2000,))
```

In [ ]:
```
from sklearn.neighbors import LocalOutlierFactor

# fit the model for outlier detection (default)
clf = LocalOutlierFactor(n_neighbors=20, contamination="auto")
# use fit_predict to compute the predicted labels of the training samples
# (when LOF is used for outlier detection, the estimator has no predict,
# decision_function and score_samples methods).

y_pred = clf.fit_predict(X_train)
#n_errors = (y_pred != y).sum()
X_scores = clf.negative_outlier_factor_


plt.figure(figsize=(8,8))
plt.title("Local Outlier Factor (LOF)")
plt.scatter(X[:, 0], X[:, 1], c=y_pred, s=10., label='Data points')

# plot circles with radius proportional to the outlier scores
radius = (X_scores.max() - X_scores) / (X_scores.max() - X_scores.min())
plt.scatter(X_train[:, 0], X_train[:, 1], s=1000 * radius, edgecolors='r', facecolors=
legend = plt.legend(loc='lower left')
plt.show()

print("prediction errors: {}".format(n_errors))
print("Negative LOF scores: {}".format(clf.negative_outlier_factor_))
print("Offset (threshold to consider sample as anomaly or not): {}".format(clf.offset_
```