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1 Оглавление ¶

2 Задание (к оглавлению)

1. Выберите набор данных (датасет) для решения задачи классификации или регрессии.
2. В случае необходимости проведите удаление или заполнение пропусков и кодирование категориальных признаков.
3. С использованием метода train_test_split разделите выборку на обучающую и тестовую.
4. Обучите следующие модели:
   - одну из линейных моделей (линейную или полиномиальную регрессию при решении задачи регрессии, логистическую регрессию при решении задачи классификации);
   - SVM;
   - дерево решений.
5. Оцените качество моделей с помощью двух подходящих для задачи метрик. Сравните качество полученных моделей.
6. Постройте график, показывающий важность признаков в дереве решений.
7. Визуализируйте дерево решений или выведите правила дерева решений в текстовом виде.

3 Описание датасета (к оглавлению)

Digital payments are evolving, but so are cyber criminals.

According to the Data Breach Index, more than 5 million records are being stolen on a daily basis, a concerning statistic that shows - fraud is still very common both for Card-Present and Card-not Present type of payments.

In today's digital world where trillions of Card transaction happens per day, detection of fraud is challenging.

This Dataset sourced by some unnamed institute.

Feature Explanation:

`distancefromhome` - the distance from home where the transaction happened.

`distancefromlast_transaction` - the distance from last transaction happened.

`ratiotomedianpurchaseprice` - Ratio of purchased price transaction to median purchase price.

`repeat_retailer` - Is the transaction happened from same retailer.

`used_chip` - Is the transaction through chip (credit card).

`usedpinnumber` - Is the transaction happened by using PIN number.

`online_order` - Is the transaction an online order.

`fraud` - Is the transaction fraudulent.

4 Импорт библиотек (к оглавлению)

Ввод [1]:
```
import numpy as np
import pandas as pd

from io import StringIO
import graphviz
import pydotplus
from IPython.core.display import HTML, Image
from operator import itemgetter

from sklearn.preprocessing import StandardScaler

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier, export_text, export_graphviz
from sklearn.svm import SVC

from sklearn.pipeline import Pipeline

from sklearn.metrics import recall_score
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve, roc_auc_score

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

5 Загрузка и первичный анализ данных (к оглавлению)

5.1 Подготовка данных

Ввод [2]:
```
df = pd.read_csv("card_transdata.csv")
df = df.head(100000)
df.head()
```

Out[2]:

	distance_from_home	distance_from_last_transaction	ratio_to_median_purchase_price	repeat_retailer	used_chip	used_pin_number	online_order
0	57.877857	0.311140	1.945940	1.0	1.0	0.0	0.0
1	10.829943	0.175592	1.294219	1.0	0.0	0.0	0.0
2	5.091079	0.805153	0.427715	1.0	0.0	0.0	1.0
3	2.247564	5.600044	0.362663	1.0	1.0	0.0	1.0
4	44.190936	0.566486	2.222767	1.0	1.0	0.0	1.0

Ввод [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 8 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   distance_from_home              100000 non-null  float64
 1   distance_from_last_transaction  100000 non-null  float64
 2   ratio_to_median_purchase_price  100000 non-null  float64
 3   repeat_retailer                 100000 non-null  float64
 4   used_chip                       100000 non-null  float64
 5   used_pin_number                 100000 non-null  float64
 6   online_order                    100000 non-null  float64
 7   fraud                           100000 non-null  float64
dtypes: float64(8)
memory usage: 6.1 MB
```

Ввод [4]:
```
df = df.rename(columns={
    "distance_from_home": "dist_home",
    "distance_from_last_transaction": "dist_last",
    "ratio_to_median_purchase_price": "ratio",
    "repeat_retailer": "repeat",
    "used_chip": "chip",
    "used_pin_number": "pin",
    "online_order": "online"
})
df.head()
```

Out[4]:

	dist_home	dist_last	ratio	repeat	chip	pin	online	fraud
0	57.877857	0.311140	1.945940	1.0	1.0	0.0	0.0	0.0
1	10.829943	0.175592	1.294219	1.0	0.0	0.0	0.0	0.0
2	5.091079	0.805153	0.427715	1.0	0.0	0.0	1.0	0.0
3	2.247564	5.600044	0.362663	1.0	1.0	0.0	1.0	0.0
4	44.190936	0.566486	2.222767	1.0	1.0	0.0	1.0	0.0

Ввод [5]:
```
df.describe()
```

Out[5]:

	dist_home	dist_last	ratio	repeat	chip	pin	online	fraud
count	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000
mean	26.688487	5.023716	1.819374	0.882090	0.351060	0.103250	0.650660	0.087100
std	65.132078	24.439420	2.912849	0.322503	0.477304	0.304287	0.476764	0.281983
min	0.021322	0.000488	0.011373	0.000000	0.000000	0.000000	0.000000	0.000000
25%	3.864892	0.295815	0.476392	1.000000	0.000000	0.000000	0.000000	0.000000
50%	9.965281	0.996695	0.996081	1.000000	0.000000	0.000000	1.000000	0.000000
75%	25.726777	3.333064	2.089016	1.000000	1.000000	0.000000	1.000000	0.000000
max	4601.011222	2160.499922	266.689692	1.000000	1.000000	1.000000	1.000000	1.000000

Ввод [6]:
```
discrete_features = [
    "repeat",
    "chip",
    "pin",
    "online",
    "fraud"
]

discrete_features = [
    "repeat",
    "chip",
    "pin",
    "online",
    "fraud"
]

for feat in discrete_features:
    df[feat] = df[feat].astype(int)
    print(f'Колонка {feat}: {df[feat].unique()}')
```

```
Колонка repeat: [1 0]
Колонка chip: [1 0]
Колонка pin: [0 1]
Колонка online: [0 1]
Колонка fraud: [0 1]
```

5.2 Корреляционный анализ

Ввод [7]:
```
df.corr()
```

Out[7]:

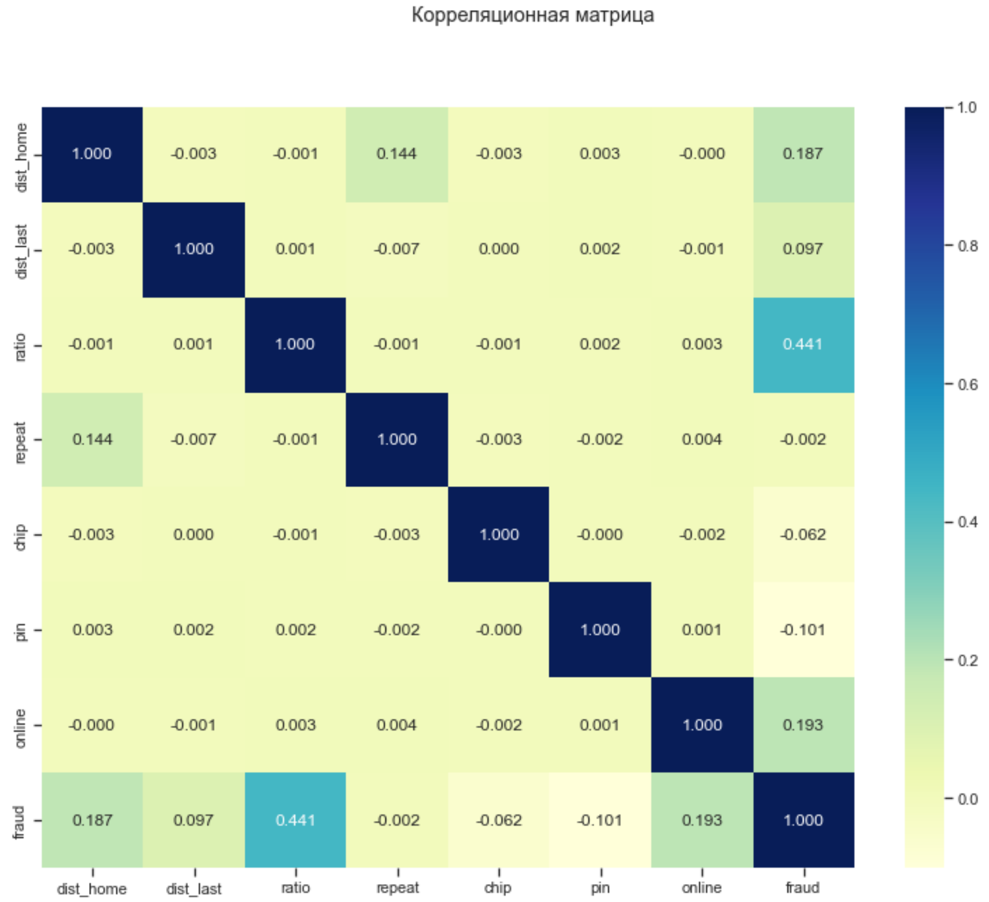
	dist_home	dist_last	ratio	repeat	chip	pin	online	fraud
dist_home	1.000000	-0.002562	-0.000656	0.143589	-0.002928	0.002518	-0.000250	0.187143
dist_last	-0.002562	1.000000	0.000531	-0.006873	0.000284	0.001851	-0.001003	0.097031
ratio	-0.000656	0.000531	1.000000	-0.001365	-0.000684	0.001522	0.002817	0.441085
repeat	0.143589	-0.006873	-0.001365	1.000000	-0.002641	-0.002301	0.003508	-0.002200
chip	-0.002928	0.000284	-0.000684	-0.002641	1.000000	-0.000048	-0.001629	-0.062392
pin	0.002518	0.001851	0.001522	-0.002301	-0.000048	1.000000	0.000616	-0.101431
online	-0.000250	-0.001003	0.002817	0.003508	-0.001629	0.000616	1.000000	0.192710
fraud	0.187143	0.097031	0.441085	-0.002200	-0.062392	-0.101431	0.192710	1.000000

Ввод [8]:
```
df.corr()['fraud']
```

Out[8]:
```
dist_home    0.187143
dist_last    0.097031
ratio        0.441085
repeat      -0.002200
chip        -0.062392
pin         -0.101431
online       0.192710
fraud        1.000000
Name: fraud, dtype: float64
```

Ввод [9]:
```
fig, ax = plt.subplots(1, 1, sharex='col', sharey='row', figsize=(13,10))
fig.suptitle('Корреляционная матрица')
sns.heatmap(df.corr(), ax=ax, annot=True, fmt='.3f', cmap='YlGnBu')
```

Out[9]:
```
<AxesSubplot:>
```



6 Построение модели (к оглавлению)

6.1 Разделение выборки

Ввод [10]:
```
X = df.loc[:, df.columns != 'fraud']
y = df["fraud"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

Ввод [11]:
```
# Отрисовка ROC-кривой
def draw_roc_curve(y_true, y_score, pos_label, average):
    fpr, tpr, thresholds = roc_curve(y_true, y_score, pos_label=pos_label)
    roc_auc_value = roc_auc_score(y_true, y_score, average=average)
    plt.figure()
    lw = 2
    plt.plot(fpr, tpr, color='darkorange', lw=lw, label='ROC curve (area = %0.2f)' % roc_auc_value)
    plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()
```

6.2 Линейная модель

Ввод [12]:
```
%%time
pipe = Pipeline([('scaler', StandardScaler()),
                 ('logisticregression', LogisticRegression())])

lnr = pipe.fit(X_train, y_train)
```

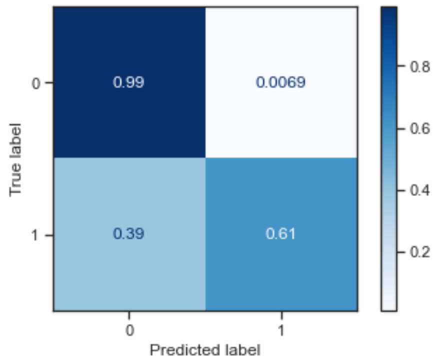
```
CPU times: user 194 ms, sys: 5.95 ms, total: 200 ms
Wall time: 114 ms
```

Ввод [13]:
```
lnr_predict = lnr.predict(X_test)
lnr.score(X_test, y_test)
```

Out[13]:
```
0.96055
```

Ввод [14]:
```
plot_confusion_matrix(lnr, X_test, y_test, cmap=plt.cm.Blues, normalize='true')
```

Out[14]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fd428446f10>
```



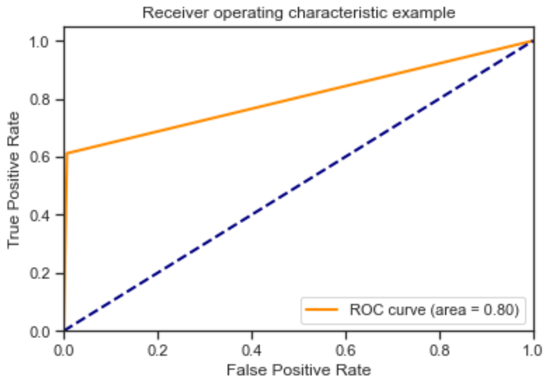
Ввод [15]:
```
print(classification_report(y_test, lnr_predict))
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.98     18294
           1       0.89      0.61      0.73      1706

    accuracy                           0.96     20000
   macro avg       0.93      0.80      0.85     20000
weighted avg       0.96      0.96      0.96     20000
```

Ввод [16]:
```
recall_score(y_test, lnr_predict)
```

Out[16]:
```
0.611957796014068
```

Ввод [17]:
```
draw_roc_curve(y_test, lnr_predict, pos_label=1, average='micro')
```



6.3 Машина опорных векторов

Ввод [18]:
```
%%time
pipe = Pipeline([('scaler', StandardScaler()),
                 ('svc', SVC(kernel='rbf', C=1E6))])

svc = pipe.fit(X_train, y_train)
```

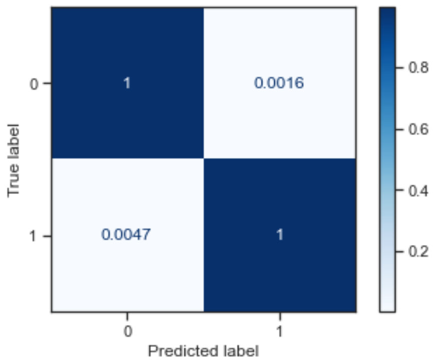
```
CPU times: user 4.45 s, sys: 76.6 ms, total: 4.53 s
Wall time: 4.55 s
```

Ввод [19]:
```
svc_predict = svc.predict(X_test)
svc.score(X_test, y_test)
```

Out[19]: 0.99815

Ввод [20]:
```
plot_confusion_matrix(svc, X_test, y_test, cmap=plt.cm.Blues, normalize='true')
```

Out[20]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fd417001fd0>



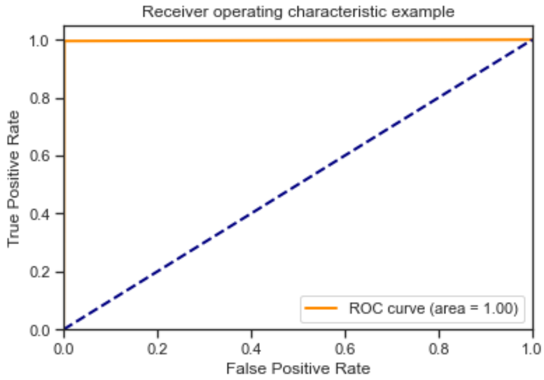
Ввод [21]:
```
print(classification_report(y_test, svc_predict))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     18294
           1       0.98      1.00      0.99      1706

    accuracy                           1.00     20000
   macro avg       0.99      1.00      0.99     20000
weighted avg       1.00      1.00      1.00     20000
```

Ввод [22]:
```
recall_score(y_test, svc_predict)
```

Out[22]: 0.9953106682297772

Ввод [23]:
```
draw_roc_curve(y_test, svc_predict, pos_label=1, average='micro')
```



6.4 Дерево решений

Ввод [24]:
```
%%time
tree = DecisionTreeClassifier(random_state=1).fit(X_train, y_train)
```

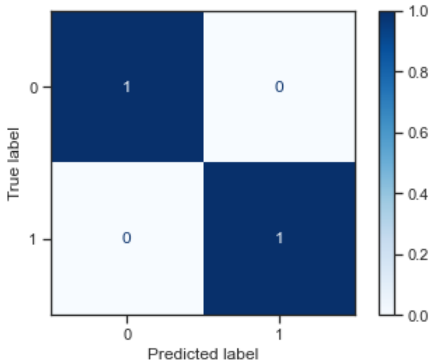
```
CPU times: user 107 ms, sys: 4.91 ms, total: 112 ms
Wall time: 117 ms
```

Ввод [25]:
```
tree_predict = tree.predict(X_test)
tree.score(X_test, y_test)
```

Out[25]: 1.0

Ввод [26]:
```
plot_confusion_matrix(tree, X_test, y_test, cmap=plt.cm.Blues, normalize='true')
```

Out[26]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fd41107fd30>



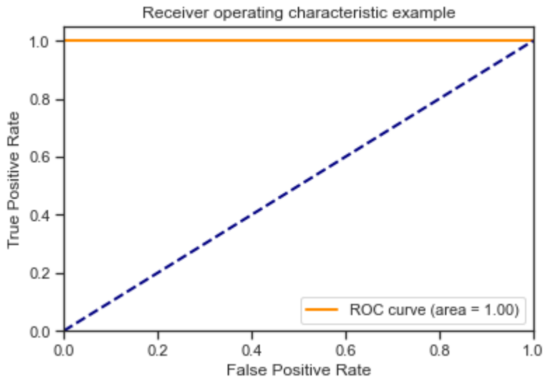
Ввод [27]:
```
print(classification_report(y_test, tree_predict))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     18294
           1       1.00      1.00      1.00      1706

    accuracy                           1.00     20000
   macro avg       1.00      1.00      1.00     20000
weighted avg       1.00      1.00      1.00     20000
```

Ввод [28]:
```
recall_score(y_test, tree_predict)
```

Out[28]: 1.0

Ввод [29]:
```
draw_roc_curve(y_test, tree_predict, pos_label=1, average='micro')
```



Ввод [30]:
```
feature_colums = list(df.columns[df.columns != 'fraud'])
feature_colums
```

Out[30]:
```
['dist_home', 'dist_last', 'ratio', 'repeat', 'chip', 'pin', 'online']
```

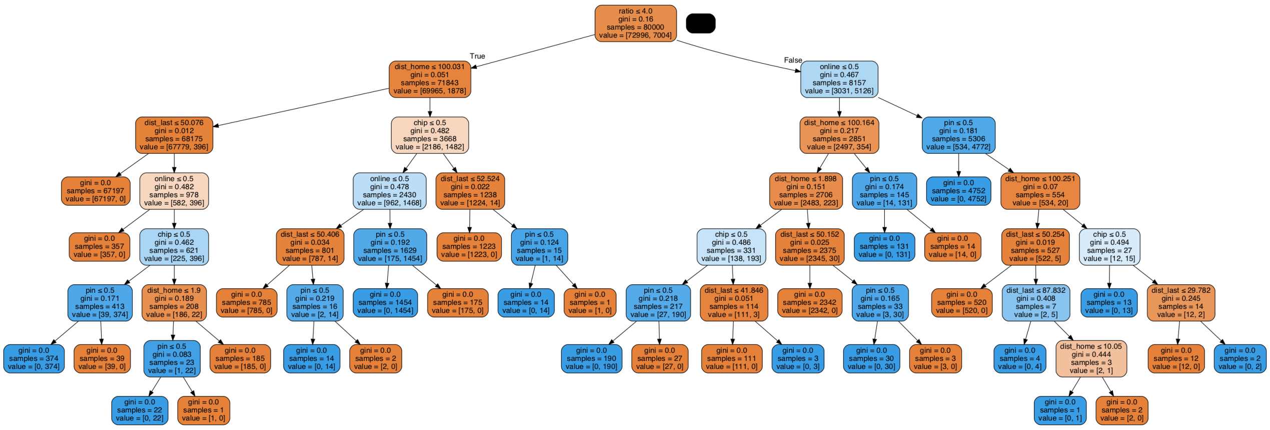
Ввод [31]:
```
tree_rules = export_text(tree, feature_colums)
HTML('<pre>' + tree_rules + '</pre>')
```

```
/usr/local/anaconda3/lib/python3.9/site-packages/sklearn/utils/validation.py:70: FutureWarning: Pass featur
e_names=['dist_home', 'dist_last', 'ratio', 'repeat', 'chip', 'pin', 'online'] as keyword args. From versio
n 1.0 (renaming of 0.25) passing these as positional arguments will result in an error
  warnings.warn(f"Pass {args_msg} as keyword args. From version "
```

Ввод [32]:
```
# Визуализация дерева
def get_png_tree(tree_model_param, feature_names_param):
    dot_data = StringIO()
    export_graphviz(tree_model_param, out_file=dot_data, feature_names=feature_names_param,
                    filled=True, rounded=True, special_characters=True)
    graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
    return graph.create_png()
```

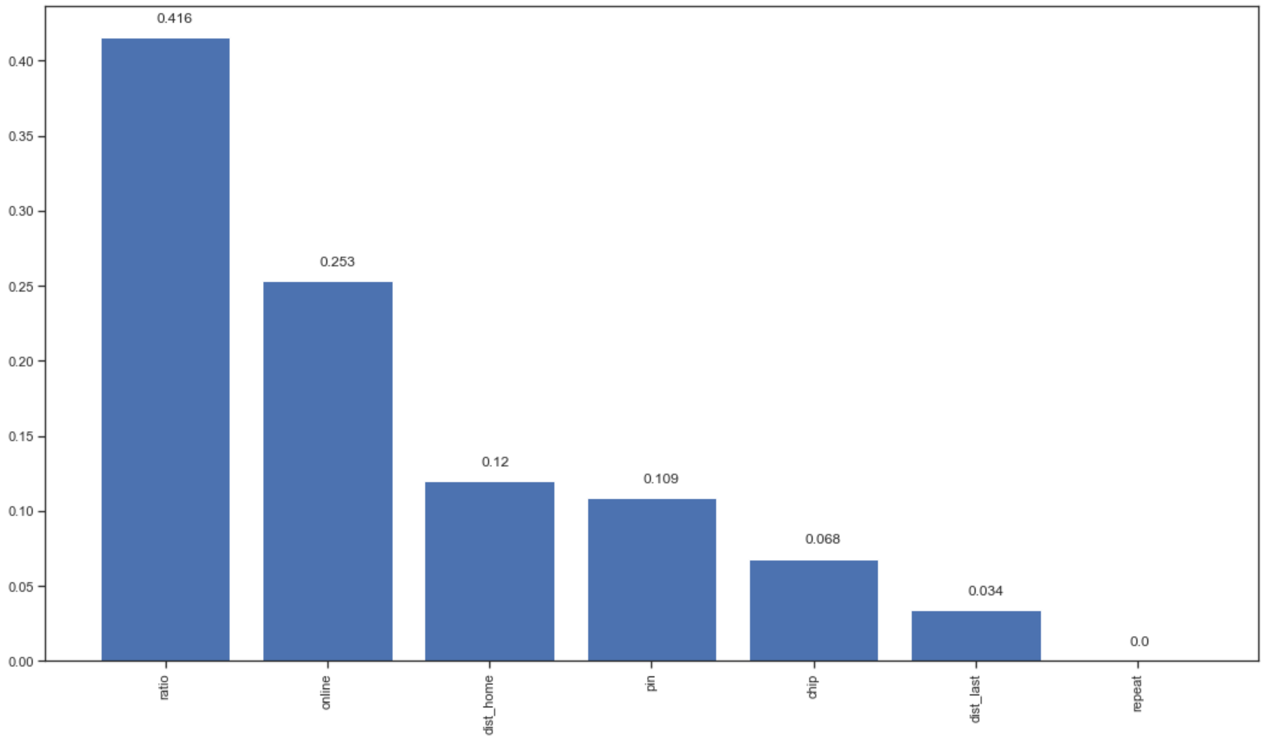
Ввод [33]:
```
Image(get_png_tree(tree, feature_colums), width='100%')
```

Out[33]:



Ввод [34]:
```
def draw_feature_importances(tree_model, X_dataset, figsize=(18,10)):
    """
    Вывод важности признаков в виде графика
    """
    # Сортировка значений важности признаков по убыванию
    list_to_sort = list(zip(X_dataset.columns.values, tree_model.feature_importances_))
    sorted_list = sorted(list_to_sort, key=itemgetter(1), reverse = True)
    # Названия признаков
    labels = [x for x,_ in sorted_list]
    # Важности признаков
    data = [x for _,x in sorted_list]
    # Вывод графика
    fig, ax = plt.subplots(figsize=figsize)
    ind = np.arange(len(labels))
    plt.bar(ind, data)
    plt.xticks(ind, labels, rotation='vertical')
    # Вывод значений
    for a,b in zip(ind, data):
        plt.text(a-0.05, b+0.01, str(round(b,3)))
    plt.show()
    return labels, data
```

Ввод [35]:
```
draw_feature_importances(tree, X)
```



Out[35]:
```
(['ratio', 'online', 'dist_home', 'pin', 'chip', 'dist_last', 'repeat'],
 [0.41577870728627975,
  0.2531469925808649,
  0.11991310551319533,
  0.10877404009904783,
  0.06815481537280876,
  0.0342323391478034,
  0.0])
```

7 Сравнение моделей (к оглавлению)

Метрика	LogisticRegression	SVC	DesicionTree
Recall	0.612	0.995	1.00
AUC	0.80	1.00	1.00