Data mining - final

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Dataset Description:

- types.csv - reference of transaction types
- codes.csv - reference of transaction codes
- transactions.csv - transactional data on banking operations
- train_set.csv - training set with client gender marking (0/1 - client gender)
- test_set.csv - no need to use.

Transactions.csv columns description:

- client_id - client is id
- datetime -transaction date (format - ordered day number hh:mm:ss - 421 06:33:15)
- code - transaction code
- type - transaction type
- sum - sum of transaction

In [1]:

```
import warnings
warnings.filterwarnings('ignore')
import datetime
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
from sklearn.metrics import confusion_matrix, classification_report, precision_score, recal
from warnings import filterwarnings
from sklearn import tree
from matplotlib import pyplot as plt
from sklearn import preprocessing
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import accuracy_score
```

In [2]:

```
types = pd.read_csv('types.csv', sep = ';')
codes = pd.read_csv('codes.csv', sep = ';')
transactions = pd.read_csv('transactions.csv', sep = ';')
train_set = pd.read_csv('train_set.csv', sep = ';')
```

Descriptive Analysis

In [3]:

```
types.describe(include = 'all').T
```

Out[3]:

	count	unique	top	freq	mean	std	min	25%	50%	75%	ma
type	155	NaN	NaN	NaN	10819	80000.3	1000	2385.5	4040	7027.5	99999
type_description	155	139	н/д	13	NaN	NaN	NaN	NaN	NaN	NaN	Nal

In [4]:

```
codes.describe(include = 'all').T
```

Out[4]:

	count	unique	top	freq	mean	std	min	25%	50%
code	184	NaN	NaN	NaN	6046.79	1470.33	742	5208.25	5813.5
code_description	184	184	Книги, периодические издания и газеты	1	NaN	NaN	NaN	NaN	NaN

In [5]:

```
transactions.describe(include = 'all').T
# mean value of sum(-18129.1) is less than median value(-5502.49)
# also we have very big difference between max value and 75%tile, it means that most of our
```

Out[5]:

	count	unique	top	freq	mean	std	min	25%
client_id	130039	NaN	NaN	NaN	5.08686e+07	2.87285e+07	22899	2.57717e+07
datetime	130039	114770	456 00:00:00	60	NaN	NaN	NaN	NaN
code	130039	NaN	NaN	NaN	5594.63	606.087	742	5211
type	130039	NaN	NaN	NaN	2489.37	2253.3	1000	1030
sum	130039	NaN	NaN	NaN	-18129.1	558445	-4.15003e+07	-22449.2

In [3]:

```
#merge transactions, types, codes and train_set
df = pd.merge(pd.merge(pd.merge(transactions, types), codes), train_set)
df.head()
```

Out[3]:

	client_id	datetime	code	type	sum	type_description	code_description	target
0	96372458	421 06:33:15	6011	2010	-561478.94	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
1	96372458	68 02:04:11	6011	2010	-426724.00	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
2	96372458	433 06:45:32	6011	2010	-112295.79	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
3	96372458	270 06:16:18	6011	7010	224591.58	Взнос наличных через АТМ (в своем тер.банке)	Финансовые институты — снятие наличности автом...	0
4	96372458	4 09:33:46	4814	1030	-2245.92	Оплата услуги. Банкоматы	Звонки с использованием телефонов, считывающих...	0

In [4]:

```
df.mode()
```

Out[4]:

	client_id	datetime	code	type	sum	type_description	code_description	target
0	70780820	456 00:00:00	6011	1010	-2245.92	Покупка. POS	Финансовые институты — снятие наличности автом...	0

In [5]:

```
print('Range:', max(transactions['sum']) - min(transactions['sum'])) # Measures of spread
print('IQR:', transactions['sum'].quantile(0.75) - transactions['sum'].quantile(0.25))
print('Variance:', transactions['sum'].var())
print('Standart deviation:',  transactions['sum'].std())
```

```
Range: 108877774.3
IQR: 21326.2
Variance: 311860284637.53296
Standart deviation: 558444.5224348905
```

Explanatory Data Analysis

In [9]:

```
df.shape
# Dataset comprises of 129998 observations and 7 characteristics
```

Out[9]:

```
(91800, 8)
```

In [10]:

```
df.columns
```

Out[10]:

```
Index(['client_id', 'datetime', 'code', 'type', 'sum', 'type_description',
       'code_description', 'target'],
      dtype='object')
```

In [11]:

```
df.nunique() # number of unique values for every column
```

Out[11]:

```
client_id            6000
datetime            81491
code                  173
type                   58
sum                 20856
type_description       53
code_description      173
target                  2
dtype: int64
```

In [12]:

```
df.info()
# our data have integer, float and object values, object values used for datetime and text
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 91800 entries, 0 to 91799
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   client_id         91800 non-null  int64  
 1   datetime          91800 non-null  object 
 2   code              91800 non-null  int64  
 3   type              91800 non-null  int64  
 4   sum               91800 non-null  float64
 5   type_description  91800 non-null  object 
 6   code_description  91800 non-null  object 
 7   target            91800 non-null  int64  
dtypes: float64(1), int64(4), object(3)
memory usage: 6.3+ MB
```

In [13]:

```
df.isna().any()
# as we can see we have no null/missing values, so we dont need to delete them
```

Out[13]:

```
client_id           False
datetime            False
code                False
type                False
sum                 False
type_description    False
code_description    False
target              False
dtype: bool
```

In [14]:

```
clients = np.array(df['client_id'].unique())
len(clients) # number of unique clients
```

Out[14]:

```
6000
```

In [6]:

```
df.drop_duplicates(inplace = True)
df.shape
# shape of dataframe before deleting dublicates = (129998, 7)
# 129998-129969 = 29 rows was deleted
```

Out[6]:

```
(91781, 8)
```

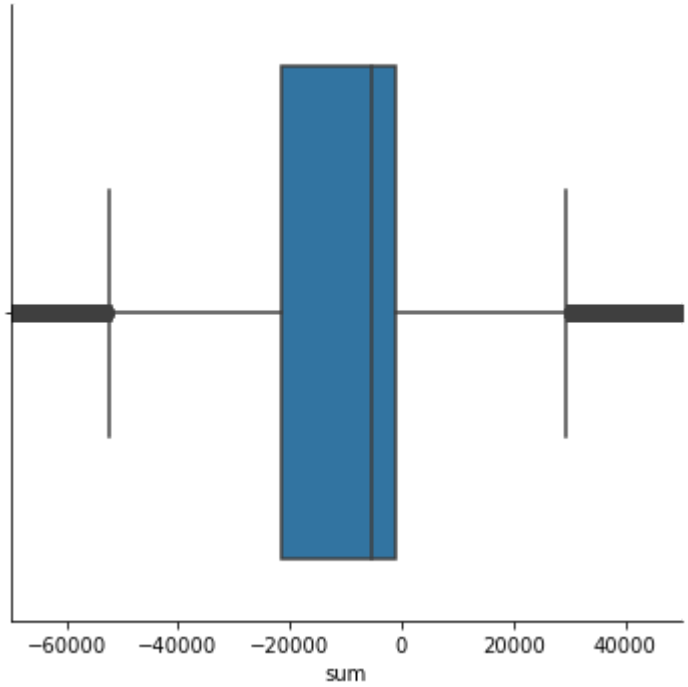
Visualizations

In [16]:

```
# Realtionship analysis based on correlation matrix
correlation = df.corr()
sns.heatmap(correlation, xticklabels = correlation.columns, yticklabels = correlation.colum
plt.show()
# the higher correlation coefficient between type and code
# type of transaction has the greatest influence on sum
```

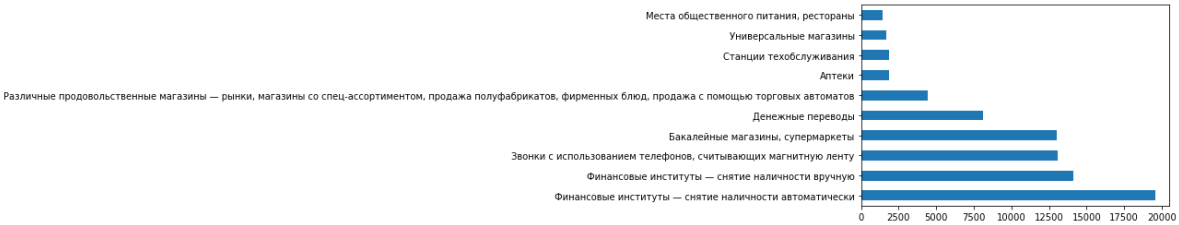
In [17]:

```
# box plot
sns.catplot(x = 'sum', kind = 'box', data = df)
plt.xlim(-70000, 50000)
plt.show()
```



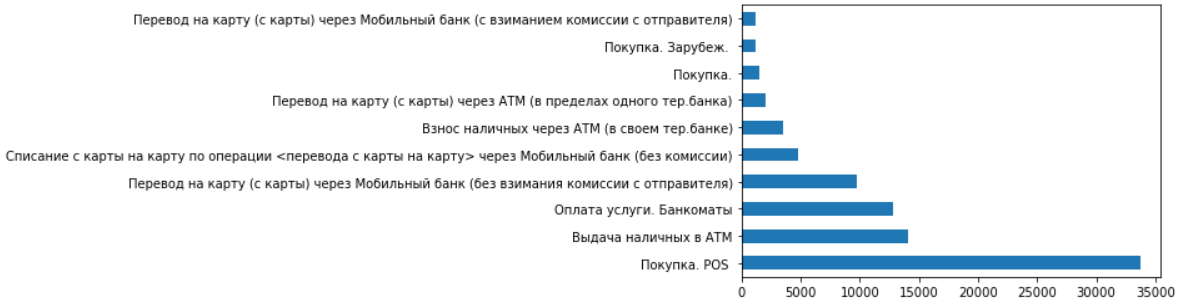
In [18]:

```
# graphs show Top 10 codes of transactions
df['code_description'].value_counts()[0:10].plot.barh()
plt.show()
```



In [19]:

```
# graphs show Top 10 types of transactions
df['type_description'].value_counts()[0:10].plot.barh()
plt.show()
```



Feature engineering and Data cleaning

In [7]:

```
# divide datetime column to date and time columns
df[['day', 'time']] = df['datetime'].str.split(' ', expand = True)
df[['hour', 'minute','second']] = df['time'].str.split(':', expand=True)
```

In [8]:

```
df.head()
```

Out[8]:

	client_id	datetime	code	type	sum	type_description	code_description	target	day
0	96372458	421 06:33:15	6011	2010	-561478.94	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0	421
1	96372458	68 02:04:11	6011	2010	-426724.00	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0	68
2	96372458	433 06:45:32	6011	2010	-112295.79	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0	433
3	96372458	270 06:16:18	6011	7010	224591.58	Взнос наличных через АТМ (в своем тер.банке)	Финансовые институты — снятие наличности автом...	0	270
4	96372458	4 09:33:46	4814	1030	-2245.92	Оплата услуги. Банкоматы	Звонки с использованием телефонов, считывающих...	0	4

In [9]:

```
df = df.astype({'day': int})
df = df.astype({'hour': int})
df = df.astype({'minute': int})
df = df.astype({'second': int})
```

In [10]:

```
date = datetime.datetime(2021, 1, 1) # start date is 1 january of 2021
step = datetime.timedelta(days = 1)
dates = {} # dictionary will store the serial number of the date and date
date_list = []
for i in range(0, 457):
    dates[i] = date.strftime('%Y-%m-%d')
    date += step

for i in df['day']:
    date_list.append(dates[i])
#new column date
df['date'] = date_list
df
```

Out[10]:

	client_id	datetime	code	type	sum	type_description	code_description	target
0	96372458	421 06:33:15	6011	2010	-561478.94	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
1	96372458	68 02:04:11	6011	2010	-426724.00	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
2	96372458	433 06:45:32	6011	2010	-112295.79	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
3	96372458	270 06:16:18	6011	7010	224591.58	Взнос наличных через АТМ (в своем тер.банке)	Финансовые институты — снятие наличности автом...	0
4	96372458	4 09:33:46	4814	1030	-2245.92	Оплата услуги. Банкоматы	Звонки с использованием телефонов, считывающих...	0
...	...	...	...	...	...	...	...	...
91795	77171868	194 08:39:03	4829	2340	-112295.79	Списание с карты по операции “перевода с карты...	Денежные переводы	0
91796	79803584	151 13:46:48	4829	2340	-56147.89	Списание с карты по операции “перевода с карты...	Денежные переводы	1
91797	66391854	425 15:33:02	4829	2331	-228364.72	Списание с карты по операции “перевода с карты...	Денежные переводы	1

	client_id	datetime	code	type	sum	type_description	code_description	target
91798	15166647	432 00:00:00	5964	1200	-10284.50	Покупка. Зарубеж.	Прямой маркетинг — торговля через каталог	0
91799	15166647	403 00:00:00	5964	1200	-1309.14	Покупка. Зарубеж.	Прямой маркетинг — торговля через каталог	0

91781 rows × 14 columns

In [11]:

```
df['date']
```

Out[11]:

```
0        2022-02-26
1        2021-03-10
2        2022-03-10
3        2021-09-28
4        2021-01-05
            ...
91795    2021-07-14
91796    2021-06-01
91797    2022-03-02
91798    2022-03-09
91799    2022-02-08
Name: date, Length: 91781, dtype: object
```

In [12]:

```
df[['year', 'month', 'day']] = df['date'].str.split('-', expand = True)
df
```

Out[12]:

	client_id	datetime	code	type	sum	type_description	code_description	target
0	96372458	421 06:33:15	6011	2010	-561478.94	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
1	96372458	68 02:04:11	6011	2010	-426724.00	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
2	96372458	433 06:45:32	6011	2010	-112295.79	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
3	96372458	270 06:16:18	6011	7010	224591.58	Взнос наличных через АТМ (в своем тер.банке)	Финансовые институты — снятие наличности автом...	0
4	96372458	4 09:33:46	4814	1030	-2245.92	Оплата услуги. Банкоматы	Звонки с использованием телефонов, считывающих...	0
...	...	...	...	...	...	...	...	...
91795	77171868	194 08:39:03	4829	2340	-112295.79	Списание с карты по операции “перевода с карты...	Денежные переводы	0
91796	79803584	151 13:46:48	4829	2340	-56147.89	Списание с карты по операции “перевода с карты...	Денежные переводы	1
91797	66391854	425 15:33:02	4829	2331	-228364.72	Списание с карты по операции “перевода с карты...	Денежные переводы	1
91798	15166647	432 00:00:00	5964	1200	-10284.50	Покупка. Зарубеж.	Прямой маркетинг — торговля через каталог	0
91799	15166647	403 00:00:00	5964	1200	-1309.14	Покупка. Зарубеж.	Прямой маркетинг — торговля через каталог	0

91781 rows × 16 columns

In [13]:

```
# change types of columns to int
df = df.astype({'year': int})
df = df.astype({'month': int})
df = df.astype({'day': int})
```

In [14]:

```
def f(x):
    if (x > 4) and (x <= 8):
        return 'Early Morning'
    elif (x > 8) and (x <= 12 ):
        return 'Morning'
    elif (x > 12) and (x <= 16):
        return'Noon'
    elif (x > 16) and (x <= 20) :
        return 'Eve'
    elif (x > 20) and (x <= 23):
        return'Night'
    elif (x <= 4):
        return'Late Night'
```

In [15]:

```
# new column sessions
df['sessions'] = df['hour'].apply(f)
df
```

Out[15]:

	client_id	datetime	code	type	sum	type_description	code_description	target
0	96372458	421 06:33:15	6011	2010	-561478.94	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
1	96372458	68 02:04:11	6011	2010	-426724.00	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
2	96372458	433 06:45:32	6011	2010	-112295.79	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...	0
3	96372458	270 06:16:18	6011	7010	224591.58	Взнос наличных через АТМ (в своем тер.банке)	Финансовые институты — снятие наличности автом...	0
4	96372458	4 09:33:46	4814	1030	-2245.92	Оплата услуги. Банкоматы	Звонки с использованием телефонов, считывающих...	0
...	...	...	...	...	...	...	...	...
91795	77171868	194 08:39:03	4829	2340	-112295.79	Списание с карты по операции “перевода с карты...	Денежные переводы	0
91796	79803584	151 13:46:48	4829	2340	-56147.89	Списание с карты по операции “перевода с карты...	Денежные переводы	1
91797	66391854	425 15:33:02	4829	2331	-228364.72	Списание с карты по операции “перевода с карты...	Денежные переводы	1
91798	15166647	432 00:00:00	5964	1200	-10284.50	Покупка. Зарубеж.	Прямой маркетинг — торговля через каталог	0
91799	15166647	403 00:00:00	5964	1200	-1309.14	Покупка. Зарубеж.	Прямой маркетинг — торговля через каталог	0

91781 rows × 17 columns

In [16]:

```
#convert to the positive values
df['sum'] = df['sum'].abs()
df.drop(['datetime', 'type_description', 'code_description', 'hour', 'minute','second','tim
# copy dataframe
df1 = df.copy()
df.head()
```

Out[16]:

	client_id	code	type	sum	target	sessions
0	96372458	6011	2010	561478.94	0	Early Morning
1	96372458	6011	2010	426724.00	0	Late Night
2	96372458	6011	2010	112295.79	0	Early Morning
3	96372458	6011	7010	224591.58	0	Early Morning
4	96372458	4814	1030	2245.92	0	Morning

In [17]:

```
df = pd.get_dummies(data = df, drop_first = True)
```

In [18]:

```
df.shape
```

Out[18]:

```
(91781, 10)
```

In [19]:

```
df.head()
```

Out[19]:

	client_id	code	type	sum	target	sessions_Eve	sessions_Late Night	sessions_Morning	s
0	96372458	6011	2010	561478.94	0	0	0	0	
1	96372458	6011	2010	426724.00	0	0	1	0	
2	96372458	6011	2010	112295.79	0	0	0	0	
3	96372458	6011	7010	224591.58	0	0	0	0	
4	96372458	4814	1030	2245.92	0	0	0	1	

In [20]:

```
scaler = MinMaxScaler()
df[['sum']] = scaler.fit_transform(df[['sum']])
```

In [21]:

```
df
```

Out[21]:

	client_id	code	type	sum	target	sessions_Eve	sessions_Late Night	sessions_Morning
0	96372458	6011	2010	0.008333	0	0	0	0
1	96372458	6011	2010	0.006333	0	0	1	0
2	96372458	6011	2010	0.001667	0	0	0	0
3	96372458	6011	7010	0.003333	0	0	0	0
4	96372458	4814	1030	0.000033	0	0	0	1
...	...	...	...	...	...	...	...	..
91795	77171868	4829	2340	0.001667	0	0	0	0
91796	79803584	4829	2340	0.000833	1	0	0	0
91797	66391854	4829	2331	0.003389	1	0	0	0
91798	15166647	5964	1200	0.000153	0	0	1	0
91799	15166647	5964	1200	0.000019	0	0	1	0

91781 rows × 10 columns

In [22]:

```
df_sales = df.loc[df.type.isin([1000, 1100, 1110, 1010, 1210, 1200])]
df_sales # dataframe consist only sales type of transactions
# тут мы вывели наши оснавные переменные для анализа а конкретнее code, type
# и дополнительная переменная это время суток в котором происходит транзакция
# переделанная в вид подходящий рандомфорест и тд при помощи функций get_dummies
```

Out[22]:

	client_id	code	type	sum	target	sessions_Eve	sessions_Late Night	sessions_Morning
23	21717441	4814	1100	0.000080	0	0	0	1
24	21717441	5411	1010	0.001068	0	0	0	0
25	21717441	5732	1110	0.006157	0	0	0	1
27	21717441	7993	1200	0.000120	0	0	1	0
30	2444292	5411	1010	0.000046	0	0	0	1
...	...	...	...	...	...	...	...	..
91710	58819313	7995	1200	0.000057	0	0	1	0
91763	73117692	7311	1100	0.000033	0	0	1	0
91768	8890644	7995	1200	0.000052	1	0	1	0
91798	15166647	5964	1200	0.000153	0	0	1	0
91799	15166647	5964	1200	0.000019	0	0	1	0

36668 rows × 10 columns

In [23]:

```
len(df_sales['client_id'].unique())
```

Out[23]:

4741

Supervised learning. kNN, Decision Trees,Random Forest.

In [24]:

```
X = df.drop(['client_id', 'target'], axis = 1)
y = df['target']
X1 = df_sales.drop(['client_id', 'target'], axis = 1)
y1 = df_sales['target']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 2
X1_train, X1_test, y1_train, y1_test = train_test_split(X1, y1, test_size = 0.2, random_sta
# разделяем наши данные на train и test часть с перемешиваем их в рандомном порядке(2022)
```

In [25]:

```
X
```

Out[25]:

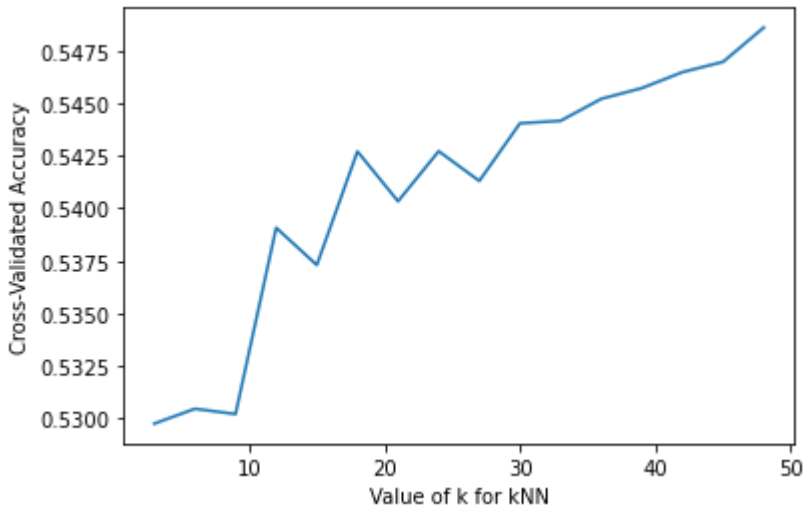
	code	type	sum	sessions_Eve	sessions_Late Night	sessions_Morning	sessions_Night
0	6011	2010	0.008333	0	0	0	0
1	6011	2010	0.006333	0	1	0	0
2	6011	2010	0.001667	0	0	0	0
3	6011	7010	0.003333	0	0	0	0
4	4814	1030	0.000033	0	0	1	0
...	...	...	...	...	...	...	...
91795	4829	2340	0.001667	0	0	0	0
91796	4829	2340	0.000833	0	0	0	0
91797	4829	2331	0.003389	0	0	0	0
91798	5964	1200	0.000153	0	1	0	0
91799	5964	1200	0.000019	0	1	0	0

91781 rows × 8 columns

KNN

In [26]:

```
# KNN - это алгоритм обучения который используют в классстеризаций(или регрессии)
#  который для определения классификации точки объединяет классификацию K ближайших точек.
# Он является контролируемым, поскольку вы пытаетесь классифицировать точку на основе извес
# отличается от k-means тем что KNN учитывает классификации других точек а k-means нет

filterwarnings(action = 'ignore', category = DeprecationWarning, message = '`np.bool` is a

num_folds = 5

neighbors = range(3, 51, 3)

k_scores = []

for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors = k)
    scores = cross_val_score(knn, X, y, cv = num_folds, scoring = 'accuracy')
    k_scores.append(scores.mean())

plt.plot(neighbors, k_scores)
plt.xlabel('Value of k for kNN')
plt.ylabel('Cross-Validated Accuracy')
plt.show()
# здесь мы используем cross validation accuracy для нахождения лучшего k(количество ближайш
```



As we can see the best K is approximately between 47 and 51.

In [ ]:

```
# здесь мы тоже находим лучший k но уже другим методом(для сравнения результатов)
# GridSearchCV это функция для удобного подбора гиперпараметров в алгоритмах машинного обуч
knn2 = KNeighborsClassifier()
param_grid = {'n_neighbors': np.arange(1, 51)}

#use gridsearch to test all values for n_neighbors
knn_gscv = GridSearchCV(knn2, param_grid, cv = 5)
#fit model to data
knn_gscv.fit(X, y)

knn_gscv.best_params_
```

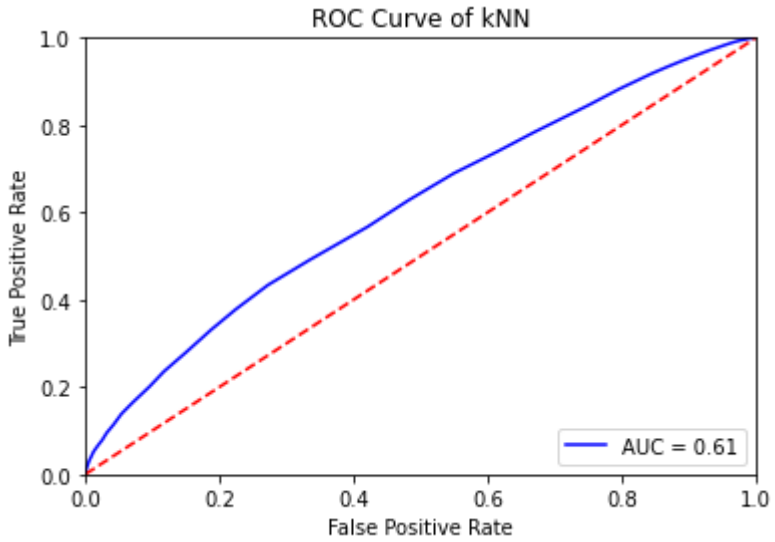
In [ ]:

```
# здесь мы тоже находим лучший k но уже другим методом(для сравнения результатов)
# GridSearchCV это функция для удобного подбора гиперпараметров в алгоритмах машинного обуч
knn2 = KNeighborsClassifier()
param_grid = {'n_neighbors': np.arange(49, 51)}

#use gridsearch to test all values for n_neighbors
knn_gscv = GridSearchCV(knn2, param_grid, cv = 5)
#fit model to data
knn_gscv.fit(X, y)

knn_gscv.best_params_
```

результат вышел один и тот же в двух случаях что говорит о правильности результатов

In [41]:

```
# здесь мы строим ROC curve of KNN для того чтобы оценить степень шума в наших данных
# из ROC cuve видно что AUC = 0.61 что говорит либо низкой либо о высокой степени шума в на
from warnings import filterwarnings
filterwarnings(action = 'ignore', category = DeprecationWarning, message = '`np.int` is a d

knn = KNeighborsClassifier(n_neighbors = 50)
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
y_scores = knn.predict_proba(X_test)
fpr, tpr, threshold = roc_curve(y_test, y_scores[:, 1])
roc_auc = auc(fpr, tpr)

plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve of kNN')
plt.show()
```



In [42]:

```
print(classification_report(y_test, y_pred, target_names = ['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.58      0.67      0.62      9415
           1       0.58      0.49      0.53      8942

    accuracy                           0.58     18357
   macro avg       0.58      0.58      0.58     18357
weighted avg       0.58      0.58      0.58     18357
```

In [43]:

```
conf_matrix = confusion_matrix(y_test, y_pred).T #.transpose()
conf_matrix
```

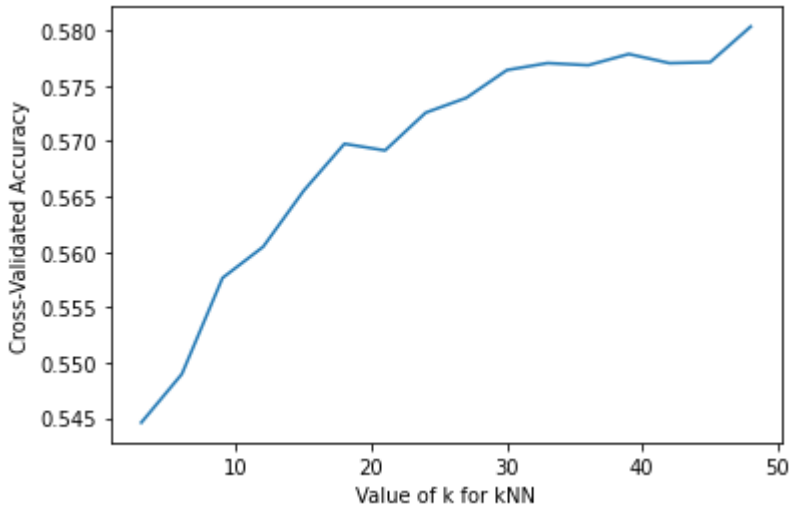
Out[43]:

```
array([[6268, 4553],
       [3147, 4389]], dtype=int64)
```

For the sales dataframe

In [44]:

```
# cross-validation

from warnings import filterwarnings
filterwarnings(action = 'ignore', category = DeprecationWarning, message = '`np.bool` is a

num_folds = 5

neighbors = range(3,51,3)

k_scores = []

for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors = k)
    scores = cross_val_score(knn, X1, y1, cv = num_folds, scoring = 'accuracy')
    k_scores.append(scores.mean())

plt.plot(neighbors, k_scores)
plt.xlabel('Value of k for kNN')
plt.ylabel('Cross-Validated Accuracy')
plt.show()
```



As we can see the best K is approximately between 47 and 51.

In [45]:

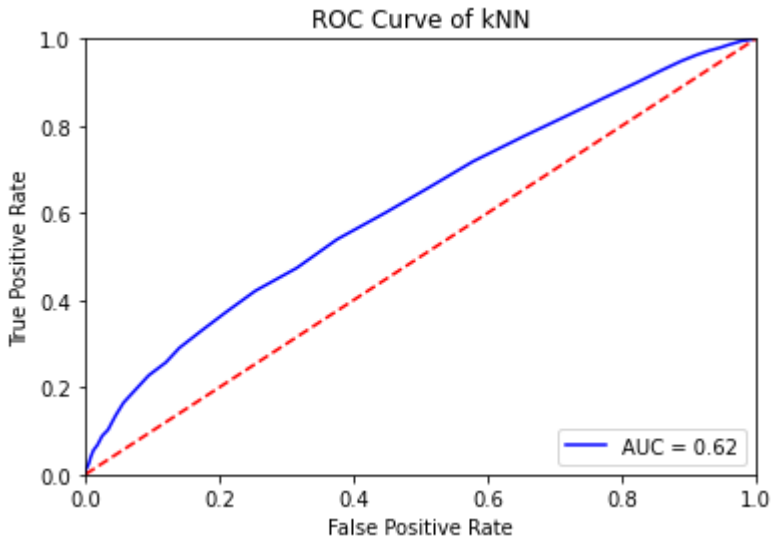
```
knn2 = KNeighborsClassifier()
param_grid = {'n_neighbors': np.arange(48, 51)}

#use gridsearch to test all values for n_neighbors
knn_gscv = GridSearchCV(knn2, param_grid, cv=5)
#fit model to data
knn_gscv.fit(X1, y1)

knn_gscv.best_params_
```

Out[45]:

```
{'n_neighbors': 48}
```

In [46]:

```
filterwarnings(action='ignore', category = DeprecationWarning, message = '`np.int` is a dep

knn = KNeighborsClassifier(n_neighbors = 48)
knn.fit(X1_train, y1_train)

y_pred = knn.predict(X1_test)
y_scores = knn.predict_proba(X1_test)
fpr, tpr, threshold = roc_curve(y1_test, y_scores[:, 1])
roc_auc = auc(fpr, tpr)

plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve of kNN')
plt.show()
```



In [47]:

```
print(classification_report(y1_test, y_pred, target_names = ['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.58      0.62      0.60      3694
           1       0.59      0.54      0.56      3640

    accuracy                           0.58      7334
   macro avg       0.58      0.58      0.58      7334
weighted avg       0.58      0.58      0.58      7334
```

In [48]:

```
conf_matrix = confusion_matrix(y1_test, y_pred).T #.transpose()
conf_matrix
```

Out[48]:

```
array([[2307, 1676],
       [1387, 1964]], dtype=int64)
```

Decision Trees

In [49]:

```
#grid search

parameters = {'max_depth': range(3, 20)}
dt = GridSearchCV(DecisionTreeClassifier(), parameters, n_jobs = 4)
dt.fit(X = X, y = y)
dt_model = dt.best_estimator_
print (dt.best_score_, dt.best_params_)
```

```
0.5493076292618377 {'max_depth': 12}
```

As we can see the best max_depth is 12.

In [50]:

```
dt = DecisionTreeClassifier(max_depth = 12)
dt.fit(X_train, y_train)
```

Out[50]:

```
DecisionTreeClassifier(max_depth=12)
```

In [51]:

```
dt.get_params()
```

Out[51]:

```
{'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': 12,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'random_state': None,
 'splitter': 'best'}
```

In [52]:

```
predictions = dt.predict(X_test)
predictions
```

Out[52]:

```
array([0, 1, 0, ..., 0, 1, 0], dtype=int64)
```

In [53]:

```
y_scores = dt.predict_proba(X_test)
y_scores
```

Out[53]:

```
array([[0.54377147, 0.45622853],
       [0.47460686, 0.52539314],
       [0.54377147, 0.45622853],
       ...,
       [0.55178571, 0.44821429],
       [0.47623486, 0.52376514],
       [0.5140809 , 0.4859191 ]])
```

In [54]:

```
accuracy_score(y_test, predictions)
```

Out[54]:

```
0.5746036934139566
```

In [55]:

```
conf_matrix = confusion_matrix(y_test, predictions, labels = [0, 1]).T #.transpose()
conf_matrix
```

Out[55]:

```
array([[6307, 4701],
       [3108, 4241]], dtype=int64)
```

In [56]:

```
precision_score(y_test, predictions)
```

Out[56]:

```
0.5770853177303035
```

In [57]:

```
recall_score(y_test, predictions)
```

Out[57]:

```
0.4742786848579736
```

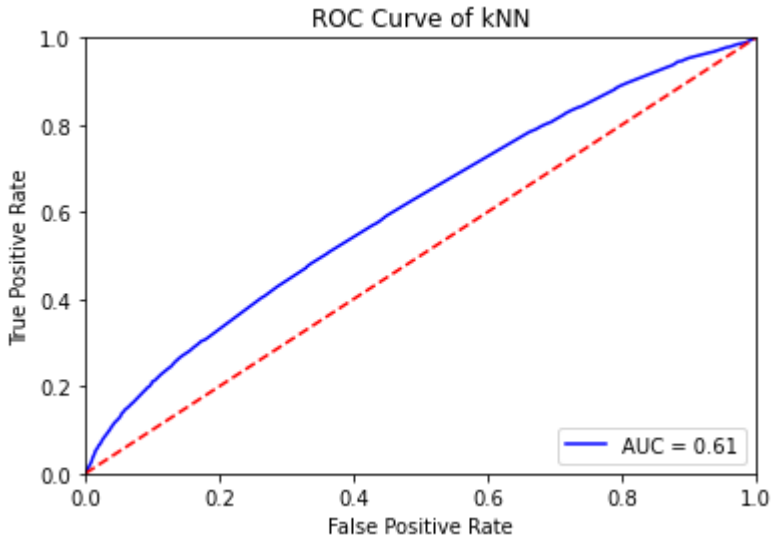
In [58]:

```
print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.57      0.67      0.62      9415
           1       0.58      0.47      0.52      8942

    accuracy                           0.57     18357
   macro avg       0.58      0.57      0.57     18357
weighted avg       0.57      0.57      0.57     18357
```

In [59]:

```
fpr, tpr, threshold = roc_curve(y_test, y_scores[:, 1])
roc_auc = auc(fpr, tpr)

plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve of kNN')
plt.show()
```



In [60]:

```
feature_names = X.columns
feature_names
```

Out[60]:

```
Index(['code', 'type', 'sum', 'sessions_Eve', 'sessions_Late Night',
       'sessions_Morning', 'sessions_Night', 'sessions_Noon'],
      dtype='object')
```

In [61]:

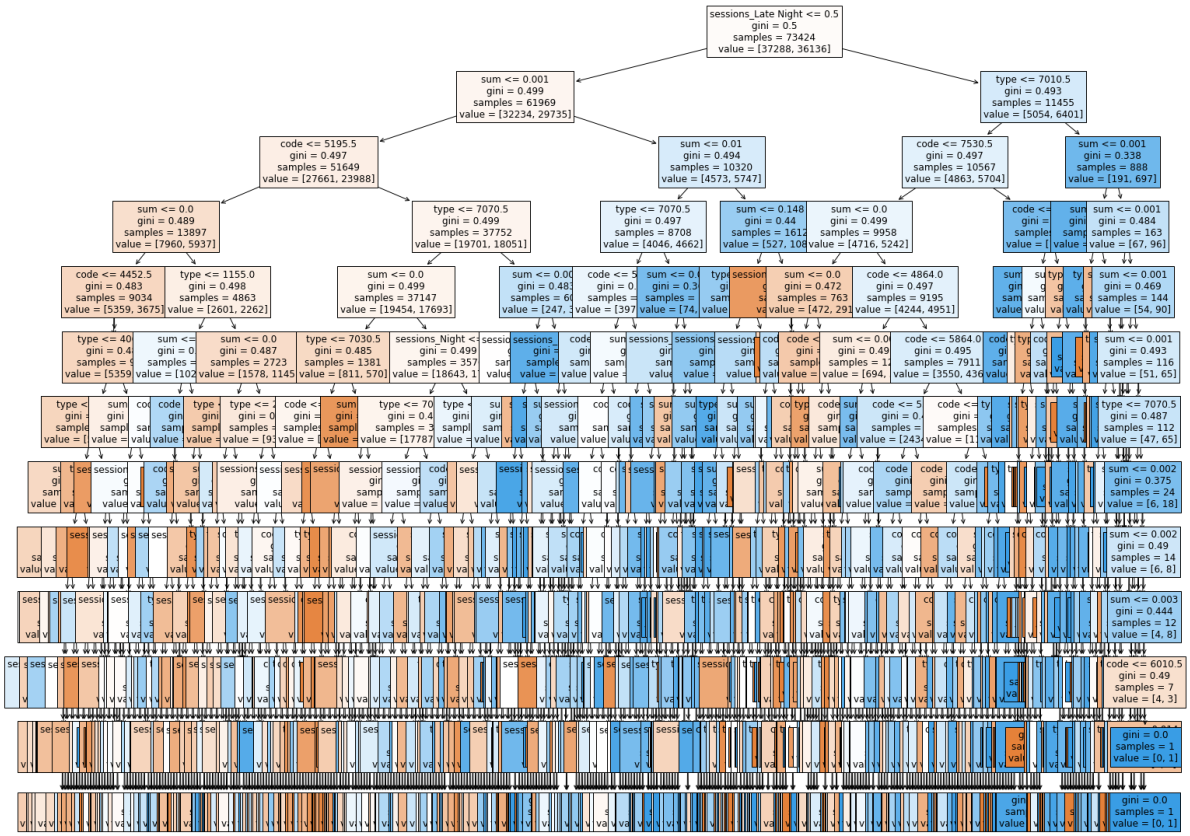
```
dt.feature_importances_
```

Out[61]:

```
array([0.26214092, 0.15780432, 0.44017625, 0.05993283, 0.03788173,
       0.00942628, 0.01413568, 0.01850199])
```

In [62]:

```
fig = plt.figure(figsize = (25, 20))
_= tree.plot_tree(dt,
                  feature_names = feature_names,
                  filled = True,
                  fontsize = 12)
```



For the sales dataframe

In [63]:

```
parameters = {'max_depth': range(3, 20)}
dt = GridSearchCV(DecisionTreeClassifier(), parameters, n_jobs = 4)
dt.fit(X = X1, y = y1)
dt_model = dt.best_estimator_
print (dt.best_score_, dt.best_params_)
```

```
0.5802335326916277 {'max_depth': 10}
```

In [64]:

```
dt = DecisionTreeClassifier(max_depth = 10)
dt.fit(X1_train, y1_train)
predictions = dt.predict(X1_test)
predictions
```

Out[64]:

```
array([0, 1, 1, ..., 1, 0, 1], dtype=int64)
```

In [65]:

```
y1_scores = dt.predict_proba(X1_test)
y1_scores
```

Out[65]:

```
array([[0.52      , 0.48      ],
       [0.46666667, 0.53333333],
       [0.45415473, 0.54584527],
       ...,
       [0.28089888, 0.71910112],
       [0.71428571, 0.28571429],
       [0.49923547, 0.50076453]])
```

In [66]:

```
print('Accuracy:', accuracy_score(y1_test, predictions), '\n')
print('Precision:', precision_score(y1_test, predictions), '\n')
print('Recall:', recall_score(y1_test, predictions), '\n')
print(classification_report(y1_test, predictions))
```

```
Accuracy: 0.5743114262339787

Precision: 0.5755983654407473

Recall: 0.5417582417582417

              precision    recall  f1-score   support

           0       0.57      0.61      0.59      3694
           1       0.58      0.54      0.56      3640

    accuracy                           0.57      7334
   macro avg       0.57      0.57      0.57      7334
weighted avg       0.57      0.57      0.57      7334
```

In [67]:

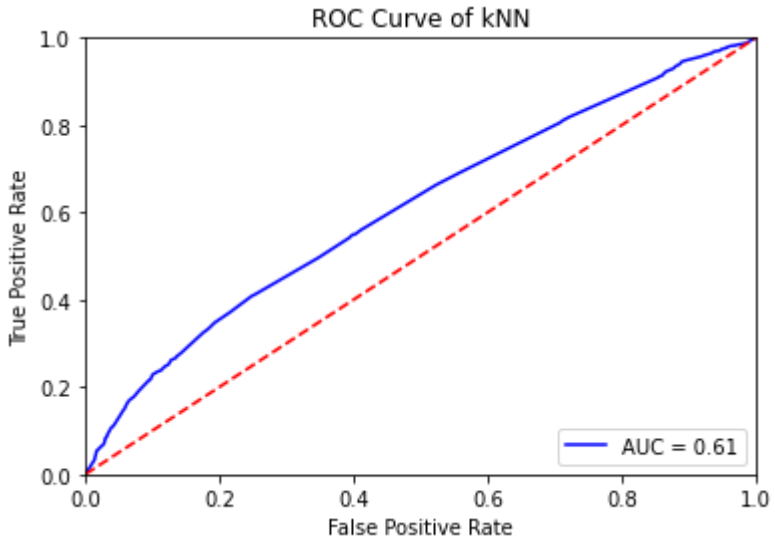
```
confusion_matrix(y1_test, predictions, labels = [0, 1]).T
```

Out[67]:

```
array([[2240, 1668],
       [1454, 1972]], dtype=int64)
```

In [68]:

```
fpr, tpr, threshold = roc_curve(y1_test, y1_scores[:, 1])
roc_auc = auc(fpr, tpr)

plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve of kNN')
plt.show()
```



In [69]:

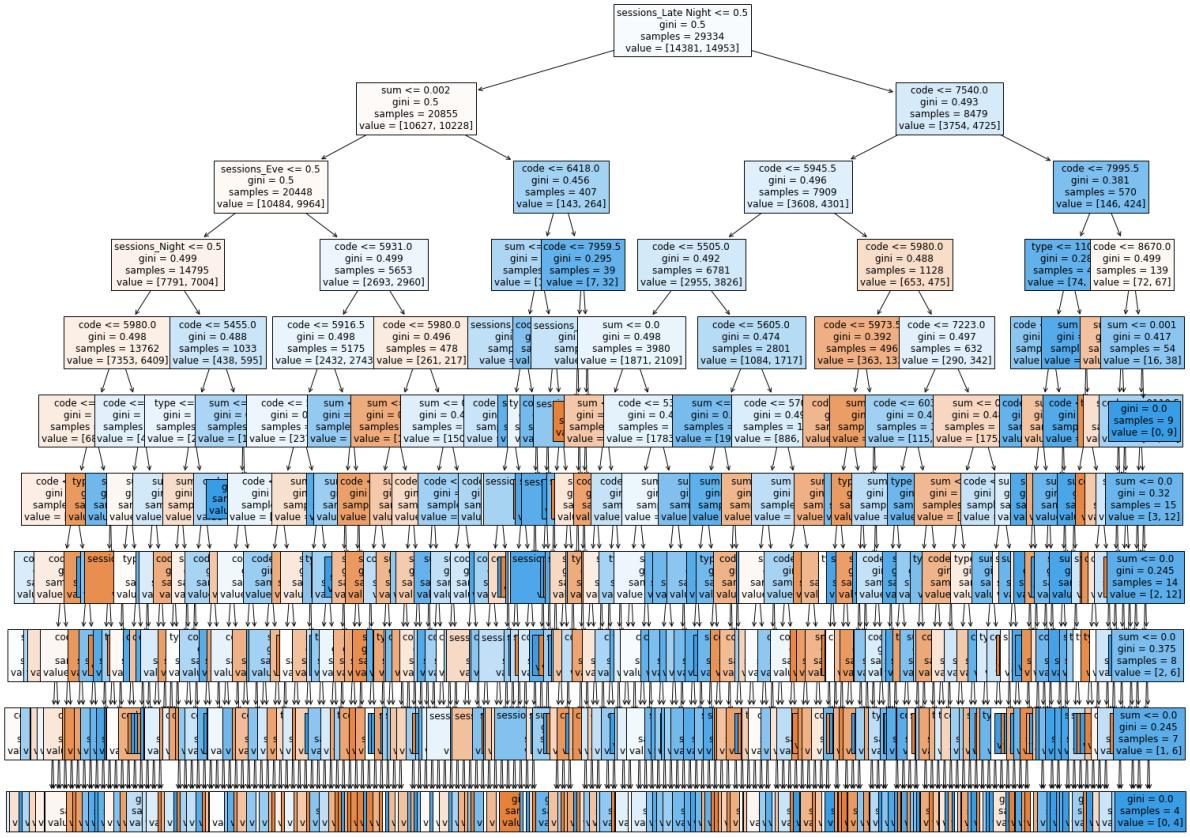
```
dt.feature_importances_
```

Out[69]:

```
array([0.55464821, 0.03565256, 0.33403897, 0.01510125, 0.03483475,
       0.00274476, 0.01652425, 0.00645526])
```

In [70]:

```
fig = plt.figure(figsize = (25, 20))
_= tree.plot_tree(dt,
                  feature_names = feature_names,
                  filled = True,
                  fontsize = 12)
```



Random Forest

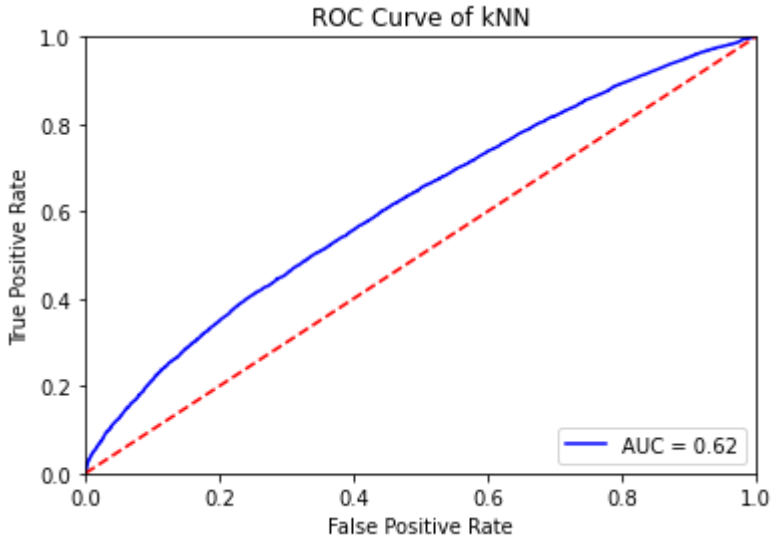
In [71]:

```
parameters = {'max_depth':range(3, 20)}
rf = GridSearchCV(RandomForestClassifier(), parameters, n_jobs = 4)
rf.fit(X = X, y = y)
rf_model = rf.best_estimator_
print (rf.best_score_, rf.best_params_)
```

```
0.5488718828107311 {'max_depth': 12}
```

In [72]:

```
rf = RandomForestClassifier(max_depth = 13, random_state = 0)
rf.fit(X_train, y_train)

y_pred = rf.predict(X_test)
y_scores = rf.predict_proba(X_test)
fpr, tpr, threshold = roc_curve(y_test, y_scores[:, 1])
roc_auc = auc(fpr, tpr)

plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve of kNN')
plt.show()
```



In [73]:

```
print(classification_report(y_test, y_pred, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.58      0.66      0.62      9415
           1       0.58      0.50      0.54      8942

    accuracy                           0.58     18357
   macro avg       0.58      0.58      0.58     18357
weighted avg       0.58      0.58      0.58     18357
```

In [74]:

```
conf_matrix = confusion_matrix(y_test, y_pred).T #.transpose()
conf_matrix
```

Out[74]:

```
array([[6232, 4484],
       [3183, 4458]], dtype=int64)
```

For sales dataframe

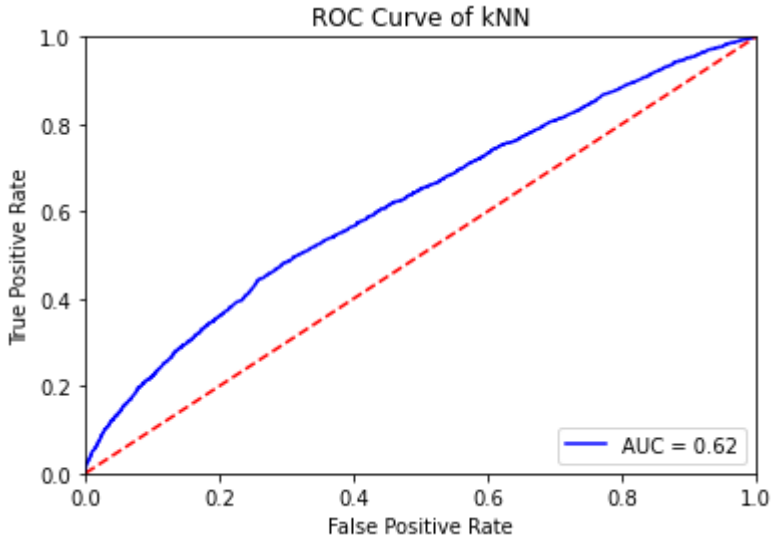
In [75]:

```
parameters = {'max_depth':range(3, 20)}
rf = GridSearchCV(RandomForestClassifier(), parameters, n_jobs = 4)
rf.fit(X = X1, y = y1)
rf_model = rf.best_estimator_
print (rf.best_score_, rf.best_params_)
```

```
0.5748063665486542 {'max_depth': 11}
```

In [76]:

```
rf = RandomForestClassifier(max_depth = 10, random_state = 0)
rf.fit(X1_train, y1_train)

y_pred = rf.predict(X1_test)
y_scores = rf.predict_proba(X1_test)
fpr, tpr, threshold = roc_curve(y1_test, y_scores[:, 1])
roc_auc = auc(fpr, tpr)

plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve of kNN')
plt.show()
```



In [77]:

```
print(classification_report(y1_test, y_pred, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.59      0.55      0.57      3694
           1       0.57      0.61      0.59      3640

    accuracy                           0.58      7334
   macro avg       0.58      0.58      0.58      7334
weighted avg       0.58      0.58      0.58      7334
```

In [78]:

```
conf_matrix = confusion_matrix(y1_test, y_pred).T #.transpose()
conf_matrix
```

Out[78]:

```
array([[2037, 1420],
       [1657, 2220]], dtype=int64)
```

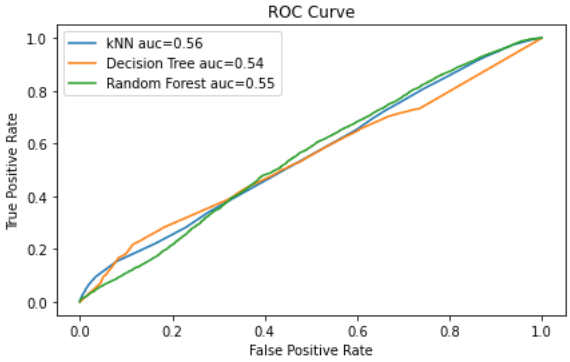
Analysis

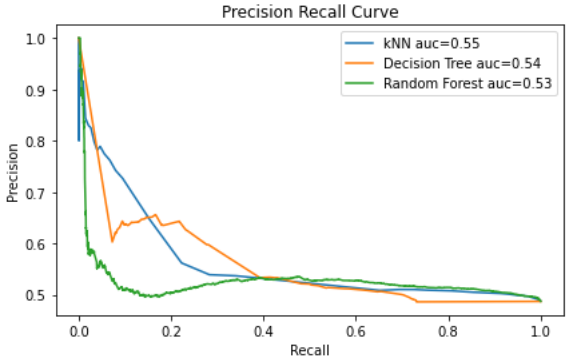
In [79]:

```
def plot_roc_curve_multiple_classifiers(X_test, y_true, clf_list,
                                        clf_names, class_num=1):
    for i, clf in enumerate(clf_list):
        pred = clf.predict_proba(X_test)[:, class_num]
        fpr, tpr, thresh = metrics.roc_curve(y_true, pred)
        auc = metrics.roc_auc_score(y_true, pred)
        label_plot = clf_names[i] + ' auc=' +str(auc.round(2))
        plt.plot(fpr,tpr,label=label_plot)
        plt.legend(loc='best')
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')

def plot_precision_recall_curve_multiple_classifiers(X_test, y_true,
                                                     clf_list,
                                                     clf_names,
                                                     class_num=1):
    for i, clf in enumerate(clf_list):
        pred = clf.predict_proba(X_test)[:, class_num]
        precision, recall, thresholds = metrics.precision_recall_curve(y_true, pred)
        auc = metrics.average_precision_score(y_true, pred)

        label_plot = clf_names[i] + ' auc=' +str(auc.round(2))
        plt.plot(recall,precision,label=label_plot)
        plt.legend(loc='best')
        plt.xlabel('Recall')
        plt.ylabel('Precision')

def plot_multiple_model_evaluation(X_test, y_true,
                                   clf_list, clf_names, class_num=1):

    plt.subplots(figsize=(15, 4))

    plt.subplot(121)
    plt.title('ROC Curve')
    plot_roc_curve_multiple_classifiers(X_test, y_test, clf_list, clf_names)

    plt.subplot(122)
    plt.title('Precision Recall Curve')
    plot_precision_recall_curve_multiple_classifiers(X_test, y_test, clf_list, clf_names)
    plt.show()
```

In [80]:

```
#sales dataset
clf_names = ['kNN', 'Decision Tree', 'Random Forest']
clf_list = [knn, dt, rf]
plot_multiple_model_evaluation(X_test, y_test, clf_list, clf_names)
```





Evaluating the Random Forest model, decision tree, knn on Validation data. Analysing the result in the validation dataset with a prediction threshold of 61%

We were able to correctly classify our data, but the overall accuracy score of 0.55 to 0.59 is not very good. It looks like we need more data (more features or a larger data set) to build a more reliable model.

Also from the ROC curve plot we got AUC = 0.61-0.62 which tells us Acceptable discrimination

Comparing Random forest and Decision tree, Random fores has a higher precision (0.58 vs. 0.57) and higher AUC (0.55 vs. 0.54). Their Sensitivity also differs by 0.01. Which says that Random forest is more suitable for our data

Random forest is the best algorithm for our dataset

We can see from the data visualization analysis that the transaction code "financial institution - manual withdrawal" appears the most in the transaction data. The highest number of transaction code descriptions were "Calls Using a Recorded Phone," "Grocery Stores, Supermarkets," and "Financial Institutions - Manual Withdrawals," all of which had similar numbers.

If we talk about the types of transactions, then most often we met "Purchase. Foreign POS." .

By evaluating the correlation between the values in our database, we can conclude that the values among themselves have a low correlation, which indicates a weak relationship. At the same time, the largest correlation coefficient was found between the type and transaction code.

If we talk about the amount of the transaction, then it has too much difference, since it includes both negative and positive values(depending on the operation), therefore they have a huge number of deviations

Conclusion

In short, we tried to predict the sex of the client based on the available dataset, to this end we had to help KNN, Desicion tree, Random forest machine learning algorithms

Neither KNN, Random Forest, nor the Decision tree algorithm are very useful in predicting customer gender based on time of day, code, type and sum attributes. This indicates that the data does not have the ability to predict. This is not a big surprise, indicating that there is no significant difference between genders when it

comes to these variables.

Possible solutions could be to extract new variables from the dataset (e.g. try to divide transactions by the time of year in which they occurred based on days), Optimize our current model - Find new hyperparameters that improve the roc AUC metric;