Credit card fraud predictive model

Decision tree - Random forest

0.1 Introduction

This project is aimed at generating a predictive model of credit card fraud using the decision tree algorithm and random forest. Registers are used with variables from the transaction and the card record

The work is carried out based on analysis, compression, data cleaning, metrics, exploration, testing and validation of the model, with the following work path:

- Development
- Understanding the data
- Data cleaning
  - Check null values
- Exploratory data analysis
  - Correlation matrix
  - Outlier detection
  - Data standardization
  - Split training, testing and validation data
- Predictive model - Decision tree
  - Create and train the model
  - Model evaluation
  - Evaluate the model with cross validation
  - Check feature importances
  - Impact of maximum depth
- Predictive model - Random Forest
  - Create and train the model
  - Model evaluation
  - Impact of maximum n_estimators on the model
- Demonstration of model classification
- Conclusions

0.2 Data

The de kaggel dataset "Credit card fraud", contains medical records whether the breast cancer is benign or malignant. The characteristics are transaction data and card records with their respective label, whether it was a fraudulent transaction or not.

Attribute Information:

- distance_from_home: The distance from the home where the transaction took place.
- distance_from_last_transaction: The distance from the last transaction made.
- ratio_to_median_purchase_price: Ratio between the purchase price of the transaction and the average purchase price.
- repeat_retailer: Was the transaction at the same retailer?
- used_chip - It is the transaction through chip (credit card).
- used_pin_number: Was the transaction made using the PIN number?
- online_order: Is the transaction an online order?
- Fraud: Is the transaction fraudulent? ____

0.3 Development

Importing Libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import LinearSegmentedColormap
import seaborn as sns
import sklearn.metrics as metrics
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from imblearn.under_sampling import RandomUnderSampler
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.tree import plot_tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix

print('Imported libraries')
```

```
Imported libraries
```

Import the dataset

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

[2]:
```
   distance_from_home  distance_from_last_transaction  \
0           57.877857                        0.311140
1           10.829943                        0.175592
2            5.091079                        0.805153
```

```
3          2.247564                          5.600044
4         44.190936                          0.566486

   ratio_to_median_purchase_price  repeat_retailer  used_chip  \
0                        1.945940              1.0        1.0
1                        1.294219              1.0        0.0
2                        0.427715              1.0        0.0
3                        0.362663              1.0        1.0
4                        2.222767              1.0        1.0

   used_pin_number  online_order  fraud
0              0.0           0.0    0.0
1              0.0           0.0    0.0
2              0.0           1.0    0.0
3              0.0           1.0    0.0
4              0.0           1.0    0.0
```

[3]:
```
df.describe()
```

[3]:
```
       distance_from_home  distance_from_last_transaction  \
count      1000000.000000                  1000000.000000
mean            26.628792                        5.036519
std             65.390784                       25.843093
min              0.004874                        0.000118
25%              3.878008                        0.296671
50%              9.967760                        0.998650
75%             25.743985                        3.355748
max          10632.723672                    11851.104565

       ratio_to_median_purchase_price  repeat_retailer       used_chip  \
count                  1000000.000000   1000000.000000  1000000.000000
mean                         1.824182         0.881536        0.350399
std                          2.799589         0.323157        0.477095
min                          0.004399         0.000000        0.000000
25%                          0.475673         1.000000        0.000000
50%                          0.997717         1.000000        0.000000
75%                          2.096370         1.000000        1.000000
max                        267.802942         1.000000        1.000000

       used_pin_number    online_order           fraud
count   1000000.000000  1000000.000000  1000000.000000
mean          0.100608        0.650552        0.087403
std           0.300809        0.476796        0.282425
min           0.000000        0.000000        0.000000
25%           0.000000        0.000000        0.000000
50%           0.000000        1.000000        0.000000
75%           0.000000        1.000000        0.000000
```

```
max            1.000000         1.000000         1.000000
```

[4]:
```
df.dtypes
```

[4]:
```
distance_from_home                float64
distance_from_last_transaction    float64
ratio_to_median_purchase_price    float64
repeat_retailer                   float64
used_chip                         float64
used_pin_number                   float64
online_order                      float64
fraud                             float64
dtype: object
```

Check null values

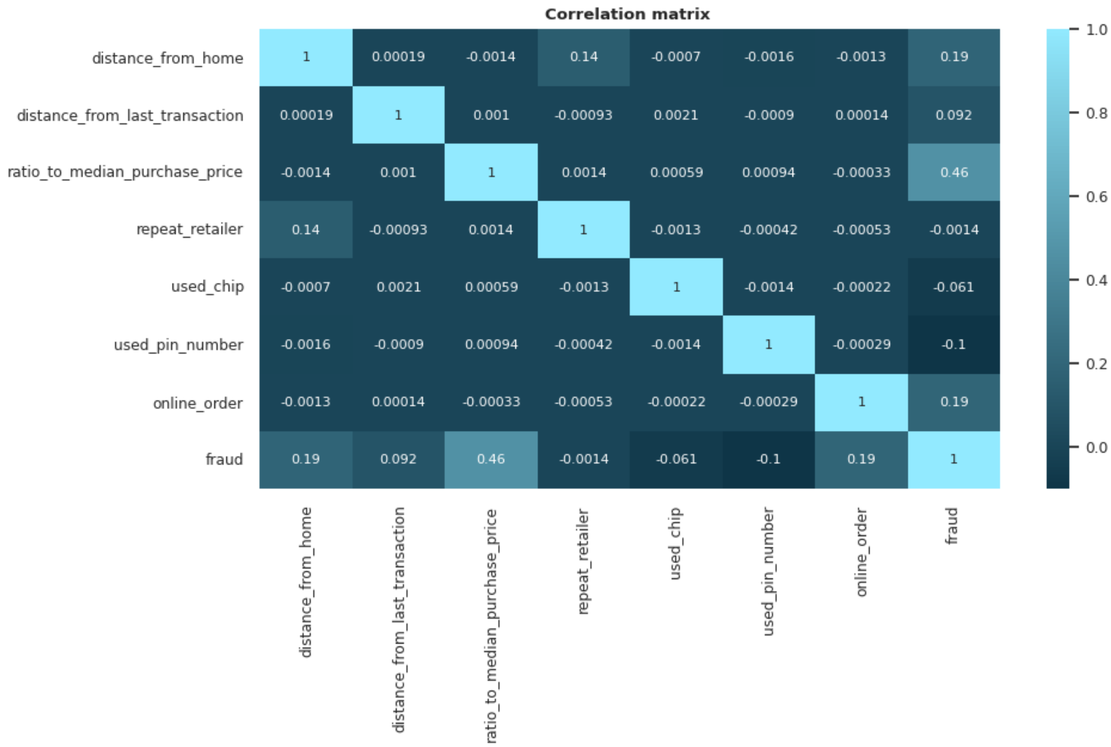
[5]:
```
df.isna().sum()
```

[5]:
```
distance_from_home                0
distance_from_last_transaction    0
ratio_to_median_purchase_price    0
repeat_retailer                   0
used_chip                         0
used_pin_number                   0
online_order                      0
fraud                             0
dtype: int64
```

0.4 Exploratory data analysis

A correlation analysis is carried out with a scatter plot and for that we use the pairplot

[250]:
```
colors = ["#0E3547", "#92EAFF", "#6B6B6B"]
cmap = LinearSegmentedColormap.from_list('Custom', colors[:2], N=256)

plt.figure(figsize=(10,5))
sns.set(style="whitegrid", context="notebook", font_scale=0.8)
sns.heatmap(df.corr(), cmap=cmap, annot=True, annot_kws={"size": 8})
plt.title("Correlation matrix ", fontweight='bold')
plt.show()
```

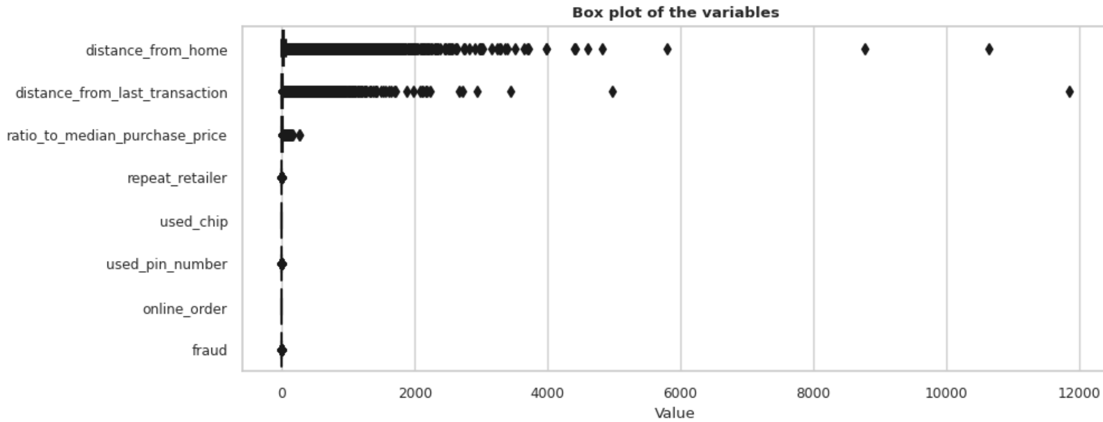


There is a positive correlation with respect to the objective variable "fraud" in the variables: * ratio_to_median_purchase_price * online_order

And a negative relationship with: * used_pin_number

Outlier detection

[7]:
```
plt.figure(figsize=(10, 4))

sns.boxplot(data=df, orient="h", color=colors[0])
plt.title("Box plot of the variables", fontweight='bold')
plt.xlabel("Value")
plt.show()
```



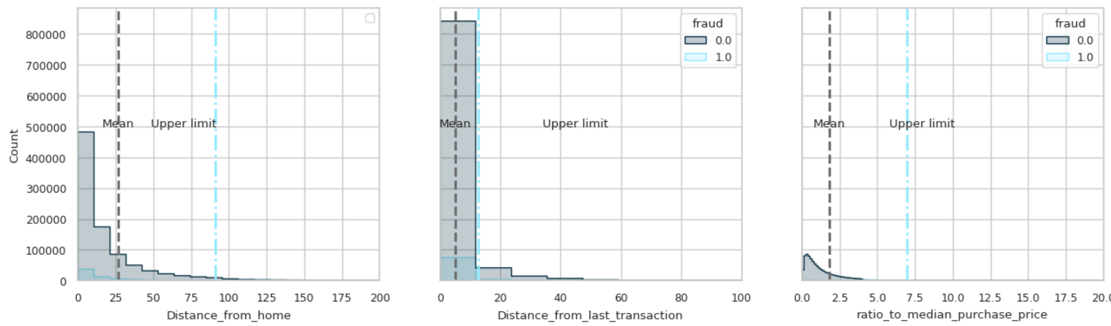
Visualize the greatest concentration of data in the variables with the greatest number of outliers:

[219]:
```
def value_iqr(df, variable):
      q1 = round(df[variable].quantile(q = 0.25),2)
      q3 = round(df[variable].quantile(q = 0.75), 2)
      IQR = q3 - q1

      upper_limit = round(q3 + 3 * IQR , 2)
      return upper_limit

upper_limit_distance_from_home = value_iqr(df, "distance_from_home")
upper_limit_distance_from_last_transaction = value_iqr(df,␣
 ↪"distance_from_last_transaction")
upper_limit_ratio_to_median_purchase_price = value_iqr(df,␣
 ↪"ratio_to_median_purchase_price")
```

[220]:
```
fig, ax = plt.subplots(1, 3, figsize=(15,4), sharey=True)
sns.histplot(data=df, x="distance_from_home", bins=1000, color=colors[0],␣
 ↪hue="fraud", ax=ax[0], element="step", palette=colors)
ax[0].set_xlim(0, 200)
ax[0].axvline(np.mean(df["distance_from_home"]), linewidth=2, color=colors[2],␣
 ↪linestyle='--')
ax[0].axvline(upper_limit_distance_from_home, linewidth=2, color=colors[1],␣
 ↪linestyle='-.')
ax[0].annotate("Mean", (np.mean(df["distance_from_home"]),  500000),␣
 ↪ha='center')
ax[0].annotate("Upper limit", (70,  500000), ha='center')
ax[0].set_xlabel("Distance_from_home")
ax[0].set_ylabel("Count")
ax[0].legend()
```

```python
sns.histplot(data=df, x="distance_from_last_transaction", bins=1000,␣
↪color=colors[0], hue="fraud", ax=ax[1], element="step", palette=colors)
ax[1].set_xlabel("Distance_from_last_transaction")
ax[1].set_xlim(0, 100)
ax[1].axvline(np.mean(df["distance_from_last_transaction"]), linewidth=2,␣
↪color=colors[2], linestyle='--')
ax[1].annotate("Mean", (np.mean(df["distance_from_last_transaction"]), ␣
↪500000), ha='center')
ax[1].axvline(upper_limit_distance_from_last_transaction , linewidth=2,␣
↪color=colors[1], linestyle='-.')
ax[1].annotate("Upper limit", (45,  500000), ha='center')

sns.histplot(data=df, x="ratio_to_median_purchase_price", bins=2000,␣
↪color=colors[0], hue="fraud", ax=ax[2],  element="step", palette=colors)
ax[2].set_xlabel("ratio_to_median_purchase_price")
ax[2].set_xlim(0, 20)
ax[2].axvline(np.mean(df["ratio_to_median_purchase_price"]), linewidth=2,␣
↪color=colors[2], linestyle='--')
ax[2].annotate("Mean", (np.mean(df["ratio_to_median_purchase_price"]), ␣
↪500000), ha='center')
ax[2].axvline( upper_limit_ratio_to_median_purchase_price , linewidth=2,␣
↪color=colors[1], linestyle='-.')
ax[2].annotate("Upper limit", (8,  500000), ha='center')

plt.subplots_adjust(wspace=0.2)
plt.show()
```

```
/tmp/ipykernel_15996/3594476168.py:2: UserWarning: The palette list has more
values (3) than needed (2), which may not be intended.
  sns.histplot(data=df, x="distance_from_home", bins=1000, color=colors[0],
hue="fraud", ax=ax[0], element="step", palette=colors)
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
/tmp/ipykernel_15996/3594476168.py:12: UserWarning: The palette list has more
values (3) than needed (2), which may not be intended.
  sns.histplot(data=df, x="distance_from_last_transaction", bins=1000,
color=colors[0], hue="fraud", ax=ax[1], element="step", palette=colors)
/tmp/ipykernel_15996/3594476168.py:20: UserWarning: The palette list has more
values (3) than needed (2), which may not be intended.
  sns.histplot(data=df, x="ratio_to_median_purchase_price", bins=2000,
color=colors[0], hue="fraud", ax=ax[2],  element="step", palette=colors)
```



- The largest number of records for the distance_from_home variable are found within a distance of less than 100 miles.
- The largest number of records for the Distance_from_last_transaction variable are within a distance of less than 50 miles.
- A similar distribution is observed between fraud and non-fraud labels

---

Outlier detection The interquartile range is used with a factor of 1.5 in a normal distribution, to determine outliers: * Define the interquartile range (IQR) * *Upper bound: q3 + 1.5* IQR *Lower limit: q1 - 1.5* IQR*

As the distribution of the three variables analyzed is strongly skewed to the left, the factor is increased to 3.0 * *Upper bound: q3 + 3.0* IQR *Lower limit: q1 - 3.0* IQR*

Relation of the distribution of the target class of the raw data and the data without outliers

[139]:
```
# Raw data
df["fraud"].value_counts()
```

[139]:
```
fraud
0.0    912597
1.0     87403
Name: count, dtype: int64
```

[222]:
```
# Data without outliers
df[(df["distance_from_home"] < upper_limit_distance_from_home) &␣
↪(df["distance_from_last_transaction"] <␣
↪upper_limit_distance_from_last_transaction)
  & (df["ratio_to_median_purchase_price"] <␣
↪upper_limit_ratio_to_median_purchase_price)]["fraud"].value_counts()
```

[222]:
```
fraud
0.0    800526
1.0     34150
Name: count, dtype: int64
```

Since it does not contain a major difference, we choose to eliminate the outliers to avoid bias in our model

[225]:
```
df_clean = df[(df["distance_from_home"] < upper_limit_distance_from_home) &␣
↪(df["distance_from_last_transaction"] <␣
↪upper_limit_distance_from_last_transaction)
  & (df["ratio_to_median_purchase_price"] <␣
↪upper_limit_ratio_to_median_purchase_price)]
df_clean.shape
```

[225]:
```
(834676, 8)
```

Data standardization We use the MinMaxScaler method from sklearn

[226]:
```
scaler = StandardScaler()
columns_scaled = ['distance_from_home', 'distance_from_last_transaction',␣
↪'ratio_to_median_purchase_price']

df_processing_scaler = scaler.fit_transform(df_clean[columns_scaled])
df_processing_scaler = pd.DataFrame(df_processing_scaler,␣
↪columns=columns_scaled)
df_processing_scaler = pd.concat([df_processing_scaler, df_clean.
↪drop(columns_scaled, axis=1)], axis=1)
df_processing_scaler.head()
```

[226]:
```
   distance_from_home  distance_from_last_transaction  \
0            2.282309                       -0.631022
1           -0.290274                       -0.684709
2           -0.604076                       -0.435356
3           -0.759559                        1.463774
4            1.533907                       -0.529886

   ratio_to_median_purchase_price  repeat_retailer  used_chip  \
0                        0.386347              1.0        1.0
1                       -0.093039              1.0        0.0
2                       -0.730413              1.0        0.0
3                       -0.778263              1.0        1.0
4                        0.589973              1.0        1.0

   used_pin_number  online_order  fraud
0              0.0           0.0    0.0
1              0.0           0.0    0.0
2              0.0           1.0    0.0
3              0.0           1.0    0.0
4              0.0           1.0    0.0
```

Distribution of predictor classes

[227]:
```
print("Number of registers:", df_clean["fraud"].value_counts())
```

```
Number of registers: fraud
0.0    800526
1.0     34150
Name: count, dtype: int64
```

The dataset is unbalanced in its predictive class. It is ideal to balance the dominant class [0 - No fraud] by randomly deleting records matching the minority class

[228]:
```
X = df_clean.drop(["fraud"], axis = 1)
y = df_clean["fraud"]

undersampler = RandomUnderSampler(sampling_strategy='majority', random_state=42)
X_resampled, y_resampled = undersampler.fit_resample(X, y)
print("Number of registers:", y_resampled.value_counts())
```

```
Number of registers: fraud
0.0    34150
1.0    34150
Name: count, dtype: int64
```

Split training, testing and validation data

[229]:
```
X_train, X_test_validation, y_train, y_test_validation =␣
 ↪train_test_split(X_resampled, y_resampled, test_size=0.2, random_state=42)

X_test, X_validation, y_test, y_validation =␣
 ↪train_test_split(X_test_validation, y_test_validation, test_size=0.5,␣
 ↪random_state=42)
X_test.shape
```

[229]: (6830, 7)

0.5 Predictive model - Decision tree

Create and train the model

[230]:
```
model_tree = DecisionTreeClassifier(max_depth=2, random_state=42)
model_tree.fit(X_train, y_train)
```

[230]: DecisionTreeClassifier(max_depth=2, random_state=42)

Model evaluation Calculation of predictions in Train and Test

[231]:
```python
# Predictions
y_train_pred = model_tree.predict(X_train)
y_test_pred = model_tree.predict(X_test)
y_validation_pred = model_tree.predict(X_validation)

# Accuracy predictions
train_accuracy = accuracy_score(y_train, y_train_pred)
test_accuracy = accuracy_score(y_test, y_test_pred)
validation_accuracy = accuracy_score(y_validation, y_validation_pred)

print("The accuracy in Train:", train_accuracy)
print("The accuracy in Test:", test_accuracy)
print("The accuracy in Validation:", validation_accuracy)
```

```
The accuracy in Train: 0.987024158125915
The accuracy in Test: 0.9875549048316252
The accuracy in Validation: 0.9856515373352855
```

An accuracy of approximately 97% was obtained for the three data sets, ideal values for the model.

Evaluate the model with cross validation

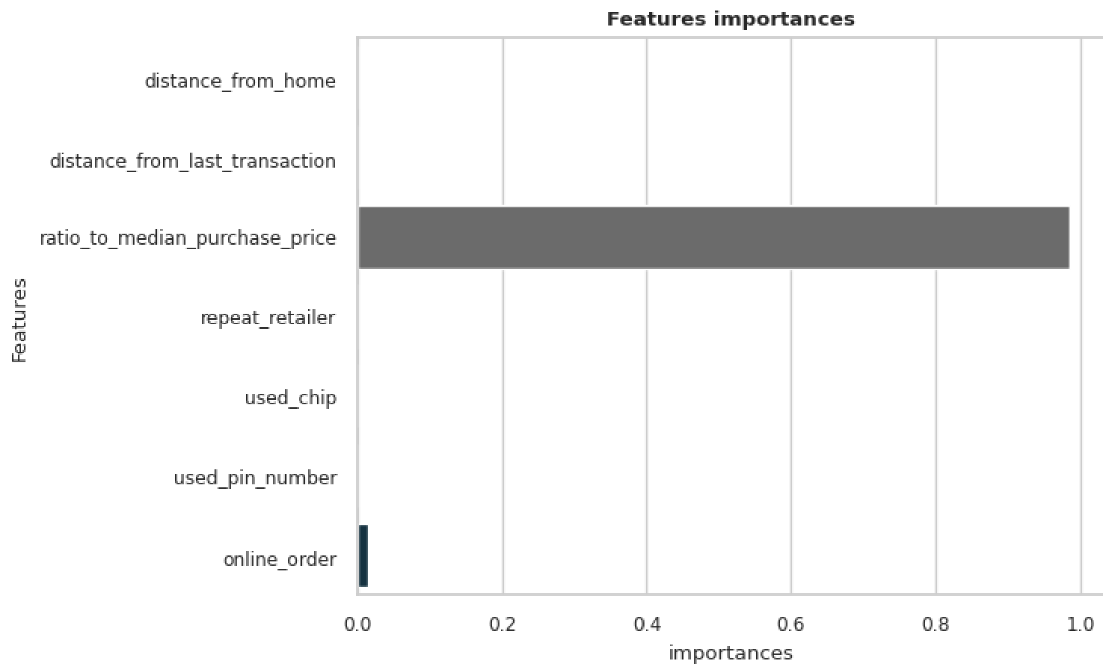
[232]:
```python
# Perform cross validation
precision = cross_val_score(model_tree, X_resampled, y_resampled, cv=10,␣
↪scoring="precision")

# Print the cross validation result
print("Mean precision:", precision.mean())
```

```
Mean precision: 0.974550154834444
```

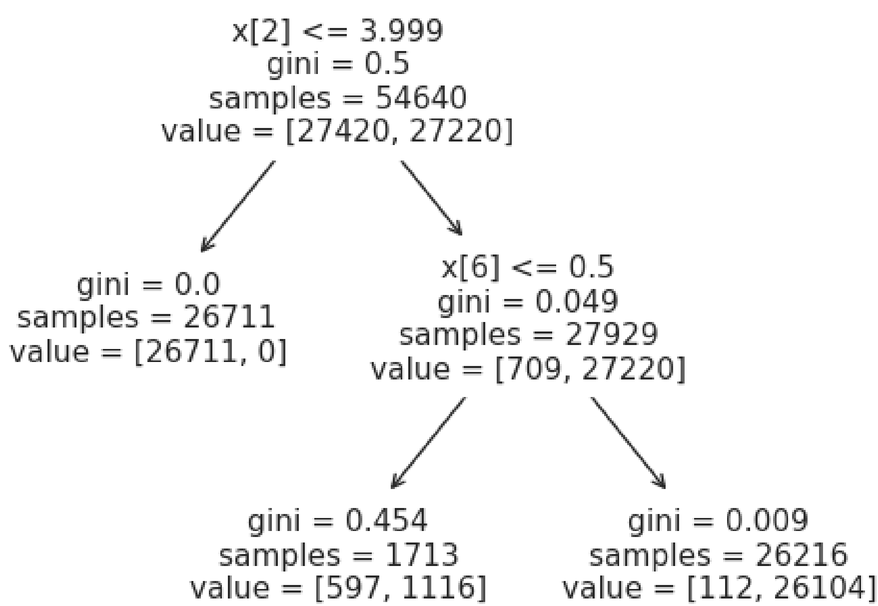
Cross validation confirms the accuracy of the model

Check feature importances

[249]:
```python
importances = model_tree.feature_importances_
columns = X.columns

sns.barplot(y = columns, x = importances, linewidth = 1, palette = colors)
plt.title("Features importances", fontweight='bold')
plt.xlabel("importances")
plt.ylabel("Features")
plt.show()
```



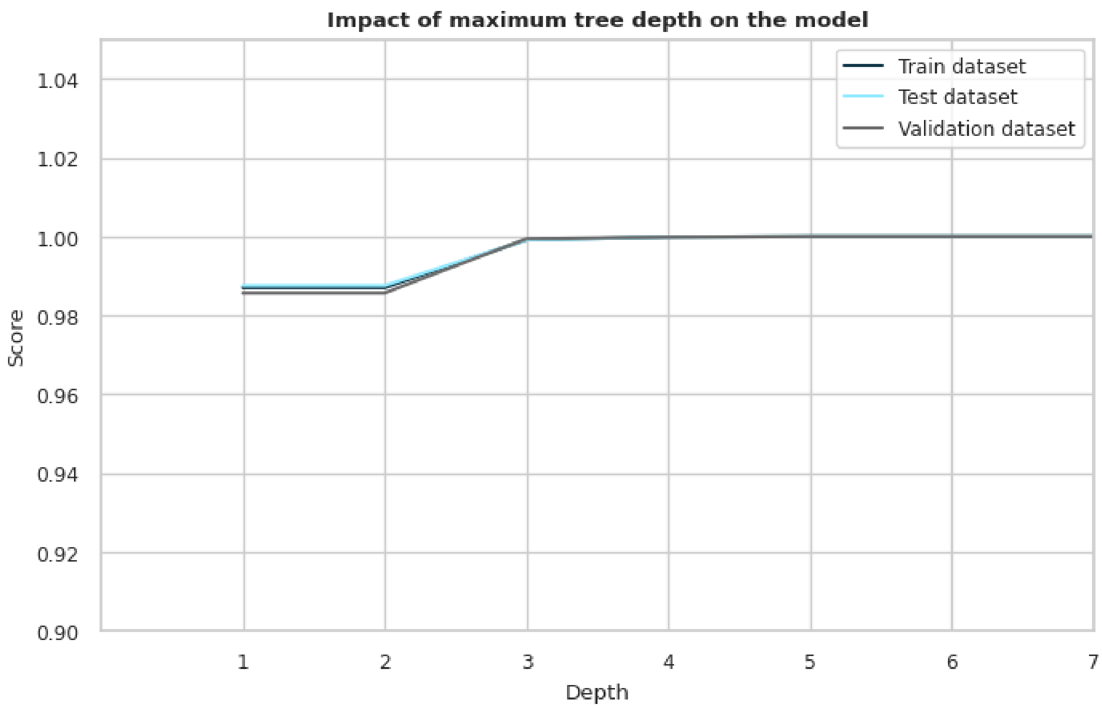
[234]:
```
plot_tree(model_tree);
```



0.6 Impact of maximum depth

We can easily check the effect of setting a maximum depth on the training, testing and validation data set: just train several models with maximum depths between 1 and 7, display the percentage of success in each case.

[235]:
```
train_scores = []
test_scores = []
validation_scores = []
for depth in range(1, 8):
    model = DecisionTreeClassifier(max_depth = depth)
    model.fit(X_train, y_train)
    train_scores.append(model.score(X_train, y_train))
    test_scores.append(model.score(X_test, y_test))
    validation_scores.append(model.score(X_validation, y_validation))


#Visualicemos ahora el resultado:
fig, ax = plt.subplots(figsize=(8, 4.8))

ax.plot(range(1, 8), train_scores, label="Train dataset", color=colors[0])
ax.plot(range(1, 8), test_scores, label="Test dataset", color=colors[1])
ax.plot(range(1, 8), validation_scores, label="Validation dataset",␣
 ↪color=colors[2])

ax.set_xlabel("Depth")
ax.set_ylabel("Score")
plt.title("Impact of maximum tree depth on the model", fontweight='bold')
ax.set_xticks(range(1, 8), labels=range(1, 8))
ax.grid(zorder=0.5)
ax.set_ylim(0.9, 1.05)
ax.set_xlim(0, 7)
ax.legend()
plt.show()
```



When the model exceeds the depth of 2 nodes, it tends to overfit.

0.7 Predictive model - Random Forest

Create and train the model

[251]:
```
random_forest = RandomForestClassifier(n_estimators=10, random_state =0,␣
↪max_depth = 2)
random_forest.fit(X_train, y_train)
```

[251]:
```
RandomForestClassifier(max_depth=2, n_estimators=10, random_state=0)
```

Model evaluation Calculation of predictions in Train and Test

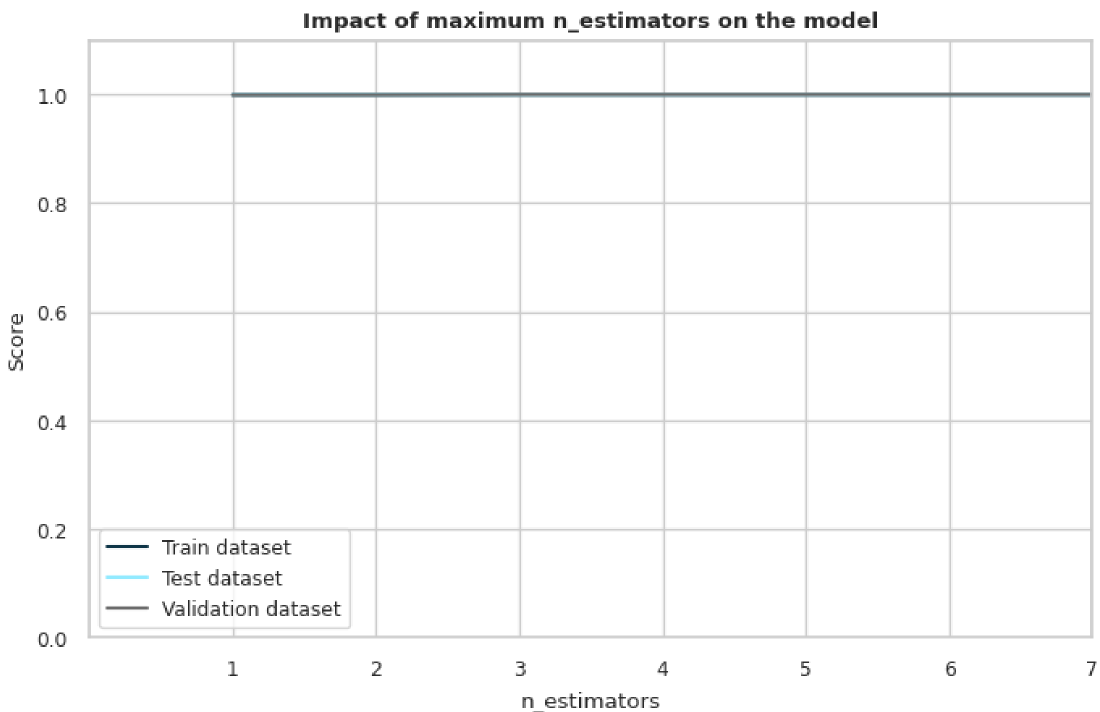
[252]:
```
# Predictions
y_train_pred_f = random_forest.predict(X_train)
y_test_pred_f = random_forest.predict(X_test)
y_validation_pred_f = random_forest.predict(X_validation)

# Accuracy predictions
train_accuracy = accuracy_score(y_train, y_train_pred_f)
test_accuracy = accuracy_score(y_test, y_test_pred_f)
validation_accuracy = accuracy_score(y_validation, y_validation_pred_f)
```

```python
print("The accuracy in Train:", train_accuracy)
print("The accuracy in Test:", test_accuracy)
print("The accuracy in Validation:", validation_accuracy)
```

```
The accuracy in Train: 0.989586383601757
The accuracy in Test: 0.9897510980966325
The accuracy in Validation: 0.9887262079062957
```

Impact of maximum n_estimators on the model

[238]:
```python
train_scores = []
test_scores = []
validation_scores = []

for i in range(1,8):
  random_forest_t = RandomForestClassifier(n_estimators=i, random_state =0)
  random_forest_t.fit(X_train, y_train)

  # Cálculo de las predicciones en Tran y Test
  train_scores.append(random_forest_t.score(X_train, y_train))
  test_scores.append(random_forest_t.score(X_test, y_test))
  validation_scores.append(random_forest_t.score(X_validation, y_validation))


#Visualicemos ahora el resultado:
fig, ax = plt.subplots(figsize=(8, 4.8))

ax.plot(range(1, 8), train_scores, label="Train dataset", color=colors[0])
ax.plot(range(1, 8), test_scores, label="Test dataset", color=colors[1])
ax.plot(range(1, 8), validation_scores, label="Validation dataset",␣
 ↪color=colors[2])

ax.set_xlabel("n_estimators")
ax.set_ylabel("Score")
plt.title("Impact of maximum n_estimators on the model", fontweight='bold')
ax.set_xticks(range(1, 8), labels=range(1, 8))
ax.grid(zorder=0.5)
ax.set_ylim(0, 1.1)
ax.set_xlim(0, 7)
ax.legend()
plt.show()
```



The accuracy of the model is almost perfect with the minimum number of n_estimators and becomes perfect from 3 onwards.

0.8 Demonstration of model classification

Creation of a record taking random values from the scaled data frame to make the prediction and subsequently reconvert to the original scale

[239]:
```
# Random values
value_distance_from_home =  X_resampled["distance_from_home"].sample(1).values
value_distance_from_last_transaction =␣
 ↪X_resampled["distance_from_last_transaction"].sample(1).values
value_ratio_to_median_purchase_price =␣
 ↪X_resampled["ratio_to_median_purchase_price"].sample(1).values
value_repeat_retailer = X_resampled["repeat_retailer"].sample(1).values
value_used_chip = X_resampled["used_chip"].sample(1).values
value_used_pin_number = X_resampled["used_pin_number"].sample(1).values
value_online_order = X_resampled["online_order"].sample(1).values
```

The prediction of the random forest model is non-fraud

[240]:
```
random_values_columns = pd.array(data=[value_distance_from_home,␣
 ↪value_distance_from_last_transaction, value_ratio_to_median_purchase_price,
```

```
                                                        value_repeat_retailer, value_used_chip,␣
↪value_used_pin_number, value_online_order], dtype="float")

predict_random_values = random_forest.predict(random_values_columns.
↪reshape(1,7))
print(predict_random_values)
```

```
[1.]
```

```
/home/williamccs/miniconda3/envs/cookiecutter-personal/lib/python3.11/site-
packages/sklearn/base.py:464: UserWarning: X does not have valid feature names,
but RandomForestClassifier was fitted with feature names
  warnings.warn(
```

[241]:
```
probability = random_forest.predict_proba(random_values_columns.reshape(1,7))
print("Probability of credit card fraud in this record is:", probability[0,␣
↪1]*100, "%")
```

```
Probability of credit card fraud in this record is: 100.0 %
```

```
/home/williamccs/miniconda3/envs/cookiecutter-personal/lib/python3.11/site-
packages/sklearn/base.py:464: UserWarning: X does not have valid feature names,
but RandomForestClassifier was fitted with feature names
  warnings.warn(
```

Reverse data transformation

[242]:
```
random_values_2d = random_values_columns.reshape(1,7)[0, :3].reshape(1, -1)

inverse_random_values = scaler.inverse_transform(random_values_2d).reshape(3)
print(inverse_random_values)
```

```
[313.19720121   2.87600727   7.03770938]
```

[243]:
```
random_values_columns = random_values_columns[-4:].reshape(4)
print(random_values_columns)
```

```
<PandasArray>
[1.0, 0.0, 0.0, 1.0]
Length: 4, dtype: float64
```

[244]:
```
concatenated_array = np.concatenate([inverse_random_values,␣
↪random_values_columns], axis=0)
print(concatenated_array)
```

```
[313.19720121   2.87600727   7.03770938   1.           0.
   0.           1.        ]
```

[245]:
```
df_random_values_columns = pd.DataFrame(data = concatenated_array.reshape(1,7),␣
↪columns=X.columns)
df_random_values_columns
```

[245]:
```
   distance_from_home  distance_from_last_transaction  \
0          313.197201                        2.876007

   ratio_to_median_purchase_price  repeat_retailer  used_chip  \
0                        7.037709              1.0        0.0

   used_pin_number  online_order
0              0.0           1.0
```

Random value summary and prediction

[248]:
```
print("The distance since the last transaction made:", df_random_values_columns.
↪iloc[:, 0].values)
print("The relationship between the transaction purchase price and the average␣
↪purchase price:", df_random_values_columns.iloc[:, 1].values)
print("The transaction took place at the same retailer:",␣
↪df_random_values_columns.iloc[:, 2].values)
print("It is the transaction through chip (credit card):",␣
↪bool(df_random_values_columns.iloc[:, 3].values))
print("The transaction was carried out using the PIN number:",␣
↪bool(df_random_values_columns.iloc[:, 4].values))
print("Is the transaction an online order:", bool(df_random_values_columns.
↪iloc[:, 5].values), "\n")

print("Fraud: Is the transaction fraudulent?:", bool(df_random_values_columns.
↪iloc[:, 6].values))
```

```
The distance since the last transaction made: [313.19720121]
The relationship between the transaction purchase price and the average purchase
price: [2.87600727]
The transaction took place at the same retailer: [7.03770938]
It is the transaction through chip (credit card): True
The transaction was carried out using the PIN number: False
Is the transaction an online order: False

Fraud: Is the transaction fraudulent?: True
```

Conclutions

- One of the weaknesses of decision trees and random forests is that bias is generated when there are dominant classes. To do this, the outliers of the biased variables were eliminated using the interquartile range and increasing the factor.

- By reducing the bias of the variables and balancing the predictive class, better accuracy was obtained in the models
- By knowing in advance that one of the weaknesses of the decision trees is overtraining, it was possible to confirm that with a depth of maximum 2 nodes the model behaves appropriately, avoiding overtraining
- The random forest model has a greater accuracy than that of decision trees, almost tending towards the perfection of predictions