adj-olfa-1-notebook-analyse-112023

May 28, 2024

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

[49]:
```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler #pour standaridiser les données
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
from sklearn import metrics
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier
from scipy.stats import mode
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_score
from statsmodels.stats.stattools import durbin_watson
from statsmodels.stats.diagnostic import het_breuschpagan
from scipy import stats
```

[652]:
```
import pickle
```

[60]:
```
import math
```

[653]:
```
df_billets = pd.read_csv('/Users/helmisaddem/Documents/billets.csv', sep=';')
```

[5]:
```
df_billets.head()
```

[5]:
```
   is_genuine  diagonal  height_left  height_right  margin_low  margin_up  \
0        True    171.81       104.86        104.95        4.52       2.89
1        True    171.46       103.36        103.66        3.77       2.99
2        True    172.69       104.48        103.50        4.40       2.94
```

```
3         True    171.36       103.91        103.94        3.62        3.01
4         True    171.73       104.28        103.46        4.04        3.48

   length
0  112.83
1  113.09
2  113.16
3  113.51
4  112.54
```

[7]:
```
df_billets.nunique()
```

[7]:
```
is_genuine        2
diagonal        159
height_left     155
height_right    170
margin_low      285
margin_up       123
length          336
dtype: int64
```

[655]:
```
df_billets.isna().sum()
```

[655]:
```
is_genuine       0
diagonal         0
height_left      0
height_right     0
margin_low      37
margin_up        0
length           0
dtype: int64
```

[654]:
```
df_billets.describe()
```

[654]:
```
          diagonal  height_left  height_right   margin_low    margin_up  \
count  1500.000000  1500.000000   1500.000000  1463.000000  1500.000000
mean    171.958440   104.029533    103.920307     4.485967     3.151473
std       0.305195     0.299462      0.325627     0.663813     0.231813
min     171.040000   103.140000    102.820000     2.980000     2.270000
25%     171.750000   103.820000    103.710000     4.015000     2.990000
50%     171.960000   104.040000    103.920000     4.310000     3.140000
75%     172.170000   104.230000    104.150000     4.870000     3.310000
max     173.010000   104.880000    104.950000     6.900000     3.910000

           length
count  1500.00000
mean    112.67850
```

```
std       0.87273
min     109.49000
25%     112.03000
50%     112.96000
75%     113.34000
max     114.44000
```

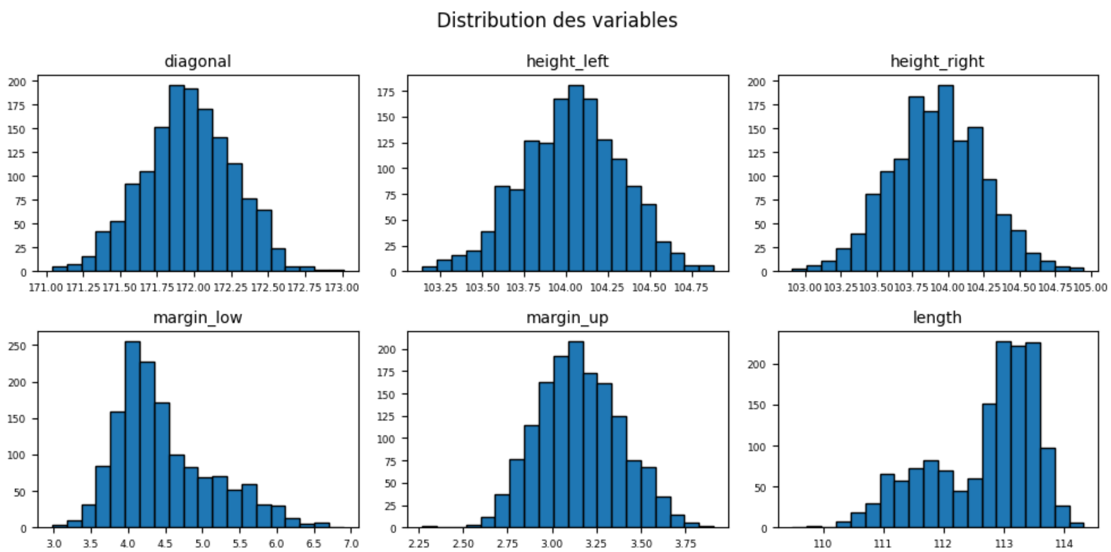
[656]:
```
billets_witnout_nan = df_billets.loc[
    ~df_billets.isna().any(axis='columns')]
```

[ ]:
```
billets_witnout_nan.info()
```

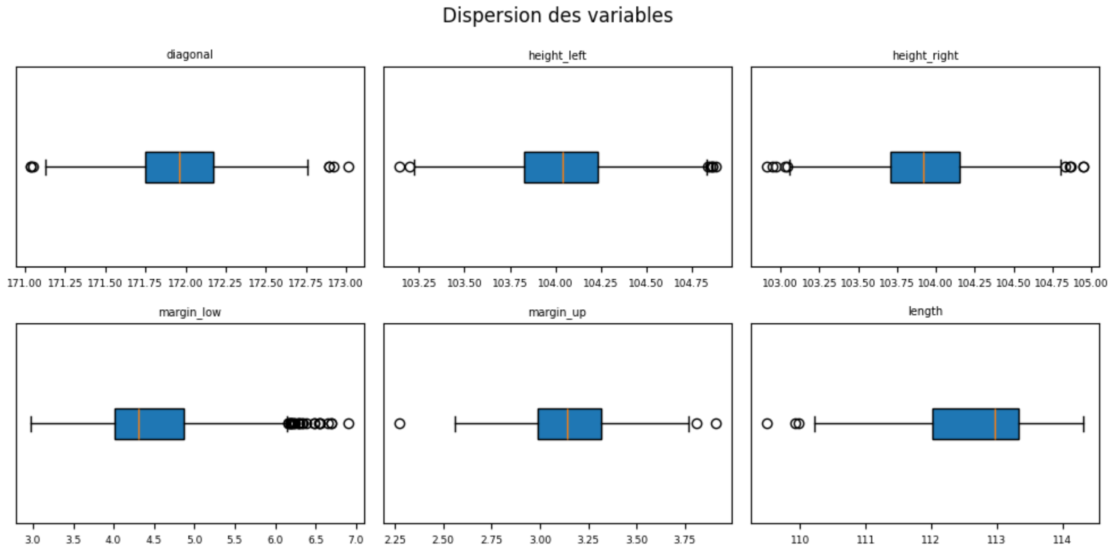
[657]:
```
print(f'Valeur(s) manquante(s) : {billets_witnout_nan.isna().any().any()}')
```

```
Valeur(s) manquante(s) : False
```

[658]:
```
#Distribution des variables :
variables = df_billets.columns.to_list()
variables.remove('is_genuine')

fig, axs = plt.subplots(2, 3, figsize=(10, 5))

for i, var in enumerate(variables):
    r = i // 3
    c = i % 3
    axs[r, c].hist(var, data=billets_witnout_nan[['diagonal', 'height_left',␣
 ↪'height_right',
                                                  'margin_low', 'margin_up',␣
 ↪'length']],
                   edgecolor='k', bins=20)
    axs[r, c].set_title(var, size=10)
    axs[r, c].tick_params(axis='both', which='both', labelsize=6.5)

# Supprime les graphiques vides
[fig.delaxes(ax) for ax in axs.flatten() if not ax.has_data()]

fig.suptitle('Distribution des variables')

plt.tight_layout()

plt.show()

del fig, axs, i, r, c, var
```



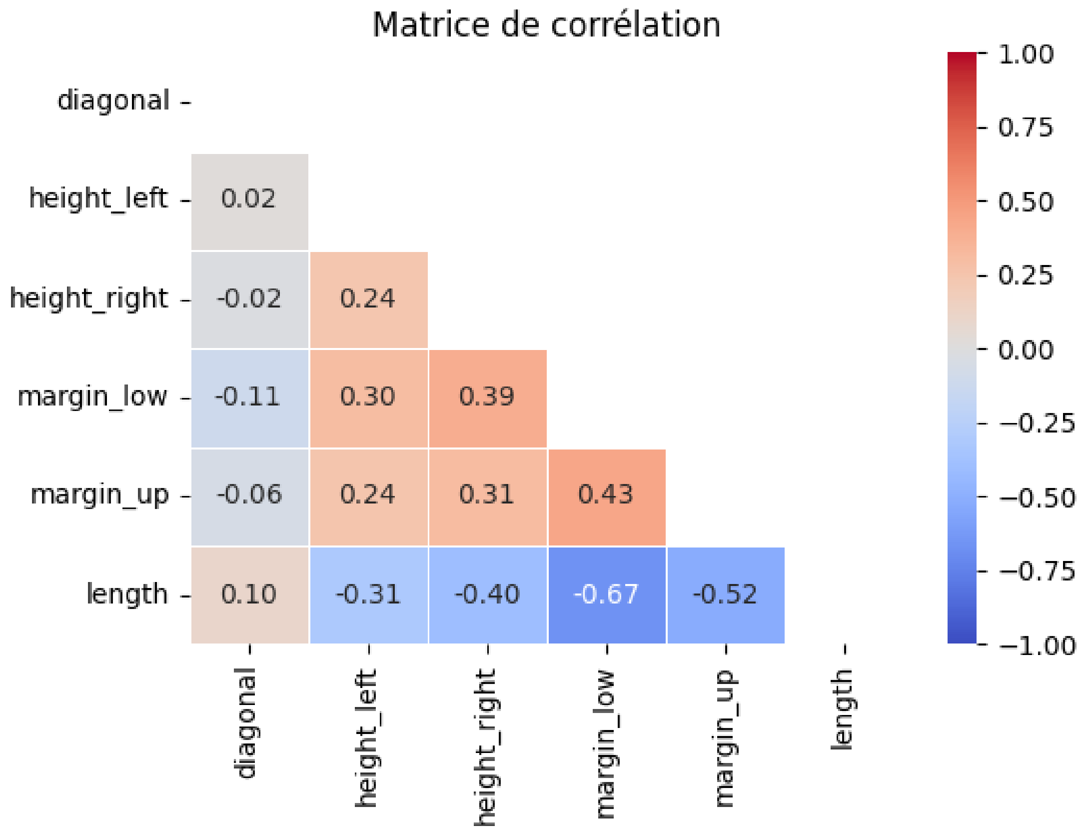
[222]:
```
# Dispersion des variables
variables = df_billets.columns.to_list()
variables.remove('is_genuine')

fig, axs = plt.subplots(2, 3, figsize=(10, 5))

for i, var in enumerate(variables):
    r = i // 3
    c = i % 3
    axs[r, c].boxplot(var, data=billets_witnout_nan[['diagonal', 'height_left',␣
↪'height_right',
                                                    'margin_low', 'margin_up',␣
↪'length']],
                      patch_artist=True, vert=False)
    axs[r, c].set_title(var, size=7)
    axs[r, c].yaxis.set_major_locator(plt.NullLocator())
    axs[r, c].tick_params(axis='x', which='both', labelsize=6.5)


[fig.delaxes(ax) for ax in axs.flatten() if not ax.has_data()]

fig.suptitle('Dispersion des variables')

plt.tight_layout()

plt.show()

del fig, axs, i, var, r, c
```



[223]:
```
#heatmap : corrélation entre les variables:
matrice_corr = billets_witnout_nan[['diagonal', 'height_left', 'height_right',
                                    'margin_low', 'margin_up', 'length']].
  ↪corr(numeric_only=True, method='pearson')
matrice_corr.style.background_gradient(axis='rows', cmap='coolwarm').format('{:.
  ↪2f}')
```

[223]: <pandas.io.formats.style.Styler at 0x136786650>

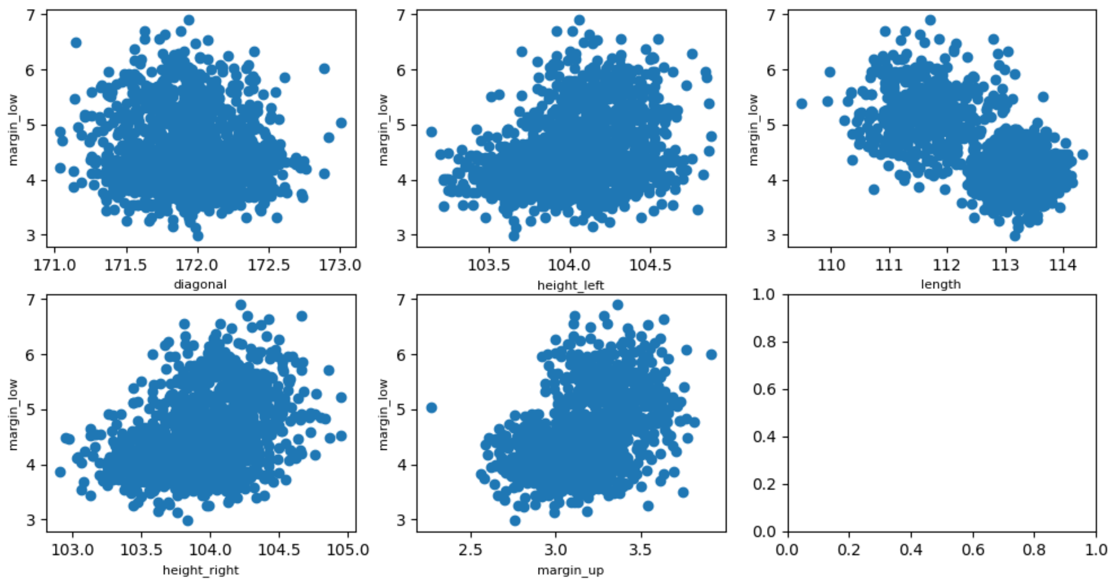
[224]:
```
fig, ax = plt.subplots(figsize=(6, 4))
mask = np.triu(np.ones_like(matrice_corr, dtype=bool))
sns.heatmap(matrice_corr, annot=True, fmt='.2f', vmin=-1, vmax=1,
annot_kws=None, linewidths=0.6, cmap='coolwarm', ax=ax, mask=mask)

ax.set_title('Matrice de corrélation')

plt.show()

del fig, ax
```



[659]:
```
#scatter pour voir la linéarité entre la variable dépendante margin_low et les␣
↪autres variables
variables = df_billets.columns.to_list()
variables.remove('is_genuine')
variables.remove('margin_low')

fig, axs = plt.subplots(nrows=2, ncols=3,
                        figsize=(12, 6))

i = 0
for r in range(2):
   for c in range(2):
       axs[r, c].scatter(billets_witnout_nan[variables[i]],␣
↪billets_witnout_nan['margin_low'])
       axs[r, c].set_xlabel(variables[i], size=8)
       axs[r, c].set_ylabel('margin_low', size=8)
       i += 1
axs[0,2].scatter(billets_witnout_nan[variables[4]],␣
↪billets_witnout_nan['margin_low'])
axs[0,2].set_xlabel(variables[4], size=8)
```

```
axs[0,2].set_ylabel('margin_low', size=8)
```

[659]: Text(0, 0.5, 'margin_low')



[231]:
```
variables = df_billets.columns.to_list()
variables.remove('margin_low')
# Créer un modèle de régression linéaire
model = LinearRegression()

for i in range(5):
    #Adapater le modèle aux données
    model.fit(billets_witnout_nan[[variables[i]]],␣
 ↪billets_witnout_nan['margin_low'])
    #coefficient de détermination
    r_squared = model.score(billets_witnout_nan[[variables[i]]],␣
 ↪billets_witnout_nan['margin_low'])
    print('Coefficient de détermination ou R² entre',variables[i],'et␣
 ↪margin_low', r_squared) #Coefficient de détermination (R²)
#Un R² proche de 1 indique que le modèle de régression linéaire ajusté explique
# une grande partie de la variance de la variable dépendante.
```

```
Coefficient de détermination ou R² entre is_genuine et margin_low
0.6131393378084237
Coefficient de détermination ou R² entre diagonal et margin_low
0.012439850430716826
Coefficient de détermination ou R² entre height_left et margin_low
0.09159276027592533
Coefficient de détermination ou R² entre height_right et margin_low
```

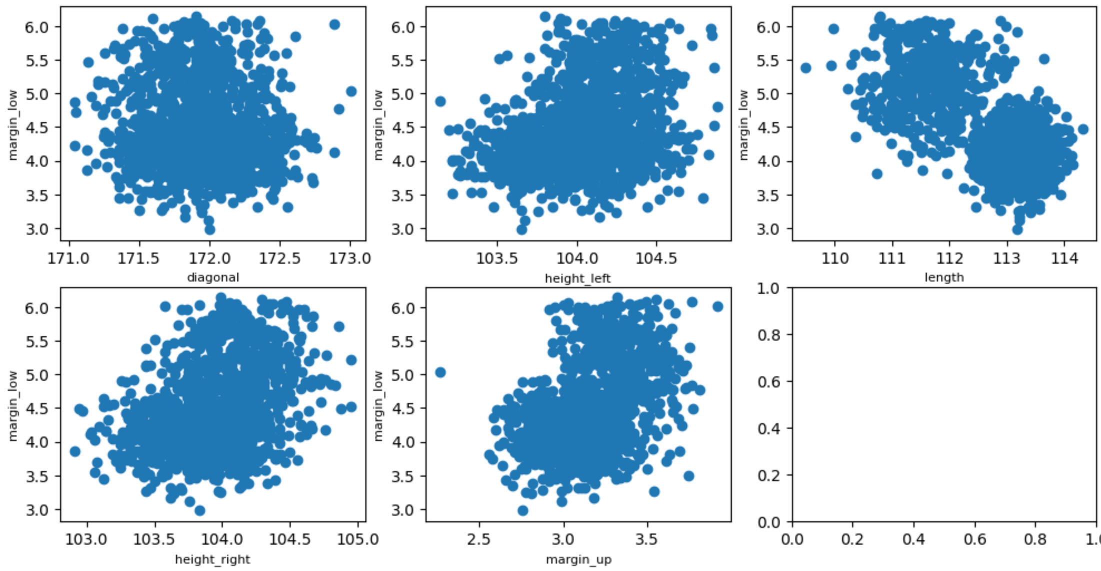
```
0.15294759201240649
Coefficient de détermination ou R² entre margin_up et margin_low
0.18628380252698062
```

[76]:
```
#supprimer les outliers de margin low et revoir si la relation se linéarise :
#Q1 = billets_witnout_nan['margin_low'].quantile(0.25)
#Q3 = billets_witnout_nan['margin_low'].quantile(0.75)
#IQR = Q3 - Q1
#max_boxplot = 1.5 * IQR + Q3
#min_boxplot = Q1 - 1.5 * IQR
#df = billets_witnout_nan.loc[
            #(billets_witnout_nan['margin_low'] < max_boxplot) &
 ↪(billets_witnout_nan['margin_low'] > min_boxplot)]
```

[ ]:
```
#px.box(data_frame= df, y='margin_low').update_layout(height=600, width=300)
```

[660]:
```
#scatter plot de margin_low en fonction du reste des variables après
 ↪suppression des outliers:
fig, axs = plt.subplots(nrows=2, ncols=3,
                            figsize=(12, 6))

i = 0
for r in range(2):
   for c in range(2):
       axs[r, c].scatter(df[variables[i]], df['margin_low'])
       axs[r, c].set_xlabel(variables[i], size=8)
       axs[r, c].set_ylabel('margin_low', size=8)
       i += 1
axs[0,2].scatter(df[variables[4]], df['margin_low'])
axs[0,2].set_xlabel(variables[4], size=8)
axs[0,2].set_ylabel('margin_low', size=8)
```

[660]:
```
Text(0, 0.5, 'margin_low')
```



[67]:
```
billets_witnout_nan.head()
```

[67]:
```
   is_genuine  diagonal  height_left  height_right  margin_low  margin_up  \
0        True    171.81       104.86        104.95        4.52       2.89
1        True    171.46       103.36        103.66        3.77       2.99
2        True    172.69       104.48        103.50        4.40       2.94
3        True    171.36       103.91        103.94        3.62       3.01
4        True    171.73       104.28        103.46        4.04       3.48

   length
0  112.83
1  113.09
2  113.16
3  113.51
4  112.54
```

[661]:
```
# Créez un objet PolynomialFeatures pour une transformation polynomiale d'ordre␣
↪2
poly = PolynomialFeatures(degree=2)
# Appliquez la transformation polynomiale à vos données
X_poly = poly.fit_transform(billets_witnout_nan[['diagonal', 'height_left',␣
↪'height_right',
                                    'margin_up', 'length']])
# Convertissez les données transformées en un DataFrame pandas pour visualiser
original_feature_names = billets_witnout_nan[['diagonal', 'height_left',␣
↪'height_right',
                                    'margin_up', 'length']].columns.to_list()
new_feature_names = poly.get_feature_names_out(original_feature_names)
```

```
X_poly_df = pd.DataFrame(X_poly, columns=new_feature_names)
```

[662]:
```
X_poly_df.drop('1', axis=1, inplace=True)
```

[663]:
```
# créer une table avec margin low inclus:
poly = PolynomialFeatures(degree=2)
poly.fit(billets_witnout_nan[['diagonal', 'height_left', 'height_right',
                              'margin_up', 'length', 'margin_low']])
names = billets_witnout_nan[['diagonal', 'height_left', 'height_right',
                              'margin_up', 'length', 'margin_low']].
↪columns.to_list()
new_names = poly.get_feature_names_out(names)
X_poly_margin_low = poly.transform(billets_witnout_nan[['diagonal',␣
↪'height_left', 'height_right',
                              'margin_up', 'length', 'margin_low']])
X_poly_df_margin_low = pd.DataFrame(X_poly_margin_low, columns=new_names)
```

[664]:
```
X_poly_df_margin_low.drop('1', axis=1, inplace=True)
```

[665]:
```
X_poly_df_margin_low = X_poly_df_margin_low.iloc[:
↪,[5,6,7,8,9,10,12,13,14,15,17,18,19,21,22,24]]
```

[666]:
```
X_poly_df_margin_low.describe()
```

[666]:

	margin_low	diagonal^2	diagonal height_left	diagonal height_right	\
count	1463.000000	1463.000000	1463.000000	1463.000000	
mean	4.485967	29570.057448	17889.145764	17870.251343	
std	0.663813	105.048572	61.023314	63.610612	
min	2.980000	29254.681600	17708.739600	17650.348200	
25%	4.015000	29498.062500	17847.381400	17828.991050	
50%	4.310000	29570.241600	17891.352000	17868.644800	
75%	4.870000	29642.508900	17929.889700	17912.008100	
max	6.900000	29932.460100	18095.115900	18066.329400	

	diagonal margin_up	diagonal length	height_left^2	\
count	1463.000000	1463.000000	1463.000000	
mean	542.197380	19375.487251	10822.607922	
std	39.753988	157.383190	62.328225	
min	390.553500	18804.907500	10637.859600	
25%	513.861400	19262.065050	10779.630650	
50%	540.205600	19422.076600	10824.321600	
75%	569.994200	19494.981200	10863.892900	
max	672.363600	19693.715600	10999.814400	

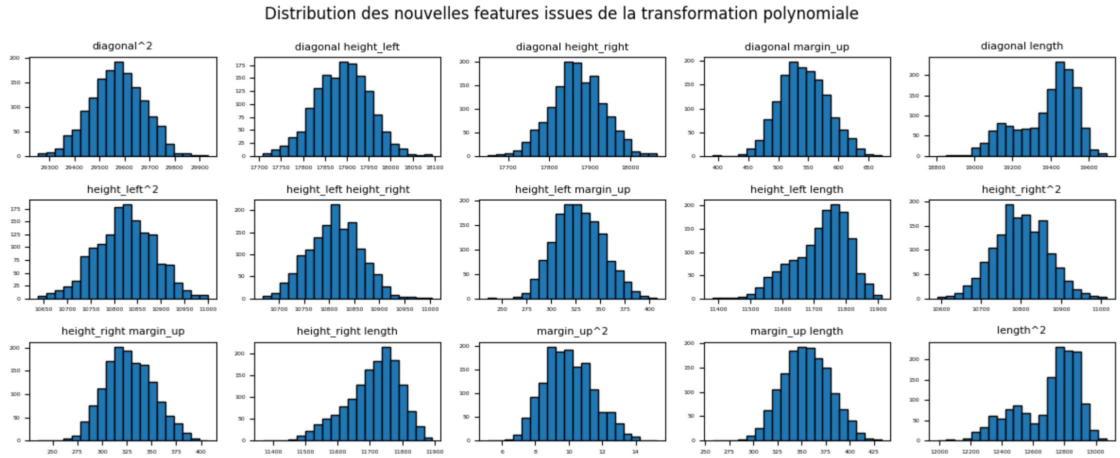
	height_left height_right	height_left margin_up	height_left length	\
count	1463.000000	1463.000000	1463.000000	
mean	10811.112528	328.036293	11721.623005	

```
std                 50.998731            24.332463            86.469862
min              10668.823700           235.399000         11382.580400
25%              10775.476400           310.410000         11665.362000
50%              10810.791600           326.748400         11737.528500
75%              10846.595950           344.859400         11784.978400
max              11005.057000           407.773900         11911.900000

       height_right^2  height_right margin_up  height_right length  \
count     1463.000000             1463.000000          1463.000000
mean     10799.778283              327.696021         11709.212775
std         67.380337               24.399170            83.090890
min      10590.468100              235.512500         11368.346700
25%      10755.764100              310.110750         11658.562000
50%      10799.366400              326.365100         11723.191400
75%      10847.222500              344.782000         11768.928700
max      11014.502500              406.757300         11893.620000

       margin_up^2  margin_up length      length^2
count  1463.000000       1463.000000   1463.000000
mean      9.995470        355.167568  12696.362938
std       1.469298         24.722164    196.162230
min       5.152900        257.758500  11988.060100
25%       8.940100        337.572950  12548.480400
50%       9.859600        354.525600  12759.961600
75%      10.989250        372.713050  12845.955600
max      15.288100        433.345300  13069.062400
```

[667]:

```
feature = X_poly_df.iloc[:,5:20].columns.to_list()

fig, axs = plt.subplots(3, 5, figsize=(12, 5))


for i, var in enumerate(feature):
    r = i // 5
    c = i % 5
    axs[r, c].hist(var, data=X_poly_df.iloc[:,5:20],
               edgecolor='k', bins=20)
    axs[r, c].set_title(var, size=8)
    axs[r, c].tick_params(axis='both', which='both', labelsize=4.5)

# Supprime les graphiques vides
[fig.delaxes(ax) for ax in axs.flatten() if not ax.has_data()]

fig.suptitle('Distribution des nouvelles features issues de la transformation␣
↪polynomiale')

plt.tight_layout()
```

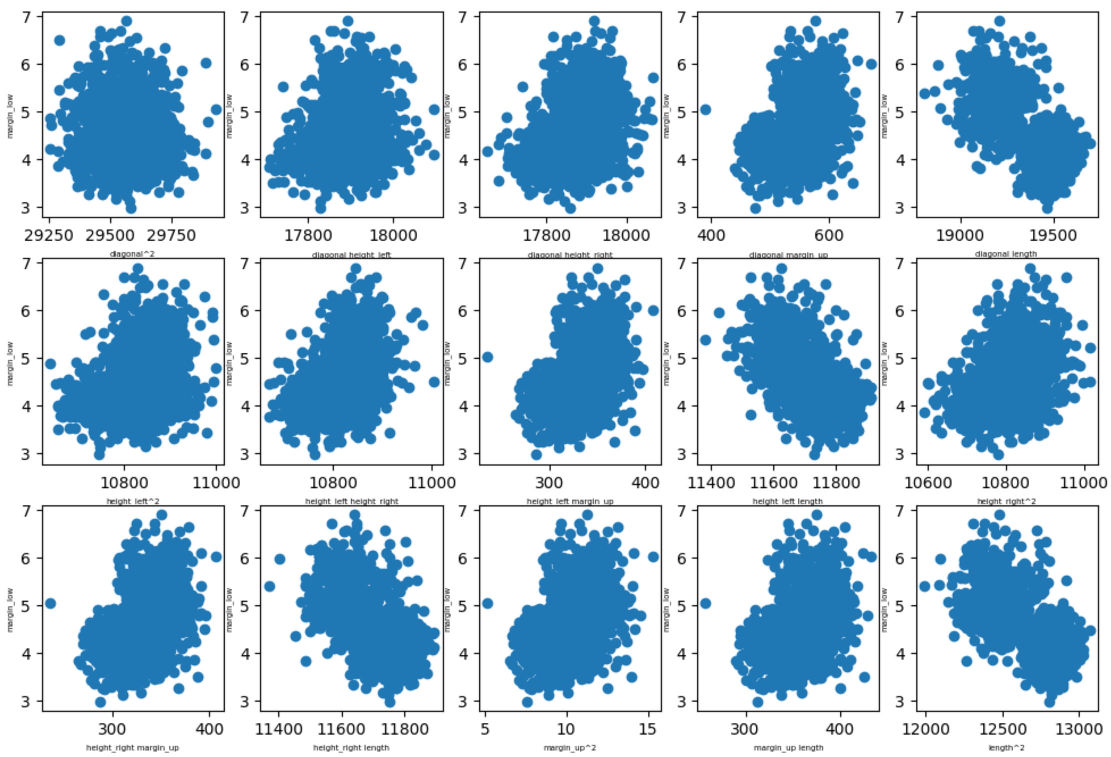
```python
plt.show()

del fig, axs, i, r, c, var
```



[255]:
```python
X_poly_df_margin_low.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1463 entries, 0 to 1462
Data columns (total 16 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   margin_low                 1463 non-null   float64
 1   diagonal^2                 1463 non-null   float64
 2   diagonal height_left       1463 non-null   float64
 3   diagonal height_right      1463 non-null   float64
 4   diagonal margin_up         1463 non-null   float64
 5   diagonal length            1463 non-null   float64
 6   height_left^2              1463 non-null   float64
 7   height_left height_right   1463 non-null   float64
 8   height_left margin_up      1463 non-null   float64
 9   height_left length         1463 non-null   float64
 10  height_right^2             1463 non-null   float64
 11  height_right margin_up     1463 non-null   float64
 12  height_right length        1463 non-null   float64
 13  margin_up^2                1463 non-null   float64
 14  margin_up length           1463 non-null   float64
 15  length^2                   1463 non-null   float64
dtypes: float64(16)
memory usage: 183.0 KB
```

[668]:
```
feature = X_poly_df_margin_low.iloc[:,1:16].columns.to_list()
fig, axs = plt.subplots(nrows=3, ncols=5,
                        figsize=(12, 8))

i = 0
for r in range(3):
   for c in range(5):
       axs[r, c].scatter(X_poly_df_margin_low[feature[i]],␣
 ↪X_poly_df_margin_low['margin_low'])
       axs[r, c].set_xlabel(feature[i], size=5)
       axs[r, c].set_ylabel('margin_low', size=5)
       i += 1
```



[669]:
```
#correlation entre nouvelles features et ma variable margin_low
matrice_corr = X_poly_df_margin_low.corr(numeric_only=True, method='pearson')
matrice_corr.style.background_gradient(axis='rows', cmap='coolwarm').format('{:.
 ↪2f}')
```

[669]: <pandas.io.formats.style.Styler at 0x13b718dd0>

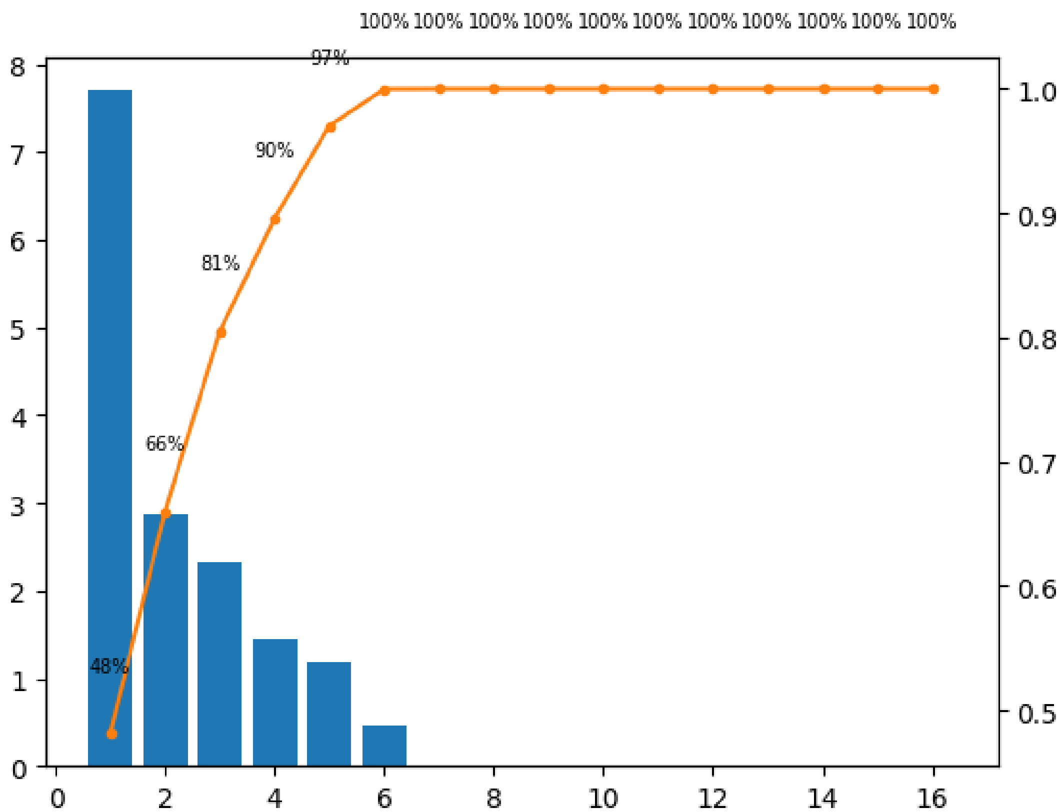
[670]:
```
# Calcul du R^2 pour chaque nouvelle feature et la margin_low
model = LinearRegression()
feature = X_poly_df_margin_low.columns.to_list()
```

```
feature.remove('margin_low')
for i in range(15):
    #Adapater le modèle aux données
    model.fit(X_poly_df_margin_low[[feature[i]]],␣
 ↪X_poly_df_margin_low['margin_low'])
    #coefficient de détermination
    r_squared = model.score(X_poly_df_margin_low[[feature[i]]],␣
 ↪X_poly_df_margin_low['margin_low'])
    print('Coefficient de détermination ou R² entre',feature[i],'et␣
 ↪margin_low', r_squared) #Coefficient de détermination (R²)
#Un R² proche de 1 indique que le modèle de régression linéaire ajusté explique
# une grande partie de la variance de la variable dépendante.
```

```
Coefficient de détermination ou R² entre diagonal^2 et margin_low
0.012441446892789365
Coefficient de détermination ou R² entre diagonal height_left et margin_low
0.038951449346347644
Coefficient de détermination ou R² entre diagonal height_right et margin_low
0.08233505895418802
Coefficient de détermination ou R² entre diagonal margin_up et margin_low
0.18434212368123915
Coefficient de détermination ou R² entre diagonal length et margin_low
0.436138729345381
Coefficient de détermination ou R² entre height_left^2 et margin_low
0.09155461917745966
Coefficient de détermination ou R² entre height_left height_right et margin_low
0.19678188236312044
Coefficient de détermination ou R² entre height_left margin_up et margin_low
0.19283511979378054
Coefficient de détermination ou R² entre height_left length et margin_low
0.33969262906533415
Coefficient de détermination ou R² entre height_right^2 et margin_low
0.15303504154890268
Coefficient de détermination ou R² entre height_right margin_up et margin_low
0.19569661423413132
Coefficient de détermination ou R² entre height_right length et margin_low
0.3103304180339681
Coefficient de détermination ou R² entre margin_up^2 et margin_low
0.18889239072370678
Coefficient de détermination ou R² entre margin_up length et margin_low
0.1434565578071968
Coefficient de détermination ou R² entre length^2 et margin_low
0.44454737041394987
```

[479]:
```
#PCA sur les nouvelles features :
from sklearn.decomposition import PCA
scaler = StandardScaler()
```

```
data_scaled = scaler.fit_transform(X_poly_df_margin_low)
#Diagramme des éboulis :
plt.bar(np.arange(1, (len(PCA().fit(data_scaled).explained_variance_)+1)),␣
 ↪PCA().fit(data_scaled).explained_variance_)
plt.twinx()
plt.plot(np.arange(1, (len(PCA().fit(data_scaled).explained_variance_)+1)),␣
 ↪PCA().fit(data_scaled).explained_variance_ratio_.cumsum(), color='C1',␣
 ↪marker='.')
for x, y in enumerate(PCA().fit(data_scaled).explained_variance_ratio_.
 ↪cumsum()):
    plt.text(x+1, (y+0.05) , f'{y:.0%}', ha='center', size=7)
```

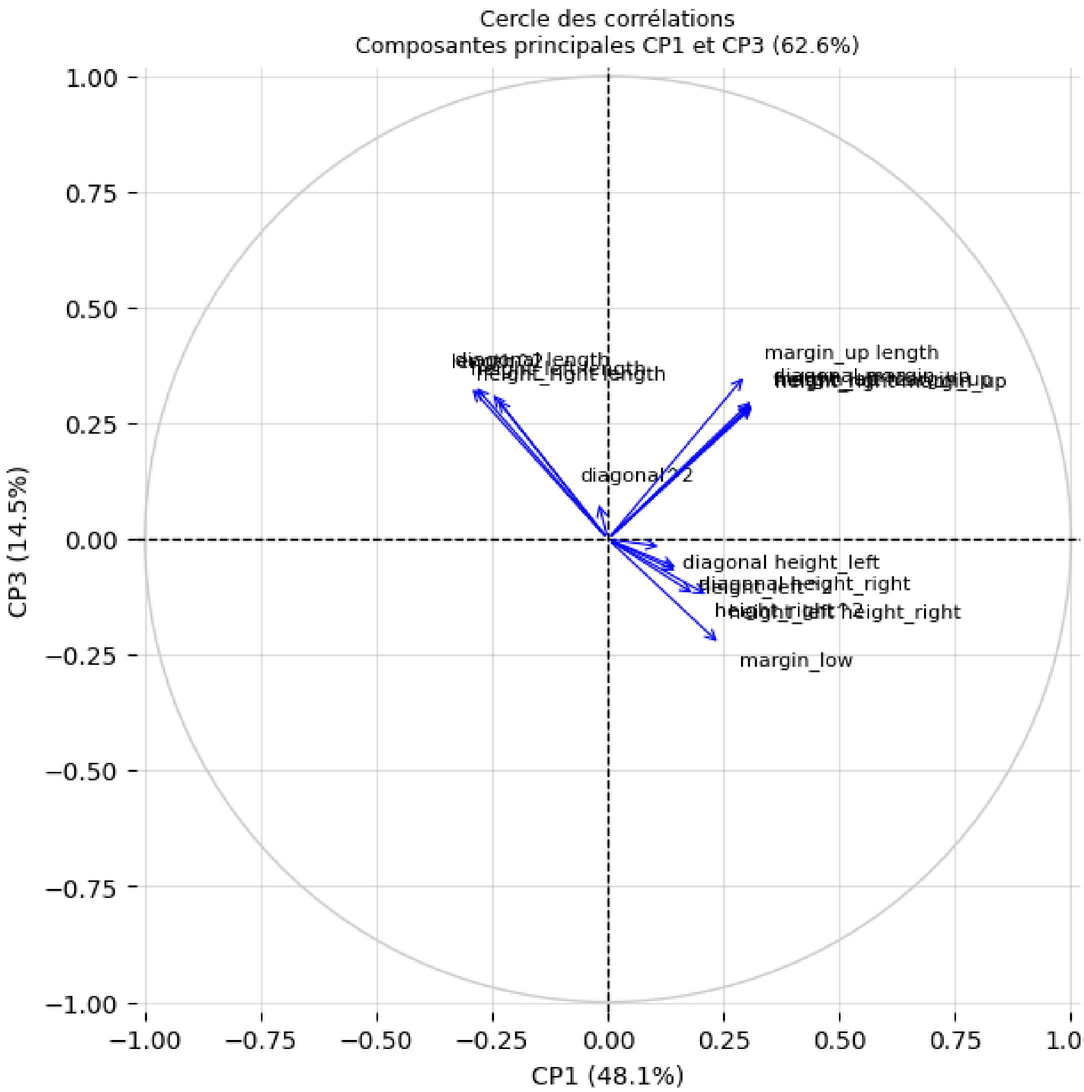



```
[271]: def cercle_correlation_graph(dimension_sur_x, dimension_sur_y,␣
 ↪pca=PCA(n_components=4).fit(data_scaled), text_offset=0.04):

    vecteurs_propres = pca.components_.T
    cum_variance_ratio = (pca.explained_variance_ratio_[dimension_sur_x]
                          + pca.explained_variance_ratio_[dimension_sur_y])
```

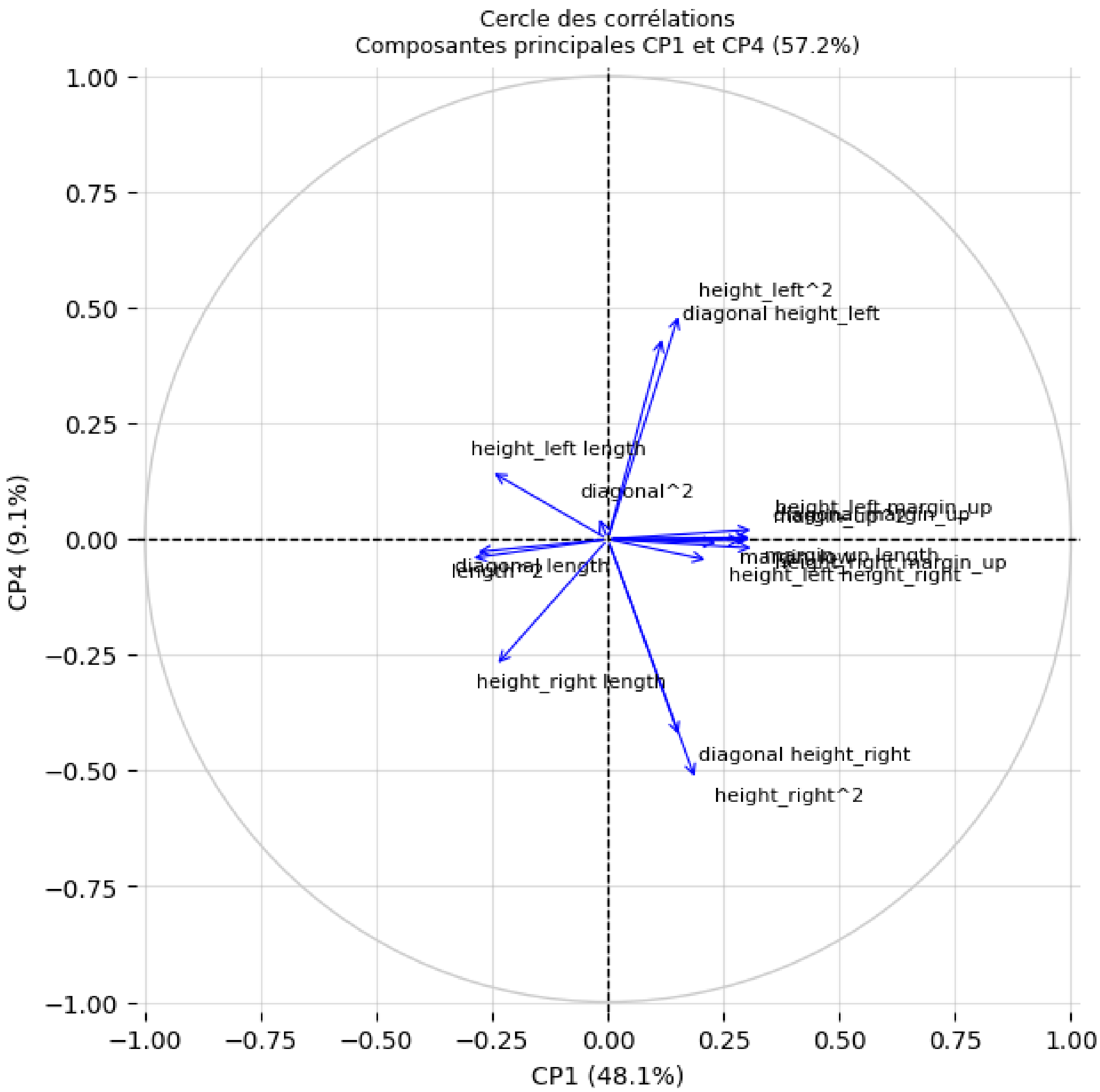
```python
fig, ax = plt.subplots(figsize=(6.4, 6.4))


ax.set_aspect('equal')
ax.grid(alpha=0.4)
ax.set_axisbelow(True)
ax.set_xlim(-1.02, 1.02)
ax.set_ylim(-1.02, 1.02)

for spine in ax.spines.values():
    spine.set_visible(False)

circle = plt.Circle((0, 0), 1, fill=False, linewidth=1, color='0.8')
ax.add_patch(circle)
ax.axhline(y=0, linestyle = '--', linewidth=0.9, color='k')
ax.axvline(x=0, linestyle = '--', linewidth=0.9, color='k')


for i in range(len(vecteurs_propres)):

    ax.annotate(
        text='',
        xy=(vecteurs_propres[i, dimension_sur_x], vecteurs_propres[i,␣
↪dimension_sur_y]),
        xytext=(0, 0),
        arrowprops=dict(arrowstyle='->', linewidth=0.8, color='b')
    )


    if vecteurs_propres[i, dimension_sur_x] > 0:
        h_offset=text_offset
    elif vecteurs_propres[i, dimension_sur_x] < 0:
        h_offset=-text_offset

    if vecteurs_propres[i, dimension_sur_y] > 0:
        v_offset=text_offset
    elif vecteurs_propres[i, dimension_sur_y] < 0:
        v_offset=-text_offset


    ax.text(
        x=(vecteurs_propres[i, dimension_sur_x]+h_offset),
        y=(vecteurs_propres[i, dimension_sur_y]+v_offset),
        s=X_poly_df_margin_low.columns.to_list()[i], fontsize=8
    )
```

```
    ax.set_xlabel(f'CP{dimension_sur_x + 1} ({pca.
↪explained_variance_ratio_[dimension_sur_x]:.1%})')
    ax.set_ylabel(f'CP{dimension_sur_y + 1} ({pca.
↪explained_variance_ratio_[dimension_sur_y]:.1%})')

    ax.set_title(
        f'Cercle des corrélations\n'
        f'Composantes principales CP{dimension_sur_x + 1} et CP{dimension_sur_y␣
↪+ 1} ({cum_variance_ratio:.1%})',
        fontsize= 9)

    plt.tight_layout()

    plt.show()
```

[272]:
```
cercle_correlation_graph(0, 2)
```




```
[290]: cercle_correlation_graph(0, 3)
```



[ ]:

```python
# Diviser les données en ensembles d'entraînement et de test
# X est votre DataFrame contenant vos features, y est votre variable cible
billets_witnout_nan['diagonal_length'] = billets_witnout_nan['diagonal'] * billets_witnout_nan['length']
billets_witnout_nan['length^2'] = billets_witnout_nan['length'] * billets_witnout_nan['length']
X_train, X_test, y_train, y_test = train_test_split(billets_witnout_nan[['diagonal_length', 'length^2']], billets_witnout_nan['margin_low'], test_size=0.3, random_state=42)
```

[274]:

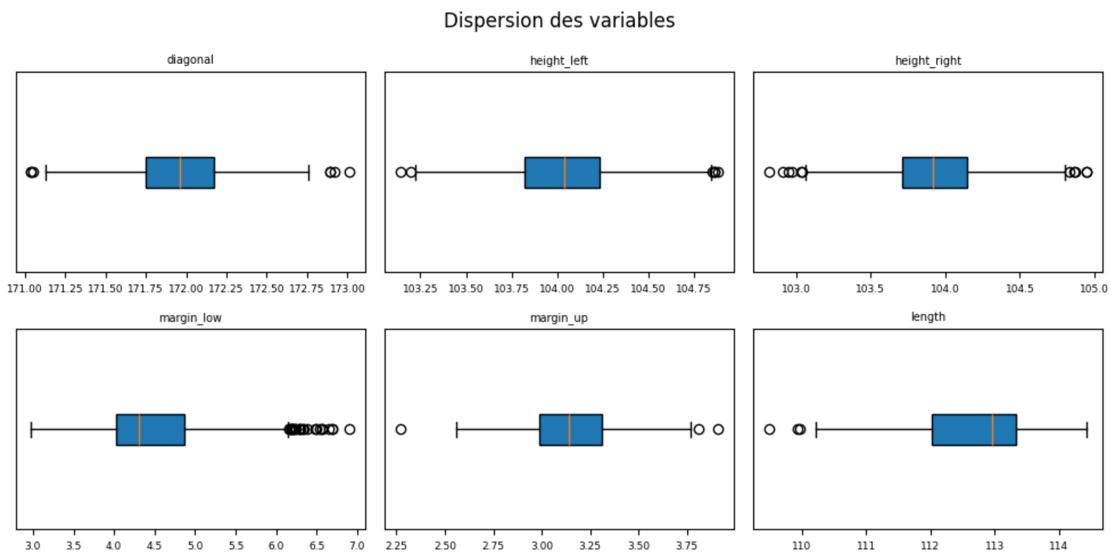
```python
df_billets['diagonal_length'] = df_billets['diagonal'] * df_billets['length']
df_billets['length^2'] = df_billets['length'] * df_billets['length']
# Créez et entraînez un modèle de régression linéaire
```

```
model = LinearRegression()
model.fit(X_train, y_train)

# Prédisez les valeurs manquantes dans la variable cible
missing_values = df_billets[df_billets['margin_low'].
↪isna()][['diagonal_length', 'length^2']]  # features est la liste des␣
↪features sélectionnées
predicted_values = model.predict(missing_values)

# Remplacez les valeurs manquantes par les valeurs prédites
df_billets.loc[df_billets['margin_low'].isna(), 'margin_low'] = predicted_values
```

[281]:
```
#moyenne des valeurs manquantes prédites par notre régression linéaire
print(predicted_values.mean())
print(predicted_values.std())
```

```
4.411567886045393
0.4232528658515769
```

[193]:
```
variables = ['diagonal', 'height_left', 'height_right', 'margin_low',␣
↪'margin_up', 'length']
fig, axs = plt.subplots(2, 3, figsize=(10, 5))

for i, var in enumerate(variables):
    r = i // 3
    c = i % 3
    axs[r, c].boxplot(var, data=df_billets[['diagonal', 'height_left',␣
↪'height_right',
                                            'margin_low', 'margin_up',␣
↪'length']],
                      patch_artist=True, vert=False)
    axs[r, c].set_title(var, size=7)
    axs[r, c].yaxis.set_major_locator(plt.NullLocator())
    axs[r, c].tick_params(axis='x', which='both', labelsize=6.5)


[fig.delaxes(ax) for ax in axs.flatten() if not ax.has_data()]

fig.suptitle('Dispersion des variables')

plt.tight_layout()

plt.show()

del fig, axs, i, var, r, c
```



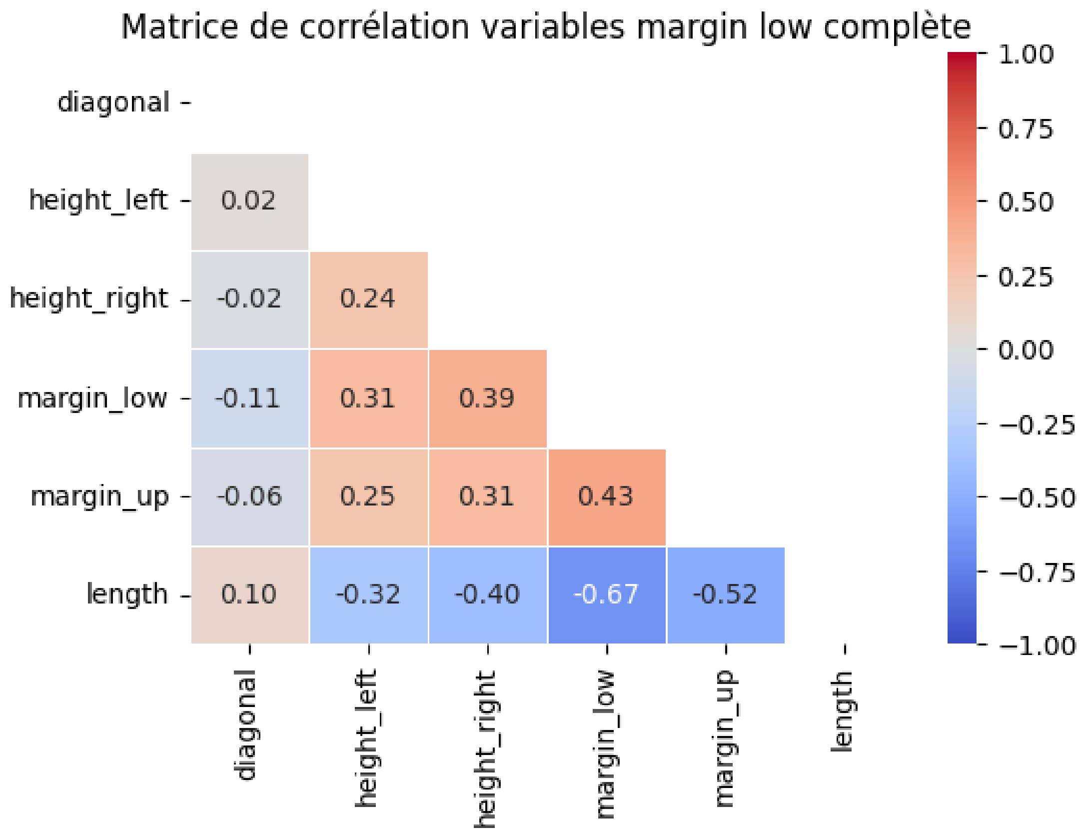
[643]:
```
df_billets.describe().style.background_gradient(axis='rows', cmap='coolwarm').
↪format('{:.2f}')
```

[643]: <pandas.io.formats.style.Styler at 0x136fb5a10>

[196]:
```
#heatmap : corrélation entre les variables après traitement des 37 valeurs␣
↪manquantes :
matrice_corr = df_billets[['diagonal', 'height_left', 'height_right',
                                    'margin_low', 'margin_up', 'length']].
↪corr(numeric_only=True, method='pearson')
matrice_corr.style.background_gradient(axis='rows', cmap='coolwarm').format('{:.
↪2f}')
```

[196]: <pandas.io.formats.style.Styler at 0x134e10b90>

[197]:
```
#Heatmap après traitement des 37 valeurs manquantes
fig, ax = plt.subplots(figsize=(6, 4))
mask = np.triu(np.ones_like(matrice_corr, dtype=bool))
sns.heatmap(matrice_corr, annot=True, fmt='.2f', vmin=-1, vmax=1,
annot_kws=None, linewidths=0.6, cmap='coolwarm', ax=ax, mask=mask)

ax.set_title('Matrice de corrélation variables margin low complète')

plt.show()

del fig, ax
```



[284]:

```
#Vérification de la fiabilité de mon modèle de régression après transformation␣
↪polynomiale:
#Calculs des résidus : différence entre les valeurs observées et les valeurs␣
↪prédites par le modèle: c'est à dire que je vais calculer des
#valeurs selon mon modèle pour chaque valeur de ma partie test et je compare␣
↪(différence) avec la valeur qu'on m'a donnée
# Ils représentent l'erreur de prédiction pour chaque observation


X_train, X_test, y_train, y_test =␣
↪train_test_split(df_billets[['diagonal_length', 'length^2']],␣
↪df_billets['margin_low'], test_size=0.3, random_state=42)
y_pred = model.predict(X_test)
r2 = model.score(X_train, y_train)
```

[289]:

```
mse = metrics.mean_squared_error(y_test, y_pred)
print(r2, mse)
# Calcule R² ajusté
n = len(y_test)
k = 2
```

```python
ajusted_r2 = 1 - ((1-r2)*(n-1)/(n-k-1))

# Affiche la valeur de R² ajusté
print(f'R2 ajusté : {ajusted_r2:.6f}')

del n, k, r2, ajusted_r2
```

```
0.4500029478337716 0.24015017406403918
R2 ajusté : 0.447542
```

[ ]:

```python
#Je vais essayer d'inclure 2 autres nouvelles features dans mon modèle et␣
 ↪revoir si çà augmente sa fiabilité :
# Diviser les données en ensembles d'entraînement et de test
# X est votre DataFrame contenant vos features, y est votre variable cible
#billets_witnout_nan['diagonal_length'] = billets_witnout_nan['diagonal'] *␣
 ↪billets_witnout_nan['length']
#billets_witnout_nan['length^2'] = billets_witnout_nan['length'] *␣
 ↪billets_witnout_nan['length']
billets_witnout_nan['height_right_length'] =␣
 ↪billets_witnout_nan['height_right'] * billets_witnout_nan['length']
billets_witnout_nan['height_left_length'] = billets_witnout_nan['height_left']␣
 ↪* billets_witnout_nan['length']
X_train, X_test, y_train, y_test =␣
 ↪train_test_split(billets_witnout_nan[['diagonal_length', 'length^2',
                                                                              ␣
 ↪'height_right_length', 'height_left_length']],
                                                                ␣
 ↪billets_witnout_nan['margin_low'],
                                                    test_size=0.3,␣
 ↪random_state=42)
df_billets = pd.read_csv('/Users/helmisaddem/Documents/billets.csv', sep=';')
df_billets['diagonal_length'] = df_billets['diagonal'] * df_billets['length']
df_billets['length^2'] = df_billets['length'] * df_billets['length']
df_billets['height_right_length'] = df_billets['height_right'] *␣
 ↪df_billets['length']
df_billets['height_left_length'] = df_billets['height_left'] *␣
 ↪df_billets['length']
# Créez et entraînez un modèle de régression linéaire
model = LinearRegression()
model.fit(X_train, y_train)

# Prédisez les valeurs manquantes dans la variable cible
missing_values = df_billets[df_billets['margin_low'].
 ↪isna()][['diagonal_length', 'length^2', 'height_right_length',␣
 ↪'height_left_length']]  # features est la liste des features sélectionnées
predicted_values = model.predict(missing_values)
```

```
# Remplacez les valeurs manquantes par les valeurs prédites
df_billets.loc[df_billets['margin_low'].isna(), 'margin_low'] = predicted_values
```

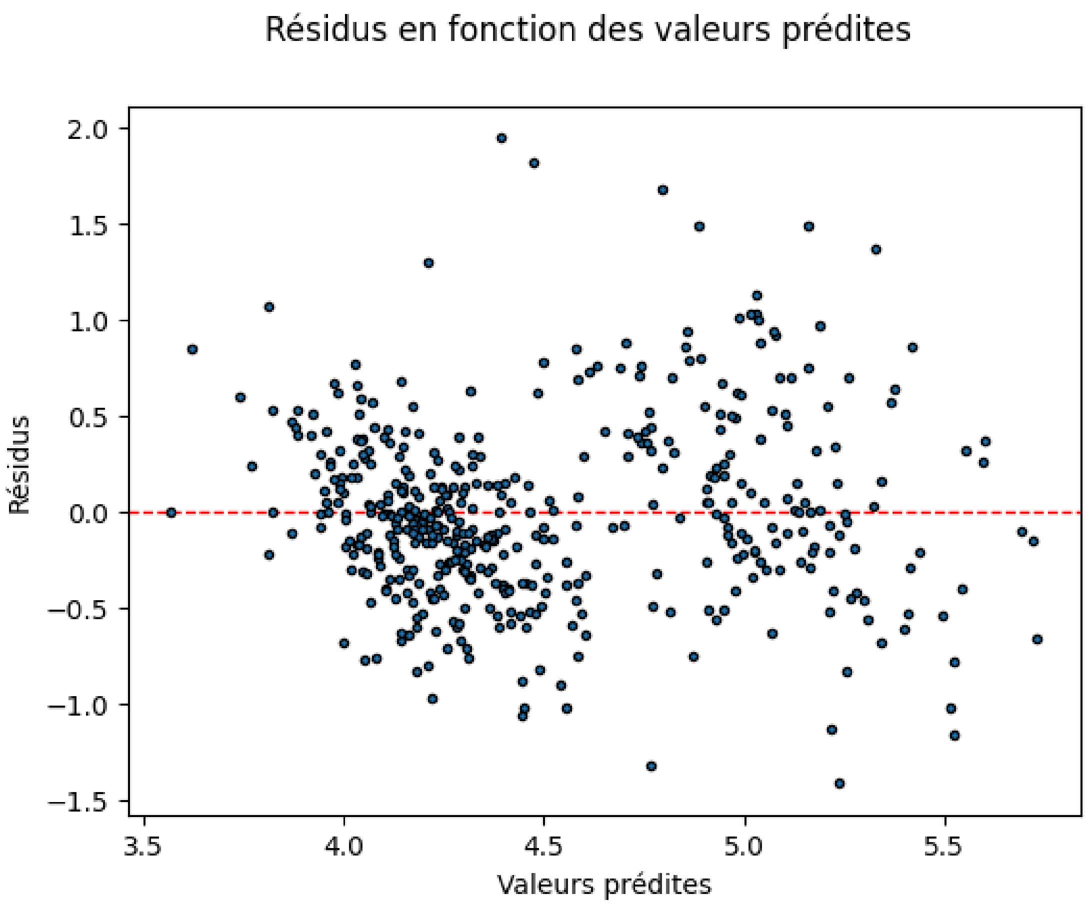
[673]:
```
X_train, X_test, y_train, y_test =␣
 ↪train_test_split(df_billets[['diagonal_length', 'length^2',␣
 ↪'height_right_length', 'height_left_length']],
                                                    df_billets['margin_low'],␣
 ↪test_size=0.3, random_state=42)
y_pred = model.predict(X_test)
r2 = model.score(X_train, y_train)
print(r2)

#Reapplication du modèle avec 4 feature donne un r2 meilleur qu'avec seulement 2
```

0.47323524316395826

[674]:
```
#R2 ajusté :
n = len(y_test)
k = 4
ajusted_r2 = 1 - ((1-r2)*(n-1)/(n-k-1))
print(ajusted_r2)
```

0.46850027905756686

[675]:
```
# Répartition des résidus en fonction des valeurs prédites : motifs aléatoires ?
residus = y_test - y_pred
fig, ax = plt.subplots()

ax.scatter(x=y_pred, y=residus, marker='.', edgecolors='k')
ax.axhline(y=0, color='r', linestyle='--', linewidth=1, zorder=0)

ax.set_xlabel('Valeurs prédites')
ax.set_ylabel('Résidus')
fig.suptitle('Résidus en fonction des valeurs prédites')

plt.show()

del fig, ax
```

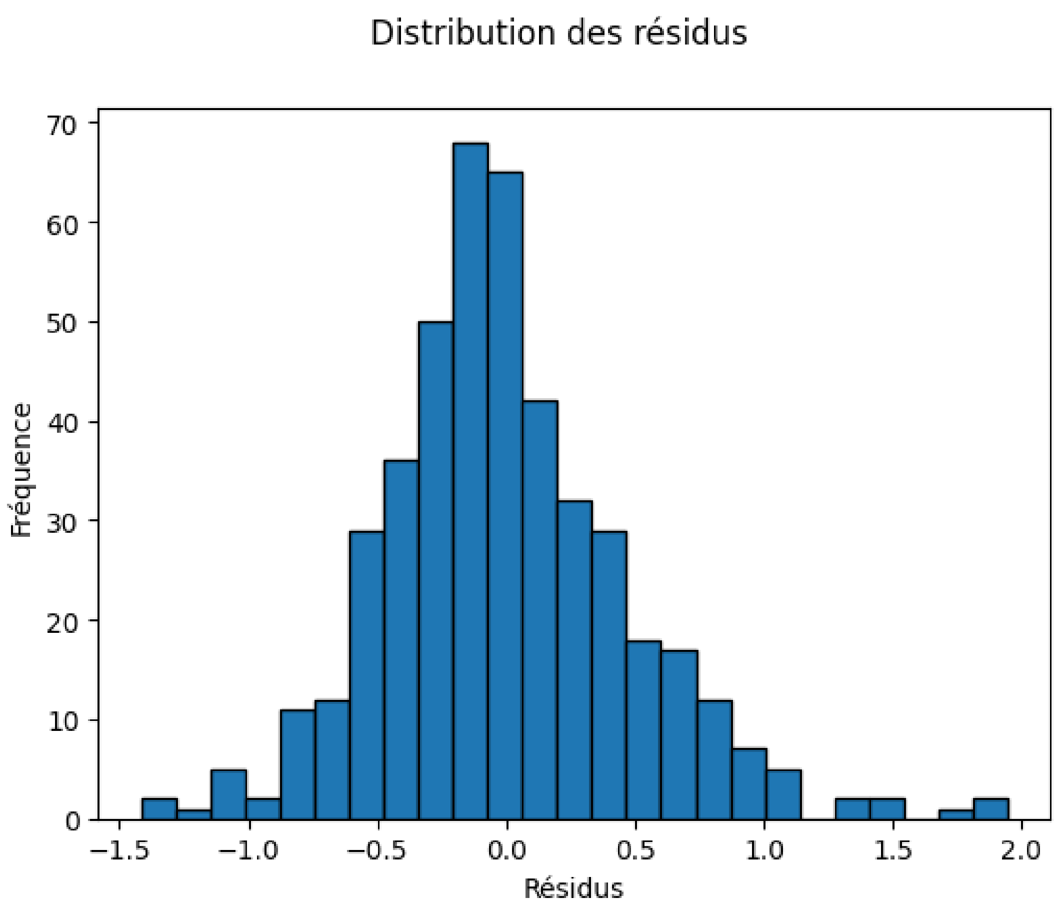


[676]:
```python
# Tester l'auto corrélation entre résidus par le test de Durbin-Watson:
print(f'Durbin-Watson : {durbin_watson(residus):.3f}')

# Tester l'homoscédasticité entre résidus par le test de Breusch-Pagan :
print(f'p-value : {het_breuschpagan(residus, X_test.assign(constant=1))[1]:.
↪3e}')

#Si la p-valeur est inférieure à un seuil de significativité donné (par␣
↪exemple, 0,05), on rejette
# l'hypothèse nulle selon laquelle il n'y a pas d'hétéroscédasticité dans le␣
↪modèle. Cela signifie qu'il y a suffisamment
# de preuves pour conclure que les résidus présentent une hétéroscédasticité␣
↪statistiquement significative,
# ce qui indique que la variance des erreurs de régression n'est pas constante␣
↪à travers
# toutes les valeurs de la variable indépendante.
#Si la p-valeur est supérieure au seuil de significativité,
```

```
# on ne rejette pas l'hypothèse nulle. Cela signifie qu'il n'y a pas␣
↪suffisamment de
# preuves pour conclure à la présence d'une hétéroscédasticité statistiquement␣
↪significative dans le modèle
```

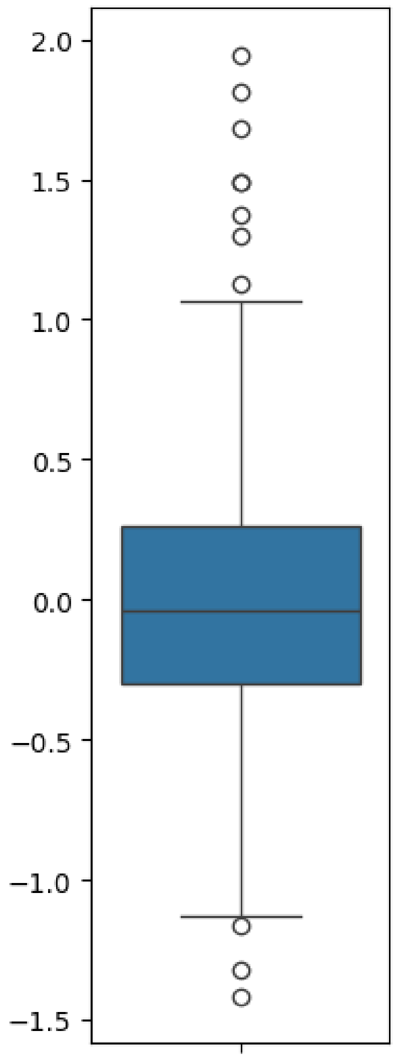
```
Durbin-Watson : 1.927
p-value : 4.096e-04
```

[677]:
```
# Trace le graphique
fig, ax = plt.subplots()

ax.hist(x=residus, bins=25, edgecolor='k')
#ax.axvline(x=0, linestyle='--', linewidth=1, color='r')

ax.set_xlabel('Résidus')
ax.set_ylabel('Fréquence')
fig.suptitle('Distribution des résidus')

plt.show()

del fig, ax
```



[678]:
```
# Boxplot des résidus pour vérifier la normalité :
plt.figure(figsize=(2, 7))
sns.boxplot(y=residus)
plt.ylabel("")
```

[678]: Text(0, 0.5, '')



[ ]:
```
# Une fois le dataset est complet, on va appliquer les algorithmes : K-Means,␣
↪KNN, Random-Forest, Regression logistique
```

[679]:
```
# Vérification du nombre de vrais/faux billets
df_billets.drop(columns=['diagonal_length', 'length^2', 'height_right_length',␣
↪'height_left_length'], inplace=True)
df_billets['is_genuine'].value_counts()
```

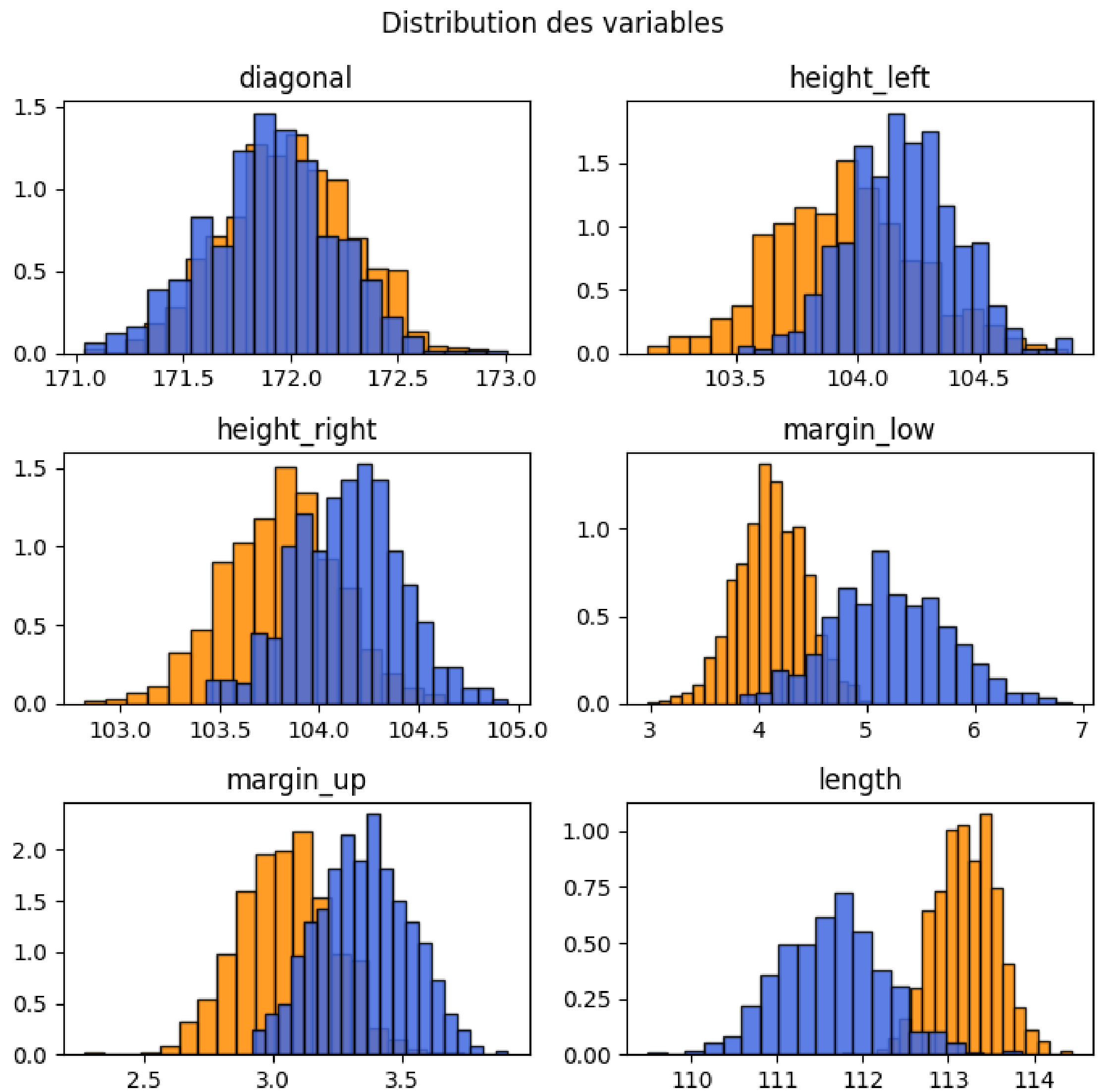
[679]:
```
is_genuine
True     1000
False     500
Name: count, dtype: int64
```

[680]:
```
# Affichage de la moyenne et de la médiane des variables pour les vrais et faux␣
↪billets
df_billets.groupby('is_genuine').agg({'mean', 'median'}).round(3).stack()
```

[680]:
```
                   diagonal  height_left  height_right  margin_low  margin_up  \
is_genuine
False      mean     171.901      104.190       104.144       5.214      3.350
           median   171.910      104.180       104.160       5.180      3.350
True       mean     171.987      103.949       103.809       4.118      3.052
           median   171.990      103.950       103.810       4.120      3.050

                    length
is_genuine
False      mean    111.631
           median  111.630
True       mean    113.202
           median  113.205
```

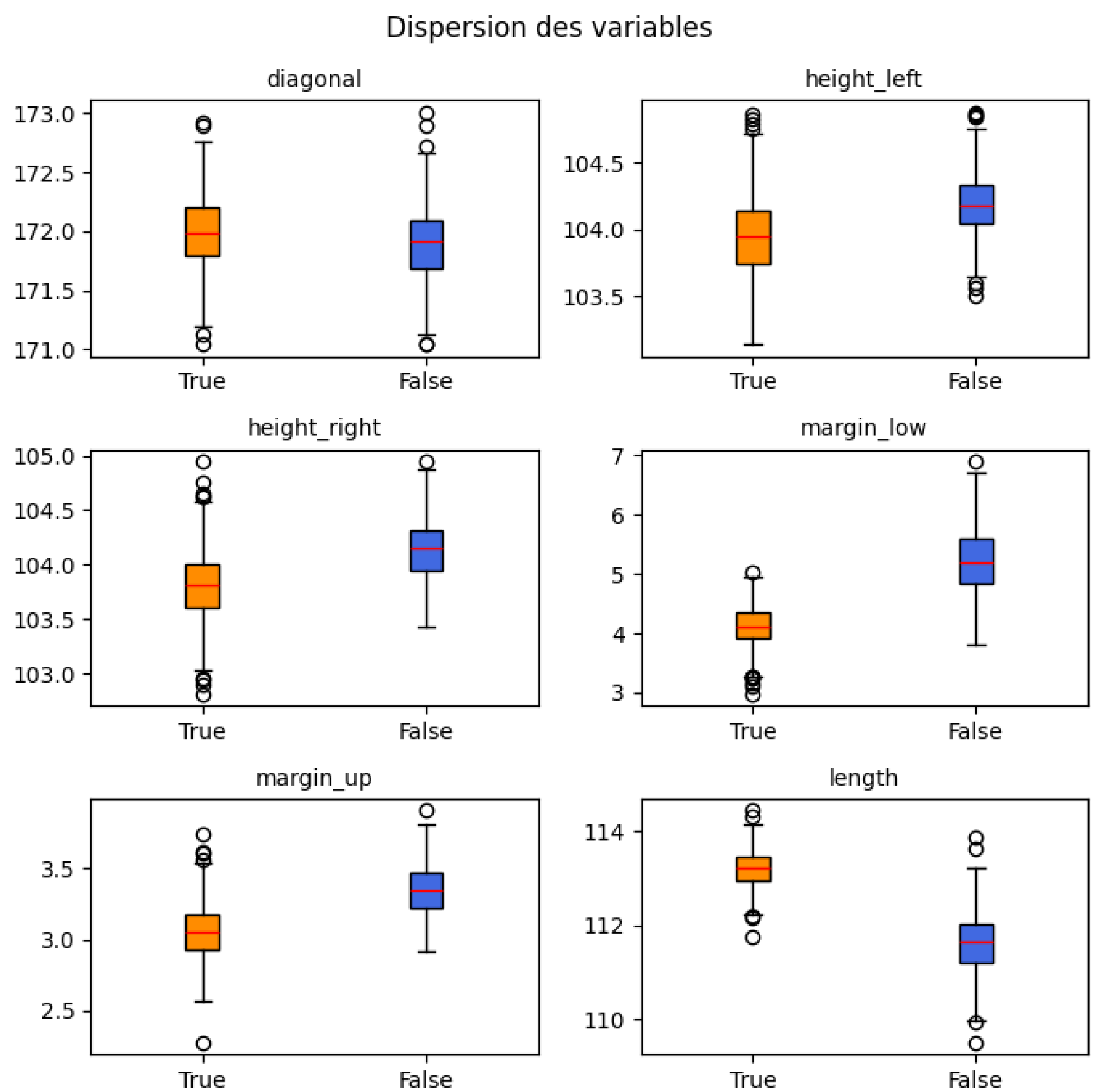
[360]:
```
#Histogrammes genuine_True et genuine_False en fonction des différentes␣
↪variables
genuine_values = df_billets['is_genuine'].unique()

fig, axs = plt.subplots(3, 2, figsize=(7, 7))
axs = axs.flatten()
colors = ['darkorange', 'royalblue']
for i, column in enumerate(df_billets.columns[1:]):
    for j, k in enumerate(genuine_values):
        axs[i].hist(df_billets.loc[df_billets['is_genuine'] == k, column],␣
↪alpha=0.85, bins=20, edgecolor='k', density=True, color= colors[j])
        axs[i].set_title(column, size=10)

fig.suptitle('Distribution des variables')

fig.tight_layout()

plt.show()
```

```python
del genuine_values, colors, fig, axs, i, column, j, k
```

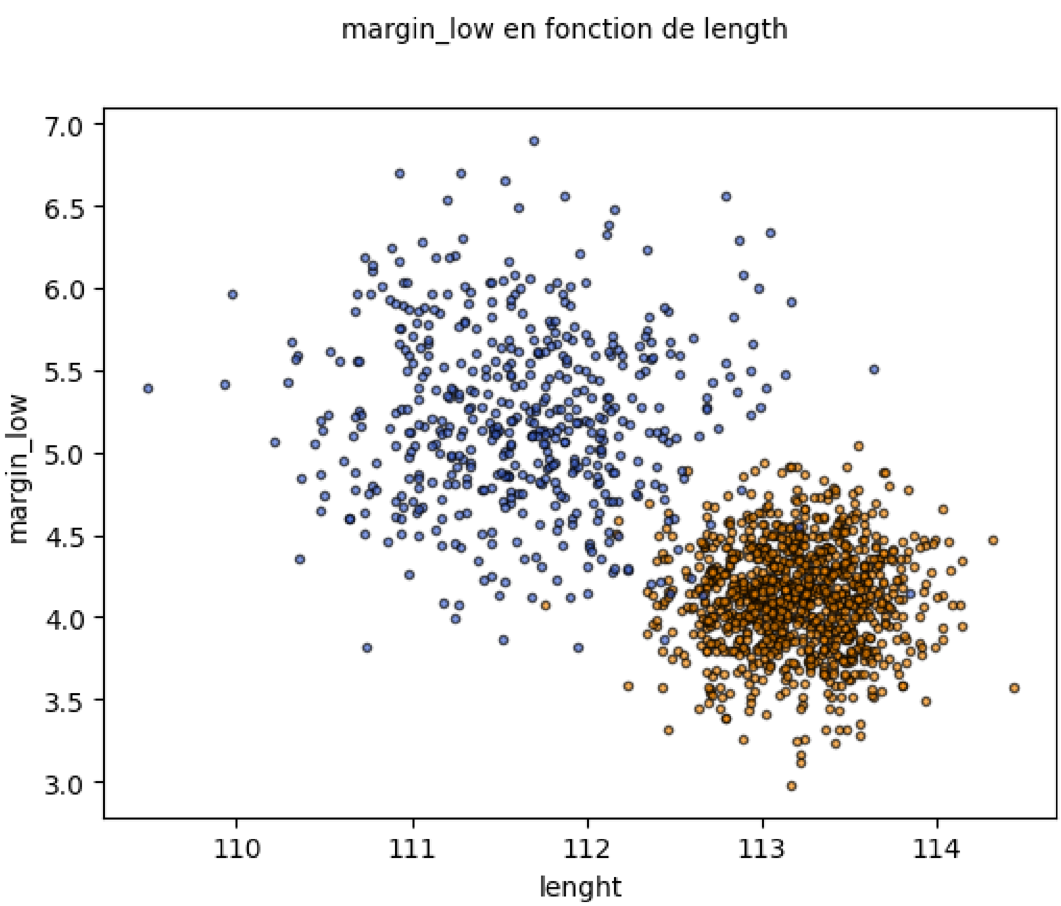


[361]:
```python
genuine_values = df_billets['is_genuine'].unique()
colors = ['darkorange', 'royalblue']
# Trace les boxplots de chaque variable
fig, axs = plt.subplots(3, 2, figsize=(7, 7))
axs = axs.flatten()

for i, column in enumerate(df_billets.columns[1:]):
    for j, k in enumerate(genuine_values):
        axs[i].boxplot(df_billets.loc[df_billets['is_genuine'] == k, column],␣
↪positions=[j], patch_artist=True,  # Remplir les boîtes avec des couleurs
```

```
            boxprops=dict(facecolor= colors [j]),␣
↪medianprops=dict(color='red'))  # Couleur des boîtes
        axs[i].set_title(column, size =10)

    axs[i].set_xticklabels(genuine_values)

fig.suptitle('Dispersion des variables')

fig.tight_layout()

plt.show()

del genuine_values, fig, axs, i, column, j, k
```



[362]:
```
# 'margin_low' en fonction de 'length': 2 populations
fig, ax = plt.subplots()

ax.scatter(data=df_billets[df_billets['is_genuine'] == True],
           x='length', y='margin_low', marker='.', edgecolors='k', alpha=0.65,␣
 ↪color = 'darkorange')
ax.scatter(data=df_billets[df_billets['is_genuine'] == False],
           x='length', y='margin_low', marker='.', edgecolors='k', alpha=0.65,␣
 ↪color = 'royalblue')

ax.set_xlabel('lenght')
ax.set_ylabel('margin_low')

fig.suptitle('margin_low en fonction de length', size=10)

plt.show()

del fig, ax
```



[368]:
```
df_billets.columns
```

[368]:
```
Index(['is_genuine', 'diagonal', 'height_left', 'height_right', 'margin_low',
       'margin_up', 'length'],
      dtype='object')
```

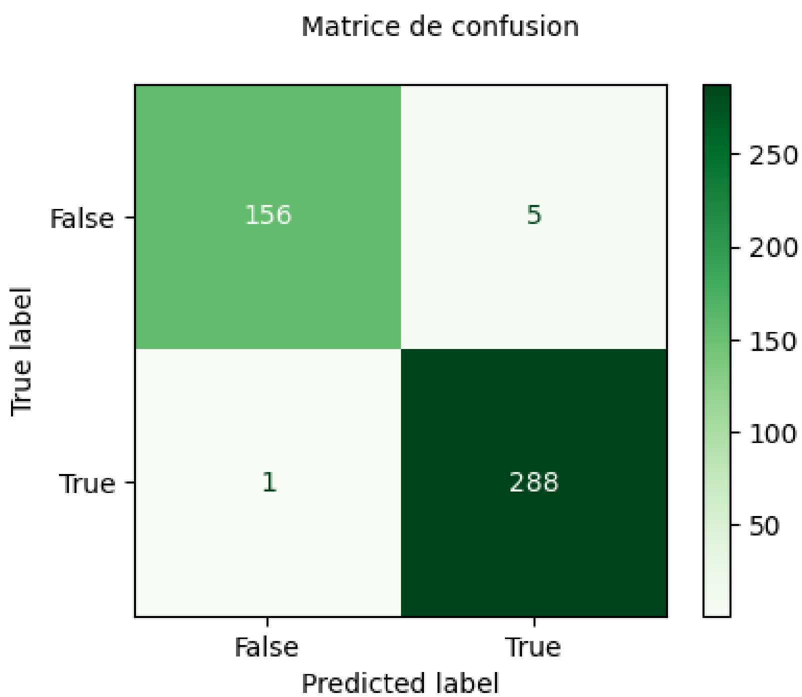
[681]:
```
X_train, X_test, y_train, y_test = train_test_split(df_billets[['diagonal',␣
 ↪'height_left',
                                                                 'height_right',␣
 ↪'margin_low',
                                                                 'margin_up',␣
 ↪'length']],
                                                    df_billets['is_genuine'],␣
 ↪test_size=0.3, random_state=42)
```

[552]:
```
# Fonction qui regroupe les crières d'évaluation d'un modèle :
def criteres_evaluation_model(y_test, y_pred):
    metrics_results = pd.DataFrame({'accuracy': [metrics.accuracy_score(y_test,␣
 ↪y_pred)],
              'recall_true': [metrics.recall_score(y_test, y_pred,␣
 ↪pos_label=True)],     #sensibilité
              'recall_False': [metrics.recall_score(y_test, y_pred,␣
 ↪pos_label=False)],   #spécificité
              'precision_true': [metrics.precision_score(
            y_test, y_pred, pos_label=True)],     #VPP
              'precision_false': [metrics.precision_score(
            y_test, y_pred, pos_label=False)],      #VPN
              'f1_score': [metrics.f1_score(
            y_test, y_pred, pos_label=False)]})
    return metrics_results
```

[682]:
```
#Application des algorithmes de détection de faux billets
#1- Régression Logistique:

regression_logistiq = LogisticRegression()
regression_logistiq.fit(X_train, y_train)


y_pred = regression_logistiq.predict(X_test)
#plt.figure(figsize=(2, 4))
#plt.bar(['predicted_True', 'predicted_False'], [sum(y_pred), len(y_pred) -␣
 ↪sum(y_pred)], color=['darkorange', 'royalblue'])
#plt.xticks(size=6)
```

[683]:
```
# Matrice de confusion
fig, ax = plt.subplots(figsize=(4.8, 3.6))
```

```
metrics.ConfusionMatrixDisplay.from_predictions(
    y_test, y_pred, ax=ax, cmap='Greens')

fig.suptitle('Matrice de confusion', size=10)

plt.show()

del fig, ax
```

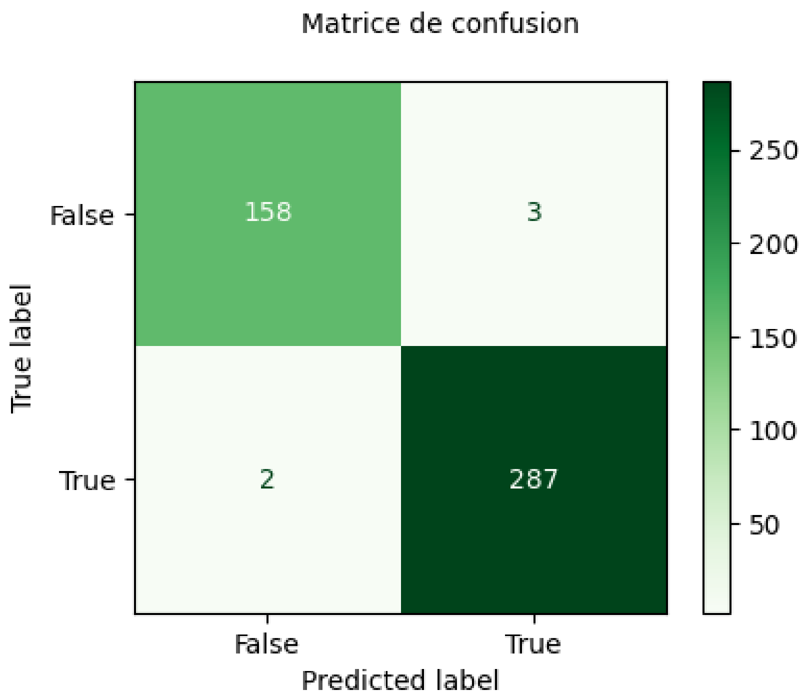


[684]:
```
df1 = criteres_evaluation_model(y_test, y_pred)
```

[ ]:
```
#Optimisation avec GridSearchCV :
GridSearchCV(
    LogisticRegression(max_iter=1000, random_state=0),
    param_grid={'C': [0.01, 0.1, 1, 10, 100, 1000]}, scoring=metrics.
 ↪make_scorer(
        metrics.f1_score, pos_label=False), cv=5).fit(
            X_train, y_train).best_params_
```

[705]:
```
#Valeur optimale de C = 10: on va refaire la regression logistique en precisant␣
 ↪C = 10
y_pred = LogisticRegression(C=10, max_iter=100).fit(X_train, y_train).
 ↪predict(X_test)
```

```python
fig, ax = plt.subplots(figsize=(4.8, 3.6))

#Matrice de confusion:
metrics.ConfusionMatrixDisplay.from_predictions(
    y_test, y_pred, ax=ax, cmap='Greens')
fig.suptitle('Matrice de confusion', size=10)

plt.show()
```



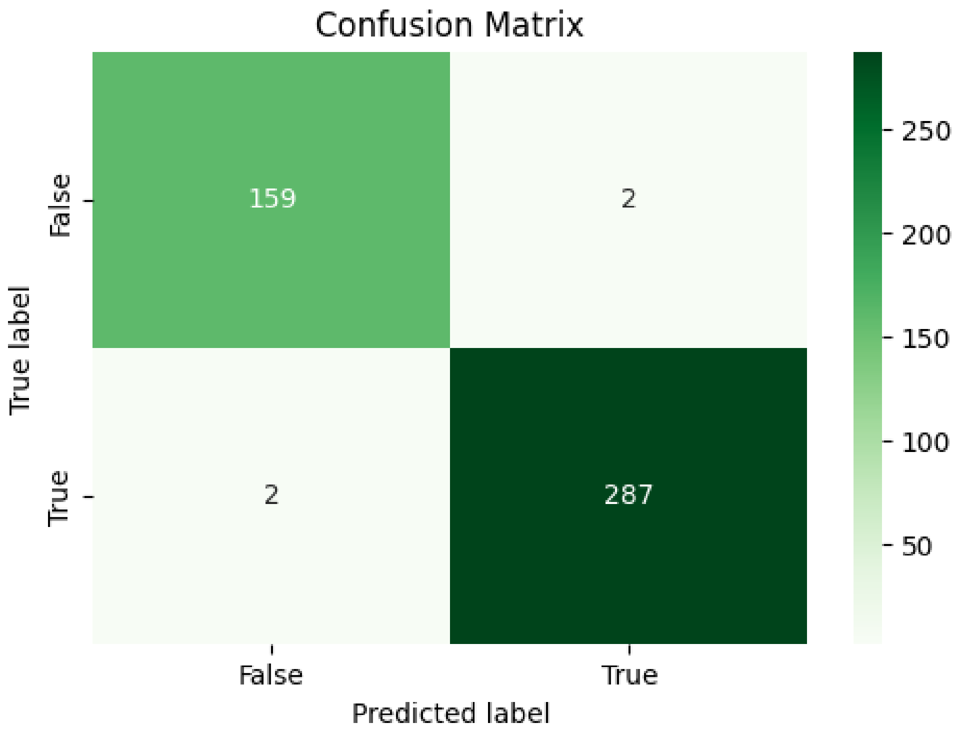
[687]:
```python
# modele après optimisation :
df2 = criteres_evaluation_model(y_test, y_pred)
#Amélioration de la spécificité 0.98 contre 0.96
```

[688]:
```python
# Sauvegarde du modèle choisi
with open('reg_logistiq.pkl', 'wb') as file:
    pickle.dump(LogisticRegression(C=10, max_iter=100).fit(X_train, y_train),␣
 ↪file)
```

[ ]:
```python
#Il est important que l'algorithme soit plus précis sur la détection des faux␣
 ↪billets que sur celle des vrais billets :
# il est plus problématique de détecter les faux billet parmi les vrais
# Ce sont donc les métriques des faux billets qui nous interesse
```

[565]:
```
# 2eme méthode K-Means: normalisation nécessaires des données
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

#cluster_labels = KMeans(n_clusters=2, init='k-means++', n_init='auto',␣
↪random_state=42).fit(X_train_scaled).labels_
#cluster_labels = np.asarray(cluster_labels)
#true_labels = y_train * 1

true_labels_test = y_test * 1


# Predict the clusters for the same training data
y_pred = KMeans(n_clusters=2, init='k-means++', n_init='auto', random_state=42).
↪fit(X_train_scaled).predict(X_test_scaled)

# Map the predicted cluster labels to the original true labels
mapped_predicted_labels = np.zeros_like(y_pred)
for cluster in np.unique(y_pred):
    mask = (y_pred == cluster)
    mapped_predicted_labels[mask] = mode(true_labels_test[mask])[0]

# Create confusion matrix with mapped predicted labels
conf_matrix = confusion_matrix(true_labels_test, mapped_predicted_labels)
print("Confusion Matrix:\n", conf_matrix)

# Plot the confusion matrix
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Greens",␣
↪xticklabels=[False, True], yticklabels=[False, True])
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix')
plt.show()
```

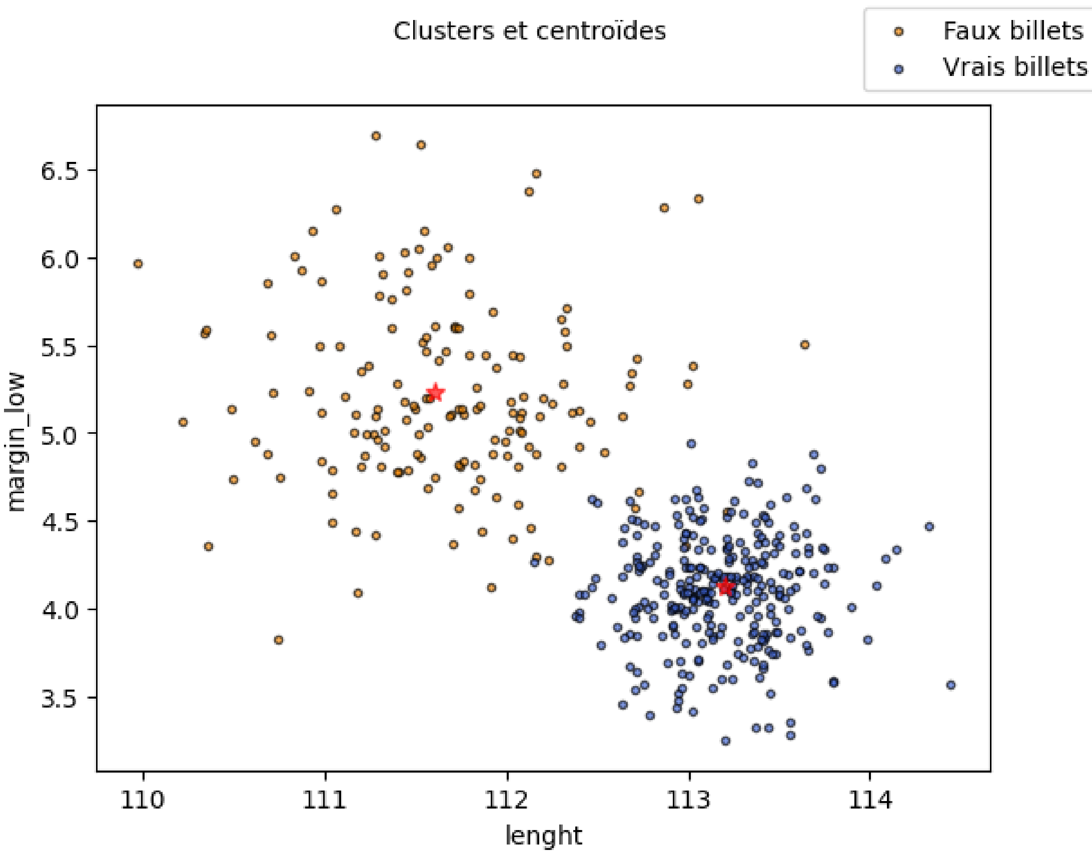
```
Confusion Matrix:
 [[159   2]
 [  2 287]]
```



[567]:
```
df_3 = criteres_evaluation_model(true_labels_test, mapped_predicted_labels)
```

[568]:
```
# Trace les clusters et leur centroïde avec 'margin_low' et 'length'
df_temp = X_test.copy()
df_temp['cluster'] = y_pred

fig, ax = plt.subplots()

ax.scatter(data=df_temp[df_temp['cluster'] == 1],
           x='length', y='margin_low', marker='.', edgecolors='k', alpha=0.65,␣
 ↪color = 'darkorange')
ax.scatter(data=df_temp[df_temp['cluster'] == 0],
           x='length', y='margin_low', marker='.', edgecolors='k', alpha=0.65,␣
 ↪color = 'royalblue')

ax.plot(scaler.inverse_transform(KMeans(n_clusters=2, init='k-means++',␣
 ↪n_init='auto', random_state=42).fit(X_train_scaled).cluster_centers_)[1][5],
        scaler.inverse_transform(KMeans(n_clusters=2, init='k-means++',␣
 ↪n_init='auto', random_state=42).fit(X_train_scaled).cluster_centers_)[1][3],
        marker='*', markersize=8, color='r', alpha=0.65)

ax.plot(scaler.inverse_transform(KMeans(n_clusters=2, init='k-means++',␣
 ↪n_init='auto', random_state=42).fit(X_train_scaled).cluster_centers_)[0][5],
```

```
        scaler.inverse_transform(KMeans(n_clusters=2, init='k-means++',␣
↪n_init='auto', random_state=42).fit(X_train_scaled).cluster_centers_)[0][3],
        marker='*', markersize=8, color='r', alpha=0.65)

ax.set_xlabel('lenght')
ax.set_ylabel('margin_low')

fig.suptitle('Clusters et centroïdes', size=10)

fig.legend(['Faux billets', 'Vrais billets'])

plt.show()

del fig, ax, df_temp
```

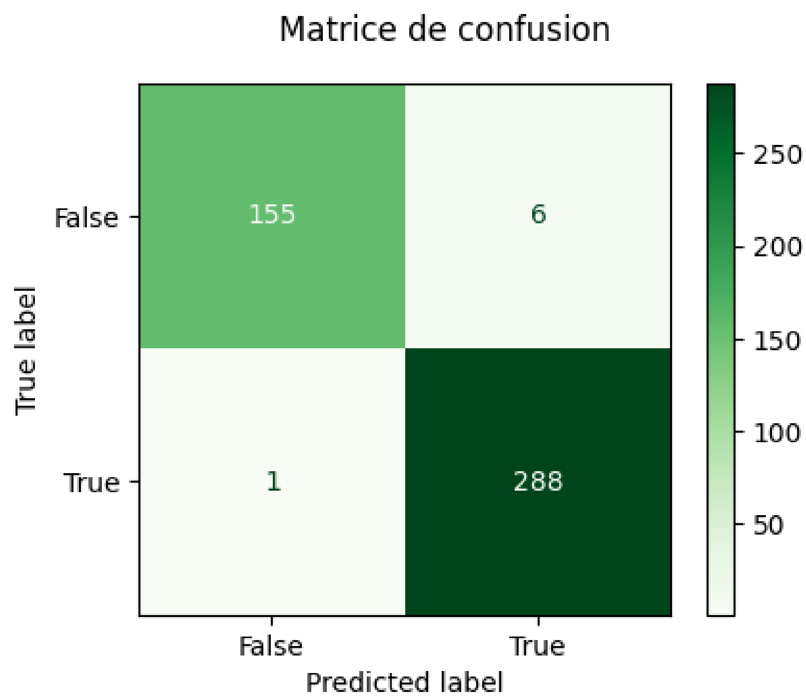


[569]:
```
# Calcul 'accuracy' pour 5 'folds'
scoring = metrics.make_scorer(metrics.f1_score, pos_label=False)
scores = cross_val_score(
    KMeans(n_clusters=2, init='k-means++', n_init='auto', random_state=42),
    X_train_scaled, y_train, cv=5, scoring=scoring
```

```
)

# Affiche les résulatats
print(
    f'f1-score_Faux_billets\n'
    f'min. :\t{np.min(scores):.6f}\n'
    f'max. :\t{np.max(scores):.6f}\n'
    f'moy. :\t{np.average(scores):.6f}'
)

del scores
```

```
f1-score_Faux_billets
min. :  0.967213
max. :  0.983051
moy. :  0.974873
```

[570]:
```
# Méthode 3 : KNN sans optimisation
y_pred = KNeighborsClassifier(n_neighbors=3).fit(X_train_scaled, y_train).
 ↪predict(X_test_scaled)

# Matrice de confusion
fig, ax = plt.subplots(figsize=(4.8, 3.6))

metrics.ConfusionMatrixDisplay.from_predictions(
    y_test, y_pred, ax=ax, cmap='Greens')

fig.suptitle('Matrice de confusion')

plt.show()

del fig, ax
```



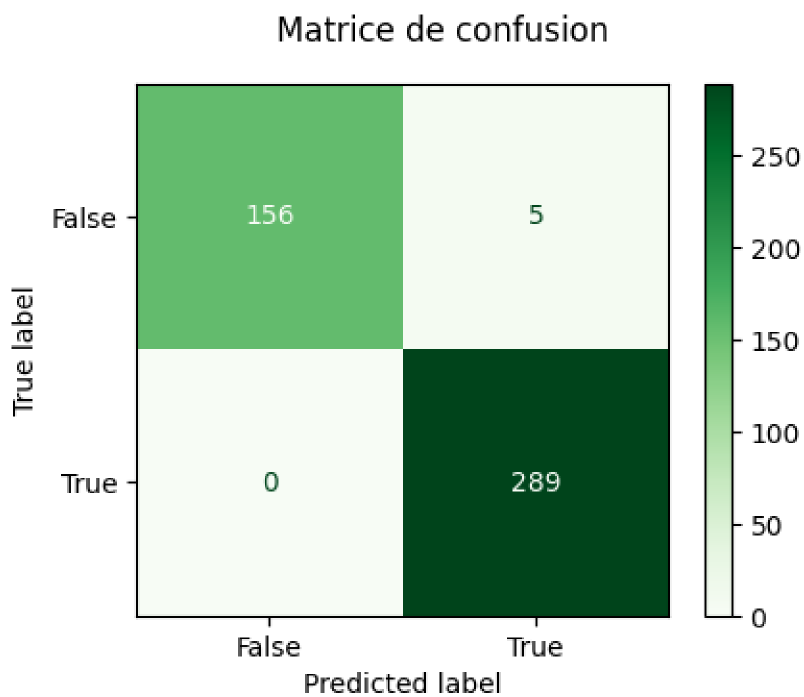
[572]:
```
df_4 = criteres_evaluation_model(y_test, y_pred)
```

[573]:
```
# Optimisation de KNN avec GridSearchCV:
param_grid = {
    'n_neighbors' : np.arange(1, 100, 3)
}

scoring = metrics.make_scorer(metrics.f1_score, pos_label=False)


# Meilleur paramètre
print(GridSearchCV(
    KNeighborsClassifier(),
    param_grid=param_grid, scoring=scoring, cv=5).fit(X_train_scaled, y_train).
 ↪best_params_)

del param_grid
```

```
{'n_neighbors': 10}
```

[574]:
```
# Prediction avec KNN en précisant n neighbors 10
y_pred = KNeighborsClassifier(n_neighbors=10).fit(X_train_scaled, y_train).
 ↪predict(X_test_scaled)
```

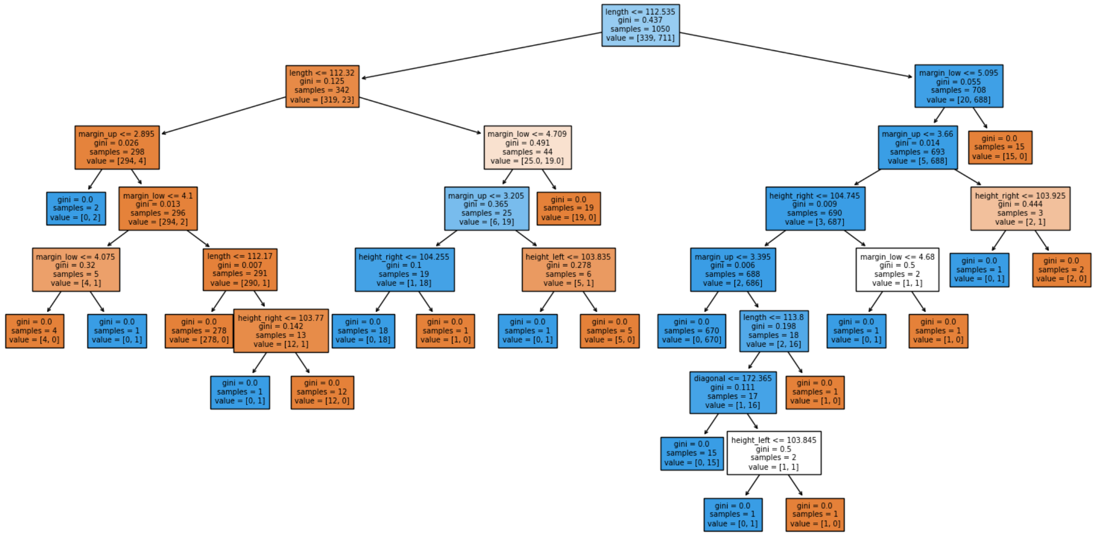
```
# Matrice de confusion
fig, ax = plt.subplots(figsize=(4.8, 3.6))

metrics.ConfusionMatrixDisplay.from_predictions(
    y_test, y_pred, ax=ax, cmap='Greens')

fig.suptitle('Matrice de confusion')

plt.show()

del fig, ax
```



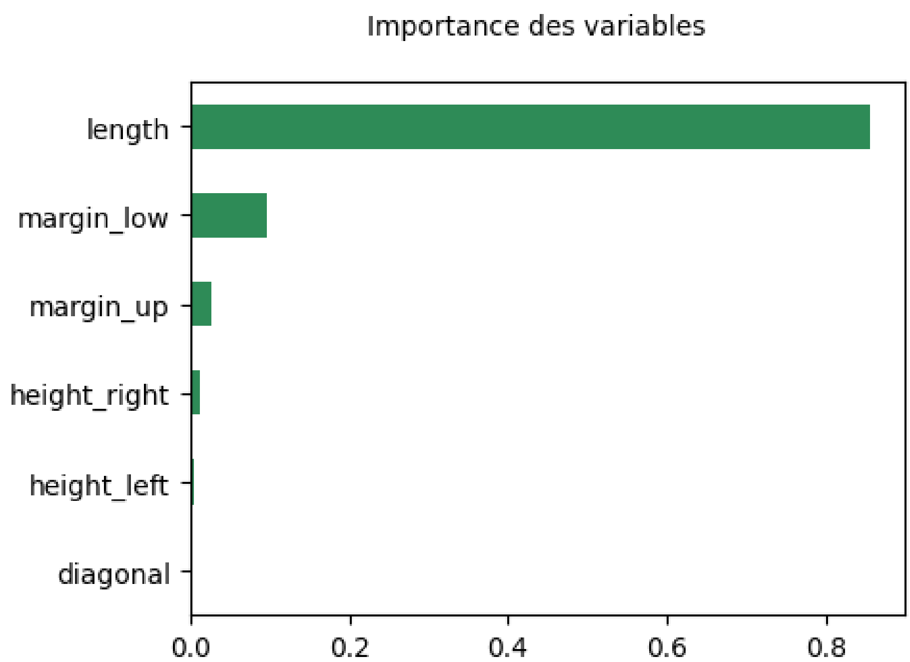
[576]:
```
df_5 = criteres_evaluation_model(y_test, y_pred)
```

[599]:
```
# Méthode 4 : Arbre de décision
y_pred = DecisionTreeClassifier(random_state=0).fit(X_train, y_train).
 ↪predict(X_test)


fig, ax = plt.subplots(figsize=(19.2, 9.6))
plot_tree(DecisionTreeClassifier(random_state=0).fit(X_train, y_train),␣
 ↪feature_names=X_train.columns, filled=True, fontsize=7, ax=ax)
plt.show()
```

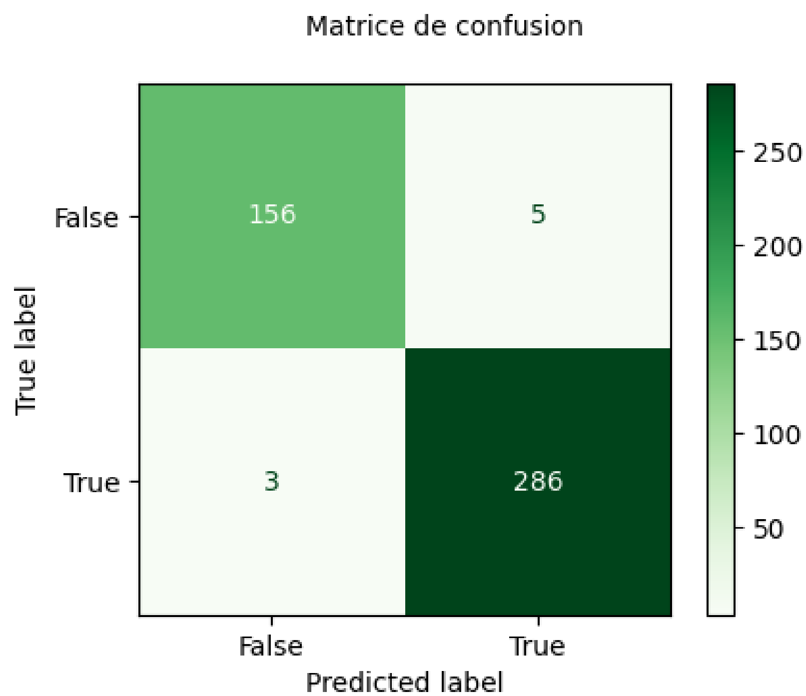
```python
#df_billets[['diagonal', 'height_left',
#'height_right', 'margin_low',
#'margin_up', 'length']]
```



[600]:
```python
# Importance des variables :
fig, ax = plt.subplots(figsize=(4.8, 3.6))

pd.DataFrame(
    DecisionTreeClassifier(random_state=0).fit(X_train, y_train).
 ↪feature_importances_,
    index=X_train.columns,
    columns=['Importance']
).sort_values(by='Importance').plot.barh(ax=ax, color='seagreen')

ax.get_legend().remove()

fig.suptitle('Importance des variables', size=10)

plt.show()
```



[601]:
```
# Matrice de confusion de l'arbre de décision :

fig, ax = plt.subplots(figsize=(4.8, 3.6))

metrics.ConfusionMatrixDisplay.from_predictions(
    y_test, y_pred, ax=ax, cmap='Greens')

fig.suptitle('Matrice de confusion', size=10)

plt.show()

del fig, ax
```



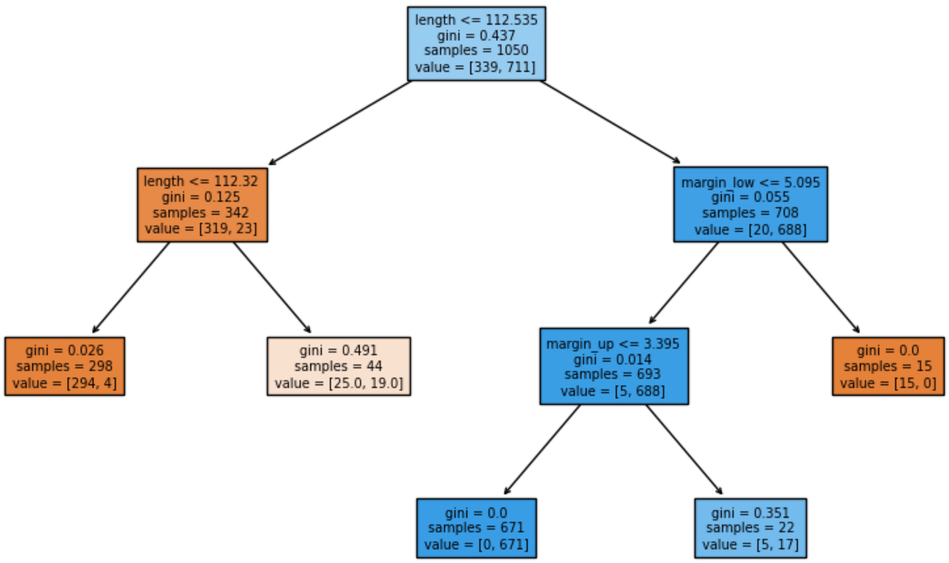

```
[602]: df_6 = criteres_evaluation_model(y_test, y_pred)
```

```
[689]: # Optimisation GridSearchCV :
param_grid = {
    'max_depth' : np.arange(start=1, stop=200, step=10),
    'min_samples_leaf' : np.arange(start=5, stop=250, step=50),
    'min_samples_split' : np.arange(start=10, stop=500, step=50)
}

print(GridSearchCV(
    DecisionTreeClassifier(random_state=0),
    param_grid=param_grid, scoring=scoring, cv=5).fit(X_train, y_train).
 ↪best_params_)

del param_grid
```

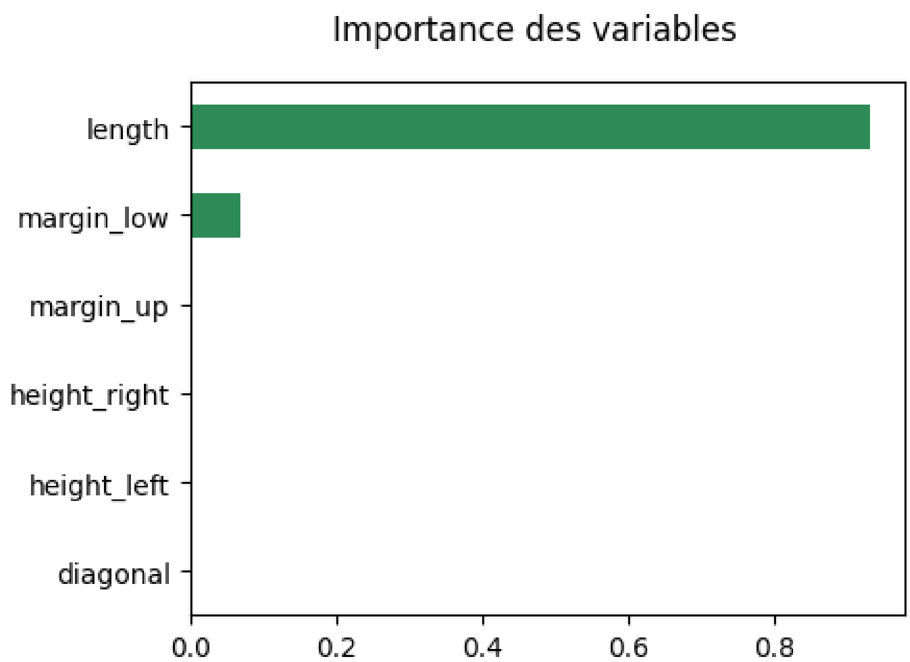
```
{'max_depth': 11, 'min_samples_leaf': 5, 'min_samples_split': 310}
```

```
[690]: y_pred = DecisionTreeClassifier(
    max_depth=11, min_samples_leaf=5, min_samples_split=310).fit(X_train,␣
 ↪y_train).predict(X_test)

fig, ax = plt.subplots(figsize=(10.8, 6.4))
plot_tree(DecisionTreeClassifier(
```

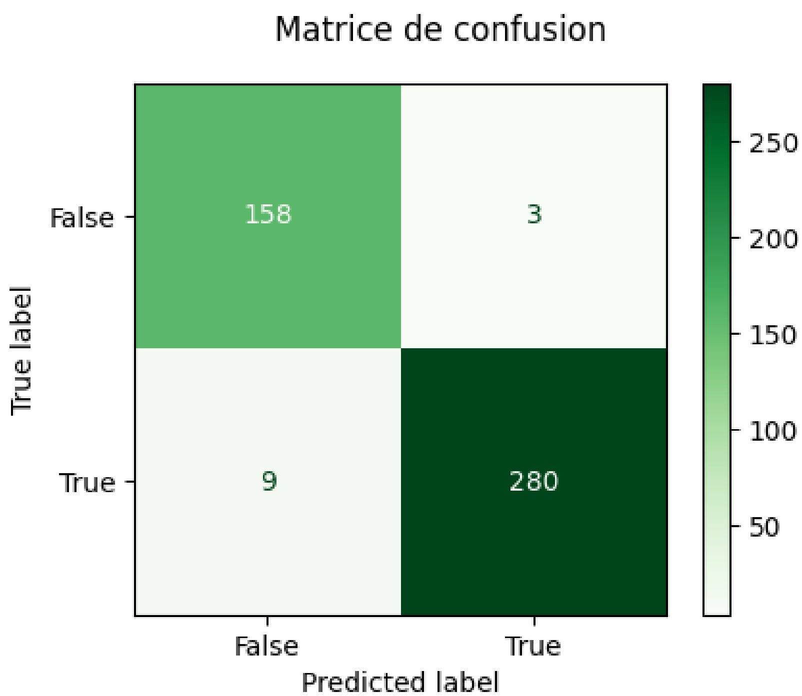
```
    max_depth=11, min_samples_leaf=5, min_samples_split=310).fit(X_train,␣
↪y_train), feature_names=df_billets[['diagonal', 'height_left',
                                                                                ␣
↪                       'height_right', 'margin_low',
                                                                                ␣
↪     'margin_up', 'length']].columns, filled=True, fontsize=7, ax=ax)
plt.show()
```



[605]:
```
fig, ax = plt.subplots(figsize=(4.8, 3.6))

pd.DataFrame(
    DecisionTreeClassifier(
    max_depth=11, min_samples_leaf=5, min_samples_split=310).fit(X_train,␣
↪y_train).feature_importances_,
    index=X_train.columns,
    columns=['Importance']
).sort_values(by='Importance').plot.barh(ax=ax, color='seagreen')


ax.get_legend().remove()

fig.suptitle('Importance des variables')

plt.show()
```



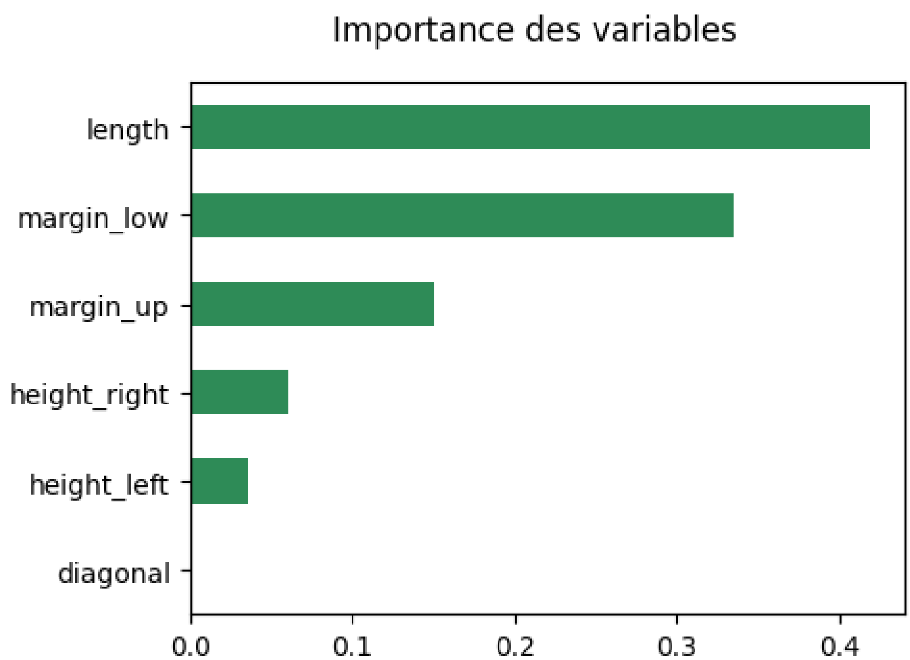
[606]:
```
fig, ax = plt.subplots(figsize=(4.8, 3.6))

metrics.ConfusionMatrixDisplay.from_predictions(
    y_test, y_pred, ax=ax, cmap='Greens')

fig.suptitle('Matrice de confusion')

plt.show()

del fig, ax
```

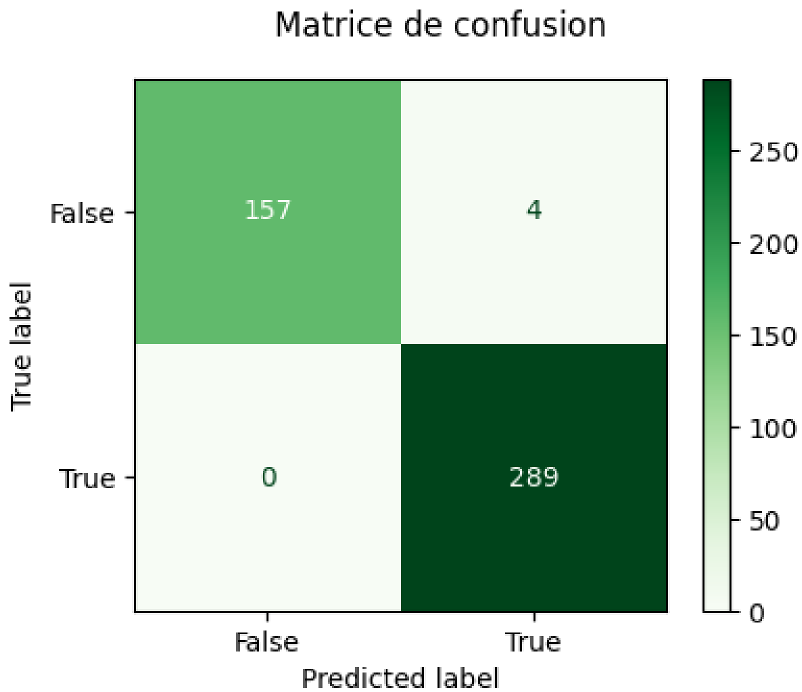


[607]:
```
df_7 = criteres_evaluation_model(y_test, y_pred)
```

[608]:
```
# Méthode 5 : Random forest : forêt aléatoire
y_pred = RandomForestClassifier(max_depth=2, random_state=0).fit(X_train,␣
↪y_train).predict(X_test)

# Importance des variables :
fig, ax = plt.subplots(figsize=(4.8, 3.6))

pd.DataFrame(
    RandomForestClassifier(max_depth=2, random_state=0).fit(X_train, y_train).
↪feature_importances_,
    index=X_train.columns,
    columns=['Importance']
).sort_values(by='Importance').plot.barh(ax=ax, color='seagreen')

ax.get_legend().remove()

fig.suptitle('Importance des variables')

plt.show()

# Matrice de confusion
fig, ax = plt.subplots(figsize=(4.8, 3.6))
```

```
metrics.ConfusionMatrixDisplay.from_predictions(
    y_test, y_pred, ax=ax, cmap='Greens')

fig.suptitle('Matrice de confusion')

plt.show()

del fig, ax
```





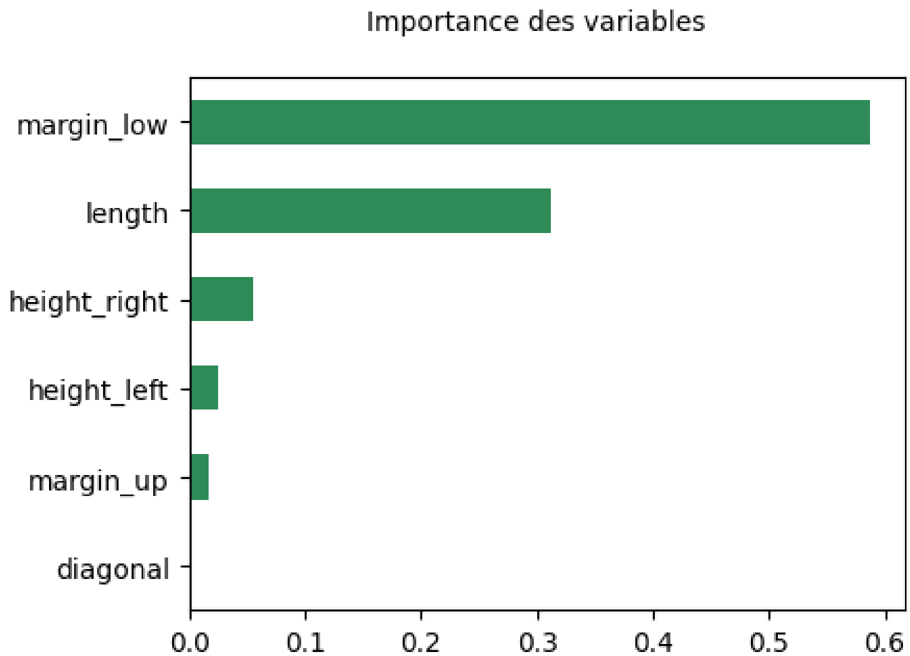
[609]:
```
df_8 = criteres_evaluation_model(y_test, y_pred)
```

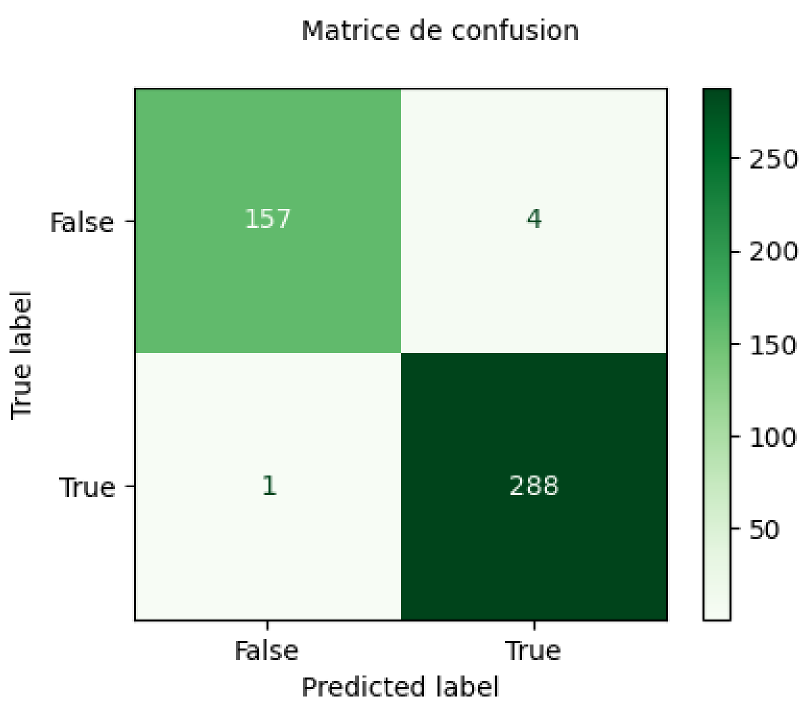
[693]:
```
# Optimisation de la forêt aléatoire avec GridSearchCV :
param_grid = {
    #'n_estimators': np.arange(start=1, stop=6, step=1),
    'max_depth': np.arange(start=1, stop=200, step=10),
    'min_samples_leaf': np.arange(start=5, stop=50, step=10),
    'min_samples_split': np.arange(start=10, stop=100, step=50)
}
# meilleur paramètre
print(GridSearchCV(
    RandomForestClassifier(random_state=0),
    param_grid=param_grid, scoring=scoring, cv=5).fit(X_train, y_train).
  ↪best_params_)

del param_grid
```

KeyboardInterrupt

[696]:
```
# Prédiction après optimisation:
y_pred = RandomForestClassifier( #n_estimators=5,
    max_depth=10, min_samples_leaf=5, min_samples_split=10,
```

```
    random_state=0
).fit(X_train, y_train).predict(X_test)

# Importance des variables après optimisation
fig, ax = plt.subplots(figsize=(4.8, 3.6))

pd.DataFrame(
    RandomForestClassifier(  n_estimators=5,
    max_depth=10, min_samples_leaf=5, min_samples_split=10,
    random_state=0
).fit(X_train, y_train).feature_importances_,
    index=X_train.columns,
    columns=['Importance']
).sort_values(by='Importance').plot.barh(ax=ax, color='seagreen')

ax.get_legend().remove()

fig.suptitle('Importance des variables', size = 10)

plt.show()

fig, ax = plt.subplots(figsize=(4.8, 3.6))

metrics.ConfusionMatrixDisplay.from_predictions(
    y_test, y_pred, ax=ax, cmap='Greens')

fig.suptitle('Matrice de confusion', size = 10)

plt.show()

del fig, ax
```





[697]:
```
df_9 = criteres_evaluation_model(y_test, y_pred)
```

[617]:
```
recap_table = pd.concat([df1, df2, df_3, df_4, df_5, df_6, df_7, df_8, df_9],␣
↪ignore_index=True)
```

[618]:
```
list = ['Regression_logistiq', 'Regression_logistiq_optimise', 'K_means',
        'KNN', 'KNN_optimise', 'Arbre_decision',
        'Arbre_decision_optimise', 'Foret_aleatoire',␣
↪'foret_aleatoire_optimise']
recap_table.insert(0, 'Model', list)
```

[698]:
```
recap_table.head(10)
```

[698]:
```
                          Model  accuracy  recall_true  recall_False  \
0           Regression_logistiq  0.986667     0.996540      0.968944
1  Regression_logistiq_optimise  0.988889     0.993080      0.981366
2                       K_means  0.991111     0.993080      0.987578
3                           KNN  0.984444     0.996540      0.962733
4                  KNN_optimise  0.988889     1.000000      0.968944
5                Arbre_decision  0.982222     0.989619      0.968944
6       Arbre_decision_optimise  0.973333     0.968858      0.981366
7               Foret_aleatoire  0.991111     1.000000      0.975155
8      foret_aleatoire_optimise  0.984444     0.989619      0.975155

   precision_true  precision_false  f1_score
0        0.982935         0.993631  0.981132
1        0.989655         0.987500  0.984424
2        0.993080         0.987578  0.987578
3        0.979592         0.993590  0.977918
4        0.982993         1.000000  0.984227
5        0.982818         0.981132  0.975000
6        0.989399         0.946108  0.963415
7        0.986348         1.000000  0.987421
8        0.986207         0.981250  0.978193
```

[651]:
```
recap_table.head(10).style.background_gradient(axis='rows', cmap='Blues').
↪format('{:.2}')
```

[651]:
```
<pandas.io.formats.style.Styler at 0x133b90dd0>
```

[ ]:
```
#metrics.accuracy_score(y_test, y_pred)
#metrics.recall_score(y_test, y_pred, pos_label=True)
#metrics.recall_score(y_test, y_pred, pos_label=False)
#metrics.precision_score(
            #true_labels_test, mapped_predicted_labels, pos_label=True) # VPP
#metrics.precision_score(
            #true_labels_test, mapped_predicted_labels, pos_label=False) #VPN
#metrics.f1_score(
            #y_test, y_pred, pos_label=False)
```

[628]:
```
df_billets.to_csv('/Users/helmisaddem/Downloads/billets.csv',index=False)
```