Fake Bills Detection

1.1 Introduction

In this notebook we are going to predict if a bank note is true or false based on different measurements. There are five measurements:

- length, the length of the banknote in mm
- height left, the height of the left side of the banknote in mm

- height right, the height of the right side of the bank note in mm
- diagonal, the diagonal of the bank note in mm
- margin low, lower side margin in mm
- margin up, upper side margin in mm

The last column is_genuine is the target

1.2 Loading Libraries

In [1]:

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
plt.style.use('ggplot')
```

1.3 Loading Data

In [2]:

```
df = pd.read_csv('billets.txt', sep=';')
df.head()
```

Out[2]:

	is_genuine	diagonal	height_left	height_right	margin_low	margin_up	length
0	True	171.81	104.86	104.95	4.52	2.89	112.83
1	True	171.46	103.36	103.66	3.77	2.99	113.09
2	True	172.69	104.48	103.50	4.40	2.94	113.16
3	True	171.36	103.91	103.94	3.62	3.01	113.51
4	True	171.73	104.28	103.46	4.04	3.48	112.54

In [3]:

```
df.shape
```

Out[3]:

```
(1500, 7)
```

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1500 entries, 0 to 1499
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   is_genuine    1500 non-null   bool   
 1   diagonal      1500 non-null   float64
 2   height_left   1500 non-null   float64
 3   height_right  1500 non-null   float64
 4   margin_low    1463 non-null   float64
 5   margin_up     1500 non-null   float64
 6   length        1500 non-null   float64
dtypes: bool(1), float64(6)
memory usage: 71.9 KB
```

1.4 Data Distribution

In [5]:

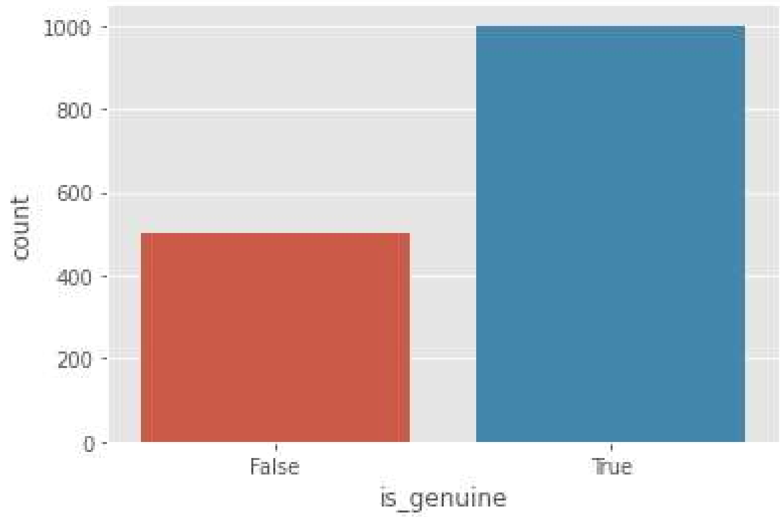
```
df.is_genuine.value_counts(normalize=True)
```

Out[5]:

```
True     0.666667
False    0.333333
Name: is_genuine, dtype: float64
```

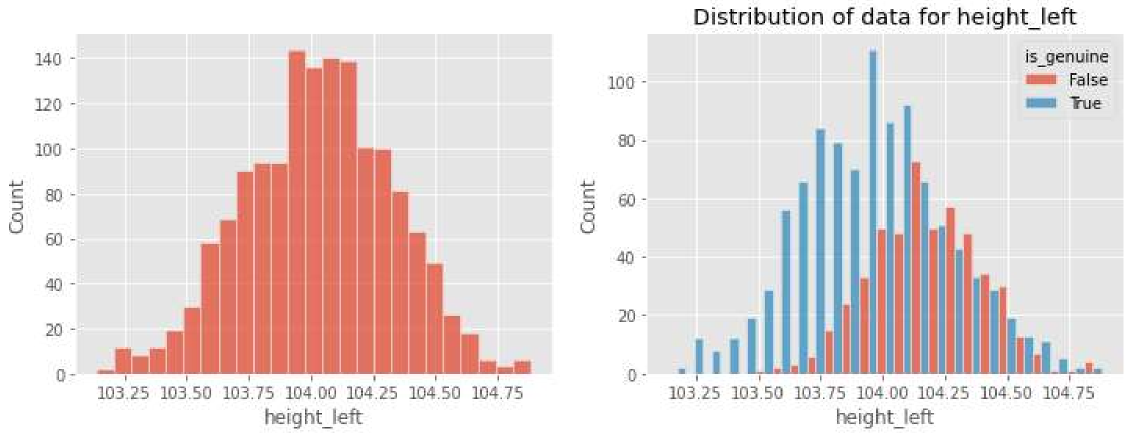
In [6]:

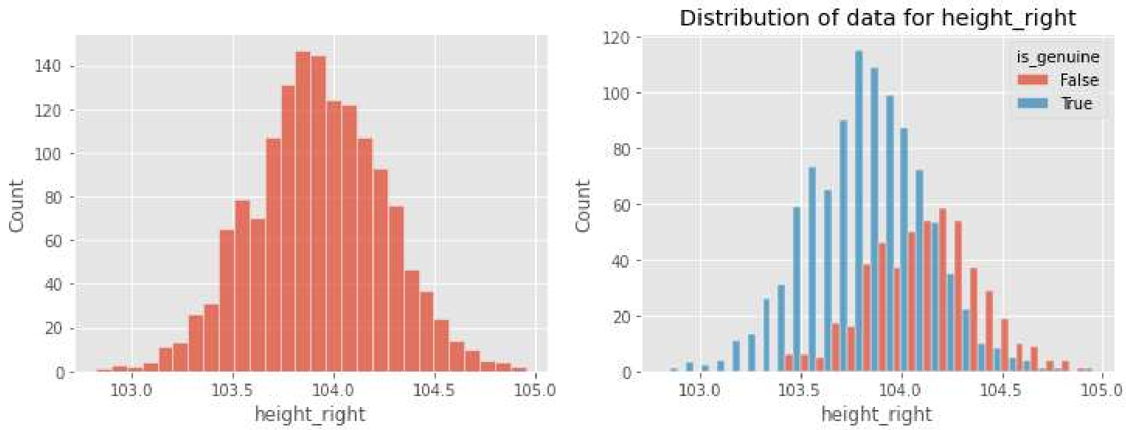
```
sns.countplot(data=df, x='is_genuine');
```

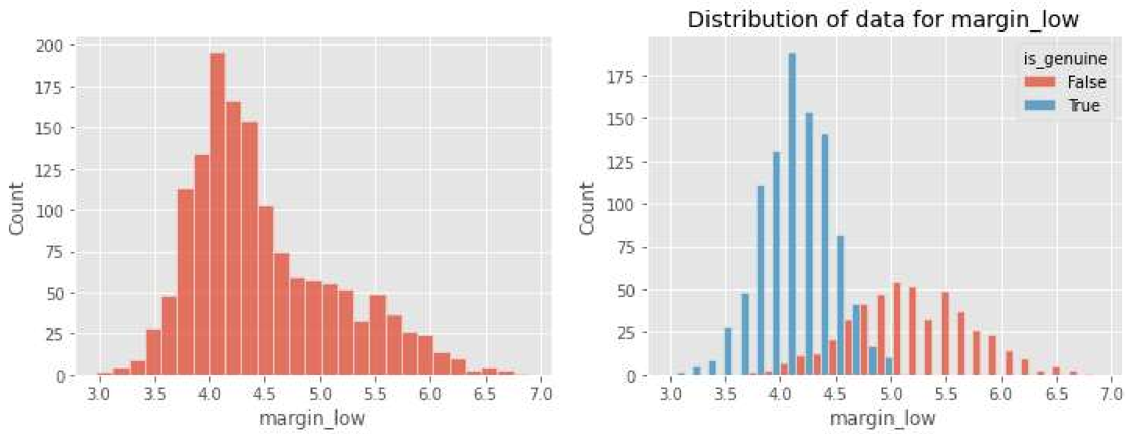


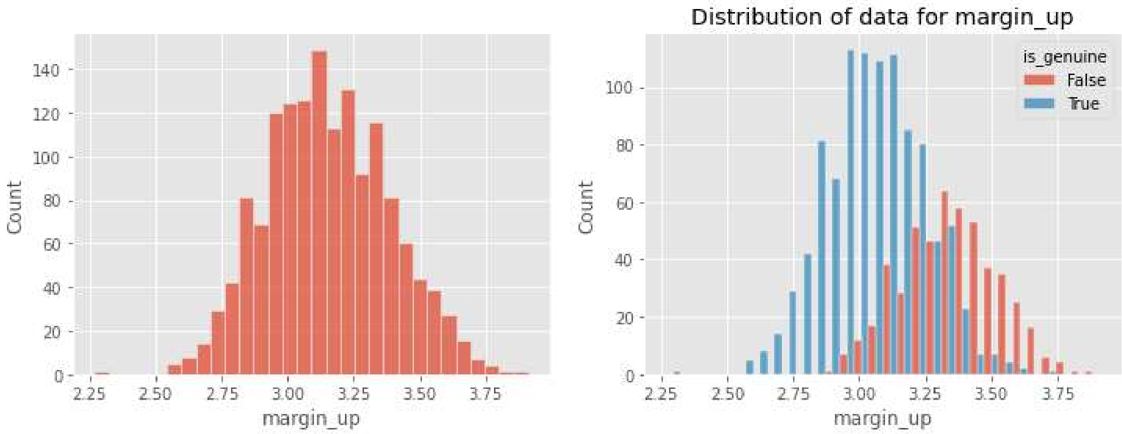
In [7]:

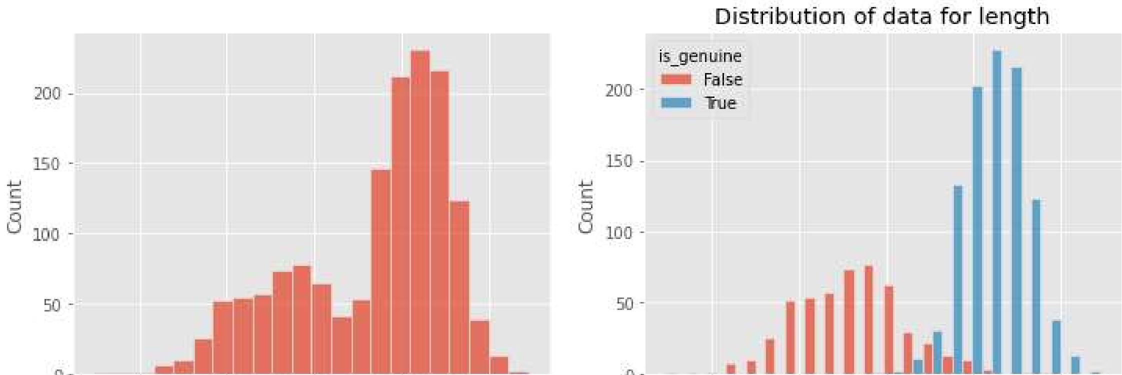
```
for col in df.columns[2:]:
    fig, ax = plt.subplots(1,2,figsize=(12,4))
    sns.histplot(data=df, x=col, ax=ax[0])
    sns.histplot(data=df, x=col, hue='is_genuine', ax=ax[1], multiple='dodge')
    plt.title(f"Distribution of data for {col}")
    plt.show()
```



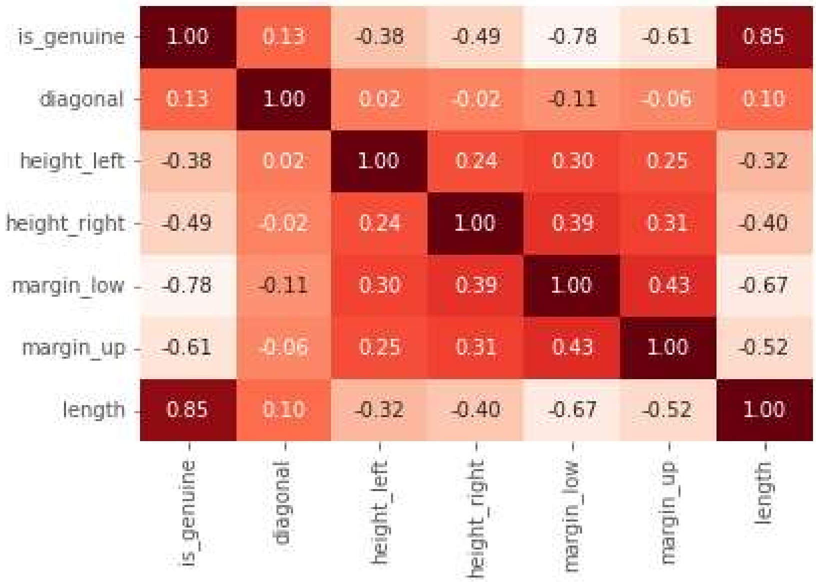









```
corr = df.corr()
sns.heatmap(corr, annot=True, fmt='.2f', cbar=None, cmap='Reds');
```



The correlation between variables is high. We can use a PCA to reduce the number of dimensions

In [9]:

```
from sklearn.model_selection import cross_validate, cross_val_predict, train_test_split


from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.cluster import KMeans

from sklearn.metrics import mean_absolute_percentage_error, r2_score, accuracy_score, cc
```

2. Missing Values

2.1 Separating Train and Test Splits

In [34]:

```
train = df[df['margin_low'].notna()].copy()
test = df[df['margin_low'].isna()].copy()


y_train = train['margin_low']
X_train = train.drop(['margin_low', 'is_genuine'], axis=1)

#y_test = test['margin_low']
X_test = test.drop(['margin_low', 'is_genuine'], axis=1)
```

2.2 Model Evaluation

In [11]:

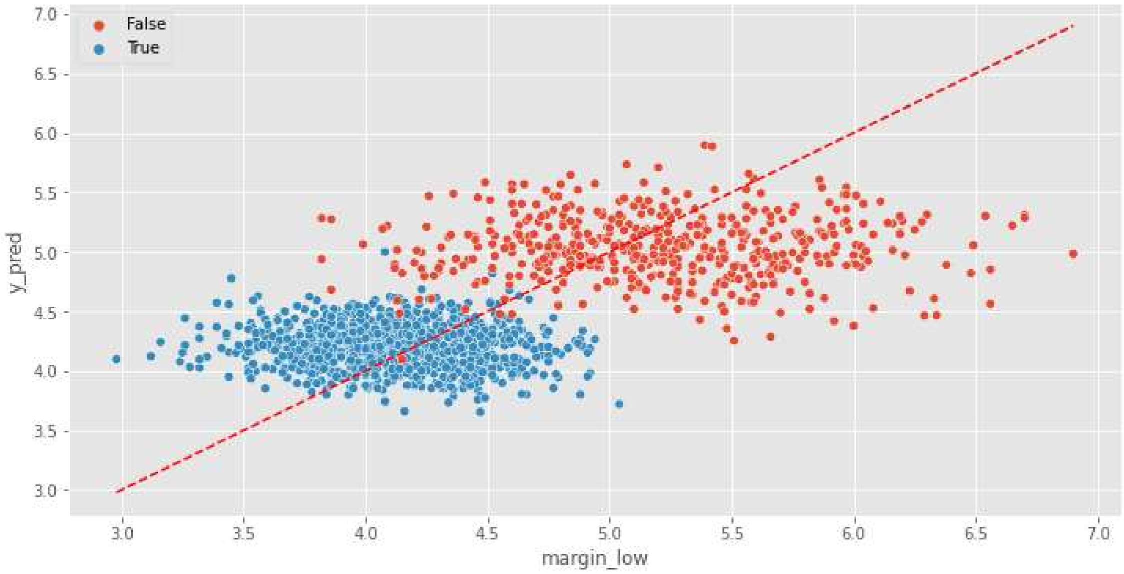
```
model = LinearRegression()

y_pred_val = cross_val_predict(model, X_train, y_train, cv=10, n_jobs=-1)

mape_val = mean_absolute_percentage_error(y_train, y_pred_val)
r2_val = r2_score(y_train, y_pred_val)

print(f'The mean absolute error for the validation data is: {mape_val:.3f}')
print(f'The r2 for the validation data is: {r2_val:.3f}')
```

```
The mean absolute error for the validation data is: 0.083
The r2 for the validation data is: 0.463
```

2.3 Visualizing Predictions

In [12]:

```
min_y_train = np.min(y_train)
min_y_pred = np.min(y_pred_val)

max_y_train = np.max(y_train)
max_y_pred = np.max(y_pred_val)

min_xy = min(min_y_train, min_y_pred)
max_xy = max(max_y_train, max_y_pred)

results=train.copy()
results['y_pred'] = y_pred_val

plt.figure(figsize=(12,6))
sns.scatterplot(data=results, x='margin_low', y='y_pred', hue='is_genuine')
sns.lineplot(x=[min_xy, max_xy], y=[min_xy, max_xy], linestyle='--', color='red');
```



At first the results don't look good, because many points are far from the identity line. However the Mean Absolute Percentage Error is only 8% and the r2 is 0.46. Our predictions are better than filling the missing values with the mean (r2 of 0)

2.4 Final Model and Prediction of Missing Values

In [13]:

```
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

test['margin_low'] = y_pred
```

In [14]:

```
df = pd.concat([train, test])
```

In [15]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1500 entries, 0 to 1438
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   is_genuine    1500 non-null   bool   
 1   diagonal      1500 non-null   float64
 2   height_left   1500 non-null   float64
 3   height_right  1500 non-null   float64
 4   margin_low    1500 non-null   float64
 5   margin_up     1500 non-null   float64
 6   length        1500 non-null   float64
dtypes: bool(1), float64(6)
memory usage: 83.5 KB
```

2.5 Creating New Columns

As long as we had missing values, we couldn't create columns based on margin_low

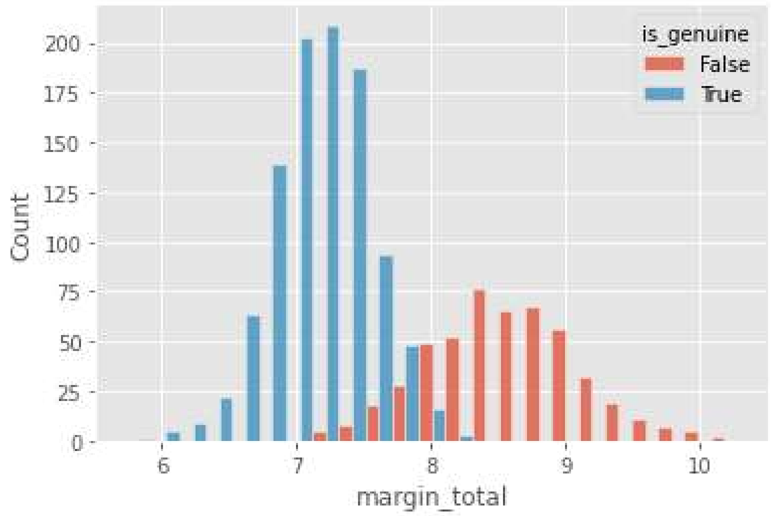
Let's try to create a few columns with a clearer distinction between genuine and fake bills

In [16]:

```
df['margin_total'] = df['margin_up'] + df['margin_low']
df['margin_diff'] = df['margin_up'] - df['margin_low']
```

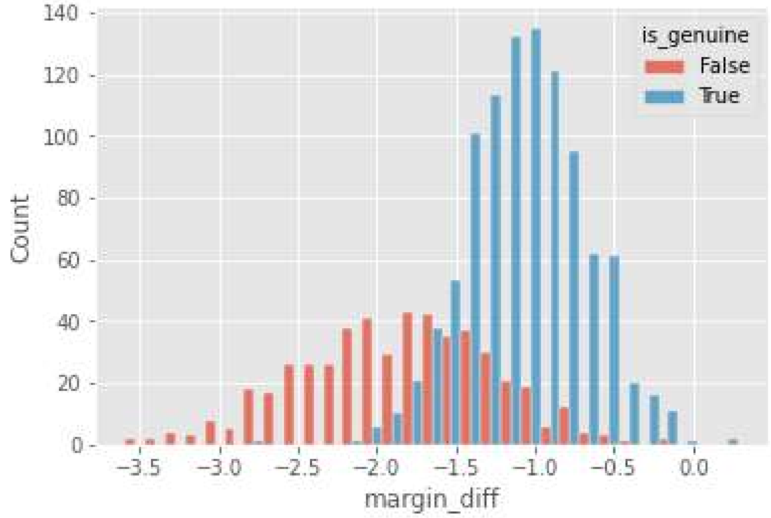
In [17]:

```
sns.histplot(data=df, x='margin_total', hue='is_genuine', multiple='dodge');
```



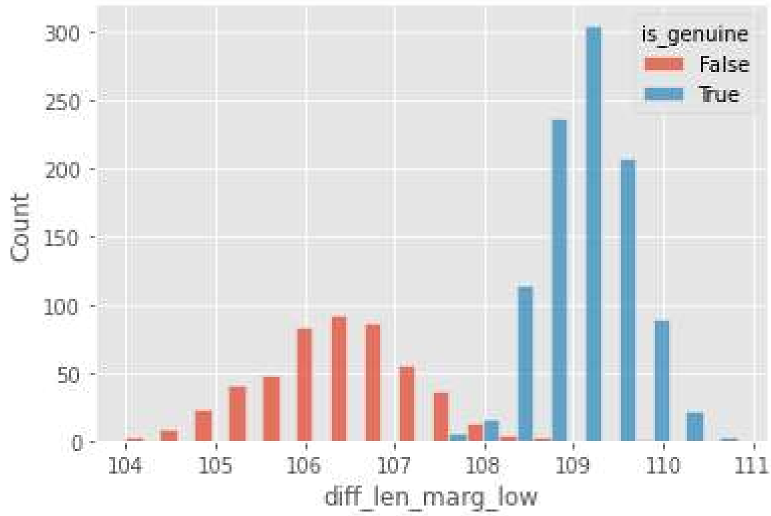
In [18]:

```
sns.histplot(data=df, x='margin_diff', hue='is_genuine', multiple='dodge');
```



In [19]:

```
df['diff_len_marg_low'] = df['length'] - df['margin_low']

sns.histplot(data=df, x='diff_len_marg_low', hue='is_genuine', multiple='dodge');
```



3. Modeling Without Data Transform

In [20]:

```
y = df['is_genuine']
X = df.drop('is_genuine', axis=1)
```

3.1 Logistic Regression

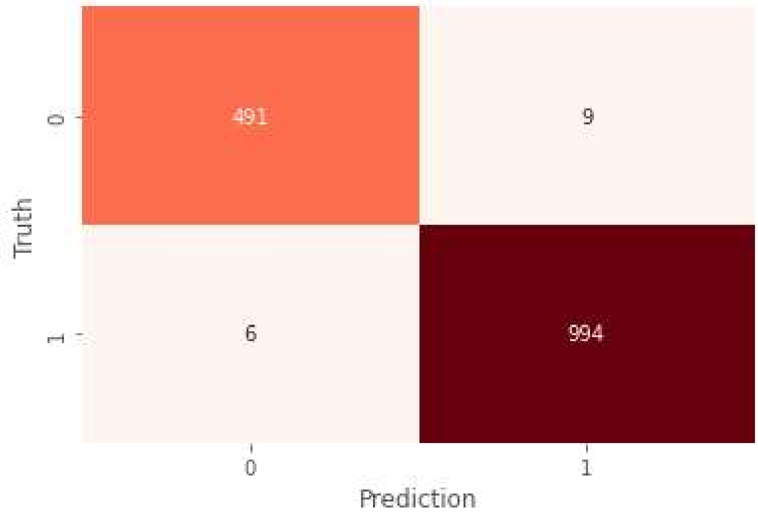
In [21]:

```
model = LogisticRegression()

y_pred = cross_val_predict(model, X, y, cv=10, n_jobs=-1)

acc = accuracy_score(y, y_pred)

print(f'The accuracy score for Logistic Regression is: {acc:.3f}')
```

```
The accuracy score for Logistic Regression is: 0.990
```

In [22]:

```
conf_mat = confusion_matrix(y, y_pred)
sns.heatmap(conf_mat, annot=True, cbar=None, cmap='Reds', fmt='.0f')
plt.ylabel('Truth')
plt.xlabel('Prediction');
```



In [23]:

```
report = classification_report(y, y_pred)
print(report)
```

```
              precision    recall  f1-score   support

       False       0.99      0.98      0.98       500
        True       0.99      0.99      0.99      1000

    accuracy                           0.99      1500
   macro avg       0.99      0.99      0.99      1500
weighted avg       0.99      0.99      0.99      1500
```

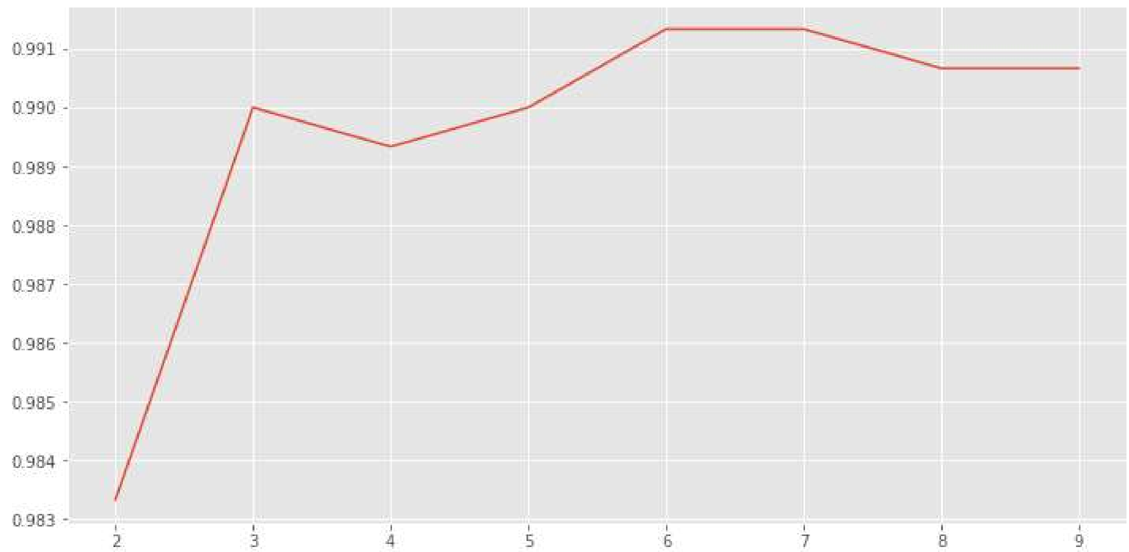
3.2 K Neighbors Classifier

In [24]:

```
from sklearn.model_selection import cross_val_score
```

In [25]:

```
neighbors = [2,3,4,5,6,7,8,9]
scores = []


for n in neighbors:
    model = KNeighborsClassifier(n_neighbors=n)
    acc = cross_val_score(model, X, y, cv=10, n_jobs=-1)

    scores.append(np.mean(acc))

plt.figure(figsize=(12,6))
sns.lineplot(x=neighbors, y=scores);
```



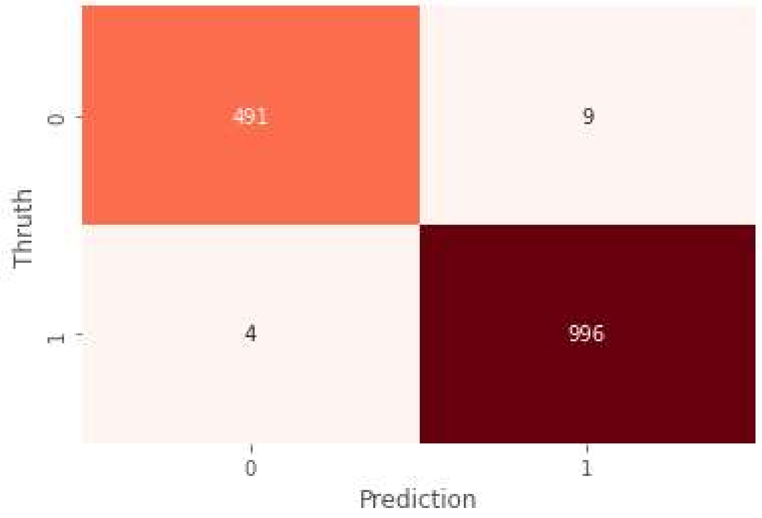
In [26]:

```
model = KNeighborsClassifier(n_neighbors=7)

y_pred = cross_val_predict(model, X, y, cv=10, n_jobs=-1)

acc = accuracy_score(y, y_pred)

print(f'The accuracy score for K-Neighbors Classifier is: {acc:.3f}')
```

```
The accuracy score for K-Neighbors Classifier is: 0.991
```

In [27]:

```
conf_mat = confusion_matrix(y, y_pred)

sns.heatmap(conf_mat, annot=True, cmap='Reds', cbar=None, fmt='.0f')
plt.ylabel('Thruth')
plt.xlabel('Prediction');
```



In [ ]:

```
report = classification_report(y, y_pred)
print(report)
```

3.3 K-Means

In [28]:

```
X.drop(['margin_diff', 'margin_total', 'diff_len_marg_low'], axis=1, inplace=True)
```

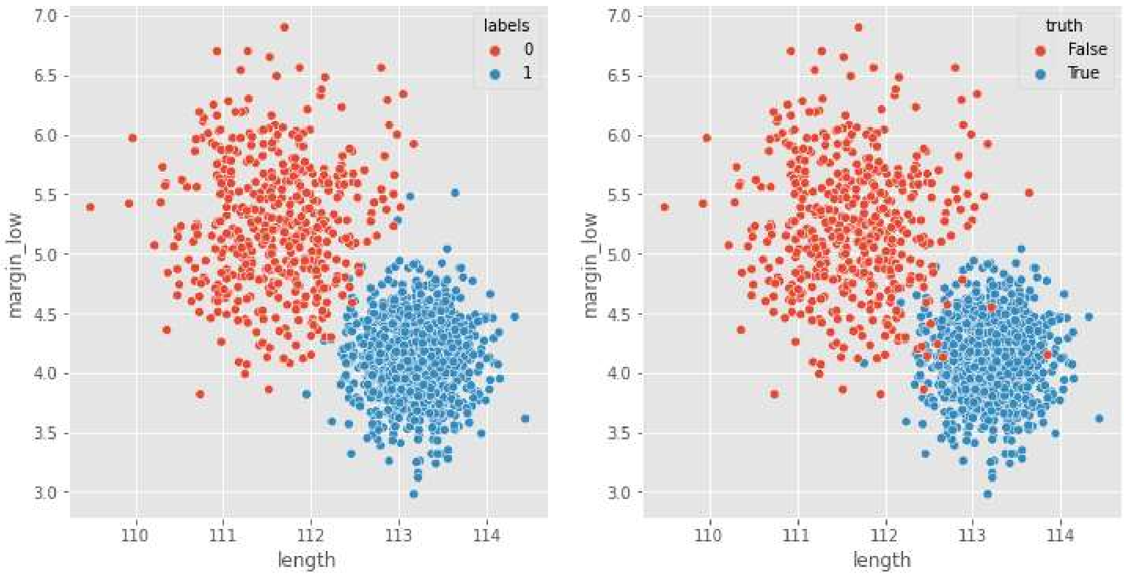
In [29]:

```
kmeans = KMeans(n_clusters=2, random_state=42)
kmeans.fit(X)

results = X.copy()
results['labels'] = kmeans.labels_
results['truth'] = y
```

```
C:\Users\petit\anaconda3\envs\pyimagesearch\lib\site-packages\sklearn\clu
ster\_kmeans.py:1332: UserWarning: KMeans is known to have a memory leak
on Windows with MKL, when there are less chunks than available threads. Y
ou can avoid it by setting the environment variable OMP_NUM_THREADS=6.
  warnings.warn(
```

In [30]:

```
fig, ax = plt.subplots(1,2,figsize=(12,6))
sns.scatterplot(data=results, x='length', y='margin_low', hue='labels', ax=ax[0])
sns.scatterplot(data=results, x='length', y='margin_low', hue='truth', ax=ax[1]);
```



The two plots look quite similar despite a slight imperfection in the decision boundaries. Our K-Means seem to have done a good job at splitting the real and fake bills in two groups

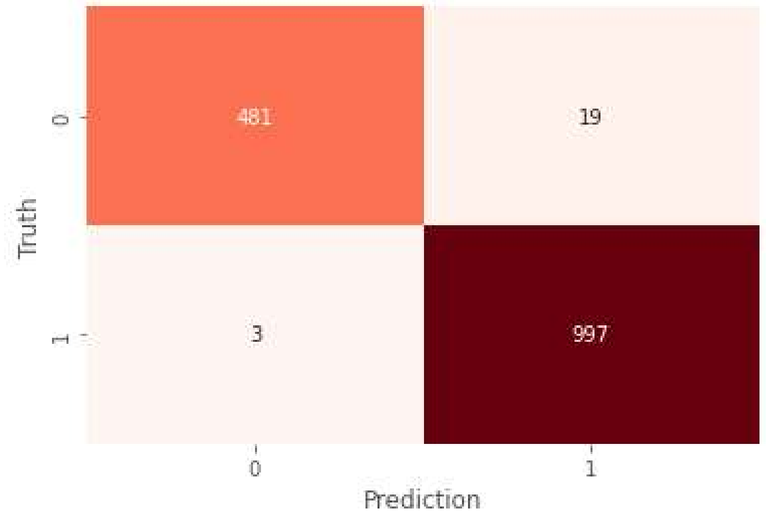
In [31]:

```
dic_label = {True: 1, False: 0}
results['truth'] = results['truth'].map(dic_label)

acc = accuracy_score(results['truth'], results['labels'])

print(f'The accuracy score for K-Means Clustering is : {acc:.3f}')
```

```
The accuracy score for K-Means Clustering is : 0.985
```

In [32]:

```
conf_mat = confusion_matrix(results['truth'], results['labels'])

sns.heatmap(conf_mat, annot=True, cmap='Reds', cbar=None, fmt='.0f')
plt.ylabel('Truth')
plt.xlabel('Prediction');
```



In [33]:

```
report = classification_report(results['truth'], results['labels'])

print(report)
```

```
              precision    recall  f1-score   support

           0       0.99      0.96      0.98       500
           1       0.98      1.00      0.99      1000

    accuracy                           0.99      1500
   macro avg       0.99      0.98      0.98      1500
weighted avg       0.99      0.99      0.99      1500
```

4. Summary

- Using Logistic Regression and KNN we achieve a 99% accuracy
- The K-Means did nearly as well with an accuracy of 98.5%

To choose the best model, we need to decide if it is better to let a few fake bills beeing unnoticed or if it is better to have real bills labelled as fake bills.