Machine Learning and Data Mining
Project Work

Alessandro Tutone

Alma Mater Studiorum, Università degli Studi di Bologna

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Task Description

Objective: Identify which customers *will make a specific transaction in the future*, regardless of the amount of money transacted.

Data structure: Same structure used for the *real data*

Type of classification: *Binary*

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Dataset Description

Anonymized dataset containing *numeric feature* variables, the *binary target* column, and a *string ID_code* column.

The task is to predict the value of **target column** in the test set.

File descriptions:

- **train.csv** - the training set.
- **test.csv** - the test set.
- **sample_submission.csv** - a sample submission file.

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Training dataset

Lets take a look inside the file **train.csv**

In [4]:
```
train_df.head()
```

Out[4]:

	ID_code	target	var_0	var_1	var_2	var_3	var_4	var_5	var_6	var_7	...
0	train_0	0	8.9255	-6.7863	11.9081	5.0930	11.4607	-9.2834	5.1187	18.6266	...
1	train_1	0	11.5006	-4.1473	13.8588	5.3890	12.3622	7.0433	5.6208	16.5338	...
2	train_2	0	8.6093	-2.7457	12.0805	7.8928	10.5825	-9.0837	6.9427	14.6155	...
3	train_3	0	11.0604	-2.1518	8.9522	7.1957	12.5846	-1.8361	5.8428	14.9250	...
4	train_4	0	9.8369	-1.4834	12.8746	6.6375	12.2772	2.4486	5.9405	19.2514	...

5 rows × 202 columns

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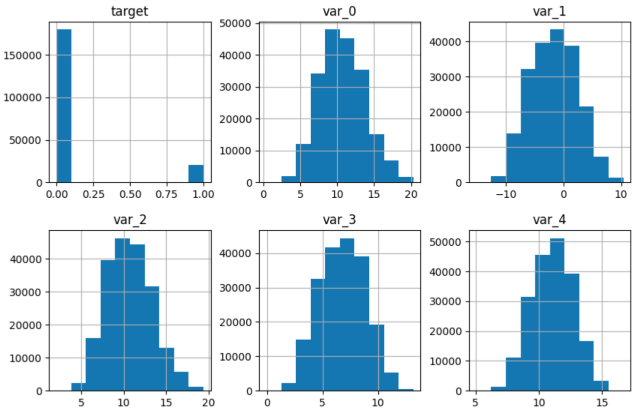
Data distribution

Considering the **distributions**, we can learn something new about the data.

In [6]:
```
train_df[train_df.columns[0:10]].hist(figsize=(10,10));
```



Data distribution

All features follow a **normal distribution**.

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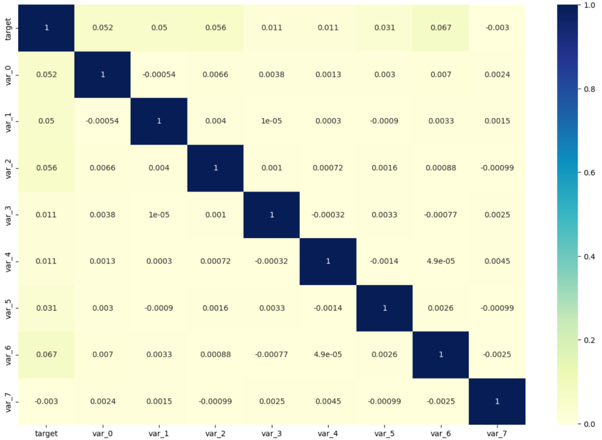
Correlation matrix

What about the **correlations** between variables?

In [7]:
```
corr = train_df[train_df.columns[0:10]].corr(numeric_only=True)

plt.figure(figsize=(15,10)) # set X and Y size
sns.heatmap(corr, cmap="YlGnBu", annot=True);
```



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Train-Test split

Since the only file that contains the **target column** is **train.csv**, this dataset is used for both *training* and *testing*

The data available are divided in the following way:

- 80% for **training**
- 20% for **testing**

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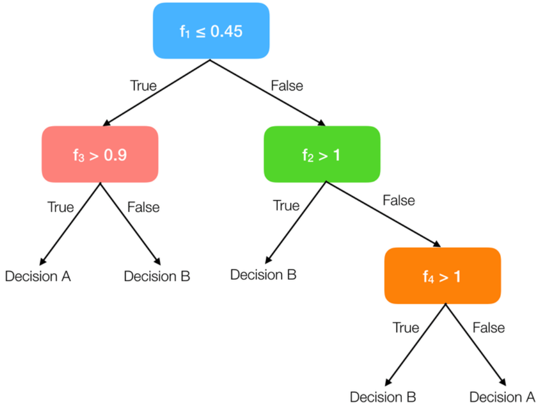
First model: **DecisionTreeClassifier**

This model works by building a **tree-like structure** where each node represents a *decision* based on a *feature*. After traversing the **tree**, the **leaf node** reached represents the **final prediction** or **classification**.



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First model: **DecisionTreeClassifier**

A first training, using the **default parameters**, has been done.

In [10]:
```
model = DecisionTreeClassifier(criterion = 'entropy')

model.fit(X_train, y_train)

y_pred_train = model.predict(X_train)
y_pred_test = model.predict(X_test)
```

In [11]:
```
print(classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.91      0.90      0.91      9047
           1       0.17      0.19      0.18       953

    accuracy                           0.84     10000
   macro avg       0.54      0.55      0.54     10000
weighted avg       0.84      0.84      0.84     10000
```

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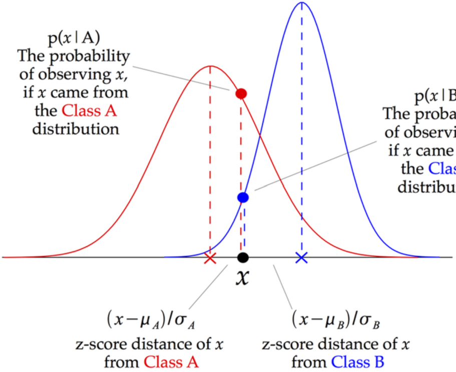
Second model: **GaussianNB**

This is a classification algorithm that assumes *features* are **normally distributed** and **independent**. It calculates the probability of a *feature value* given a *class*, then uses **Bayes' theorem** to determine the most likely *class* for a new data point.



Second model: **GaussianNB**

A first training, using the **default parameters**, has been done.

In [13]:
```
model = GaussianNB()

model.fit(X_train, y_train)

y_pred_train = model.predict(X_train)
y_pred_test = model.predict(X_test)
```

In [14]:
```
print(classification_report(y_test, y_pred_test))
```

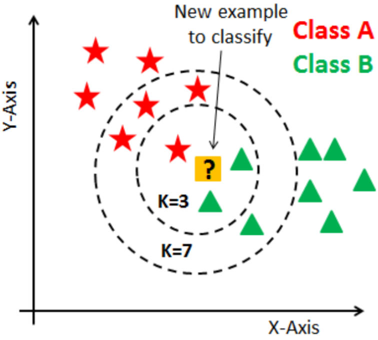
```
              precision    recall  f1-score   support

           0       0.94      0.98      0.96      9047
           1       0.70      0.37      0.48       953

    accuracy                           0.92     10000
   macro avg       0.82      0.68      0.72     10000
weighted avg       0.91      0.92      0.91     10000
```

Third model: **KNeighborsClassifier**

This algorithm is a non-parametric, supervised learning classifier, which uses **proximity** to make classifications or predictions about the *grouping* of an individual data point.
This algorithm assumes that *similar things* exist in *close* **proximity**



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Third model: **KNeighborsClassifier**

A first training, using the **default parameters**, has been done.

In [16]:
```
model = KNeighborsClassifier()

model.fit(X_train, y_train)

y_pred_train = model.predict(X_train)
y_pred_test = model.predict(X_test)
```

In [17]:
```
print(classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.90      1.00      0.95      9047
           1       0.30      0.00      0.01       953

    accuracy                           0.90     10000
   macro avg       0.60      0.50      0.48     10000
weighted avg       0.85      0.90      0.86     10000
```

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Comparing all models

The code used for comparing all the **models** (with different *parameters*):

In [19]:
```
model_lbls = ['decision_tree', 'gaussian_nb','knn']

models = {
    'decision_tree': {'name': 'Decision Tree',
           'estimator': DecisionTreeClassifier(random_state=random_state),
           'param': [{'max_depth': [*range(1,20)],'class_weight':[None,'balanced']}],
          },
    'gaussian_nb': {'name': 'Gaussian Naive Bayes',
           'estimator': GaussianNB(),
           'param': [{'var_smoothing': [10**exp for exp in range(-3,-13,-1)]}]
          },
    'knn':{'name': 'K Nearest Neighbor',
           'estimator': KNeighborsClassifier(),
           'param': [{'n_neighbors': list(range(1,7))}]
           },
}

scorings = ['accuracy','precision_macro','recall_macro','f1_macro']
clfs = []
```

In [20]:
```
for scoring in scorings:
    for m in model_lbls:
        clf = GridSearchCV(models[m]['estimator'], models[m]['param'], cv = cv, scoring = scoring)
        clf.fit(X_train, y_train)
        clfs.append(clf)

        y_true, y_pred = y_test, clf.predict(X_test)

        cr = classification_report(y_true,y_pred, output_dict=True, zero_division=1)

        comparison_df.loc[len(comparison_df)] = [scoring, models[m]['name'], clf.best_params_,
                                                 cr['accuracy'],
                                                 cr['macro avg']['precision'],
                                                 cr['macro avg']['recall'],
                                                 cr['macro avg']['f1-score']]
```

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Comparing all models

Operating a **grid search** with all *models*, and comparing them using different **metrics**, it is possible to find the model that stands out.

```
The best models, considering <accuracy>, are the following:
```

	Model name	Parameters	accuracy	precision_macro	recall_macro	f1_macro
1	Gaussian Naive Bayes	{'var_smoothing': 1e-08}	0.9244	0.815485	0.676114	0.720708
0	Decision Tree	{'class_weight': None, 'max_depth': 1}	0.9047	0.952350	0.500000	0.474983
2	K Nearest Neighbor	{'n_neighbors': 6}	0.9047	0.702390	0.500469	0.476027

```
The best models, considering <precision_macro>, are the following:
```

	Model name	Parameters	accuracy	precision_macro	recall_macro	f1_macro
4	Gaussian Naive Bayes	{'var_smoothing': 0.001}	0.9189	0.847935	0.602196	0.644121
5	K Nearest Neighbor	{'n_neighbors': 5}	0.9043	0.602452	0.501187	0.477980
3	Decision Tree	{'class_weight': None, 'max_depth': 3}	0.9038	0.584089	0.501850	0.479865

```
The best models, considering <recall_macro>, are the following:
```

	Model name	Parameters	accuracy	precision_macro	recall_macro	f1_macro
7	Gaussian Naive Bayes	{'var_smoothing': 1e-09}	0.9246	0.816524	0.676694	0.721446
6	Decision Tree	{'class_weight': 'balanced', 'max_depth': 4}	0.6377	0.529828	0.580092	0.488019
8	K Nearest Neighbor	{'n_neighbors': 1}	0.8749	0.519650	0.508878	0.506180

```
The best models, considering <f1_macro>, are the following:
```

	Model name	Parameters	accuracy	precision_macro	recall_macro	f1_macro
10	Gaussian Naive Bayes	{'var_smoothing': 1e-09}	0.9246	0.816524	0.676694	0.721446
9	Decision Tree	{'class_weight': None, 'max_depth': 19}	0.8723	0.562244	0.538421	0.544558
11	K Nearest Neighbor	{'n_neighbors': 1}	0.8749	0.519650	0.508878	0.506180

```
The best model is: GaussianNB()
```

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The best model

After all the comparisons, the best model has been found: the metric used to pick the best one is the **F1-Score**.

Best model: *GaussianNB(var_smoothing = 1e-09)*

To speed up the computations, all the **trainings** before have been done with a smaller number of samples with respect to the all available samples for **training**.

Now it is possible to operate a **full training** on the best model.

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Final results

After a complete training (using all the **160.000** samples) the results obtained with the **best model** are the following:

In [26]:
```
print(classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.93      0.98      0.96     35903
           1       0.72      0.37      0.49      4097

    accuracy                           0.92     40000
   macro avg       0.83      0.68      0.72     40000
weighted avg       0.91      0.92      0.91     40000
```

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