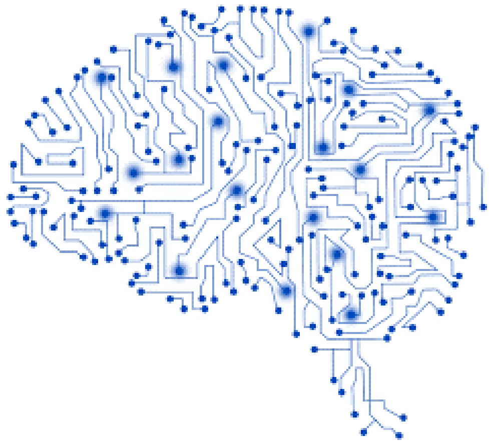
University of Minho
School of Engineering

Intelligent Systems Associate Laboratory



Dados e Aprendizagem Automática

Ensemble Learning

DAA @ MEI-1º/MiEI-4º – 1º Semestre

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Part VI

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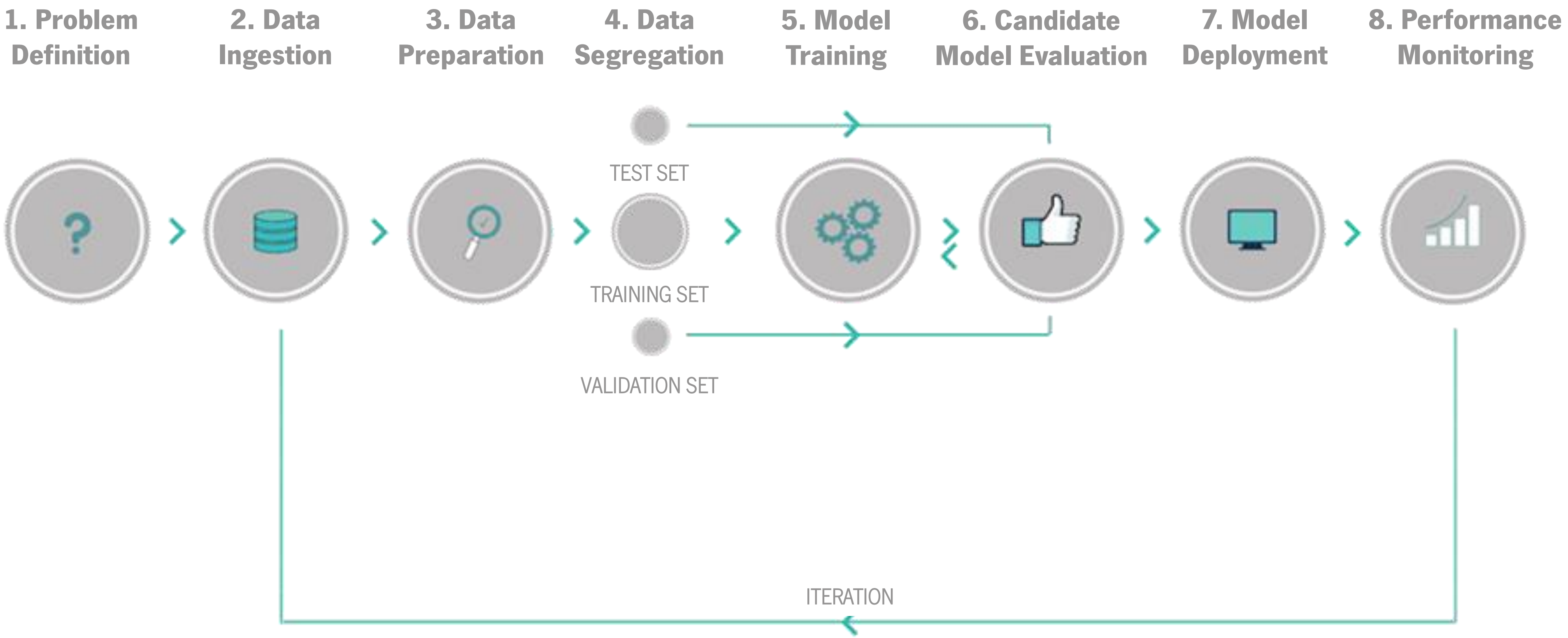
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Ensemble Learning

The Problem and the Data

Problem: development of a Machine Learning model capable of **predicting the passenger survived** to the Titanic disaster

Dataset: table with information regarding the **passengers** with 891 entries and 12 features, including:

- *PassengerId*
- *Survived*
- *Pclass*
- *Name*
- *Sex*
- *Age*
- *SibSp*
- *Parch*
- *Ticket*
- *Fare*
- *Cabin*
- *Embarked*

You may need to install `xgboost`. Use one of the following commands:

```
conda install -c conda-forge xgboost
```

```
pip install xgboost
```

EDA


```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

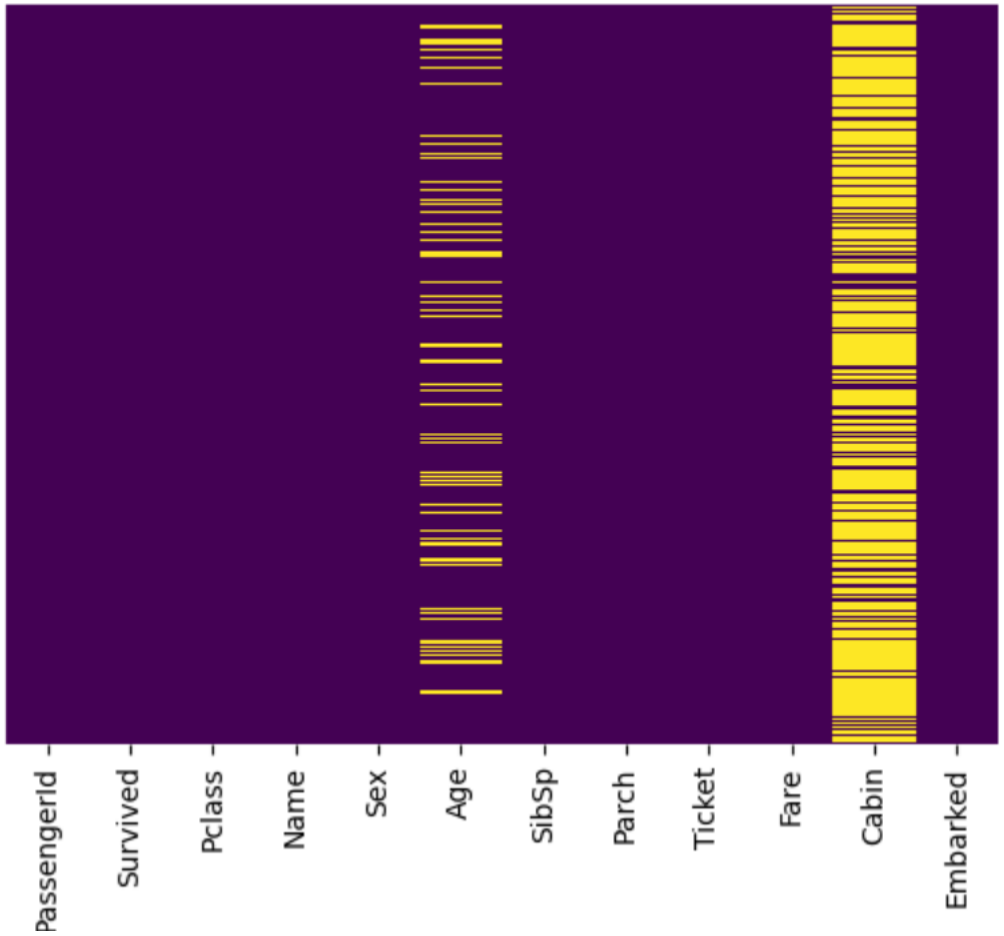
```
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S

EDA

Let's check the missing values:

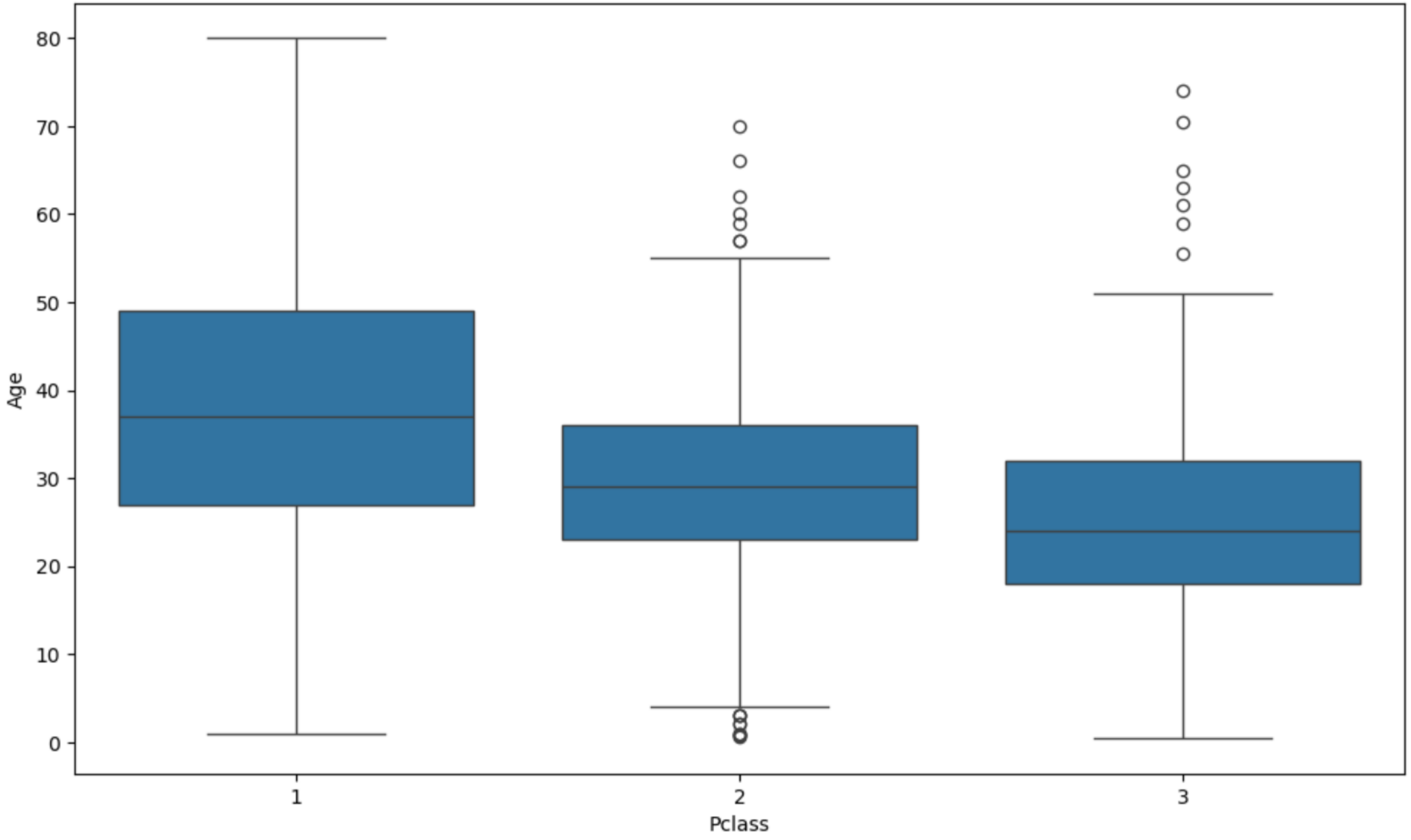
```
sns.heatmap(df.isnull(), yticklabels=False, cbar=False, cmap='viridis')
```



EDA

Let's analyze the *Age* distribution with the ticket class, *Pclass*:

```
plt.figure(figsize = (12, 7))
sns.boxplot(x = 'Pclass', y = 'Age', data = df)
```



Data Preprocessing

Let's impute the missing values in *Age* with the ticket class, *Pclass*, like we did on a previous class:

```
def impute_age(cols):
    Age = cols[0]
    Pclass = cols[1]

    if pd.isnull(Age):

        if Pclass == 1:
            return 37

        elif Pclass == 2:
            return 29

        else:
            return 24

    else:
        return Age
```

```
df['Age'] = df[['Age','Pclass']].apply(impute_age, axis = 1)
```

Data Preprocessing

We will drop features *Cabin*, *Sex*, *Embarked*, *Name* and *Ticket*:

```
df.drop('Cabin', axis = 1, inplace = True)
df.dropna(inplace = True)
```

```
df.drop(['Sex', 'Embarked', 'Name', 'Ticket'], axis = 1,inplace = True)
```

```
df.head()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
0	1	0	3	22.0	1	0	7.2500
1	2	1	1	38.0	1	0	71.2833
2	3	1	3	26.0	0	0	7.9250
3	4	1	1	35.0	1	0	53.1000
4	5	0	3	35.0	0	0	8.0500

Let's define the X and y and split the data:

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

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, random_state = 2022)
```

```
X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

```
((622, 6), (622,), (267, 6), (267,))
```

Comparison Models: Decision Tree

Let's try different models. We will implement a Decision Tree and a Support Vector Machine for comparison with the Ensemble Learning Models.

Decision Tree

```
dt_model = DecisionTreeClassifier(max_depth = 2, random_state = 2022)
dt_model.fit(X_train, y_train)
```

```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=2, random_state=2022)
```

```
dt_score = dt_model.score(X_test, y_test)
print("Accuracy: %.2f%%" % (dt_score * 100))
```

```
Accuracy: 69.29%
```

```
dt_predictions = dt_model.predict(X_test)
print(classification_report(y_test, dt_predictions))
```

```
              precision    recall  f1-score   support

           0       0.76      0.76      0.76       173
           1       0.56      0.56      0.56        94

    accuracy                           0.69       267
   macro avg       0.66      0.66      0.66       267
weighted avg       0.69      0.69      0.69       267
```

Saving the model's accuracy for latter comparison:

```
results = {'DT': dt_score}
```

Comparison Models: Support Vector Machine

Support Vector Machine

```
svm_model = SVC(random_state = 2022)
svm_model.fit(X_train, y_train)
```

```
SVC
SVC(random_state=2022)
```

```
svm_score = svm_model.score(X_test, y_test)
```

```
print("Accuracy: %.2f%%" % (svm_score * 100))
```

```
Accuracy: 68.16%
```

```
svm_predictions = svm_model.predict(X_test)
```

```
print(classification_report(y_test, svm_predictions))
```

	precision	recall	f1-score	support
0	0.68	0.97	0.80	173
1	0.71	0.16	0.26	94
accuracy			0.68	267
macro avg	0.70	0.56	0.53	267
weighted avg	0.69	0.68	0.61	267

```
results['SVM'] = svm_score
```

```
sklearn.svm.SVC(*, C=1.0, kernel='rbf', degree=3, gamma='scale',
        coef0=0.0, shrinking=True, probability=False, tol=0.001,
        cache_size=200, class_weight=None, verbose=False,
        max_iter=-1, decision_function_shape='ovr',
        break_ties=False, random_state=None)
```

Ensemble Learning Models: BAGGing *(Bootstrap AGGregating)*

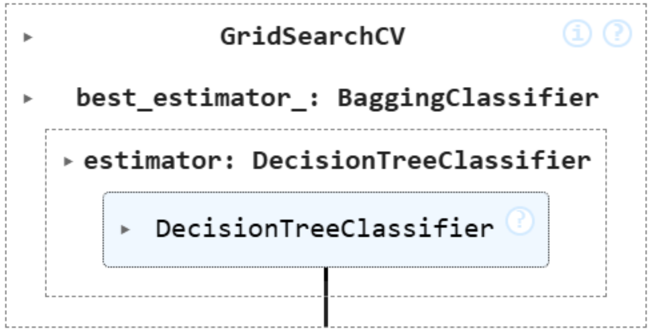
We will use *StratifiedShuffleSplit* which is another split technique:

```
sss = StratifiedShuffleSplit(n_splits = 10, test_size = 20, random_state = 2022)
```

```
sklearn.model_selection.StratifiedShuffleSplit(n_splits=10, *,
                test_size=None, train_size=None, random_state=None)
```

Let's implement the *Bagging Classifier* from Sklearn:

```
bg_model = BaggingClassifier(estimator = dt_model, bootstrap = True)
n_estimators = [10, 40, 60, 80, 100, 160]
parameters = {'n_estimators': n_estimators}
grid_bg = GridSearchCV(estimator = bg_model, param_grid = parameters, cv = sss)
grid_bg.fit(X_train, y_train)
```




```
sklearn.ensemble.BaggingClassifier(estimator=None,
                n_estimators=10, *, max_samples=1.0,
                max_features=1.0, bootstrap=True,
                bootstrap_features=False, oob_score=False,
                warm_start=False, n_jobs=None, random_state=None,
                verbose=0)
```

BAGGing involves adjusting decision trees to different samples from the same dataset, evaluating by calculating the average of these predictions.

Ensemble Learning Models: Bagging

Best estimator

```
bst_bg_model = grid_bg.best_estimator_
print(bst_bg_model)
```

```
BaggingClassifier(estimator=DecisionTreeClassifier(max_depth=2,
                                                   random_state=2022),
                  n_estimators=100)
```

```
bst_bg_model.fit(X_train, y_train)
```

```
▸ BaggingClassifier
▸ estimator: DecisionTreeClassifier
    ▸ DecisionTreeClassifier
```

```
bst_bg_score = bst_bg_model.score(X_test, y_test)
print("Accuracy: %.2f%%" % (bst_bg_score*100))
```

```
Accuracy: 70.41%
```

```
bg_predictions = bst_bg_model.predict(X_test)
print(classification_report(y_test, bg_predictions))
```

	precision	recall	f1-score	support
0	0.77	0.78	0.77	173
1	0.58	0.56	0.57	94
accuracy			0.70	267
macro avg	0.67	0.67	0.67	267
weighted avg	0.70	0.70	0.70	267

```
results['Bagg']= bst_bg_score
```

Ensemble Learning Models: Bagging

Now, bagging with **Random Forest**:

```
sklearn.ensemble.RandomForestClassifier(n_estimators=100, *,
          criterion='gini', max_depth=None, min_samples_split=2,
          min_samples_leaf=1, min_weight_fraction_leaf=0.0,
          max_features='sqrt', max_leaf_nodes=None,
          min_impurity_decrease=0.0, bootstrap=True, oob_score=False,
          n_jobs=None, random_state=None, verbose=0, warm_start=False,
          class_weight=None, ccp_alpha=0.0, max_samples=None,
          monotonic_cst=None)
```

```
rf_model = RandomForestClassifier(bootstrap = False, max_depth = 2, verbose = 1)
rf_model.fit(X_train, y_train)
```

```
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
```

```
RandomForestClassifier
RandomForestClassifier(bootstrap=False, max_depth=2, verbose=1)
```

```
rf_score = rf_model.score(X_test, y_test)
```

```
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
```

```
print("Accuracy: %.2f%%" % (rf_score * 100))
```

```
Accuracy: 73.41%
```

Ensemble Learning Models: Bagging


```
rf_predictions = rf_model.predict(X_test)
```

```
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
```

```
rf_predictions = rf_model.predict(X_test)
```

```
print(classification_report(y_test, rf_predictions))
```

```
              precision    recall  f1-score   support

           0       0.77      0.83      0.80       173
           1       0.64      0.55      0.59        94

    accuracy                           0.73       267
   macro avg       0.71      0.69      0.70       267
weighted avg       0.73      0.73      0.73       267
```

```
results['RF'] = rf_score
```

Ensemble Learning Models: Boosting

Gradient Boosting

```
gbc_model = GradientBoostingClassifier(n_estimators = 100, learning_rate = 1.0,
                                       max_depth = 1, random_state = 2022)
gbc_model.fit(X_train, y_train)
```

```
GradientBoostingClassifier
GradientBoostingClassifier(learning_rate=1.0, max_depth=1, random_state=2022)
```

```
gbc_score = gbc_model.score(X_test, y_test)
print("Accuracy: %.2f%%" % (gbc_score*100))
```

```
Accuracy: 71.16%
```

```
gbc_predictions = gbc_model.predict(X_test)
print(classification_report(y_test, gbc_predictions))
```

	precision	recall	f1-score	support
0	0.76	0.81	0.78	173
1	0.60	0.53	0.56	94
accuracy			0.71	267
macro avg	0.68	0.67	0.67	267
weighted avg	0.71	0.71	0.71	267

```
results['GB'] = gbc_score
```

```
sklearn.ensemble.GradientBoostingClassifier(*, loss='log_loss',
        learning_rate=0.1, n_estimators=100, subsample=1.0,
        criterion='friedman_mse', min_samples_split=2,
        min_samples_leaf=1, min_weight_fraction_leaf=0.0,
        max_depth=3, min_impurity_decrease=0.0, init=None,
        random_state=None, max_features=None, verbose=0,
        max_leaf_nodes=None, warm_start=False,
        validation_fraction=0.1, n_iter_no_change=None,
        tol=0.0001, ccp_alpha=0.0)
```

Boosting involves the sequential addition of ensemble members that correct the predictions made by previous models and produce a weighted average of the predictions.

Ensemble Learning Models: Boosting

XGBoost

```
xgb_model = XGBClassifier(max_depth = 1, objective = 'reg:squarederror')
xgb_model.fit(X_train, y_train)
```

```
XGBClassifier

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=1, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
```

```
xgb_score = xgb_model.score(X_test, y_test)
print("Accuracy: %.2f%%" % (xgb_score * 100))
```

```
Accuracy: 73.03%
```

```
xgboost.sklearn.XGBClassifier(base_score=None, booster=None,
                callbacks=None, colsample_bylevel=None,
                colsample_bynode=None, colsample_bytree=None,
                device=None, early_stopping_rounds=None,
                enable_categorical=False, eval_metric=None,
                feature_types=None, gamma=None,
                grow_policy=None, importance_type=None,
                interaction_constraints=None,
                learning_rate=None, max_bin=None,
                max_cat_threshold=None, max_cat_to_onehot=None,
                max_delta_step=None, max_depth=None,
                max_leaves=None, min_child_weight=None,
                missing=nan, monotone_constraints=None,
                multi_strategy=None, n_estimators=None,
                n_jobs=None, num_parallel_tree=None,
                random_state=None, ...)
```

Ensemble Learning Models: Boosting


```
xgb_predictions = xgb_model.predict(X_test)
print(classification_report(y_test, xgb_predictions))
```

```
              precision    recall  f1-score   support

           0       0.76      0.85      0.80       173
           1       0.65      0.51      0.57        94

    accuracy                           0.73       267
   macro avg       0.71      0.68      0.69       267
weighted avg       0.72      0.73      0.72       267
```

```
results['XGB'] = xgb_score
```

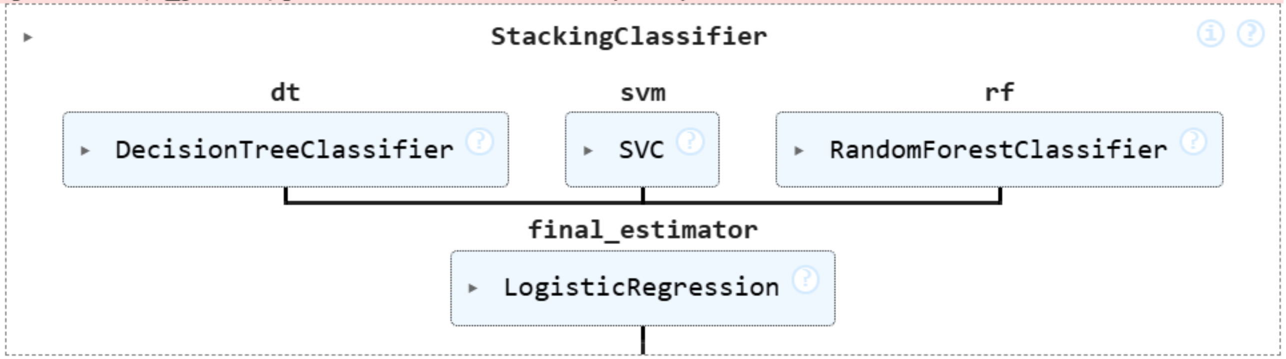
Ensemble Learning Models: Stacking

Stacking Classifier

```
estimators = [("dt", dt_model), ("svm", svm_model), ("rf", rf_model)]
st_model = StackingClassifier(estimators = estimators,
                              final_estimator = LogisticRegression())
```

```
st_model.fit(X_train, y_train)
```

```
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
```




```
sklearn.ensemble.StackingClassifier(estimators,
                final_estimator=None, *, cv=None,
                stack_method='auto', n_jobs=None,
                passthrough=False, verbose=0)
```

Stacking involves fitting different types of models to the same dataset, using another model to learn the best way to combine the predictions.

Ensemble Learning Models: Stacking


```
st_score = st_model.score(X_test, y_test)
```

```
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
```

```
print("Accuracy: %.2f%%" % (st_score*100))
```

```
Accuracy: 72.28%
```

```
st_predictions = st_model.predict(X_test)
```

```
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
```

```
print(classification_report(y_test, st_predictions))
```

```
              precision    recall  f1-score   support

           0       0.76      0.84      0.80       173
           1       0.63      0.51      0.56        94

    accuracy                           0.72       267
   macro avg       0.70      0.67      0.68       267
weighted avg       0.71      0.72      0.72       267
```

```
results['Stack']= st_score
```

Ensemble Learning Models: Max Voting

Majority Class Labels (Majority/Hard Voting)

```
hvt_model = VotingClassifier(estimators = [("dt", dt_model), ("svm", svm_model), ("rf", rf_model)],
                             voting = 'hard', weights = [2, 1, 2])
```

```
hvt_model.fit(X_train, y_train)
```

```
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
```

```
VotingClassifier
dt                          svm        rf
DecisionTreeClassifier      SVC        RandomForestClassifier
```

```
for model, label in zip([dt_model, svm_model, rf_model, hvt_model], ['dt', 'svm', 'rf', 'Ensemble']):
    hvt_score = cross_val_score(model, X_test, y_test, scoring = 'accuracy', cv = 5)
    print("Accuracy: %0.2f (+/- %0.2f) [%s]" % (hvt_score.mean(), hvt_score.std(), label))
```

```
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
Accuracy: 0.69 (+/- 0.05) [dt]
Accuracy: 0.66 (+/- 0.04) [svm]
[Parallel(n_jobs=1)]: Done  49 tasks      | elapsed:    0.0s
```

```
sklearn.ensemble.VotingClassifier(estimators,
        *, voting='hard', weights=None,
        n_jobs=None,
        flatten_transform=True,
        verbose=False)
```

Max voting involves fitting several models, each making a prediction and voting on each sample. Only the class with the highest votes is included in the final prediction class.

Ensemble Learning Models: Max Voting


```
hvt_score = hvt_model.score(X_test, y_test)
print("Accuracy: %.2f%%" % (hvt_score*100))
```

```
Accuracy: 70.79%
```

```
hvt_predictions = hvt_model.predict(X_test)
print(classification_report(y_test, hvt_predictions))
```

```
              precision    recall  f1-score   support

           0       0.77      0.79      0.78       173
           1       0.59      0.56      0.58        94

    accuracy                           0.71       267
   macro avg       0.68      0.67      0.68       267
weighted avg       0.71      0.71      0.71       267
```

```
results['HVotW']= hvt_score
```

Models Accuracy Comparison

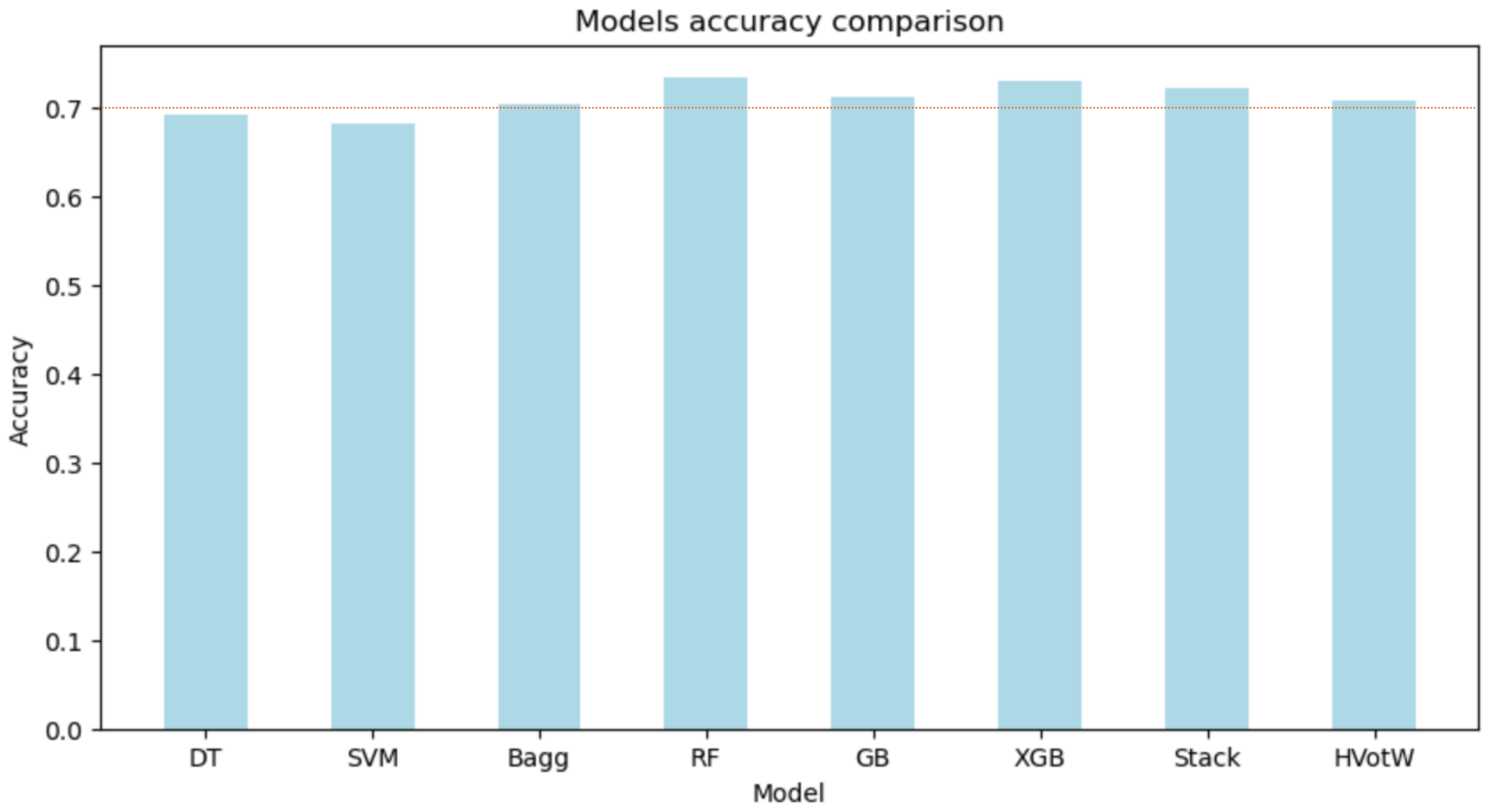
Let's create a bar chart with the accuracy of each model created:

```
fig = plt.figure(figsize = (10, 5))

mod = list(results.keys())
acc =list(results.values())

plt.bar(mod, acc, color ='lightblue',
        width = 0.5)

plt.xlabel("Model")
plt.ylabel("Accuracy")
plt.title("Models accuracy comparison")
plt.show()
```



Models Accuracy Comparison

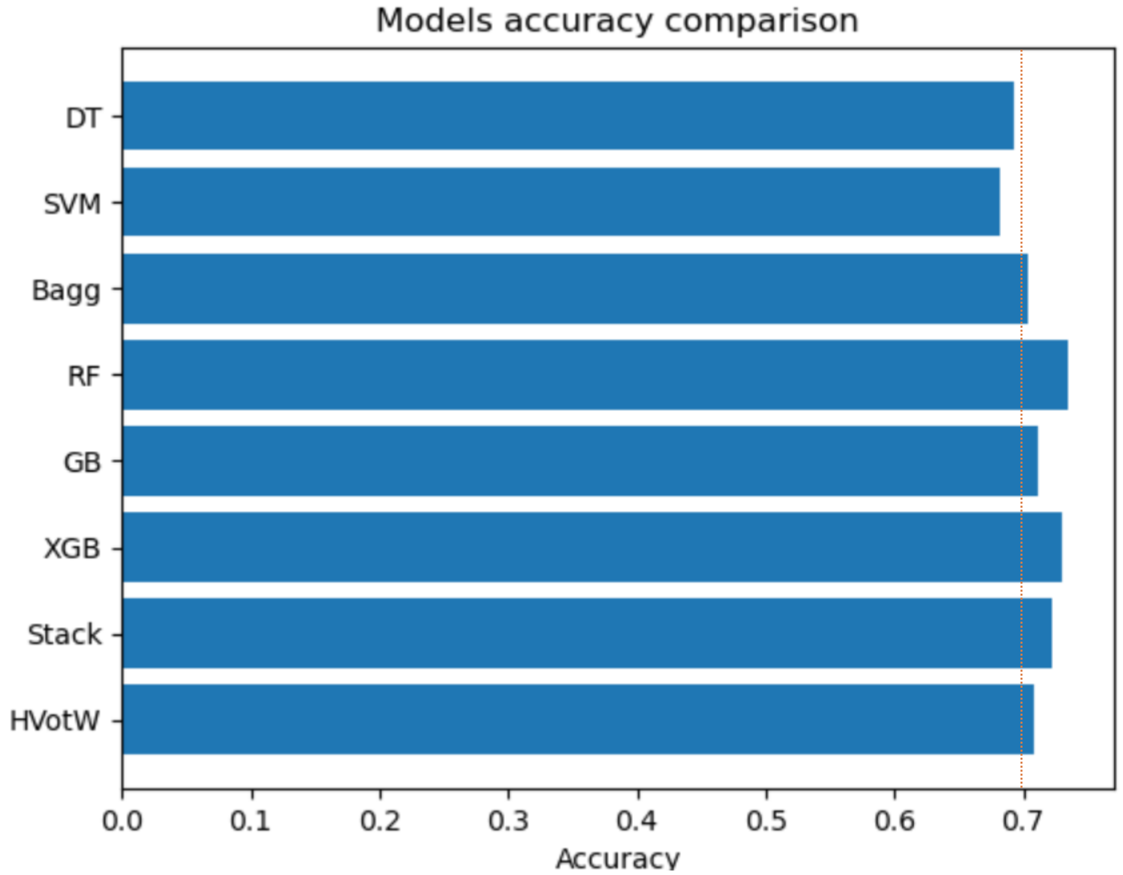
We can visualize it with horizontal bars:

```
fig, ax = plt.subplots()

y_values = np.arange(len(mod))

ax.barh(y_values, acc, align='center')
ax.set_yticks(y_values, labels = mod)
ax.invert_yaxis()
ax.set_xlabel('Accuracy')
ax.set_title('Models accuracy comparison')

plt.show()
```



Models Accuracy Comparison

Or we can print the results:

```
print("Models accuracy comparison")
for key, value in results.items():
    print("%s \t %.2f" % (key, value))
```

```
Models accuracy comparison
DT       0.69
SVM      0.68
Bagg     0.70
RF       0.73
GB       0.71
XGB      0.73
Stack    0.72
HVotW    0.71
```

Which model performed better?
Which models are worth tuning?

Models Accuracy Comparison

Or we can print the results:

```
print("Models accuracy comparison")
for key, value in results.items():
    print("%s \t %.2f" % (key, value))
```

```
Models accuracy comparison
DT      0.69
SVM     0.68
Bagg    0.70
RF      0.73
GB      0.71
XGB     0.73
Stack   0.72
HVotW   0.71
```

Which model perfomed better?
Which models are worth tunning?

Hands On