Stacking in Machine Learning

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Stacking is a ensemble learning technique where the final model known as the “stacked model" combines the predictions from multiple base models. The goal is to create a stronger model by using different models and combining them.

Architecture of Stacking

Stacking architecture is like a team of models working together in two layers to improve prediction accuracy. Each layer has a specific job and the process is designed to make the final result more accurate than any single model alone. It has two parts:

1. Base Models (Level-0)

These are the first models that directly learn from the original training data. You can think of them as the “helpers” that try to make predictions in their own way.

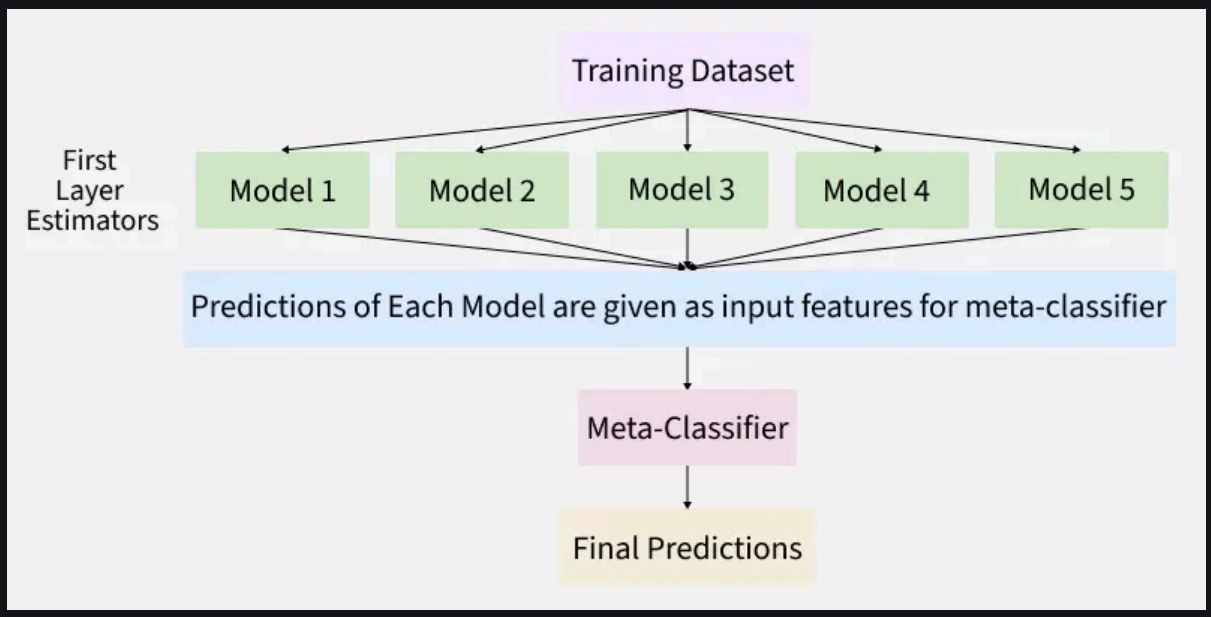
- Base models can be Decision Tree, Logistic Regression, Random Forest, etc.
- Each model is trained separately using the same training data.

2. Meta-Model (Level-1)

This is the final model that learns from the output of the base models instead of the raw data. Its job is to combine the base models predictions in a smart way to make the final prediction.

- A simple Linear Regression or Logistic Regression can act as a meta-model.

- It looks at the outputs of the base models and finds patterns in how they make mistakes or agree.



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Working of Stacking

The process can be summarized in the following steps:

- **Start with training data**: We begin with the usual training data that contains both input features and the target output.
- **Train base models**: The base models are trained on this training data. Each model tries to make predictions based on what it learns.
- **Generate predictions**: After training the base models make predictions on new data called validation data or out-of-fold data. These predictions are collected.
- **Train meta-model**: The meta-model is trained using the predictions from the base models as new features. The target output stays the same and the meta-model learns how to combine the base model predictions.
- **Final prediction**: When testing the base models make predictions on new, unseen data. These predictions are passed to the meta-model which then gives the final prediction.

With stacking we can improve our models performance and its accuracy.

Implementation of Stacking

Lets see its implementation step by step:

Step 1: Importing the required Libraries

We will import pandas, matplotlib and scikit learn for data handling, visualization and modeling.

```
import pandas as pd
import matplotlib.pyplot as plt
from mlxtend.classifier import StackingClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
```

Step 2: Loading the Dataset

We will load the dataset into a pandas DataFrame and separate features from the target variable.

- **pd.read_csv():** Reads the dataset from a CSV file.
- **drop():** Removes the target column from features.
- **df['target']:** Selects the target column for prediction.

You can Download the dataset from this link Heart Dataset.

```
df = pd.read_csv('heart.csv')

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

df.head()
```

Output:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	52	1	0	125	212	0	1	168	0	1.0	2	2	3	0
1	53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
2	70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
3	61	1	0	148	203	0	1	161	0	0.0	2	1	3	0
4	62	0	0	138	294	1	1	106	0	1.9	1	3	2	0

Step 3: Splitting the Data into Training and Testing Sets

We will split the dataset into training and testing sets so we can train models and evaluate their performance.

- **train_test_split():** Splits data into train and test sets.
- **test_size = 0.2:** Specifies that 20% of the data should be used for testing, leaving 80% for training.
- **random_state = 42:** Ensures reproducibility by setting a fixed seed for random number generation.

```
X_train, X_test, y_train, y_test = train_test_sp
y, test_size = 0.2, random_state = 42)
```

Step 4: Standardizing the Data

We will standardize numerical features so they have a mean of 0 and standard deviation of 1. This helps some models perform better.

- **StandardScaler():** Standardizes features.
- **fit_transform():** Learns scaling parameters from training data and applies them.
- **transform()**: Applies learned scaling to test data.
- **var_transform:** Specifies the list of feature columns that need to be standardized.
- **X_train[var_transform]:** Applies the **fit_transform** method to standardize the selected columns in the training data.
- **X_test[var_transform]:** Applies the transform method to standardize the corresponding columns in the test data using the scaling parameters from the training data.

```
sc = StandardScaler()

var_transform = ['thalach', 'age', 'trestbps', 'oldpeak', '
X_train[var_transform] = sc.fit_transform(X_train[var_trans
X_test[var_transform] = sc.transform(X_test[var_transform])

X_train.head()
```

Output:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
835	-0.585840	1	2	-0.779454	-1.935031	0	0	-1.019094	0	-0.210661	2	3	2
137	1.051477	0	0	2.741732	1.610634	0	1	0.202882	1	-0.912152	2	0	2
534	-0.040068	0	2	-1.347387	0.442176	0	0	0.770228	0	-0.912152	2	0	2
495	0.505705	1	0	0.186033	-0.222636	0	1	0.508376	0	-0.473720	1	0	3
244	-0.367531	1	2	-0.381900	-0.001032	1	0	0.726586	0	1.192321	1	0	2

Step 5: Building First Layer Estimators

We will create base models that will form the first layer of our stacking model. For this example we'll use K-Nearest Neighbors classifier and Naive Bayes classifier.

- **KNeighborsClassifier():** A model based on nearest neighbors.
- **GaussianNB():** A Naive Bayes classifier assuming Gaussian distribution.

```
KNC = KNeighborsClassifier()
NB = GaussianNB()
```

Step 6: Training and Evaluating KNeighborsClassifier

We will Train the KNN model and check its accuracy on the test set.

- **fit():** Trains the model.
- **predict():** Makes predictions on test data.


```
model_kNeighborsClassifier = KNC.fit(X_train, y_t i
pred_knc = model_kNeighborsClassifier.predict(X_test)
```

```
acc_knc = accuracy_score(y_test, pred_knc)
print('Accuracy Score of KNeighbors Classifier:', acc_knc *
100)
```

Output:

Accuracy Score of KNeighbors Classifier: 86.88524590163934

Step 7: Training and Evaluating Naive Bayes Classifier

Similarly, we will train the Naive Bayes model and check its accuracy.

```
model_NaiveBayes = NB.fit(X_train, y_train)
pred_nb = model_NaiveBayes.predict(X_test)

acc_nb = accuracy_score(y_test, pred_nb)
print('Accuracy of Naive Bayes Classifier:', acc_nb *
100)
```

Output:

Accuracy of Naive Bayes Classifier: 86.88524590163934

Step 8: Implementing the Stacking Classifier

Now, we will combine the base models using a Stacking Classifier. The meta-model will be a logistic regression model which will take the predictions of KNN and Naive Bayes as input.

- **StackingClassifier():** Combines base models and a meta-model.
- **classifiers:** List of base learners.
- **meta_classifier:** Model that learns from base learners' predictions.
- **use_probas=True:** Passes probability outputs to the meta-model instead of class labels.

```
base_learners = [
    KNeighborsClassifier(),
    GaussianNB()
]
```

```
meta_model = LogisticRegression()

stacking_model =
StackingClassifier(classifiers=base_learners,
meta_classifier=meta_model, use_probas=True)
```

Step 9: Training Stacking Classifier

Next we will rain the stacking classifier and evaluate its accuracy.

```
model_stack = stacking_model.fit(X_train, y_train)
pred_stack = model_stack.predict(X_test)

acc_stack = accuracy_score(y_test, pred_stack)
print('Accuracy Score of Stacked Model:', acc_stack *
100)
```

Output:

Accuracy Score of Stacked Model: 88.52459016393442

Both individual models (KNN and Naive Bayes) achieved an accuracy of approximately 86.88%, while the stacked model achieved an accuracy of around 88.52%. This shows that combining the predictions of multiple models using stacking can slightly improve overall performance compared to using a single model.

Advantages of Stacking

Here are some of the key advantages of stacking:

- **Better Performance:** Stacking often results in higher accuracy by combining predictions from multiple models making the final output more reliable.
- **Combines Different Models:** It allow to use various types of models like decision trees, logistic regression, SVM made from each model's unique strengths.
- **Reduces Overfitting:** When implemented with proper cross-validation it can reduce the risk of overfitting by balancing out the weaknesses of individual models.

- **Learns from Mistakes:** The meta-model is trained to recognize where base models go wrong and improves the final prediction by correcting those errors.
- **Customizable:** We can choose any combination of base and meta-models depending on our dataset and problem type making it highly flexible.

Limitations of Stacking

Stacking also have some limitations as well:

- **Complex to Implement**: Compared to simple models or even bagging or boosting, stacking requires more steps and careful setup.
- **Slow Training Time**: Since you're training multiple models plus a meta-model it can be slow and computationally expensive.
- **Hard to Interpret**: With multiple layers of models it becomes difficult to explain how the final prediction was made.
- **Risk of Overfitting**: If the meta-model is too complex or if there's data leakage it can overfit the training data.
- **Needs More Data**: It performs better when you have enough data, especially for training both base and meta-models effectively

Related Articles:

- *Ensemble Learning*
- *Types of Ensemble Learning*
- *Bagging vs Boosting in Machine Learning*.