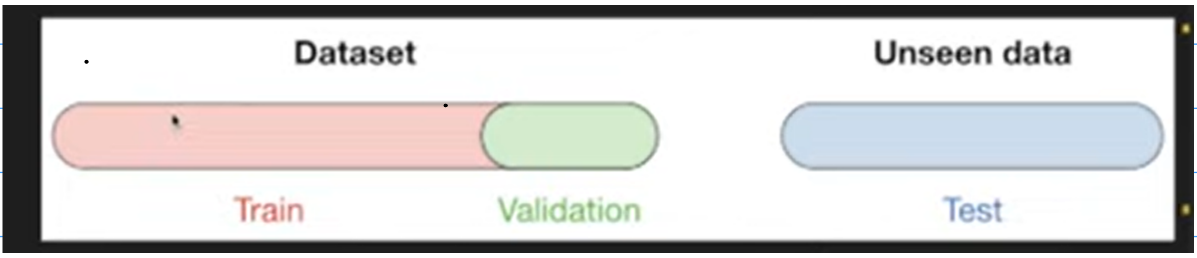
What is GridSearchCV ?

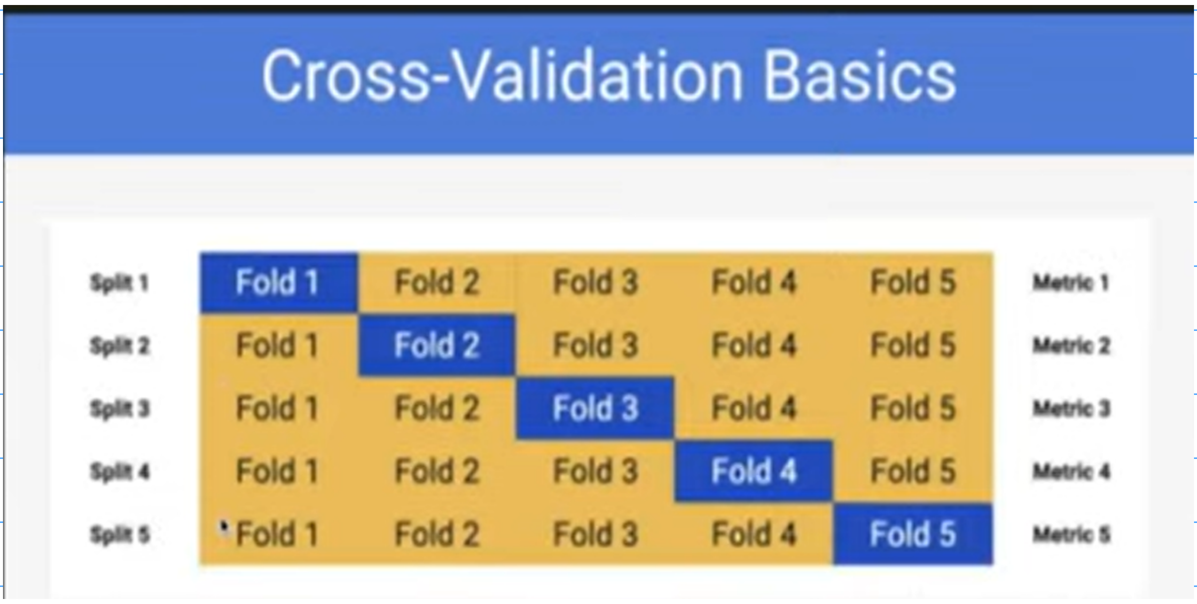
GridSearchCV tests different hyperparameter values to find the best one for your model.

You should use GridSearchCV instead of KFold and cross_val_score
when you're not only looking to evaluate a model but also want to
tune hyperparameters to find the best combination for your model.

How GridSearchCV Works?

GridSearchCV splits the training data in k equal parts (folds).
Each fold is used as a validation set and the remaining is used as training

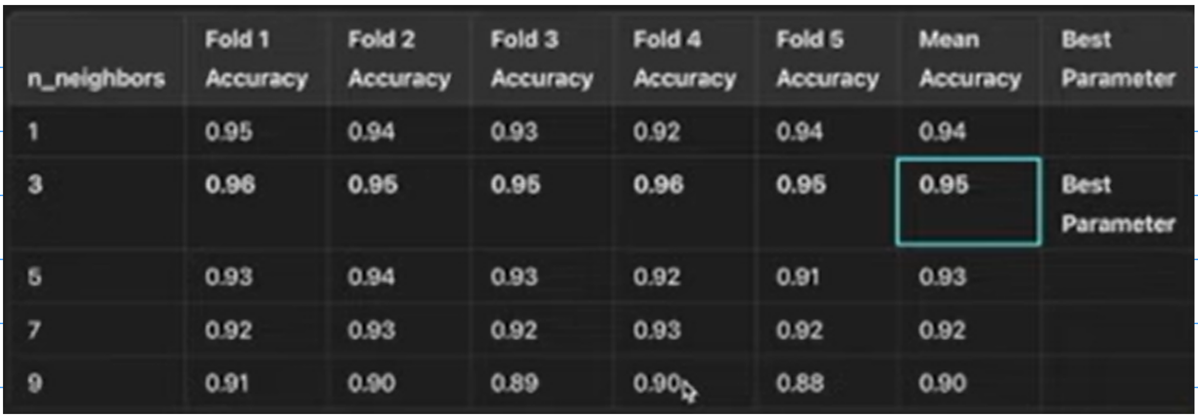




- train data using first fold in validation set and get a metric out of it like maybe the accuracy score and then the rest is the training data

Perform cross-validation(eg: with KFold) for each combination of hyper parameters.
Returns the best hyperparameters based on average performance across the cross validation folds
CV - cross validation done by model itself to check accuracy and if accuracy is not good then it tries to perform the iteration again.

```
grid_search_cv.best_params_    # best parameters
grid_search_cv.best_score_     # best cross-validation score
grid_search_cv.best_estimator_  # trained model with best params
```



n_neighbors	Fold 1 Accuracy	Fold 2 Accuracy	Fold 3 Accuracy	Fold 4 Accuracy	Fold 5 Accuracy	Mean Accuracy	Best Parameter
1	0.95	0.94	0.93	0.92	0.94	0.94	
3	0.96	0.95	0.95	0.96	0.95	0.95	Best Parameter
5	0.93	0.94	0.93	0.92	0.91	0.93	
7	0.92	0.93	0.92	0.93	0.92	0.92	
9	0.91	0.90	0.89	0.90	0.88	0.90	

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For SVM(hyperparameters)

```
from sklearn.model_selection import GridSearchCV, KFold

# create cross validator
k_fold = KFold(n_splits=5)
```

$\leftarrow$ creates a 5-fold cross-validation

Your training data is split into 5 equal parts

The model is trained 5 times(Your training data is split into 5 equal parts

The final score is the average across all 5 runs

This helps estimate how well the model generalizes to unseen data.

```
# which hyperparameters GridSearchCV should try.
parameters = {
    "C": np.arange(10) * 0.1,
    "kernel": ['linear', 'poly', 'rbf', 'sigmoid'],
    "gamma": np.arange(10) * 0.1
}
grid_search_cv = GridSearchCV(estimator=model, param_grid=parameters, cv=k_fold)
grid_search_cv.fit(x_train, y_train)
```

"C" ==> [0.1, 0.2, ..., 0.9]

C controls the regularization strength in SVMs

Small C → more regularization (simpler model)

Large C → less regularization (more complex model)

C=0.0 is invalid for SVMs

Usually starts from something like 0.1 or 0.01.

"kernel" ===> ['linear', 'poly', 'rbf', 'sigmoid']

These are different SVM kernel functions:

linear: straight line / hyperplane
poly: polynomial decision boundary
rbf: radial basis function (most common)
sigmoid: neural-network-like behavior

"gamma" ===>gamma controls how far the influence of a single training
example reaches

Small gamma → smoother decision boundary
Large gamma → more complex boundary
gamma=0.0 is also invalid for svm

```
GridSearchCV object ===>grid_search_cv = GridSearchCV(
                                estimator=model,
                                param_grid=parameters,
                                cv=k_fold)
```

This creates a grid search object that:
Tries every possible combination of:

C
kernel
gamma
Uses 5-fold cross-validation for each combination
Evaluates which combination performs best

```
grid_search_cv.fit(x_train, y_train)
```

trains all those models
Finds the best hyperparameter combination
Stores the results

```
grid_search_cv.best_params_    # best C, kernel, gamma
grid_search_cv.best_score_     # best cross-validation score
grid_search_cv.best_estimator_  # trained model with best params
```