

Introduction to PyCaret and installation







# Installation on Windows and Google Colab



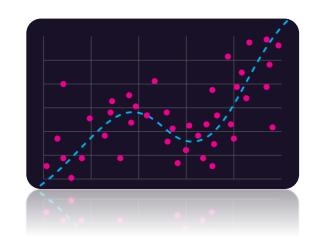








# Tutorial notebook for Machine Learning Regression

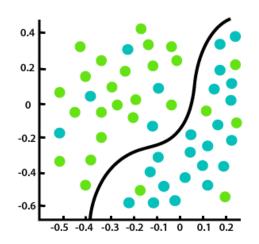








# Tutorial notebook for Machine Learning Classification









### What is PyCaret?

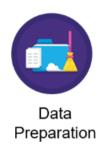
- PyCaret is an open-source, low-code machine learning library in Python that automates machine learning workflows.
- PyCaret can be used to replace hundreds of lines of code with few lines only. You spend less time coding and more time on analysis
- PyCaret is essentially a Python wrapper around several machine learning libraries and frameworks such as scikit-learn, XGBoost, LightGBM, CatBoost, and few more.

- Exploratory Data Analysis
- Data Preprocessing
- Model Training
- **Model Explainability**
- **MLOps**



### PyCaret is ideal for:

- Experienced Data Scientists who want to increase productivity.
- Citizen Data Scientists who prefer a low code machine learning solution.
- Data Science Professionals who want to build rapid prototypes.
- Data Science and Machine Learning students and enthusiasts.

















# Preprocessing (setup)

	Data Preparation		Scale and Transform		Feature Engineering		Feature Selection
•	Missing values	•	Normalize	•	Feature interaction	•	Feature Selection
•	Data Types	•	Feature Transform	•	Polynomial Features	•	Remove Multicollinearity
•	One-Hot Encoding	•	Target Transform	•	Group Features	•	Principal Component Analysis
•	Ordinal Encoding			•	Bin Numeric Features	•	Ignore Low Variance
•	Cardinal Encoding			•	Combine Rare Levels		
•	Handle Unknown Levels			•	Create Clusters		
•	Target Imbalance						
•	Remove outliers						





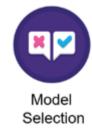
### Model training

PyCaret trains multiple models simultaneously and outputs a table comparing the performance of each model by considering a few performance metrics.

- Creating models: create\_model('dt', fold=n, ...)
- Comparing models: compare\_models(n\_select = n, sort='Accuracy', ...)
- Tuning hyperparameters: tune\_model(dt, custom\_grid: Optional, ...)





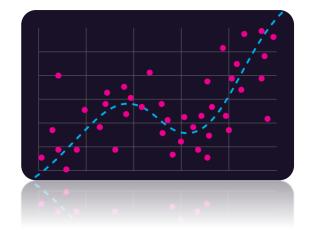






# List of models (Regression)

ID	Name
'lr'	Linear Regression
'lasso'	Lasso Regression
'ridge'	Ridge Regression
'en'	Elastic Net
'lar'	Least Angle Regression
ʻllar'	Lasso Least Angle Regression
'omp'	Orthogonal Matching Pursuit
'br'	Bayesian Ridge
'ard'	Automatic Relevance Determination
'par'	Passive Aggressive Regressor
'ransac'	Random Sample Consensus
'tr'	TheilSen Regressor
'huber'	Huber Regressor
'kr'	Kernel Ridge
'svm'	Support Vector Machine
'knn'	K Neighbors Regressor
'dt'	Decision Tree
'rf'	Random Forest
'et'	Extra Trees Regressor
'ada'	AdaBoost Regressor
ʻgbr'	Gradient Boosting Regressor
'mlp'	Multi Level Perceptron
'xgboost'	Extreme Gradient Boosting
'lightgbm'	Light Gradient Boosting
'catboost'	CatBoost Regressor

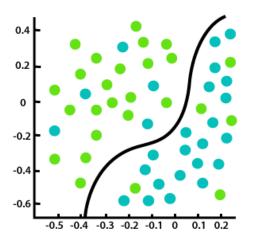






## List of models (Classification)

ID	Name
ʻlr'	Logistic Regression
'knn'	K Nearest Neighbour
'nb'	Naives Bayes
'dt'	Decision Tree Classifier
'svm'	SVM – Linear Kernel
'rbfsvm'	SVM – Radial Kernel
'gpc'	Gaussian Process Classifier
'mlp'	Multi Level Perceptron
'ridge'	Ridge Classifier
rf'	Random Forest Classifier
ʻqda'	Quadratic Discriminant Analysis
'ada'	Ada Boost Classifier
'gbc'	Gradient Boosting Classifier
ʻlda'	Linear Discriminant Analysis
'et'	Extra Trees Classifier
'xgboost'	Extreme Gradient Boosting
'lightgbm'	Light Gradient Boosting
'catboost'	CatBoost Classifier





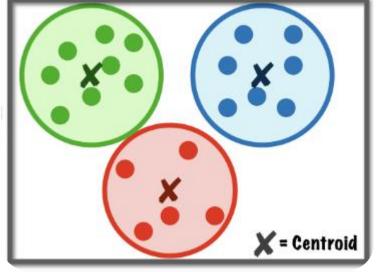




# List of models (Clustering)

ID	Name
'kmeans'	K-Means Clustering
'ap'	Affinity Propagation
'meanshift'	Mean shift Clustering
'sc'	Spectral Clustering
'hclust'	Agglomerative Clustering
'dbscan'	Density-Based Spatial Clustering
'optics'	OPTICS Clustering
'birch'	Birch Clustering
'kmodes'	K-Modes Clustering

### **Labelled Clusters**



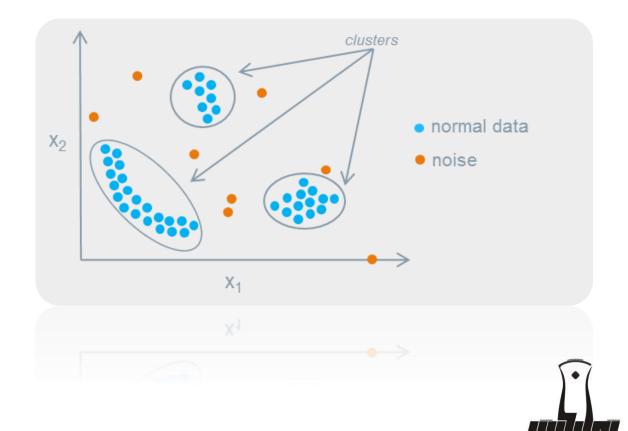






## List of models (Anomaly Detection)

ID	+   Name
<pre>'abod' 'iforest' 'cluster' 'cof' 'histogram' 'knn' 'lof' 'svm' 'pca' 'mcd' 'sod' 'sos</pre>	Angle-base Outlier Detection Isolation Forest Clustering-Based Local Outlier Connectivity-Based Outlier Factor Histogram-based Outlier Detection k-Nearest Neighbors Detector Local Outlier Factor One-class SVM detector Principal Component Analysis Minimum Covariance Determinant Subspace Outlier Detection Stochastic Outlier Selection
'mcd' 'sod' 'sos	Minimum Covariance Determinant Subspace Outlier Detection Stochastic Outlier Selection



Pedram, Jahangin



## Analysis and interpretability

My\_model = create\_model('Model\_name')

- plot\_model(my\_model)
- interpret\_model(model)



Name	Plot
Area Under the Curve Discrimination Threshold Precision Recall Curve Confusion Matrix Class Prediction Error Classification Report Decision Boundary Recursive Feature Selection Learning Curve Manifold Learning Calibration Curve Validation Curve Dimension Learning Feature Importance Model Hyperparameter	'auc'   'threshold'   'pr'   'confusion_matrix'   'error'   'class_report'   'boundary'   'rfe'   'learning'   'manifold'   'calibration'   'vc'   'dimension'   'feature'   'parameter'

Name	Plot
Residuals Plot Prediction Error Plot Cooks Distance Plot Recursive Feature Selection Learning Curve Validation Curve Manifold Learning Feature Importance Model Hyperparameter	<pre>'residuals' 'error' 'cooks' 'rfe' 'learning' 'vc' 'manifold' 'feature' 'parameter'</pre>

Cluster PCA Plot (2d)	+   'cluster'
Cluster TSnE (3d)   Elbow Plot   Silhouette Plot   Distance Plot   Distribution Plot	'tsne' 'elbow' 'silhouette' 'distance' 'distribution'



## Finalize, Predict, Save and Deploy model

Google Cloud Platform

```
My_model = create_model('Model_name')
  finalize_model(my_model)
  predict_model(my_model)
  save model(my model)
  deploy model(model)
☐ Finalize: This function trains a given estimator on the entire dataset including the
  holdout set
predict: This function makes predictions on the test data set.
□ Save: This function saves the transformation pipeline and trained model object
  into the current working directory as a pickle file for later use (load_model)
Deploy: This function deploys the transformation pipeline and trained model on
  cloud.
```

aws

**Microsoft** 

### Workflow

PyCaret offers both supervised and unsupervised workflow

### Classification

```
import pandas as pd
train = pd.read_csv('train.csv')
test = pd.read csv('test.csv')
from pycaret.classification import *
s = setup(train, target= 'target')
# model training and selection
best = compare models()
evaluate model(best)
# predict on new data
predictions = predict model(best, data =test )
save model(best, 'my best pipeline')
```

### Regression

```
import pandas as pd
train = pd.read csv('train.csv')
test = pd.read csv('test.csv')
from pycaret.regression import *
s = setup(train, target= 'target')
# model training and selection
best = compare_models()
evaluate_model(best)
# predict on new data
predictions = predict_model(best, data =test )
save_model(best, 'my_best_pipeline')
```



### Workflow

PyCaret offers both supervised and unsupervised workflow

### Clustering

```
import pandas as pd
data = pd.read csv('data.csv')
from pycaret.clustering import *
s = setup(data, normalize= True)
kmeans = create model('kmeans')
# assign cluster labels on training data
kmeans results = assign model(kmeans)
new_data = pd.read_csv('new_data.csv')
predictions = predict model(kmeans, data= new data)
save_model(kmeans, 'kmeans pipeline')
```

```
# save kmeans pipeline
save_model(kmeans, 'kmeans_pipeline')
```

### Anomaly detection

```
import pandas as pd
data = pd.read csv('data.csv')
from pycaret.anomaly import *
s = setup(data, normalize= True)
# train isolation forest model
iforest = create model('iforest')
# assign anomaly labels on training data
iforest results = assign model(iforest)
new_data = pd.read_csv('new_data.csv')
predictions = predict model(iforest, data= new data)
# save iforest pipeline
save model(iforest, 'iforest pipeline')
                                                             Pedram, Jahangiry
```

### Installation

- The most efficient way of installing PyCaret is through a virtual environment! Here are the steps:
- 1. Install anaconda <a href="https://www.anaconda.com/products/distribution">https://www.anaconda.com/products/distribution</a>
- 2. Create a conda environment: conda create --name yourenvname python=3.8
- 3. Activate conda environment: conda activate yourenvname
- 4. Install pycaret 3.0: pip install pycaret[full]
- 5. Create notebook kernel:

python -m ipykernel install --user --name yourenvname --display-name "display-name"





# ⇒ Important Links

<b>★</b> <u>Tutorials</u>	New to PyCaret? Checkout our official notebooks!
<b>Example Notebooks</b>	Example notebooks created by community.
Official Blog	Tutorials and articles by contributors.
<b>Documentation</b>	The detailed API docs of PyCaret
<b>Video Tutorials</b>	Our video tutorial from various events.
<b>Cheat sheet</b>	Cheat sheet for all functions across modules.
Discussions	Have questions? Engage with community and contributors.
<b>Changelog</b>	Changes and version history.
Roadmap	PyCaret's software and community development plan.



### PyCaret Time Series Module

PyCaret new time series module is now available with the main pycaret installation. Staying true to simplicity of PyCaret, it is consistent with the existing API and fully loaded with functionalities

<b>★</b> Time Series Quickstart	Get started with Time Series Analysis
Time Series Notebooks	New to Time Series? Checkout our official (detailed) notebooks!
<b>Time Series Video Tutorials</b>	Our video tutorial from various events.
? Time Series FAQs	Have questions? Queck out the FAQ's
<b>Time Series API Interface</b>	The detailed API interface for the Time Series Module
Time Series Features and Roadmap	PyCaret's software and community development plan.





### Practical example in Python

Now let's look at some practical examples in Python!

https://github.com/PJalgotrader/platforms-and-tools/tree/main/PyCaret

