



## TP3



Parcours Progis

Etudes, Medias, communication, Marketing

Bahareh Afshinpour

03.11.2025

# Customer Lifetime Value (CLV)

- **CLV** is the **total amount of money** a customer is expected to spend on your business **over their entire relationship** with you.

If a customer buys a \$50 product every month and stays with your brand for 2 years, their CLV is about \$1,200.

## Why is CLV Important?

**Marketing:** Helps decide how much to spend to acquire a new customer.

**Social Media:** Helps identify which customers to target with ads or promotions.

**Business Strategy:** Helps focus on high-value customers and improve their experience.

## Step 1- Load data from a CSV file into a DataFrame

- What is a CSV file?
  - ✓ A CSV (Comma-Separated Values) file is a simple text file where each line represents a data record, and each value is separated by a comma.
- Goal: Load data from a CSV file into a DataFrame, which is a table-like data structure provided by the Pandas library in Python.

## Tips

- Make sure your CSV file is **in the same folder** as your Python script(code), or provide the correct path to the file.
- Check the first few rows to make sure your data was loaded correctly: **`print(df.head())`**

# Step 1- Load data from a CSV file into a DataFrame

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
data = pd.read_csv('./WA_Fn-UseC_-Marketing-Customer-Value-Analysis.csv', encoding='latin1')
data.columns
```

```
[3]: data.head()
```

```
[3]:
```

|   | Customer | State      | Customer<br>Lifetime<br>Value | Response | Coverage | Education | Effective<br>To Date | EmploymentStatus | Gender | Income | ... |
|---|----------|------------|-------------------------------|----------|----------|-----------|----------------------|------------------|--------|--------|-----|
| 0 | BU79786  | Washington | 2763.519279                   | No       | Basic    | Bachelor  | 2/24/11              | Employed         | F      | 56274  | ... |
| 1 | QZ44356  | Arizona    | 6979.535903                   | No       | Extended | Bachelor  | 1/31/11              | Unemployed       | F      | 0      | ... |

## Step 2- Checking for the Missing values

```
data.isnull().mean()
```

|                         |     |
|-------------------------|-----|
| Customer                | 0.0 |
| State                   | 0.0 |
| Customer Lifetime Value | 0.0 |
| Response                | 0.0 |
| Coverage                | 0.0 |
| Education               | 0.0 |
| Effective To Date       | 0.0 |
| EmploymentStatus        | 0.0 |
| Gender                  | 0.0 |

## Step 3- Defining Independent and Target features

- Before identifying the target (dependent) and independent variables, remember:
- You should only use **numerical** data when performing regression analysis.

```
num=data.select_dtypes(include='number')  
num.head()
```

|   | Customer<br>Lifetime Value | Income | Monthly<br>Premium Auto | Months Since<br>Last Claim |
|---|----------------------------|--------|-------------------------|----------------------------|
| 0 | 2763.519279                | 56274  | 69                      | 32                         |
| 1 | 6979.535903                | 0      | 94                      | 13                         |
| 2 | 12887.431650               | 48767  | 108                     | 18                         |
| 3 | 7645.861827                | 0      | 106                     | 18                         |

## Step 3- Defining Independent and Target features

**Independent Features** : The variables used to predict the target.

**Target Feature** : The variable you want to predict.

Example: Independent Feature (X): Hours\_Studied      Target Feature (Y): Test\_Score

How to take our data frame and split it into two important parts.

Target variable

```
y = num['Customer Lifetime Value']  
X = num.drop(columns=['Customer Lifetime Value'])
```

Tip: Always check the shape and content of X and y:

```
print(X.head())
```

```
print(y.head())
```

## Step 3- Defining Independent and Target features

| Income | Monthly Premium Auto | Customer Lifetime Value | ... |
|--------|----------------------|-------------------------|-----|
| 56274  | 384.811147           |                         |     |
| 3665   | 1131.46493           |                         |     |
|        |                      |                         |     |
|        |                      |                         |     |
|        |                      |                         |     |

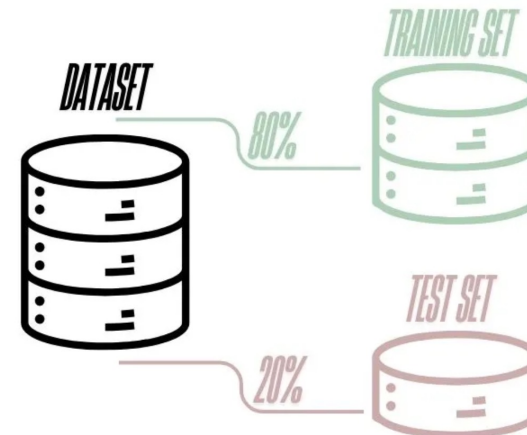


| X      |                      |                    |     | Y                       |  |
|--------|----------------------|--------------------|-----|-------------------------|--|
| Income | Monthly Premium Auto | Total Claim Amount | ... | Customer Lifetime Value |  |
| 56274  | 384.811147           |                    |     | 2763.519279             |  |
| 3665   | 1131.46493           |                    |     | 6979.535903             |  |
|        |                      |                    |     |                         |  |
|        |                      |                    |     |                         |  |
|        |                      |                    |     |                         |  |



## Step 4- Split the data into Train and Test datasets

- Why do we split the data?
  - To **train** the model on one part of the data (training set) and **test** its performance on **unseen data** (test set)
  - This helps us check if the model can generalize to new data and is not just memorizing the examples



## Step 4- Split the data into Train and Test datasets

- The train-test split is a technique for evaluating the **performance** of a machine learning algorithm.
- It can be used for classification or regression problems and can be used for any supervised learning algorithm.
- **Train Dataset:** Used to fit the machine learning model.
- **Test Dataset:** Used to evaluate the fit machine learning model.

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33)
```

```
# split again, and we should see the same split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1)
```

## Example

```
>>> x
array([[ 1,  2],
       [ 3,  4],
       [ 5,  6],
       [ 7,  8],
       [ 9, 10],
       [11, 12],
       [13, 14],
       [15, 16],
       [17, 18],
       [19, 20],
       [21, 22],
       [23, 24]])
>>> y
array([0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0])
```

**You probably got different results from what you see here. This is because dataset splitting is random by default.**

```
>>> x_train, x_test, y_train, y_test = train_test_split(x, y)
>>> x_train
array([[15, 16],
       [21, 22],
       [11, 12],
       [17, 18],
       [13, 14],
       [ 9, 10],
       [ 1,  2],
       [ 3,  4],
       [19, 20]])
>>> x_test
array([[ 5,  6],
       [ 7,  8],
       [23, 24]])
>>> y_train
array([1, 1, 0, 1, 0, 1, 0, 1, 0])
>>> y_test
array([1, 0, 0])
```

## Step 4- Split the data into Train and Test datasets

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

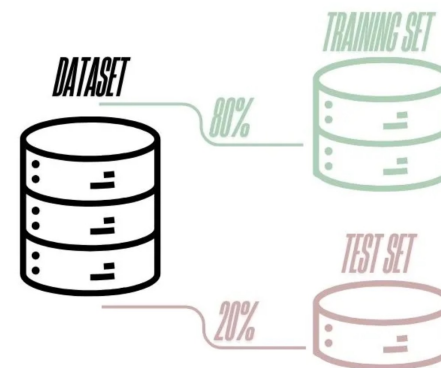
print("shape of X_train ",X_train.shape)
print("shape of X_test ",X_test.shape)
```

shape of X\_train (7307, 7)

shape of X\_test (1827, 7)

Every time we change the random state, different observation gets selected into the training and testing.

**If the averaging value of the dependent variable differs significantly between training and testing, the model does not have a fair opportunity of learning what it can from the data.**



## Step 5- Fitting the simple regression model

```
from sklearn.linear_model import LinearRegression
reg = LinearRegression()
reg.fit(X_train, y_train)
print (reg.intercept_)
#linear_predict_all=reg.predict(X)
```

```
reg.intercept_
```

```
193.6434424279978
```

```
reg.coef_
```

$$Y=a*x+b$$

$$Y=\text{coef}*x+\text{intercept}$$

## Step 5- Linear Regression

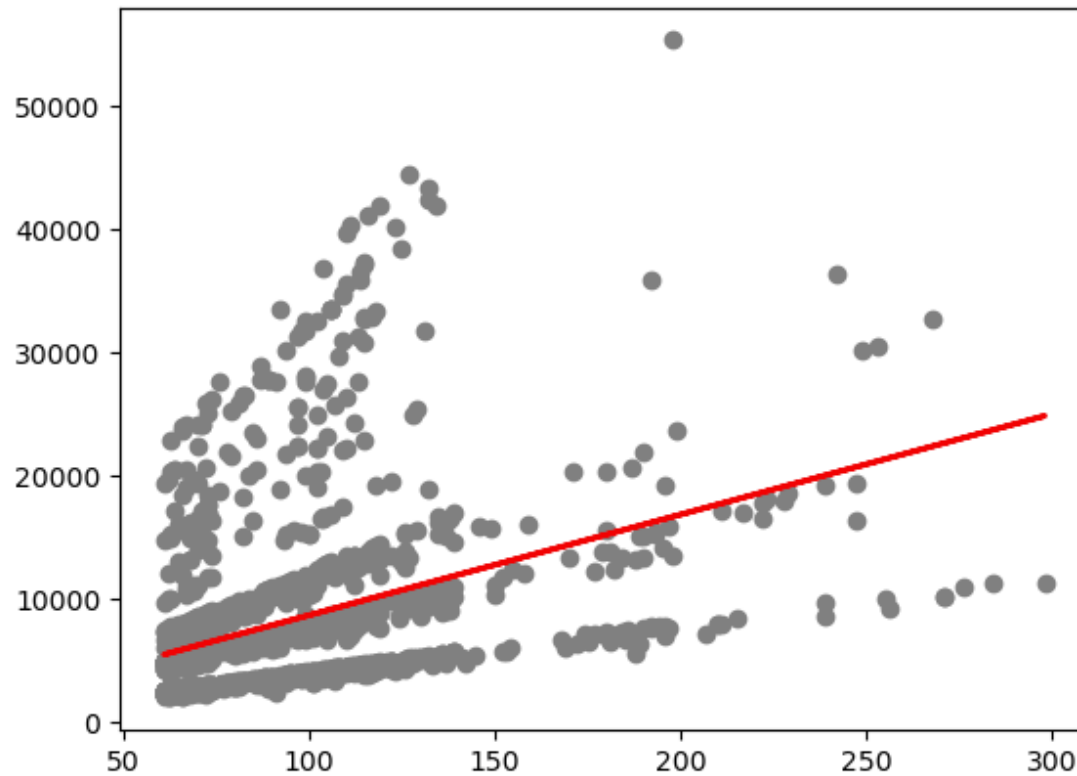
```
from sklearn.linear_model import LinearRegression
reg = LinearRegression().fit(X_train, y_train)
acc_log_train = round(reg.score(X_train, y_train)*100,2)
acc_log_test = round(reg.score(X_test, y_test)*100,2)
print("Training Accuracy:%{}".format(acc_log_train))
print("Testing Accuracy:%{}".format(acc_log_test))
```

Training Accuracy:%16.2  
Testing Accuracy:%15.3

**It is not good**

```
|
test_p = reg.predict(X_test)

from sklearn.metrics import r2_score
print('R-Squared for Test set: %0.2f' % r2_score(y_true=y_test, y_pred=test_p))
```



**It is not good**  
**We can do**  
**Linear Regression By**  
**filtering with**  
**'Number of Policies'**

# Why Not All Columns Improve Regression?

- When building a regression model to predict something like Customer Lifetime Value, it's tempting to include all available columns (features) in your dataset.
- However, using every column doesn't always lead to a better model. **Sometimes, it can even make your predictions worse**

## Not All Features Are Useful:

- Some columns have little or no relationship with the target variable (Customer Lifetime Value).
- Including unrelated or random columns can introduce noise and confuse the model.
- Unnecessary features can "drown out" the effect of important ones, making it harder for the model to learn real relationships.

**Try Feature Selection Techniques**

- Factors positively influencing CLV include **Monthly Premium** and **Number of Policies**, while **Open Complaints** and **Claim Amount** have the potential to decrease CLV. These factors should be carefully managed to optimize customer value.

# FUNCTION

There are two kinds of functions in Python.

- Built-in functions that are provided as part of Python
  - `print()`, `input()`, `type()`, `float()`, `int()` ...
- Functions that we define ourselves and then use

# FUNCTION

- In Python a function is some **reusable** code that takes arguments(s) as input, does some computation, and then returns a result or results
- We define a function using the **def** reserved word
- We **call/invoke** the function by using the function name, parentheses, and arguments in an expression

# Function example

## Creating a Function

```
def my_function():  
    print("Hello from a function")
```

## Calling a Function

```
.....
```

```
....
```

```
my_function()
```

# Arguments

- An argument is a value we pass into the function as its input when we call the function

# Parameters

A parameter is a variable which we use in the function definition. It is a “handle” that allows the code in the function to access the arguments for a particular function invocation.

```
>>> greet('en')
```

```
Hello
```

```
>>> greet('fr')
```

```
Bonjour
```

```
>>>
```

**Argument**



**Parameter**



```
>>> def greet(lang):  
...     if lang == 'en':  
...         print('Hello')  
...     elif lang == 'fr':  
...         print('Bonjour')
```

# Return Values

```
def my_function(x):  
    return 5 * x
```

```
print(my_function(3))  
print(my_function(5))  
print(my_function(9))
```

**End**