End to End Machine Learning Project Pipeline

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Beginner Data Exploration Linear Regression Machine Learning Python Regression Structured Data

Introduction

Understanding project pipelines is paramount for your machine learning career. This pipeline encompasses components like Feature Selection, Exploratory Data Analysis, Feature Engineering, Model Building, Evaluation, and Model Saving. A common question that arises in our minds is – Why do we need end to end machine learning project pipeline? The answer lies in the ability to execute any Machine Learning Project in a structured manner meticulously. This systematic approach not only enhances project clarity but also enables effective communication of results, eliminating the "Black-box" mystique.

This article delves into the comprehensive world of the Machine Learning pipeline. Through the lens of a practical machine learning project, we'll dissect each step, unraveling the nuances and importance of this end-to-end journey.

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Pre-Requisites

Basic understanding of Linear Regression Algorithm. If you have no idea about the algorithm, please refer to the link before going to the later part of the article, so that you have a basic understanding of all the concepts which we will cover.

Step 1: Import Necessary Dependencies

In this step, we will import the necessary libraries such as:

- **For Linear Algebra:** Numpy
- **For Data Preprocessing, and CSV File I/O:** Pandas
- **For Model Building and Evaluation:** Scikit-Learn
- **For Data Visualization:** Matplotlib, and Seaborn, etc.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Step 2: Study the Data

Here we will work on the **E-commerce Customers dataset (CSV file)**. It has Customer information, such as Email, Address, and color Avatar. Then it also has numerical value columns:

- **Average Session Length:** Average session of in-store style advice sessions.
- **Time on App:** Average time spent by the customer on App in minutes
- **Time on Website:** Average time spent by the customer on Website in minutes
- **Length of Membership:** From how many years the customer has been a member.

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Step 3: Read and Load the Dataset

In this step, we will read and load the dataset using some basic function of pandas such as

- **For Load the CSV file:** pd.read_csv( )
- **To print some initial rows of the dataset:** df.head( )
- **Statistical Details for Numerical Columns:** df.describe( )
- **Basic Information About the dataset:** df.info ( )

Load the Dataset

```
df = pd.read_csv('Ecommerce Customers.csv')
```

Print Some Initial Rows of the Dataset

```
df.head()
```

Output:

	Email	Address	Avatar	Avg. Session Length	Time on App	Time on Website
0	mstephenson@fernandez.com	835 Frank Tunnel\nWrightmouth, MI 82180-9605	Violet	34.497268	12.655651	39.577668
1	hduke@hotmail.com	4547 Archer Common\nDiazchester, CA 06566-8576	DarkGreen	31.926272	11.109461	37.268959
2	pallen@yahoo.com	24645 Valerie Unions Suite 582\nCobbborough, D...	Bisque	33.000915	11.330278	37.110597
3	riverarebecca@gmail.com	1414 David Throughway\nPort Jason, OH 22070-1220	SaddleBrown	34.305557	13.717514	36.721283
4	mstephens@davidson-herman.com	14023 Rodriguez Passage\nPort Jacobville, PR 3...	MediumAquaMarine	33.330673	12.795189	37.536653

Statistical Details for Numerical Columns

```
df.describe()
```

Output:

	Avg. Session Length	Time on App	Time on Website	Length of Membership	Yearly Amount Spent
count	500.000000	500.000000	500.000000	500.000000	500.000000
mean	33.053194	12.052488	37.060445	3.533462	499.314038
std	0.992563	0.994216	1.010489	0.999278	79.314782
min	29.532429	8.508152	33.913847	0.269901	256.670582
25%	32.341822	11.388153	36.349257	2.930450	445.038277
50%	33.082008	11.983231	37.069367	3.533975	498.887875
75%	33.711985	12.753850	37.716432	4.126502	549.313828
max	36.139662	15.126994	40.005182	6.922689	765.518462

Basic Information About the Dataset

```
df.info()
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
Email                   500 non-null object
Address                 500 non-null object
Avatar                  500 non-null object
Avg. Session Length     500 non-null float64
Time on App             500 non-null float64
Time on Website         500 non-null float64
Length of Membership    500 non-null float64
Yearly Amount Spent     500 non-null float64
dtypes: float64(5), object(3)
memory usage: 31.3+ KB
```

Step 4: Exploratory Data Analysis(EDA)

In this step, we will explore the data and try to find some insights by visualizing the data properly, by using the **Seaborn** library functions such as

Joint plot:

- Time on Website vs Yearly Amount Spent
- Time on App vs Yearly Amount Spent
- Time on App vs Length of membership

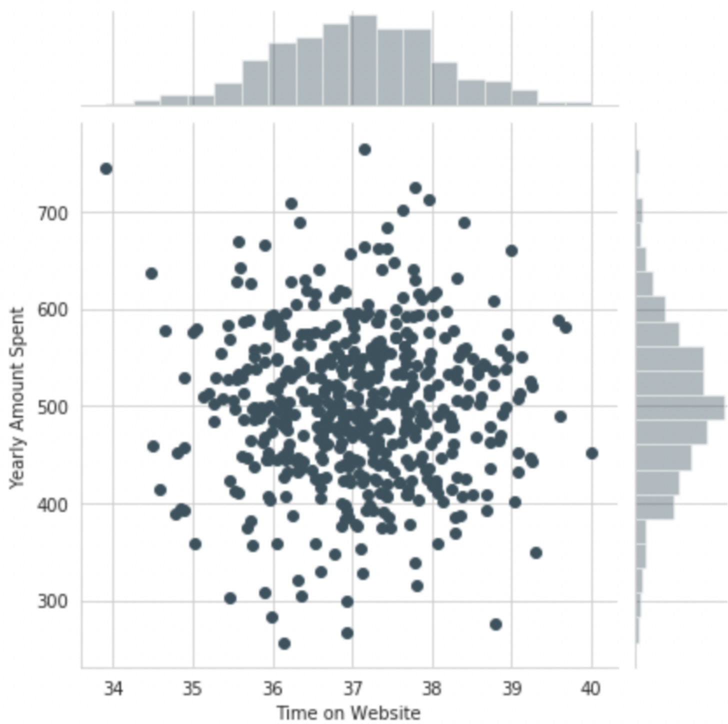
Pair plot: for the complete dataset

Implot: Length of Membership vs Yearly Amount Spent

Use seaborn to create a joint plot to compare the Time on Website and Yearly Amount Spent columns.

```
sns.jointplot(x='Time on Website',y='Yearly Amount Spent',data=df)
```

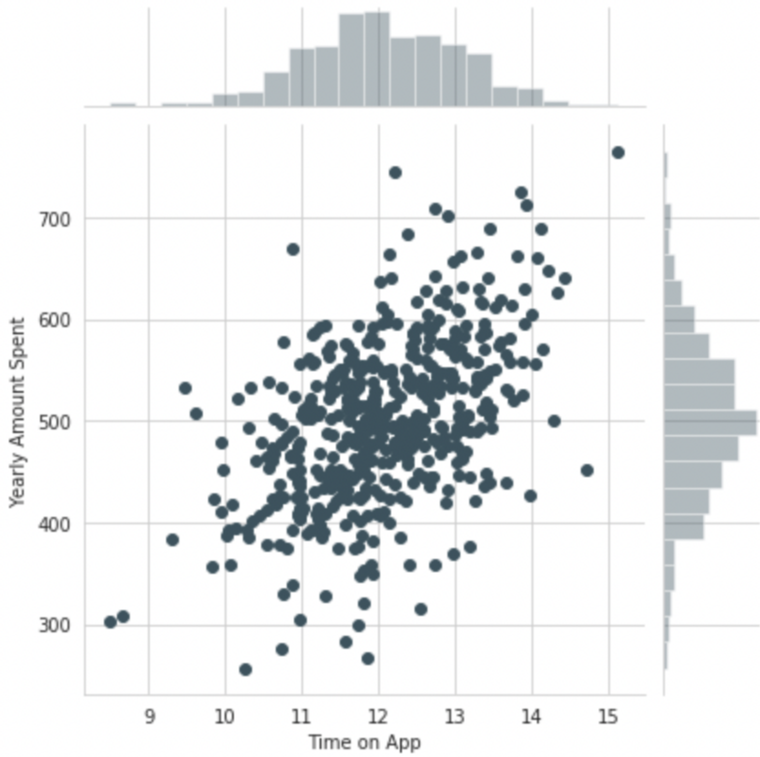
Output:



Do the same but with the Time on App column instead

```
sns.jointplot(x='Time on App',y='Yearly Amount Spent',data=df)
```

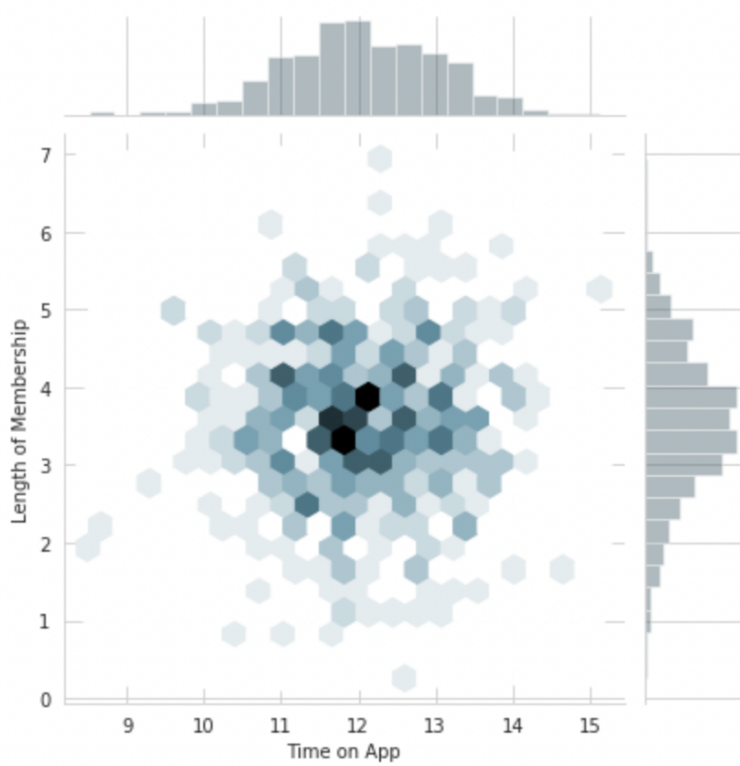
Output:



Use joint plot to create a 2D hex bin plot comparing Time on App and Length of Membership

```
sns.jointplot(x='Time on App',y='Length of Membership',kind="hex",data=df)
```

Output:



Let's explore these types of relationships across the entire data set. Use Pair plot to recreate the plot below:

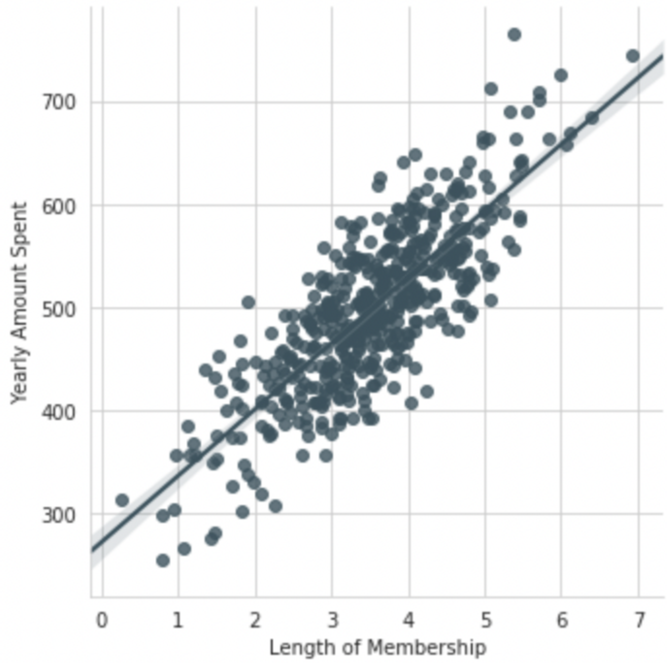
```
sns.pairplot(df)
```

Based on this plot what looks to be the most correlated feature with the Yearly Amount Spent?

```
Length of Membership
```

Create a linear model plot (using seaborn's lmplot) of Yearly Amount Spent vs. Length of Membership

```
sns.lmplot(x='Length of Membership',y='Yearly Amount Spent',data=df)
```



Step 5: Splitting of Data into Training and Testing Data

Now that we have explored the data a bit, it's time to go ahead and split our initial data into training and testing subsets. Here we set a variable X i.e, independent columns as the numerical features of the customers, and a variable y i.e, dependent column as the "Yearly Amount Spent" column.

Separate Dependent and Independent Variable

```
X = customers[['Avg. Session Length', 'Time on App', 'Time on Website', 'Length of Membership']]
y = customers['Yearly Amount Spent']
```

Use model_selection.train_test_split from sklearn to split the data into training and testing sets

Set test_size=0.20 and random_state=105

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=105)
```

Step 6: Training the Model using Linear Regression

Now, at this step we are able to train our model on our training data using Linear Regression.

Import LinearRegression from sklearn.linear_model

```
from sklearn.linear_model import LinearRegression
```

Create an instance of a LinearRegression() model named lm.

```
lr_model = LinearRegression()
```

Train/fit lm on the training data

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

Output:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Print out the coefficients of the model

```
lr_model.coef_
```

Output:

```
array([25.98154972, 38.59015875,  0.19040528, 61.27909654])
```

Step 7: Predictions on Test Data

Now that we have train our model, let's evaluate its performance by doing the predictions on the unseen data.

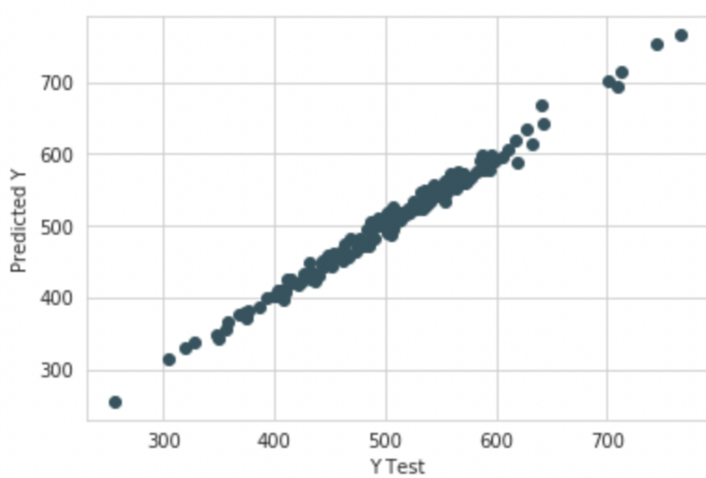
Use lr_model.predict() to predict off the X_test set of the data

```
predictions = lr_model.predict(X_test)
```

Create a scatterplot of the real test values versus the predicted values

```
plt.scatter(y_test,predictions)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

Output:



Step 8: Evaluating the Model

To evaluate our model performance, we will be calculating the residual sum of squares and the explained variance score (R^2).

Determine the metrics such as Mean Absolute Error, Mean Squared Error, and the Root Mean Squared Error.

```
from sklearn import metrics
print('MAE :'," ", metrics.mean_absolute_error(y_test,predictions))
print('MSE :'," ", metrics.mean_squared_error(y_test,predictions))
print('RMAE :'," ", np.sqrt(metrics.mean_squared_error(y_test,predictions)))
```

Output:

```
MAE :   7.2281486534308295
MSE :   79.8130516509743
RMAE :   8.933815066978626
```

Step 9: Explore the Residuals

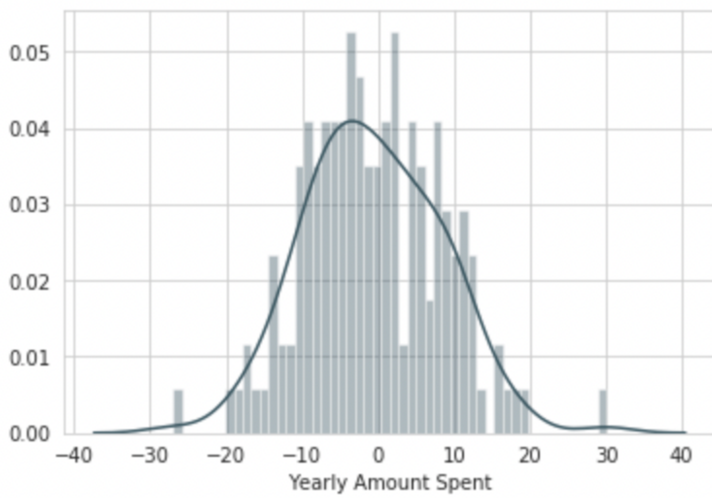
By observed the metrics calculated in the above steps, we should have a very good model with a good fit. Now, let's quickly explore the residuals to make sure that everything was okay with our dataset and finalize our model.

To see the above thing, try to plot a histogram of the residuals and make sure it looks normally distributed.

Use seaborn distplot, or just plt.hist()

```
sns.distplot(y_test - predictions,bins=50)
```

Output:



Step 10: Model Evaluation

Now, it's time to conclude our model i.e, let's see the interpretation of all the coefficients of the model to get a better idea.

Recreate the dataframe below

```
coeffecients = pd.DataFrame(lm.coef_,X.columns)
coeffecients.columns = ['Coeffecient']
coeffecients
```

Output:

	Coeffecient
Avg. Session Length	25.981550
Time on App	38.590159
Time on Website	0.190405
Length of Membership	61.279097

How can you interpret these coefficients?

- Keeping all other features constant, a one-unit increase in **Avg. Session Length** is associated with an **increase of 25.98 total dollars spent**.
- By Keeping all other features constant, a one-unit increase in **Time on App** is associated with an **increase of 38.59 total dollars spent**.
- Keeping all other features constant, a one-unit increase in **Time on the Website** is associated with an **increase of 0.19 total dollars spent**.
- Also, Keeping all other features constant, a one-unit increase in **Length of Membership** is associated with an **increase of 61.27 total dollars spent**.

Conclusion

Mastering the end-to-end machine learning project pipeline in data science is a transformative skill. It empowers you to navigate the intricate journey from data preprocessing to model deployment confidently and clearly. As you've delved into the details of this article, you've taken a significant step toward becoming a proficient data scientist.

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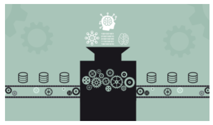

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Frequently Asked Questions

Q1. What is an end-to-end machine learning project?

A. An end-to-end machine learning project covers the entire lifecycle, from data collection and preprocessing to model training, evaluation, deployment, and monitoring, resulting in a functional solution.

Q2. How do you make an end-to-end ML project?

A. To create an end-to-end ML project, follow steps like defining objectives, gathering data, preprocessing, selecting models, training, evaluating, optimizing, and finally deploying the model into production.

Q3. What is an end-to-end data science project?

A. An end-to-end data science project encompasses the entire process, from data acquisition, cleaning, and analysis to building models, interpreting results, and delivering actionable insights to stakeholders.

Q4. What is an end-to-end pipeline in ML?

A. An end-to-end pipeline in ML refers to a complete workflow that integrates various stages of a project, from data ingestion and preprocessing to model training, evaluation, and deployment, ensuring a seamless process.