

Customer-Churn _ Feature Engineering & Data Transformation(Week_4)

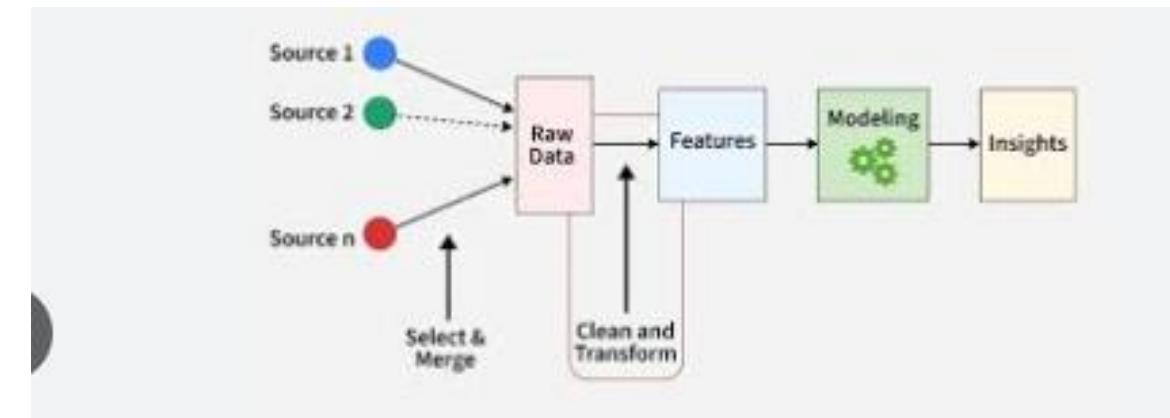
DATA SCIENCE INTERNSHIP -FUTUREXCEL

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Introduction

- ▶ This task focuses on feature engineering for the Customer Churn dataset. The aim was to transform existing customer information into meaningful features that help in understanding customer behavior and retention patterns.



Dataset Used

- ▶ The cleaned Customer Churn dataset from Week 1 was used as input for this task. The dataset was already prepared and suitable for feature transformation

```
Load Data

import pandas as pd
df = pd.read_csv("/content/cleaned_customer_churn_data (3).csv")
df.head()

customerID  gender  SeniorCitizen  Partner  Dependents  tenure  PhoneService  MultipleLines  InternetService  OnlineSecurity  ...  Dev
0           7590-VHVEG  Female          0    Yes        No       1      No  No phone service  DSL        No  ...
1           5575-GNVDE   Male          0     No        No      34     Yes      No  DSL        Yes  ...
2           3668-QPYBK   Male          0     No        No       2     Yes      No  DSL        Yes  ...
3           7795-CFOCW   Male          0     No        No      45      No  No phone service  DSL        Yes  ...
4           9237-UQITII  Female         0     No        No       2     Yes      No  Fiber optic  No  ...
```

Feature Engineering

- ▶ New features such as customer tenure groups, charge levels, and churn indicators were created. These features help simplify complex data and make customer behavior easier to analyze.

Feature Engineering

```
[ ] df['tenure_group'] = df['tenure'].apply(  
    lambda x: 'Short' if x<12 else 'Medium' if x<36 else 'Long'  
)  
  
df['monthly_charge_level'] = df['MonthlyCharges'].apply(  
    lambda x: 'Low' if x<35 else 'Medium' if x<70 else 'High'  
)  
  
df['is_long_term'] = df['tenure'].apply(lambda x: 1 if x>=24 else 0)  
  
df['churn_flag'] = df['Churn'].apply(lambda x: 1 if x=='Yes' else 0)  
df.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	... Con
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	Mo
1	5575-GNVD	Male	0	No	No	34	Yes	No	DSL	Yes	On
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	Mo
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	On
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	Mo

Encoding and Scaling

- ▶ Categorical features were encoded into numerical values, while important numerical features were scaled. This ensures uniformity and improves the dataset's readiness for future modeling tasks.

The screenshot shows a Jupyter Notebook interface with two code cells and their corresponding output tables.

Encoding:

```
from sklearn.preprocessing import LabelEncoder  
  
le = LabelEncoder()  
df['tenure_group_encoded'] = le.fit_transform(df['tenure_group'])  
df.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	Pap...
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...

Scaling:

```
from sklearn.preprocessing import StandardScaler  
scaler = StandardScaler()  
df['MonthlyCharges_scaled'] = scaler.fit_transform(df[['MonthlyCharges']])  
df
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	Pap...
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...

Before and After Comparison

- ▶ After transformation, the dataset shows better numerical consistency and improved feature representation compared to the original version.

Before vs After

	MonthlyCharges	MonthlyCharges_scaled
count	7043.000000	7.043000e+03
mean	64.761692	-6.406285e-17
std	30.090047	1.000071e+00
min	18.250000	-1.545860e+00
25%	35.500000	-9.725399e-01
50%	70.350000	1.857327e-01
75%	89.850000	8.338335e-01
max	118.750000	1.794352e+00



Conclusion

- ▶ Through this task, I gained practical experience in feature engineering and learned how transformed features can support better decision-making and predictive analysis.