

tdnzxp3dl

July 21, 2023

```
[1]: import pandas as pd
import numpy as np
data = pd.read_csv("https://raw.githubusercontent.com/amankharwal/Website-data/
↪master/supplement.csv")
data
```

```
[1]:
```

	ID	Store_id	Store_Type	Location_Type	Region_Code	Date	\
0	T1000001	1	S1	L3	R1	2018-01-01	
1	T1000002	253	S4	L2	R1	2018-01-01	
2	T1000003	252	S3	L2	R1	2018-01-01	
3	T1000004	251	S2	L3	R1	2018-01-01	
4	T1000005	250	S2	L3	R4	2018-01-01	
...	
188335	T1188336	149	S2	L3	R2	2019-05-31	
188336	T1188337	153	S4	L2	R1	2019-05-31	
188337	T1188338	154	S1	L3	R2	2019-05-31	
188338	T1188339	155	S3	L1	R2	2019-05-31	
188339	T1188340	152	S2	L1	R1	2019-05-31	

	Holiday	Discount	#Order	Sales
0	1	Yes	9	7011.84
1	1	Yes	60	51789.12
2	1	Yes	42	36868.20
3	1	Yes	23	19715.16
4	1	Yes	62	45614.52
...
188335	1	Yes	51	37272.00
188336	1	No	90	54572.64
188337	1	No	56	31624.56
188338	1	Yes	70	49162.41
188339	1	No	47	37977.00

[188340 rows x 10 columns]

```
[2]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 188340 entries, 0 to 188339
```

Data columns (total 10 columns):

#	Column	Non-Null Count	Dtype
0	ID	188340 non-null	object
1	Store_id	188340 non-null	int64
2	Store_Type	188340 non-null	object
3	Location_Type	188340 non-null	object
4	Region_Code	188340 non-null	object
5	Date	188340 non-null	object
6	Holiday	188340 non-null	int64
7	Discount	188340 non-null	object
8	#Order	188340 non-null	int64
9	Sales	188340 non-null	float64

dtypes: float64(1), int64(3), object(6)

memory usage: 14.4+ MB

```
[3]: data.isnull().sum()
```

```
[3]: ID                0
Store_id             0
Store_Type           0
Location_Type        0
Region_Code          0
Date                 0
Holiday              0
Discount             0
#Order               0
Sales                0
dtype: int64
```

```
[4]: data.describe()
```

```
[4]:
```

	Store_id	Holiday	#Order	Sales
count	188340.000000	188340.000000	188340.000000	188340.000000
mean	183.000000	0.131783	68.205692	42784.327982
std	105.366308	0.338256	30.467415	18456.708302
min	1.000000	0.000000	0.000000	0.000000
25%	92.000000	0.000000	48.000000	30426.000000
50%	183.000000	0.000000	63.000000	39678.000000
75%	274.000000	0.000000	82.000000	51909.000000
max	365.000000	1.000000	371.000000	247215.000000

```
[5]: import plotly.express as px
pie = data["Store_Type"].value_counts()
store = pie.index
orders = pie.values
```

```
fig = px.pie(data, values=orders, names=store)
fig.show()
```

```
[6]: pie2 = data["Location_Type"].value_counts()
location = pie2.index
orders = pie2.values

fig = px.pie(data, values=orders, names=location)
fig.show()
```

```
[7]: pie3 = data["Discount"].value_counts()
discount = pie3.index
orders = pie3.values

fig = px.pie(data, values=orders, names=discount)
fig.show()
```

```
[8]: pie4 = data["Holiday"].value_counts()
holiday = pie4.index
orders = pie4.values

fig = px.pie(data, values=orders, names=holiday)
fig.show()
```

```
[9]: data["Discount"] = data["Discount"].map({"No": 0, "Yes": 1})
data
```

```
[9]:
```

	ID	Store_id	Store_Type	Location_Type	Region_Code	Date	\
0	T1000001	1	S1	L3	R1	2018-01-01	
1	T1000002	253	S4	L2	R1	2018-01-01	
2	T1000003	252	S3	L2	R1	2018-01-01	
3	T1000004	251	S2	L3	R1	2018-01-01	
4	T1000005	250	S2	L3	R4	2018-01-01	
...	
188335	T1188336	149	S2	L3	R2	2019-05-31	
188336	T1188337	153	S4	L2	R1	2019-05-31	
188337	T1188338	154	S1	L3	R2	2019-05-31	
188338	T1188339	155	S3	L1	R2	2019-05-31	
188339	T1188340	152	S2	L1	R1	2019-05-31	

	Holiday	Discount	#Order	Sales
0	1	1	9	7011.84
1	1	1	60	51789.12
2	1	1	42	36868.20
3	1	1	23	19715.16
4	1	1	62	45614.52
...

188335	1	1	51	37272.00
188336	1	0	90	54572.64
188337	1	0	56	31624.56
188338	1	1	70	49162.41
188339	1	0	47	37977.00

[188340 rows x 10 columns]

```
[10]: data["Store_Type"] = data["Store_Type"].map({"S1": 1, "S2": 2, "S3": 3, "S4": 4})
data
```

```
[10]:
```

	ID	Store_id	Store_Type	Location_Type	Region_Code	Date	\
0	T1000001	1	1	L3	R1	2018-01-01	
1	T1000002	253	4	L2	R1	2018-01-01	
2	T1000003	252	3	L2	R1	2018-01-01	
3	T1000004	251	2	L3	R1	2018-01-01	
4	T1000005	250	2	L3	R4	2018-01-01	
...	
188335	T1188336	149	2	L3	R2	2019-05-31	
188336	T1188337	153	4	L2	R1	2019-05-31	
188337	T1188338	154	1	L3	R2	2019-05-31	
188338	T1188339	155	3	L1	R2	2019-05-31	
188339	T1188340	152	2	L1	R1	2019-05-31	

	Holiday	Discount	#Order	Sales
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188335	1	1	51	37272.00
188336	1	0	90	54572.64
188337	1	0	56	31624.56
188338	1	1	70	49162.41
188339	1	0	47	37977.00

[188340 rows x 10 columns]

```
[11]: data["Location_Type"] = data["Location_Type"].map({"L1": 1, "L2": 2, "L3": 3,
↪ "L4": 4, "L5": 5})
data
```

```
[11]:
```

	ID	Store_id	Store_Type	Location_Type	Region_Code	Date	\
0	T1000001	1	1	3	R1	2018-01-01	
1	T1000002	253	4	2	R1	2018-01-01	
2	T1000003	252	3	2	R1	2018-01-01	

3	T1000004	251	2	3	R1	2018-01-01
4	T1000005	250	2	3	R4	2018-01-01
...
188335	T1188336	149	2	3	R2	2019-05-31
188336	T1188337	153	4	2	R1	2019-05-31
188337	T1188338	154	1	3	R2	2019-05-31
188338	T1188339	155	3	1	R2	2019-05-31
188339	T1188340	152	2	1	R1	2019-05-31

	Holiday	Discount	#Order	Sales
0	1	1	9	7011.84
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188339	1	0	47	37977.00

[188340 rows x 10 columns]

```
[12]: X=np.array(data[["Store_Type","Location_Type","Holiday","Discount"]])
      y=np.array(data["#Order"])
```

```
[13]: X
```

```
[13]: array([[1, 3, 1, 1],
            [4, 2, 1, 1],
            [3, 2, 1, 1],
            ...,
            [1, 3, 1, 0],
            [3, 1, 1, 1],
            [2, 1, 1, 0]], dtype=int64)
```

```
[14]: y
```

```
[14]: array([ 9, 60, 42, ..., 56, 70, 47], dtype=int64)
```

```
[15]: from sklearn.model_selection import train_test_split
```

```
[16]: X_train, X_test, y_train,y_test= train_test_split(X,y,test_size=0.2,
      ↪random_state=42)
```

```
[17]: len(X_train)
```

```
[17]: 150672
```

```
[18]: !pip install lightgbm
```

```
Requirement already satisfied: lightgbm in c:\users\hp\anaconda3\lib\site-  
packages (4.0.0)  
Requirement already satisfied: numpy in c:\users\hp\anaconda3\lib\site-packages  
(from lightgbm) (1.21.5)  
Requirement already satisfied: scipy in c:\users\hp\anaconda3\lib\site-packages  
(from lightgbm) (1.9.1)
```

```
[19]: import lightgbm as ltb  
      model=ltb.LGBMRegressor()
```

```
[21]: model.fit(X_train,y_train)
```

```
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of  
testing was 0.001399 seconds.  
You can set `force_row_wise=true` to remove the overhead.  
And if memory is not enough, you can set `force_col_wise=true`.  
[LightGBM] [Info] Total Bins 15  
[LightGBM] [Info] Number of data points in the train set: 150672, number of used  
features: 4  
[LightGBM] [Info] Start training from score 68.163401
```

```
[21]: LGBMRegressor()
```

```
[22]: y_pred=model.predict(X_test)
```

```
[23]: y_pred
```

```
[23]: array([47.35189701, 97.06871721, 66.57778822, ..., 47.35189701,  
          61.74938636, 85.34103853])
```

```
[24]: y_test
```

```
[24]: array([ 54, 111,  59, ...,  40,  69,  68], dtype=int64)
```

```
[26]: data_pred=pd.DataFrame(data={"Predicted Orders":y_pred.flatten()})
```

```
[27]: data
```

```
[27]:
```

	ID	Store_id	Store_Type	Location_Type	Region_Code	Date	\
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1	T1000002	253	4	2	R1	2018-01-01	
2	T1000003	252	3	2	R1	2018-01-01	
3	T1000004	251	2	3	R1	2018-01-01	

4	T1000005	250	2	3	R4	2018-01-01
...
188335	T1188336	149	2	3	R2	2019-05-31
188336	T1188337	153	4	2	R1	2019-05-31
188337	T1188338	154	1	3	R2	2019-05-31
188338	T1188339	155	3	1	R2	2019-05-31
188339	T1188340	152	2	1	R1	2019-05-31

	Holiday	Discount	#Order	Sales
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[]: