Scooter Rental Data Analysis

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Description: This notebook explores a dataset of scooter rentals. We'll analyze how weather and time-related features affect ridership, visualize trends, and build a simple linear regression model to predict scooter demand.

```
> === 1. Import Libraries ===
# Import the appropriate Python libraries.
import pandas as pd
=== 2. Load Dataset ===
# Load the CSV file into a dataframe.
scooter_data = pd.read_csv('https://bit.ly/scooter-rentals')
=== 3. Data Exploration ===
# Calculate the dimensions of the dataset.
scooter_data.shape # 731 records, 14 columns
→▼ (731, 14)
# List the columns in the dataset along with their data types.
scooter_data.info()
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 731 entries, 0 to 730
     Data columns (total 14 columns):
                      Non-Null Count
     # Column
                                      Dtype
     0 ID
                       731 non-null
                       731 non-null
         date
                                      object
                       731 non-null
                                      int64
         mnth
                       731 non-null
                                      int64
         weekday
                       731 non-null
                                      int64
                       731 non-null
         workday
                                      int64
                       731 non-null
         season
                                      int64
                       731 non-null
                                      int64
         holiday
      8 temp
                       731 non-null
                                      float64
                       731 non-null
         atemp
                                      float64
      10 hum
                       731 non-null
                                      float64
      11 wind
                       731 non-null
                                      float64
      12 unregistered 731 non-null
                                      int64
     13 registered
                       731 non-null
                                      int64
     dtypes: float64(4), int64(9), object(1)
```

=== 4. Rename Columns ===

memory usage: 80.1+ KB

New interactive sheet

```
'hum': 'humidity_norm',
'temp': 'temp_norm',
'atemp': 'temp_felt_norm',
'wind': 'wind_norm',
'registered': 'rentals_registered',
'unregistered': 'rentals_unregistered'})
```

Preview the first 5 records in the dataset.
scooter_data.head()

₹		ID	date	year	month	weekday	workday	season	holiday	temp_norm	temp_felt_norm	humidity_norm	wind_norm	rentals_unregistered
	0	1	1/1/2011	0	1	6	0	1	0	0.344167	0.363625	0.805833	0.160446	331
	1	2	1/2/2011	0	1	0	0	1	0	0.363478	0.353739	0.696087	0.248539	131
	2	3	1/3/2011	0	1	1	1	1	0	0.196364	0.189405	0.437273	0.248309	120
	3	4	1/4/2011	0	1	2	1	1	0	0.200000	0.212122	0.590435	0.160296	108
	4	5	1/5/2011	0	1	3	1	1	0	0.226957	0.229270	0.436957	0.186900	82
	4													

Generate code with scooter data

```
# In the "season" field, replace the numbers (1, 2, 3, 4) with the following season names:
```

- # 1 = "winter"
- # 2 = "spring"

Next steps:

3 = "summer"

4 = "fall"

scooter_data['season'] = scooter_data['season'].replace([1, 2, 3, 4], ['winter', 'spring', 'summer', 'fall'])
scooter_data.head()

View recommended plots

→		ID	date	year	month	weekday	workday	season	holiday	temp_norm	temp_felt_norm	humidity_norm	wind_norm	rentals_unregistered
	0	1	1/1/2011	0	1	6	0	winter	0	0.344167	0.363625	0.805833	0.160446	331
	1	2	1/2/2011	0	1	0	0	winter	0	0.363478	0.353739	0.696087	0.248539	131
	2	3	1/3/2011	0	1	1	1	winter	0	0.196364	0.189405	0.437273	0.248309	120
	3	4	1/4/2011	0	1	2	1	winter	0	0.200000	0.212122	0.590435	0.160296	108
	4	5	1/5/2011	0	1	3	1	winter	0	0.226957	0.229270	0.436957	0.186900	82

Next steps: Generate code with scooter_data

View recommended plots

New interactive sheet

=== 6. Feature Engineering ===

Creating a new column called "rentals_total" that sums registered and unregistered rentals.
scooter_data['rentals_total'] = scooter_data['rentals_registered'] + scooter_data['rentals_unregistered']
scooter_data.head()

→		ID	date	year	month	weekday	workday	season	holiday	temp_norm	temp_felt_norm	humidity_norm	wind_norm	rentals_unregistered
	0	1	1/1/2011	0	1	6	0	winter	0	0.344167	0.363625	0.805833	0.160446	331
	1	2	1/2/2011	0	1	0	0	winter	0	0.363478	0.353739	0.696087	0.248539	131
	2	3	1/3/2011	0	1	1	1	winter	0	0.196364	0.189405	0.437273	0.248309	120
	3	4	1/4/2011	0	1	2	1	winter	0	0.200000	0.212122	0.590435	0.160296	108
	4	5	1/5/2011	0	1	3	1	winter	0	0.226957	0.229270	0.436957	0.186900	82
	4													

[#] Descriptive stats for the numeric columns in the dataset. scooter_data.describe()

₹		ID	year	month	weekday	workday	holiday	temp_norm	temp_felt_norm	humidity_norm	wind_norm	rental
	count	731.000000	731.000000	731.000000	731.000000	731.000000	731.000000	731.000000	731.000000	731.000000	731.000000	
	mean	366.000000	0.500684	6.519836	2.997264	0.683995	0.028728	0.495385	0.474354	0.627894	0.190486	
	std	211.165812	0.500342	3.451913	2.004787	0.465233	0.167155	0.183051	0.162961	0.142429	0.077498	
	min	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.059130	0.079070	0.000000	0.022392	
	25%	183.500000	0.000000	4.000000	1.000000	0.000000	0.000000	0.337083	0.337842	0.520000	0.134950	
	50%	366.000000	1.000000	7.000000	3.000000	1.000000	0.000000	0.498333	0.486733	0.626667	0.180975	
	75%	548.500000	1.000000	10.000000	5.000000	1.000000	0.000000	0.655417	0.608602	0.730209	0.233214	
	max	731.000000	1.000000	12.000000	6.000000	1.000000	1.000000	0.861667	0.840896	0.972500	0.507463	
	4											

> === 7. Missing Values & Duplicates ===

Seeing if there are any missing values in the dataset.
scooter_data.isnull().sum()



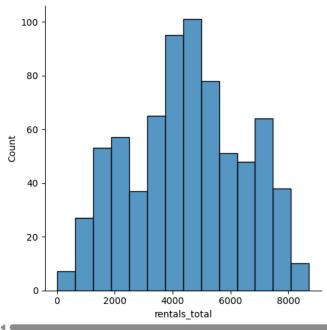
sum(scooter_data.duplicated(scooter_data.columns))



=== 8. Visualizations & Correlation ===

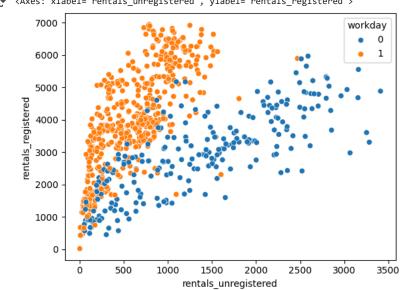
import seaborn as sns
Generating a histogram to visualize the distribution of "rentals_total" column.
sns.displot(scooter_data['rentals_total'])

<seaborn.axisgrid.FacetGrid at 0x7816e772b990>



- # Generating a scatterplot that has "rentals_unregistered" on the x-axis and "rentals_registered" on the y-axis.
- # Then, I colored the datapoints based on whether or not it was a workday.
- # This was to help me understand the types of scooter rentals on weekdays versus weekends.
- # (As a note, when "workday" is 0, it is a weekend Saturday or Sunday.)

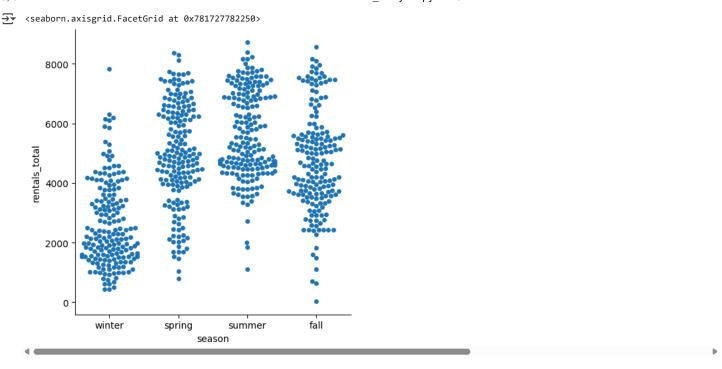
 $sns.scatterplot(data=scooter_data, \ x='rentals_unregistered', \ y='rentals_registered', \ hue='workday')$



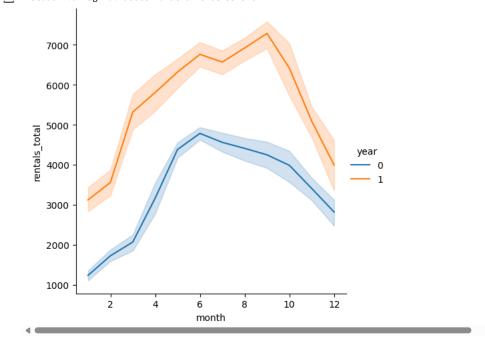
Axes: xlabel='rentals_unregistered', ylabel='rentals_registered'>

Based on the scatterplot, we have more registered rentals on weekdays and more unregistered rentals on weekends.

Generating a swarmplot to explore the total rentals by season. The "season" is on the x-asis and "rentals_total" on the y-axis. sns.catplot(data=scooter_data, x='season', y='rentals_total', kind='swarm')



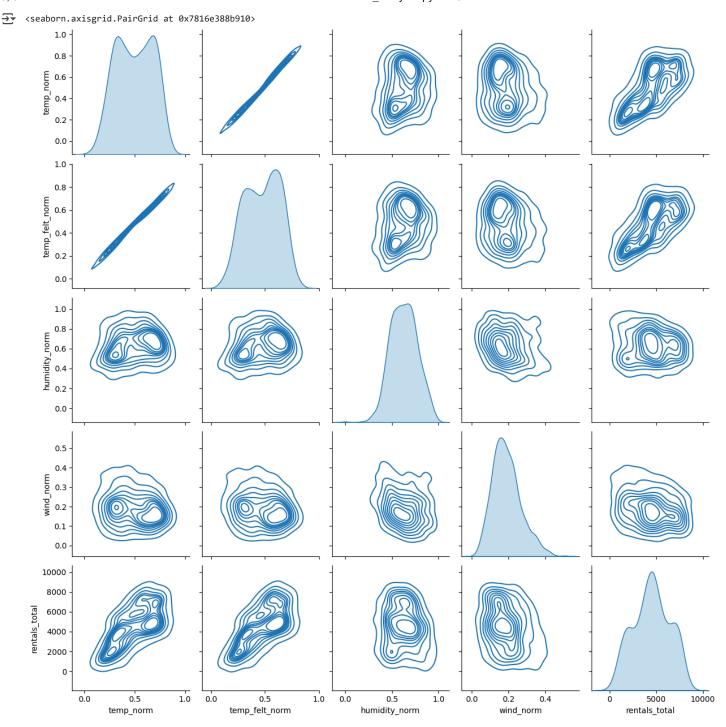
- # Based on the swarmplot, it appears that winter has the lowest average daily rentals.
- # Generating a line plot that shows average daily rentals by month with the lines split by year.
- # The "month" should on the x-axis, the "rentals_total" on the y-axis, and there should be a line for each value in the "year" column. sns.relplot(data=scooter_data, x='month', y='rentals_total', hue='year', kind='line')



<seaborn.axisgrid.FacetGrid at 0x7816e7552390>

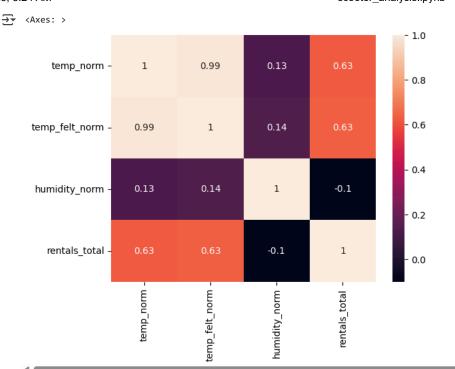
Based on the lineplot, the average daily rentals increased between the first year in the data ("year" = 0) and the second year ("year" = 1

Generating a pairplot to show the relationship between "rentals_total" and the weather indicators ("temp_norm", "temp_felt_norm", "humidit sns.pairplot(scooter_data, vars=['temp_norm', 'temp_felt_norm', 'humidity_norm', 'wind_norm', 'rentals_total'], kind='kde')



[#] As "temp_norm" decreases, "rentals_total" tends to decrease.

[#] Generating a heatmap to visualize the correlation between "rentals_total" and the weather indicators mentioned in the pairplot with their scooter_data_dp = scooter_data.drop(columns=['ID', 'date', 'year', 'month', 'weekday', 'workday', 'season', 'holiday', 'wind_norm', 'rentals sns.heatmap(scooter_data_dp.corr(), annot=True)



The correlation coefficient (r) that quantifies the strength of the relationship between "rentals_total" and "temp_norm" is 0.63

scooter_data_dp.corr() # double-checking

₹		temp_norm	temp_felt_norm	humidity_norm	rentals_total	\blacksquare
	temp_norm	1.000000	0.991702	0.126963	0.627494	11.
	temp_felt_norm	0.991702	1.000000	0.139988	0.631066	
	humidity_norm	0.126963	0.139988	1.000000	-0.100659	
	rentals_total	0.627494	0.631066	-0.100659	1.000000	
4	4					

=== 9. Modeling Preparation ===

```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics

# Separate the dependent variable (use "rentals_total") (y) and the independent variable (use "temp_norm") (X).
X = scooter_data[['temp_norm']]
y = scooter_data['rentals_total']

# Split the data into training and test sets. (I put 25% into the test set.)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)
```

=== 10. Model Building & Evaluation ===

```
# Train ("fit") the linear regression model using the training data.
model = LinearRegression()
model.fit(X_train, y_train)
```

```
LinearRegression ()
```

Model Building

```
# The intercept of my regression equation
print(model.intercept_) # 1,327.93

→ 1327.930810368468

# The coefficient for the "temp_norm" variable within my regression equation
print(model.coef_) # 6,463.97

→ [6463.96764523]

# Using my regression equation, I predicted the "rentals_total" when "temp_norm" = 0.30.
new_X = [[0.30]]
print(model.predict(new_X)) # Answer is 3,267.12 rentals
```