Warsztaty Badawcze

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1 Bike Sharing Demand

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[1]:
```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import pylab
import calendar
import seaborn as sn
from scipy import stats
# import missingno as msno
from datetime import datetime
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

reads two CSV files, 'train.csv' and 'test.csv', into pandas DataFrames (df_train and df_test) using the pd.read_csv()

[2]:
```
df_train = pd.read_csv('train.csv',header = 0)
df_test = pd.read_csv('test.csv', header = 0)
```

1.1.1 We are to predict the count column so we will separate it from the train dataframe

1.1.2 Functions

[3]:
```
def modify_datetime(df):

    # We will simply extract year, month, day, weekday, and hour from the␣
↪datetime feature
    df['year'] = pd.DatetimeIndex(df.datetime).year
    df['month'] = pd.DatetimeIndex(df.datetime).month
    df['day'] = pd.DatetimeIndex(df.datetime).day
    df['weekday'] = pd.DatetimeIndex(df.datetime).dayofweek
    df['hour'] = pd.DatetimeIndex(df.datetime).hour
    return df
```

[5]:
```
#modifies certain columns to the category data type, specifically "season,"␣
↪"weather," "holiday," and
#"workingday,"
def modify_to_category(df):
    categoryVariableList = ["season","weather","holiday","workingday"]
    for var in categoryVariableList:
        df[var] = df[var].astype("category")

    return df
```

1.2 Data exploration

[6]:
```
print("Dimensions of dataframe: ", df_train.shape)
```

```
Dimensions of dataframe:  (10886, 12)
```

1.2.1 Checking NaN Values

[7]:
```
nan_values = df_train[df_train.isna().any(axis=1)]
print(nan_values)
```

```
Empty DataFrame
Columns: [datetime, season, holiday, workingday, weather, temp, atemp, humidity,
windspeed, casual, registered, count]
Index: []
```

1.2.2 As we see there is no NaN values in the dataframe, that is good

[8]:
```
df_train.head()
```

[8]:
```
              datetime  season  holiday  workingday  weather  temp   atemp  \
0  2011-01-01 00:00:00       1        0           0        1  9.84  14.395
1  2011-01-01 01:00:00       1        0           0        1  9.02  13.635
2  2011-01-01 02:00:00       1        0           0        1  9.02  13.635
3  2011-01-01 03:00:00       1        0           0        1  9.84  14.395
4  2011-01-01 04:00:00       1        0           0        1  9.84  14.395

   humidity  windspeed  casual  registered  count
0        81        0.0       3          13     16
1        80        0.0       8          32     40
2        80        0.0       5          27     32
3        75        0.0       3          10     13
4        75        0.0       0           1      1
```

Data Fields

- datetime - hourly date + timestamp

- season - 1 = spring, 2 = summer, 3 = fall, 4 = winter
- holiday - whether the day is considered a holiday
- workingday - whether the day is neither a weekend nor holiday
- weather -
  - 1: Clear, Few clouds, Partly cloudy, Partly cloudy
  - 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
  - 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
  - 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
- temp - temperature in Celsius
- atemp - "feels like" temperature in Celsius
- humidity - relative humidity
- windspeed - wind speed
- casual - number of non-registered user rentals initiated
- registered - number of registered user rentals initiated
- count - number of total rentals (Dependent Variable)

1.2.3 Firstly, we'll check the feature types

[9]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  object
 1   season      10886 non-null  int64
 2   holiday     10886 non-null  int64
 3   workingday  10886 non-null  int64
 4   weather     10886 non-null  int64
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64
 10  registered  10886 non-null  int64
 11  count       10886 non-null  int64
dtypes: float64(3), int64(8), object(1)
memory usage: 1020.7+ KB
```

[10]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6493 entries, 0 to 6492
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    6493 non-null   object
```

```
 1   season      6493 non-null   int64
 2   holiday     6493 non-null   int64
 3   workingday  6493 non-null   int64
 4   weather     6493 non-null   int64
 5   temp        6493 non-null   float64
 6   atemp       6493 non-null   float64
 7   humidity    6493 non-null   int64
 8   windspeed   6493 non-null   float64
dtypes: float64(3), int64(5), object(1)
memory usage: 456.7+ KB
```

1.2.4 We see there is no casual and registered column in test frame so we will drop them

[11]:
```
df_train = df_train.drop(["casual", "registered"], axis=1)
```

1.2.5 We have to deal with datetime, namely convert it from object to something useful.

[12]:
```
def modify_datetime(df):

    # We will simply extract year, month, day, weekday, and hour from the␣
 ↪datetime feature
    df['year'] = pd.DatetimeIndex(df.datetime).year
    df['month'] = pd.DatetimeIndex(df.datetime).month
    df['day'] = pd.DatetimeIndex(df.datetime).day
    df['weekday'] = pd.DatetimeIndex(df.datetime).dayofweek
    df['hour'] = pd.DatetimeIndex(df.datetime).hour
    return df
```

[13]:
```
modify_datetime(df_train)
modify_datetime(df_test)
```

[13]:
```
                 datetime  season  holiday  workingday  weather   temp  \
0     2011-01-20 00:00:00       1        0           1        1  10.66
1     2011-01-20 01:00:00       1        0           1        1  10.66
2     2011-01-20 02:00:00       1        0           1        1  10.66
3     2011-01-20 03:00:00       1        0           1        1  10.66
4     2011-01-20 04:00:00       1        0           1        1  10.66
...                   ...     ...      ...         ...      ...    ...
6488  2012-12-31 19:00:00       1        0           1        2  10.66
6489  2012-12-31 20:00:00       1        0           1        2  10.66
6490  2012-12-31 21:00:00       1        0           1        1  10.66
6491  2012-12-31 22:00:00       1        0           1        1  10.66
6492  2012-12-31 23:00:00       1        0           1        1  10.66

       atemp  humidity  windspeed  year  month  day  weekday  hour
0     11.365        56    26.0027  2011      1   20        3     0
```

```
1     13.635        56     0.0000  2011      1   20        3     1
2     13.635        56     0.0000  2011      1   20        3     2
3     12.880        56    11.0014  2011      1   20        3     3
4     12.880        56    11.0014  2011      1   20        3     4
...      ...       ...        ...   ...    ...  ...      ...   ...
6488  12.880        60    11.0014  2012     12   31        0    19
6489  12.880        60    11.0014  2012     12   31        0    20
6490  12.880        60    11.0014  2012     12   31        0    21
6491  13.635        56     8.9981  2012     12   31        0    22
6492  13.635        65     8.9981  2012     12   31        0    23

[6493 rows x 14 columns]
```

1.2.6 We can now drop the datetime column

[15]:
```
df_train = df_train.drop('datetime', axis=1)
df_test = df_test.drop('datetime', axis=1)
```

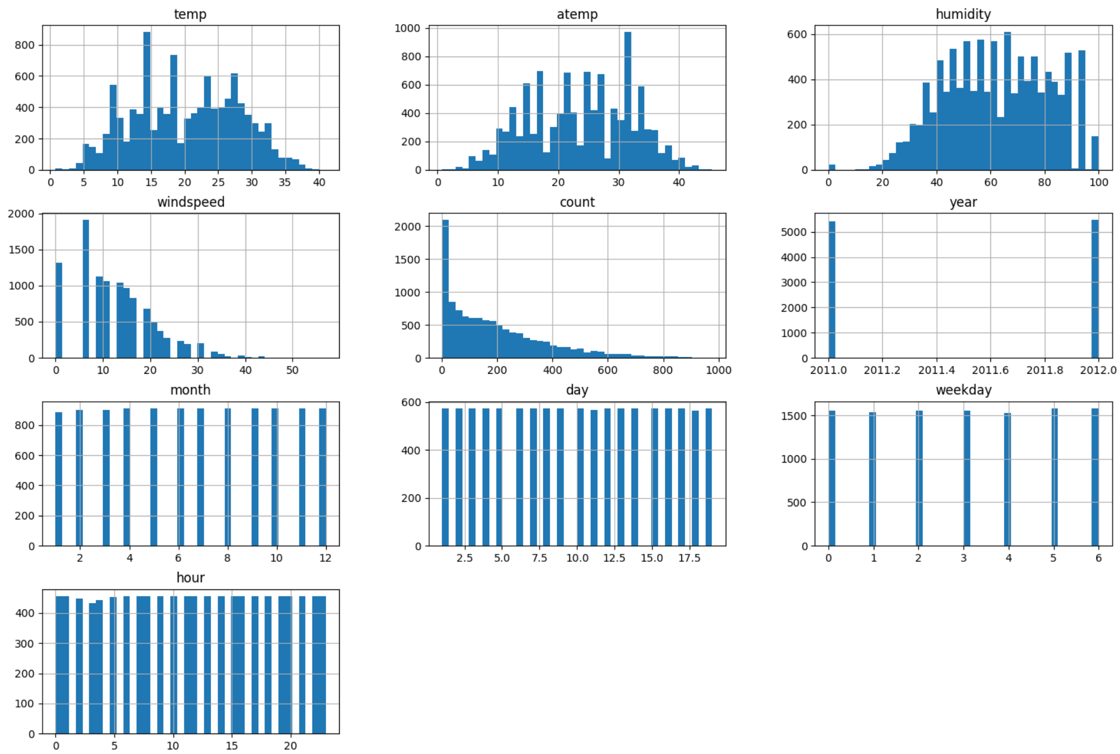
1.2.7 We will also change to type of season, weather, workingday, and holiday columns to category type as it is more apt

[16]:
```
def modify_to_category(df):
    categoryVariableList = ["season","weather","holiday","workingday"]
    for var in categoryVariableList:
        df[var] = df[var].astype("category")

    return df
```

[17]:
```
df_train = modify_to_category(df_train)
df_test = modify_to_category(df_test)
```

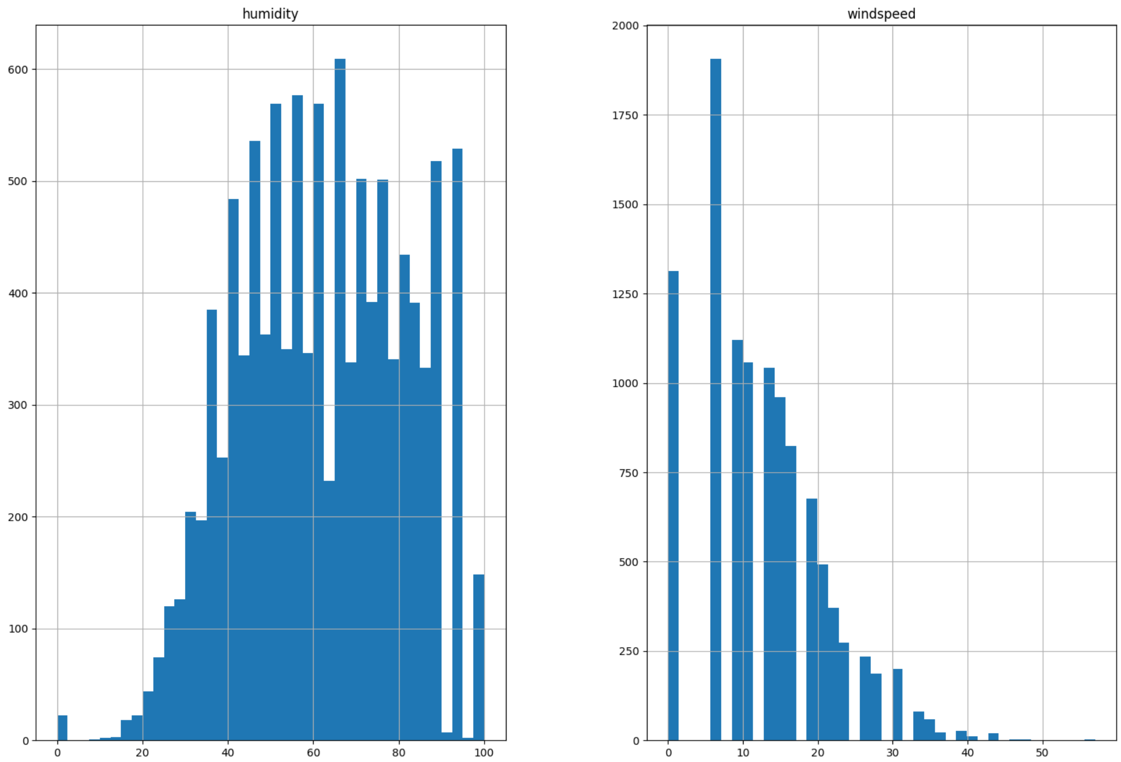
1.2.8 Let's see how the features are distributed

[18]:
```
df_train.hist(bins = 40, figsize=(18, 12))

plt.show()
```



1.2.9 We can see a strange number of zero values in humidity and windspeed features

[19]:
```
df_train.iloc[:, 6:8].hist(bins = 40, figsize=(18, 12))

plt.show()
```



[20]:
```
print("number of zeros in the humidity column: ", df_train["humidity"].
 ↪value_counts()[0])
print("number of zeros in the windspeed column: ", df_train["windspeed"].
 ↪value_counts()[0])
```

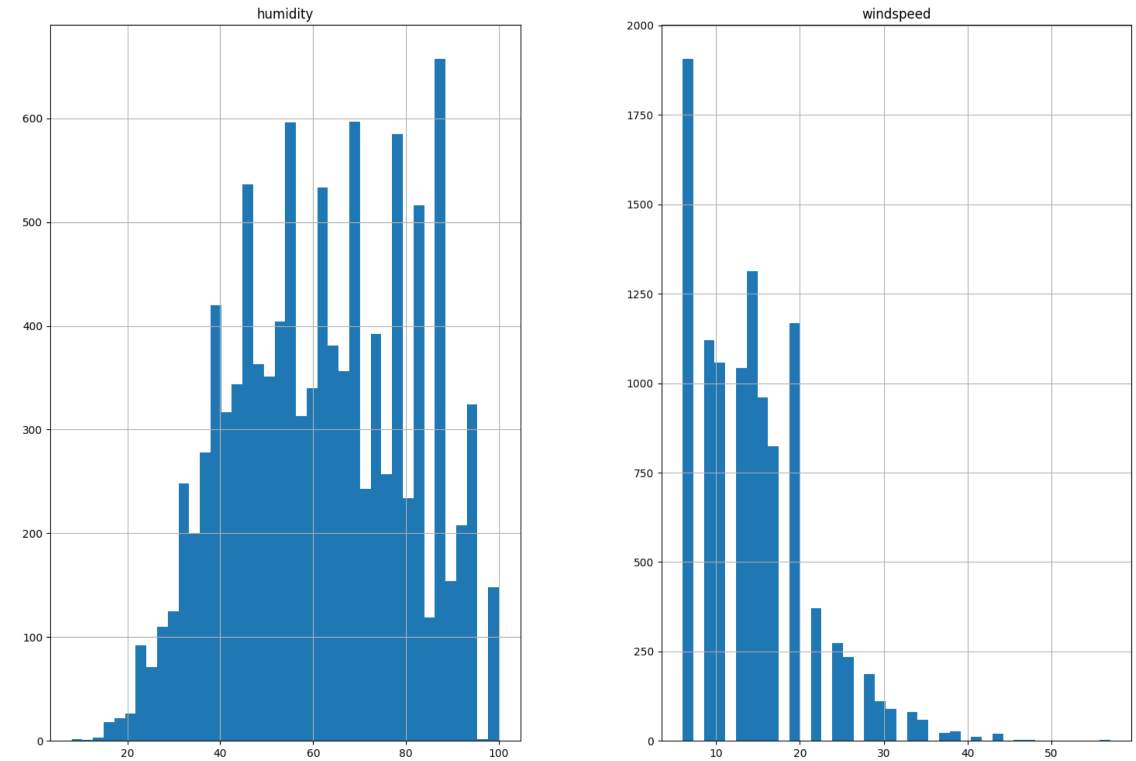
```
number of zeros in the humidity column:  22
number of zeros in the windspeed column:  1313
```

1.2.10 Obviously, the value zero in both of those columns does not make sense in real life, so we should treat is a missing value, hence we are to handle it in some way.

1.2.11 Let's use KNNImputer tree model to replace missing values in windspeed column.

[21]:
```
from sklearn.impute import KNNImputer
imputer = KNNImputer(missing_values=0)
df_train["windspeed"] = imputer.fit_transform(df_train[["windspeed"]]).ravel()
df_train["humidity"] = imputer.fit_transform(df_train[["humidity"]]).ravel()
```

[22]:
```
df_train.iloc[:, 6:8].hist(bins = 40, figsize=(18, 12))

plt.show()
```



[23]:

```
#  prints the number of unique values and a corresponding message for specific␣
↪columns
for col in df_train.select_dtypes(include=["object"]).columns[:-1]:
    print(col)
print('---------------------------------------------')

names = df_train['temp'].unique().tolist()
print(len(names))
print('unique temp')

names = df_train['atemp'].unique().tolist()
print(len(names))
print('unique atemp')

names = df_train['humidity'].unique().tolist()
print(len(names))
print('unique humidity')

names = df_train['windspeed'].unique().tolist()
print(len(names))
print('unique windspeed')
```

```
names = df_train['count'].unique().tolist()
print(len(names))
print('unique count')


names = df_train['month'].unique().tolist()
print(len(names))
print('unique month')

names = df_train['day'].unique().tolist()
print(len(names))
print('unique day')

names = df_train['weekday'].unique().tolist()
print(len(names))
print('unique weekday')

names = df_train['hour'].unique().tolist()
print(len(names))
print('unique hour')
```

```
---------------------------------------------
49
unique temp
60
unique atemp
89
unique humidity
28
unique windspeed
822
unique count
12
unique month
19
unique day
7
unique weekday
24
unique hour
```

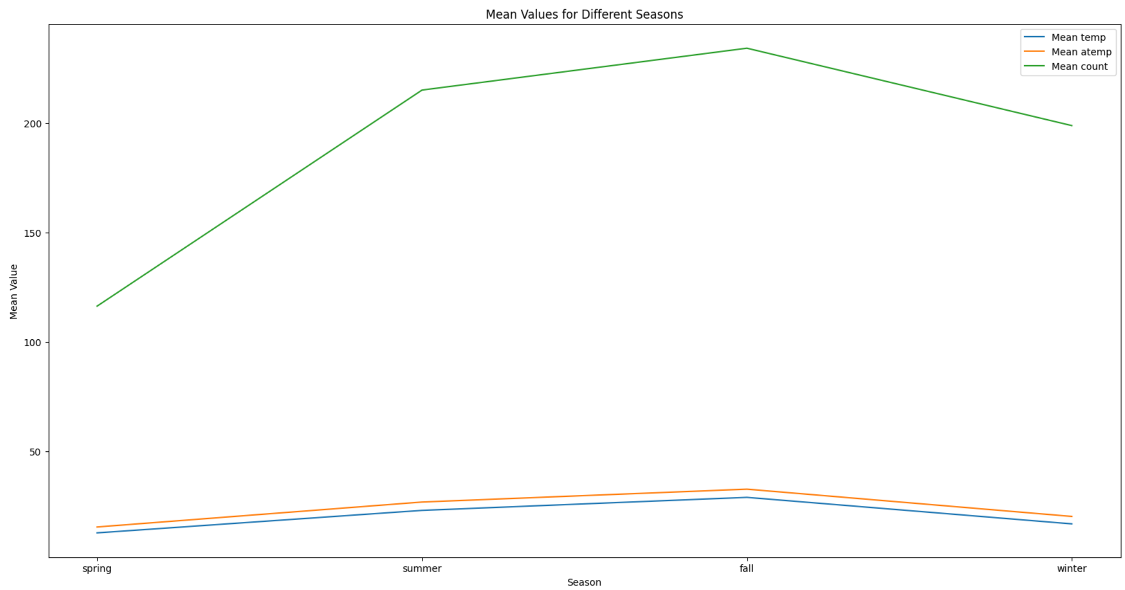
[24]:

```
unique_temp = df_train['day'].unique()
print(unique_temp)
```

```
[ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19]
```

1.2.12 Let's see how the temp changes with the season

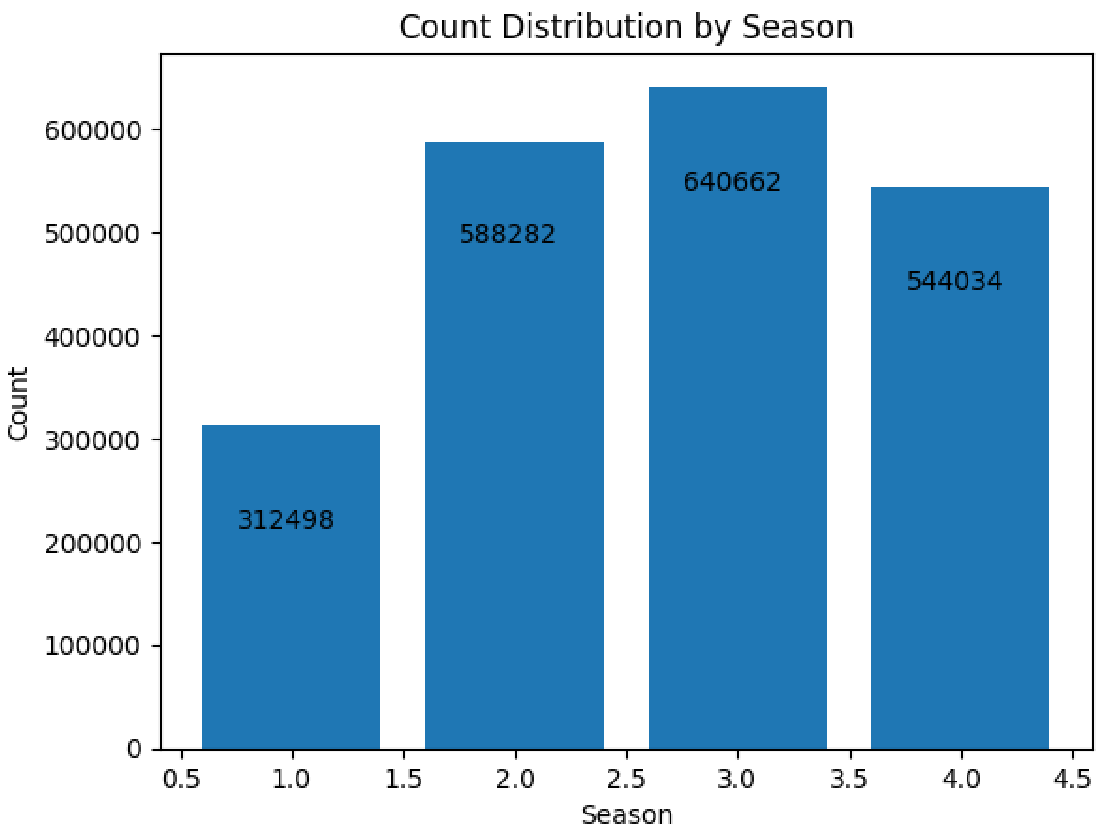
[25]:
```
x = ["spring", "summer", "fall", "winter"]
y, y1, y2 = [], [], []

for i in range(1, 5):
    y.append(np.mean(df_train[df_train["season"] == i]["temp"].values.tolist()))
    y1.append(np.mean(df_train[df_train["season"] == i]["atemp"].values.
 ↪tolist()))
    y2.append(np.mean(df_train[df_train["season"] == i]["count"].values.
 ↪tolist()))

plt.figure(figsize=(20, 10))
plt.plot(x, y, label="Mean temp")
plt.plot(x, y1, label="Mean atemp")
plt.plot(x, y2, label="Mean count")
plt.legend()
plt.xlabel("Season")
plt.ylabel("Mean Value")
plt.title("Mean Values for Different Seasons")
plt.show()
```



1.2.13 Let's how the count is distributed over the seasons

[26]:
```
season_counts = df_train.groupby('season')['count'].sum()

plt.bar(season_counts.index, season_counts.values)
plt.xlabel('Season')
```

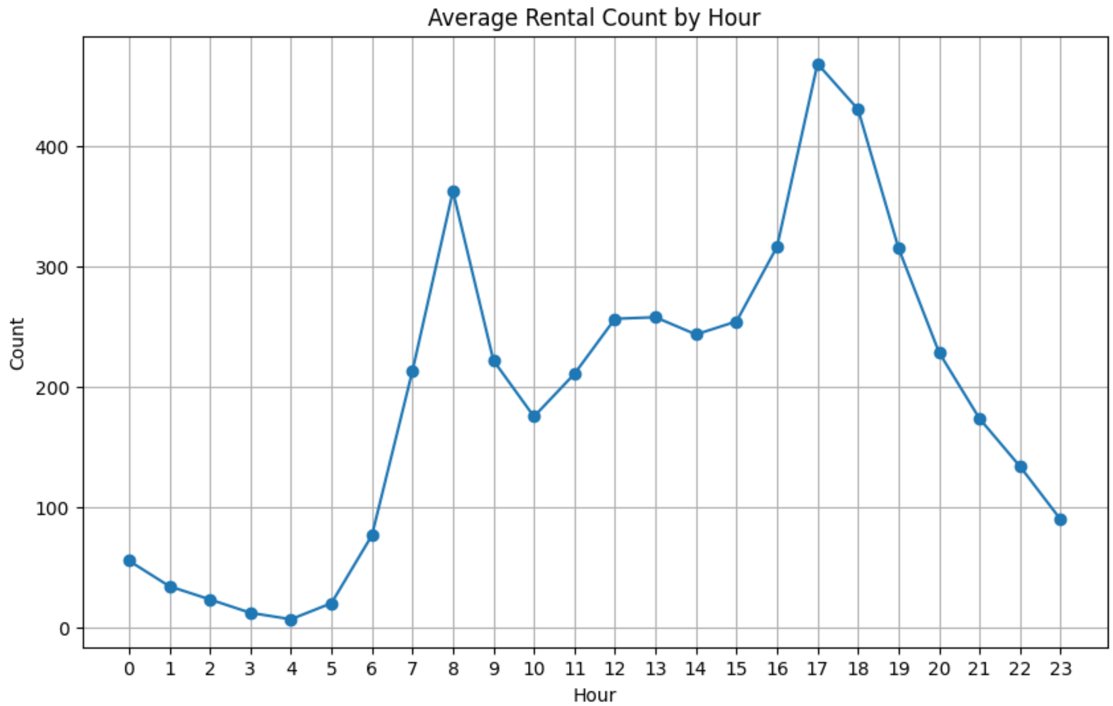
```
plt.ylabel('Count')
plt.title('Count Distribution by Season')

# Annotate the count values on the bars
for i, count in enumerate(season_counts.values):
    plt.text(i + 1.2, count- 105000 , str(count), ha='right', va='bottom',␣
 ↪fontsize=10)

plt.show()
```



1.2.14 Let's see how the rental is distributed over the hours of the day

[27]:
```
hourly_counts = df_train.groupby('hour')['count'].mean()

# Create a line plot
plt.figure(figsize=(10, 6))
plt.plot(hourly_counts.index, hourly_counts.values, marker='o', linestyle='-')
plt.xlabel('Hour')
plt.ylabel('Count')
plt.title('Average Rental Count by Hour')
```

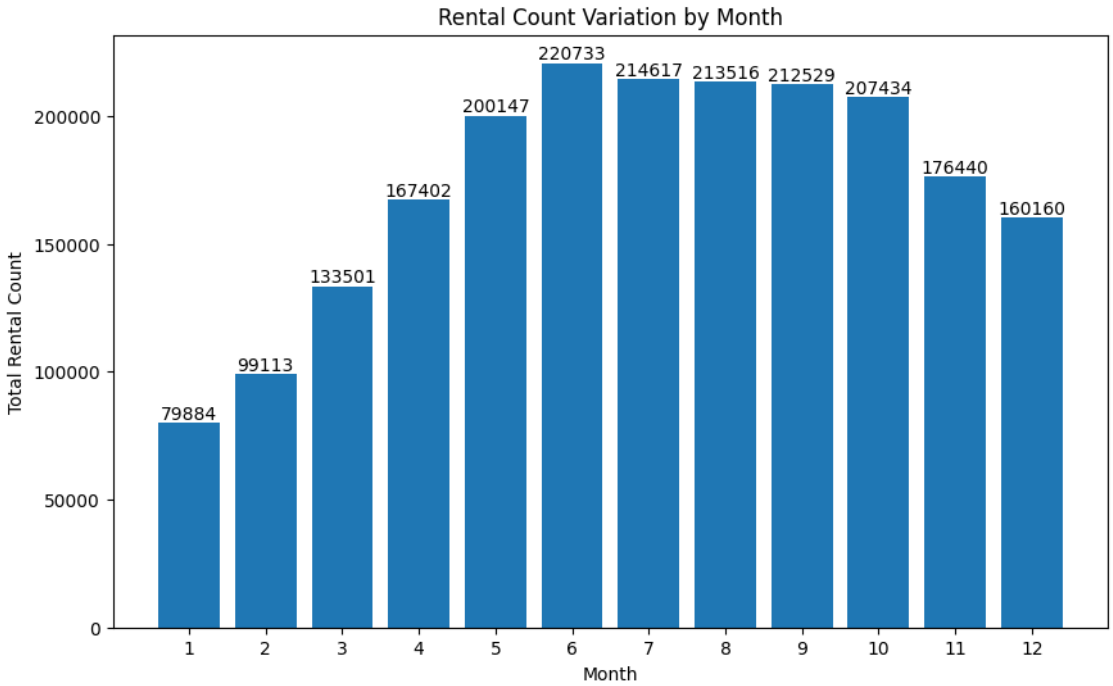
```
plt.xticks(hourly_counts.index)
plt.grid(True)
plt.show()
```



1.2.15 Let's see how the rental is distributed over the months of the year

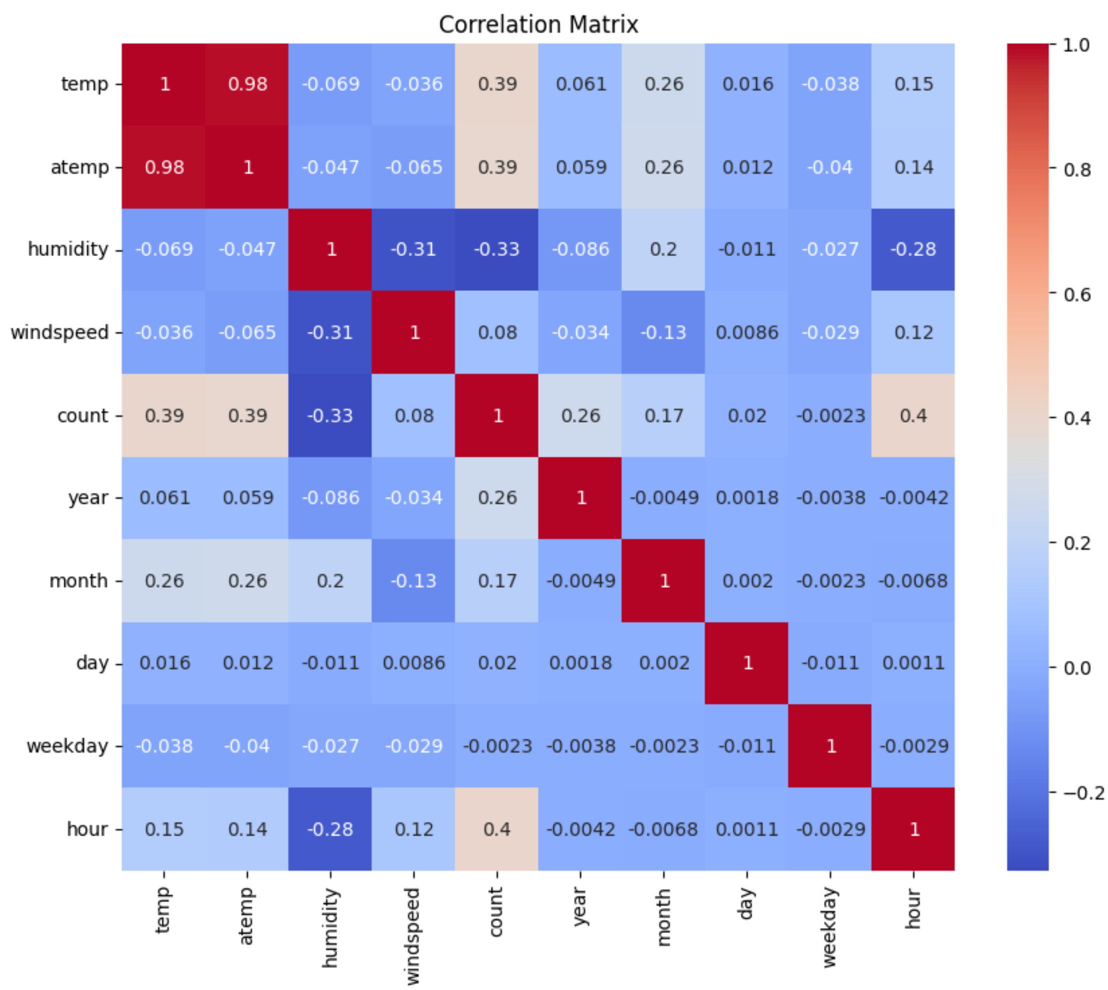
[28]:
```
rental_count_per_month = df_train.groupby('month')['count'].sum()
months = rental_count_per_month.index
count = rental_count_per_month.values

plt.figure(figsize=(10, 6))
bars = plt.bar(months, count, color = "blue")
plt.bar(months, count)
plt.xlabel('Month')
plt.ylabel('Total Rental Count')
plt.title('Rental Count Variation by Month')
plt.xticks(months)

for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, height, str(height),␣
 ↪ha='center', va='bottom')
```

```
plt.show()
```



1.2.16 Correlation Matrix

[29]:
```
corr_matrix = df_train.corr()

# Plot correlation matrix using a heatmap
plt.figure(figsize=(10, 8))
sn.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



1.2.17 There is a strong correlation between temp and atemp so we will drop the atemp column

[30]:
```python
df_train = df_train.drop('atemp',axis=1)
```

1.2.18 Models Implementation

From the evaluation tab we know that our models are going to be evaluated with the Root Mean Squared Logarithmic Error

[31]:
```python
from sklearn import linear_model
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_log_error
from sklearn.ensemble import␣
↪RandomForestRegressor,BaggingRegressor,AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor
```

```
from sklearn.neighbors import KNeighborsClassifier
```

1.2.19 Splitting Dataset

[32]:
```
# Split training dataset
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(df_train.
 ↪drop('count',axis=1),df_train['count'],random_state=0)
```

[33]:
```
#trains multiple regression models, evaluates their performance using RMSLE, and␣
 ↪returns a dictionary
#with the model names and their corresponding RMSLE values.
models=[RandomForestRegressor(), AdaBoostRegressor(),BaggingRegressor(),␣
 ↪DecisionTreeRegressor(), KNeighborsClassifier()]
model_names=['RandomForestRegressor', 'AdaBoostRegressor','BaggingRegressor',␣
 ↪'DecisionTreeRegressor', 'KNeighborsClassifier']
rmsle=[]
out={}
for model in range (len(models)):
    clf=models[model]
    clf.fit(x_train,y_train)
    test_pred=clf.predict(x_test)
    rmsle.append(mean_squared_log_error(test_pred,y_test, squared=False))
out={'Model':model_names,'RMSLE':rmsle}
out
```

[33]:
```
{'Model': ['RandomForestRegressor',
  'AdaBoostRegressor',
  'BaggingRegressor',
  'DecisionTreeRegressor',
  'KNeighborsClassifier'],
 'RMSLE': [0.3333476718876542,
  1.071129137154223,
  0.3459437826930999,
  0.43441861997409037,
  1.3801782699796281]}
```

[34]:
```
#creates a DataFrame rmsle_frame using the dictionary out and returns the␣
 ↪DataFrame.
rmsle_frame=pd.DataFrame(out)
rmsle_frame
```

[34]:

	Model	RMSLE
0	RandomForestRegressor	0.333348
1	AdaBoostRegressor	1.071129
2	BaggingRegressor	0.345944
3	DecisionTreeRegressor	0.434419

```
4   KNeighborsClassifier  1.380178
```

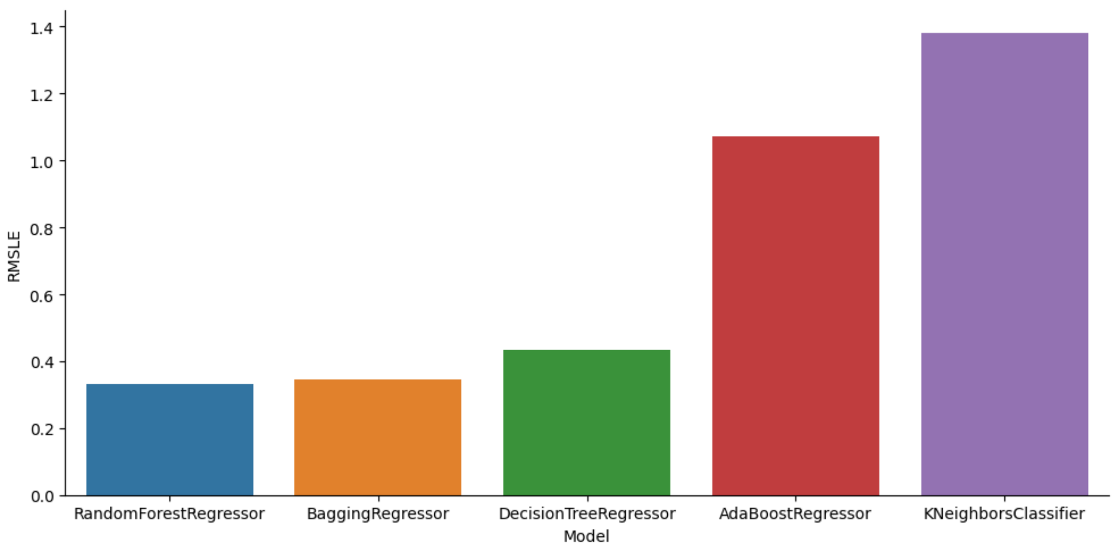
[58]:
```python
rmsle_frame.columns
```

[58]:
```
Index(['Model', 'RMSLE'], dtype='object')
```

1.2.20 the 'Model' column represents the x-axis, the 'RMSLE' column represents the y-axis

[64]:
```python
sn.catplot(x='Model',y='RMSLE',data=rmsle_frame,kind='bar',aspect=2, order =␣
↪['RandomForestRegressor',
  'BaggingRegressor',
  'DecisionTreeRegressor',
  'AdaBoostRegressor',
  'KNeighborsClassifier'])
```

[64]:
```
<seaborn.axisgrid.FacetGrid at 0x1eb86ad3c10>
```



1.2.21 Let's now tune our parameters

[55]:
```python
from sklearn.model_selection import GridSearchCV
```

[ ]:
```python
# Random forest

params_dict={'n_estimators':[300,350,400,450,500],'n_jobs':[-1],'max_features':
↪["auto",'sqrt','log2']}
clf_rf=GridSearchCV(estimator=RandomForestRegressor(),param_grid=params_dict,scoring='neg_mean_
clf_rf.fit(x_train,y_train)
```

```
pred=clf_rf.predict(x_test)
print(mean_squared_log_error(pred,y_test, squared=False))
```

0.3329560677350912

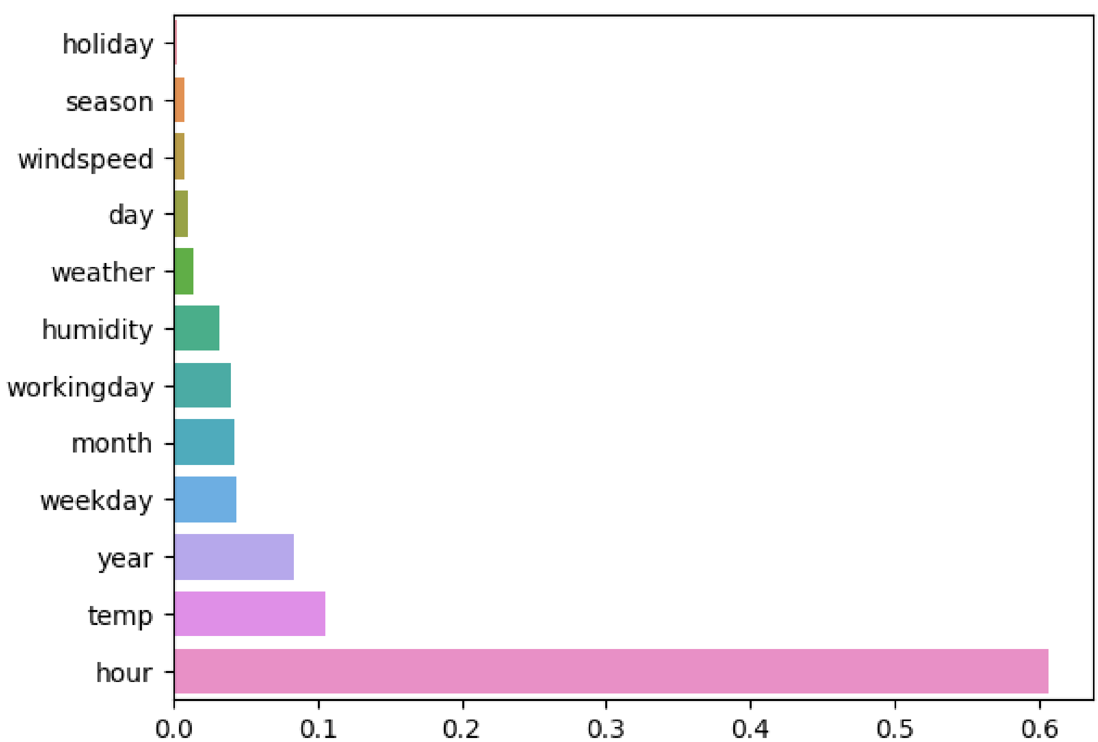
[ ]:
```
clf_rf.best_params_
```

[ ]: {'max_features': 'auto', 'n_estimators': 350, 'n_jobs': -1}

1.2.22 The graph visualizes the feature importances of a Random Forest Regressor model on the x-axis against the corresponding feature names

[53]:
```
clf_rf = RandomForestRegressor(max_features= 'auto', n_estimators = 350, n_jobs␣
 ↪= -1)
clf_rf.fit(x_train,y_train)
sorted_idx = clf_rf.feature_importances_.argsort()
sn.barplot(x = clf_rf.feature_importances_[sorted_idx], y=x_train.columns.
 ↪values[sorted_idx])
```

[53]: <Axes: >



1.2.23 Podział pracy

Wspólnie współpracowaliśmy nad projektem w Kaggle Competition, oddając się pracy w atmosferze pełnej harmonii i konstruktywnej współpracy. Mikołaj zajął się przygotowaniem prezentacji oraz środowiska, tworząc solidne fundamenty naszego projektu. Michał poświęcił dużo uwagi na przetwarzanie danych, dbając o ich dokładność i odpowiednie przygotowanie do analizy. Paweł z kolei skupił się na tworzeniu modelu i precyzyjnym strojeniu jego parametrów, zapewniając optymalne wyniki. Jednocześnie wszyscy wspólnie angażowaliśmy się w eksplorację danych i tworzenie wizualizacji, aby pełniej zrozumieć zbiór danych i uzyskać cenne wglądy. Nasza wspólna praca pozwoliła stworzyć solidny projekt, w którym każdy z nas wnosił unikalne umiejętności i zaangażowanie.

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