Fields in the dataset:

- instant: record index
- dteday: date
- season: season (1:spring, 2:summer, 3:fall, 4:winter)
- yr: year (0: 2011, 1: 2012)
- mnth: month (1 to 12)
- hr: hour (0 to 23)
- holiday : whether the day is a holiday or not
- weekday : day of the week
- workingday : if the day is neither weekend nor a holiday is 1, otherwise is 0
- weathersit :

1. Clear, Few clouds, Partly cloudy
2. Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
3. Light Snow, Light Rain + Thunderstorm + Scattered clouds
4. Heavy Rain + Ice Pellets + Thunderstorm + Mist, Snow + Fog

- temp : normalized temperature in Celsius; the values are divided to 41 (max)
- atemp: normalized temperature felt in Celsius; the values are divided to 50 (max)
- hum: normalized humidity; the values are divided to 100 (max)
- windspeed: normalized wind speed; the values are divided to 67 (max)
- casual: count of casual users

- registered: count of registered users
- cnt: count of total rental bikes including both casual and registered

In [175…

```
import numpy as np;
import pandas as pd;
import matplotlib.pyplot as plt;
import seaborn as sns;
from sklearn.model_selection import train_test_split,cross_val_score,cross_val_predict, GridSearchCV;
from sklearn.linear_model import LinearRegression,Ridge;
```

1. Load the data file.

In [2]:

```
bikeshare_data=pd.read_csv('hour.csv')
```

In [3]:

```
bikeshare_data
```

Out[3]:

	instant	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
0	1	2011-01-01	1	0	1	0	0	6	0	1	0.24	0.2879	0.81	0.0000	3	13	16
1	2	2011-01-01	1	0	1	1	0	6	0	1	0.22	0.2727	0.80	0.0000	8	32	40
2	3	2011-01-01	1	0	1	2	0	6	0	1	0.22	0.2727	0.80	0.0000	5	27	32
3	4	2011-01-01	1	0	1	3	0	6	0	1	0.24	0.2879	0.75	0.0000	3	10	13
4	5	2011-01-01	1	0	1	4	0	6	0	1	0.24	0.2879	0.75	0.0000	0	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
17374	17375	2012-12-31	1	1	12	19	0	1	1	2	0.26	0.2576	0.60	0.1642	11	108	119
17375	17376	2012-12-31	1	1	12	20	0	1	1	2	0.26	0.2576	0.60	0.1642	8	81	89

	instant	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
17376	17377	2012-12-31	1	1	12	21	0	1	1	1	0.26	0.2576	0.60	0.1642	7	83	90
17377	17378	2012-12-31	1	1	12	22	0	1	1	1	0.26	0.2727	0.56	0.1343	13	48	61
17378	17379	2012-12-31	1	1	12	23	0	1	1	1	0.26	0.2727	0.65	0.1343	12	37	49

17379 rows × 17 columns

2. Check for null values in the data and drop records with NAs.

In [5]:
```
bikeshare_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17379 entries, 0 to 17378
Data columns (total 17 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   instant     17379 non-null  int64  
 1   dteday      17379 non-null  object 
 2   season      17379 non-null  int64  
 3   yr          17379 non-null  int64  
 4   mnth        17379 non-null  int64  
 5   hr          17379 non-null  int64  
 6   holiday     17379 non-null  int64  
 7   weekday     17379 non-null  int64  
 8   workingday  17379 non-null  int64  
 9   weathersit  17379 non-null  int64  
 10  temp        17379 non-null  float64
 11  atemp       17379 non-null  float64
 12  hum         17379 non-null  float64
 13  windspeed   17379 non-null  float64
 14  casual      17379 non-null  int64  
 15  registered  17379 non-null  int64  
 16  cnt         17379 non-null  int64  
dtypes: float64(4), int64(12), object(1)
memory usage: 2.3+ MB
```

In [7]:
```
bikeshare_data.columns
```

Out[7]:
```
Index(['instant', 'dteday', 'season', 'yr', 'mnth', 'hr', 'holiday', 'weekday',
       'workingday', 'weathersit', 'temp', 'atemp', 'hum', 'windspeed',
       'casual', 'registered', 'cnt'],
      dtype='object')
```

In [10]:
```
len(bikeshare_data[bikeshare_data['instant'].isnull()])
```

Out[10]:
```
0
```

In [11]:
```
for i in bikeshare_data.columns:
    print('Number of null values in column ',i, ' are:', len(bikeshare_data[bikeshare_data[i].isnull()]))
```

```
Number of null values in column  instant  are: 0
Number of null values in column  dteday  are: 0
Number of null values in column  season  are: 0
Number of null values in column  yr  are: 0
Number of null values in column  mnth  are: 0
Number of null values in column  hr  are: 0
Number of null values in column  holiday  are: 0
Number of null values in column  weekday  are: 0
Number of null values in column  workingday  are: 0
Number of null values in column  weathersit  are: 0
Number of null values in column  temp  are: 0
Number of null values in column  atemp  are: 0
Number of null values in column  hum  are: 0
Number of null values in column  windspeed  are: 0
Number of null values in column  casual  are: 0
Number of null values in column  registered  are: 0
Number of null values in column  cnt  are: 0
```

In [13]:
```
bikeshare_data.dropna(inplace=True);
bikeshare_data.reset_index(inplace=True,drop=True)
```

3. Sanity checks:

- Check if registered + casual = cnt for all the records. If not, the row is junk and should be dropped.

In [21]:
```
bikeshare_data=bikeshare_data[(bikeshare_data['registered']+bikeshare_data['casual'])==bikeshare_data['cnt']]
bikeshare_data.reset_index(inplace=True,drop=True)
```

- Month values should be 1-12 only

In [22]:
```
bikeshare_data=bikeshare_data[(bikeshare_data['mnth']>=1) & (bikeshare_data['mnth']<=12)]
```

```
bikeshare_data.reset_index(inplace=True,drop=True)
```

- Hour values should be 0-23

In [24]:
```
bikeshare_data=bikeshare_data[(bikeshare_data['hr']>=0) & (bikeshare_data['hr']<=23)]
bikeshare_data.reset_index(inplace=True,drop=True)
```

In [25]:
```
bikeshare_data
```

Out[25]:

	instant	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
0	1	2011-01-01	1	0	1	0	0	6	0	1	0.24	0.2879	0.81	0.0000	3	13	16
1	2	2011-01-01	1	0	1	1	0	6	0	1	0.22	0.2727	0.80	0.0000	8	32	40
2	3	2011-01-01	1	0	1	2	0	6	0	1	0.22	0.2727	0.80	0.0000	5	27	32
3	4	2011-01-01	1	0	1	3	0	6	0	1	0.24	0.2879	0.75	0.0000	3	10	13
4	5	2011-01-01	1	0	1	4	0	6	0	1	0.24	0.2879	0.75	0.0000	0	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
17374	17375	2012-12-31	1	1	12	19	0	1	1	2	0.26	0.2576	0.60	0.1642	11	108	119
17375	17376	2012-12-31	1	1	12	20	0	1	1	2	0.26	0.2576	0.60	0.1642	8	81	89
17376	17377	2012-12-31	1	1	12	21	0	1	1	1	0.26	0.2576	0.60	0.1642	7	83	90
17377	17378	2012-12-31	1	1	12	22	0	1	1	1	0.26	0.2727	0.56	0.1343	13	48	61
17378	17379	2012-12-31	1	1	12	23	0	1	1	1	0.26	0.2727	0.65	0.1343	12	37	49

17379 rows × 17 columns

4. Drop redundancy (Basic preprocessing)

- The variables 'casual' and 'registered' are redundant and need to be dropped.
- 'Instant' is the index and needs to be dropped too.
- The date column dteday will not be used in the model building, and therefore needs to be dropped.
- Create a new dataframe named inp1.

In [28]:
```
inp1=bikeshare_data.drop(axis=1,columns=['casual','registered','instant','dteday'])
```

In [29]:
```
inp1
```

Out[29]:

	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	cnt
0	1	0	1	0	0	6	0	1	0.24	0.2879	0.81	0.0000	16
1	1	0	1	1	0	6	0	1	0.22	0.2727	0.80	0.0000	40
2	1	0	1	2	0	6	0	1	0.22	0.2727	0.80	0.0000	32
3	1	0	1	3	0	6	0	1	0.24	0.2879	0.75	0.0000	13
4	1	0	1	4	0	6	0	1	0.24	0.2879	0.75	0.0000	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
17374	1	1	12	19	0	1	1	2	0.26	0.2576	0.60	0.1642	119
17375	1	1	12	20	0	1	1	2	0.26	0.2576	0.60	0.1642	89
17376	1	1	12	21	0	1	1	1	0.26	0.2576	0.60	0.1642	90
17377	1	1	12	22	0	1	1	1	0.26	0.2727	0.56	0.1343	61
17378	1	1	12	23	0	1	1	1	0.26	0.2727	0.65	0.1343	49

17379 rows × 13 columns

5. Univariate analysis:

- Describe the numerical fields in the dataset using pandas describe method.

In [31]:
```
inp1.describe()
```

Out[31]:

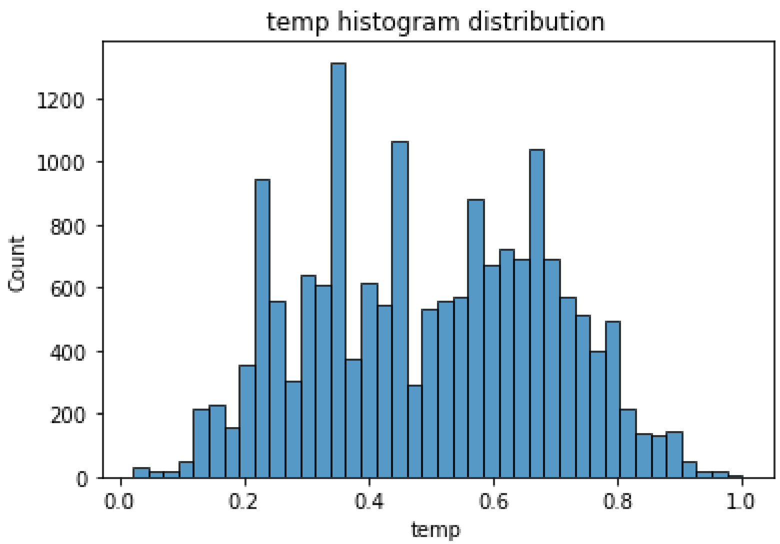
	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	
count	17379.000000	17379.000000	17379.000000	17379.000000	17379.000000	17379.000000	17379.000000	17379.000000	17379.000000	17379.000000	1737
mean	2.501640	0.502561	6.537775	11.546752	0.028770	3.003683	0.682721	1.425283	0.496987	0.475775	(
std	1.106918	0.500008	3.438776	6.914405	0.167165	2.005771	0.465431	0.639357	0.192556	0.171850	(
min	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.020000	0.000000	(
25%	2.000000	0.000000	4.000000	6.000000	0.000000	1.000000	0.000000	1.000000	0.340000	0.333300	(
50%	3.000000	1.000000	7.000000	12.000000	0.000000	3.000000	1.000000	1.000000	0.500000	0.484800	(
75%	3.000000	1.000000	10.000000	18.000000	0.000000	5.000000	1.000000	2.000000	0.660000	0.621200	(
max	4.000000	1.000000	12.000000	23.000000	1.000000	6.000000	1.000000	4.000000	1.000000	1.000000	

Make density plot for temp.

- This would give a sense of the centrality and the spread of the distribution.

In [36]:

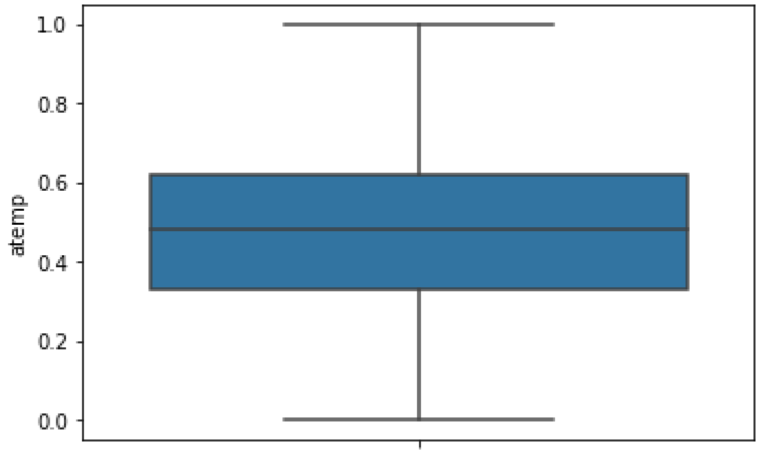
```
fig1,ax1=plt.subplots(1,1);
sns.histplot(data=inp1,x='temp',ax=ax1);
ax1.set_title('temp histogram distribution',fontsize=12);
```



Boxplot for atemp

- Are there any outliers?

In [39]:
```
sns.boxplot(data=inp1,y='atemp');
```

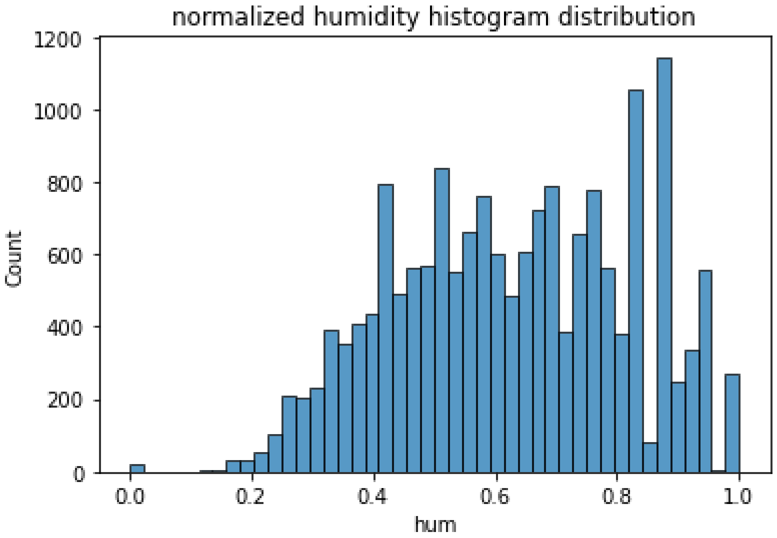


No significant outlier observed for atemp

Histogram for hum

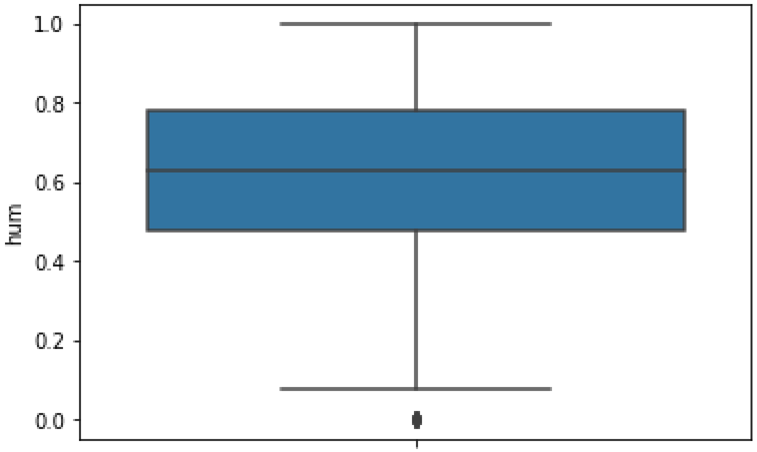
- Do you detect any abnormally high values?

In [43]:
```
fig2,ax2=plt.subplots(1,1);
sns.histplot(data=inp1,x='hum',ax=ax2);
ax2.set_title('normalized humidity histogram distribution',fontsize=12);
```



- Very high humidity is observed but it is not abnormal since there are significant number of instances of such high humidity
- Infact, very low humidity value is outlier

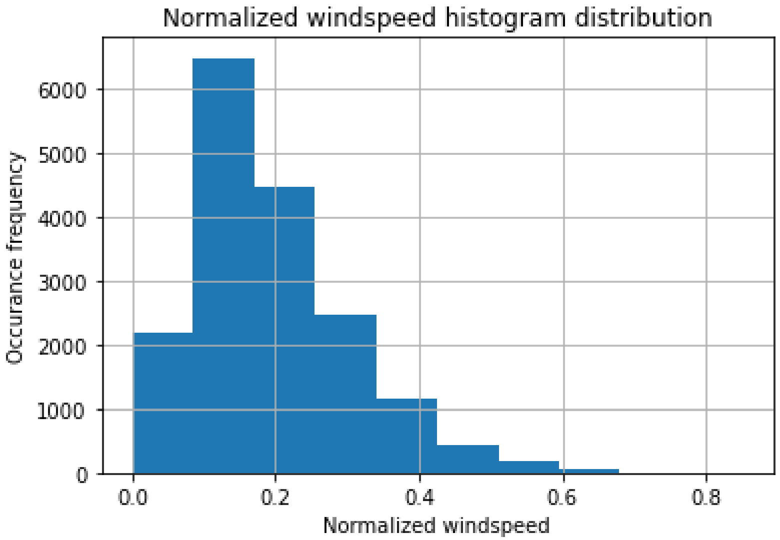
In [45]:
```
sns.boxplot(data=inp1,y='hum');
```



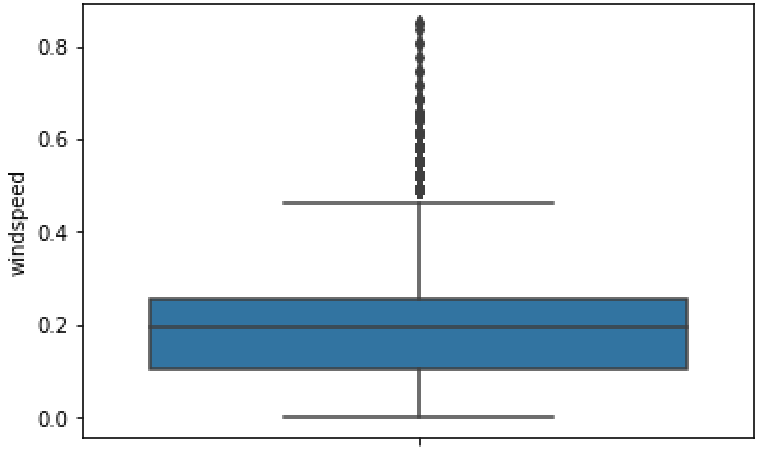
Density plot for windspeed

In [50]:
```
fig3,ax3=plt.subplots(1,1);
inp1.hist(column='windspeed',ax=ax3);
```

```
ax3.set_title('Normalized windspeed histogram distribution',fontsize=12);
ax3.set_xlabel('Normalized windspeed',fontsize=10);
ax3.set_ylabel('Occurance frequency',fontsize=10);
```



In [52]:
```
sns.boxplot(data=inp1,y='windspeed');
```

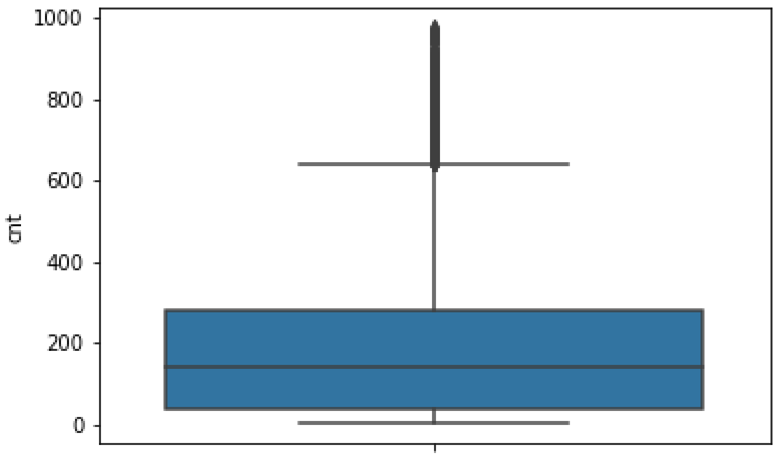


Box and density plot for cnt – this is the variable of interest

- Do you see any outliers in the boxplot?

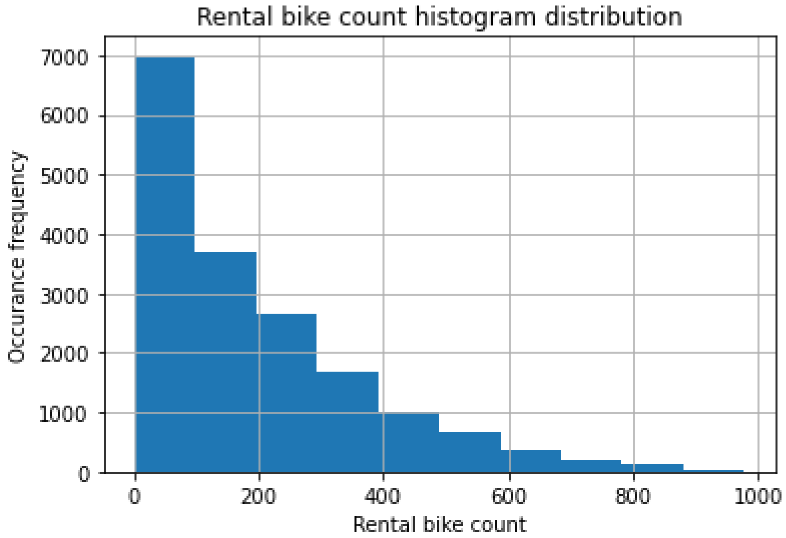
- Does the density plot provide a similar insight?

In [53]:
```
sns.boxplot(data=inp1,y='cnt');
```



Outliers are observed in the boxplot

In [54]:
```
fig4,ax4=plt.subplots(1,1);
inp1.hist(column='cnt',ax=ax4);
ax4.set_title('Rental bike count histogram distribution',fontsize=12);
ax4.set_xlabel('Rental bike count',fontsize=10);
ax4.set_ylabel('Occurance frequency',fontsize=10);
```



6. Outlier treatment:

- Cnt looks like some hours have rather high values.
- You’ll need to treat these outliers so that they don’t skew the analysis and the model.

- Find out the following percentiles: 10, 25, 50, 75, 90, 95, 99

- Decide the cutoff percentile and drop records with values higher than the cutoff. Name the new dataframe as inp2.

In [64]:
```
np.percentile(inp1['cnt'],q=[10,25,50,75,90,95,97,99])
```

Out[64]:
```
array([  9.  ,  40.  , 142.  , 281.  , 451.2 , 563.1 , 638.  , 782.22])
```

In [62]:
```
IQR=281+1.5*(281 -40)
```

In [63]:
```
IQR
```

Out[63]:
```
642.5
```

In [68]:
```
temp1=inp1.drop(index=inp1[inp1['cnt']>650].index)
```

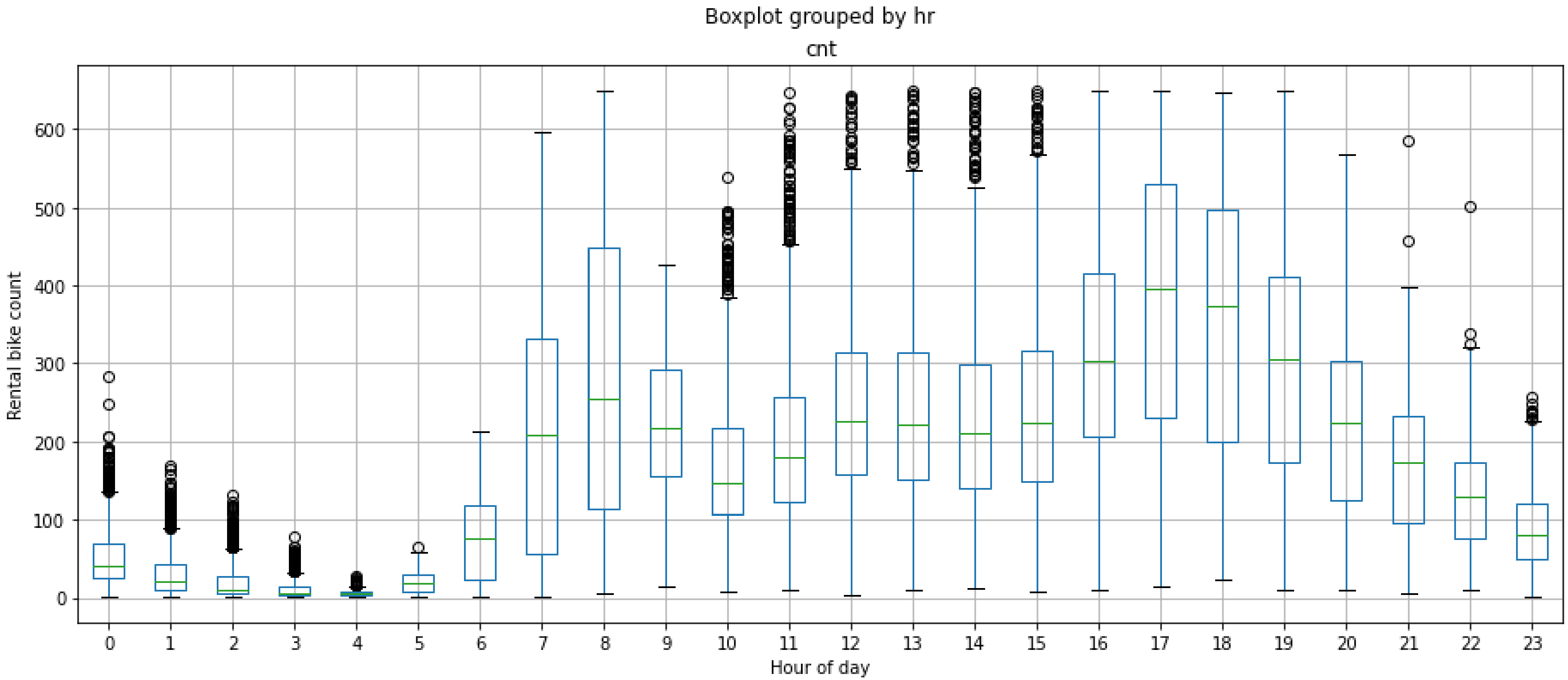
In [71]:
```
inp2=temp1.reset_index(drop=True)
```

7. Bivariate analysis

Make boxplot for cnt vs. hour

- What kind of pattern do you see?

In [78]:
```
fig5,ax5=plt.subplots(1,1, figsize=(15,6));
inp2.boxplot(column='cnt',by='hr',ax=ax5);
ax5.set_xlabel('Hour of day',fontsize=10);
ax5.set_ylabel('Rental bike count',fontsize=10);
```



- Based on observation more bikes are rented between 7 hours to 21 hours
- Peak time observed to be between 16 to 19 hours

In [82]:
```
inp2[['cnt','hr']].corr()
```

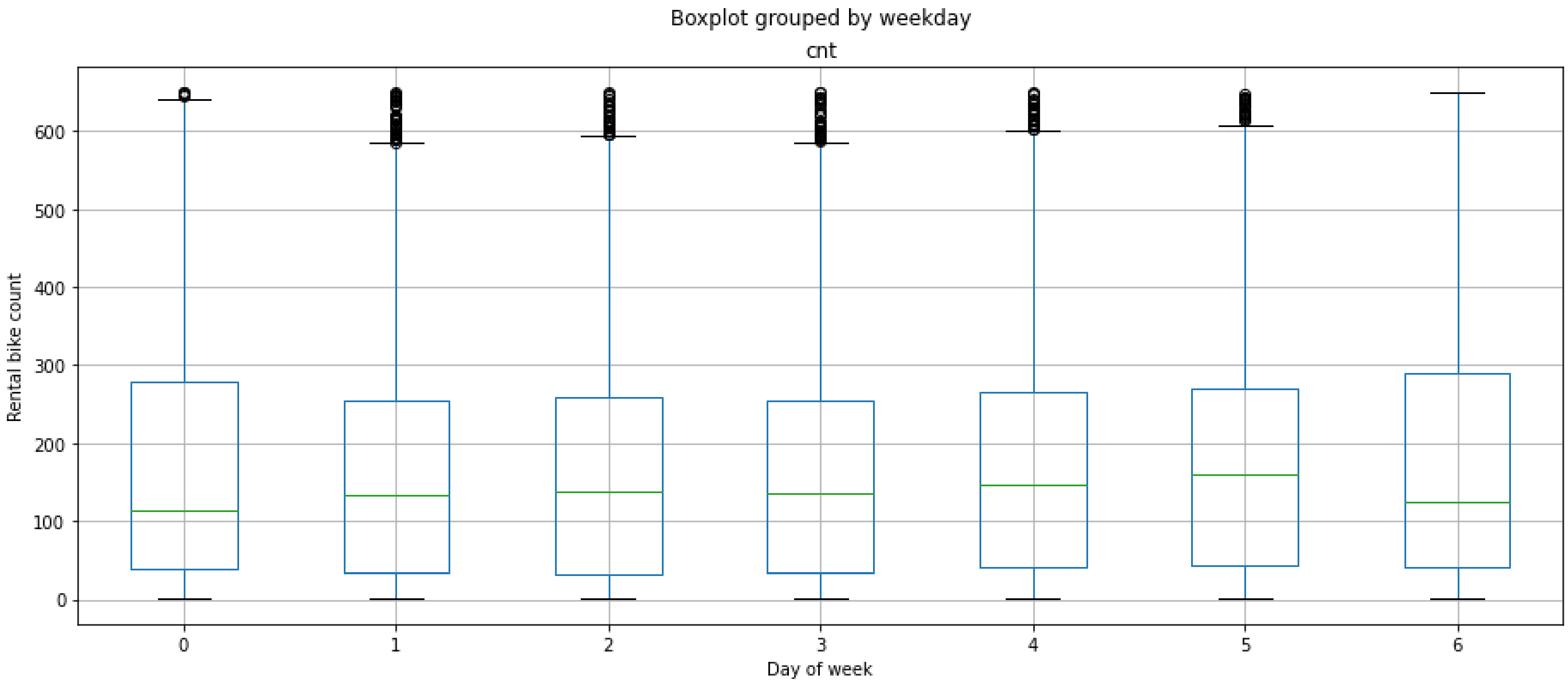
Out[82]:

	cnt	hr
cnt	1.000000	0.419212
hr	0.419212	1.000000

Make boxplot for cnt vs. weekday

- Is there any difference in the rides by days of the week?

In [79]:
```
fig6,ax6=plt.subplots(1,1, figsize=(15,6));
inp2.boxplot(column='cnt',by='weekday',ax=ax6);
ax6.set_xlabel('Day of week',fontsize=10);
ax6.set_ylabel('Rental bike count',fontsize=10);
```



- Similar rental bike share count is observed on all days of week
- Difficult to differentiate

In [84]:
```
inp2[['cnt','weekday']].corr()
```

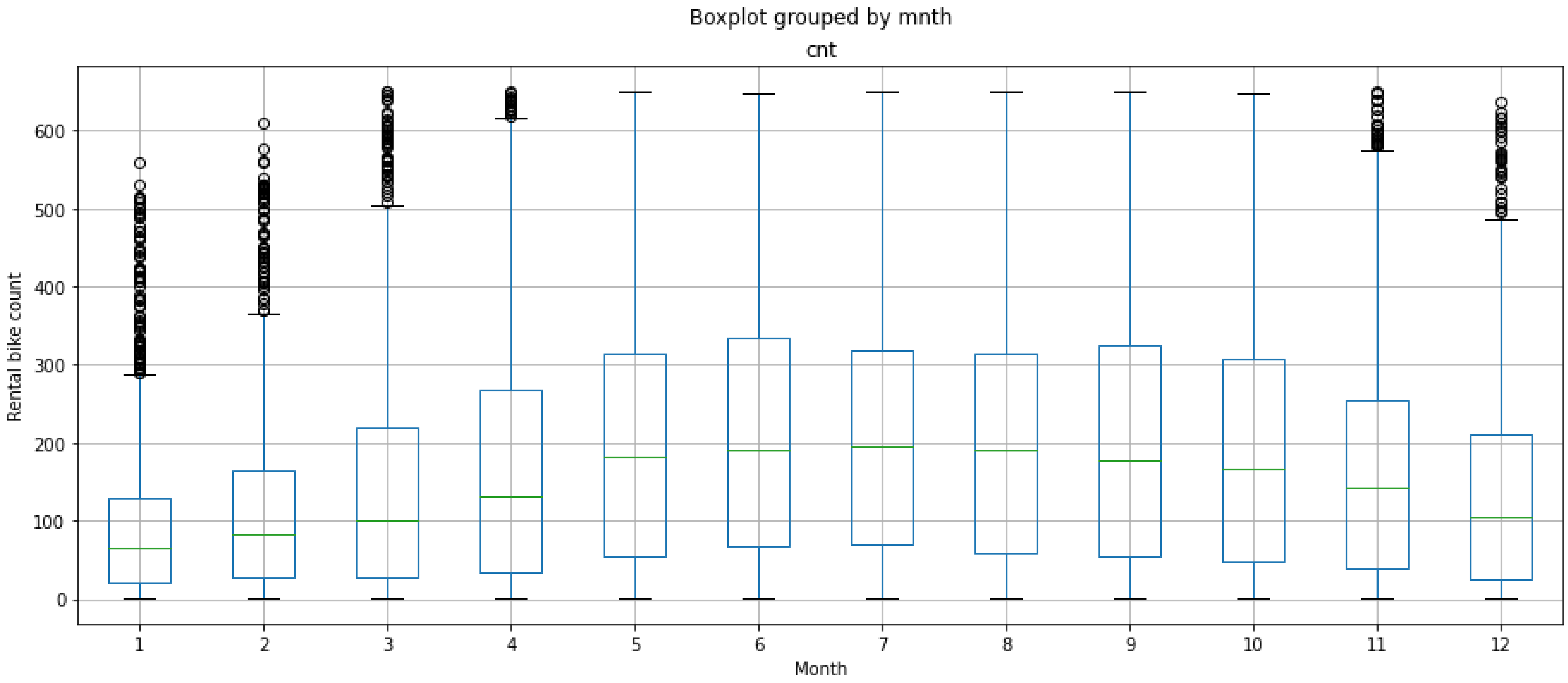
Out[84]:

	cnt	weekday
cnt	1.00000	0.02378
weekday	0.02378	1.00000

Make boxplot for cnt vs. month

- Look at the median values. Any month(s) that stand out?

In [85]:
```
fig7,ax7=plt.subplots(1,1, figsize=(15,6));
inp2.boxplot(column='cnt',by='mnth',ax=ax7);
ax7.set_xlabel('Month',fontsize=10);
ax7.set_ylabel('Rental bike count',fontsize=10);
```



- Month 5 to 10 have similar distribution

In [87]:
```
inp2[['cnt','mnth']].corr()
```

Out[87]:

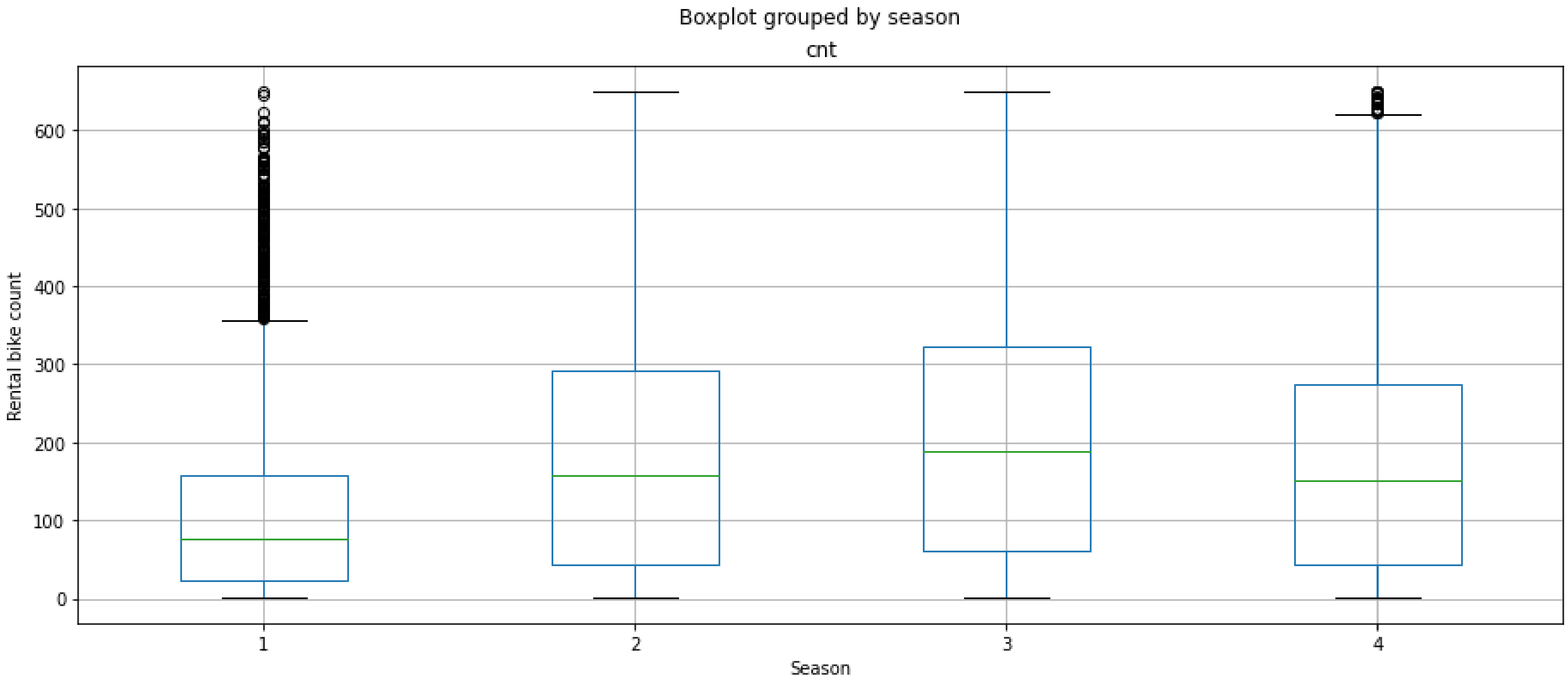
	cnt	mnth
cnt	1.000000	0.115148
mnth	0.115148	1.000000

Make boxplot for cnt vs. season

- Which season has the highest rides in general? Expected?

In [88]:
```
fig8,ax8=plt.subplots(1,1, figsize=(15,6));
inp2.boxplot(column='cnt',by='season',ax=ax8);
```

```
ax8.set_xlabel('Season',fontsize=10);
ax8.set_ylabel('Rental bike count',fontsize=10);
```



- Fall season appears to have more riders, followed by summer and winter, followed by spring.

In [89]:
```
inp2[['cnt','season']].corr()
```

Out[89]:

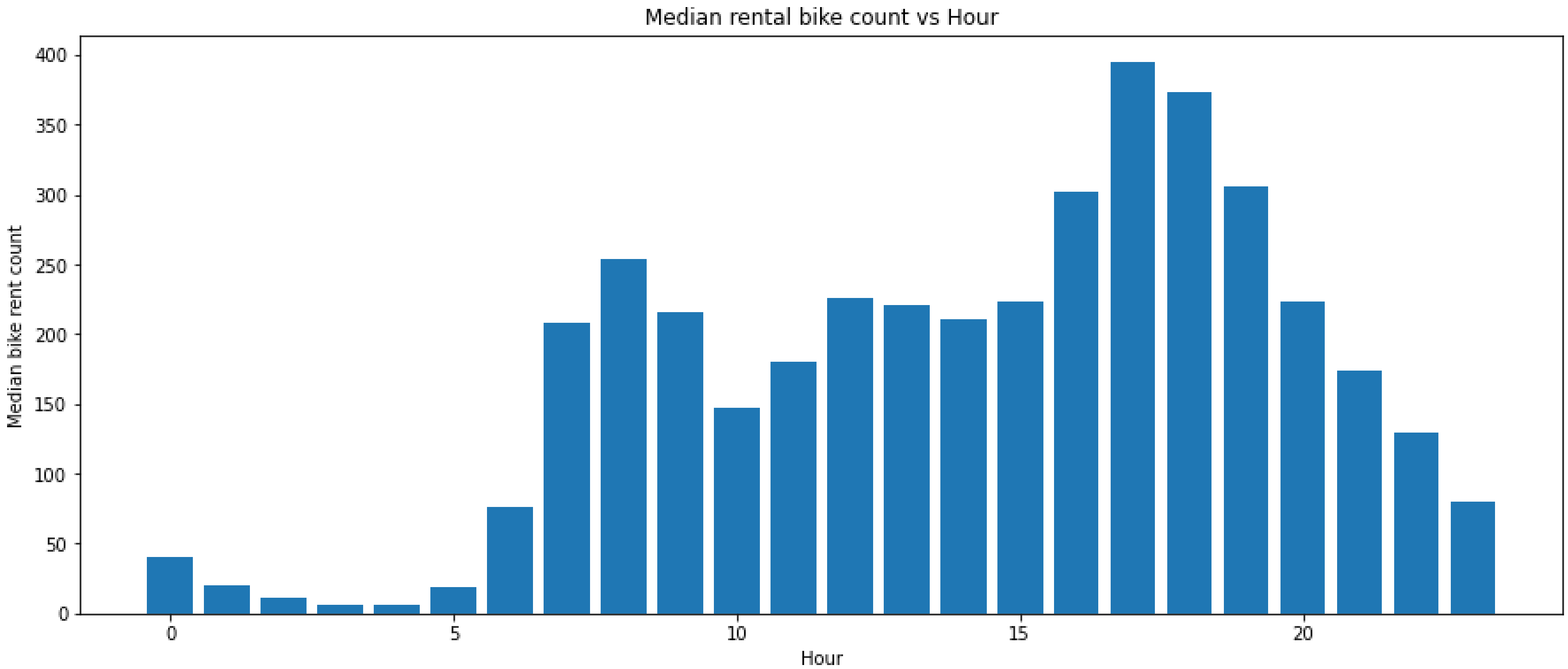
	cnt	season
cnt	1.000000	0.172791
season	0.172791	1.000000

Make a bar plot with the median value of cnt for each hr

Does this paint a different picture from the box plot?

In [100…

```
med_cnt=[];
for val in inp2.hr.unique():
    med_cnt.append(inp2[inp2['hr']==val]['cnt'].median());
fig9,ax9=plt.subplots(1,1, figsize=(15,6));
ax9.bar(x=inp2.hr.unique(),height=med_cnt);
ax9.set_title('Median rental bike count vs Hour',fontsize=12);
ax9.set_xlabel('Hour',fontsize=10);
ax9.set_ylabel('Median bike rent count',fontsize=10);
```



Make a correlation matrix for variables atemp, temp, hum, and windspeed

Which variables have the highest correlation?

In [101…

```
inp2[['atemp','temp','hum','windspeed']].corr()
```

Out[101…

	atemp	temp	hum	windspeed
atemp	1.000000	0.988283	-0.038183	-0.068444

	atemp	temp	hum	windspeed
temp	0.988283	1.000000	-0.055624	-0.028413
hum	-0.038183	-0.055624	1.000000	-0.289056
windspeed	-0.068444	-0.028413	-0.289056	1.000000

- Temp and atemp have very high positive correlation (0.988)
- hum and windspeed have reasonably significant negative correlation (-0.289) implies inverse relation

8. Data preprocessing

A few key considerations for the preprocessing:

There are plenty of categorical features. Since these categorical features can't be used in the predictive model, you need to convert to a suitable numerical representation. Instead of creating dozens of new dummy variables, try to club levels of categorical features wherever possible. For a feature with high number of categorical levels, you can club the values that are very similar in value for the target variable.

Treating mnth column

- For values 5,6,7,8,9,10, replace with a single value 5. This is because these have very similar values for cnt.

- Get dummies for the updated 6 mnth values

In [114…

```
inp2['mnth']=inp2['mnth'].apply(lambda val: 5 if((val>=5) & (val<=10)) else val);
```

In [115…

```
inp2.mnth.value_counts()
```

Out[115…

```
5     8410
12    1470
3     1441
1     1429
11    1418
4     1396
2     1341
Name: mnth, dtype: int64
```

Treating hr column

- Create new mapping: 0-5: 0, 11-15: 11; other values are untouched.
- Again, the bucketing is done in a way that hr values with similar levels of cnt are treated the same.

In [116…

```
inp2['hr']=inp2['hr'].apply(lambda val: 0 if((val>=0) & (val<=5)) else 11 if((val>=11) & (val<=15)) else val);
```

- Get dummy columns for season, weathersit, weekday, mnth, and hr.
- You needn't club these further as the levels seem to have different values for the median cnt, when seen from the box plots.

In [157…

```
inp2=pd.get_dummies(data=inp2,columns=['season','weathersit','weekday','mnth','hr'],drop_first=True);
```

In [158…

```
inp2
```

Out[158…

	yr	holiday	workingday	temp	atemp	hum	windspeed	cnt	season_2	season_3	...	hr_10	hr_11	hr_16	hr_17	hr_18	hr_19	hr_20	hr_21	h
0	0	0	0	0.24	0.2879	0.81	0.0000	16	0	0	...	0	0	0	0	0	0	0	0	
1	0	0	0	0.22	0.2727	0.80	0.0000	40	0	0	...	0	0	0	0	0	0	0	0	
2	0	0	0	0.22	0.2727	0.80	0.0000	32	0	0	...	0	0	0	0	0	0	0	0	
3	0	0	0	0.24	0.2879	0.75	0.0000	13	0	0	...	0	0	0	0	0	0	0	0	
4	0	0	0	0.24	0.2879	0.75	0.0000	1	0	0	...	0	0	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
16900	1	0	1	0.26	0.2576	0.60	0.1642	119	0	0	...	0	0	0	0	0	1	0	0	
16901	1	0	1	0.26	0.2576	0.60	0.1642	89	0	0	...	0	0	0	0	0	0	1	0	
16902	1	0	1	0.26	0.2576	0.60	0.1642	90	0	0	...	0	0	0	0	0	0	0	1	
16903	1	0	1	0.26	0.2727	0.56	0.1343	61	0	0	...	0	0	0	0	0	0	0	0	
16904	1	0	1	0.26	0.2727	0.65	0.1343	49	0	0	...	0	0	0	0	0	0	0	0	

16905 rows × 40 columns

9. Train test split: Apply 70-30 split.

- call the new dataframes df_train and df_test

In [160…

```
df_train,df_test=train_test_split(inp2,test_size=0.3);
```

In [162…

```
print(inp2.shape)
print(df_train.shape)
print(df_test.shape)
```

```
(16905, 40)
(11833, 40)
(5072, 40)
```

10. Separate X and Y for df_train and df_test. For example, you should have X_train, y_train from df_train. y_train should be the cnt column from inp3 and X_train should be all other columns.

In [164…

```
X_train=df_train.drop(axis=1,columns='cnt');
y_train=df_train.cnt;
X_test=df_test.drop(axis=1,columns='cnt');
y_test=df_test.cnt;
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(11833, 39)
(11833,)
(5072, 39)
(5072,)
```

Model building

Use linear regression as the technique

Report the R2 on the train set

In [170…

```
lr=LinearRegression();
cvs=cross_val_score(lr,X_train,y_train,n_jobs=-1,cv=10)
```

In [174…

```
print(cvs)
print("Average R2 cross-validation score = ",np.mean(cvs))
```

```
[0.67590282 0.67491212 0.66387713 0.66908494 0.67502011 0.6622007
 0.64421179 0.68917525 0.67648882 0.67229778]
Average R2 cross-validation score =  0.6703171459086555
```

In [177…

```
grid_pred=GridSearchCV(Ridge(),[{'alpha':[0,0.1,1,10,100],'fit_intercept':[True,False],'normalize':[True,False]}],n_jobs=-1,cv=10)
```

In [178…
```
grid_pred.fit(X_train,y_train)
```

Out[178…
```
GridSearchCV(cv=10, estimator=Ridge(), n_jobs=-1,
             param_grid=[{'alpha': [0, 0.1, 1, 10, 100],
                          'fit_intercept': [True, False],
                          'normalize': [True, False]}])
```

In [179…
```
grid_pred.best_estimator_
```

Out[179…
```
Ridge(alpha=1)
```

In [181…
```
grid_pred.best_score_
```

Out[181…
```
0.6704473590245815
```

In [184…
```
grid_pred.cv_results_['mean_test_score']
```

Out[184…
```
array([0.67030748, 0.67034636, 0.66423825, 0.66423825, 0.64880409,
       0.67038728, 0.66428473, 0.66428473, 0.45275653, 0.67044736,
       0.66433758, 0.66433758, 0.13075954, 0.66911437, 0.6631346 ,
       0.6631346 , 0.01538883, 0.61573751, 0.61516348, 0.61516348])
```

Since best Ridge regression R2 score is very close to the LinearRegression R2 score, LinearRegression can be used directly

In [185…
```
lr_model=LinearRegression();
lr_model.fit(X_train,y_train);
```

In [186…
```
print('R^2 score on training set =',lr_model.score(X_train,y_train))
```

```
R^2 score on training set = 0.6733897713082271
```

11. Make predictions on test set and report R2.

In [188…
```
print('R^2 score on test set =',lr_model.score(X_test,y_test))
```

```
R^2 score on test set = 0.6613346525574706
```

In [194…
```
pred=pd.Series(lr_model.predict(X_test),name='prediction')
```

In [195…
```
y_test.reset_index(inplace=True,drop=True)
```

In [196…

```
y_test
```

Out[196…

```
0       438
1       162
2        48
3        56
4       225
       ... 
5067    202
5068    198
5069     46
5070     22
5071    499
Name: cnt, Length: 5072, dtype: int64
```

In [198…

```
pred_vs_target=pd.concat([pred,y_test],axis=1,join='inner')
```

In [199…

```
pred_vs_target
```

Out[199…

	prediction	cnt
0	418.156860	438
1	217.176596	162
2	39.071293	48
3	4.451471	56
4	221.596936	225
...	...	...
5067	188.581353	202
5068	261.939018	198
5069	-11.508562	46
5070	-47.293113	22
5071	243.949138	499

5072 rows × 2 columns

In [200…
```
lr_model.intercept_
```

Out[200…
```
-89.659661171723
```

In [201…
```
lr_model.coef_
```

Out[201…
```
array([ 6.68767639e+01, -3.89123291e+14, -3.89123291e+14,  7.81858851e+01,
        1.37127408e+02, -7.07430748e+01, -1.72536003e+01,  3.62448293e+01,
        2.39431463e+01,  5.82984194e+01, -7.66779279e+00, -6.07723417e+01,
       -8.06823110e+01,  3.89123291e+14,  3.89123291e+14,  3.89123291e+14,
        3.89123291e+14,  3.89123291e+14,  1.58897757e+01,  9.65483324e-01,
        9.70288878e+00,  5.12738129e+00,  1.38287839e+01, -5.59222934e+00,
        4.00424480e-01,  5.54655656e+01,  1.95430833e+02,  2.72733799e+02,
        1.89678514e+02,  1.34082395e+02,  1.79257473e+02,  2.53768685e+02,
        3.49057424e+02,  3.17529874e+02,  2.63976700e+02,  1.82891636e+02,
        1.34990313e+02,  9.61111325e+01,  5.74255908e+01])
```

In [202…
```
X_train.columns
```

Out[202…
```
Index(['yr', 'holiday', 'workingday', 'temp', 'atemp', 'hum', 'windspeed',
       'season_2', 'season_3', 'season_4', 'weathersit_2', 'weathersit_3',
       'weathersit_4', 'weekday_1', 'weekday_2', 'weekday_3', 'weekday_4',
       'weekday_5', 'weekday_6', 'mnth_2', 'mnth_3', 'mnth_4', 'mnth_5',
       'mnth_11', 'mnth_12', 'hr_6', 'hr_7', 'hr_8', 'hr_9', 'hr_10', 'hr_11',
       'hr_16', 'hr_17', 'hr_18', 'hr_19', 'hr_20', 'hr_21', 'hr_22', 'hr_23'],
      dtype='object')
```

In [210…
```
print("Final Model is-")
printing_model=y_train.name+'='+str(lr_model.intercept_);
for idx in range(len(lr_model.coef_)):
    if (lr_model.coef_[idx]>=0):
        printing_model+='+';
    printing_model+=str(lr_model.coef_[idx]);
    printing_model+='*';
    printing_model+=X_train.columns[idx];

printing_model
```

```
Final Model is-
```

Out[210…
```
'cnt=-89.659661171723+66.87676390255233*yr-389123291070272.56*holiday-389123291070251.2*workingday+78.18588510384282*temp+137.1274
0768792307*atemp-70.74307480108072*hum-17.253600301414274*windspeed+36.244829348524554*season_2+23.943146250167903*season_3+58.298
41935840124*season_4-7.667792794375536*weathersit_2-60.77234173422313*weathersit_3-80.68231104418406*weathersit_4+389123291070255.
4*weekday_1+389123291070254.0*weekday_2+389123291070258.2*weekday_3+389123291070259.94*weekday_4+389123291070265.3*weekday_5+15.88
9775678589594*weekday_6+0.9654833236593672*mnth_2+9.702888777540691*mnth_3+5.127381285515619*mnth_4+13.82878388909847*mnth_5-5.592
229339003997*mnth_11+0.40042448027456734*mnth_12+55.465565648003434*hr_6+195.4308327107412*hr_7+272.733798946706*hr_8+189.67851389
```

```
92186*hr_9+134.0823952425801*hr_10+179.25747335469842*hr_11+253.76868543776075*hr_16+349.0574243973603*hr_17+317.52987413871807*hr
_18+263.97670009450064*hr_19+182.89163638991738*hr_20+134.9903131535375*hr_21+96.11113245179709*hr_22+57.42559082873638*hr_23'
```

In [ ]: