DataExploration-LondonBikeSharing

October 3, 2021

1 London Bike Sharing

This is a preliminary analisys of the "London Bike Sharing" dataset. The goal is to practice exploratory data analysis with feature construction. The data comprise data from 1/1/2015 to 31/12/2016 and have been preprocessed from three original sources:

- Https://cycling.data.tfl.gov.uk/ 'Contains OS data © Crown copyright and database rights 2016' and Geomni UK Map data © and database rights [2019] 'Powered by TfL Open Data'
- freemeteo.com - weather data
- https://www.gov.uk/bank-holidays

The data from cycling dataset is grouped by "Start time", this represent the count of new bike shares grouped by hour. The long duration shares are not taken in the count.

There are ten attributes: - timestamp: the timestamp - cnt: number of bikes - t1: actual temperature - t2: temperature as it feels - hum: humidity % - wind_speed: km/h - weather_code: code - is_holiday: boolean - is_weekend: boolean - season: season_code

[ ]:
```
import pandas as pd
import numpy as np
from datetime import date
import datetime
import matplotlib.pyplot as plt
%matplotlib inline

# Seaborn
import seaborn as sns
sns.set(style="white", color_codes=True)
sns.set_context(rc={"font.family":'sans',"font.size":24,"axes.titlesize":
↪24,"axes.labelsize":24})

# ignore the warnings
import warnings
warnings.filterwarnings("ignore")
```

[ ]:
```
df = pd.read_csv("london_merged.csv")
df.head(5)
```

```
[ ]:              timestamp  cnt   t1   t2    hum  wind_speed  weather_code  \
     0  2015-01-04 00:00:00  182  3.0  2.0   93.0         6.0           3.0
     1  2015-01-04 01:00:00  138  3.0  2.5   93.0         5.0           1.0
     2  2015-01-04 02:00:00  134  2.5  2.5   96.5         0.0           1.0
     3  2015-01-04 03:00:00   72  2.0  2.0  100.0         0.0           1.0
     4  2015-01-04 04:00:00   47  2.0  0.0   93.0         6.5           1.0

        is_holiday  is_weekend  season
     0         0.0         1.0     3.0
     1         0.0         1.0     3.0
     2         0.0         1.0     3.0
     3         0.0         1.0     3.0
     4         0.0         1.0     3.0
```

2 Feature Creation

Timestamp encodes a lot of information that is unusable when contained in one variable. So first, let's extract all the information we might be interested in.

```
[ ]: df['weekday'] = df['timestamp'].apply(lambda x: datetime.datetime.
      ↪strptime(x,"%Y-%m-%d %H:%M:%S").weekday())
```

```
[ ]: df['year'] = df['timestamp'].apply(lambda x: datetime.datetime.
      ↪strptime(x,"%Y-%m-%d %H:%M:%S").year)
```

```
[ ]: df['month'] = df['timestamp'].apply(lambda x: datetime.datetime.
      ↪strptime(x,"%Y-%m-%d %H:%M:%S").month)
```

```
[ ]: df['hour'] = df['timestamp'].apply(lambda x: datetime.datetime.
      ↪strptime(x,"%Y-%m-%d %H:%M:%S").hour)
```

```
[ ]: df['minute'] = df['timestamp'].apply(lambda x: datetime.datetime.
      ↪strptime(x,"%Y-%m-%d %H:%M:%S").minute)
```

Let's check minutes, since I want to check whether the measurements are done hourly.

```
[ ]: df['minute'].describe()
```

```
[ ]: count    17414.0
     mean         0.0
     std          0.0
     min          0.0
     25%          0.0
     50%          0.0
     75%          0.0
     max          0.0
     Name: minute, dtype: float64
```

Yes, they are hourly so let's eliminate this attribute and obviously also *timestamp*

[ ]:
```
df.drop(['minute','timestamp'],axis=1,inplace=True)
```

[ ]:
```
df.describe()
```

[ ]:
```
                cnt            t1            t2           hum    wind_speed  \
count  17414.000000  17414.000000  17414.000000  17414.000000  17414.000000
mean    1143.101642     12.468091     11.520836     72.324954     15.913063
std     1085.108068      5.571818      6.615145     14.313186      7.894570
min        0.000000     -1.500000     -6.000000     20.500000      0.000000
25%      257.000000      8.000000      6.000000     63.000000     10.000000
50%      844.000000     12.500000     12.500000     74.500000     15.000000
75%     1671.750000     16.000000     16.000000     83.000000     20.500000
max     7860.000000     34.000000     34.000000    100.000000     56.500000

       weather_code    is_holiday    is_weekend        season      weekday  \
count  17414.000000  17414.000000  17414.000000  17414.000000  17414.00000
mean       2.722752      0.022051      0.285403      1.492075      2.99265
std        2.341163      0.146854      0.451619      1.118911      2.00406
min        1.000000      0.000000      0.000000      0.000000      0.00000
25%        1.000000      0.000000      0.000000      0.000000      1.00000
50%        2.000000      0.000000      0.000000      1.000000      3.00000
75%        3.000000      0.000000      1.000000      2.000000      5.00000
max       26.000000      1.000000      1.000000      3.000000      6.00000

               year         month          hour
count  17414.000000  17414.000000  17414.000000
mean    2015.507810      6.514643     11.513265
std        0.508157      3.452509      6.915893
min     2015.000000      1.000000      0.000000
25%     2015.000000      4.000000      6.000000
50%     2016.000000      7.000000     12.000000
75%     2016.000000     10.000000     18.000000
max     2017.000000     12.000000     23.000000
```

Also note that we have two temperatures, the real one t1 and the perceived one t2. It might be interesting to check the difference so that we can get extra information about the weather. If t2-t1 is higher, it means that the perceived temperature is higher, so it might depend on a warmer wind or else. Similarly if the difference is negative.

[ ]:
```
df['dt'] = df['t2'] - df['t1']
```

3 Other Ideas about how to explore and preprocess the data

- check for missing values => No missing values
- stats
- plot cnt with respect to the other attributes

- groupby weekday and plot …
- % of cnt for each hour over day …
- correlations …

[ ]:
```
df.describe()
```

[ ]:
```
                cnt            t1            t2           hum    wind_speed  \
count  17414.000000  17414.000000  17414.000000  17414.000000  17414.000000
mean    1143.101642     12.468091     11.520836     72.324954     15.913063
std     1085.108068      5.571818      6.615145     14.313186      7.894570
min        0.000000     -1.500000     -6.000000     20.500000      0.000000
25%      257.000000      8.000000      6.000000     63.000000     10.000000
50%      844.000000     12.500000     12.500000     74.500000     15.000000
75%     1671.750000     16.000000     16.000000     83.000000     20.500000
max     7860.000000     34.000000     34.000000    100.000000     56.500000

       weather_code    is_holiday    is_weekend        season     weekday  \
count  17414.000000  17414.000000  17414.000000  17414.000000  17414.00000
mean       2.722752      0.022051      0.285403      1.492075     2.99265
std        2.341163      0.146854      0.451619      1.118911     2.00406
min        1.000000      0.000000      0.000000      0.000000     0.00000
25%        1.000000      0.000000      0.000000      0.000000     1.00000
50%        2.000000      0.000000      0.000000      1.000000     3.00000
75%        3.000000      0.000000      1.000000      2.000000     5.00000
max       26.000000      1.000000      1.000000      3.000000     6.00000

               year         month          hour            dt
count  17414.000000  17414.000000  17414.000000  17414.000000
mean    2015.507810      6.514643     11.513265     -0.947255
std        0.508157      3.452509      6.915893      1.395621
min     2015.000000      1.000000      0.000000     -7.000000
25%     2015.000000      4.000000      6.000000     -2.000000
50%     2016.000000      7.000000     12.000000      0.000000
75%     2016.000000     10.000000     18.000000      0.000000
max     2017.000000     12.000000     23.000000      1.000000
```

We note that there are no missing values and cnt might be skewed

[ ]:
```
target_variable = 'cnt'
input_variables = df.columns[df.columns!=target_variable]
```

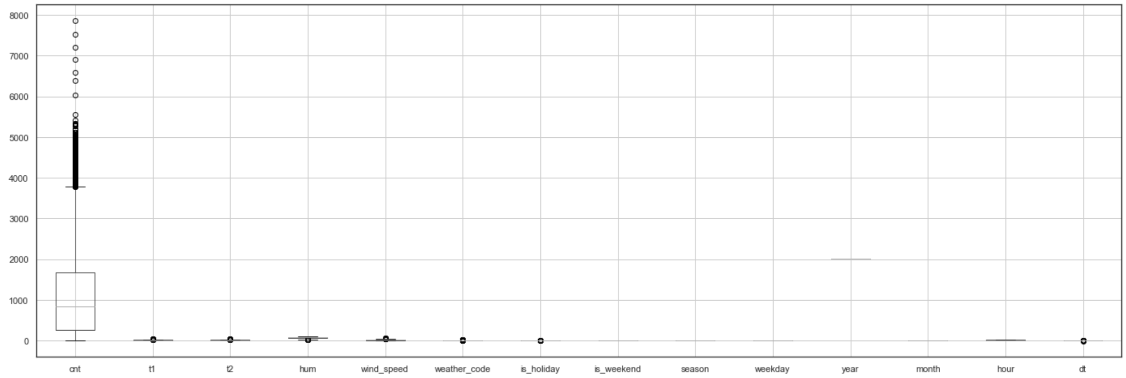
[ ]:
```
target_variable
```

[ ]:
```
'cnt'
```

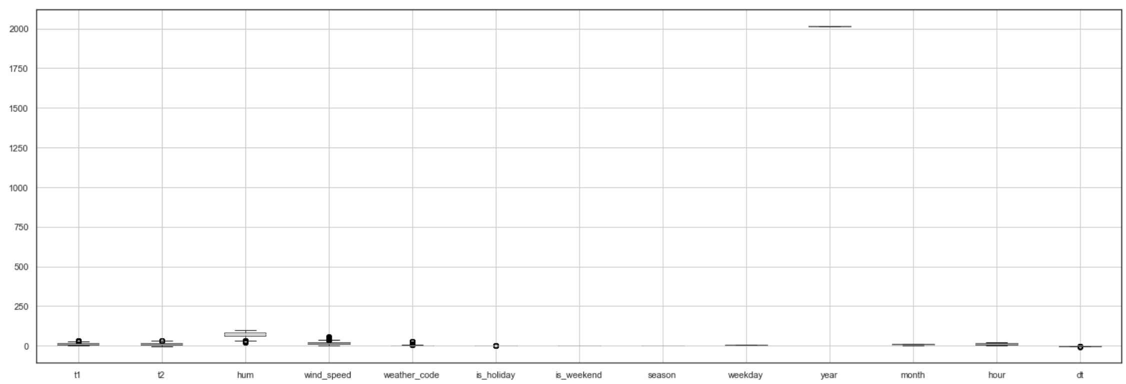
[ ]:
```
input_variables
```

```
[ ]: Index(['t1', 't2', 'hum', 'wind_speed', 'weather_code', 'is_holiday',
       'is_weekend', 'season', 'weekday', 'year', 'month', 'hour', 'dt'],
      dtype='object')
```

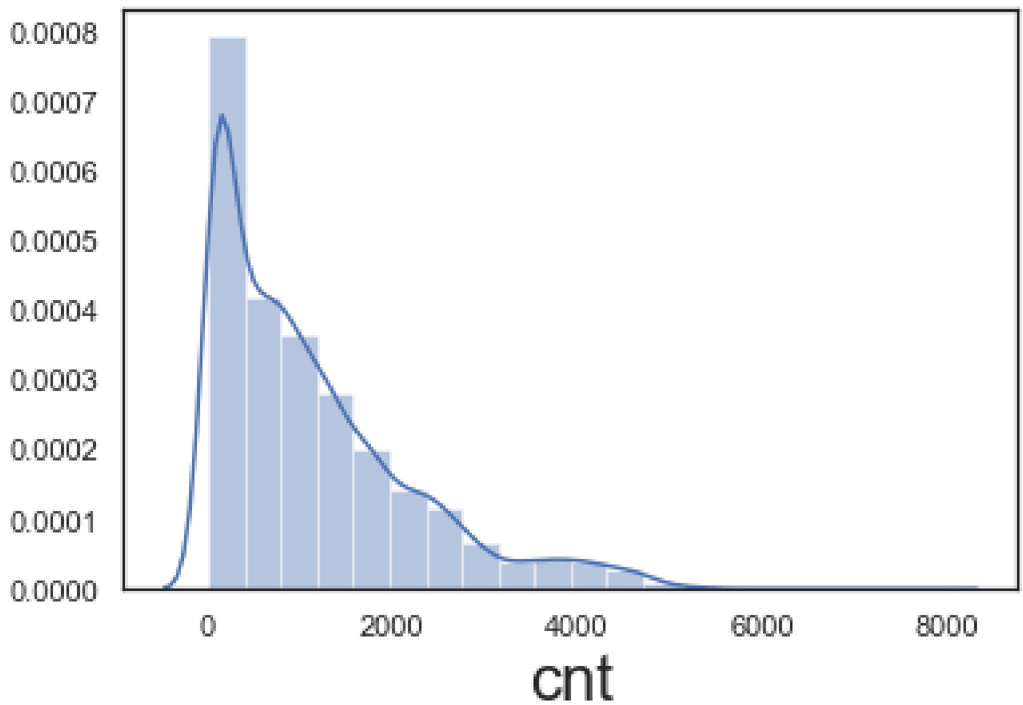
```
[ ]: df.boxplot(figsize=(24,8));
```




```
[ ]: df[input_variables].boxplot(figsize=(24,8));
```

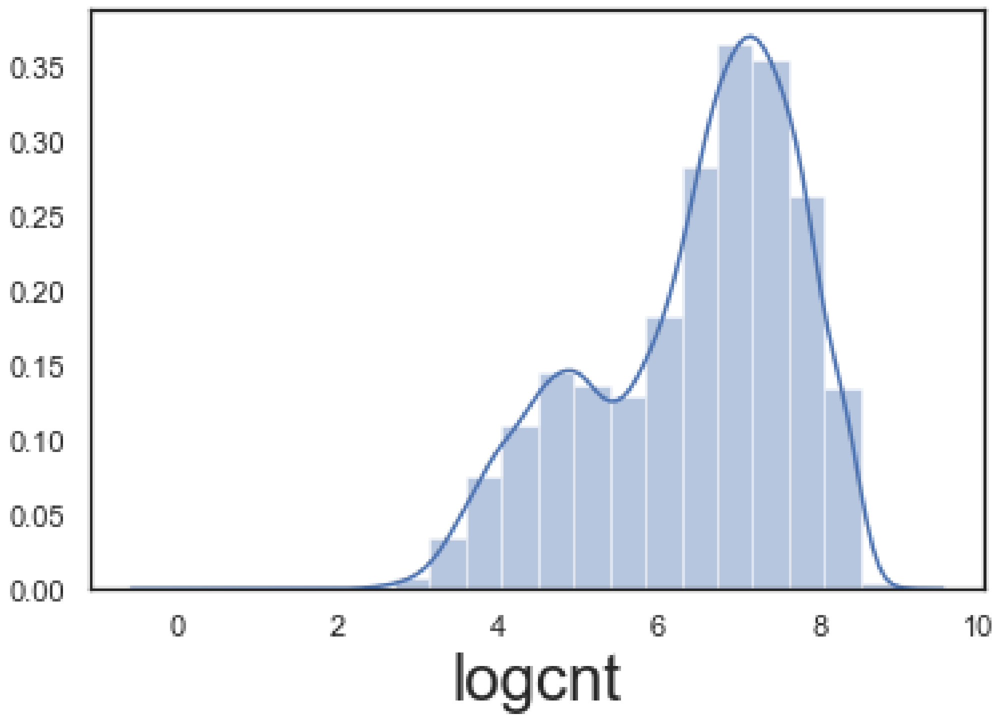



```
[ ]: sns.distplot(df['cnt'], bins=20);
```



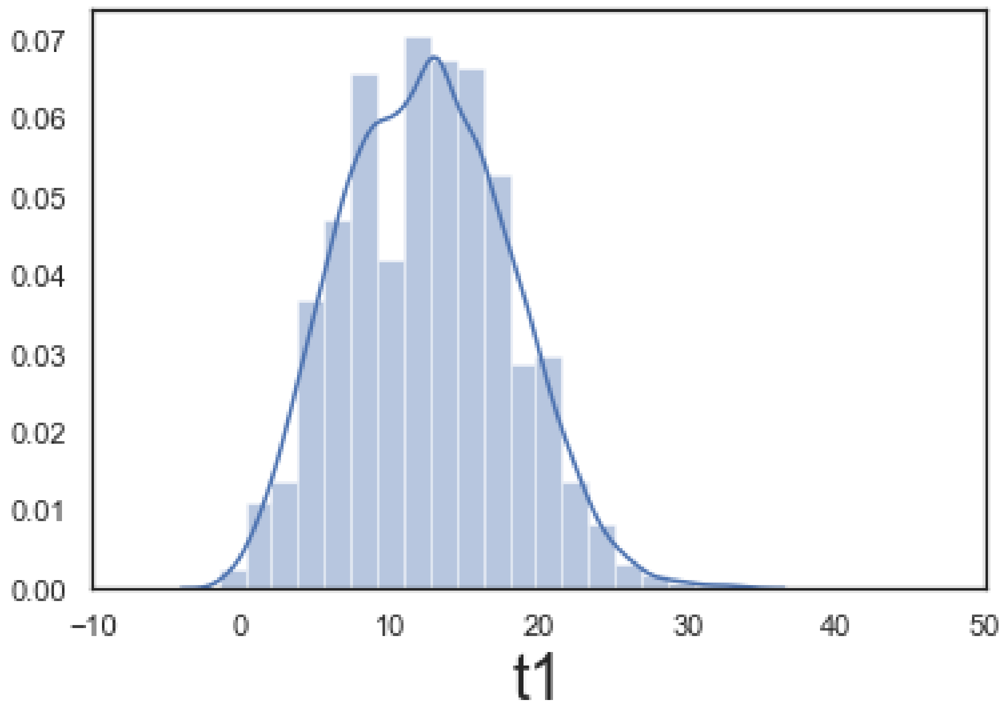
[ ]:
```
df['logcnt'] = np.log1p(df['cnt'])
```

[ ]:
```
sns.distplot(df['logcnt'], bins=20);
```

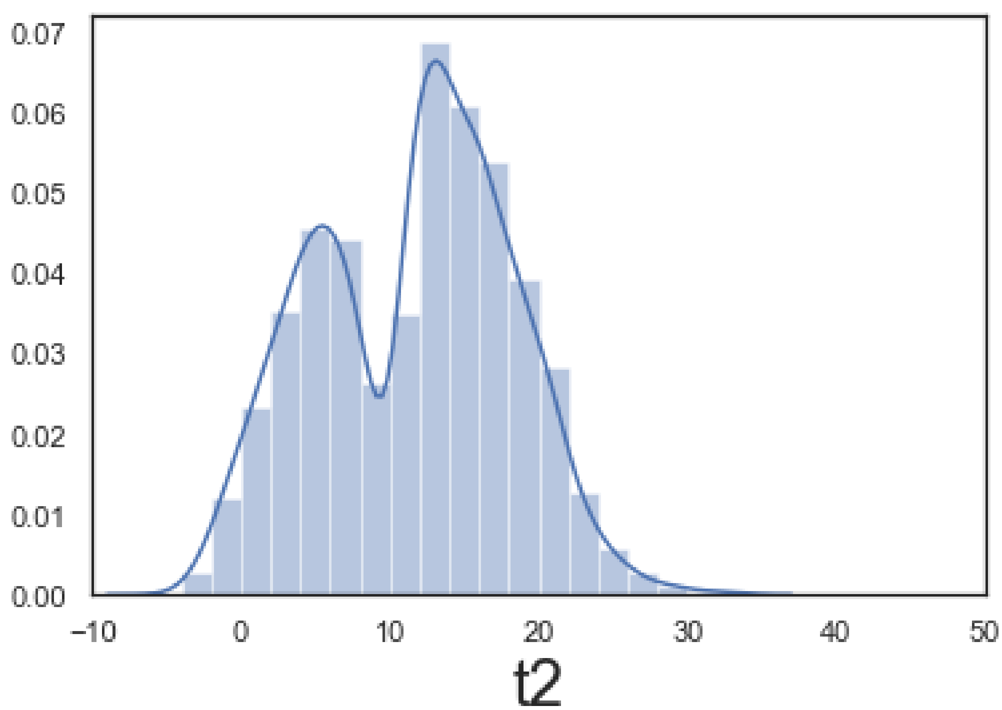


[ ]:
```
target_variable = 'logcnt'
```

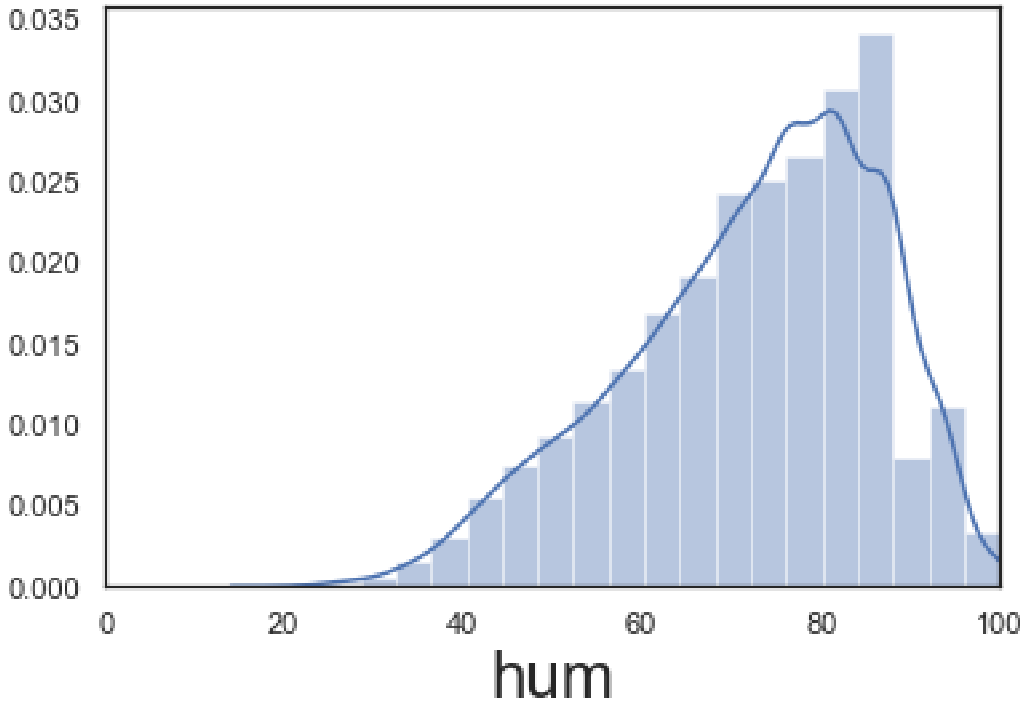
[ ]:
```
sns.distplot(df['t1'], bins=20);
plt.xlim([-10,50]);
```



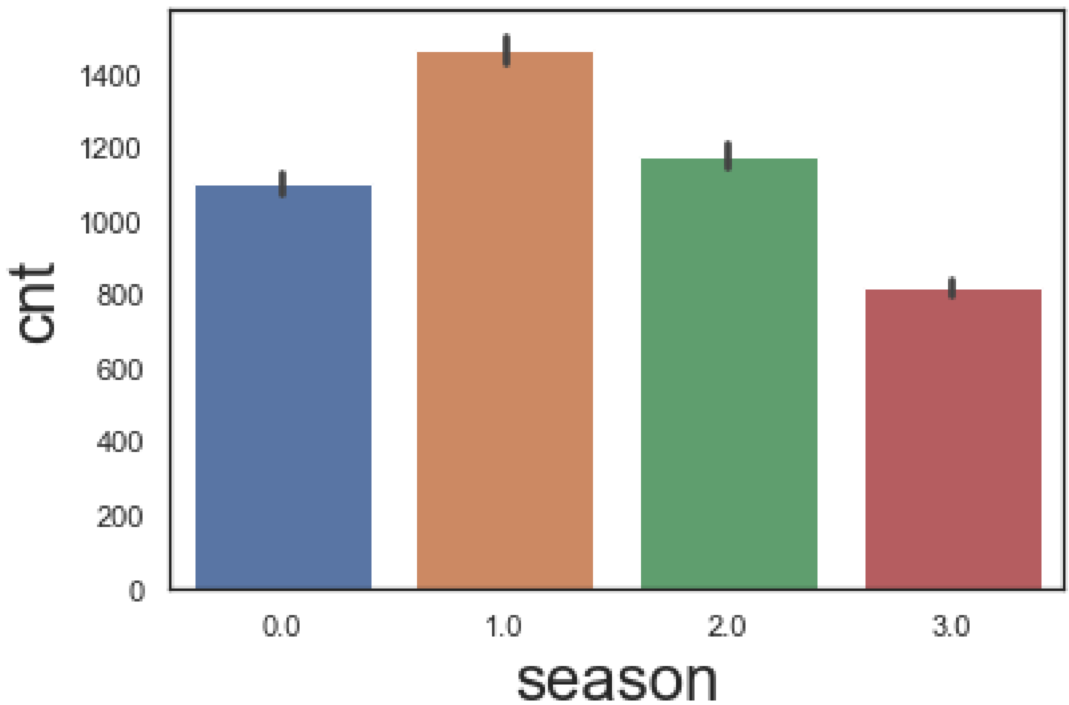
[ ]:
```
sns.distplot(df['t2'], bins=20);
plt.xlim([-10,50]);
```



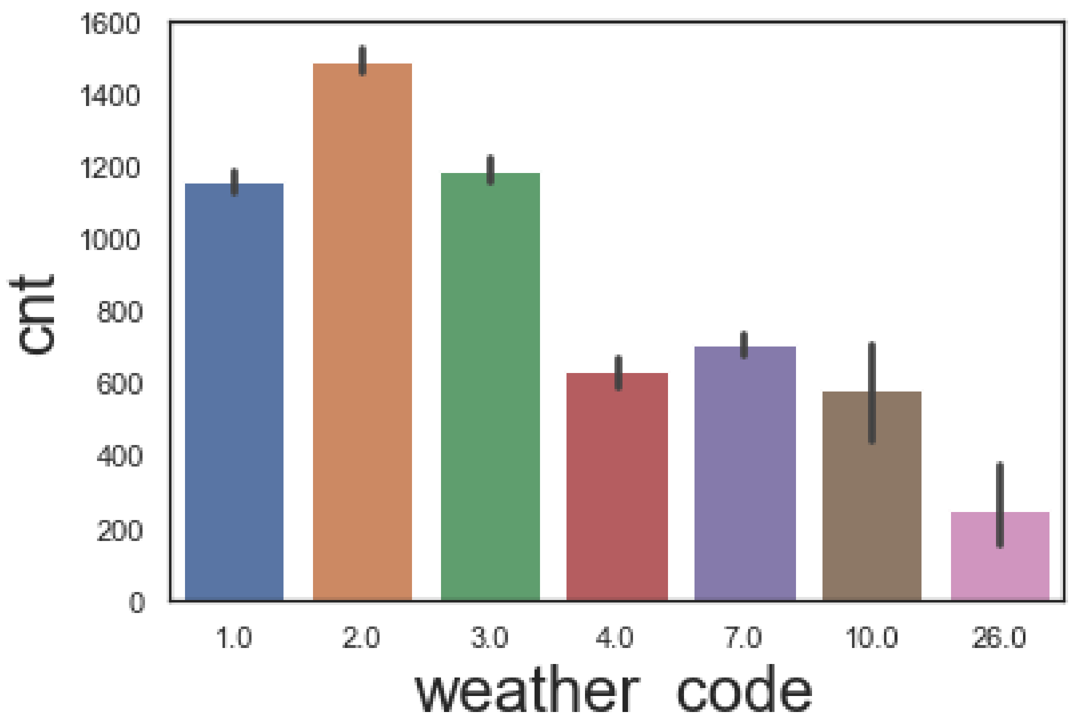
[ ]:
```
sns.distplot(df['hum'], bins=20);
plt.xlim([0,100]);
```



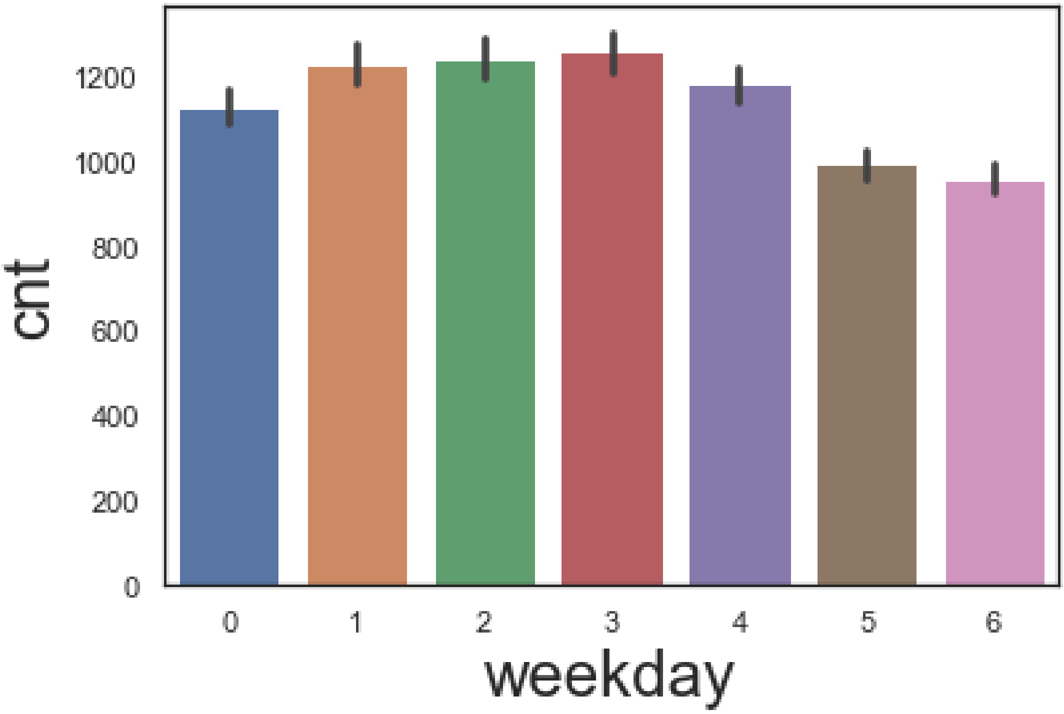
[ ]:
```
sns.barplot(x=df['season'],y=df['cnt']);
```



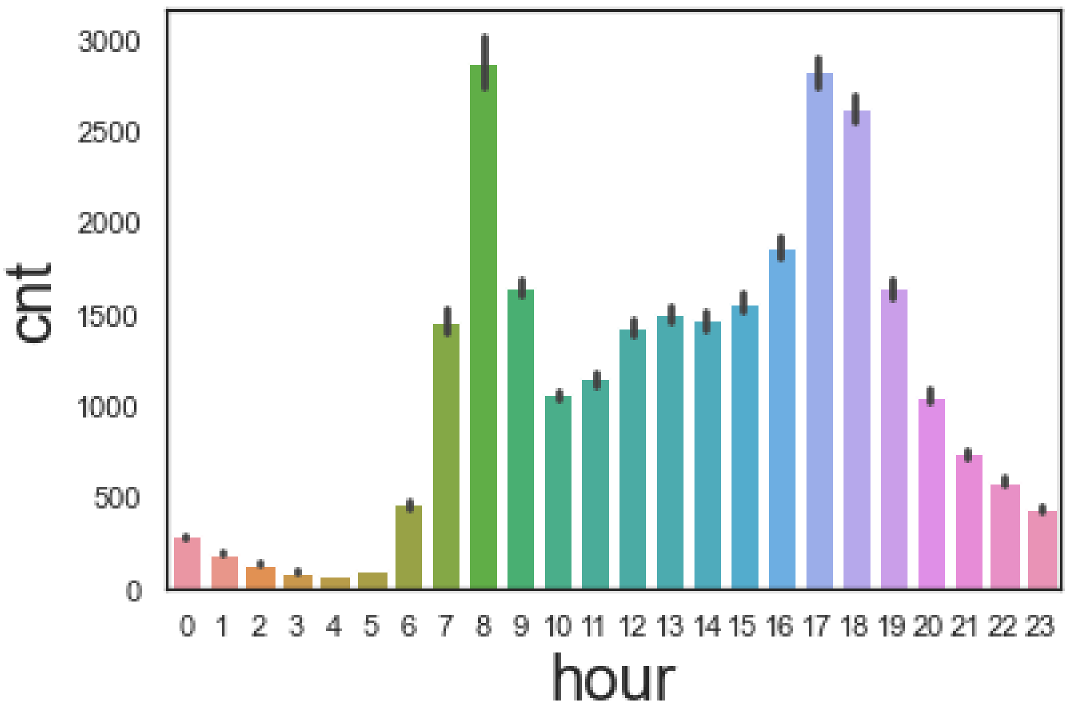
[ ]:
```
sns.barplot(x=df['weather_code'],y=df['cnt']);
```



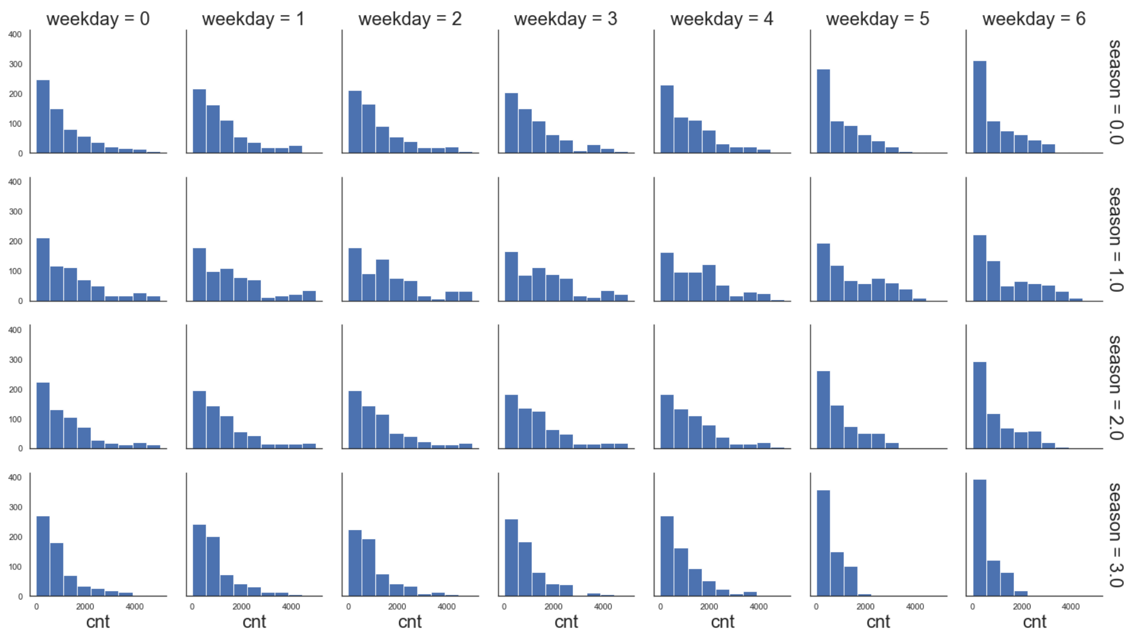
[ ]:
```
sns.barplot(x=df['weekday'],y=df['cnt']);
```



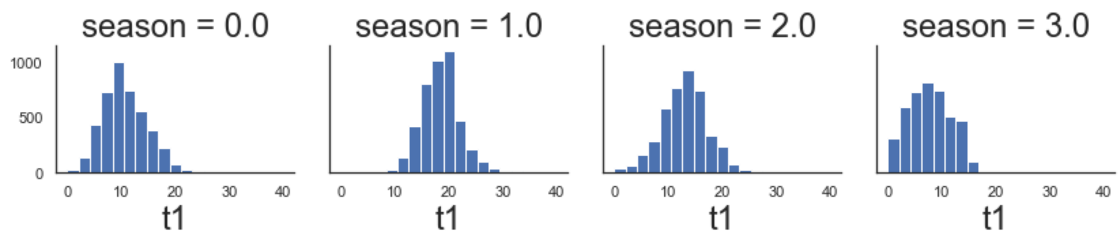
[ ]:
```
sns.barplot(x=df['hour'],y=df['cnt']);
```



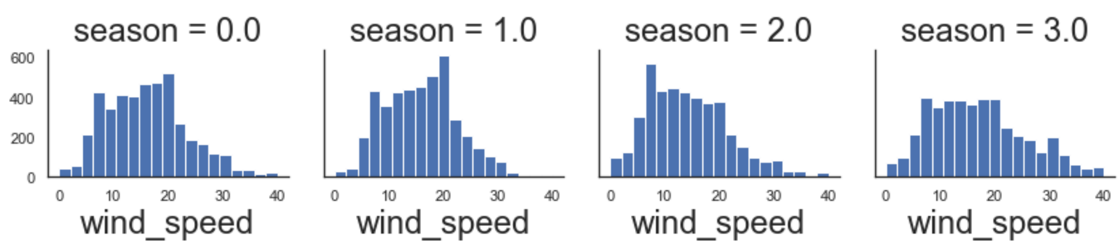
[ ]:
```
g = sns.FacetGrid(df, row='season', col='weekday',margin_titles=True);
g = g.map(plt.hist, "cnt", bins=np.linspace(0,5000,10));
```



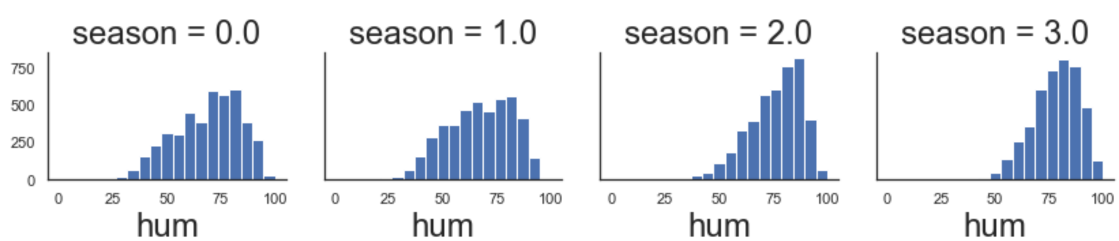
[ ]:
```python
g = sns.FacetGrid(df, col='season', margin_titles=True);
g = g.map(plt.hist, "t1", bins=np.linspace(0,40,20));
```



[ ]:
```python
g = sns.FacetGrid(df, col='season', margin_titles=True);
g = g.map(plt.hist, "wind_speed", bins=np.linspace(0,40,20));
```



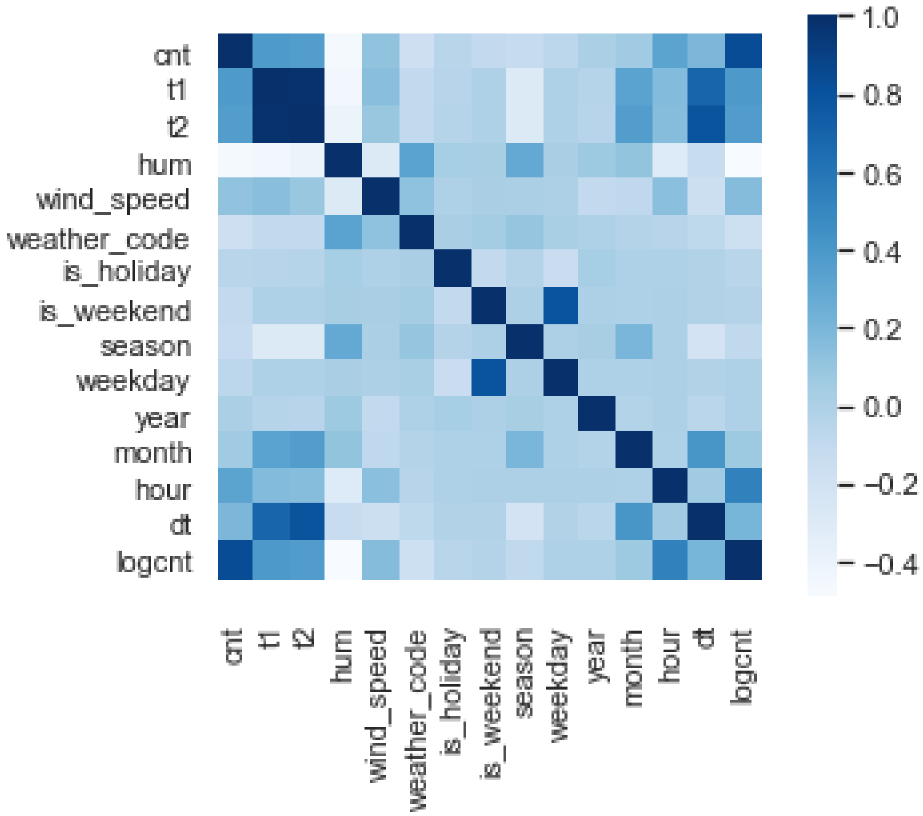
[ ]:
```python
g = sns.FacetGrid(df, col='season', margin_titles=True);
g = g.map(plt.hist, "hum", bins=np.linspace(0,100,20));
```



[ ]:
```python
#sns.pairplot(df);
```

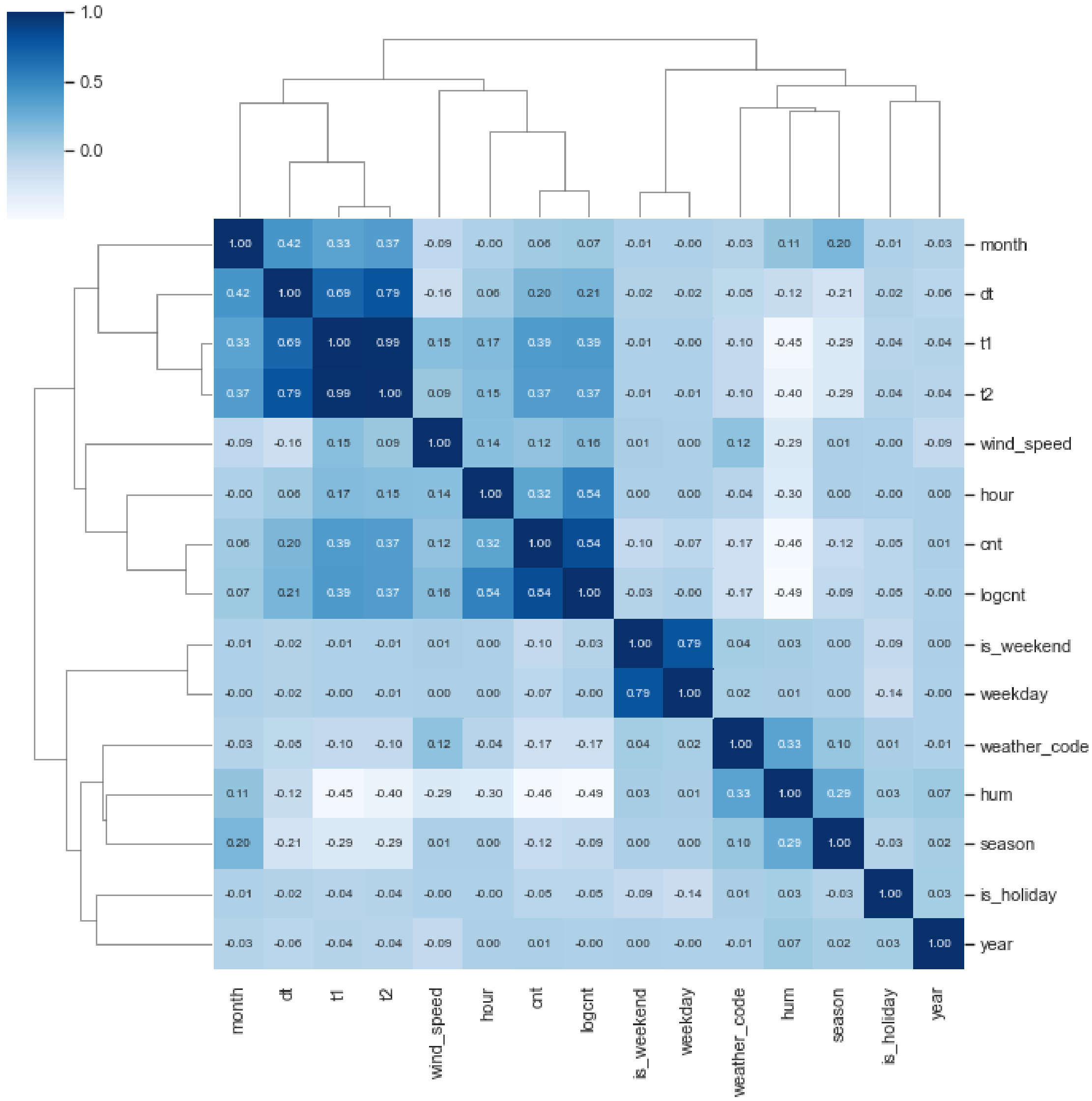
[ ]:
```python
cov=df.corr(method='pearson')
sns.heatmap(cov,square=True,annot=False,cmap="Blues");
b, t = plt.ylim() # discover the values for bottom and top
b += 0.5 # Add 0.5 to the bottom
t -= 0.5 # Subtract 0.5 from the top
plt.ylim(b, t) # update the ylim(bottom, top) values
```

```
plt.show()
```

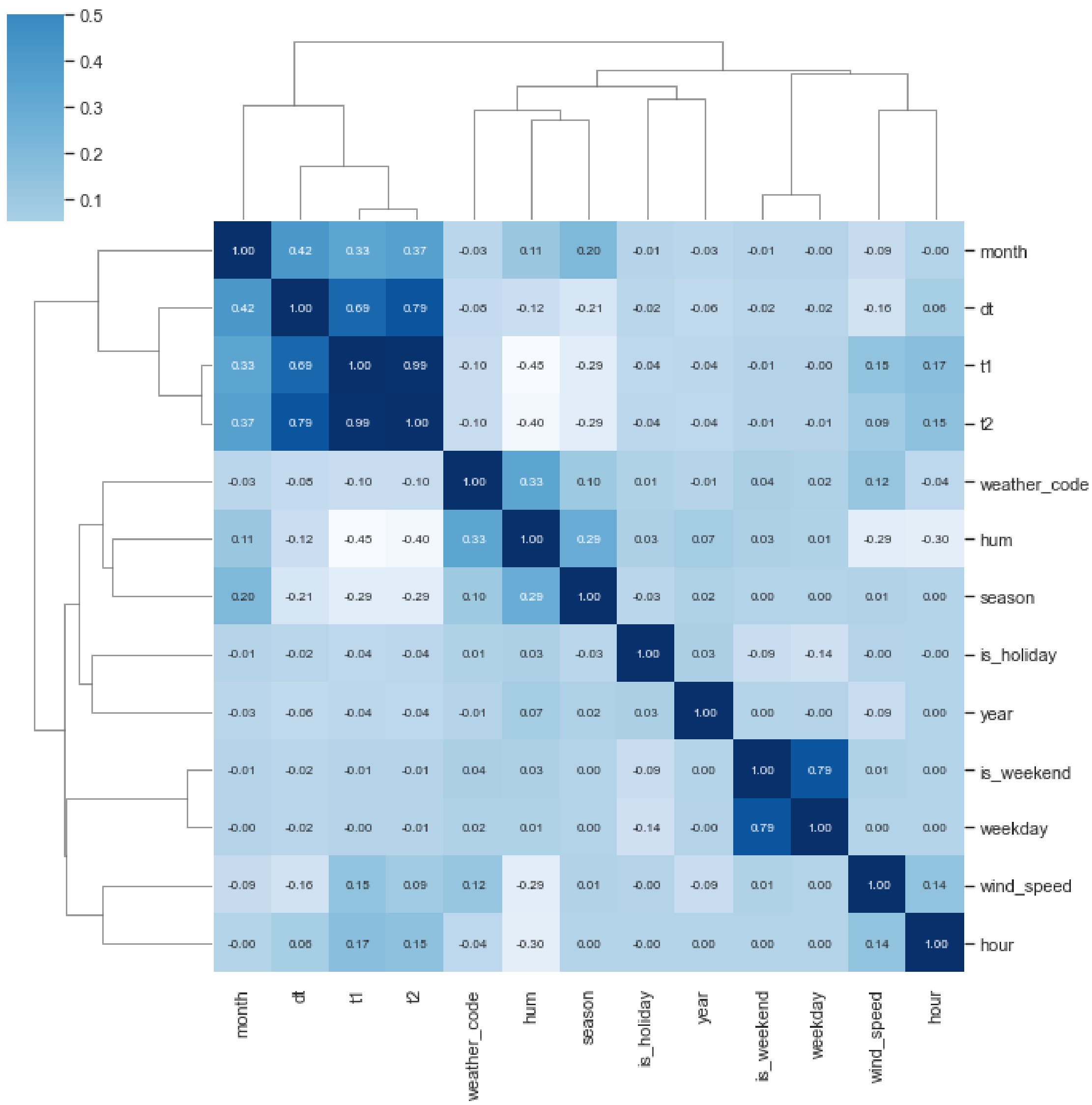


[ ]:
```
plt.figure(figsize=(15, 15));
sns.clustermap(cov,square=True,annot=True,cmap="Blues",annot_kws={"size":␣
↪8},fmt='.2f');
```

```
<Figure size 1080x1080 with 0 Axes>
```



[ ]:
```
cov2=df[input_variables].corr(method='pearson')
sns.clustermap(cov2,square=True,annot=False,cmap="Blues",annot_kws={"size":␣
↪8},fmt='.2f');
b, t = plt.ylim() # discover the values for bottom and top
b += 0.5 # Add 0.5 to the bottom
t -= 0.5 # Subtract 0.5 from the top
plt.ylim(b, t) # update the ylim(bottom, top) values
plt.show()
```




```
[ ]: from sklearn.linear_model import LinearRegression
     from sklearn.linear_model import LassoCV
     from sklearn.model_selection import cross_val_score
     from sklearn.model_selection import KFold
```

[ ]:
```
X = df[input_variables]
y = df[target_variable]
```

[ ]:
```
lr_model = LinearRegression();
lr_score = cross_val_score(lr_model,X,y,cv=KFold(n_splits=10, shuffle=True,␣
↪random_state=1234))
```

[ ]:
```
lr_score.mean()
```

[ ]: 0.4447209894684473

[ ]:
```
lr_score.std()
```

[ ]: 0.02023832969066747

[ ]:
```
lasso_model = LassoCV();
lasso_score = cross_val_score(lasso_model,X,y,cv=KFold(n_splits=10,␣
↪shuffle=True, random_state=1234))
```

[ ]:
```
lasso_score.mean()
```

[ ]: 0.43776946564538016

[ ]:
```
lasso_score.std()
```

[ ]: 0.020462238509046892

[ ]:
```
from sklearn.svm import SVR
svr_lin_model = SVR(kernel="linear")
svr_rbf_model = SVR(kernel="rbf")
```

[ ]:
```
#svr_lin_score = cross_val_score(svr_lin_model,X,y,cv=KFold(n_splits=10,␣
↪shuffle=True, random_state=1234))
#svr_rbf_score = cross_val_score(svr_rbf_model,X,y,cv=KFold(n_splits=10,␣
↪shuffle=True, random_state=1234))
```

[ ]:
```
from sklearn.neighbors import KNeighborsRegressor
knn_model = KNeighborsRegressor(n_neighbors=5, algorithm='kd_tree');
knn_score = cross_val_score(knn_model,X,y,cv=KFold(n_splits=10, shuffle=True,␣
↪random_state=1234))
```

[ ]:
```
knn_score.mean()
```

[ ]: 0.802673066886505

[ ]:
```
knn_score.std()
```

[ ]: 0.010229184332164987

[ ]:
```
from sklearn.ensemble import RandomForestRegressor
rf_model = RandomForestRegressor(oob_score=True, random_state=1234);
```

[ ]:
```
rf_model.fit(X,y)
```

[ ]:
```
RandomForestRegressor(oob_score=True, random_state=1234)
```

[ ]:
```
rf_model.oob_score_
```

[ ]:
```
0.9685679568797737
```