Assignment 4

Part 1: Data Exploration

1. Read in bike_share_hour.csv as a pandas dataframe.
2. Look at the dataset, and convert the columns that are categorical to a pandas “category” type.
3. Calculate non-null values in each variable in the dataset.
4. Do a descriptive analysis of the numeric columns.
5. Implement code to figure out which months belong to which seasons.
6. Implement a bar plot of cnt versus season. Document which season has the most bike rides and which season has the least.
7. Implement a bar chart for working day versus count. Document how bike rides are distributed across these two classes.
8. Implement a bar chart for month versus count. Document which months have the most bike rides.
9. Implement a bar plot of weathersit versus cnt. Document which weather situation has less bike rentals.
10. Implement a point plot of weathersit on the x-axis, count on the y-axis, and the season as the hue. Document how season and weathersit are related.
11. Implement a bar plot of hour versus count. Are there any specific hours that are busier than others?
12. Implement a bar plot of hour versus count on weekends and holidays (when workingday = 0). Does the hourly trend change on weekends?

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

bike_share = pd.read_csv(r'https://raw.githubusercontent.com/arjayit/cs4432_

# Convert Categorical and Boolean types
bike_share[['season', 'yr', 'mnth', 'hr', 'weekday', 'weathersit']] = \
bike_share[['season', 'yr', 'mnth', 'hr', 'weekday', 'weathersit']].astype('
bike_share[['holiday', 'workingday']] = bike_share[['holiday', 'workingday']
bike_share.dtypes
```

Out[1]:
```
instant          int64
dteday          object
season        category
yr            category
mnth          category
hr            category
holiday           bool
weekday       category
workingday        bool
weathersit    category
temp           float64
atemp          float64
hum            float64
windspeed      float64
casual           int64
registered       int64
cnt              int64
dtype: object
```

In [2]:
```
# Calculate the null values per variable
bike_share.isnull().sum()
```

Out[2]:
```
instant       0
dteday        0
season        0
yr            0
mnth          0
hr            0
holiday       0
weekday       0
workingday    0
weathersit    0
temp          0
atemp         0
hum           0
windspeed     0
casual        0
registered    0
cnt           0
dtype: int64
```

There are no null values in any of the variables.

In [3]:
```
bike_share_nums = bike_share.select_dtypes(include=['int64', 'float64'])
bike_share_nums.describe().T
```

Out[3]:

	count	mean	std	min	25%	50%	75
instant	17379.0	8690.000000	5017.029500	1.00	4345.5000	8690.0000	13034.50
temp	17379.0	0.496987	0.192556	0.02	0.3400	0.5000	0.66
atemp	17379.0	0.475775	0.171850	0.00	0.3333	0.4848	0.62
hum	17379.0	0.627229	0.192930	0.00	0.4800	0.6300	0.78
windspeed	17379.0	0.190098	0.122340	0.00	0.1045	0.1940	0.25
casual	17379.0	35.676218	49.305030	0.00	4.0000	17.0000	48.00
registered	17379.0	153.786869	151.357286	0.00	34.0000	115.0000	220.00
cnt	17379.0	189.463088	181.387599	1.00	40.0000	142.0000	281.00

The descriptive statistics above show that all of the weather stats are normalized so the minimumn is 0 and the maximum is 1 (although there seems to be a discrepancy with windspeed). The mean and median of these features are fairly close, so these appear to have a normal distribution with a slight skew to the left. The user counts are not standardized at all, which is fine given that it's the target, and each count is skewed to the right.

In [4]:

```
# Which month belongs to which season
bike_share.groupby(by='season', observed=True)['mnth'].unique()
```

Out[4]:

```
season
1    [1, 2, 3, 12]
Categories (12, int64): [1, 2, 3...
2    [3, 4, 5, 6]
Categories (12, int64): [1, 2, 3,...
3    [6, 7, 8, 9]
Categories (12, int64): [1, 2, 3,...
4    [9, 10, 11, 12]
Categories (12, int64): [1, 2,...
Name: mnth, dtype: object
```

Season 1 (Winter) has months 1, 2, 3, 12.

Season 2 (Spring) has months 3, 4, 5, 6.

Season 3 (Summer) has months 6, 7, 8, 9.

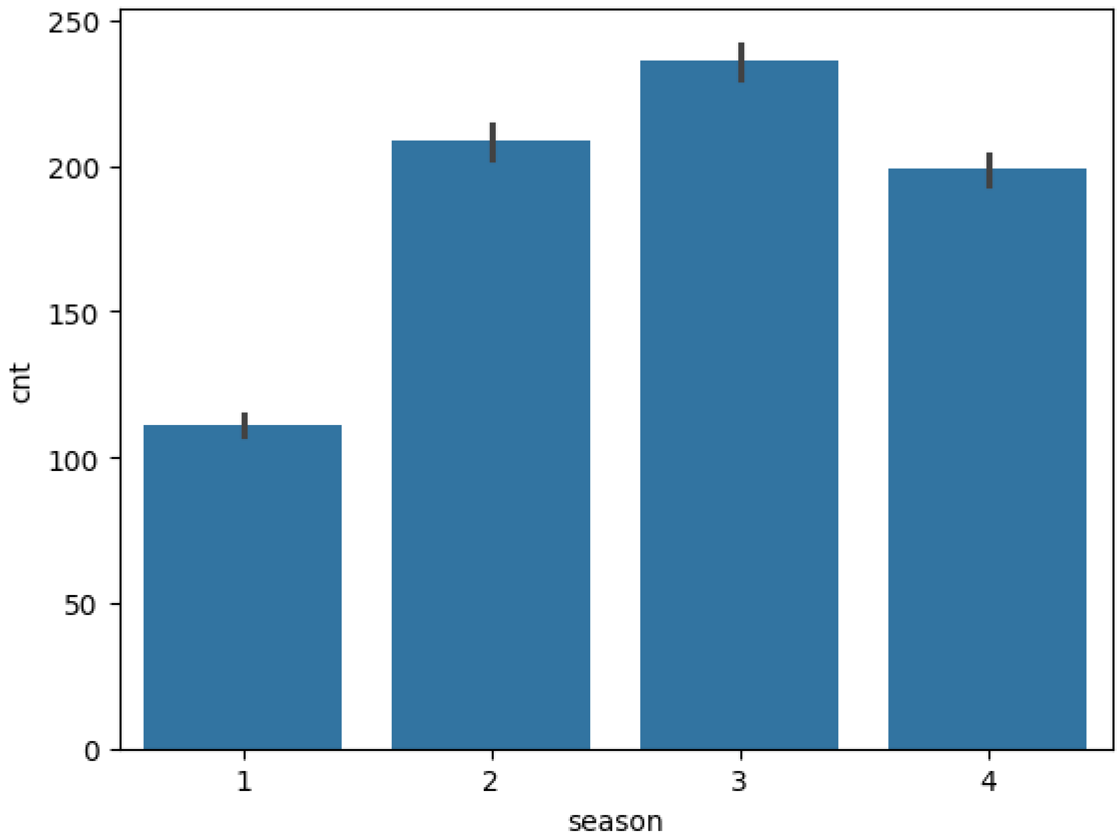
Season 4 (Fall) has months 9, 10, 11, 12.

In [5]:

```
# Implement a bar plot of Season vs Count
sns.barplot(data=bike_share, x='season', y='cnt')
```

Out[5]:

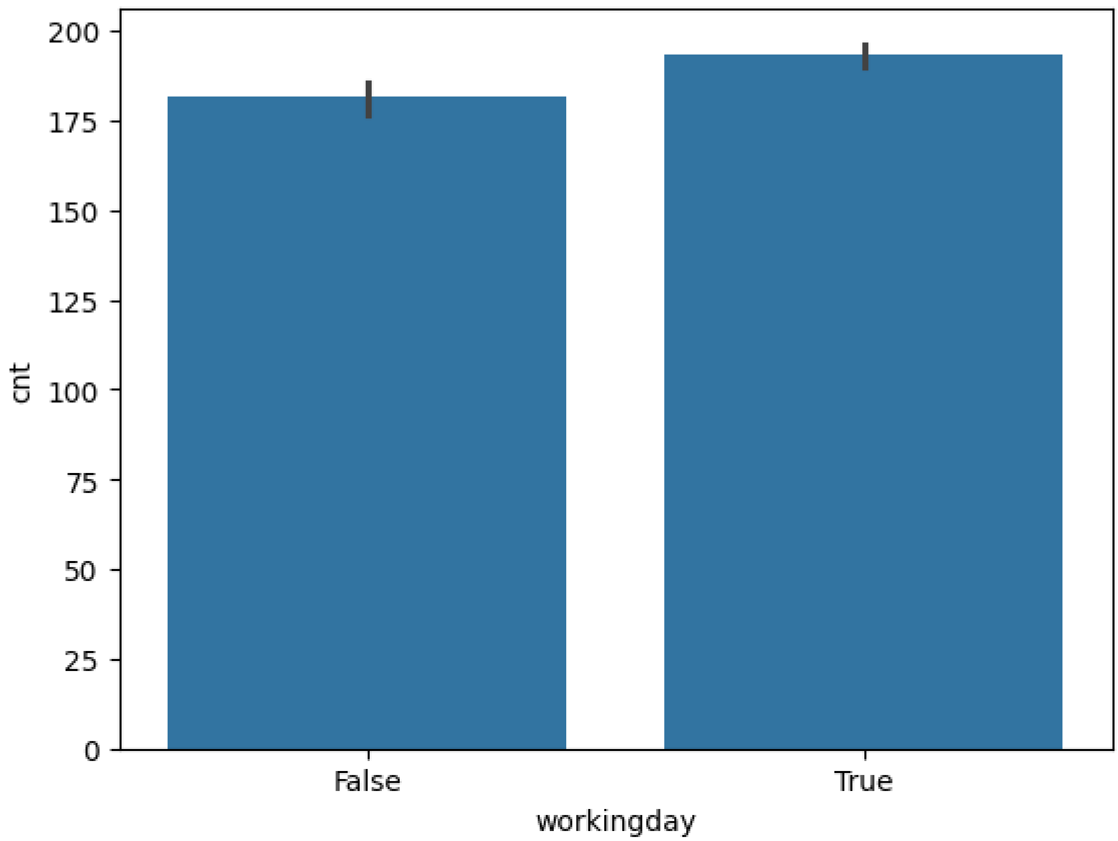
```
<Axes: xlabel='season', ylabel='cnt'>
```



Winter has the least amount of bike rides, while Summer has the most, which makes intuitive sense.

In [6]:
```
# Implement a bar chart for working day versus count.
sns.barplot(data=bike_share, x='workingday', y='cnt')
```

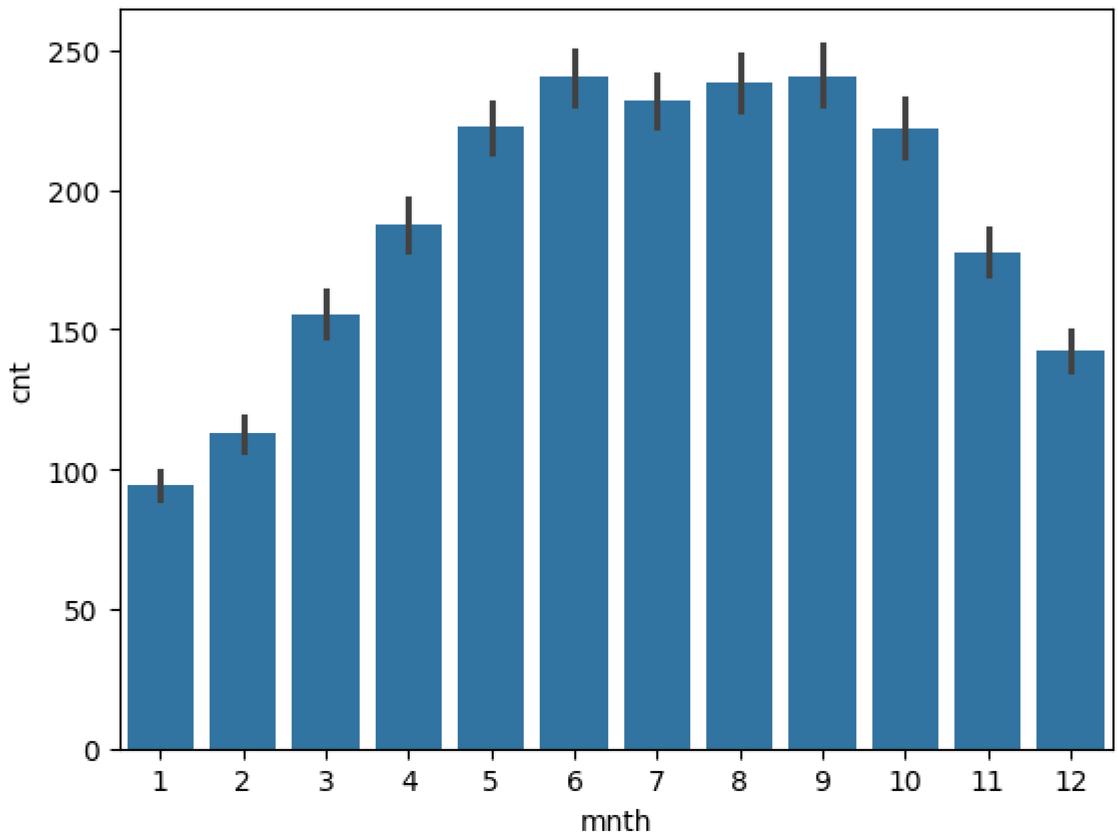
Out[6]: `<Axes: xlabel='workingday', ylabel='cnt'>`



The bar plot shows that on average there are less bike rentals on weekends and holidays than during weekdays.

In [7]:
```
# Implement a bar chart for month versus count.
sns.barplot(data=bike_share, x='mnth', y='cnt')
```

Out[7]:
```
<Axes: xlabel='mnth', ylabel='cnt'>
```



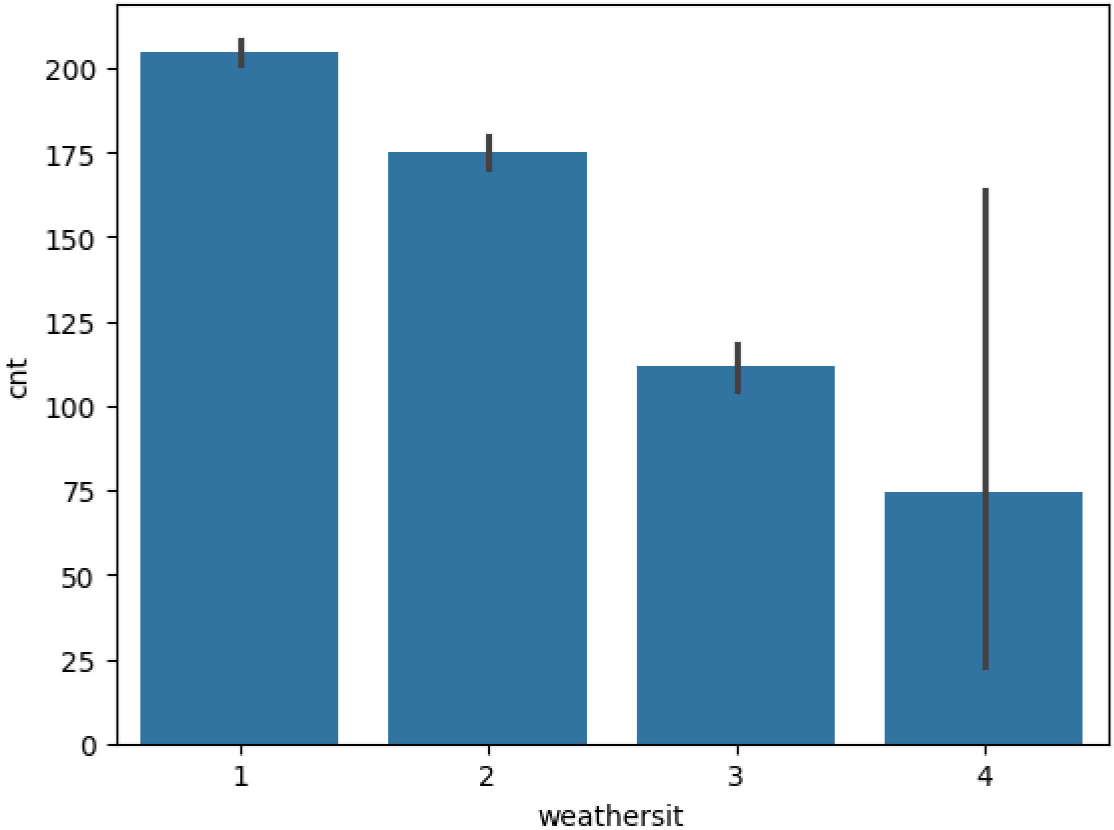
The summer months see the most biek rentals, with the top months being June and September.

In [8]:

```
# Implement a bar plot of weathersit versus cnt.
sns.barplot(data=bike_share, x='weathersit', y='cnt')
```

Out[8]:

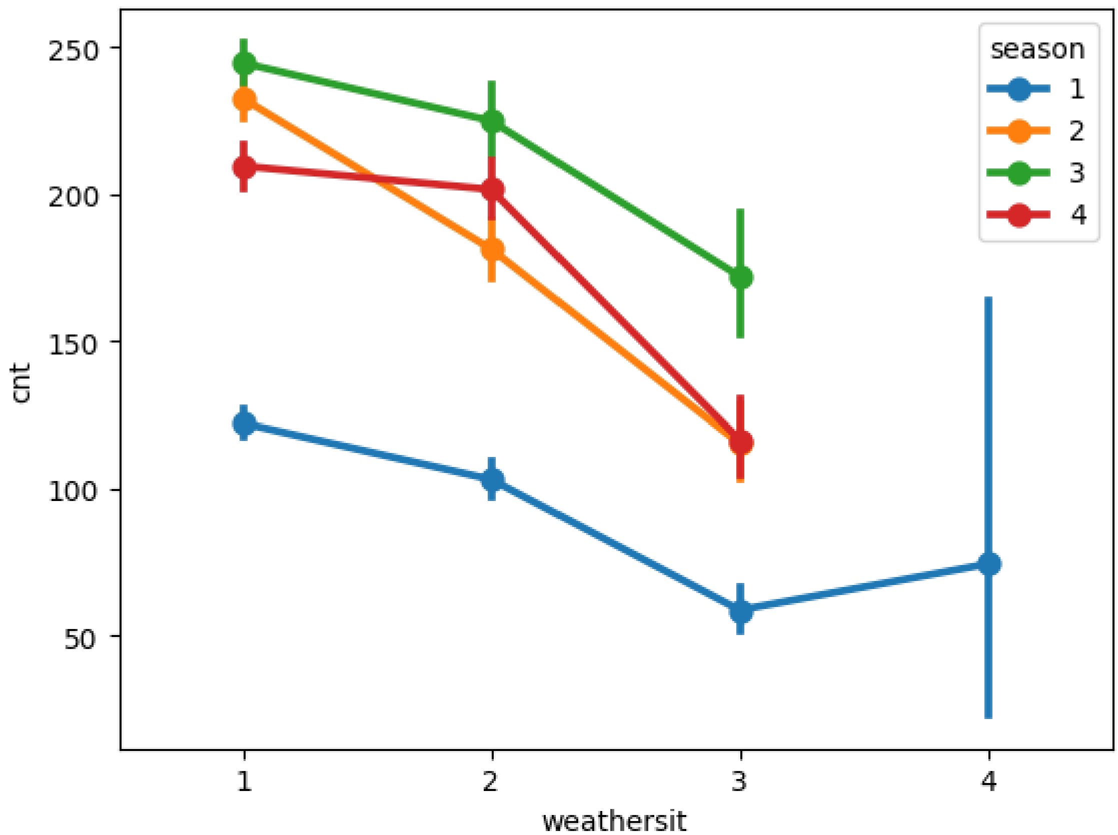
```
<Axes: xlabel='weathersit', ylabel='cnt'>
```



Intuitively, there are far less bike rentals on average in extreme weather conditions such as a thunderstorm. The large error bar suggests there are only a few data points for a `weathersit` of 4.

In [9]:
```
# Implement a point plot of weathersit on the x-axis, count on the y-axis, a
sns.pointplot(data=bike_share, x='weathersit', y='cnt', hue='season')
```

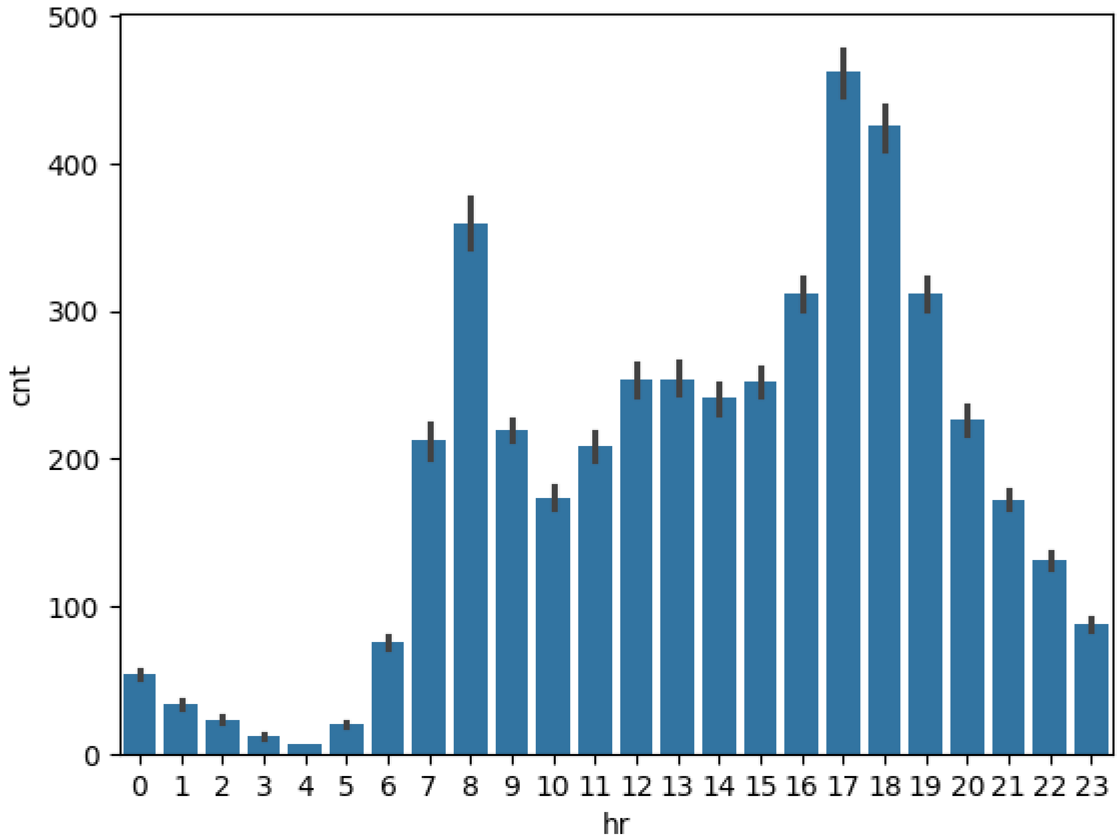
Out[9]: <Axes: xlabel='weathersit', ylabel='cnt'>



All four seasons have bike rentals for the first three weather conditions, and each season has a downward trend in bike rentals as the weather worsens. Winter is the only season in which there were bike rentals during the worst weather conditions. There is a shallow decrease in bike rentals in Fall when between when the weather is clear and when the weather is misty, but there is a sharp decrease from misty to precipitation.

In [10]:
```
# Implement a bar plot of hour versus count.
sns.barplot(data=bike_share, x='hr', y='cnt')
```

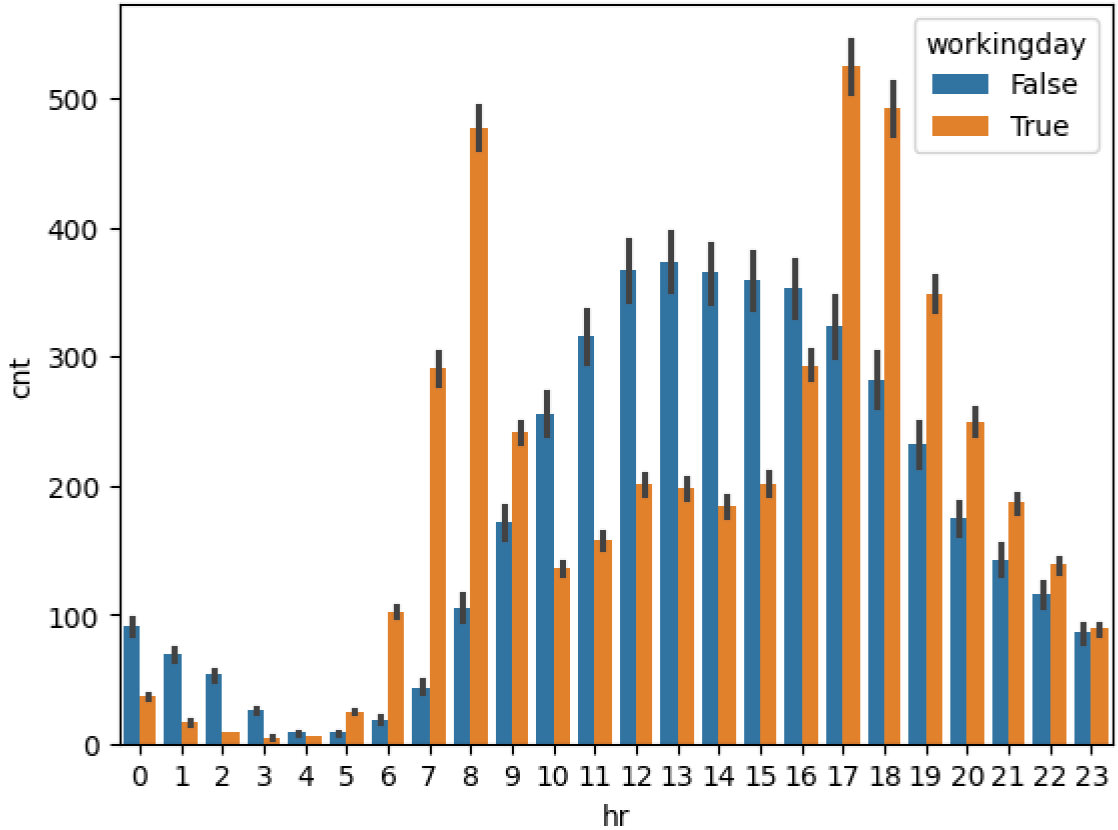
Out[10]:
```
<Axes: xlabel='hr', ylabel='cnt'>
```



The evening hours, 5 and 6 PM, have the most bike rentals on average. There is a spike at 8AM as well.

In [11]:
```
# Implement a bar plot of hour versus count on weekends and holidays (when w
sns.barplot(data=bike_share, x='hr', y='cnt', hue='workingday')
```

Out[11]: <Axes: xlabel='hr', ylabel='cnt'>



For weekdays, bike rentals occur most often in the evening at 5 PM and in the morning at 8 AM. On weekends and holidays, bike rentals happend most often in the afternoon, betweem 12 and 2 PM.

Part 2: Data Preperation

- Implement and graph a correlation matrix with the remaining numeric features. Any interesting relationships?
- Scale the numerical features using StandardScaler(), and replace the original columns in your dataframe.
- Drop the following columns from your dataset: casual, registered, dteday, instant.
- Implement a histogram of the count column. What can be said based on the resulting distribution?
- Implement a train/test split with a test size of 33%.
- Implement a baseline linear regression algorithm. Use cross-validation to output r2 and mse. Calculate RMSE base on mse.

In [12]:

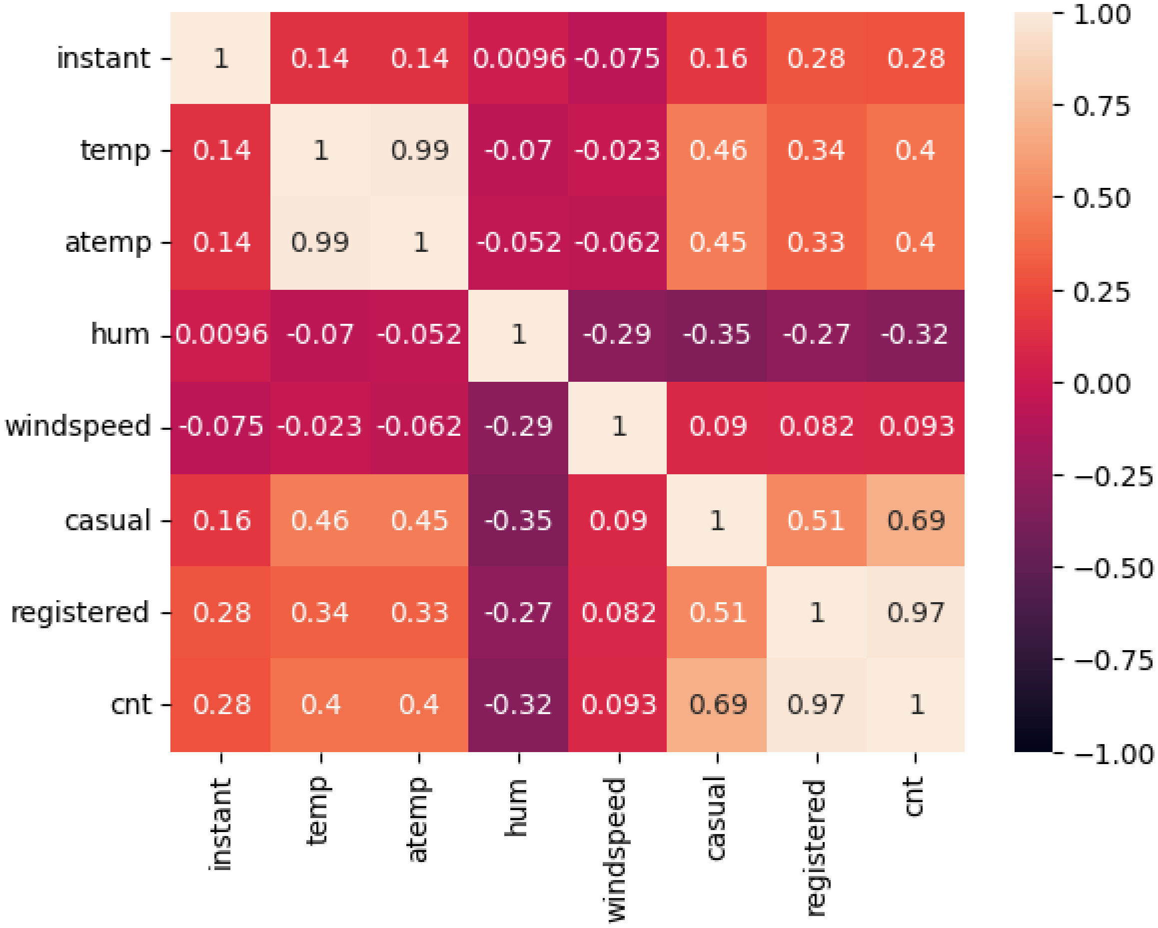
```
# Implement and graph a correlation matrix with the numeric features
bike_share_nums.corr()
```

Out[12]:

	instant	temp	atemp	hum	windspeed	casual	regist
instant	1.000000	0.136178	0.137615	0.009577	-0.074505	0.158295	0.282
temp	0.136178	1.000000	0.987672	-0.069881	-0.023125	0.459616	0.33
atemp	0.137615	0.987672	1.000000	-0.051918	-0.062336	0.454080	0.33
hum	0.009577	-0.069881	-0.051918	1.000000	-0.290105	-0.347028	-0.27
windspeed	-0.074505	-0.023125	-0.062336	-0.290105	1.000000	0.090287	0.08
casual	0.158295	0.459616	0.454080	-0.347028	0.090287	1.000000	0.50
registered	0.282046	0.335361	0.332559	-0.273933	0.082321	0.506618	1.00
cnt	0.278379	0.404772	0.400929	-0.322911	0.093234	0.694564	0.97

In [13]:
```
sns.heatmap(bike_share_nums.corr(), vmin=-1, vmax=1, annot=True)
```

Out[13]: <Axes: >



All of the weather paramters - temperature, humidty, and windspeed - are negative correlated with each other. The biggest positive correlation with bike rentals is temperature, so higher temperatures mean more bike rentals. The biggest negative correlation is with humidty, meaning less bike rentals as humidity increases.

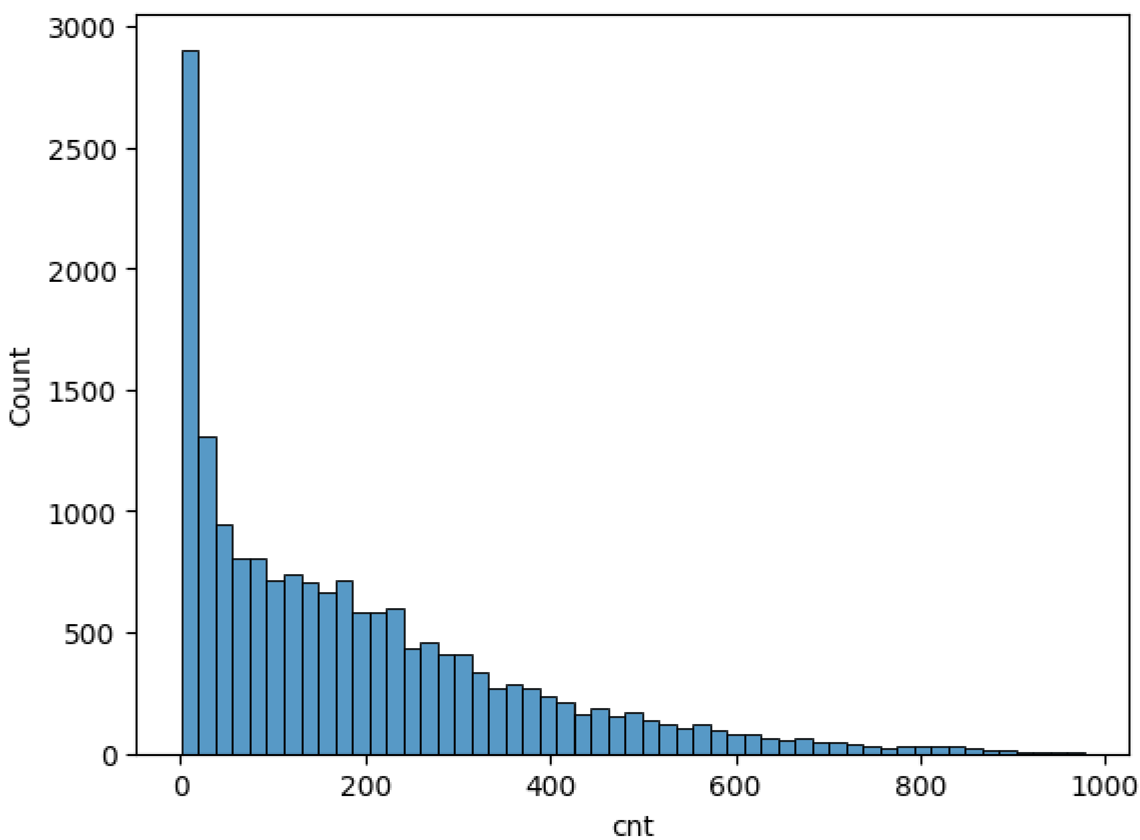
In [14]:
```
# Scale the numerical features using StandardScaler(), and replace the origi
# from sklearn.preprocessing import StandardScaler

# scaler = StandardScaler()
# scaled_nums = pd.DataFrame(scaler.fit_transform(bike_share_nums))
# bike_share[bike_share_nums.columns] = scaled_nums
```

It doens't make sense to scale the numerical data as the temperature values are already normalized and the rental counts don't need to be scaled since they are the target values. Above is the code that would replace the original data with scaled data if it were necessary.

In [15]:
```
# Drop the following columns from the dataset: casual, registered, dteday, i
bike_share.drop(columns=['casual', 'registered', 'dteday', 'instant'], inpla
```

In [16]:
```
# Implement a histogram of the count column
sns.histplot(bike_share, x='cnt')
```

Out[16]:
```
<Axes: xlabel='cnt', ylabel='Count'>
```



The distribution of count is very right skewed - most of the values are 0 or close to 0 and it tapers off from there. The distribution resembles an exponential decay.

In [17]:
```
# Implement a train/test split with a test size of 33%
from sklearn.model_selection import train_test_split

target = bike_share['cnt']
```

```
bike_share.drop(columns='cnt', inplace=True)
X_train, X_test, y_train, y_test = train_test_split(bike_share, target, test
```

In [18]:
```
X_train
```

Out[18]:

	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	aten
9271	1	1	1	5	False	5	True	2	0.42	0.424
6651	4	0	10	17	False	0	False	1	0.62	0.60
6496	4	0	10	6	False	1	True	2	0.36	0.378
12808	3	1	6	21	False	5	True	3	0.68	0.636
67	1	0	1	22	False	1	True	1	0.14	0.15
...	...	...	...	...	...	...	...	...	...	
9225	1	1	1	7	False	3	True	1	0.24	0.227
13123	3	1	7	0	False	5	True	1	0.78	0.742
9845	1	1	2	5	True	1	False	2	0.24	0.21
10799	2	1	3	2	False	6	False	2	0.42	0.424
2732	2	0	4	18	False	4	True	1	0.64	0.62

11643 rows × 12 columns

In [19]:
```
# Implement a baseline linear regression algorithm. Use cross-validation to
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
```

Out[19]:
```
▾ LinearRegression
LinearRegression()
```

In [20]:
```
rmse = np.sqrt(-cross_val_score(lin_reg, X_train, y_train, scoring='neg_mean
r2 = cross_val_score(lin_reg, X_train, y_train, scoring='r2')

print("RMSE: ", rmse, "Average: ", rmse.mean())
print("R2 Score: ", r2, "Average: ", r2.mean())
```

```
RMSE:  [140.82986037 142.38827425 143.17525738 144.80160386 140.22767564] Av
erage:  142.2845342997129
R2 Score:  [0.38715312 0.38729955 0.38336996 0.37076991 0.38790142] Average:
0.38329879251550747
```

Part 3

Model Training

- Create one-hot-encoded values for your categorical columns using get_dummies and add them to your source dataset.
- Drop the original categorical columns from your source dataset.
- Do a test/train split based on your new source dataset. Implement and fit a new linear model on your new training set.
- What are the new values for r2, mse, and rmse?
- Implement and score a decision tree regressor with random_state=0.
- Implement and score a RandomForestRegressor with random_state=0 and n_esitmators=30.
- Implement and score an SGDRegressor with max_iter=1000 and tol=1e-3).
- Implement and score a Lasso Regressor with alpha=0.1.
- Implement and score an ElasticNet Regressor with random_state=0.
- Implement and score a Ridge Regressor with alpha=0.5.
- Implement and score a BaggingRegressor

In [21]:
```
# Defining a function to fit and score different models using cross validati
def fit_and_score_model(model, X, y):
    rmse = np.sqrt(-cross_val_score(model, X, y, scoring='neg_mean_squared_e
    r2 = cross_val_score(model, X, y, scoring='r2')

    print("RMSE: ", rmse, "Average: ", rmse.mean())
    print("R2 Score: ", r2, "Average: ", r2.mean())
```

In [22]:
```
# Create one-hot-encoded values for your categorical columns using get_dummi
bike_share = pd.get_dummies(bike_share, columns=['season', 'yr', 'mnth', 'hr

# Do a test/train split implement and fit a new linear model on your new tra
X_train, X_test, y_train, y_test = train_test_split(bike_share, target, test
lin_reg.fit(X_train, y_train)

# New values for RMSE and R2
fit_and_score_model(lin_reg, X_train, y_train)
```

```
RMSE:  [100.4005626  100.7682368  103.88662935 103.27219005  99.9121132 ] Av
erage:  101.64794640098009
R2 Score:  [0.68851669 0.69313521 0.6753555  0.67994139 0.68926499] Average:
0.6852427570297925
```

The RMSE and R2 Score of the encoded model is much improved over the previous one. The average RMSE decreased from 142 to 102, and the R2 score increased from 0.38 to 0.68.

In [23]:
```
# Implement and score a decision tree regressor
from sklearn.tree import DecisionTreeRegressor

tree_reg = DecisionTreeRegressor(random_state=0)
fit_and_score_model(tree_reg, X_train, y_train)
```

```
RMSE:  [75.41913512 78.72722227 77.06256554 76.15074239 76.30833355] Averag
e:  76.73359977589617
R2 Score:  [0.82423776 0.8126949  0.82136125 0.82597525 0.81874173] Average:
0.8206021781040398
```

The decision tree performs better than the linear regressor with a lower RMSE and higher R2 score.

In [24]:
```
# Implement a random forest regressor
from sklearn.ensemble import RandomForestRegressor

forest_reg = RandomForestRegressor(random_state=0, n_estimators=30)
fit_and_score_model(forest_reg, X_train, y_train)
```

```
RMSE:  [53.97684469 53.80275023 53.91431342 57.99527102 54.7763343 ] Averag
e:  54.89310273021815
R2 Score:  [0.90997203 0.91252002 0.91256267 0.89906358 0.90660152] Average:
0.9081439612532506
```

The random forest regressor is even better than the decision tree, further improving on the RMSE and R2 score.

In [25]:
```
# Implement an SGD Regressor
from sklearn.linear_model import SGDRegressor

sgd_reg = SGDRegressor(max_iter=1000, tol=0.001, random_state=0)
fit_and_score_model(sgd_reg, X_train, y_train)
```

```
RMSE:  [100.36688013 100.51323192 104.04087322 103.30206121  99.96504954] Av
erage:  101.63761920329831
R2 Score:  [0.68872565 0.69468635 0.67439077 0.67975622 0.68893563] Average:
0.6852989224394916
```

The SGD Regressor performs on par with the linear regressor.

In [26]:
```
# Implement and score a Lasso Regressor
from sklearn.linear_model import Lasso

lasso_reg = Lasso(alpha=0.1, random_state=0)
fit_and_score_model(lasso_reg, X_train, y_train)
```

```
RMSE:  [100.51710416 100.50391653 104.09423048 103.29184527  99.92708799] Av
erage:  101.66683688565244
R2 Score:  [0.68779316 0.69474294 0.6740567  0.67981955 0.68917184] Average:
0.6851168374265022
```

The lasso regressor also performs on par with the linear regressor

In [27]:
```
# Implement and score an Elastic Net regressor
from sklearn.linear_model import ElasticNet

enet_reg = ElasticNet(random_state=0)
fit_and_score_model(enet_reg, X_train, y_train)
```

```
RMSE:  [161.02850444 163.44060907 164.09799974 164.27572276 160.94233411] Av
erage:  162.75703402465768
R2 Score:  [0.19875007 0.19272838 0.1899808  0.19014082 0.19370403] Average:
0.19306082006059583
```

The Elastic Net model has performed the worst so far.

In [28]:
```
# Implement and score a Ridge Regressor
from sklearn.linear_model import Ridge

ridge_reg = Ridge(alpha=0.5, random_state=0)
fit_and_score_model(ridge_reg, X_train, y_train)
```

```
RMSE:  [100.47781157 100.5129763  103.88586304 103.27432195  99.92172439] Av
erage:  101.61453944969965
R2 Score:  [0.68803719 0.6946879  0.67536029 0.67992818 0.6892052 ] Average:
0.685443754194723
```

The Ridge regressor performs on par with the linear, lasso, and SGD regressors.

In [29]:
```
# Implement and score a Bagging Regressor
from sklearn.ensemble import BaggingRegressor

bag_reg = BaggingRegressor(random_state=0)
fit_and_score_model(bag_reg, X_train, y_train)
```

```
RMSE:  [55.80137833 57.32415954 56.39846754 59.88961502 57.87666711] Averag
e:  57.458057507339184
R2 Score:  [0.90378288 0.90069408 0.90431952 0.89236196 0.89572963] Average:
0.8993776145016946
```

The Bagging Regressor is the second best performing model, next to the Random Forest Regressor.

Part 4. Model Tuning

- Take the top three performing models and implement cross-validation on them.
- Take your top performing model and do a randomize search cv with 20 iterations and three folds with the following parameters.
  - Bootstrap: true, false
  - Max_depth: 10-110, number of bins 11
  - Max_features: auto, sqrt
  - Min_samples_split: 2,5,10
  - Min_samples_leaf: 1,2,4
  - N_estimators: 200 – 2000, number of bins 10
- Take your best_estimator_ and see how it compares by doing cross_vals for r2, mse, and calculating rmse.
- Finally, run predictions on your test set with this model, and see how your r2 score and RMSE look.

In [30]:
```python
# Cross validation was already performed on each of the models above.  Repea
from sklearn.model_selection import cross_validate
cross_validate(tree_reg, X_train, y_train)
```

Out[30]:
```
{'fit_time': array([0.10291219, 0.09460402, 0.09462595, 0.09724092, 0.09591
007]),
 'score_time': array([0.00397992, 0.00261188, 0.00301886, 0.00328302, 0.003
28898]),
 'test_score': array([0.82423776, 0.8126949 , 0.82136125, 0.82597525, 0.818
74173])}
```

In [31]:
```python
cross_validate(forest_reg, X_train, y_train)
```

Out[31]:
```
{'fit_time': array([1.90416884, 1.843678  , 1.86017799, 1.82170606, 1.81914
878]),
 'score_time': array([0.02412605, 0.0188899 , 0.02078724, 0.02099395, 0.020
6871 ]),
 'test_score': array([0.90997203, 0.91252002, 0.91256267, 0.89906358, 0.906
60152])}
```

In [32]:
```python
cross_validate(bag_reg, X_train, y_train)
```

Out[32]:
```
{'fit_time': array([0.64153481, 0.6474328 , 0.60970807, 0.61096978, 0.65311
193]),
 'score_time': array([0.01314425, 0.01414013, 0.01125598, 0.01272511, 0.016
8581 ]),
 'test_score': array([0.90378288, 0.90069408, 0.90431952, 0.89236196, 0.895
72963])}
```

In [34]:
```python
# Randomized search CV with the top model
from sklearn.model_selection import RandomizedSearchCV

params = {
    'bootstrap': [True, False],
    'max_depth': np.linspace(10, 110, 11, dtype='int'),
    'max_features': ['sqrt', None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'n_estimators': np.linspace(200, 2000, 10, dtype='int'),
}

rand_search = RandomizedSearchCV(forest_reg, params, n_iter=20, cv=3, n_jobs
rand_search.fit(X_train, y_train)
rand_search.best_params_
```

Out[34]:
```
{'n_estimators': 1200,
 'min_samples_split': 2,
 'min_samples_leaf': 1,
 'max_features': None,
 'max_depth': 40,
 'bootstrap': True}
```

In [36]:
```python
best_model = rand_search.best_estimator_

fit_and_score_model(best_model, X_train, y_train)
```

```
RMSE:  [52.76520671 52.53198555 53.05298485 55.91172984 53.38677528] Averag
e:  53.5297364452277
R2 Score:  [0.91396845 0.91660359 0.91533413 0.9061858  0.91128005] Average:
0.9126744018256266
```

In [37]:

```python
from sklearn.metrics import mean_squared_error, r2_score

y_predict = best_model.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, y_predict))
r2 = r2_score(y_test, y_predict)

print("RMSE: ", rmse)
print("R2 Score: ", r2)
```

```
RMSE:  52.03833854260479
R2 Score:  0.9180180243364973
```

The hypertuned model performed just slightly better than the original Random Forest Regressor in Part 3. The model does seem to generalize well, as the RMSE and R2 score on the test data was the same as the training scores.