Kaggle 입문하기 - 데이터 분석 입문

- 특성 자동 선택 함수를 사용해 봅니다.
- 다양한 모델을 활용해 봅니다.

Data Fields

필드명	설명
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 (온도)
atemp	"feels like" temperature in Celsius (체감온도)
humidity	relative humidity (습도)
windspeed	wind speed (바람속도)
casual	number of non-registered user rentals initiated (비가입자 사용유저)
registered	number of registered user rentals initiated (가입자 사용유저)
count	number of total rentals (전체 렌탈 대수)

In [75]:

```
import pandas as pd
```

In [76]:

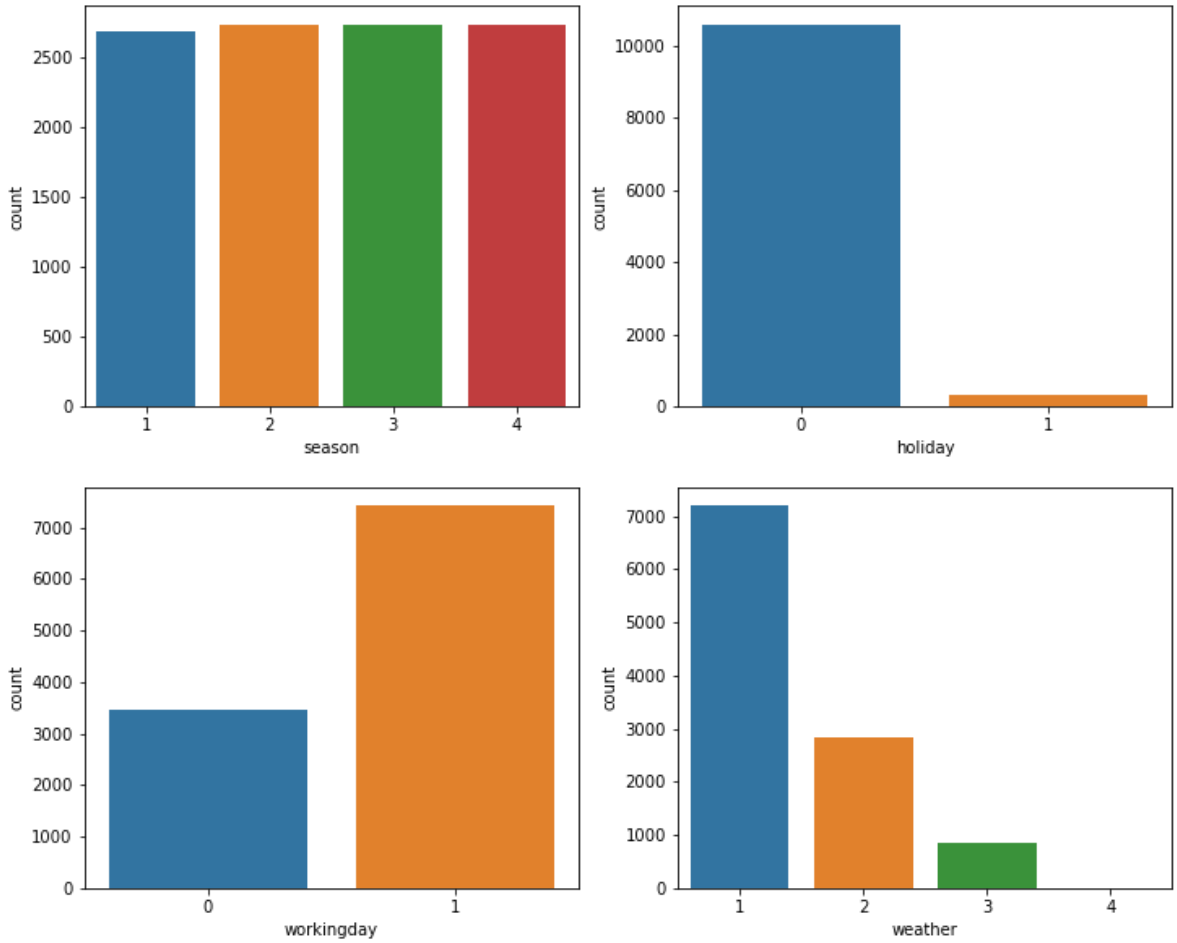
```
train = pd.read_csv("bike/train.csv", parse_dates=['datetime'])
test = pd.read_csv("bike/test.csv", parse_dates=['datetime'])
```

In [77]:

```
import matplotlib.pyplot as plt ## seaborn 보다 고급 시각화 가능. but 코드 복잡
import seaborn as sns           ## seaborn은 matplotlib보다 간단하게 사용 가능
```

In [78]:

```
col_names = [ 'season', 'holiday', 'workingday', 'weather'  ]
i = 0
plt.figure(figsize=(12,10))   # 전체 그래프의 크기 지정

for name in col_names:         # 컬럼명을 전달 리스트 수 만큼 반복 -> 4회
    i = i + 1                  # 숫자를 1씩 증가.
    plt.subplot(2,2,i)         # 2행 2열에 i번째 그래프 선택
    sns.countplot(x=name, data=train)  # i번째 그래프에 sns.countplot를 그리겠다.

plt.show()  # 주피터에서 보여주지만, 다른곳(editor, pycharm)에서는 이걸 실행시켜야 한다.
```



수치형 데이터 선택

In [79]:

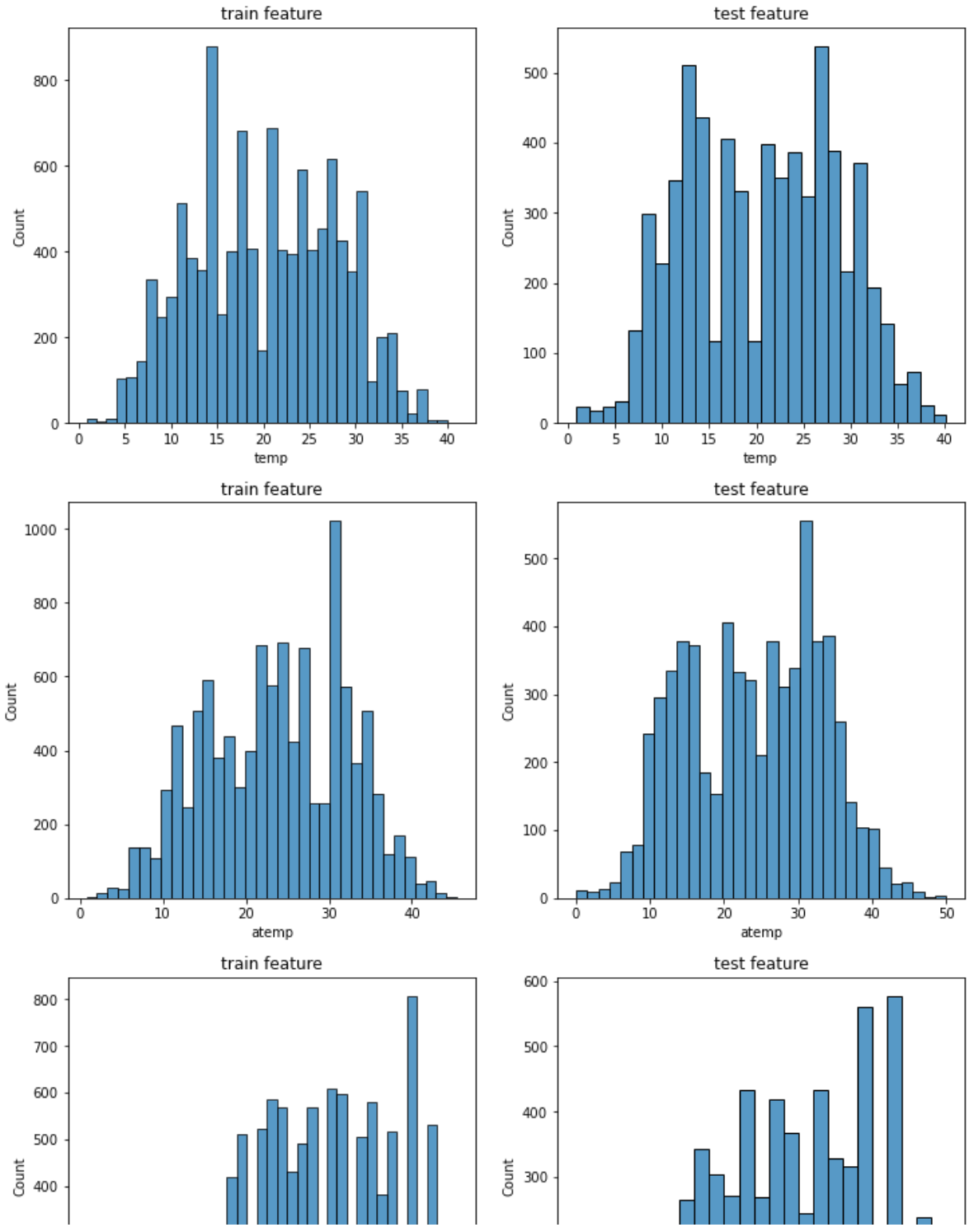
```
### temp, atemp, humidity, windspeed

num_names = ['temp', 'atemp', 'humidity', 'windspeed']
train.columns
```

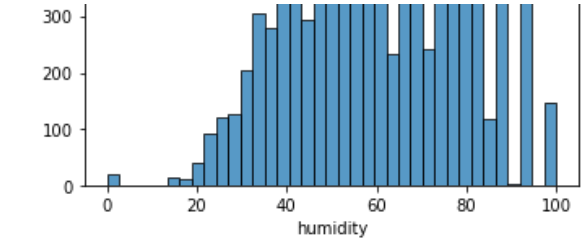
Out[79]:

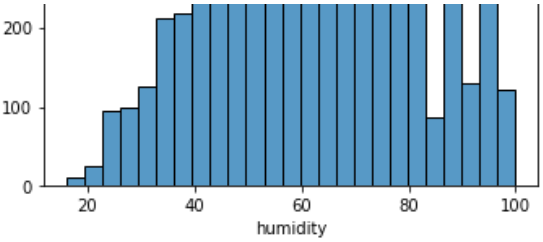
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

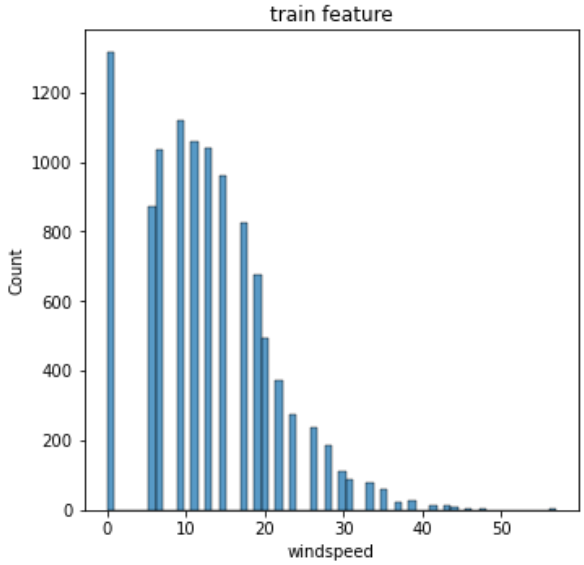
In [80]:

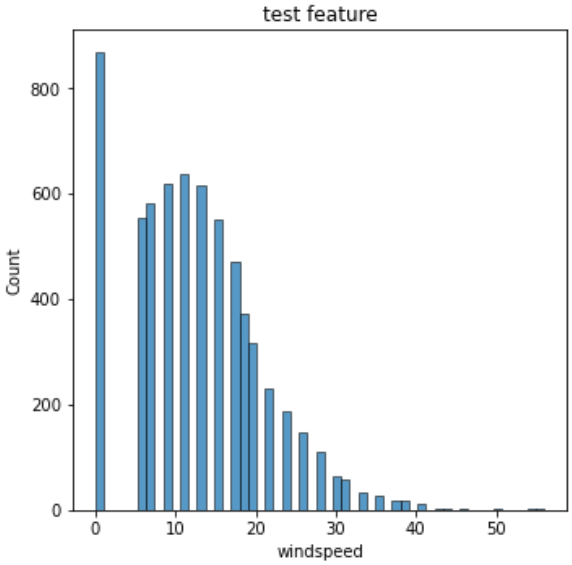
```
i = 0
plt.figure(figsize=(12,25))   # 전체 그래프의 크기 지정 (가로, 세로)

for name in num_names:         # 컬럼명을 전달 리스트 수 만큼 반복 -> 4회
    i = i + 1                  # 숫자를 1씩 증가.
    plt.subplot(4,2,i*2-1)        # 2행 2열에 i번째 그래프 선택
    sns.histplot(x=name, data=train)  # i번째 그래프에 sns.histplot를 그리겠다.
    plt.title("train feature")

    plt.subplot(4,2,i*2)        # 2행 2열에 i번째 그래프 선택
    sns.histplot(x=name, data=test)  # i번째 그래프에 sns.histplot를 그리겠다.
    plt.title("test feature")

plt.show()
```











In [81]:

```
new_tr = train.copy()   # 데이터 백업
new_test = test.copy()
new_tr.columns
```

Out[81]:

```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

특징 추출 - 날짜 피처로부터 추출

In [82]:

```
## 더미변수, 파생변수 생성
new_tr['year'] = new_tr['datetime'].dt.year
new_tr.head()
```

Out[82]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0

In [83]:

```
new_tr['month'] = new_tr['datetime'].dt.month
new_tr['day'] = new_tr['datetime'].dt.day
new_tr['hour'] = new_tr['datetime'].dt.hour
new_tr['minute'] = new_tr['datetime'].dt.minute
new_tr['second'] = new_tr['datetime'].dt.second
new_tr['dayofweek'] = new_tr['datetime'].dt.dayofweek
new_tr.head()
```

Out[83]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0

In [84]:

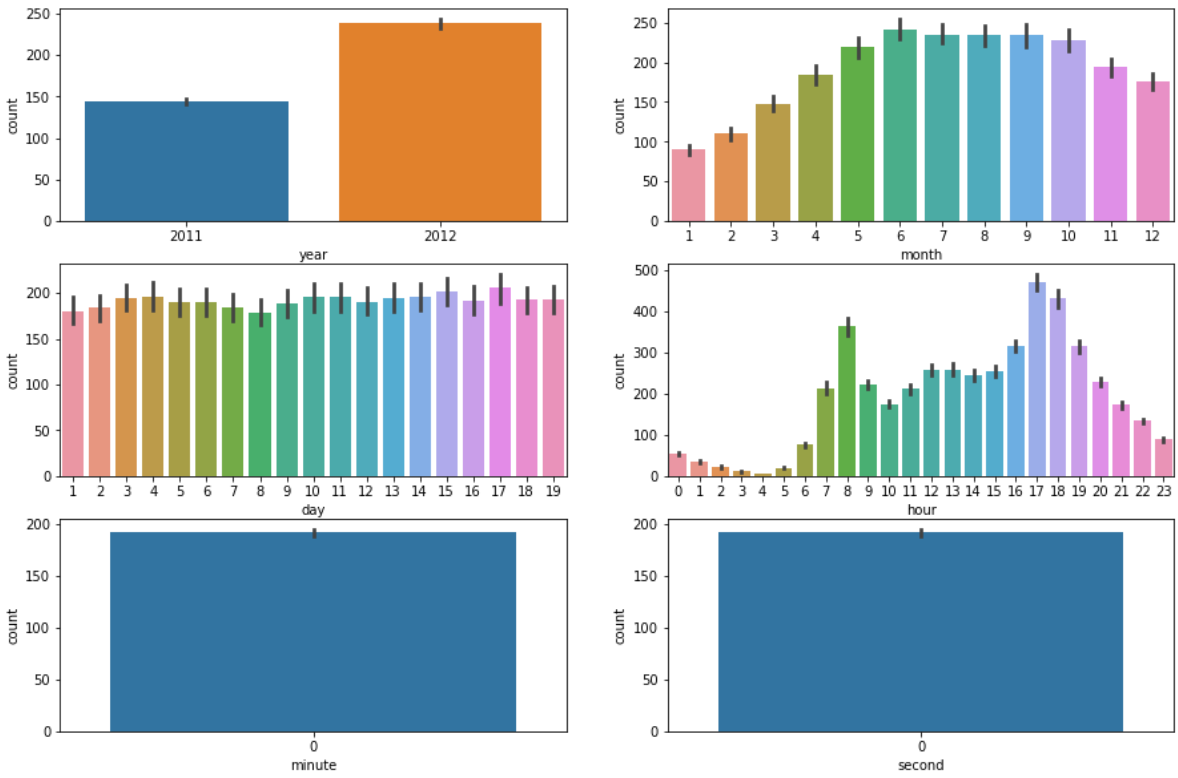
```
train.columns
```

Out[84]:

```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

In [85]:

```
datetime_names = ['year', 'month', 'day', 'hour', 'minute', 'second']

i=0
plt.figure(figsize=(15,10))
for name in datetime_names:
    i = i + 1
    plt.subplot(3,2,i)
    sns.barplot(x=name, y='count', data=new_tr)

plt.show()
```

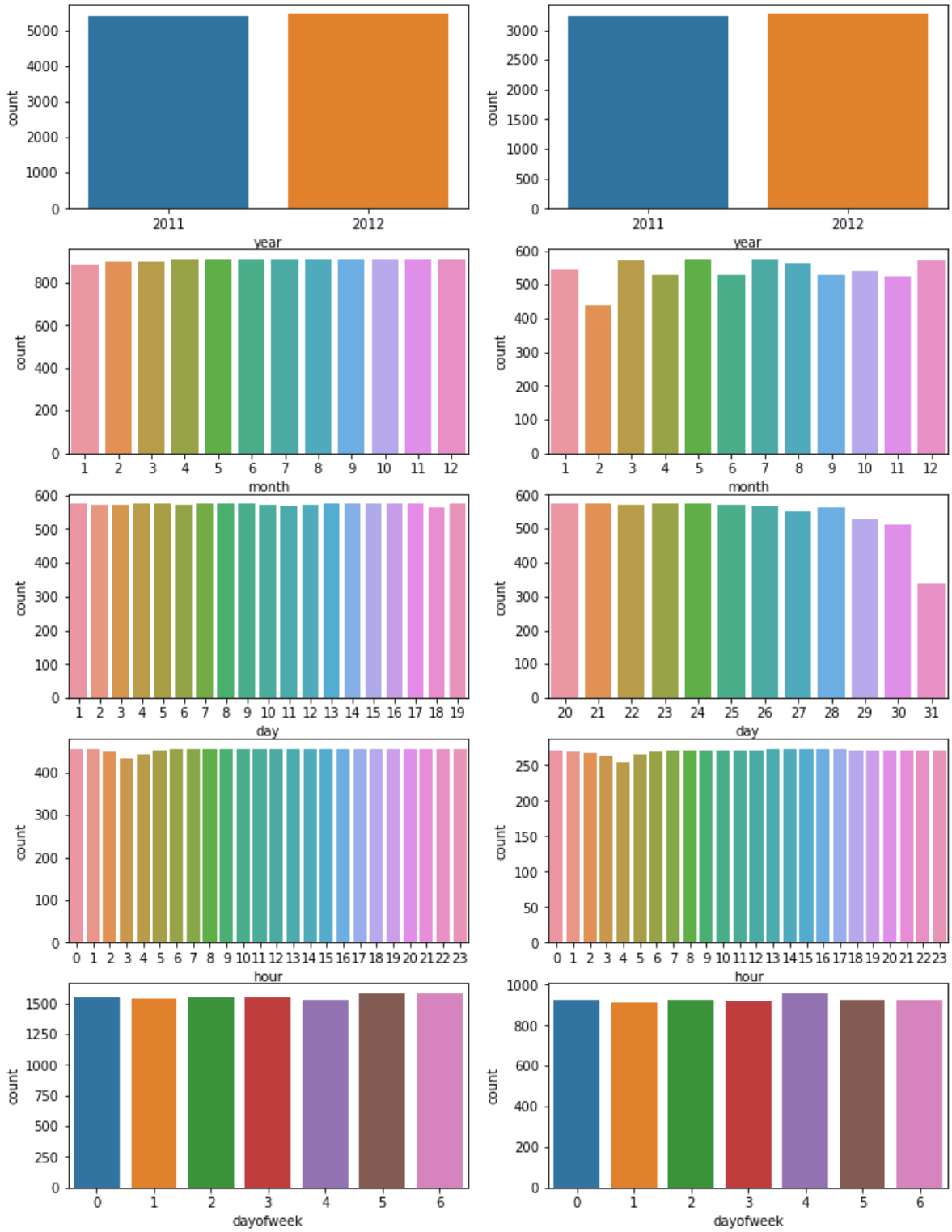


In [86]:

```
new_test['year'] = new_test['datetime'].dt.year
new_test['month'] = new_test['datetime'].dt.month
new_test['day'] = new_test['datetime'].dt.day
new_test['dayofweek'] = new_test['datetime'].dt.dayofweek
new_test['hour'] = new_test['datetime'].dt.hour
new_test['minute'] = new_test['datetime'].dt.minute
new_test['second'] = new_test['datetime'].dt.second
```

In [87]:

```
col_names = ['year','month','day','hour','dayofweek']
i = 0

plt.figure(figsize=(12,20))  ##전체 그래프 크기 지정

for name in col_names: ## 컬럼명으로 반복
  i = i+1
  plt.subplot(6,2,i)  ##2행2열, i = 1,2,3,4 (왼쪽 상단부터 시계방향으로 순번 지정)
  sns.countplot(x = name, data = new_tr)

  i = i+1
  plt.subplot(6,2,i)  ##2행2열, i = 1,2,3,4 (왼쪽 상단부터 시계방향으로 순번 지정)
  sns.countplot(x = name, data = new_test)

plt.show()
```

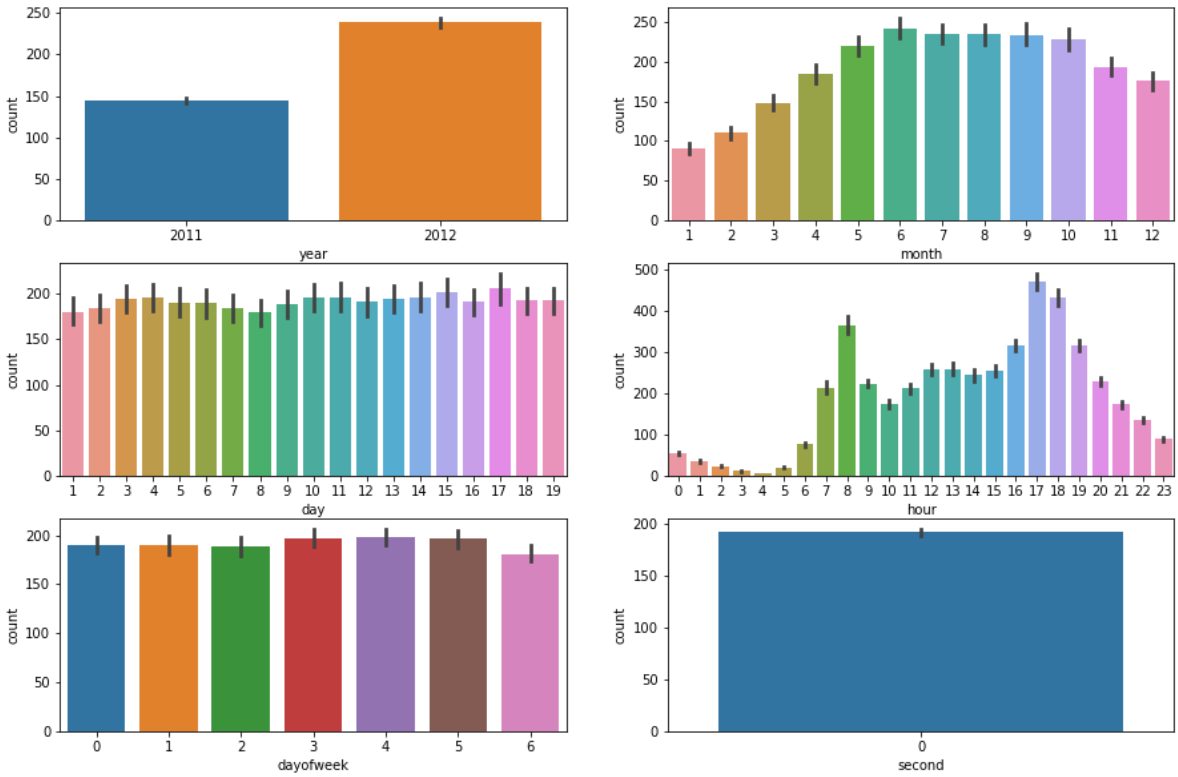


In [88]:

```
new_tr['dayofweek'] = new_tr['datetime'].dt.dayofweek  # Monday=0, Sunday=6
```

In [89]:

```
datetime_names = ['year', 'month', 'day', 'hour', 'dayofweek', 'second']

i=0
plt.figure(figsize=(15,10))
for name in datetime_names:
    i = i + 1
    plt.subplot(3,2,i)
    sns.barplot(x=name, y='count', data=new_tr)

plt.show()
```



In [94]:

```
print(new_test.shape)
new_test[["datetime", "year", "month", "day", "hour", "minute", "second", "dayofweek"]].head()
```

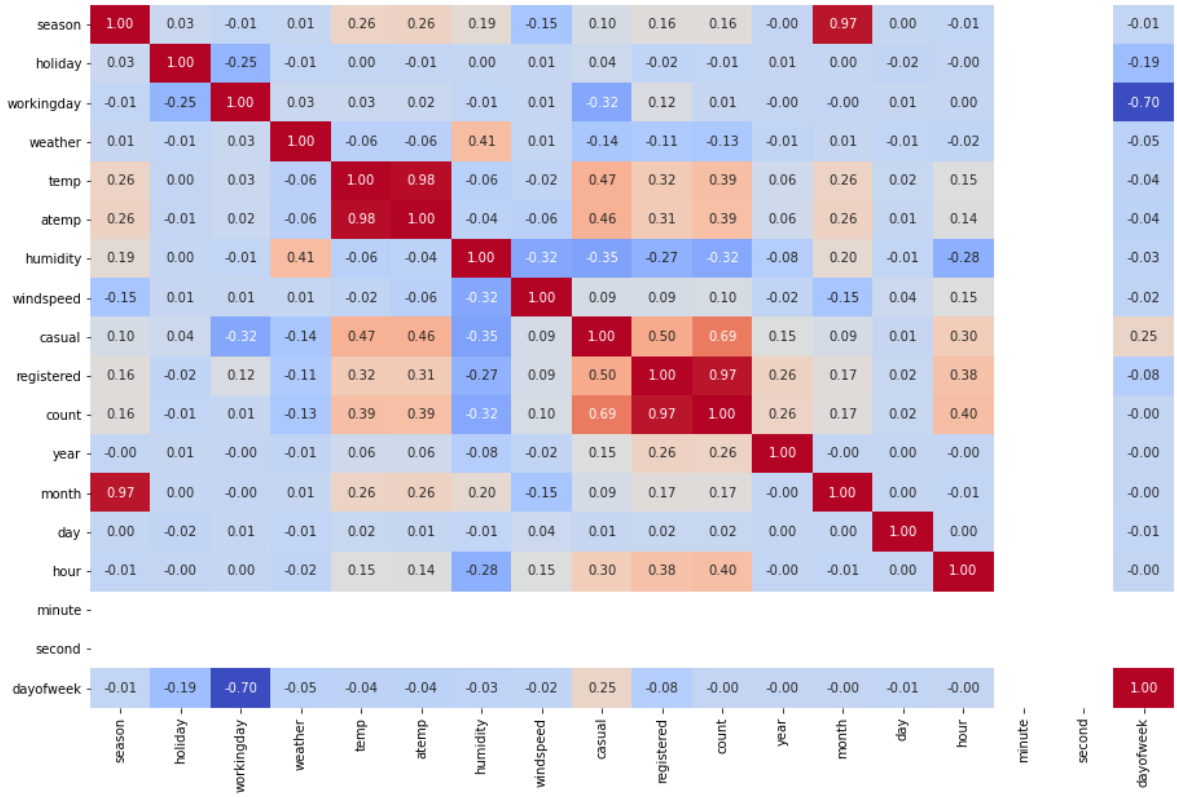
(6493, 16)

Out[94]:

	datetime	year	month	day	hour	minute	second	dayofweek
0	2011-01-20 00:00:00	2011	1	20	0	0	0	3
1	2011-01-20 01:00:00	2011	1	20	1	0	0	3
2	2011-01-20 02:00:00	2011	1	20	2	0	0	3
3	2011-01-20 03:00:00	2011	1	20	3	0	0	3
4	2011-01-20 04:00:00	2011	1	20	4	0	0	3

In [95]:

```
plt.figure(figsize=(15,10))
g = sns.heatmap(new_tr.corr(), annot=True, fmt=".2f", cmap="coolwarm", cbar=False)
```



In [96]:

```
feature_names = [ 'season', 'holiday', 'workingday', 'weather',
                  'temp', 'atemp', 'humidity', 'windspeed',
                  "year", "hour", "dayofweek"]  # 공통 변수

X_tr_all = new_tr[feature_names]  # 학습용 데이터 변수 선택
X_test_all = new_test[feature_names]    # 테스트 데이터의 변수 선택
print(X_tr_all.head())
```

```
   season  holiday  workingday  weather   temp    atemp  humidity  windspeed  ₩
0       1        0           0        1   9.84   14.395        81        0.0
1       1        0           0        1   9.02   13.635        80        0.0
2       1        0           0        1   9.02   13.635        80        0.0
3       1        0           0        1   9.84   14.395        75        0.0
4       1        0           0        1   9.84   14.395        75        0.0

   year  hour  dayofweek
0  2011     0          5
1  2011     1          5
2  2011     2          5
3  2011     3          5
4  2011     4          5
```

In [97]:

```
label_name = 'count'                # 렌탈 대수 (종속변수)
y_tr_all = new_tr[label_name]       # 렌탈 대수 변수 값 선택
```

In [98]:

```
from sklearn.model_selection import train_test_split
```

In [99]:

```
X_train, X_test, y_train, y_test = train_test_split(X_tr_all,
                                                    y_tr_all,
                                                    test_size=0.3,
                                                    random_state=77)
```

In [100]:

```
from sklearn.linear_model import LinearRegression

model = LinearRegression()  # 모델 객체 생성.
model.fit(X_train, y_train)
pred = model.predict(X_test)

# 결정계수 확인
print("학습용 데이터 결정계수: {:.3f}".format(model.score(X_train, y_train)))
print("테스트 데이터 결정계수: {:.3f}".format(model.score(X_test, y_test)))

# MSE(mean squared error) 확인
mse_val = ( (pred - y_test) ** 2 ).sum() / len(pred)
print("mse value : {:.3f}".format(mse_val))
```

```
학습용 데이터 결정계수: 0.391
테스트 데이터 결정계수: 0.377
mse value : 20134.965
```

In [101]:

```
from sklearn.tree import DecisionTreeRegressor

model = DecisionTreeRegressor()  # 모델 객체 생성.
model.fit(X_train, y_train)
pred = model.predict(X_test)

# 결정계수 확인
print("학습용 데이터 결정계수: {:.3f}".format(model.score(X_train, y_train)))
print("테스트 데이터 결정계수: {:.3f}".format(model.score(X_test, y_test)))

# MSE(mean squared error) 확인
mse_val = ( (pred - y_test) ** 2 ).sum() / len(pred)
print("mse value : {:.3f}".format(mse_val))
```

```
학습용 데이터 결정계수: 1.000
테스트 데이터 결정계수: 0.897
mse value : 3325.572
```

In [102]:

```
from sklearn.ensemble import RandomForestRegressor   # 앙상블(의사결정트리 확장판)

seed = 37
model = RandomForestRegressor(n_jobs=-1, random_state=seed)  # 모델 객체 생성.
model.fit(X_train, y_train)           # 모델 학습(공부가 되었다.)
pred = model.predict(X_test)

# 결정계수 확인
print("학습용 데이터 결정계수: {:.3f}".format(model.score(X_train, y_train)))
print("테스트 데이터 결정계수: {:.3f}".format(model.score(X_test, y_test)))

# MSE(mean squared error) 확인
mse_val = ( (pred - y_test) ** 2 ).sum() / len(pred)
print("mse value : {:.3f}".format(mse_val))
```

```
학습용 데이터 결정계수: 0.992
테스트 데이터 결정계수: 0.946
mse value : 1752.403
```

In [103]:

```
from sklearn.ensemble import GradientBoostingRegressor

seed = 37
model = GradientBoostingRegressor(random_state=seed)  # 모델 객체 생성.
model.fit(X_train, y_train)           # 모델 학습(공부가 되었다.)
pred = model.predict(X_test)

# 결정계수 확인
print("학습용 데이터 결정계수: {:.3f}".format(model.score(X_train, y_train)))
print("테스트 데이터 결정계수: {:.3f}".format(model.score(X_test, y_test)))

# MSE(mean squared error) 확인
mse_val = ( (pred - y_test) ** 2 ).sum() / len(pred)
print("mse value : {:.3f}".format(mse_val))
```

```
학습용 데이터 결정계수: 0.860
테스트 데이터 결정계수: 0.849
mse value : 4892.054
```

In [104]:

```
sub = pd.read_csv("bike/sampleSubmission.csv")
sub.head()
```

Out[104]:

	datetime	count
0	2011-01-20 00:00:00	0
1	2011-01-20 01:00:00	0
2	2011-01-20 02:00:00	0
3	2011-01-20 03:00:00	0
4	2011-01-20 04:00:00	0

In [105]:

```
from sklearn.ensemble import RandomForestRegressor   # 앙상블(의사결정트리 확장판)

seed = 37
model = RandomForestRegressor(n_jobs=-1, random_state=seed)  # 모델 객체 생성.
model.fit(X_train, y_train)           # 모델 학습(공부가 되었다.)
```

Out[105]:

```
RandomForestRegressor(n_jobs=-1, random_state=37)
```

In [106]:

```
pred = model.predict(X_test_all)   # 예측
sub['count'] = pred
sub.loc[sub['count'] < 0, 'count'] = 0
sub.head(3)
```

Out[106]:

	datetime	count
0	2011-01-20 00:00:00	11.75
1	2011-01-20 01:00:00	4.20
2	2011-01-20 02:00:00	4.78

In [107]:

```
# 처음 만는 제출용 csv 파일, 행번호를 없애기
sub.to_csv("third_sub.csv", index=False)
```

score : 0.43006

실습 : 특징 상호작용으로 특징을 더 생성해 보자.

In [108]:

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import PolynomialFeatures
```

In [109]:

```
feature_names = [ 'season', 'holiday', 'workingday', 'weather',
                  'temp', 'atemp', 'humidity', 'windspeed',
                  "year", "hour", "dayofweek"]  # 공통 변수

X_tr_all = new_tr[feature_names]        # 학습용 데이터 변수 선택
X_test_all = new_test[feature_names]    # 테스트 데이터의 변수 선택
print(X_tr_all.head())
```

```
   season  holiday  workingday  weather  temp   atemp  humidity  windspeed  W
0       1        0           0        1  9.84  14.395        81        0.0
1       1        0           0        1  9.02  13.635        80        0.0
2       1        0           0        1  9.02  13.635        80        0.0
3       1        0           0        1  9.84  14.395        75        0.0
4       1        0           0        1  9.84  14.395        75        0.0

   year  hour  dayofweek
0  2011     0          5
1  2011     1          5
2  2011     2          5
3  2011     3          5
4  2011     4          5
```

In [110]:

```
scaler = MinMaxScaler().fit(X_tr_all)

nor_X_tr_all = scaler.transform(X_tr_all)
ex_X_tr = PolynomialFeatures(degree=2,
                             include_bias=False).fit_transform(nor_X_tr_all)
y_tr_all = new_tr['count']
```

In [111]:

```
X_train, X_test, y_train, y_test = train_test_split(ex_X_tr,
                                                    y_tr_all,
                                                    test_size=0.2,
                                                    random_state=42)
```

In [113]:

```
from sklearn.ensemble import RandomForestRegressor   # 앙상블(의사결정트리 확장판)

seed = 37
model = RandomForestRegressor(n_jobs=-1, random_state=seed)  # 모델 객체 생성.
model.fit(X_train, y_train)           # 모델 학습
pred = model.predict(X_test)

# 결정계수 확인
print("학습용 데이터 결정계수: {:.3f}".format(model.score(X_train, y_train)))
print("테스트 데이터 결정계수: {:.3f}".format(model.score(X_test, y_test)))

# MSE(mean squared error) 확인
mse_val = ( (pred - y_test) ** 2 ).sum() / len(pred)
print("mse value : {:.3f}".format(mse_val))
```

```
학습용 데이터 결정계수: 0.992
테스트 데이터 결정계수: 0.950
mse value : 1659.031
```

In [114]:

```
nor_X_test_all = scaler.transform(X_test_all)
ex_X_test = PolynomialFeatures(degree=2,
                               include_bias=False).fit_transform(nor_X_test_all)
```

In [115]:

```
pred = model.predict(ex_X_test)   # 예측
sub['count'] = pred
sub.loc[sub['count'] < 0, 'count'] = 0
sub.head(3)
```

Out[115]:

	datetime	count
0	2011-01-20 00:00:00	13.66
1	2011-01-20 01:00:00	5.08
2	2011-01-20 02:00:00	3.53

In [116]:

```
sub.to_csv("four_sub.csv", index=False)
```

score : 0.41328

다양한 특징 중에 모델을 활용한 중요한 특징을 선택해 보자.

In [117]:

```
import warnings
warnings.filterwarnings(action='ignore')
from sklearn.feature_selection import SelectPercentile, f_classif
from sklearn.feature_selection import SelectFromModel
from sklearn.ensemble import RandomForestRegressor
```

In [118]:

```
select = SelectFromModel(RandomForestRegressor(random_state=37),
                                               threshold="0.1 * median")

select.fit(X_train, y_train)
```

Out[118]:

```
SelectFromModel(estimator=RandomForestRegressor(random_state=37),
                threshold='0.1 * median')
```

In [119]:

```
X_train_l1 = select.transform(X_train)
X_test_l1 = select.transform(X_test)

X_train_l1.shape, X_test_l1.shape
```

Out[119]:

```
((8708, 68), (2178, 68))
```

In [120]:

```
### 어떤 특성이 선택되었는지 확인
mask = select.get_support()
print(mask)
plt.matshow(mask.reshape(1, -1), cmap='gray_r')
plt.xlabel("특성 번호")
```

```
[ True False  True  True  True  True  True  True  True  True  True  True
 False  True  True  True  True  True  True  True  True False False
 False  True  True  True False False False False  True  True  True  True
  True  True  True  True  True  True  True  True  True  True  True  True
  True  True  True  True  True  True  True  True  True  True  True  True
  True  True  True  True  True  True  True  True  True  True  True  True
  True  True  True  True  True]
```

Out[120]:

```
Text(0.5, 0, '특성 번호')
```

In [121]:

```
seed = 37
model = RandomForestRegressor(n_jobs=-1, random_state=seed)  # 모델 객체 생성.
model.fit(X_train_l1, y_train)           # 모델 학습(공부가 되었다.)
pred = model.predict(X_test_l1)

# 결정계수 확인
print("학습용 세트 결정계수: {:.3f}".format(model.score(X_train_l1, y_train)))
print("테스트 세트 결정계수: {:.3f}".format(model.score(X_test_l1, y_test)))
mse_val = ( (pred - y_test)**2  ).sum() / len(pred)
print("MSE : {:.3f}".format( mse_val ))
```

```
학습용 세트 결정계수: 0.992
테스트 세트 결정계수: 0.950
MSE : 1644.395
```

In [122]:

```
X_test_l1_all = select.transform(ex_X_test)
X_test_l1_all.shape
```

Out[122]:

```
(6493, 68)
```

In [123]:

```
pred = model.predict(X_test_l1_all)
sub['count'] = pred
sub.loc[ sub['count'] <0 , 'count' ] =0
sub.to_csv('five_sub.csv', index=False)
```

전 제출 점수에 비해 약간 더 향상되었다.

대표적인 모델 xgboost 사용해 보기

In [61]:

```
import xgboost as xgb
```

xgb.DMatrix

- dense matrix, sparse matrix, local file로부터 DMatrix object 객체를 만든다.

In [62]:

```
# data_dmatrix = xgb.DMatrix(data=ex_X_tr,label=y_tr_all)
```

In [64]:

```
X_train, X_test, y_train, y_test = train_test_split(ex_X_tr,
                                                    y_tr_all,
                                                    test_size=0.2,
                                                    random_state=42)
```

In [65]:

```
# 기본 옵션 확인
xg_reg = xgb.XGBRegressor()
xg_reg
```

Out[65]:

```
XGBRegressor(base_score=None, booster=None, colsample_bylevel=None,
             colsample_bynode=None, colsample_bytree=None, gamma=None,
             gpu_id=None, importance_type='gain', interaction_constraints=None,
             learning_rate=None, max_delta_step=None, max_depth=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             random_state=None, reg_alpha=None, reg_lambda=None,
             scale_pos_weight=None, subsample=None, tree_method=None,
             validate_parameters=None, verbosity=None)
```

- learning_rate: 0~1사이의 값. 과적합을 방지하기 위한 단계 크기
- max_depth: 각각의 나무 **모델의 최대 깊이**
- subsample: 각 나무마다 사용하는 샘플 퍼센트, 낮은 값은 underfitting(과소적합)을 야기할 수 있음.
- colsample_bytree: 각 나무마다 사용하는 **feature 퍼센트**. High value can lead to overfitting.
- n_estimators: **트리의 수**(우리가 모델을 생성할)
- loss function(손실함수)결정.
- objective(목적함수)
  - **reg:linear** for regression problems(회귀 문제),
  - **reg:logistic** for classification problems with only decision(분류 문제),
  - **binary:logistic** for classification problems with probability.
- alpha : L1 규제에 대한 항

In [66]:

```
xg_reg = xgb.XGBRegressor(objective ='reg:linear',
                          colsample_bytree = 0.3, # 각나무마다 사용하는 feature 비율
                          learning_rate = 0.1,
                          max_depth = 4,
                          alpha = 0.1,
                          n_estimators = 100)  # n_estimators=100
xg_reg
```

Out[66]:

```
XGBRegressor(alpha=0.1, base_score=None, booster=None, colsample_bylevel=None,
             colsample_bynode=None, colsample_bytree=0.3, gamma=None,
             gpu_id=None, importance_type='gain', interaction_constraints=None,
             learning_rate=0.1, max_delta_step=None, max_depth=4,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             objective='reg:linear', random_state=None, reg_alpha=None,
             reg_lambda=None, scale_pos_weight=None, subsample=None,
             tree_method=None, validate_parameters=None, verbosity=None)
```

학습

In [67]:

```
xg_reg.fit(X_train, y_train)          # 모델 학습(공부가 되었다.)
```

```
[15:54:22] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/sr
c/objective/regression_obj.cu:171: reg:linear is now deprecated in favor of reg:squa
rederror.
```

Out[67]:

```
XGBRegressor(alpha=0.1, base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.3, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.1, max_delta_step=0, max_depth=4,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=100, n_jobs=8, num_parallel_tree=1,
             objective='reg:linear', random_state=0, reg_alpha=0.100000001,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

In [68]:

```
# 결정계수 확인
print("학습용 데이터 결정계수: {:.3f}".format(model.score(X_train, y_train)))
print("테스트 데이터 결정계수: {:.3f}".format(model.score(X_test, y_test)))
```

```
학습용 데이터 결정계수: 0.992
테스트 데이터 결정계수: 0.950
```

실습

- 나무의 개수를 조정해 보면서 확인해 보자.

In [69]:

```
%%time

num_list = [100,200,300,500,1000, 1500]

for num in num_list:
    xg_reg = xgb.XGBRegressor(objective ='reg:linear',
            colsample_bytree = 0.3, # 각나무마다 사용하는 feature 비율
            learning_rate = 0.1,
            max_depth = 3,
            alpha = 0.1,
            n_estimators = num)
    xg_reg.fit(X_train, y_train)
    pred = xg_reg.predict(X_test)

    # 결정계수 확인
    print("학습용 데이터 결정계수: {:.3f}".format(model.score(X_train, y_train)))
    print("테스트 데이터 결정계수: {:.3f}".format(model.score(X_test, y_test)))

    # MSE(mean squared error) 확인
    mse_val = ( (pred - y_test) ** 2 ).sum() / len(pred)
    print("mse value : {:.3f}".format(mse_val))
```

```
[15:55:09] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/sr
c/objective/regression_obj.cu:171: reg:linear is now deprecated in favor of reg:squa
rederror.
학습용 데이터 결정계수: 0.992
테스트 데이터 결정계수: 0.950
mse value : 3257.375
[15:55:09] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/sr
c/objective/regression_obj.cu:171: reg:linear is now deprecated in favor of reg:squa
rederror.
학습용 데이터 결정계수: 0.992
테스트 데이터 결정계수: 0.950
mse value : 2368.006
[15:55:10] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/sr
c/objective/regression_obj.cu:171: reg:linear is now deprecated in favor of reg:squa
rederror.
학습용 데이터 결정계수: 0.992
테스트 데이터 결정계수: 0.950
mse value : 2104.320
[15:55:12] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/sr
c/objective/regression_obj.cu:171: reg:linear is now deprecated in favor of reg:squa
rederror.
학습용 데이터 결정계수: 0.992
테스트 데이터 결정계수: 0.950
mse value : 1865.287
[15:55:14] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/sr
c/objective/regression_obj.cu:171: reg:linear is now deprecated in favor of reg:squa
rederror.
학습용 데이터 결정계수: 0.992
테스트 데이터 결정계수: 0.950
mse value : 1647.236
[15:55:18] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/sr
c/objective/regression_obj.cu:171: reg:linear is now deprecated in favor of reg:squa
rederror.
학습용 데이터 결정계수: 0.992
테스트 데이터 결정계수: 0.950
```

```
mse value : 1582.021
Wall time: 15.3 s
```

최종 모델

In [70]:

```
xg_reg = xgb.XGBRegressor(objective ='reg:linear',
            colsample_bytree = 0.3, # 각나무마다 사용하는 feature 비율
            learning_rate = 0.05,
            max_depth = 5,
            alpha = 0.1,
            n_estimators = 500)

xg_reg.fit(X_train, y_train)
print("학습용 세트 정확도: {:.3f}".format(xg_reg.score(X_train, y_train)))
print("테스트 세트 정확도: {:.3f}".format(xg_reg.score(X_test, y_test)))
```

```
[15:55:34] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/sr
c/objective/regression_obj.cu:171: reg:linear is now deprecated in favor of reg:squa
rederror.
학습용 세트 정확도: 0.979
테스트 세트 정확도: 0.956
```

In [71]:

```
nor_X_test_all = scaler.transform(X_test_all)
ex_X_test = PolynomialFeatures(degree=2,
                               include_bias=False).fit_transform(nor_X_test_all)
```

In [72]:

```
pred = xg_reg.predict(ex_X_test)   # 예측
sub['count'] = pred
sub.loc[sub['count'] < 0, 'count'] = 0
sub.head(3)
```

Out[72]:

	datetime	count
0	2011-01-20 00:00:00	12.755984
1	2011-01-20 01:00:00	2.368304
2	2011-01-20 02:00:00	1.013963

In [73]:

```
# 처음 만는 제출용 csv 파일, 행번호를 없애기
sub.to_csv("five_xgb_sub.csv", index=False)
```

다양한 실습해보기 - 아래 각각의 경우에 대한 score확인해 보기

- lr_rate=0.1, max_depth = 4, 1000개 트리
- lr_rate=0.1, max_depth = 3, 1500개 트리
- lr_rate = 0.001, max_depth = 3, 1000개 트리

- lr_rate = 0.05, max_depth = 5, 500개 트리

History

- 2021-10 update v12

교육용으로 작성된 것으로 배포 및 복제시에 사전 허가가 필요합니다.
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