

Ch04-classification-lab

February 26, 2026

```
[2]: import numpy as np
import pandas as pd
from matplotlib.pyplot import subplots
import statsmodels.api as sm
from ISLP import load_data
from ISLP.models import (ModelSpec as MS,
                           summarize)
```

```
[3]: from ISLP import confusion_table
from ISLP.models import contrast
from sklearn.discriminant_analysis import \
    (LinearDiscriminantAnalysis as LDA,
     QuadraticDiscriminantAnalysis as QDA)
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

```
[4]: Smarket = load_data('Smarket')
Smarket
```

```
[4]:      Year   Lag1   Lag2   Lag3   Lag4   Lag5   Volume  Today Direction
0      2001  0.381 -0.192 -2.624 -1.055  5.010  1.19130  0.959      Up
1      2001  0.959  0.381 -0.192 -2.624 -1.055  1.29650  1.032      Up
2      2001  1.032  0.959  0.381 -0.192 -2.624  1.41120 -0.623     Down
3      2001 -0.623  1.032  0.959  0.381 -0.192  1.27600  0.614      Up
4      2001  0.614 -0.623  1.032  0.959  0.381  1.20570  0.213      Up
...
1245   2005  0.422  0.252 -0.024 -0.584 -0.285  1.88850  0.043      Up
1246   2005  0.043  0.422  0.252 -0.024 -0.584  1.28581 -0.955     Down
1247   2005 -0.955  0.043  0.422  0.252 -0.024  1.54047  0.130      Up
1248   2005  0.130 -0.955  0.043  0.422  0.252  1.42236 -0.298     Down
1249   2005 -0.298  0.130 -0.955  0.043  0.422  1.38254 -0.489     Down
```

[1250 rows x 9 columns]

```
[5]: Smarket.columns
```

```
[5]: Index(['Year', 'Lag1', 'Lag2', 'Lag3', 'Lag4', 'Lag5', 'Volume', 'Today',  
         'Direction'],  
        dtype='str')
```

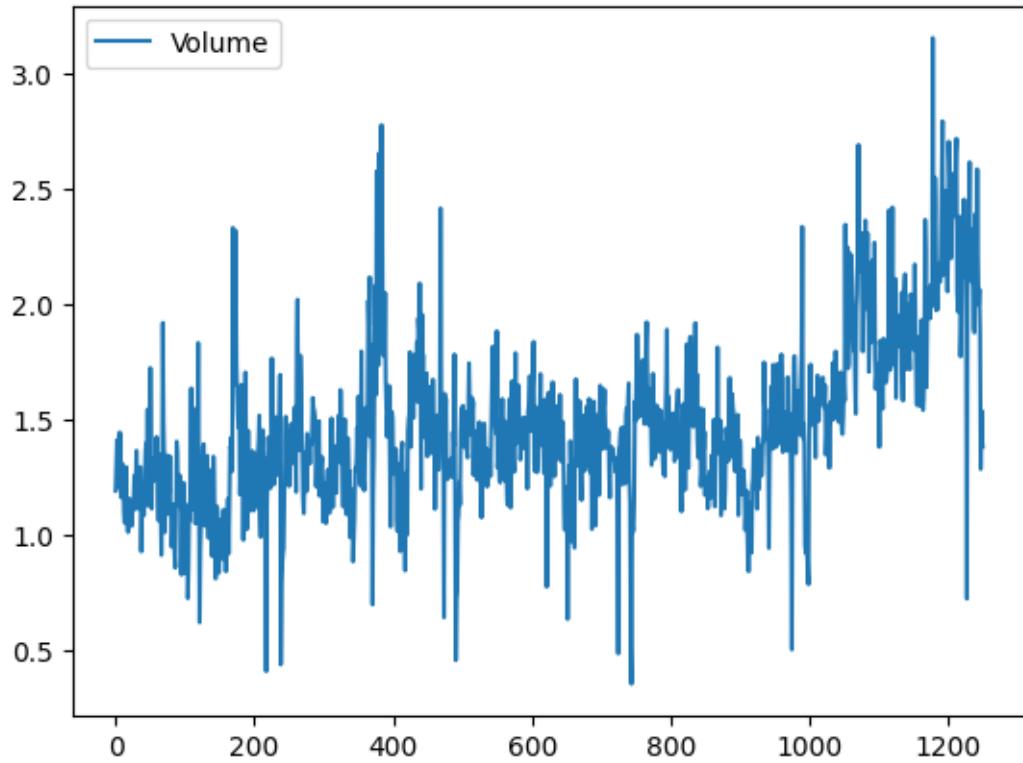
```
[6]: Smarket.corr(numeric_only=True)
```

```
[6]:
```

	Year	Lag1	Lag2	Lag3	Lag4	Lag5	Volume	Today
Year	1.000000	0.029700	0.030596	0.033195	0.035689	0.029788	0.539006	
Lag1	0.029700	1.000000	-0.026294	-0.010803	-0.002986	-0.005675	0.040910	
Lag2	0.030596	-0.026294	1.000000	-0.025897	-0.010854	-0.003558	-0.043383	
Lag3	0.033195	-0.010803	-0.025897	1.000000	-0.024051	-0.018808	-0.041824	
Lag4	0.035689	-0.002986	-0.010854	-0.024051	1.000000	-0.027084	-0.048414	
Lag5	0.029788	-0.005675	-0.003558	-0.018808	-0.027084	1.000000	-0.022002	
Volume	0.539006	0.040910	-0.043383	-0.041824	-0.048414	-0.022002	1.000000	
Today	0.030095	-0.026155	-0.010250	-0.002448	-0.006900	-0.034860	0.014592	

	Today
Year	0.030095
Lag1	-0.026155
Lag2	-0.010250
Lag3	-0.002448
Lag4	-0.006900
Lag5	-0.034860
Volume	0.014592
Today	1.000000

```
[7]: Smarket.plot(y='Volume');
```



```
[8]: allvars = Smarket.columns.drop(['Today', 'Direction', 'Year'])
design = MS(allvars)
X = design.fit_transform(Smarket)
y = Smarket.Direction == 'Up'
glm = sm.GLM(y,
              X,
              family=sm.families.Binomial())
results = glm.fit()
summarize(results)
```

	coef	std err	z	P> z
intercept	-0.1260	0.241	-0.523	0.601
Lag1	-0.0731	0.050	-1.457	0.145
Lag2	-0.0423	0.050	-0.845	0.398
Lag3	0.0111	0.050	0.222	0.824
Lag4	0.0094	0.050	0.187	0.851
Lag5	0.0103	0.050	0.208	0.835
Volume	0.1354	0.158	0.855	0.392

```
[9]: results.params
```

```
[9]: intercept -0.126000
      Lag1      -0.073074
      Lag2      -0.042301
      Lag3      0.011085
      Lag4      0.009359
      Lag5      0.010313
      Volume    0.135441
      dtype: float64
```

```
[10]: results.pvalues
```

```
[10]: intercept 0.600700
      Lag1        0.145232
      Lag2        0.398352
      Lag3        0.824334
      Lag4        0.851445
      Lag5        0.834998
      Volume     0.392404
      dtype: float64
```

```
[11]: probs = results.predict()
      probs[:10]
```

```
[11]: array([0.50708413, 0.48146788, 0.48113883, 0.51522236, 0.51078116,
           0.50695646, 0.49265087, 0.50922916, 0.51761353, 0.48883778])
```

```
[12]: labels = np.array(['Down']*1250)
      labels[probs>0.5] = "Up"
```

```
[13]: confusion_table(labels, Smarket.Direction)
```

```
[13]: Truth      Down   Up
      Predicted
      Down       145   141
      Up         457   507
```

```
[14]: (507+145)/1250, np.mean(labels == Smarket.Direction)
```

```
[14]: (0.5216, np.float64(0.5216))
```

```
[15]: train = (Smarket.Year < 2005)
      Smarket_train = Smarket.loc[train]
      Smarket_test = Smarket.loc[~train]
      Smarket_test.shape
```

```
[15]: (252, 9)
```

```
[16]: X_train, X_test = X.loc[train], X.loc[~train]
y_train, y_test = y.loc[train], y.loc[~train]
glm_train = sm.GLM(y_train,
                    X_train,
                    family=sm.families.Binomial())
results = glm_train.fit()
probs = results.predict(exog=X_test)
```

```
[17]: D = Smarket.Direction
L_train, L_test = D.loc[train], D.loc[~train]
```

```
[18]: labels = np.array(['Down']*252)
labels[probs>0.5] = 'Up'
confusion_table(labels, L_test)
```

```
[18]: Truth      Down  Up
Predicted
Down        77   97
Up          34   44
```

```
[19]: np.mean(labels == L_test), np.mean(labels != L_test)
```

```
[19]: (np.float64(0.4801587301587302), np.float64(0.5198412698412699))
```

```
[20]: model = MS(['Lag1', 'Lag2']).fit(Smarket)
X = model.transform(Smarket)
X_train, X_test = X.loc[train], X.loc[~train]
glm_train = sm.GLM(y_train,
                    X_train,
                    family=sm.families.Binomial())
results = glm_train.fit()
probs = results.predict(exog=X_test)
labels = np.array(['Down']*252)
labels[probs>0.5] = 'Up'
confusion_table(labels, L_test)
```

```
[20]: Truth      Down  Up
Predicted
Down        35   35
Up          76  106
```

```
[21]: (35+106)/252, 106/(106+76)
```

```
[21]: (0.5595238095238095, 0.5824175824175825)
```

```
[22]: newdata = pd.DataFrame({'Lag1':[1.2, 1.5],
                           'Lag2':[1.1, -0.8]});
newX = model.transform(newdata)
```

```
results.predict(newX)
```

```
[22]: 0    0.479146  
       1    0.496094  
      dtype: float64
```

```
[23]: lda = LDA(store_covariance=True)
```

```
[24]: X_train, X_test = [M.drop(columns=['intercept'])  
                      for M in [X_train, X_test]]  
lda.fit(X_train, L_train)
```

```
[24]: LinearDiscriminantAnalysis(store_covariance=True)
```

```
[25]: lda.means_
```

```
[25]: array([[ 0.04279022,  0.03389409],  
           [-0.03954635, -0.03132544]])
```

```
[26]: lda.classes_
```

```
[26]: array(['Down', 'Up'], dtype='<U4')
```

```
[27]: lda.priors_
```

```
[27]: array([0.49198397, 0.50801603])
```

```
[28]: lda.scalings_
```

```
[28]: array([[-0.64201904],  
           [-0.51352928]])
```

```
[29]: lda_pred = lda.predict(X_test)
```

```
[30]: confusion_table(lda_pred, L_test)
```

```
[30]: Truth      Down     Up  
Predicted  
Down        35     35  
Up          76   106
```

```
[31]: lda_prob = lda.predict_proba(X_test)  
np.all(  
       np.where(lda_prob[:,1] >= 0.5, 'Up', 'Down') == lda_pred  
     )
```

```
[31]: np.True_
```

```
[32]: np.all(
    [lda.classes_[i] for i in np.argmax(lda_prob, 1)] == lda_pred
)
```

```
[32]: np.True_
```

```
[33]: np.sum(lda_prob[:,0] > 0.9)
```

```
[33]: np.int64(0)
```

```
[34]: qda = QDA(store_covariance=True)
qda.fit(X_train, L_train)
```

```
[34]: QuadraticDiscriminantAnalysis(store_covariance=True)
```

```
[35]: qda.means_, qda.priors_
```

```
[35]: (array([[ 0.04279022,  0.03389409],
   [-0.03954635, -0.03132544]]),
 array([0.49198397,  0.50801603]))
```

```
[36]: qda.covariance_[0]
```

```
[36]: array([[ 1.50662277, -0.03924806],
   [-0.03924806,  1.53559498]])
```

```
[37]: qda_pred = qda.predict(X_test)
confusion_table(qda_pred, L_test)
```

```
[37]: Truth      Down     Up
Predicted
Down        30     20
Up          81    121
```

```
[38]: np.mean(qda_pred == L_test)
```

```
[38]: np.float64(0.5992063492063492)
```

```
[39]: NB = GaussianNB()
NB.fit(X_train, L_train)
```

```
[39]: GaussianNB()
```

```
[40]: NB.classes_
```

```
[40]: array(['Down', 'Up'], dtype='<U4')
```

```
[41]: NB.class_prior_
```

```
[41]: array([0.49198397, 0.50801603])
```

```
[42]: NB.theta_
```

```
[42]: array([[ 0.04279022,  0.03389409],  
           [-0.03954635, -0.03132544]])
```

```
[43]: NB.var_
```

```
[43]: array([[1.50355429, 1.53246749],  
           [1.51401364, 1.48732877]])
```

```
[44]: X_train[L_train == 'Down'].mean()
```

```
[44]: Lag1      0.042790  
Lag2      0.033894  
dtype: float64
```

```
[45]: X_train[L_train == 'Down'].var(ddof=0)
```

```
[45]: Lag1      1.503554  
Lag2      1.532467  
dtype: float64
```

```
[46]: nb_labels = NB.predict(X_test)  
confusion_table(nb_labels, L_test)
```

```
[46]: Truth      Down    Up  
Predicted  
Down        29     20  
Up          82    121
```

```
[47]: NB.predict_proba(X_test)[:,5]
```

```
[47]: array([[0.4873288 , 0.5126712 ],  
           [0.47623584, 0.52376416],  
           [0.46529531, 0.53470469],  
           [0.47484469, 0.52515531],  
           [0.49020587, 0.50979413]])
```

```
[48]: knn1 = KNeighborsClassifier(n_neighbors=1)  
X_train, X_test = [np.asarray(X) for X in [X_train, X_test]]  
knn1.fit(X_train, L_train)  
knn1_pred = knn1.predict(X_test)  
confusion_table(knn1_pred, L_test)
```

```
[48]: Truth      Down    Up  
Predicted
```

```
Down      43  58
Up       68  83
```

```
[49]: (83+43)/252, np.mean(knn1_pred == L_test)
```

```
[49]: (0.5, np.float64(0.5))
```

```
[50]: knn3 = KNeighborsClassifier(n_neighbors=3)
knn3_pred = knn3.fit(X_train, L_train).predict(X_test)
np.mean(knn3_pred == L_test)
```

```
[50]: np.float64(0.5317460317460317)
```

```
[51]: Caravan = load_data('Caravan')
Purchase = Caravan.Purchase
Purchase.value_counts()
```

```
[51]: Purchase
No      5474
Yes     348
Name: count, dtype: int64
```

```
[52]: 348 / 5822
```

```
[52]: 0.05977327378907592
```

```
[53]: feature_df = Caravan.drop(columns=['Purchase'])
```

```
[54]: scaler = StandardScaler(with_mean=True,
                             with_std=True,
                             copy=True)
```

```
[55]: scaler.fit(feature_df)
X_std = scaler.transform(feature_df)
```

```
[56]: feature_std = pd.DataFrame(
        X_std,
        columns=feature_df.columns);
feature_std.std()
```

```
[56]: MOSTYPE      1.000086
MAANTHUI      1.000086
MGEMOMV       1.000086
MGEMLEEF      1.000086
MOSHOOFD      1.000086
...
AZEILPL       1.000086
APLEZIER      1.000086
```

```
AFIETS      1.000086
AINBOED     1.000086
ABYSTAND    1.000086
Length: 85, dtype: float64
```

```
[57]: (X_train,
       X_test,
       y_train,
       y_test) = train_test_split(np.asarray(feature_std),
                                  Purchase,
                                  test_size=1000,
                                  random_state=0)
```

```
[58]: knn1 = KNeighborsClassifier(n_neighbors=1)
knn1_pred = knn1.fit(X_train, y_train).predict(X_test)
np.mean(y_test != knn1_pred), np.mean(y_test != "No")
```

```
[58]: (np.float64(0.111), np.float64(0.067))
```

```
[59]: confusion_table(knn1_pred, y_test)
```

```
[59]: Truth      No  Yes
      Predicted
      No        880   58
      Yes       53    9
```

```
[60]: 9/(53+9)
```

```
[60]: 0.14516129032258066
```

```
[61]: for K in range(1,6):
    knn = KNeighborsClassifier(n_neighbors=K)
    knn_pred = knn.fit(X_train, y_train).predict(X_test)
    C = confusion_table(knn_pred, y_test)
    templ = ('K={0:d}: # predicted to rent: {1:>2}, ' +
             '# who did rent {2:d}, accuracy {3:.1%}')
    pred = C.loc['Yes'].sum()
    did_rent = C.loc['Yes', 'Yes']
    print(templ.format(
        K,
        pred,
        did_rent,
        did_rent / pred))
```

```
K=1: # predicted to rent: 62, # who did rent 9, accuracy 14.5%
K=2: # predicted to rent: 6, # who did rent 1, accuracy 16.7%
K=3: # predicted to rent: 20, # who did rent 3, accuracy 15.0%
K=4: # predicted to rent: 4, # who did rent 0, accuracy 0.0%
```

```
K=5: # predicted to rent: 7, # who did rent 1, accuracy 14.3%
```

```
[62]: logit = LogisticRegression(C=1e10, solver='liblinear')
logit.fit(X_train, y_train)
logit_pred = logit.predict_proba(X_test)
logit_labels = np.where(logit_pred[:,1] > .5, 'Yes', 'No')
confusion_table(logit_labels, y_test)
```

```
[62]: Truth      No  Yes
Predicted
No        931   67
Yes       2     0
```

```
[63]: logit_labels = np.where(logit_pred[:,1]>0.25, 'Yes', 'No')
confusion_table(logit_labels, y_test)
```

```
[63]: Truth      No  Yes
Predicted
No        913   58
Yes       20    9
```

```
[64]: 9/(20+9)
```

```
[64]: 0.3103448275862069
```

```
[65]: Bike = load_data('Bikeshare')
```

```
[66]: Bike.shape, Bike.columns
```

```
[66]: ((8645, 15),
Index(['season', 'mnth', 'day', 'hr', 'holiday', 'weekday', 'workingday',
       'weathersit', 'temp', 'atemp', 'hum', 'windspeed', 'casual',
       'registered', 'bikers'],
       dtype='str'))
```

```
[67]: X = MS(['mnth',
            'hr',
            'workingday',
            'temp',
            'weathersit']).fit_transform(Bike)
Y = Bike['bikers']
M_lm = sm.OLS(Y, X).fit()
summarize(M_lm)
```

```
[67]:             coef  std err      t  P>|t|
intercept      -68.6317    5.307 -12.932  0.000
mnth[Feb]        6.8452    4.287   1.597  0.110
mnth[March]     16.5514    4.301   3.848  0.000
```

mnth[April]	41.4249	4.972	8.331	0.000
mnth[May]	72.5571	5.641	12.862	0.000
mnth[June]	67.8187	6.544	10.364	0.000
mnth[July]	45.3245	7.081	6.401	0.000
mnth[Aug]	53.2430	6.640	8.019	0.000
mnth[Sept]	66.6783	5.925	11.254	0.000
mnth[Oct]	75.8343	4.950	15.319	0.000
mnth[Nov]	60.3100	4.610	13.083	0.000
mnth[Dec]	46.4577	4.271	10.878	0.000
hr[1]	-14.5793	5.699	-2.558	0.011
hr[2]	-21.5791	5.733	-3.764	0.000
hr[3]	-31.1408	5.778	-5.389	0.000
hr[4]	-36.9075	5.802	-6.361	0.000
hr[5]	-24.1355	5.737	-4.207	0.000
hr[6]	20.5997	5.704	3.612	0.000
hr[7]	120.0931	5.693	21.095	0.000
hr[8]	223.6619	5.690	39.310	0.000
hr[9]	120.5819	5.693	21.182	0.000
hr[10]	83.8013	5.705	14.689	0.000
hr[11]	105.4234	5.722	18.424	0.000
hr[12]	137.2837	5.740	23.916	0.000
hr[13]	136.0359	5.760	23.617	0.000
hr[14]	126.6361	5.776	21.923	0.000
hr[15]	132.0865	5.780	22.852	0.000
hr[16]	178.5206	5.772	30.927	0.000
hr[17]	296.2670	5.749	51.537	0.000
hr[18]	269.4409	5.736	46.976	0.000
hr[19]	186.2558	5.714	32.596	0.000
hr[20]	125.5492	5.704	22.012	0.000
hr[21]	87.5537	5.693	15.378	0.000
hr[22]	59.1226	5.689	10.392	0.000
hr[23]	26.8376	5.688	4.719	0.000
workingday	1.2696	1.784	0.711	0.477
temp	157.2094	10.261	15.321	0.000
weathersit[cloudy/misty]	-12.8903	1.964	-6.562	0.000
weathersit[heavy rain/snow]	-109.7446	76.667	-1.431	0.152
weathersit[light rain/snow]	-66.4944	2.965	-22.425	0.000

```
[68]: hr_encode = contrast('hr', 'sum')
mnth_encode = contrast('mnth', 'sum')
```

```
[69]: X2 = MS([mnth_encode,
            hr_encode,
            'workingday',
            'temp',
            'weathersit']).fit_transform(Bike)
M2_lm = sm.OLS(Y, X2).fit()
```

```
S2 = summarize(M2_lm)
S2
```

[69] :

	coef	std err	t	P> t
intercept	73.5974	5.132	14.340	0.000
mnth[Jan]	-46.0871	4.085	-11.281	0.000
mnth[Feb]	-39.2419	3.539	-11.088	0.000
mnth[March]	-29.5357	3.155	-9.361	0.000
mnth[April]	-4.6622	2.741	-1.701	0.089
mnth[May]	26.4700	2.851	9.285	0.000
mnth[June]	21.7317	3.465	6.272	0.000
mnth[July]	-0.7626	3.908	-0.195	0.845
mnth[Aug]	7.1560	3.535	2.024	0.043
mnth[Sept]	20.5912	3.046	6.761	0.000
mnth[Oct]	29.7472	2.700	11.019	0.000
mnth[Nov]	14.2229	2.860	4.972	0.000
hr[0]	-96.1420	3.955	-24.307	0.000
hr[1]	-110.7213	3.966	-27.916	0.000
hr[2]	-117.7212	4.016	-29.310	0.000
hr[3]	-127.2828	4.081	-31.191	0.000
hr[4]	-133.0495	4.117	-32.319	0.000
hr[5]	-120.2775	4.037	-29.794	0.000
hr[6]	-75.5424	3.992	-18.925	0.000
hr[7]	23.9511	3.969	6.035	0.000
hr[8]	127.5199	3.950	32.284	0.000
hr[9]	24.4399	3.936	6.209	0.000
hr[10]	-12.3407	3.936	-3.135	0.002
hr[11]	9.2814	3.945	2.353	0.019
hr[12]	41.1417	3.957	10.397	0.000
hr[13]	39.8939	3.975	10.036	0.000
hr[14]	30.4940	3.991	7.641	0.000
hr[15]	35.9445	3.995	8.998	0.000
hr[16]	82.3786	3.988	20.655	0.000
hr[17]	200.1249	3.964	50.488	0.000
hr[18]	173.2989	3.956	43.806	0.000
hr[19]	90.1138	3.940	22.872	0.000
hr[20]	29.4071	3.936	7.471	0.000
hr[21]	-8.5883	3.933	-2.184	0.029
hr[22]	-37.0194	3.934	-9.409	0.000
workingday	1.2696	1.784	0.711	0.477
temp	157.2094	10.261	15.321	0.000
weathersit[cloudy/misty]	-12.8903	1.964	-6.562	0.000
weathersit[heavy rain/snow]	-109.7446	76.667	-1.431	0.152
weathersit[light rain/snow]	-66.4944	2.965	-22.425	0.000

[70] : np.sum((M_lm.fittedvalues - M2_lm.fittedvalues)**2)

```
[70]: np.float64(4.844666422825268e-20)
```

```
[71]: np.allclose(M_lm.fittedvalues, M2_lm.fittedvalues)
```

```
[71]: True
```

```
[72]: coef_month = S2[S2.index.str.contains('mnth')]['coef']
coef_month
```

```
[72]: mnth[Jan]      -46.0871
mnth[Feb]       -39.2419
mnth[March]     -29.5357
mnth[April]      -4.6622
mnth[May]        26.4700
mnth[June]       21.7317
mnth[July]      -0.7626
mnth[Aug]         7.1560
mnth[Sept]      20.5912
mnth[Oct]        29.7472
mnth[Nov]       14.2229
Name: coef, dtype: float64
```

```
[73]: months = Bike['mnth'].dtype.categories
coef_month = pd.concat([
    coef_month,
    pd.Series([-coef_month.sum()],
              index=['mnth[Dec]'])
])
coef_month
```

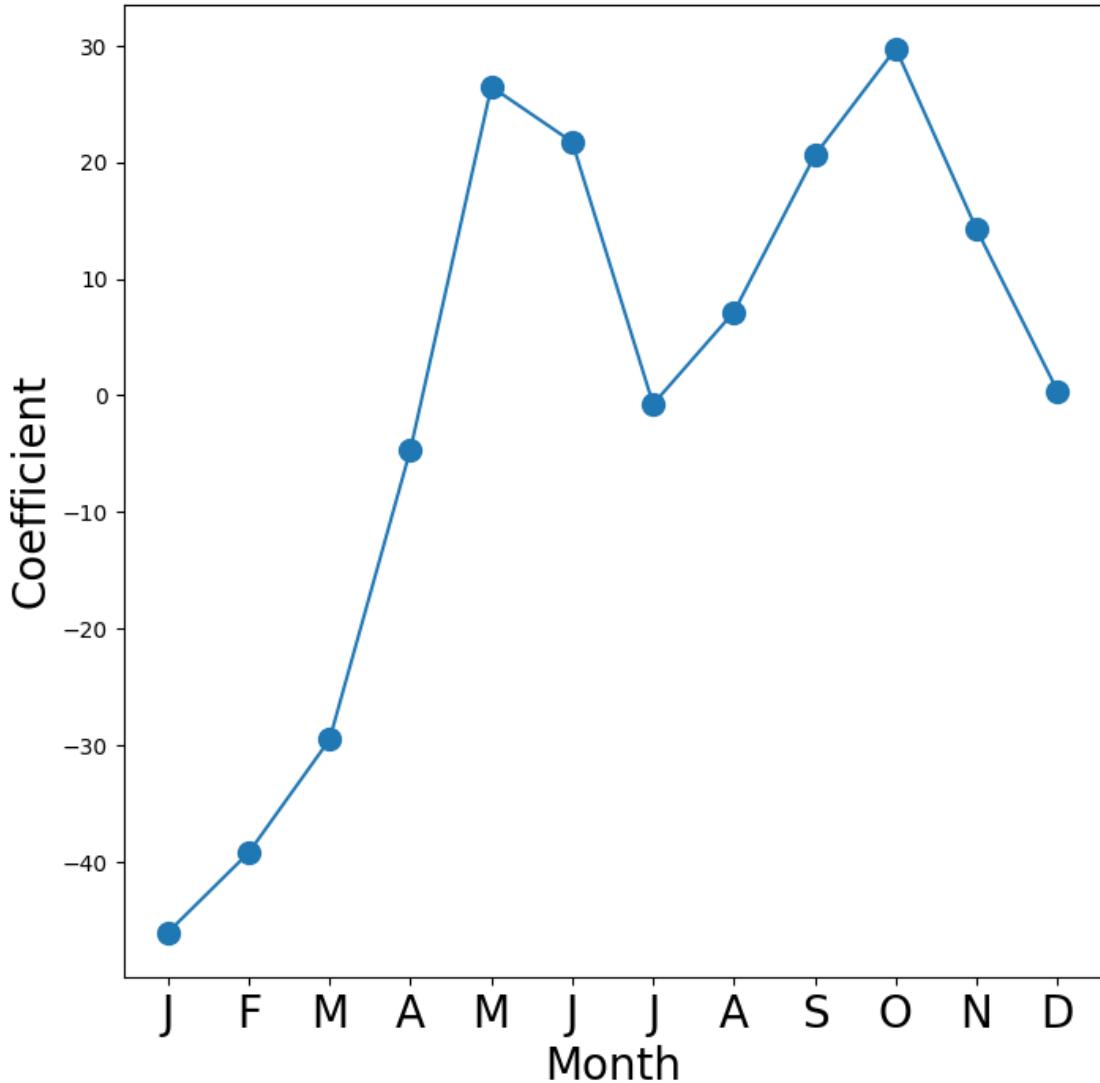
```
[73]: mnth[Jan]      -46.0871
mnth[Feb]       -39.2419
mnth[March]     -29.5357
mnth[April]      -4.6622
mnth[May]        26.4700
mnth[June]       21.7317
mnth[July]      -0.7626
mnth[Aug]         7.1560
mnth[Sept]      20.5912
mnth[Oct]        29.7472
mnth[Nov]       14.2229
mnth[Dec]        0.3705
dtype: float64
```

```
[74]: fig_month, ax_month = subplots(figsize=(8,8))
x_month = np.arange(coef_month.shape[0])
ax_month.plot(x_month, coef_month, marker='o', ms=10)
```

```

ax_month.set_xticks(x_month)
ax_month.set_xticklabels([l[5] for l in coef_month.index], fontsize=20)
ax_month.set_xlabel('Month', fontsize=20)
ax_month.set_ylabel('Coefficient', fontsize=20);

```



```

[75]: coef_hr = S2[S2.index.str.contains('hr')]['coef']
coef_hr = coef_hr.reindex(['hr[{:0}].format(h) for h in range(23)])
coef_hr = pd.concat([coef_hr,
                     pd.Series([-coef_hr.sum()], index=['hr[23]'])])

```

```

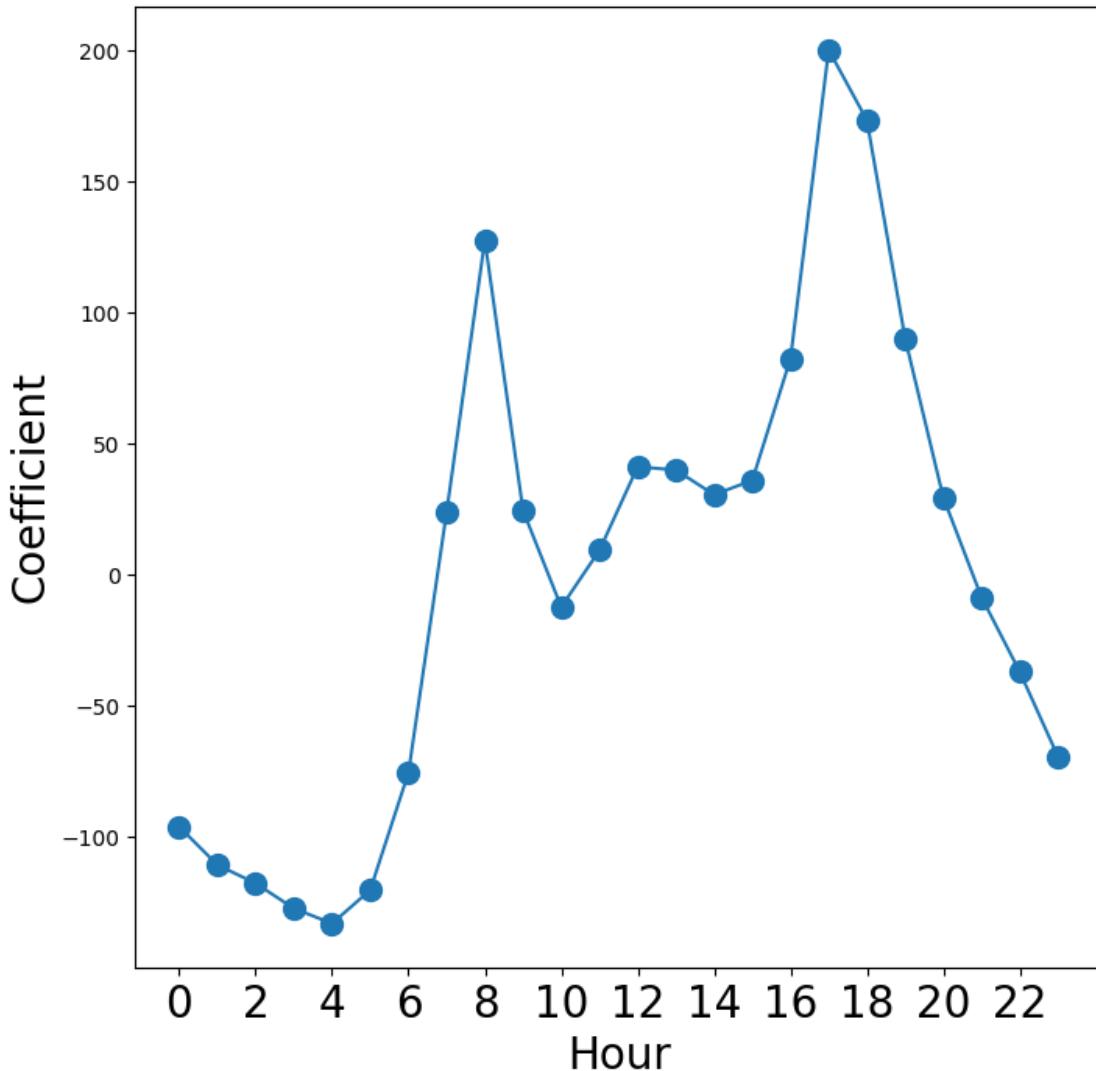
[76]: fig_hr, ax_hr = subplots(figsize=(8,8))
x_hr = np.arange(coef_hr.shape[0])

```

```

ax_hr.plot(x_hr, coef_hr, marker='o', ms=10)
ax_hr.set_xticks(x_hr[::2])
ax_hr.set_xticklabels(range(24)[::2], fontsize=20)
ax_hr.set_xlabel('Hour', fontsize=20)
ax_hr.set_ylabel('Coefficient', fontsize=20);

```



[77]: M_pois = sm.GLM(Y, X2, family=sm.families.Poisson()).fit()

[78]: S_pois = summarize(M_pois)
coef_month = S_pois[S_pois.index.str.contains('mnth')]['coef']
coef_month = pd.concat([coef_month,
pd.Series([-coef_month.sum()]),
index=['mnth[Dec]'])])

```

coef_hr = S_pois[S_pois.index.str.contains('hr')]['coef']
coef_hr = pd.concat([coef_hr,
                     pd.Series([-coef_hr.sum()]),
                     index=['hr[23]']])

```

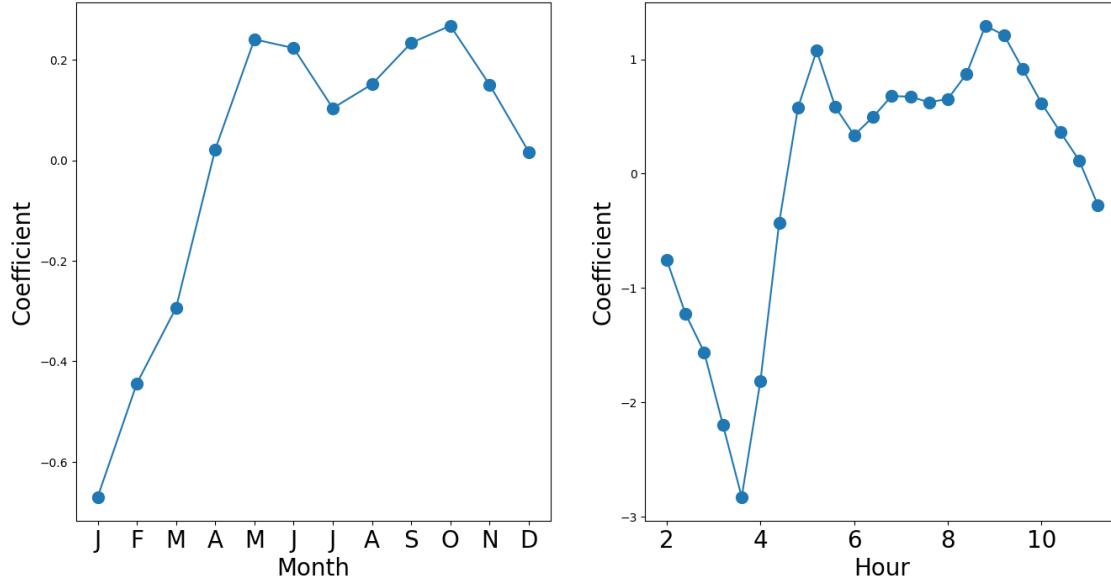
```

[79]: fig_pois, (ax_month, ax_hr) = subplots(1, 2, figsize=(16,8))
ax_month.plot(x_month, coef_month, marker='o', ms=10)
ax_month.set_xticks(x_month)
ax_month.set_xticklabels([l[5] for l in coef_month.index], fontsize=20)
ax_month.set_xlabel('Month', fontsize=20)
ax_month.set_ylabel('Coefficient', fontsize=20)
ax_hr.plot(x_hr, coef_hr, marker='o', ms=10)
ax_hr.set_xticklabels(range(24)[::2], fontsize=20)
ax_hr.set_xlabel('Hour', fontsize=20)
ax_hr.set_ylabel('Coefficient', fontsize=20);

```

C:\Users\archa\AppData\Local\Temp\ipykernel_24196\3779905754.py:8: UserWarning:
set_ticklabels() should only be used with a fixed number of ticks, i.e. after
set_ticks() or using a FixedLocator.

```
    ax_hr.set_xticklabels(range(24)[::2], fontsize=20)
```



```

[80]: fig, ax = subplots(figsize=(8, 8))
ax.scatter(M2_lm.fittedvalues,
           M_pois.fittedvalues,
           s=20)
ax.set_xlabel('Linear Regression Fit', fontsize=20)
ax.set_ylabel('Poisson Regression Fit', fontsize=20)
ax.axline([0,0], c='black', linewidth=3,

```

```
linestyle='--', slope=1);
```

