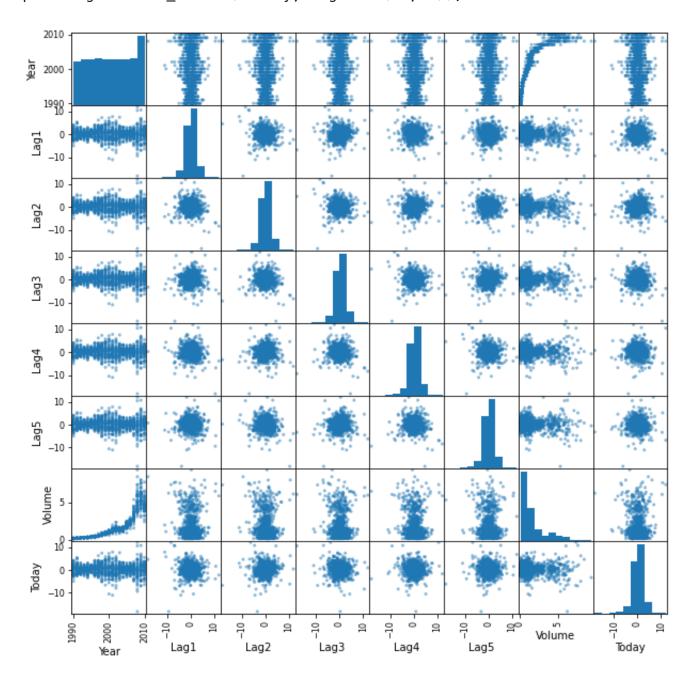
→ Problem 5 (Chapter 4, Exercise 10)

```
import pandas as pd
weekly = pd.read_csv("Weekly.csv")
weekly.info()
   <class 'pandas.core.frame.DataFrame'>
   RangeIndex: 1089 entries, 0 to 1088
   Data columns (total 9 columns):
         Column
                       Non-Null Count
    #
        rear 1089 non-null
Lag1 1089 non-null
Lag2 1089 non-null
Lag3 1089 non-null
Lag4 1089 non-null
Lag5 1089 non-null
Volume 1089 non-null
                                            Dtype
                                            int64
    0
    1
                                            float64
    2
                                            float64
    3
                                            float64
    4
                                            float64
    5
                                            float64
    6
                                            float64
    7
         Today
                       1089 non-null
                                            float64
         Direction 1089 non-null
                                            object
   dtypes: float64(7), int64(1), object(1)
   memory usage: 76.7+ KB
```

▼ Problem 5(a)

	Year	Lag1	Lag2	Lag3	Lag4	Lag5	
count	1089.000000	1089.000000	1089.000000	1089.000000	1089.000000	1089.000000	10
unique	NaN	NaN	NaN	NaN	NaN	NaN	
top	NaN	NaN	NaN	NaN	NaN	NaN	
freq	NaN	NaN	NaN	NaN	NaN	NaN	
mean	2000.048669	0.150585	0.151079	0.147205	0.145818	0.139893	
std	6.033182	2.357013	2.357254	2.360502	2.360279	2.361285	
min	1990.000000	-18.195000	-18.195000	-18.195000	-18.195000	-18.195000	
25%	1995.000000	-1.154000	-1.154000	-1.158000	-1.158000	-1.166000	
50%	2000.000000	0.241000	0.241000	0.241000	0.238000	0.234000	
75%	2005.000000	1.405000	1.409000	1.409000	1.409000	1.405000	
max	2010.000000	12.026000	12.026000	12.026000	12.026000	12.026000	



	Year	Lag1	Lag2	Lag3	Lag4	Lag5	Volume	Tod
Year	1.000000	-0.032289	-0.033390	-0.030006	-0.031128	-0.030519	0.841942	-0.0324
Lag1	-0.032289	1.000000	-0.074853	0.058636	-0.071274	-0.008183	-0.064951	-0.0750
Lag2	-0.033390	-0.074853	1.000000	-0.075721	0.058382	-0.072499	-0.085513	0.059 ⁻
Lag3	-0.030006	0.058636	-0.075721	1.000000	-0.075396	0.060657	-0.069288	-0.0712
Lag4	-0.031128	-0.071274	0.058382	-0.075396	1.000000	-0.075675	-0.061075	-0.0078
Lag5	-0.030519	-0.008183	-0.072499	0.060657	-0.075675	1.000000	-0.058517	0.011(
Volume	0.841942	-0.064951	-0.085513	-0.069288	-0.061075	-0.058517	1.000000	-0.0330
Today	-0.032460	-0.075032	0.059167	-0.071244	-0.007826	0.011013	-0.033078	1.0000

▼ Problem 5(b)

```
print(log_reg.summary())
```

Logit Regression Results

Dep. Varia Model: Method: Date: Time: converged: Covariance	Fr	i, 16 Jul 20 19:36	git Df Re MLE Df Mo 021 Pseud :57 Log-L rue LL-Nu	o R-squ.: ikelihood:	:	1089 1082 (0.006580 -743.18 -748.10 0.1313
=======	coef	std err	Z	P> z	[0.025	0.975
const Lag1 Lag2 Lag3 Lag4 Lag5 Volume	0.2669 -0.0413 0.0584 -0.0161 -0.0278 -0.0145 -0.0227	0.086 0.026 0.027 0.027 0.026 0.026 0.037	3.106 -1.563 2.175 -0.602 -1.050 -0.549 -0.616	0.002 0.118 0.030 0.547 0.294 0.583 0.538	0.098 -0.093 0.006 -0.068 -0.080 -0.066 -0.095	0.435 0.010 0.111 0.036 0.024 0.037 0.050

▼ Problem 5(c)

```
print(log_reg.pred_table())
    [[ 54. 430.]
    [ 48. 557.]]

acc = (54 + 557) / (54 + 430 + 48 + 557)
print(acc)
    0.5610651974288338

print(54/(54+430))
print(557/(557+48))
    0.1115702479338843
    0.9206611570247933
```

▼ Problem 5(d)

```
weekly1990to2008 = weekly.copy()
weekly1990to2008 = weekly1990to2008[weekly1990to2008['Year'] >= 1990]
weekly1990to2008 = weekly1990to2008[weekly1990to2008['Year'] <= 2008]</pre>
X_train = weekly1990to2008['Lag2']
X train = sm.add constant(X train)
y_train = weekly1990to2008['Direction'].astype('category').cat.codes
log reg = sm.Logit(y train, X train).fit()
   Optimization terminated successfully.
            Current function value: 0.685555
            Iterations 4
weekly2009to2010 = weekly.copy()
weekly2009to2010 = weekly2009to2010[weekly2009to2010['Year'] >= 2009]
weekly2009to2010 = weekly2009to2010[weekly2009to2010['Year'] <= 2010]</pre>
X test = weekly2009to2010['Lag2']
X_test = sm.add_constant(X_test)
y_test = weekly2009to2010['Direction'].astype('category').cat.codes
y pred = (log reg.predict(X test) >= 0.5).astype(int)
import numpy as np
cm = np.zeros((2,2))
for i in range(2):
  for j in range(2):
    cm[i, j] = sum(yt==i and yp==j for yt, yp in zip(y_test, y_pred))
\mathsf{cm}
  array([[ 9., 34.],
          [5., 56.]])
acc = (9 + 56) / (9 + 56 + 5 + 34)
print(acc)
  0.625
print(9/(9+34))
print(56/(5+56))
  0.20930232558139536
  0.9180327868852459
```

▼ Problem 5(e)

```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
lda = LDA()
lda.fit(X_train, y_train)
  LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
                              solver='svd', store_covariance=False, tol=0.0001)
from sklearn.metrics import confusion_matrix
y_pred = lda.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
   [[ 9 34]
    [ 5 56]]
acc = (9 + 56) / (9 + 56 + 5 + 34)
print(acc)
  0.625
print(9/(9+34))
print(56/(5+56))
  0.20930232558139536
  0.9180327868852459
```

▼ Problem 5(f)

```
y_pred = qda.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
  [[43 0]
   [61 0]]
  /usr/local/lib/python3.7/dist-packages/sklearn/discriminant_analysis.py:715: F
    X2 = np.dot(Xm, R * (S ** (-0.5)))
  /usr/local/lib/python3.7/dist-packages/sklearn/discriminant_analysis.py:715: F
    X2 = np.dot(Xm, R * (S ** (-0.5)))
  /usr/local/lib/python3.7/dist-packages/sklearn/discriminant_analysis.py:718: F
    u = np.asarray([np.sum(np.log(s)) for s in self.scalings_])
acc = (43) / (43+61)
print(acc)
  0.41346153846153844
print(43/(43+0))
print(0/(61+0))
  1.0
  0.0
```

▼ Problem 5(g)

```
acc = (21+30) / (21+30+22+31)
print(acc)

0.49038461538461536

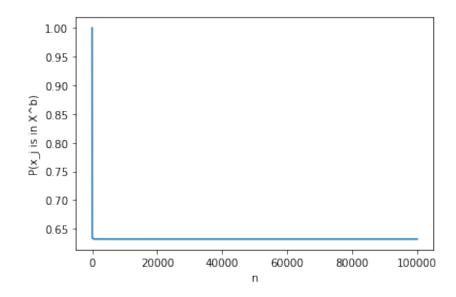
print(21/(21+22))
print(30/(31+30))

0.4883720930232558
0.4918032786885246
```

→ Problem 6 (Chapter 5, Exercise 2)

▼ Problem 6(g)

```
import matplotlib.pyplot as plt
plt.plot(np.arange(1, 100000), [1-(1-1/n)**n for n in np.arange(1, 100000)])
plt.xlabel("n")
plt.ylabel("P(x_j is in X^b)");
```



▼ Problem 6(h)

```
np.random.seed(1)

ctr = 0
for i in range(10000):
    a = np.random.choice(range(100), size=100, replace=True)
    if 4 in a:
        ctr += 1

print(ctr)
6302
```

Problem 7 (Chapter 5, Exercise 5)

```
default = pd.read_csv("Default.csv")
np.random.seed(1)
```

▼ Problem 7(a)

▼ Problem 7(b)

▼ Problem 7(c)

```
# trial 1
X_train, X_test, y_train, y_test = train_test_split(X, y)
log_reg = sm.Logit(y_train, X_train).fit()
y_pred = (log_reg.predict(X_test) >= 0.5).astype(int)
error = np.mean([yt != yp for yt, yp in zip(y_test, y_pred)])
print(error)
# trial 2
X_train, X_test, y_train, y_test = train_test_split(X, y)
log_reg = sm.Logit(y_train, X_train).fit()
y_pred = (log_reg.predict(X_test) >= 0.5).astype(int)
error = np.mean([yt != yp for yt, yp in zip(y_test, y_pred)])
print(error)
# trial 3
X_train, X_test, y_train, y_test = train_test_split(X, y)
log_reg = sm.Logit(y_train, X_train).fit()
y_pred = (log_reg.predict(X_test) >= 0.5).astype(int)
error = np.mean([yt != yp for yt, yp in zip(y_test, y_pred)])
print(error)
  Optimization terminated successfully.
            Current function value: 0.079030
            Iterations 10
  0.0236
  Optimization terminated successfully.
            Current function value: 0.076866
            Iterations 10
  0.0276
  Optimization terminated successfully.
            Current function value: 0.079056
            Iterations 10
  0.0272
```

▼ Problem 7(d)

→ Problem 8 (Chapter 5, Exercise 6)

```
default = pd.read_csv("Default.csv")
np.random.seed(1)
```

▼ Problem 8(a)

Logit Regression Results

Dep. Varia Model: Method: Date: Time: converged: Covariance		Fri, 16 Jul 19:3	ogit Df MLE Df 2021 Pse 6:59 Log True LL-	Observation Residuals: Model: udo R-squ.: -Likelihood: Null: p-value:		1000(999) 0.4594 -789.48 -1460.3 4.541e-292
=======	coef	std err	z	P> z	[0.025	0.975
const income balance	-11.5405 2.081e-05 0.0056	4.99e-06	-26.544 4.174 24.835	0.000	-12.393 1.1e-05 0.005	-10.688 3.06e-0! 0.000

Possibly complete quasi-separation: A fraction 0.14 of observations can be perfectly predicted. This might indicate that there is complete quasi-separation. In this case some parameters will not be identified.

▼ Problem 8(b)

```
def boot_fn(default, indices):
    X = default[['income', 'balance']]
    X = X.iloc[indices, :]
    X = sm.add_constant(X)

    y = default['default'].astype('category').cat.codes
    y = y.iloc[indices]

log_reg = sm.Logit(y, X).fit()

return log_reg.params[1:]
```

▼ Problem 8(c)

```
beta_is, beta_bs = [], []
B = 100

for i in range(B):
```

```
beta_i.beta_n (\bar{b}eta_n) (\bar{b}eta_n) (\bar{b}eta_n) (\bar{b}eta_n)
beta bs.append(beta b)
         Current function value: 0.070837
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.075469
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.074056
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.080399
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.079418
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.075494
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.076585
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.078997
          Iterations 10
Optimization terminated successfully.
         Current function value: 0.077621
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.077644
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.078250
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.076597
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.082268
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.079406
          Iterations 10
Optimization terminated successfully.
         Current function value: 0.080869
          Iterations 10
Optimization terminated successfully.
         Current function value: 0.075792
         Iterations 10
Optimization terminated successfully.
         Current function value: 0.079341
          Iterations 10
```

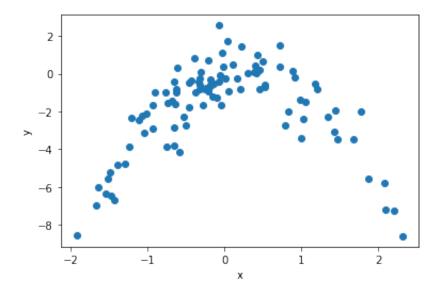
```
upilmization reminared successinity.
                                           Current function value: 0.076661
                                           Iterations 10
          Optimization terminated successfully.
                                           Current function value: 0.086022
                                           Iterations 10
          Optimization terminated successfully.
                                           Current function value: 0.083204
                                           Iterations 10
beta_i_mean = np.mean(beta_is)
                                     = np.sqrt(1/(B-1)*np.sum( [(beta_i - beta_i_mean)**2 for beta_i in bε
beta i se
beta_b_mean = np.mean(beta_bs)
beta_b_se = np.sqrt(1/(B-1)*np.sum([(beta_b - beta_b_mean)**2 for beta_b in beta_b)**2 for beta_b in beta_b_se = np.sqrt(1/(B-1)*np.sum([(beta_b - beta_b_mean)**2 for beta_b)**2 for beta_b in beta_b_se = np.sqrt(1/(B-1)*np.sum([(beta_b - beta_b_mean)**2 for beta_b)**2 for beta_b in beta_b_se = np.sqrt(1/(B-1)*np.sum([(beta_b - beta_b_mean)**2 for beta_b)**2 for beta_b_se = np.sqrt(1/(B-1)*np.sum([(beta_b - beta_b_mean)**2 for beta_b_se = np.sqrt(1/(B-1)*np.sum([(beta_b - beta_
print("beta_income (mean & SE)", beta_i_mean, beta_i_se)
print("beta_balance (mean & SE)", beta_b_mean, beta_b_se)
          beta income (mean & SE) 2.016973494321125e-05 5.4383662396369285e-06
          beta_balance (mean & SE) 0.005677686072213888 0.00022069873134705593
```

Problem 9 (Chapter 5, Exercise 8)

▼ Problem 9(a)

▼ Problem 9(b)

```
plt.scatter(data.x, data.y)
plt.xlabel("x")
plt.ylabel("y");
```



▼ Problem 9(c)

```
np.random.seed(1)
```

```
from sklearn.preprocessing import PolynomialFeatures
X = np.array(data['x']).reshape(-1, 1)
y = np.array(data['y']).reshape(-1, 1)
for k in [1, 2, 3, 4]:
  loocv_errors = []
  for i in range(data.shape[0]):
    X_{loo} = np.delete(X, i).reshape(-1, 1)
    y_loo = np.delete(y, i).reshape(-1, 1)
    pf
           = PolynomialFeatures(degree=k)
    Xp_loo = pf.fit_transform(X_loo)
    lin_reg = sm.OLS(y_loo, Xp_loo).fit()
    y_pred = lin_reg.predict(pf.transform(X[i].reshape(1,1)))
    loocv_error = (y_pred - y[i])**2
    loocv_errors.append(loocv_error)
  loocv_errors = np.array(loocv_errors)
  print("degree %d LOOCV error:" %k, "%+3.2e" %loocv_errors.mean())
  degree 1 L00CV error: +5.89e+00
  degree 2 L00CV error: +1.09e+00
  degree 3 L00CV error: +1.10e+00
  degree 4 L00CV error: +1.11e+00
```

▼ Problem 9(d)

```
np.random.seed(2)
```

```
for k in [1, 2, 3, 4]:
  loocv_errors = []
  for i in range(data.shape[0]):
   X_{loo} = np.delete(X, i).reshape(-1, 1)
   y_loo = np.delete(y, i).reshape(-1, 1)
           = PolynomialFeatures(degree=k)
   pf
   Xp_loo = pf.fit_transform(X_loo)
   lin_reg = sm.OLS(y_loo, Xp_loo).fit()
   y_pred = lin_reg.predict(pf.transform(X[i].reshape(1,1)))
    loocv_error = (y_pred - y[i])**2
    loocv errors.append(loocv error)
  loocv_errors = np.array(loocv_errors)
  print("degree %d LOOCV error:" %k, "%+3.2e" %loocv_errors.mean())
  degree 1 L00CV error: +5.89e+00
  degree 2 L00CV error: +1.09e+00
  degree 3 L00CV error: +1.10e+00
  degree 4 LOOCV error: +1.11e+00
```

▼ Problem 9(f)

```
X = np.array(data['x']).reshape(-1, 1)
y = np.array(data['y']).reshape(-1, 1)

for k in [1, 2, 3, 4]:

   pf = PolynomialFeatures(degree=k)
   Xp = pf.fit_transform(X)

   lin_reg = sm.OLS(y, Xp).fit()
   print(lin_reg.summary())
```

OLS Regression Results

```
Dep. Variable:
                                         R-squared:
                                                                            0.010
Model:
                                   0LS
                                         Adi. R-squared:
                                                                           -0.000
Method:
                         Least Squares
                                         F-statistic:
                                                                           0.9616
                                         Prob (F-statistic):
Date:
                      Fri, 16 Jul 2021
                                                                            0.329
                                                                          -226.84
                              19:37:03
                                         Log-Likelihood:
Time:
Nia Obaaniatiana.
```

Df Residuals:

Df Model:

100 AIC:

45/...

462.9

Covariance Type: nonrobust

=======	coef	std err	t	 P> t	[0.025	0.975
const x1	-1.8185 0.2430	0.236 0.248	-7.692 0.981	0.000 0.329	-2.288 -0.249	-1.349 0.73
Omnibus: Prob(Omnib Skew: Kurtosis:	ous):	-1.0	000 Jarque	•	=======	2.198 2.198 20.491 3.55e-0! 1.00

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correct OLS Regression Results

============			==========
Dep. Variable:	у	R-squared:	0.81
Model:	0LS	Adj. R-squared:	0.809
Method:	Least Squares	F-statistic:	210.6
Date:	Fri, 16 Jul 2021	<pre>Prob (F-statistic):</pre>	5.10e-36
Time:	19:37:03	Log-Likelihood:	-143.5!
No. Observations:	100	AIC:	293.1
Df Residuals:	97	BIC:	300.9

Df Model: 2 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975
const	-0 . 0954	0.133	-0.715	0.476	-0.360	0.169
x1	0.8996	0.113	7.961	0.000	0.675	1.124
x2	-1.8666	0.092	-20.399	0.000	-2.048	-1.68!
Omnibus:		1.	.794 Durbir	 n-Watson:		2.236
Prob(Omnib	bus):	0.	408 Jarque	e-Bera (JB):		1.22
Skew:		-0.	183 Prob(3	JB):		0.542
Kurtosis:		3.	399 Cond.	No.		2.47

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correct OLS Regression Results

Dep. Variable:	у	R-squared:	0.813
Model:	0LS	Adj. R-squared:	0.807
Method:	Least Squares	F-statistic:	139.1
Date:	Fri, 16 Jul 2021	<pre>Prob (F-statistic):</pre>	8.04e-3
Time:	19:37:03	Log-Likelihood:	-143.51
No. Observations:	100	AIC:	295.(
Df Dociduals:	ne ne	DTC.	30E 1

→ Problem 10 (Chapter 5, Exercise 9)

```
boston = pd.read_csv("Boston.csv")
```

▼ Problem 10(a)

```
mu_hat = boston['medv'].mean()
print(mu_hat)

22.532806324110698
```

▼ Problem 10(b)

```
SE_mu_hat = boston['medv'].std()/np.sqrt(boston.shape[0])
print(SE_mu_hat)
    0.4088611474975351
```

▼ Problem 10(c)

▼ Problem 10(d)

▼ Problem 10(e)

▼ Problem 10(f)

▼ Problem 10(g)

▼ Problem 10(h)