```
%matplotlib inline

from pathlib import Path

import numpy as np
import pandas as pd
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.metrics import roc_curve, auc

!pip install mord
from mord import LogisticIT
import matplotlib.pylab as plt
import seaborn as sns

!pip install dmba
from dmba import classificationSummary, gainsChart, liftChart
from dmba.metric import AIC_score
```

```
Requirement already satisfied: mord in /usr/local/lib/python3.11/dist-packages (0.7)
Requirement already satisfied: dmba in /usr/local/lib/python3.11/dist-packages (0.2.4)
Requirement already satisfied: graphviz in /usr/local/lib/python3.11/dist-packages (from dmba) (0.20.3)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (from dmba) (3.10.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from dmba) (1.26.4)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (from dmba) (2.2.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (from dmba) (1.6.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from dmba) (1.13.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (1.3
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (4.
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (1.
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (24.2
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (11.1.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba) (3.2
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib->dmba)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas->dmba) (2025.1)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas->dmba) (2025.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn->dmba) (1.4.
```

```
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn->dmba
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotl
```

```
mowers = pd.read_csv("RidingMowers.csv")
mowers.head()
```

	Income	Lot_Size	Ownership
0	60.0	18.4	Owner
1	85.5	16.8	Owner
2	64.8	21.6	Owner
3	61.5	20.8	Owner
4	87.0	23.6	Owner

1. What percentage of households in the study were owners of a riding mower?

```
num_owners = mowers[mowers["Ownership"] == "Owner"].shape[0]
num_owners
```

```
12
```

```
total_households = mowers.shape[0]
total_households
```

```
24
```

```
percent_owners=(num_owners/total_households) * 100
percent_owners
```

```
50.0
```

The percentage of households in the study that were owners is 50%

2. Use all the data to fit a logistic regression of ownership on the two predictors. Remember to create dummy variables, if appropriate.

```
mowers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24 entries, 0 to 23
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Income     24 non-null     float64
 1   Lot_Size   24 non-null     float64
 2   Ownership  24 non-null     object 
dtypes: float64(2), object(1)
memory usage: 708.0+ bytes
```

```
mowers.Ownership.unique()
```

```
array(['Owner', 'Nonowner'], dtype=object)
```

Changed ownershipnto category

```
mowers['Ownership'] = mowers['Ownership'].astype('category')
```

Created Dummies

```
mowers = pd.get_dummies(mowers, columns=['Ownership'], prefix='Ownership', drop_first=True)
```

```
print(mowers.columns)
```

```
Index(['Income', 'Lot_Size', 'Ownership_Owner'], dtype='object')
```

```
X = mowers[['Income', 'Lot_Size']]
y = mowers['Ownership_Owner']
train_X, valid_X, train_y,valid_y = train_test_split(X, y, test_size=0.4, random_state=1)
```

```
logit_reg = LogisticRegression(random_state=1,C= 1,solver='liblinear')
logit_reg.fit(train_X, train_y)
```

```
LogisticRegression
LogisticRegression(C=1, random_state=1, solver='liblinear')
```

```
logit_reg.intercept_
```

```
array([-0.40424044])
```

```
logit_reg.coef_
```

```
array([[ 0.05457264, -0.16890291]])
```

```
pd.DataFrame({'coef': logit_reg.coef_[0], 'variable': X.columns})
```

	coef	variable
0	0.054573	Income
1	-0.168903	Lot_Size

```
odds_ratios_mowers = pd.DataFrame({'coef': logit_reg.coef_[0], 'odds': np.e**logit_reg.coef_[0], 'variable': X.columns})
print(odds_ratios_mowers)
```

```
       coef      odds  variable
0  0.054573  1.056089    Income
```

```
   1 -0.168903  0.844591  Lot_Size
```

3. Generate the odds ratios and interpret insights.

Income (Odds Ratio = 1.0561) A 1-unit increase in income increases the odds of owning a riding mower by 5.61%. ((1.056089−1)×100=5.61%) An odds ratio > 1, means higher income increases ownership probability.

Lot Size (Odds Ratio = 0.8449) A 1-unit increase in lot size decreases the odds of owning a riding mower by 15.51%. ((0.8446−1)×100=−15.54%) An odds ratio < 1, means larger lot sizes decrease ownership probability.

```
Start coding or generate with AI.
```

```
logit_reg_prob = logit_reg.predict_proba(valid_X)
logit_reg_pred = logit_reg.predict(valid_X)
```

```
logit_result = pd.DataFrame({'actual': valid_y,
                             'p_0': [p[0] for p in logit_reg_prob],
                             'p_1': [p[1] for p in logit_reg_prob],
                             'predicted': logit_reg_pred})
logit_result
```

	actual	p_0	p_1	predicted
13	False	0.738075	0.261925	False
18	False	0.466319	0.533681	True
3	True	0.636731	0.363269	False
14	False	0.443508	0.556492	True
20	False	0.642792	0.357208	False
17	False	0.666402	0.333598	False
10	True	0.791980	0.208020	False
4	True	0.411572	0.588428	True
2	True	0.626267	0.373733	False
19	False	0.477580	0.522420	True

```
classes = ['Owner', 'Nonowner']
print(classificationSummary(valid_y,logit_reg.predict(valid_X)))
print(classificationSummary(train_y,logit_reg.predict(train_X)))
```

```
Confusion Matrix (Accuracy 0.4000)

       Prediction
Actual 0 1
     0 3 3
     1 3 1
None
Confusion Matrix (Accuracy 0.5714)

       Prediction
Actual 0 1
     0 2 4
     1 2 6
None
```

Double-click (or enter) to edit

4. Among nonowners, what is the percentage of households classified correctly?

From the confusioin matrix(valid),

Correctly Classified Nonowners

True Negatives (TN): 3 (Nonowners correctly classified as Nonowners).

False Positives (FP): 3 (Nonowners incorrectly classified as Owners).

- Percentage of Nonowners Correctly Classified:

True negative/total Nonowners

true negative = 3

Total non owners= 6

% of non owners= 3/6*100= 50 %

50.00% of household was classified correctly among non owners.

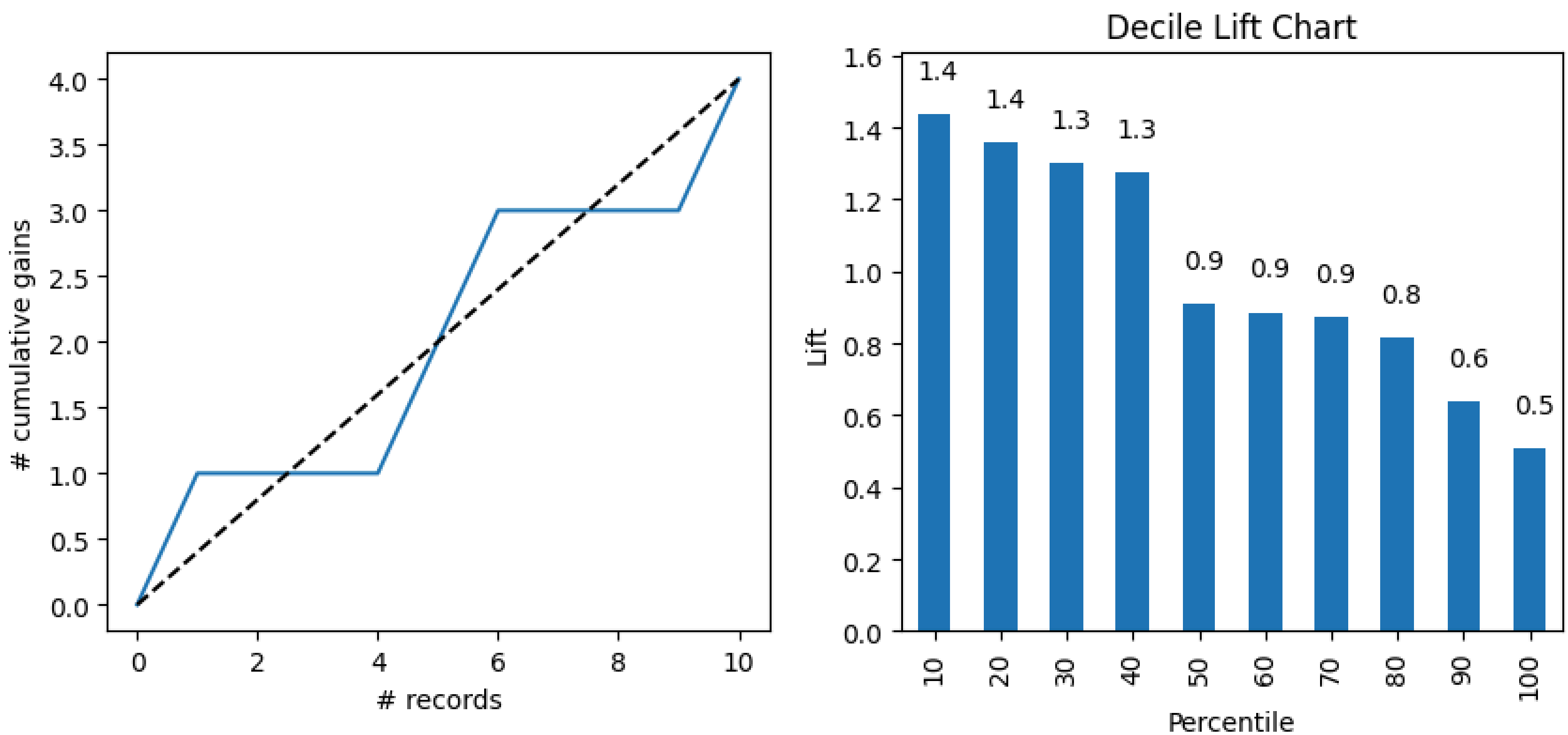
```
logit_result = logit_result.sort_values(by=['p_1'], ascending=False)
```

```
logit_result.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 10 entries, 4 to 10
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   actual     10 non-null     bool   
 1   p_0        10 non-null     float64
 2   p_1        10 non-null     float64
 3   predicted  10 non-null     bool   
dtypes: bool(2), float64(2)
memory usage: 260.0 bytes
```

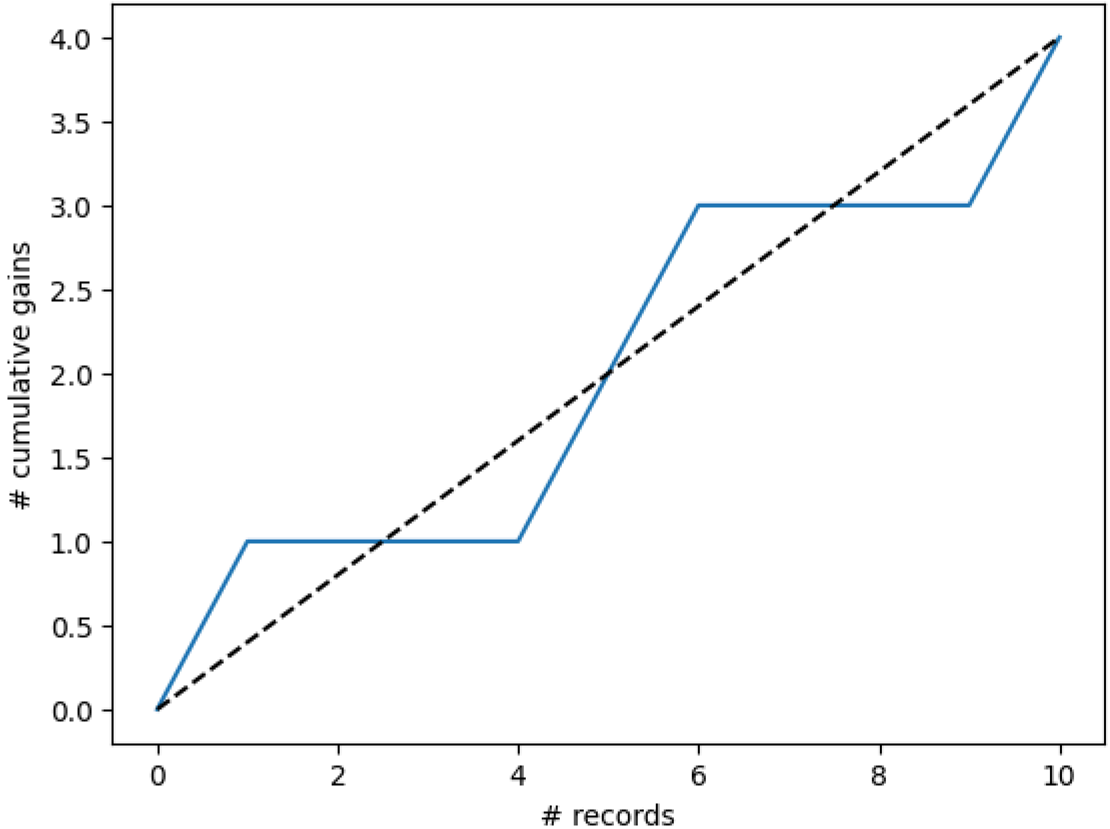
```
fig, axes = plt.subplots(1, 2, figsize=(10,4))
gainsChart(logit_result.actual, ax=axes[0])
liftChart(logit_result['p_1'], ax=axes[1])
```

```
<Axes: title={'center': 'Decile Lift Chart'}, xlabel='Percentile', ylabel='Lift'>
```



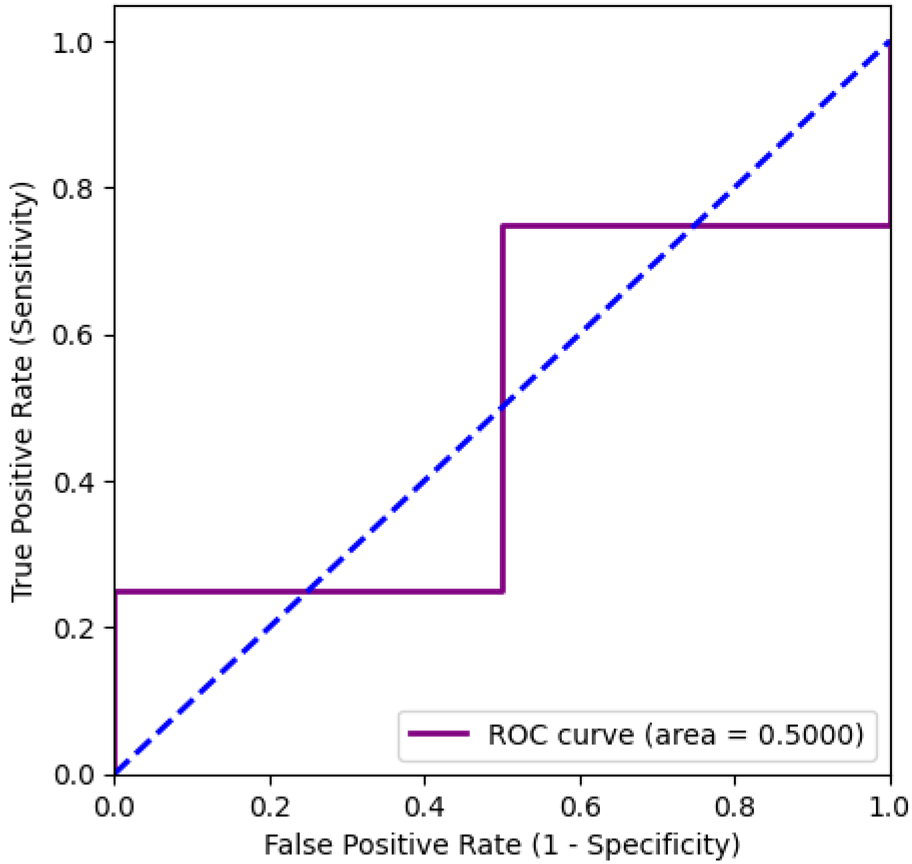

```
logit_result = logit_result.sort_values(by='p_1', ascending=False)
gainsChart(logit_result.actual)
```

<Axes: xlabel='# records', ylabel='# cumulative gains'>




```
fpr, tpr, _ = roc_curve(logit_result['actual'], logit_result['p_1'])
roc_auc = auc(fpr, tpr)
plt.figure(figsize=[5, 5])
plt.plot(fpr, tpr, color='purple',
 lw=2, label='ROC curve (area = %0.4f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='blue', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.legend(loc="lower right")
```

```
&lt;matplotlib.legend.Legend at 0x7c009e7ca090&gt;
```



Double-click (or enter) to edit

5. What is the probability that a household with a $60K income and a lot size of 20,000 ft2 is an owner?

```
Ownership_Nonowner_Riding_Mower= pd.DataFrame({'Income':[60.0],'Lot_Size':[20.0]})
Ownership_Nonowner_Riding_Mower
```

```
logit_reg.predict_proba(Ownership_Nonowner_Riding_Mower)
```

```
array([[0.6243235, 0.3756765]])
```

Double-click (or enter) to edit

```
#From the array displayed,
#The probability of being a non-owner is 0.6243 (62.43%).
#The probability  OF a household  being an owner is 0.3757 (37.57%).
```

6. What is the classification of a household with a $60K income and a lot size of 20,000 ft2? Use cutoff = 0.5

```
logit_reg.predict(Ownership_Nonowner_Riding_Mower)
```

```
array([False])
```