STAT3612: Statistical Machine Learning

Assignment 1: Python basics and logistic regression

DUE: Feb 16, 2025, Sunday, 11:59 PM

In [17]:
```
# TODO: please make sure you have Python 3.6+
# please install these packages:
# ! pip install numpy pandas matplotlib seaborn sklearn umap-learn
```

In [18]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from typing import Tuple
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_recall_fscore_support, accuracy_score, classi
# from sklearn.model_selection import train_test_split

import umap
sns.set_style("darkgrid")
```

Question 1

1a) False. Classification problems involve predicting discrete labels or categories, whereas regression problems involve predicting continuous or integer-valued quantities. Here, the goal is to predict a count (number of customers), which is a regression task.

1b) True.

1c) False. A model with lower bias overfits and performs well on train data, leading to poor generalization on test data. A model with slightly higher bias but lower variance might perform better on test data.

1d) True.

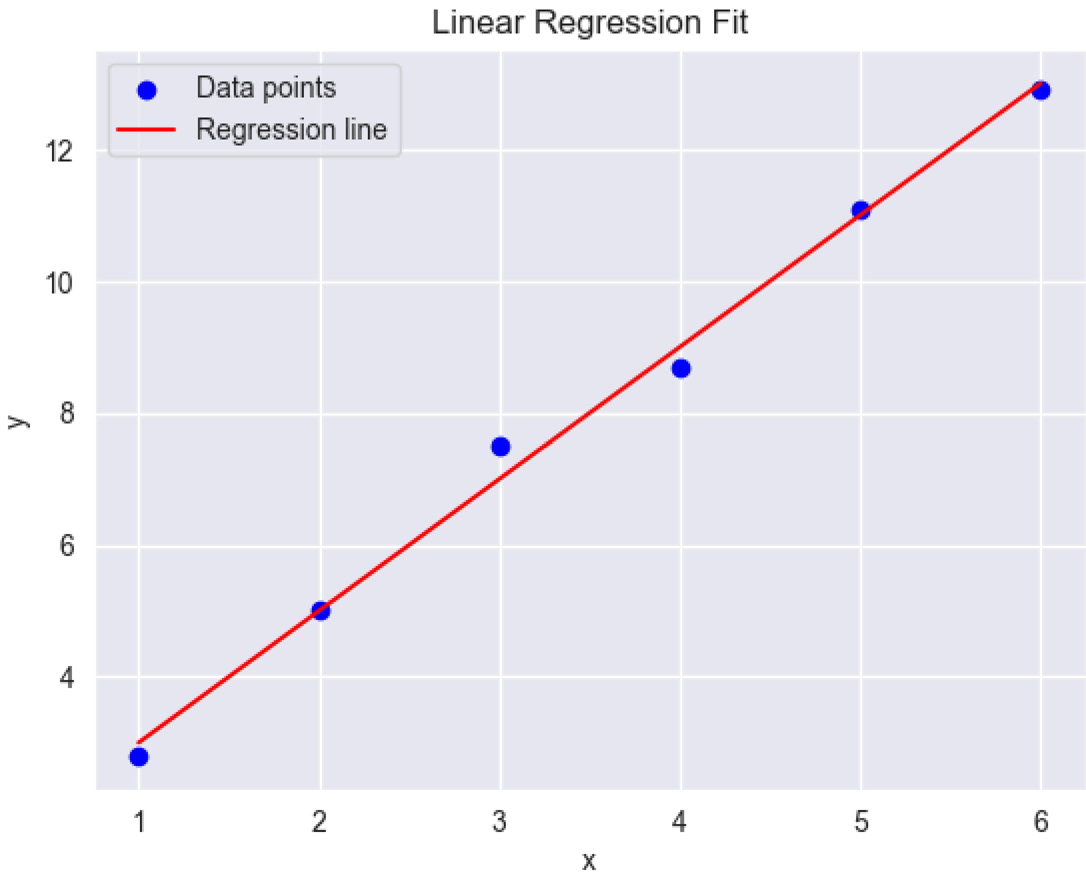
Question 2

2a)

In [19]:
```
# Given data
q2_x = np.array([1, 2, 3, 4, 5, 6])
q2_y = np.array([2.8, 5.0, 7.5, 8.7, 11.1, 12.9])

# Calculate the coefficients (theta0 and theta1) using numpy's polyfit
theta1, theta0 = np.polyfit(q2_x, q2_y, 1)

# Print the coefficients
print(f"theta0 (intercept): {theta0}")
print(f"theta1 (slope): {theta1}")

# Create the regression line
regression_line = theta0 + theta1 * q2_x
```

```
# Plot the data points
plt.scatter(q2_x, q2_y, color='blue', label='Data points')

# Plot the regression line
plt.plot(q2_x, regression_line, color='red', label='Regression line')

# Add labels and legend
plt.xlabel('x')
plt.ylabel('y')
plt.title('Linear Regression Fit')
plt.legend()

# Show the plot
plt.show()
```

```
theta0 (intercept): 1.0000000000000042
theta1 (slope): 2.0
```



2b)

In [20]:
```
# Construct matrix with increasing power
X = np.vander(q2_x, 6, increasing=True)

# Solve for the coefficients
theta = np.linalg.inv(X.T @ X) @ X.T @ q2_y

# Calculate the predicted values
q2y_pred = X @ theta

# Compute the training error
training_error = np.sum((q2_y - q2y_pred) ** 2)

print(f"Coefficients (theta): {theta}")
print(f"Predicted values: {q2y_pred}")
print(f"Training error: {training_error}")
```

```
Coefficients (theta): [ 14.9999999  -28.9049999   23.4791666   -7.92499998   1.220
83333
  -0.07      ]
Predicted values: [ 2.79999996  4.99999997  7.49999998  8.69999998 11.09999998 12.
89999998]
Training error: 4.035041436580033e-15
```

Using cost function

$$J(\theta) = \sum_{i=1}^{6} (y_i - \hat{y}_\theta(x_i))^2$$

, the training error computed is 4.035*10^-15.

Part 2: Python and NumPy basics

Question 3

3a)

In [21]:
```
file_path = "Employee-Attrition-Classification.csv"
col_names = ["Age", "Years at Company",  "Monthly Income",
             "Distance from Home", "Company Tenure", "Number of Promotions",
             "Number of Dependents", "Attrition"]

# Q3 (a)

# ------------------
# Write your code here
df = pd.read_csv(file_path)
df["Attrition"] = df["Attrition"].apply(lambda x: 1 if x == "Stayed" else 0)
display(df)

# ------------------
```

	Employee ID	Age	Gender	Years at Company	Job Role	Monthly Income	Work-Life Balance	Job Satisfaction	Performar Rati
0	8410	31	Male	19	Education	5390	Excellent	Medium	Avera
1	64756	59	Female	4	Media	5534	Poor	High	L
2	30257	24	Female	10	Healthcare	8159	Good	High	L
3	65791	36	Female	7	Education	3989	Good	High	H
4	65026	56	Male	41	Education	4821	Fair	Very High	Avera
...	...	...	...	...	...	...	...	...	
59593	37195	50	Female	12	Education	4414	Fair	High	Avera
59594	6266	18	Male	4	Healthcare	8040	Fair	High	H
59595	54887	22	Female	14	Technology	7944	Fair	High	H
59596	861	23	Male	8	Education	2931	Fair	Very High	Avera
59597	15796	56	Male	19	Technology	6660	Good	High	Avera

59598 rows × 24 columns

3b)

In [22]:
```
# Q3 (b)

attr_names = ["Age", "Years at Company",  "Monthly Income",
              "Distance from Home", "Company Tenure", "Number of Promotions",
              "Number of Dependents"]

# -----------------
# Write your code here
df_attr = df[attr_names]
df_attr_describe = df_attr.describe()
df_attr_describe.drop("count", inplace=True)
display(df_attr_describe)

# -----------------
```

	Age	Years at Company	Monthly Income	Distance from Home	Company Tenure	Number of Promotions	Number of Dependents
mean	38.565875	15.753901	7302.397983	50.007651	55.758415	0.832578	1.648075
std	12.079673	11.245981	2151.457423	28.466459	25.411090	0.994991	1.555689
min	18.000000	1.000000	1316.000000	1.000000	2.000000	0.000000	0.000000
25%	28.000000	7.000000	5658.000000	25.000000	36.000000	0.000000	0.000000
50%	39.000000	13.000000	7354.000000	50.000000	56.000000	1.000000	1.000000
75%	49.000000	23.000000	8880.000000	75.000000	76.000000	2.000000	3.000000
max	59.000000	51.000000	16149.000000	99.000000	128.000000	4.000000	6.000000

3c)

In [23]:
```
# Q3 (c)

# -----------------
# Write your code here
corr_matrix = df_attr.corr()
display(corr_matrix)

# -----------------
```

	Age	Years at Company	Monthly Income	Distance from Home	Company Tenure	Number of Promotions	Number of Dependents
Age	1.000000	0.539806	-0.001989	-0.007063	0.237048	0.000167	0.002927
Years at Company	0.539806	1.000000	-0.005288	-0.006888	0.442180	-0.000229	0.003973
Monthly Income	-0.001989	-0.005288	1.000000	-0.002528	-0.005397	0.006418	0.002582
Distance from Home	-0.007063	-0.006888	-0.002528	1.000000	-0.005595	-0.007882	0.000659
Company Tenure	0.237048	0.442180	-0.005397	-0.005595	1.000000	0.003903	0.001600
Number of Promotions	0.000167	-0.000229	0.006418	-0.007882	0.003903	1.000000	-0.000558
Number of Dependents	0.002927	0.003973	0.002582	0.000659	0.001600	-0.000558	1.000000

3d)

In [24]:
```
# Q3 (d)

attr_names = ["Age", "Years at Company",  "Monthly Income",
              "Distance from Home", "Company Tenure", "Number of Promotions",
              "Number of Dependents"]

# -----------------
# Write your code here
df_attr_standardised = (df_attr - df_attr.mean()) / df_attr.std()
display(df_attr_standardised)

# -----------------
```

	Age	Years at Company	Monthly Income	Distance from Home	Company Tenure	Number of Promotions	Number of Dependents
0	-0.626331	0.288645	-0.888885	-0.983883	1.308153	1.173299	-1.059386
1	1.691612	-1.045165	-0.821954	-1.019012	-1.367844	2.178333	0.869020
2	-1.205817	-0.511641	0.398150	-1.370302	0.717859	-0.836770	0.869020
3	-0.212413	-0.778403	-1.540071	-0.808237	-0.226610	0.168265	0.226218
4	1.443261	2.244900	-1.153357	0.737442	0.481742	-0.836770	-1.059386
...	...	...	...	...	...	...	...
59593	0.946559	-0.333799	-1.342531	0.561796	-0.816904	0.168265	0.226218
59594	-1.702519	-1.045165	0.342838	-0.281301	0.678506	2.178333	-1.059386
59595	-1.371384	-0.155958	0.298217	-0.562334	-1.053021	-0.836770	0.226218
59596	-1.288601	-0.689482	-2.031831	0.421280	-1.840079	-0.836770	-1.059386
59597	1.443261	0.288645	-0.298587	-1.054141	0.993330	-0.836770	0.869020

59598 rows × 7 columns

3e)

In [25]:
```
# Q3 (e)

# ------------------
# Write your code here
df_attributes = df[col_names]
df_80 = df_attributes.sample(frac=0.8, random_state=1)
df_20 = df_attributes.drop(index=df_80.index)

df_80_attr = df_80[attr_names]
df_20_attr = df_20[attr_names]

df_80_standardised = (df_80_attr - df_80_attr.mean()) / df_80_attr.std()
df_20_standardised = (df_20_attr - df_20_attr.mean()) / df_20_attr.std()

# ------------------
```

Ans: By standardizing the entire dataset before splitting, the test set indirectly influences the scaling of the training set as the mean and standard deviation are computed using information from the test set.

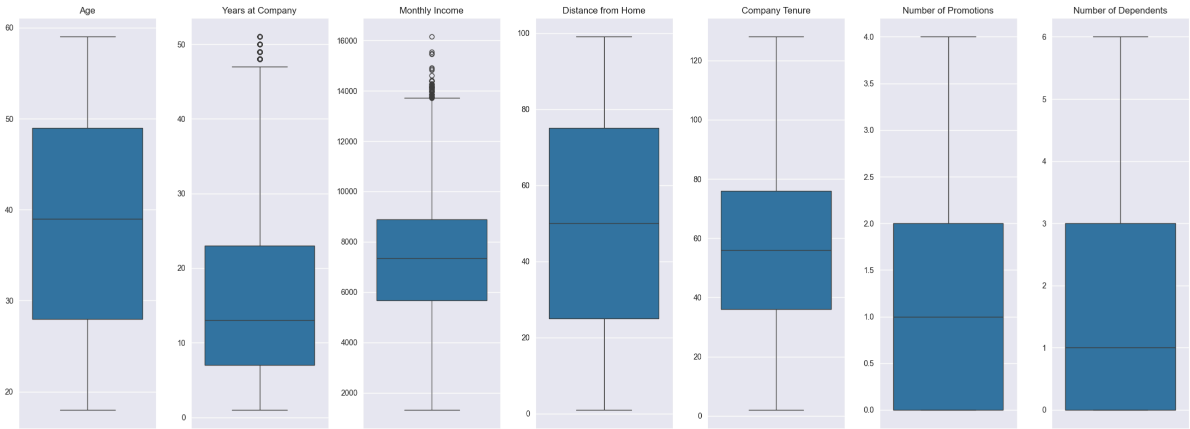
This introduces data leakage, where the trained model has access to information about the test set during training, leading to biased performance metrics.

We should calculate the mean and std only rely on training data, as testing data is considered as not known during training.

Part 2: Data visualization

4a)

In [26]:
```
# Q4 (a)

# ------------------
# Write your code here
fig, axes = plt.subplots(1, 7, figsize=(22, 8))

# Loop through each column and create a box plot
for i, col in enumerate(df_attr.columns):
    sns.boxplot(y=df[col], ax=axes[i])
    axes[i].set_title(col)
    axes[i].set_ylabel("")

plt.tight_layout()
plt.show()

# ------------------
```

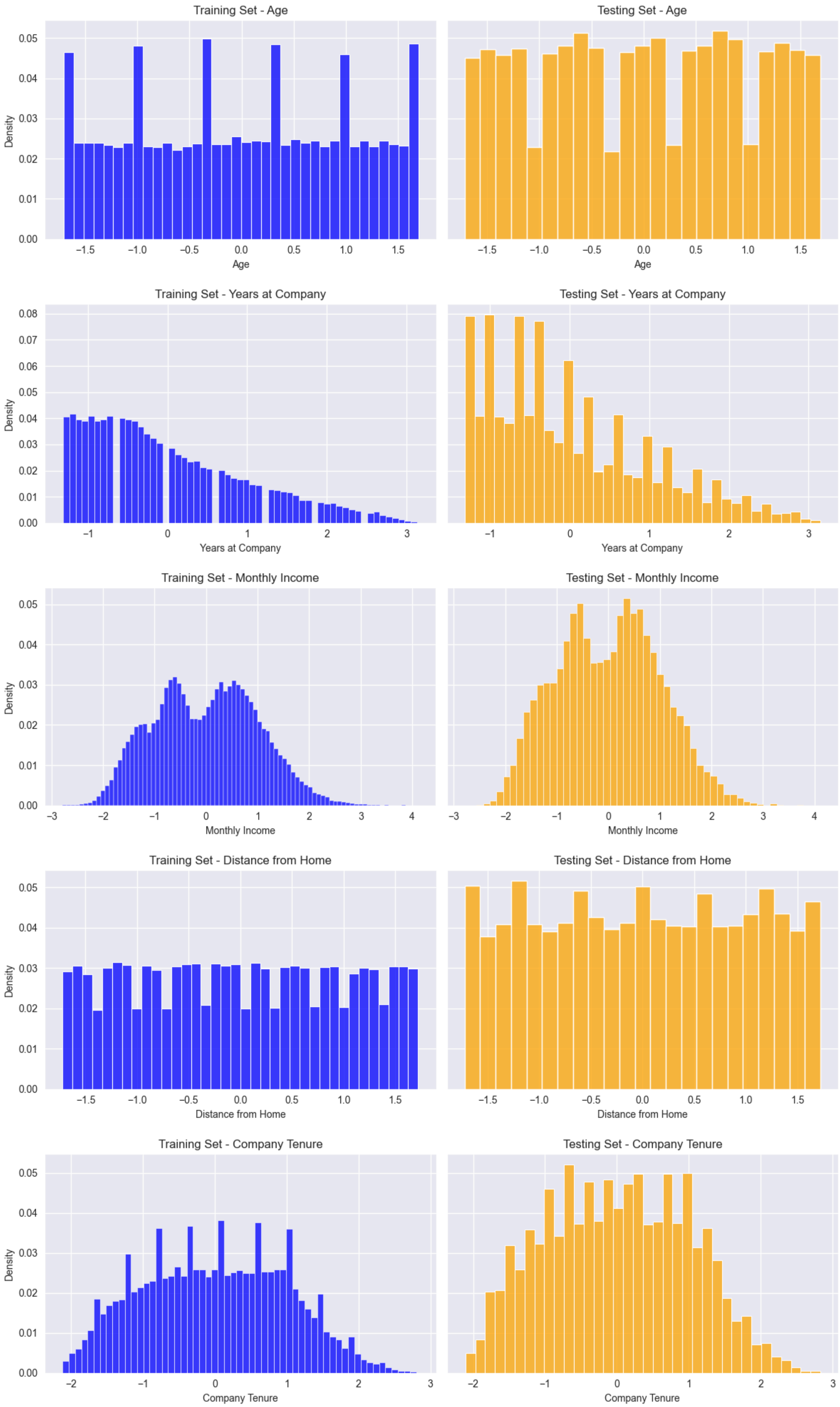


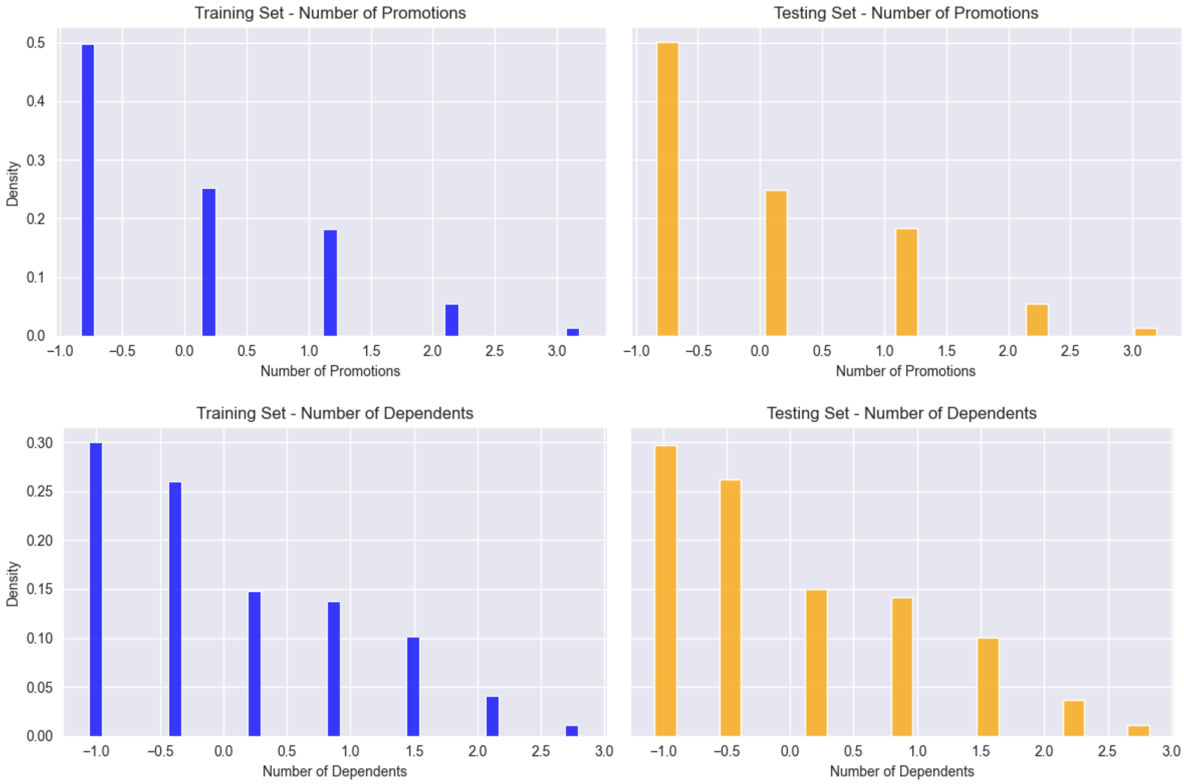
4b)

In [27]:
```
# Q4 (b)
#  -------------------
# Write your code here
plt.figure(figsize=(8, 6))
sns.heatmap(
    corr_matrix,
    annot=True,
    fmt=".2f",
    cmap="coolwarm",
    cbar=True,
    square=True,
    linewidths=0.5,
    linecolor="gray",
)

plt.title("Correlation Matrix Heatmap")
plt.show()

# -------------------
```

4c)

In [28]:
```
# Q4 (c)
#  -------------------
# Write your code here
for col in df_80_standardised.columns:
    fig, axes = plt.subplots(1, 2, figsize=(12, 4), sharex=True, sharey=True)

    # Plot training set distribution
    sns.histplot(df_80_standardised[col], color="blue", ax=axes[0], stat="probabili
    axes[0].set_title(f"Training Set - {col}")
    axes[0].set_xlabel(col)
    axes[0].set_ylabel("Density")

    # Plot testing set distribution
    sns.histplot(
        df_20_standardised[col], color="orange", ax=axes[1], stat="probability"
    )
    axes[1].set_title(f"Testing Set - {col}")
    axes[1].set_xlabel(col)
    axes[1].set_ylabel("Density")

    plt.tight_layout()
    plt.show()

#  -------------------
```


Training Set - Age
Testing Set - Age
Density
Age
Training Set - Years at Company
Testing Set - Years at Company
Years at Company
Training Set - Monthly Income
Testing Set - Monthly Income
Monthly Income
Training Set - Distance from Home
Testing Set - Distance from Home
Distance from Home
Training Set - Company Tenure
Testing Set - Company Tenure
Company Tenure



Part 3: Logistic regression

5a)

In [29]:

```
# Q5 (a)
train_columns = [
    "Age",
    "Years at Company",
    "Monthly Income",
    "Distance from Home",
    "Company Tenure",
    "Number of Promotions",
    "Number of Dependents",
]
test_columns = ["Attrition"]

# -------------------
# Write your code here
X_train, y_train, X_test, y_test = (
    df_80_standardised,
    df_80["Attrition"],
    df_20_standardised,
    df_20["Attrition"],
)

model = LogisticRegression()
model.fit(X_train, y_train)

model_coefficients = pd.DataFrame(
    {"Attribute": attr_names, "Coefficient": model.coef_[0]}
)
print(model_coefficients)

# -------------------
```

```
               Attribute  Coefficient
0                    Age     0.048789
1       Years at Company     0.099969
2         Monthly Income     0.016129
3     Distance from Home    -0.197254
4         Company Tenure     0.003194
5   Number of Promotions     0.169220
6   Number of Dependents     0.161791
```

5b)

Based on the model's output, the important positive features are "Number of Promotions" and "Number of Dependents", having the largest positive coefficients, suggesting they are the strongest predictors of retention. While "Age", "Years at Company", "Monthly Income", "Company Tenure" all have positive coefficients, its magnitude is not as large compared to "Number of Promotions" and "Number of Dependents", 0.169 and 0.162 respectively.

The feature "Distance from Home" with a negative coefficient, makes it a predictor of attrition.

Intuitively, this makes sense as employees who are promoted would be happy that they are recognised by peers and seniors, while those who have dependents need to continue working for provide for their dependents. Thus, these groups of workers are more likely to stay. On the other hand, employees who live far from work are more likely to leave, likely due to commute-related stress and time wasted on commuting everyday.

5c)

In [30]:

```
# Q5 (c)

# -------------------
# Write your code here

y_test_pred = model.predict(X_test)
y_train_pred = model.predict(X_train)

print("\nTraining Set Metrics:")
print(classification_report(y_train, y_train_pred))

print("\nTesting Set Metrics:")
print(classification_report(y_test, y_test_pred))

# -------------------
```

```
Training Set Metrics:
              precision    recall  f1-score   support

           0       0.55      0.45      0.50     22562
           1       0.58      0.67      0.62     25116

    accuracy                           0.57     47678
   macro avg       0.56      0.56      0.56     47678
weighted avg       0.56      0.57      0.56     47678


Testing Set Metrics:
              precision    recall  f1-score   support

           0       0.56      0.44      0.49      5776
           1       0.56      0.67      0.61      6144

    accuracy                           0.56     11920
   macro avg       0.56      0.55      0.55     11920
weighted avg       0.56      0.56      0.55     11920
```

5d)

I would like to introduce additional predictors "Job Satisfaction", "Employee Recognition", "Overtime", "Work-Life Balance", "Job Level".

In [31]:
```
# Introduce additional predictors and data cleaning
additional_columns = [
    "Job Satisfaction",
    "Employee Recognition",
    "Overtime",
    "Work-Life Balance",
    "Job Level",
]

attr_names.extend(additional_columns)
col_names.extend(additional_columns)

df["Job Satisfaction"] = df["Job Satisfaction"].apply(
    lambda x: 0 if x == "Low" else 1 if x == "Medium" else 2 if x == "High" else 3
)
df["Employee Recognition"] = df["Employee Recognition"].apply(
    lambda x: 0 if x == "Low" else 1 if x == "Medium" else 2 if x == "High" else 3
)
df["Overtime"] = df["Overtime"].apply(lambda x: 0 if x == "No" else 1)
df["Work-Life Balance"] = df["Work-Life Balance"].apply(
    lambda x: 0 if x == "Poor" else 1 if x == "Fair" else 2 if x == "Good" else 3
)
df["Job Level"] = df["Job Level"].apply(
    lambda x: 0 if x == "Entry" else 1 if x == "Mid" else 2
)
```

In [32]:
```
# Q5 (d)
# -------------------
# Write your code here
dff_attributes = df[col_names]
dff_80 = dff_attributes.sample(frac=0.8, random_state=1)
dff_20 = dff_attributes.drop(index=dff_80.index)

dff_80_attr = dff_80[attr_names]
dff_20_attr = dff_20[attr_names]
```

```
dff_80_standardised = (dff_80_attr - dff_80_attr.mean()) / dff_80_attr.std()
dff_20_standardised = (dff_20_attr - dff_20_attr.mean()) / dff_20_attr.std()

# Fit model
X_train_2, y_train_2, X_test_2, y_test_2 = (
    dff_80_standardised,
    dff_80["Attrition"],
    dff_20_standardised,
    dff_20["Attrition"],
)

model2 = LogisticRegression()
model2.fit(X_train_2, y_train)

model2_coefficients = pd.DataFrame(
    {"Attribute": attr_names, "Coefficient": model2.coef_[0]}
)
print(model2_coefficients)

# Report summary
y_test_pred_2 = model2.predict(X_test_2)
y_train_pred_2 = model2.predict(X_train_2)

print("\nTraining Set Metrics:")
print(classification_report(y_train_2, y_train_pred_2))

print("\nTesting Set Metrics:")
print(classification_report(y_test_2, y_test_pred_2))
# -------------------
```

```
                Attribute  Coefficient
0                     Age     0.057908
1        Years at Company     0.111990
2          Monthly Income     0.023430
3      Distance from Home    -0.228861
4          Company Tenure     0.004037
5    Number of Promotions     0.197314
6    Number of Dependents     0.187384
7        Job Satisfaction    -0.030714
8    Employee Recognition     0.019771
9                Overtime    -0.126311
10      Work-Life Balance     0.431720
11              Job Level     0.718147

Training Set Metrics:
              precision    recall  f1-score   support

           0       0.65      0.64      0.65     22562
           1       0.68      0.69      0.69     25116

    accuracy                           0.67     47678
   macro avg       0.67      0.67      0.67     47678
weighted avg       0.67      0.67      0.67     47678


Testing Set Metrics:
              precision    recall  f1-score   support

           0       0.67      0.64      0.66      5776
           1       0.68      0.71      0.69      6144

    accuracy                           0.67     11920
   macro avg       0.67      0.67      0.67     11920
weighted avg       0.67      0.67      0.67     11920
```

Simply include more attributes could improve the performance easily.