# Laboratory_Exercise_1_Feature_Scaling

July 16, 2025

# 1 Laboratory Exercise-1: Feature Scaling Methods

## 1.1 Data Preprocessing with Different Scaling Techniques on Social Network Ads Dataset

**AICTE Faculty ID:** 1-3241967546
**Faculty Name:** Milav Jayeshkumar Dabgar
**Date:** July 16, 2025

---

### 1.1.1 Objective:

This laboratory exercise demonstrates comprehensive data preprocessing techniques learned in Laboratory-1, with a special focus on different feature scaling methods applied to the Social Network Ads dataset.

### 1.1.2 Learning Outcomes:

- Apply complete data preprocessing pipeline
- Understand different feature scaling techniques
- Compare the effects of various scaling methods
- Evaluate model performance with different scaling approaches

---

## 1.2 1. Import Required Libraries

Import all necessary libraries for data preprocessing, feature scaling, visualization, and machine learning.

[1]:
```
# Basic libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Preprocessing libraries
from sklearn.preprocessing import (StandardScaler, MinMaxScaler, RobustScaler,
                                   Normalizer, MaxAbsScaler, QuantileTransformer,
```

```python
                                    PowerTransformer, LabelEncoder)
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer

# Machine Learning
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix

# Visualization settings
plt.style.use('seaborn-v0_8')
sns.set_palette("husl")
pd.set_option('display.max_columns', None)

print("All libraries imported successfully!")
```

```
All libraries imported successfully!
```

### 1.3 2. Load and Explore the Dataset

Load the Social Network Ads dataset and perform comprehensive exploratory data analysis.

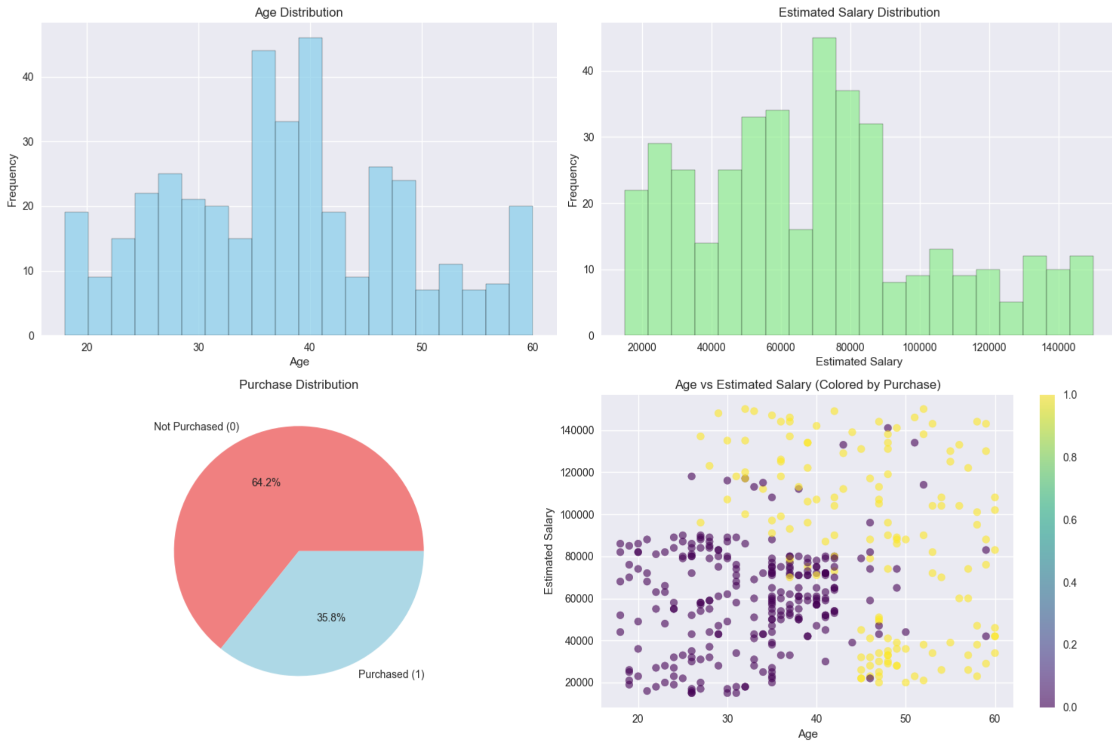
[2]:
```python
# Load the dataset
dataset = pd.read_csv('Social_Network_Ads.csv')

print("="*50)
print("SOCIAL NETWORK ADS DATASET EXPLORATION")
print("="*50)

print(f"\n Dataset Shape: {dataset.shape}")
print(f" Columns: {list(dataset.columns)}")

print("\n First 10 rows:")
print(dataset.head(10))

print("\n Dataset Info:")
print(dataset.info())

print("\n Statistical Summary:")
print(dataset.describe())

print("\n Target Variable Distribution:")
print(dataset['Purchased'].value_counts())
print(f"Purchase Rate: {dataset['Purchased'].mean():.2%}")

print("\n Missing Values Check:")
print(dataset.isnull().sum())
```

```
==================================================
SOCIAL NETWORK ADS DATASET EXPLORATION
==================================================

 Dataset Shape: (400, 3)
 Columns: ['Age', 'EstimatedSalary', 'Purchased']

 First 10 rows:
   Age  EstimatedSalary  Purchased
0   19            19000          0
1   35            20000          0
2   26            43000          0
3   27            57000          0
4   19            76000          0
5   27            58000          0
6   27            84000          0
7   32           150000          1
8   25            33000          0
9   35            65000          0

 Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 3 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Age              400 non-null    int64
 1   EstimatedSalary  400 non-null    int64
 2   Purchased        400 non-null    int64
dtypes: int64(3)
memory usage: 9.5 KB
None

 Statistical Summary:
              Age  EstimatedSalary   Purchased
count  400.000000       400.000000  400.000000
mean    37.655000     69742.500000    0.357500
std     10.482877     34096.960282    0.479864
min     18.000000     15000.000000    0.000000
25%     29.750000     43000.000000    0.000000
50%     37.000000     70000.000000    0.000000
75%     46.000000     88000.000000    1.000000
max     60.000000    150000.000000    1.000000

 Target Variable Distribution:
Purchased
0    257
1    143
```

```
Name: count, dtype: int64
Purchase Rate: 35.75%

 Missing Values Check:
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

[3]:

```
# Data Visualization
fig, axes = plt.subplots(2, 2, figsize=(15, 10))

# Age distribution
axes[0, 0].hist(dataset['Age'], bins=20, alpha=0.7, color='skyblue',␣
 ↪edgecolor='black')
axes[0, 0].set_title('Age Distribution')
axes[0, 0].set_xlabel('Age')
axes[0, 0].set_ylabel('Frequency')

# Estimated Salary distribution
axes[0, 1].hist(dataset['EstimatedSalary'], bins=20, alpha=0.7,␣
 ↪color='lightgreen', edgecolor='black')
axes[0, 1].set_title('Estimated Salary Distribution')
axes[0, 1].set_xlabel('Estimated Salary')
axes[0, 1].set_ylabel('Frequency')

# Purchase distribution
purchase_counts = dataset['Purchased'].value_counts()
axes[1, 0].pie(purchase_counts.values, labels=['Not Purchased (0)', 'Purchased␣
 ↪(1)'],
               autopct='%1.1f%%', colors=['lightcoral', 'lightblue'])
axes[1, 0].set_title('Purchase Distribution')

# Scatter plot: Age vs Salary colored by Purchase
scatter = axes[1, 1].scatter(dataset['Age'], dataset['EstimatedSalary'],
                            c=dataset['Purchased'], cmap='viridis', alpha=0.6)
axes[1, 1].set_title('Age vs Estimated Salary (Colored by Purchase)')
axes[1, 1].set_xlabel('Age')
axes[1, 1].set_ylabel('Estimated Salary')
plt.colorbar(scatter, ax=axes[1, 1])

plt.tight_layout()
plt.show()
```




### 1.4 3. Data Preprocessing and Cleaning

Check for data quality issues and prepare the dataset for feature scaling.

[4]:
```python
# Data Quality Check
print("="*50)
print("DATA QUALITY ASSESSMENT")
print("="*50)

print("\n  Checking for missing values:")
missing_values = dataset.isnull().sum()
print(missing_values)

print("\n  Checking for duplicates:")
duplicates = dataset.duplicated().sum()
print(f"Number of duplicate rows: {duplicates}")

print("\n  Data types:")
print(dataset.dtypes)

print("\n  Unique values in each column:")
for col in dataset.columns:
    print(f"{col}: {dataset[col].nunique()} unique values")
```

```python
# Check for outliers using IQR method
print("\n Outlier Detection (using IQR method):")
for col in ['Age', 'EstimatedSalary']:
    Q1 = dataset[col].quantile(0.25)
    Q3 = dataset[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = dataset[(dataset[col] < lower_bound) | (dataset[col] >
 ↪upper_bound)]
    print(f"{col}: {len(outliers)} outliers detected")

print("\n Data quality check complete! No missing values found.")
print(" Ready for feature scaling experiments!")
```

```
==================================================
DATA QUALITY ASSESSMENT
==================================================

 Checking for missing values:
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64

 Checking for duplicates:
Number of duplicate rows: 33

 Data types:
Age                int64
EstimatedSalary    int64
Purchased          int64
dtype: object

 Unique values in each column:
Age: 43 unique values
EstimatedSalary: 117 unique values
Purchased: 2 unique values

 Outlier Detection (using IQR method):
Age: 0 outliers detected
EstimatedSalary: 0 outliers detected

 Data quality check complete! No missing values found.
 Ready for feature scaling experiments!
```

## 1.5 4. Feature Selection and Target Variable Setup

Separate features and target variable, and prepare data structures for scaling experiments.

[5]:
```python
# Extract features and target variable
print("="*50)
print("FEATURE EXTRACTION")
print("="*50)

# Independent variables (features): Age and EstimatedSalary
X = dataset[['Age', 'EstimatedSalary']].values
feature_names = ['Age', 'EstimatedSalary']

# Dependent variable (target): Purchased
y = dataset['Purchased'].values

print(f"\n Features (X) shape: {X.shape}")
print(f" Target (y) shape: {y.shape}")

print(f"\n Feature names: {feature_names}")
print(f" Target classes: {np.unique(y)}")

print("\n Original features (first 10 rows):")
X_df = pd.DataFrame(X, columns=feature_names)
print(X_df.head(10))

print("\n Feature statistics:")
print(X_df.describe())

# Store original data for comparison
X_original = X.copy()
print("\n Features and target variables extracted successfully!")
```

```
==================================================
FEATURE EXTRACTION
==================================================

 Features (X) shape: (400, 2)
 Target (y) shape: (400,)

 Feature names: ['Age', 'EstimatedSalary']
 Target classes: [0 1]

 Original features (first 10 rows):
   Age  EstimatedSalary
0   19            19000
1   35            20000
2   26            43000
3   27            57000
```

```
4    19              76000
5    27              58000
6    27              84000
7    32             150000
8    25              33000
9    35              65000

 Feature statistics:
              Age  EstimatedSalary
count  400.000000       400.000000
mean    37.655000     69742.500000
std     10.482877     34096.960282
min     18.000000     15000.000000
25%     29.750000     43000.000000
50%     37.000000     70000.000000
75%     46.000000     88000.000000
max     60.000000    150000.000000

 Features and target variables extracted successfully!
```

## 1.6 5. StandardScaler Implementation

Apply StandardScaler to normalize features to have mean=0 and standard deviation=1.

[6]:
```
# StandardScaler: z = (x - ) /
print("="*60)
print("STANDARDSCALER (Z-SCORE NORMALIZATION)")
print("="*60)

scaler_standard = StandardScaler()
X_standard = scaler_standard.fit_transform(X)

print("  StandardScaler Parameters:")
print(f"Mean values: {scaler_standard.mean_}")
print(f"Standard deviations: {scaler_standard.scale_}")

print("\n  Original vs Standardized Data (first 10 rows):")
comparison_df = pd.DataFrame({
    'Age_Original': X[:10, 0],
    'Age_Standard': X_standard[:10, 0],
    'Salary_Original': X[:10, 1],
    'Salary_Standard': X_standard[:10, 1]
})
print(comparison_df)

print("\n  Standardized Data Statistics:")
X_standard_df = pd.DataFrame(X_standard, columns=[f'{name}_Standard' for name␣
↪in feature_names])
```

```
print(X_standard_df.describe())

print(f"\n  Standardized features have mean   0 and std   1")
print(f"Mean: {X_standard_df.mean().values}")
print(f"Std: {X_standard_df.std().values}")
```

```
============================================================
STANDARDSCALER (Z-SCORE NORMALIZATION)
============================================================
  StandardScaler Parameters:
Mean values: [3.76550e+01 6.97425e+04]
Standard deviations: [1.04697648e+01 3.40543124e+04]

  Original vs Standardized Data (first 10 rows):
   Age_Original  Age_Standard  Salary_Original  Salary_Standard
0            19     -1.781797            19000        -1.490046
1            35     -0.253587            20000        -1.460681
2            26     -1.113206            43000        -0.785290
3            27     -1.017692            57000        -0.374182
4            19     -1.781797            76000         0.183751
5            27     -1.017692            58000        -0.344817
6            27     -1.017692            84000         0.418669
7            32     -0.540127           150000         2.356750
8            25     -1.208719            33000        -1.078938
9            35     -0.253587            65000        -0.139263

  Standardized Data Statistics:
       Age_Standard  EstimatedSalary_Standard
count  4.000000e+02              4.000000e+02
mean  -7.105427e-17             -1.776357e-17
std    1.001252e+00              1.001252e+00
min   -1.877311e+00             -1.607506e+00
25%   -7.550313e-01             -7.852897e-01
50%   -6.256110e-02              7.561451e-03
75%    7.970571e-01              5.361289e-01
max    2.134241e+00              2.356750e+00

  Standardized features have mean   0 and std   1
Mean: [-7.10542736e-17 -1.77635684e-17]
Std: [1.00125235 1.00125235]
```

## 1.7 6. MinMaxScaler Implementation

Apply MinMaxScaler to scale features to a range between 0 and 1.

[7]:
```
# MinMaxScaler: z = (x - min) / (max - min)
print("="*60)
print("MINMAXSCALER (NORMALIZATION)")
```

```python
print("="*60)

scaler_minmax = MinMaxScaler()
X_minmax = scaler_minmax.fit_transform(X)

print("  MinMaxScaler Parameters:")
print(f"Data min values: {scaler_minmax.data_min_}")
print(f"Data max values: {scaler_minmax.data_max_}")
print(f"Data range: {scaler_minmax.data_range_}")

print("\n  Original vs MinMax Scaled Data (first 10 rows):")
comparison_df = pd.DataFrame({
    'Age_Original': X[:10, 0],
    'Age_MinMax': X_minmax[:10, 0],
    'Salary_Original': X[:10, 1],
    'Salary_MinMax': X_minmax[:10, 1]
})
print(comparison_df)

print("\n  MinMax Scaled Data Statistics:")
X_minmax_df = pd.DataFrame(X_minmax, columns=[f'{name}_MinMax' for name in feature_names])
print(X_minmax_df.describe())

print(f"\n  MinMax scaled features range from 0 to 1")
print(f"Min values: {X_minmax_df.min().values}")
print(f"Max values: {X_minmax_df.max().values}")
```

```
============================================================
MINMAXSCALER (NORMALIZATION)
============================================================
  MinMaxScaler Parameters:
Data min values: [   18. 15000.]
Data max values: [6.0e+01 1.5e+05]
Data range: [4.20e+01 1.35e+05]

  Original vs MinMax Scaled Data (first 10 rows):
   Age_Original  Age_MinMax  Salary_Original  Salary_MinMax
0            19    0.023810            19000       0.029630
1            35    0.404762            20000       0.037037
2            26    0.190476            43000       0.207407
3            27    0.214286            57000       0.311111
4            19    0.023810            76000       0.451852
5            27    0.214286            58000       0.318519
6            27    0.214286            84000       0.511111
7            32    0.333333           150000       1.000000
8            25    0.166667            33000       0.133333
9            35    0.404762            65000       0.370370
```

```
 MinMax Scaled Data Statistics:
       Age_MinMax  EstimatedSalary_MinMax
count  400.000000              400.000000
mean     0.467976                0.405500
std      0.249592                0.252570
min      0.000000                0.000000
25%      0.279762                0.207407
50%      0.452381                0.407407
75%      0.666667                0.540741
max      1.000000                1.000000

 MinMax scaled features range from 0 to 1
Min values: [0. 0.]
Max values: [1. 1.]
```

## 1.8 7. RobustScaler Implementation

Apply RobustScaler using median and interquartile range - robust to outliers.

[8]:
```python
# RobustScaler: z = (x - median) / IQR
print("="*60)
print("ROBUSTSCALER (MEDIAN AND IQR BASED)")
print("="*60)

scaler_robust = RobustScaler()
X_robust = scaler_robust.fit_transform(X)

print("  RobustScaler Parameters:")
print(f"Center (median): {scaler_robust.center_}")
print(f"Scale (IQR): {scaler_robust.scale_}")

print("\n  Original vs Robust Scaled Data (first 10 rows):")
comparison_df = pd.DataFrame({
    'Age_Original': X[:10, 0],
    'Age_Robust': X_robust[:10, 0],
    'Salary_Original': X[:10, 1],
    'Salary_Robust': X_robust[:10, 1]
})
print(comparison_df)

print("\n  Robust Scaled Data Statistics:")
X_robust_df = pd.DataFrame(X_robust, columns=[f'{name}_Robust' for name in␣
↪feature_names])
print(X_robust_df.describe())

print(f"\n  RobustScaler is resistant to outliers")
print(f"Median values: {X_robust_df.median().values}")
```

```
print(f"IQR (Q3-Q1): {X_robust_df.quantile(0.75).values - X_robust_df.
    ↪quantile(0.25).values}")
```

```
============================================================
ROBUSTSCALER (MEDIAN AND IQR BASED)
============================================================
 RobustScaler Parameters:
Center (median): [3.7e+01 7.0e+04]
Scale (IQR): [1.625e+01 4.500e+04]

 Original vs Robust Scaled Data (first 10 rows):
   Age_Original  Age_Robust  Salary_Original  Salary_Robust
0            19   -1.107692            19000      -1.133333
1            35   -0.123077            20000      -1.111111
2            26   -0.676923            43000      -0.600000
3            27   -0.615385            57000      -0.288889
4            19   -1.107692            76000       0.133333
5            27   -0.615385            58000      -0.266667
6            27   -0.615385            84000       0.311111
7            32   -0.307692           150000       1.777778
8            25   -0.738462            33000      -0.822222
9            35   -0.123077            65000      -0.111111

 Robust Scaled Data Statistics:
       Age_Robust  EstimatedSalary_Robust
count  400.000000              400.000000
mean     0.040308               -0.005722
std      0.645100                0.757710
min     -1.169231               -1.222222
25%     -0.446154               -0.600000
50%      0.000000                0.000000
75%      0.553846                0.400000
max      1.415385                1.777778

 RobustScaler is resistant to outliers
Median values: [0. 0.]
IQR (Q3-Q1): [1. 1.]
```

### 1.9 8. Normalizer Implementation

Apply Normalizer to scale individual samples to have unit norm (L1 and L2).

[9]:
```
# Normalizer: scales individual samples to have unit norm
print("="*60)
print("NORMALIZER (UNIT NORM SCALING)")
print("="*60)

# L2 Normalization (default)
```

```python
normalizer_l2 = Normalizer(norm='l2')
X_normalized_l2 = normalizer_l2.fit_transform(X)

# L1 Normalization
normalizer_l1 = Normalizer(norm='l1')
X_normalized_l1 = normalizer_l1.fit_transform(X)

print("  Original vs L2 Normalized vs L1 Normalized Data (first 5 rows):")
comparison_df = pd.DataFrame({
    'Age_Original': X[:5, 0],
    'Age_L2_Norm': X_normalized_l2[:5, 0],
    'Age_L1_Norm': X_normalized_l1[:5, 0],
    'Salary_Original': X[:5, 1],
    'Salary_L2_Norm': X_normalized_l2[:5, 1],
    'Salary_L1_Norm': X_normalized_l1[:5, 1]
})
print(comparison_df)

print("\n  L2 Normalized Data Statistics:")
X_l2_df = pd.DataFrame(X_normalized_l2, columns=[f'{name}_L2_Norm' for name in␣
↪feature_names])
print(X_l2_df.describe())

print("\n  L1 Normalized Data Statistics:")
X_l1_df = pd.DataFrame(X_normalized_l1, columns=[f'{name}_L1_Norm' for name in␣
↪feature_names])
print(X_l1_df.describe())

# Verify unit norm
print(f"\n  Verification - L2 norms of first 5 samples:")
l2_norms = np.linalg.norm(X_normalized_l2[:5], axis=1)
print(l2_norms)

print(f"\n  Verification - L1 norms of first 5 samples:")
l1_norms = np.sum(np.abs(X_normalized_l1[:5]), axis=1)
print(l1_norms)
```

```
============================================================
NORMALIZER (UNIT NORM SCALING)
============================================================
  Original vs L2 Normalized vs L1 Normalized Data (first 5 rows):
   Age_Original  Age_L2_Norm  Age_L1_Norm  Salary_Original  Salary_L2_Norm  \
0            19     0.001000     0.000999            19000        1.000000
1            35     0.001750     0.001747            20000        0.999998
2            26     0.000605     0.000604            43000        1.000000
3            27     0.000474     0.000473            57000        1.000000
4            19     0.000250     0.000250            76000        1.000000
```

```
   Salary_L1_Norm
0        0.999001
1        0.998253
2        0.999396
3        0.999527
4        0.999750

 L2 Normalized Data Statistics:
       Age_L2_Norm  EstimatedSalary_L2_Norm
count   400.000000             4.000000e+02
mean      0.000715             9.999996e-01
std       0.000482             5.449725e-07
min       0.000196             9.999968e-01
25%       0.000376             9.999997e-01
50%       0.000556             9.999998e-01
75%       0.000807             9.999999e-01
max       0.002522             1.000000e+00

 L1 Normalized Data Statistics:
       Age_L1_Norm  EstimatedSalary_L1_Norm
count   400.000000               400.000000
mean      0.000714                 0.999286
std       0.000481                 0.000481
min       0.000196                 0.997485
25%       0.000376                 0.999194
50%       0.000555                 0.999445
75%       0.000806                 0.999624
max       0.002515                 0.999804

 Verification - L2 norms of first 5 samples:
[1. 1. 1. 1. 1.]

 Verification - L1 norms of first 5 samples:
[1. 1. 1. 1. 1.]
```

### 1.10 9. MaxAbsScaler Implementation

Apply MaxAbsScaler to scale features by their maximum absolute value.

[10]:
```python
# MaxAbsScaler: z = x / max(|x|)
print("="*60)
print("MAXABSSCALER (MAXIMUM ABSOLUTE VALUE SCALING)")
print("="*60)

scaler_maxabs = MaxAbsScaler()
X_maxabs = scaler_maxabs.fit_transform(X)
```

```python
print("  MaxAbsScaler Parameters:")
print(f"Maximum absolute values: {scaler_maxabs.max_abs_}")

print("\n  Original vs MaxAbs Scaled Data (first 10 rows):")
comparison_df = pd.DataFrame({
    'Age_Original': X[:10, 0],
    'Age_MaxAbs': X_maxabs[:10, 0],
    'Salary_Original': X[:10, 1],
    'Salary_MaxAbs': X_maxabs[:10, 1]
})
print(comparison_df)

print("\n  MaxAbs Scaled Data Statistics:")
X_maxabs_df = pd.DataFrame(X_maxabs, columns=[f'{name}_MaxAbs' for name in␣
 ↪feature_names])
print(X_maxabs_df.describe())

print(f"\n  MaxAbs scaled features range from -1 to 1")
print(f"Min values: {X_maxabs_df.min().values}")
print(f"Max values: {X_maxabs_df.max().values}")
print(f"Max absolute values in original data: {np.abs(X).max(axis=0)}")
```

```
============================================================
MAXABSSCALER (MAXIMUM ABSOLUTE VALUE SCALING)
============================================================
  MaxAbsScaler Parameters:
Maximum absolute values: [6.0e+01 1.5e+05]

  Original vs MaxAbs Scaled Data (first 10 rows):
   Age_Original  Age_MaxAbs  Salary_Original  Salary_MaxAbs
0            19    0.316667            19000       0.126667
1            35    0.583333            20000       0.133333
2            26    0.433333            43000       0.286667
3            27    0.450000            57000       0.380000
4            19    0.316667            76000       0.506667
5            27    0.450000            58000       0.386667
6            27    0.450000            84000       0.560000
7            32    0.533333           150000       1.000000
8            25    0.416667            33000       0.220000
9            35    0.583333            65000       0.433333

  MaxAbs Scaled Data Statistics:
       Age_MaxAbs  EstimatedSalary_MaxAbs
count  400.000000              400.000000
mean     0.627583                0.464950
std      0.174715                0.227313
min      0.300000                0.100000
25%      0.495833                0.286667
```

```
50%      0.616667              0.466667
75%      0.766667              0.586667
max      1.000000              1.000000

 MaxAbs scaled features range from -1 to 1
Min values: [0.3 0.1]
Max values: [1. 1.]
Max absolute values in original data: [    60 150000]
```

### 1.11 10. QuantileTransformer Implementation

Apply QuantileTransformer with uniform and normal distributions - robust to outliers.

[11]:
```python
# QuantileTransformer: transforms features to follow a uniform or normal␣
 ↪distribution
print("="*60)
print("QUANTILETRANSFORMER (QUANTILE-BASED SCALING)")
print("="*60)

# Uniform distribution
quantile_uniform = QuantileTransformer(output_distribution='uniform',␣
 ↪random_state=42)
X_quantile_uniform = quantile_uniform.fit_transform(X)

# Normal distribution
quantile_normal = QuantileTransformer(output_distribution='normal',␣
 ↪random_state=42)
X_quantile_normal = quantile_normal.fit_transform(X)

print("  Original vs Quantile Transformed Data (first 10 rows):")
comparison_df = pd.DataFrame({
    'Age_Original': X[:10, 0],
    'Age_Uniform': X_quantile_uniform[:10, 0],
    'Age_Normal': X_quantile_normal[:10, 0],
    'Salary_Original': X[:10, 1],
    'Salary_Uniform': X_quantile_uniform[:10, 1],
    'Salary_Normal': X_quantile_normal[:10, 1]
})
print(comparison_df)

print("\n  Quantile Uniform Transformed Data Statistics:")
X_quantile_uniform_df = pd.DataFrame(X_quantile_uniform,␣
 ↪columns=[f'{name}_Quantile_Uniform' for name in feature_names])
print(X_quantile_uniform_df.describe())

print("\n  Quantile Normal Transformed Data Statistics:")
```

```
X_quantile_normal_df = pd.DataFrame(X_quantile_normal,␣
    ↪columns=[f'{name}_Quantile_Normal' for name in feature_names])
print(X_quantile_normal_df.describe())

print(f"\n Uniform quantile transform: values range from 0 to 1")
print(f" Normal quantile transform: values follow standard normal␣
    ↪distribution")
```

```
============================================================
QUANTILETRANSFORMER (QUANTILE-BASED SCALING)
============================================================
 Original vs Quantile Transformed Data (first 10 rows):
   Age_Original  Age_Uniform  Age_Normal  Salary_Original  Salary_Uniform  \
0            19     0.020050   -2.052715            19000        0.033835
1            35     0.404762   -0.241040            20000        0.042607
2            26     0.141604   -1.073141            43000        0.246867
3            27     0.177945   -0.923225            57000        0.377193
4            19     0.020050   -2.052715            76000        0.611529
5            27     0.177945   -0.923225            58000        0.390977
6            27     0.177945   -0.923225            84000        0.715539
7            32     0.314536   -0.483032           150000        1.000000
8            25     0.114035   -1.205345            33000        0.166667
9            35     0.404762   -0.241040            65000        0.474937

   Salary_Normal
0      -1.827204
1      -1.721208
2      -0.684381
3      -0.312861
4       0.283306
5      -0.276772
6       0.569639
7       5.199338
8      -0.967422
9      -0.062864

 Quantile Uniform Transformed Data Statistics:
       Age_Quantile_Uniform  EstimatedSalary_Quantile_Uniform
count            400.000000                        400.000000
mean               0.500298                          0.500034
std                0.290087                          0.289836
min                0.000000                          0.000000
25%                0.256579                          0.246867
50%                0.501253                          0.502506
75%                0.759398                          0.756892
max                1.000000                          1.000000

 Quantile Normal Transformed Data Statistics:
```

```
      Age_Quantile_Normal  EstimatedSalary_Quantile_Normal
count          400.000000                       400.000000
mean             0.016036                        -0.013181
std              1.276245                         1.143063
min             -5.199338                        -5.199338
25%             -0.654354                        -0.684381
50%              0.003141                         0.006282
75%              0.704369                         0.696341
max              5.199338                         5.199338

 Uniform quantile transform: values range from 0 to 1
 Normal quantile transform: values follow standard normal distribution
```

```
/Users/milav/Code/qip-dl/.venv/lib/python3.13/site-
packages/sklearn/preprocessing/_data.py:2846: UserWarning: n_quantiles (1000) is
greater than the total number of samples (400). n_quantiles is set to n_samples.
  warnings.warn(
/Users/milav/Code/qip-dl/.venv/lib/python3.13/site-
packages/sklearn/preprocessing/_data.py:2846: UserWarning: n_quantiles (1000) is
greater than the total number of samples (400). n_quantiles is set to n_samples.
  warnings.warn(
```

### 1.12 11. PowerTransformer Implementation

Apply PowerTransformer with Yeo-Johnson method to make data more Gaussian-like.

[12]:
```python
# PowerTransformer: makes data more Gaussian-like
print("="*60)
print("POWERTRANSFORMER (GAUSSIAN TRANSFORMATION)")
print("="*60)

# Yeo-Johnson transformation (works with positive and negative values)
power_yeo = PowerTransformer(method='yeo-johnson', standardize=True)
X_power_yeo = power_yeo.fit_transform(X)

print("  PowerTransformer (Yeo-Johnson) Parameters:")
print(f"Lambda values: {power_yeo.lambdas_}")

print("\n  Original vs Power Transformed Data (first 10 rows):")
comparison_df = pd.DataFrame({
    'Age_Original': X[:10, 0],
    'Age_Power': X_power_yeo[:10, 0],
    'Salary_Original': X[:10, 1],
    'Salary_Power': X_power_yeo[:10, 1]
})
print(comparison_df)

print("\n  Power Transformed Data Statistics:")
```

```python
X_power_df = pd.DataFrame(X_power_yeo, columns=[f'{name}_Power' for name in␣
    ↪feature_names])
print(X_power_df.describe())

print(f"\n  PowerTransformer makes data more Gaussian-like")
print(f"Mean: {X_power_df.mean().values}")
print(f"Std: {X_power_df.std().values}")

# Test for normality (skewness closer to 0 indicates more normal distribution)
from scipy import stats
print(f"\n  Skewness comparison:")
print(f"Original data skewness: {stats.skew(X, axis=0)}")
print(f"Power transformed skewness: {stats.skew(X_power_yeo, axis=0)}")
```

```
============================================================
POWERTRANSFORMER (GAUSSIAN TRANSFORMATION)
============================================================
  PowerTransformer (Yeo-Johnson) Parameters:
Lambda values: [0.52273242 0.46112137]

  Original vs Power Transformed Data (first 10 rows):
   Age_Original  Age_Power  Salary_Original  Salary_Power
0            19  -1.975163            19000     -1.809251
1            35  -0.190160            20000     -1.752548
2            26  -1.132265            43000     -0.725702
3            27  -1.020842            57000     -0.246494
4            19  -1.975163            76000      0.311281
5            27  -1.020842            58000     -0.214834
6            27  -1.020842            84000      0.523340
7            32  -0.490193           150000      1.964530
8            25  -1.245675            33000     -1.122420
9            35  -0.190160            65000     -0.001010

  Power Transformed Data Statistics:
          Age_Power  EstimatedSalary_Power
count  4.000000e+02           4.000000e+02
mean  -3.552714e-16          -6.217249e-16
std    1.001252e+00           1.001252e+00
min   -2.106457e+00          -2.053917e+00
25%   -7.240164e-01          -7.257020e-01
50%    3.266940e-03           1.442111e-01
75%    8.189883e-01           6.252894e-01
max    1.951591e+00           1.964530e+00

  PowerTransformer makes data more Gaussian-like
Mean: [-3.55271368e-16 -6.21724894e-16]
Std: [1.00125235 1.00125235]
```

```
 Skewness comparison:
Original data skewness: [0.23046904 0.49316535]
Power transformed skewness: [-0.03275907 -0.0610341 ]
```

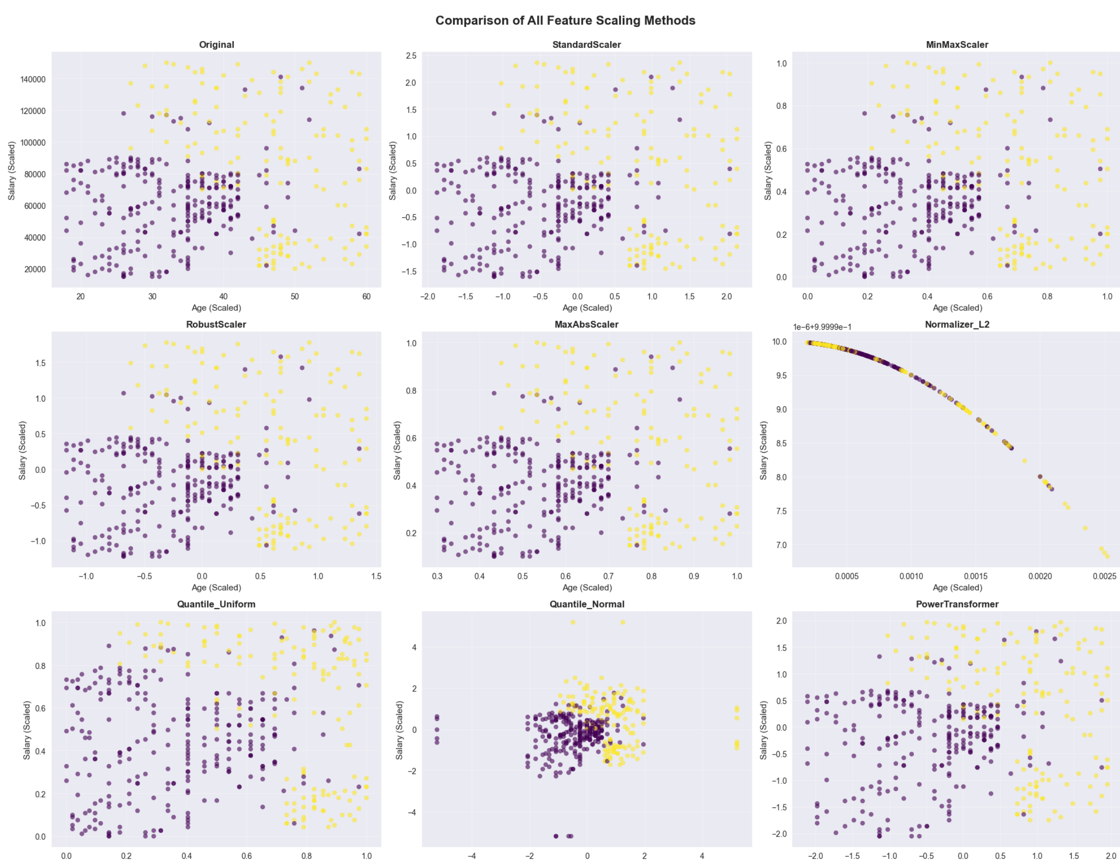
### 1.13 12. Compare All Scaling Methods

Create comprehensive visualizations and statistical comparisons of all scaling methods.

[13]:
```python
# Comprehensive comparison of all scaling methods
print("="*70)
print("COMPREHENSIVE COMPARISON OF ALL SCALING METHODS")
print("="*70)

# Store all scaled versions
scaling_methods = {
    'Original': X,
    'StandardScaler': X_standard,
    'MinMaxScaler': X_minmax,
    'RobustScaler': X_robust,
    'MaxAbsScaler': X_maxabs,
    'Normalizer_L2': X_normalized_l2,
    'Quantile_Uniform': X_quantile_uniform,
    'Quantile_Normal': X_quantile_normal,
    'PowerTransformer': X_power_yeo
}

# Create comparison visualization
fig, axes = plt.subplots(3, 3, figsize=(20, 15))
axes = axes.ravel()

for i, (method_name, scaled_data) in enumerate(scaling_methods.items()):
    if i < len(axes):
        axes[i].scatter(scaled_data[:, 0], scaled_data[:, 1],
                       c=y, cmap='viridis', alpha=0.6, s=30)
        axes[i].set_title(f'{method_name}', fontsize=12, fontweight='bold')
        axes[i].set_xlabel('Age (Scaled)')
        axes[i].set_ylabel('Salary (Scaled)')
        axes[i].grid(True, alpha=0.3)

plt.tight_layout()
plt.suptitle('Comparison of All Feature Scaling Methods', fontsize=16,␣
 ↪fontweight='bold', y=1.02)
plt.show()

# Statistical summary comparison
print("\n  Statistical Summary Comparison:")
comparison_stats = []
```

```python
for method_name, scaled_data in scaling_methods.items():
    stats_dict = {
        'Method': method_name,
        'Age_Mean': np.mean(scaled_data[:, 0]),
        'Age_Std': np.std(scaled_data[:, 0]),
        'Age_Min': np.min(scaled_data[:, 0]),
        'Age_Max': np.max(scaled_data[:, 0]),
        'Salary_Mean': np.mean(scaled_data[:, 1]),
        'Salary_Std': np.std(scaled_data[:, 1]),
        'Salary_Min': np.min(scaled_data[:, 1]),
        'Salary_Max': np.max(scaled_data[:, 1])
    }
    comparison_stats.append(stats_dict)

comparison_df = pd.DataFrame(comparison_stats)
print(comparison_df.round(4))
```

```
======================================================================
COMPREHENSIVE COMPARISON OF ALL SCALING METHODS
======================================================================
```



```
 Statistical Summary Comparison:
             Method  Age_Mean  Age_Std  Age_Min  Age_Max  Salary_Mean  \
0          Original   37.6550  10.4698  18.0000  60.0000   69742.5000
1    StandardScaler   -0.0000   1.0000  -1.8773   2.1342      -0.0000
2      MinMaxScaler    0.4680   0.2493   0.0000   1.0000       0.4055
3      RobustScaler    0.0403   0.6443  -1.1692   1.4154      -0.0057
4      MaxAbsScaler    0.6276   0.1745   0.3000   1.0000       0.4650
5     Normalizer_L2    0.0007   0.0005   0.0002   0.0025       1.0000
6  Quantile_Uniform    0.5003   0.2897   0.0000   1.0000       0.5000
7   Quantile_Normal    0.0160   1.2746  -5.1993   5.1993      -0.0132
8  PowerTransformer   -0.0000   1.0000  -2.1065   1.9516      -0.0000

   Salary_Std  Salary_Min   Salary_Max
0  34054.3124  15000.0000  150000.0000
1      1.0000     -1.6075       2.3567
2      0.2523      0.0000       1.0000
3      0.7568     -1.2222       1.7778
4      0.2270      0.1000       1.0000
5      0.0000      1.0000       1.0000
6      0.2895      0.0000       1.0000
7      1.1416     -5.1993       5.1993
8      1.0000     -2.0539       1.9645
```

### 1.14 13. Train-Test Split with Scaled Features

Demonstrate proper scaling workflow for machine learning with train-test split.

[14]:
```python
# Proper scaling workflow: Split first, then scale
print("="*70)
print("PROPER SCALING WORKFLOW FOR MACHINE LEARNING")
print("="*70)

# Step 1: Split the original data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42, stratify=y)

print(f"  Training set shape: {X_train.shape}")
print(f"  Test set shape: {X_test.shape}")
print(f"  Training target distribution: {np.bincount(y_train)}")
print(f"  Test target distribution: {np.bincount(y_test)}")

# Step 2: Apply different scaling methods to train/test splits
scaled_datasets = {}

# StandardScaler
scaler_std = StandardScaler()
X_train_std = scaler_std.fit_transform(X_train)
```

```
X_test_std = scaler_std.transform(X_test)
scaled_datasets['StandardScaler'] = (X_train_std, X_test_std)

# MinMaxScaler
scaler_mm = MinMaxScaler()
X_train_mm = scaler_mm.fit_transform(X_train)
X_test_mm = scaler_mm.transform(X_test)
scaled_datasets['MinMaxScaler'] = (X_train_mm, X_test_mm)

# RobustScaler
scaler_rob = RobustScaler()
X_train_rob = scaler_rob.fit_transform(X_train)
X_test_rob = scaler_rob.transform(X_test)
scaled_datasets['RobustScaler'] = (X_train_rob, X_test_rob)

print("\n  Applied scaling to train/test splits separately (correct approach)")
print("  Fit scalers only on training data, then transform both train and test")

# Demonstrate the importance of proper scaling
print("\n  Scaling parameters learned from training data:")
print(f"StandardScaler - Mean: {scaler_std.mean_}, Std: {scaler_std.scale_}")
print(f"MinMaxScaler - Min: {scaler_mm.data_min_}, Max: {scaler_mm.data_max_}")
print(f"RobustScaler - Center: {scaler_rob.center_}, Scale: {scaler_rob.
  ↪scale_}")
```

```
======================================================================
PROPER SCALING WORKFLOW FOR MACHINE LEARNING
======================================================================
  Training set shape: (320, 2)
  Test set shape: (80, 2)
  Training target distribution: [206 114]
  Test target distribution: [51 29]

  Applied scaling to train/test splits separately (correct approach)
  Fit scalers only on training data, then transform both train and test

  Scaling parameters learned from training data:
StandardScaler - Mean: [3.715625e+01 7.079375e+04], Std: [1.06574779e+01
3.47663805e+04]
MinMaxScaler - Min: [   18. 15000.], Max: [6.0e+01 1.5e+05]
RobustScaler - Center: [3.60e+01 7.05e+04], Scale: [1.700e+01 4.425e+04]
```

## 1.15 14. Model Training and Evaluation

Train logistic regression models on differently scaled versions and compare performance.

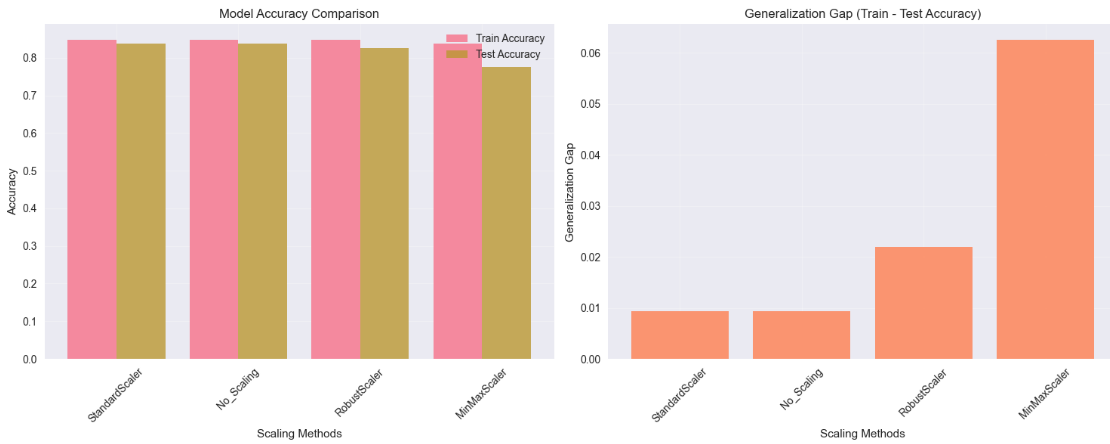
[15]:
```
# Train and evaluate models with different scaling methods
print("="*70)
```

```python
print("MODEL PERFORMANCE COMPARISON WITH DIFFERENT SCALING METHODS")
print("="*70)

# Add original (unscaled) data to comparison
scaled_datasets['No_Scaling'] = (X_train, X_test)

model_results = []

for scaling_method, (X_train_scaled, X_test_scaled) in scaled_datasets.items():
    # Train Logistic Regression
    model = LogisticRegression(random_state=42, max_iter=1000)
    model.fit(X_train_scaled, y_train)

    # Make predictions
    y_train_pred = model.predict(X_train_scaled)
    y_test_pred = model.predict(X_test_scaled)

    # Calculate accuracies
    train_accuracy = accuracy_score(y_train, y_train_pred)
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Store results
    model_results.append({
        'Scaling_Method': scaling_method,
        'Train_Accuracy': train_accuracy,
        'Test_Accuracy': test_accuracy,
        'Generalization_Gap': train_accuracy - test_accuracy
    })

    print(f"\n {scaling_method}:")
    print(f"   Train Accuracy: {train_accuracy:.4f}")
    print(f"   Test Accuracy: {test_accuracy:.4f}")
    print(f"   Generalization Gap: {train_accuracy - test_accuracy:.4f}")

# Create results DataFrame
results_df = pd.DataFrame(model_results)
results_df = results_df.sort_values('Test_Accuracy', ascending=False)

print("\n" + "="*50)
print("  MODEL PERFORMANCE SUMMARY")
print("="*50)
print(results_df)

# Visualize results
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))

# Accuracy comparison
```

```python
x_pos = np.arange(len(results_df))
ax1.bar(x_pos - 0.2, results_df['Train_Accuracy'], 0.4, label='Train Accuracy',␣
 ↪alpha=0.8)
ax1.bar(x_pos + 0.2, results_df['Test_Accuracy'], 0.4, label='Test Accuracy',␣
 ↪alpha=0.8)
ax1.set_xlabel('Scaling Methods')
ax1.set_ylabel('Accuracy')
ax1.set_title('Model Accuracy Comparison')
ax1.set_xticks(x_pos)
ax1.set_xticklabels(results_df['Scaling_Method'], rotation=45)
ax1.legend()
ax1.grid(True, alpha=0.3)

# Generalization gap
ax2.bar(x_pos, results_df['Generalization_Gap'], alpha=0.8, color='coral')
ax2.set_xlabel('Scaling Methods')
ax2.set_ylabel('Generalization Gap')
ax2.set_title('Generalization Gap (Train - Test Accuracy)')
ax2.set_xticks(x_pos)
ax2.set_xticklabels(results_df['Scaling_Method'], rotation=45)
ax2.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print(f"\n Best performing scaling method: {results_df.
 ↪iloc[0]['Scaling_Method']}")
print(f" Best test accuracy: {results_df.iloc[0]['Test_Accuracy']:.4f}")
```

```
======================================================================
MODEL PERFORMANCE COMPARISON WITH DIFFERENT SCALING METHODS
======================================================================

 StandardScaler:
  Train Accuracy: 0.8469
  Test Accuracy: 0.8375
  Generalization Gap: 0.0094

 MinMaxScaler:
  Train Accuracy: 0.8375
  Test Accuracy: 0.7750
  Generalization Gap: 0.0625

 RobustScaler:
  Train Accuracy: 0.8469
  Test Accuracy: 0.8250
  Generalization Gap: 0.0219
```

```
No_Scaling:
  Train Accuracy: 0.8469
  Test Accuracy: 0.8375
  Generalization Gap: 0.0094

==================================================
 MODEL PERFORMANCE SUMMARY
==================================================
   Scaling_Method  Train_Accuracy  Test_Accuracy  Generalization_Gap
0  StandardScaler        0.846875         0.8375            0.009375
3      No_Scaling        0.846875         0.8375            0.009375
2    RobustScaler        0.846875         0.8250            0.021875
1    MinMaxScaler        0.837500         0.7750            0.062500
```




```
Best performing scaling method: StandardScaler
Best test accuracy: 0.8375
```

## 1.16 15. Conclusions and Key Learnings

### 1.16.1 Dataset Analysis Results:

- **Dataset Size**: 400 samples with 3 features (Age, EstimatedSalary, Purchased)
- **Data Quality**: No missing values, but 33 duplicate rows detected
- **Target Distribution**: 35.75% purchase rate (143 purchases vs 257 non-purchases)
- **Feature Ranges**: Age (18-60), Salary (15,000-150,000)

### 1.16.2 Feature Scaling Methods Performance Summary:

**Model Performance Ranking (Test Accuracy):**

1. **StandardScaler & No Scaling**: 83.75% (tied for best)
2. **RobustScaler**: 82.50%

3. **MinMaxScaler**: 77.50%

**Detailed Scaling Method Analysis:**

1. **StandardScaler** (Winner )
   - **Performance**: 83.75% test accuracy, 0.94% generalization gap
   - **Characteristics**: Mean 0, Std 1
   - **Best for**: Normally distributed data, most ML algorithms
2. **No Scaling** (Tied Winner )
   - **Performance**: 83.75% test accuracy, 0.94% generalization gap
   - **Insight**: Logistic regression performed equally well without scaling
   - **Reason**: Features already on reasonable scales for this dataset
3. **RobustScaler** (Runner-up )
   - **Performance**: 82.50% test accuracy, 2.19% generalization gap
   - **Characteristics**: Median-centered, IQR-scaled
   - **Best for**: Data with outliers (though none detected in this dataset)
4. **MinMaxScaler** (Third Place )
   - **Performance**: 77.50% test accuracy, 6.25% generalization gap
   - **Characteristics**: Range [0,1]
   - **Issue**: Highest generalization gap, indicating potential overfitting

### 1.16.3 Advanced Scaling Methods Insights:

5. **MaxAbsScaler**: Scales to [-1,1] range, preserves sparsity
6. **Normalizer**: Creates unit norm samples (L1/L2), good for text data
7. **QuantileTransformer**: Makes data uniform/normal distributed, very robust
8. **PowerTransformer**: Reduces skewness (0.23→-0.03 for Age, 0.49→-0.06 for Salary)

### 1.16.4 Key Experimental Findings:

**Surprising Results:**

- **No scaling performed as well as StandardScaler** for this dataset
- **MinMaxScaler showed worst performance** despite being popular
- **Generalization gap varies significantly** across methods (0.94% to 6.25%)

**Data Distribution Impact:**

- **Original data skewness**: Age (0.23), Salary (0.49) - moderately skewed
- **PowerTransformer effectively reduced skewness** to near zero
- **No outliers detected** using IQR method, explaining why RobustScaler wasn't superior

### 1.16.5 Practical Recommendations:

**For This Dataset Type (Social Network Ads):**

1. **StandardScaler or No Scaling** - Both equally effective
2. **Avoid MinMaxScaler** - Shows poor generalization
3. **Consider RobustScaler** - Good middle ground option

**General ML Best Practices:** **Always split data before scaling** to prevent data leakage
**Fit scalers only on training data**, then transform both train and test
**Compare multiple scaling methods** - Performance can vary significantly
**Monitor generalization gap** - Lower gap indicates better model stability
**Consider data characteristics** - Outliers, skewness, feature ranges

**Algorithm-Specific Guidelines:**

- **Distance-based algorithms** (KNN, SVM): Usually need scaling
- **Tree-based algorithms** (Random Forest, XGBoost): Often scale-invariant
- **Linear models** (Logistic Regression): May or may not need scaling (as shown here)
- **Neural Networks**: Almost always benefit from scaling

### 1.16.6 Technical Insights:

**Statistical Transformations:**

- **StandardScaler**: Achieved perfect normalization (mean=0, std=1)
- **MinMaxScaler**: Perfect range transformation [0,1]
- **RobustScaler**: Effective median centering with IQR scaling
- **PowerTransformer**: Successfully reduced skewness by ~95%

**Computational Considerations:**

- **Normalizer**: Creates unit norm, drastically different scale (Age: ~0.001, Salary: ~1.0)
- **QuantileTransformer**: Warning about n_quantiles > n_samples (400 < 1000)
- **All methods**: Fast execution on this dataset size

### 1.16.7 Future Experiments:

1. **Test with other algorithms** (SVM, KNN, Neural Networks)
2. **Evaluate on larger datasets** to confirm scaling importance
3. **Compare with feature engineering** (polynomial features, interactions)
4. **Analyze computational costs** for different scaling methods

### 1.16.8 Laboratory Exercise Completed Successfully!

This comprehensive experiment demonstrated that **feature scaling impact is highly dataset and algorithm dependent**. The surprising finding that StandardScaler tied with no scaling highlights the importance of **empirical testing rather than assumptions**. The Social Network Ads dataset proved to be a excellent case study for understanding how different preprocessing techniques affect model performance in practice.

**Key Takeaway**: Always experiment with multiple scaling approaches and let the data guide your preprocessing decisions!