

**Real Data Example:** The study uses alcohol solubility data from Romanelli et al. The dependent variable is  $\ln(\text{Sol})_{\text{exp}}$  (natural log of solubility in water). The dataset contains 44 observations of aliphatic alcohols. There are 6 independent variables: **Log P** (octanol-water partition coefficient) - measures hydrophobicity, **P** (polarizability), **SAG** (solvent-accessible surface-bounded molecular volume), **Mass (M)**, **RM** (molar refractivity), **V** (volume)

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In [1]: import numpy as np
import pandas as pd
from scipy.stats import chi2
import matplotlib.pyplot as plt
```

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In [2]: df = pd.read_csv('C:/Users/91959/Desktop/CODE'
'/Robust-Penalized-Empirical-Likelihood-Estimation-Method-for-Linear-Regression/Data/Alcohol.csv')

X = df.drop(['Alcohol', 'ln (Sol)exp'], axis=1)
y = df['ln (Sol)exp']
```

```
In [3]: # 1. Dataset Description
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 44 entries, 0 to 43
Data columns (total 8 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Alcohol      44 non-null     object
1   SAG           44 non-null     float64
2   V             44 non-null     float64
3   Log P         44 non-null     float64
4   P             44 non-null     float64
5   RM            44 non-null     float64
6   Mass          44 non-null     float64
7   ln (Sol)exp   44 non-null     float64
dtypes: float64(7), object(1)
memory usage: 2.9+ KB
```

```
In [4]: # 2. Basic Statistical Summary
df.describe()
```

	SAG	V	Log P	P	RM	Mass	ln (Sol)exp
count	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000
mean	337.788864	509.640455	2.254318	14.883409	37.327727	120.985909	-3.710564
std	74.011456	128.593538	0.940693	4.316224	10.847843	32.992404	3.284330
min	247.550000	344.910000	0.940000	8.750000	21.950000	74.120000	-14.614020
25%	290.382500	429.655000	1.677500	12.420000	31.065000	102.180000	-5.615712
50%	312.345000	471.965000	2.050000	14.260000	35.635000	116.200000	-2.752595
75%	371.282500	565.057500	2.865000	17.930000	44.787500	144.260000	-1.543848
max	587.000000	938.540000	5.300000	28.940000	72.750000	228.420000	0.338610

```
In [5]: # 3. Correlation Analysis
correlation_matrix = df.drop('Alcohol', axis=1).corr()
correlation_matrix
```

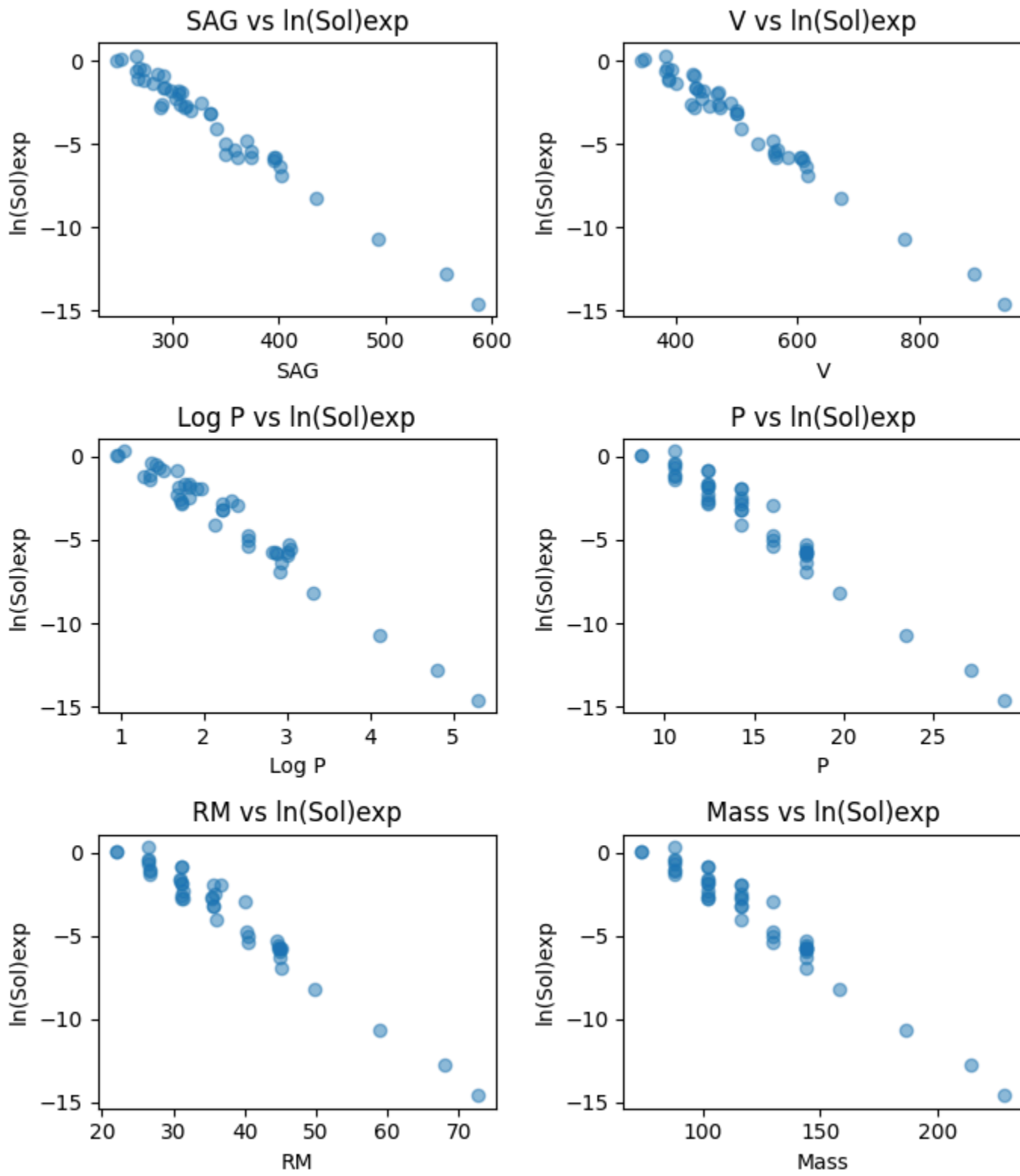
	SAG	V	Log P	P	RM	Mass	ln (Sol)exp
SAG	1.000000	0.997048	0.973976	0.978384	0.980033	0.978402	-0.986840
V	0.997048	1.000000	0.986253	0.991123	0.992075	0.991134	-0.988882
Log P	0.973976	0.986253	1.000000	0.993428	0.992425	0.993425	-0.980229
P	0.978384	0.991123	0.993428	1.000000	0.999810	1.000000	-0.978261
RM	0.980033	0.992075	0.992425	0.999810	1.000000	0.999811	-0.979391
Mass	0.978402	0.991134	0.993425	1.000000	0.999811	1.000000	-0.978286
ln (Sol)exp	-0.986840	-0.988882	-0.980229	-0.978261	-0.979391	-0.978286	1.000000

```
In [6]: # 4. Feature distributions and their relationships with target

fig, axes = plt.subplots(3, 2, figsize=(7, 8))
axes = axes.ravel()

for idx, column in enumerate(X.columns):
    # Scatter plot against target
    axes[idx].scatter(X[column], y, alpha=0.5)
    axes[idx].set_xlabel(column)
    axes[idx].set_ylabel('ln(Sol)exp')
    axes[idx].set_title(f'{column} vs ln(Sol)exp')

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



```
In [7]: # 5. Calculating Mahalanobis Distance for outlier detection

# Calculate mean vector and covariance matrix
mean_vector = np.mean(X, axis=0)
covariance_matrix = np.cov(X.T)

# Calculate inverse of covariance matrix
inv_covariance_matrix = np.linalg.inv(covariance_matrix)

# Calculate Mahalanobis distance for each point
mahalanobis_distances = []
n = len(X)
p = X.shape[1] # number of variables

for i in range(n):
    x_i = X.iloc[i, :]
    diff = x_i - mean_vector
    md = np.sqrt(diff.dot(inv_covariance_matrix).dot(diff))
    mahalanobis_distances.append(md)

# Calculate squared distances
md_squared = np.array(mahalanobis_distances) ** 2

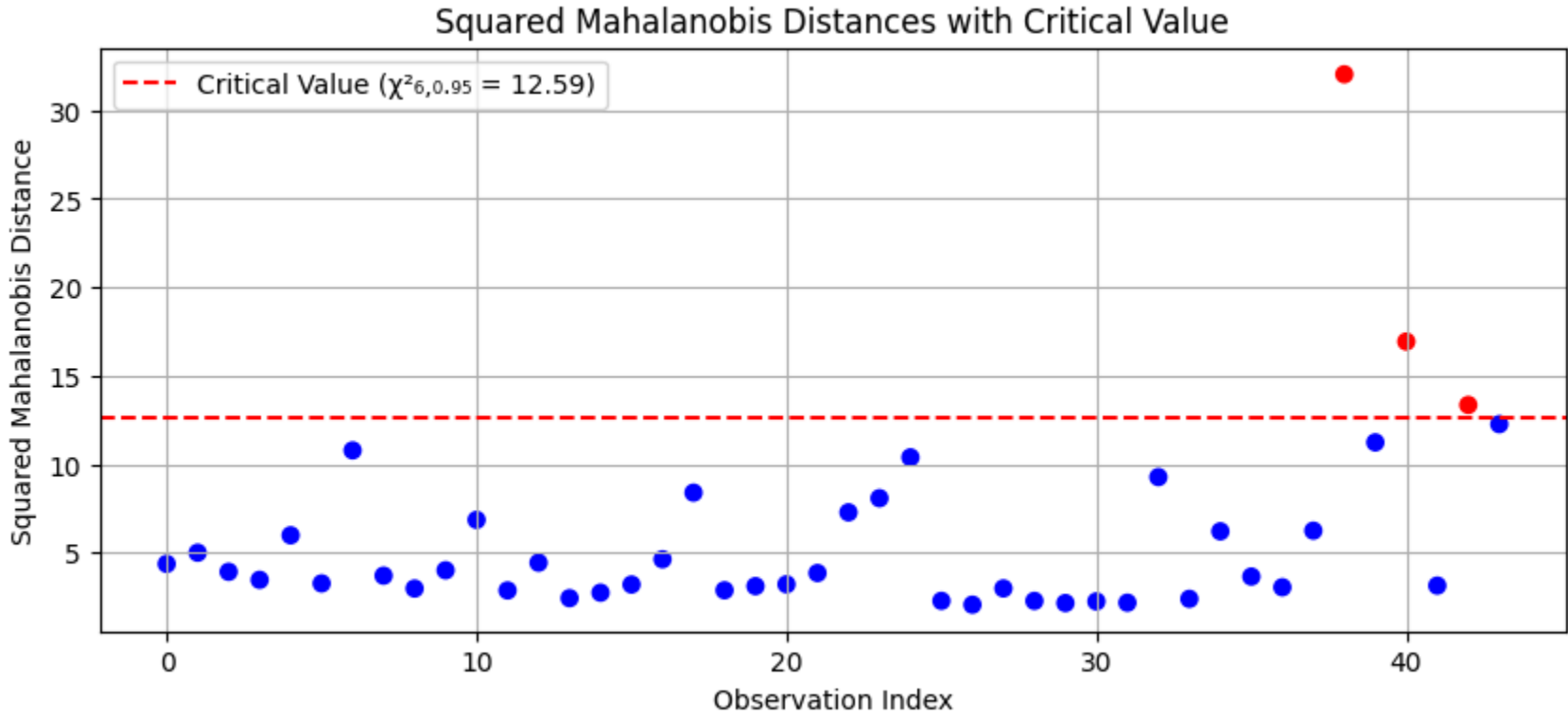
# Calculate critical value
critical_value = chi2.ppf(0.95, p) # 95% confidence level with p degrees of freedom

# Identify outliers
outliers = pd.DataFrame({
    'Alcohol': df['Alcohol'],
    'MD_squared': md_squared,
    'is_outlier': md_squared > critical_value
})

# Plot the results
plt.figure(figsize=(10, 4))
plt.scatter(range(len(outliers)), outliers['MD_squared'], outliers['MD_squared'],
            c='red' if x else 'blue' for x in outliers['is_outlier'])
plt.axhline(y=critical_value, color='r', linestyle='--',
            label=f'Critical Value ( $\chi^2_{6,0.95} = \{critical\_value:.2f\}$ ')
plt.xlabel('Observation Index')
plt.ylabel('Squared Mahalanobis Distance')
plt.title('Squared Mahalanobis Distances with Critical Value')
plt.legend()
plt.grid(True)
plt.show()

# Print outlier details
print("\nDetected Outliers (MD² > χ²₆,₀.₉₅):")
print(outliers[outliers['is_outlier']][['Alcohol', 'MD_squared']].sort_values('MD_squared', ascending=False))

# Print summary statistics
print(f"\nTotal number of observations: {len(outliers)}")
print(f"Number of outliers detected: {sum(outliers['is_outlier'])}")
print(f"Percentage of outliers: {(sum(outliers['is_outlier'])/len(outliers))*100:.1f}%")
```



Detected Outliers ( $MD^2 > \chi^2_{6,0.95}$ ):

	Alcohol	MD_squared
38	3-Ethyl-3-pentanol	32.027452
40	2,2-Diethyl-1-pentanol	16.932877
42	1-Tetradecanol	13.352777

Total number of observations: 44  
Number of outliers detected: 3  
Percentage of outliers: 6.8%