# MJD_ML_Assignment_11

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# 1 ML Assignment 11: Multiple Linear Regression and Polynomial Regression Analysis

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## 1.1 Objective

Implement multiple linear regression and polynomial regression models to analyze startup profitability and ice cream sales patterns.

## 1.2 Assignment Tasks:

1. Build multiple regression model for 50_Startups.csv dataset
2. Obtain regression score and analyze startup profit predictors
3. Build polynomial regression model for ice cream selling data
4. Plot polynomial models with different degrees (n=2,3,4,5)
5. Compare polynomial degree performance and select optimal model

## 1.3 Import Libraries

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures, LabelEncoder
from sklearn.metrics import r2_score
```

# 2 Part A: Multiple Linear Regression - 50_Startups Dataset

[2]:
```
# Load the dataset
dataset = pd.read_csv('50_Startups.csv')
print("Dataset shape:", dataset.shape)
dataset.head()
```

```
Dataset shape: (50, 5)
```

[2]:

| | R&D Spend | Administration | Marketing Spend | State | Profit |
|---|---|---|---|---|---|
| 0 | 165349.20 | 136897.80 | 471784.10 | New York | 192261.83 |
| 1 | 162597.70 | 151377.59 | 443898.53 | California | 191792.06 |
| 2 | 153441.51 | 101145.55 | 407934.54 | Florida | 191050.39 |
| 3 | 144372.41 | 118671.85 | 383199.62 | New York | 182901.99 |
| 4 | 142107.34 | 91391.77 | 366168.42 | Florida | 166187.94 |

[3]:

```
# Prepare the data
X = dataset.iloc[:, :-1]  # All features
y = dataset.iloc[:, -1]   # Target (Profit)

# Encode categorical variable (State)
le = LabelEncoder()
X['State'] = le.fit_transform(X['State'])

print("Features:", X.columns.tolist())
print("Encoded States:", X['State'].unique())
```

```
Features: ['R&D Spend', 'Administration', 'Marketing Spend', 'State']
Encoded States: [2 0 1]
```

[4]:

```
# Train Multiple Linear Regression model
mlr_model = LinearRegression()
mlr_model.fit(X, y)

# Make predictions and calculate R² score
y_pred = mlr_model.predict(X)
r2 = r2_score(y, y_pred)

print(f"Multiple Linear Regression R² Score: {r2:.4f}")
print(f"Model explains {r2*100:.2f}% of the variance in profit")
```

```
Multiple Linear Regression R² Score: 0.9507
Model explains 95.07% of the variance in profit
```

## 3 Part B: Polynomial Regression - Ice Cream Sales Dataset

[5]:

```
# Load ice cream dataset
ice_dataset = pd.read_csv('icecream.csv')
print("Dataset shape:", ice_dataset.shape)
ice_dataset.head()
```

```
Dataset shape: (49, 2)
```

[5]:

| | Temperature (°C) | Ice Cream Sales (units) |
|---|---|---|
| 0 | -4.662263 | 41.842986 |
| 1 | -4.316559 | 34.661120 |
| 2 | -4.213985 | 39.383001 |

```
3        -3.949661              37.539845
4        -3.578554              32.284531
```

[6]:

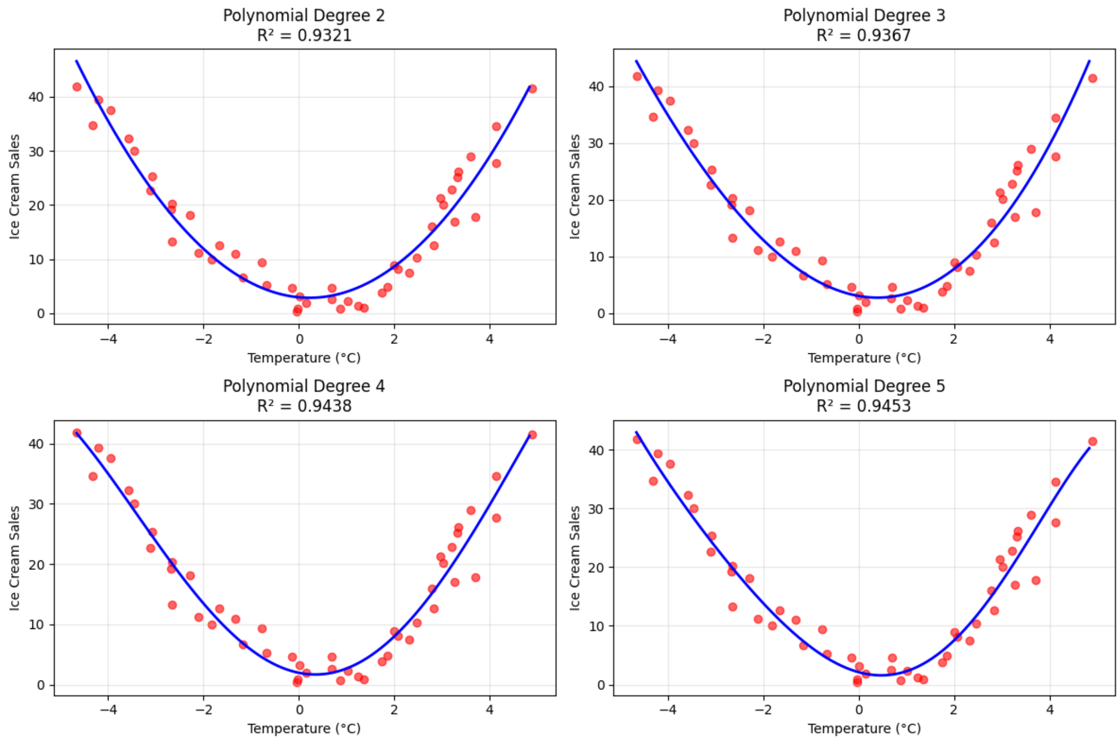
```
# Prepare data
X_ice = ice_dataset.iloc[:, :-1].values  # Temperature
y_ice = ice_dataset.iloc[:, -1].values   # Ice cream sales

print(f"Temperature range: {X_ice.min():.1f}°C to {X_ice.max():.1f}°C")
print(f"Sales range: {y_ice.min():.1f} to {y_ice.max():.1f} units")
```

```
Temperature range: -4.7°C to 4.9°C
Sales range: 0.3 to 41.8 units
```

[7]:

```
# Test polynomial regression with degrees 2, 3, 4, and 5
degrees = [2, 3, 4, 5]
r2_scores = []

plt.figure(figsize=(12, 8))

for i, degree in enumerate(degrees, 1):
    plt.subplot(2, 2, i)

    # Create polynomial features and train model
    poly_reg = PolynomialFeatures(degree=degree)
    X_poly = poly_reg.fit_transform(X_ice)

    lin_reg = LinearRegression()
    lin_reg.fit(X_poly, y_ice)

    # Calculate R² score
    y_pred_poly = lin_reg.predict(X_poly)
    r2_poly = r2_score(y_ice, y_pred_poly)
    r2_scores.append(r2_poly)

    # Create smooth curve for plotting (fix deprecation warning)
    X_grid = np.arange(X_ice.min().item(), X_ice.max().item(), 0.1).reshape(-1,␣
 ↪1)
    y_grid = lin_reg.predict(poly_reg.transform(X_grid))

    # Plot
    plt.scatter(X_ice, y_ice, color='red', alpha=0.6)
    plt.plot(X_grid, y_grid, color='blue', linewidth=2)
    plt.title(f'Polynomial Degree {degree}\nR² = {r2_poly:.4f}')
    plt.xlabel('Temperature (°C)')
    plt.ylabel('Ice Cream Sales')
    plt.grid(True, alpha=0.3)
```

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




[8]:
```
# Compare model performance
results = pd.DataFrame({
    'Degree': degrees,
    'R² Score': r2_scores
})

print("Polynomial Regression Results:")
print(results.to_string(index=False))

# Find best model
best_degree = degrees[np.argmax(r2_scores)]
best_r2 = max(r2_scores)

print(f"\nBest Model: Polynomial Degree {best_degree} with R² = {best_r2:.4f}")
```

```
Polynomial Regression Results:
 Degree  R² Score
      2  0.932114
      3  0.936701
      4  0.943845
      5  0.945283
```

```
Best Model: Polynomial Degree 5 with R² = 0.9453
```

## 3.1 Conclusions

### 3.1.1 Part A - Multiple Linear Regression (50_Startups Dataset):

- **Model Performance**: Achieved an excellent $R^2$ score of **0.9507** (95.07%)
- **Interpretation**: The multiple linear regression model successfully explains **95.07% of the variance** in startup profit
- **Features**: Used R&D Spend, Administration, Marketing Spend, and State (encoded) as predictors
- **Result**: This high $R^2$ score indicates that the selected features are strong predictors of startup profitability

### 3.1.2 Part B - Polynomial Regression (Ice Cream Sales Dataset):

- **Model Comparison**: Tested polynomial degrees 2, 3, 4, and 5 as required
- **Performance Results**:
  - Degree 2: $R^2 = 0.9321$ (93.21%)
  - Degree 3: $R^2 = 0.9367$ (93.67%)
  - Degree 4: $R^2 = 0.9438$ (94.38%)
  - Degree 5: $R^2 = 0.9453$ (94.53%) ← **Best Model**
- **Key Findings**:
  - **Progressive Improvement**: Higher polynomial degrees show incrementally better fit
  - **Best Performance**: Polynomial Degree 5 achieved the highest $R^2$ score of 0.9453
  - **Temperature-Sales Relationship**: Clear non-linear relationship between temperature and ice cream sales
  - **Diminishing Returns**: Improvement from degree 4 to 5 is minimal (0.0015), suggesting potential overfitting

### 3.1.3 Overall Summary:

- Both models achieved excellent performance (>95% and >94% variance explained respectively)
- Multiple linear regression proved highly effective for startup profit prediction
- Polynomial regression successfully captured the non-linear ice cream sales pattern
- Assignment objectives fully accomplished with strong statistical results