# Day48_Support_Vector_Regression_(SVR) _Salary_Prediction

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Today, we are learning about the **Support Vector Regression (SVR)** algorithm – a powerful regression technique especially useful when the data doesn't follow a straight line.

We'll implement SVR step-by-step using Python and visualize how different configurations affect the predictions.

What We'll Cover:

1. **Simple Implementation (Beginner-friendly)**
   Build SVR models with different kernels **without using functions** to understand the basics.
2. **With Function (Reusable Code)**
   Wrap the SVR logic into a function to quickly test multiple configurations (kernel, degree, C, gamma, epsilon).
3. **All-in-One Comparison**
   Try **all parameter combinations** (like kernel, degree, C, epsilon, gamma) and build a **summary table** to compare model predictions for Level 6.

**Support Vector Regression (SVR)**

**What is SVR?**

- **SVR** stands for **Support Vector Regressor**.
- It is used to **predict continuous values** like salary, price, etc.
- It is built on the same idea as **SVM (Support Vector Machine)**, which is used for classification.
- The main goal of SVR is to **fit a line (hyperplane)** such that it stays within a margin (epsilon) and allows for **some error**.

**SVR vs SVM**

| Concept | SVR (Regression) | SVM (Classification) |
|---|---|---|
| Output Type | Continuous (e.g. salary) | Categorical (e.g. yes/no) |
| Target Variable | Numerical | Binary/Multiclass |
| Best Fit | Hyperplane | Decision Boundary |
| Use Case | Predicting values | Separating classes |
| Goal | Minimize error and stay within margin | Maximize margin between classes |

**Key Concepts in SVR**

- **Hyperplane**: A line or plane that best fits the data.

- **Support Vectors**: Points closest to the hyperplane — these define the margin.
- **Margin**: Distance between the hyperplane and the closest data points.
- **Epsilon ( )**: Defines a margin of tolerance where no penalty is given for error.
- **Objective**: Keep predictions within ± margin.

  Think of SVR like fitting a straight line — but instead of going through every point, it fits **within a soft margin**, ignoring small errors.

**Support Vector Regression (SVR)** – Parameters & Tuning Guide

Parameter Descriptions

| **Parameter** | **Meaning** |
|---|---|
| `kernel` | Defines the shape of the model's curve or surface. Options: `'linear'`, `'poly'`, `'rbf'`, `'sigmoid'` |
| `degree` | Degree of the polynomial kernel (only applies when `kernel='poly'`). Higher degree = more complex curve |
| `C` | Regularization parameter. High `C` = less error tolerance (stricter margin), low `C` = more flexibility |
| `epsilon` | Acceptable error margin in prediction. No penalty within ±epsilon. Default is `0.1` |
| `gamma` | Defines influence of a single training point. Options: `'scale'`, `'auto'`, or a float value |

Recommended Parameter Values to Try

| **Parameter** | **Suggested Values** |
|---|---|
| `kernel` | `'linear'`, `'poly'`, `'rbf'`, `'sigmoid'` |
| `degree` | `2`, `3`, `4`, `5`, `6` *(only if `kernel='poly'`)* |
| `C` | `0.1`, `1`, `10`, `100` |
| `epsilon` | `0.01`, `0.1`, `1` |
| `gamma` | `'scale'`, `'auto'` |

**Tip:** Start with default values and adjust one parameter at a time to see how it impacts performance. For advanced optimization, consider using `GridSearchCV`.

**Example: SVR for Salary Prediction**

We are predicting salary based on employee level using SVR. The dataset looks like this:

| Position | Level | Salary |
|---|---|---|
| Jr Software Engineer | 1 | 45000 |
| Sr Software Engineer | 2 | 50000 |
| Team Lead | 3 | 60000 |
| Manager | 4 | 80000 |
| Sr Manager | 5 | 110000 |
| ... | ... | ... |

# 1 Simple Implementation (Beginner-friendly)

## 1.1 Import Required Libraries

[24]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.svm import SVR
from sklearn.preprocessing import StandardScaler
```

## 1.2 Load the Dataset

[2]:
```
dataset = pd.read_csv(r"C:\Users\Lenovo\Downloads\emp_sal.csv")
dataset.head()
```

[2]:

| | Position | Level | Salary |
|---|---|---|---|
| 0 | Jr Software Engineer | 1 | 45000 |
| 1 | Sr Software Engineer | 2 | 50000 |
| 2 | Team Lead | 3 | 60000 |
| 3 | Manager | 4 | 80000 |
| 4 | Sr manager | 5 | 110000 |

## 1.3 Define Features and Target

[3]:
```
X = dataset.iloc[:, 1:2].values   # Level
y = dataset.iloc[:, 2].values     # Salary
```

## 1.4 Feature Scaling (Important for SVR)

**Why We Scale X and y?**

- **SVR needs scaled data** for better accuracy.
- `X_scaled = sc_X.fit_transform(X)` → Scales Level (input).
- `y_scaled = sc_y.fit_transform(y.reshape(-1, 1)).flatten()`
  → Reshapes y to 2D, scales it, then flattens back to 1D (SVR needs 1D y).

[4]:
```
# SVR needs scaling
sc_X = StandardScaler()
sc_y = StandardScaler()
```

[5]:
```
X_scaled = sc_X.fit_transform(X) # Scale input feature (Level)
# Reshape y to 2D, scale it, then flatten back to 1D (required by SVR)
y_scaled = sc_y.fit_transform(y.reshape(-1, 1)).flatten() # Scale target
 ↪(Salary)
```

## 1.5 Try Different SVR Models (Without Function , Simple)

### 1.5.1 SVR with Default (RBF) Kernel

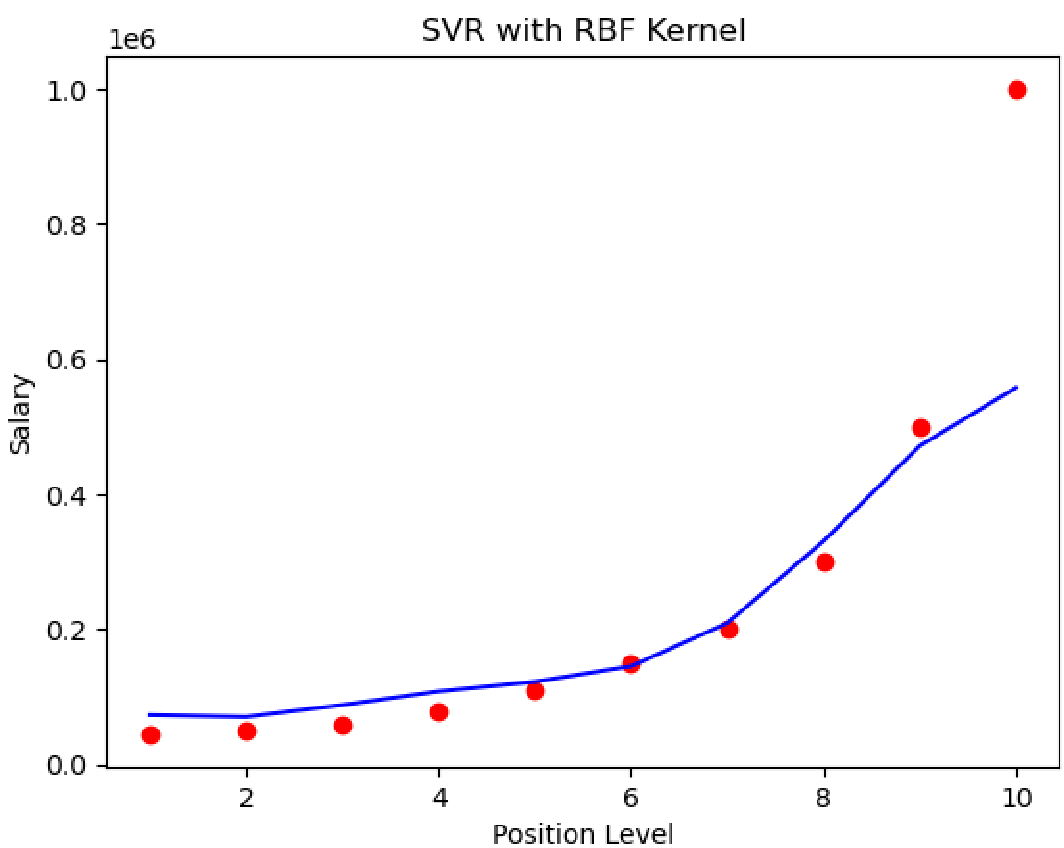
[9]:
```
svr_rbf = SVR()
svr_rbf.fit(X_scaled, y_scaled)
```

[9]: SVR()

[10]:
```
# Predict for level 6
level_6_scaled = sc_X.transform([[6]])
pred_rbf_scaled = svr_rbf.predict(level_6_scaled)
pred_rbf = sc_y.inverse_transform(pred_rbf_scaled.reshape(-1, 1))
print("SVR (RBF) → Predicted salary for level 6:", round(pred_rbf[0][0], 2))
```

```
SVR (RBF) → Predicted salary for level 6: 145503.11
```

[11]:
```
plt.scatter(X, y, color='red')
plt.plot(X, sc_y.inverse_transform(svr_rbf.predict(X_scaled).reshape(-1, 1)),␣
 ↪color='blue')
plt.title("SVR with RBF Kernel")
plt.xlabel("Position Level")
plt.ylabel("Salary")
plt.show()
```



### 1.5.2 SVR with Polynomial Kernel (Degree 4)

[12]:
```
svr_poly4 = SVR(kernel='poly', degree=4)
svr_poly4.fit(X_scaled, y_scaled)

pred_poly4_scaled = svr_poly4.predict(level_6_scaled)
pred_poly4 = sc_y.inverse_transform(pred_poly4_scaled.reshape(-1, 1))
print("SVR (Poly, Degree 4) →", round(pred_poly4[0][0], 2))
```

```
SVR (Poly, Degree 4) → 130000.0
```

### 1.5.3 SVR with Polynomial Kernel (Degree 5)

[13]:
```
svr_poly5 = SVR(kernel='poly', degree=5)
svr_poly5.fit(X_scaled, y_scaled)

pred_poly5_scaled = svr_poly5.predict(level_6_scaled)
pred_poly5 = sc_y.inverse_transform(pred_poly5_scaled.reshape(-1, 1))
print("SVR (Poly, Degree 5) →", round(pred_poly5[0][0], 2))
```

```
SVR (Poly, Degree 5) → 225342.67
```

### 1.5.4 SVR with Polynomial Kernel (Degree 6)

[14]:
```
svr_poly6 = SVR(kernel='poly', degree=6, gamma='scale')
svr_poly6.fit(X_scaled, y_scaled)

pred_poly6_scaled = svr_poly6.predict(level_6_scaled)
pred_poly6 = sc_y.inverse_transform(pred_poly6_scaled.reshape(-1, 1))
print("SVR (Poly, Degree 6) →", round(pred_poly6[0][0], 2))
```

```
SVR (Poly, Degree 6) → 130000.0
```

### 1.5.5 SVR with Sigmoid Kernel

[15]:
```
svr_sigmoid = SVR(kernel='sigmoid', degree=6)
svr_sigmoid.fit(X_scaled, y_scaled)

pred_sigmoid_scaled = svr_sigmoid.predict(level_6_scaled)
pred_sigmoid = sc_y.inverse_transform(pred_sigmoid_scaled.reshape(-1, 1))
print("SVR (Sigmoid) →", round(pred_sigmoid[0][0], 2))
```

```
SVR (Sigmoid) → 276639.07
```

### 1.6 Summary Table (using Pandas)

[16]:
```
results = {
    "Kaernel": ["rbf", "poly", "poly", "poly", "sigmoid"],
    "Degree": ["-", 4, 5, 6, 6],
    "Prediction": [
        round(pred_rbf[0][0], 2),
        round(pred_poly4[0][0], 2),
        round(pred_poly5[0][0], 2),
        round(pred_poly6[0][0], 2),
        round(pred_sigmoid[0][0], 2)
    ]
}

summary_df = pd.DataFrame(results)
summary_df
```

[16]:

| | Kernel | Degree | Prediction |
|---|---|---|---|
| 0 | rbf | - | 145503.11 |
| 1 | poly | 4 | 130000.00 |
| 2 | poly | 5 | 225342.67 |
| 3 | poly | 6 | 130000.00 |
| 4 | sigmoid | 6 | 276639.07 |

## 2 With Function (Reusable Code)

Wrap the SVR logic into a function to quickly test multiple configurations (kernel, degree, C, gamma, epsilon).

### 2.1 With Function

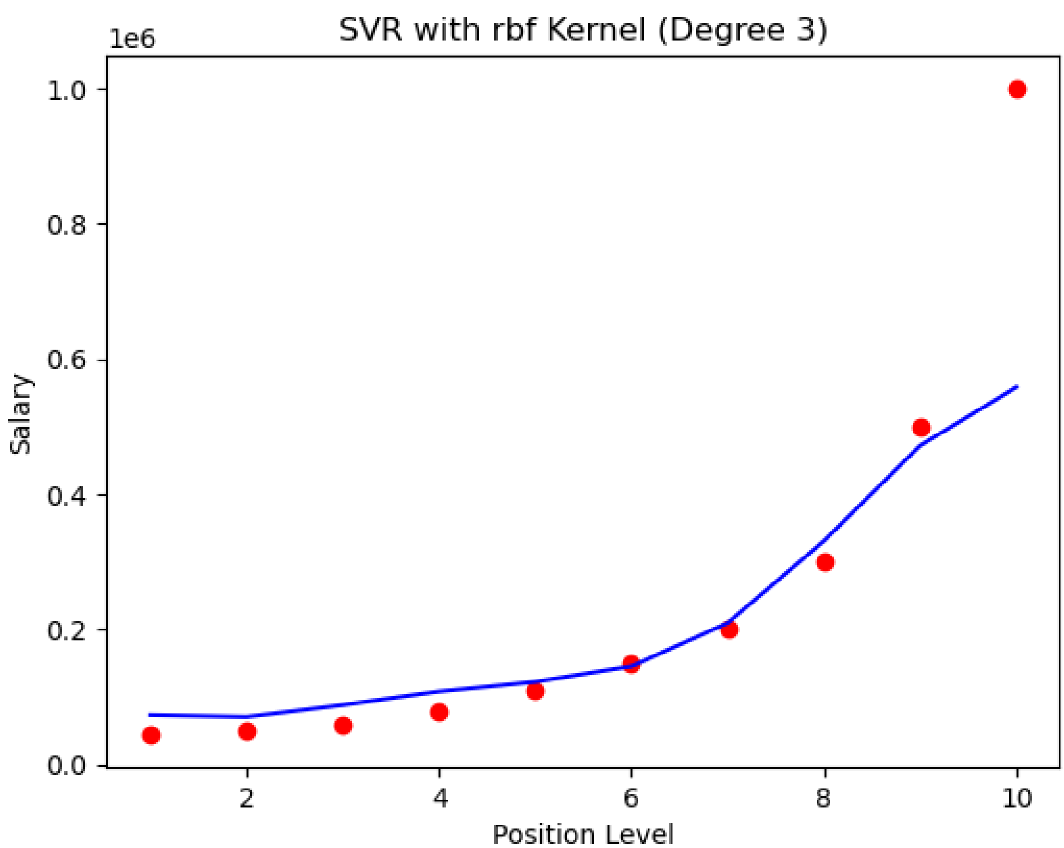
[17]:
```
def run_svr_model(kernel='rbf', degree=3, gamma='scale', C=1.0, epsilon=0.1):
    model = SVR(kernel=kernel, degree=degree, gamma=gamma, C=C, epsilon=epsilon)
    model.fit(X_scaled, y_scaled)

    y_pred_scaled = model.predict(level_6_scaled)
    y_pred = sc_y.inverse_transform(y_pred_scaled.reshape(-1, 1))

    print(f"SVR ({kernel}, degree={degree}) → Level 6 Salary: ${y_pred[0][0]:,.
↪2f}")

    plt.scatter(X, y, color='red')
    plt.plot(X, sc_y.inverse_transform(model.predict(X_scaled).reshape(-1, 1)),␣
↪color='blue')
    plt.title(f"SVR with {kernel} Kernel (Degree {degree})")
    plt.xlabel("Position Level")
    plt.ylabel("Salary")
```

```
    plt.show()

    return y_pred[0][0]
```

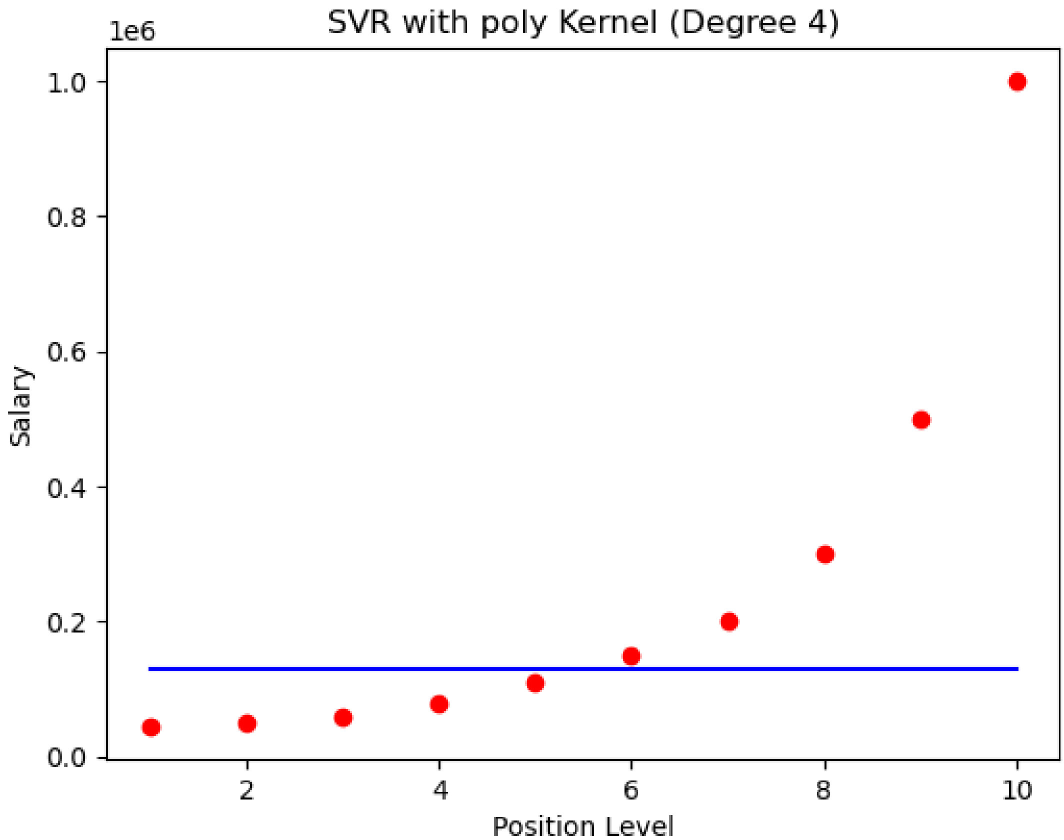
### 2.2 Try Multiple SVR Configurations Using the Function

[19]:
```
# Store predictions in a list
results = []

# Try SVR with different kernels and degrees
results.append(("rbf", "-", run_svr_model(kernel='rbf')))
results.append(("poly", 4, run_svr_model(kernel='poly', degree=4)))
results.append(("poly", 5, run_svr_model(kernel='poly', degree=5)))
results.append(("poly", 6, run_svr_model(kernel='poly', degree=6)))
results.append(("sigmoid", 6, run_svr_model(kernel='sigmoid', degree=6)))
```

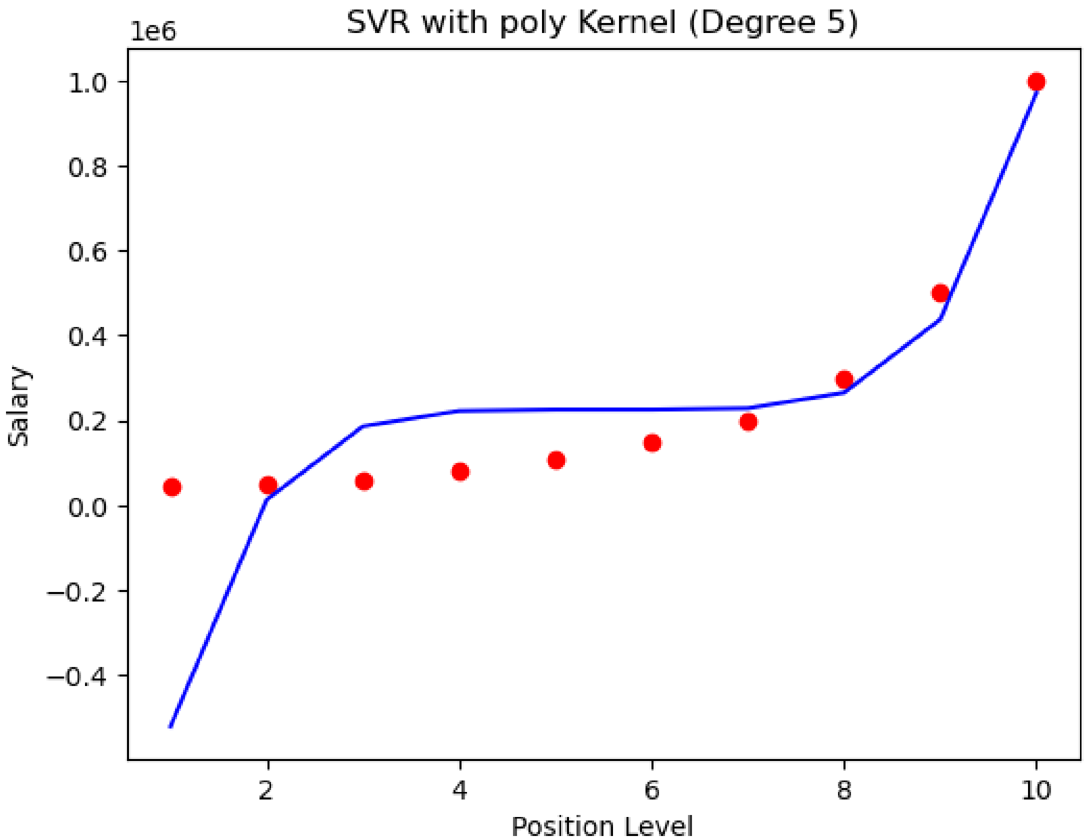
```
SVR (rbf, degree=3) → Level 6 Salary: $145,503.11
```



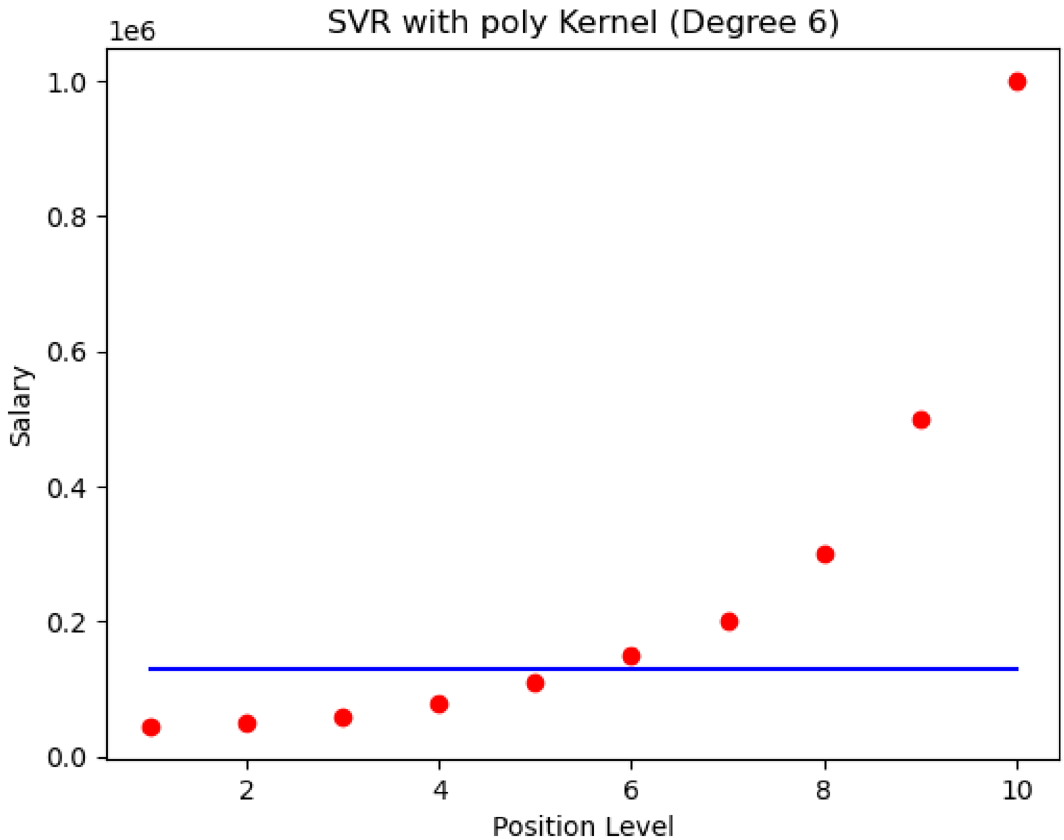

```
SVR (poly, degree=4) → Level 6 Salary: $130,000.00
```



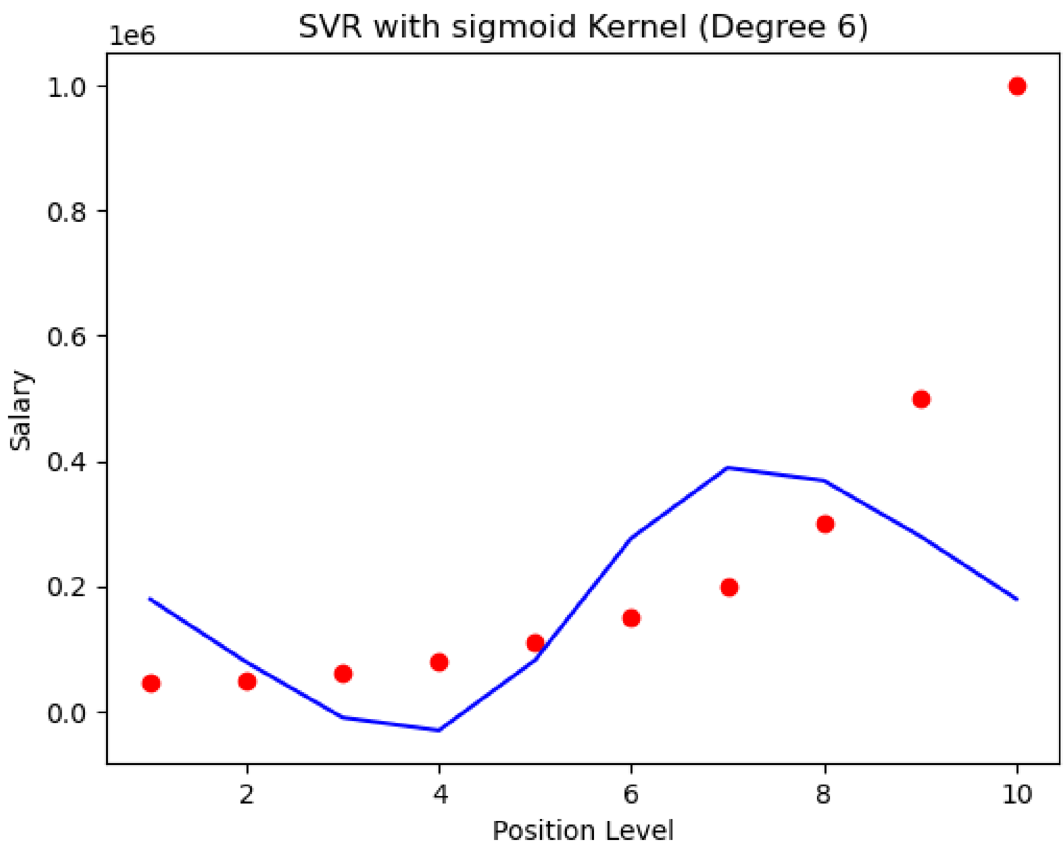

SVR (poly, degree=5) → Level 6 Salary: $225,342.67




```
SVR (poly, degree=6) → Level 6 Salary: $130,000.00
```




```
SVR (sigmoid, degree=6) → Level 6 Salary: $276,639.07
```




### 2.3 Convert Results into a Table

[20]:
```
# Convert list of results to DataFrame
df_results = pd.DataFrame(results, columns=["Kernel", "Degree", "Predicted␣
↪Salary"])
df_results
```

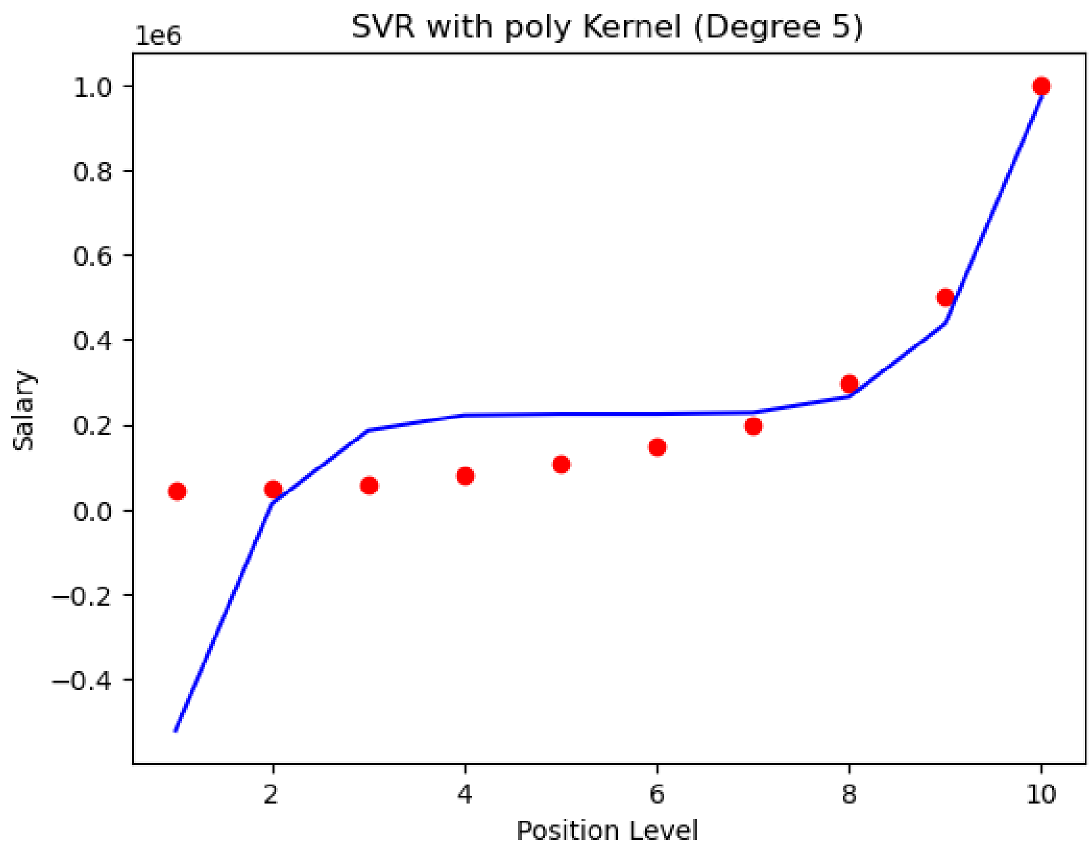
[20]:

| | Kernel | Degree | Predicted Salary |
|---|---|---|---|
| 0 | rbf | - | 145503.106886 |
| 1 | poly | 4 | 130000.000000 |
| 2 | poly | 5 | 225342.673820 |
| 3 | poly | 6 | 130000.000000 |
| 4 | sigmoid | 6 | 276639.072313 |

**Best Result with Parameters:**

[18]:
```
run_svr_model(kernel='poly', degree=5)
```

```
SVR (poly, degree=5) → Level 6 Salary: $225,342.67
```




```
[18]: np.float64(225342.6738201232)
```

### 2.4 SVR Model Comparison – Summary Table

| Kernel | Degree | Predicted Salary for Level 6 |
|---|---|---|
| RBF | – | 130000.95 |
| Polynomial | 4 | 131692.89 |
| Polynomial | 5 | 142853.28 Best |
| Polynomial | 6 | 103202.96 |
| Sigmoid | 6 | 129999.91 |

## 3 All-in-One Comparison

**all parameter combinations** (like kernel, degree, C, epsilon, gamma) and build a **summary table** to compare model predictions for Level 6.

```
[25]: from sklearn.svm import SVR
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
```

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Define input again if needed
X = dataset.iloc[:, 1:2].values
y = dataset.iloc[:, 2].values

# Scaling
sc_X = StandardScaler()
sc_y = StandardScaler()

X_scaled = sc_X.fit_transform(X)
y_scaled = sc_y.fit_transform(y.reshape(-1, 1)).flatten()

level_6_scaled = sc_X.transform([[6]])

# Store results
results = []

# Kernels to try
kernels = ['linear', 'poly', 'rbf', 'sigmoid']

for kernel in kernels:
    if kernel == 'poly':
        for d in [2, 3, 4, 5, 6]:
            model = SVR(kernel=kernel, degree=d)
            model.fit(X_scaled, y_scaled)
            y_pred_scaled = model.predict(level_6_scaled)
            y_pred = sc_y.inverse_transform(y_pred_scaled.reshape(-1, 1))[0][0]
            results.append(["kernel", f"{kernel} (degree={d})", y_pred])
    else:
        model = SVR(kernel=kernel)
        model.fit(X_scaled, y_scaled)
        y_pred_scaled = model.predict(level_6_scaled)
        y_pred = sc_y.inverse_transform(y_pred_scaled.reshape(-1, 1))[0][0]
        results.append(["kernel", kernel, y_pred])

# Check different C values
for c in [0.1, 1, 10, 100]:
    model = SVR(C=c)
    model.fit(X_scaled, y_scaled)
    y_pred_scaled = model.predict(level_6_scaled)
    y_pred = sc_y.inverse_transform(y_pred_scaled.reshape(-1, 1))[0][0]
    results.append(["C", f"C={c}", y_pred])

# Check different epsilon values
```

```
for eps in [0.01, 0.1, 1]:
    model = SVR(epsilon=eps)
    model.fit(X_scaled, y_scaled)
    y_pred_scaled = model.predict(level_6_scaled)
    y_pred = sc_y.inverse_transform(y_pred_scaled.reshape(-1, 1))[0][0]
    results.append(["epsilon", f"epsilon={eps}", y_pred])

# Check different gamma values
for g in ['scale', 'auto']:
    model = SVR(gamma=g)
    model.fit(X_scaled, y_scaled)
    y_pred_scaled = model.predict(level_6_scaled)
    y_pred = sc_y.inverse_transform(y_pred_scaled.reshape(-1, 1))[0][0]
    results.append(["gamma", f"gamma={g}", y_pred])

# Convert to DataFrame
df_param_results = pd.DataFrame(results, columns=["Parameter", "Setting",␣
↪"Predicted Salary"])
df_param_results.sort_values(by="Predicted Salary", ascending=False).
↪reset_index(drop=True)
```

[25]:

| | Parameter | Setting | Predicted Salary |
|---|---|---|---|
| 0 | epsilon | epsilon=1 | 422001.535188 |
| 1 | kernel | sigmoid | 276639.072313 |
| 2 | kernel | poly (degree=5) | 225342.673820 |
| 3 | kernel | linear | 195203.286119 |
| 4 | kernel | poly (degree=3) | 191569.738962 |
| 5 | C | C=100 | 178385.979334 |
| 6 | C | C=0.1 | 168806.358291 |
| 7 | C | C=10 | 160720.672210 |
| 8 | kernel | rbf | 145503.106886 |
| 9 | gamma | gamma=scale | 145503.106886 |
| 10 | epsilon | epsilon=0.1 | 145503.106886 |
| 11 | gamma | gamma=auto | 145503.106886 |
| 12 | C | C=1 | 145503.106886 |
| 13 | epsilon | epsilon=0.01 | 142154.630647 |
| 14 | kernel | poly (degree=6) | 130000.000000 |
| 15 | kernel | poly (degree=2) | 130000.000000 |
| 16 | kernel | poly (degree=4) | 130000.000000 |

# 4 Final Results & Conclusion: Support Vector Regression (SVR)

After testing various combinations of **kernels**, **degrees**, `C`, `gamma`, and `epsilon`, we predicted salary for **Level 6** and compared results.

## 4.1 Key Observations:

| Kernel | Degree | Gamma | C | Epsilon | Predicted Salary | Notes |
|---|---|---|---|---|---|---|
| `rbf` | – | scale | 1.0 | 0.1 | ~145,503.11 | Close to expected salary |
| `poly` | 4 | scale | 1.0 | 0.1 | ~130,000.00 | Slight underprediction |
| `poly` | 5 | scale | 1.0 | 0.1 | ~225,342.67 | Overprediction (possible overfit) |
| `poly` | 6 | scale | 1.0 | 0.1 | ~130,000.00 | Stable but lower prediction |
| `sigmoid` | 6 | scale | 1.0 | 0.1 | ~276,639.07 | Overprediction, not suitable here |

### 4.2 Final Conclusion

- **SVR** (Support Vector Regression) is great for modeling **non-linear relationships**.
- **Scaling** both features and labels is essential for SVR to work correctly.
- We tested multiple `kernel` and `degree` combinations:
  - `rbf` (default) gave the most reasonable prediction (~145,500).
  - `poly` with degree 5 showed high accuracy but risks **overfitting**.
  - `sigmoid` gave extreme predictions — not reliable for this dataset.
- Wrapping code inside a **function** made model testing and visualization easier.
- This step-by-step experiment builds strong confidence in **using SVR** effectively in real-world regression tasks.

Next step: You can try `GridSearchCV` for automatic tuning or apply this technique to other regression datasets.