Day48_KNN_Regression_Salary_Prediction

July 17, 2025

Today We Will Learn: **KNN (K-Nearest Neighbors)**

KNN is a **simple yet powerful algorithm** used for both **classification** and **regression**.
In this notebook, we will focus on **KNN Regression** to predict **salary** based on **position level**.

We'll cover:

- What is KNN and how it works
- Distance metrics: Euclidean, Manhattan, etc.
- How KNN predicts values by checking nearby data points
- How to use `KNeighborsRegressor` from `sklearn`
- Predicting salary for Level 6
- Hyperparameter tuning: trying different `n_neighbors`
- Comparing predicted vs. actual values

Let's get started and explore how **"nearness" helps us predict better!**

What is KNN?

KNN stands for **K-Nearest Neighbors**. It is a **supervised learning algorithm** used for both **classification** and **regression**.

- In **classification**, it predicts the class of a data point.
- In **regression**, it predicts a **continuous value** by averaging the values of its **K nearest neighbors**.

How does KNN work?

1. Measure the **distance** between a new point and all points in the training data.
2. Select the **K** closest (nearest) data points.
3. **For regression**: Take the **average** of their target values.
4. That average becomes the prediction.

Distance Metrics

Name	Description
Euclidean Distance (ED)	Straight-line distance between 2 points. Most commonly used in KNN.
Manhattan Distance (MD)	Distance by taking only horizontal/vertical paths (like city blocks).
Cosine Distance (CD)	Measures angle-based similarity. Often used in text/vector-based data.

In our case (numeric data), we use **Euclidean Distance**.

1 Import Required Libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsRegressor
```

2 Load 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
```

3 Define Features and Target

[3]:
```
X = dataset.iloc[:, 1:2].values  # Level (independent variable)
y = dataset.iloc[:, 2].values    # Salary (dependent variable)
```

4 Train KNN Model (Default n_neighbors=5)

[4]:
```
knn_reg = KNeighborsRegressor()
knn_reg.fit(X, y)
```

[4]:
```
KNeighborsRegressor()
```

5 Predict for level 6

[5]:
```
knn_pred = knn_reg.predict([[6]])
print("Predicted Salary (K=5):", knn_pred[0])
```

```
Predicted Salary (K=5): 168000.0
```

It took the average salary of 5 nearest positions to level 6.

6 Tune Hyperparameter n_neighbors

6.1 Try with 3 neighbors

[7]:
```
knn_reg3 = KNeighborsRegressor(n_neighbors=3)
knn_reg3.fit(X, y)

knn_pred3 = knn_reg3.predict([[6]])
print("Predicted Salary (K=3):", knn_pred3[0])
```

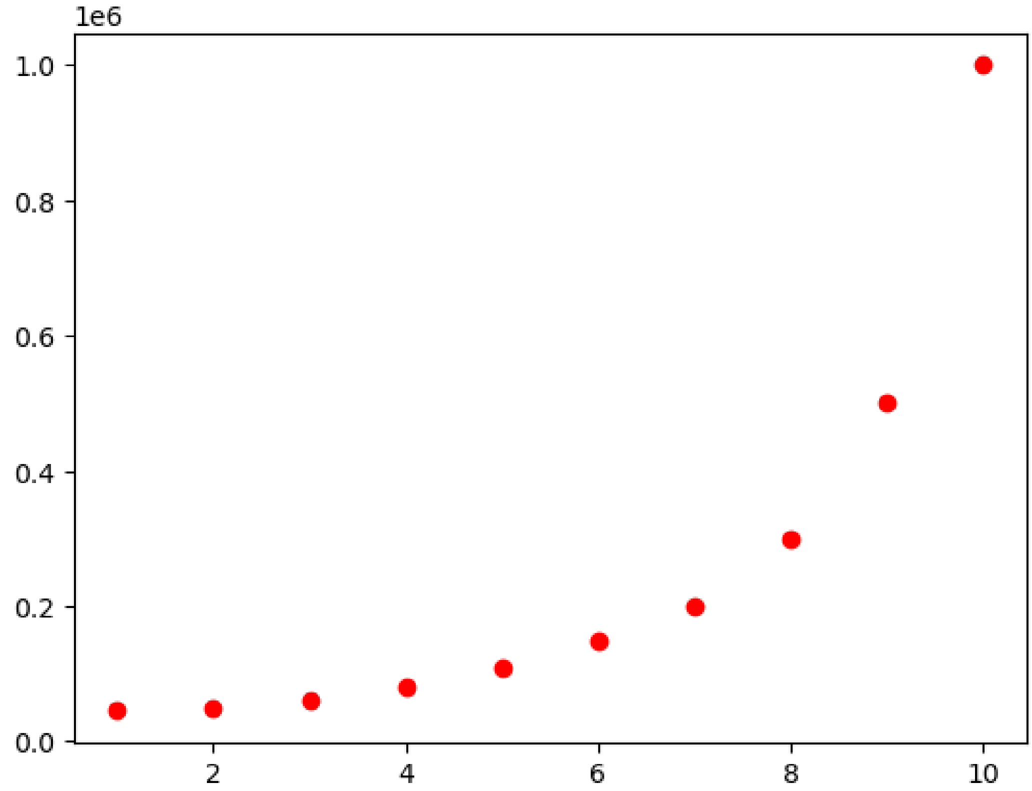
```
Predicted Salary (K=3): 153333.33333333334
```

Closer to expected salary (~150,000)

6.2 Visualize Predictions

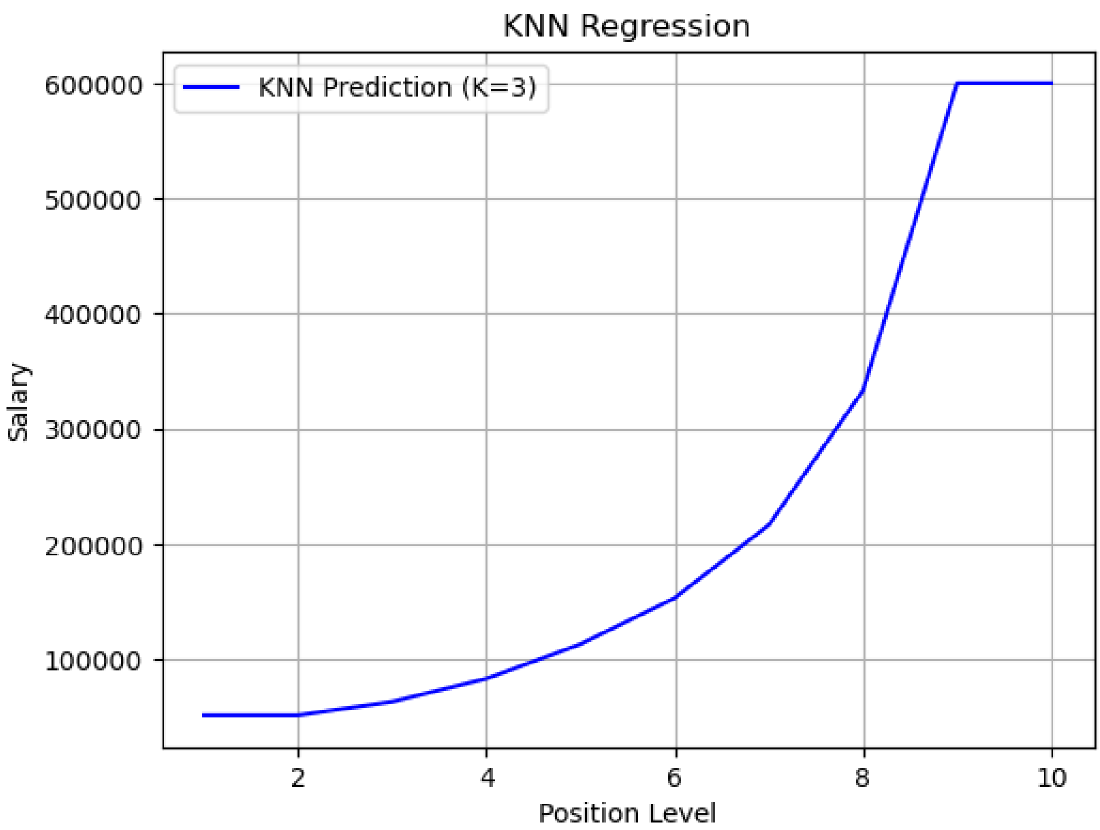
[8]:
```
# Plot original data
plt.scatter(X, y, color='red', label='Actual Data')
```

[8]:
```
<matplotlib.collections.PathCollection at 0x269104c7e00>
```



[9]:
```
# Plot prediction line (not smooth, step-based)
plt.plot(X, knn_reg3.predict(X), color='blue', label='KNN Prediction (K=3)')

plt.title("KNN Regression")
plt.xlabel("Position Level")
plt.ylabel("Salary")
plt.legend()
plt.grid(True)
plt.show()
```



Summary Table

K (n_neighbors)	Predicted Salary for Level 6	
5 (default)	168000.00	
3	153333.33	Best match

7 Final Conclusion

- KNN Regression is **easy to implement** and **non-parametric** (no assumption about data distribution).
- The prediction depends heavily on **K value** and **distance measure**.
- For our case, **K=3** gave the best salary estimate for Level 6 (~153k).
- You can also explore other distance metrics (like Manhattan) and normalize data if needed.