Import libraries

```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LinearRegression
```

Import data

```
# Get dataset
df_sal = pd.read_csv('/content/Position_Salaries.csv')
df_sal.head()
```

	Position	Level	Salary
0	Business Analyst	1	45000
1	Junior Consultant	2	50000
2	Senior Consultant	3	60000
3	Manager	4	80000
4	Country Manager	5	110000

Next steps: Generate code with df_sal View recommended plots

Analyze Data

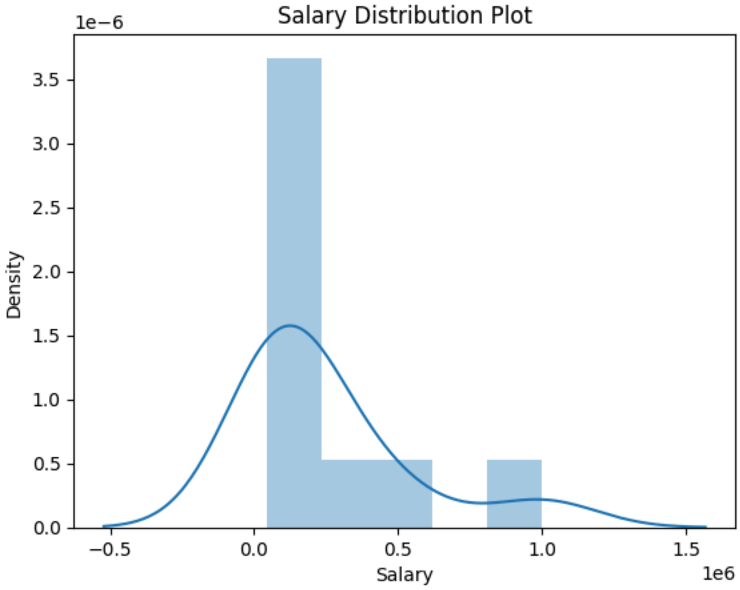
```
# Describe data
df_sal.describe()
```

	Level	Salary
count	10.00000	10.000000
mean	5.50000	249500.000000
std	3.02765	299373.883668
min	1.00000	45000.000000
25%	3.25000	65000.000000
50%	5.50000	130000.000000
75%	7.75000	275000.000000
max	10.00000	1000000.000000

Distribution

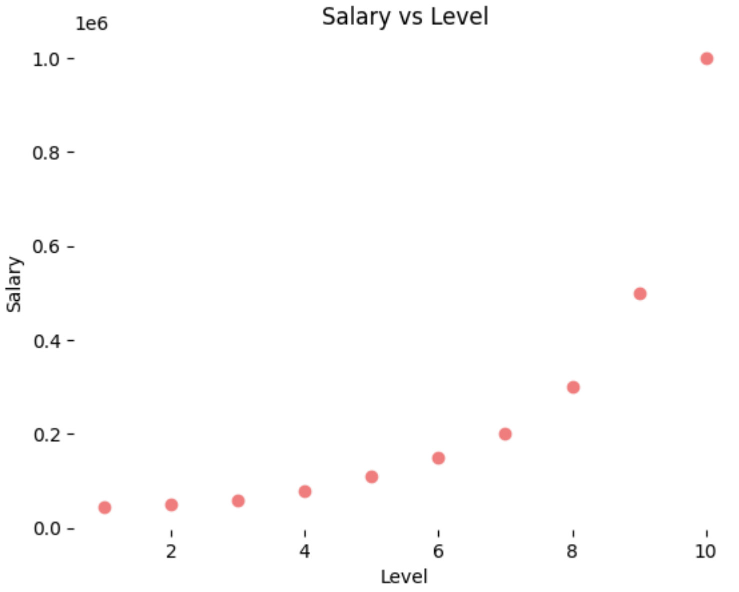
```
# Data distribution
plt.title('Salary Distribution Plot')
sns.distplot(df_sal['Salary'])
plt.show()
```

```
<ipython-input-6-d6ace42bc912>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df_sal['Salary'])
```



Relation between Salary and Level

```
# Relationship between Salary and Level
plt.scatter(df_sal['Level'], df_sal['Salary'], color = 'lightcoral')
plt.title('Salary vs Level')
plt.xlabel('Level')
plt.ylabel('Salary')
plt.box(False)
plt.show()
```



Split data into Independent/Dependent variables

```
# Splitting variables
X = df_sal.iloc[:, 1:-1].values   # independent
y = df_sal.iloc[:, -1].values     # dependent
```

Train model

Linear Regression

```
# Train linear regression model on whole dataset
lr = LinearRegression()
lr.fit(X, y)
```

```
▾ LinearRegression
LinearRegression()
```

Polynomial Regression

```
# Train polynomial regression model on the whole dataset
pr = PolynomialFeatures(degree = 4)
X_poly = pr.fit_transform(X)
lr_2 = LinearRegression()
lr_2.fit(X_poly, y)
```

```
▾ LinearRegression
LinearRegression()
```

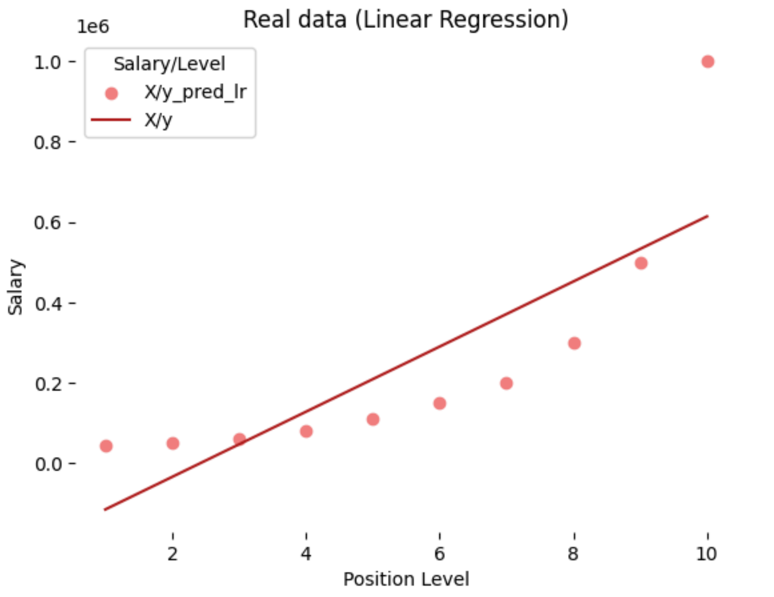
Predict results

```
# Predict results
y_pred_lr = lr.predict(X)           # Linear Regression
y_pred_poly = lr_2.predict(X_poly)  # Polynomial Regression
```

Visualize predictions

Prediction with Linear Regression

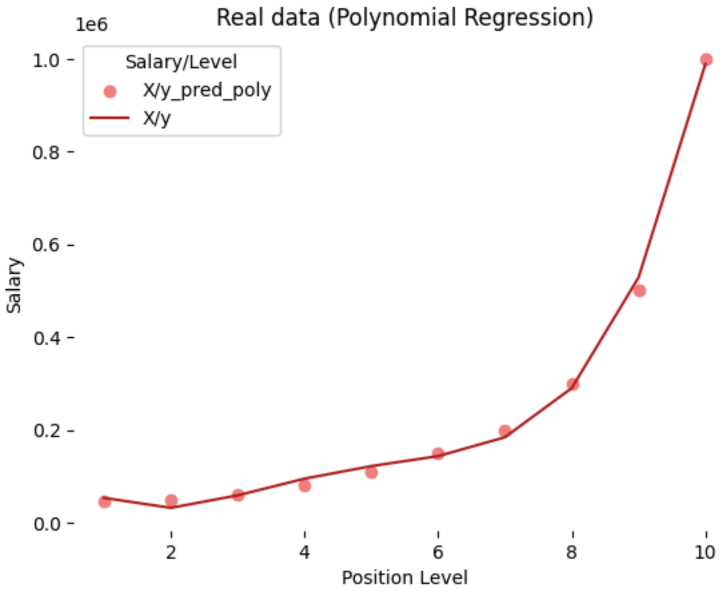
```
# Visualize real data with linear regression
plt.scatter(X, y, color = 'lightcoral')
plt.plot(X, lr.predict(X), color = 'firebrick')
plt.title('Real data (Linear Regression)')
plt.xlabel('Position Level')
plt.ylabel('Salary')
plt.legend(['X/y_pred_lr', 'X/y'], title = 'Salary/Level', loc='best', facecolor='white')
plt.box(False)
plt.show()
```



Prediction with Polynomial Regression

```
# Visualize real data with polynomial regression
X_grid = np.arange(min(X), max(X), 0.1)
X_grid = X_grid.reshape((len(X_grid), 1))
plt.scatter(X, y, color = 'lightcoral')
plt.plot(X, lr_2.predict(X_poly), color = 'firebrick')
plt.title('Real data (Polynomial Regression)')
plt.xlabel('Position Level')
plt.ylabel('Salary')
plt.legend(['X/y_pred_poly', 'X/y'], title = 'Salary/Level', loc='best', facecolor='white')
plt.box(False)
plt.show()
```

```
<ipython-input-20-585c47313e9f>:2: DeprecationWarning: Conversion of an array with ndim > 0 to a scalar is deprecated, and will err
  X_grid = np.arange(min(X), max(X), 0.1)
```



Test with an example

```
# Predict a new result with linear regression
print(f'Linear Regression result : {lr.predict([[6.5]])}')
# Predict a new result with polynomial regression
print(f'Polynomial Regression result : {lr_2.predict(pr.fit_transform([[6.5]]))}')
```

```
Linear Regression result : [330378.78787879]
Polynomial Regression result : [158862.45265155]
```

Based on the results, the linear regression model might be a better fit for the data compared to the polynomial regression model.