Polynomial Regression

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
```

In [2]:
```
os.chdir(r'C:\Users\acer\Desktop\P14-Machine-Learning-AZ-Template-Folder\Machine
```

In [3]:
```
dataset = pd.read_csv('Position_Salaries.csv')
dataset
```

Out[3]:

	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
5	Region Manager	6	150000
6	Partner	7	200000
7	Senior Partner	8	300000
8	C-level	9	500000
9	CEO	10	1000000

Independent and dependent variables.

In [5]:
```
X = dataset['Level'].values.reshape(-1,1)
y = dataset['Salary'].values
```

Building a Simple Linear Regression model.

In [8]:
```
from sklearn.linear_model import LinearRegression
```

In [10]:
```
lin1 = LinearRegression()
```

In [11]:
```
lin1.fit(X,y)
```

Out[11]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Building a Polynomial Regression model.

In [12]:
```
from sklearn.preprocessing import PolynomialFeatures
```

In [13]:
```
poly_model = PolynomialFeatures(degree = 2)
X_poly = poly_model.fit_transform(X)
poly_model.fit(X_poly, y)
```

Out[13]:
```
PolynomialFeatures(degree=2, include_bias=True, interaction_only=False,
                   order='C')
```

The fit_transform adds new terms to the model like in our case, the quadratic term.

In [14]:
```
X_poly
```

Out[14]:
```
array([[  1.,   1.,   1.],
       [  1.,   2.,   4.],
       [  1.,   3.,   9.],
       [  1.,   4.,  16.],
       [  1.,   5.,  25.],
       [  1.,   6.,  36.],
       [  1.,   7.,  49.],
       [  1.,   8.,  64.],
       [  1.,   9.,  81.],
       [  1.,  10., 100.]])
```

The First column represents the constant section,
the second column represents the linear section and
the third column represents the quadratic section.

In [15]:
```
# Creating a new linear regression object.
lin2 = LinearRegression()
lin2.fit(X_poly,y)
```

Out[15]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Intercepts and Weights.

In [17]:
```
print('Intercept = ', lin2.intercept_.round(2), '\n', 'Weights = ', lin2.coef_.r
```

```
Intercept =  232166.67
 Weights =  [      0.    -132871.21   19431.82]
```

Predictions using lin1 and lin2.

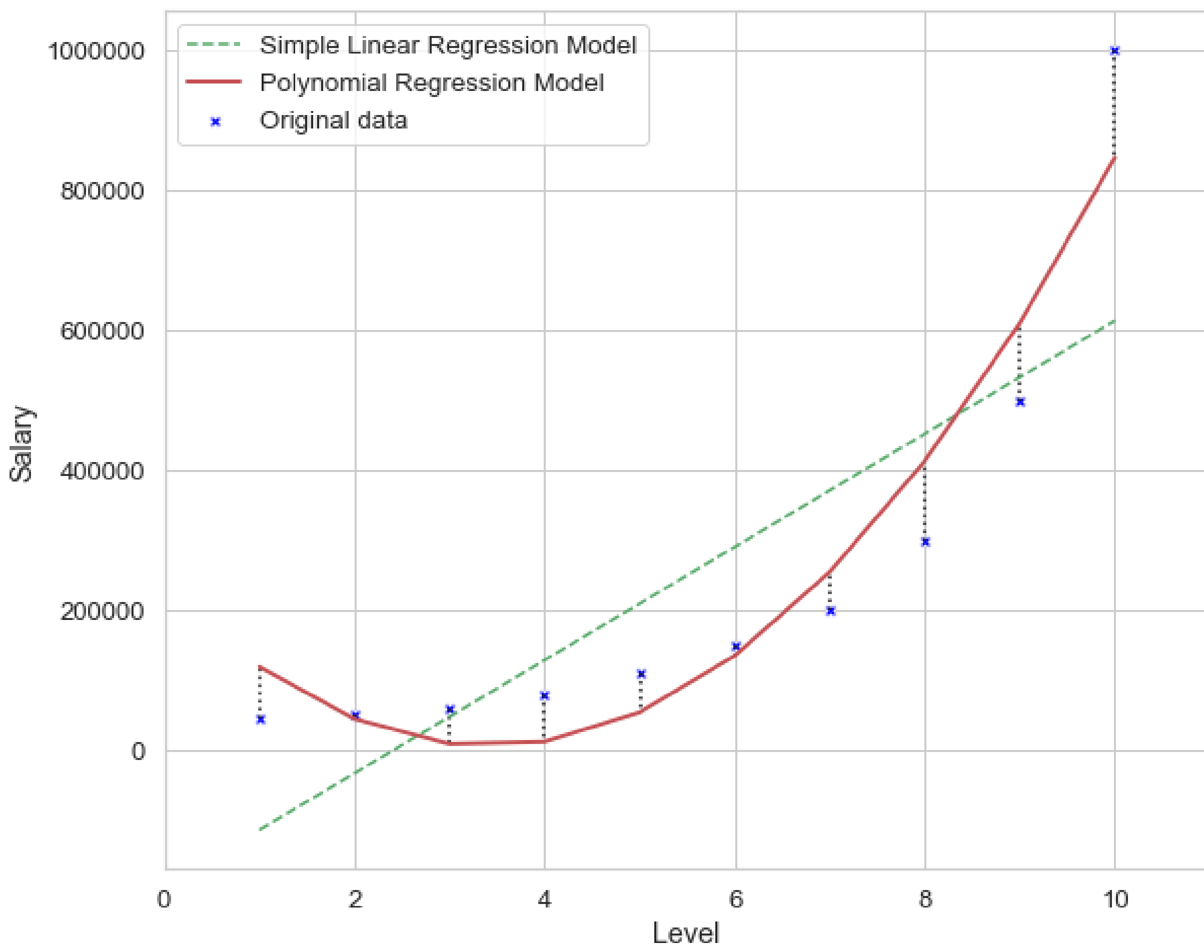
In [29]:
```
predictedbylin1 = lin1.predict(X)
predictedbylin2 = lin2.predict(X_poly)
```

Using Plots.

In [18]:
```
lin2.predict(X_poly)
```

Out[18]:
```
array([118727.27272727,  44151.51515151,   8439.39393939,  11590.90909091,
        53606.06060606, 134484.84848485, 254227.27272727, 412833.33333333,
       610303.03030303, 846636.36363636])
```

In [57]:
```
plt.figure(figsize = (9.5,8))
sns.set(style = 'whitegrid', font_scale = 1.2)

sns.scatterplot(x = dataset.Level, y = dataset.Salary, color = 'blue', marker =

#PLotting the straight line predicted by lin1 object.
plt.plot(X, lin1.predict(X), 'g--', label = 'Simple Linear Regression Model')

#PLotting the curve predicted by the lin2 object.
plt.plot(X, lin2.predict(X_poly), 'r', linewidth = 2, label = 'Polynomial Regres:


for ii in range(len(X)):
    plt.vlines(X[ii], y[ii], predictedbylin2[ii], linestyles = 'dotted')
    #plt.vlines(X_position, ymin, ymax)




plt.xlim(0,11)

plt.legend()
plt.show()
```



Using a function to ease things up.

In [64]:
```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures

# We define a function that returns a predicted value of the response variable g
def myPolyFitter(X,y,n = 1):
    '''n = degree of the polynomial.'''
    poly_model = PolynomialFeatures(degree = n)
    X_poly = poly_model.fit_transform(X)
    poly_model.fit(X_poly, y)

    # Creating a new linear regression object.
    lin2 = LinearRegression()
    lin2.fit(X_poly,y)

    #Intercept and weights.
    #print('Intercept = ', lin2.intercept_.round(2), '\n', 'Weights = ', lin2.coe

    #Predictions.
    predictedbylin2 = lin2.predict(X_poly)

    return predictedbylin2
```

Creating a dataframe to store all the predicted values upto order 'n'.

In [100]:
```
def createDataFrame(X,y,n = 1):
    myDF = pd.DataFrame()
    myDF['y'] = y
    for ii in range(1,n+1):
        #Inserting values into the data frame.
        #myDF['polynomial_degree'] = ii
        myDF[ii] = myPolyFitter(X,y,ii)

    return myDF
```

In [101]:
```
polyfit_summary = createDataFrame(X,y,n = 4)
polyfit_summary = polyfit_summary.round(2)
polyfit_summary
```

Out[101]:

	y	1	2	3	4
0	45000	-114454.55	118727.27	14902.10	53356.64
1	50000	-33575.76	44151.52	78759.91	31759.91
2	60000	47303.03	8439.39	94960.37	58642.19
3	80000	128181.82	11590.91	88223.78	94632.87
4	110000	209060.61	53606.06	83270.40	121724.94
5	150000	289939.39	134484.85	104820.51	143275.06
6	200000	370818.18	254227.27	177594.41	184003.50
7	300000	451696.97	412833.33	326312.35	289994.17
8	500000	532575.76	610303.03	575694.64	528694.64
9	1000000	613454.55	846636.36	950461.54	988916.08

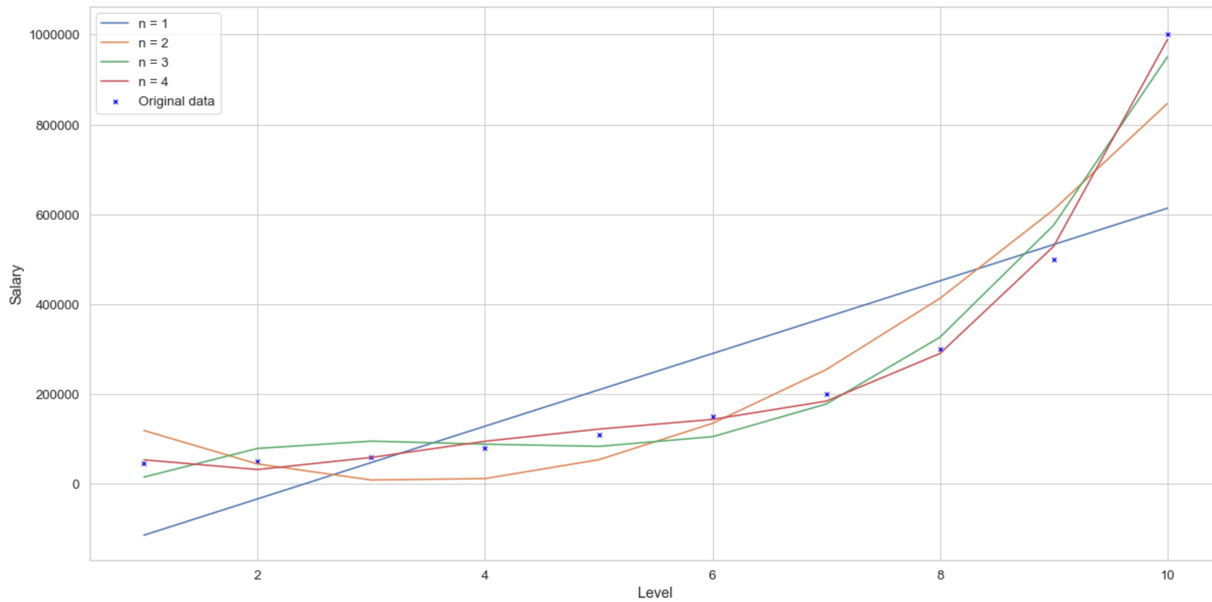
Testing:

In [102]:
```
for ii in range(1,4+1):
    print(myPolyFitter(X,y,ii).round(2), '\n\n')
```

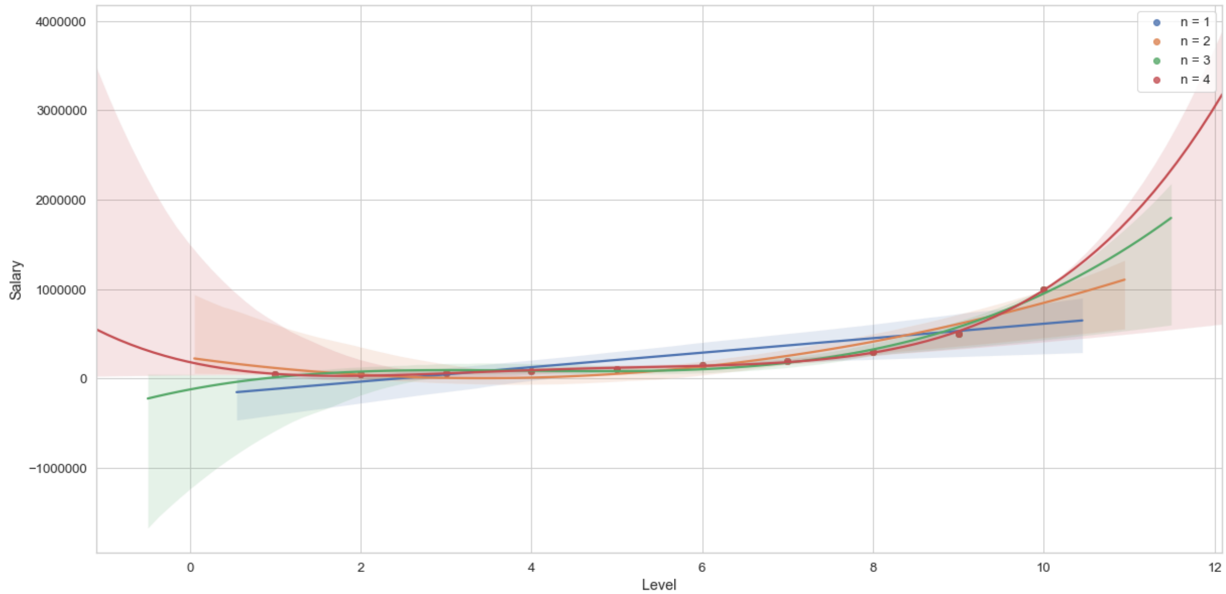
```
[-114454.55  -33575.76   47303.03  128181.82  209060.61  289939.39
  370818.18  451696.97  532575.76  613454.55]


[118727.27  44151.52   8439.39  11590.91  53606.06 134484.85 254227.27
 412833.33 610303.03 846636.36]


[ 14902.1    78759.91  94960.37  88223.78  83270.4   104820.51 177594.41
 326312.35 575694.64 950461.54]


[ 53356.64  31759.91  58642.19  94632.87 121724.94 143275.06 184003.5
 289994.17 528694.64 988916.08]
```

Making a grand plot to summarize everything into one figure.

In [111]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize = (20,10))
sns.set(style = 'whitegrid', font_scale = 1.2)

for ii in range(1,4+1):
        #PLotting the straight line predicted by lin2 object.
        plt.plot(X, polyfit_summary[ii], label = 'n = %i' %ii)

sns.scatterplot(x = dataset.Level, y = dataset.Salary, color = 'blue', marker =


plt.legend()
plt.show()
```



In [133]:
```
plt.figure(figsize = (20,10))
sns.set(style = 'whitegrid', font_scale = 1.2)

for ii in range(1,4+1):
    sns.regplot(dataset.Level, dataset.Salary, order = ii, label = "n = %i" %ii)
plt.legend()
plt.show()
```



Making Predictions.

In [141]:
```
def predictor(jj,n = 1):
    # Making the model once again.
    poly_model = PolynomialFeatures(degree = n)
    X_poly = poly_model.fit_transform(X)
    poly_model.fit(X_poly, y)

    lin2 = LinearRegression()
    lin2.fit(X_poly,y)
    temp = lin2.predict(poly_model.fit_transform(np.array([[jj]]))).round(2)   #
    return temp[0]

predictor(6.5,2)
```

Out[141]: 189498.11

Better format.

In [130]:
```
def modified_predictor(jj, n = 1):
    '''Returns a dataframe with predicted values for order 1,2,3,...,n.
        Here,
            jj = value of the independent variable.
            n = order of the polynomial function.
    '''
    df = pd.DataFrame()

    for ii in range(1,n+1):
        poly_model = PolynomialFeatures(degree = ii)
        X_poly = poly_model.fit_transform(X)
        poly_model.fit(X_poly, y)

        lin2 = LinearRegression()
        lin2.fit(X_poly,y)
        temp = lin2.predict(poly_model.fit_transform(np.array( [[jj]] ))).round(

        df[ii] = temp

    return df

modified_predictor(6.5,5)
```

Out[130]:

	1	2	3	4	5
0	330378.79	189498.11	133259.47	158862.45	174878.08

A handy way to minimize the warning signs.

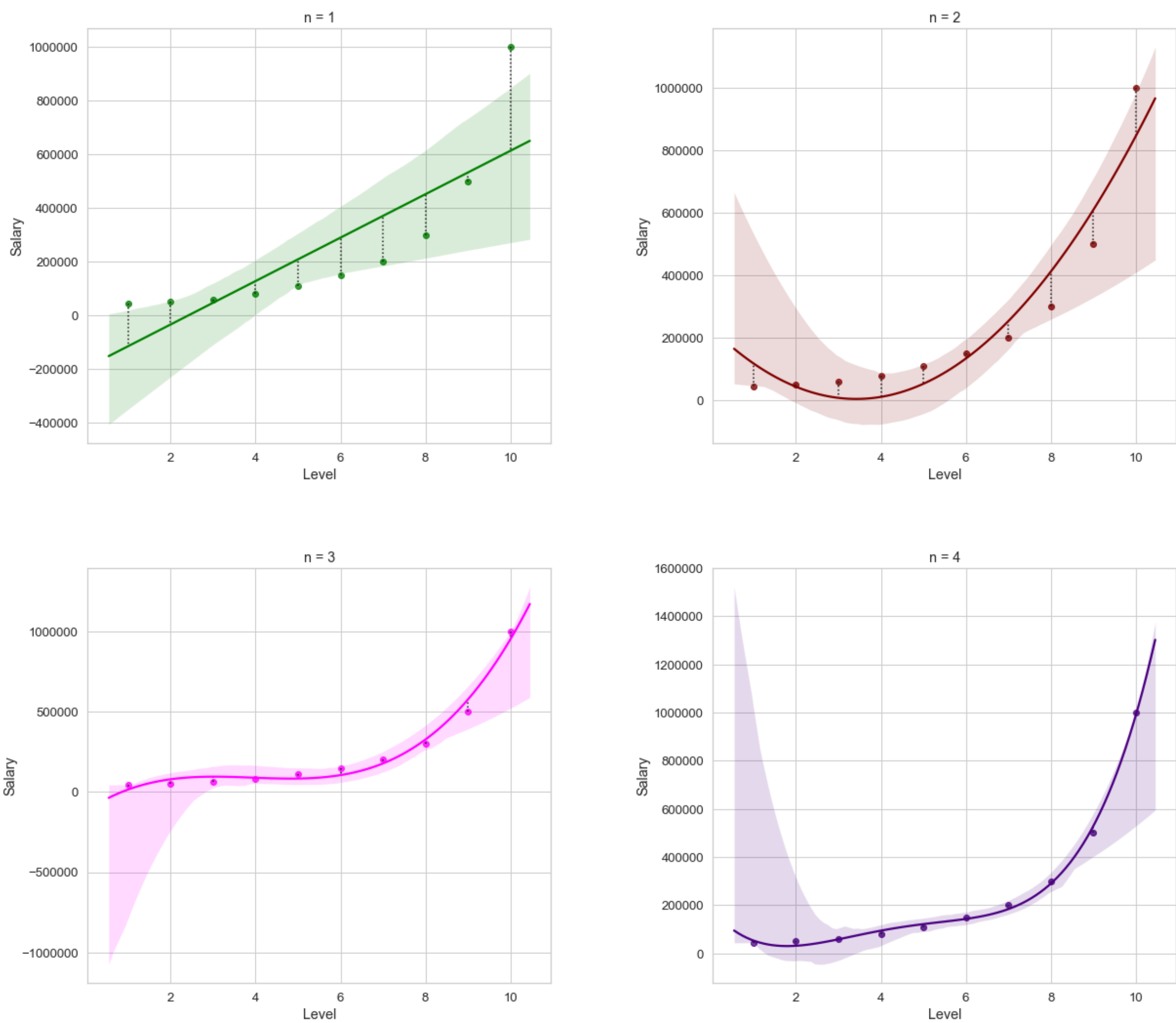
Source: [Stack Overflow (https://stackoverflow.com/questions/9031783/hide-all-warnings-in-ipython)](https://stackoverflow.com/questions/9031783/hide-all-warnings-in-ipython)

In [159]:
```
from IPython.display import HTML
HTML('''<script>
code_show_err=false;
function code_toggle_err() {
 if (code_show_err){
 $('div.output_stderr').hide();
 } else {
 $('div.output_stderr').show();
 }
 code_show_err = !code_show_err
}
$( document ).ready(code_toggle_err);
</script>
To toggle on/off output_stderr, click <a href="javascript:code_toggle_err()">here
```

Out[159]: To toggle on/off output_stderr, click here.

Finally, a summarized figure.

In [160]:
```
plt.figure(figsize = (20,18))
sns.set(style = 'whitegrid', font_scale = 1.2)
plt.subplots_adjust(wspace = 0.35, hspace = 0.3)

colors = ['lightred', 'green', 'maroon', 'magenta', 'indigo']

for ii in range(1,4+1):
    plt.subplot(2,2,ii)
    sns.regplot(dataset.Level, dataset.Salary, order = ii, color = colors[ii])

    for jj in range(len(y)):
        plt.vlines(X[jj], y[jj], predictor(dataset['Level'][jj],ii), linestyles

    plt.title('n = %i' %ii)

plt.show()
```



Conclusion:

It seems the polynomial fit of order 4 is the best fit to model the regression.

The End.