Customer Spend Prediction - Using Polynomial Regression

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Class Problem Statement

Build a model to predict customer spend based on the hour for shopping

Please take note that the illustrations in this notebook is NOT for results/accuracy but for explaining the various concepts

Data Description

This data is proprietory and cannot be shared to anyone who is NOT attending A4Ayub Data Science Labs.!

Each row in the dataset corresponds to one unique product in a basket (e.g. if there are three occurences of the same product in that basket, it will have one row for the product in that basket, with quantity equal to three)

The file has the below structure:

Column Name	Description	Type	Sample Values
shop_week	Identifies the week of the basket	Char	Format is YYYYWW where the first 4 characters identify the fiscal year and the other two characters identify the specific week within the year (e.g. 200735). Being the fiscal year, the first week doesn't start in January. (See time.csv file for start/end dates of each week)
shop_date	Date when shopping has been made. Date is specified in the yyyymmdd format	Char	20060413, 20060412
shop_weekday	Identifies the day of the week	Num	1=Sunday, 2=Monday, …, 7=Saturday
shop_hour	Hour slot of the shopping	Num	0=00:00-00:59, 1=01:00-01:59, …23=23:00-23:59
Quantity	Number of items of the same product bought in this basket	Num	Integer number
spend	Spend associated to the items bought	Num	Number with two decimal digits
prod_code	Product Code	Char	PRD0900001, PRD0900003
prod_code_10	Product Hierarchy Level 10 Code	Char	CL00072, CL00144
prod_code_20	Product Hierarchy Level 20 Code	Char	DEP00021, DEP00051
prod_code_30	Product Hierarchy Level 30 Code	Char	G00007, G00015
prod_code_40	Product Hierarchy Level 40 Code	Char	D00002, D00003

Column Name	Description	Type	Sample Values
cust_code	Customer Code	Char	CUST0000001624, CUST0000001912
cust_price_sensitivity	Customer's Price Sensitivity	Char	LA=Less Affluent, MM=Mid Market, UM=Up Market, XX=unclassified
cust_lifestage	Customer's Lifestage	Char	YA=Young Adults, OA=Older Adults, YF=Young Families, OF=Older Families, PE=Pensioners, OT=Other, XX=unclassified
basket_id	Basket ID. All items in a basket share the same basket_id value.	Num	994100100000020, 994100100000344
basket_size	Basket size	Char	L=Large, M=Medium, S=Small
basket_price_sensitivity	Basket price sensitivity	Char	LA=Less Affluent, MM=Mid Market, UM=Up Market, XX=unclassified
basket_type	Basket type	Char	Small Shop, Top Up, Full Shop, XX
basket_dominant_mission	Shopping dominant mission	Char	Fresh, Grocery, Mixed, Non Food, XX
store_code	Store Code	Char	STORE00001, STORE00002
store_format	Format of the Store	Char	LS, MS, SS, XLS
store_region	Region the store belongs to	Char	E02, W01, E01, N03

Workbench

Importing the required libraries

In [148]:

```
# Import the numpy and pandas package
import numpy as np
import pandas as pd

# Import Standard operations
import operator

# Data Visualisation
import matplotlib.pyplot as plt
import seaborn as sns

# Import the warnings
import warnings

# Import statsmodels
import statsmodels.formula.api as smf
import statsmodels.api as sm

from statsmodels.sandbox.regression.predstd import wls_prediction_std

# Import RMSE
from statsmodels.tools.eval_measures import rmse

# Imort Linear Regression from scikit-learn
from sklearn.linear_model import LinearRegression

# Import Polynomial Features
from sklearn.preprocessing import PolynomialFeatures

# Import the Train Test Split capability from sk-learn
from sklearn.model_selection import train_test_split

# Import the metrics
from sklearn.metrics import mean_squared_error, r2_score

# configuration settings
%matplotlib inline
sns.set(color_codes=True)
warnings.filterwarnings('ignore') ## Surpress the warnings
```

Load the data into a dataframe

In [149]:

```
# load the data into a dataframe called supermarket_till_transactions_df
supermarket_till_transactions_df = pd.read_csv("../data/beginner/supermarket_till_transacti
```

In [150]:

```
# view the top five records
supermarket_till_transactions_df.head(5)
```

Out[150]:

	SHOP_WEEK	SHOP_DATE	SHOP_WEEKDAY	SHOP_HOUR	QUANTITY	SPEND	PROD_COD
0	200607	20060413	5	20	1	103	PRD090009
1	200607	20060412	4	19	1	28	PRD090035
2	200607	20060413	5	20	3	84	PRD090055
3	200607	20060412	4	19	1	221	PRD090164
4	200607	20060413	5	20	1	334	PRD090206

5 rows × 22 columns

In order to illustrate Polynomial Linear Regression we just need two variables which are:

1. SHOP_HOUR
2. SPEND

In [151]:

```
supermarket_till_transactions_df = supermarket_till_transactions_df[["SHOP_HOUR","SPEND"]]
supermarket_till_transactions_df.head(5)
```

Out[151]:

	SHOP_HOUR	SPEND
0	20	103
1	19	28
2	20	84
3	19	221
4	20	334

Visualise the linear regression and compare to polynomial regression line

In [152]:

```
x = supermarket_till_transactions_df.iloc[:,:-1].values
y = supermarket_till_transactions_df.iloc[:,-1].values
```

Display the Linear Regression Line

In [154]:

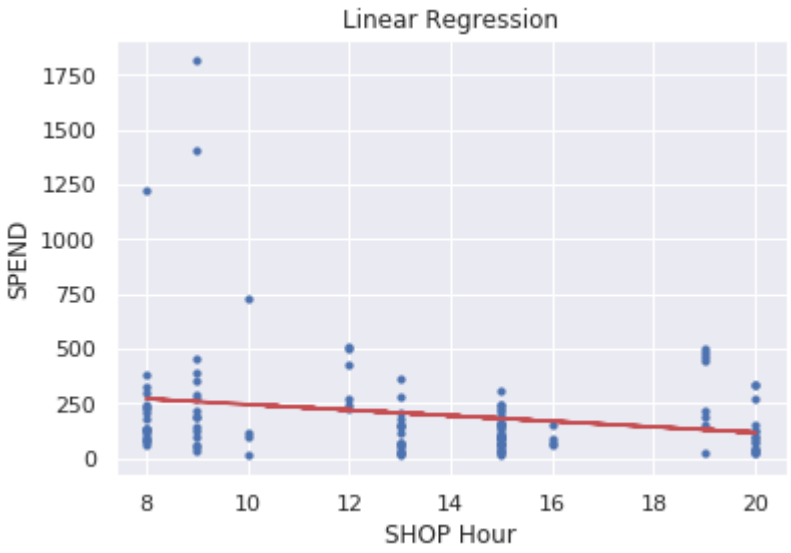
```
linear_regression_model = LinearRegression()
linear_regression_model.fit(x, y)
y_pred = linear_regression_model.predict(x)

linear_rmse = np.sqrt(mean_squared_error(y,y_pred))
linear_r2 = r2_score(y,y_pred)

# Visualizing the Linear Regression results
def display_linear_regression():
    plt.scatter(x, y, s=10)
    plt.plot(x, y_pred, color='r')
    plt.title('Linear Regression')
    plt.xlabel('SHOP Hour')
    plt.ylabel('SPEND')
    plt.show()
    return
```

In [155]:

```
# Plot the Line regression line
display_linear_regression()
```



Calculate the RMSE

We can see that the straight line is unable to capture the patterns in the data. Which shows it is an example of under-fitting

To overcome the under-fitting, we need to increase the complexity of the model

In [156]:

```
print("The RMSE is : {} ".format(linear_rmse))
print("The R-Squared is : {} ".format(linear_r2))
```

```
The RMSE is : 242.29255053490624
The R-Squared is : 0.04339450056928995
```

To generate a higher order equation we can add powers of the original features as new features and thus the linear model

$$Y = \theta_0 + \theta_1 x$$

can be transformed to

$$Y = \theta_0 + \theta_1 x + \theta_2 x^2$$

To convert the original features into their higher order terms we will use the PolynomialFeatures class provided by scikit-learn and then train using Linear Regression

Display the Polynomial Regression Line

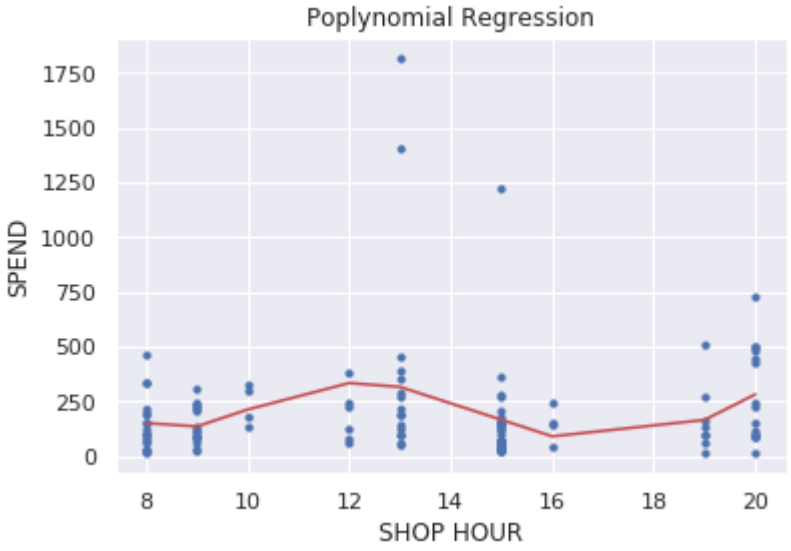
In [171]:

```
polynomial_features= PolynomialFeatures(degree=5)
x_poly = polynomial_features.fit_transform(x)

polynomial_regression_model = LinearRegression()
polynomial_regression_model.fit(x_poly, y)
y_poly_pred = polynomial_regression_model.predict(x_poly)

polynomial_regression_rmse = np.sqrt(mean_squared_error(y,y_poly_pred))
polynomial_regression_r2 = r2_score(y,y_poly_pred)

plt.scatter(x, y, s=10)
# sort the values of x before line plot
sort_axis = operator.itemgetter(0)
sorted_zip = sorted(zip(x,y_poly_pred), key=sort_axis)
x, y_poly_pred = zip(*sorted_zip)
plt.plot(x, y_poly_pred, color='r')
plt.title('Poplynomial Regression')
plt.xlabel('SHOP HOUR')
plt.ylabel('SPEND')
plt.show()
```



Calculate the RMSE

We can see that the line is tries to capture as many data points as possible and when we check the R-Squared value it should increase.

It is quite clear the new line tries to fit it better than the linear one.

In [172]:

```
print("The RMSE is : {} ".format(polynomial_regression_rmse))
print("The R-Squared is : {} ".format(polynomial_regression_r2))
```

```
The RMSE is : 236.81387071025406
The R-Squared is : 0.08616660932667741
```

We can see that the RMSE has decreased and the R-Squared has increased as compared to the linear regression model

Using statsmodel

Simple linear regression can easily be extended to include multiple features. This is called multiple linear regression:

$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$

Each x represents a different feature, and each feature has its own coefficient. In this case:

$y = \beta_0 + \beta_1 \times SHOPHOUR$

Let's use Statsmodels to estimate these coefficients:

In [159]:

```
# Initialise and fit linear regression model using `statsmodels`
polynomial_features= PolynomialFeatures(degree=5)
xp = polynomial_features.fit_transform(x)
xp.shape
```

Out[159]:

```
(119, 6)
```

In [160]:

```
stats_model = sm.OLS(y, xp).fit()
ypred = stats_model.predict(xp)

ypred.shape
```

Out[160]:

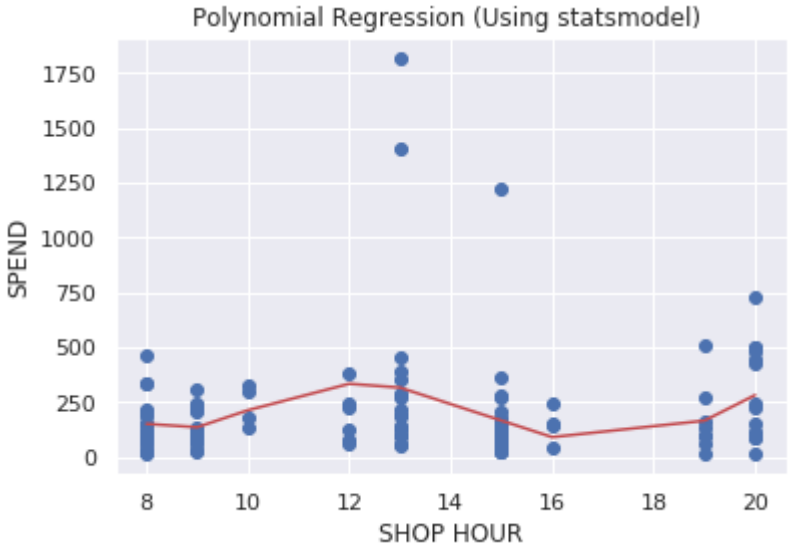
```
(119,)
```

In [161]:

```
plt.scatter(x,y)
plt.plot(x, ypred, color='r')
plt.title('Polynomial Regression (Using statsmodel) ')
plt.xlabel('SHOP HOUR')
plt.ylabel('SPEND')
```

Out[161]:

```
Text(0, 0.5, 'SPEND')
```



Plotting the upper and lower confidence intervals

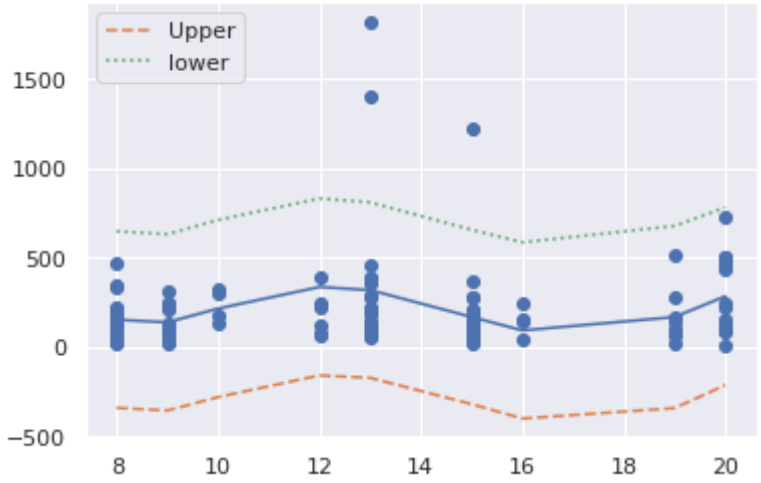
In [162]:

```
_, upper,lower = wls_prediction_std(stats_model)

plt.scatter(x,y)
plt.plot(x,ypred)
plt.plot(x,upper,'--',label="Upper") # confid. intrvl
plt.plot(x,lower,':',label="lower")
plt.legend(loc='upper left')
```

Out[162]:

```
<matplotlib.legend.Legend at 0x7f3893f67bd0>
```



In [163]:

```
stats_model.summary()
```

Out[163]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.086
Model:	OLS	**Adj. R-squared:**	0.046
Method:	Least Squares	**F-statistic:**	2.131
Date:	Tue, 07 Jan 2020	**Prob (F-statistic):**	0.0668
Time:	10:01:28	**Log-Likelihood:**	-819.46
No. Observations:	119	**AIC:**	1651.
Df Residuals:	113	**BIC:**	1668.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3.475e+04	2.34e+04	1.486	0.140	-1.16e+04	8.11e+04
x1	-1.371e+04	9240.838	-1.484	0.141	-3.2e+04	4597.328
x2	2086.6658	1424.972	1.464	0.146	-736.460	4909.792
x3	-152.3023	107.283	-1.420	0.158	-364.850	60.245
x4	5.3441	3.949	1.353	0.179	-2.480	13.168
x5	-0.0724	0.057	-1.271	0.206	-0.185	0.040

Omnibus:	124.892	**Durbin-Watson:**	2.064
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1873.898
Skew:	3.711	**Prob(JB):**	0.00
Kurtosis:	20.968	**Cond. No.**	1.57e+09

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.57e+09. This might indicate that there are
strong multicollinearity or other numerical problems.

We no longer have to calculate alpha and beta ourselves as this method does it automatically for us! Calling model.params will show us the model's parameters:

From the results above:

1. β0 = 366.8018 - This is the y intercept when x is zero
2. β2 = -12.306012 - This is the regression coefficient that measures a unit change in SPEND when SHOP_HOUR changes

R Squared

The Coefficient of determination, R-Squared – This is used to measure how much of the variation in the outcome can be explained by the variation in the independent variables. R-Squared always increases as more predictors are added to the MLR model even though the predictors may not be related to the outcome variable.

R2 by itself can't thus be used to identify which predictors should be included in a model and which should be excluded. R2 can only be between 0 and 1, where 0 indicates that the outcome cannot be predicted by any of the independent variables and 1 indicates that the outcome can be predicted without error from the independent variables.

In [164]:

```
# print the R-squared value for the model
stats_model.rsquared
```

Out[164]:

```
0.08616660932665154
```

This means that 8.62% of the SPEND can be explained by SHOP_HOUR

Adjusted R-Squared

When we add more predictor variables into the equation, R-Squared will always increase making R-Squared not accurate as the number of predictor variables increases.

Adjusted R-Squared, accounts for the increase of the predictor variables.

Because of the nature of the equation, the adjusted R-Squared should always be lower or equal to the R-Squared

In [165]:

```
# print the Adjusted R-squared value for the model
stats_model.rsquared_adj
```

Out[165]:

```
0.04573150354464495
```

RMSE

The root-mean-square error (RMSE) is a frequently used measure of the differences between values (sample and population values) predicted by a model and the values actually observed

The smaller the value the better

In [166]:

```
# calc rmse
stats_model_rmse = rmse(y, ypred)
stats_model_rmse
```

Out[166]:

```
236.81387071025745
```

Confidence in the model

A confidence interval gives an estimated range of values which is likely to include an unknown population parameter, the estimated range being calculated from a given set of sample data.

A confidence interval is how much uncertainty there is with any particular statistic. Confidence intervals are often used with a margin of error. It tells you how confident you can be that the results reflect what you would expect to find if it were possible to study the entire population.

In [167]:

```
# print the confidence intervals for the model coefficients
stats_model.conf_int()
```

Out[167]:

```
array([[-1.15757701e+04,  8.10753000e+04],
       [-3.20182055e+04,  4.59732808e+03],
       [-7.36459968e+02,  4.90979154e+03],
       [-3.64849819e+02,  6.02453035e+01],
       [-2.47976789e+00,  1.31679714e+01],
       [-1.85172906e-01,  4.04464787e-02]])
```

Hypothesis Testing and P-Values

p-values tell you how statistically significant the variable is. Removing variables with high p-values can cause your accuracy/R squared to increase, and even the p-values of the other variables to increase as well — and that's a good sign.

In [173]:

```
# print the p-values for the model coefficients
stats_model.pvalues
```

Out[173]:

```
array([0.14003072, 0.14067799, 0.14587323, 0.15846917, 0.1786777 ,
       0.20639086])
```

Notes

To be prevent over-fitting, we can add more training samples so that the algorithm doesn't learn the noise in the system and can become more generalized.

To strike a blance between under-fitting and over-fitting you need to understand a statistical term called **Bias-Variance Trade-Off**