Foster Mosden
Marketing Analytics
Home Assignment 2

Question 1: Pizza

1. 12 points
    a. Using the data provided, I learned the dependence of store sales on price by visualizing the data with a simple scatter plot.
    b. For every dollar that the price increases, the number of pizzas sold decreases by approximately 69.5 pizzas.
    c. Based on the output of the OLS regression and the profit formula of
        Sales = intercept coefficient + price coefficient * price
        Profit = sales * (price - cost per pizza)
    I found the optimal pizza price to be $5.20
    d. Based on the csv provided, the cost per pizza of $2, and the optimal price found of $5.20, I found the total expected profit as $1165091.81
        i. *I computed this by multiplying the total sum of sales in the dataset by the optimal price - cost. I wasn't sure if there was some other way to do this, but this was how I computed it consistently for Q1.*
2. 18 points
    a. I would include the one-hot encoded variable "Margherita" as another independent variable in the OLS regression. This means when we write our new equation for sales, both the price and the type of pizza contribute to computing the sales.
    b. Sales = 401.54 + -57.21 * Price + 50.41 * Margherita
    c. The impact of increasing the price by $1 for margherita and pepperoni pizzas would similarly decrease sales by 57.21 pizzas. The margherita column is one hot encoded, and can only hold a value of 0 or 1. So, for the same margherita pizza, the increase of price by $1 results in the same decrease in sales of 57.21 pizzas that a pepperoni would see.
    d. Optimal price for Margherita pizza: $4.95
    Optimal price for Pepperoni pizza: $4.51
    e. The prices are not identical. The difference can be explained by the impact the margherita coefficient has on the maximization of the profit function. Compared to a pepperoni pizza of the same price, a margherita pizza will have 50.41 more sales on average according to the results of the OLS regression. For this reason, it makes sense that the optimal price for pepperoni is lower.
    f. Total expected profit: $964521.28
        i. *I computed this by splitting the dataset into a margherita and a pepperoni subset. Then multiplying the total sum of sales in the dataset by the optimal price for that pizza type - cost,. I wasn't sure if there was some other way to do this, but this was how I computed it consistently for Q1.*
3. 9 points
    a. Like in the previous question, I updated the model by including "Price Competitor" as another x variable to the OLS regression in Python.
    b. The result does make intuitive sense. The coefficient for the "Price Competitor" variable is ~15.3. This indicates that for every dollar the competitor's price

increases, our sales go up by about 15 pizzas. This makes a lot of sense; we'd expect more people to be interested in buying our pizza as the competitor raises their price while ours remains constant.

c. Based on the optimal prices in 2D, the change in total expected profit if the competitor lowers their price by $0.50 is a loss of $393499.72

Question 2: Fashion

1. 6 points
    a. There are 42 unprofitable products out of 5297 total products, meaning approximately 0.79% of products in the dataset are unprofitable.
    b. If we assume that the dataset reflects each product having equal sales, then the average profit per product is approximately $2.94.
2. 9 points
    a. Computed in Python
    b. There are 284 unprofitable online products out of 5297 total products. This means that for online products, unprofitable online products make up 5.36%.
    c. The average profit per product in the online channel is $2.44
3. 15 points
    a. Completed in Python
    b. Completed in Python by creating a simple logistic regression model using Category, Color, and Season as one-hot encoded x variables, and the new column "Bad Product" as the y-variable. This provided me with coefficients for each category, color, and season option we have, each serving as the relationship between the characteristic and the product being bad or not.
    c. When it comes to product categories, we will focus on blouses and skirts, as they tend to correlate with profitable products. Dresses, jackets, shirts, and knit products are more likely to be unprofitable. For colors, black, blue, gray, pink, and white are the most correlated with profitable products while brown, green, red, and yellow correlate with unprofitable one's. Finally, Spring and Winter products are more favorable for online sales, especially when compared to fall. In all, I found that focusing on blouses in skirts, in black, blue, gray, pink, and white, tailored to the spring and winter seasons, are most likely to be profitable online based on the data at hand.