Deliverable 1

The main focus of this project is to compare the popularity of different price catogeorys of video games. As this interested me to compare if the more a game cost should lead to an increased amount of recommendation it would receive. As seen with the popularity of triple A games including the Call Of Duty games.

The higher the price category a game is in the higher the amount of recommendations it will receive. As a game's initial price should be chosen within the peak part of the parabola to limit the amount of dimminshing returns to the customer.

The dataset represents a vast majority of all games release from 1997 to 2022. With information given for each title including, the release date, price, the meta critic score, the recommendation count, and a series of true/false statements to represent the genre the game is in. The source of the dataset is from Kaggle. From Kaggle the data was gathered from the Steam store using an API for the collection of the Dataset.

There is little chance for bias from the dataset, as it is a direct observation of the information from the source. Possible place for indirect biases is that Steam is only for PC games, meaning any games not made for PC is left out of the dataset.

The short comings of this dataset is that it there are repeats titles, some which it will repeat up to three times. Along with a number of the entries being without a release date, price, meta critic score, or the recommendation count. These short coming pose little to no problem, as they are a rare occurrence compared to dataset as a whole.

The steps taken to create the end result were creating a goal to create a conclusions of how game prices work. With this in mind I choose two variables to focus on, those variables are the initial price, and recommendation price. The first step that was taken was importing the dataset into the python program as csv. From there a loop was created to add another column to the dataset, this would create the column containing the values of the price group value for each game. As this can allow for easier access of the information. The next step of the process is creating a counter, for counting the number of recommendation given for each price group. After that step puting the information in graphs is next, The main calculations used were simple if else statements. To create to new sets of information, a method that was used to calculate the recommendation count divided by the initial price group. As to create a better way to group by price to create a more concise information gathering.

The next step was to create a method that would count the number of recommendations given to each price group to compare which price group receives more praise. Along with which individua game received the highest amount of recommendation.

The end result of the analysis has been that the most popular price group has been revealed to be 10 to 20 dollars. This proves my hypothesis incorrect that tha higher price tag would lead to a better reception for the player base. As the amount of recommendation given the 10 to 20 price group dwarfs all the other price groups. This could be the end, and that lower price, lower expectations, than higher recommendation count. As this only part of the story as this is for PC, where there are plenty other factors. As games stay relevant longer as seen with top choice Counter strike, meaning it can accumulate more recommendation over time. Along with the fact that it isn’t a hard game to run on a computer, meaning more people can play without trouble.