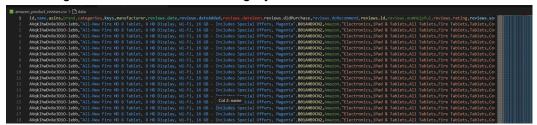
## 5.1. A description of the dataset used.

The dataset that I am using are the reviews of user feedback on a product on amazon. There are almost 3,000 reviews for one product and over 30,000 reviews in this dataset. As the image below shows how the header column splits each category. The dataset that I will be looking into is the review.text category.



## 5.2. Details of the preprocessing steps.

To facilitate the preprocessing steps, we'll start by importing the necessary tools. We'll use Pandas to read the CSV file, spaCy for natural language processing, and TextBlob for sentiment analysis. Since dealing with a large DataFrame could be cumbersome, we'll streamline the process by initially focusing on the 'reviews.text' column. This approach helps us efficiently manage the data we need to analyse. After importing the tools, the next step involves data cleansing. We'll use the '.dropna()' method to remove any missing information or values from the dataset, minimising the potential for errors during analysis.

Following data cleansing, we'll create a list specifically for storing the reviews. This list will undergo preprocessing steps such as removing stopwords and tokenization, which aids in sentiment analysis and polarity identification.

Additionally, we'll implement a function that enables users to input a review for analysis. This function will output the sentiment score along with a classification indicating whether the sentiment is positive, negative, or neutral.

```
| Import pending on policy pending on policy pending of the pendin
```

## 5.3. Evaluation of results.

In conclusion of my results, my model works. It is able to produce positive, negative and neutral results with their corresponding polarity. I have tested it with the first 20 results and as the picture showed how it would look. Looking at these results the polarity seems to sit in the region of 0.3-0.5.

## 5.4. Insights into the model's strengths and limitations.

With my model I decided to check what would happen if I did not remove any stop words as you could see in the pictures below. I would be able to conclude that the strength of my model with no stop words helps the accuracy of the model. However, the limitation would be with the small library with spacy 'en\_core\_web\_sm' rather than having 'en\_core\_web\_md'. With a larger library this might be able to produce much more accurate results to my model.

```
Review Sentiment: Positive 0.6 a sentiment: Positive 0.7 sentiment: Positive 0.8 a sentiment: Positive 0.8 sentiment: Positive 0.7 sentiment: Positive
```

(These images are from the code from the left, producing results to the right.)

(Image 1 and 2, are the code and terminal results to help explain)