# CS519 Group Project - Gamma Stage 3 Report

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### 1. Motivation

E-commerce defines the activity of buying or selling goods through an online, digital platform which has become a critical part of the global economy. Retailers of every size, from small home-based businesses to large corporate entities utilize online selling platforms to increase their reach to new customers. This is particularly important for small businesses, who can avoid the large overhead costs of a brick-and-mortar storefront.

According to the article "38 eCommerce Statistics of 2023" (Forbes Advisor Online):

- By 2026, the e-commerce market is expected to total over \$8.1 trillion.
- By 2026, 24% of retail purchases are expected to take place online.
- 20.8% of retail purchases are expected to take place online in 2023.

## 2. Problem Definition

E-commerce does come with the caveat of trying to sell an item based on listing information and photos to a customer who cannot physically interact with the item before deciding to purchase. A business involved in e-commerce must consider which attributes of their products or services are most critical to translating an online shopping session into a purchase.

## 3. Machine Learning Tasks (Refined)

## 3.1 Online Shoppers Purchasing Intention

### Classification

We can utilize the 'Revenue' attribute (0 or 1) already incorporated into the dataset, which indicates whether a session ended in a sales transaction, where 0 is the negative class (unsuccessful) and 1 is a positive class (successful).

# **3.2 Sales of Summer Clothes in E-commerce Wish** Classification

While there is no readily available class label attribute for this dataset, we can create one by converting a numerical attribute into a categorical one. For example, we can convert the 'units\_sold' numerical attribute into a category class label that indicates how well the products sell and classify items as Top, Mid, and Bottom Tier products based on units sold.

We could possibly cluster merchants and products based on rating counts to determine which products and business will appear to audiences first.

### Regression

How do the other attributes change when products utilize additional paid ad boosts within the website (uses\_ad\_boosts attribute) or offer express shipping (shipping\_is\_express attribute).

### 4. Datasets

## **4.1 Online Shoppers Purchasing Intention Dataset**

#### 4.1.1 Instances and Features

- Number of Instances: 12,330
  - 10,422 Negative Class and 1908 Positive Class
- Number of Features: 18
  - 10 numerical and 8 categorical attributes
  - 'Revenue' attribute used as class label
- Missing Data: None

## 4.1.2 Attribute Descriptions

Attribute	Description	Data Type
Administra tive	Number of page visits	Integer
Administra tive_Durati on	Duration of visit (seconds)	Integer
Informatio nal	Number of page visits	Integer
Informatio nal_Durati on	Duration of visit (seconds)	Integer

ProductRel ated	Number of page visits	Integer
ProductRel ated_Durat ion	Duration of visit (seconds)	Contin uous
BounceRat es	Percentage of visitors who enter the site from that page and then leave ("bounce") without triggering any other requests to the analytics server during that session	Contin
ExitRates	The percentage that were the last in the session	Contin uous
PageValue s	Average value for a web page that a user visited before completing an e-commerce transaction	Integer
SpecialDay	Closeness of the site visiting time to a specific special day (e.g. Mother's Day, Valentine's Day)	Integer
Month	Month of visit	Catego rical
OperatingS ystems	OS of the visitor	Integer
Browser	Browser of visitor	Integer
Region	Geographic Region of Visitor	Integer
TrafficTyp e	Traffic Source	Integer
VisitorTyp e	Returning or New Visitor or Other	Catego rical
Weekend	Weekend or Not Weekend	Binary
Revenue	Class Label whether a session ends in a transaction (positive) or not (negative)	Binary

Table 1: Attribute description of Online Shoppers
Purchasing Intention dataset

## 4.1.3 Statistics

Histogram plots were made showing distribution of the values of various feature found in the dataset.

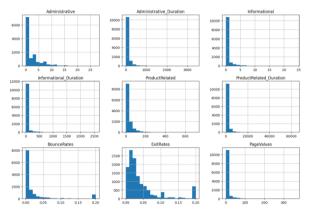


Figure 1. Distribution of numerical variables

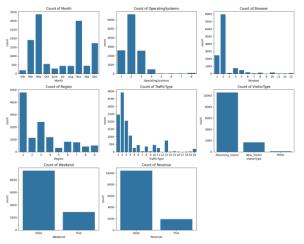


Figure 2. Distribution of categorical variables

# **4.1.4 Preliminary Data Analysis**

Timing is a critical component of ensuring successful sales and understanding when the 'busy' and 'slow' seasons occur would benefit any business. Based on this quick analysis, we can see that the busiest times for this particular business peak in May and November. This may be due to the occurrence of celebrations and holidays, where graduations, Mother's and Father's Day occur during the late Spring peak and the peak of the winter holiday shopping season in late Fall.

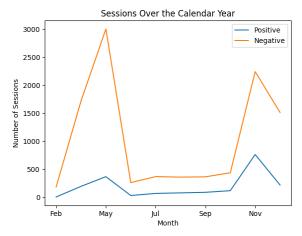


Figure 3: Session over the calendar year

We also performed a correlation analysis, allowing us to evaluate the relationship between two variables in a dataset. Values obtained in the matrix indicate the direction of the correlation (positive or negative) and the strength of the correlation, indicated by the heatmap colors.

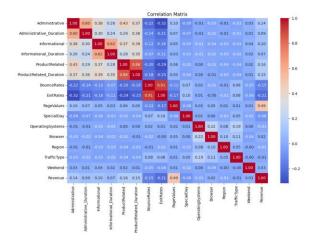


Figure 4: Correlation matrix

# **4.1.5** Preliminary Machine Learning Task for Online Shoppers Purchasing Intention

# • Classification

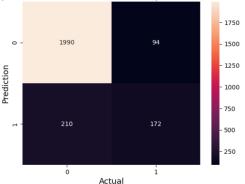
Utilizing the 'Revenue' attribute, we can classify sessions as either successful (positive class) or unsuccessful (negative class) and here we compare several different models. The hyperparameter settings are summarized in the table below and the confusion matrixes are also included.

Model	Paramete rs	Time Elapsed	Test Acc	Train Acc	CrossVal Score
Perceptro n	max_iter= 40, eta=0.1	0.01s	0.8 8	0.8	0.85
Non- Linear (RBF)	C=1.0, gamma=0 .10	2.11s	0.8 9	0.8 5	0.85
KNN	KNN n_neighb ors=10		0.8 9	0.9 4	0.86

**Table 2: Preliminary Classification Comparison** 

Execution time: 0.01 seconds Perceptron Test Accuracy for Revenue: 0.88 Perceptron Train Accuracy for Revenue: 0.88 CrossVal Mean for Revenue: 0.8505271695052719

Perceptron Confusion Matrix-Perceptron for Revenue



**Figure 5: Perceptron confusion matrix** 

Execution time: 2.52 seconds
Non-Linear SVM (RBF Kernel) Test Accuracy for Revenue: 0.89
Non-Linear SVM (RBF Kernel) Train Accuracy for Revenue: 0.85
CrossVal Mean for Revenue: 0.8450932684509327

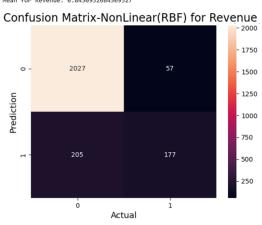


Figure 6: Non Linear (RBF) confusion matrix

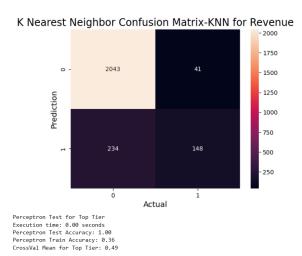


Figure 7: KNN confusion matrix

# 4.2 Summer Products with Rating and Performance 2020-08 Dataset

# **4.2.1 Instances and Features**

• Number of Instances: 1,574

• Number of Features: 34

 24 numerical and 19 categorical attributes

• Missing Data: 45 products missing rating attribute data

# **4.2.2** Attribute Descriptions

Attribute	Description	Data Type
title	Title for localized for European countries	Catego rical
title_orig	Original English title of the product	Catego rical
price	price you would pay to get the product	Contin uous
retail_price	reference price for similar articles on the market, or in other stores/places. Used by the seller to indicate a regular value or the price before discount.	Integer

currency_bu yer	currency of the prices	Catego rical
units_sold	Number of units sold. Lower bound approximation by steps	Integer
uses_ad_boo sts	Whether the seller paid to boost his product within the platform	Binary
rating	Mean product rating	Contin uous
rating_count	Total number of ratings of the product	Integer
rating_five_ count	Number of 5-star ratings	Integer
rating_four_ count	Number of 4-star ratings	Integer
rating_three _count	Number of 3-star ratings	Integer
rating_two_	Number of 2-star ratings	Integer
rating_one_c ount	Number of 1-star ratings	Integer
badges_coun t	Number of badges the product or the seller have	Integer
badge_local _product	A badge that denotes the product is a local product. Conditions may vary (being produced locally, or something else). Some people may prefer buying local products rather than. 1 means Yes, has the badge	Binary
badge_produ ct_quality	Badge awarded when many buyers consistently gave good evaluations 1 means Yes, has the badge	Binary

badge_fast_s hipping	Badge awarded when this product's order is consistently shipped rapidly	Binary
tags	tags set by the seller	Catego rical
product_col or	Product's main color	Catego rical
product_vari ation_size_i d	One of the available size variation for this product	Catego rical
product_vari ation_invent ory	Inventory the seller has. Max allowed quantity is 50	Integer
shipping_opt ion_name	Name of shipping option	Catego rical
shipping_opt ion_price	shipping price	Contin uous
shipping_is_ express	whether the shipping is express or not. 1 for True	Binary
countries_sh ipped_to	Number of countries this product is shipped to	Integer
inventory_to tal	Total inventory for all the product's variations (size/color variations for instance)	Integer
has_urgency _banner	whether there was an urgency banner with an urgency	Binary
urgency_text	A text banner that appear over some products in the search results.	Binary
origin_count ry	Country of Origin	Catego rical
merchant_tit le	Merchant's displayed name (show in the UI as the seller's shop name)	Catego rical

merchant_na me	Merchant's canonical name. A name not shown publicly. Used by the website under the hood as a canonical name. Easier to process since all lowercase without	Catego rical
merchant_in fo_subtitle	white space  The subtitle text as shown on a seller's info section to the user.	Catego rical
merchant_ra ting_count	Number of ratings of this seller	Integer
merchant_ra ting	merchant's rating	Contin
merchant_id	merchant unique id	Catego rical
merchant_ha s_profile_pi cture	Convenience boolean that says whether there is a `merchant_profile_pictur e` url	Binary
merchant_pr ofile_picture	Custom profile picture of the seller (if the seller has one). Empty otherwise.	URL
product_url	url to the product page	URL
product_pict ure	Url to product picture	URL
product_id	product identifier.	Catego rical
theme	the search term used in the search bar of the website to get these search results.	Catego rical
crawl_mont h	Metadata info	Date

Table 3: Attribute description of Summer Products with Rating and Performance dataset

## 4.2.3 Statistics

Histogram plots were made showing distribution of the values of some important features found in the dataset.

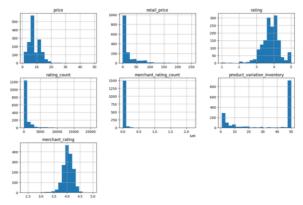


Figure 8. Distribution of some important variables

## 4.2.4 Preliminary Data Analysis

Collecting data on e-commerce is more about basic product listings. It's necessary to find data that helps with computing whether a product sells "well" or does not. By showcasing graphs of different columns from our dataset we can see that not all products have the same rating compared to others. Similarly the merchants also follow this trend. This can impact customer activity and sales of certain products. When listing products on an e-commerce application, it's imperative that the highest rated products with the highest rated merchants are shown first to customers.

## 4.2.5 Preliminary Machine Learning Task

Utilizing the units\_sold' attribute, we can classify how well a product sells by categorizing the data into class labels. Where the Bottom Tier consists of products that are below 100 units sold, Mid Tier consists of the number of units sold between 100 and 5000, and Top Tier being any product with over 5000 units sold. Here we compare several different models. The hyperparameter settings are summarized in the table below and a sample of the confusion matrixes are also included.

Preliminary Classification Comparison					
Model	Parame ters	Time	Test Acc Top Tier	Train Acc Mid Tier	CrossV al Score
Percep tron	max_it er=40, eta=0.1	Top Tier: 0.00 Mid Tier: 0.00 Botto m Tier: 0.00	Top Tier: 1.00 Mid Tier: 0.83 Botto m Tier: 1.00	Top Tier: 0.36 Mid Tier: 0.52 Bottom Tier: 0.84	Top Tier: 0.49 Mid Tier: 0.52 Bottom Tier: 0.95
Non- Linear (RBF)	C=1.0, gamma =0.10	Top Tier: 0.00- 0.001 Mid Tier: 0.00- 0.001 Botto m Tier: 0.00- 0.001	Top Tier: 1.00 Mid Tier: 1.00 Botto m Tier: 1.00	Top Tier: 1.00 Mid Tier: 1.00 Bottom Tier: 1.00	Top Tier: 1.00 Mid Tier: 1.00 Bottom Tier: 1.00
KNN	n_neig hbors= 10	Top Tier: 0.00 Mid Tier: 0.00 Botto m Tier: 0.00	Top Tier: 1.00 Mid Tier: 1.00 Botto m Tier: 1.00	Top Tier: 1.00 Mid Tier: 1.00 Bottom Tier: 1.00	Top Tier: 1.00 Mid Tier: 1.00 Bottom Tier: 1.00

**Table 4: Preliminary Classification Comparison** 

Perceptron Test for Mid Tier Execution time: 0.00 seconds Perceptron Test Accuracy: 0.83 Perceptron Train Accuracy: 0.52 CrossVal Mean for Mid Tier: 0.52

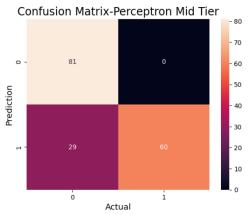


Figure 9: Perceptron Mid Tier confusion matrix

Kernel SVM Test for Top Tier Execution time: 0.01 seconds Non-Linear SVM (RBF Kernel) Test Accuracy for Top Tier: 1.00 Non-Linear SVM (RBF Kernel) Train Accuracy for Top Tier: 1.00 CrossVal Mean for Top Tier: 1.0

Confusion Matrix-NonLinear(RBF) for Top Tier

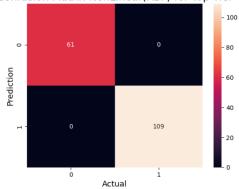


Figure 10: SVM Top Tier confusion matrix

Kennel SVM Test for Bottom Tier Execution time: 0.01 seconds Non-Linear SVM (RBF Kernel) Test Accuracy for Bottom Tier: 1.00 Non-Linear SVM (RBF Kernel) Train Accuracy for Bottom Tier: 1.00 CrossVal Mean for Bottom Tier: 1.0

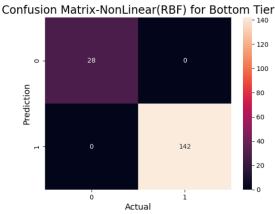


Figure 11: SVM Bottom Tier confusion matrix

### 4.2.6 Dataset Justification

We believe that both of these datasets have a desirable high number of instances and a mix of numerical and categorical attributes that allow for multiple avenues of analysis. We can perform a wide range of machine learning tasks with these datasets, including classification, regression, and clustering to provide recommendations for attributes that may contribute most to successful E-commerce transactions.

#### 4.2.7 Initial Solution:

Our proposed solution is to incorporate more ML tasks and algorithms to answer the original problem: To consider which attributes of their products or services are most critical to translating an online shopping session into a purchase. We have already made good strides with our preliminary classifications and hope to expand more into regression. There are many attributes that both our datasets provide us that we can dive into. We hope to find more relationships that will produce an ideal solution to any e-commerce business.

#### References

### **Dataset Sources**

- 1. Online Shoppers Purchasing Intention Data Set <a href="https://archive.ics.uci.edu/dataset/468/online+shoppers-purchasing+intention+dataset">https://archive.ics.uci.edu/dataset/468/online+shoppers-purchasing+intention+dataset</a>
- 2. Sales of Summer Clothes in E-commerce Wish <a href="https://www.kaggle.com/datasets/jmmvutu/summer-products-and-sales-in-ecommerce-wish/data?select=summer-products-with-rating-and-performance\_2020-08.csv">https://www.kaggle.com/datasets/jmmvutu/summer-products-and-sales-in-ecommerce-wish/data?select=summer-products-with-rating-and-performance\_2020-08.csv</a>

## **Literature Sources**

[1] Akarsh654, Machine Learning Project, 2020, GitHub Repository https://github.com/Akarsh654/Machine-Learning-Projects/blob/master/Linear%20Regression/Ecommer ce/Ecommerce%20Project.ipynb

[2] Baluch, A. "38 eCommece Statistics of 2023", Forbes Advisor, 8 February 2023, <a href="https://www.forbes.com/advisor/business/ecommerce-statistics/#sources\_section">https://www.forbes.com/advisor/business/ecommerce-statistics/#sources\_section</a> [3] Sakar, C. O., Polat, S. O., Katircioglu, M., & Kastro, Y. (2018). Real-time prediction of online shoppers' purchasing intention using multilayer perceptron and LSTM recurrent neural networks. In Neural Computing and Applications (Vol. 31, Issue 10, pp. 6893–6908). Springer Science and Business Media LLC. <a href="https://doi.org/10.1007/s00521-018-3523-0">https://doi.org/10.1007/s00521-018-3523-0</a>