Report pdf

There are two common workflows for data integration: ELT(Extract, Load, Transform) and ETL (Extract, Transform, Load)

The major difference between ELT and ETL is that in the ELT stage, normalization is performed after the datasets are imported into the database. In the ETL stage, the data is normalized and transformed before it is loaded into the database.

In our work, we chose ETL (Extract, Transform, Load) instead of ELT as our workflow and used SQL and R interchangeably to perform transformations. This is because we have found that ETL workflow is more suitable for small data sets, so we thought that it would be more compromised with our work.

Part 1: Database Design and Implementation

Task 1.1: E-R Diagram

Entities

Our E-R Diagram for an E-commerce database consisted of five main entities:

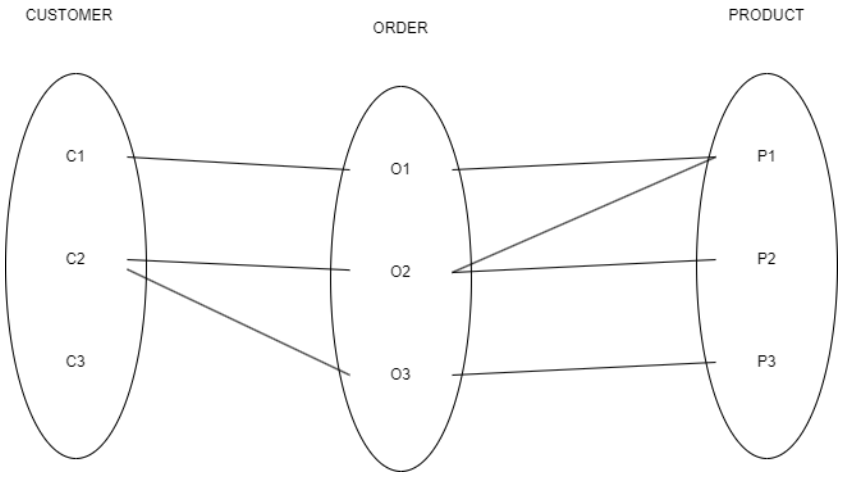
1. CUSTOMER: Represents details of individuals or entities who purchase products, including attributes such as customer ID, customer name, contact information, and gender.
2. PRODUCT: Represents details of items available for sale, including attributes such as product ID, product name, description, rating, price, and available stock.
3. ADVERTISEMENT: Represents details of promotional activities used to advertise products, including attributes such as advertisement ID, number of times the advertisement is shown, cost of the advertisement, and the place the advertisement was placed.
4. SUPPLIER: Represents details of entities providing products to businesses or customers, including attributes such as supplier ID, supplier name, and contact information.
5. CATEGORY: Represents product classifications or groupings, including attributes such as category unique ID, name, and fee amount as a percentage.

Relationships

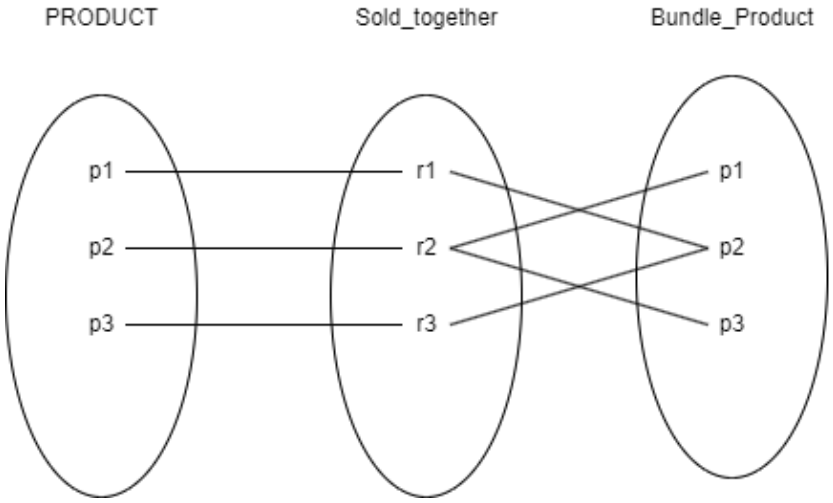
The relationships among these entities are as follows:

- CUSTOMER and PRODUCT have an M-N relationship meaning one customer can order many products, and one product can be ordered by many customers.

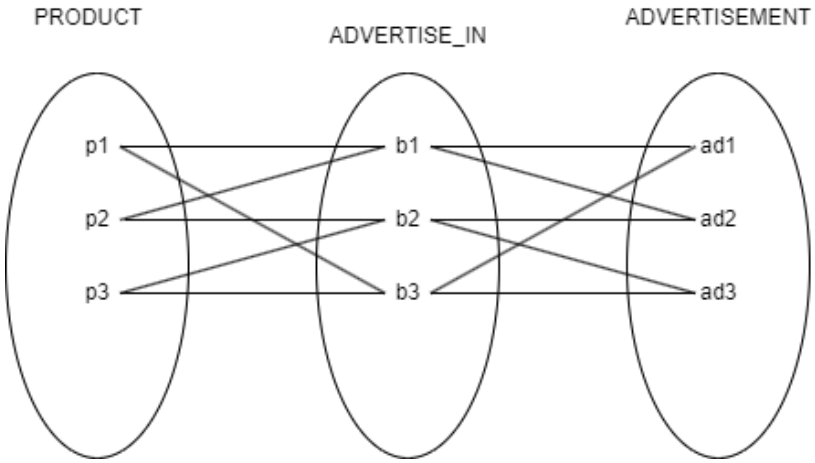
  The relationship is shown as ORDER, representing a customer placing an order to purchase products. It also contains some attributes to store the details of each order, including order ID, order date, order status, order quantity, promo code, payment method, and delivery fee.



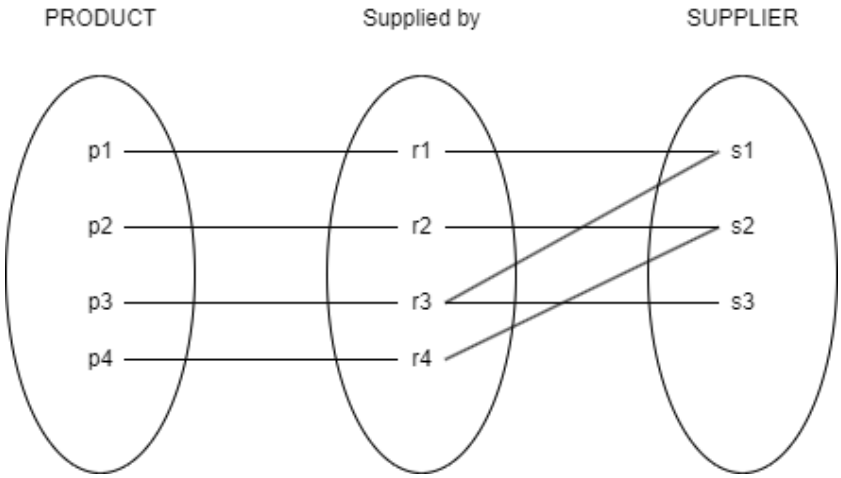
- PRODUCT has a self-referencing relationship of 1 to many. The relationship is shown as Sold_Together, indicating that one product can be sold together with others as a bundle.



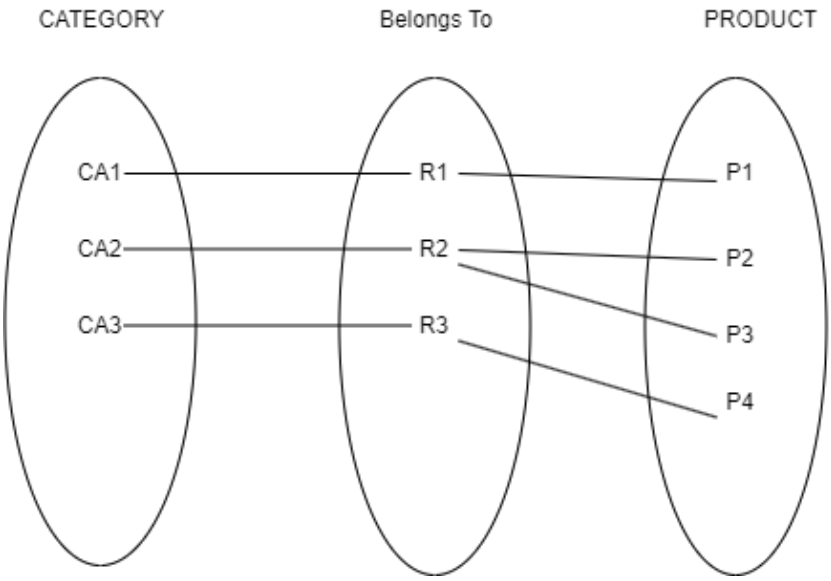
- PRODUCT and ADVERTISEMENT have an M-N relationship. This relationship is shown as ADVERTISE_IN to reflect products presented in the advertisements, meaning multiple advertisements can promote one product, and one advertisement can promote multiple products.



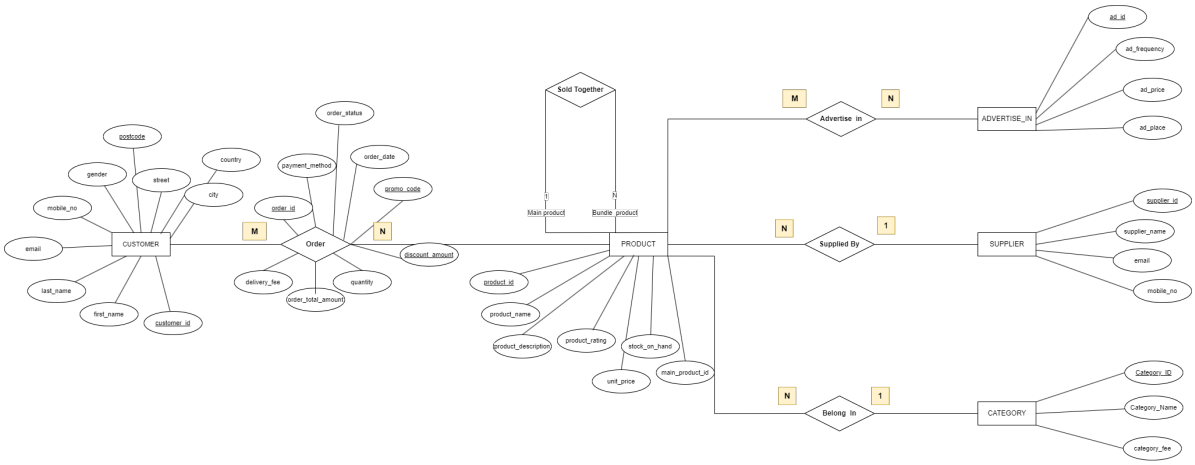
- PRODUCT and SUPPLIER have an N-1 relationship, indicating that one product can be supplied by only one supplier, but one supplier can provide multiple products.



- CATEGORY and PRODUCT have an 1-N relationship, meaning one product can belong to only one category, but one category can contain multiple products.



As a result, this is our E-R diagram.



Task 1.2: SQL Database Schema Creation

Normalization:

According to our first draft of the E-R diagram, two main adjustments were made in order to comply with 3NF

The first adjustment was on the ORDER table. After reviewing the order of normal forms, it was found that the ORDER entity still did not comply with 3NF.

Functional Dependency:

{order_id, customer_id, product_id } -> { order_date , order_status, order_quantity, promo_code, discount amount, payment_method, delivery_fee}

{promo_code} -> { discount_amount}

As we assumed that order_id could be duplicated to represent products ordered by the same customer simultaneously, there would be UPDATE anomalies. If there is an update on any attributes, such as payment_methods, we must alter more than one row in case there is more than one product in that order_id. In addition, discount_amount is also transitively dependent on promo_code.

Therefore, we separated the ORDER table into three entities including:

1. ORDER_DETAIL is similar to the ORDER table but has fewer attributes to contain each order's details. It has product_id as a primary key, customer_id and promo_code as foreign keys, and other attributes like order_date, order_status, and payment_method.
2. ORDER_ITEM contains product IDs and the quantities ordered in each order. The table has order_id and product_id as foreign keys and a composite primary key, and quantity as another attribute.
3. DISCOUNT is created to store the data of available promotional discounts, which consists of promo_code as a primary key and discount_amount.

The next adjustment was on the CUSTOMER table, which was initially on 2NF. Based on its function dependency, street, city, and country can also be determined by postcode and customer_id.

Functional Dependency:

{customer_id} ->{ first_name , last_name , gender , email, mobile_no , street , city , country , postcode } {postcode} -> { street, city , country }

This indicated that street, city, and country were transitively dependent on postcode. As a result, a new table is created as ADDRESS, which has postcode as a primary key and stores street, city, and country as other attributes.

In summary, four new entities were created from the normalization, which were ORDER_DETAIL, ORDER_ITEM, DISCOUNT, and ADDRESS. This resulted in a total of ten entities in our schema.

Logical Schema

According to the E-R diagram and normalization s, we can list the logical schema as follows:

- ADDRESS(address_id, postcode, street, city, country)
- DISCOUNT(promo_code, discount_amount)
- ADVERTISEMENT(ad_id, ad_frequency, ad_place, ad_price)

- SUPPLIER(supplier_id, supplier_name, email, mobile_no)
- CATEGORY(category_id, category_name, category_fee)
- CUSTOMER(customer_id, first_name, last_name, gender, email, mobile_no, address_id)
- PRODUCT(product_id, product_name, product_description, product_rating, unit_price, stock_at_hand, main_product_id, category_id, supplier_id)
- ORDER_DETAIL(order_id, customer_id, order_date, order_status, promo_code, payment_method, delivery_fee)
- ORDER_ITEM(order_id, product_id, quantity)
- ADVERTISE_IN(product_id, ad_id)

Physical Schema

Firstly, we created a connection to our database named "database.db"

```
connect <- dbConnect(RSQLite::SQLite(), "database.db")
```

Then, we first created parent entities, including ADDRESS, DISCOUNT, ADVERTISEMENT, SUPPLIER, and CATEGORY.

1. Create CUSTOMER entity

```
CREATE TABLE IF NOT EXISTS CUSTOMER (
  customer_id VARCHAR(50) PRIMARY KEY,
  first_name VARCHAR(50) NOT NULL,
  last_name VARCHAR(50) NOT NULL,
  gender VARCHAR(10),
  customer_email VARCHAR(50) NOT NULL UNIQUE,
  customer_mobile VARCHAR(15) NOT NULL UNIQUE,
  address_id VARCHAR(50) NOT NULL,
  FOREIGN KEY (address_id) REFERENCES ADDRESS (address_id)
);
```

2. Create DISCOUNT entity

```
CREATE TABLE IF NOT EXISTS DISCOUNT (
  promo_code VARCHAR(20) PRIMARY KEY,
  discount_percent INT NOT NULL
);
```

3. Create ADVERTISEMENT entity

```
CREATE TABLE IF NOT EXISTS ADVERTISEMENT (
  ad_id VARCHAR(50) PRIMARY KEY,
  ad_frequency INT NOT NULL,
  ad_place VARCHAR(50) NOT NULL,
  ad_price DECIMAL(10, 2) NOT NULL
);
```

4. Create SUPPLIER entity

```
CREATE TABLE IF NOT EXISTS SUPPLIER (
  supplier_id VARCHAR(50) PRIMARY KEY,
  supplier_name VARCHAR(50) NOT NULL,
  supplier_email VARCHAR(50) NOT NULL UNIQUE,
  supplier_mobile VARCHAR(20) NOT NULL UNIQUE
);
```

5. Create CATEGORY entity

```
CREATE TABLE IF NOT EXISTS CATEGORY (
  category_id VARCHAR(50) PRIMARY KEY,
  category_name VARCHAR(50) NOT NULL,
  category_fee INT NOT NULL
);
```

Then, we created entities that are children entities and entities that have referential integrity, which consist of CUSTOMER, PRODUCT, ORDER_DETAIL, ORDER_ITEM, and ADVERTISE_IN

6. Create ADDRESS entity

```
CREATE TABLE IF NOT EXISTS ADDRESS (
  address_id VARCHAR(50) PRIMARY KEY,
  postcode VARCHAR(20) NOT NULL,
  street VARCHAR(50) NOT NULL,
  city VARCHAR(100) NOT NULL,
  country VARCHAR(100) NOT NULL
  );
```

7. Create PRODUCT entity

```
CREATE TABLE IF NOT EXISTS PRODUCT (
  product_id VARCHAR(50) PRIMARY KEY,
  product_name VARCHAR(50) NOT NULL,
  product_description VARCHAR(50),
```

```
  product_rating DECIMAL(5,2),
  unit_price DECIMAL(10,2) NOT NULL,
  stock_on_hand INT NOT NULL,
  main_product_id VARCHAR(50),
  category_id VARCHAR(50) NOT NULL,
  supplier_id VARCHAR(50) NOT NULL,
  FOREIGN KEY (supplier_id) REFERENCES SUPPLIER (supplier_id),
  FOREIGN KEY (category_id) REFERENCES CATEGORY (category_id)
);
```

8. Create ORDER_DETAIL entity

```
CREATE TABLE IF NOT EXISTS ORDER_DETAIL (
  order_id VARCHAR(50) PRIMARY KEY,
  customer_id VARCHAR(50),
  order_date DATE NOT NULL,
  order_status VARCHAR(50) NOT NULL,
  promo_code VARCHAR(20),
  payment_method TEXT NOT NULL,
  delivery_fee DECIMAL(10, 2) NOT NULL,
  FOREIGN KEY (customer_id) REFERENCES CUSTOMER (customer_id),
  FOREIGN KEY (promo_code)  REFERENCES DISCOUNT (promo_code)
);
```

9. Create ORDER_ITEM entity

```
CREATE TABLE IF NOT EXISTS ORDER_ITEM (
  order_id VARCHAR(50),
  product_id VARCHAR(50),
  order_quantity INT NOT NULL,
  PRIMARY KEY (order_id, product_id),
  FOREIGN KEY (order_id)   REFERENCES ORDER_DETAIL (order_id)
  FOREIGN KEY (product_id) REFERENCES PRODUCT (product_id)
);
```

10. Create ADVERTISE_IN entity

```
CREATE TABLE IF NOT EXISTS ADVERTISE_IN (
  product_id VARCHAR(50),
  ad_id VARCHAR(50),
  PRIMARY KEY (product_id, ad_id),
  FOREIGN KEY (product_id) REFERENCES PRODUCT (product_id),
  FOREIGN KEY (ad_id)      REFERENCES ADVERTISEMENTS (ad_id)
);
```

Part 2: Data Generation and Implementation

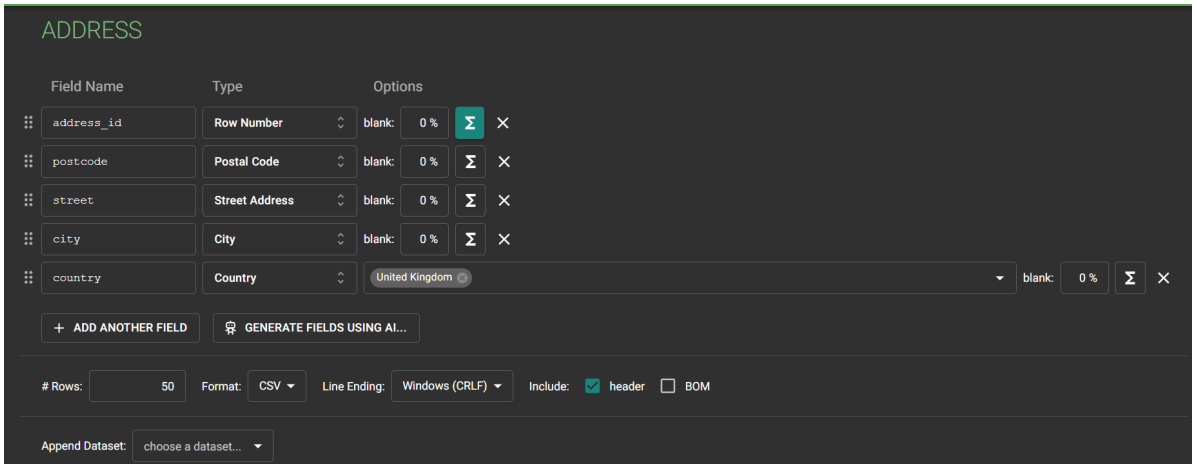
Task 2.1: Synthetic Data Generation

The synthetic data of each table was created based on the normalised schema using Mockaroo, a mock data generator platform. We first generated the data for the parent entities to ensure that the referential integrity exists on the children entities or the entities that need a reference for foreign keys from parent entities

Data generation for parent entities

1. ADDRESS

50 observations for the ADDRESS table were created using the following setting:

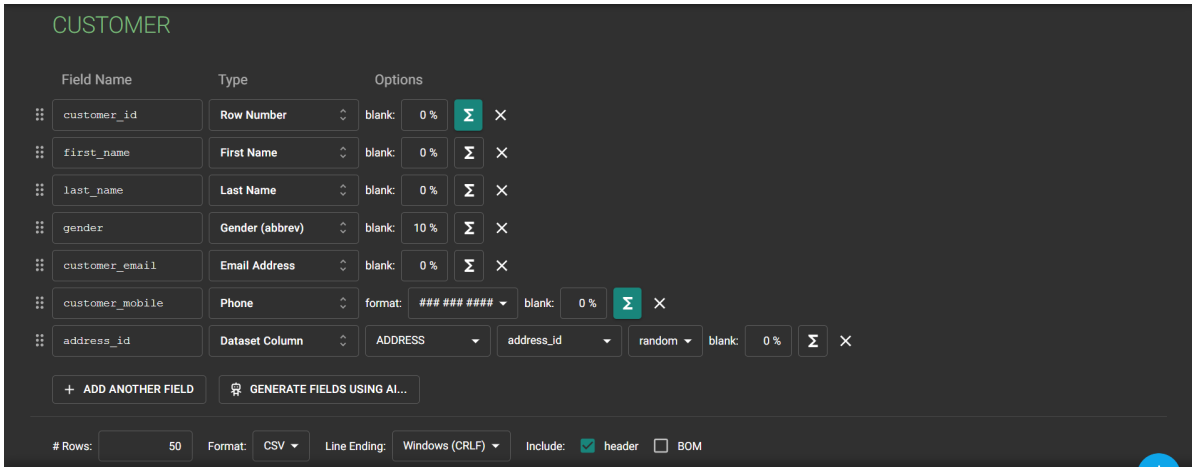


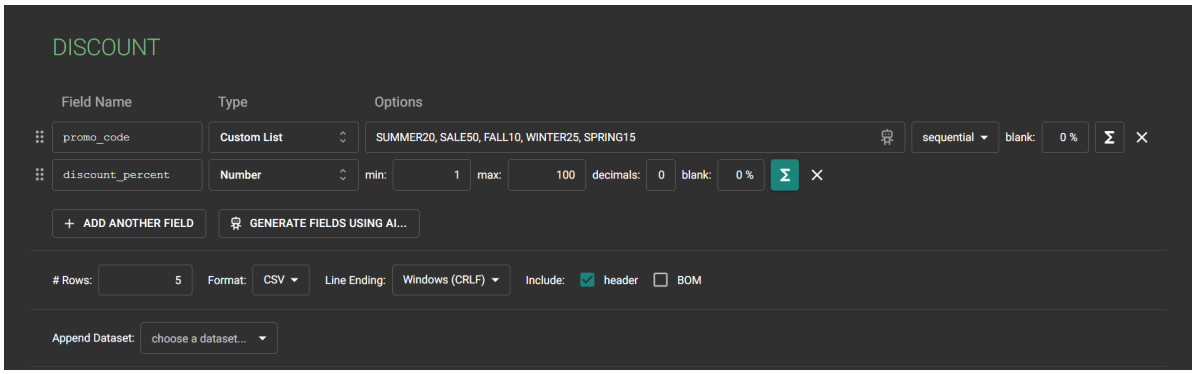
As we would like to focus on the customers who live in the United Kingdom, the generated address information will only be in the United Kingdom.

In addition, we have set the address_id, which is the primary of the table, to start with 'ADDR' and followed by a number.

2. DISCOUNT

5 observations for the DISCOUNT table were created using the following setting:





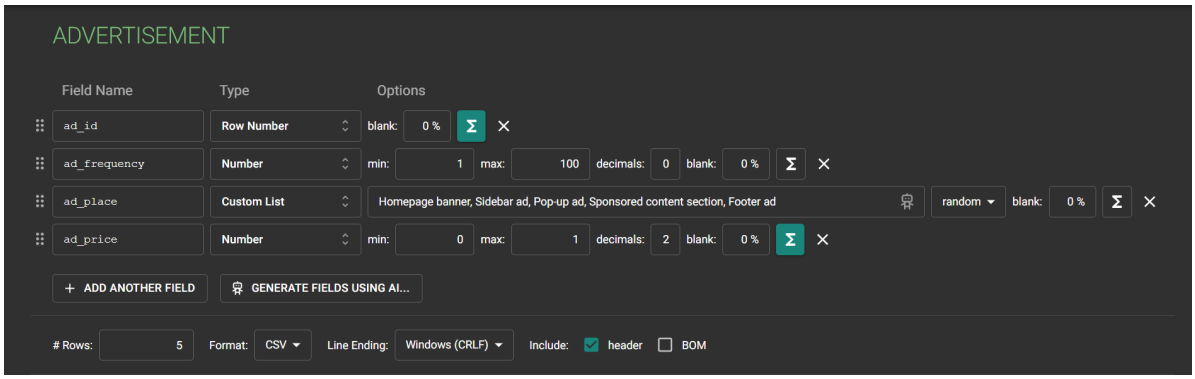
For the promo_code, which is a primary key, the values are created using an AI generator, and the values of the discount_percent, which stores the discount amount as percentages stores, are assigned manually to particular promo_code using this formula:

Formula

```
if promo_code == 'SUMMER20' then 20
elsif promo_code == 'SALE50' then 50
elsif promo_code == 'FALL10' then 10
elsif promo_code == 'WINTER25' then 25
elsif promo_code == 'SPRING15' then 15 end
```

3. ADVERTISEMENT

5 observations for the ADVERTISEMENT table were created using the following setting:



We set the condition for the primary key, ad_id, to start with 'AD' followed by a number. For the ad_place attribute, we used an AI generator to generate places where advertisements can be shown. We assumed that different places would cause different amounts of ad_price, so we manually assigned ad_price values based on different ad_place with the formula attached below.

Formula

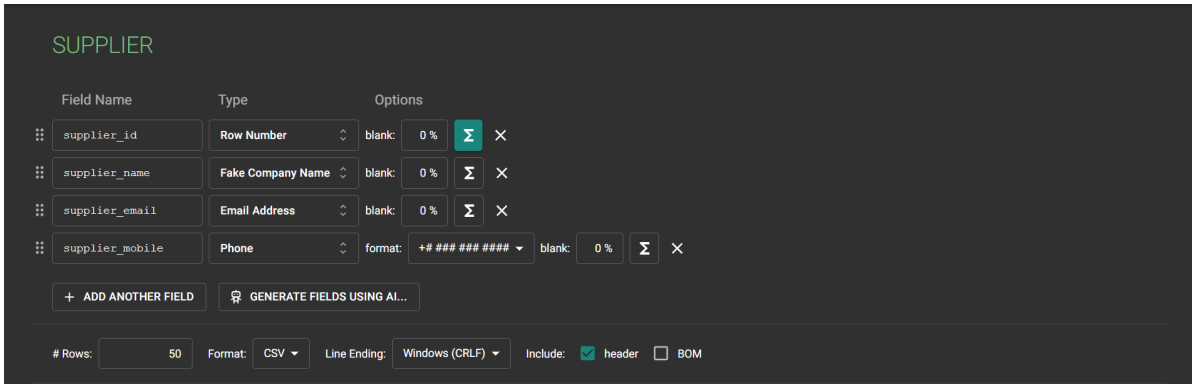
```
'AD' + this.to_s
```

Formula

```
if ad_place == 'Homepage banner' then 0.50
elsif ad_place == 'Sidebar ad' then 0.4
elsif ad_place == 'Pop-up ad' then 0.43
elsif ad_place == 'Sponsored content section' then 0.33
elsif ad_place == 'Footer ad' then 0.28
end
```

4. SUPPLIER

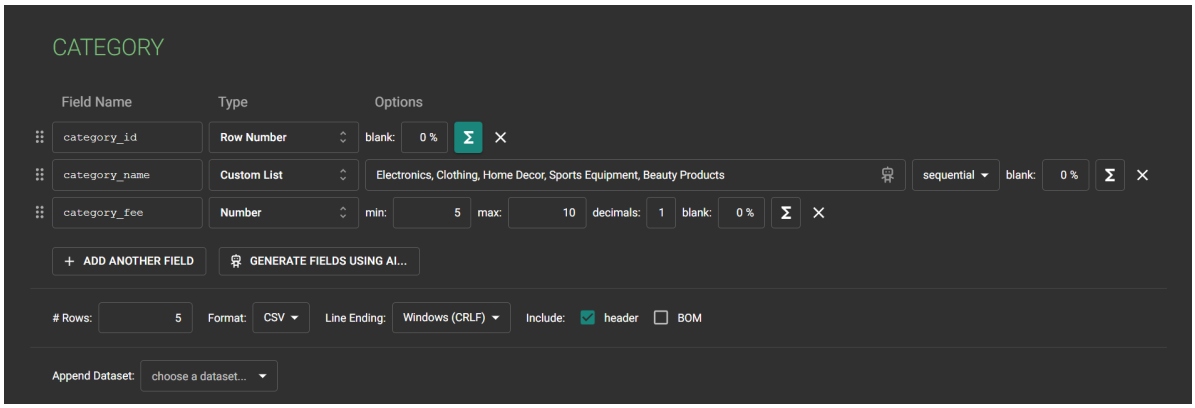
50 observations for the SUPPLIER table were created using the following setting:



We have set the supplier_id, which is the primary of the table, to start with 'SUP' and then follow with a number.

5. CATEGORY

5 observations for the CATEGORY table were created using the following setting:

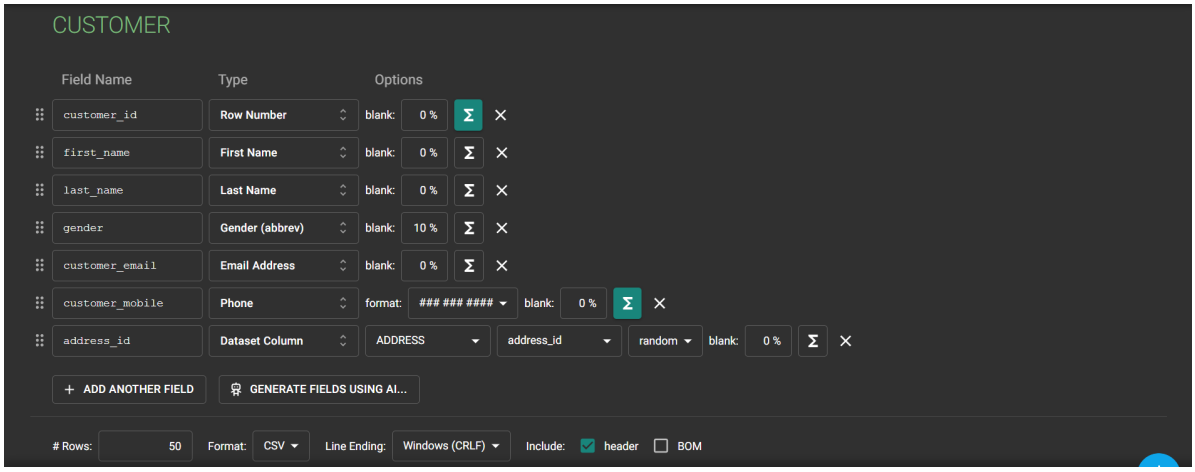


We have set the category_id, which is the primary of the table, to start with 'CATG' and then follow with a number.

Data generation for children entities

6. CUSTOMER

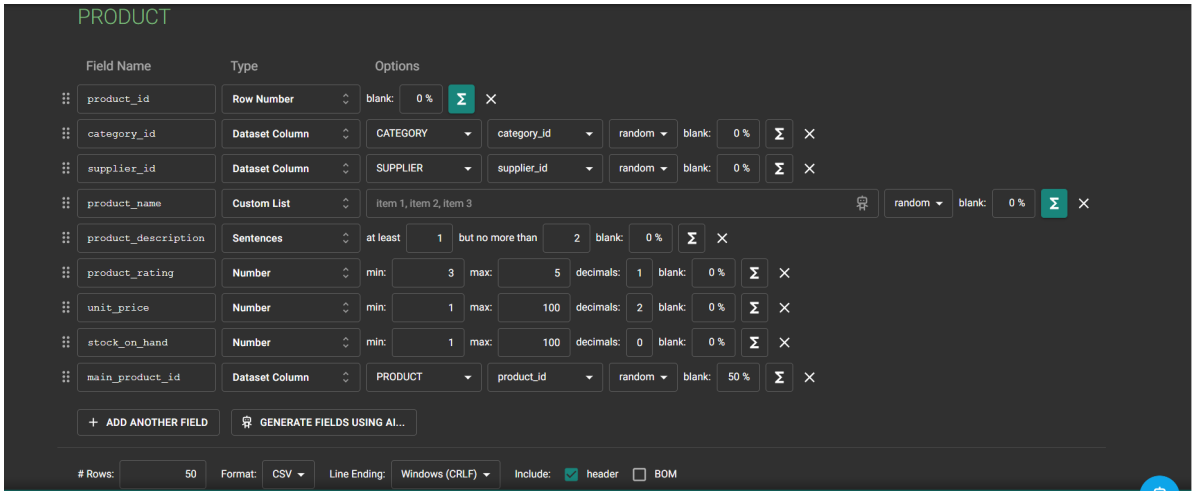
50 observations for the CUSTOMER table were created using the following setting:



There were additional constraints that we set in the formula. Firstly, we set to condition the customer_id to start with 'CUS' and followed by a number. Moreover, we gave a condition on customer_mobile to start with +44, which is the United Kingdom country code, before generating the rest of the numbers to comply with our focus on United Kingdom customers only. The formulas for those conditions are as followed

7. PRODUCT

50 observations for the PRODUCT table were created using the following setting:



There were two conditions we set in this table. The first condition is on the primary key, product_id, to start the value with 'PROD' and then a number. The second condition is on product_name. To ensure consistency between the products and categories, we manually assigned the values of product_name to the categories they were supposed to belong to. These formulas were used to set those conditions.

Formula

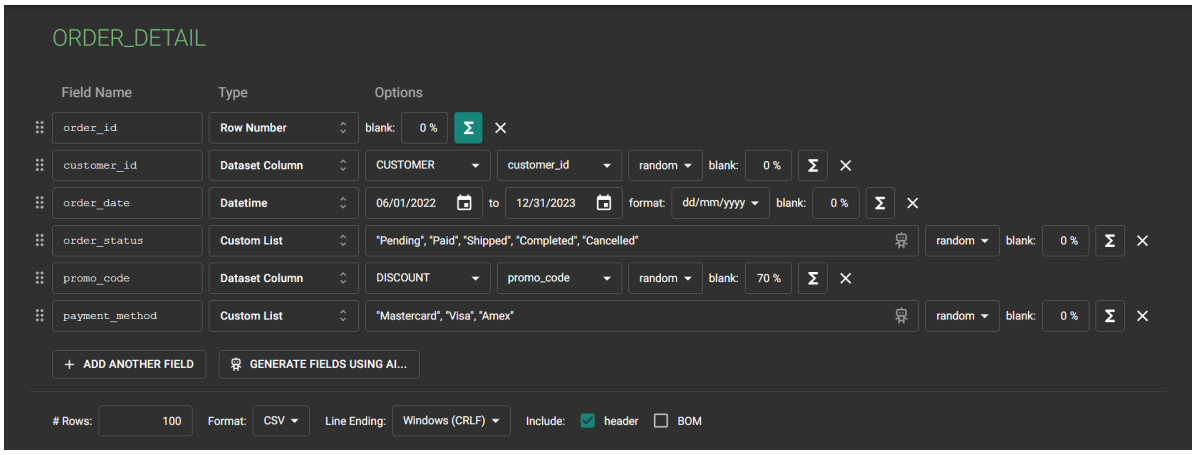
```
'PROD' + this.to_s
```

Formula

```
this =
if category_id == 'CATG1'
['QuantumX Gaming Mouse', 'Lumina Wireless Earbuds', 'NeoTech Smart Watch', 'NovaTech VR Headset', 'Infinity Bluetooth Speaker',
 'CyberX Gaming Keyboard', 'Apollo Portable Charger', 'Solaris HD Webcam', 'TitanX Noise-Canceling Headphones', 'Nebula Smart LED Bulbs',
 'FusionX Gaming Console', 'Zenith Ultra HD Monitor', 'Sparkle USB-C Hub', 'LunaTech Digital Camera', 'ZenTech Fitness Tracker',
 'Skyline Drone with HD Camera', 'Stellar Wireless Charging Pad', 'Matrix Smart Thermostat', 'Sonic Boom Portable Speaker',
 'HyperDrive External SSD'].sample
elsif category_id == 'CATG2'
['Aurora Shift Dress', 'Nova Denim Jacket', 'Celestial Leggings', 'Galaxy Hoodie', 'Eclipse Bomber Jacket', 'Lunar Maxi Skirt',
 'Solar Flare Sweater', 'Stardust T-Shirt', 'Comet Crop Top', 'Solar Eclipse Sunglasses', 'Meteorite Joggers', 'Nebula Scarf',
 'Cosmic Print Blouse', 'Constellation Dress Shirt', 'Supernova Sweatpants', 'Solar System Hooded Sweatshirt', 'Satellite Silk Tie',
 'Stellar Puffer Vest', 'Moonbeam Cardigan', 'Zenith Yoga Pants'].sample
elsif category_id == 'CATG3'
['Zen Garden Set', 'Serenity Wall Art', 'Harmony Throw Pillow', 'Tranquility Scented Candles', 'Blissful Bedding Set', 'Reflections Mirror',
 'Solace Area Rug', 'Symphony Table Lamp', 'Oasis Indoor Fountain', 'Essence Room Diffuser', 'Aura Decorative Vase', 'Zenith Wall Clock',
 'Dreamcatcher Wall Hanging', 'Enchanted Fairy Lights', 'Haven Decorative Tray', 'Radiance Window Curtains', 'Utopia Throw Blanket',
 'Sanctuary Plant Stand', 'Paradise Accent Chair', 'Euphoria Decorative Bowl'].sample
elsif category_id == 'CATG4'
['TitanX Carbon Fiber Tennis Racket', 'NovaTech Running Shoes', 'Eclipse Yoga Mat', 'Zenith Golf Club Set', 'Solaris Cycling Helmet',
 'Blaze Basketball Hoop', 'Nebula Soccer Ball', 'FusionX Fitness Bands', 'Comet CrossFit Gloves', 'Stellar Surfboard', 'Galaxy Hiking Backpack',
 'Lunar Jump Rope', 'Sonic Boom Resistance Bands', 'Celestial Climbing Harness', 'Aurora Weightlifting Gloves', 'Meteorite Mountain Bike',
 'Cosmic Compression Socks', 'Satellite Ski Poles', 'Zenith Zumba Shoes', 'Stellar Swimming Goggles'].sample
elsif category_id == 'CATG5'
['Luna Glow Facial Serum', 'Celestial Shampoo & Conditioner Set', 'Solar Flare Hair Straightener',
 'Zenith Facial Cleansing Brush', 'NovaTech Hair Dryer', 'Aurora Lip Gloss Collection', 'Nebula Nail Polish Kit', 'Stellar Eyeshadow Palette',
 'Lunar Face Mask Set', 'Harmony Body Lotion', 'Radiance Highlighter Stick', 'Cosmic Perfume', 'Eclipse Eyeliner Pen', 'Serenity Bath Bombs',
 'Stardust Makeup Brushes', 'Blissful Body Scrub', 'Tranquility Sleep Mask', 'Solaris Sunscreen Spray', 'Zenith Anti-Aging Cream',
 'Aura Lip Balm Trio'].sample
end
```

8. ORDER_DETAIL

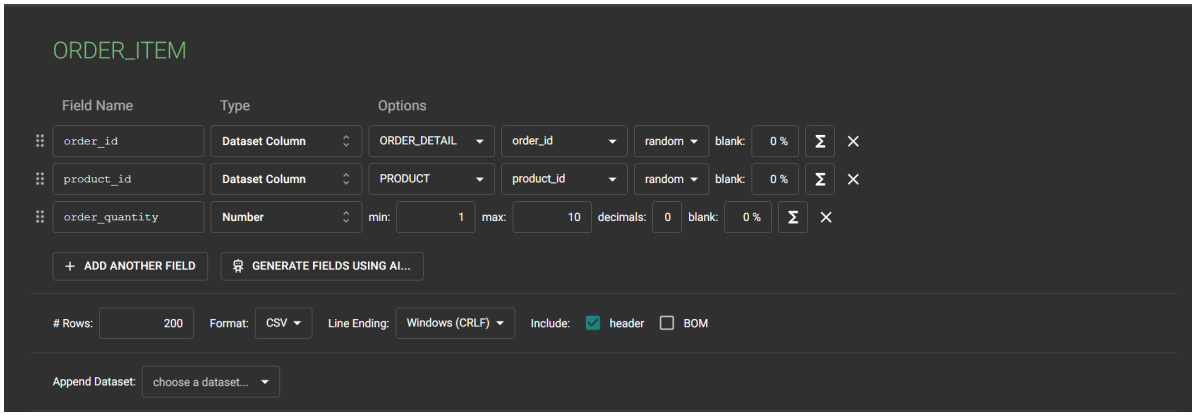
100 observations for the ORDER_DETAIL table were created using the following setting:



We have set the order_id, which is the primary of the table, to start with 'ORD' and then follow with a number.

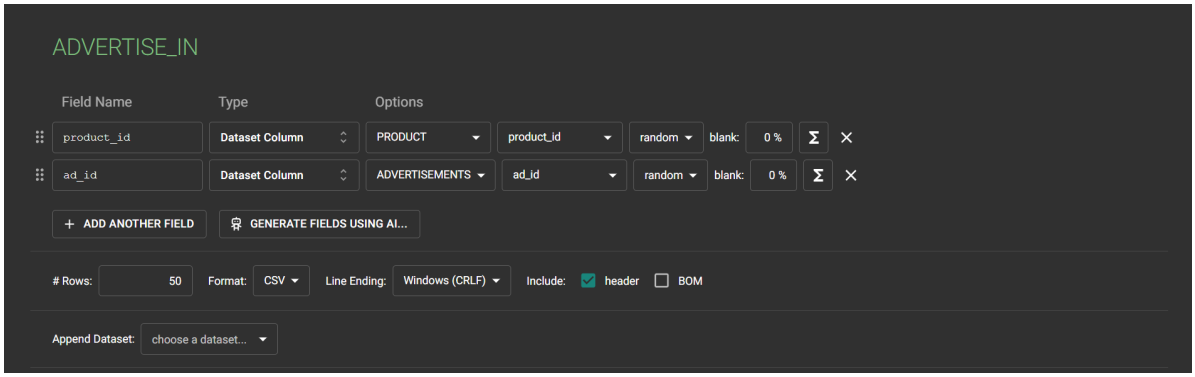
9. ORDER_ITEM

100 observations for the ORDER_ITEM table were created using the following setting:



10. ADVERTISE_IN

50 observations for the ADVERTISE_IN table were created using the following setting:



Task 2.2: Data Import and Quality Assurance

Data Import

Loading all generated data sets using read_csv to each entity

```
customer <- readr::read_csv("data_upload/CUSTOMER.csv")
```

```
Rows: 50 Columns: 7
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (7): customer_id, first_name, last_name, gender, customer_email, custome...

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
address <- readr::read_csv("data_upload/ADDRESS.csv")
```

```
Rows: 50 Columns: 5
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (5): address_id, postcode, street, city, country

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
category <- readr::read_csv("data_upload/CATEGORY.csv")
```

```
Rows: 5 Columns: 3
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): category_id, category_name
dbl (1): category_fee

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
supplier <- readr::read_csv("data_upload/SUPPLIER.csv")
```

```
Rows: 50 Columns: 4
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (4): supplier_id, supplier_name, supplier_email, supplier_mobile

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
discount <- readr::read_csv("data_upload/DISCOUNT.csv")
```

```
Rows: 5 Columns: 2
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (1): promo_code
dbl (1): discount_percent

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
product <- readr::read_csv("data_upload/PRODUCT.csv")
```

```
Rows: 50 Columns: 9
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (6): product_id, category_id, supplier_id, product_name, product_descrip...
dbl (3): product_rating, unit_price, stock_on_hand

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
order_item <- readr::read_csv("data_upload/ORDER_ITEM.csv")
```

```
Rows: 200 Columns: 3
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): order_id, product_id
dbl (1): order_quantity

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
order_detail <- readr::read_csv("data_upload/ORDER_DETAIL.csv")
```

```
Rows: 100 Columns: 7
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (6): order_id, customer_id, order_date, order_status, promo_code, paymen...
dbl (1): delivery_fee

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
advertisement <- readr::read_csv("data_upload/ADVERTISEMENT.csv")
```

```
Rows: 5 Columns: 4
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): ad_id, ad_place
dbl (2): ad_frequency, ad_price

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
advertise_in <- readr::read_csv("data_upload/ADVERTISE_IN.csv")
```

```
Rows: 50 Columns: 2
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (2): product_id, ad_id
```

```
i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Quality Assurance

The imported data sets were validated before being added to the database to ensure they aligned with the nature of the keys and data type specified in the physical schema. First, we validated parent entities including ADDRESS, DISCOUNT, ADVERTISEMENT, SUPPLIER, CATEGORY. Once all parent entities were validated, we continued validating children entities CUSTOMER, PRODUCT, ORDER_ITEM, ORDER_DETAIL, and ADVERTISE_IN.

The general validation processes that were performed to check on the data quality for all entities included:

1. Check if the values of the primary key are unique
2. Check if there is any missing data in the attributes that should not have missing values
3. Check if there are any values of a foreign key in the children table that do not exist in the parent table
4. Remove unqualified data

However, there would be some additional validation methods that were used to validate specific attribute for specific entity. The additional method will be provided on each entity if there is any.

Parent Entities Validation

1. ADDRESS

```r
#Check duplicate pk
duplicate_address_id <- address[duplicated(address$address_id), "address_id"]

#Check for missing data
na_address_address_id <- address[is.na(address$address_id), "address_id"]
na_address_postcode <- address[is.na(address$postcode), c("address_id", "postcode")]
na_address_street <- address[is.na(address$street), c("address_id", "street")]
na_address_city <- address[is.na(address$city), c("address_id", "city")]
na_address_country <- address[is.na(address$country), c("address_id", "country")]

#Remove unclean data
bad_address_record <- unique(c(duplicate_address_id$address_id,
                               na_address_address_id$address_id,
                               na_address_postcode$address_id,
                               na_address_street$address_id,
                               na_address_city$address_id,
```

```
                                    na_address_country$address_id))
address <- address[!(address$address_id %in% bad_address_record), ]
```

2. DISCOUNT

   Additional validation method:

   - Check the datatype of discount_amount, which should be integers

```
#Check duplicate pk
duplicate_promo_code <- discount[duplicated(discount$promo_code), "promo_code"]

#Check percent
invalid_discount_percent <- discount[!grepl("^[0-9]+$", discount$discount_percent), c("p

#Check for missing data
na_discount_promo_code <- discount[is.na(discount$promo_code), "promo_code"]
na_discount_discount_percent <- discount[is.na(discount$discount_percent), c("promo_code

#Remove unclean data
bad_discount_record <- unique(c(duplicate_promo_code$promo_code,
                                invalid_discount_percent$promo_code,
                                na_discount_promo_code$promo_code,
                                na_discount_discount_percent$promo_code))
discount <- discount[!(discount$promo_code %in% bad_discount_record), ]
```

3. ADVERTISEMENT

   Additional validation method:

   - Check the datatype of ad_frequency, which should be integers
   - Check if there is any negative value in the attributes that the values should only be positive

```
#Check duplicate pk
duplicate_ad_id <- advertisement[duplicated(advertisement$ad_id), "ad_id"]

#Check ad frequency (can only contain integer)
invalid_ad_frequency <- advertisement[!grepl("^[0-9]+$", advertisement$ad_frequency), c(

#Check for negative ad frequency
negative_ad_frequency <- advertisement[advertisement$ad_frequency < 0, c("ad_id", "ad_fr

#Check for negative prices
```

```
negative_ad_prices <- advertisement[advertisement$ad_price < 0, c("ad_id", "ad_price")]

#Check for missing data
na_advertisement_ad_id <- advertisement[is.na(advertisement$ad_id), "ad_id"]
na_advertisement_ad_frequency <- advertisement[is.na(advertisement$ad_frequency), c("ad_
na_advertisement_ad_price <- advertisement[is.na(advertisement$ad_price), c("ad_id", "ad
na_advertisement_ad_place <- advertisement[is.na(advertisement$ad_place), c("ad_id", "ad

#Remove unclean data
bad_advertisement_record <- unique(c(duplicate_ad_id$ad_id,
                                     invalid_ad_frequency$ad_id,
                                     negative_ad_frequency$ad_id,
                                     negative_ad_prices$ad_id,
                                     na_advertisement_ad_id$ad_id,
                                     na_advertisement_ad_frequency$ad_id,
                                     na_advertisement_ad_price$ad_id,
                                     na_advertisement_ad_place$ad_id))
advertisement <- advertisement[!(advertisement$ad_id %in% bad_advertisement_record), ]
```

4. SUPPLIER

   Additional validation method:

   - Check the format of suppliers' names
   - Check the format of the email
   - Check the format of the mobile number, which should start with a plus sign followed by 12 integer values

```
#Check duplicate pk
duplicate_supplier_id <- supplier[duplicated(supplier$supplier_id), "supplier_id"]

#Check supplier (can contain alphabets, comma, hyphen, dot)
invalid_supplier_name <- supplier[!grepl("^[A-Za-z,.-]+( [A-Za-z,.-]+)*$", supplier$supp

#Check email format
invalid_supplier_email <- supplier[!grepl("^[A-Za-z0-9._%+-]+@[A-Za-z0-9.-]+\\.[A-Za-z]{

#Check format of mobile number (+xx xxx xxx xxxx)
invalid_supplier_mobile <- supplier[!grepl("^^\\+\\d{1,3}\\s[0-9]{3}\\s[0-9]{3}\\s[0-9]{

#Check for missing data
na_supplier_supplier_id <- supplier[is.na(supplier$supplier_id), "supplier_id"]
```

```
na_supplier_supplier_name <- supplier[is.na(supplier$supplier_name), c("supplier_id", "s
na_supplier_supplier_email <- supplier[is.na(supplier$supplier_email), c("supplier_id",
na_supplier_supplier_mobile <- supplier[is.na(supplier$supplier_mobile), c("supplier_id'

#Remove unclean data
bad_supplier_record <- unique(c(duplicate_supplier_id$supplier_id,
                                invalid_supplier_name$supplier_id,
                                invalid_supplier_email$supplier_id,
                                invalid_supplier_mobile$supplier_id,
                                na_supplier_supplier_id$supplier_id,
                                na_supplier_supplier_name$supplier_id,
                                na_supplier_supplier_email$supplier_id,
                                na_supplier_supplier_mobile$supplier_id))
supplier <- supplier[!(supplier$supplier_id %in% bad_supplier_record), ]
```

5. CATEGORY

   Additional validation method:

   - Check the datatype of categories' names

```
#Check duplicate pk
duplicate_category_id <- category[duplicated(category$category_id), "category_id"]

#Check category (can contain alphabets)
invalid_category_name <- category[!grepl("^[A-Za-z]+( [A-Za-z]+)*$", category$category_n

#Check for duplicate category name
duplicate_category_name <- category[duplicated(category$category_name), c("category_id",

#Check for negative prices
negative_category_fee <- category[category$category_fee < 0, c("category_id", "category_

#Check for missing data
na_category_category_id <- category[is.na(category$category_id), "category_id"]
na_category_category_name <- category[is.na(category$category_name), c("category_id", "c
na_category_category_fee <- category[is.na(category$category_fee), c("category_id", "cat

#Remove unclean data
bad_category_record <- unique(c(duplicate_category_id$category_id,
                                invalid_category_name$category_id,
                                duplicate_category_name$category_id,
                                negative_category_fee$category_id,
```

```
                                  na_category_category_id$category_id,
                                  na_category_category_name$category_id,
                                  na_category_category_fee$category_id))
category <- category[!(category$category_id %in% bad_category_record), ]
```

Children Entities Validation

6. CUSTOMER

   Additional validation method:

   - Check the format of the customers' first and last names. The format is expected to be first uppercase alphabet followed by lowercase alphabet.
   - Check the format of the email
   - Check the format of the mobile number, which should start with a plus sign followed by 12 integer values

```
#Check duplicate pk
duplicate_customer_id <- customer[duplicated(customer$customer_id), "customer_id"]

#Check format of first and last name (1st alphabet is uppercase, rest is lowercase)
invalid_customer_firstname <- customer[!grepl("^[A-Z][a-z]*$", customer$first_name), c('
invalid_customer_lastname <- customer[!grepl("^[A-Z][a-z]*$", customer$last_name), c("cu

#Check email format
invalid_customer_email <- customer[!grepl("^[A-Za-z0-9._%+-]+@[A-Za-z0-9.-]+\\.[A-Za-z]{

#Check format of mobile number (+xx xxx xxx xxxx)
invalid_customer_mobile <- customer[!grepl("^\\+\\d{1,3}\\s[0-9]{3}\\s[0-9]{3}\\s[0-9]{4

#Check if address_id exists in the ADDRESS table
invalid_address_fk <- customer[!customer$address_id %in% address$address_id, c("customer

#Check for missing data
na_customer_customer_id <- customer[is.na(customer$customer_id), "customer_id"]
na_customer_first_name <- customer[is.na(customer$first_name), c("customer_id", "first_n
na_customer_last_name <- customer[is.na(customer$last_name), c("customer_id", "last_name
na_customer_customer_email <- customer[is.na(customer$customer_email), c("customer_id",
na_customer_customer_mobile <- customer[is.na(customer$customer_mobile), c("customer_id'

#Remove unclean data
bad_customer_record <- unique(c(duplicate_customer_id$customer_id,
```

```
                                invalid_customer_firstname$customer_id,
                                invalid_customer_lastname$customer_id,
                                invalid_customer_email$customer_id,
                                invalid_customer_mobile$customer_id,
                                invalid_address_fk$customer_id,
                                na_customer_customer_id$customer_id,
                                na_customer_first_name$customer_id,
                                na_customer_last_name$customer_id,
                                na_customer_customer_email$customer_id,
                                na_customer_customer_mobile$customer_id))
customer <- customer[!(customer$customer_id %in% bad_customer_record), ]
```

7. PRODUCT

   Additional validation method:

   - Check the datatype of product_name
   - Check if there is any negative value in unit_price where the values should only be positive
   - Check on the validity of stock_on_hand to see if there are any missing or negative values
   - Check if the values in main_product_id are self-referential to product_id and ensure that the values differ from those of product_id.

```
#Check duplicate pk
duplicate_product_id <- product[duplicated(product$product_id), "product_id"]

#Check product name (can contain alphabets, comma, hyphen, dot)
invalid_product_name <- product[!grepl("^[A-Za-z,.-]+( [A-Za-z,.-]+)*$", product$pro

#Check for negative prices
negative_unit_prices <- product[product$unit_price < 0, c("product_id", "unit_price"

#Check invalid stock
invalid_stock <- product[!grepl("^[0-9]+$", product$stock_on_hand), c("product_id",
negative_stock <- product[product$stock_on_hand < 0, c("product_id", "stock_on_hand"

#Check if supplier_id exists in the SUPPLIER table
invalid_supplier_fk <- product[!product$supplier_id %in% supplier$supplier_id, c("pr

#Check if category_id exists in the CATEGORY table
invalid_category_fk <- product[!product$category_id %in% category$category_id, c("pr
```

```
#Check if main product is self referential and it cannot be the same as product_id
invalid_main_product_ids <- product[!is.na(product$main_product_id) &
                                    !(product$main_product_id %in% product$product
                                        product$main_product_id != product$product

#Check for missing data
na_product_product_id <- product[is.na(product$product_id), "product_id"]
na_product_category_id <- product[is.na(product$category_id), c("product_id", "categ
na_product_supplier_id <- product[is.na(product$supplier_id), c("product_id", "suppl
na_product_product_name <- product[is.na(product$product_name), c("product_id", "pro
na_product_unit_price <- product[is.na(product$unit_price), c("product_id", "unit_pr
na_product_stock_on_hand <- product[is.na(product$stock_on_hand), c("product_id", "s

#Remove unclean data
bad_product_record <- unique(c(duplicate_product_id$product_id,
                               invalid_product_name$product_id,
                               negative_unit_prices$product_id,
                               invalid_stock$product_id,
                               negative_stock$product_id,
                               invalid_supplier_fk$product_id,
                               invalid_category_fk$product_id,
                               invalid_main_product_ids$product_id,
                               na_product_product_id$product_id,
                               na_product_category_id$product_id,
                               na_product_supplier_id$product_id,
                               na_product_product_name$product_id,
                               na_product_unit_price$product_id,
                               na_product_stock_on_hand$product_id))
product <- product[!(product$product_id %in% bad_product_record), ]
```

8. ORDER_ITEM

   Additional validation method:

   - Check on the values of order_status. The values of this attribute are expected to be Pending, Paid, Shipped, Complete, or Cancelled
   - Check on the values of payment_method. The values of this attribute are expected to be Mastercard, Visa, or Amex
   - Check on the date format
   - Check if there is any negative value in delivery_fee where the values should only be positive

```r
#Check duplicate pk
duplicate_order_id <- order_detail[duplicated(order_detail$order_id), "order_id"]

#Check if customer_id exists in the CUSTOMER table
invalid_customer_fk <- order_detail[!order_detail$customer_id %in% customer$customer_id,

#Check if promo_code exists in the DISCOUNT table
discounted_order <- order_detail[!is.na(order_detail$promo_code), ]
invalid_promo_fk <- discounted_order[!discounted_order$promo_code %in% discount$promo_co

#Check order status
status <- c("Pending", "Paid", "Shipped", "Completed", "Cancelled")
invalid_order_status <- order_detail[!order_detail$order_status %in% status, c("order_id

#Check payment method
payment <- c("Mastercard", "Visa", "Amex")
invalid_payment_method <- order_detail[!order_detail$payment_method %in% payment, c("orc

#Check date format (dd/mm/yyyy)
invalid_order_date <- order_detail[!grepl("^\\d{2}/\\d{2}/\\d{4}$", order_detail$order_d

#Check for negative delivery fee
negative_delivery_fee <- order_detail[order_detail$delivery_fee < 0, c("order_id", "deli

#Check for missing data
na_order_order_id <- order_detail[is.na(order_detail$order_id), "order_id"]
na_order_customer_id <- order_detail[is.na(order_detail$customer_id), c("order_id", "cus
na_order_order_status <- order_detail[is.na(order_detail$order_status), c("order_id", "o
na_order_order_date <- order_detail[is.na(order_detail$order_date), c("order_id", "order
na_order_payment_method <- order_detail[is.na(order_detail$payment_method), c("order_id"
na_order_delivery_fee <- order_detail[is.na(order_detail$delivery_fee), c("order_id", "o

#Remove unclean data
bad_order_record <- unique(c(duplicate_order_id$order_id,
                             invalid_customer_fk$order_id,
                             invalid_promo_fk$order_id,
                             invalid_order_status$order_id,
                             invalid_payment_method$order_id,
                             invalid_order_date$order_id,
                             negative_delivery_fee$order_id,
                             na_order_order_id$order_id,
                             na_order_customer_id$order_id,
```

```
                              na_order_order_status$order_id,
                              na_order_order_date$order_id,
                              na_order_payment_method$order_id,
                              na_order_delivery_fee$order_id))
order_detail <- order_detail[!(order_detail$order_id %in% bad_order_record), ]
```

9. ORDER_DETAIL

   Additional validation method:Check if the values of the primary key are unique

   - Check on the validity of order_quantity to see if there are any missing or negative values

```
#Check duplicate for composite primary key
order_item_composite <- paste(order_item$order_id, order_item$product_id)
duplicate_order_item_composite <- order_item[duplicated(order_item_composite), c("order_

#Check if order_id exists in the ORDER_ITEM table
invalid_order_fk <- order_item[!order_item$order_id %in% order_detail$order_id, c("order

#Check if product_id exists in the PRODUCT table
invalid_product_fk <- order_item[!order_item$product_id %in% product$product_id, c("orde

#Check invalid order quantity
invalid_quantity <- order_item[!grepl("^[0-9]+$", order_item$order_quantity), c("order_i
negative_zero_quantity <- order_item[order_item$order_quantity < 1, c("order_id", "order

#Check for missing data
na_order_item_order_id <- order_item[is.na(order_item$order_id), "order_id"]
na_order_item_product_id <- order_item[is.na(order_item$order_id), c("order_id", "produc
na_order_item_order_quantity <- order_item[is.na(order_item$order_quantity), c("order_id

#Remove unclean data
bad_order_item_record <- unique(c())
order_item <- order_item[!(order_item$order_id %in% bad_order_item_record), ]

#Remove unclean data
# Combine all unclean data
bad_order_item_record <- rbind(duplicate_order_item_composite,
                               invalid_order_fk,
                               invalid_product_fk,
                               invalid_quantity,
                               negative_zero_quantity,
```

```
                                na_order_item_order_id,
                                na_order_item_product_id,
                                na_order_item_order_quantity)

# Remove duplicates from bad records
bad_order_item_record <- unique(bad_order_item_record)

# Remove unclean data based on composite key
order_item <- order_item[!paste(order_item$order_id, order_item$product_id) %in% paste(b
```

10. ADVERTISE_IN

```
#Check duplicate for composite primary key
advertise_in_composite <- paste(advertise_in$ad_id, advertise_in$product_id)
duplicate_advertise_in_composite <- advertise_in[duplicated(advertise_in_composite), c('

#Check if ad_id exists in the ADVERTISEMENT table
invalid_advertisement_fk <- advertise_in[!advertise_in$ad_id %in% advertisement$ad_id, c

#Check if product_id exists in the PRODUCT table
invalid_product_fk <- advertise_in[!advertise_in$product_id %in% product$product_id, c('

#Check for missing data
na_advertise_in_ad_id <- advertise_in[is.na(advertise_in$ad_id), "ad_id"]
na_advertise_in_product_id <- advertise_in[is.na(advertise_in$product_id), c("ad_id", "p

#Remove unclean data
# Combine all unclean data
bad_advertise_in_record <- rbind(duplicate_advertise_in_composite,
                                 invalid_advertisement_fk,
                                 invalid_product_fk,
                                 na_advertise_in_ad_id,
                                 na_advertise_in_product_id)

# Remove duplicates from bad records
bad_advertise_in_record <- unique(bad_advertise_in_record)

# Remove unclean data based on composite key
advertise_in <- advertise_in[!paste(advertise_in$ad_id, advertise_in$product_id) %in% pa
```

Once the dataset was validated, it was imported to the database, where the schema is already created.

```r
#add new records into table
connect <- dbConnect(RSQLite::SQLite(), "database.db")

tables <- c("CUSTOMER", "ADDRESS", "CATEGORY", "SUPPLIER", "PRODUCT", "DISCOUNT",
            "ORDER_ITEM", "ORDER_DETAIL", "ADVERTISEMENT", "ADVERTISE_IN")

table_new <- list(customer, address, category, supplier, product, discount,
                  order_item, order_detail, advertisement, advertise_in)

# Loop through each table
for (i in seq_along(tables)) {
  table <- tables[i]
  new_records <- table_new[[i]]

  # Read existing records from the table
  existing <- dbGetQuery(connect, paste("SELECT * FROM", table))

  # Convert data types if needed (e.g., order_date column)
  if ("order_date" %in% colnames(existing)) {
    existing$order_date <- as.character(existing$order_date)
    new_records$order_date <- as.character(new_records$order_date)
  }

  # Find new records not present in existing table
  new <- anti_join(new_records, existing)

  # Append new records to the table
  if (nrow(new) > 0) {
    dbWriteTable(connect, table, new, append = TRUE)
  }}
```

```
Joining with `by = join_by(customer_id, first_name, last_name, gender,
customer_email, customer_mobile, address_id)`
Joining with `by = join_by(address_id, postcode, street, city, country)`
Joining with `by = join_by(category_id, category_name, category_fee)`
Joining with `by = join_by(supplier_id, supplier_name, supplier_email,
supplier_mobile)`
Joining with `by = join_by(product_id, category_id, supplier_id, product_name,
product_description, product_rating, unit_price, stock_on_hand,
main_product_id)`
Joining with `by = join_by(promo_code, discount_percent)`
Joining with `by = join_by(order_id, product_id, order_quantity)`
```

```
Joining with `by = join_by(order_id, customer_id, order_date, order_status,
promo_code, payment_method, delivery_fee)`
Joining with `by = join_by(ad_id, ad_frequency, ad_place, ad_price)`
Joining with `by = join_by(product_id, ad_id)`
```

Part 3: Data Pipeline Generation

Task 3.1: GitHub Repository and Workflow Setup

We first created a new public repository named **DM_Group3** on GitHub and created the following files:

1. **README** file to include all student ID numbers of our group.
2. **database_schema** file to create a database and build the database schema.
3. **data_validation_and_load** file to create code for validating data and loading the cleaned data into the database.
4. **data_analysis** file to perform data analysis and visualise essential results.
5. two folders, named **data_upload** to store 10 datasets generated by Mockaroo, and **images** to store E-R diagrams.
6. **Report** as a qmd. file to report the tasks and how they were done.

Secondly, we create a new project in RStudio and connect it to Git for version control to manage code in a local development environment, leading to easier tracking of changes, creating branches, merging code, etc.

For setting up workflow, as GitHub Actions can automate workflows, such as running tests, building, and deploying tasks after pushing code, which can improve development efficiency and ensure code stability, we created the **.github/workflows** directory and an **etl.yaml** file within it.

Task 3.2: Data Import and Quality Assurance

Our GitHub Actions workflow was designed to execute a task named "ETL workflow for group 3.", triggering by pushing events to the 'main' branch. In this part, we defined a sequence of steps to be executed on the latest version of Ubuntu:

1. Use GitHub Actions checkout action to check out code into the working directory.
2. Set up R environment and specify the R version as '4.3.3'.
3. Cache R packages to avoid reinstalling them on each run.
4. Install required packages if the cache misses.
5. Run database_schema.Rmd to render database schema.
6. Run data_validation_and_load.Rmd to render validation and load data into database.
7. Run data_analysis.Rmd to render data analysis.

8. Utilize an authentication token to push changes to the 'main' branch.

Part 4: Data Analysis and Reporting with Quarto in R

Task 4.1: Advanced Data Analysis in R

```
library(DBI)
library(RSQLite)
library(readr)
library(dplyr)
library(plotly)
```

```
Warning: package 'plotly' was built under R version 4.3.3
```

```
Attaching package: 'plotly'
```

```
The following object is masked from 'package:ggplot2':

    last_plot
```

```
The following object is masked from 'package:stats':

    filter
```

```
The following object is masked from 'package:graphics':

    layout
```

```
# Connecting to the database
connect <- dbConnect(RSQLite::SQLite(), "database.db")
```

```
# Report 1

# Top 10 products based on the Profit Generated

# Getting the tables from the database
product <- RSQLite::dbGetQuery(connect,'SELECT * FROM PRODUCT')
```

```r
order_item <- RSQLite::dbGetQuery(connect,'SELECT * FROM ORDER_ITEM')
order_detail <- RSQLite::dbGetQuery(connect,'SELECT * FROM ORDER_DETAIL')
discount <- RSQLite::dbGetQuery(connect,'SELECT * FROM DISCOUNT')
# Creating a profit table that includes a total_profit column for each product
#incorporating the discount percent
#filtering out all "cancelled" orders.

profit_data <- order_item %>%
  inner_join(order_detail, by = "order_id") %>%
  filter(order_status != "Cancelled") %>%
  inner_join(product, by = "product_id") %>%
  left_join(discount, by = c("promo_code" = "promo_code")) %>%
  mutate(
    discount_percentage = ifelse(is.na(discount_percent), 0, discount_percent),
    total_profit = (order_quantity * unit_price) *
      (1 - discount_percentage / 100)
  ) %>%
  group_by(product_id, product_name) %>%
  summarise(
    total_profit = sum(total_profit),
    .groups = 'drop'
  ) %>%
  arrange(desc(total_profit))

# Selecting the top 10 profitable products
top_10_profit_data <- head(profit_data, 10)


# Visualizing the results
ggplot(top_10_profit_data, aes(x = reorder(product_id, total_profit),
                               y = total_profit,
                               fill = product_name)) +
  geom_bar(stat = "identity") +
  scale_fill_discrete(name = "product Name") +
  labs(title = "Top 10 Most Profitable Products", x = "Product ID",
       y = "Total Profit", caption="Figure 1") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        legend.title = element_text(size = 12),
        legend.text = element_text(size = 10),
        plot.title = element_text(hjust = 0.5))
```

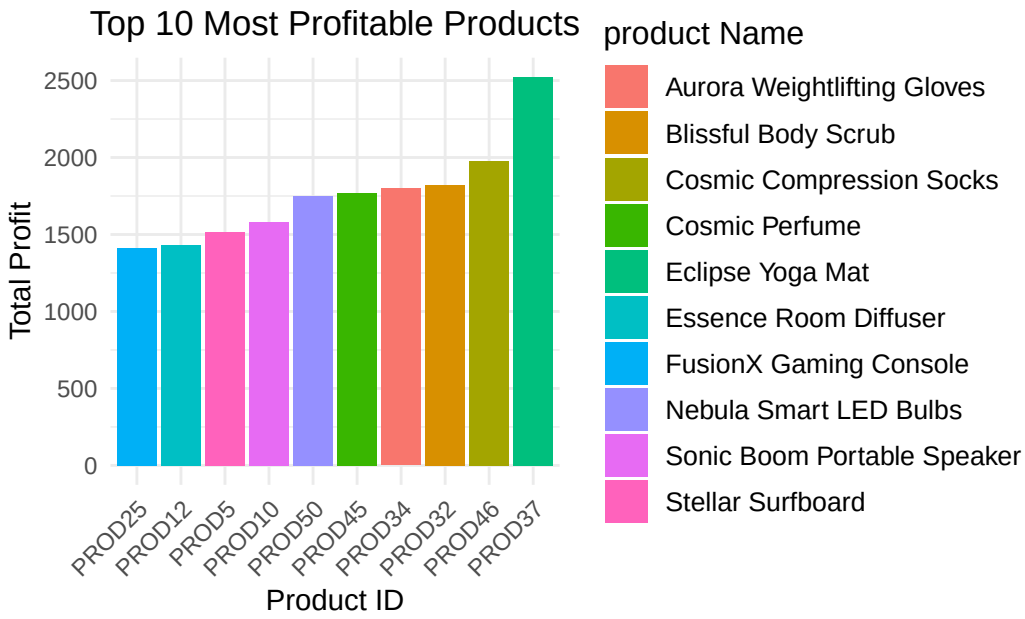


Figure 1

```
# Top Most Selling Products

# Creating a sales that that includes the total quantity sold for each product
# selecting the top 10.
sales_data <- order_item %>%
  group_by(product_id) %>%
  summarise(Total_Sales = sum(order_quantity, na.rm = TRUE)) %>%
  arrange(desc(Total_Sales))

top_selling_products <- sales_data %>%
  left_join(product, by = "product_id") %>%
  select(product_id, product_name, Total_Sales) %>%
  top_n(10, Total_Sales)

# Visualizing the results
ggplot(top_selling_products, aes(x = reorder(product_id, Total_Sales),
                                 y = Total_Sales, fill = product_name)) +
  geom_bar(stat = "identity") +
  scale_fill_discrete(name = "product Name") +
  labs(title = "Top Most Selling Products", x = "Product ID",
       y = "Total Sales", caption="Figure 2") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
```

```
        legend.title = element_text(size = 12),
        legend.text = element_text(size = 10),
        plot.title = element_text(hjust = 0.5))
```

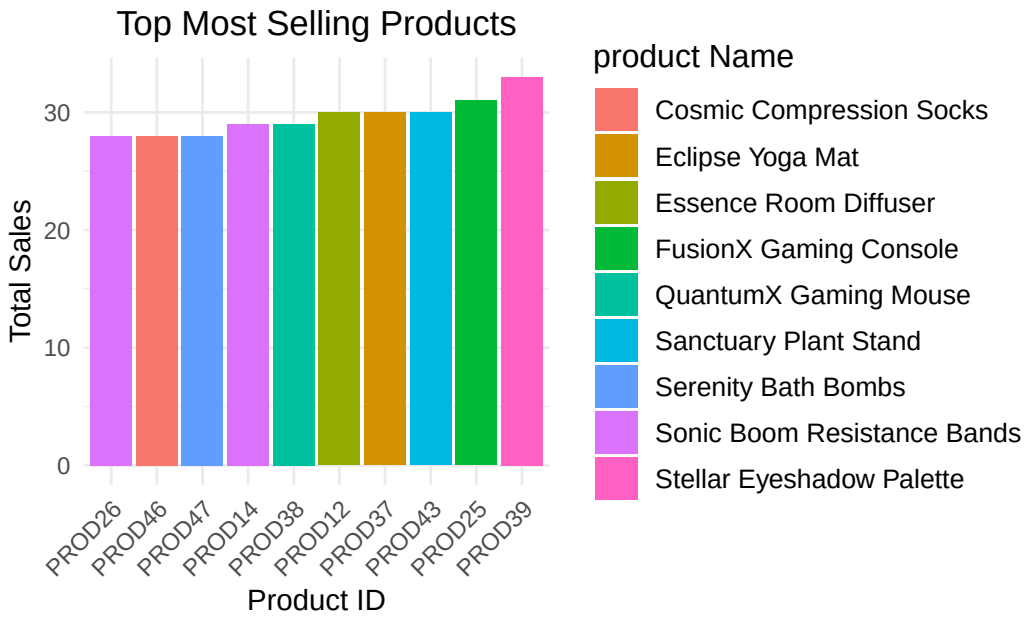


Figure 2

Figure 1 represents the profitability of individual products sold by the e-commerce company. The "Eclipse Yoga Mat" generates the highest profit for the company among the assortment. This could indicate a higher margin or a premium pricing strategy. Conversely, Figure 2 illustrates sales volume, where items like the "Stellar Eyeshadow Palette" and "Fusion X Gaming Console" lead, suggesting they are favored choices among consumers.

Some products, including the "Aurora Weightlifting Gloves", "Cosmic Compression Socks" and "Tranquility Scented Candles," appear in both graphs, showcasing their strength in both popularity and profitability. This dual presence is indicative of a successful product strategy by the company. However, there are also noticeable discrepancies. For example, "QuantumX Gaming Mouse" appears as a top seller, yet it's absent from the most profitable items, implying a lower profit margin. In contrast, "Nebula Smart LED Bulbs" are among the most profitable but not the top sellers, suggesting a high margin compensating for lesser sales.

The e-commerce company could focus on marketing strategies for high-margin products to boost their volume of sales, thus increasing overall profitability. For products that sell well but are less profitable, the company may need to assess whether they can improve margins through better supplier negotiations.

Products that are both top sellers and highly profitable should be kept in optimum stock to avoid lost sales opportunities. For less profitable items, the company may consider keeping lower stock levels or even discontinuing them if they do not contribute significantly to overall profits.

```
#Report 2

# Bundles vs Individual products Comparison by Sales Volume

# Join product with order item
product_order_item <- order_item %>%
  inner_join(product, by = "product_id")

# Calculate total quantity sold for bundled products
bundled_sales <- product_order_item %>%
  filter(!is.na(main_product_id)) %>%
  group_by(main_product_id) %>%
  summarise(Total_Quantity_Sold = sum(order_quantity, na.rm = TRUE)) %>%
  ungroup() %>%
  mutate(Product_Type = "Bundled")

# Calculate total quantity sold for individual products
individual_sales <- product_order_item %>%
  filter(is.na(main_product_id)) %>%
  group_by(product_id) %>%
  summarise(Total_Quantity_Sold = sum(order_quantity, na.rm = TRUE)) %>%
  ungroup() %>%
  mutate(Product_Type = "Individual")

# Combining the results
total_sales_by_type <- bind_rows(bundled_sales, individual_sales) %>%
  group_by(Product_Type) %>%
  summarise(Total_Quantity_Sold = sum(Total_Quantity_Sold, na.rm = TRUE)) %>%
  ungroup()

print(total_sales_by_type)
```

```
# A tibble: 2 x 2
  Product_Type Total_Quantity_Sold
  <chr>                      <int>
1 Bundled                      548
2 Individual                   520
```

```r
# Visualizing the results
ggplot(total_sales_by_type, aes(x = Product_Type, y = Total_Quantity_Sold,
                                fill = Product_Type)) +
  geom_bar(stat = "identity", width = 0.5) +  # Adjust width here
  scale_fill_manual(values = c("Bundled" = "skyblue",
                               "Individual" = "salmon")) +
  labs(title = "Total Quantity Sold by Product Type",
       x = "Product Type",
       y = "Total Quantity Sold") +
  theme_minimal() +
  theme(legend.position = "none")
```

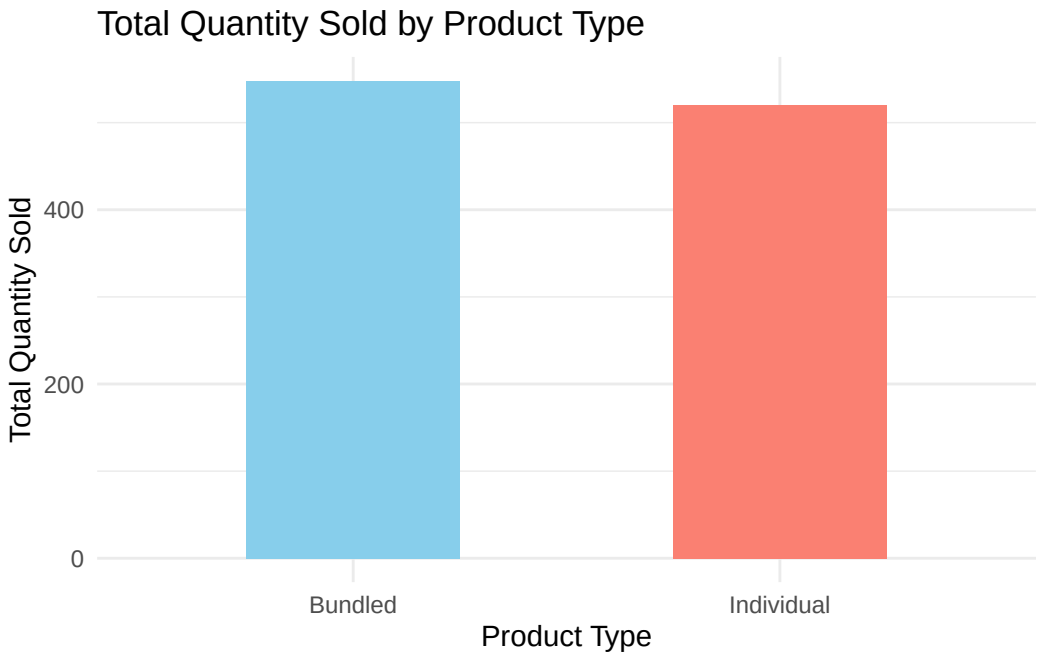


Figure 3

As the table shows, the total sales for individual products (products sold without bundles) and bundled products yield nearly equal quantities sold. Individual products slightly outperform bundled products (499 vs 491). This suggests that the e-commerce company's bundling strategy to boost sales was not as effective as anticipated. However, it is difficult to conclude the efficacy of this deal based solely on the volume of sales.

Optimizing bundle offerings by analyzing and aligning them with customer preferences, based on the average product ratings, can significantly enhance their appeal. Experimenting with different bundle types and conducting a cost-benefit analysis might uncover ways to refine the strategy. The results (Figure 3) suggest a market demand for both types of products, indicating

that customers prefer some flexibility in their buying options. Rather than discontinuing the bundle products, the company should look deeper into the performance metrics of this deal considering the inventory turnover and profit margins.

```
#Report 3

#SQL Query to get the sales over a time period

time_period_sales<- RSQLite::dbGetQuery(connect,'SELECT ORDITM.order_id,
                                        order_quantity,order_date FROM
                                        ORDER_DETAIL ORDDET INNER JOIN
                                        ORDER_ITEM ORDITM ON ORDITM.order_id =
                                        ORDDET.order_id')
#test

#Conversion of order_date field to appropiate format
time_period_sales$order_date <- as.Date(time_period_sales$order_date,
                                        format="%d/%m/%Y")

time_period_sales$order_date_mnth_yr <- format(
  time_period_sales$order_date,'%Y/%m')

#Conversion of order_date field to factors with levels

time_period_sales$order_date_mnth_yr <- factor(
  time_period_sales$order_date_mnth_yr, levels=c('2022/06',
'2022/07','2022/08',
'2022/09','2022/10','2022/11','2022/12',
'2023/01','2023/02','2023/03','2023/04',
'2023/05','2023/06','2023/07','2023/08'
,'2023/09','2023/10','2023/11','2023/12'))

#Group by sales for each year
time_period_sales_group_by<- time_period_sales %>%
group_by(order_date_mnth_yr)%>%
summarise(quantity=sum(order_quantity))

# Time series graph to show the quantity sold over a given time period

(ggplot(time_period_sales_group_by, aes(x = order_date_mnth_yr,
y = quantity,group=1)) +
geom_point()+geom_line()+
xlab('Time Period(year/month)')+ylab('Quantity Sold'))+
```

```
theme(axis.text.x=element_text(angle=45,hjust = 1))
```

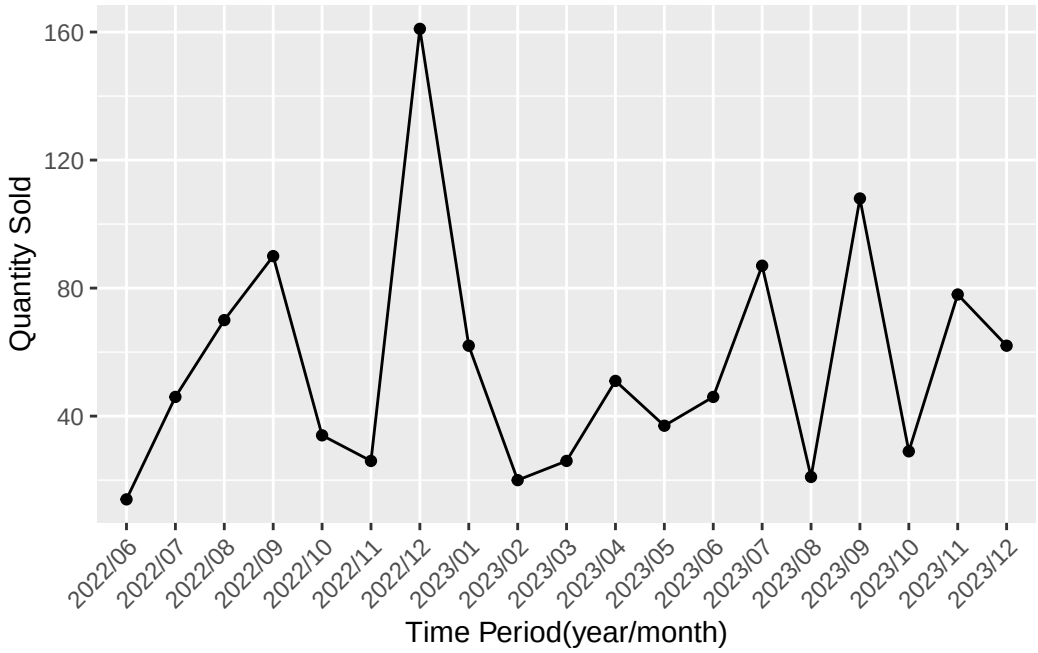


Figure 4: Time Series Graph to depict the seasonal trends in sales

Purchase pattern analysis is significant for an e-commerce company as different strategies could be deployed to maximize sales and revenue. Figure 4 illustrates that the sales was maximum at September and December months over the time-period from 2022 to 2023. Hence appropriate pricing strategies could be deployed to increase revenue from top selling products. Also, a sharp decline in sales is identified in October month which is later followed by an increase in succeeding months. This study could help in an efficient inventory management in place for perishable products. Overall, this variation in sales across different seasons provides important insights for better management decisions.

```
#Report 4:

#SQL query to join customer and order tables to get the sales for each city

cust_order_join<- RSQLite::dbGetQuery(connect,
                                      'SELECT city,ORDITM.order_quantity
                                      FROM ADDRESS ADR
                                      INNER JOIN CUSTOMER CUST
                                      ON ADR.address_id= CUST.address_id
                                      INNER JOIN ORDER_DETAIL ORDDET
```

```
                                        ON ORDDET.customer_id = CUST.customer_id
                                        INNER JOIN ORDER_ITEM ORDITM
                                        ON ORDITM.order_id = ORDDET.order_id')

#cust_order_join<- inner_join(Customer,Order,by="customer_id")

#Grouping by city to get the overall sales per city

sales_per_region<- cust_order_join %>% group_by(city)%>%
  summarise(quantity=sum(order_quantity))

#Get the top 10 cities for sales
top_10_sales_per_region <- sales_per_region[order(-sales_per_region$quantity),]

top_10_sales_per_region <- head(top_10_sales_per_region,10)

#Bar graph to show the sales per region

ggplot1 <- ggplot(top_10_sales_per_region,
aes(x = reorder(city,-quantity), y = quantity,fill=quantity)) +
geom_bar(stat='identity') +
scale_fill_gradient(low = "lightblue", high = "darkblue")+
xlab('Top 10 cities where sales is maximum')+ylab('Quantity Sold')+
theme(axis.text.x=element_text(angle=45,
hjust = 1))

#Table to get the revenue per city

cust_order_product_join <-RSQLite::dbGetQuery(connect,
'SELECT city,ORDITM.order_quantity,unit_price
FROM ADDRESS ADR
INNER JOIN
CUSTOMER CUST ON ADR.address_id= CUST.address_id
INNER JOIN
ORDER_DETAIL ORDDET ON ORDDET.customer_id = CUST.customer_id
INNER JOIN
ORDER_ITEM ORDITM ON ORDITM.order_id = ORDDET.order_id
INNER JOIN
PRODUCT PRD ON PRD.product_id = ORDITM.product_id')

#SQL Query to get the top 5 products
```

```
top_5_products <-RSQLite::dbGetQuery(connect,
'SELECT city,ORDITM.order_quantity,unit_price,
PRD.product_id,PRD.product_name FROM
ADDRESS ADR INNER JOIN
CUSTOMER CUST ON ADR.address_id= CUST.address_id
INNER JOIN
ORDER_DETAIL ORDDET ON ORDDET.customer_id = CUST.customer_id
INNER JOIN
ORDER_ITEM ORDITM ON ORDITM.order_id = ORDDET.order_id
INNER JOIN
PRODUCT PRD ON PRD.product_id = ORDITM.product_id')

#Revenue calculation

cust_order_product_join$revenue<- cust_order_product_join$order_quantity*
cust_order_product_join$unit_price

#Grouping by the get the revenue for each city
revenue_per_region <- cust_order_product_join %>% group_by(city) %>%
  summarise(revenue= sum(revenue))

#Get the top 10 cities for revenue

top_5_revenue_per_region <-
revenue_per_region[order(-revenue_per_region$revenue),]

top_5_revenue_per_region <- head(top_5_revenue_per_region,10)

#Bar graph to show the revenue per region

ggplot2 <- ggplot(top_5_revenue_per_region,aes(x = reorder(city, -revenue),
y=revenue,fill=revenue))+
geom_bar(stat='identity')+
scale_fill_gradient(low = "lightblue", high = "darkblue")+
xlab('Top 10 cities with the maximum revenue')+ylab('Revenue')+
theme(axis.text.x=element_text(angle=45,hjust = 1))



#Revenue calculation to show the top 5 products for each city
#with maximum revenue
```

```
top_5_products$revenue <-
top_5_products$order_quantity*top_5_products$unit_price

top_5_products_region <- top_5_products %>% group_by(city,product_name) %>%
summarise(rev= sum(revenue))
```

```
`summarise()` has grouped output by 'city'. You can override using the
`.groups` argument.
```

```
#Table to show the products that are
#sold for the top 2 revenue producing cities
(top_5_products_region <- top_5_products_region %>%
filter(city %in% head(top_5_revenue_per_region$city,2))
%>% select(product_name))
```

```
Adding missing grouping variables: `city`
```

```
# A tibble: 24 x 2
# Groups:   city [2]
   city       product_name
   <chr>      <chr>
 1 Birmingham Cosmic Compression Socks
 2 Birmingham Essence Room Diffuser
 3 Birmingham FusionX Gaming Console
 4 Birmingham Moonbeam Cardigan
 5 Birmingham Nebula Scarf
 6 Birmingham Solar Flare Sweater
 7 Birmingham Sonic Boom Portable Speaker
 8 Birmingham Sonic Boom Resistance Bands
 9 Birmingham Stellar Eyeshadow Palette
10 Birmingham Tranquility Scented Candles
# i 14 more rows
```

```
grid.arrange(ggplot1,ggplot2)
```

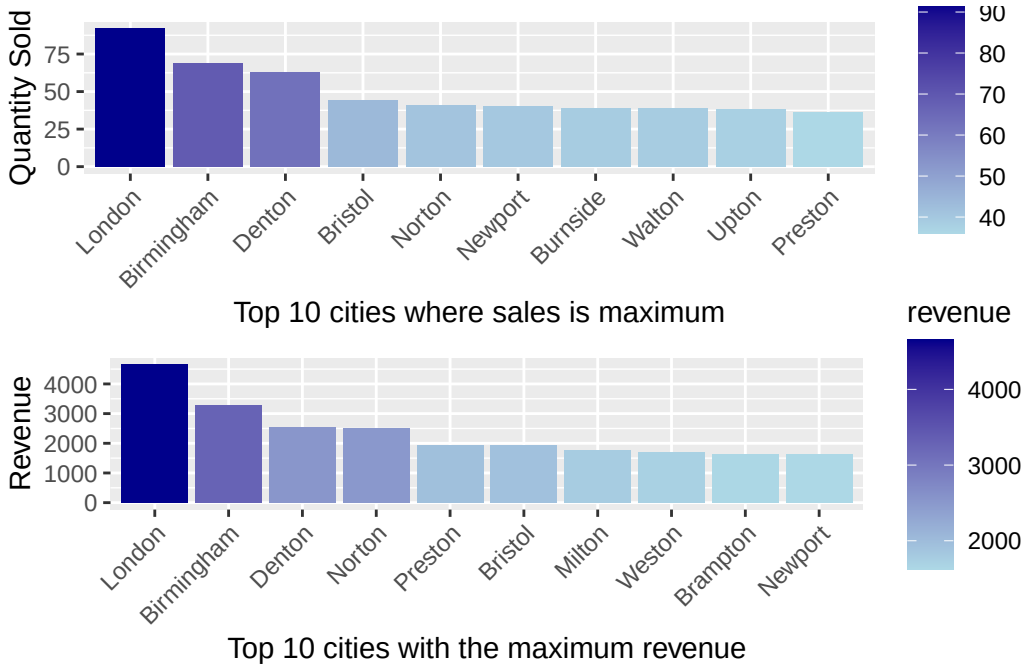


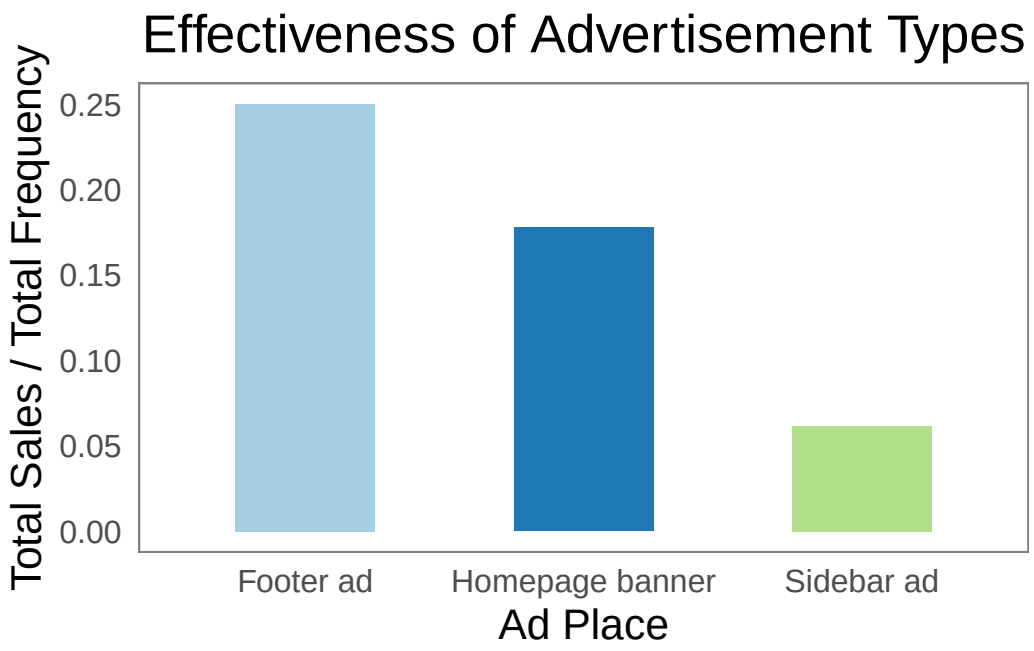
Figure 5: Top 10 cities with maximum revenue and sales

Figure 5 gives a crucial insight of cities that generated significant revenue with lesser quantity of products sold. Top Products from these cities could be identified as shown in table 1 as their sales could improvise revenue to a great extent. Also, cities like Ford, Manchester and Milton generated outstanding revenue even though their sales were limited.

```
#Report 5
# Joining Product with advertise_in and advertisement to get advertisement
#details
advertise_in <- RSQLite::dbGetQuery(connect,'SELECT * FROM ADVERTISE_IN')
advertisement <- RSQLite::dbGetQuery(connect,'SELECT * FROM ADVERTISEMENT')

advertisement_data <- product %>%
  inner_join(advertise_in, by = "product_id") %>%
  inner_join(advertisement, by = "ad_id") %>%
  group_by(product_id, product_name, ad_place) %>%
  summarise(
    total_frequency = sum(ad_frequency),
    .groups = 'drop' )


# Joining product with order to get the number of sales per product
number_of_sales <- product %>%
```

```r
  inner_join(order_item, by = "product_id") %>%
  group_by(product_id, product_name) %>%
  summarise(sales_count = n(), .groups = 'drop')



merged_data <- merge(number_of_sales, advertisement_data, by =
c("product_id", "product_name"))



# Analyzing which ad place is most effective by calculating a
#ratio of total sales to total ad frequency
effective_ad_type <- merged_data %>%
  group_by(ad_place) %>%
  summarise( total_sales = sum(sales_count),
             total_frequency = sum(total_frequency), .groups = 'drop') %>%
  mutate( effectiveness = total_sales / total_frequency) %>%
  arrange(desc(effectiveness))




ggplot(effective_ad_type, aes(x = ad_place, y = effectiveness,
fill = ad_place))+geom_col(show.legend = FALSE, width = 0.5) +
# Adjust bar width here
scale_fill_brewer(palette = "Paired") +
# Use a more appealing color palette
labs(title = "Effectiveness of Advertisement Types",
x = "Ad Place",
y = "Total Sales / Total Frequency") +
theme_minimal(base_size = 14) +
# Increase base text size for better readability
theme(plot.title = element_text(hjust = 0.5, size = 20),
# Center and style title
axis.title = element_text(size = 16),
# Style axis titles
axis.text = element_text(size = 12),
# Style axis texts
panel.grid.major = element_blank(),
# Remove major grid lines
panel.grid.minor = element_blank(),
```

```
# Remove minor grid lines
panel.background = element_rect(fill = "white", colour = "grey50"))
```




```
#Style panel background
```

Figure 6: Sales of products per 1 advertisement of each type

We analysed 3 types of advertisements on the Marketplace to find that Products that are advertised with the Figure 6 shows that Footer ads on average have higher sales in units. The intention was to compare the number of units sold depending on the type of advertisement this product was in. This finding can be used to assign higher price for more efficient advertisement types to be charged from suppliers.

```
#Report 6

## Calculating Average Review for each category

category <- RSQLite::dbGetQuery(connect,'SELECT * FROM CATEGORY')

# Join product_df with category_df to include category names
product_with_category <- product %>%
  inner_join(category, by = "category_id")
```

```
avg_rating_by_category <- product_with_category %>%
  group_by(category_id, category_name) %>%
  summarise(Average_Rating = round(mean(product_rating, na.rm = TRUE),2),
            .groups = 'drop') %>%
  arrange(category_id)


#Calculating Marketplace fee
merged_product_fee <- product %>%
  inner_join(select(category, category_id, category_fee, category_name),
             by = "category_id")
category_fee <- order_item %>%
  inner_join(select(order_detail, order_id, order_status), by = "order_id") %>%
  inner_join(select(merged_product_fee, product_id, product_name, unit_price,
                    category_fee, category_id, category_name),
             by = "product_id") %>%
  filter(order_status == "Completed") %>%
  mutate(marketplace_fee = order_quantity * unit_price * category_fee/100) %>%
  mutate(cat_total_sales = order_quantity * unit_price) %>%
  group_by(category_id, category_name) %>%
  summarise(total_fee = sum(marketplace_fee),
            total_sales = sum(cat_total_sales),
            total_sales_unit = sum(order_quantity)) %>%
  inner_join(select(avg_rating_by_category, category_id, Average_Rating),
               by= 'category_id')
```

```
`summarise()` has grouped output by 'category_id'. You can override using the
`.groups` argument.
```

```
#Visualise


#graph to compare category sales vs category fee
ggplot(category_fee, aes(x = reorder(category_name, -total_fee))) +
  geom_bar(aes(y = total_sales, fill = "Total Sales"), stat = "identity",
           position = position_dodge(width = 0.9), alpha = 0.7) +
  geom_bar(aes(y = total_fee, fill = "marketplace fee"), stat = "identity",
           position = position_dodge(width = 0.9)) +
  scale_fill_manual(name = "category", values =
                      c("marketplace fee" = "#3182bd",
```

```
                          "Total Sales" = "#31a354")) +
  labs(title = "Marketplace Fee vs Total Sales by Category", x = "Category",
       y = "Amount, GBP") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

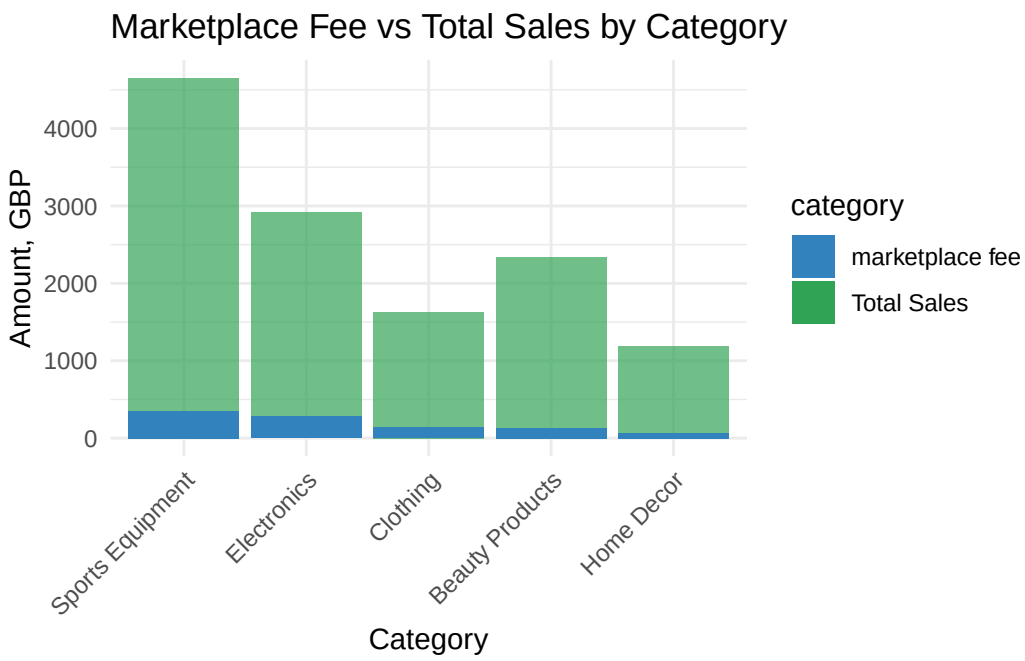


Figure 7: Comparing Marketplace fees to the sales in each Category of products

The marketplace is the mediator between the customer and seller, allowing convenience for both. This service is not free. Sellers pay fees for each transaction. These fees and advertisements make the marketplace profit. The fee varies depending on the category of goods. We compared the combined amount of fees for each sold item by category to find out which category brings the Marketplace more profit.

On Figure 7 we see that the higher the sales of the Category, the more fees Marketplace earns on it. We consider increasing fees for the categories with higher sales and decreasing fees for the categories with low sales to maximise Marketplace profit by selling more in less popular categories and getting higher fees for already popular ones. Sports Equipment has the highest sales in terms of money, however, as we will see later most units are sold in the Electronics category.

```
#Report 7
# Graph to compare Category sales VS Category average rating
```

```r
ggplot(category_fee, aes(x = reorder(category_name, -Average_Rating))) +
  geom_bar(aes(y = total_sales_unit, fill = "Total Sales in Units"),
           stat = "identity", position = position_dodge(width = 0.9),
           alpha = 0.6) +
  geom_bar(aes(y = (Average_Rating-3)*20, fill = "Average Rating"),
           stat = "identity", position = position_dodge(width = 0.9),
           alpha = 1) +
  geom_text(aes(label = sprintf("%.2f", Average_Rating),
                y = Average_Rating, x = category_name),
            color = "black", size = 4, hjust = 0.5) +
  scale_fill_manual(name = "Category", values =
                      c("Average Rating" = "#FFCC80",
                        "Total Sales in Units" = "#31a354")) +
  labs(title = "Average Rating vs Total Sales in Units by Category",
       x = "Category", y = "Total Sales in Units") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_y_continuous(name = "Total Sales in Units")
```

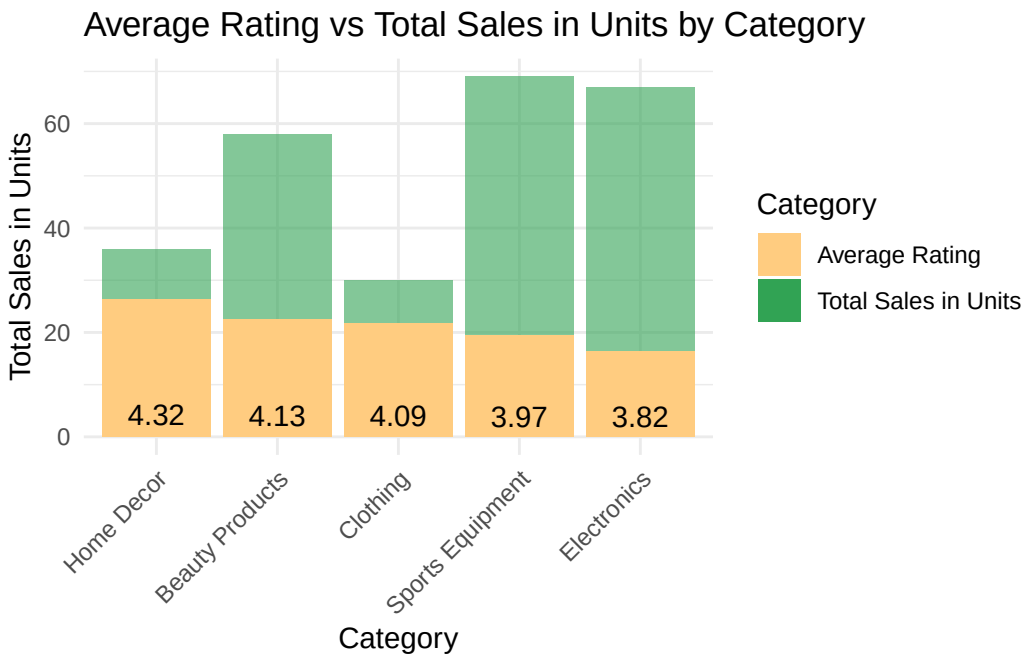


Figure 8: Average customers' rating for the category and category's sales in units

It was found that categories that have products with higher ratings have lower sales in units. This may appear wrong but most likely with the increase in sales the number of negative

reviews increases at a higher rate. Marketplace may want to reconsider suppliers for the categories with lower average ratings.

```
#pdf("Report.pdf",width=20,height = 8)
```