Project Report for Data Science

Business Intelligence

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ABSTRACT

Business Intelligence (BI) refers to the suite of strategies and technologies that are used by organizations for the analysis of business information (data). BI helps us to identify new opportunities and implement strategies effectively. BI enables organizations take effective and informed decisions. For the processes that are involved in BI, firstly, data has to be collected. This can be from internal or external systems/ sources. It then has to be prepared for analysis for running queries against the extracted data. Visualizations are created using special tools to help users understand the data better and make relevant changes to the processes/ decisions.

This project aims to derive insights from the **SalesProd_Database**. We attempt to understand trends based on the current data and extrapolate these trends to help the organization better their processes.

The dataset is multi-dimensional, in the sense that we have information regarding the Employees, Products, Vendors and Sales. If analyzed properly, we will not only be able to unearth current trends but will also be able to provide suggestions for changes that will help the organization further their current successes and minimize their losses. The process will involve data extraction, data cleansing and processing, loading into the database and finally, data visualization.

The tools that will help us achieve the steps listed above are MS access (raw data), R (data cleansing and processing), PostgreSQL server (the server that houses the cleansed and processed data) and Tableau (for data visualization). The outcome of our analytics is a set of dashboards, which will clearly elucidate our KPIs (defined below).

KEYWORDS

Business Intelligence, insights, trends, KPIs, dashboards

1 INTRODUCTION

BI aims to drive better (business) decisions. The benefits of these may be multifold: increased revenue, increased operational efficiency and a competitive advantage over other business players [1].

BI data can contain the following classes of information: historical information and real-time data. Historical data is what is available in the organization's database, possibly accumulated over a long period of time. Real time data is gathered from source systems as and when it is generated (sensors, detectors etc.). Before the data is used in BI applications, the data must be collated, enhanced, and sanitized using data integration tools to make sure that the information being analyzed has integrity, accuracy and consistency.

It is also important for every organization to define Key Performance Indicators (KPIs). KPIs are definitive goals, which can be measured. These help the organization determine how effectively they are achieving their primary business targets. Highlevel KPIs usually stress upon the overall performance of the company, while low-level KPIs address processes of each division/department within the organization such as sales, marketing HR etc. The KPIs for our case have been listed in *section 2.4.1*.

The process employed for the data processing and the development of the dashboards have been explained below in detail. The list of steps for performing the BI analytics have been listed below.

- 1. Extraction (E)
- 2. Transformation (T)
- 3. Loading (L)
- 4. Analysis (Visualization)

2 BACKGROUND - ETL PROCESS

Extract, Transform, Load (abbreviated as ETL) is the process of transferring the data from a source system (such as a database) into a destination system (such as an analytics tool). The destination system may have features that represents the data in a different manner, as compared to the source system(s).

A good ETL system is expected to perform the following functions effectively: data extraction from the source system; data quality, integrity and consistency checks; joining/ combination of data tables from different sources (if necessary); delivery of data in a format that is ready to present to stakeholders. Using this,

application developers can build tools that end users can utilize to make decisions [2]. *Figure 1* depicts the ETL process. The process is applied to our BI case and each step is explained in detail in the subsequent sections.

It is crucial that each step is performed with care. Flawed or improper input-data produces flawed or improper output(s) and/or interpretations. This is known as *Garbage In, Garbage Out* (GIGO). "Garbage in – garbage out" is an idiomatic way of saying that poor-quality data used as input can cause unreliable data output. Performing any amount of visualization on incorrect data will be of little or no use to the organization. It would lead to incorrect interpretations/ analysis and could even cause catastrophic consequences to the company.

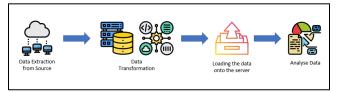


Figure 1: ETL and Analysis Process

2.1 Data Extraction (E)

The ETL process starts off with the data extraction from the source system. In our case, we extracted the data provided to us for the Data Science project from *Canvas*. The dataset used for this project is **SalesProd_Database**. The file is of the extension .accdb. This file opens with the help of the Microsoft Access Database.

A fundamental part of data extraction necessitates data validation to confirm that the data obtained from the source system(s) has the appropriate/ anticipated values under each domain. These are also referred to as columns/ attributes. The dataset contained the following tables with the number of records and columns, respectively. For this, we first extracted the data imported it into *R* for data transformation and cleansing. We then ensured that the rows and columns from the source data have been imported correctly for processing.

S.No.	Table Name	No. of Rows	No. of Columns
1	Employee	296	26
2	Product	504	23
3	Product Category	4	2
4	ProductSubCategory	37	3
5	ProductVendor	457	10
6	SalesOrderDetail	119108	10

Table 1:Dataset details (Raw Data)

2.2 Data Transformation (T)

In this stage, a sequence of rules or semantics are applied to the extracted data to prepare it for loading into the destination system.

A vital function of data transformation is data cleansing (or) data cleaning, which aims to pass only "correct"/ "sanitized" data to the destination system. This is vital to maintain consistency in data types, handle null values appropriately, handle fields with special/

unrecognizable characters etc. Also, the tables are joined so that all the necessary fields are available and accessible in the relevant tables for the data visualization. Some fields (profit, sales amount, average revenue per unit, net profit margin for instance) require minor computations using the existing fields. These values are computed accordingly and are added as columns to the final table that must be visualized.

The more time we spend on the cleansing, the better our output will be. This is because we would have a thorough understanding of the dataset. As mentioned earlier more meaningful data leads to better analysis.

Our data transformations are performed using *R*. The **SalesProd_Database** is first loaded into the *R* engine. *Note: We must have the Microsoft Access Database Engine installed to load the extracted data.*

The Open Database Connectivity (*ODBC*) driver makes use of the interface by Microsoft that allows engines such as R to retrieve data from Database Management Systems (*DBMS*). This is achieved by querying using SQL. ODBC allows multiple systems to work together (i.e., interoperability). This simply means that a single application such as R can access different databases/ data warehouses. The user can include the ODBC database drivers on their engine to connect the application to their preferred DBMS (in our case, Microsoft Access Database and *PostgreSQL* server).

Next, the following standard set of data cleansing steps are performed:

- Filtering choosing only selected columns to load.
- Data-type Conversion/ Check For instance, all date fields must be in one of the date formats and not in any other format.
- Null value validation blanks must be appropriately labelled, wherever necessary.
- Joining Tables Data flow validation from the staging area to the intermediate tables.
- Adding computed columns Performing minor arithmetic operations on the data fields and adding the resulting columns into the final table.

Note: We have listed the steps that have been used in this project to cleanse the data set. However, this is not an exhaustive list of all the data cleansing activities.

2.2.1 Star Schema of the data

The star schema is a visual representation of the dataset. The star schema renders the business data into fact tables and dimension tables. Facts tables house all the quantifiable data about a business. Dimension tables contain the descriptive attributes or fields related to the fact tables. So, to sum up, every star schema comprises fact and dimension tables. The star schema of our dataset is given in *figure 2*.

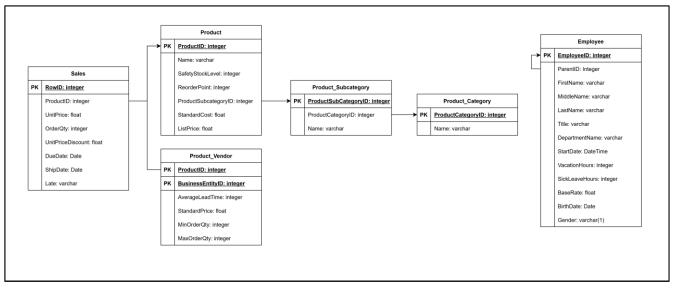


Figure 2: Star Schema of the dataset

- **Fact table** (*sales*) Fact tables usually have numeric values and the foreign keys that link to the dimensional data tables where all the descriptive (qualitative) information is stored. They usually have many records and can also be referred to as a "transaction table".
- Dimension tables: Dimension tables generally have relatively fewer rows as compared to fact tables. However, but each record may have a very large number of attributes/ columns to describe the fact data.

Star schemas are denormalized. This means that the standard rules of normalization applied to transactional relational databases are not considered strictly during star-schema design and implementation. The advantages of denormalization are simple queries, simple business logic, fast aggregations etc.

2.3 Data Loading (L)

This step loads the data into the server (*PostgreSQL server*). This is where the data tables rest. Since this phase communicates with a database, the conditions and constraints specified in the database schema provide the overall data quality execution of the ETL process.

Once the data is prepared, we load it into the *PostgreSQL* server with the help of *R*. Our tables rest in the *PostgreSQL 10.16* running on server *bronto.ewi.utwente.nl*. This server also runs a web-based database tool, called **PhpPgAdmin**, from where we can easily access, view and modify our tables. We have specific credentials provided to us by the university to access the database. The screenshots of the server and the tables resting in it have been displayed in *figure 3 and figure 4*, respectively.

There are two types of tables in the database: Fact Tables and Dimension Tables (as explained in the previous section). Once the data is loaded into fact and dimension tables, we utilize this to improve performance for BI data by creating aggregates.

The *R* source code used for data processing (transformation) and loading can be found in *Appendix A*. We used *RStudio* for running the source code.



Figure 3: "Project" schema within the PostgreSQL server



Figure 4: Tables within the database

2.4 Data Visualization

Data visualization is the representation of information and data using charts and graphs. These visual elements provide an accessible way to see and understand trends, outliers, patterns and models in data [3]. Visualization also provides a rapid and useful method to convey information in a comprehensive manner using visual stimuli. This can improve the identification of factors that impact buyer actions; identify zones that need to be upgraded or need more attention; make data more meaningful for participants; identify when and where to position particular products and forecast sales volumes and patterns. However, the scope of data visualization is not limited to the points mentioned above.

For visualizing our data, we make use of *Tableau 2020.4*. As mentioned in the previous stages, the data is extracted, transformed, and loaded into the *PostgreSQL server*. A connection is established between Tableau and the *PostgreSQL* server.

Note: Tableau can establish a connection with a variety of data sources. Since our data rests on PostgreSQL server, in the project schema, we choose PostgreSQL under the connection options in Tableau. We then must specify the credentials – server name, username and password – to access the database. See Figure 5 for the same.

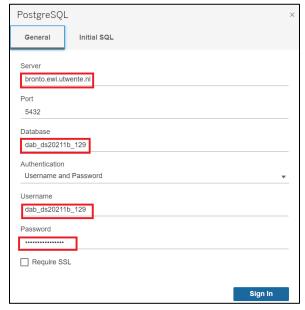


Figure 5: Establishing the database connection with Tableau.

Next, we proceed to load the tables in Tableau with the star schema as a guide. The connections between the tables will have to be specified, i.e., the references are the primary key/ foreign keys for the tables. $Figure\ 6$ shows the tables that have been loaded successfully in Tableau.

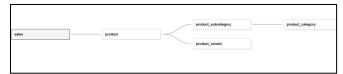


Figure 6: Tables and their relationships in Tableau

Following this, the data is visualized using charts, graphs, and other visualization tools. Colors and shapes help us accentuate our ideas better and aid in identifying trends and patterns effectively.

The dashboards will be constructed with a view of these KPIs. Our KPIs have been defined in the following section. We expect to find some interesting trends and patterns apart from the intended results.

2.4.1 Key Performance Indicators (KPIs)

We have developed our Key Performance Indicators (KPIs) based on the 'Balanced Scorecard Perspective' given in the BI project course guide. The main questions or indicators of the Balanced Scorecard Perspective have been listed below.

- Financial Perspective: How do we appear to our Shareholders?
- Customer Perspective: How do our Customers see/ perceive Us?
- 3. Internal Business Process Perspective: What should we do that is Excellent?
- 4. Employee and Organization Innovation and Learning Perspective: Can we continue to Improve and Add Value?

For these lists of indicators, we have come up with a set of indicators that will help us define our dashboards and metrics better.

- Financial Questions: How do we look to our Shareholders?
 - a. What is our gross sales per product category/ subcategory/ overall?
 - b. What is our profit per product category/ subcategory/ overall?
 - c. What is our Net Profit Margin?
 - d. What is our Average Revenue Per Unit?
- 2. Customer: How do our customers see us?
 - a. What are our top 5 products?
 - b. What are the products/ categories/ subcategories of products that are shipped late?
 - c. What can be done to reduce late shipments?
- 3. Internal Business Process: What should we do that is Excellent?
 - a. How can we improve our strategy based on findings from the analysis?
 - b. What can we do to improve profit?
 - c. Should we improve our marketing strategy towards any product in particular?

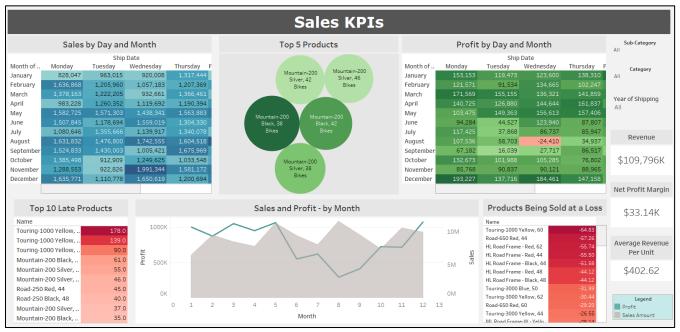


Figure 7: Dashboard 1 - Analysis of Sales KPIs

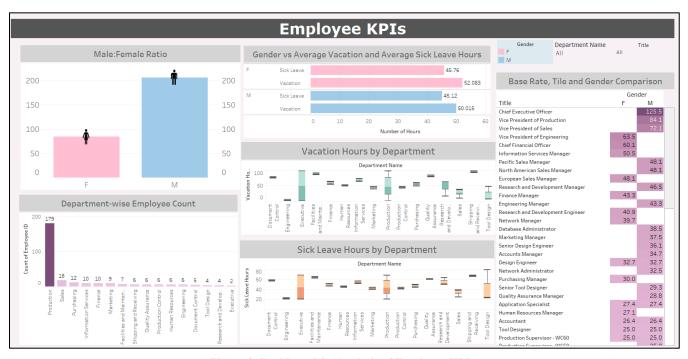


Figure 8: Dashboard 2 - Analysis of Employee KPIs

- d. How can we improve our HR capabilities to better our organization?
- 4. Employee and Organization Innovation and Learning: Can we continue to Improve and Add Value?
 - a. What is the *male:female* ratio our organization?
- b. Do men and women in the same level/designation receive a comparable salary?
- c. What are the vacation trends of men and women? What changes can be made to this to improve employee satisfaction?

2.4.2 Dashboards

We present two dashboards that help us describe the KPIs listed above. The first one describes the Sales KPIs. The second one represents the Employee related analysis for the dataset. Figures 7 and 8 give us a glimpse into the visualizations that we have carried out. Note: The dashboards are dynamic, i.e., the views in each dashboard can be customized based on the filters provided in each one of them. Also, we have established a "LIVE" connection with the dataset. Hence, any changes to the dataset can be refreshed and directly updated on the dashboard. The screenshots of the dashboard are static and do not allow us to apply these filters. For more details, please look at the Tableau workbook.

3 RESULTS

We have listed some findings from the visualizations. We have also included supporting snapshots from the visuals as evidence for our findings. *Appendix B* has the screenshots of the findings.

- Finding 1: The Sales Price of some products is lesser than the cost incurred by the organization for procuring/ producing them. This results in quite a few losses for the company.
- Finding 2: Products will lowest profit margin are caps, jerseys, and road frames. These products have done badly over all 4 years (2006, 2007, 2008 and 2009).
 - In 2009, caps performed slightly better than the other years.
 - The sales of jerseys are inversely proportional to profit in 2008.
- Finding 3: Products with high and fluctuating profit margins have been listed below:
 - High profit Margin Cleaners, Hydration Packs, Gloves, Vests
 - Fluctuating Profit Margin Mountain bikes, Road bikes, touring bikes, touring frame,
- Finding 4: The highest revenue per unit is given by the category "Bikes", specifically "Mountain Bikes", although it has a fluctuating profit margin.
- Finding 5: The male to female ratio is not proportional (84:206 males to females).
- Finding 6: There are very few people in marketing (9) and shipping and receiving (6) as compared to production (179).
- Finding 7: The trends in vacation are similar across both genders.
- Finding 8: Base rates of people in the same level are comparable. But some roles do not have women employees at all.

4 DISCUSSION

Based on our analysis, we propose the following improvements in the organization's strategy for a better throughput.

 The marketing strategy towards some products such as caps, jerseys and road frames needs to be improved. The

- organization could focus on creating target specific or seasonal campaigns to improve the sales of these products.
- 2. Some products incur heavy losses because the amount spent on them by the organization is higher than the price at which it is sold. For this, the organization will have to revamp their price list (or) remove these products from the store is their demands are not very high.
- 3. Every organization today is striving towards a gender equal work environment. As we have seen the previous section the *male:female* ratio is not proportional. There are fewer women working in many of the designations than males. The organizations should look at recruiting more women to equalize this ratio.
- 4. The number of people in sales and shipping are quite low as compared to those in the production division. We also see that there are quite a few products that are shipped late and quite a few products that are incurring losses. The organization should recruit more people in the sales and shipping and control division to mitigate this.

However, it should be noted that the dataset spans the years 2006, 2007, 2008 and 2009. It is highly possible that the organization has considered these effects and is already aware of these limitations, since the data is quite old. Also, the company could have made the relevant changes and could have altered their processes in order to realize better strategies. There could be some new findings that could be unearthed, if a more recent dataset is provided to us.

All the findings that we have listed and the proposed improvements to the strategy of the organization will hopefully also be applicable to similar areas of other organizations. Multidimensional data, such as this one provides immense scope and capabilities for analysis and visualization. All organizations should strive to store consistent, reliable, authentic and clean data. The better the data quality is, the better the outputs of our analysis will be.

5 CONCLUSIONS

We have performed the ETL procedure and using a variety of tools such as MS Access, R, PostgreSQL, Excel and Tableau. These have helped us unearth some interesting patterns, trends and have given us some interesting findings on the data. The visualizations help us analyze the data well and we have been able to point out some areas of improvement for the organization. These findings and suggestions might be scalable to other products and other domains as well.

Data translates to insights; insights translate to information and information ultimately translates to knowledge. BI has tremendous potential that should be made use by all organizations to understand their data. The knowledge that can be mined from these methods have capabilities that can do wonders to the functioning of the organizations. There are multiple tools that can be used for the ETL and analysis processes. The best fit will have to be evaluated considering the sector and context for which it is being used.

REFERENCES

- [1] Business Intelligence (BI) https://searchbusinessanalytics.techtarget.com/
- [2] ETL Database https://www.stitchdata.com/etldatabase/etl-process/
- [3] Data Visualization: A Beginner's Guide https://www.tableau.com/learn/articles

APPENDIX

A. R Source Code for Data Processing and Loading

```
library(RODBC)
library(dplyr)
library(lubridate)
library(DBI)
library(RPostgreSQL)
#Step 1 - download data set from - http://castle.ewi.utwente.nl/datasciencedata/BI/
#Step 2 - Microsoft access database engine installed - https://www.microsoft.com/en-
us/download/details.aspx?id=13255 (mine is the 32-bit version)
#Step 3 - Load the data into data0
data0 <- odbcConnectAccess2007('D:/Masters/Q1/DS/Project/SalesProd Database.accdb')</pre>
#Step 4 - load the different sheets into the respective tables
employee <- sqlFetch(data0, 'Employee') %>%
  # Select relevant rows
 select(EmployeeBusinessEntityID, ParentEmployeeBusinessEntityID,
         FirstName, MiddleName, LastName, Title, DepartmentName,
         StartDate, VacationHours, SickLeaveHours, BaseRate,
         BirthDate, Gender) %>%
  # Rename columns
  rename (EmployeeID = EmployeeBusinessEntityID,
         ParentID = ParentEmployeeBusinessEntityID) %>%
  # Filter out duplicates by grouping by EmployeeID
  group by (EmployeeID) %>%
  # Since each employee still works at the company,
  # summarising StartDate by using the min() function is enough
 mutate(StartDate = min(StartDate),
         BirthDate = ymd(BirthDate),
         StartDate = ymd(StartDate)) %>%
  # Ungroup the data again and filter out duplicate rows
 ungroup() %>%
 distinct()
sales <- sqlFetch(data0, 'SalesOrderDetail') %>%
  # Select relevant columns
  select(ProductID, UnitPrice, OrderQty,
       UnitPriceDiscount, DueDate, ShipDate) %>%
  # Add Late column
 mutate(RowID = row number(),
```

```
Late = factor(ifelse(ShipDate > DueDate, "Late", "NotLate")),
         DueDate = ymd(DueDate),
         ShipDate = ymd(ShipDate))
product <- sqlFetch(data0, 'Product') %>%
  # Select relevant columns
  select (ProductID, Name, SafetyStockLevel, ReorderPoint, ProductSubcategoryID,
         StandardCost, ListPrice) %>%
  # Only keep rows for which we have Sales data
  filter(ProductID %in% sales$ProductID)
product category <- sqlFetch(data0, 'ProductCategory')</pre>
product subcategory <- sqlFetch(data0, 'ProductSubcategory') %>%
  filter(ProductSubcategoryID %in% product$ProductSubcategoryID)
product vendor <- sqlFetch(data0, 'ProductVendor') %>%
  select (ProductID, BusinessEntityID, AverageLeadTime, StandardPrice,
         MinOrderQty, MaxOrderQty) %>%
  filter(ProductID %in% sales$ProductID)
close (data0)
drv <- dbDriver("PostgreSQL")</pre>
con <- dbConnect(drv, port = 5432, host = "bronto.ewi.utwente.nl",</pre>
                 dbname = "dab ds20211b 129",
                 user = "dab ds20211b 129",
                 password = "Mp2+Dw6Cyohz0ZiT",
                 options="-c search_path=project")
dbWriteTable(con, "employee", value = employee, overwrite = T, row.names = F)
dbWriteTable(con, "product", value = product, overwrite = T, row.names = F)
dbWriteTable(con, "product_category", value = product_category, overwrite = T, row.names = F)
dbWriteTable(con, "product subcategory", value = product subcategory, overwrite = T, row.names
dbWriteTable(con, "product vendor", value = product vendor, overwrite = T, row.names = F)
dbWriteTable(con, "sales", value = sales, overwrite = T, row.names = F)
dbListTables(con)
str(dbReadTable(con, "employee"))
str(dbReadTable(con, "product"))
str(dbReadTable(con, "product_category"))
str(dbReadTable(con, "product subcategory"))
str(dbReadTable(con, "product vendor"))
str(dbReadTable(con, "sales"))
dbGetQuery(con,"SELECT
                                              FROM
                                                          information schema.tables
                                                                                          WHERE
                             table name
table schema='project'")
## to get the tables from schema project
str(dbReadTable(con, c("project", "employee")))
str(dbReadTable(con, c("project", "product")))
str(dbReadTable(con, c("project", "product category")))
str(dbReadTable(con, c("project", "product_subcategory")))
str(dbReadTable(con, c("project", "product vendor")))
str(dbReadTable(con, c("project", "sales")))
```

B. Screenshots of the findings

Finding 1 - The Sales Price of some products is lesser than the cost incurred by the organization for procuring/ producing them. This results in quite a few losses for the company.

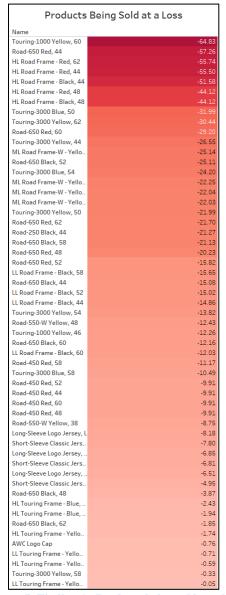


Figure 7: Finding 1 - Products being sold at a loss

- Finding 2: Products will lowest profit margin are caps, jerseys, and road frames. These products have done badly over all 4 years (2006, 2007, 2008 and 2009).
 - In 2009, caps performed slightly better than the other years.
 - The sales of jerseys is inversely proportional to profit in 2008.



Figure 8: Finding 2a - Caps - Low profit Margin



Figure 9: Finding 2b - Jerseys - Low profit Margin

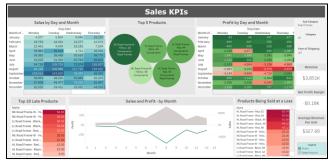


Figure 10: Finding 2c - Road Frames - Low profit Margin

- Finding 3: Products with high and fluctuating profit margins have been listed below:
 - High profit Margin Cleaners, Hydration Packs, Gloves, Vests
 - Fluctuating Profit Margin Mountain bikes, Road bikes, touring bikes, touring frames



Figure 11: Finding 3a - Products with High Profit Margin – Cleaners, Hydration Packs, Gloves, Vests

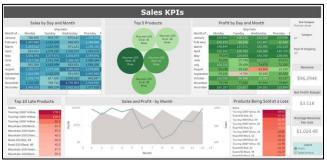


Figure 12: Finding 3b - Mountain Bikes, Road Bikes, Touring Bikes, Touring Frames

Finding 4: The highest revenue per unit is given by the category "Bikes", specifically "Mountain Bikes", although it has a fluctuating profit margin.



Figure 13: Finding 4 - Highest Average Revenue per Unit - Mountain Bikes

Finding 5: The male to female ratio is not proportional (84:206 males to females).

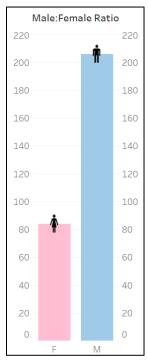


Figure 14: Disproportionate Male-Female Ratio

Finding 6: There are very few people in marketing (9) and shipping and receiving (6) as compared to production (179).

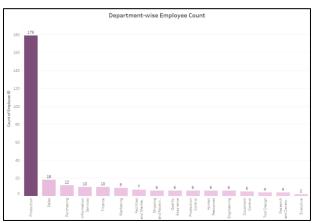


Figure 15: Finding 6 - Employee distribution across departments

Finding 7: The trends in vacation are similar across both genders.



Figure 16: Finding 7 - Proportional average Vacation and Sick Leave hours for males and females

Finding 8: Base rates of people in the same level are comparable. But some roles do not have women employees at all.



Figure 17: Finding 8 - Comparison between base rates for designations and roles where there are very few women employees.