Analysis of laundromats and vending machine events and transactions for I.L.R Limited using R Shiny

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Abstract

The report describes how Exploratory Data Analysis (EDA) was used to analyse transaction and machine Error data for laundromats and vending machines at ILR Limited. The analysis involved building two R Shiny applications to construct all the summaries and visualisations in this report.

A total of 20 visualisations were created. The report also compares the charts created in R Shiny with those made in Power BI, a platform which the company was interested in exploring.

1. Introduction

1.1. Organisation:

ILR Limited specialises in hardware and embedded software engineering. They offer design and engineering expertise to manufacturing and engineering companies that require hardware and embedded software engineering. The company is based in Christchurch and only has six employees.

One of their clients provides EFTPOS support for laundromats and vending machines in the North and South Islands of New Zealand. Since laundromats and vending machines operate 24 hours a day, large amounts of data on machine status and EFTPOS transactions were sent to the cloud for analysis, with about 15 000 records of daily transaction data.

At laundromats, the washers and dryers (appliances) connect to a machine (also called a pi), which then connects to a payment terminal, usually an EFTPOS or coin-drop machine. A machine/pi can connect to more than one washer or dryer. Figure 1.1 below illustrates this connection.

Set up at a laundromat

Machine/ Pi

Appliance 1
(Washer/Drver)

Figure 1.1. Diagram showing how appliances were connected to machines/pis

1.2. Goals:

This project aimed to use Exploratory Data Analysis (EDA) to understand what was happening at each site and minimise the impact of machine errors by proactively sending technicians to fix them.

1.3. Constraints

The data did not have information on the sites' latitudes and longitudes, which could have been used to create a map in R Shiny showing the locations of the appliances. A map would be helpful to new technicians visiting sites to attend to machine or appliance faults.

It would have been good to know more about models, makes, capacities and machine ages as extra dimensions to plot. These could have been used to investigate whether specific machines lasted longer than others. Unfortunately, that information was not available in the datasets provided.

2. Data

2.1. Descriptive statistics:

The company stored all its data in google cloud, and for this project, two datasets, Transaction data and Error data, were provided. The data was supposed to be queried directly from the cloud without downloading.

The datasets had a shared ID ("serialNumber" in the Transaction data and "gateway_serialNumber" in the Error data) which could be used to join them in R. Since the data was sent directly to the cloud from the machines, there were no problems related to data authenticity.

The quantity of the data varied due to the period selected for reporting, though data for one day would have an average of 15 000 records and about 400 000 records for a month. Data for the period January 2021 to December 2022 had more than 6.7 million records.

The tables and graphs in this report were created using data for December 2022, which had 396 735 entries for Transaction data and 1950 entries for Error data.

Transaction data

Transaction data comprised thirty-two variables. The variables were a mixture of strings, integers and date-time. Since one of the company's goals was to maximise sales, the variable "total_cost_dollars" was considered the most important.

Error data

The Error data had only eight variables. These were a mixture of strings, integers and date-time, just like Transaction data. Errors were categorised into three levels, namely "error", "critical", and "fatal".

2.2. Missing:

There was high missingness in the Transaction data. The variables "siteId" and "applianceName" had high missingness. Some variables with excessively high missingness were of low importance and were not used in making the EDAs.

There were sites with missing site names, site IDs, and appliance names, a problem caused by machines using an older firmware version that did not support showing all this information. The missing values could not be backfilled programmatically since we did not know which appliance raised how much in sales.

3. Methodology

3.1. Data retrieval and cleaning:

The data was retrieved from BigQuery using an SQL code run in R studio, and EDAs generated using a purpose-built R Shiny app.

A series of cleaning steps were taken to ensure meaningful graphs were constructed. The variable "siteName" was concatenated with the variable "contractName", which solved the problem of sites with the same names but different contractors.

BigQuery uses the Coordinated Universal Time "UTC", so time was converted into local New Zealand time in R after retrieval. This was because the SQL code in BigQuery did not convert time from UTC to New Zealand Daylight Time "NZDT", but it only retrieved data 13 hours ahead of UTC. New columns were created in the dataset to restore the "UTC" datetime to "NZDT". Then, the Datetime variable was converted to a Date variable used to make all the plots and summaries.

Duplicate rows were removed from the data using the SQL code "distinct", and the data was ordered by date from the newest to the oldest, and strings were converted to factors.

A date range input was added in the Shiny UI file, prompting the user to enter the required dates for the reporting period.

Transaction data

"Transaction_datetime" was converted to a date variable because the company was interested in daily transactions. The variable "Terminal_transaction_type" was filtered to include "purchase" transaction types only since non-purchase transaction types ("logon", "restock", and "status") were irrelevant in the analysis.

The variable "Terminal_result_string" had strings "DENIED", "DECLINED", Cancelled", "CANCELLED", "TERMINAL BUSY", and "Busy". "DENIED" was renamed "DECLINED" whilst "Cancelled" was renamed "CANCELLED" and "TERMINAL BUSY" was renamed "Busy". The sales in BigQuery were in cents, so these were transformed into dollars by dividing by 100.

Error data

The variable "Timestamp", which was a datetime variable, was converted to a date variable. There were no missing observations in the Error data since the variables of importance were "Timestamp", "Message", "SerialNumber", and "Machineld".

3.2. Methods:

To create data visualisations that could easily be understood and generated anytime, R Shiny and Power-BI were used to perform the data analytics.

Generating charts in Power BI was easy since it did not require coding expertise. The charts were readily available, and assembling visualisations was "a drag-and-drop process" (Becker, 2019), making it a preferred choice for interactive visualisations at first glance. However, only simple charts with little filtering could be created. Some of the visualisations required a lot of filtering and coding, making R Shiny a better option than Power BI. In addition, Power BI did not have an accessible source code, and data transformation was impossible while working in DirectQuery mode.

The company also wanted the visuals and tables to be hyperlinked to the cloud data so the user could be directed to the appliance and the site name in the payments cloud web app when clicked. This requirement could be done easily in a Shiny app but was impossible in Power BI DirectQuery mode.

Though more time was required to code reports in R Shiny, the generated visualisations could be tailored to suit the company's requirements.

4. Results:

4.1. Charts and tables

Thirteen visualisations (nine plots and four tables) were created using Transaction data, whilst seven visualisations (four plots and three tables) were created using the Error data, making a total of twenty visualisations.

Transaction data

Figure 4.1.1. Transactions data Shiny app starter page

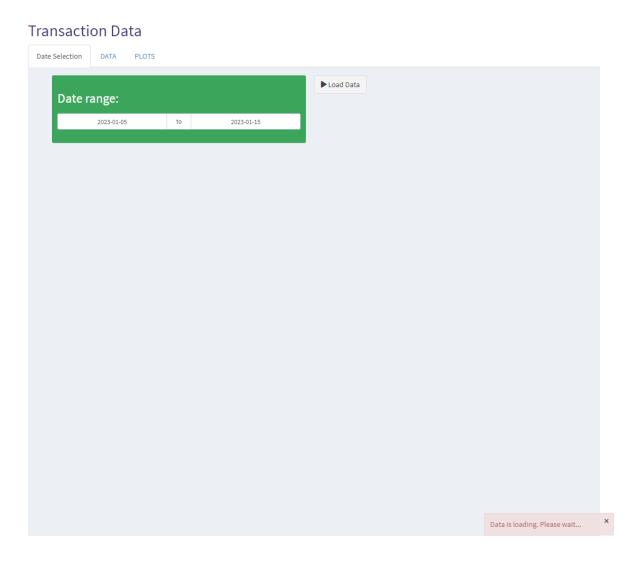


Figure 4.1.1 above shows the Shiny main page where the users entered the dates for the reporting period. When the "Load Data" button was pressed, a red dialogue box would pop up to let the user know that the data was loading, and when loading was complete, a blue dialogue box would pop up to let the user know that loading was complete.

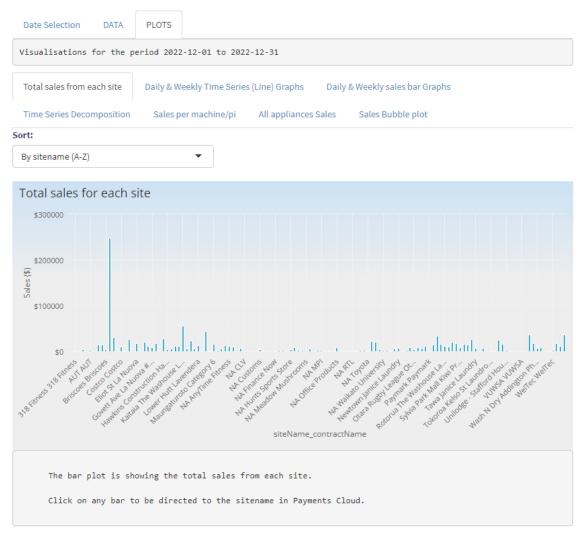
The company must keep an eye on approved and unapproved transactions. Though approved transactions were expected to be higher than unapproved ones, machines and appliances with a high percentage of unapproved transactions had to be checked in the system. The figure below shows transaction results.

Figure 4.1.2. Terminal result string summary and plot

Transaction Data for DATA 601 PLOTS Date Selection DATA Visualisations for the period 2022-12-01 to 2022-12-31 Terminal result string summary and plot Total sales from each site Daily & Weekly Time Series Graphs of Sales Time Series Decomposition All appliances and all machine sales Sales Bubble plot Terminal result strings bar chart \$1500000 \$1250000 \$1000000 \$500000 \$250000 APPROVED CANCELLED HOST UNAVAILABLE terminal_result_string terminal_result_string Amount APPROVED 1308732.8 CANCELLED 624877.5 DECLINED 109457.8 Busy 13793.6 HOST UNAVAILABLE 8690.6 FAILED 93.0 6 If APPROVED transactions are less than the sum of the other strings, we have problems that need to be investigated. A look into the 'Terminal result string details' table and 'Approved transactions as a percentage' table can give us some light into the appliances with issues that need to be checked.

Figure 4.1.3. Transactions data Total sales plot

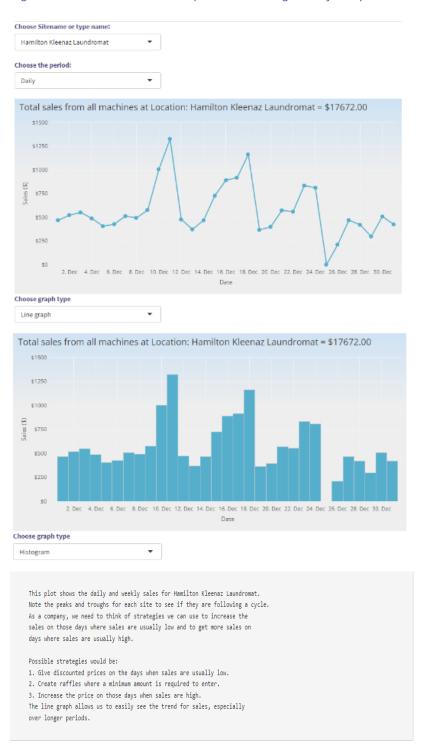
Transaction Data for DATA 601



The plot above shows the total sales from each site for December 2022. The chart could sort by site name or sales, from largest to smallest.

When clicked, each bar would direct the user to the payments cloud web application where the site name would open, showing all the appliances that transacted to give the amount in the bar chart.

Figure 4.1.4. Time series line plot and histogram of daily and weekly sales



The time series plot shows daily sales from the site "Hamilton". For the graphs that showed cyclic trends, possible actions were discussed to increase sales on those days when they were periodically low and to maintain high sales on the days when peaks were observed.

The chart had options to choose the site name, as well as choosing between a daily and a weekly time series and between a line graph and a histogram, as shown in Figure 4.1.4 above. The line graph and histogram for the weekly sales are shown in Appendix 4 and 5.

The plot also showed the name of the selected site and the total sales collected. The trend and cyclic behaviours portrayed in the line graphs were analysed further using time series decomposition.

Transaction Data for DATA 601 DATA Visualisations for the period 2022-12-01 to 2022-12-31 Daily & Weekly Time Series Graphs of Sales Total sales from each site Time Series Decomposition Terminal result string summary and plot All appliances and all machine sales Sales Bubble plot data trend

Figure 4.1.5. Time Series decomposition of the daily transactions

The daily sales time series was decomposed into the seasonal, the trend, and the remainder components, with a slider to choose the values of t.window. STL decomposition was used instead of SEATS and X11 due to its ability to handle any seasonality, not only monthly and quarterly data (Hyndman and Athanasopoulos, 2018).

The seasonal chart shows weekly cycles in the Transaction data. This was because the data showed recurring patterns as most sites had high sales over the weekends and low sales in the midweek, on days like Wednesday and Thursday.

The time series decomposition for the Error data is illustrated in Appendix 2.

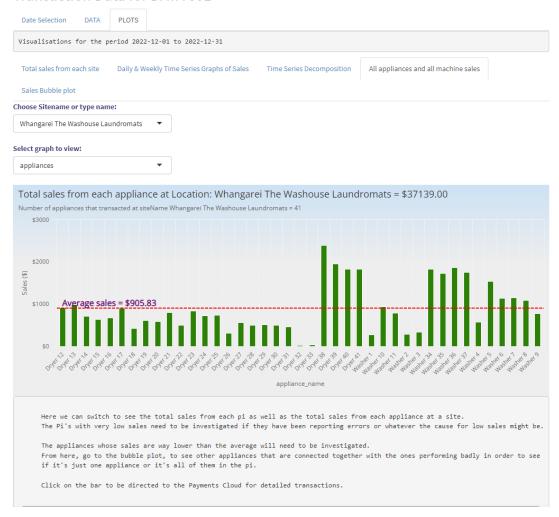
Figure 4.1.6. Bar plot for machine sales

Transaction Data for DATA 601 Date Selection PLOTS Visualisations for the period 2022-12-01 to 2022-12-31 Terminal result string summary and plot Total sales from each site Daily & Weekly Time Series Graphs of Sales Time Series Decomposition All appliances and all machine sales Sales Bubble plot Choose Sitename or type name: CityFitness CityFitness Select graph to view: machines Total sales from all machines at Location: CityFitness CityFitness = \$249115.15 Number of Machines that transacted at CityFitness CityFitness = 46 \$15000 Here we can switch to see the total sales from each pi as well as the total sales from each appliance at a site. The Pi's with very low sales need to be investigated if they have been reporting errors or whatever the cause for low sales might be. The appliances whose sales are way lower than the average will need to be investigated. From here, go to the bubble plot, to see other appliances that are connected together with the ones performing badly in order to see if it's just one appliance or it's all of them in the pi. Click on the bar to be directed to the Payments Cloud for detailed transactions.

The bar plot shows all the machines and the sales they raised from each site. The bars were hyperlinked to the company web app, where detailed transactions for the machines could be found. The machines with significantly low sales had to be checked to see if they were operating well. Usually, those machines would have a high number of unapproved transactions. The chart enabled the users to choose between the bar plot for the machine sales or the appliance sales.

Figure 4.1.7. Bar plot for appliance sales

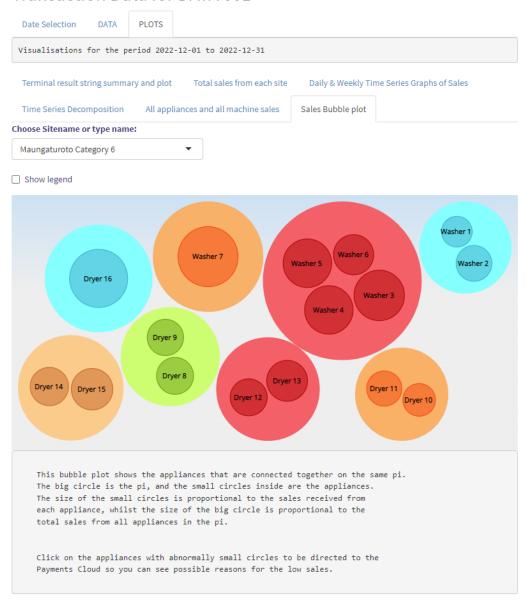
Transaction Data for DATA 601



The plot above shows all the appliances and their sales on each site. The red horizontal line is the average sales for the site for the period chosen. This plot was used to see which appliances were underperforming (had significantly low sales compared to the average sales).

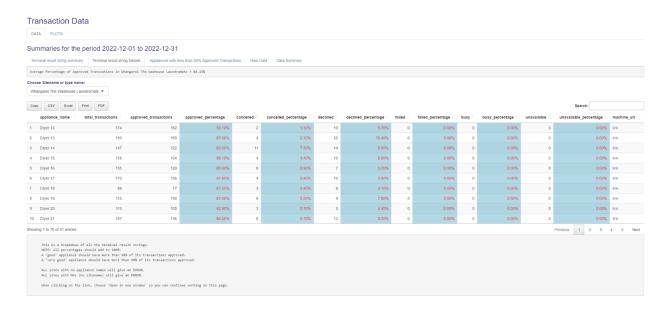
Figure 4.1.8. Bubble plot for sales from each appliance and machine

Transaction Data for DATA 601



The bubble plot showed the appliances connected to a machine (pi). The sizes of the inner circles were proportional to the sales from each appliance, whilst the sizes of the outer circles (pis) were proportional to the total sales from the appliances inside those circles. The bubbles were also hyperlinked to the web app, so clicking on each of them would open a link to the payments cloud web where the clicked appliances would be revealed.

Table 4.1.1. Terminal result string table



As shown in Table 4.1.1 above, different terminal results were summarised for each appliance at a site. Information from this table was used to give an overview of how approved transactions compared to unapproved transactions per appliance. For different approved transaction percentages, table 4.1.2 below was used.

Table 4.1.2. Approved transactions as a percentage

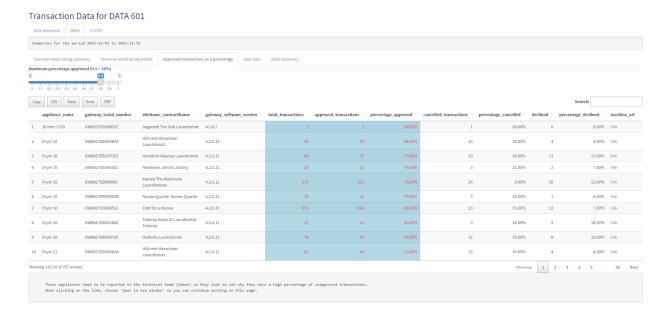


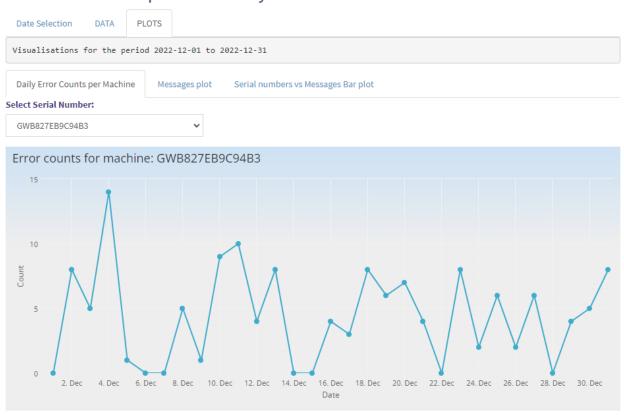
Table 4.1.2 shows a list of appliances with a selected percentage of approved transactions. The table above shows appliances with a maximum of 80% approved transactions. Usually, appliances with less than 50% approved transactions would be checked in the payments cloud web app to see if there were any issues with their functionality. If they were reported to be

working correctly in the web app, someone would ask the technical team to check these appliances physically.

Error data

Figure 4.1.8. Time series plot for machine error reports

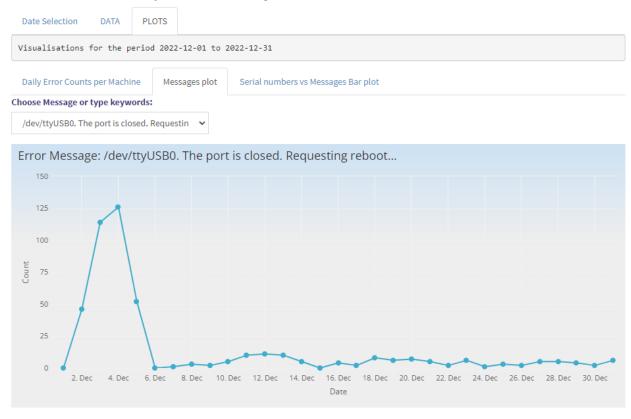
Pushdev Error Report Summary



The plot shows the number of errors reported by machine GWB827EB9C94B3 between the 1st of December and the 31st of December 2022. The highest number of errors was seen on the 4th of December, when 14 error messages were recorded.

Figure 4.1.9. Time series plot for daily error reports

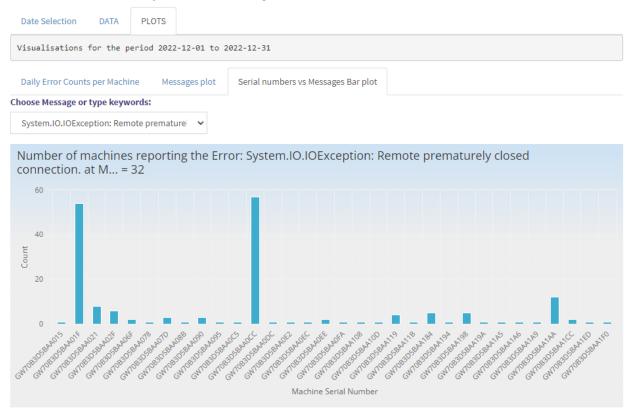
Pushdev Error Report Summary



The time series plot in figure 4.1.9 shows the number of times the Port-0 error was reported each day in December. About 125 Port-0 error messages were reported on the 4th of December.

Figure 4.1.10. Bar plot for machines that reported the same error

Pushdev Error Report Summary



The chart above shows the machines that reported the same error and the number of times each machine reported that error. In this figure, a total of 32 machines reported the error message "Remote prematurely closed connection", and machines GW70B3D5BAA01F and GW70B3D5BAA0CC reported this error more than 50 times each. This chart made it easy for the company to see the top machines reporting a particular error.

Table 4.1.4. Machine, message and error count table

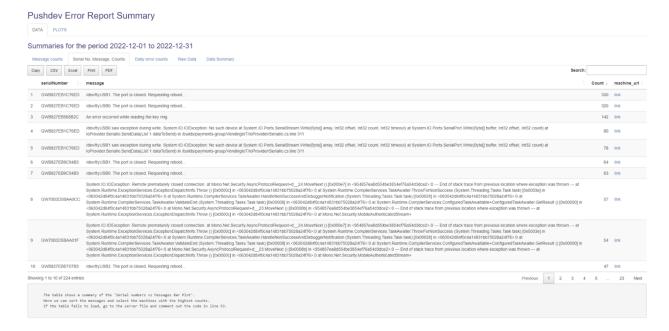
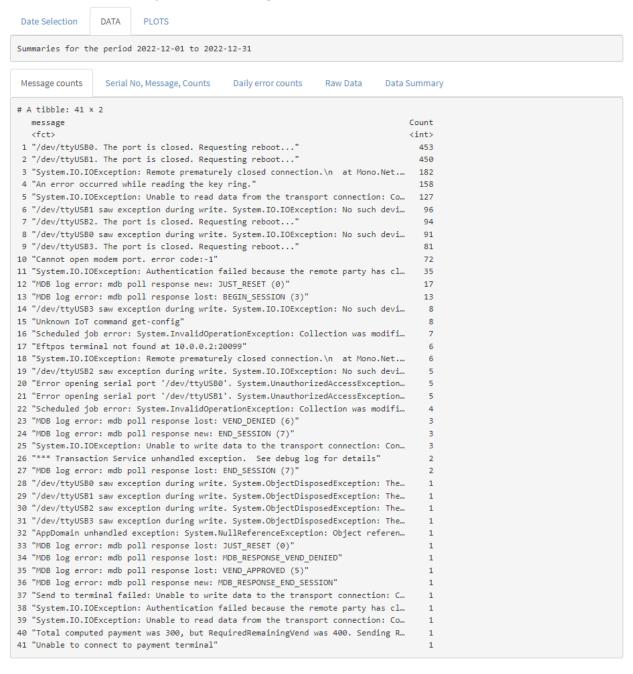


Table 4.1.4 is the table version of Figure 4.1.10. It shows a summary of the error messages reported by each machine and the number of times the errors were reported. The link, when clicked, would open the company's web application where the machine will be displayed.

Table 4.1.5. Error message counts

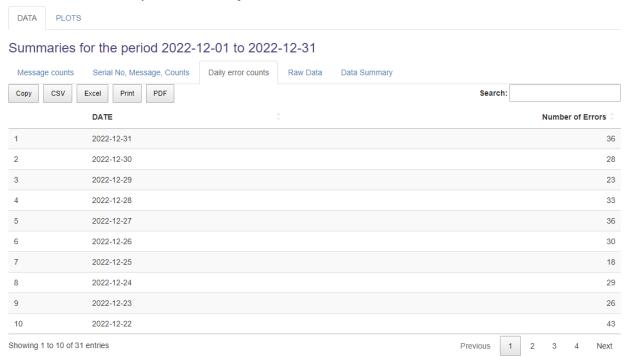
Pushdev Error Report Summary



The table above, which shows the frequency of errors reported from 1 December to 31 December, was used to decide on the actions needed to solve the problems caused by the errors. Some errors required machine system updates, and others required machine replacements, among other reasons.

Table 4.1.6. Error counts by date

Pushdev Error Report Summary



This table shows the total number of error messages recorded each day from the 1st to the 31st of December 2022. The users would know when most errors were reported.

Total sales from each site for the month of December 2022

Sales (\$) by siteName and terminal_result_string terminal_result_string @APPROVED

15 0.2M

16 0.2M

18 0.2M

18 0.2M

18 0.2M

18 0.2M

19 0.2M

19 0.2M

10 0.

Sum of total_cost_dollars started trending down on Wednesday, December 21, 2022, falling by 66.26% (42665) in 10 days.

Sum of total_cost_dollars started trending down on Wednesday, December 21, 2022, falling by 66.26% (42665) in 10 days.

Sum of total_cost_dollars dropped from 64388 to 21723 during its steepest decline between Wednesday, December 21, 2022 and Saturday, December 31, 2022.

Sum of total_cost_dollars trended down, resulting in a 44.79% decrease between Wednesday, November 30, 2022 and Saturday, December 31, 2022.

Figure 4.1.11. Monthly sales visualisations using Power BI

18 Dec

Sum of total_cost_dollars trended down, resulting in a 44.79% decrease betw

25 Dec

Figure 4.1.11 shows three plots and a summary. The plots were interactive, so choosing a site in the top bar graph resulted in the line and bar charts underneath to give the plots for the selected site. Likewise, the summary would also give the transaction summary for the selected site, and the total sales changed to give the amount collected at the selected site. The visualisations above are similar to those in Figure 4.1.2, Figure 4.1.3 and Figure 4.1.4

4.2. Preferred reporting platform:

Shiny was better than Power BI for the company's data visualisations and presentations as it housed all the reports together and could be used to generate reports for any period at any time. Graphs and tables that required a lot of filtering and coding were more straightforward to create in Shiny than in Power BI.

It was easy to clean the data in Shiny, whereas in Power BI, transforming the data while working in DirectQuery mode was impossible.

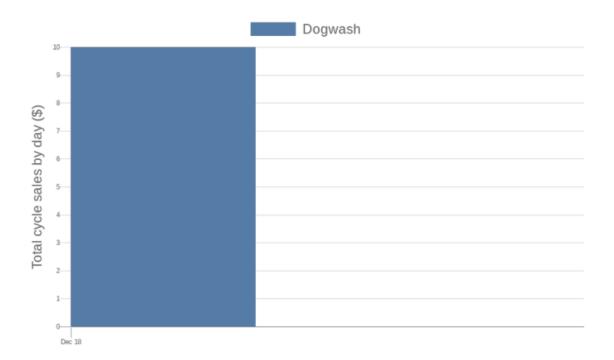
5. Conclusions/Discussion:

5.1. Authenticity of the summaries and visualisations:

The summaries and visualisations generated in the Shiny app were cross-checked against those in the company's payments cloud web app, and they all proved authentic and accurate.

When transactions were only recorded in a single day, the Shiny bar plots were better than those generated in the company web app. An example is shown in the two plots in Figure 5.1.1 (plot created in the company web app) and Figure 5.1.2 (plot created in Shiny app) below.

Figure 5.1.1. Sales for December 2022 at the site Dogwash from the company web app.



Total sales from all machines at Location: Dogwash The Hub Laundromat = \$10.00

\$12

\$10

\$8

\$2

\$0

2. Dec 4. Dec 6. Dec 8. Dec 10. Dec 12. Dec 14. Dec 16. Dec 18. Dec 20. Dec 22. Dec 24. Dec 26. Dec 28. Dec 30. Dec Date

Choose graph type

Histogram

Figure 5.1.2. Sales for December 2022 at site Dogwash from the Shiny app.

5.2. Future work:

The two Shiny applications should be merged into one app, giving users choices of data they want to use.

Combining the two applications will make it easy if more datasets are added, as everything will be under one application.

The app can be embellished with tab icons and company logos.

The deployment of the app needs to be resolved. Currently, users will have the app and RStudio installed on their computers. This should be hosted on a Shiny server (such as shinyapps.io) so that no local software installation is necessary.

Time series analysis can be used to predict machine errors and sales.

5.3. Problems:

Using date ranges in the data filter proved difficult because Dates are not UTC-corrected. In March and September, an assessment of whether the application handles daylight saving time changes should be made.

6. References:

- 1. Chang, Winston, et al. "Package 'shiny'." See http://citeseerx. ist. psu. edu/viewdoc/download (2015).
- 2. Becker, Louis T., and Elyssa M. Gould. "Microsoft Power BI: extending excel to manipulate, analyze, and visualize diverse data." *Serials Review* 45.3 (2019): 184-188.
- 3. Negrut, Viorel. "Power bi: Effective data aggregation." Quaestus 13 (2018): 146-152.
- 4. Hyndman, Rob J., and George Athanasopoulos. *Forecasting: principles and practice*. OTexts, 2018.
- 5. http://shiny.rstudio.com/tutorial/
- 6. https://www.highcharts.com/blog/tutorials/highcharts-for-r-users/
- 7. https://shiny.rstudio.com/reference/shiny/1.7.4/

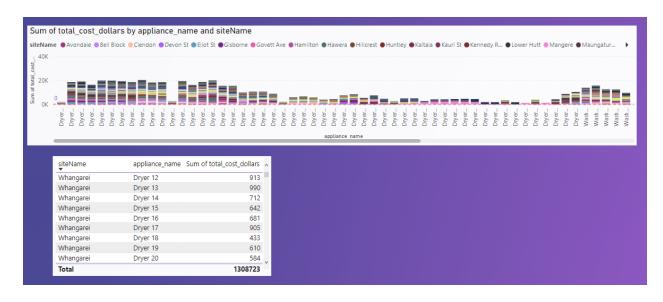
7. Appendices:

Appendix 1. Time series decomposition for the error messages

Pushdev Error Report Summary for DATA 601



Appendix 2. Sales from individual appliances using Power BI



Appendix 3. Line graph of the weekly sales

Transaction Data for DATA 601

Date Selection DATA PLOTS	
Visualisations for the period 2022-12-01 to 2022-12-31	
Terminal result string summary and plot Total sales from each:	site Daily & Weekly Time Series Graphs of Sales
Time Series Decomposition All appliances and all machine sale	es Sales Bubble plot
Choose Sitename or type name:	
Hamilton Kleenaz Laundromat ▼	
Choose the period:	
Weekly ▼	



Choose graph type

Line graph

This plot shows the daily and weekly sales for Hamilton Kleenaz Laundromat. Note the peaks and troughs for each site to see if they are following a cycle. As a company, we need to think of strategies we can use to increase the sales on those days where sales are usually low and to get more sales on days where sales are usually high.

Possible strategies would be:

- 1. Give discounted prices on the days where sales are usually low.
- 2. Create raffles where a minimum amount is required to enter.
- 3. Increase the price on those days where sales are high.

The line graph allows us to easily see the trend for the sales, especially over longer periods.

Appendix 4. Histogram of the weekly sales

Transaction Data for DATA 601

Date Selection DATA PLOTS	
Visualisations for the period 2022-12-01 to 2022-12-31	
Terminal result string summary and plot Total sales from each site	Daily & Weekly Time Series Graphs of Sales
Time Series Decomposition All appliances and all machine sales	Sales Bubble plot
Choose Sitename or type name:	
Hamilton Kleenaz Laundromat ▼	
Choose the period:	
Weekly ▼	



Choose graph type

Histogram ▼

This plot shows the daily and weekly sales for Hamilton Kleenaz Laundromat. Note the peaks and troughs for each site to see if they are following a cycle. As a company, we need to think of strategies we can use to increase the sales on those days where sales are usually low and to get more sales on days where sales are usually high.

Possible strategies would be:

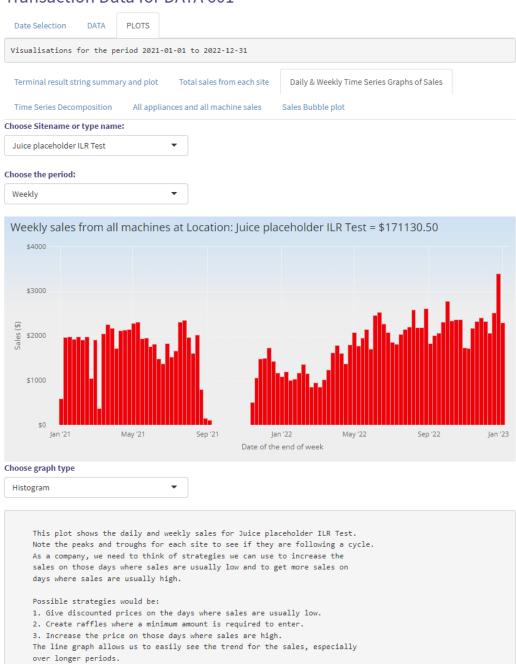
- 1. Give discounted prices on the days where sales are usually low.
- 2. Create raffles where a minimum amount is required to enter.
- 3. Increase the price on those days where sales are high.

The line graph allows us to easily see the trend for the sales, especially over longer periods.

Appendix 5. Effects of Covid-19 on transaction data sales

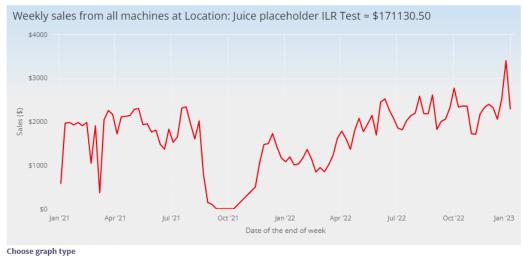
The two charts below show how Covid-19 affected sales at the site Juice Placeholder when the country went into a lockdown. This dataset had 6 788 798 records of data. The data was for the period from January 2021 up to December 2022.

Transaction Data for DATA 601



Transaction Data for DATA 601

Date Selection DATA PLOTS			
Visualisations for the period 2021-01-01 to 2022-12-31			
Terminal result string summary and plot Total sales from each site	Daily & Weekly Time Series Graphs of Sales		
Time Series Decomposition All appliances and all machine sales	Sales Bubble plot		
Choose Sitename or type name:			
Juice placeholder ILR Test ▼			
Choose the period:			
Weekly ▼			



Line graph ▼

This plot shows the daily and weekly sales for Juice placeholder ILR Test. Note the peaks and troughs for each site to see if they are following a cycle. As a company, we need to think of strategies we can use to increase the sales on those days where sales are usually low and to get more sales on days where sales are usually high.

Possible strategies would be:

- 1. Give discounted prices on the days where sales are usually low.
- 2. Create raffles where a minimum amount is required to enter.
- 3. Increase the price on those days where sales are high.

The line graph allows us to easily see the trend for the sales, especially over longer periods.