Technical Report for Turtle Games

Background and Context

Turtle Games designs, manufactures and retails board games, video games, books and toys to customers worldwide. Over time, the company has collected detailed sales records and thousands of customer reviews. To improve sales performance and deepen loyalty, Turtle Games set out to discover how points are accrued, to divide its customer base into actionable segments, to mine review text for themes and to assess whether loyalty-point balances support robust predictive models. This report brings together analyses conducted in Python and R, summarises the key findings and recommends next steps.

Analytical Approach

We began by importing the cleaned CSV into pandas and performing initial data preparation. Column names were standardised, data types corrected and categorical fields (Gender, Education) were encoded. Missing numerical values were imputed to the median and missing categories to the mode. We then split the data into training (80 per cent) and test (20 per cent) sets using a fixed random seed (42) for reproducibility.

A multiple linear regression was fitted on the training set with Spending Score, Remuneration, Age and a binary Gender indicator. On the training data this model achieved an R^2 of 0.844, while on the hold-out test set it delivered an R^2 of 0.829, a root-mean-square error (RMSE) of 526.8 points and a mean absolute error (MAE) of 400.1 points. Spending Score alone explained 45 per cent of the variance (≈ 33 points per score unit) and Remuneration 38 per cent (≈ 34 points per extra £ 1000). Age contributed under 0.2 per cent and was not statistically significant.

We next trained a decision-tree regressor using scikit-learn. The pruned tree achieved an R^2 of 0.945 on the training set and 0.941 on the test set. This pruning reduced overfitting (unpruned R^2_train ≈ 1.00 vs R^2_test ≈ 0.996) while retaining excellent generalisation. Figure 11 shows the final tree structure, and Figure 12 its feature-importance ranking, which confirms that Spending Score (threshold ≈ 67) and income (threshold ≈ £ 44 000) dominate the splits, with Gender and Age not appearing in the top four levels.

For customer segmentation, we applied K-means to the four standardised features (Spending Score, Remuneration, Age and Loyalty Points). Both the elbow method and the silhouette analysis pointed to k = 5 (Figure 14). The cluster scatter plot in Figure 15 clearly delineates five groups: mid-range earners/spenders, high/high, high/low, low/high and low/low.

In parallel, we performed text analytics on reviews using NLTK (tokenisation, stop-word removal, lemmatisation) and TextBlob with a custom lexicon for sentiment scoring. Polarity histograms for full reviews and summaries (Figures 16–17) show a concentration between 0.1 and 0.4, indicating mild positivity. The bar chart of the 15 most frequent words (Figure

18) highlights “quality”, “fun” and “support”, and the top-20 positive/negative review tables (Figure 19) surface critical feedback about delivery delays and pricing.

Finally, in R we reloaded the same cleaned data using read.csv to match the client’s workflow. With tidyverse, skimr and DataExplorer we produced histograms with density overlays (Figure 1), scatterplots with trend lines (Figures 2–3), violin + boxplots across gender, education and age (Figures 4–6) and a bubble chart combining income, loyalty points and Spending Score (Figure 7). A multiple linear regression was then fitted with the same four predictors. Residual diagnostics flagged heteroscedasticity (Breusch–Pagan $p \approx 4.30 \times 10^{-9}$) and non-normality (Jarque–Bera $\chi^2 \approx 24.54$, $p \approx 4.68 \times 10^{-6}$), so we applied heteroscedasticity-robust standard errors. The final model explains about 84 per cent of variance, with coefficients matching the Python estimates and a −78-point offset for male customers. Actual-versus-predicted (Figure 20), residuals-versus-fitted (Figure 21) and prediction-interval plots (Figure 22) confirm the model’s accuracy and business relevance.

Visualisation and Insights

The histogram of loyalty-point balances (Figure 1) shows a pronounced right skew with heavy tails, suggesting tier thresholds at around 1,000 and 3,000 points. Scatterplots of Spending Score (Figure 2) and of income by gender (Figure 3) confirm moderate positive trends, with high scoring spenders who under-earn points clearly visible. Violin-boxplots (Figures 4–6) compare distributions across gender, education and age, highlighting activation gaps among under-25s and diploma graduates, as well as extreme outliers in a small basic-education cohort. A multivariate bubble chart (Figure 7) integrates income, loyalty and Spending Score, isolating under-earning high-value customers in one view.

In Python, bivariate regression plots (Figures 8–10) validated feature selection. The pruned decision tree (Figure 11) and its feature-importance chart (Figure 12) pinpoint Spending Score ≈ 67 and income ≈ £ 44 000 as primary loyalty drivers. Clustering visuals (Figures 13–15) define five actionable segments. Sentiment histograms (Figures 16–17), the word-frequency bar chart (Figure 18) and curated review tables (Figure 19) surface common praise for product quality and support, and rare complaints about boringness and pricing.

Regression diagnostics in R (Figures 20–21) confirm residuals centred on zero with no clear pattern. A prediction-interval plot (Figure 22) shows the model’s ability to forecast loyalty points for customer archetypes—for instance, predicting about 3 450 points for a 30-year-old high-spender female with a tight confidence band. These insights support tiered rewards, personalised communications and dynamic campaign planning to drive engagement and revenue.

Patterns, Predictions and Segment-Specific Actions

Loyalty-point balances cluster between 500 and 2 500 for most customers, with a small power-user group above 5 000. Spending Score and income dominate as predictors, while age and education add minimal explanatory power. Five customer segments emerged:

These insights support tiered rewards, personalised communications and dynamic campaign planning to drive engagement and revenue.

Mid-range earners & mid-range spenders (774 customers, 39 per cent):

These core customers sit at median income and Spending Score. Broad-appeal campaigns-point multipliers, bundled promotions and cross-sell nudges - will deepen engagement and move them into higher tiers.

High earners & high spenders (271 customers, 14 per cent)

Affluent heavy spenders form a premium group. VIP treatment - early access, exclusive events and concierge-style service - will reward loyalty and boost advocacy.

High earners & low spenders (356 customers, 18 per cent)

Wealthy but cautious customers may respond to prestige-focused upsells, subscription models or premium add-ons that emphasise quality and status.

Low earners & high spenders (330 customers, 17 per cent)

Cost-sensitive yet loyal customers benefit from entry-level bundles, flexible financing and referral bonuses to sustain their high share of wallet.

Low earners & low spenders (269 customers, 13 per cent)

Price-conscious infrequent buyers should be engaged via low-cost, high-ROI channels such as email drips and social media ads promoting value deals.

Finally, the multiple regression coefficients of +34 points per one-point increase in Spending Score, +34 points per £1,000 of income, +11 points per additional year of age and −78 points for male customers versus female customers underline that this model - having achieved an R^2 of approximately 0.84 and outperforming all alternatives - was the most accurate of those tested and supports detailed scenario planning and tiered rewards design.

Next Steps

Integrate additional behavioural metrics (basket size, transaction count), test for non-linear and cohort effects, monitor segment migration and launch targeted A/B tests for each group. Enhance review analysis with aspect-based sentiment and topic modelling, build a live dashboard, deploy segmentation rules in campaigns, track performance via dashboards and retrain models regularly to capture evolving customer behaviour.

Appendix

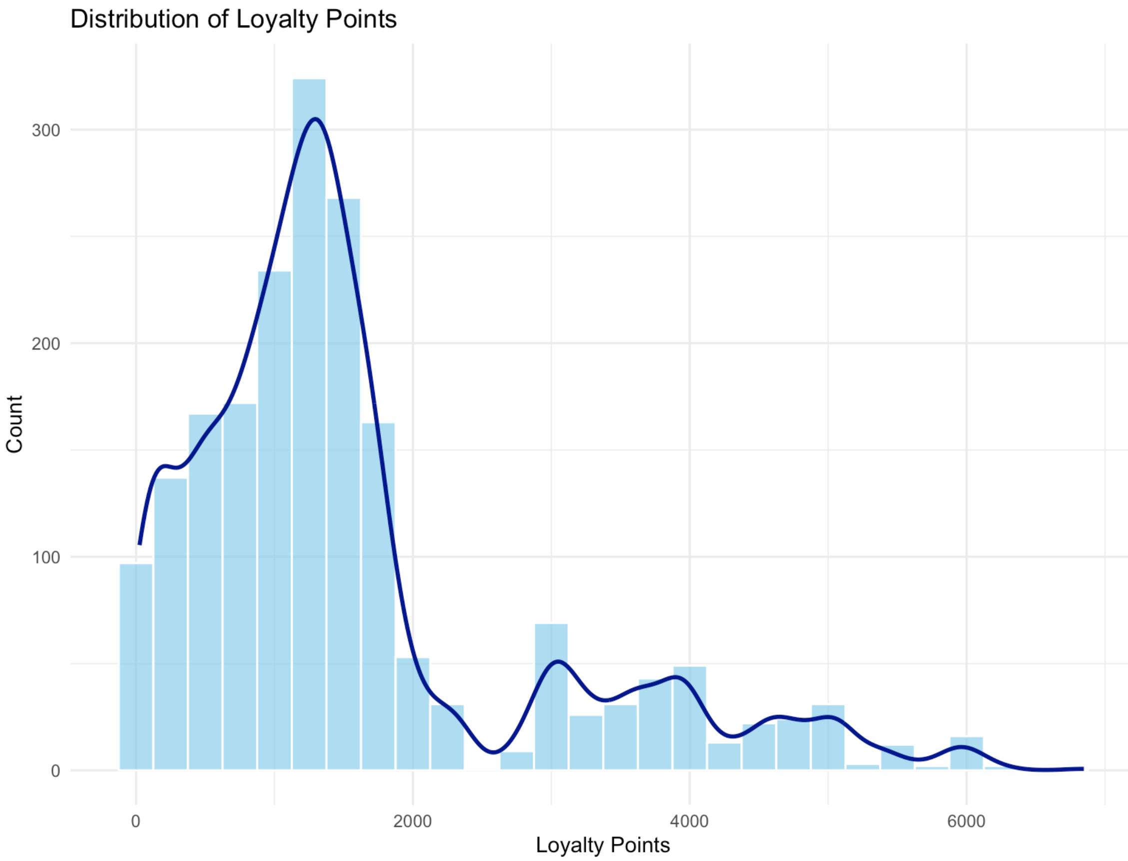

Figure 1 (R): Histogram of loyalty-point distribution

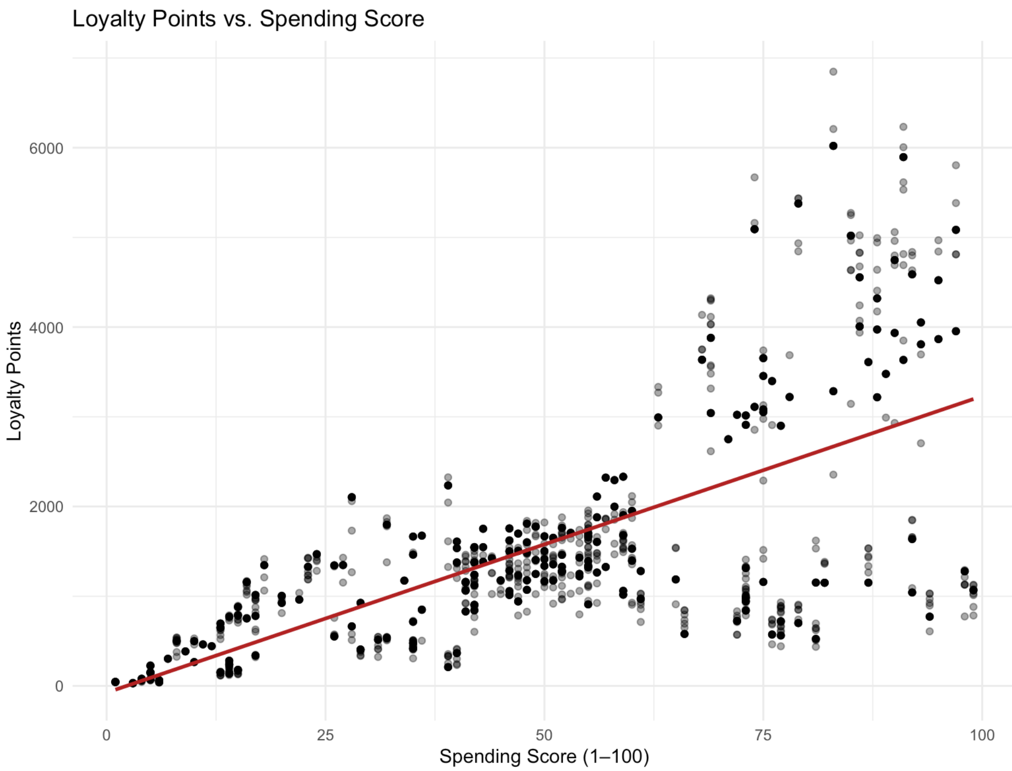

Figure 2 (R): Scatterplot of Spending Score vs loyalty points with trend line

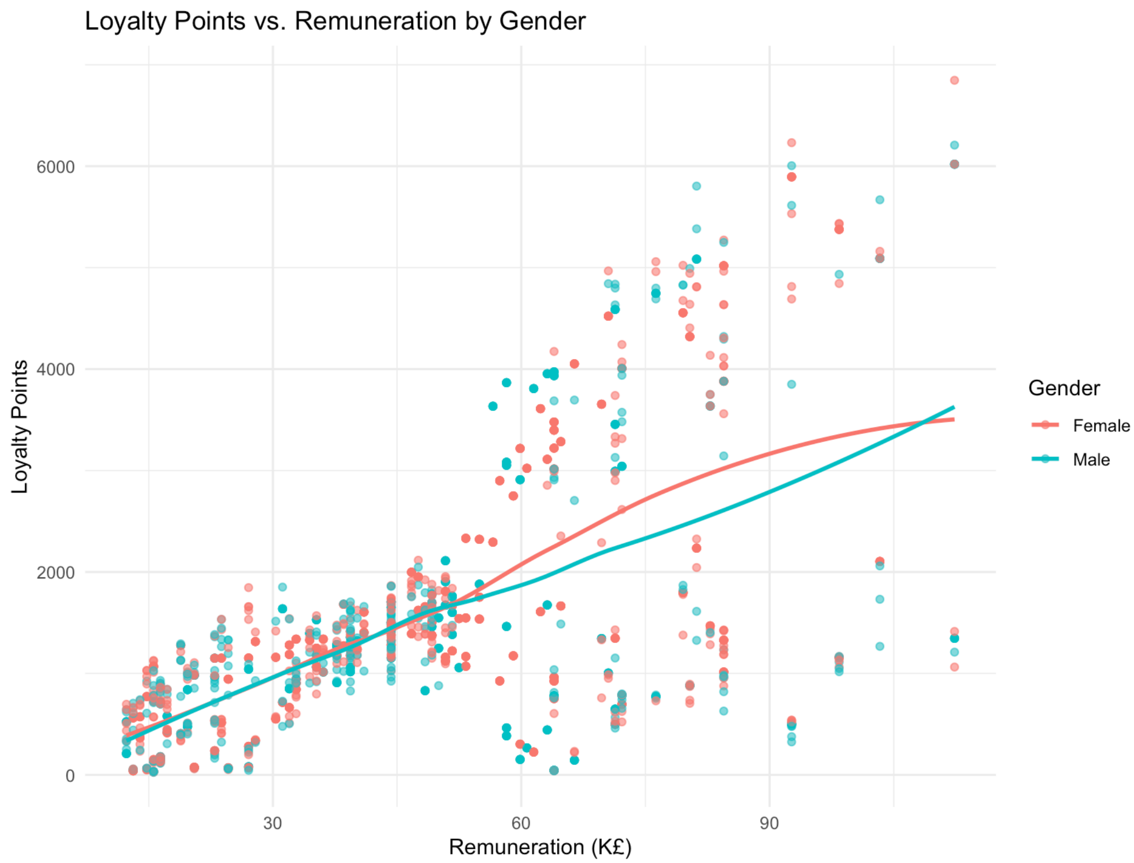

Figure 3 (R): Scatterplot of remuneration vs loyalty points by gender

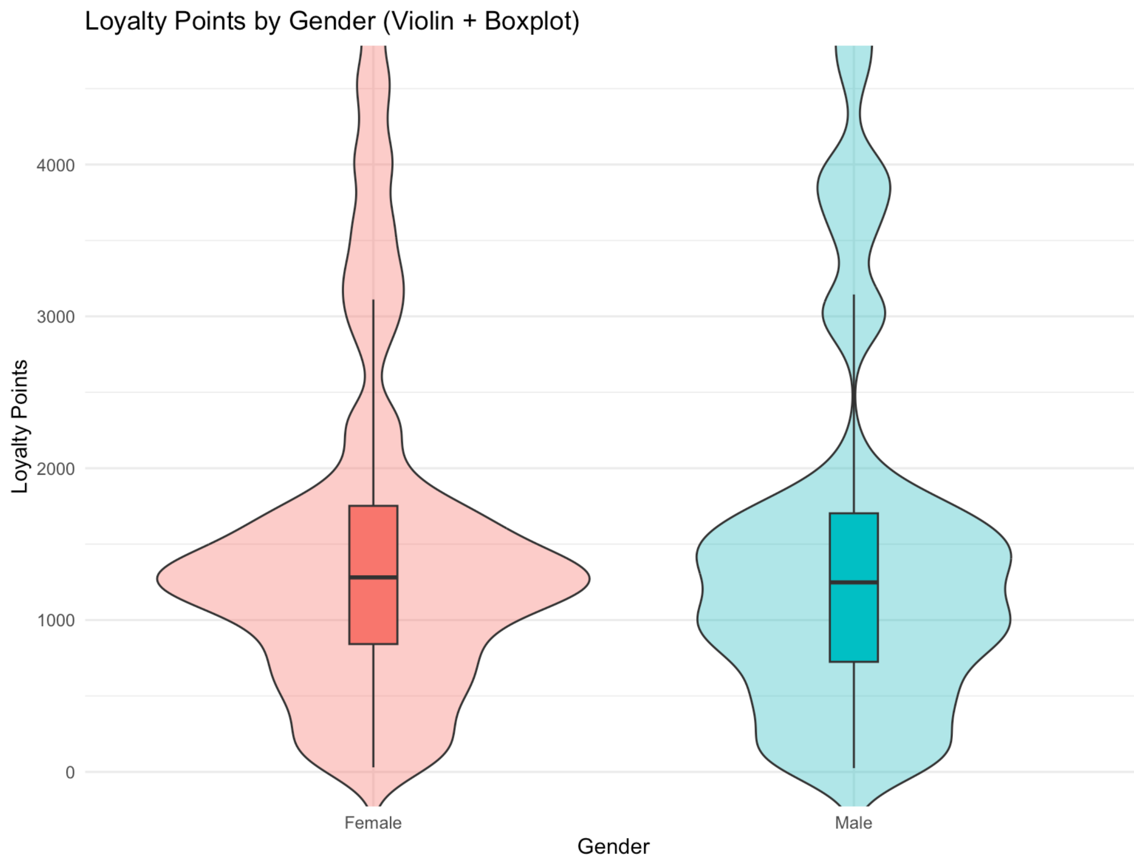

Figure 4 (R): Violin and boxplot of loyalty points by gender

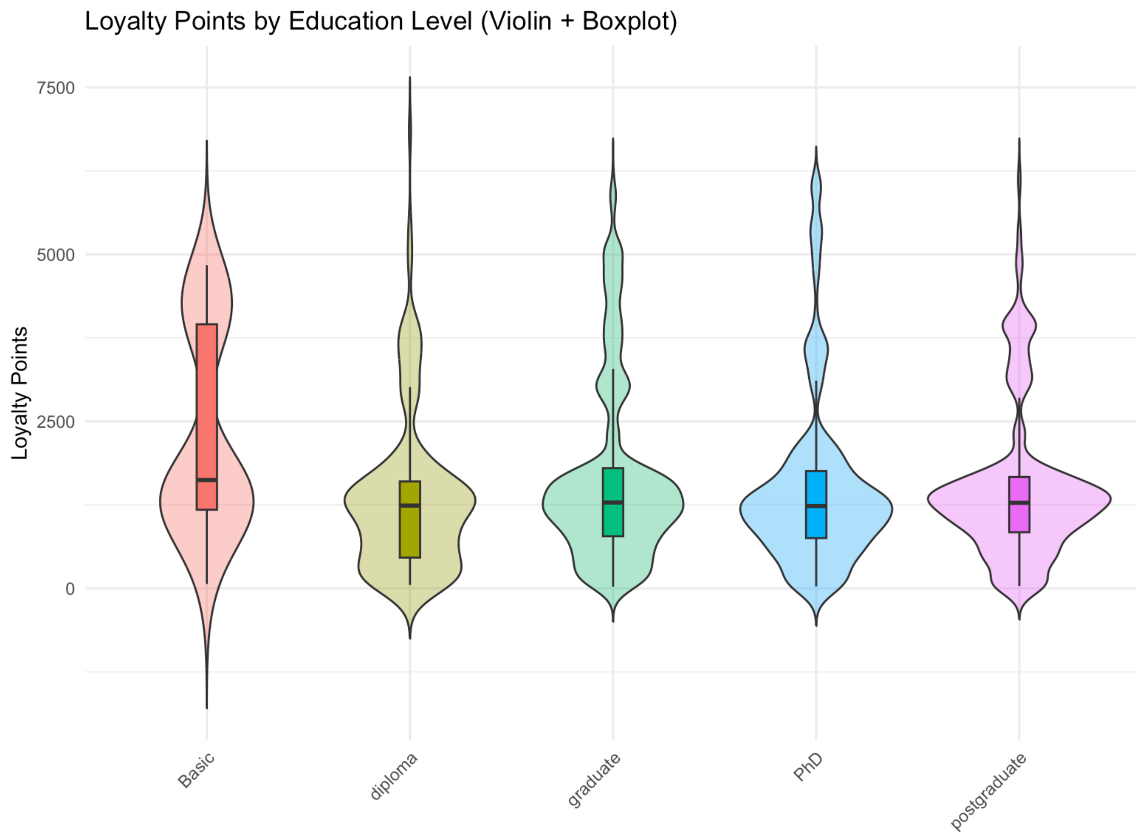

Figure 5 (R): Violin and boxplot of loyalty points by education level

Figure 6 (R): Violin and boxplot of loyalty points by age group

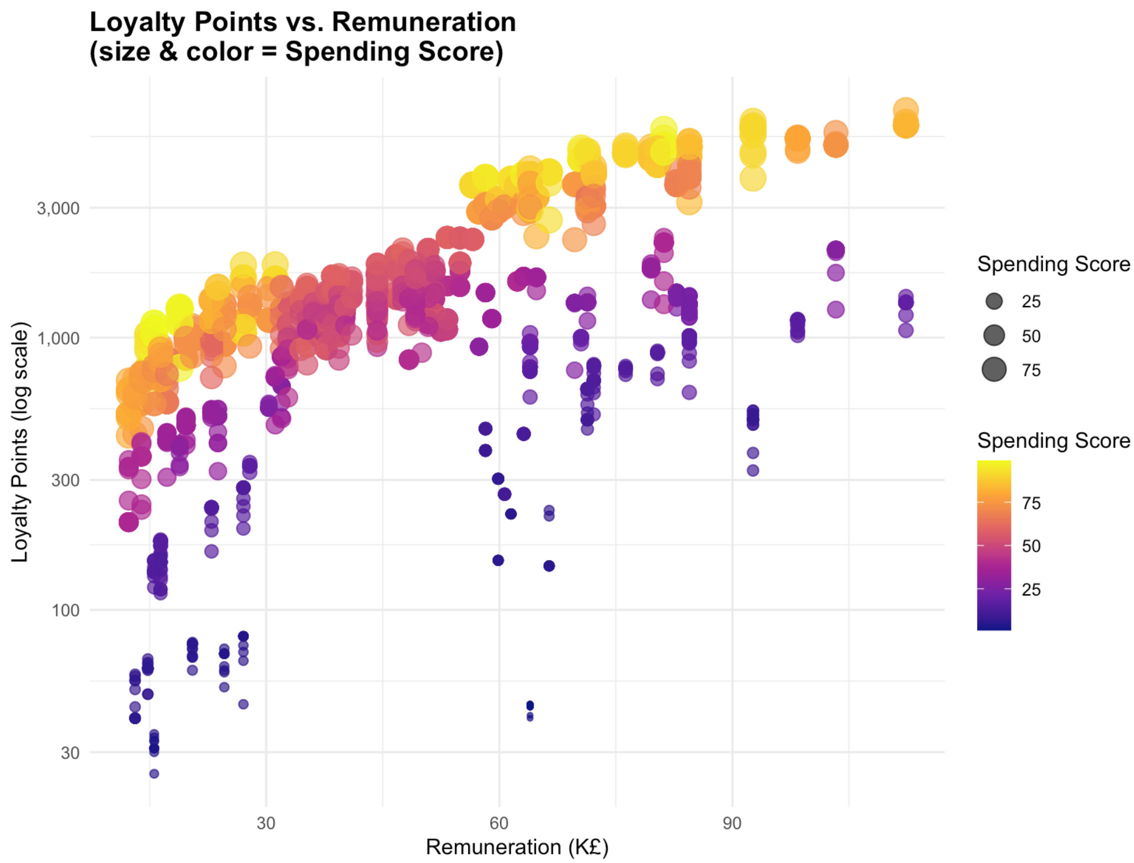

Figure 7 (R): Bubble chart of loyalty vs remuneration coloured by Spending Score

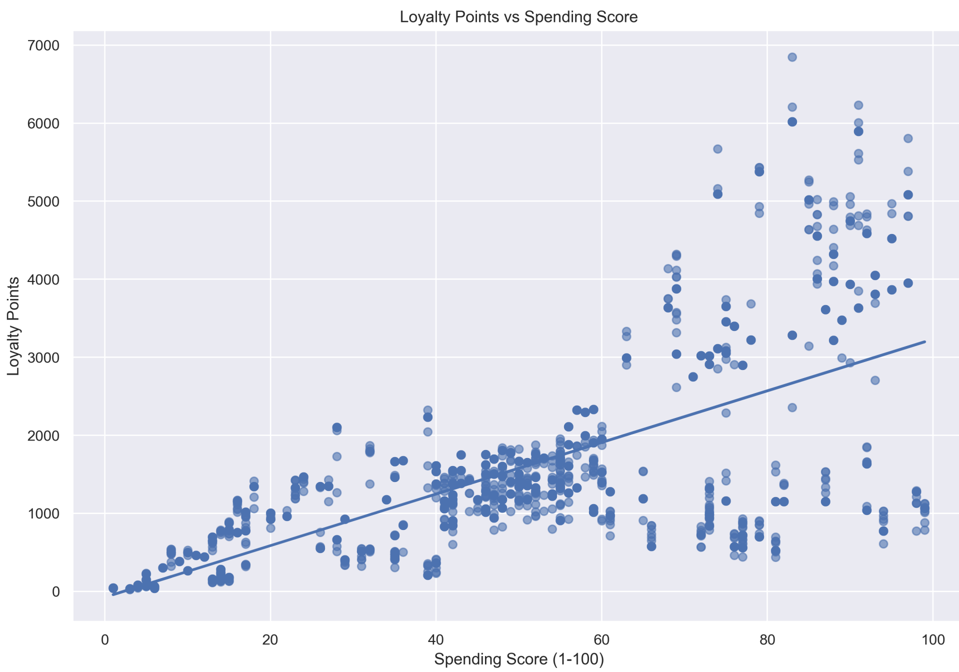

Figure 8 (Python): Bivariate regression – Spending Score vs loyalty points

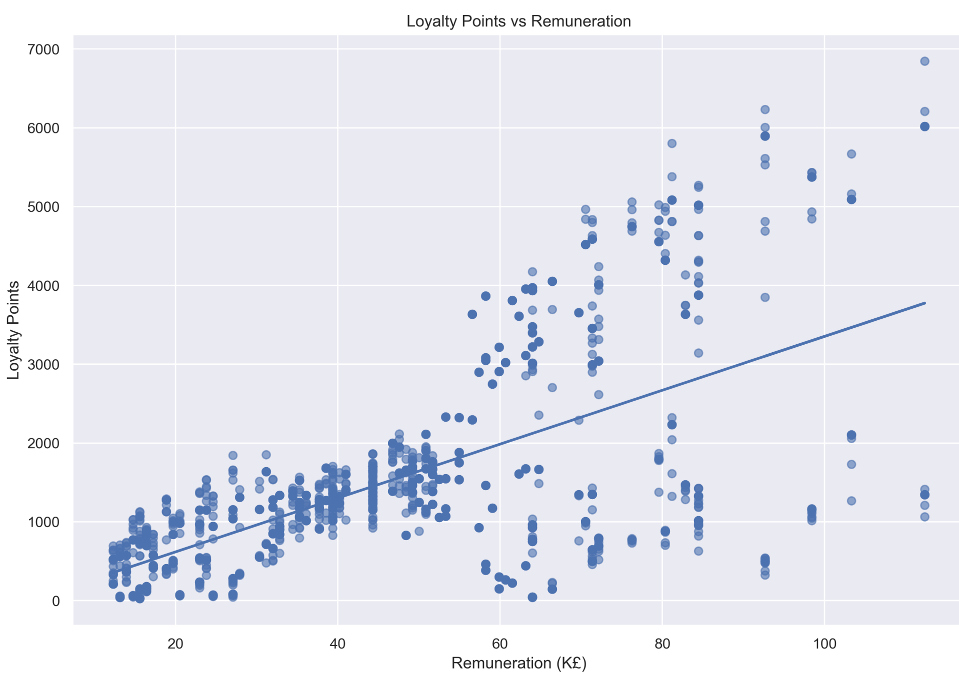

Figure 9 (Python): Bivariate regression – Remuneration vs loyalty points

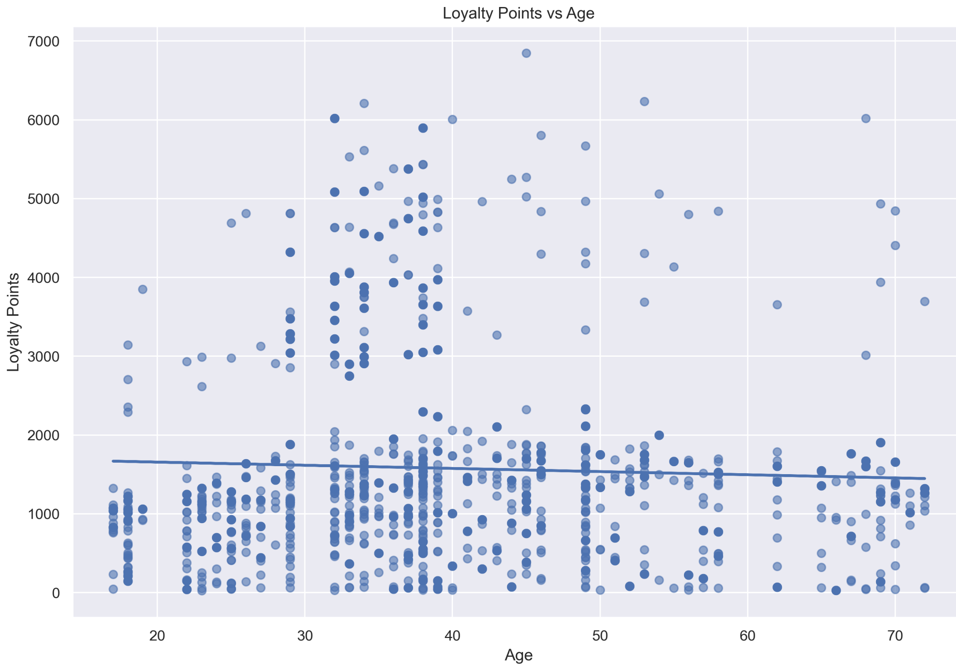

Figure 10 (Python): Bivariate regression – Age vs loyalty points

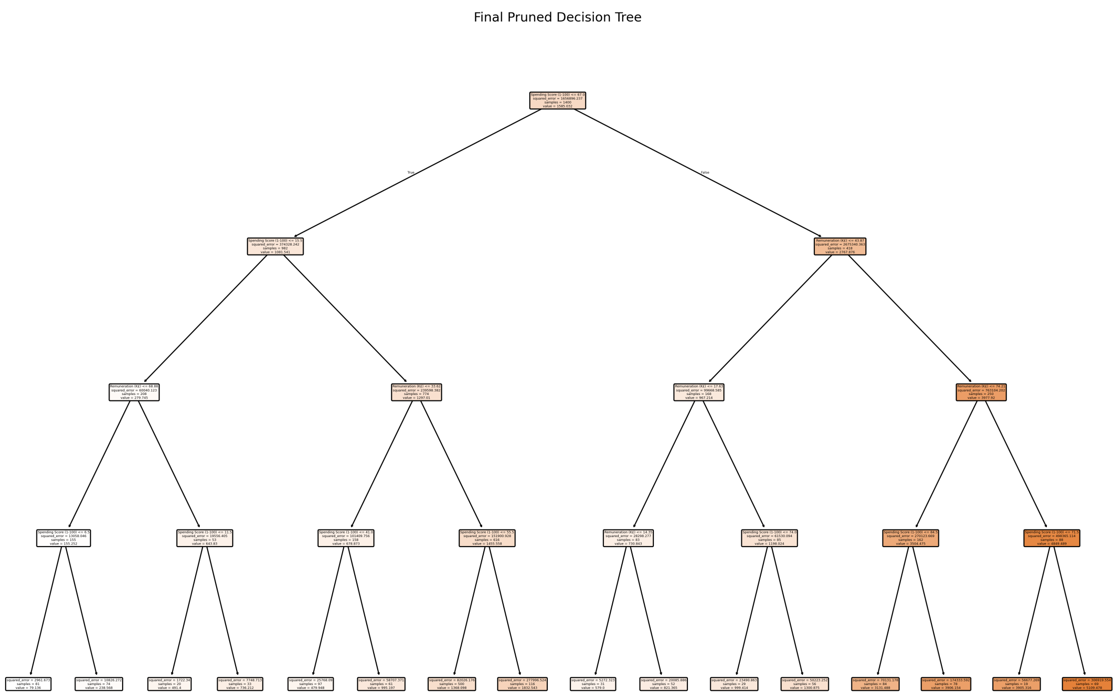

Figure 11 (Python): Decision tree diagram (Pruned).

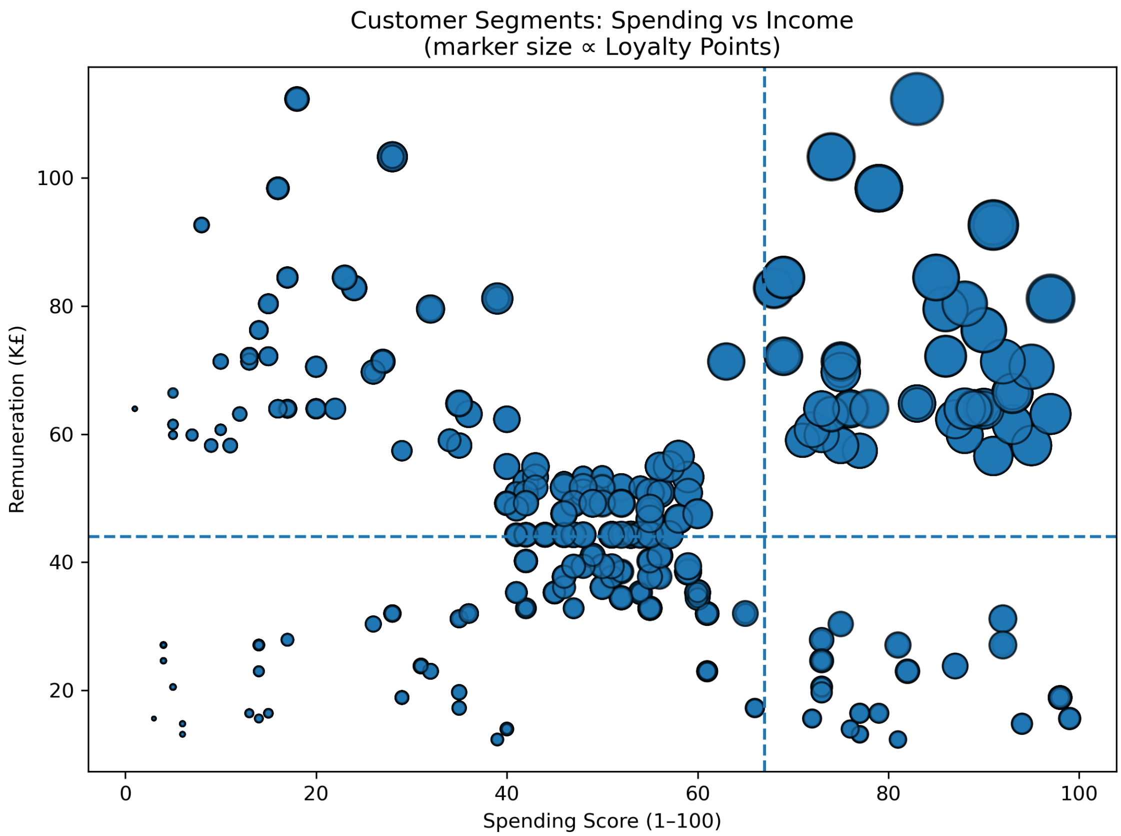

Figure 12 (Python): Feature-importance bar chart from the decision tree

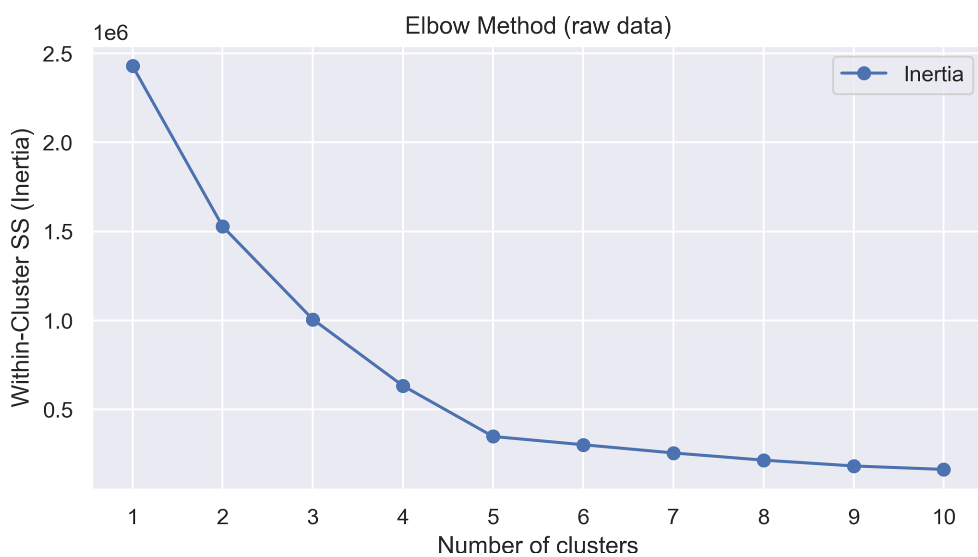

Figure 13 (Python): Elbow plot for K-means clustering

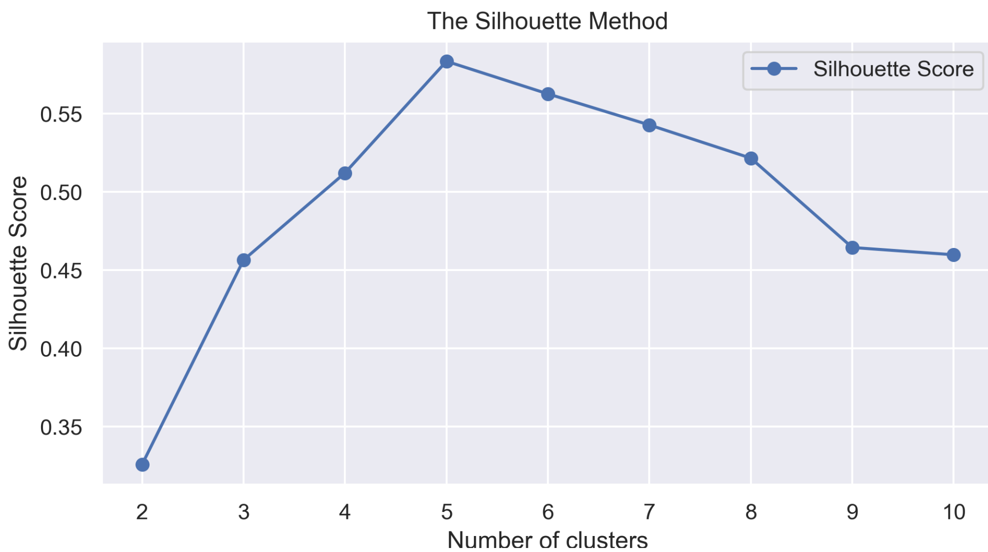

Figure 14 (Python): Silhouette score analysis for K-means clustering

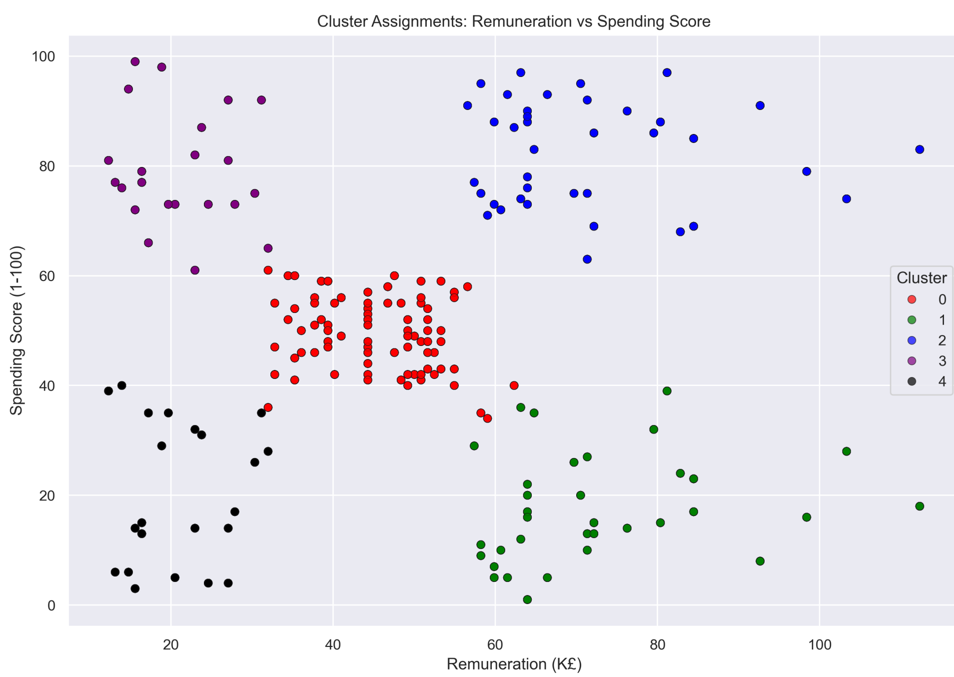

Figure 15 (Python): Cluster scatter plot of customer segments

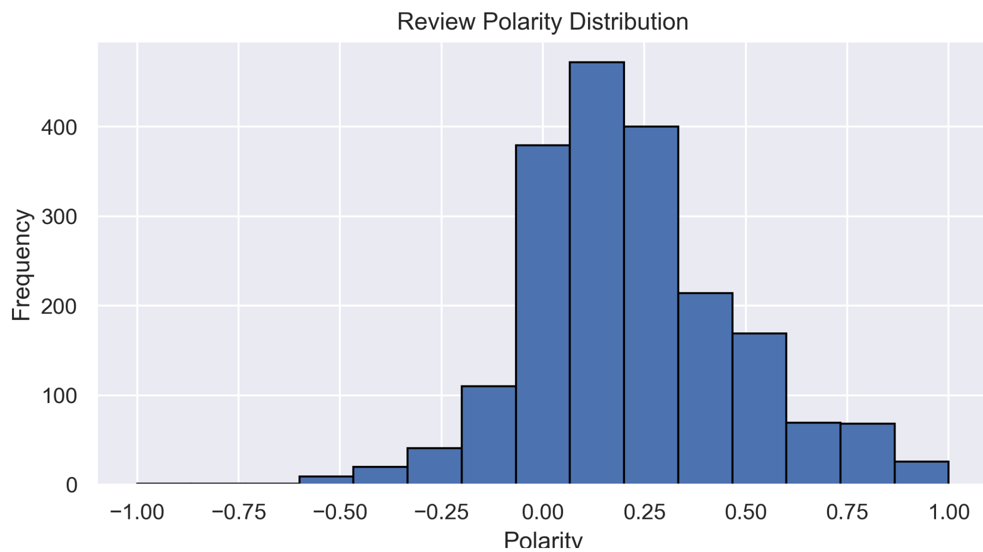

Figure 16 (Python): Histogram of review polarity scores

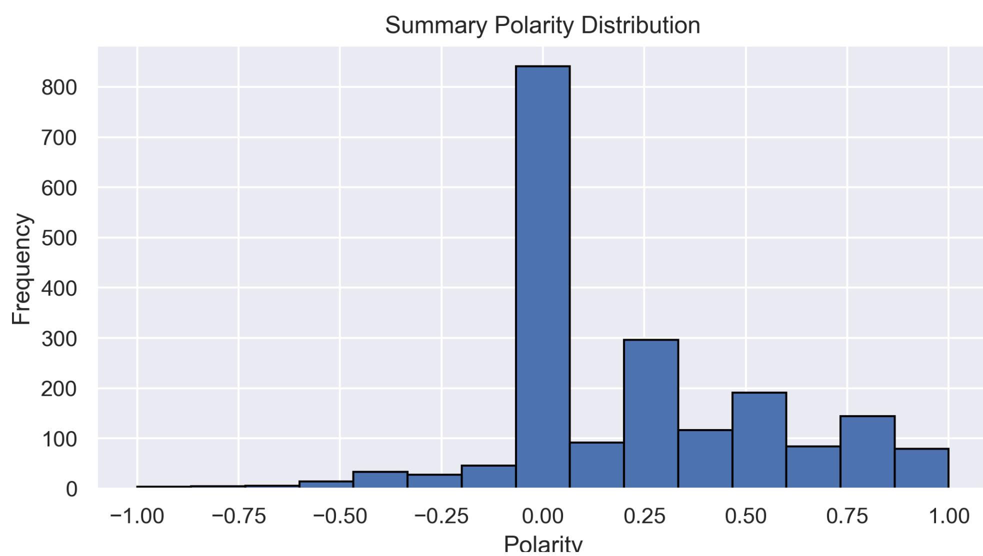

Figure 17 (Python): Histogram of summary polarity scores

Figure 18 (Python): Bar chart of top 15 most frequent words in reviews

Top 20 Positive Review	**Review Polarity**
came in perfect condition	1.000000
awesome book	1.000000
awesome gift	1.000000
excellent activity for teaching self management skills	1.000000
perfect just what i ordered	1.000000
wonderful product	1.000000
delightful product	1.000000
wonderful for my grandson to learn the resurrection story	1.000000
perfect	1.000000
awesome	1.000000
awesome set	1.000000
best set buy 2 if you have the means	1.000000
awesome addition to my rpg gm system	1.000000
it s awesome	1.000000
one of the best board games i played in along time	1.000000
my daughter loves her stickers awesome seller thank you	1.000000
this was perfect to go with the 7 bean bags i just wish they were not separate orders	1.000000
awesome toy	1.000000
it is the best thing to play with and also mind blowing in some ways	1.000000
excellent toy to simulate thought	1.000000

Top 20 Negative Reviews	Review Polarity
booo unles you are patient know how to measure i didn t have the patience neither did my daughter boring unless you are a craft person which i am not	-1.000000
incomplete kit very disappointing	-0.780000
used with anger management group and they like it gave them opportunity to share events in their life with the usage of the cues on the cards	-0.700000
i m sorry i just find this product to be boring and to be frank juvenile	-0.583333
one of my staff will be using this game soon so i don t know how well it works as yet but after looking at the cards i believe it will be helpful in getting a conversation started regarding anger and what to do to control it	-0.550000
i bought this as a christmas gift for my grandson its a sticker book so how can i go wrong with this gift	-0.500000
this was a gift for my daughter i found it difficult to use	-0.500000
i found the directions difficult	-0.500000
instructions are complicated to follow	-0.500000
difficult	-0.500000
expensive for what you get	-0.500000
i sent this product to my granddaughter the pom pom maker comes in two parts and is supposed to snap together to create the pom poms however both parts were the same making it unusable if you can t make the pom poms the kit is useless since this was sent as a gift i do not have it to return very disappointed	-0.491667
i purchased this on the recommendation of two therapists working with my adopted children the children found it boring and put it down half way through	-0.440741
very hard complicated to make these	-0.439583
kids i work with like this game	-0.400000
this game although it appears to be like uno and have an easier play method it was still too time consuming and wordy for my children with learning disabilities	-0.400000
my son loves playing this game it was recommended by a counselor at school that works with him	-0.400000

this game is a blast	-0.400000
i bought this for my son he loves this game	-0.400000
was a gift for my son he loves the game	-0.400000

Figure 19 (Python): Tables of the top 20 positive and top 20 negative reviews

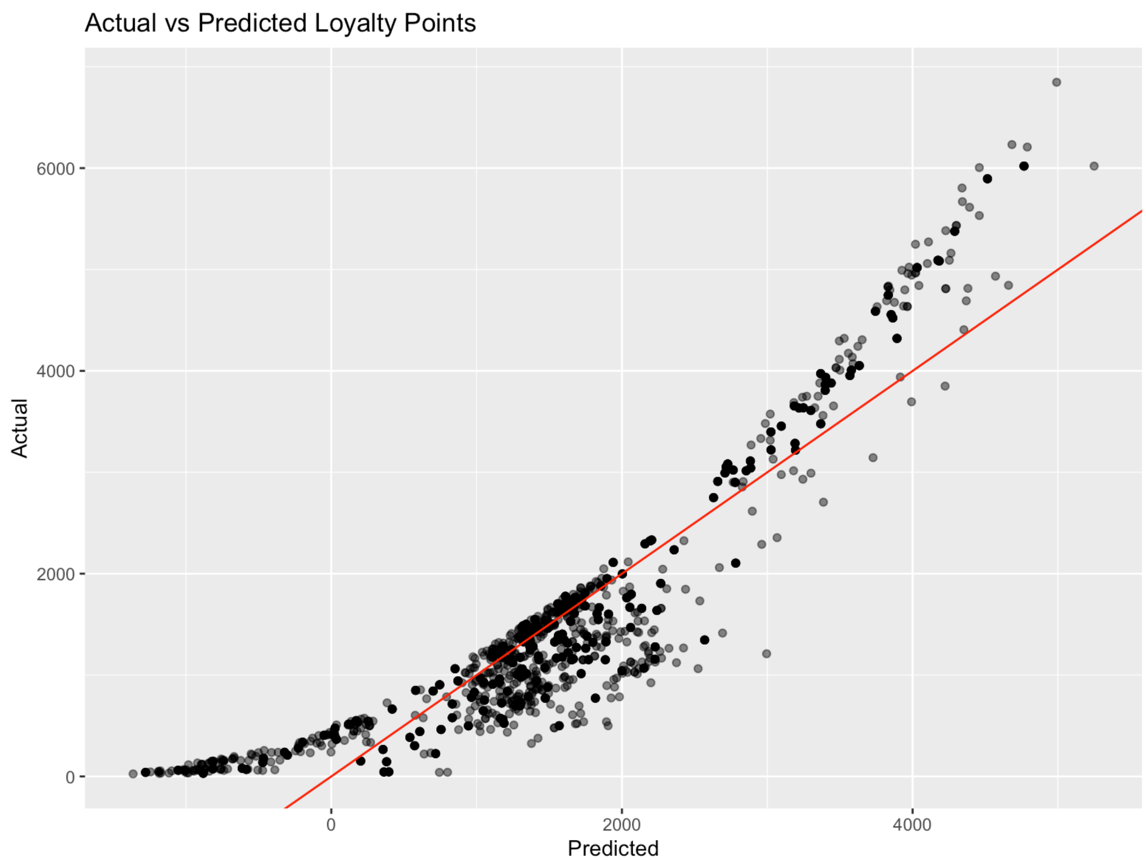

Figure 20 (R): R regression diagnostic – actual vs predicted loyalty points

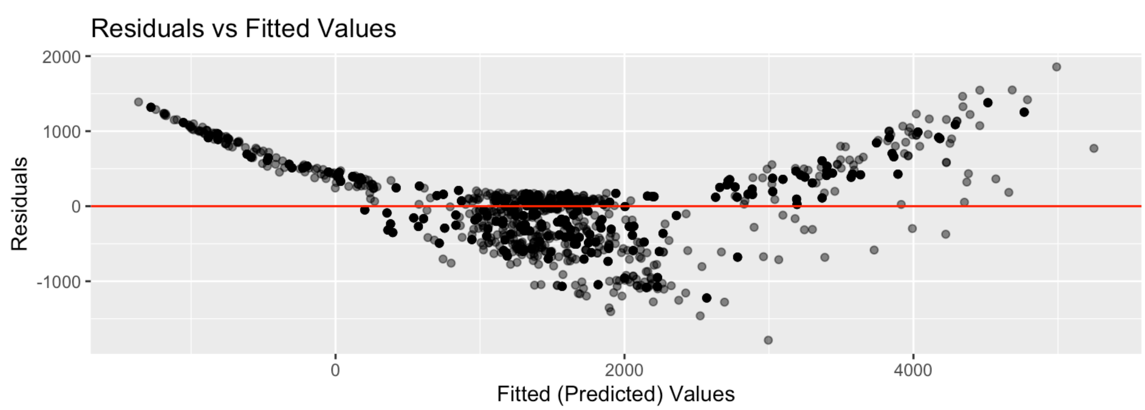

Figure 21 (R): R regression diagnostic – residuals vs fitted values

	Spending.Score..1.100.	Remuneration..K..	Age	Gender	fit	lwr	upr
1	85	70	30	Female	3448.4319	3400.26931	3496.5946
2	20	30	55	Male	67.3623	17.61137	117.1132
3	60	50	40	Female	2025.2595	1993.81866	2056.7002
4	50	48	38	Male	1514.6077	1480.47281	1548.7425

Figure 22 (R): Scenario-based prediction intervals for select customer archetypes