



Course 3: Final Assignment Python/R Presentation

Javier Conde Pascual | 12th September 2022

1. Scenario and system set up

Figure 1.1: Background, project goal and initial set of questions to answer

ROLE: assuming the role of data analyst working with game manufacturer and retailer Turtle Games. Its product range includes books, board games, video games, and toys.

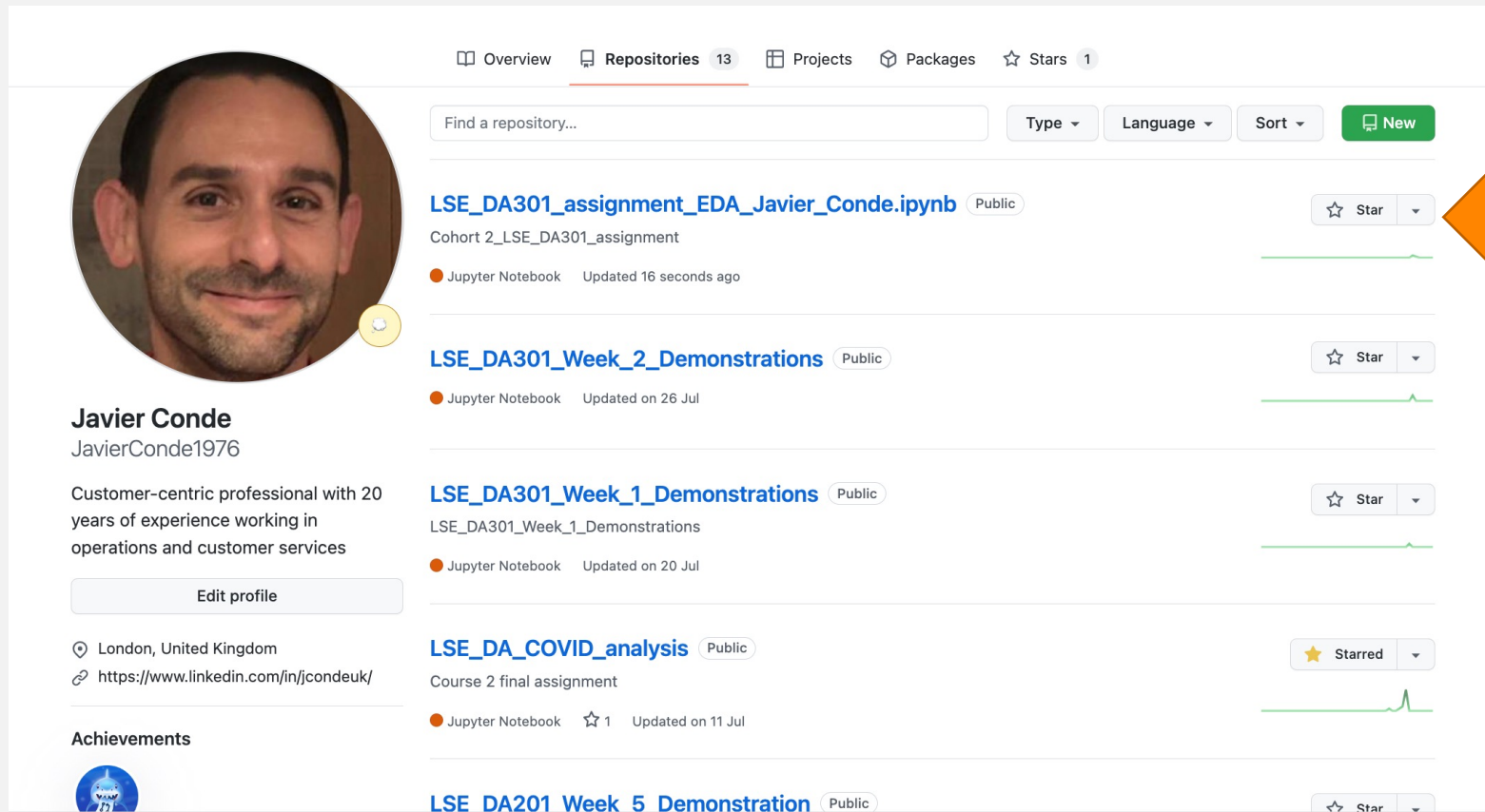
PROJECT GOAL: analyse available data from sales and customer reviews to extract and share insights with stakeholders. The ultimate target is improving overall sales performance by utilising customer trends.

INITIAL SET OF QUESTIONS:

- how customers accumulate loyalty points
- how groups within the customer base can be used to target specific market segments
- how social data (e.g. customer reviews) can be used to inform marketing campaigns
- the impact that each product has on sales
- how reliable the data is (e.g. normal distribution, skewness, or kurtosis)
- what the relationship(s) is/are (if any) between North American, European, and global sales.

Source: LSE (2022)

Figure 1.2: Project Github repository (I)



The screenshot displays the GitHub profile of Javier Conde. The profile includes a circular profile picture, the name "Javier Conde", and the username "JavierConde1976". A bio describes him as a "Customer-centric professional with 20 years of experience working in operations and customer services". Below the bio is an "Edit profile" button. The location is listed as "London, United Kingdom" with a link to his LinkedIn profile. The "Achievements" section shows a "VAMP" badge. The "Repositories" tab is active, showing a list of repositories. The first repository, "LSE_DA301_assignment_EDA_Javier-Conde.ipynb", is highlighted with a large orange arrow pointing to its "Star" button. Other repositories include "LSE_DA301_Week_2_Demonstrations", "LSE_DA301_Week_1_Demonstrations", "LSE_DA_COVID_analysis", and "LSE DA201 Week 5 Demonstration".

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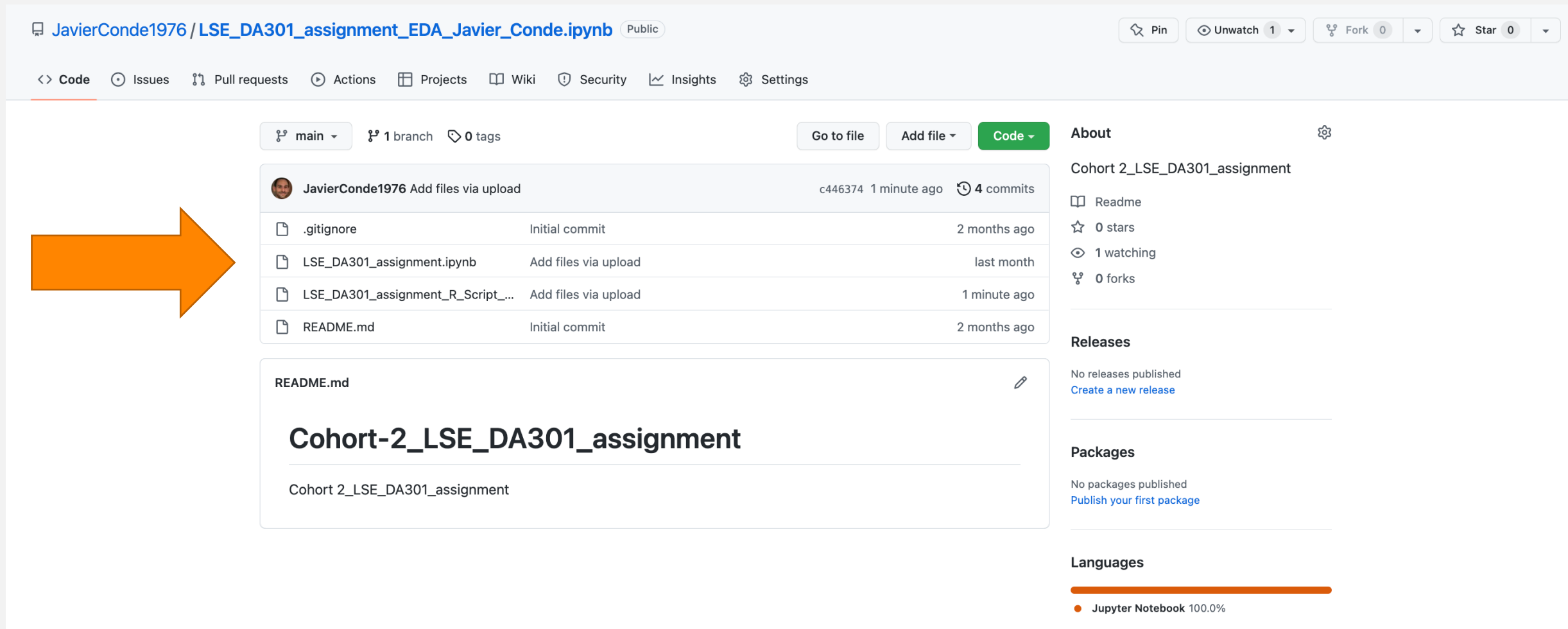
Course 2 final assignment

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Source: Javier Conde (2022)

Figure 1.3: Project Github repository (II)



JavierConde1976 / LSE_DA301_assignment_EDA_Javier_Conde.ipynb Public

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JavierConde1976 Add files via upload c446374 1 minute ago 4 commits

.gitignore	Initial commit	2 months ago
LSE_DA301_assignment.ipynb	Add files via upload	last month
LSE_DA301_assignment_R_Script_...	Add files via upload	1 minute ago
README.md	Initial commit	2 months ago

README.md

Cohort-2_LSE_DA301_assignment

Cohort 2_LSE_DA301_assignment

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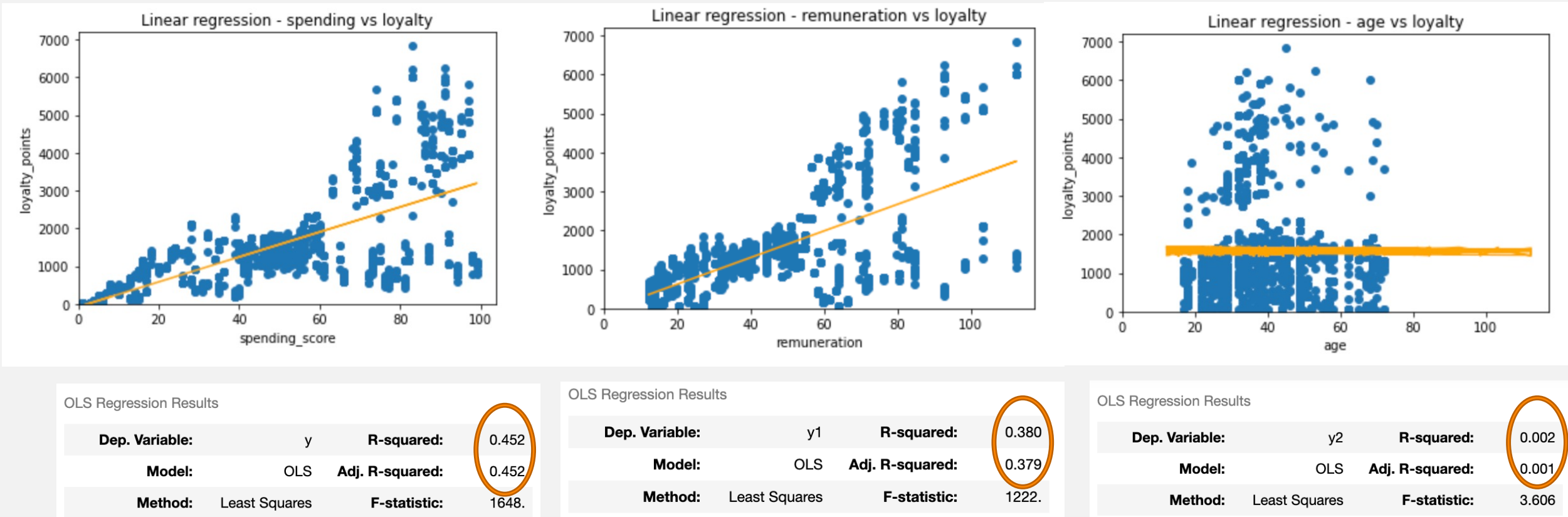
Figure 3.1: Insights on customer reviews

Customer reviews

- Loyalty has a slight correlation with spending and remunerations score. This is advised to be studied further.
- Loyalty has almost no correlation with customer's age
- K-means clustering analysis reveals 5 potential groups marketing department could consider:
 - low income/low spending
 - low income/higher spending
 - average income/average spending
 - higher income/low spending
 - higher income/higher spending
- The 5 most used words in the reviews are 'stars' (427) 'five' (342), 'game'(319), 'great' (295) and 'fun'(218), suggesting a positive sentiment confirmed by the polarity analysis (Mean +0.2 to +0.25)

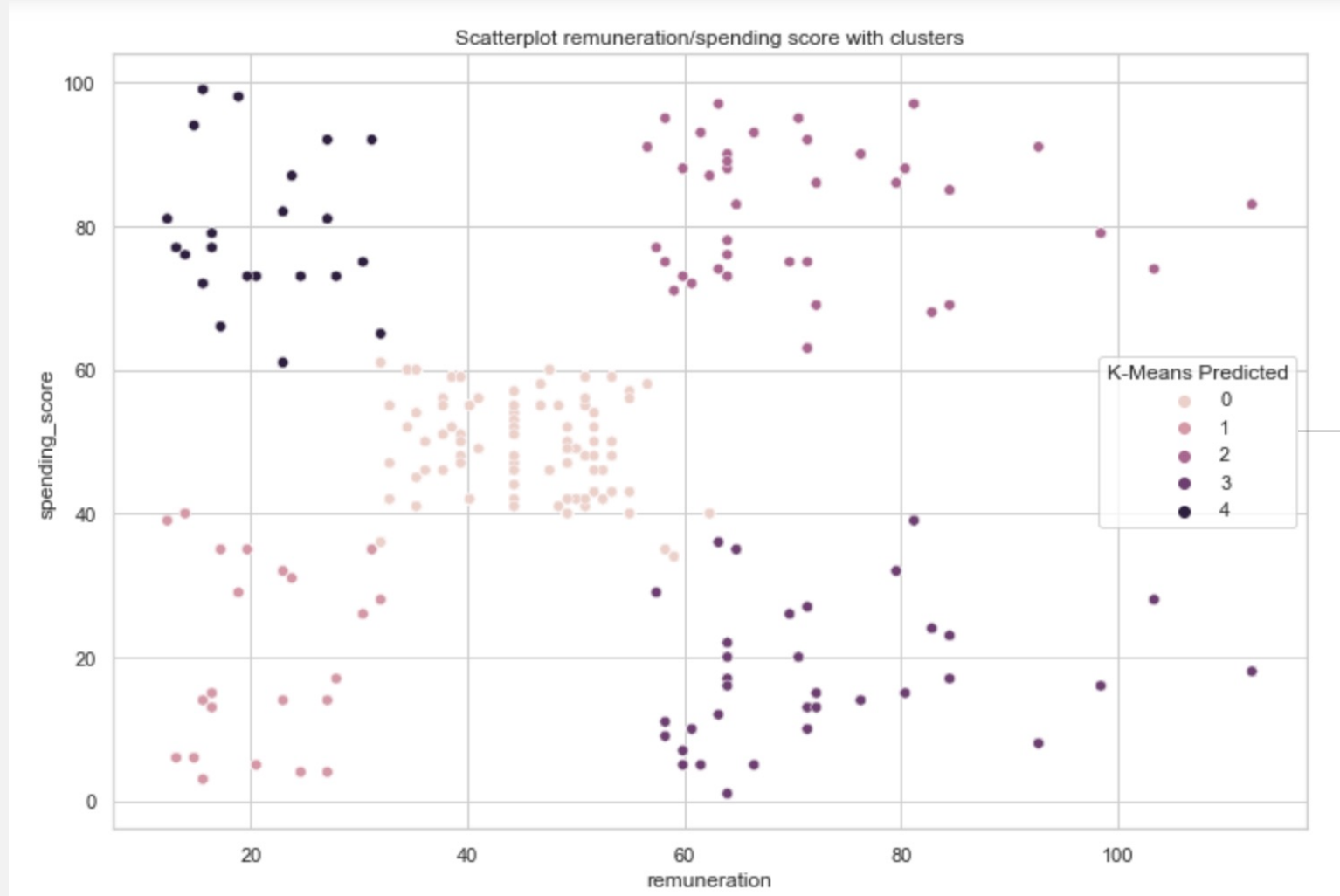
Source: Javier Conde (2022)

Figure 2.3: Loyalty vs spending, remuneration, age



Source: Javier Conde (2022)

Figure 2.8: K-means chosen model for $k=5$ with cluster interpretation

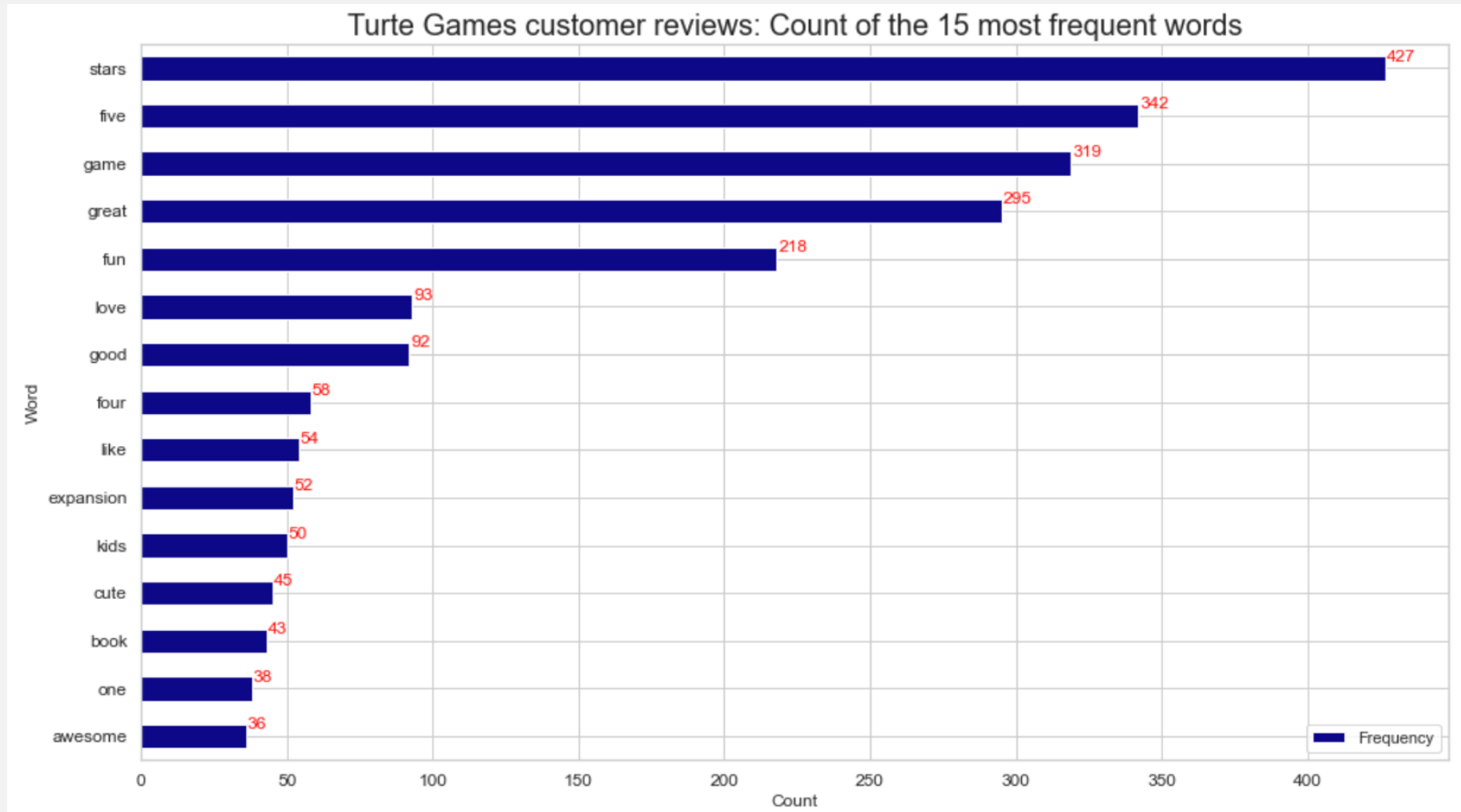


Cluster interpretation:

- group 1, low income and low spending
- group 4, low income and higher spending
- group 0, average income and average spending
- group 3, higher income and low spending
- group 2, higher income and higher spending

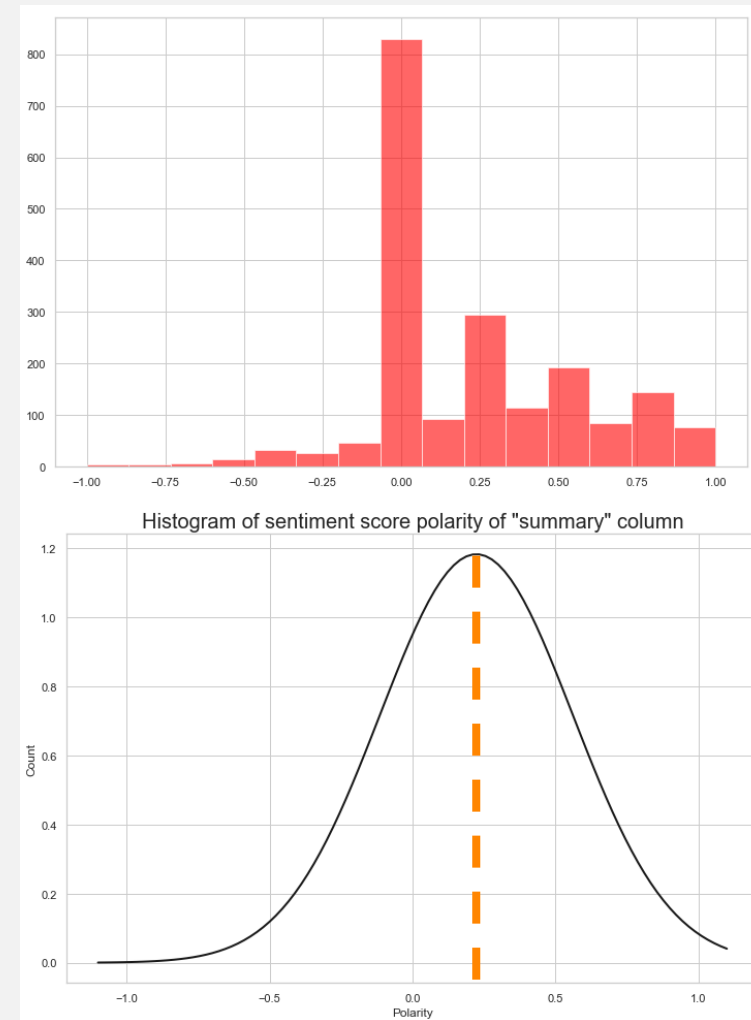
Source: Javier Conde (2022)

Figure 2.11: Plot for the data frame 15 most frequent words



Source: Javier Conde (2022)

Figure 2.12: Sentiment score polarity analysis for columns 'review' and 'summary'



Source: Javier Conde (2022)

Turtle Games sales

- The 'turtle_sales' data set provided is of great data quality (no duplicates, just two NA in 'Year' column). Outliers are not eliminated and they need to be closely monitored in further calculations
- From the initial scatterplot is visible a possible relationship between the variables 'Global_Sales' and 'NA/EU_Sales' robust enough to allow predictive studies on future global sales through a Multiple Linear Regression model with EU and NA sales as independent variables (modelA)
- Data sets provided on sales are far from normality (according to tests run on Q-Q plots, Shapiro-Wilk, skewness, and kurtosis), very relevant for further study
- Building a second model (modelB) including the variable "Product" for further exploration could be considered, as it adds some robustness (but also complexity) to modelA.
- Tested on 5 aleatory observations, predictive accuracy of modelA results average to good

Source: Javier Conde (2022)

Figure 2.14: Data cleaning and subset creation: NA, duplicated observations, unnecessary columns

```

49 # Explore NA and duplicates.
50
51 is.na(turtle_sales)
52 apply(is.na(turtle_sales), 2, which)
53
54 # Only two NA in 'Year' column, rows 180 and 258. Remove these columns in next
55 # step so no action taken.
56
57 duplicated(turtle_sales)
58
59 # No duplicated observations.
60
61 # Create a new data frame from a subset of the sales data frame.
62 # Remove unnecessary columns (Ranking, Year, Genre, Publisher).
63
64 turtle_sales2 <- subset(turtle_sales, select=-c(Ranking, Year, Genre, Publisher))
65
66 # View the data frame and structure.
67
68 turtle_sales2
69 str(turtle_sales2)
70
71 # View the descriptive statistics.
72
73 summary(turtle_sales2)
74

```

```

> apply(is.na(turtle_sales), 2, which)
$Ranking
integer(0)

$Product
integer(0)

$Platform
integer(0)

$Year
[1] 180 258

$Genre
integer(0)

$Publisher
integer(0)

$NA_Sales
integer(0)

$EU_Sales
integer(0)

$Global_Sales
integer(0)

```

```

> duplicated(turtle_sales)
[1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[12] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[23] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[34] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[45] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[56] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[67] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[78] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[89] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[100] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[111] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[122] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[133] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[144] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[155] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[166] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[177] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[188] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[199] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[210] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[221] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[232] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[243] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[254] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[265] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[276] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[287] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[298] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[309] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[320] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[331] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[342] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE

```

```

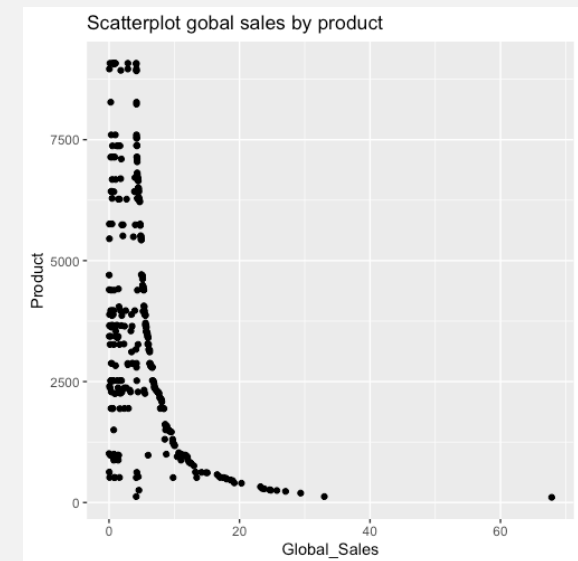
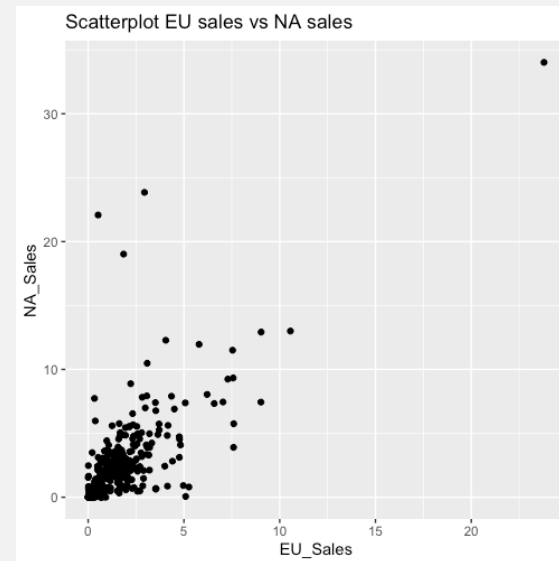
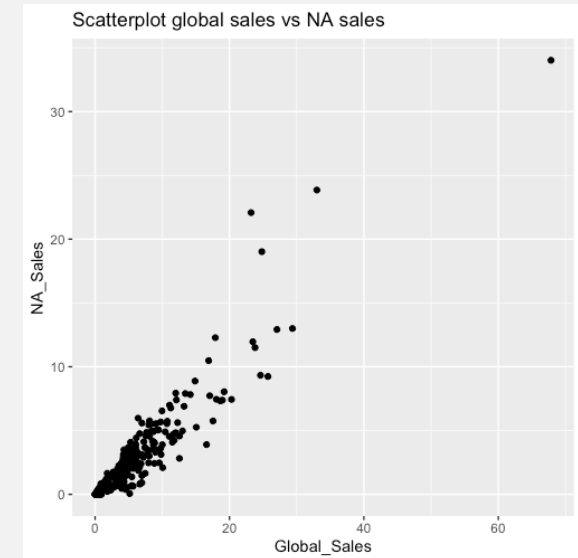
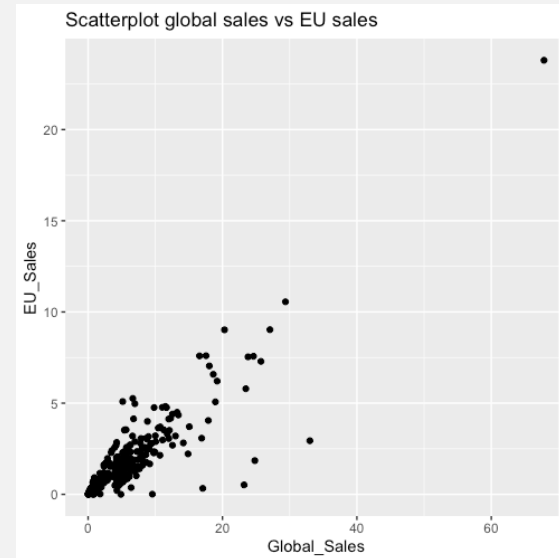
> summary(turtle_sales2)
      Product      Platform      NA_Sales      EU_Sales      Global_Sales
Min.   : 107   Length:352   Min.   : 0.0000   Min.   : 0.000   Min.   : 0.010
1st Qu.:1945   Class :character 1st Qu.: 0.4775   1st Qu.: 0.390   1st Qu.: 1.115
Median :3340   Mode  :character  Median : 1.8200   Median : 1.170   Median : 4.320
Mean    :3607                Mean    : 2.5160   Mean    : 1.644   Mean    : 5.335
3rd Qu.:5436                3rd Qu.: 3.1250   3rd Qu.: 2.160   3rd Qu.: 6.435
Max.    :9080                Max.    :34.0200   Max.    :23.800   Max.    :67.850
>

```

Source: Javier Conde (2022)

Figure 2.15: Exploratory scatterplots with qplot

```
83 qplot(Global_Sales, EU_Sales, data=turtle_sales2,  
84       main='Scatterplot global sales vs EU sales')  
85  
86 qplot(Global_Sales, NA_Sales, data=turtle_sales2,  
87       main='Scatterplot global sales vs NA sales')  
88  
89 qplot(EU_Sales, NA_Sales, data=turtle_sales2,  
90       main='Scatterplot EU sales vs NA sales')  
91  
92 qplot(Global_Sales, Product, data=turtle_sales2,  
93       main='Scatterplot gobal sales by product')  
94
```

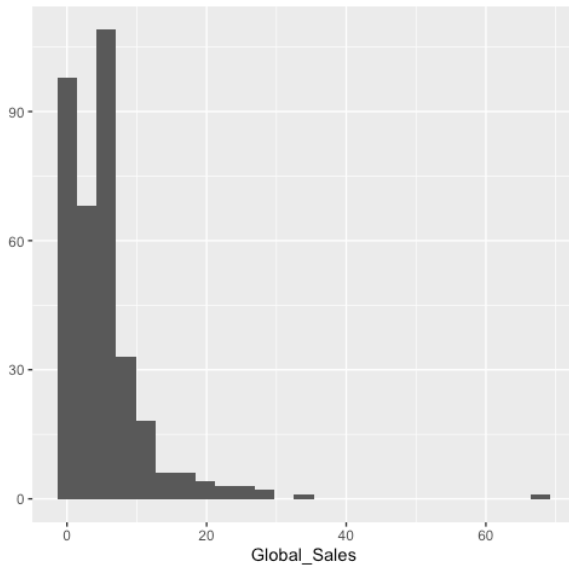


Source: Javier Conde (2022)

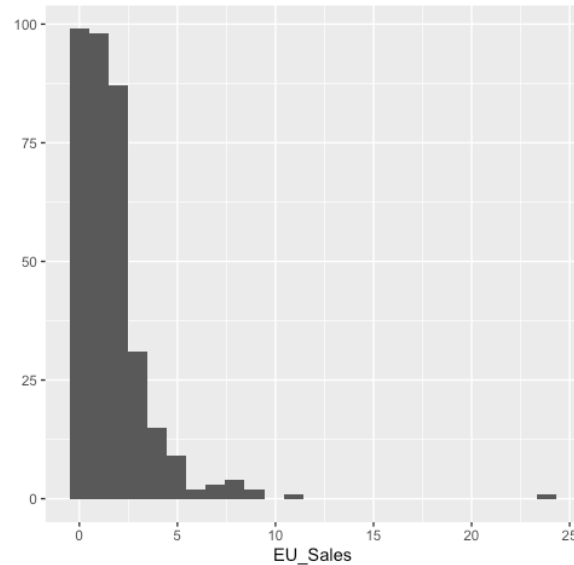
Figure 2.16: Exploratory histograms with qplot

```
98 qplot(Global_Sales, bins=25, data=turtle_sales2, main='Histogram global sales')
99 qplot(EU_Sales, bins=25, data=turtle_sales2, main='Histogram EU sales')
100 qplot(NA_Sales, bins=25, data=turtle_sales2, main='Histogram NA sales')
101 qplot(Product, bins=25, data=turtle_sales2, main='Histogram product by ID')
```

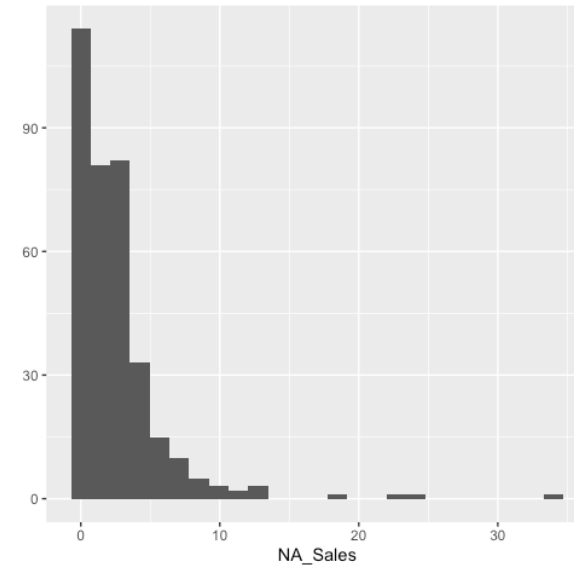
Histogram global sales



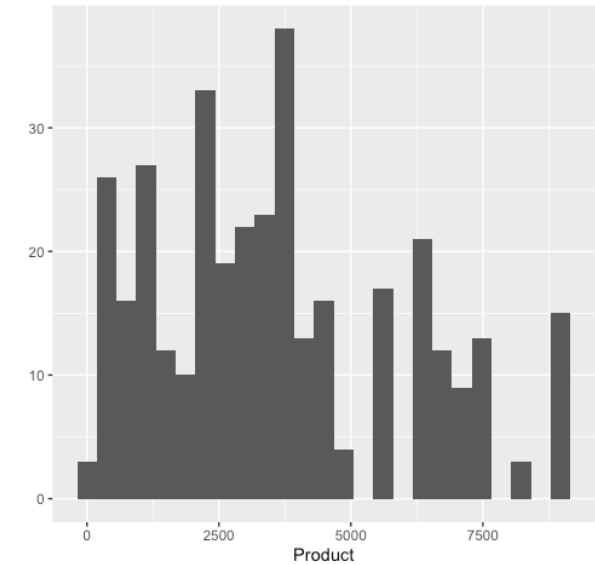
Histogram EU sales



Histogram NA sales



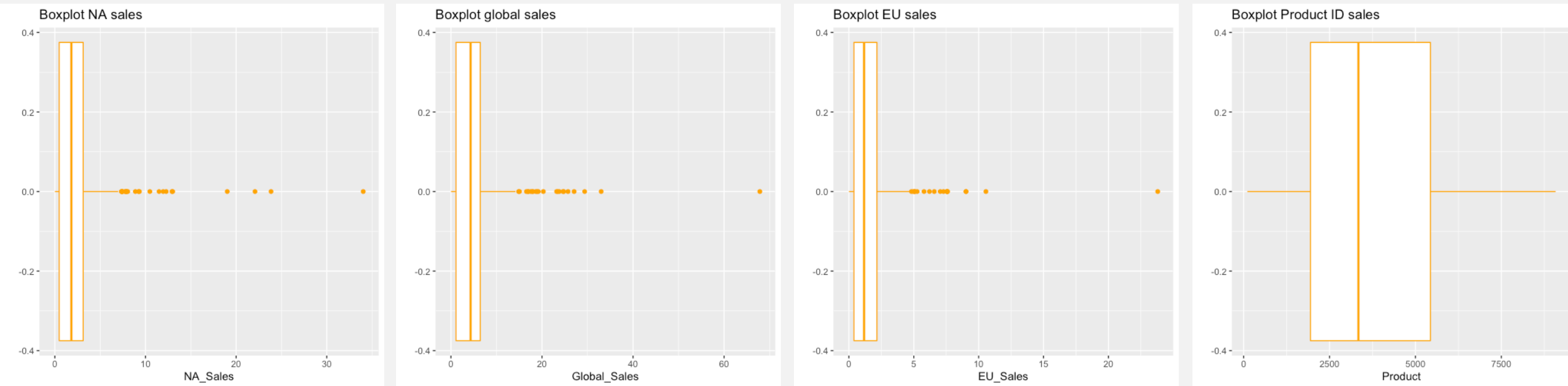
Histogram product by ID



Source: Javier Conde (2022)

Figure 2.17: Exploratory boxplots with qplot

```
106 qplot(Global_Sales, data=turtle_sales2, colour=I('orange'),  
107       main='Boxplot global sales', geom='boxplot')  
108  
109 qplot(EU_Sales, data=turtle_sales2, colour=I('orange'),  
110       main='Boxplot EU sales', geom='boxplot')  
111  
112 qplot(NA_Sales, data=turtle_sales2, colour=I('orange'),  
113       main='Boxplot NA sales', geom='boxplot')  
114  
115 qplot(Product, data=turtle_sales2, colour=I('orange'),  
116       main='Boxplot NA sales', geom='boxplot')
```



Source: Javier Conde (2022)

Figure 2.23: Variables correlation

```
287 # Correlation between the sales data columns.  
288  
289 round(cor(turtle_sales_product), digits=2)
```

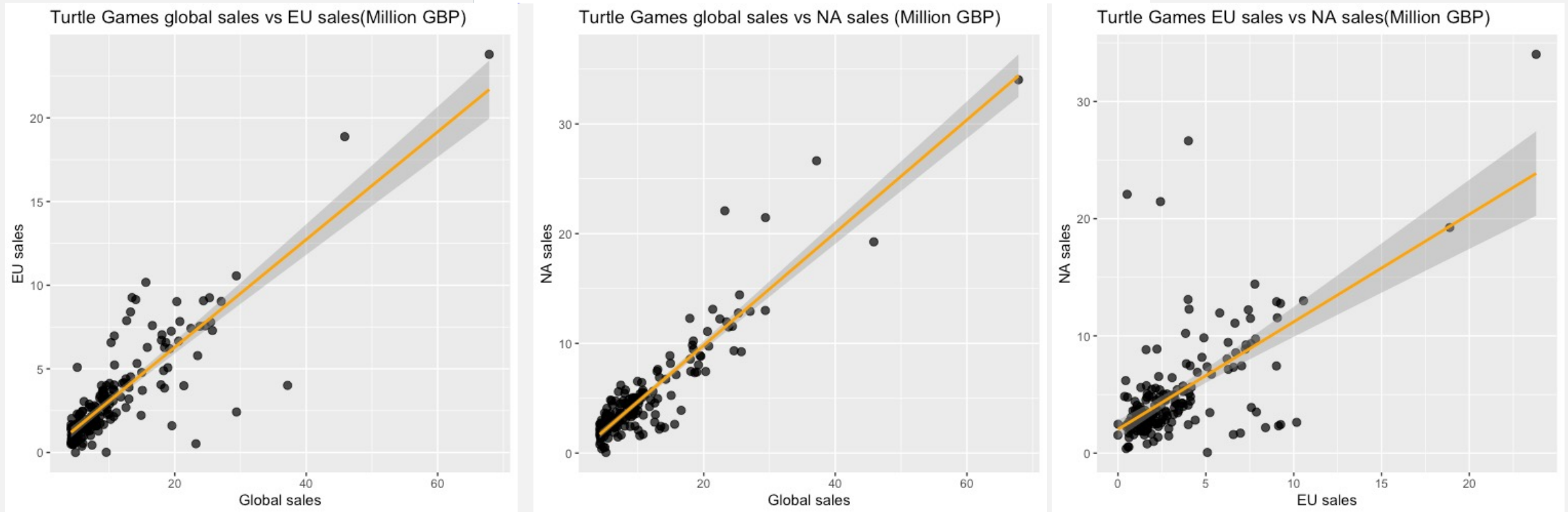
```
> round(cor(turtle_sales_product), digits=2)
```

	Product	NA_Sales	EU_Sales	Global_Sales
Product	1.00	-0.54	-0.45	-0.61
NA_Sales	-0.54	1.00	0.62	0.92
EU_Sales	-0.45	0.62	1.00	0.85
Global_Sales	-0.61	0.92	0.85	1.00

Source: Javier Conde (2022)

Figure 2.24: Advanced plotting (ggplot with linear approach)

```
> ggplot(data=turtle_sales_product,mapping=aes(x=Global_Sales, y=NA_Sales)) +  
+   geom_point(color='black',  
+             alpha=0.75,  
+             size=2.5) +  
+   geom_smooth(method='lm', color='orange') +  
+   scale_x_continuous("Global sales") +  
+   scale_y_continuous("North America sales") +  
+   labs(title="Turtle Games global sales vs North America sales (Million GBP)")  
`geom_smooth()` using formula 'y ~ x'
```



Source: Javier Conde (2022)

Figure 2.31: Multiple linear regression model (sales)

```
> modelA = lm(Global_Sales~NA_Sales+EU_Sales, data=turtle_sales_noproduct)
> summary(modelA)
```

Call:
lm(formula = Global_Sales ~ NA_Sales + EU_Sales, data = turtle_sales_noproduct)

Residuals:


Min	1Q	Median	3Q	Max
-3.4156	-1.0112	-0.3344	0.6516	6.6163

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	1.04242	0.17736	5.877	2.11e-08	***
NA_Sales	1.13040	0.03162	35.745	< 2e-16	***
EU_Sales	1.19992	0.04672	25.682	< 2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.49 on 172 degrees of freedom
Multiple R-squared: 0.9668, Adjusted R-squared: 0.9664
F-statistic: 2504 on 2 and 172 DF, p-value: < 2.2e-16



Source: Javier Conde (2022)

Figure 2.32: Multiple linear regression model (sales and product ID)

```
> modelB = lm(Global_Sales~NA_Sales+EU_Sales+Product, data=turtle_sales_product)
> summary(modelB)
```

Call:
lm(formula = Global_Sales ~ NA_Sales + EU_Sales + Product, data = turtle_sales_product)

Residuals:


	Min	1Q	Median	3Q	Max
	-3.3388	-0.9149	-0.2399	0.7364	5.9643

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	2.451e+00	3.167e-01	7.741	8.24e-13	***
NA_Sales	1.068e+00	3.179e-02	33.601	< 2e-16	***
EU_Sales	1.160e+00	4.421e-02	26.233	< 2e-16	***
Product	-2.753e-04	5.278e-05	-5.215	5.26e-07	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.388 on 171 degrees of freedom
Multiple R-squared: 0.9714, Adjusted R-squared: 0.9709
F-statistic: 1933 on 3 and 171 DF, p-value: < 2.2e-16



Source: Javier Conde (2022)

Figure 2.33: Value prediction (model A, sales) (I)

```
457 # A. NA_Sales_sum of 34.02 and EU_Sales_sum of 23.80
```

```
458
```

```
459 NA_Sales <- c(34.02)
```

```
460 EU_Sales <- c(23.80)
```

```
461
```

```
462 sales1 <- data.frame(NA_Sales, EU_Sales)
```

```
463
```

```
464 # Predicted Global_Sales value
```

```
465 predict(modelA, newdata = sales1)
```

```
466
```

```
467 # Predicted value 68.056 vs observation value 67.85 good
```

```
469 # B. NA_Sales_sum of 3.93 and EU_Sales_sum of 1.56.
```

```
470 # Values not on provided data set
```

```
471 # Most similar 3.94/1.28 with observed Global_sales value 8.36
```

```
472
```

```
473 NA_Sales <- c(3.94)
```

```
474 EU_Sales <- c(1.28)
```

```
475
```

```
476 sales2 <- data.frame(NA_Sales, EU_Sales)
```

```
477
```

```
478 # Predicted Global_Sales value
```

```
479 predict(modelA, newdata = sales2)
```

```
480
```

```
481 # Predicted value 7.03 vs observation value 8.36: average
```

Source: Javier Conde (2022)

Figure 2.34: Value prediction (model A, sales)(II)

```
483 # C. NA_Sales_sum of 2.73 and EU_Sales_sum of 0.65, observed value 4.32
484
485 NA_Sales <- c(2.73)
486 EU_Sales <- c(0.65)
487
488 sales3 <- data.frame(NA_Sales, EU_Sales)
489
490 # Predicted Global_Sales value
491 predict(modelA, newdata = sales3)
492
493 # Predicted value 4.90 vs observation value 4.32 good
494
495 # D. NA_Sales_sum of 2.26 and EU_Sales_sum of 0.97.
496 # Values not on provided data set
497 # Most similar 2.27/2.30 with observed Global_sales value 5.60
498
499 NA_Sales <- c(2.27)
500 EU_Sales <- c(2.30)
501
502 sales4 <- data.frame(NA_Sales, EU_Sales)
503
504 # Predicted Global_Sales value
505 predict(modelA, newdata = sales4)
506
507 # Predicted value 6.36 vs observation value 5.60 average
```

Source: Javier Conde (2022)

Figure 2.35: Value prediction (model A, sales)(III)

```
509 # E. NA_Sales_sum of 22.08 and EU_Sales_sum of 0.52, Global sales 23.21
510
511 NA_Sales <- c(22.08)
512 EU_Sales <- c(0.52)
513
514 sales <- data.frame(NA_Sales, EU_Sales)
515
516 # Predicted Global_Sales value
517 predict(modelA, newdata = sales)
518
519 # Predicted value 26.62 vs observation value 23.21: average
```

Source: Javier Conde (2022)

Figure 3.3: Recommendations to the marketing department

- Consider the 5 groups uncovered during the analysis to investigate further other possibly useful relationships (suggested to start with loyalty/gender, loyalty/education, loyalty/product (any product customers keep coming back for?))
- Study further the products associated to great reviews where these words appear. Are there any products with great reviews that haven't been given the marketing exposure?
- Study further also products associated to more negative reviews, data may be available here to understand lack of sales/interest and how to amend it
- Due to the good quality of the data provided, if budget and resources allow consider expanding the study to a bigger sample for more in-depth insights, maybe considering other social media (Instagram, Twitter)
- Ensure communication with other departments is fluid, this may be key to shift projects' priorities (i.e. understanding best selling products per region, provided by the sales department) (Figure 3.4)

Source: Javier Conde (2022)

Figure 3.4: Turtle Games best sellers

Product	NA_Sales	EU_Sales	Global_Sales
107	34.02	23.80	67.85
515	19.25	18.88	45.86
123	26.64	4.01	37.16
254	21.46	2.42	29.39
195	13.00	10.56	29.37
231	12.92	9.03	27.06
249	9.24	7.29	25.72
948	14.42	7.79	25.45

Product	NA_Sales	EU_Sales	Global_Sales
107	34.02	23.80	67.85
515	19.25	18.88	45.86
195	13.00	10.56	29.37
3967	2.63	10.17	15.59
2371	2.44	9.26	13.49
876	12.77	9.25	25.28
3645	2.33	9.14	14.06
979	11.55	9.07	24.36

Product	NA_Sales	EU_Sales	Global_Sales
107	34.02	23.80	67.85
123	26.64	4.01	37.16
326	22.08	0.52	23.21
254	21.46	2.42	29.39
515	19.25	18.88	45.86
948	14.42	7.79	25.45
535	13.11	3.99	21.38
195	13.00	10.56	29.37

Source: Javier Conde (2022)

Figure 3.5: Recommendations to the sales department

- Consider investing budget and resources in further study on MLR models, maybe including variables like product or game genre, with an extended data set to improve accuracy. This may also improve normality in the data set
- Consider comparing sales data from various years and establish a 3/5 year time-series study with the sales evolution of products/game genres/platforms per region
- Communicate with other departments (i.e. marketing) sales figures to develop a joint strategy on how to promote products that could be potential hits in the future. Consider creating an interactive dashboard (i.e. Tableau, interactive visualisations in RStudio) for other departments to have access to sales information in real time

Source: Javier Conde (2022)



Thank You
