The Impact of International Shipping on Product Ratings: A Bayesian Analysis

Group No. 14

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Dataset Description

Source: Global Retail Sales Data: Orders, Reviews & Trends (Kaggle)

```
merch_data <- read.csv("merch_sales.csv")
#install.packages("data.table")
head(merch_data)
```

Total Observation :7394

	Order ID	Order Date	Product ID	Product Category	Buyer Gender	Buyer Age	Order Location	International Shipping	Sales Price	Shipping Charges	Sales per Unit	Quantity	Total Sales	Rating	Review
0	189440	7/21/2024	BF1543	Clothing	Male	30	New Jersey	No	100	0	100	1	100	4	The delivery team handled the product with care.
1	187385	7/20/2024	BF1543	Clothing	Male	32	Las Vegas	No	100	0	100	1	100	3	Had slight delays but the product was in good ...
2	181844	7/21/2024	BF1544	Other	Female	26	Cardiff	Yes	9	40	49	1	49	2	Waste of Money.
3	197934	8/19/2024	BF1544	Other	Male	28	Pittsburgh	No	9	0	9	2	18	3	Had slight delays but the product was in good ...
4	122470	1/6/2024	BF1545	Other	Female	19	Miami	No	10	0	10	3	30	5	Lack of delivery delays is greatly appreciated.

Dataset Description

Features:

Order ID (Unique identifier)

Order Date

Product ID (Unique identifier for products)

Product Category Categorical (nominal)

Buyer Gender Categorical (nominal)

Buyer Age Numerical

Order Location Categorical (nominal)

International Shipping Categorical (binary)

Sales Price (continuous)

Shipping Charges (continuous)

Sales per Unit (continuous)

Quantity (discrete)

Total Sales (continuous)

Rating (Ordinal)

Review (Text)

Data Preprocessing

- **No Missing Value**

```
# Check for missing values in columns
colSums(is.na(merch_data))
```

```
[1] FALSE
```

Order.ID	Order.Date	Product.ID	Product.Category	Buyer.Gender
0	0	0	0	0
Buyer.Age	**Order.Location**	**International.Shipping**	**Sales.Price**	**Shipping.Charges**
0	0	0	0	0
Sales.per.Unit	**Quantity**	**Total.Sales**	**Rating**	**Review**
0	0	0	0	0

- **Selection of Relevant Column**

```
[1] "Product.ID"            "Product.Category"      "Buyer.Gender"          "Buyer.Age"
[5] "International.Shipping" "Sales.Price"          "Shipping.Charges"      "Sales.per.Unit"
[9] "Quantity"              "Total.Sales"           "Rating"
```

- **Factored Categorical Columns**:

Converted categorical columns (Buyer.Gender, International.Shipping, Product.Category) to factors to properly handle model fitting.

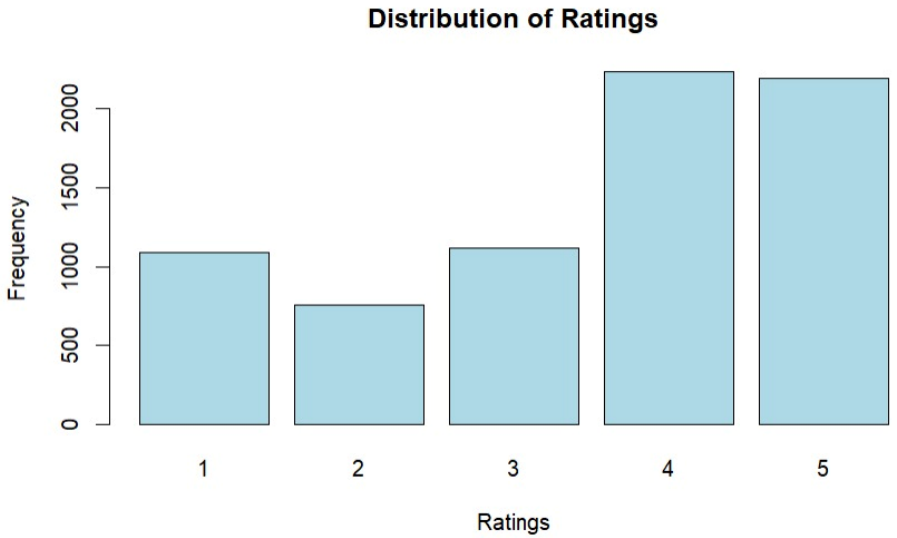

Fig 01:Frequency Distribution of Product Ratings

Fig 02:Comparison of Product Ratings: Domestic vs. International Shipping

Ordinal Logistic Regression

- **Handles Ordered Response:**

  Ideal for analyzing the ordinal target variable .For this dataset, the target variable “Rating” is an ordered categorical variable (1 to 5)

- **Supports Hierarchical Structure:**

  Captures variability across levels such as random effects for Product.Category**.**

- **Interpretability**:

  Results can be presented in terms of **log-odds** or **probabilities**, making them intuitive for conclusions.

Prior

- A prior represents the beliefs about a parameter's possible values before observing the data. Priors influence the posterior distribution.

- **Normal priors (normal(0, 5))** : **(Weakly informative)** 0 is the mean, suggesting no prior bias toward a specific direction (positive or negative) in the regression coefficients or thresholds. 5 is the standard deviation, indicating a broad prior with high uncertainty.

- **Student-t Prior (student_t(3, 0, 2))** : **(Weakly informative)** student_t(3, 0, 2) for group-level standard deviations (robust to outliers compared to normal distribution, heavy-tailed)

Why Used These Priors:
Normal prior for coefficients and intercepts prevents extreme estimates, ensuring meaningful results.
The Student-t prior allows for robust modeling of group-level effects (Hierarchical Model) to avoid over- or underestimating group-level variability.

Model 1:

- **Intercepts:**

Define thresholds for the cumulative probabilities of different ratings. 95% credibility intervals (CI) indicate well-defined thresholds as all intercepts are narrow and exclude 0.

- **Product.Category:**

Product.Category2 (-0.12): 95% CI = (-0.29, 0.05) as the CI includes 0, indicating no significance.

Product.Category3 (0.03): 95% CI = (-0.18, 0.24) indicates that no significant effect on Rating.

- **International.ShippingNo** (0.02): 95% CI = (-0.09, 0.13) as the CI includes 0, indicating no significance.

- **Buyer.Age , Sales.Price , Quantity , Total.Sales** don't affect the product ratings.

```
 Family: cumulative
  Links: mu = logit; disc = identity
Formula: Rating ~ Product.Category + Buyer.Age + International.Shipping + Sales.Price + Quantity + Total.Sales
   Data: merch_data_updated (Number of observations: 7394)
  Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup draws = 4000

Regression Coefficients:
                      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept[1]             -1.73      0.17    -2.06    -1.41 1.00     2969     2847
Intercept[2]             -1.07      0.16    -1.39    -0.76 1.00     2893     2918
Intercept[3]             -0.37      0.16    -0.70    -0.05 1.00     2783     2927
Intercept[4]              0.90      0.16     0.56     1.22 1.00     2855     2874
Product.Category2        -0.12      0.09    -0.29     0.05 1.00     1935     2630
Product.Category3         0.03      0.11    -0.18     0.24 1.00     1996     2482
Buyer.Age                 0.00      0.00    -0.00     0.01 1.00     5015     2705
International.ShippingNo  0.02      0.05    -0.09     0.13 1.00     3081     3116
Sales.Price              -0.00      0.00    -0.00     0.00 1.00     2006     2432
Quantity                  0.01      0.03    -0.06     0.07 1.00     3143     2631
Total.Sales               0.00      0.00    -0.00     0.00 1.00     2917     3017
```

Fig 03 :Model Summary

Model 1: Posterior Predictive Check

- The model's predicted ratings (y_rep) closely align with the observed ratings (y), indicating that the model effectively captures the overall distribution of the data

- The slight spread of the lighter lines (y_rep) around the dark line (y) reflects the model's ability to incorporate uncertainty, ensuring robust and realistic predictions

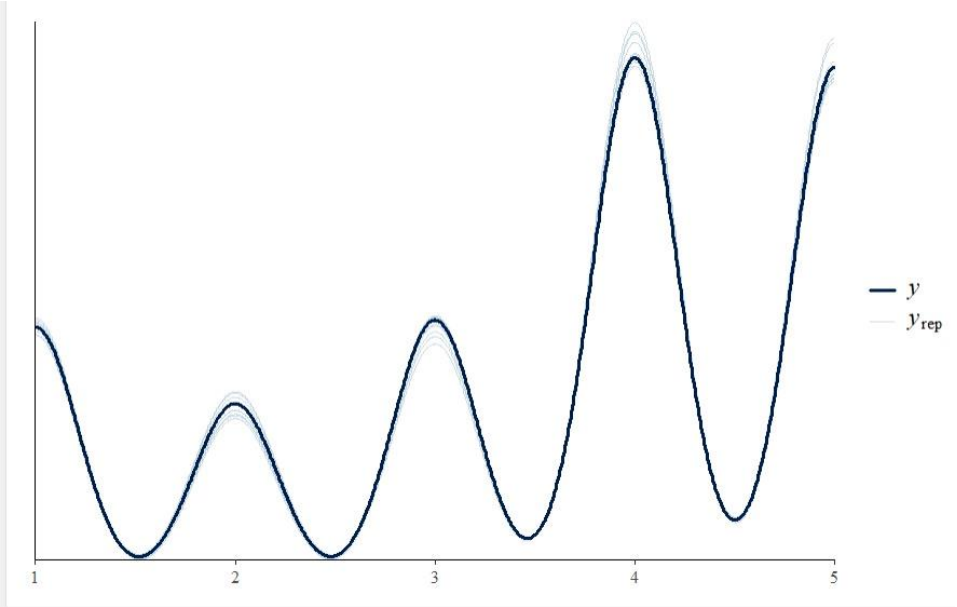

Fig 04 : Posterior Predictive Check

Model 2:

- **International.ShippingNo:** Positive coefficient (0.10), with credible intervals (-0.02, 0.23), suggests no strong evidence of significance.

- **Interaction Effects: International.ShippingNo:Product.Category 3 (-0.26):** The effect of domestic shipping on ratings decreases even more for products in Category 3. The CI (-0.50, -0.02) does not include 0, indicating a statistically significant interaction.

```
 Family: cumulative
  Links: mu = logit; disc = identity
Formula: Rating ~ International.Shipping * Product.Category
   Data: merch_data_updated (Number of observations: 7394)
  Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup draws = 4000

Regression Coefficients:
                                    Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept[1]                           -1.73      0.04    -1.81    -1.64 1.00     3301     3217
Intercept[2]                           -1.07      0.04    -1.15    -0.99 1.00     3932     3561
Intercept[3]                           -0.37      0.04    -0.44    -0.29 1.00     4073     3378
Intercept[4]                            0.90      0.04     0.82     0.97 1.00     3763     3493
International.ShippingNo                0.10      0.06    -0.02     0.23 1.00     2801     3067
Product.Category2                      -0.03      0.06    -0.14     0.08 1.00     3425     3053
Product.Category3                       0.18      0.07     0.05     0.31 1.00     3551     2940
International.ShippingNo:Product.Category2 -0.08  0.10    -0.28     0.12 1.00     2776     2600
International.ShippingNo:Product.Category3 -0.26  0.12    -0.50    -0.02 1.00     3148     3234
```

Fig 05 :Model 2 Summary

Model 2: Posterior Predictive Check

- The close alignment of these lines (y) and (y_rep) across all rating categories indicates that the model is effectively capturing the observed data distribution
- The simulated data closely mirrors the observed data's Peaks, especially for higher rating categories (4 and 5).
- Lower ratings (1, 2, and 3) also exhibit a good match between observed and predicted values

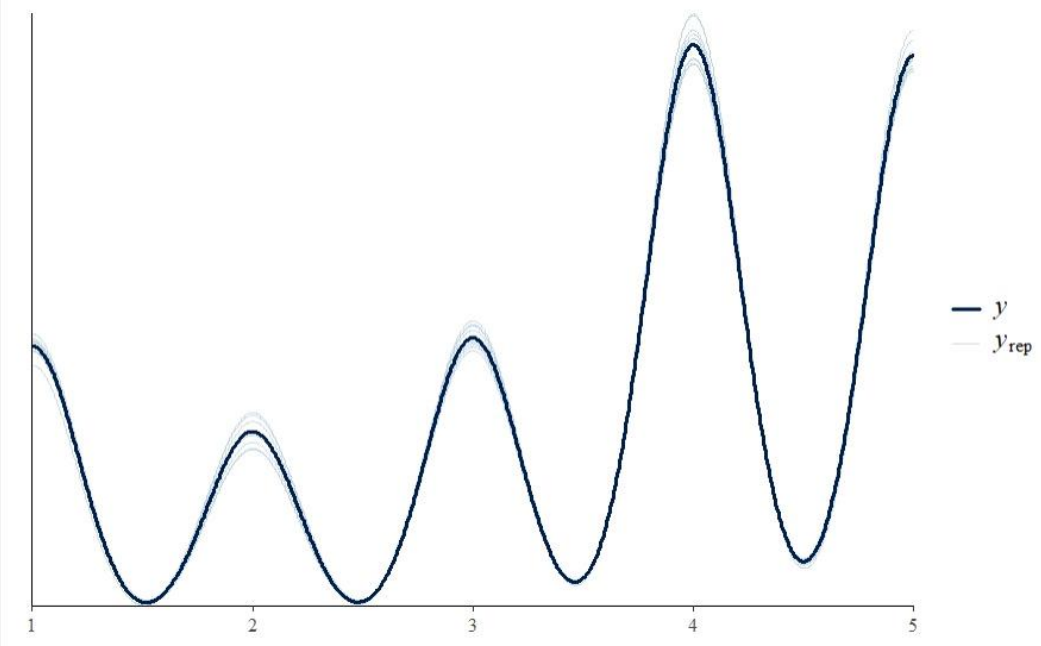

Fig 06: Posterior Predictive Check

Model 3: Hierarchical model

- **Intercepts:**

The four intercepts define the thresholds for the ordinal logistic regression, ensuring stable threshold estimates.by CI

- **Random Effect (Product.Category):**

Standard deviation of the random intercept for Product.Category is 0.23 with a 95% CI of 0.02 to 1.07, indicating variability in ratings across product categories. Therefore, there is a small but meaningful variation in customer ratings between product categories.

- From the estimates and CI, fixed effects such as International.Shipping, Total.Sales and Shipping.Charges do not have a significant effect on product ratings

```
  Links: mu = logit; disc = identity
Formula: Rating ~ International.Shipping + Total.Sales + Shipping.Charges + (1 | Product.Category)
   Data: merch_data_updated (Number of observations: 7394)
  Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup draws = 4000

Multilevel Hyperparameters:
~Product.Category (Number of levels: 3)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.23      0.28     0.02     1.07 1.00      796      865

Regression Coefficients:
                      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept[1]             -1.73      0.18    -2.05    -1.30 1.00     1133      577
Intercept[2]             -1.07      0.17    -1.38    -0.65 1.00     1187      574
Intercept[3]             -0.37      0.17    -0.68     0.05 1.00     1092      587
Intercept[4]              0.89      0.17     0.58     1.32 1.00     1040      618
International.ShippingNo -0.05      0.10    -0.25     0.15 1.00     3468     2712
Total.Sales               0.00      0.00    -0.00     0.00 1.00     4117     3389
Shipping.Charges          0.00      0.00    -0.00     0.01 1.00     3587     2671
```

Fig 07: Model 3 Summary

Model 3: Posterior Predictive Check

- The hierarchical model is accurately capturing the observed distribution of ratings.
- The slight differences in densities for lower-frequency categories (2 and 3) are minimal and within the model's uncertainty range.

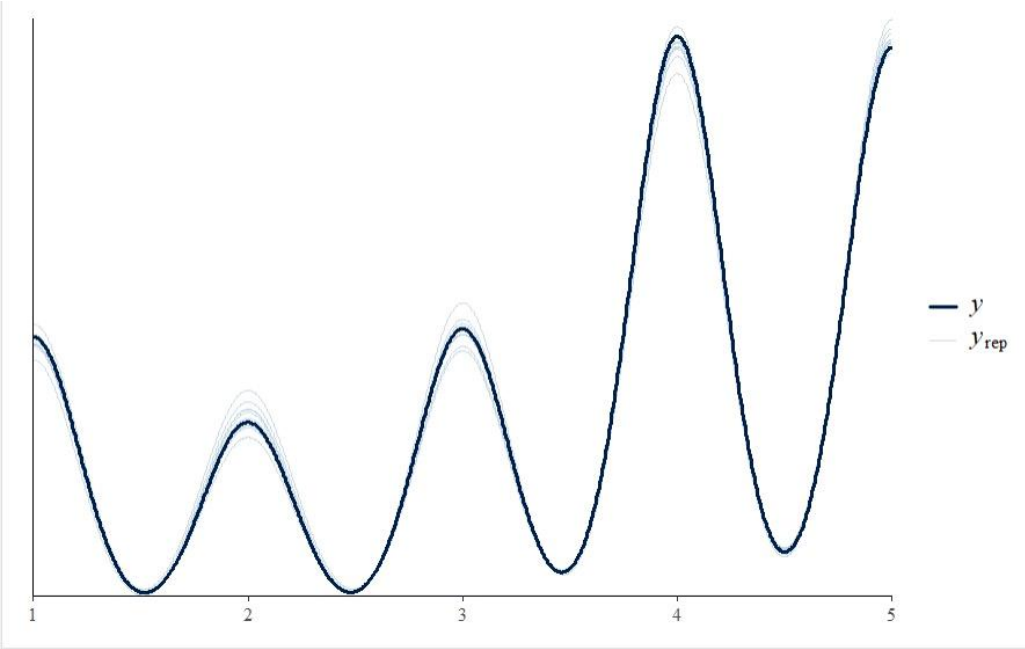

Fig 08 : Posterior Predictive Check

Model Comparison

```
# Compare the models
loo_comparison <- loo_compare(loo_ordinal_fit1, loo_ordinal_fit2,loo_hierarchical_model)
print(loo_comparison)# Print the comparison

```

```
                   elpd_diff se_diff
ordinal_model_fit2  0.0       0.0
hierarchical_model -1.8       2.4
ordinal_model_fit1 -3.1       2.7
```

Fig 09 : Model Comparison

- Ordinal_model_fit2 has the highest predictive performance with elpd_diff = 0 compared to all other models.

Limitations

- Limited predictors and missing temporal or marketing-related features such as marketing impact, customer demographics, or product quality.
- The dataset does not capture time-related trends (e.g., seasonality or sales periods) that might affect ratings.
- It's time consuming to work with a CPU specially for hierarchical model

Improvements

- Enrich dataset with additional variables and temporal trends.
- Explore customer segmentation and external factors in future studies.

Summary

- From the overall analysis, International shipping doesn’t influence the product rating.
- Ordinal Logistic Regression with all features, Ordinal Model with Interaction term and Bayesian Hierarchical Ordinal Model was fitted and compared.
- Bayesian hierarchical models are computationally intensive, especially with weakly informative priors, which can make convergence slower.
- Scopes for future studies and improvement.

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