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Master of
Management
Analytics

OPTIMIZING THE 'INSTABASKET' AISLE:
A DATA-DRIVEN APPROACH

Harnessing Data to Elevate MM&A's Customer Experience

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Agenda

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  - Defining Success: Metrics Overview
- **Analysis**
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  - Product Substitution
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Background

Business Objectives & Constraints

Main Objective

Enhancing the MM&A Experience: Responding to the high demand from Instabasket personal shoppers by populating a specialized aisle, optimizing both product selection and substitution based on data-driven insights.

Two Specific Aims

Product Configuration

Purpose: Populate the "Instabasket" aisle with top-performing products.

Based On: Historical purchasing data, focusing on products that have shown consistent high demand.

Efficient Substitution

Purpose: Seamlessly replace out-of-stock or unavailable items without disrupting the shopping experience.

Strategy: Identify and group products that can be appropriate substitutes for popular items, thus minimizing order disruptions.

Constraints

Product Capacity:

- Total products: 1000 max.
- Refrigerated items: 100 max.
- Frozen items: 100 max.

Substitution Parameters : Unrestricted substitution recommendations per product. However, the quality and relevance of substitution are considered.

Background

Defining Success: Metrics Overview

Metric #1: Product & Substitution Utilization:

Product Definition: Percentage of orders containing products from the Instabasket aisle.

Substitution Definition: Percentage of orders with at least one item from the recommended substitutes.

Target: A high percentage in both metrics signals the effectiveness and relevance of the Instabasket aisle and its substitute recommendations. ↑

Metric #2: Product & Substitution Aisle Utilization:

Product Definition: Average percentage of items in each order sourced from the Instabasket aisle.

Substitution Definition: Average percentage of substituted products in each order.

Target: Achieve a high percentage for both, reflecting the importance of aisle products and the acceptance of substitute suggestions. ↑

Metric #3: Store Flow Efficiency

Definition: Average number of other aisles visited outside the specialized aisle.

Target: Minimize, ensuring a seamless shopping experience and reduced disruptions. ↓

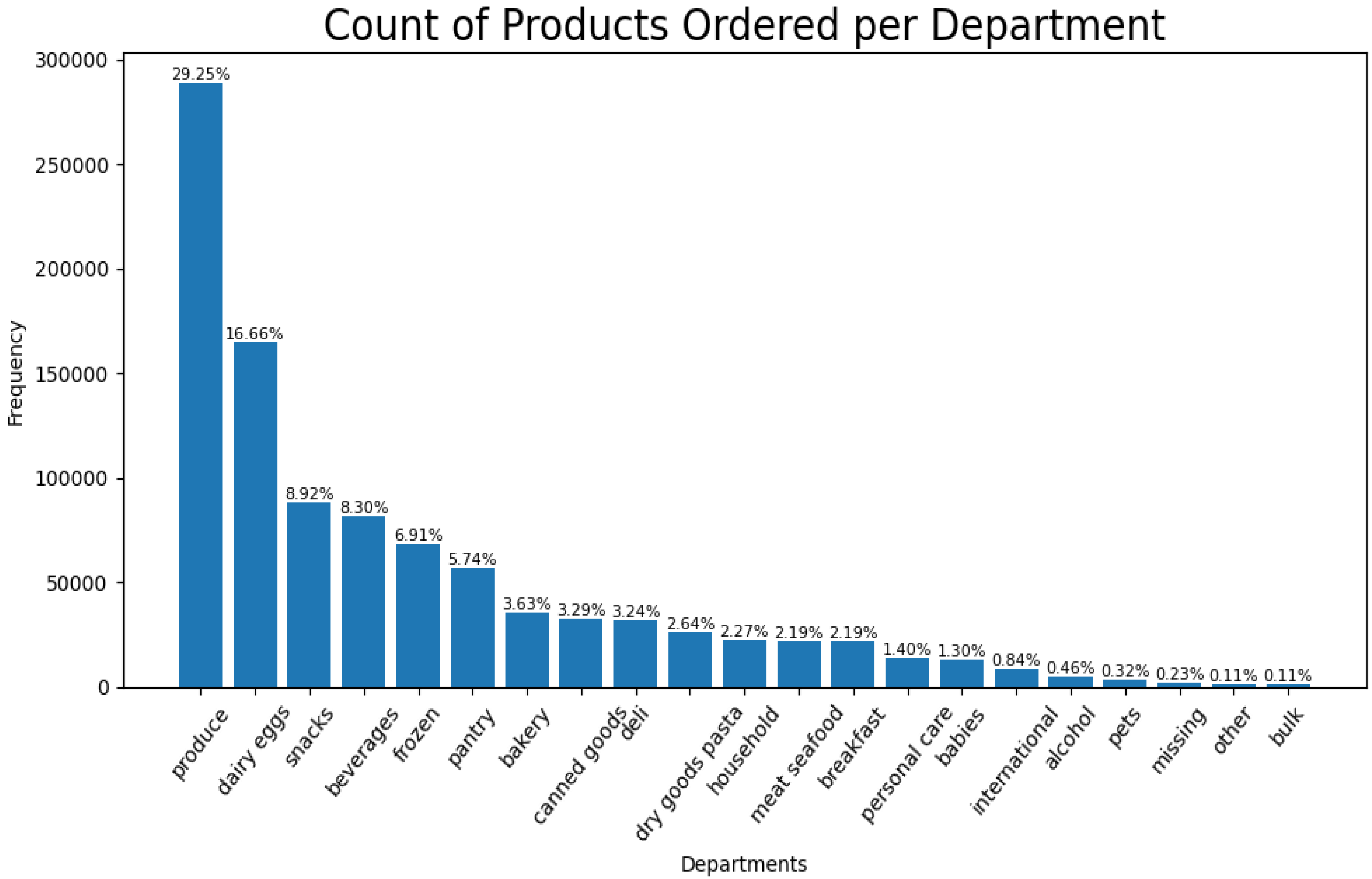
Analysis

Data Source & Key Data Tendencies

- Dataset used was from "[The Instacart Online Grocery Shopping Dataset]"
- The data collected was from 2017

- The dataset encompasses **987,000** individual records, representing about **98,000** distinct customer orders.
- Data spans **21** departments and **134** distinct product aisles
- Each order contains an average of **10** products

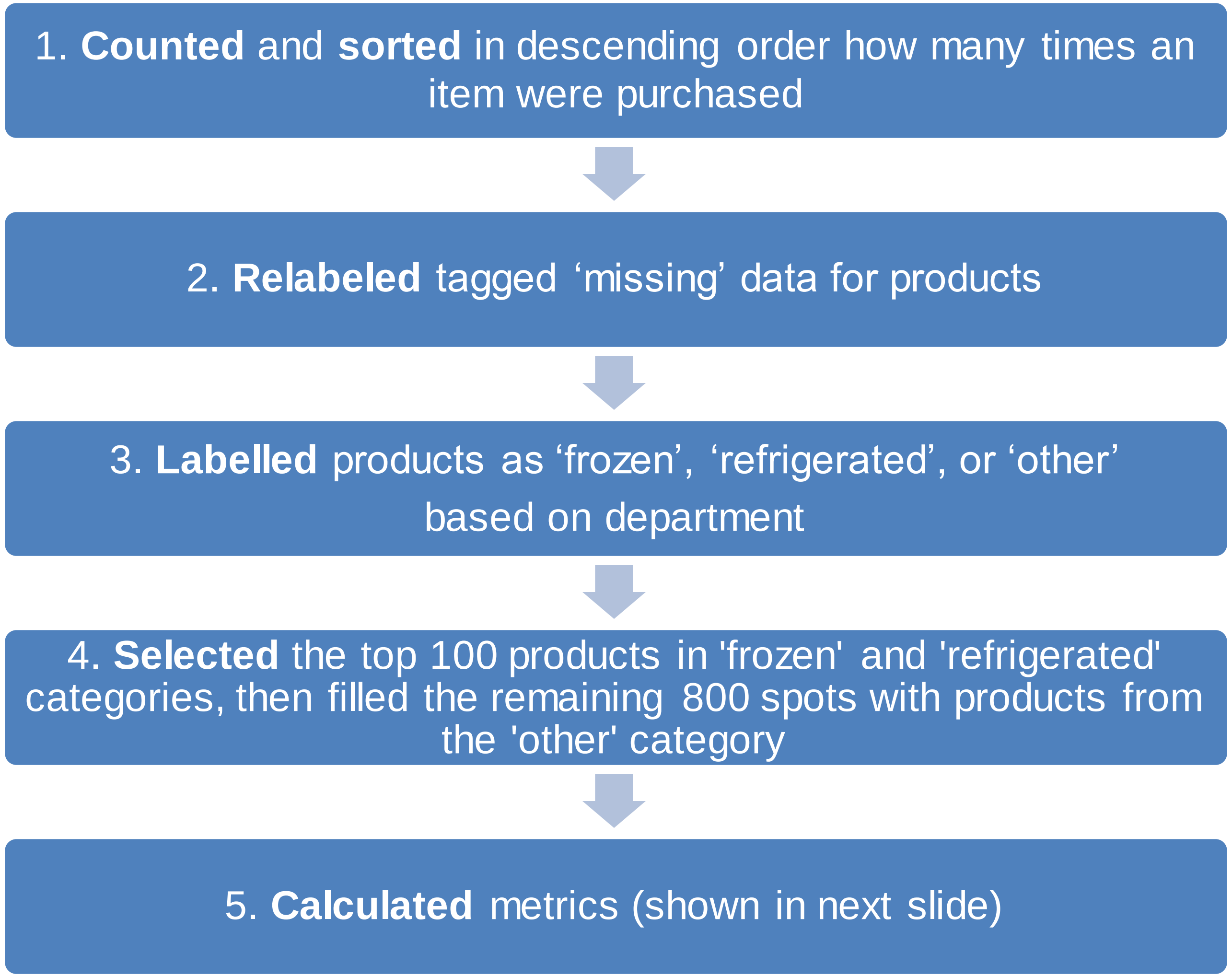
- Over **50%** of products ordered were from just 3 departments: Produce, Dairy & Eggs, and Snacks.
- The dataset contains some incomplete entries, notably with 'missing' department labels for certain products.



Count of Products Ordered per Department

Analysis

Product Selection: Methodology



1. **Counted** and **sorted** in descending order how many times an item were purchased

2. **Relabeled** tagged ‘missing’ data for products

3. **Labelled** products as ‘frozen’, ‘refrigerated’, or ‘other’ based on department

4. **Selected** the top 100 products in 'frozen' and 'refrigerated' categories, then filled the remaining 800 spots with products from the 'other' category

5. **Calculated** metrics (shown in next slide)

Key Considerations

- Our method was designed to maximize the utilization of the Instabasket aisle spaces allocated for 'frozen' and 'refrigerated' products.
- Products were determined as ‘frozen’, ‘refrigerated’, or ‘other’ (in-aisle shelves) based on department
- Some products were listed as missing or others which needed to be assigned to a more descriptive aisle before determining allocation to in-aisle, fridge, or freezer space
- Manually performed as there were few products that were highly purchased as will be shown below

Analysis

Product Selection: Model Accuracy & Expected Performance

Metric	Target*	Result
Orders that utilize the in-aisle items	97833	89846 **(91.84%)**
Average number of items in each order that utilize in-aisle items	10.09	5.23 **(51.86%)**
Median number of items in each order that utilize in-aisle items	6.0	4.0 **(66.67%)**

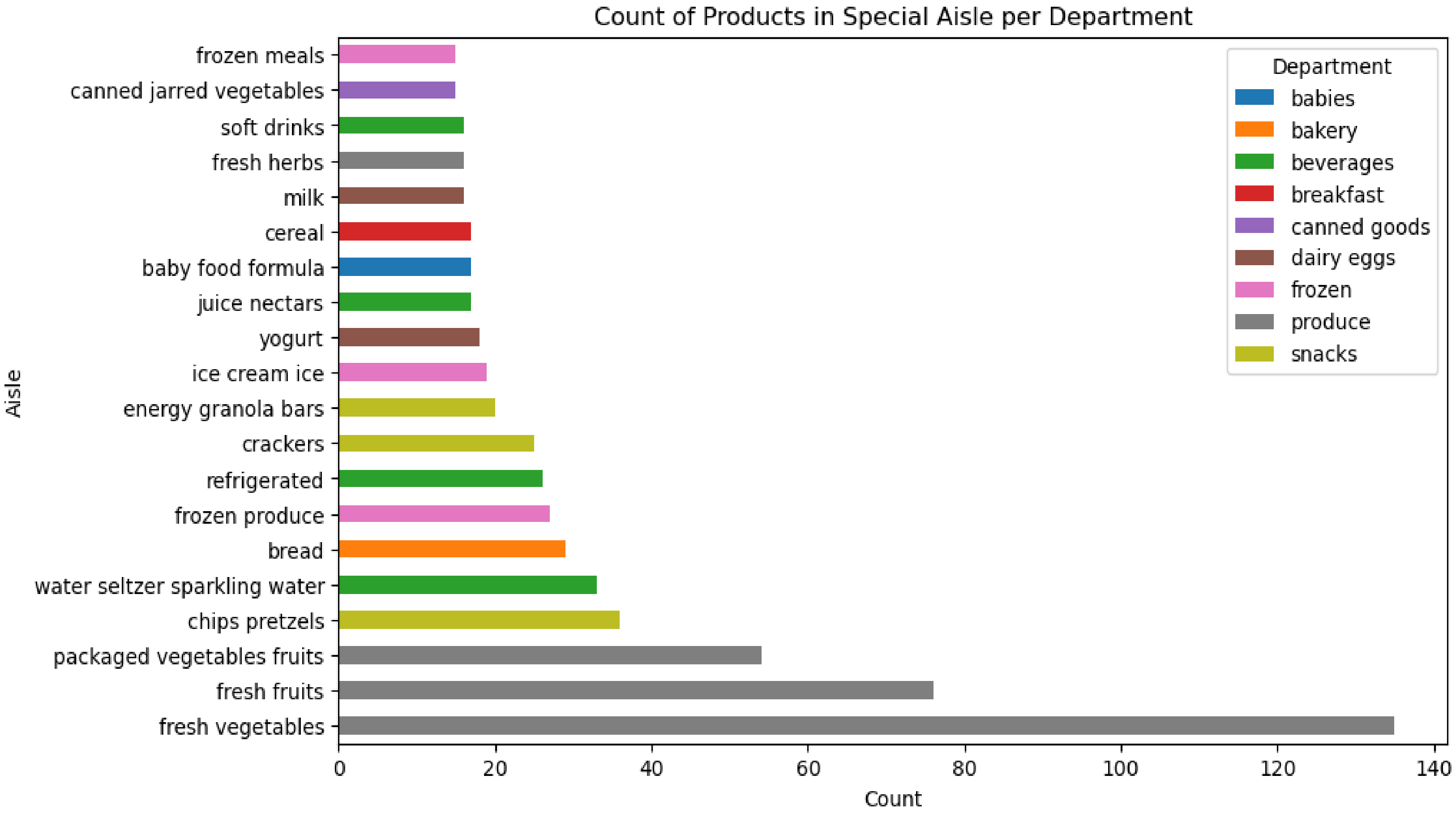
Note:

- We decided not to use a train-test split since the task isn't to build a predictive model but to identify a trend for the most frequently ordered products, so the entire dataset was used for the metrics.
- The benchmark for evaluating target outcomes is based on metrics assuming the absence of an InstaBasket aisle.

Analysis

Product Selection: Key insights

- **Produce Dominance:** The 'produce' department, encompassing fresh fruits and vegetables, significantly outnumbers other categories, emphasizing its role in customer preference.
- **Change in Dairy & Eggs**: Despite dairy and eggs showing popularity among shoppers, their prominence diminishes after filtering indicating a wide variety but fewer high-frequency items in this department.



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Analysis

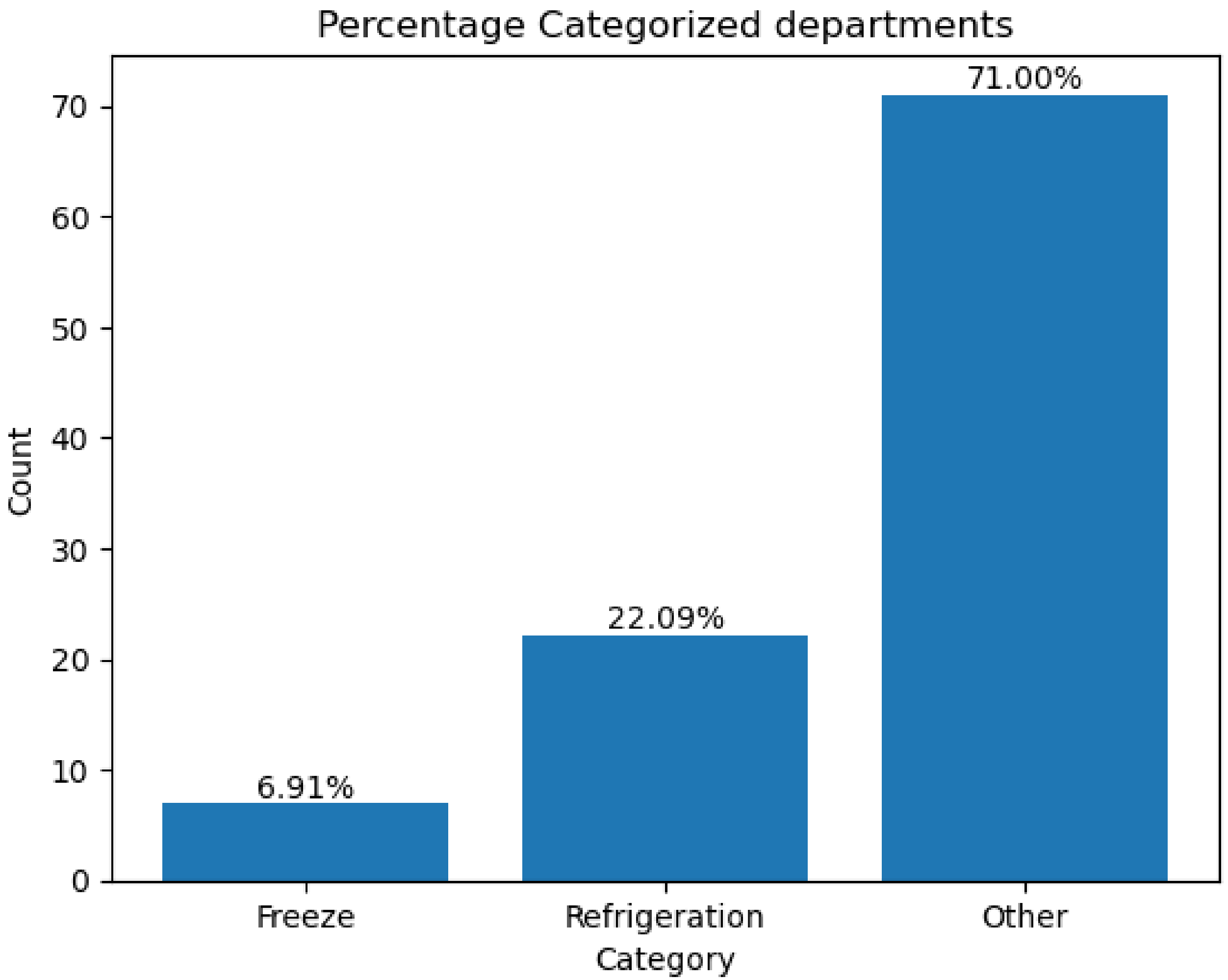
Product Selection: Limitations and Assumptions

- Given the popularity of '**Produce**' and limited refrigeration space, we decided NOT to include refrigeration categorization and classify as 'Other'.

- **Refrigeration** categorization is defined as products from the dairy eggs, meat seafood, or deli department

- **Frozen** categorization is defined as products from the frozen department

- All other products were categorized as '**Other**'



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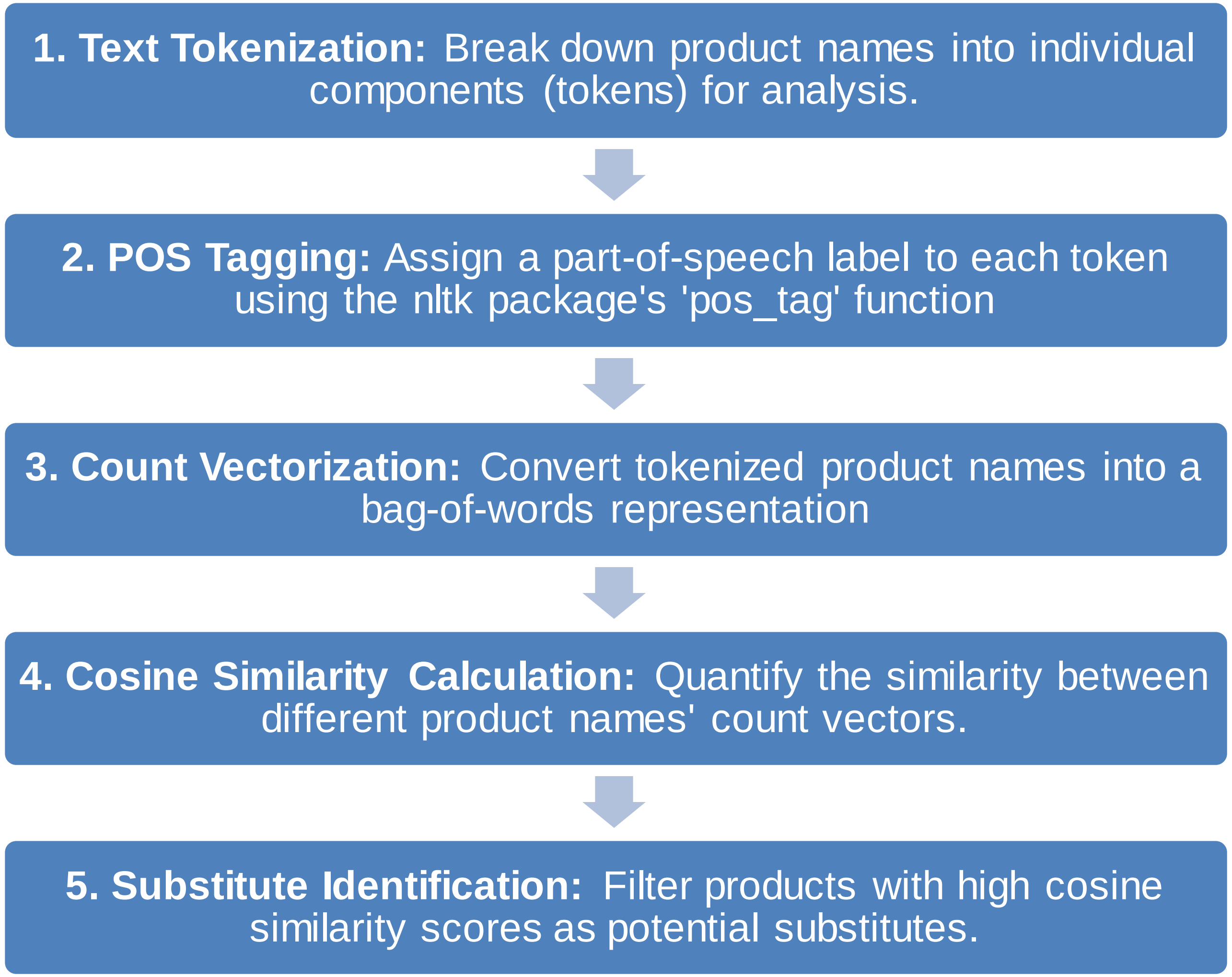
Analysis

Product Substitution: Methodology - Natural Language Processing (NLP)



1. Text Tokenization: Break down product names into individual components (tokens) for analysis.

2. POS Tagging: Assign a part-of-speech label to each token using the nltk package's 'pos_tag' function

3. Count Vectorization: Convert tokenized product names into a bag-of-words representation

4. Cosine Similarity Calculation: Quantify the similarity between different product names' count vectors.

5. Substitute Identification: Filter products with high cosine similarity scores as potential substitutes.

Key Considerations:

- **Preprocessing Filters:** Prior to word matching, excluded meaningless words, removed adjectives, omitted words with fewer than 2 characters, and converted plural nouns to singular form.
- **Quality Assurance:** Implement multiple filters to remove low similarity scores and to restrict the number of potential substitutes, to enhance the relevancy and accuracy of suggestions.
- **Accuracy Metrics:** Utilized a test-train split as well as a Precision@K metric to measure the accuracy of recommended product substitutes.

Analysis

Product Substitution: Model Accuracy & Expected Performance

Metric	Target	Result
Orders that utilize the in-aisle items	97833	92217 **(94.26%)**
Average number of items in each order that utilize in-aisle items	10.09	6.02 **(59.63%)**
Median number of items in each order that utilize in-aisle items	6.0	4.32 **(72%)**
Number of Product Substitution Recommendations	N/A	2745

Analysis

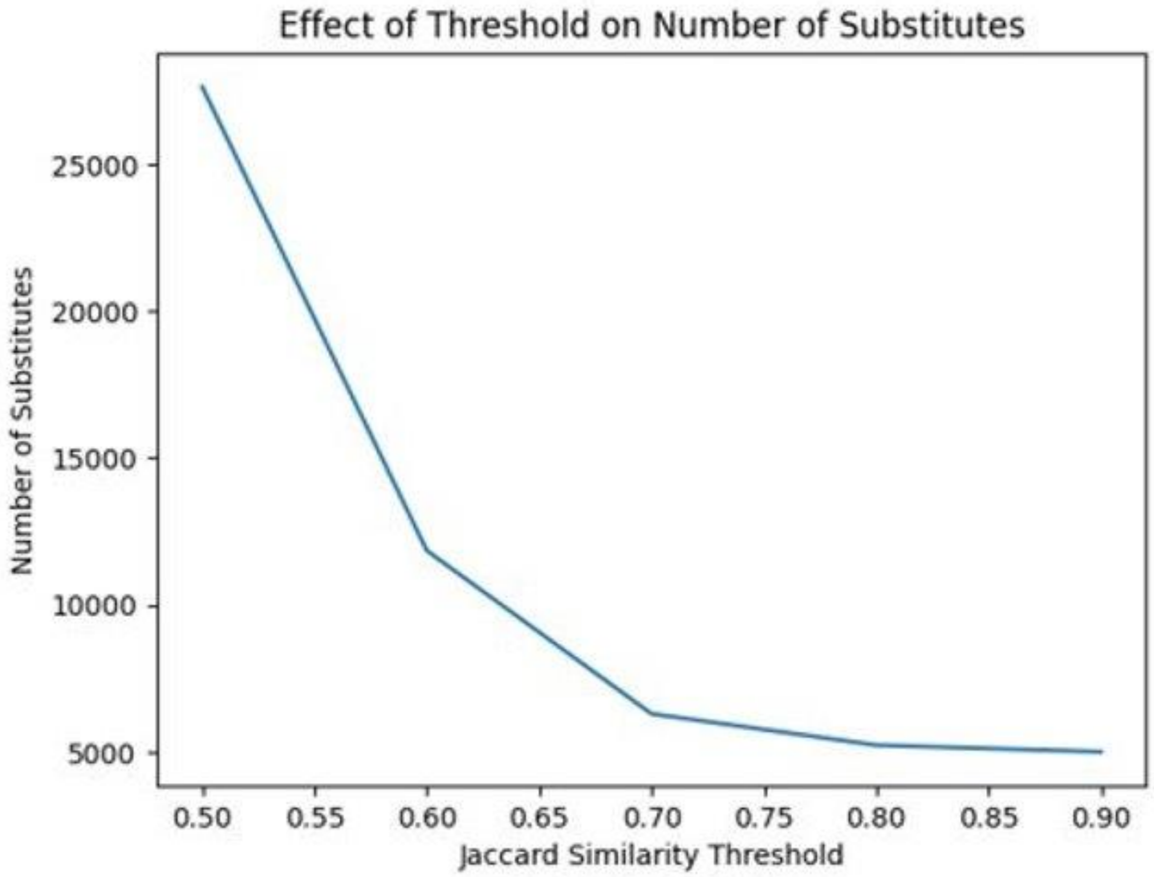
Product Substitution: Accuracy of Substitution Recommendations using Precision@K

Balancing Precision with Product Coverage

- Precision@K is a method to validate the accuracy of our substitution recommendations by comparing them against actual purchase patterns.
- By focusing on substitutes above the median threshold, our model suggests only top-tier substitutes.
- This strategy enhanced our Precision@K score, indicating a closer match with customer preferences, but reduced the overall number of product recommendations, as illustrated in the accompanying chart.

Achieved Precision@K:

- **Performance Data: 38.04%**
- **Interpretation:** Out of the product substitutes our model recommended, approximately 38.04% were actually bought together with the target product in real orders.



Analysis

Product Substitution: Assumption and Limitations

Assumptions

- **Acceptance of Substitutes:** The model presumes a full acceptance (100%) of all substitutions. Actual acceptance rates may differ, thus affecting the accuracy of the substitution recommendations.
- **Descriptiveness of Product Names:** Product names contain enough words to describe their nature and usage. Generic or vague product names affect the accuracy of substitutes.
- **Similarity Basis:** Products with similar names are assumed to be good substitutes. There is no consideration for brand loyalty.
- **Categorization Decision:** 'Produce' was classified as 'other' due to its popularity and restricted refrigeration space.

Limitations

- **Word Ordering:** Our model disregards the sequence in which words appear. Context is lost when the words are broken up.
- **Static Nature of the Model:** The NLP method misses nuances in customer buying behaviors, potentially leading to less accurate product suggestions.
- **Independence of Words:** The bag-of-words (BoW) model overlooks the interplay of words within product names.
- **Ignorance of Discounts:** The model did not focus on revenue, so the 5% discount offered for accepting substitutes wasn't considered. This may affect the actual impact of product substitutes.

Analysis

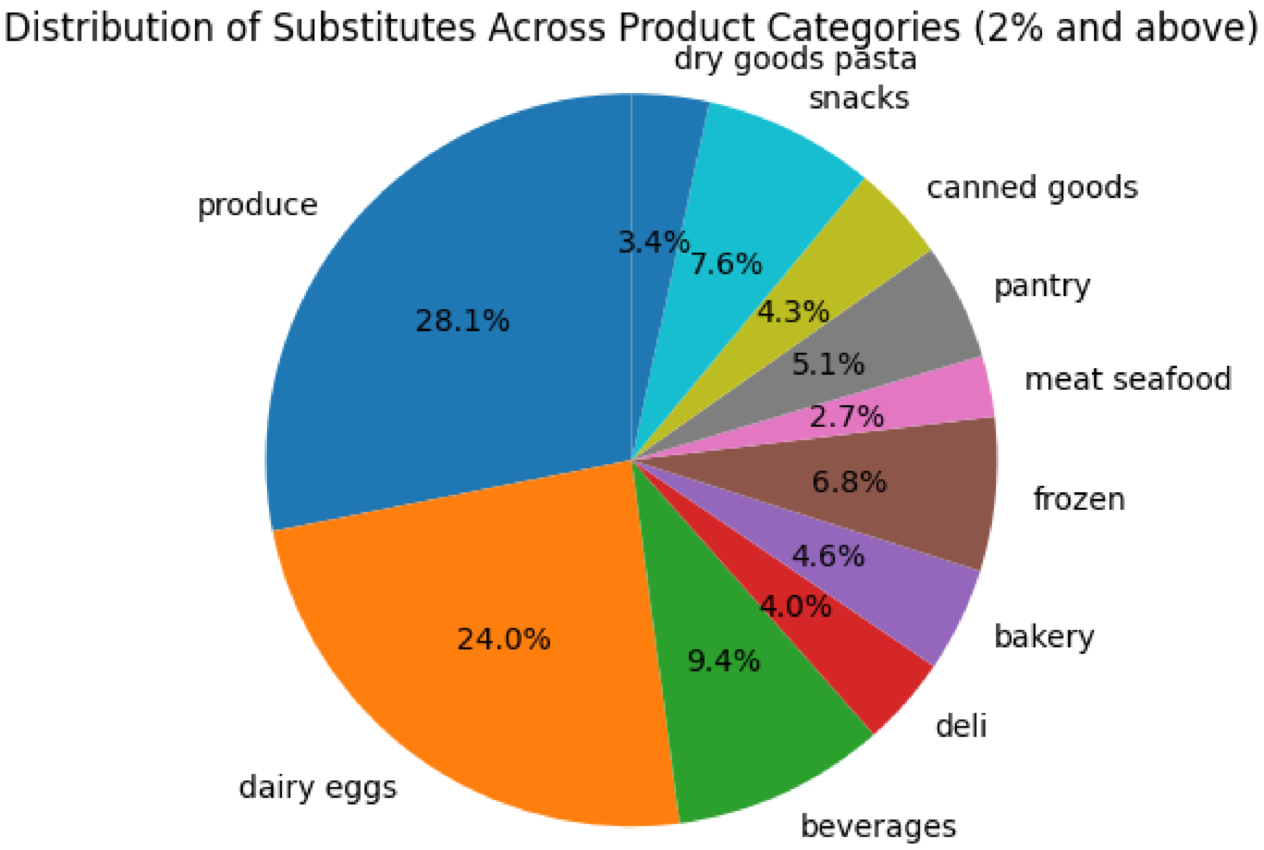
Product Substitution: Key Insights

- **Produce & Dairy Dominance**: Our model highlighted that a significant portion of substitutions pertained to the 'produce' (28.1%) and 'dairy & eggs' (24.0%) categories.

- **Tailored Recommendations:** Our model's focus on the descriptiveness of product names resulted in a nuanced distribution of substitutions across categories.

- **Substitution Opportunities:** Categories like 'meat seafood' and 'frozen' have a lower percentage of substitutions. These might represent areas where product naming might not be as descriptive, or where there are fewer available substitutes.

- **Revenue Considerations:** Categories with high substitution rates might benefit from targeted discounts or promotions.



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Conclusion

Future Work

Data Expansion: Integrate newer and more comprehensive datasets to capture changing shopping patterns.

Product Tagging: Implement auto-categorization of products to speed up selection and remove manual checks.

Enhanced Substitution Model Integration: Combine NLP and behavioural data for a holistic recommendation system. This could improve accuracy in product recommendations and lead to an increase in sales.

User Feedback Integration: Incorporate direct feedback from users and personal shoppers to get real-time enhancement of product recommendations and personalize shopping experiences.

Other Substitution Approaches Explored

Item-to-Item Based Collaborative Filtering:

- Uses customer behavior and cosine similarity metric to determine product substitution. For technical details on the Collaborative Filtering Approach, see Appendix A
- **Outcome**: Produced suboptimal results compared to our chosen NLP method.

FP-Growth & Apriori Method:

- Analyze frequent item sets in transaction data to uncover products often purchased together. For technical details on these methods, see Appendix A
- **Outcome**: Technical implementation issues and produced suboptimal results compared to our chosen NLP method.

Conclusion

Business Implications

Increased Store Aisle Efficiency: Our identification of the top 1000 and placement within an optimized "Instabasket" aisle reduces the need for shoppers to traverse multiple aisles, streamlining operations and reducing in-store customers.

Improved Customer Experience through Relevant Substitutes: Our NLP methodology offers customers top-tier product substitutes, potentially reducing out-of-stock disappointments. Suggesting high-quality product substitutions can lead to increased basket sizes and overall revenue growth.

Revenue Implications: Offering discounts for accepted substitutions may impact revenue. However, it could also enhance customer loyalty and satisfaction by offering value.

Acknowledgements

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Questions & Answers

We're open to feedback, questions, or any further discussions.

Here's
where it
changes.

Appendix A

Links to Relevant Codebases

Product Selection Code

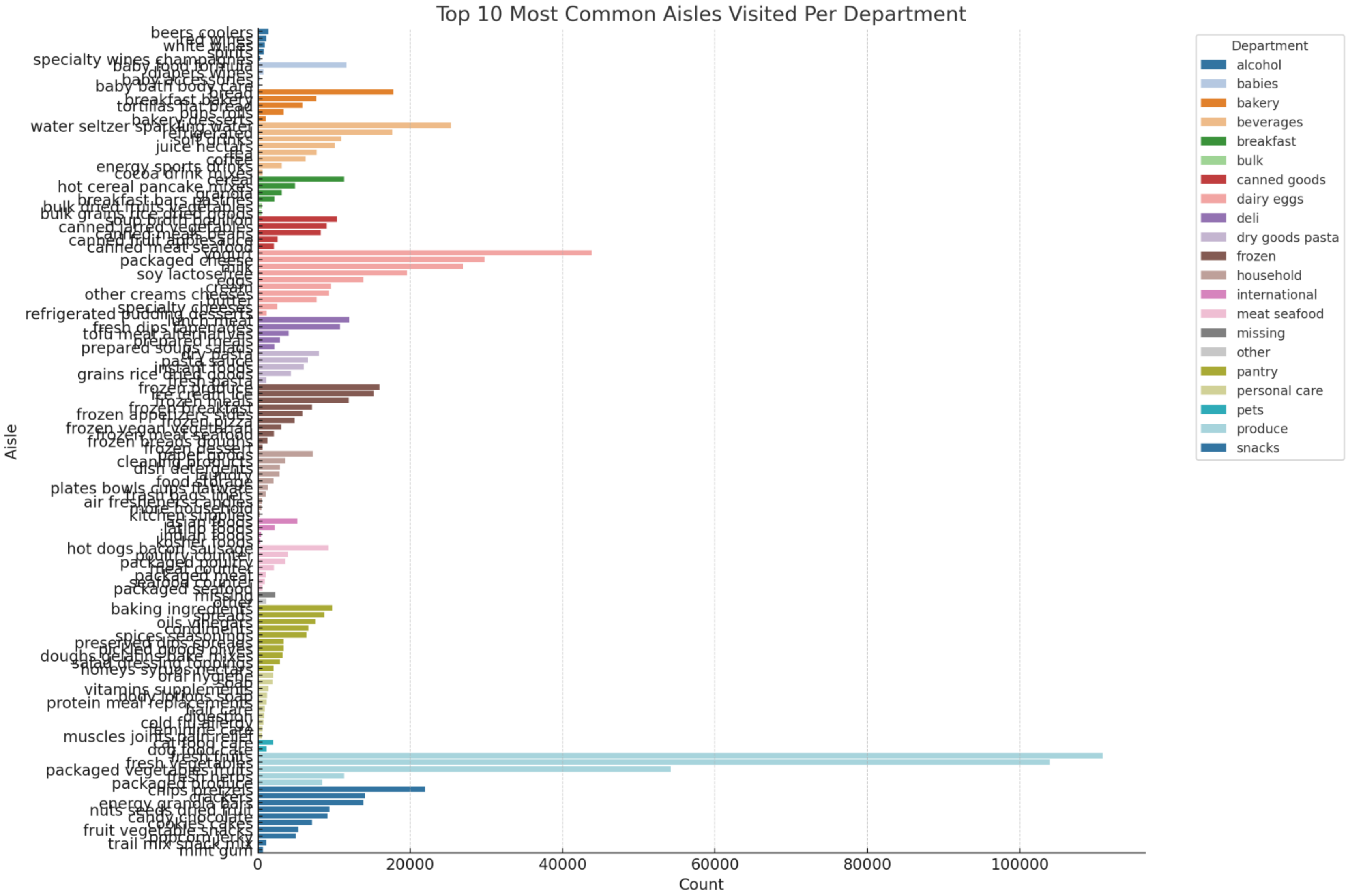
Product Substitution Code

Item-Item Collaborative Filtering Code

Apriori Method Code

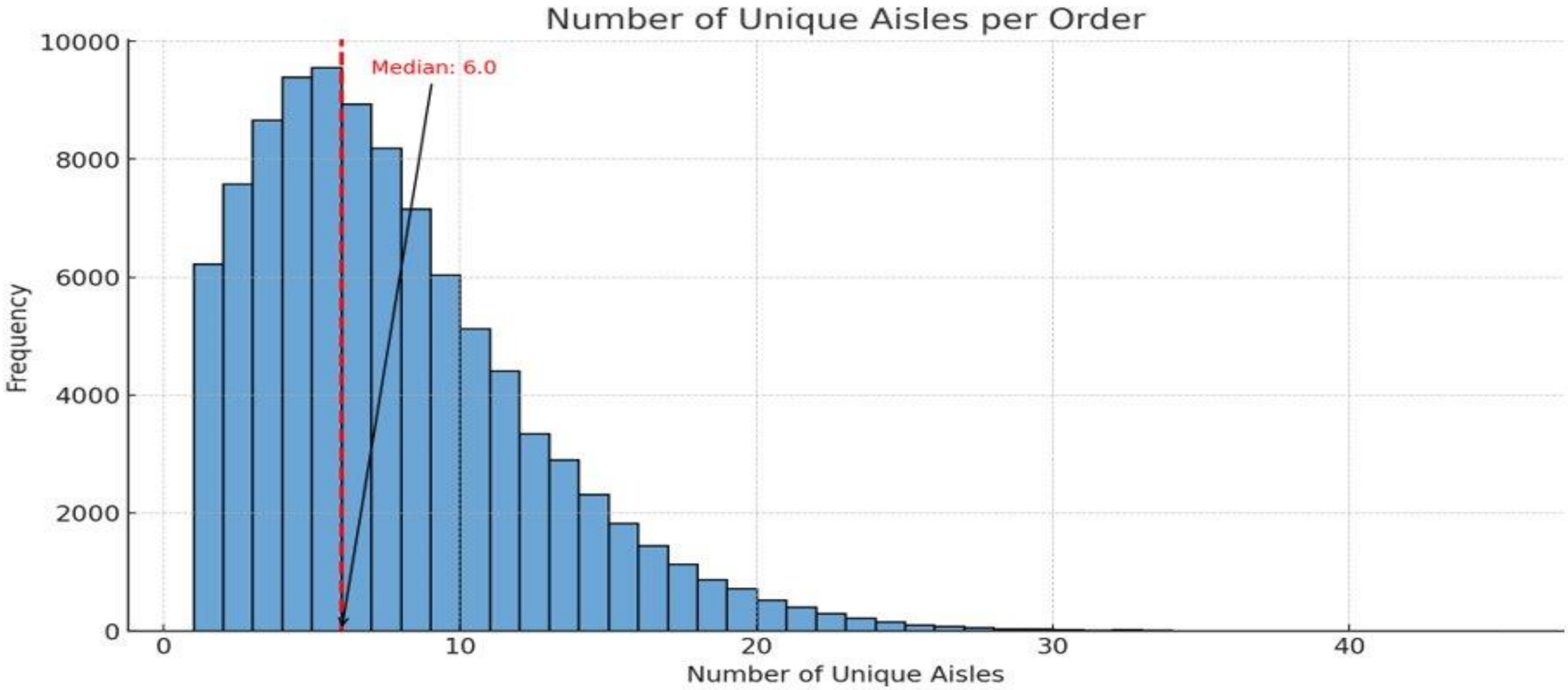
Appendix B

Data Source & Key Data Tendencies



Appendix C

Data Source & Key Data Tendencies


Number of Unique Aisles per Order
Median: 6.0
Frequency
Number of Unique Aisles