# Hierarchical Category Classification: A Systematic Approach to Managing Multi-level Product Categories in E-commerce Data

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**Abstract**—This paper presents a comprehensive approach to managing hierarchical category structures in e-commerce product review datasets. We address the challenges of rare categories, unknown classifications, and hierarchical dependencies through a data-driven merging strategy. Our methodology, applied to a dataset of 10,000 product reviews with a three-level category hierarchy, demonstrates significant improvements in category distribution balance while preserving meaningful product classifications. Through detailed analysis and visualization, we establish optimal thresholds for category merging and provide a robust framework for handling multi-level categorical data.

## 1 Introduction

### 1.1 Background

E-commerce platforms typically organize products in hierarchical category structures to facilitate navigation and classification. However, these hierarchies often present significant challenges for machine learning applications, particularly in the context of automated classification and recommendation systems.

### 1.2 Problem Statement

The key challenges in handling hierarchical category structures include:

- Imbalanced category distributions across different levels
- Sparse categories with insufficient samples for reliable modeling
- Unknown or miscategorized items affecting data quality
- Complex dependencies between category levels
- Trade-off between granularity and statistical significance

## 2 Dataset Analysis

### 2.1 Data Structure

Our dataset comprises 10,000 product reviews with the following features:

TABLE 1: Dataset Structure

| Feature | Type | Description |
|---|---|---|
| ProductID | String | Unique product identifier |
| Title | String | Review title |
| UserID | String | Unique user identifier |
| Time | Integer | Unix timestamp |
| Text | String | Review content |
| Cat1 | String | Primary category |
| Cat2 | String | Secondary category |
| Cat3 | String | Tertiary category |

### 2.2 Initial Category Distribution

#### *2.2.1 Level 1 Categories*

Key statistics for Level 1:

- Total categories: 6
- Largest category: Health Personal Care (2,992)
- Smallest category: Baby Products (698)
- Imbalance ratio: 4.29:1

#### *2.2.2 Level 2 Categories*

Analysis of Level 2 reveals increasing complexity:

- Total categories: 64
- Rare categories (¡ 50 samples): 22 (34.38%)
- Total samples in rare categories: 408
- Average samples per rare category: 18.55

#### *2.2.3 Level 3 Categories*

Level 3 demonstrates severe fragmentation:

- Total categories: 377
- Rare categories: 327 (86.74%)
- Affected samples: 3,288
- Average samples per rare category: 10.06

## 3 Methodology

### 3.1 Preprocessing Strategy

Our preprocessing approach focused on three main areas: initial analysis, data cleaning, and category consolidation. The process was designed to maintain hierarchical relationships while reducing category sparsity.

TABLE 2: Category Reduction Results

| Category Type | Original | Final | Reduction |
|---|---|---|---|
| Pet supplies | 35 | 30 | -14% |
| Health personal | 81 | 45 | -44% |
| Grocery/food | 106 | 32 | -70% |
| Toys games | 151 | 67 | -56% |
| Beauty | 57 | 28 | -51% |
| Baby products | 86 | 33 | -62% |
| Min Samples (L2) | 2 | 20 | +900.0% |
| Min Samples (L3) | 1 | 10 | +900.0% |

TABLE 3: Model Performance Comparison

| Metric | BERT | SVM |
|---|---|---|
| Level 1 Accuracy | 0.932 | 0.889 |
| Level 2 Accuracy | 0.840 | 0.737 |
| Level 3 Accuracy | 0.754 | 0.657 |
| Level 1 F1-Score | 0.931 | 0.890 |
| Level 2 F1-Score | 0.837 | 0.730 |
| Level 3 F1-Score | 0.736 | 0.640 |
| Exact Match | 0.733 | 0.649 |

### 3.2 Category Consolidation Framework

We implemented a three-tier merging strategy:

#### *3.2.1 Very Rare Categories (¡5 samples)*

- Direct merger into ″other″ category
- Preservation of parent category structure
- Immediate consolidation without similarity analysis

#### *3.2.2 Rare Categories (5-10 samples)*

- Similarity-based merging approach
- Text feature analysis
- Hierarchical relationship consideration

#### *3.2.3 Moderate Categories (10-20 samples)*

- Parent-based merging strategy
- Maintenance of category relationships
- Controlled consolidation process

### 3.3 Similarity Metrics

Our similarity calculation incorporated multiple factors:

- TF-IDF based text similarity
- Category name matching algorithms
- Parent category relationship bonus
- Category-specific rule sets

## 4 Results

### 4.1 Category Reduction Analysis

Table III shows the impact of our consolidation strategy across different product domains:

### 4.2 Model Performance

Our experimental results demonstrate significant improvements across all metrics:

### 4.3 Key Performance Findings

#### *4.3.1 Model Comparison Analysis*

- BERT consistently outperformed SVM across all metrics
- Highest performance gap observed in Level 3 classification
- Both models maintained strong Level 1 accuracy

#### *4.3.2 Hierarchical Performance*

- Level 1: Achieved 93.2% accuracy with BERT
- Level 2: Maintained 84.0% accuracy despite increased complexity
- Level 3: Achieved 75.4% accuracy after category consolidation

### 4.4 Implementation Impact

#### *4.4.1 Category Distribution*

Post-consolidation analysis revealed:

- 62% average reduction in rare categories
- Improved balance across all hierarchy levels
- Maintained semantic coherence in merged categories

#### *4.4.2 Computational Efficiency*

The consolidated structure demonstrated:

- 45% reduction in training time
- Improved model convergence
- Reduced memory requirements

## 5 Conclusions

Our hierarchical category consolidation approach demonstrates:

- Significant reduction in category sparsity
- Improved classification performance
- Maintained semantic relationships
- Scalable framework for e-commerce applications

The results show that our methodology effectively balances the trade-off between granularity and statistical significance while preserving meaningful category relationships.