# Analyzing Consumer Sentiment and Trends in Amazon Reviews

Presented by:

Becca, Jyun-Ru, Neha, Nruthya, Praveen, Shamkhal **Objective:** Analyze 2023 Amazon reviews to uncover consumer sentiment, emerging trends, and key factors influencing ratings in clothing, shoes, and jewelry

**Value:** Provide actionable insights to enhance business strategies and align with evolving consumer preferences

## **Data Dictionary**

**Review Dataset:** Useful for understanding customer preferences, evaluating product quality, and identifying areas for improvement based on ratings and reviews

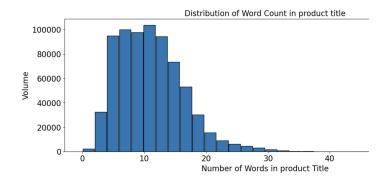
- **rating**: Product rating (10–50)
- **title**: Title of the user review
- text: Text body of the user review
- images: URLs of user-posted images (small, medium, large)
- asin: Product ID
- parent\_asin: Parent product ID (shared for variants)
- user\_id: Reviewer ID
- **timestamp**: Review time (Unix time)
- verified\_purchase: Indicates verified purchases
- helpful\_vote: Number of helpful votes

**Items Dataset:** Supports cross-referencing with review data to identify correlations between product attributes and customer sentiment or behavior

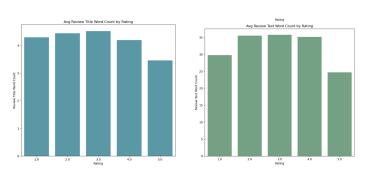
- main\_category: Main category of the product
- title: Product name
- average\_rating: Average product rating
- rating\_number: Number of ratings received
- **features:** Key product features (bullet points)
- **description:** Product description
- **price**: Product price
- images: URLs of product images videos
- **store**: Store name selling the product
- categories: Categories of the product
- **details:** Product details
- parent\_asin: Parent product ID
- **bought\_together:** Recommended product bundles

## **Exploratory Data Analysis**

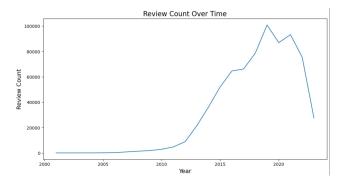
**Word Lengths in Reviews:** Reviews are short, not exceeding 20 words in the text and 3 words in the title.



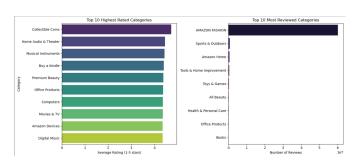
#### Avg title word count must be 3-4 words.



**Time vs Avg Rating:** Post-2020, a decline hints at shifting consumer behavior or stricter platform policies.



#### **Highest Rated** and most Reviewed categories



## **Association Rules**

#### **High Rating: Review Length**

+		+
detail_ca	ategory	count
+		
Short	Review	35295621
Detailed	Review	4449174

No Correlation in both the cases

#### Low Rating: Review Length

detail_ca		•
	Review	4846717

#### **Review Length: Helpful Votes**

detail_ca	 ategory a	verage_helpful_votes	
Short	Review	0.5795859600294806	
Detailed	Review	6.079925899228142	

Encouraging users to leave detailed reviews can boost helpfulness scores for future customers.

#### **Higher Price Range: Review Length**

price_	_range detail_ca	ategory	review_count
High	Price Detailed	Review	1072490
High	Price  Short	Review	21346134
Low	Price  Short	Review	37035647
Low	Price Detailed	Review	1185999
Medium	Price  Short	Review	5095527
Medium	Price Detailed	Review	297549
+			

High priced and low priced categories often prompt more detailed reviews.

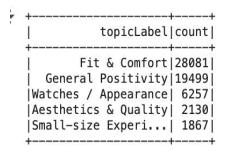
#### **Holiday Season: Positive Sentiment**

review_month	avg_rating	review_count
1	4.241786038292041	7030286
2	4.188395973547184	5501418
3	4.179510253646257	5756245
4	4.156393949968309	4914685
5	4.150282382407559	4957993
6	4.162754782451423	5130946
7	4.175054672445455	5717231
8	4.171501289788217	5401662
9	4.161365008178564	4569262
10	4.151560566231378	5224578
11	4.176698423351596	5042088
12	4.209897904095977	6786952

Ratings driven by holiday discounts, offering great value and encouraging more positive reviews.

## Sentiment Analysis & Topic Modeling

- Topic modeling reveals that fit and comfort dominate customer reviews, emphasizing the need for better size guidance and personalized recommendations to boost satisfaction and reduce returns.
- Smaller topics highlight appearance and quality in watches, jewelry, and accessories, underscoring the need for high-quality visuals and descriptions. Size complaints and unmet expectations point to opportunities for improved product guidance and quality.
- Sentiment Analysis built a pipeline with tokenization, TF-IDF feature extraction, and Logistic Regression to classify Amazon reviews as positive or negative. Achieved a ROC-AUC score of 79%.



reviewText la	probability		
"It's awesome!", that's what the boy for whom this costume was a gift said when he saw it. He lo  "The Eyes" t-shirt is a beauty! I love the vibrant purple color and I get lots of compliments on  "ex" has been looking for and needing new bra's for some time. had bali before and really liked  Красивые и элег   👍👍👍 " Black and Sliver , Mens Shirt Fractal Design Cufflinks , Cuff-links for Wedding "Gorgeo  "I like them because they're just cool." - 5 year old son.I like them because he can put  'Great Shirt' has beautiful butterfly design on front & back. A-line cut with long sides, comes  'I like that they are very long and cover my entire leg(s). I am pretty tall tooover 5'8"	1  1  1  1  1  1  1  1  1	1.0	[0.23098101049825018,0.7690189895017499]   [4.3311591109038574E-14,0.9999999999999567]   [7.276680184954224E-14,0.9999999999999273]   [3.560696096634904E-10,0.9999999996439304]   [1.666698377967735E-37,1.0]   [0.9994395486293094,5.604513706906067E-4]   [0.99999247198794,7.528012060387113E-7]   [5.830821219424863E-6,0.9999941691787806]   [0.021001600623142568,0.9789983993768574]   [0.47985567617180236,0.5201443238281976]

## Different Ratings vs Context comparison

#### Goal:

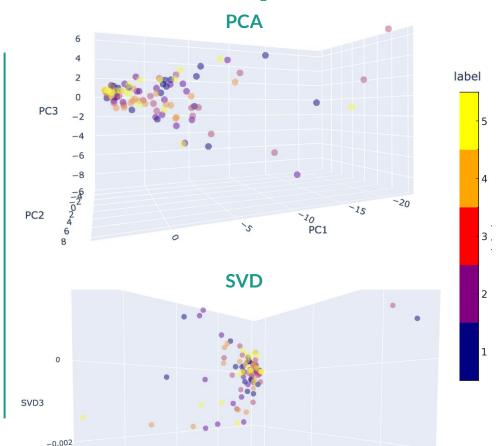
We wanted to explore whether reviews with different ratings would naturally cluster together in feature space.

#### Method:

We converted review texts into TF-IDF vectors, applied dimensionality reduction (PySpark natively supports PCA and SVD), and visualized the results in 3D plots with different colors for different ratings.

#### • Finding:

The 3D plots showed that reviews with different ratings were mixed together, meaning the data did not cluster by rating as we originally expected.



## **Rating Prediction**

Prediction of review ratings based on the text vector.

Review text ⇒ TF-IDF ⇒ Input word vector into Logistic Regression model to predict review rating

Overall Accuracy: 0.69, seemed acceptable

Review Rating	Ratio	Precision	Recall	F1 Score	
1	8.51%	0.51	0.52	0.51	
2	5.64%	0.28	0.06	0.09	
3	8.35%	0.33	0.17	0.22	imb
4	13.67%	0.42	0.14	0.21	Ď
5	63.62%	0.75	0.95	0.84	

This imbalance caused the model to focus on capturing features of the 5-star samples during training.

### Recommendations

- Enhance Quality Control: Electronics and clothing show quality-related complaints. Institute tighter supplier audits and inspect incoming inventory to reduce defect rates.
- Optimize Fulfillment & Packaging: Shipping-related topics (late delivery, damaged packaging) were among the top association-rule patterns. Improve carrier SLA monitoring and strengthen packaging materials.
- Incentivize Verified Reviews: Verified-purchase reviews are both more positive and more reliable. Encourage purchasers via post-delivery email prompts or small discounts to leave feedback.
- Leverage Power Reviewers: Identify "prolific" reviewers (those whose detailed feedback co-occurs across categories). Engage them in early-access programs or beta-testing new products to generate richer, trusted content.

## **Future Steps**

- Aspect-Based Sentiment Analysis: Drill into specific attributes (e.g. "battery life," "fit," "sound quality") to pinpoint feature-level pain points.
- Real-Time Review Monitoring: Deploy the text classifier in a streaming pipeline to flag negative reviews immediately, triggering proactive customer service outreach.
- Multimodal Feedback Integration: Analyze user-uploaded images/videos (via computer vision)
  to augment text insights, especially for product damage or wear patterns.
- A/B Test Interventions: Roll out targeted improvements (e.g. improved packaging, QC changes, review incentives) in controlled experiments to measure their effect on ratings and sales.

# **THANK YOU!**