NLP Business Case

Automated Customer Reviews Analysis

Project 3 — IronHack AI Engineering Bootcamp

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Live Demo: https://giwojno.pl/review-analyzer/

Component	Method	Key Result
Classification	RoBERTa fine-tuned	95.48% accuracy, 0.791 macro F1
Clustering	TF-IDF + K-Means	6 clusters, silhouette 0.2364
Summarization (API)	Claude Sonnet API	39 summaries, $0.43 total
Summarization (Local)	Flan-T5-base (250M)	6 summaries, $0 cost
Deployment	Static site, OVH hosting	giwojno.pl/review-analyzer

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1. Data Exploration

The dataset contains 28,332 customer reviews for 65 Amazon-branded products, sourced from the Datafiniti Amazon Consumer Reviews dataset on Kaggle. Reviews span 2009–2019 and cover products including Fire Tablets, Kindle E-Readers, AmazonBasics batteries, Echo smart speakers, and various accessories.

Dataset Overview

Metric	Value
Total reviews	28,332
Unique products	65 (all Amazon-branded)
Columns (original)	24 (14 retained, 10 dropped)
Mean rating	4.51 / 5
Median review length	17 words / 87 characters
Duplicate review texts	10,164 (35.87%) — kept as legitimate

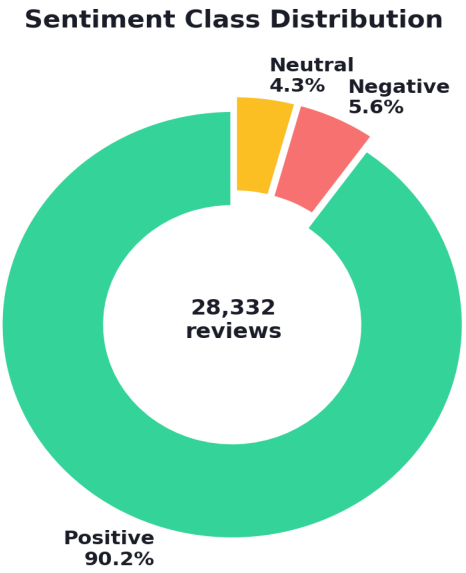
Sentiment Class Distribution

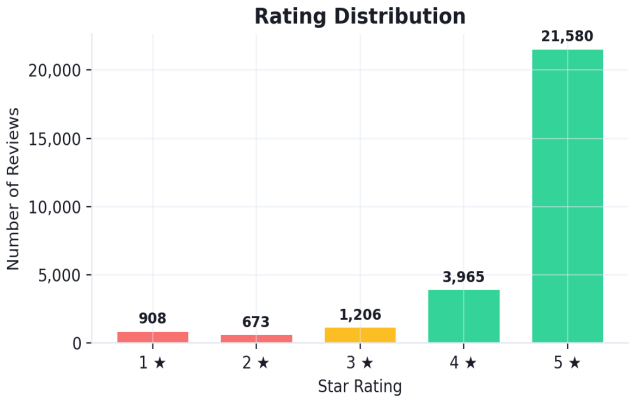
Star ratings were mapped to three sentiment classes. The resulting distribution is heavily imbalanced — Positive dominates at 90.2%, creating a major challenge for classification.

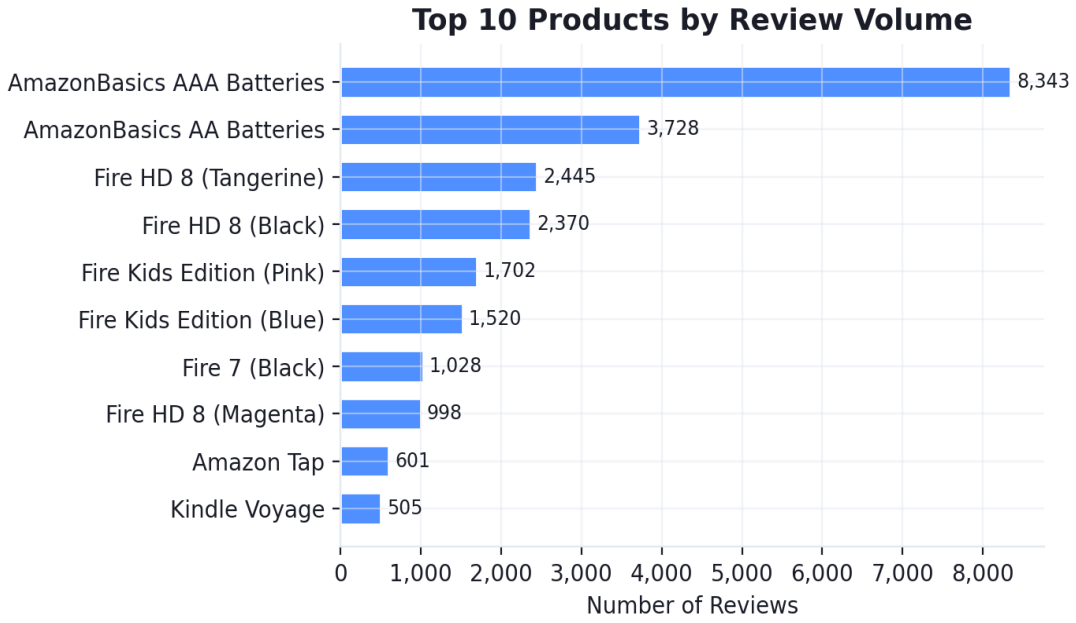
Class	Star Rating	Count	Percentage
Positive	4–5	25,545	90.2%
Negative	1–2	1,581	5.6%
Neutral	3	1,206	4.3%

Key Decisions

- Kept duplicate review texts — they are legitimate short reviews from different users (0 full row duplicates)
- Dropped 10 columns with >99% null values or metadata with no predictive value
- Used **categories** column (rich, multi-label) for clustering instead of primaryCategories (only 2 dominant values)
- No minimum review length filter — even single-word reviews carry sentiment signal
- No text preprocessing for transformers — models handle raw text; heavy cleaning can hurt performance


Sentiment Class Distribution
Neutral
4.3%
Negative
5.6%
28,332
reviews
Positive
90.2%


Rating Distribution
Number of Reviews
20,000
15,000
10,000
5,000
0
908
673
1,206
3,965
21,580
1 ★
2 ★
3 ★
4 ★
5 ★
Star Rating


Top 10 Products by Review Volume
AmazonBasics AAA Batteries
8,343
AmazonBasics AA Batteries
3,728
Fire HD 8 (Tangerine)
2,445
Fire HD 8 (Black)
2,370
Fire Kids Edition (Pink)
1,702
Fire Kids Edition (Blue)
1,520
Fire 7 (Black)
1,028
Fire HD 8 (Magenta)
998
Amazon Tap
601
Kindle Voyage
505
0
1,000
2,000
3,000
4,000
5,000
6,000
7,000
8,000
Number of Reviews

2. Sentiment Classification

We fine-tuned a RoBERTa-base transformer in two stages: first pre-trained on 650K Yelp reviews (3-class sentiment), then fine-tuned on the Amazon dataset with class weights to handle the severe class imbalance. The v2 model achieved 95.48% accuracy on a held-out test set of 5,667 reviews.

v1 vs v2 Comparison

The v1 model used Yelp-pretrained weights without Amazon fine-tuning or class weights. The v2 model added stratified splitting, class weights (Negative 6.0x, Neutral 7.8x, Positive 0.4x), and early stopping (patience 3). Best checkpoint was found at step 3,200 (epoch 2.4 of 5).

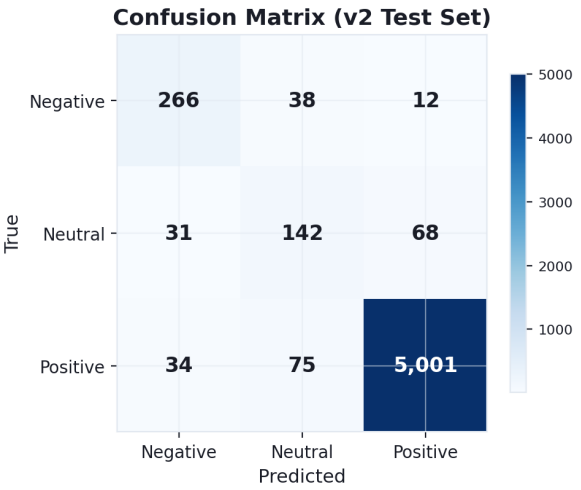
Metric	v1	v2	Improvement
Accuracy	87.23%	95.48%	+8.25%
Macro F1	0.635	0.791	+0.156
Negative F1	0.699	0.822	+0.124
Neutral F1	0.269	0.569	+0.300
Positive F1	0.937	0.982	+0.045

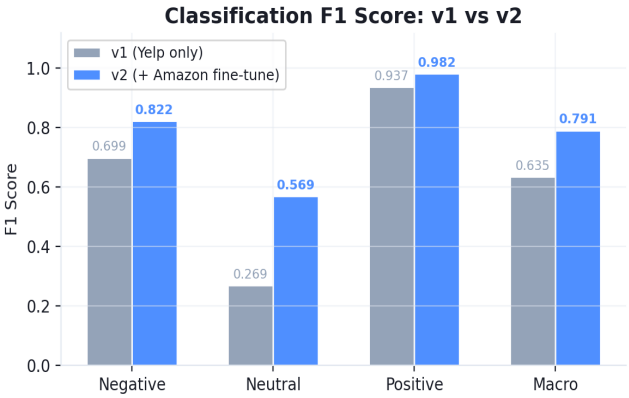
Per-Class Results (v2 Test Set)

Class	Precision	Recall	F1	Support
Positive	0.985	0.979	0.982	5,110
Negative	0.804	0.842	0.822	316
Neutral	0.550	0.589	0.569	241

Error Analysis

Only 256 errors on the test set (4.5% error rate). Most errors occur at the Positive/Neutral boundary — genuinely ambiguous reviews like 3-star reviews with mild praise. The worst error type (Negative predicted as Positive) is very rare at only 12 cases. Sample errors reveal sarcasm, mixed sentiment, and likely mislabeled training data.


Confusion Matrix (v2 Test Set)
Negative
Neutral
Positive
True
266
38
12
31
142
68
34
75
5,001
Negative
Neutral
Positive
Predicted
5000
4000
3000
2000
1000


Classification F1 Score: v1 vs v2
v1 (Yelp only)
v2 (+ Amazon fine-tune)
F1 Score
1.0
0.8
0.6
0.4
0.2
0.0
0.699
0.822
0.269
0.569
0.937
0.982
0.635
0.791
Negative
Neutral
Positive
Macro

3. Product Clustering

We clustered 65 products into 6 meta-categories using TF-IDF vectorization on product names combined with cleaned category labels, followed by K-Means clustering. Features: unigrams + bigrams, 200 max features, English stop words removed.

Cluster Selection

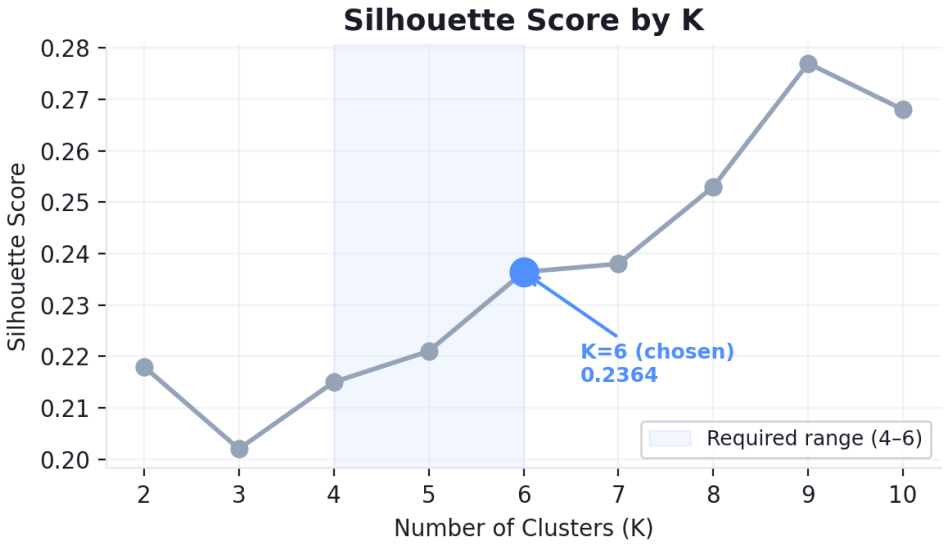
Tested K=2 to K=10. Best overall silhouette was K=9 (0.277), but the project required 4–6 clusters. Within this range, K=6 achieved the best silhouette score (0.2364).

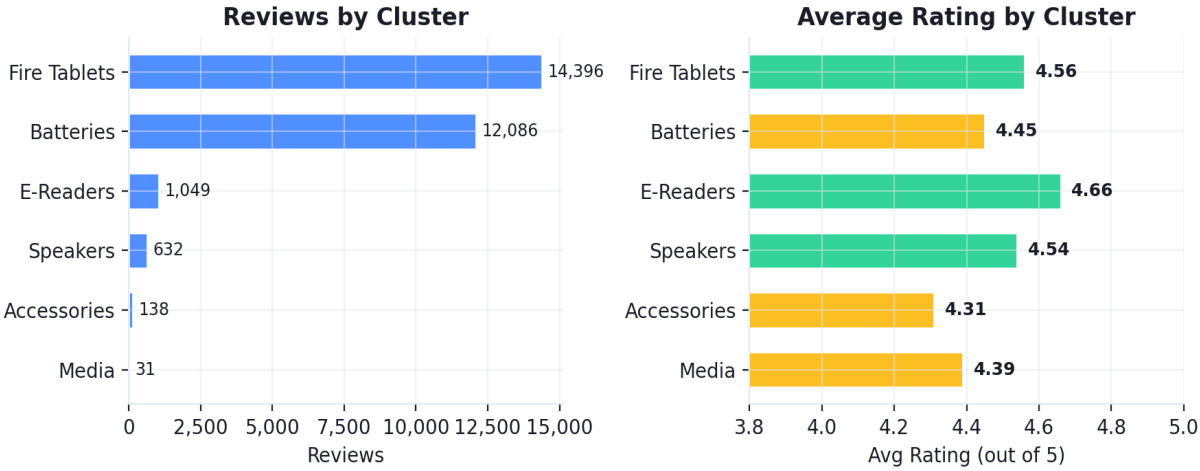
6 Clusters

Cluster	Products	Reviews	Avg Rating	% Positive
Fire Tablets	20	14,396	4.56	93.2%
Batteries & Household	7	12,086	4.45	86.1%
E-Readers	10	1,049	4.66	95.2%
Smart Speakers	9	632	4.54	91.9%
Accessories	11	138	4.31	82.6%
Media & Home	8	31	4.39	83.9%

Key Observations

- Fire Tablets and Batteries dominate with 93% of all reviews combined
- E-Readers have the highest satisfaction — 95.2% positive, only 1.5% negative
- Batteries & Household has the highest negative rate (9.5%) among major clusters
- Accessories and Media & Home are small clusters with limited review material




Reviews by Cluster
Fire Tablets
Batteries
E-Readers
Speakers
Accessories
Media
14,396
12,086
1,049
632
138
31
0
2,500
5,000
7,500
10,000
12,500
15,000
Reviews
Average Rating by Cluster
Fire Tablets
Batteries
E-Readers
Speakers
Accessories
Media
4.56
4.45
4.66
4.54
4.31
4.39
3.8
4.0
4.2
4.4
4.6
4.8
5.0
Avg Rating (out of 5)

4. Review Summarization — API

We used the Anthropic Claude Sonnet API to generate recommendation articles from customer reviews. For each product, we sampled the most informative reviews (5 positive, 5 negative, 3 neutral — prioritized by length) and sent them with aggregate statistics to the LLM via structured prompts.

Metric	Value
Model	Claude Sonnet (claude-sonnet-4-20250514)
Temperature	0.3 (consistent, factual output)
Total API calls	39
Cluster summaries	6 (~600 words each)
Product summaries	33 (products with 20+ reviews)
Total cost	$0.43 USD
Cost per summary	~$0.011

Each cluster summary includes: category overview, top 3 recommended products with evidence, common complaints (3–5 recurring issues), worst-rated product with reasoning, and buying recommendation. Product summaries include an overall verdict (Buy/Consider/Avoid), top 3 strengths, top 3 weaknesses, and target buyer profile.

5. Review Summarization — Local Model

In parallel, we ran a fully local summarization pipeline using Google's Flan-T5-base (250M parameters) on an NVIDIA RTX 4050 GPU. The approach builds structured 'evidence briefs' per category with product rankings and TF-IDF complaint extraction, then prompts T5 to generate articles.

Data Pipeline Highlights

- Product ranking: avg_rating x log(1 + review_count) — balances quality with volume
- Minimum 20 reviews required for worst-product selection
- TF-IDF complaint extraction from negative reviews (unigrams + bigrams)
- Complaint caching to avoid redundant computation

API vs Local Comparison

Aspect	API (Claude Sonnet)	Local (Flan-T5-base)
Output quality	Full recommendation articles	1–2 sentences, factual
Structure followed	All sections present	Failed to produce sections
Complaint analysis	Integrated into narrative	Raw TF-IDF terms
Cost	$0.43	Free
Infrastructure	API key + internet	GPU (RTX 4050)

Flan-T5-base (250M parameters) lacks the capacity for structured multi-paragraph generation. It excels at short factual QA but cannot follow complex output formatting or write coherent articles. Flan-T5-large (780M) or Flan-T5-xl (3B) would likely perform significantly better. The API-generated summaries are used in the web deployment.

6. Web Deployment

The project is deployed as a static single-page web application at https://giwojno.pl/review-analyzer/, hosted on OVH shared hosting. No backend, database, or API keys are needed at runtime — all results are pre-computed and served as JSON files.

Architecture

Component	Technology
Frontend	Single HTML file, vanilla CSS + JS
Data	4 JSON files generated from project outputs
Fonts	Google Fonts (DM Sans + DM Serif Display)
Hosting	OVH shared hosting
Deployment	SFTP via deploy.sh (credentials in .env)
Theme	Dark editorial design, responsive

Features

- **Dashboard** — stats overview, sentiment distribution, rating charts, reviews by category
- **Categories (API)** — browse Claude-generated recommendation articles per cluster
- **Categories (Local)** — browse Flan-T5 generated summaries for comparison
- **Products** — filterable table of all 65 products, click for AI summaries
- **Reviews** — explorer with filters (category, sentiment, rating, text search)
- **About** — model details, project info

7. Key Learnings & Conclusion

Technical Learnings

- **Class weights are critical** for imbalanced datasets — Neutral F1 jumped from 0.269 to 0.569
- **Early stopping** prevented overfitting and found the best checkpoint automatically (epoch 2.4 of 5)
- **Model size matters for generation** — Flan-T5-base (250M) cannot handle structured article generation; API models produce vastly superior output at minimal cost ($0.43)
- **Static sites work** — pre-computing results removes backend infrastructure needs, making deployment trivial on shared hosting
- **Simpler ranking formulas** can be more defensible — avg_rating x log(review_count) is clean and effective

Project Outcome

The project delivers a complete end-to-end NLP pipeline: from raw Amazon reviews to a deployed web application with sentiment classification (95.48% accuracy), product clustering (6 meaningful categories), and AI-generated recommendation articles. Both API-based and local summarization approaches were implemented and compared, demonstrating the trade-offs between cost, quality, and infrastructure requirements. The live demo at giwojno.pl/review-analyzer makes all results interactively browsable.

Krzysztof Giwojno & Felipe Doria — Group 4, IronHack AI Engineering Bootcamp, February 2026