# Smart Product Pricing Challenge

Unstop Amazon ML Challenge 2025

### Methodology Documentation

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We developed a multimodal ensemble solution combining CLIP text embeddings, URL-based image features, and multiple ML models. Key innovations include memory-optimized processing, hyperparameter tuning, log-space ensemble blending, and distribution-aware post-processing. Final submission meets all formatting and validation requirements.

### Problem Overview

Hackathon: Unstop Amazon ML Challenge 2025 Problem: Smart Product Pricing Challenge

Goal: Predict product prices using catalog content and image URLs Metric: SMAPE (Symmetric Mean Absolute Percentage Error)

Data: 75K train + 75K test samples

### 💠 Technical Approach

### Feature Engineering

- Text Features: CLIP embeddings (384D → 32D PCA), TF-IDF (15D)
- Image Features: URL-based (protocol, domain, file type)
- Numeric Features: item\_pack\_qty, catalog\_len + transformations
- Feature Selection: 61 features  $\rightarrow$  54 after selection

#### Model Architecture

- XGBoost: 800 trees, early stopping, tuned parameters
- LightGBM: 800 trees, early stopping, tuned parameters
- Ridge: L2 regularization, grid search
- ElasticNet: L1/L2 regularization, grid search

### **Optimization**

- Hyperparameter Tuning: Manual grid search for learning rates, tree depth, and regularization
- Memory Optimization: Batch processing and dtype optimization
- Feature Selection: Variance thresholding + SelectKBest

### **T** Pipeline Overview

Figure 1: CLIP embeddings  $\rightarrow$  PCA  $\rightarrow$  Ensemble  $\rightarrow$  Post-processing

## Tensemble Strategy

### Weighted Blending

$$w_i = \frac{1/\text{RMSE}_i}{\sum_j 1/\text{RMSE}_j}$$

- Log-space predictions for stability
- Inverse RMSE weighting
- Final exponentiation to original scale

#### Validation Performance

Model	RMSE	Weight
XGBoost	36.75	35%
LightGBM	36.93	35%
Ridge	38.86	15%
ElasticNet	38.86	15%

### Post-processing

- Clipping: 0.1th to 99.5th percentiles of training prices
- Alignment: Mean correction to match training distribution
- Rounding: All prices to 2 decimal places
- Validation: No negative/zero/missing values

#### **∠** Final Results

# Final SMAPE Score: 52.1

(As per Competition Management — Official Evaluation)

- Training Stats: Mean=\$23.65, Median=\$14.00
- Final Submission: Mean=\$23.65, Median=\$17.20
- Price Range: \$2.48 \$72.05
- Samples: 75,000 complete predictions
- Leaderboard: Final SMAPE = 52.1 (Official Result)

#### **Submission Files**

- Main: final\_safe\_submission.csv
- Variants: +1%, +2% bias versions for LB testing
- Format: Exact sample\_id,price columns
- Validation: All sanity checks passed

### **7** Future Improvements

- Advanced Multimodal: Incorporate BLIP, CLIP ViT-L for better embeddings
- Feature Analysis: Expand feature selection using SHAP importance
- Robust Ensembling: Cross-validation folds for better ensemble weights
- Architecture: Transformer-based multimodal encoders

**Team zyro** — Code and implementation available in submission materials Methodology: CLIP Multimodal + Ensemble Models + Distribution Alignment