Amazon x UCLA MSBA Hackathon



(Ashwin Bharathwaj, Jungjin(JJ) Park, Karthik Maddipoti, Tharun Sriram, Yash Bhatia)



Executive Summary



What is the problem?

Improve customer shopping experience

 Identify a robust way to find right products among a wide selection at Amazon

How can we fix this?

Content-based Recommendation

- Leverage product characteristics and description to identify similar products
- Build MVP that's scalable word2vec embedding & content-based recommender

Corner Case & Model Improvement

- Preferences reflected in recommendations (i.e., brand, price)
- Experiment plans to improve the model

Why does this benefit us?

Amazon's Benefits

- Capture opportunities for crossselling and up-selling
- More satisfying purchases by finding better products easily, leading to low returns
- Stronger brand awareness with seamless shopping experience
- Better understanding of customers behaviors and tastes in products

Modeling Approach



1. Data Cleaning

2. Feature Engineering

3. Unsupervised Modeling



<u>Clean raw data</u> to deal with data quality issues

<u>Transform text-based data to</u> <u>numerical vectors</u> for model ingestion Train a recommendation model



Completed below <u>data quality checks</u> for selected set of important columns

- Missing values
- Outliers
- Special characters
- Duplicate items

Explore <u>pre-trained word</u> <u>embedding methods</u> and <u>adjust</u> <u>feature weights</u>

Validate performance on handpicked samples Use <u>content-based filtering</u> <u>recommender</u> to identify similar products

Validate model's findings based on hand-picked sample cases



Explore external data sources to enrich item-level data set

Amazon Berkeley Objects (ABO)
 Dataset

Reduce feature space by re-training the text encoder on product data

Use an ensemble of models to make robust recommendation

Hybrid recommendation models

Modeling Approach Details (1/3) - Data Cleaning



Steps

Examples

1. **Excluded all non-alphanumeric characters** from all text columns

2. **Duplicates –** Description with n-2 common words removed

Item Id	Item Name	Marketplace
B009SC4W3W	Organic Carrots, 2lb	AmazonFresh
B009SC4W3W	Organic Carrots, 2lb	AmazonGo

3. **Outliers** - Imputed with 99th percentile value from same product category and type

Item Name	Outlier Feature	Original Value	Imputed Value
Solimo Capri Fabric Recliner	Item Weight	80000	176

4. **Missing values** - Imputed with average values from same product category and type

Item Name	Feature	Original Value	Imputed Value
Organic Light Cream 1 PT	Item Height	NULL	6.2

Modeling Approach Details (2/3) – Feature Engineering



To ingest data for training and prediction, textual data was converted to numerical features

Steps

Examples

1. One-hot encoding categorical features

- a. Brand
- b. Product category
- c. Product Type
- d. Marketplace

2. Word embedding methods for product identifying texts

- a. TF-IDF vectorization
- - b. Weighted Word2Vec Weights corresponding to Idf of the word
 - c. BERT inspired Sentence transformers

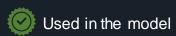


Cat	Dog	Turtle	Fish
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1
1	0	0	0

Word-embedding

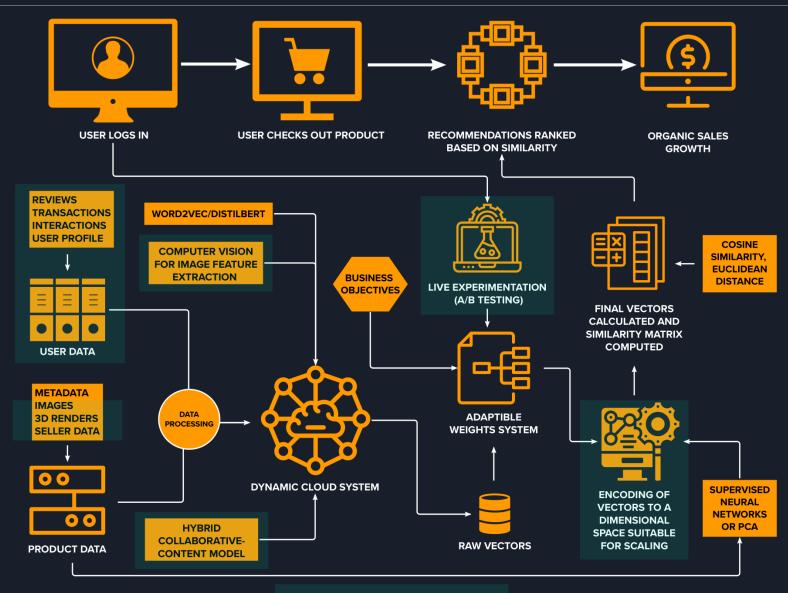
$$egin{pmatrix} the \\ cat \\ sat \\ on \\ the \\ mat \end{pmatrix} = egin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

✓ Weighted OHE vectors were concatenated to the text embeddings to create final raw vectors.



Modeling Approach Details (3/3) - Methodology





Baseline Recommendation Results



Item searched

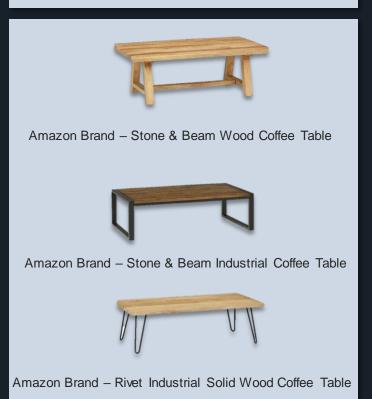






Recommended Products









BUT WAIT! What about Customer Obsession?

Happy Belly – 2% Fat Milk One Gallon

Happy Belly – 2% Fat Milk Half Gallon

Happy Belly – 1% Fat Milk One Gallo

Personalized Recommendations Ideas



Few examples of leveraging customer/product attributes for ranking/filtering/substitution

Price sensitive

Quality sensitive

Dietary preference

Brand loyalty

Use cases

- Recommendation based on customer's individual price preference
- Customers who strongly prefer high quality items
- Customized to personal dietary preference

 Positive/Negative propensity toward specific

How to catch signals

- Filtering on price range
- Tendency to buy products cheaper than median or 20% percentile
- Returns on low rating items
- High avg of ratings of items purchased (cf. having considerable volumes)
- Product classification based on description
- Frequent purchases/ views/add to carts of certain grocery type
- · Brand classification

brands

- Including brand name when querying
- Frequent purchases/views/ add to carts of brand items

Item searched



Whole Foods Market, Organic Mung Bean Gluten Free Fusilli, 8 oz

Recommended products



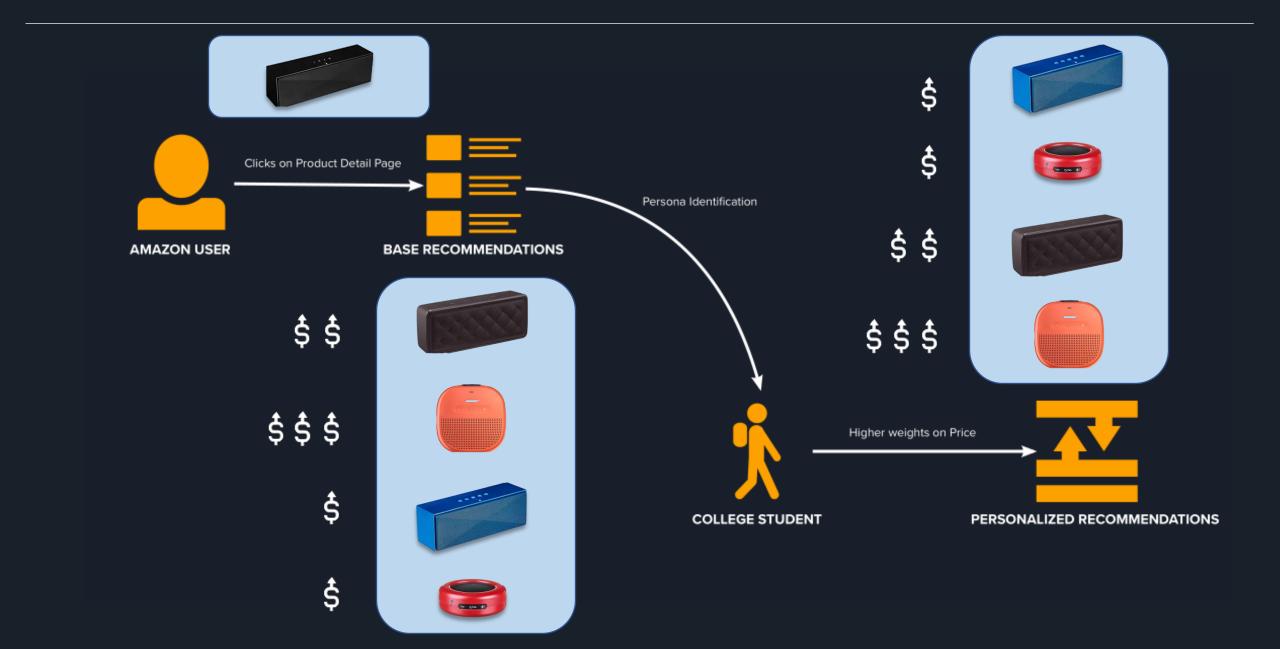
365 by Whole Foods Market, Pasta Corn & Rice Penne Rigate Gluten Free, 12 Ounce



Whole Foods Market, Organic Red Lentil <u>Gluten Free</u> Spaghetti, 8 oz

Personalized Recommendations Journey





Model Improvement Using Experimentation





Feature Engineering

- Word embedding: Word2Vec/BERT/TF-IDF
- Distance: Cosine similarity/ Euclidean distance
- Include additional data sources (ABO data, etc.)



of recommendations & ranking

Optimal # of products to display based on device type and screen orientation

Displaying products to users based on what matters to them (price, brand, etc.)

Recommendation widgets

Dynamic recommendations clusters (complimentary products, products from top sellers, etc.)



Primary KPIs

- 1. Conversion rate
- 2. Profit per visit
- 3. AOV
- 4. Avg. CTR on recommended products



Guardrail KPIs

Website-specific:

- 1. Bounce rate
- 2. Page load speed

Email-specific:

- 1. Unsubscribe rate
- 2. Open rate



Model Performance Metrics

- 1. Hit rate
- 2. Mean reciprocal ranking

Thank you!

