Offline evaluation of product search with model-based judgments

Alberto Castelo Sr. Applied Machine Learning Engineer MICES 2024

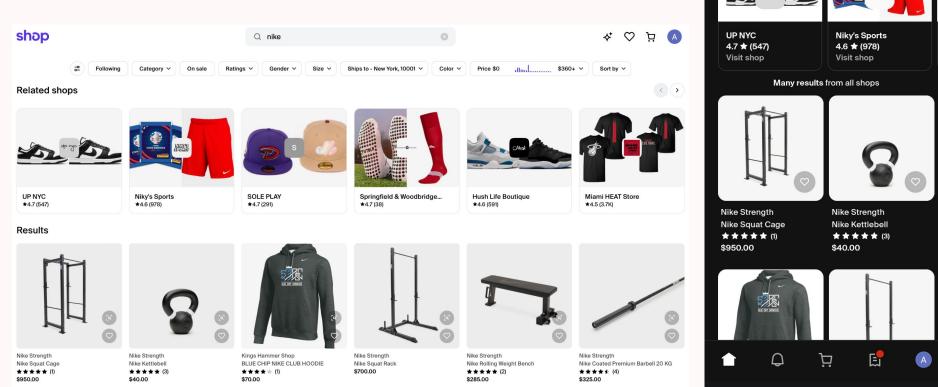


Agenda

- Search@Shopify
- Problem statement
- Solution: Model-based judgments
- Building a binary judgment model
- Conclusions

Search@Shopify

Shop



Q nike

Following

Category ~

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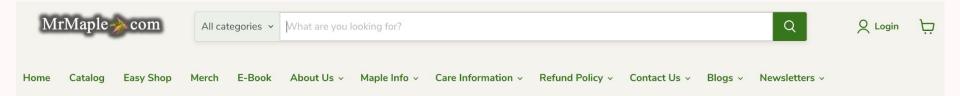
\$⁺

Ra

On sale

KIIX49 El-CLAS

Storefront - MrMaple Example

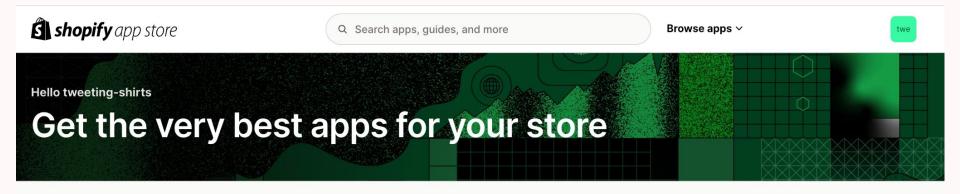




Admin

| shopify | Q Search | 8 | ж К 🗘 tweeting-shirts twe | |
|---|---|------------------------------------|---------------------------|--|
| Home Orders | 🗎 Last 30 days All char | nnels 🗸 | Next payout: \$0.00 | |
| Products Customers Content | Online store sessions ⊘ 0 − | Total salesTotal orders\$0.00 -0 - | Conversion rate | |
| Finances Analytics Marketing Discounts | No sessions in this date range Try selecting a different date range or channel. | | | |

App store



Popular with stores like yours



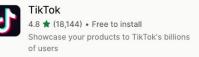
Point of Sale 4.0 ★ (504) • Free plan available Unify online and in-person sales with Shopify POS.



Google & YouTube 4.5 ★ (8,007) • Free to install Access the best of Google and YouTube



Shopify Inbox 4.8 ★ (4,592) • Free Connect with shoppers and drive sales with chat



Problem statement

Problem statement

- We need offline evaluation
 - Release with confidence
 - Faster iteration cycles
- Implicit judgments approach is not good enough:
 - Judgment scarcity
 - Bias & noise
 - Not aligned with desired UX

Implicit judgments - CTR Scarcity

• Scarcity tends towards reinforcing old good products

| Product Id | Judgment | |
|------------|-----------|--|
| 4634 | 0.23 | |
| 2156 | 0.25 | |
| 1234 | 0 or Mean | |
| 7891 | 0 or Mean | |
| 12945 | 0.12 | |

Implicit judgments - UX impact

shop \$⁺ \heartsuit Ä Α Q iphone Results .

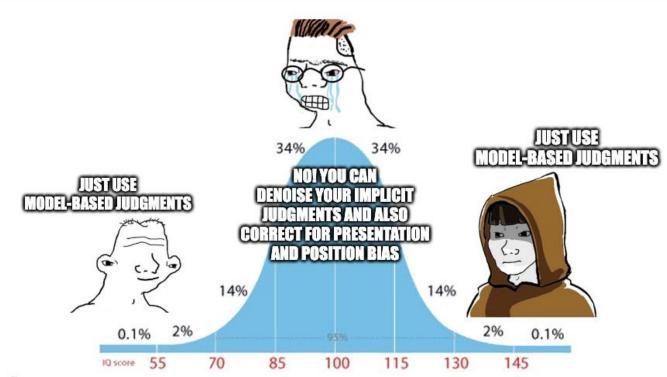
Speck Products Presidio2 Grip MagSafe with ClickLock iPhone 15 Pro...

★ ★ ★ ★ ☆ (7) \$49.99 Speck Products Presidio2 Grip MagSafe with ClickLock iPhone 15 Cases

★★★★★ (2) \$49.99 Speck Products Presidio2 Grip iPhone 15 Cases \$39.99

Solution: Model-based Judgments

Solution

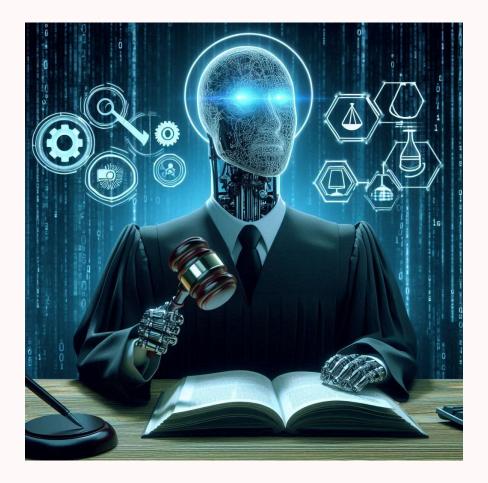


imgflip.com

Tasks

• Binary relevance

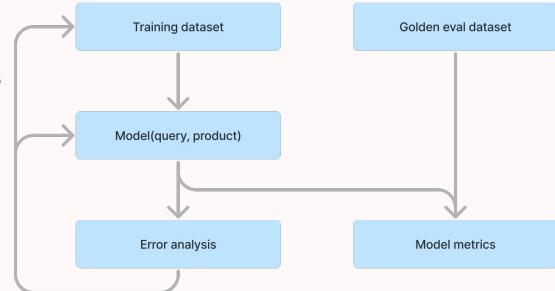
• Ranking



Building a binary judgment model

Model flywheel

- Build your golden eval dataset
 - Manual annotation
 - Representative of business objectives
- Set a training loop:
 - Train dataset
 - Model
 - Error analysis



Building a training dataset

- Leverage public datasets
 - ESCI (Amazon search)
- Synthetic data
 - Distilling from GPT4 labels
 - Real data + synthetic
- Manual annotation
 - Clear guidelines

SYSTEM_PROMPT = """

You are an expert on ecommerce working on a product search engine. Your job is to: 1. Understand the product provided.

- 2. Generate an inexact query that:
- \ast Could happening during a ecommerce product search session.
- \ast where the product does not satisfy all the conditions or characteristics of the query.
- \ast has a similar structure than the exact query provided.
- 3. Answer in JSON format.

Use these definitions:

- \ast Exact query: a query that matches the product characteristics.
- \ast Inexact query: query that do not match the product (even if the product is close to match).

Examples:

- 1. Product: an Iphone 14 phone.
- a. Exact query: "iphone 14",
- b. Inexact query: "iphone 15"
- 2. Product: jordan's sneakers
- a. Exact queries: "nike"b. Inexact queries: "adidas"
- 3. Product: A bed for dogs
- a. Exact queries: "dog bed"
- b. Inexact queries: "cat bed"
-

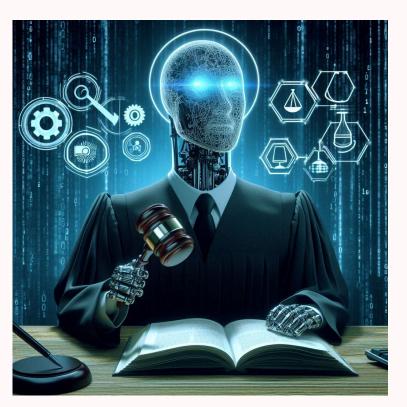
USER_PROMPT = """
Take a look at the product:
{product_dict}

In JSON format, generate a close yet inexact query with a similar structure as the exact query "{query_string}":

Binary relevance model-based judgments

• LLM as a judge

• Classifier as a judge



LLM-Llama 3

- 8B-Instruct
 - A couple of few-shot examples.

8B (un-instruct) LoRA finetune
 O(100) samples

You are a relevance engineer working on ecommerce search. Your job is to tag a pair of query and product as 'E' (exact match) or 'I' (inexact match) depending on whether the product fully satisfies/matches the intent of the query

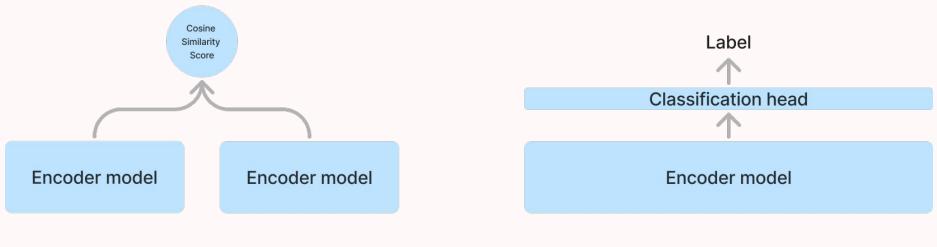
Query: nike ### Product: # title jordan's # vendor nike # shop name shoes retailer # product category shoes # product attributes black # image description A man wearing a Nike shoe # price 120 # description Great Jordan's

Response:







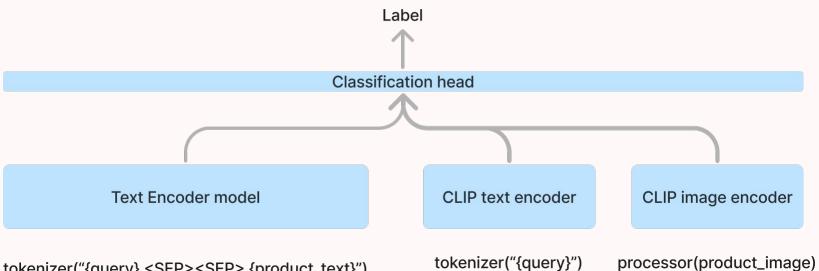


tokenizer("{query}") tokenizer("{product_text}")

tokenizer("{query} <SEP> <SEP> {product_text}")

CLIP + crossencoder

CLIP + Cross-encoder



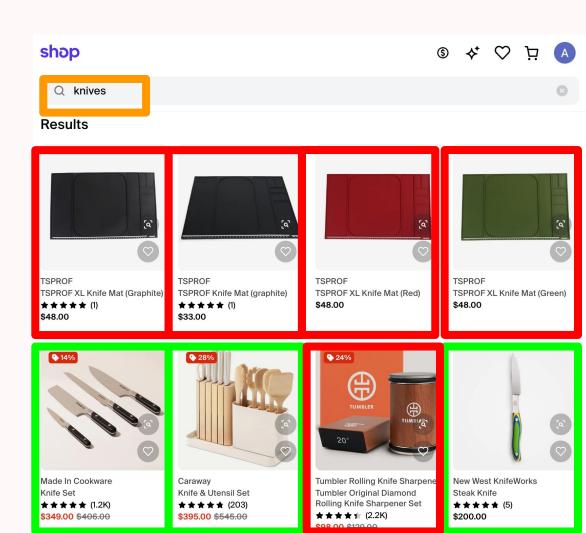
tokenizer("{query} <SEP><SEP> {product_text}")

Performance Summary

| Model | Data required | Inference Cost (1M pairs) | Classification Performance |
|---------------------|---------------|---------------------------------|-------------------------------|
| Llama 3 8B-Instruct | O(1) | O(\$100) | Low |
| Llama 3 8B LoRA FT | O(100) | O(\$100) | High |
| Crossencoder | O(1k) | O(\$10) | High |

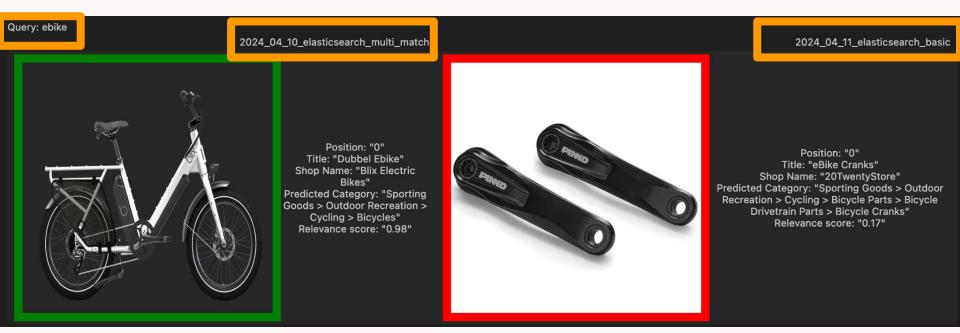
SERP-Precision

- **Precision@1**: 0/1
- **Precision@4**: 0/4
- **Precision@8**: 3/8



Winner/Loser comparison

• Comparing 2 search strategies: Precision@1





Conclusions

- Model-based judgments for the win
- Specialized models >> LLM
 For now...
- Data is key



Thank you!



acaste10





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