Scoring More Clicks

AI-Powered Personalized Emails for Customers

DICK'S SPORTING GOODS

MIT MANAGEMENT BUSINESS ANALYTICS

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Problem Statement & Objective

Dick's Sporting Goods (DSG) sends one to two emails per day to customers subscribed to their email base. Currently, the emails are manually created with limited personalization.

Our goal is to **generate personalized email templates with Large Language Models (LLMs)** to:

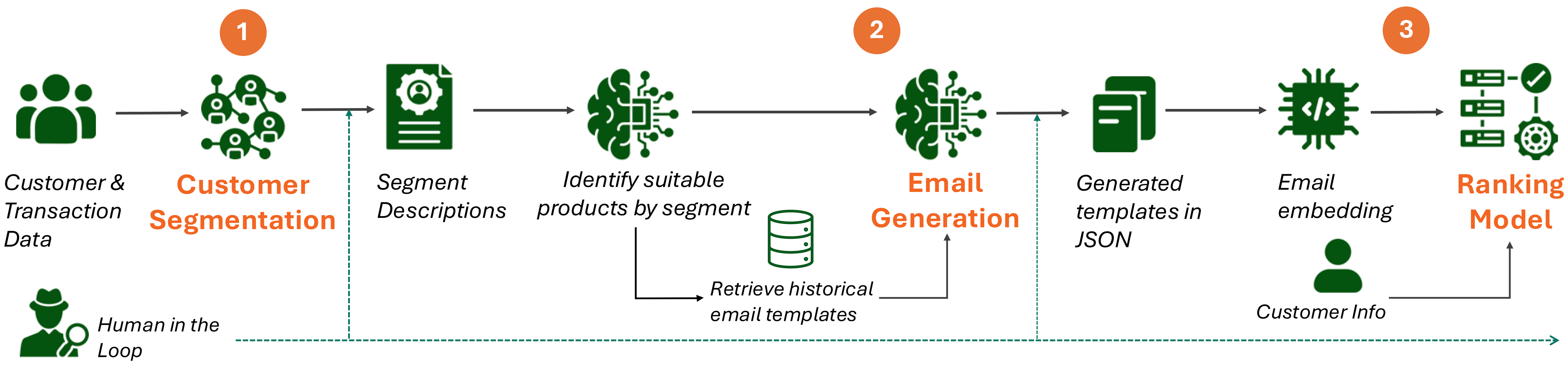
- Boost click-through rate per email
- Increase revenue per email
- Reduce time required to create an email

Data & Scope

22M	5,650	14.1M	148M
Customers	**Email Templates**	**Email Interactions**	**Transactions**
Demographics, loyalty	*HTML of past emails*	*Clicks, conversions, link types*	*Order value, channel*

Scope: Emails and transactions between May 2023 - June 2024

Methodology



End Products

Recommend Top email for each customer

Interactive Web App

Exploratory Data Analysis

0.372% **Average CTR**

Click-through Rate for an email is defined as:

$$CTR = \frac{Number\ of\ total\ clicks}{Number\ of\ total\ deliveries} \times 100$$

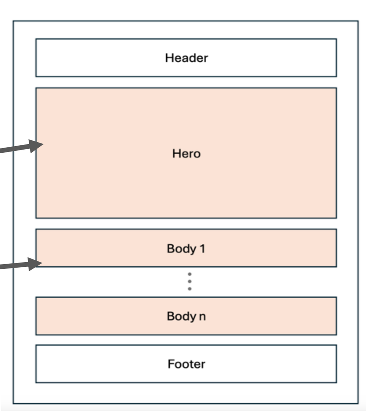
0.273% **Average CVR**

Conversion Rate for an email is defined as:

$$CVR = \frac{Number\ of\ total\ conversions}{Number\ of\ total\ clicks} \times 100$$

Among emails that were clicked,

- Hero slot = **62% of clicks**
- Body slot = **19.2% of clicks**

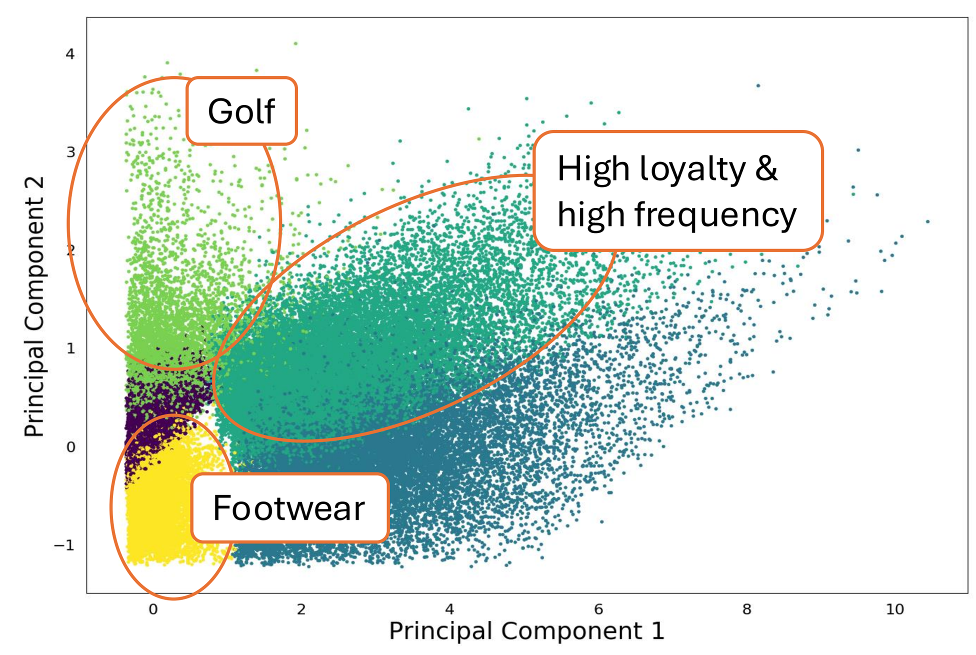


General DSG email template:

1. Identifying customer segments

Goal: Cluster customers by **purchase histories** to understand what content interests them.

Using **K-Means Clustering**, we found 7 clusters:



Silhouette Score

0.43

Cluster centroids are used to define the customer segments for the LLM. For ex.,

Golf Cluster

- $415 average order value
- 1.9 purchases in the last year
- Prefers shopping in-store over online

2. Generating email templates

Goal: Generate **personalized email templates** for customer segments using a LLM powered by **Retrieval-Augmented Generation (RAG).**

For each of the 5,650 emails, we codified their **HTML** and **interaction data** into **JSON templates.** For ex.,

```
Subject Line       → "subject_line": "Get Ready for our Golf
                                      Deals!",
Department         → "email_department": "Golf"
Click-through rate → "dpid_ctr": 0.23,
Conversion rate    → "dpid_cvr": 0.13,
                     "dpid_cvr_amount": 221,

                     "slot_1": {
Slot name          →     "link_name": "Hero_GolfBall",
Slot placement     →     "link_tag": "TAG_1",
Slot text          →     "parsed_text": "New Arrivals
                         of golf balls today!",
                         "spot_ctr": 0.12,
                         "spot_cvr":0.21…}
                     ...
```

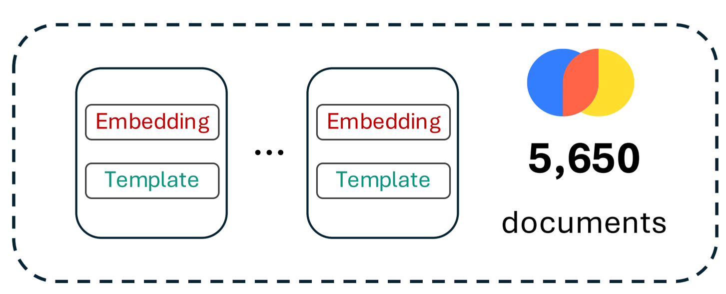
We concatenated relevant fields from each template,

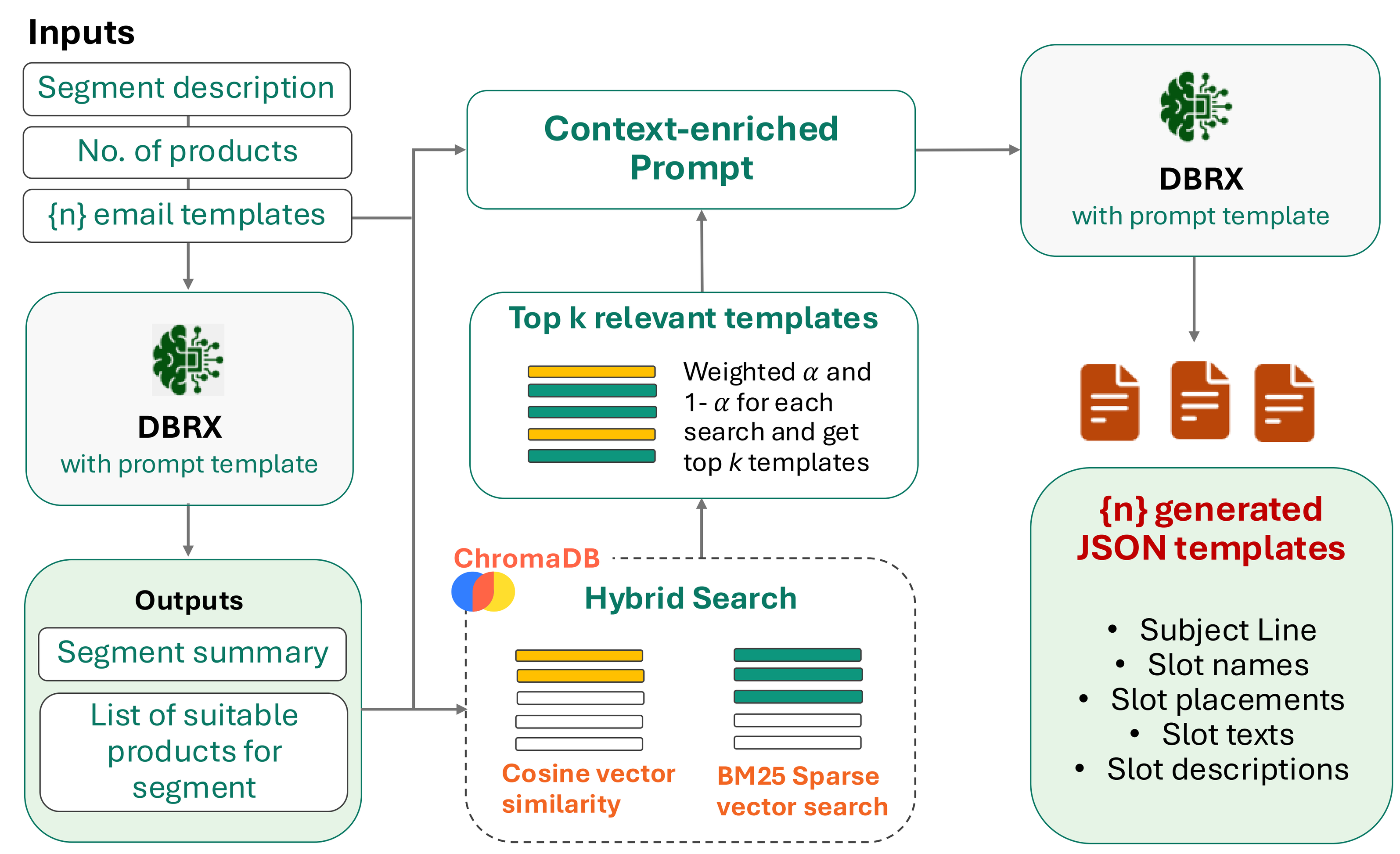
Concatenated String: `"subject_line" + "email_department" + "parsed_text"`

and used SentenceTransformer's **{all-MiniLM-L6-v2}** to embed them.

Embedding: `[1.0, 2.1, 5.2, 8…]`

We stored the **embeddings**, as well as the **full templates** in **ChromaDB:**





3. Recommending templates to individual customers

Goal: **Rank** the LLM-generated templates **for each customer** in the segment and recommend the top template.

We used the pairwise Learning To Rank (LTR) algorithm **LambdaRank**:

Inputs

- Customer data
- Transaction data
- Email interaction data
- JSON email template

Feature Engineering

Customer summary at **email receipt time**:

- Loyalty status
- Recency, Frequency, Monetary
- Historical spending in each product category
- Historical click-rate in each email category
- Month and Day-of-week

Vectorized template using **TF-IDF**

Model Selection

- **Gradient-Boosted Trees**
- Dropouts Multiple Additive Regression Trees (DART)
- Random Forest

Evaluation

Normalized Discounted Cumulative Gain (NDCG)

Mean Reciprocal Rank (MRR)

NDCG

0.53

Interpretation: Our ranking is 53% as relevant as the optimal ranking

Top Email Performance

94%

Interpretation: On average, the first relevant email is ranked in the top 6% of ~400 candidate emails

Results

Key Deliverables

- ✓ New LLM-based pipeline for automated email generation
- ✓ Clear and interpretable prompt guidelines
- ✓ User-friendly web application
- ✓ Business case outlining costs & benefits

65% predicted increase in relevance

18% predicted increase in clicks

29% estimated reduction in email creation time

Future Work

- ➢ Run 2-week A/B Test to access impact
- ➢ Deploy and scale solution for future email campaigns