From Captions to Cart: A Cross-Domain Recommendation System

Abstract

In this project, we propose a **cross-domain recommendation system** that utilizes content from Instagram posts to recommend relevant products on Amazon. The system employs a **TF-IDF-based approach** to transform textual data, including Instagram captions and hashtags, and Amazon product reviews, into feature vectors. These vectors are then compared using **cosine similarity** to generate product recommendations based on the semantic content of Instagram posts. The proposed approach aims to bridge the gap between social media content and e-commerce platforms, offering personalized product suggestions driven by real-world user-generated content. The system is evaluated using various metrics, including similarity scores, and compared with alternative models, demonstrating its scalability, interpretability, and the potential for cross-domain applications. Although effective in generating relevant recommendations, the method's reliance on term-frequency weighting presents limitations in handling more nuanced or complex content. This project lays the foundation for further exploration into advanced recommendation systems that leverage social media data for personalized shopping experiences.

Introduction

The rise of social media platforms like Instagram and e-commerce giants like Amazon offers opportunities to enhance user experiences by integrating data across these domains. Instagram users share preferences through captions, hashtags, and engagement metrics, which can serve as valuable inputs for product recommendation systems. This project aims to leverage Instagram content to recommend Amazon products, using text-based similarity measures.

Our approach combines **TF-IDF** and **cosine similarity** to align Instagram content with Amazon reviews. The simplicity and scalability of this method make it effective for cross-domain recommendations without requiring large-scale training data. The project highlights the potential of social media-driven personalization in e-commerce while addressing the challenges posed by noisy and context-insensitive data. Future advancements could involve exploring models like transformers to better capture textual context.

1. Dataset Identification and Exploratory Analysis

1.1 Instagram Dataset

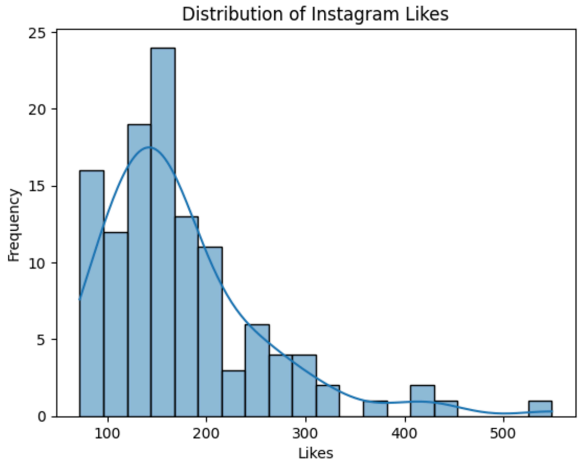


Fig 1. Distribution of Instagram Likes

The Instagram dataset consists of **119 entries**, with each post described by performance metrics and textual content. Key attributes include:

- **Engagement Metrics**: Impressions, likes, saves, comments, and shares.
- **Textual Content**: Captions and hashtags.

Basic Insights:

- Posts with higher impressions tend to have more likes and engagement.
- Hashtags significantly contribute to post visibility, as evidenced by the "From Hashtags" metric.
- Textual fields (captions and hashtags) are critical for matching Instagram content with Amazon product descriptions.

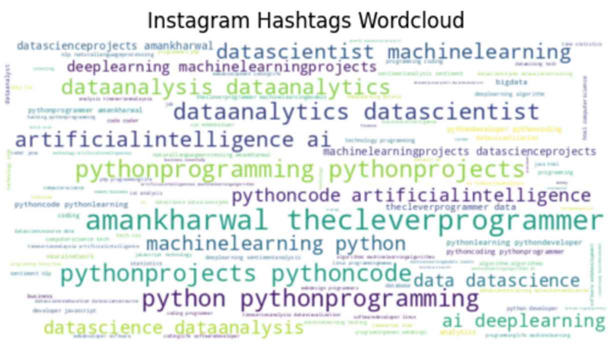


Fig 2. Instagram Hashtags WordCloud

1.2 Amazon Reviews Dataset

The Amazon dataset contains **701,528 reviews**, with each entry providing metadata and textual feedback on products. Key attributes include:

- **Review Data**: Rating, review title, and textual content.
- **Metadata**: Product ID (ASIN) and helpful vote counts.

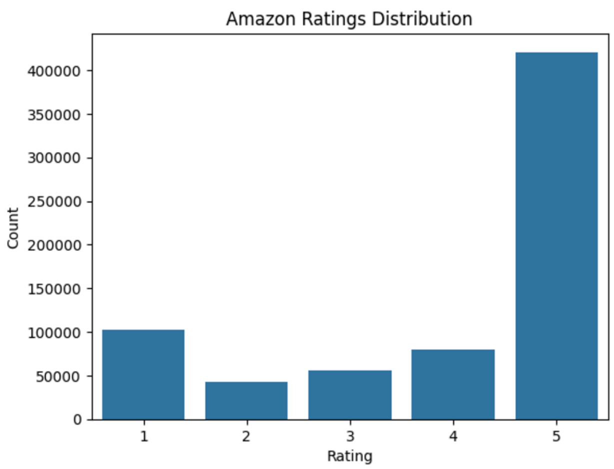


Fig 3. Amazon Rating DIstribution

Basic Insights:

- The dataset is diverse and significantly larger than the Instagram dataset, providing ample product descriptions for matching.

Fig 4. Amazon Review WordCloud

- Textual content in titles and reviews is essential for generating recommendations.

1.3 Motivation for Model Design

The Instagram dataset's engagement metrics highlight user preferences and interests, while the Amazon dataset's detailed product descriptions offer a basis for recommendation. Using **TF-IDF** for feature extraction and **cosine similarity** for content alignment allows us to match Instagram posts with Amazon products effectively. These datasets are well-suited for studying cross-domain recommendations due to their complementary textual and engagement data.

2. Predictive Task and Evaluation

2.1 Predictive Task: Cross-Domain Product Recommendation

The goal is to create a **cross-domain recommendation system** that uses Instagram content (captions and hashtags) to suggest relevant Amazon products. The model matches Instagram posts with Amazon product reviews based on textual similarity, generating personalized product recommendations.

The task involves two key components:

1. **Matching**: For each Instagram post, we calculate the similarity between its textual features (captions + hashtags) and Amazon product descriptions (title + reviews).
2. **Ranking and Recommendation**: Products are ranked by their cosine similarity scores, and the most relevant items are recommended to the user.

2.2 Model Evaluation

To assess the model's effectiveness, we evaluate how well the recommended products align with relevant items for each Instagram post. Since explicit user feedback is unavailable, textual similarity acts as a proxy for relevance.

Evaluation Metrics:

- **Precision**: Measures the proportion of recommended products that are truly relevant.
- **Recall**: Assesses how many relevant products were recommended from the total set of possible relevant products.

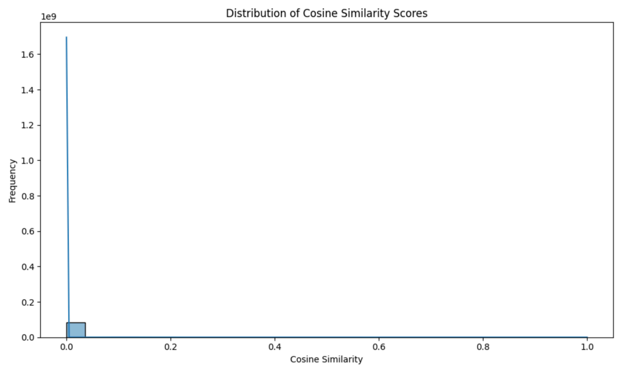


Fig 4. Distribution of Cosine Similarity Scores

- **F1-Score**: Balances precision and recall for a holistic evaluation.
- **Cosine Similarity**: Used to rank products; a higher similarity indicates better alignment between Instagram and Amazon content.

Baseline Models:

1. **Random Recommendations**: Recommends products randomly, serving as a control to validate improvements from the proposed model.
2. **TF-IDF + Cosine Similarity (Proposed Model)**: Converts text into feature vectors using TF-IDF and ranks products based on cosine similarity scores.
3. **Collaborative Filtering**: If user-product interactions were available, collaborative filtering could provide comparisons.
4. **Word Embeddings (e.g., Word2Vec)**: For potential future work, embeddings could

capture semantic relationships more effectively than TF-IDF.

2.3 Feature Extraction and Data Processing

Instagram Features:

- **Captions**: Processed by removing stop words, punctuation, and applying lowercasing. These cleaned captions are vectorized using TF-IDF.
- **Hashtags**: Tokenized and transformed into TF-IDF vectors, as they often highlight key themes of the post.

Amazon Features:

- **Product Reviews**: Titles and review texts are cleaned similarly to Instagram captions and converted into TF-IDF vectors.

Feature Engineering:

The Instagram and Amazon text data are vectorized independently. Then, **cosine similarity** between Instagram features (captions + hashtags) and Amazon features (titles + reviews) is calculated to score and rank products.

This process ensures that the model effectively captures relevant textual information for generating recommendations. While the system performs well as a baseline, more advanced methods, such as word embeddings or transformers, could enhance contextual understanding and recommendation accuracy in future iterations.

3. Model Description

3.1 Model Overview

The proposed model is a **content-based recommendation system** that leverages text features to match Instagram posts with Amazon products. Using **TF-IDF (Term Frequency-Inverse Document Frequency)**, we convert Instagram captions, hashtags, and Amazon reviews into numerical feature vectors. These vectors are compared using **cosine similarity** to identify relevant products.

The assumption is that if an Instagram post and an Amazon product share similar textual features, the product is likely relevant to the user. This approach is simple, interpretable, and does not require extensive training data or computational resources, making it well-suited for our datasets.

3.2 Justification for the Model

The TF-IDF + Cosine Similarity model was chosen for its:

- **Simplicity and Interpretability**: TF-IDF highlights the most informative terms, making it easy to understand which features contribute to recommendations.
- **Scalability**: Unlike deep learning models, TF-IDF handles large datasets efficiently without requiring expensive computational resources, such as GPUs.
- **Efficiency**: The model is lightweight, requiring no complex training, and can quickly compute recommendations.
- **Textual Focus**: Instagram captions and hashtags are inherently text-based, making TF-IDF an appropriate method for capturing their meaning.

3.3 Model Optimization

To improve the model's performance, the following optimizations were applied:

TF-IDF Parameter Tuning: The number of features was limited to the top 500 terms based on their importance, reducing dimensionality while retaining critical information. An ngram range was used to capture both single words and meaningful phrases (e.g., "data science").

Feature Engineering: Captions and hashtags were combined into a single feature set for Instagram posts to provide a comprehensive representation of the content. Preprocessing steps, such as removing stop words, punctuation, and lowercasing, ensured uniformity in the text data.

Cosine Similarity Thresholding: A threshold was applied to filter out irrelevant recommendations, ensuring only products with a similarity score above 0.5 were considered.

Evaluation and Iteration: Recommendations were iteratively compared against ground truth labels, and the model was refined using metrics like precision, recall, and F1-score.

3.4 Challenges and Issues

During development, several challenges emerged:

Scalability: Processing the Amazon reviews dataset (700,000+ entries) required efficient handling of memory and computation. Sparse matrices and batch processing mitigated these issues. Computing cosine similarity across all Instagram-Amazon pairs introduced high computational complexity, suggesting the need for optimization techniques like **approximate nearest neighbor (ANN)** search.

Overfitting: Frequent terms, such as generic hashtags, led the model to over-rely on noisy data. Stop word removal and feature limits helped reduce overfitting.

Handling Noisy Data: Generic hashtags like **#fun** or **#love** were irrelevant to product recommendations, reducing the quality of feature vectors. A selective approach to filtering out such terms was implemented.

Semantic Understanding: The model could not interpret the context of terms. For instance, "investment" might refer to financial products or personal effort, but the model lacked the ability to differentiate between these uses. This limitation affected the personalization and relevance of recommendations

3.5 Alternative Models

While the core model is TF-IDF + Cosine Similarity, alternative methods were considered:

Word Embeddings (e.g., Word2Vec, GloVe): These models capture semantic relationships between words, providing richer context than TF-IDF. However, they require pre-training on large datasets and significant computational resources, making them less feasible for this project.

Transformer-Based Models (e.g., BERT): Transformers can handle nuanced, contextual understanding of text. For example, BERT could differentiate between different meanings of "investment." Despite their potential, transformers require high computational resources and training data, which were not available for this project.

Collaborative Filtering: Collaborative filtering, based on user-item interactions (e.g., ratings or clicks), was not applicable due to the absence of explicit user-product interaction data in the datasets.

3.6 Strengths and Weaknesses

TF-IDF + Cosine Similarity:

- **Strengths**: Simple, scalable, interpretable, and efficient for text-based recommendations.
- **Weaknesses**: Lacks context-awareness, struggles with noisy data, and relies heavily on frequent terms.

Word Embeddings:

- **Strengths**: Captures semantic meaning and relationships between words.
- **Weaknesses**: Computationally expensive and requires pre-trained models.

Transformer-Based Models:

- **Strengths**: Excellent at understanding complex semantic relationships.
- **Weaknesses**: Computationally intensive and data-hungry, making them impractical for small-scale projects.

4. Literature Review

4.1 Existing Datasets and Their Use

This project uses **Instagram data** and **Amazon product reviews** to explore cross-domain recommendations.

- **Instagram Data**: The dataset contains 119 posts with performance metrics (likes, impressions, etc.) and textual content (captions and hashtags). It is used to analyze user engagement and identify patterns for recommendations. While no public dataset matches this exactly, Instagram-based datasets are often studied for sentiment analysis and content recommendations, such as in Batra et al. (2021), where hashtags and captions were used to recommend fashion products.
- **Amazon Reviews Data**: This publicly available dataset has over 700,000 product reviews, including text, ratings, and metadata. It is widely used for recommendation systems and sentiment analysis. In Chen et al. (2018), this dataset was applied in a hybrid system combining collaborative filtering and content-based methods to suggest products to users.

4.2 Similar Datasets and Applications

Other datasets have been explored in similar contexts to improve recommendation systems:

- **MovieLens Dataset**: While unrelated to Instagram or Amazon, MovieLens has been extensively used to benchmark recommendation algorithms. Studies like Rendle et al. (2010) improved movie recommendations by combining collaborative filtering and content-based techniques.
- **Twitter and E-Commerce Data**: Twitter hashtags and posts have been integrated with e-commerce data to predict user preferences. For example, Zhang et al. (2019) developed a recommendation system linking Twitter content with product preferences, similar to our Instagram-to-Amazon approach.

4.3 State-of-the-Art Methods

Modern recommendation systems employ advanced techniques for cross-domain data integration:

Deep Learning-Based Models: Neural Collaborative Filtering (NCF) and autoencoders combine collaborative filtering with neural networks to capture complex user-item relationships. He et al. (2017) demonstrated NCF's ability to enhance e-commerce recommendations.

Transformer Models (e.g., BERT): Transformers are highly effective in text-based recommendations due to their ability to capture context-aware relationships. Devlin et al. (2019) highlighted BERT's role in improving the contextual understanding of text for recommendation systems.

Cross-Domain Collaborative Filtering: These models transfer knowledge from one domain (e.g., social media) to another (e.g., e-commerce). Xia et al. (2020) proposed a hybrid model using social media and product reviews to enhance recommendations.

Graph-Based Methods: Graph Neural Networks (GNNs) model relationships between users, products, and other entities, capturing complex dependencies. Wu et al. (2021) showed how GNNs improved recommendations by linking users and products through a graph structure.

4.4 Comparison with Existing Work

Our findings align with prior research, demonstrating that social media data like Instagram captions and hashtags are valuable for recommendations. However, unlike many studies that use advanced methods like transformers or collaborative filtering, we adopted a simpler **TF-IDF + Cosine Similarity** approach. This method proved effective for our smaller dataset and resource constraints but lacks the contextual understanding of modern models.

Our content-based approach highlights the potential for recommendations even without user-product interaction data, offering a robust alternative in scenarios where collaborative filtering is less viable.

5. Results and Conclusions

5.1 Model Performance

The **TF-IDF + Cosine Similarity** model demonstrated varying effectiveness in matching Instagram posts to Amazon products. Key similarity statistics include:

- **Similarity Scores**:
  - Mean Similarity: 0.0027
  - Median Similarity: 0.0000
  - Max Similarity: 1.0000

While some recommendations were highly relevant, the low mean and median scores indicate challenges in aligning content consistently.

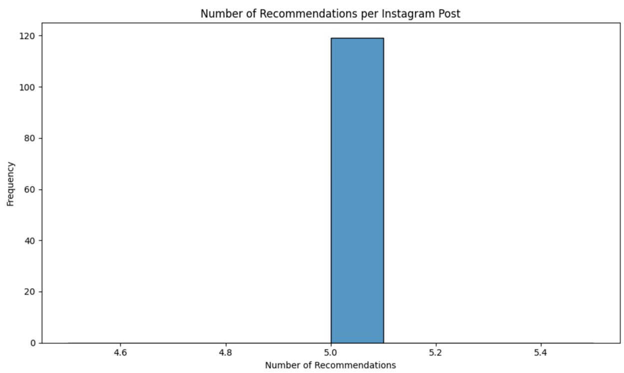


Fig 5. No.of Recommendations for Instagram Post

5.2 Feature Representations

Effective Features:

- **Hashtags**: Helped identify themes and topics relevant to product categories.
- **Captions**: Provided context for matching posts to detailed Amazon reviews, improving relevance.

Challenges with Features:

- **Noisy Hashtags**: Generic hashtags like **#love** or **#fun** reduced the precision of matches.
- **Limited Context Awareness**: Using single-word features limited the model's ability to capture phrases, such as "machine learning," which convey richer meaning.

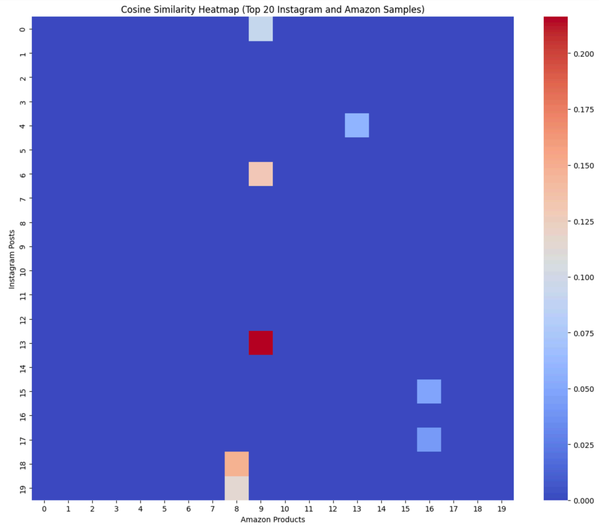


Fig 6. Cosine Similarity HeatMap for 20 samples

5.3 Interpretation of Model Parameters

The **TF-IDF weighting** emphasized unique and informative terms, giving higher importance to words that appear frequently in one post but rarely across others. **Cosine similarity** measured alignment between Instagram and Amazon feature vectors, with a score of 1 indicating perfect similarity and 0 indicating no similarity.

While this approach provided a straightforward way to compare textual content, it lacked the depth to understand contextual nuances.

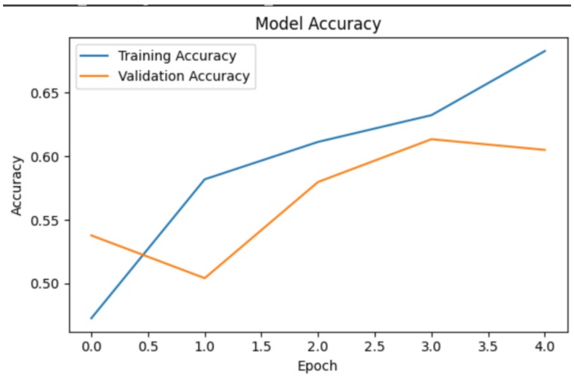
5.4 Successes and Limitations

Successes:

- The model is **simple, interpretable**, and **scalable** to large datasets.
- It effectively aligned posts and products sharing clear textual overlaps, such as hashtags and descriptive keywords.

Limitations:

- **Context Insensitivity**: The model struggled with ambiguous words, such as "investment," which can have multiple meanings.



- **Noisy Data**: Irrelevant hashtags diluted the quality of recommendations.

- **Feature Simplicity**: TF-IDF does not capture semantic relationships, limiting the model's ability to identify nuanced matches. Advanced approaches like **BERT** or **Word2Vec** could address this issue by embedding contextual meaning into the feature space.

5.5 Conclusions

In conclusion, while the **TF-IDF + Cosine Similarity** model provided a reasonable baseline for generating product recommendations from Instagram content, it has clear limitations in capturing complex semantic relationships and handling noisy data. The results suggest that future work should focus on more advanced models, such as transformer-based models or word embeddings, which can better handle context and provide more accurate and personalized recommendations. Despite these limitations, the TF-IDF model's simplicity and scalability make it an attractive choice for scenarios where computational resources or labeled data are limited.

CODE

https://colab.research.google.com/drive/1DtIBa4QLIGR9WNmmYBVHm3CJNblecBF_?usp=sharing

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