

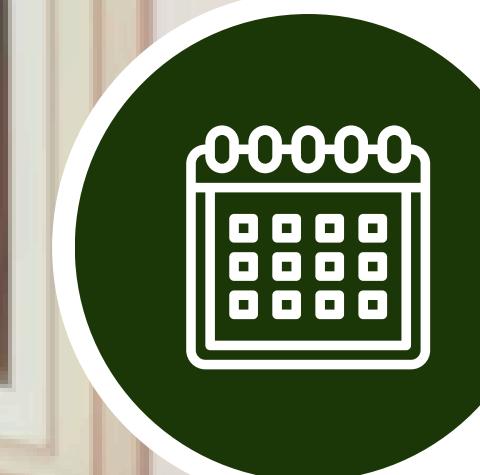


Next-Click Prediction System for Fashion Campus

Enhancing Product Recommendations,
Through Sequential Modeling



Problem Statement & Objectives



Problem:

- Users frequently leave without completing purchases due to lack of personalized recommendations.

Objectives:

- Understand user navigation behavior.
- Predict the next-clicked product using user sessions.
- Compare Markov chains and GRU (Gated Recurrent Unit) in recommendation accuracy.
- Visualize user journey and product relationships.

Data Used & Feature Engineering

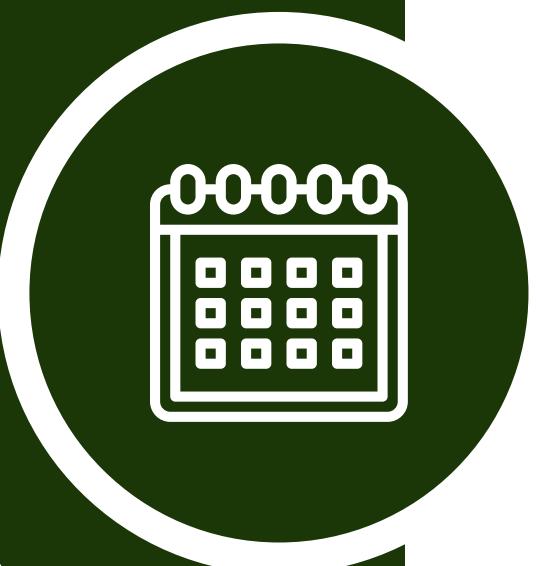
Datasets:

- Clickstream: 12.8M records (100K sampled records for efficiency)
- Customer: 100K
- Product Metadata: 44K
- Transactions: 850K



Key Features Extracted:

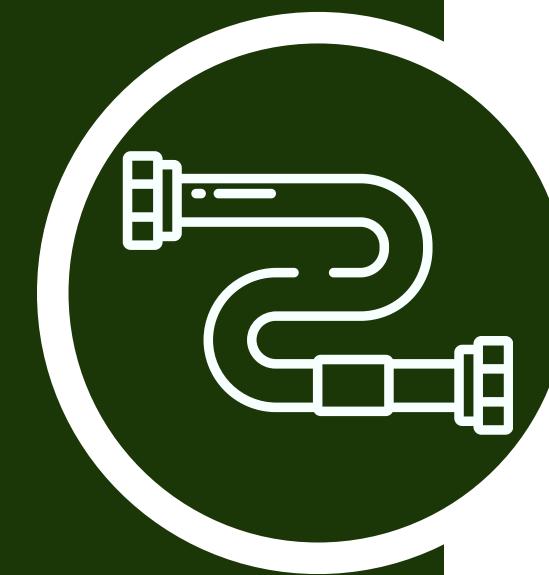
- Product sequences by session.
- Time-based features: hour, weekday, time since last click.
- Click counts, session metrics.
- Embedding-based product similarities.



Methodology & System Architecture

Pipelines:

- Preprocess → Sequence Creation
- Word2Vec: Learn product embeddings
- t-SNE: Visualize product relationships
- Markov Chain: Simple next-click modeling
- GRU (Gated Recurrent Unit): Sequential deep learning
- Simple Input-Output Setup: User interaction for next-click prediction

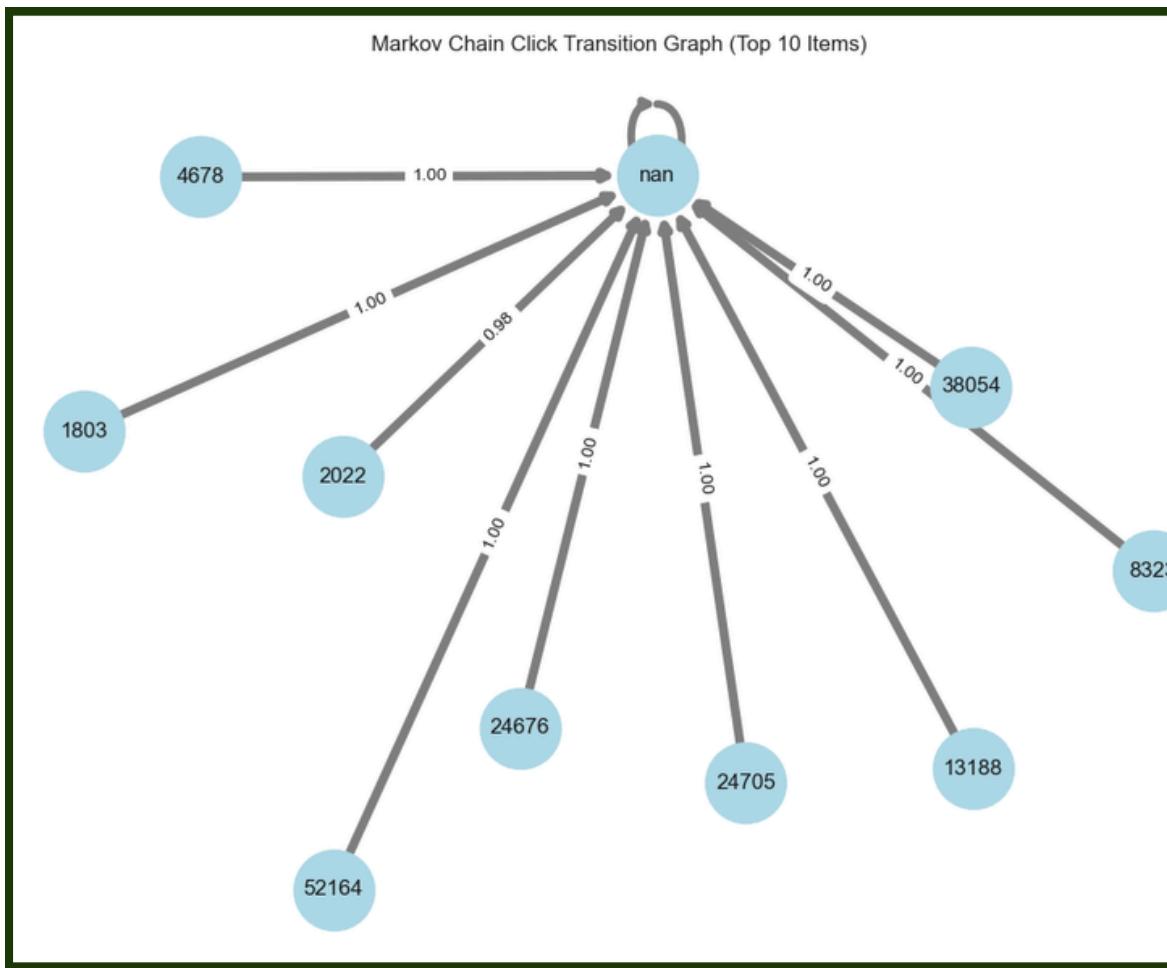


Tools & Libraries:

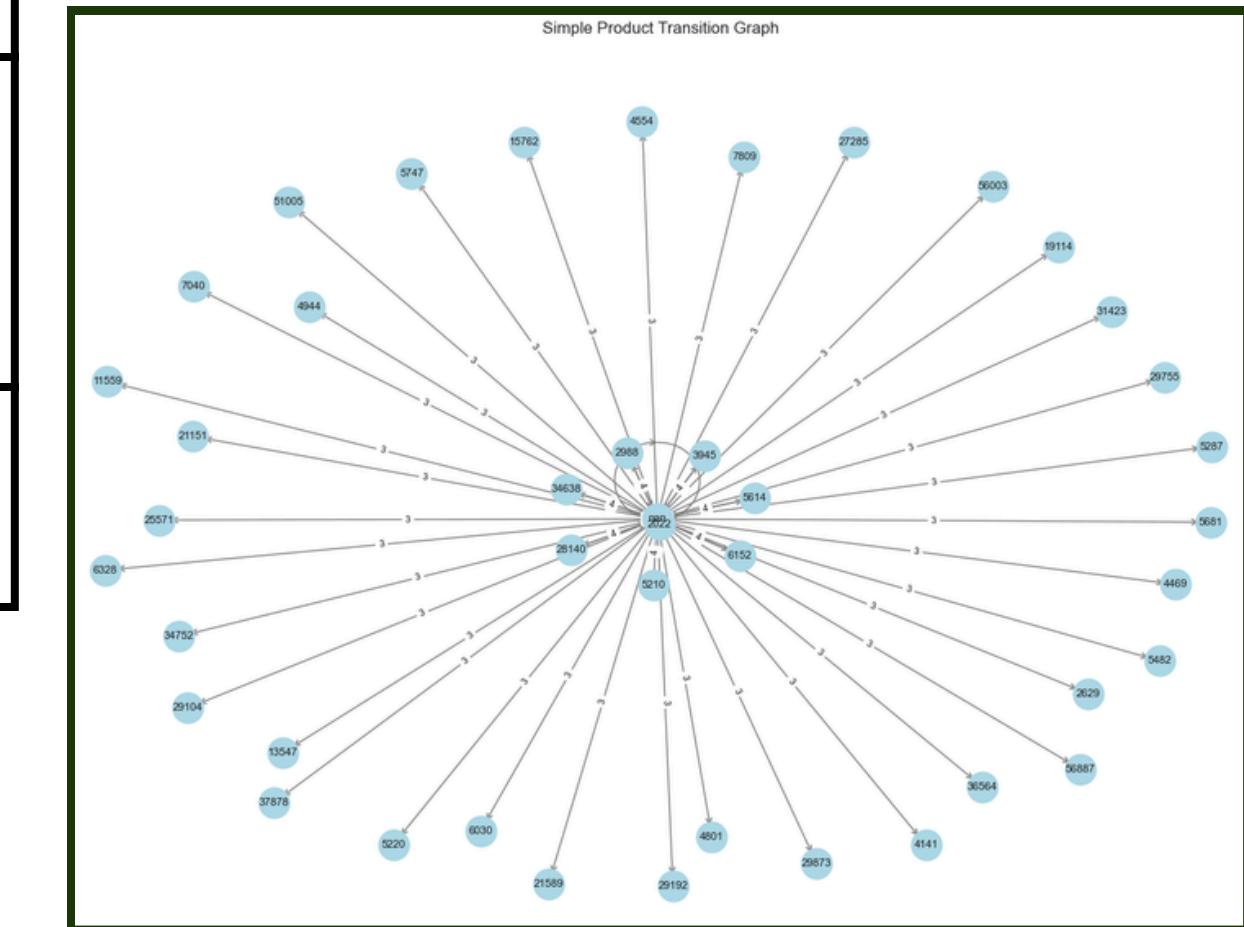
- Python,
- Pandas,
- Gensim,
- TensorFlow,
- Keras,
- Seaborn,
- NetworkX



Model Evaluation & Results



Model	Top-1 Accuracy	Top-3 Accuracy
Markov Chain	88.68%	90.07%
GRU	87.16%	88.51%



User interaction for next-click prediction

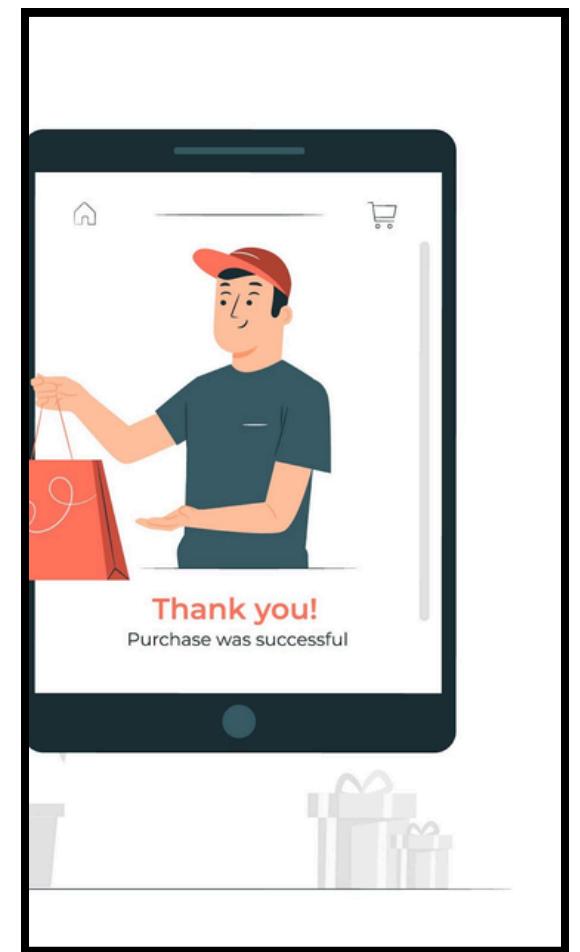
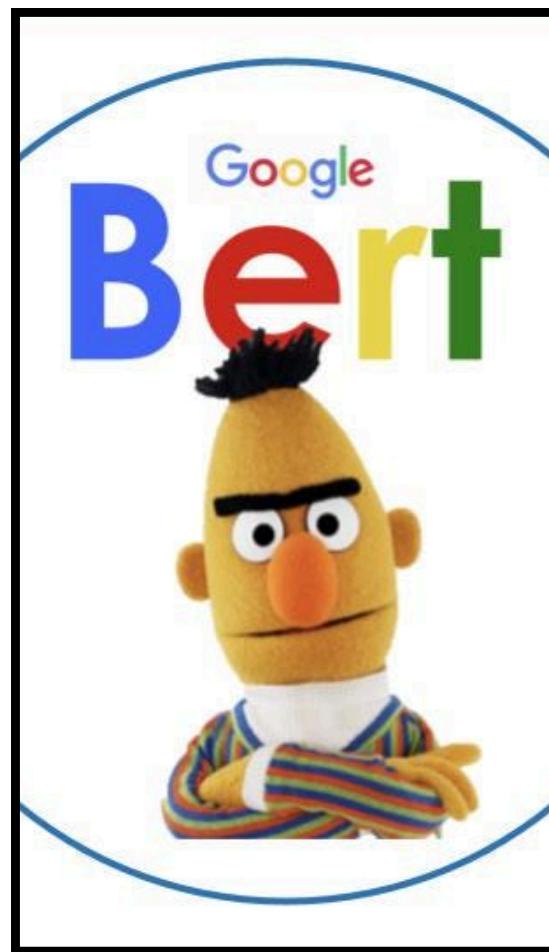
```
print( "\n[!] NO similar products found. " )  
  
==== Next-Click Prediction ===  
  
Available Product IDs (sample): ['nan', '2022', '2988', '5210', '5614', '6152', '5217', '3945', '28140', '34638'] ...  
Enter your last clicked Product ID: ↑↓ for history. Search history with c-↑/c-↓  
I: 
```

Conclusion:

- Built a scalable Next-Click Prediction System for Fashion Campus.
- Combined classical (Markov Chain) and deep learning (GRU) methods.
- Used Word2Vec to capture product semantics and user behavior.
- GRU performed well on complex sessions; Markov excelled on simpler ones.
- Implemented a simple CLI for real-time user interaction.
- Showcased the power of embeddings and sequence modeling in e-commerce.

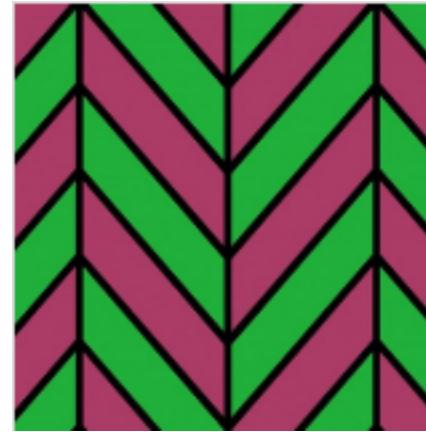
Future Work

- Integrate user demographics & real-time feedback
- Use Transformers (like BERT4Rec) for deeper context
- Deploy on cloud (AWS/GCP) for real-time scalability
- Personalized recommendations via reinforcement learning



References

- Hwangbo H. (2022). Sequence-aware recommenders for fashion e-commerce. *ElectronicCommerce Research*, 22(3), 587–605. Retrieved from <https://doi.org/10.1007/s10660-022-09627->
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- Zhang, H.,& Chen, Y. (2022). A deep Markov model for clickstream analytics in onlineshopping. In Proceedings of the 2022 Web Conference (pp. 3243–3253).ACM



Fashion Campus

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Thank You

