Recommendation & Prediction system

Class 29

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Acknowledgement

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AOTS

Ministry of Economy, Trade and Industry

OEC

Overseas Employment Corporation

What you have Learnt Last Week

We were focused on following points.

- Usage of function, loop, and Numpy
- Software development Life cycle
- Importance of Security compliance, Bash Scripting, Ansible, docker and docker compose
- API testing with Postman and Introduction of Jira
- IAM Permission and S3 bucket
- Introduction to AWS, Azure and GCP
- Supervised and Unsupervised Machine Learning Algorithms

What you will Learn Today

We will focus on following points.

1. Overview of different recommendation methodologies, including content-based filtering, collaborative filtering, and hybrid systems,
2. Explanation of algorithms commonly used in predictive systems
3. Challenges and Ethical Considerations in Recommendation and Prediction Systems
4. Q&A Session

Introduction to Recommendation Methodologies

Why Recommendation Systems Matter

Recommendation systems help users discover relevant items from huge datasets.

Used in e-commerce (Amazon), entertainment (Netflix, Spotify), and social media (YouTube, TikTok).

Improve user experience, increase engagement, and drive sales and retention.

Content-Based Filtering

Recommending Based on User Preferences

Builds a user profile using item features, preferences, and metadata.

Uses similarity measures like cosine similarity, TF-IDF, and word embeddings.

Advantages: Personalized, independent of other users.

Limitations:

- Cold-start problem (new user or item = no data).
- Lack of novelty (recommends similar items repeatedly).

Collaborative Filtering (User-Based)

Recommendations from Similar Users

Finds users with similar behavior or interests.

If User A and User B liked the same movies, recommend unseen movies from B to A.

Works well when there is enough user–item interaction data.

Problem: Struggles with sparse data and new users (cold-start).

Collaborative Filtering (Item-Based & Matrix Factorization)

Learning from Item Patterns

Item-based CF: Finds similarity between items instead of users.

Example: If two movies are watched by many of the same users → they are "similar."

Matrix Factorization (SVD, ALS):

- Decomposes user–item rating matrix into hidden factors.
- Captures latent features like user preferences for genres.

Deep Learning in Collaborative Filtering

Neural Approaches to Recommendations

Neural Collaborative Filtering (NCF): Learns complex patterns between users and items.

Uses embeddings and multi-layer neural networks.

Better handles non-linear relationships.

Examples: YouTube recommendations, Spotify playlists.

Hybrid Recommendation Systems

Combining Multiple Methods

Weighted Hybrid: Combine scores from multiple methods.

Switching Hybrid: Dynamically choose best method depending on context.

Cascade Hybrid: Use one method’s output to refine another.

Feature-Augmented Hybrid: Add extra features for better prediction.

Real-World: Netflix combines CF + content-based + time-series behavior.

Predictive Algorithms: Regression

Predicting Continuous & Categorical Outcomes

Linear Regression: Predicts numeric outcomes (e.g., sales, ratings).

Logistic Regression: Predicts probabilities (e.g., churn, fraud).

Regularization (Lasso, Ridge): Prevents overfitting by penalizing large coefficients.

Widely used in finance, healthcare, and marketing predictions.

Predictive Algorithms: Classification & Boosting

Making Class Predictions

Decision Trees: Simple interpretable models for classification.

Random Forests: Ensemble of trees for higher accuracy.

Gradient Boosting (XGBoost, LightGBM, CatBoost):

- Builds models sequentially to correct previous errors.
- Highly accurate, widely used in Kaggle competitions.

Neural Networks for Prediction

Deep Learning in Predictive Systems

Feedforward Neural Networks: Capture complex patterns.

Deep Learning Models: Handle images, text, and sequential data.

Useful for recommendation personalization, text classification, and fraud detection.

Clustering Techniques in Prediction

Grouping Similar Users or Items

K-Means: Partitions data into k clusters.

DBSCAN: Groups dense regions of data, identifies outliers.

Hierarchical Clustering: Builds tree-like cluster structures.

Role in Recommendations:

- Group users with similar preferences.
- Segment products for targeted marketing.

Sequence & Time-Series Models

Predicting Events Over Time

Classical Models: ARIMA, Prophet → forecasting demand or sales.

RNNs & LSTMs: Handle sequential dependencies (e.g., browsing sessions).

Transformers: Capture long-range dependencies (e.g., user click streams).

Used in stock prediction, demand forecasting, and session-based recommendations.

Reinforcement Learning in Recommendations

Learning by Interaction

Multi-Armed Bandit Problem: Dynamically explore vs. exploit for best recommendation.

Policy Gradient Methods: Learn personalized strategies over time.

Applications:

- Online advertising (choosing the best ad).
- Personalized news feeds.
- Adaptive learning platforms.

Technical Challenges in Recommendation Systems

Practical Limitations of Current Models

Cold-Start Problem: Difficulty recommending for new users/items with no history.

Data Sparsity: Sparse user–item interactions reduce effectiveness of collaborative filtering.

Scalability Issues: Billions of users/items need efficient algorithms.

Real-Time Constraints: Systems must deliver recommendations within milliseconds.

Ethical Challenges in Recommendations

Fairness, Transparency, and Responsibility

- **Bias in Algorithms:** Risk of reinforcing stereotypes and discrimination.

- **Filter Bubbles & Echo Chambers:** Overexposure to similar content reduces diversity.

- **Transparency:** Users demand *why* a recommendation was made → Explainable AI (XAI).

Privacy & Data Security Concerns

Protecting User Rights

- **User Privacy:** Sensitive behavioral and demographic data collected.
- **Data Security:** Preventing breaches and misuse.
- **Regulatory Compliance:** GDPR (Europe), CCPA (California) demand strict control.
- **Trust Building:** Transparency in how data is used.

Business & Societal Concerns

Broader Impacts of Recommendation Systems

- **Over-Reliance on Automation:** Businesses may depend too heavily on algorithms.

- **Manipulation vs. Personalization:** Recommendations may nudge users towards certain behaviors.

- **Accuracy vs. Diversity:** Accurate systems may lack novelty or serendipity.

Evaluation Metrics for Recommendation Systems

Measuring Success

- **Accuracy Metrics:** Precision, Recall, F1-score, Hit Rate.

- **Error Metrics:** RMSE (Root Mean Square Error), MAE (Mean Absolute Error).

- **Beyond Accuracy:** Diversity, Novelty, Serendipity → measure user satisfaction.

Evaluation Approaches

Offline vs. Online Testing

- **Offline Evaluation:** Uses historical test sets to measure predictive performance.
- **Online Evaluation:** A/B testing with live users.
- **User Engagement Metrics:** Click-through rate (CTR), dwell time, satisfaction surveys.
- **Continuous Monitoring:** Performance tracked in real-time.

Real-World Applications (Consumer Platforms)

Everyday Use Cases

E-commerce: Amazon, Flipkart → product suggestions.

Streaming: Netflix, Spotify, YouTube → movie, music, video recommendations.

Social Media: TikTok, Instagram, Twitter → personalized feeds & targeted ads.

Real-World Applications (High-Impact Domains)

Beyond Entertainment

- **Healthcare:** Drug recommendations, personalized treatment.
- **Finance:** Fraud detection, credit scoring, stock prediction.
- **Education:** Personalized learning paths.
- **IoT/Smart Systems:** Energy consumption optimization, predictive maintenance.

Future Trends in Recommendation Systems

Emerging Innovations

- **Context-Aware Recommendations:** Tailored by location, time, device.

- **Cross-Domain Systems:** Combining data across platforms for better accuracy.

- **Explainable AI (XAI):** Making recommendations understandable to users.

Advanced Future Directions

Privacy & AI-Powered Recommendations

•**Federated Learning:** Decentralized training without sharing raw data.

•**Integration with Generative AI:** GPT-powered recommenders for conversational recommendations.

•**Ethical AI Practices:** Ensuring fairness, diversity, and accountability.

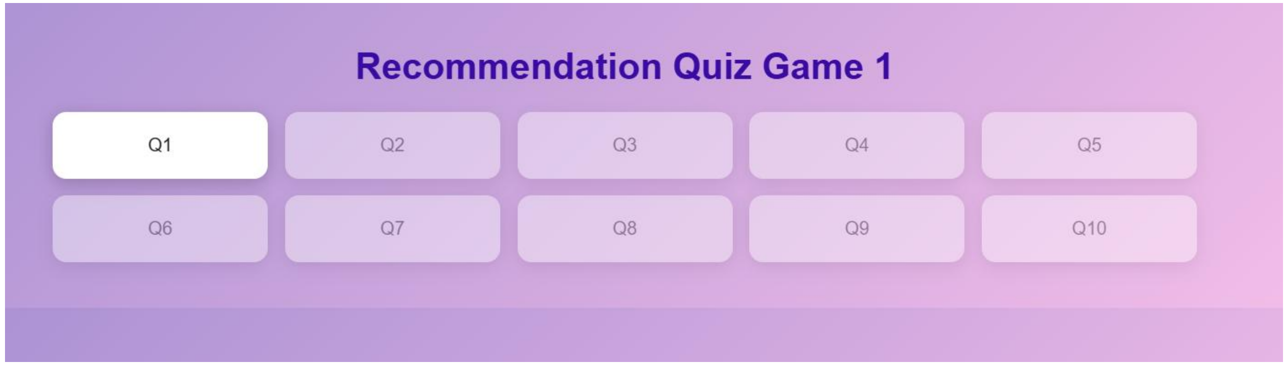
Game 1

Cloud Fundamentals Maze

Step1: Start the Game by Clicking the Link

Step2: Click on the Game It will Start

https://codepen.io/HT-Design/full/gbPOGYd



Game 2

Step1: Start the Game by Clicking the Link

Step2: Click on the Game It will Start

https://codepen.io/HT-Design/full/RNrwLNJ

Assignment

Quiz Section

Quiz

Everyone student should click on submit button before time ends otherwise MCQs will not be submitted

[Guidelines of MCQs]

1. There are 20 MCQs
2. Time duration will be 10 minutes
3. This link will be share on 12:25pm (Pakistan time)
4. MCQs will start from 12:30pm (Pakistan time)
5. This is exact time and this will not change
6. Everyone student should click on submit button otherwise MCQs will not be submitted after time will finish
7. Every student should submit Github profile and LinkedIn post link for every class. It include in your performance

Assignment

Assignment should be submit before the next class

[Assignments Requirements]

1. Create a post of today's lecture and post on LinkedIn.
2. Make sure to tag @Plus W @Pak-Japan Centre and instructors LinkedIn profile
3. Upload your code of assignment and lecture on GitHub and share your GitHub profile in respective your region group WhatsApp group
4. If you have any query regarding assignment, please share on your region WhatsApp group.
5. Students who already done assignment, please support other students

Q&A Session

ありがとうございます。

Thank you.

شکریا

For the World with Diverse Individualities