HA1

AI-driven Recommendation system

Pitch Presentation

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AI-based Recommendation System

Outline

Project objective

- Goals

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Introduction

- Background
- Motivation

01

03

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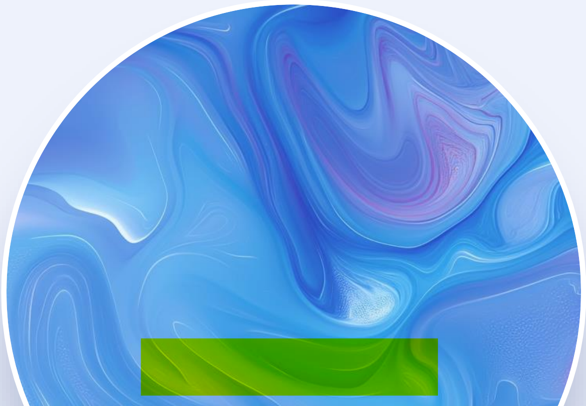
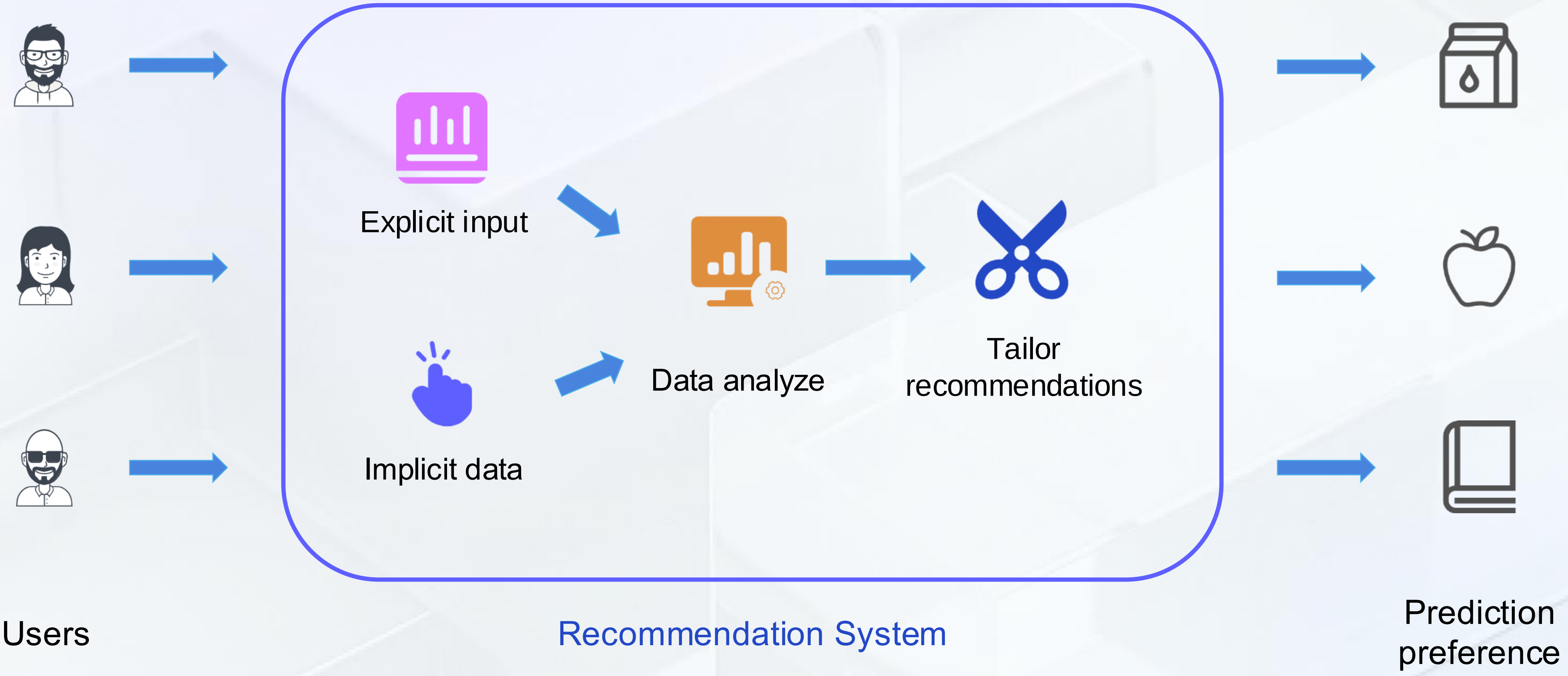
- Steps



Introduction

What is recommendation system?



Introduction

Why is recommendation system important?

Solve the Problem of Information Overload

Improve User Experience and Satisfaction

Increase Sales and Business Value

Introduction

What is AI?

Definition:

The technology of simulating human intelligent behavior by computer systems

Core Capabilities:

- learning
- reasoning
- self-correction

Practical Application:

- **Medical industry:** Analyze medical images to assist diagnosis
- **Transportation industry:** Autonomous driving
- **Financial industry:** Smart investment consulting; Fraud detection
- **Website:** Personalized recommendations

AI-based Recommendation System

Introduction

Example of RS

Example 1

Netflix: As a film and television recommendation system

Example 2

Trip is a travel recommendation system

Example 3

Amazon, as a global e-commerce platform

Motivation

AI Recommend

User prefer + User Information = Personalized service

Motivation

Key.1

Misalignment in agent expertise

The application failed because the user prepared wrong materials in vain

Key.2

Poor communication or language barrier

Low communication efficiency and high risk of misunderstanding

Key.3

Inexperienced agents are matched

Risk of misleading the applicant

Key.4

Remote unreachable proxies are recommended (time zone issues)

Unable to communicate smoothly, poor user experience

Motivation: Problem 1 - Information Overload

Problem Description:

- 7,000+ migration agents in Australia
- Different specializations, success rates, and fee structures
- Migrants face decision paralysis due to overwhelming choices

What will happen if not addressed:

□ Weeks wasted researching

❌ Higher visa rejection rates

💸 Wasted application fees

📅 Missed critical deadlines

Motivation: Problem 2 - Lack of Transparency

Problem Description:

- No reliable verification of agent performance
- Success rates and expertise claims unverified
- Reliance on word-of-mouth without metrics

What will happen if not addressed:

👎 Selections based on marketing
💰 Premium fees to poor performers
📝 Unnecessary rejections
😞 Abandoned migration plans

Case Presentation

Meet Andrew

Andrew's Challenge:

"With over 300 potential migration agents claiming expertise in skilled migration, how do I find the one best suited for my specific case?"

Andrew

🧑 💻 Software Engineer from India

💼 8 years of experience

AU Seeking Skilled Migration visa

❓ Needs to find the right agent

Without a reliable system,Andrew risks:

- Choosing an agent with limited IT migration experience
- Wasting time researching without clear metrics
- Paying premium fees without guaranteed results

How Andrew Uses Our System

Input Profile

Details about occupation, experience, visa

AI Processing

4,000+ agents analyzed

Match Results

Top 3 specialized agents

Direct Connection

Book consultation & apply

Results

Before vs After

BEFORE	AFTER
✗ Uncertain process	✓ Streamlined process
✗ High rejection risk	✓ First-time approval
✗ Extra costs	✓ Cost savings
✗ Long delays	✓ Clear timeline

AI-based Recommendation System

Progress – Top 3 popular models

Neural Collaborative Filtering

- A deep learning-based approach
- Use neural networks to model user-item interactions
- complex, non-linear patterns

Light Graph Convolutional Network

- lightweight graph neural network model (GCN)
- Inheriting the neighbor information aggregation idea of GCN
- Improved computing efficiency

Deep Neural Networks

- Two-Tower Neural Network
- Multilayer nonlinear transformation
- The accuracy of the model

AI-based Recommendation System

Progress

Progress	Literature Review	Training and Testing	Comparison and Evaluation
Focus	Existing models and algorithm Their limitations and evaluations	• Data preprocessing • Training set: 80% data • Testing set: 20% data	• Recall@K • Normalized Discounted Cumulative Gain(NDCG)@K • Computing time
Milestones	01 Model selection Data collection and generation	02 Top K recommendations for each model	03 Comparison of 3 models' evaluations

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