Recommendation Systems

For Movies

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Agenda

1. The business problem to solve
2. The Dataset
3. Recommendation models overview
4. Evaluating the models

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Introduction

In today's digital landscape, user engagement and satisfaction are pivotal for any platform's success.Recommender systems play a crucial role in achieving these goals.

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This presentation delves into our recommendation models, aiming to optimize user experiences and elevate engagement..

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Project Goals

Engagement

70% of time watched on YouTube driven by recommender system (CNet)

Retention

Recommendations saves Netflix more than $1B per year in subscriber churn (Netflix)

Revenue

35% of the purchases on Amazon are the result of their recommender system (McKinsey)

What Movies will the users be interested in?

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Dataset used

Dataset

We will use MovieLens dataset, created and maintained by GroupLens research group out of University of Minnesota: https://grouplens.org/datasets/movielens/

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Dataset info

Offers multiple versions, we will use the one targeting education: ml-latest.zip (5MB)
Dataset contains user ratings with timestamps, user-applied tags, movie genres.

100k
Ratings

1000
Users

1700
Movies

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Sparsity: 0.998 (!)

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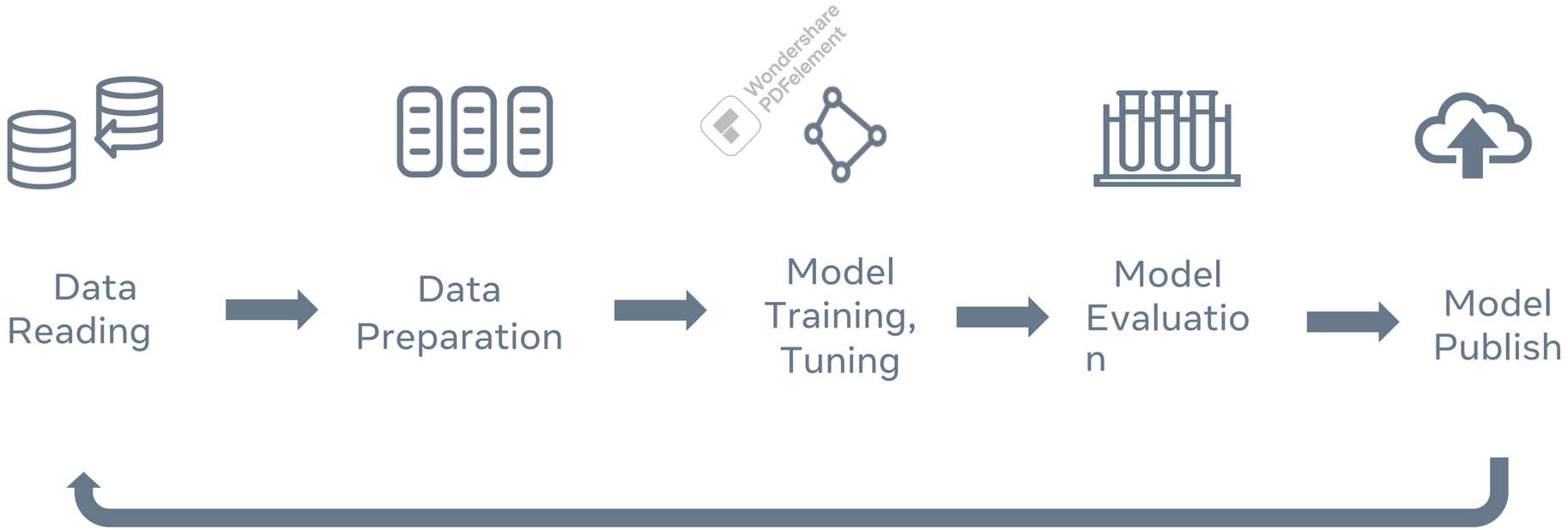
Project Steps



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2 Recommendation Models Overview

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Baseline model: Popularity

Before we start with complex modeling, it is important to set a baseline!

- We will set a baseline for a simple popularity-based model:
  - This model recommend top movies to all the users regardless of preference

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- Model Pros and Cons:
  - This model is simple to make and it appeals to a broad audience
  - The downside is it lacks personalization and user preferences

Can we do better?

Cosine similarity

How it Works

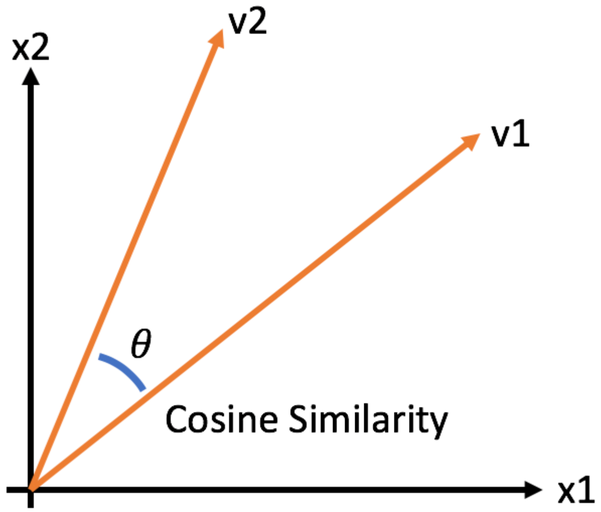
- This model works by getting the cosine of the angle to determine item similarity

Advantage

. Effective for capturing item relationship based on content

Usage

I used this model in my website to recommend similar movies to the input



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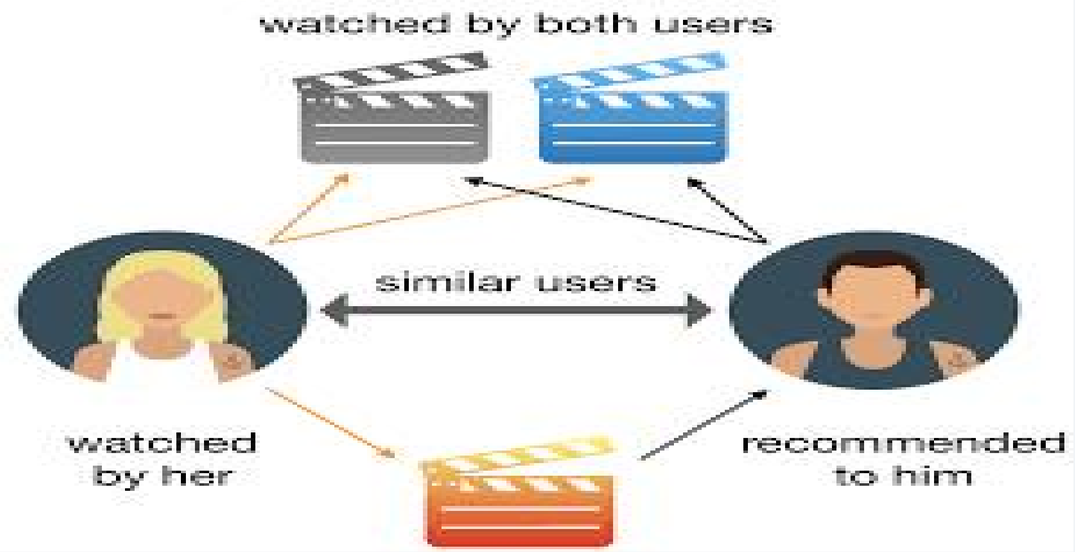
Final:AlS Model

How It Works

- This model works by using user-item interactions to make personalized recommendations
- ALS model is a collaborative model which means similiar users are recommended similiar movies



Advantages

This model performs well in making personalized user recommendation

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Business Problem

Evaluation Overview

- How Th

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Evalution

Metrics:

- Data: 100K samples (70% training, 30% test)
- Metrics used:
  - RMSE ,RME
  - Novelty ,Personalization
  - Coverage and Recall -

Findings

Results: RMSE 0.
88 and
RME 0.78

The model seems to be doing good on the test data with a good RMSE and RME

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Personalization and Novelty

Novelty

Novelty evaluates how unique recommendations are.

- High novelty means recommendation introduces fresh,less explored items
- Our ALS is 3 times more novel than the baseline model

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Personalization

Personalization measures how tailored recommendation are to individual users

High personalization means recommendations are unique while low signifies recommendations are similiar.

Findings

+3x vs PopModel with 2.70

0.05 personalization

Coverage

Increasing model capacity enables the model to:

- Coverage assesses the diversity and breadth of recommendation made by the system

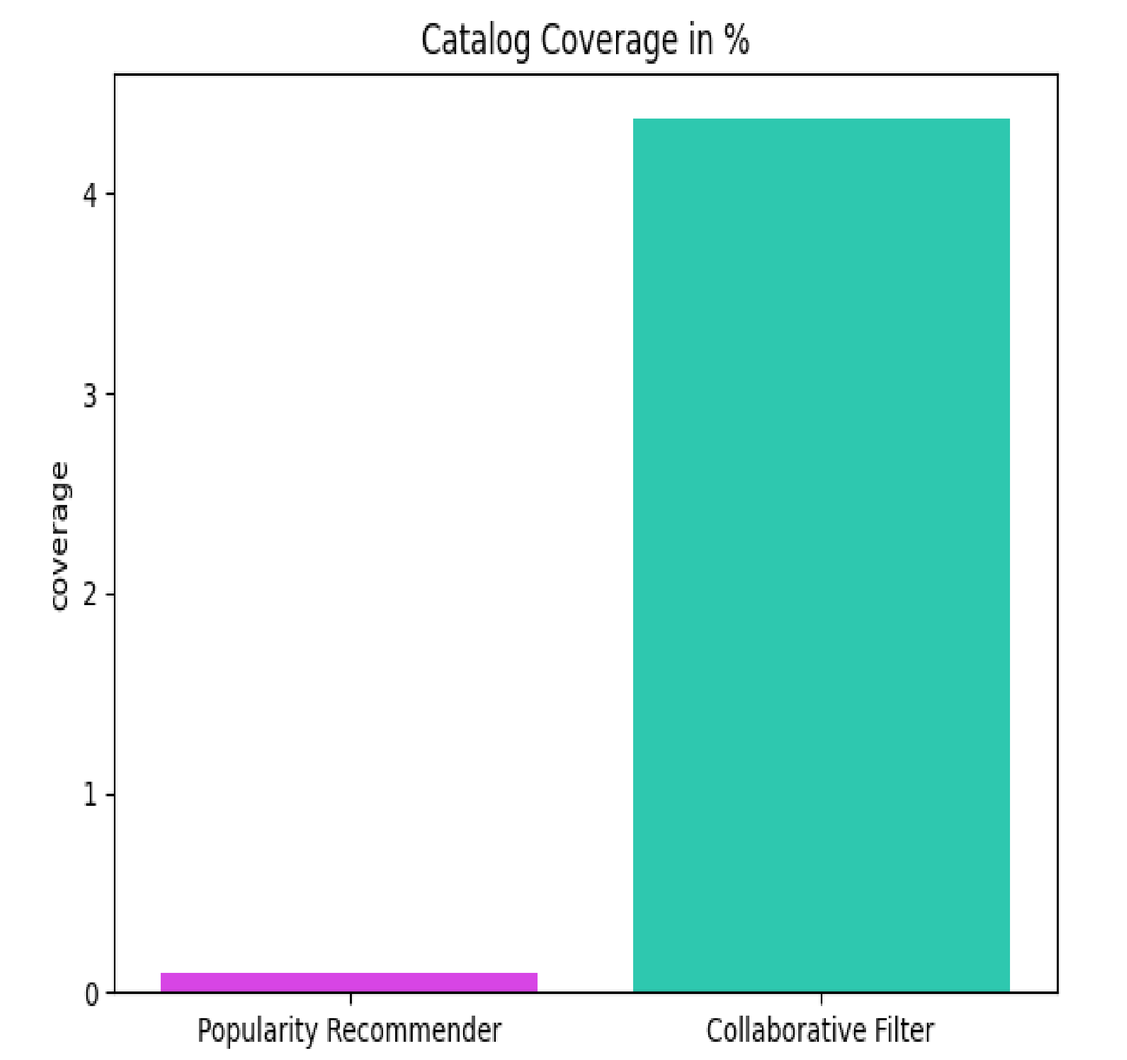
Why it matters:

- High coverage ensures that a wide variety of items are recommended to users
- Low coverage may lead to users seeing a limited subset of available items

Use Cases:

- E-commerce platforms aim for high coverage to present a range of products
- Movie Platforms strive for high coverage leading to users finding good movies

+40% vs PopModel



“Bigger is better ”

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3 EVALUATING THE MODEL

MAR@K

MAR@K:

- This metric assesses the quality of ranked recommendation by measuring how well relevant items are placed within top positions
- ALS model has lower MAR@K reflecting personalized recommendation while the popular has high MAR@K meaning it excels in promoting popular items
- This metric suffers from popularity bias

Use Case:

- This metric is used in movies and music recommendation system to ensure relevant items are prominently featured

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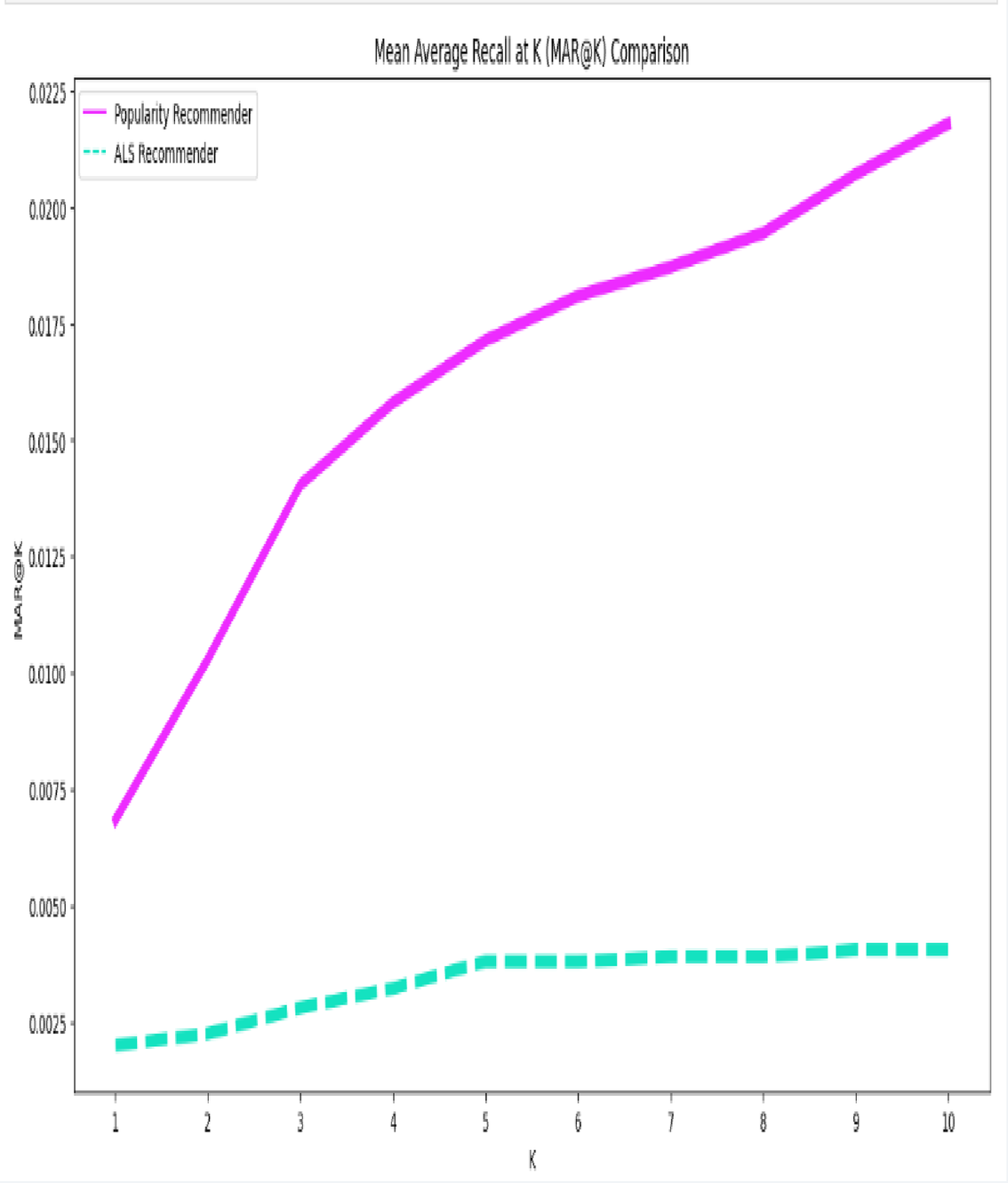
Results:+16.7% vs



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further improvement

Data

- More data
- Better data

...

Model

- Hybrid Model
- Deep Learning Model

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Other

- Better user interface
- Feedback from users

...

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Conclusion

Key takeaways:

- High coverage and personalization from our model results in user retention and engagement

- Use more data for better personalization

- Retrain the model with ratings from users

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Thank You!

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