Multi-Stakeholder aware Recommender Systems

Bereket A. Yilma

Session 3

- → A Multi-Stakeholder aware RecSys
- → Formulating the RecSys Problem? →(A framework)
- → Modern RecSys Paradigms
  - ◆ Large Language Models as RecSys (Zero & Few shot)
- → Common Issues and Challenges in RecSys

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CROSS CULT

LIST

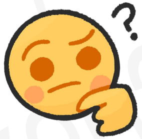
European Commission

HORIZON 2020

Formulating a RecSys Problem

Task: Design a Personalised Visual Art Recommendation engine for NG/ Louvre

Formulating a RecSys Problem

Data Pre-processing →  → Model Training → Post Processing → Evaluation

- Sort
- Filter
- Recommend

Understanding the context of the problem!

Formulating a RecSys Problem

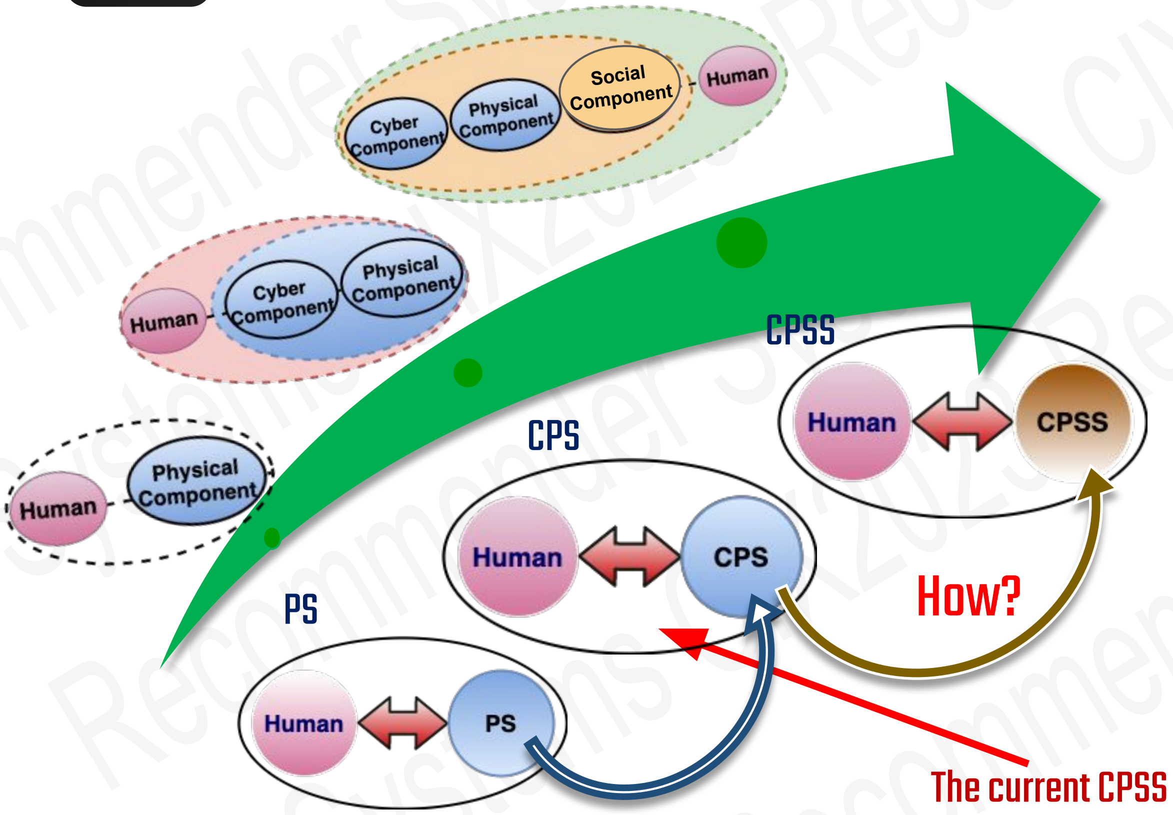
Why does understanding the context matter?

Task: Design a Personalised Visual Art Recommendation engine for NG/ Louvre

Formulating a RecSys Problem

- Points of Interest
- Sensors, cameras, (CPS)
- Smart devices (CPSS)
- Visitors

Cyber-Physical-Social System (CPSS)



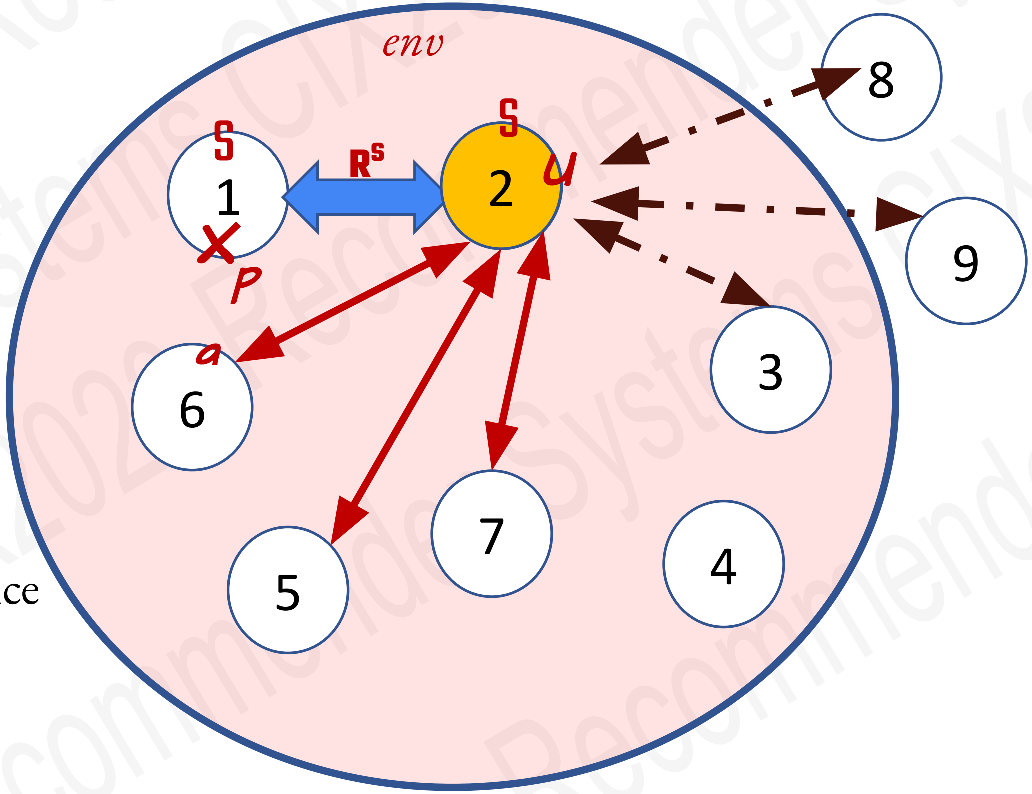
Personalisation

RecSys

Formulating a RecSys Problem

- Smart system environment *env*,
- **Personalisation** is a function of a social component **S** of a system.
- **Personaliser**($\times_{pa}$);
- **User**(U)
- **Crowd**(Cr) : direct influence
- **Context elements**(Cx): indirect influence

$$Pa^{cpss} = f(u, \times_{pa}, cr, cx, env)$$



Formulating a RecSys Problem

Personalisation in exhibition areas for a user $\boldsymbol{u}$ can be formalised as a function of

- The user $\boldsymbol{u}$, → Visitor $\boldsymbol{vs}$
- The personaliser $\boldsymbol{X_{pa}}$, → Mobile guide $\boldsymbol{mg}$
- The crowd $\boldsymbol{Cr}$, → Crowd of other Visitors $\boldsymbol{cr^{vis}}$
- The context elements $\boldsymbol{cx}$
- The Smart environment $\boldsymbol{env}$ → Exhibition area $\boldsymbol{ex}$

$$pa = f(\boldsymbol{u}, \boldsymbol{X_{pa}}, \boldsymbol{cr}, \boldsymbol{cx}, \boldsymbol{env}) \rightarrow pa^{Exhib} = g(\boldsymbol{vs}, \boldsymbol{mg}, \boldsymbol{cr^{vis}}, \boldsymbol{ex})$$

- *Yilma et al. (UMAP 2021)*

Formulating a RecSys Problem

$$pa^{Exhib} = g(vs, mg, cr^{vis}, ex)$$

- **User (Visitor):**
  - Preferences/interests
  - Time (Limited availability)
  - Crowd tolerance
  - Visiting style
  - Fatigue
  - (Disability)
  - (Age)

Ant Butterfly Fish Grasshopper

Najbrt et al. 2014

Formulating a RecSys Problem

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- **The Ant visitors:** spend a long time observing all exhibits moves close to the walls and the exhibits avoiding empty space.
- **The Fish visitors:** walk mostly through empty space making just a few stops and sees most of the exhibits but for a short time.
- **The Grasshopper visitors:** see only exhibits they are interested in and walk through empty space and stay for a long time only in front of selected exhibits.
- **The Butterfly visitors:** frequently change the direction of the tour route, usually avoiding empty space. They sees almost all exhibits, but times vary between exhibits.

Najbrt et al. 2014

Formulating a RecSys Problem

$$pa^{Exhib} = g(vs, mg, cr^{vis}, ex)$$

- **User (Visitor):**
  - Preferences/interests
  - Time (Limited availability)
  - Crowd tolerance
  - Visiting style
  - Fatigue
  - (Disability)
  - (Age)
- **Exhibition area/Curator**
  - Preferences/interests
  - Time (Opening hours)
  - Crowd capacity
- **Crowd**
  - Preferences/interests (Popularity of items)
  - Congestion (Crowd size)

Ant Butterfly Fish Grasshopper

Najbrt et al. 2014

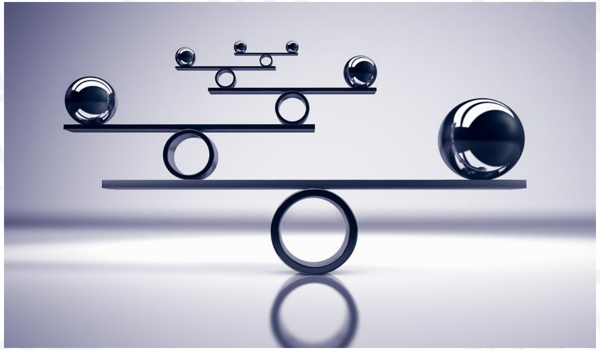
Multi-Stakeholder aware RecSys

Curator-visitor tradeoff

Multi-Stakeholder aware RecSys

$$pa^{Exhib} = g(vs,\ mg,\ cr^{vis},\ ex)$$

The personaliser needs to make the best possible compromise to satisfy the **Objectives** of the **co-existing stakeholders** while respecting environmental **Constraints**.



Constrained multi-objective optimization problem

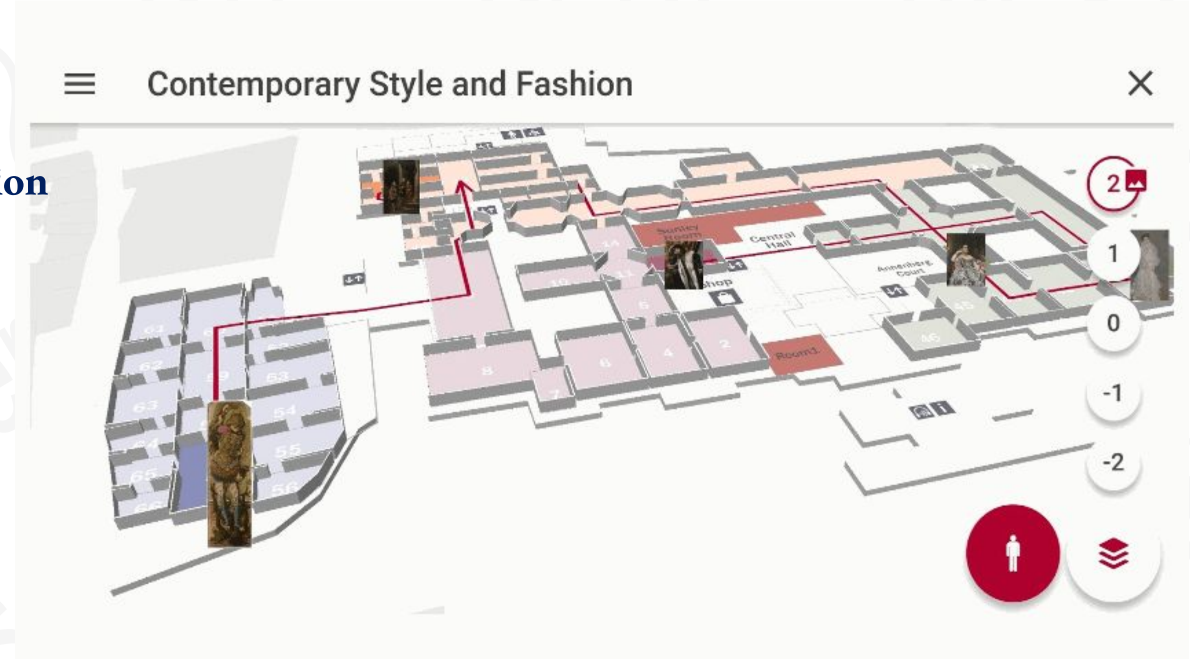
The RecSys pipeline: A case-study approach

Task: Design a **Personalised Visual Art Recommendation** engine for the National Gallery, London

Multi-Stakeholder aware RecSys

1. **POI (painting) Recommendation**

2. **Path Recommendation**



The typical RecSys Pipeline

Data Pre-processing

Model Training

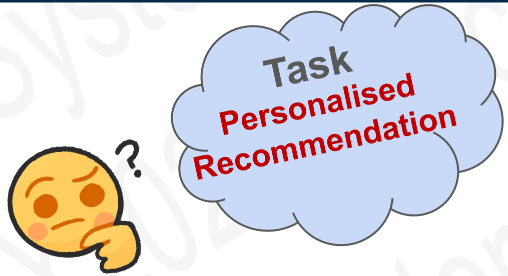
Post Processing

Evaluation

- Sort
- Filter
- Recommend

Multi-Stakeholder aware RecSys

Data Pre-processing



THE COLD START PROBLEM

Query User (Profiling)

1. Rate few paintings ★★★★★
2. Popular paintings ★★★★★
3. Visiting style
4. Available time …

Multi-Stakeholder aware RecSys

Multi-Stakeholder aware RecSys

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Data Pre-processing

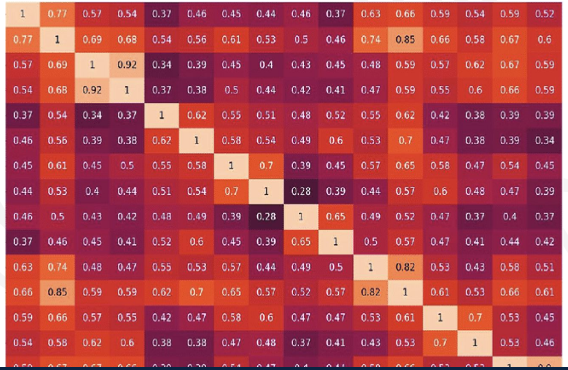
Task
Personalised Recommendation

Model Training

Good representation of the data!

$R^{m \times m}$



- If a user likes painting **A** find paintings **B, C, D** that are similar to A.

Multi-Stakeholder aware RecSys

1. Profiling

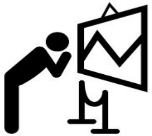
New Visitor

- List of paintings rated $\mathbf{P^u = \{P_1, P_2, \ldots, P_n\}\,;\, P^u \in P}$
- Rating of P^u, $\mathbf{W^u = \{w_1, w_2, \ldots, w_n\}}$
- Available time T_{ava}
- Visiting style (Ant, butterfly, fish, grasshopper)
- Crowd tolerance $Cr_t(u)$
- *(β, λ, ε) Popularity, Fatigue and Diversity tolerance*

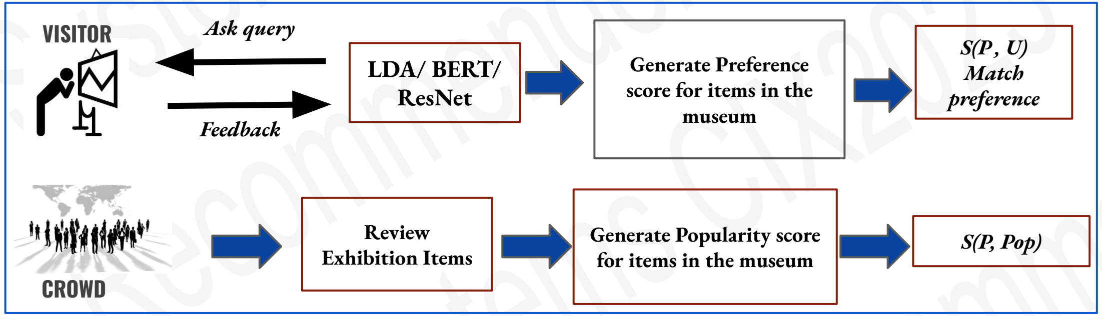
Museum

- Similarity matrix from LDA/BERT/ResNet
- Opening hours
- Crowd capacity
- Curated Stories
- Rules regarding movement in the physical space.

1. POI recommendation → 1.1 Matching User Preferences



➢ In addition to unique personal preferences users also have different tendency to be interested in visiting famous paintings. Hence, we introduces a popularity score ***S(p,Pop)*** for all the paintings in the dataset. This score is based on public review **(Crowd)** from National Gallery website.



- By taking into account the ***preference of the user*** and also the ***crowd opinion*** we generate an aggregate preference score ***S(P)*** for the paintings in the dataset.

$$\boxed{S(P) = \alpha\, S(P,U) + \beta\, S(P, Pop)}$$

- β is user provided hyper parameter determining user's interest to see popular items.

$$\alpha = 1 - \beta$$

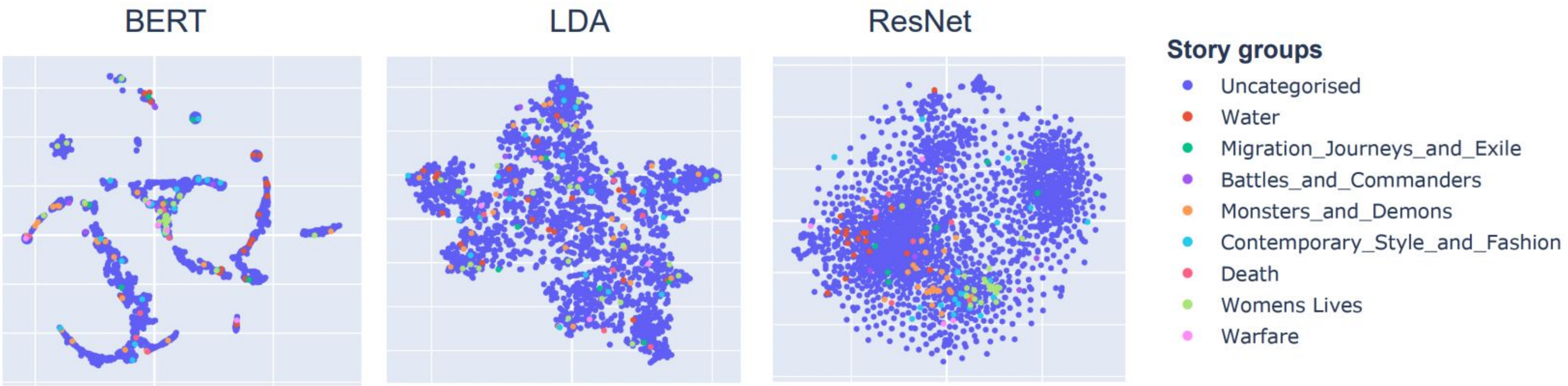
1. POI recommendation → 1.2 Matching Curator's Goal

- The exhibition curator might have different goals related to the point of interests to be presented for visitors.
- In this case study the curator's goal is to increase the number curated stories presented to visitors.

In the NG dataset we have ***8 curated stories***. each story is linked to a unique set of paintings.

1. Women's Lives,
2. Contemporary Style and Fashion,
3. Water,
4. Women Artists and Famous Women,
5. Monsters and Demons,
6. Migration: Journeys and Exile,
7. Death, Battles and Commanders,
8. Warfare.

Multi-Stakeholder aware RecSys



Latent space projection (t-SNE) of the curated story groups

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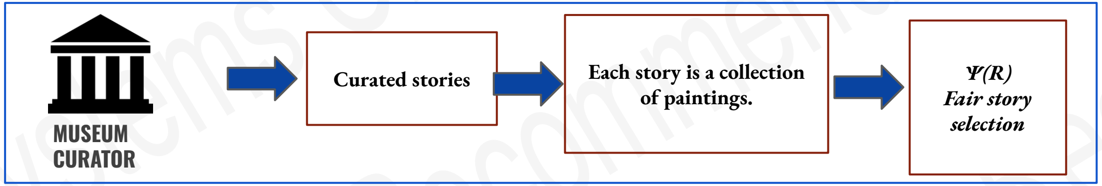
1. POI recommendation

1.2 Matching Curator's Goal

- Increasing the number curated stories in the recommendation means fairly selecting the paintings from each story.
- We define a fair story selection function *Ψ(R)*.
- The function *Ψ(R)* rewards a typical diversity of stories in the recommendation set.

$$\Psi(R) = \sum_{i=1}^{K} \sqrt{\sum_{p \in Si \cap R} \gamma p}$$

- S_i, $i = 1,...K$ is the story-partition of the dataset.
- R is the recommendation set
- γ_p is a representativeness score of story group carried by painting p in the recommendation set.



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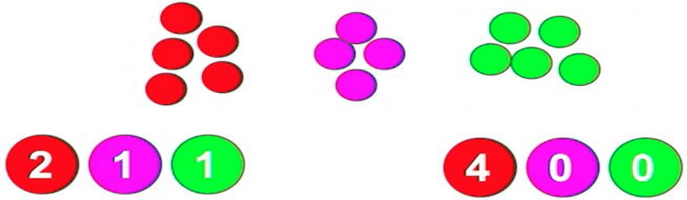
1. POI recommendation → 1.2 Matching Curator's Goal

$$\Psi(R) = \sum_{i=1}^{K} \sqrt{\sum_{p \in S_i \cap R} \Upsilon_p}$$

STORY 1 STORY 2 STORY 3



$$\left(\sqrt{2} + \sqrt{1} + \sqrt{1}\right) > \left(\sqrt{4} + \sqrt{0} + \sqrt{0}\right)$$

Representative & Informative Query Selection Yilmaz et al. SIGIR2015.

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1. POI recommendation

Recommend a set ***R*** *of* ***r*** *paintings*

$R(u) =$

Policy 1: Maximize User Preference score.

- $\arg\max \sum_{a=1}^{R} S(P_a)$

Policy 2: Maximize the number of Curated stories.

- $\arg\max \Psi(R) = \arg\max \left(\sum_{i=1}^{K} \sqrt{\sum_{p \in Si \cap R} \Upsilon p} \right)$

R(u)

- $\arg\max \left(1-\varepsilon \left(\sum_{a=1}^{R} S(P_a) \right) + \varepsilon \left(\sum_{i=1}^{K} \sqrt{\sum_{p \in Si \cap R} \Upsilon p} \right) \right)$

$S.t \quad \boxed{\sum_{a=1}^{R} Tv(P_a) \leq T_{ava}}$

Respect time constraint

User's tolerance to diversity

2. Path recommendation

We now have a recommendation Set of Paintings R.

➢ Project the painting from R on the Venues (Rooms).

The initial **Optimal route** should lead the visitor in the ***least expensive path*** and ***highest relevance***.

Such that:

- *The total sum of estimated **visiting times** and **travel time** should not exceed the **available time** of the visitor.*
- *The **crowd size** in the selected rooms should not exceed the **crowd tolerance** threshold of the visitor.*

2. Path recommendation

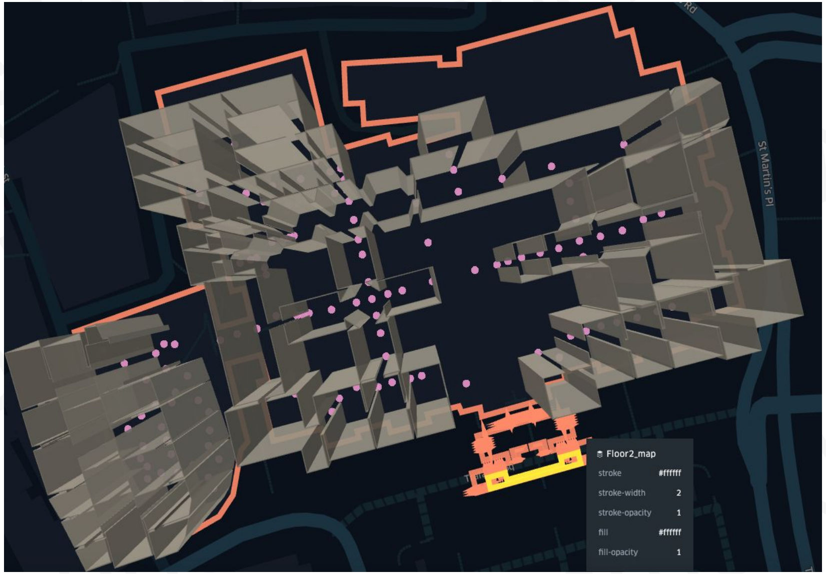
Depending on the user **Relevance** could mean two things:

1. Quality: Visit the most interesting paintings.
   - We define a quality score $\Theta(v_i)$ which is the sum of the scores of all the recommended paintings in venue i.

- $\boxed{\Theta(v_i) = \sum_{i=1}^{h} S(P_i)}$

- h is the total number of recommended paintings in Venue V

2. Quantity: Visit as many paintings as possible.
   - We define a quantity score of every venue $\boxed{\delta(v_i) = h_i}$



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2. Path recommendation

*Recommend a path **PT(u)***

(sequence of M rooms)

Policy 1: Maximize relevance score ***S(R)***

- $\mathrm{argmax} \sum_{a=1}^{M} \Theta(v_a)$ *if Quality > Quantity*
- $\mathrm{argmax} \sum_{a=1}^{M} \delta(v_a)$ *otherwise*

Policy 2: Minimize travel distance

- $\mathrm{argmin} \sum_{a=1}^{M} dist(v_a, v_{a+1})$

Subject to:

1. Time constraint:
   - $\sum_{a=1}^{M} Tv(v_a) + Tt \leq T_{ava}$

     $Tt = \sum_{a=1}^{M} Tt(v_a, v_{a+1})$
2. Crowd constraint:
   - $\forall\, v_a ; 1 \leq a \leq M$

     $Cr_s(v_a) \leq Cr_t(u)$

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2. Path recommendation

Recommend a path ***PT(u)***

(sequence of M rooms)

$$PT(u) = \text{argmax} \left(\lambda \sum_{a=1}^{M} S(v_a) + 1-\lambda \left(1/ \sum_{a=1}^{M} dist(v_a, v_{a+1})\right)\right)$$

Maximize total Score

Minimize total travel distance

S.t

$$Tv(v_a) + Tt \leq T_{ava}$$

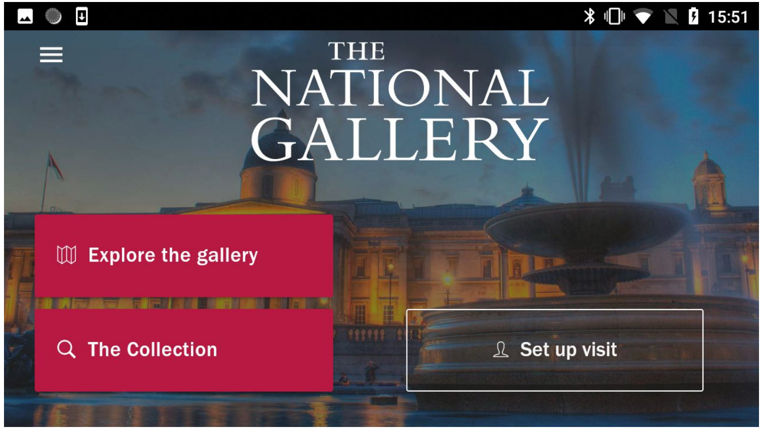
$$Tt = \sum_{a=1}^{M} Tt(v_a, v_{a+1})$$

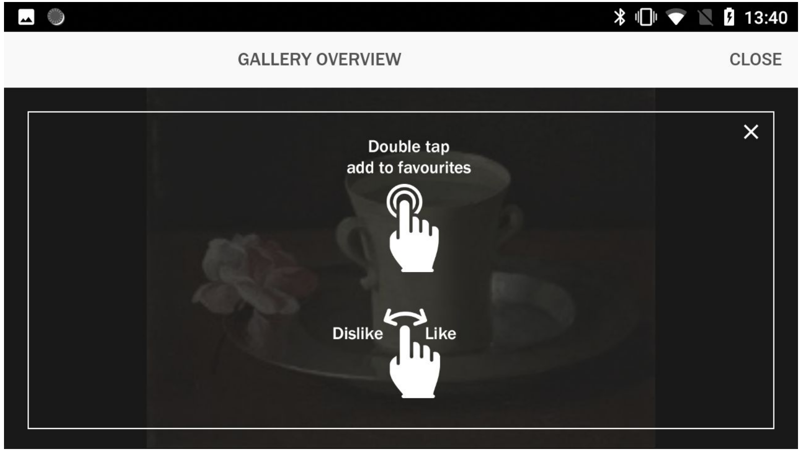
Respect time constraint

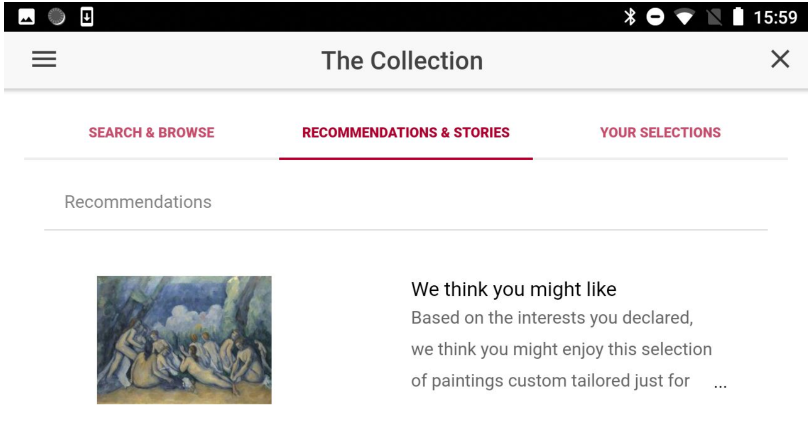
- $\forall\, v_a \; ; 1 \leq a \leq M$

  $Cr_s(v_a) \leq Cr_t(u)$

Respect Crowd tolerance





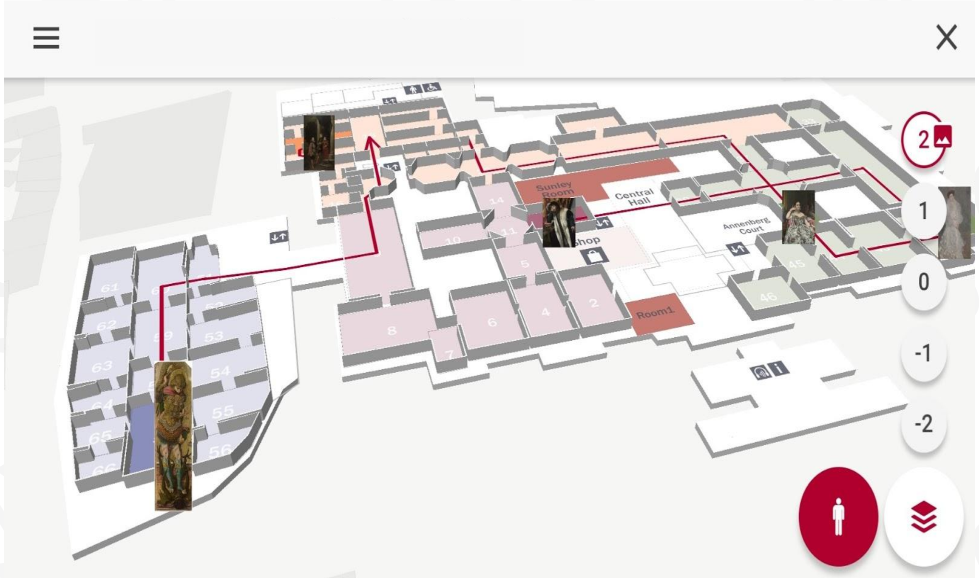


Personalized ? popularity, curator's theme,

Multi-Stakeholder aware RecSys

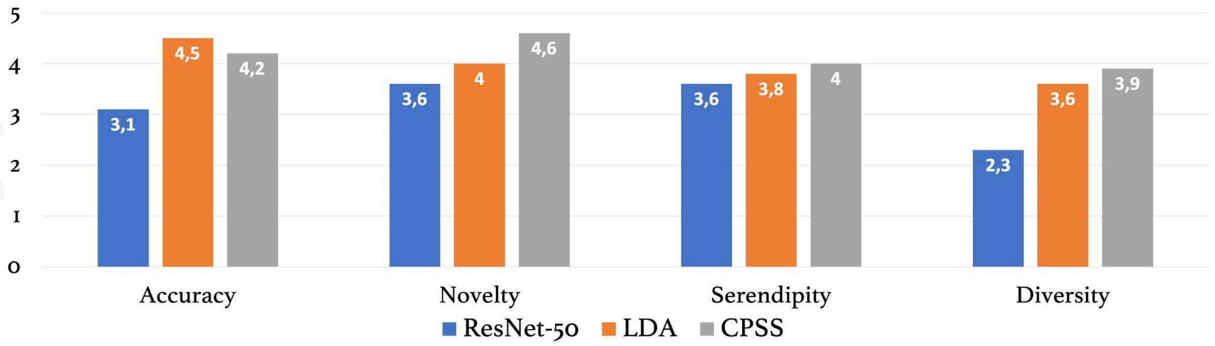
Mobile app

Mixed reality glass



Multi-Stakeholder aware RecSys

Baseline Single objective **Vs** Multi-objective



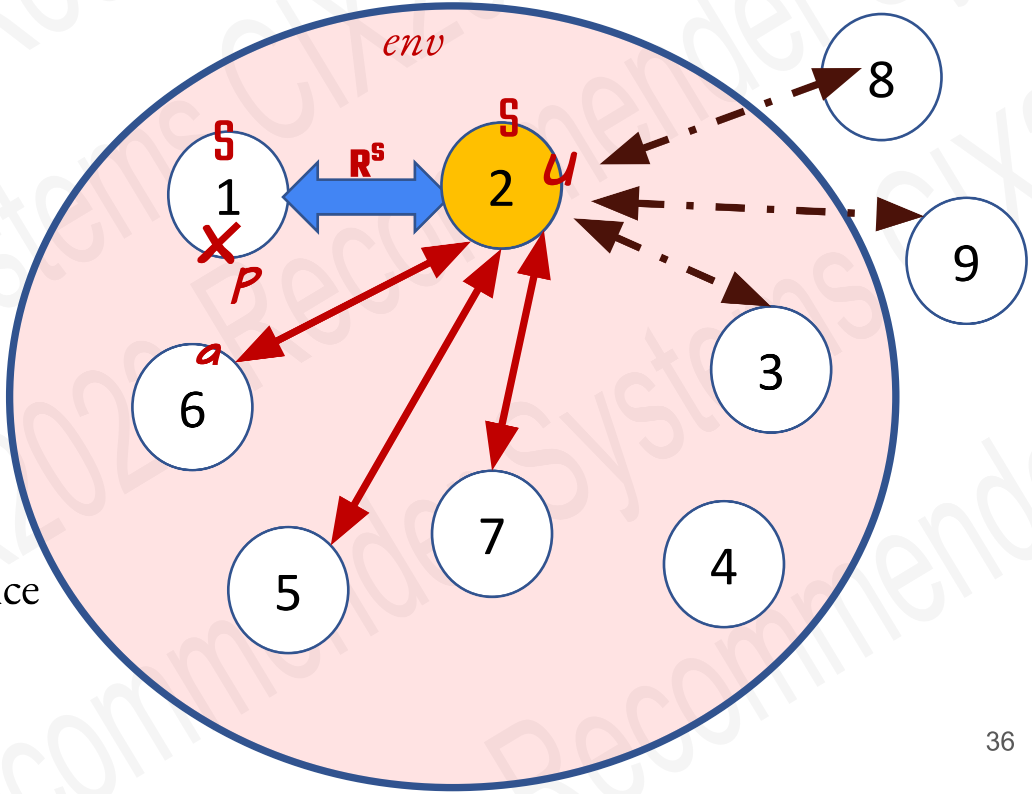
Yilma et al. (**UMAP '21**)

Multi-Stakeholder aware RecSys

- Understanding the Problem setting.
- Identifying stakeholders (**Competing objective** or **Constraints**).
- Prioritizing objectives.

Formulating a RecSys Problem

- Smart system environment *env*,
- **Personalisation** is a function of a social component **S** of a system.
- **Personaliser**($\times_{pa}$);
- **User**(U)
- **Crowd**(Cr) : direct influence
- **Context elements**(Cx): indirect influence



$$Pa^{cpss} = f(\boldsymbol{u}, \times_{pa}, \boldsymbol{cr}, \boldsymbol{cx}, \boldsymbol{env})$$

Modern RecSys paradigms

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What are LLMs?

LLMs are machine learning models capable of Natural Language Processing (NLP), as they are trained on huge amounts of text data (usually from the internet/books) via deep-learning algorithms.

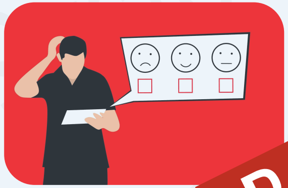
- **Pre-trained language models:** encode an extensive amount of world knowledge, and they can be applied to a multitude of downstream NLP applications with **zero** or **just a handful of demonstrations.**

Large Language Models (LLMs) as RecSys

User Preference → Pre-trained LLM → Recommendations

Explicit Feedback

Implicit Feedback



behaviour towards an item.

evious

s click

etc.

Behavior data

Store knowledge that can complement the behavior data

CHAT GPT

Predict future behaviours

buying turkey on Thanksgiving day

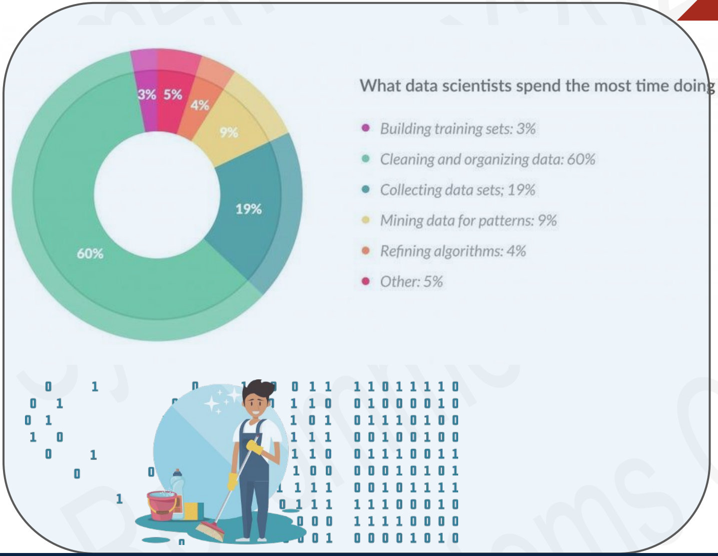
Large Language Models (LLMs) as RecSys

Data Pre-processing

Pre-trained LLM

Post Processing

Evaluation

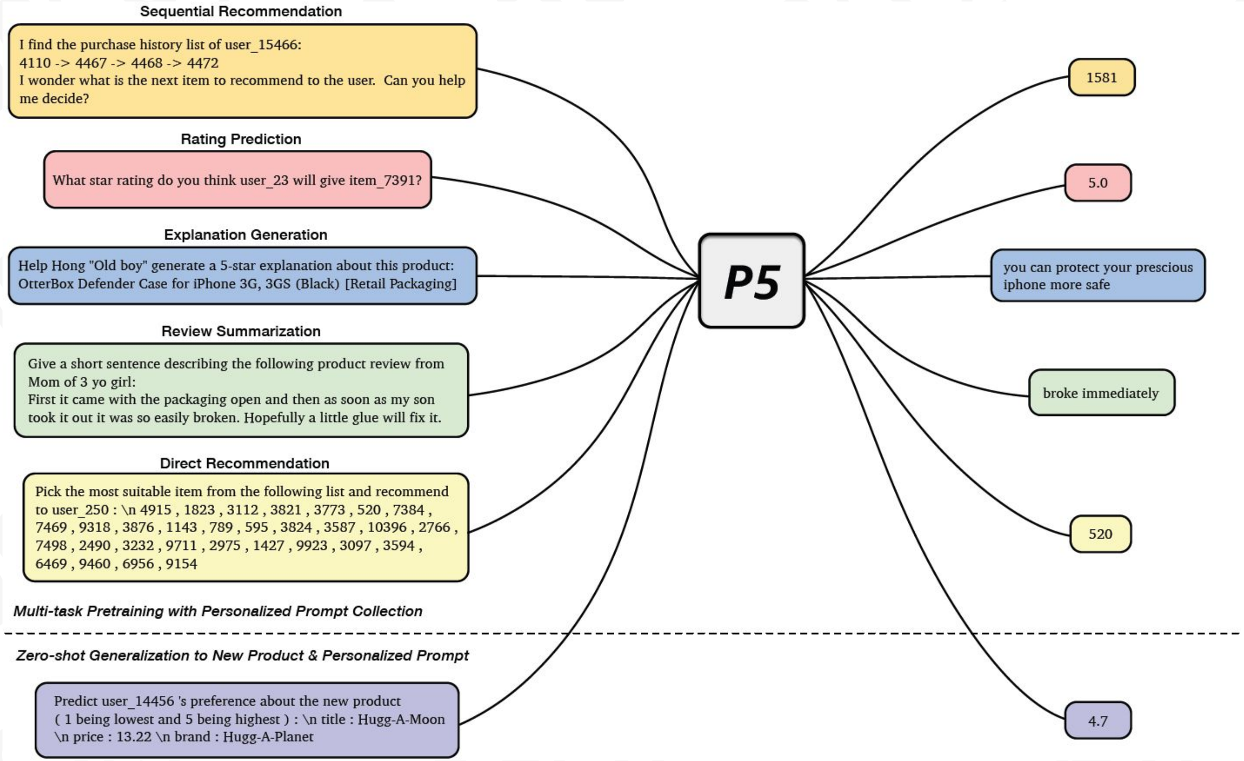


- Sort
- Filter
- Recommend

SOTA: Large Language Models (LLMs) as RecSys

1. Pretrain, Personalized Prompt & Predict Paradigm (P5)

Geng et al. 2022



SOTA: Large Language Models (LLMs) as RecSys

2. M6-Rec: Generative Pretrained Language Models are Open-Ended Recommender Systems.

Cui et al. 2022

- Model pre-trained using Alibaba's LLM (M6)
- Convert recommendation tasks
  - ➢ Retrieval,
  - ➢ Scoring,
  - ➢ Explanation generation
  - ➢ Conversational recommendation

➢ **Language understanding** or
➢ **Generation**

prompt For zero-shot scoring tasks

or

[BOS'] A user clicks hiking shoes [EOS'] [BOS] also clicks trekking poles [EOS]

[BOS'] A user clicks hiking shoes [EOS'] [BOS] also clicks yoga knee pads [EOS]

user-side features

user + item related features

The plausibility of each is calculated based on token probability from M6.

Avoids using user IDs or item IDs as input

Prompt-Tuning Pretrained Language Models

3. Language Model Recommender Systems (LMRecSys) *Zhang et al. 2022*

- Uses the user's past interaction history (watched movies), taken from the MovieLens-1M dataset, to predict the next movie that the user would watch.

prompt

A user watched One Flew Over the Cuckoo's Nest, James and the Giant Peach, and My Fair Lady. Now the user wants to watch [MASK].

GPT-2 → Estimate the probability distribution of the next item

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Prompt-Tuning Pretrained Language Models

4. **Zero-Shot Next-Item Recommendation (NIR)** *Wang et al. 2023*
5. **Augmented Recommender System (Chat-REC)** *Gao et al. 2023*

Pros & Cons of using LLMs as RecSys

Pros

- Zero-shot and few-shot capabilities
  - ➢ Sparsity scenarios **(cold start, long tail**)
- Adapting to new information
  - ➢ Without changing architecture/ retraining
- Conversational- user engagement
- No need for large amount of data
- Generalization capability: not task specific
- **Explanation Generation**

Cons

- LLMs are large, complex, and costly to train
- Highly sensitive to input prompts and may not fully follow the instruction prompt.
- Recommendations can be highly **dataset** dependent.
- LLMs may recommend items that are not present in the candidate set.

Zhang et al. 2023, suggested feeding the candidate item set into prompt.

Pros & Cons of using LLMs as RecSys

Zhang et al. 2023

Case 1

You are a movie recommender system now.
$\{\{Examples\}\}$
Input: Here is the watching history of a user: Aliens, E.T. the Extra-Terrestrial, Contact, The Matrix, X-Men. Based on this history, would this user prefer The Fox and the Hound or Steamboat Willie? Answer Choices: (A) The Fox and the Hound (B) Steamboat Willie
Output: The answer index is N/A as neither option is relevant to the user's watching history.

Case 2

You are a book recommender system now.
$\{\{Examples\}\}$
Input: Here is the reading history of a user: The Cellist of Sarajevo, After I'm Gone: A Novel, The Reason I Jump: The Inner Voice of a Thirteen-Year-Old Boy with Autism, The Serpent of Venice: A Novel, We Are All Completely Beside Ourselves: A Novel. Based on this history, would this user prefer The Secret Life of Bees or The Help? Answer Choices: (A) The Secret Life of Bees (B) The Help
Output: The answer index is N/A. It is difficult to determine the user's preference based on this reading history as neither book is similar in genre or theme to the books they have read.

Common Issues and Challenges in RecSys

Multi-Stakeholder aware RecSys

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- ➢ Understanding the Problem setting.
- ➢ Identifying stakeholders (**Competing objective** or **Constraints**).
- ➢ Prioritizing objectives.

RecSys Issues & Challenges

- **Cold start**

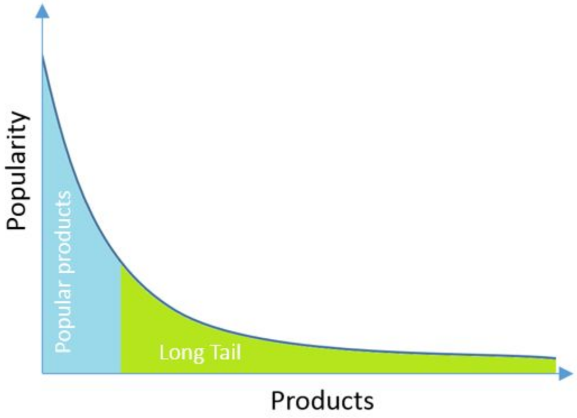
  → Sparisty

$$\text{Sparsity} = \frac{\#\ \text{ratings}}{\text{total}\ \#\ \text{cells}}$$

5				4
4				1

User-item interaction matrix

- Ratings
- Time spent
- Product clicked

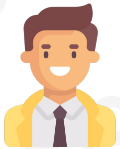


- **Diversity**

RecSys Issues & Challenges

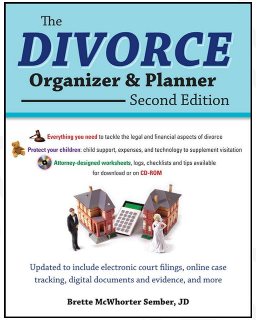
- **Privacy** : Third party, sensitive private information

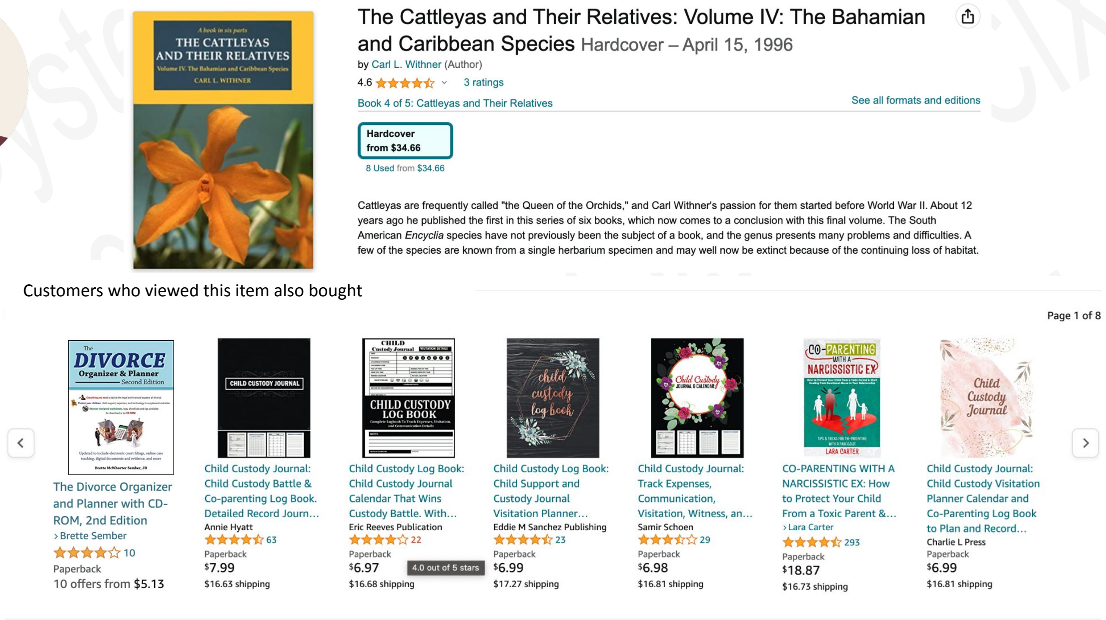
→ **Collaborative Filtering:** users willingly disclose their preferences to the system in the hope of getting useful recommendations.



Likes growing Orchid

Bought





RecSys Issues & Challenges

Privacy

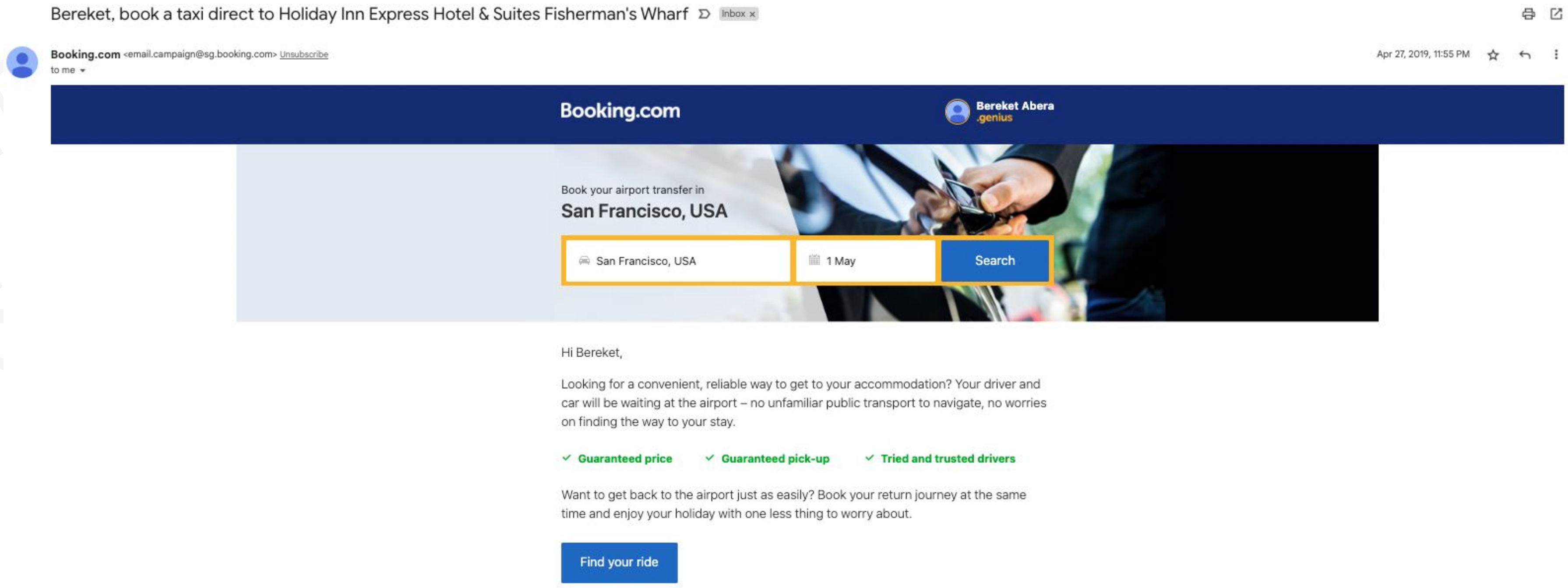
- Complete privacy may not be realistic → compromise on minimizing the privacy breaches
- Comes at the expense of the accuracy of the recommendations.
- Important to analyze this trade-off carefully.

RecSys Issues & Challenges

- **Adaptivity**: changing business needs
- **Robustness**: Attack/ stress
- **Scalability**

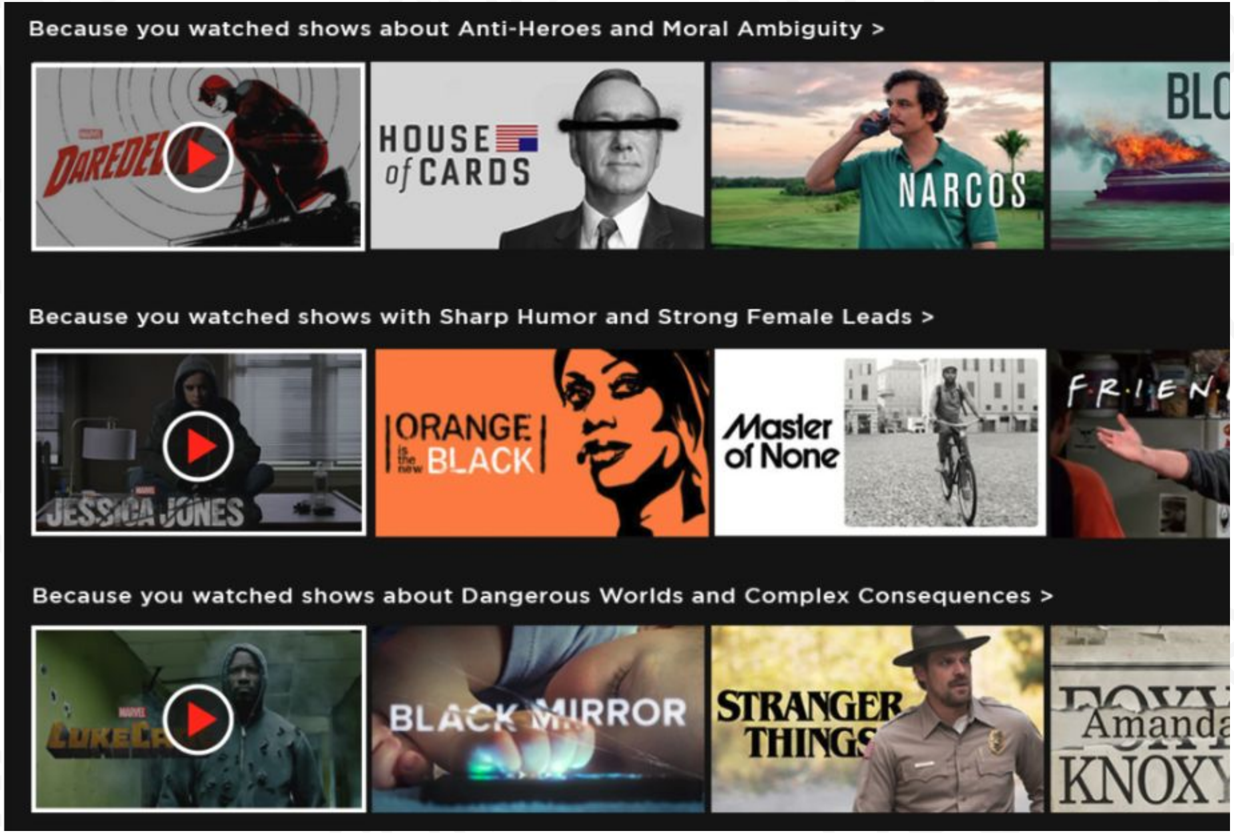
RecSys Issues & Challenges

- **Proactiveness**: Predict when and how to push Recommendations ← implicit request



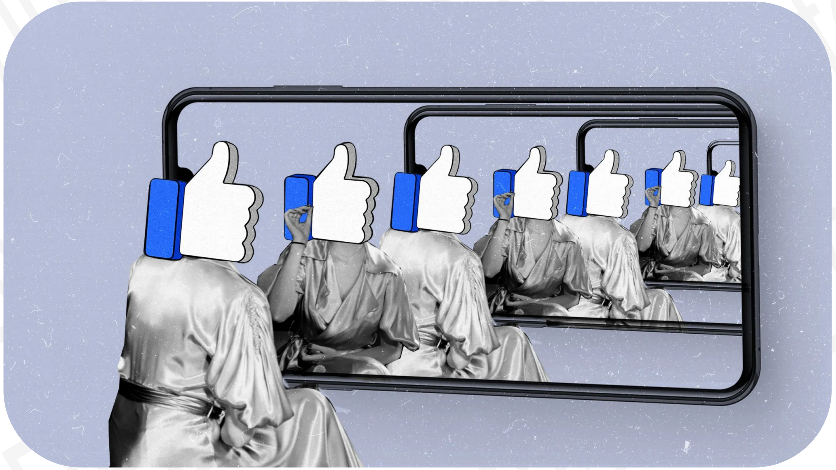
RecSys Issues & Challenges

- **Explainability**



RecSys Issues & Challenges

- **Echo Chamber**



RecSys Issues & Challenges

- **Filter bubbles**

- Limiting exposure to diverse perspectives.
- Reinforcing existing biases and stereotypes.

Course Reflection

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RECOMMENDER SYSTEMS

Contact: bereket.yilma@uni.lu

@bek_yilma

Feedback form

Come to Luxembourg for research 🇱🇺

- ➢ Research visit
- ➢ Internship
- ➢ PhD
- ➢ Postdoctoral fellowship

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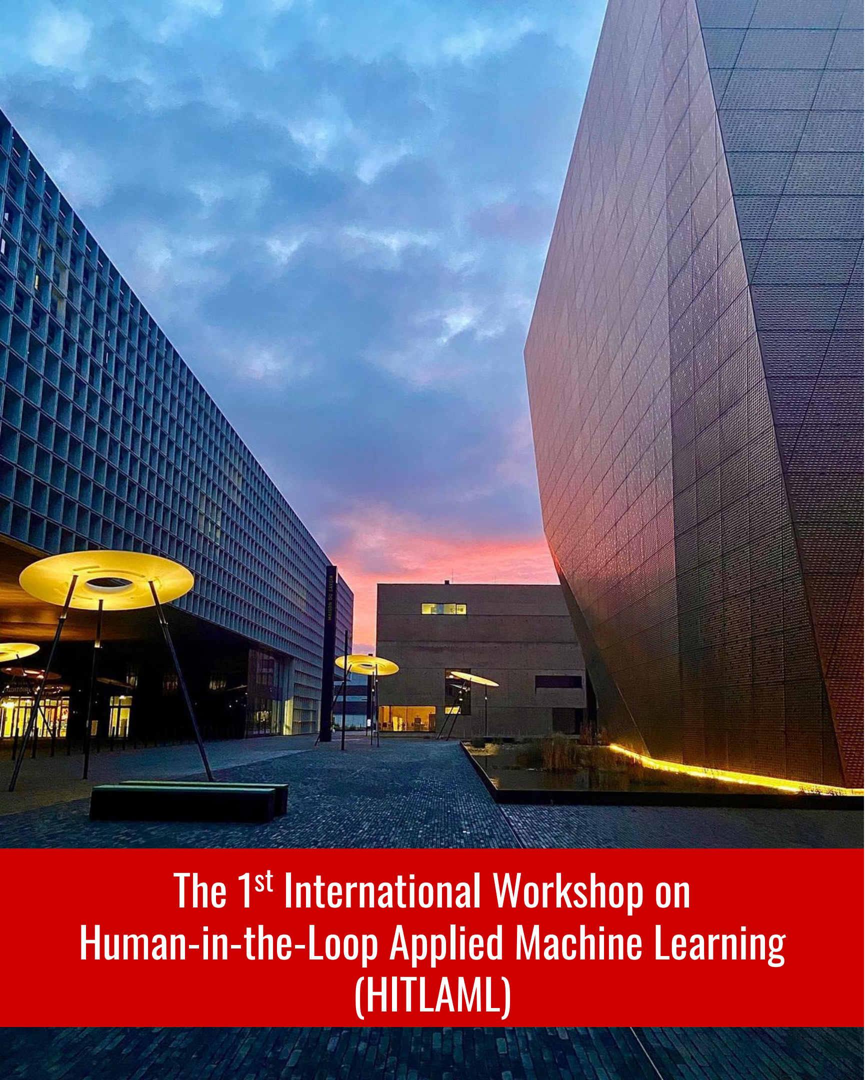
Computational Interaction (COIN) Lab

- **Human-Computer Interaction**
  - Emotion recognition using EEG, FNIRS, Eye tracking
  - Brain computer interfaces (BCI)
  - Bio-signal processing
  - Mouse tracking
  - Adaptive User Interfaces (AUI)
- **Machine Learning (Applied)**
- **Personalisation, RecSys**
- **Conversational Agents, Speech synthesis**

[Why should you come to Luxembourg for research?]



The 1st International Workshop on Human-in-the-Loop Applied Machine Learning (HITLAML)

HITLAML

CALL FOR PAPERS

MAIN DEADLINES (AOE)

uni.lu
UNIVERSITÉ DU LUXEMBOURG

PAPER & DEMO SUBMISSION DEADLINE

~~June 15, 2023 (AoE)~~

July 14, 2023 (AoE)

TRAVEL GRANT APPLICATION DEADLINE:

July 20, 2023 (AoE)

NOTIFICATION OF ACCEPTANCE

July 31, 2023

REGISTRATION OPENS

August 1, 2023 (#Free of Charge)

WORKSHOP DATE

September 04 - 06, 2023

BELVAL, LUXEMBOURG

https://hitlaml.uni.lu