# Multi-Stakeholder aware Recommender Systems

Bereket A. Yilma

# Session 3

→ A Multi-Stakeholder aware RecSys

→ Formulating the RecSys Problem?

- → (A framework)

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CROSS CULT

LIST

European Commission

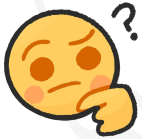
HORIZON 2020

# 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?

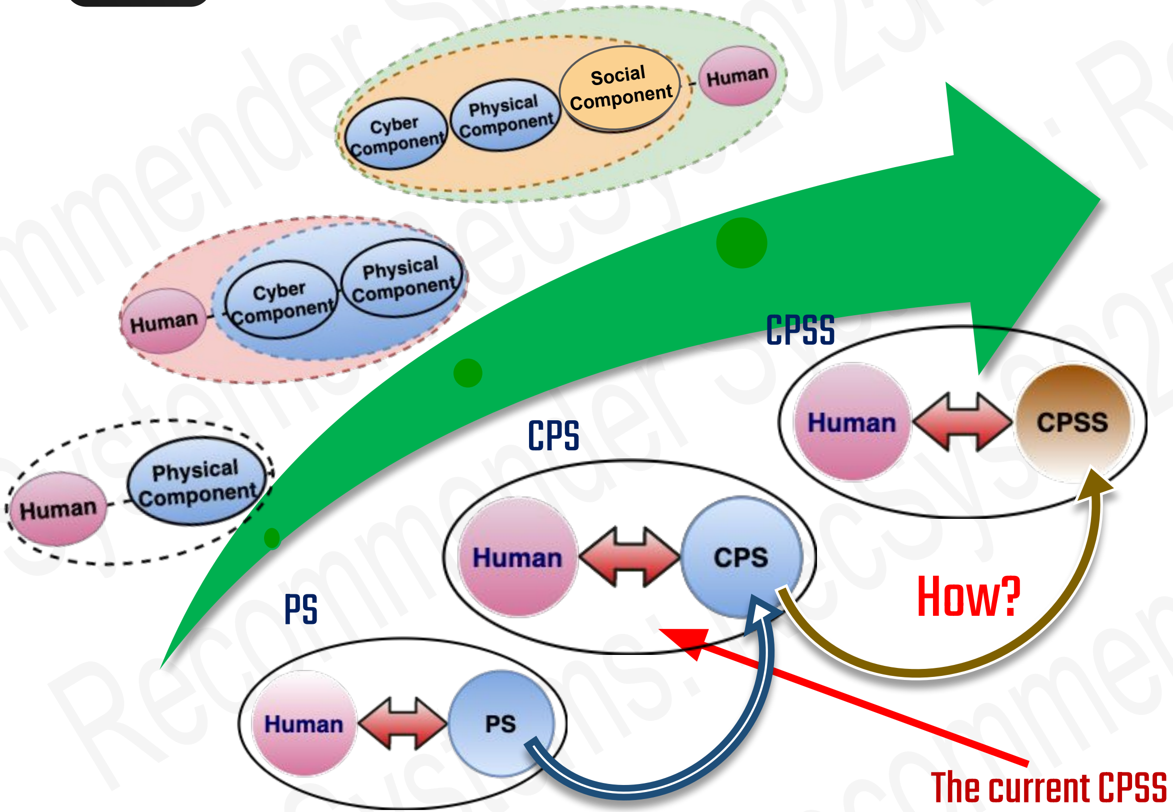
Task: Design a Personalised Visual Art Recommendation engine for NG/ Louvre

# Museums as Cyber-Physical-Social Systems

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


Personalization Task: Design a Personalized Visual Art Recommendation/ Guidance engines

# Cyber-Physical-Social System (CPSS)



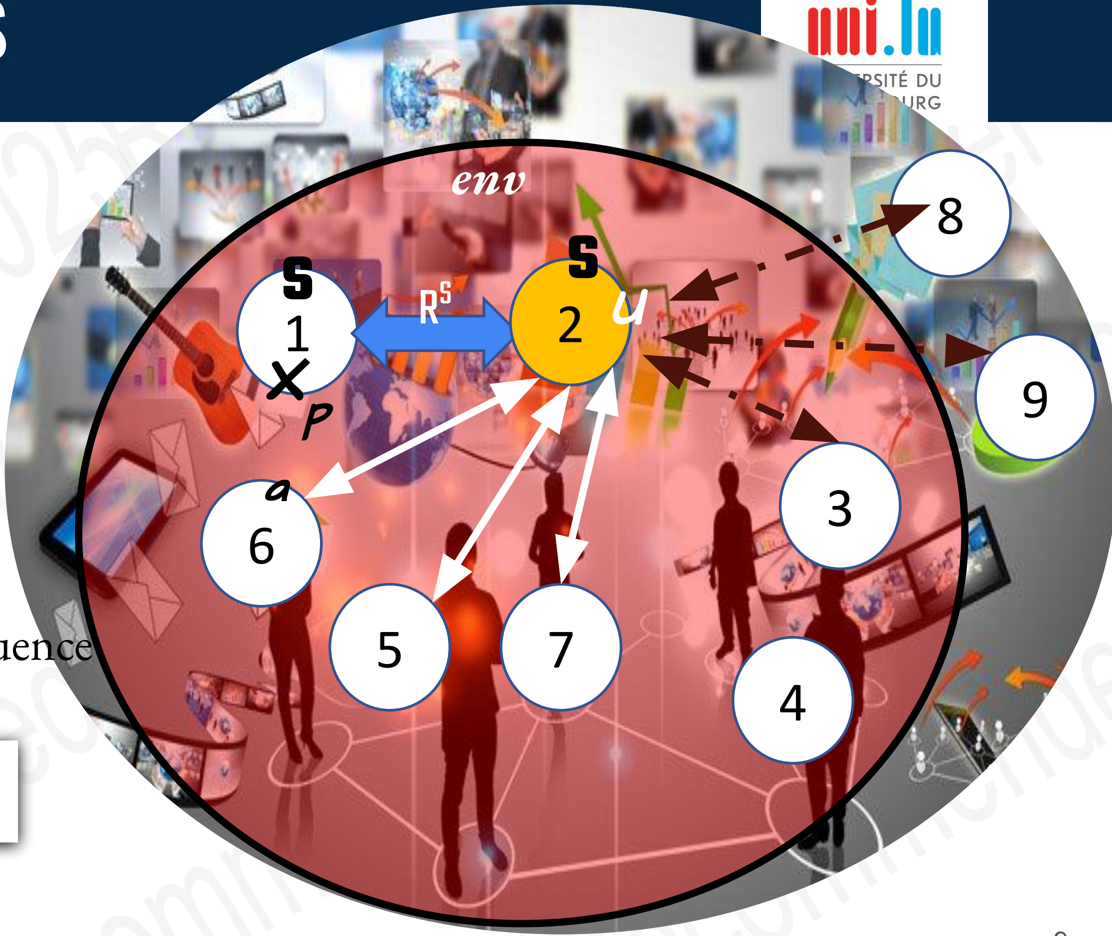

**Personalisation**

↓

**RecSys**

# Personalization in CPSS

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




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

*Yilma et al. UMAP 2021 (Personalisation in Cyber-Physical-Social Systems: A Multi-stakeholder aware Recommendation and Guidance.)*

# Formulating a RecSys Problem

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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 $\boldsymbol{ex}$

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

- *Yilma et al. (UMAP 2021)*

# Formulating a RecSys Problem

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

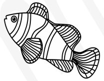
- **User (Visitor):**
  - Preferences/interests
  - Time (Limited availability)
  - Crowd tolerance
  - Visiting style
  - Fatigue
  - (Disability)
  - (Age)

Ant Butterfly Fish Grasshopper

*Najbrt et al. 2014*

# Formulating a RecSys Problem

- **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

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

- **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*

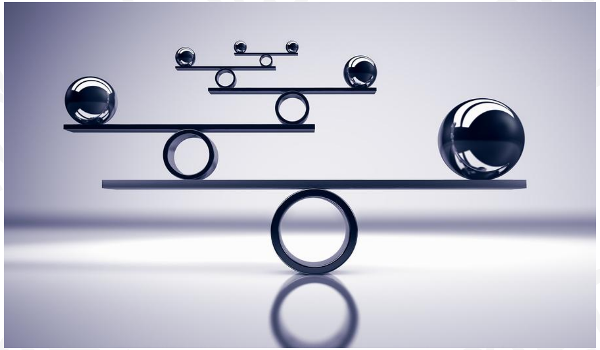
# Multi-Stakeholder aware RecSys

## Curator-visitor tradeoff

# Multi-Stakeholder aware RecSys

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

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**

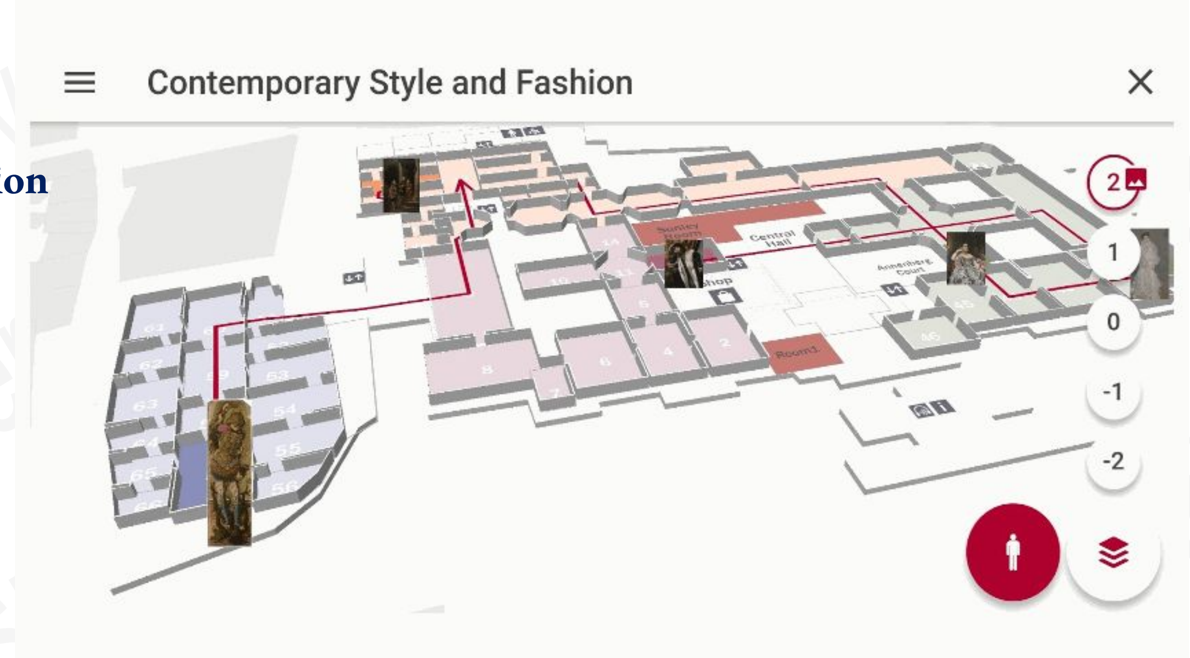
# The RecSys pipeline: A case-study approach

**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 HC RecSys Pipeline

Data Pre-processing

Model Training

Post Processing

Evaluation

- Sort
- Filter
- Recommend

# Multi-Stakeholder aware RecSys

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## Data Pre-processing



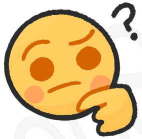
THE COLD START PROBLEM

**Query User (Profiling)**

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

# Multi-Stakeholder aware RecSys

Data Pre-processing



Task
Personalised Recommendation

Model Training

**Good representation of the data!**

$$R^{m \times m}$$




| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.77 | 0.57 | 0.54 | 0.37 | 0.46 | 0.45 | 0.44 | 0.46 | 0.37 | 0.63 | 0.66 | 0.59 | 0.54 | 0.59 | 0.52 |
| 0.77 | 1 | 0.69 | 0.68 | 0.54 | 0.56 | 0.61 | 0.53 | 0.5 | 0.46 | 0.74 | 0.85 | 0.66 | 0.58 | 0.67 | 0.6 |
| 0.57 | 0.69 | 1 | 0.92 | 0.34 | 0.39 | 0.45 | 0.4 | 0.43 | 0.45 | 0.48 | 0.59 | 0.57 | 0.62 | 0.67 | 0.59 |
| 0.54 | 0.68 | 0.92 | 1 | 0.37 | 0.38 | 0.5 | 0.44 | 0.42 | 0.41 | 0.47 | 0.59 | 0.55 | 0.6 | 0.66 | 0.59 |
| 0.37 | 0.54 | 0.34 | 0.37 | 1 | 0.62 | 0.55 | 0.51 | 0.48 | 0.52 | 0.55 | 0.62 | 0.42 | 0.38 | 0.39 | 0.39 |
| 0.46 | 0.56 | 0.39 | 0.38 | 0.62 | 1 | 0.58 | 0.54 | 0.49 | 0.6 | 0.53 | 0.7 | 0.47 | 0.38 | 0.39 | 0.34 |
| 0.45 | 0.61 | 0.45 | 0.5 | 0.55 | 0.58 | 1 | 0.7 | 0.39 | 0.45 | 0.57 | 0.65 | 0.58 | 0.47 | 0.54 | 0.45 |
| 0.44 | 0.53 | 0.4 | 0.44 | 0.51 | 0.54 | 0.7 | 1 | 0.28 | 0.39 | 0.44 | 0.57 | 0.6 | 0.48 | 0.47 | 0.39 |
| 0.46 | 0.5 | 0.43 | 0.42 | 0.48 | 0.49 | 0.39 | 0.28 | 1 | 0.65 | 0.49 | 0.52 | 0.47 | 0.37 | 0.4 | 0.37 |
| 0.37 | 0.46 | 0.45 | 0.41 | 0.52 | 0.6 | 0.45 | 0.39 | 0.65 | 1 | 0.5 | 0.57 | 0.47 | 0.41 | 0.44 | 0.42 |
| 0.63 | 0.74 | 0.48 | 0.47 | 0.55 | 0.53 | 0.57 | 0.44 | 0.49 | 0.5 | 1 | 0.82 | 0.53 | 0.43 | 0.58 | 0.51 |
| 0.66 | 0.85 | 0.59 | 0.59 | 0.62 | 0.7 | 0.65 | 0.57 | 0.52 | 0.57 | 0.82 | 1 | 0.61 | 0.53 | 0.66 | 0.61 |
| 0.59 | 0.66 | 0.57 | 0.55 | 0.42 | 0.47 | 0.58 | 0.6 | 0.47 | 0.47 | 0.53 | 0.61 | 1 | 0.7 | 0.53 | 0.45 |
| 0.54 | 0.58 | 0.62 | 0.6 | 0.38 | 0.38 | 0.47 | 0.48 | 0.37 | 0.41 | 0.43 | 0.53 | 0.7 | 1 | 0.53 | 0.46 |
| 0.59 | 0.67 | 0.67 | 0.66 | 0.39 | 0.39 | 0.54 | 0.47 | 0.4 | 0.44 | 0.58 | 0.66 | 0.53 | 0.53 | 1 | 0.9 |
| 0.52 | 0.6 | 0.59 | 0.59 | 0.39 | 0.34 | 0.45 | 0.39 | 0.37 | 0.42 | 0.51 | 0.61 | 0.45 | 0.46 | 0.9 | 1 |

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

# Multi-Stakeholder aware RecSys

## 1. Profiling

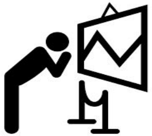
**New Visitor**

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

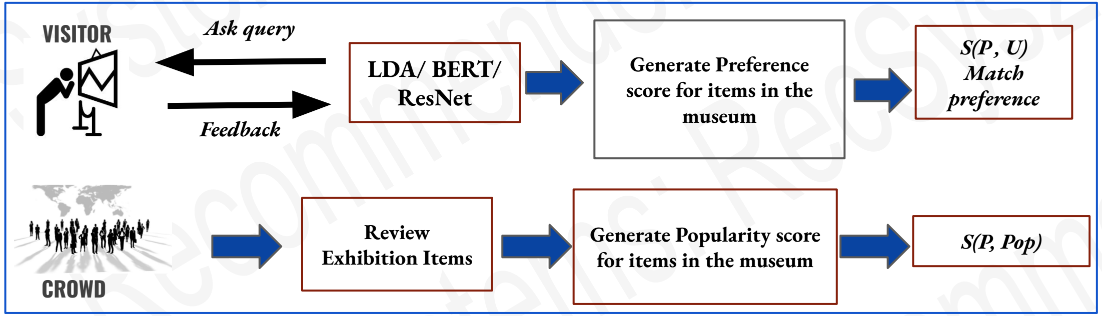
**Museum**

- 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.

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

- $\beta$ is user provided hyper parameter determining user's interest to see popular items.

$$\alpha = 1 - \beta$$

# 1. POI recommendation

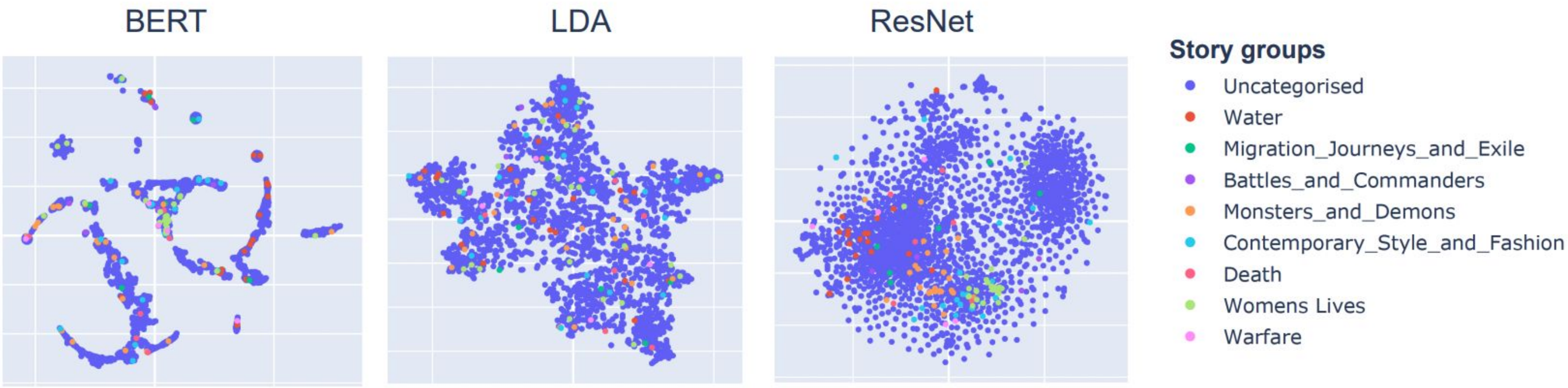
## 1.2 Matching Curator's Goal

- 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



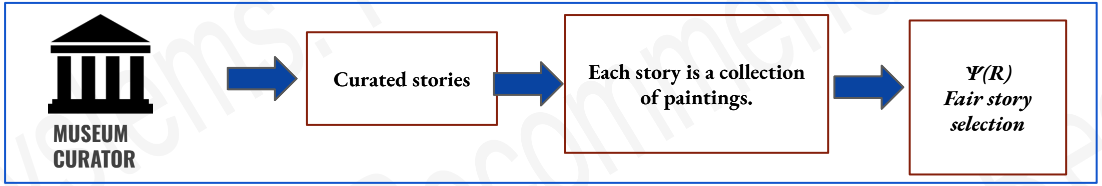

Latent space projection (t-SNE) of the curated story groups

# 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 $\Psi(R)$.
- The function $\Psi(R)$ rewards a typical diversity of stories in the recommendation set.

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

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



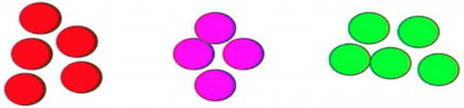
# Multi-Stakeholder aware RecSys



## 1. POI recommendation → 1.2 Matching Curator's Goal

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

STORY 1 STORY 2 STORY 3



2 1 1 4 0 0

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

*Representative & Informative Query Selection Yilmaz et al. SIGIR2015.*

# Multi-Stakeholder aware RecSys

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## 1. POI recommendation

*Recommend a set* $\boldsymbol{R}$ *of* $\boldsymbol{r}$ *paintings*

$R(u) =$

**Policy 1:** Maximize User Preference score.

- $\operatorname{argmax} \sum_{a=1}^{R} S(P_a)$

**Policy 2:** Maximize the number of Curated stories.

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

**R(u)**

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

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

Respect time constraint

User's tolerance to diversity

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# 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.*

# Multi-Stakeholder aware RecSys

## 2. Path recommendation

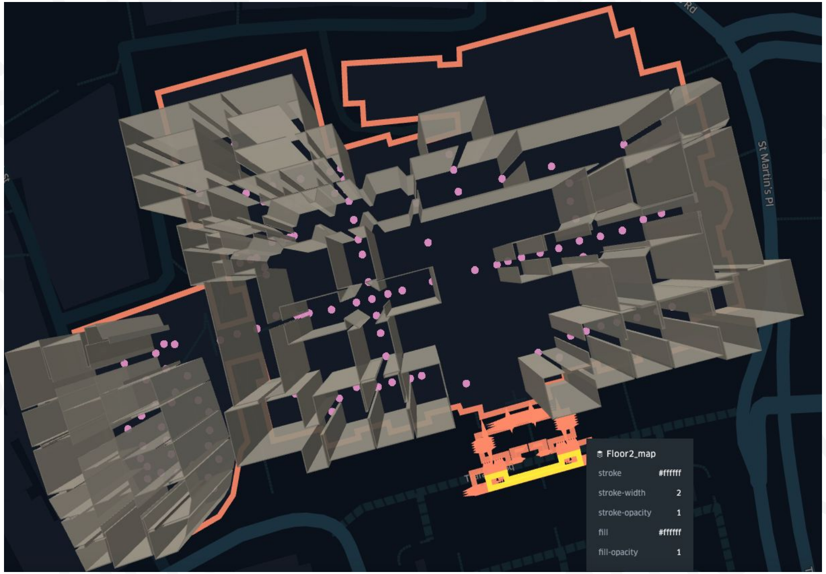
Depending on the user **Relevance** could mean two things:

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.

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

- $h$ 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 $\boldsymbol{\delta(v_i) = h_i}$



# Multi-Stakeholder aware RecSys

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## 2. Path recommendation

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

*(sequence of M rooms)*

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

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

**Policy 2:** Minimize travel distance

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

**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)*

Maximize total Score

$PT(u) =$

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

Minimize total travel distance

*S.t*

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

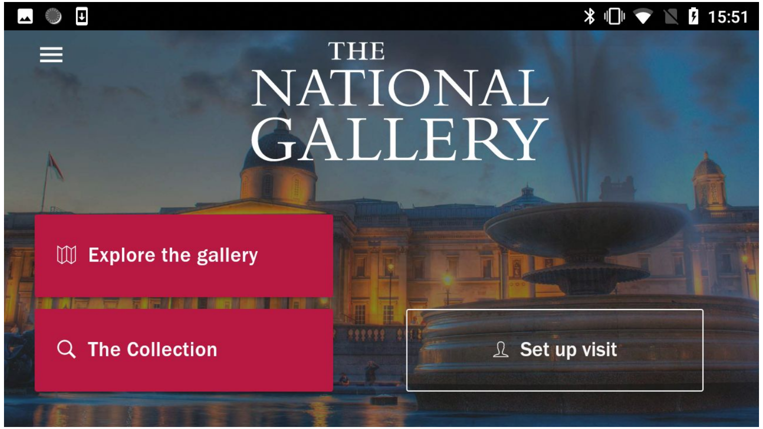
$$Tt = \sum_{a=1}^{M} Tt(v_a, v_{a+1})$$

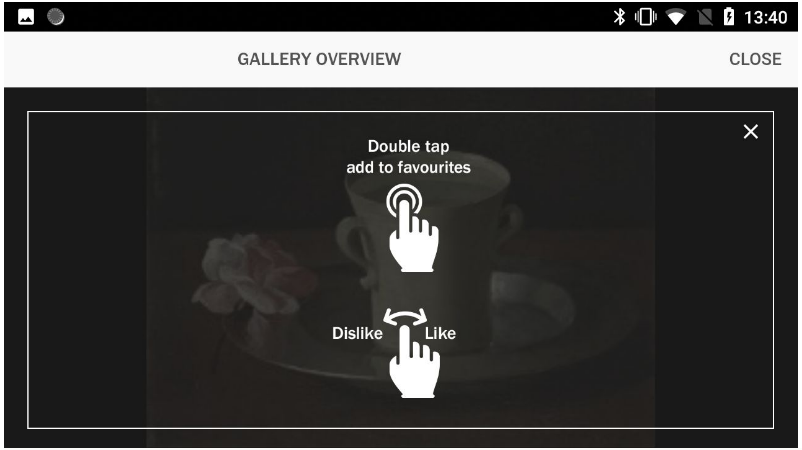
Respect time constraint

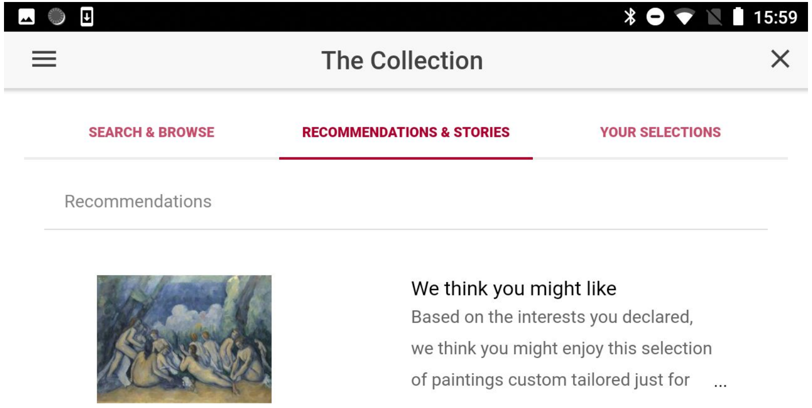
- $\forall\, v_a \,;\, 1 \leq a \leq M$

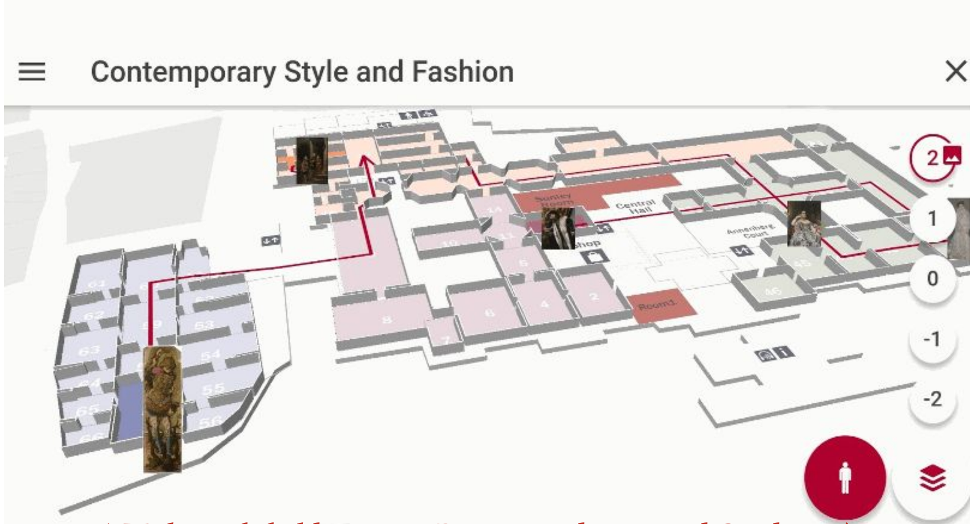
$$Cr_s(v_a) \leq Cr_t(u)$$

Respect Crowd tolerance



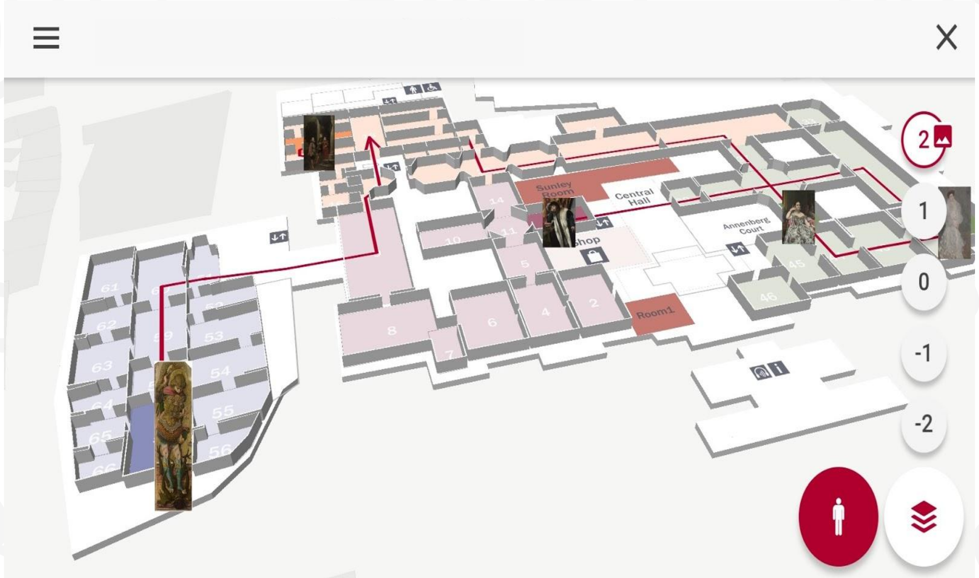

Personalized ? popularity, curator's theme,

*Yilma et al. UMAP 2021(Personalisation in Cyber-Physical-Social Systems: A Multi-stakeholder aware Recommendation and Guidance.)*

# Multi-Stakeholder aware RecSys

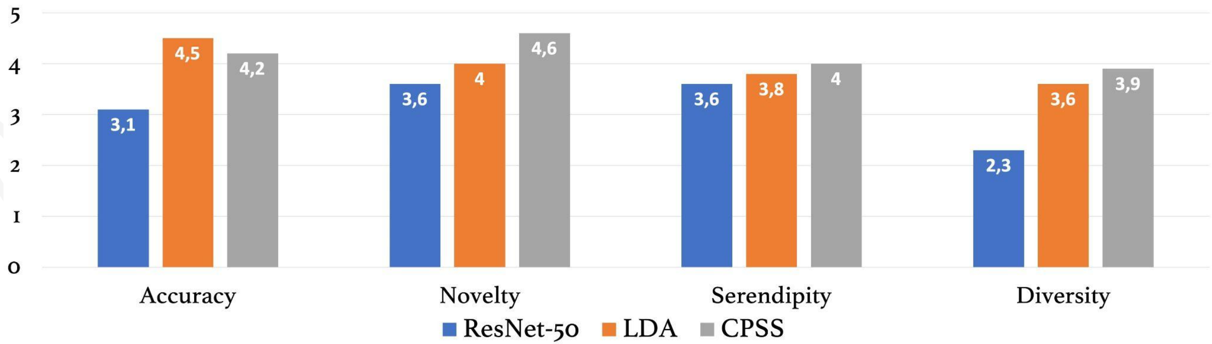
Mobile app


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**($\times_{pa}$);
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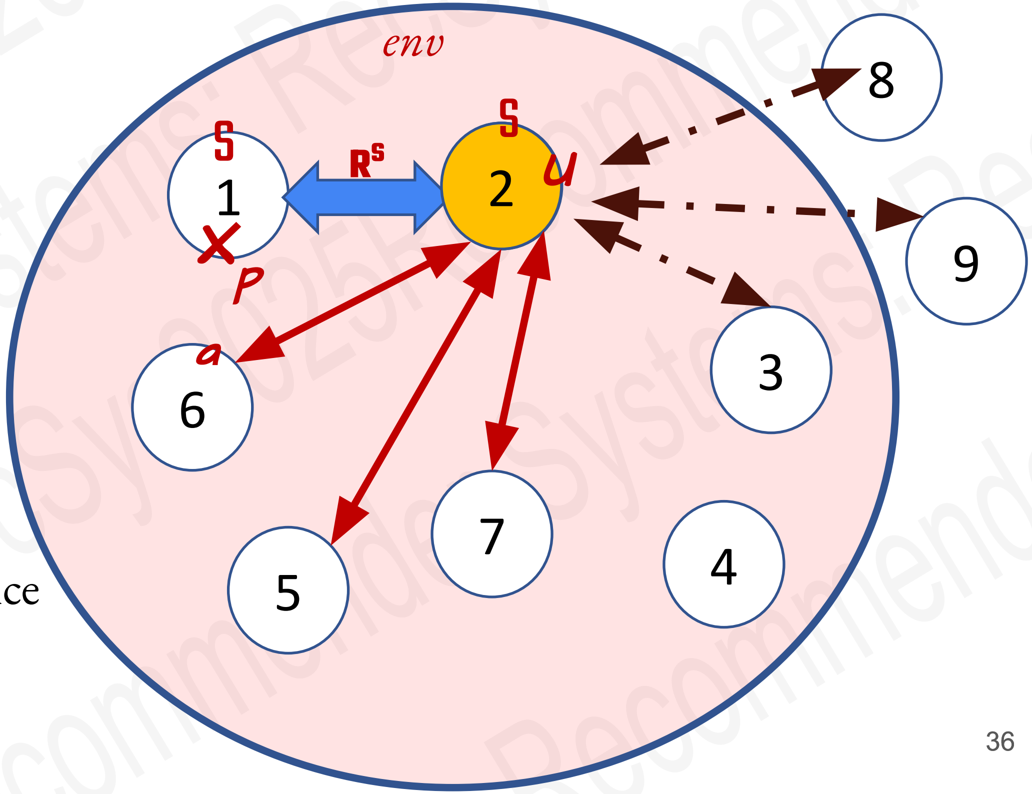

# Design Guidelines: Personalization in CPSS



Monitor and Update

Environment

Modelling the interaction environment (Systemic view)

Apply Personalization

Context

Which Computational methods work well?

Pure Personalization

Vs

Multi-stakeholder awareness

Method

User

Formulate the problem

# Downstream Applications

Cultural Heritage

**Visual Art Recsys Engines**

**Art Therapy**

Healthcare

# VA RecSys for Post-Intensive Care Syndrome (PICS) intervention