



Multi-Stakeholder aware RecSys:

A case-study approach

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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

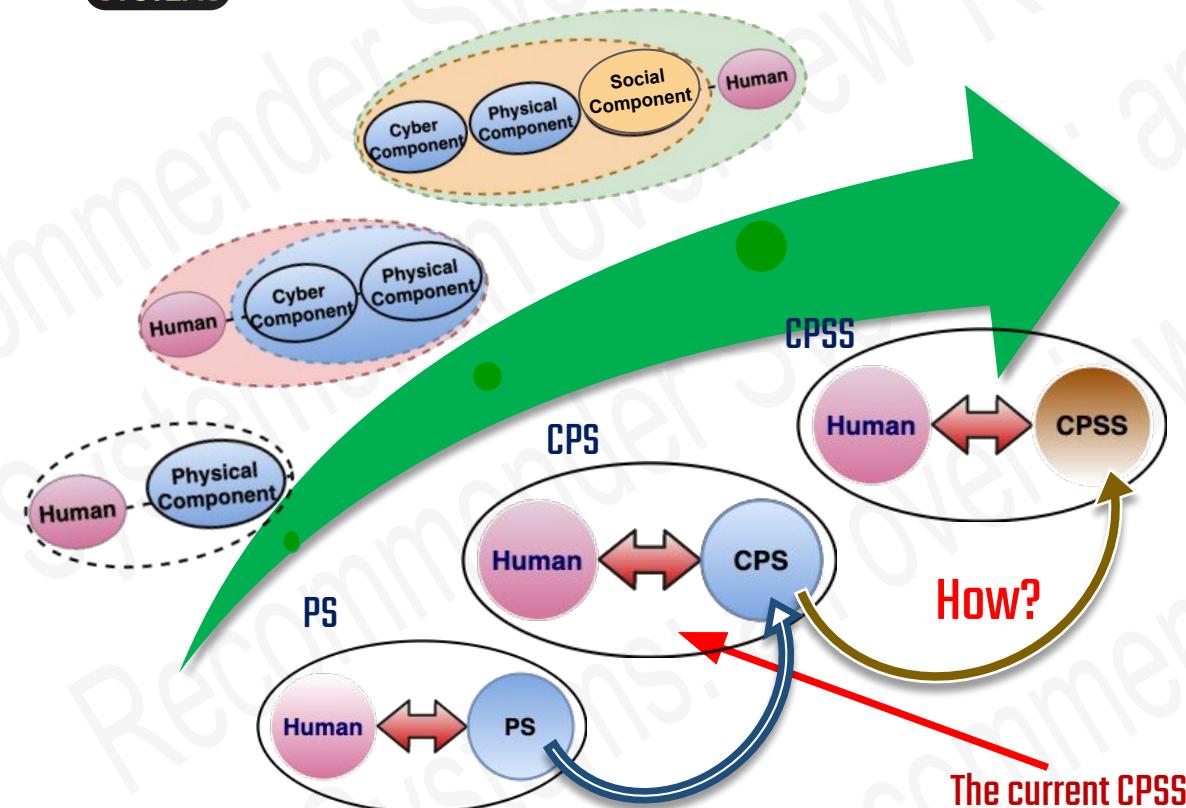
Formulating a RecSys Problem

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





Cyber-Physical-Social System (CPSS)



Personalisation

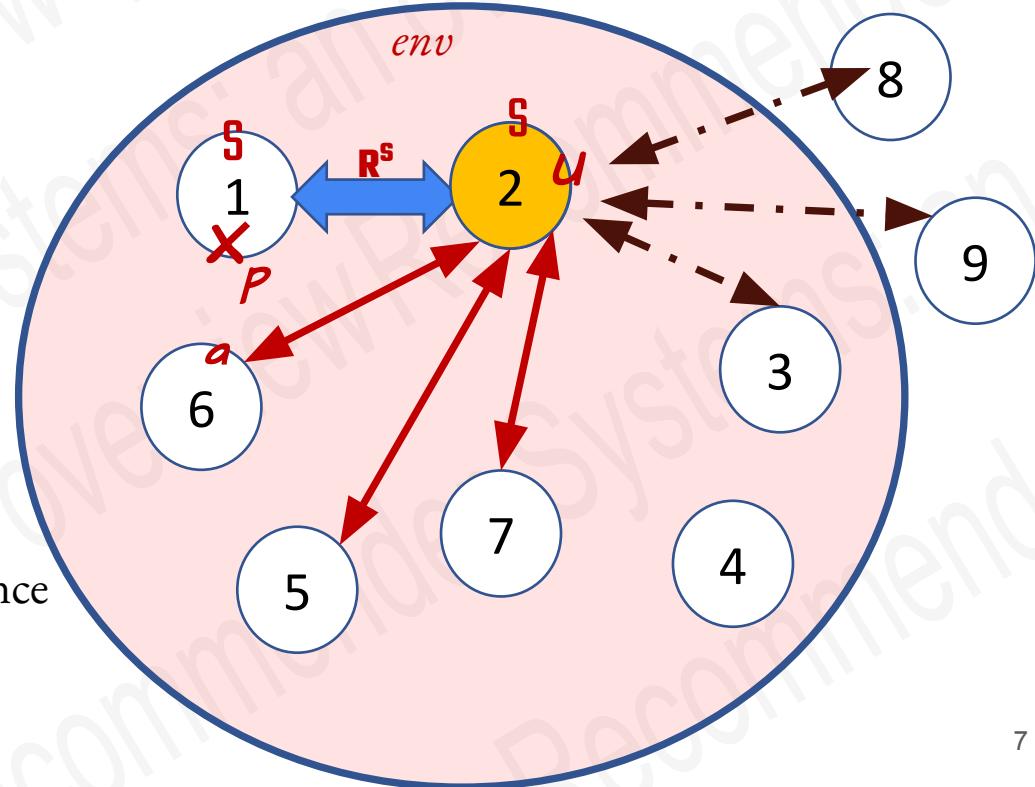
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RecSys



Formulating a RecSys Problem

- 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

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



Formulating a RecSys Problem

Personalisation in exhibition areas for a user u can be formalised as a function of

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

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

Formulating a RecSys Problem

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

- **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)
- 
- Najbri et al. 2014

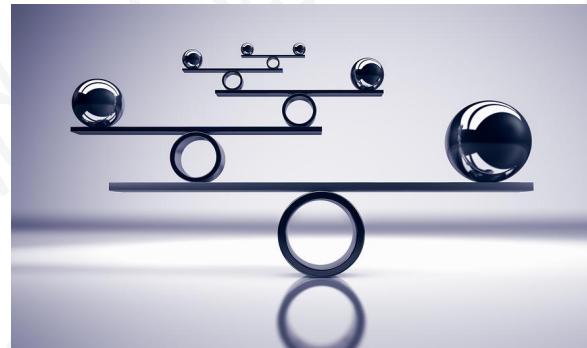
Multi-Stakeholder aware RecSys

Curator-visitor tradeoff



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

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

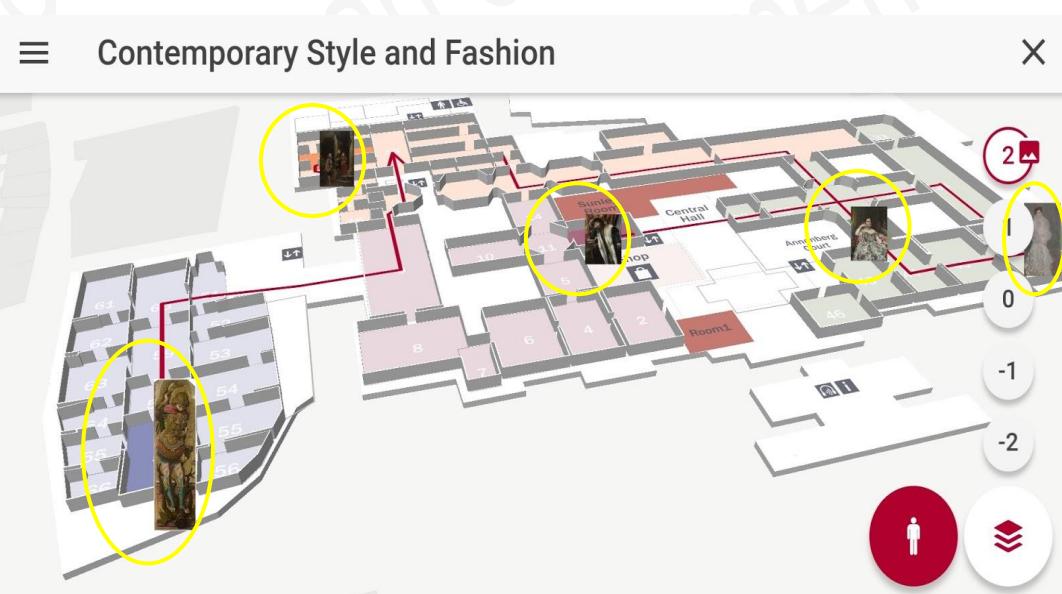
The RecSys pipeline: A case-study approach



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

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



New Visitor



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

$R^{m \times m}$



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	0.09	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.

1. Profiling

New Visitor



- List of paintings rated $P^u = \{P_1, P_2, \dots, P_n\}; P^u \in P$
- Rating of P^u , $W^u = \{w_1, w_2, \dots, w_n\}$
- Available time T_{ava}
- Visiting style (Ant, butterfly, fish, grasshopper)
- Crowd tolerance $Cr_t(u)$
- $(\beta, \lambda, \epsilon)$ 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



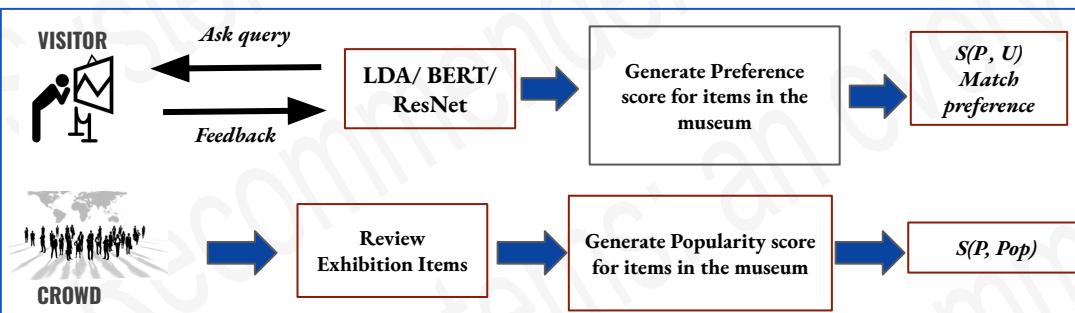
- In addition to unique personal preferences users also have different tendency to be interested in visiting famous paintings. Hence, we introduce a popularity score $S(p, Pop)$ for all the paintings in the dataset. This score is based on public review (**Crowd**) from National Gallery website.

- 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.

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

- 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



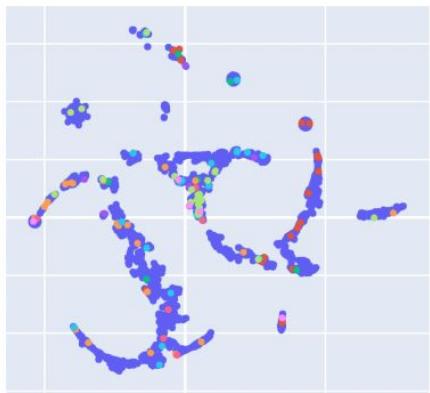
- The exhibition curator might have different goals related to the point of interests to be presented for visitors.
- In this case study the curator's goal is to increase the number curated stories presented to visitors.

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

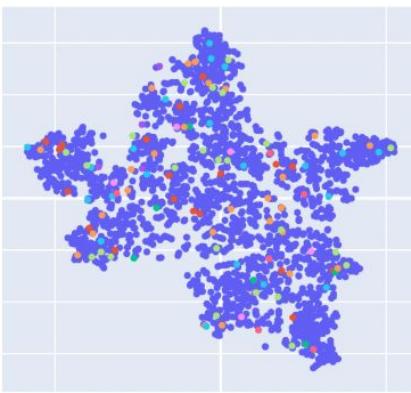
1. Women's Lives,
2. Contemporary Style and Fashion,
3. Water,
4. Women Artists and Famous Women,
5. Monsters and Demons,
6. Migration: Journeys and Exile,
7. Death, Battles and Commanders,
8. Warfare.

Multi-Stakeholder aware RecSys

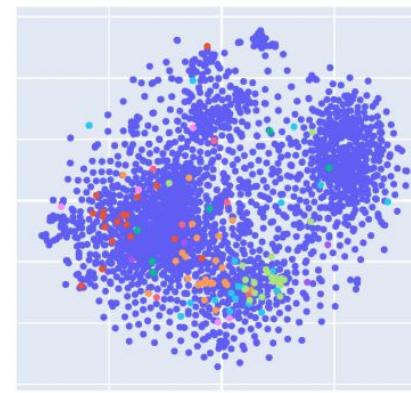
BERT



LDA



ResNet



Story groups

- Uncategorised
- Water
- Migration_Journeys_and_Exile
- Battles_and_Commanders
- Monsters_and_Demons
- Contemporary_Style_and_Fashion
- Death
- Womens Lives
- Warfare

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

1. POI recommendation →

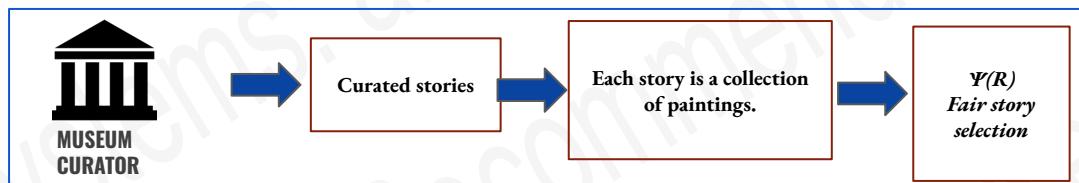
1.2 Matching Curator's Goal



- 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.

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

- $S_i, i = 1, \dots, K$ 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.

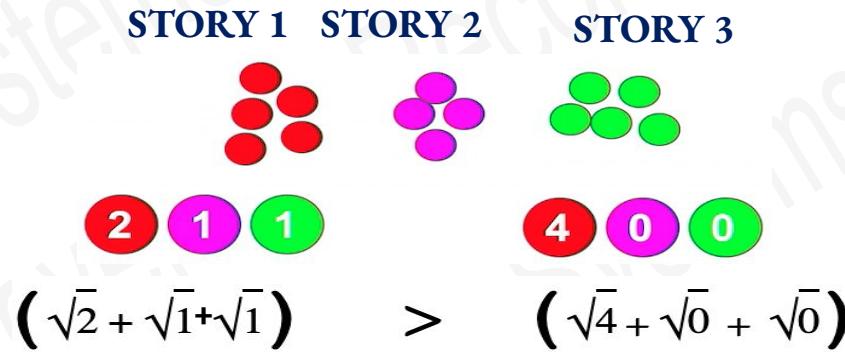


1. POI recommendation →

1.2 Matching Curator's Goal



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



1. POI recommendation →

Recommend a set R of r paintings

$$R(u) =$$

Policy 1: Maximize User Preference score.

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

Policy 2: Maximize the number of Curated stories.

- $\text{argmax } \Psi(R) = \text{argmax }$

$$\left(\sum_{i=1}^K \sqrt{\sum_{p \in Si \cap R} \gamma_p} \right)$$

$R(u)$

Respect time constraint

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

s.t.

$$\sum_{a=1}^R T v(P_a) \leq T_{ava}$$

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:

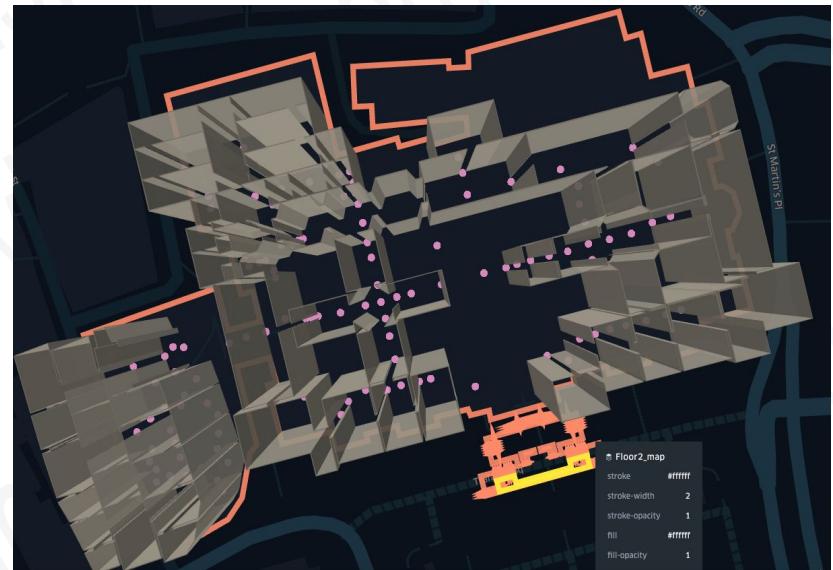
- *The total sum of estimated visiting times and travel time should not exceed the available time of the visitor.*
- *The crowd size in the selected rooms should not exceed the crowd tolerance threshold of the visitor.*



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.
- $$\bullet \quad \Theta(v_i) = \sum_{i=1}^h S(P_i)$$
- 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
- $$\delta(v_i) = b_i$$



2. Path recommendation



*Recommend a path $PT(u)$
(sequence of M rooms)*

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

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

Policy 2: Minimize travel distance

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

Subject to:

1. Time constraint:

- $\sum_{a=1}^M T(v_a) + Tt \leq T_{ava}$

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

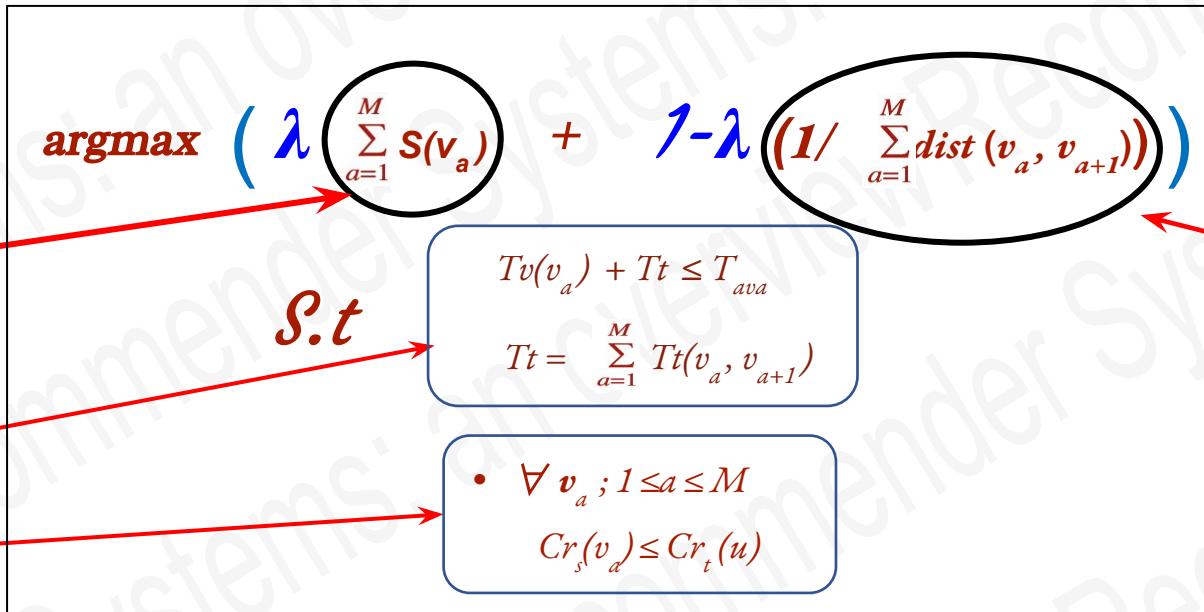
2. Crowd constraint:

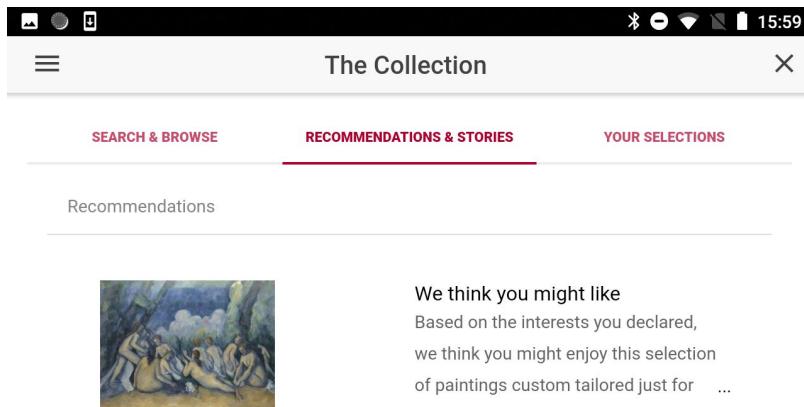
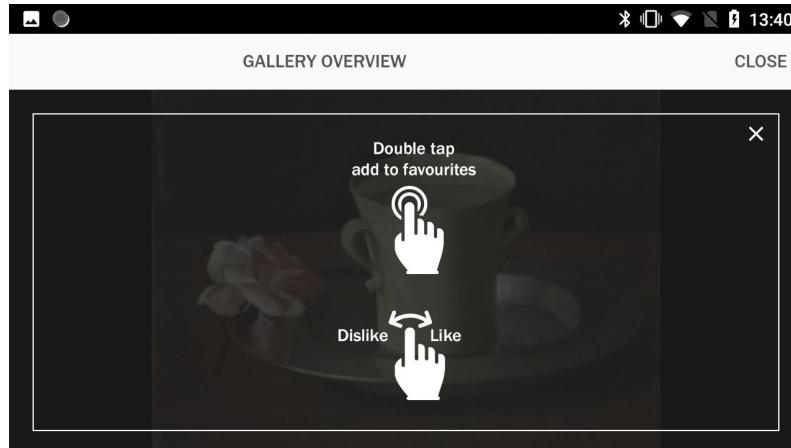
- $\forall v_a ; 1 \leq a \leq M$

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

2. Path recommendation

*Recommend a path $PT(u)$
 (sequence of M rooms)*





Personalized ? popularity, curator's theme,



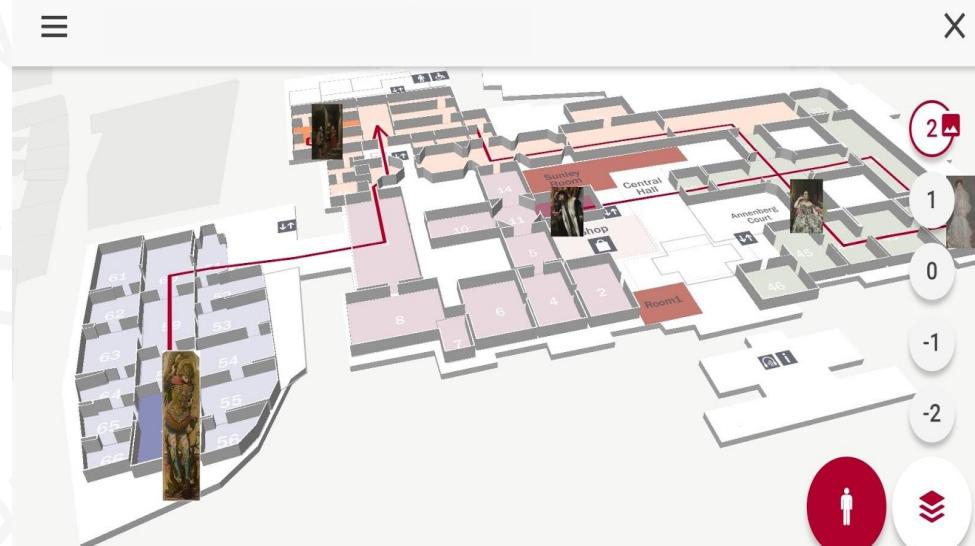
Multi-Stakeholder aware RecSys



Mobile app

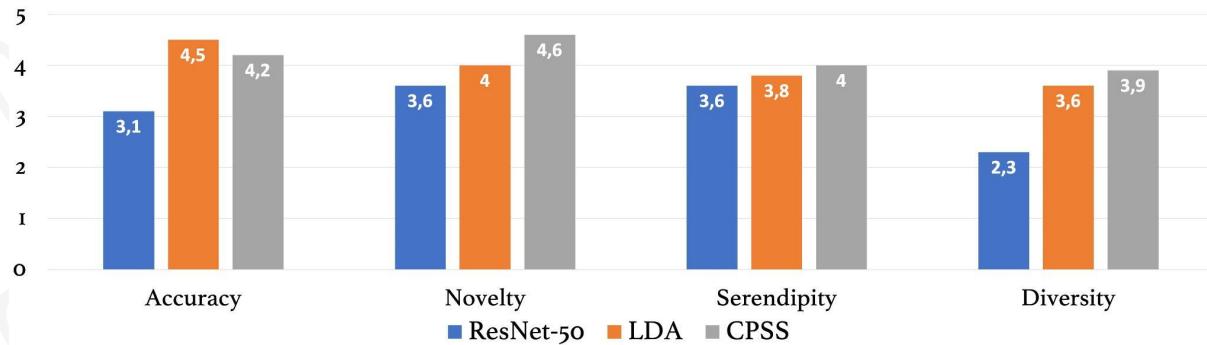


Mixed reality glass



Multi-Stakeholder aware RecSys

Baseline Single objective **Vs** Multi-objective





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**(x_{pa});
- **User**(U)
- **Crowd**(Cr): direct influence
- **Context elements**(Cx): indirect influence

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

