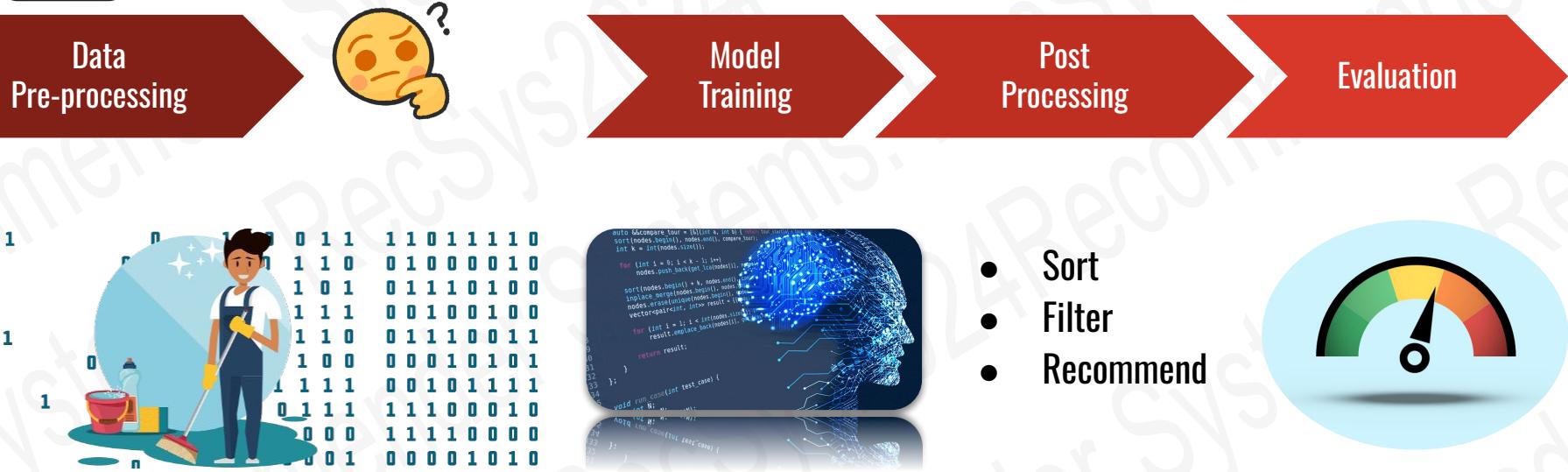




The HC RecSys Pipeline: A case-study approach



The HC RecSys Pipeline



- Sort
 - Filter
 - Recommend



The HC RecSys pipeline: A case-study approach



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



The HC RecSys pipeline: A case-study approach



DISCLAIMER



The HC RecSys pipeline: A case-study approach

Personalised Visual Art Recommendation



Context: National Gallery, London

- $\geq 2,300$ paintings dating from the mid-13th century to 1900.
- Total floor area of 46,369 square meters, 3 floors.
- 6.2 million visitors/year (2019)



The HC RecSys pipeline: A case-study approach



Task

Personalised Visual Art Recommendation

Data

Visual Art (Paintings)

Target User

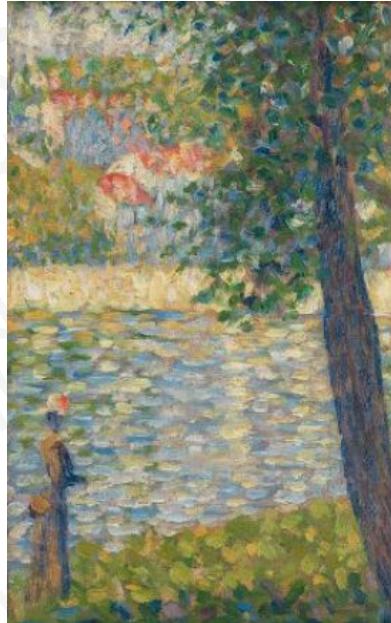
Visitors (New)

*assumptions Visitor profile

The HC RecSys pipeline: A case-study approach

1. Data: Visual Art (Paintings)

- 2,368 painting



painting_id	000-018P-0000
title	The Morning Walk
artist	Georges Seurat
publication_date	19th_century
size_format	Portrait
size	Very Small
technique	oil painting
description	A woman, silhouetted against the shimmering water, strolls along a riverbank. The red roofs of houses can be made out along the opposite bank. Between 1882 and 1886 Seurat painted numerous such landscape studies on small wooden panels, some as independent works and others in preparation for his large-scale compositions. This sketch provided the starting point for a painting of 1885, 'The Seine at Courbevoie' (private collection).



The HC RecSys pipeline: A case-study approach



Data
Pre-processing



New Visitor



THE COLD START PROBLEM

Query User (Profiling)

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



The HC RecSys pipeline: A case-study approach

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.

The HC RecSys pipeline: A case-study approach

Data
Pre-processing



Task
Personalised
Recommendation

0	1	0	1	1	1	1	0	1	1	1	1	0
1	0	1	0	0	1	0	0	0	1	0	0	1
1	1	0	1	0	0	0	1	0	0	1	0	0
0	1	1	0	1	1	0	1	0	0	1	0	0
1	1	1	1	0	0	1	0	0	1	0	0	1
1	1	0	0	1	1	0	0	1	0	1	0	0
1	1	0	0	0	1	0	1	0	1	0	1	1
1	0	0	0	0	0	1	0	1	1	1	1	0
0	1	1	1	0	1	1	0	0	0	1	0	0
0	1	1	1	1	1	0	0	0	0	1	0	0
0	0	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	1	0	1	0
0	1	0	0	0	0	1	0	1	0	1	0	1



Image



Metadata

painting_id	000-018P-0000
title	The Morning Walk
artist	Georges Seurat
publication_date	19th_century
size_format	Portrait
size	Very Small
technique	oil painting
description	A woman, silhouetted against the shimmering water, strolls along a riverbank. The red roofs of houses can be made out along the opposite bank. Between 1882 and 1886 Seurat painted numerous such landscape studies on small wooden panels, some as independent works and others in preparation for his large-scale compositions. This sketch provided the starting point for a painting of 1885, 'The Seine at Courbevoie' (private collection).

Textual description

The HC RecSys pipeline: A case-study approach

Data
Pre-processing



Task
Personalised
Recommendation

Model
Training

Good representation of
the data!

$R^{m \times m}$

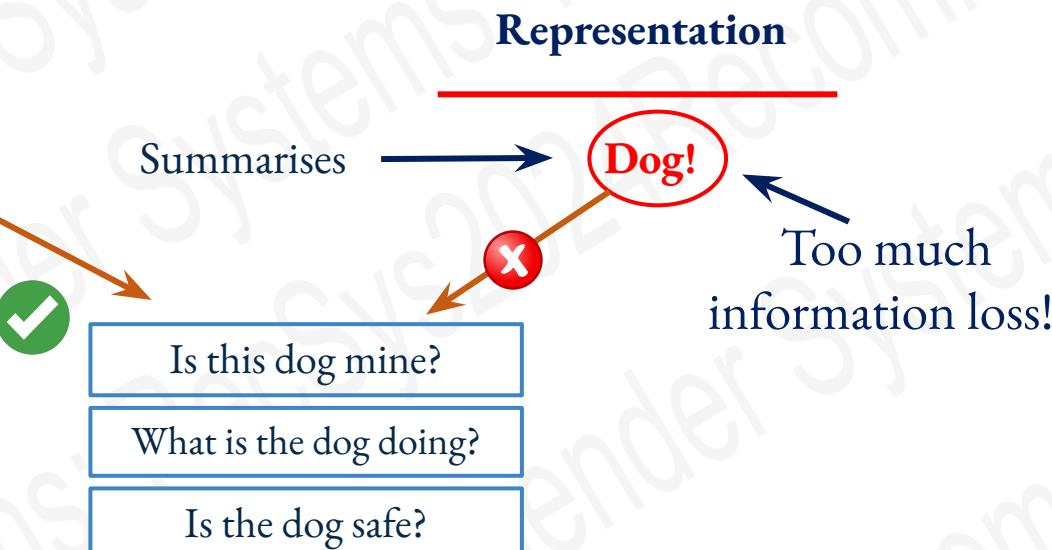
1	0.77	0.57	0.54	0.37	0.46	0.45	0.44	0.46	0.37	0.63	0.66	0.59	0.54	0.59	0.52
0.77	1	0.69	0.68	0.54	0.56	0.61	0.53	0.5	0.46	0.74	0.85	0.66	0.58	0.67	0.6
0.57	0.69	1	0.92	0.34	0.39	0.45	0.4	0.43	0.45	0.48	0.59	0.57	0.62	0.67	0.59
0.54	0.68	0.92	1	0.37	0.38	0.5	0.44	0.42	0.41	0.47	0.59	0.55	0.6	0.66	0.59
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.

Representation Learning

What is a good representation of this image?

Buddy :)



The HC RecSys pipeline: A case-study approach

Representation Learning

What is a good representation of this image?

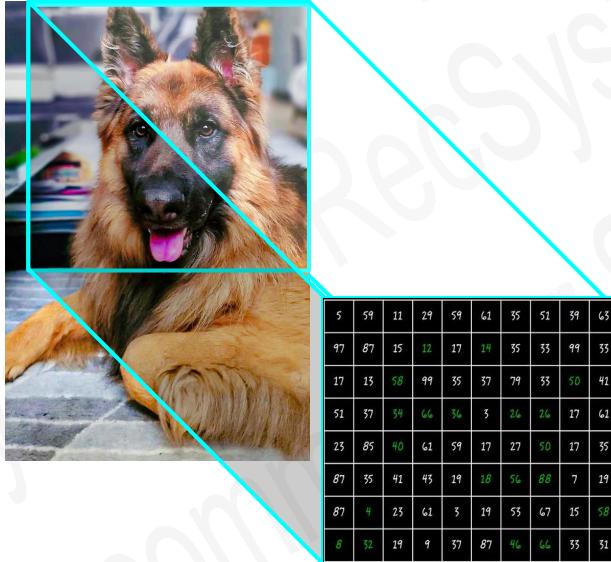


Representation

A bit more descriptive
yet a summary

German shepherd dog resting
on a floor in living room.

Representation Learning



Representation is a summary of data which:

- **Omits** unnecessary details
- **Preserves** important details

Representation

[1, 23, 0.4]

Array of numbers!

Each dimension would contain some semantic meaning

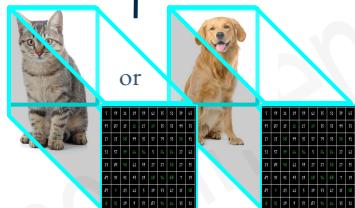
Evolution of Representation Learning

Classifier on
raw data



Task
↑
Classifier

Problem:
Too much
redundancy in the
input data



Very high dimensional
Array of numbers!

Solution
Summarize relevant
information
→ Features

Classifier with
handcrafted
features

Perform reasonably
better

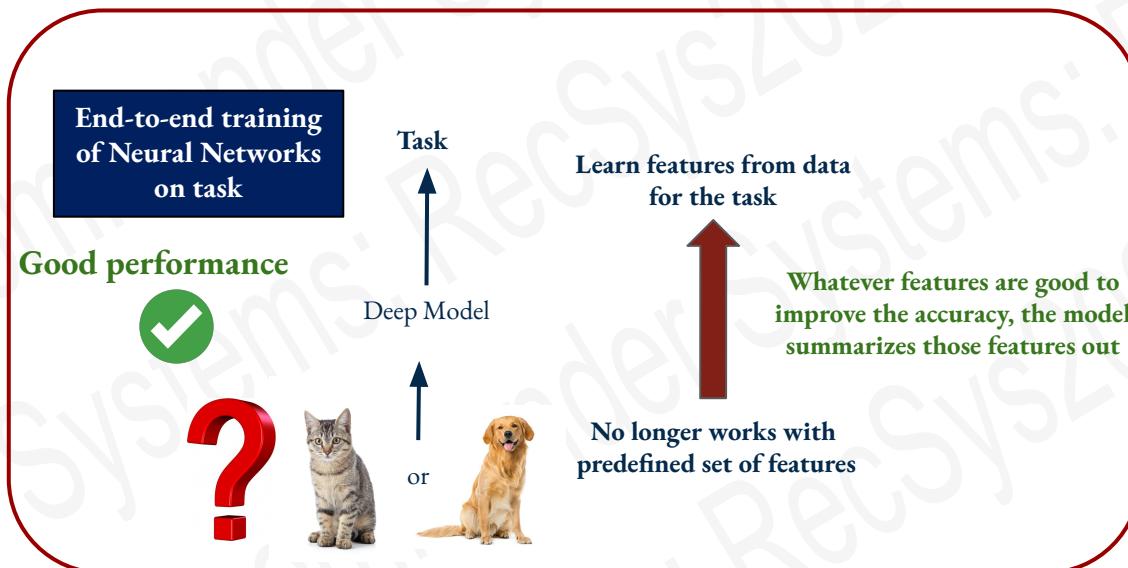


Task
↑
Classifier
↑
Features

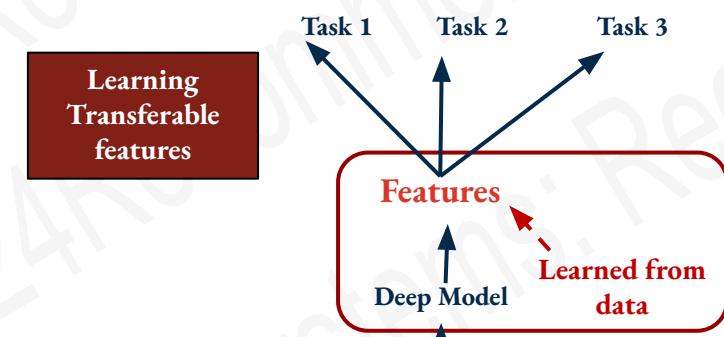
Dimensionality
Reduction
↓

handcrafted

Evolution of Representation Learning



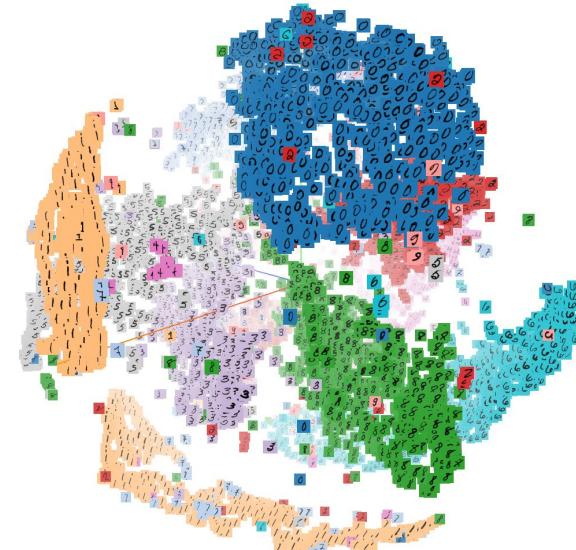
Great! Can we learn features that are useful not only for the specific task but also other tasks?



Generally useful for a wide range of tasks

What makes a good Representation?

- Low dimensional (summarize data)
- Reusable across tasks
- Smooth and spatially coherent
- Disentangled
- Hierarchical and meaningful



The HC RecSys pipeline: A case-study approach

Early approaches in VA RecSys:

Manually curated metadata to drive recommendations.



Authorship

Art History

Style



Size

Material

History



The HC RecSys pipeline: A case-study approach

- Train a model that can learn Visual features from images of paintings

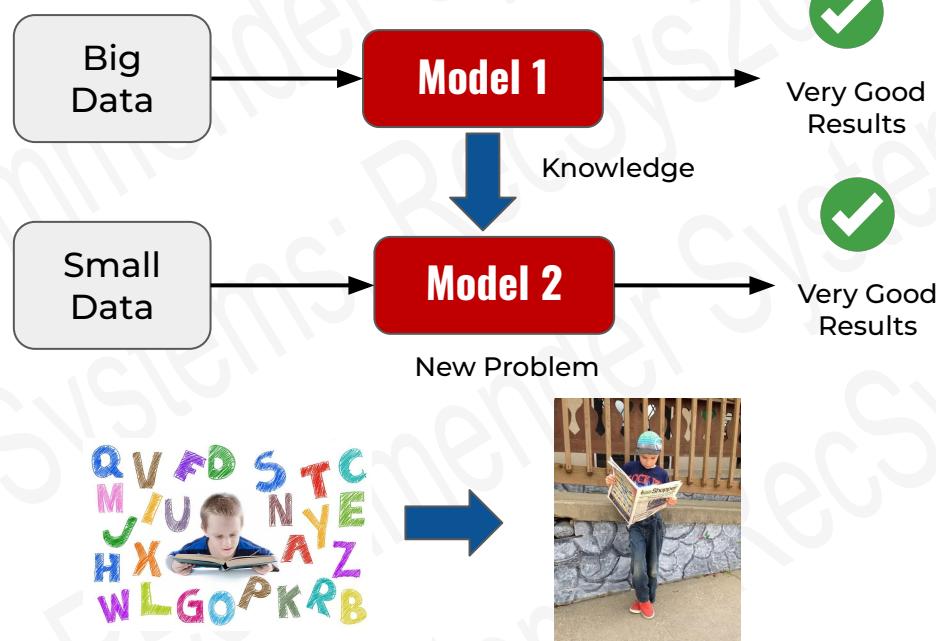


- Use pre-trained models as feature extractors
 - ResNet, AlexNet, GoogLeNet, VGG

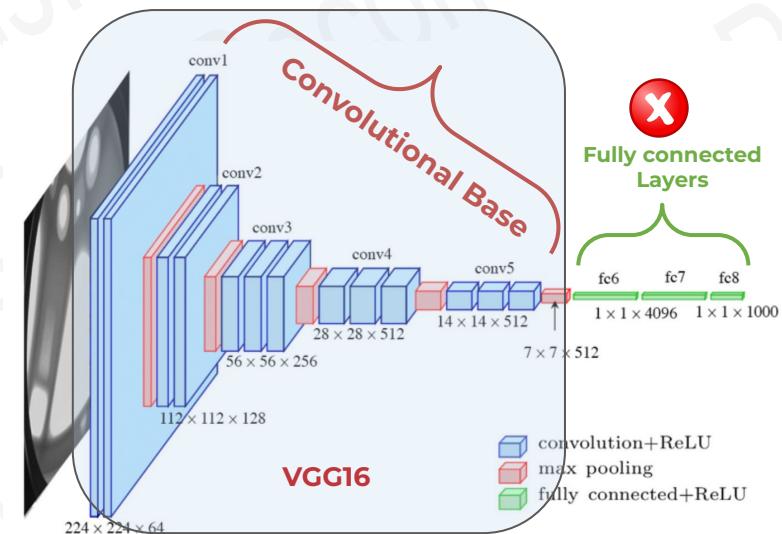
How? → **Transfer Learning**

The HC RecSys pipeline: A case-study approach

Transfer Learning



> 1,000,000 images

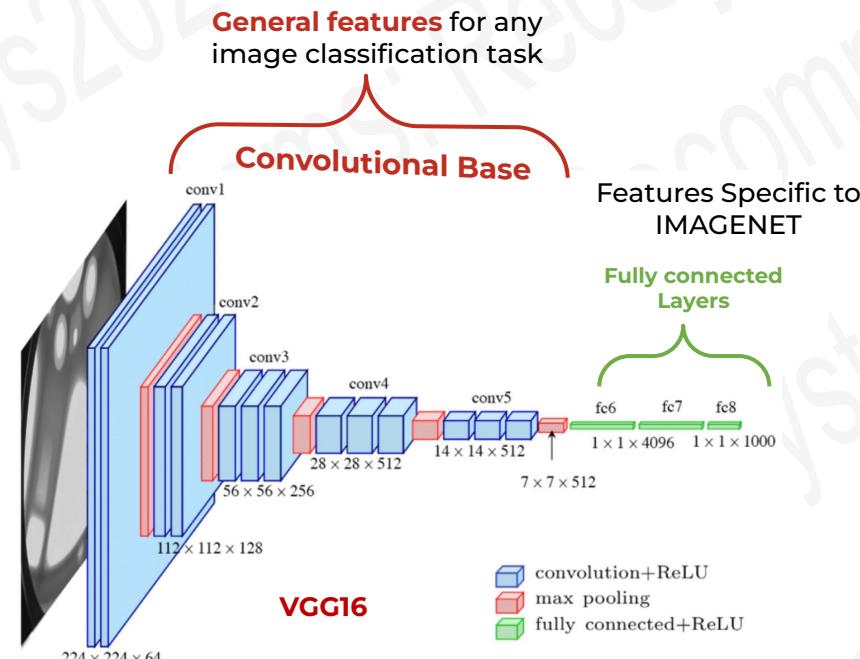


The HC RecSys pipeline: A case-study approach

Transfer Learning

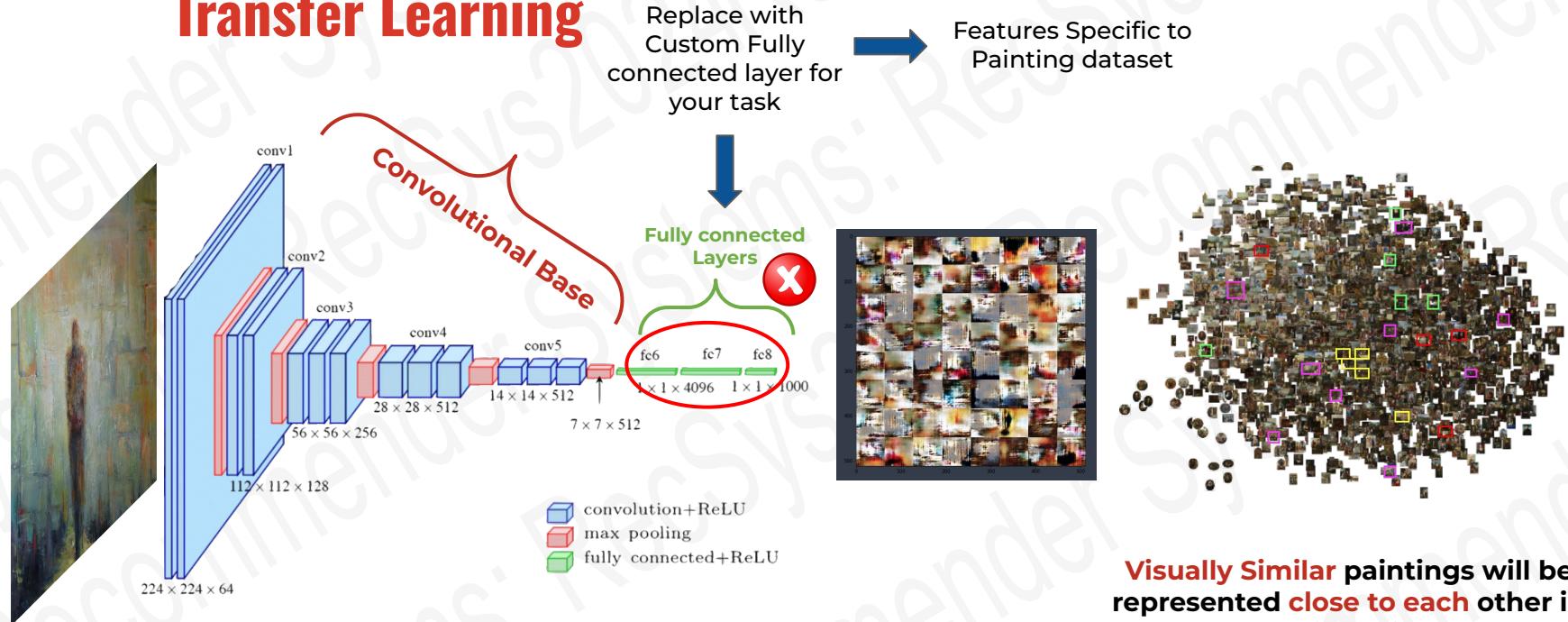


We want Features Very specific to the **Paintings** dataset



The HC RecSys pipeline: A case-study approach

Transfer Learning



Visually Similar paintings will be represented **close to each other** in the representation space

The HC RecSys pipeline: A case-study approach

Some issues:

- Recommendations don't have direct interpretation.
- Often fail to capture complex semantics



The HC RecSys pipeline: A case-study approach

The Challenge in VA Recsys:

- Capturing the complexity of the concepts embedded within the artwork,



The HC RecSys pipeline: A case-study approach

The Challenge in VA Recsys:

- The emotional and cognitive reflections VA may trigger in users.



The HC RecSys pipeline: A case-study approach

The Challenge in VA Recsys:

- Understanding how users interact with highly subjective content.



The HC RecSys pipeline: A case-study approach

Data
Pre-processing

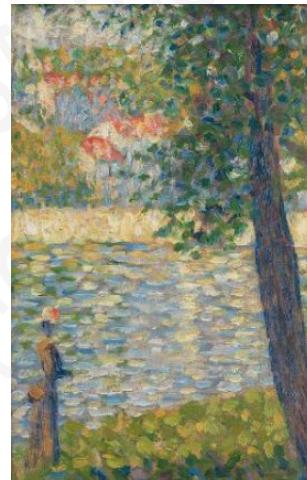


Task
Personalised
Recommendation

Model
Training

Textual description

- Public reviews
- Books
- Articles, ...

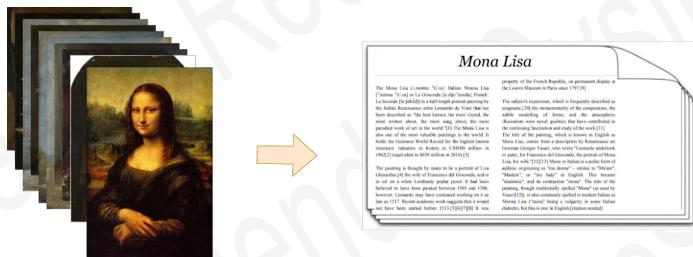


painting_id	000-018P-0000
title	The Morning Walk
artist	Georges Seurat
publication_date	19th_century
size_format	Portrait
size	Very Small
technique	oil painting
description	A woman, silhouetted against the shimmering water, strolls along a riverbank. The red roofs of houses can be made out along the opposite bank. Between 1882 and 1886 Seurat painted numerous such landscape studies on small wooden panels, some as independent works and others in preparation for his large-scale compositions. This sketch provided the starting point for a painting of 1885, 'The Seine at Courbevoie' (private collection).

The HC RecSys pipeline: A case-study approach

Latent Semantic Representation Learning

- We need representations that capture **hidden semantic relationships** between the paintings



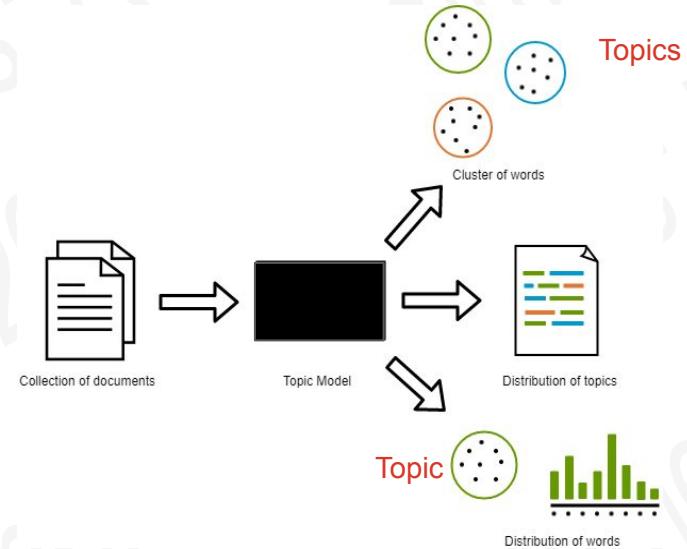
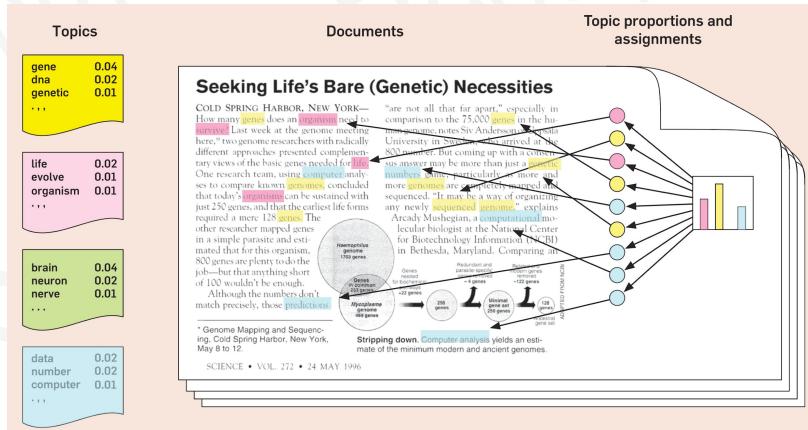
Topic Modelling

The HC RecSys pipeline: A case-study approach

Topic Modelling

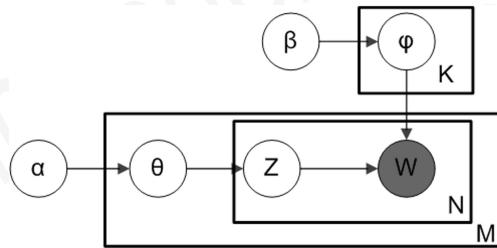
→ A way or suit of techniques to identify **latent themes** in a corpus/ collection of documents.

1. Latent Dirichlet Allocation (LDA)



Blei, D. M. (2012). Probabilistic Topic Models. Communications Of The Acm, 55(4), 77-84

Latent Dirichlet Allocation (LDA)



M denotes the number of documents

N is number of words in a given document (document i has N_i words)

α is the parameter of the Dirichlet prior on the per-document topic distributions

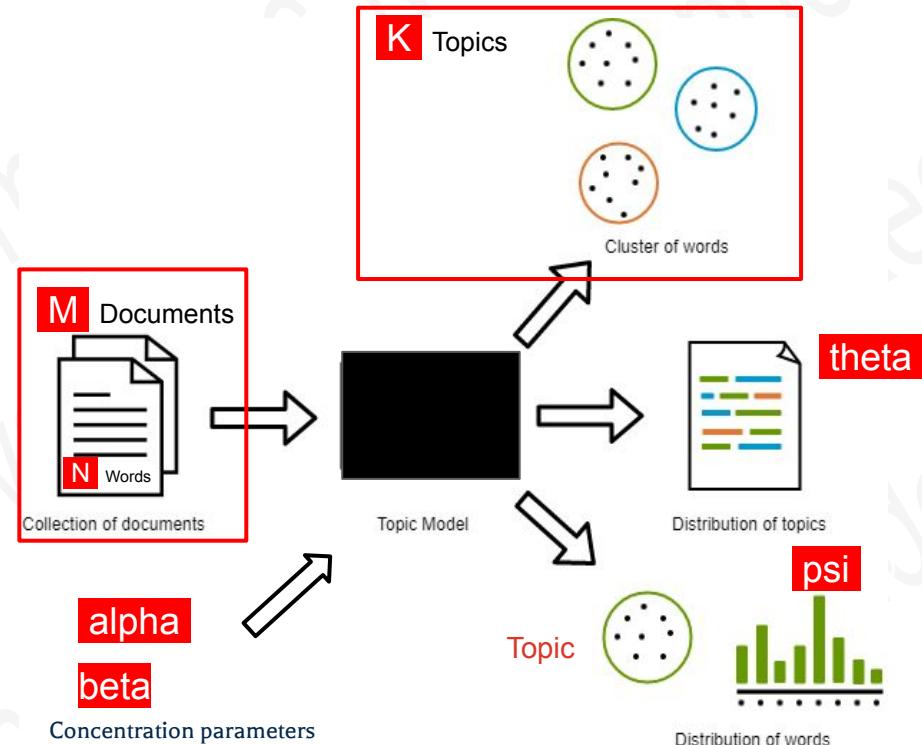
β is the parameter of the Dirichlet prior on the per-topic word distribution

θ_i is the topic distribution for document i

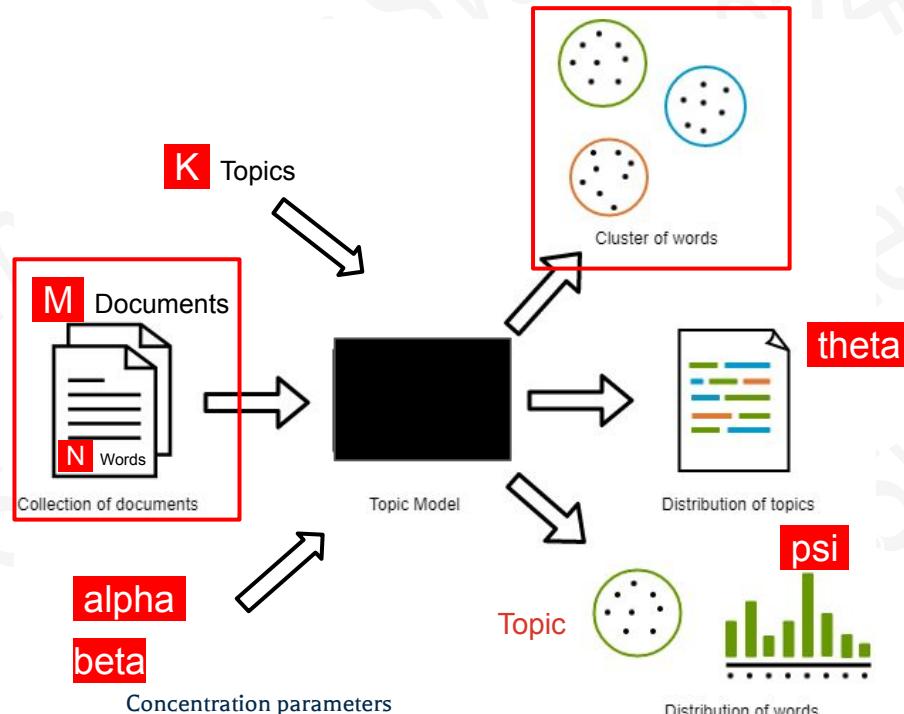
φ_k is the word distribution for topic k

z_{ij} is the topic for the j -th word in document i

w_{ij} is the specific word.



The HC RecSys pipeline: A case-study approach

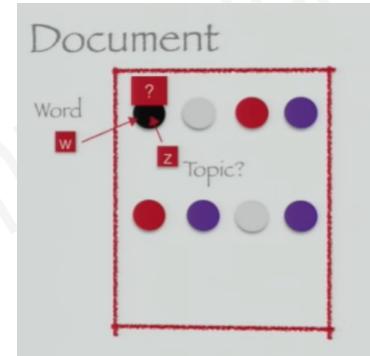
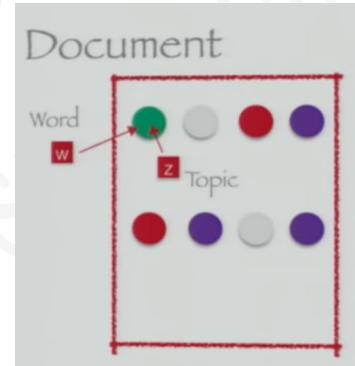
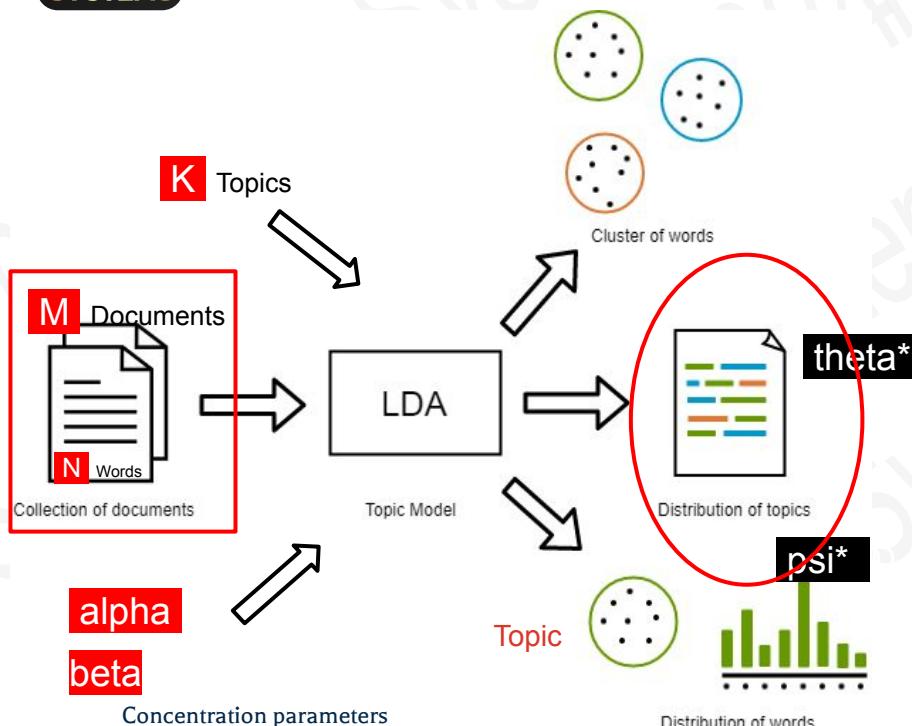


LDA Algorithm

Iterative Algorithm

1. Initialize parameters
2. Initialize Topic assignments randomly
3. Iterate : For each word in each document
 - Resample topic for word given all other words and their current topic assignments
5. Get results
6. Evaluate model

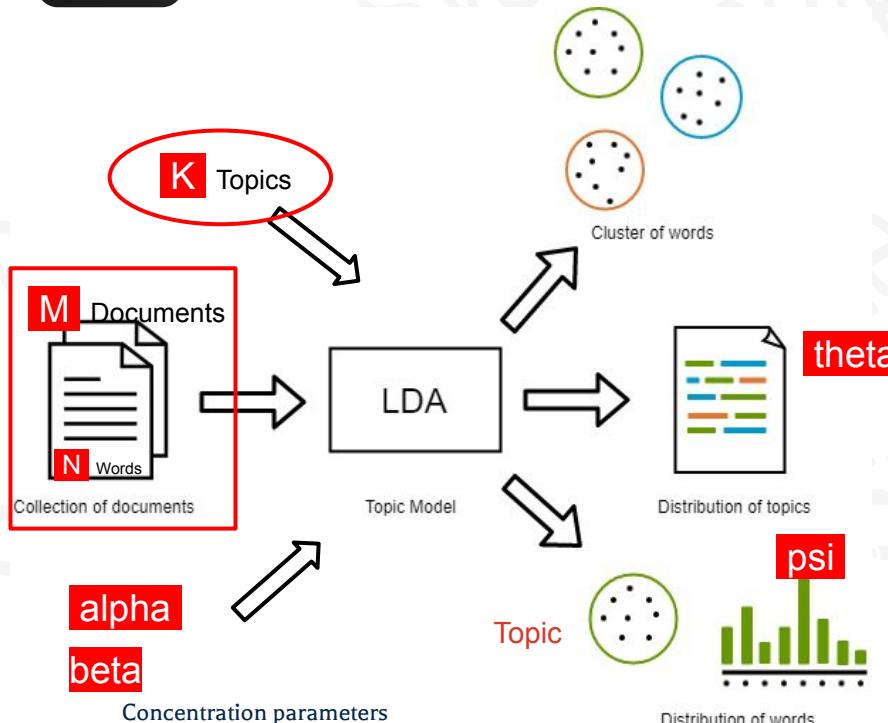
The HC RecSys pipeline: A case-study approach



Resample topic for word given all other words and their current topic assignments

1. Which topics occur in this document?
2. Which topics like the word X

The HC RecSys pipeline: A case-study approach



→ What is the optimal number of Topics?
Topic coherence

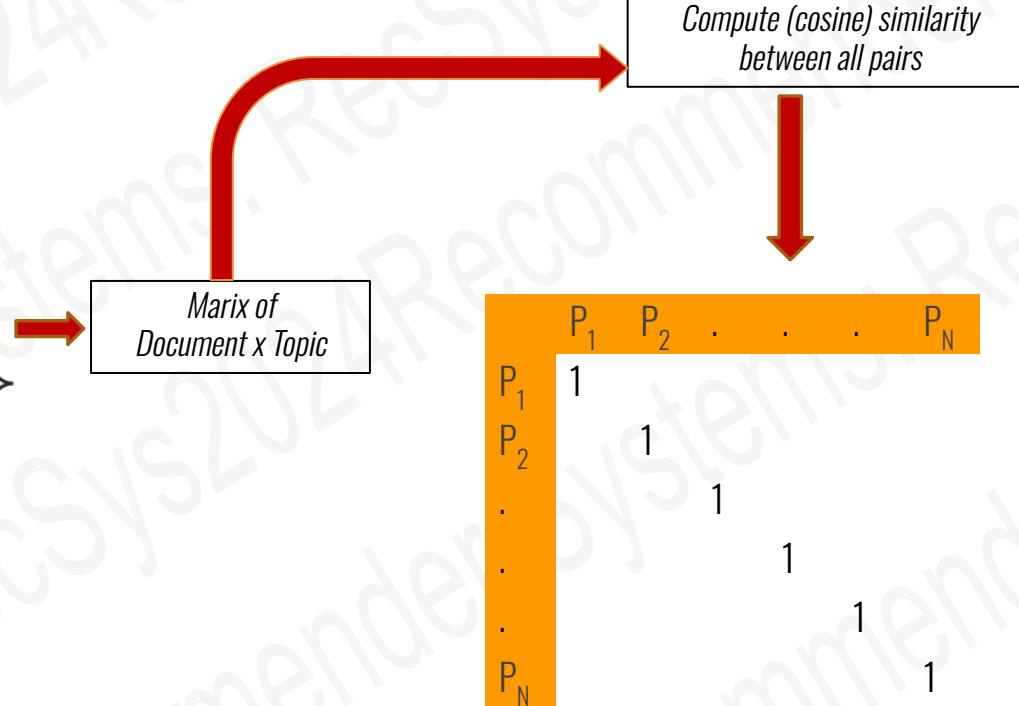
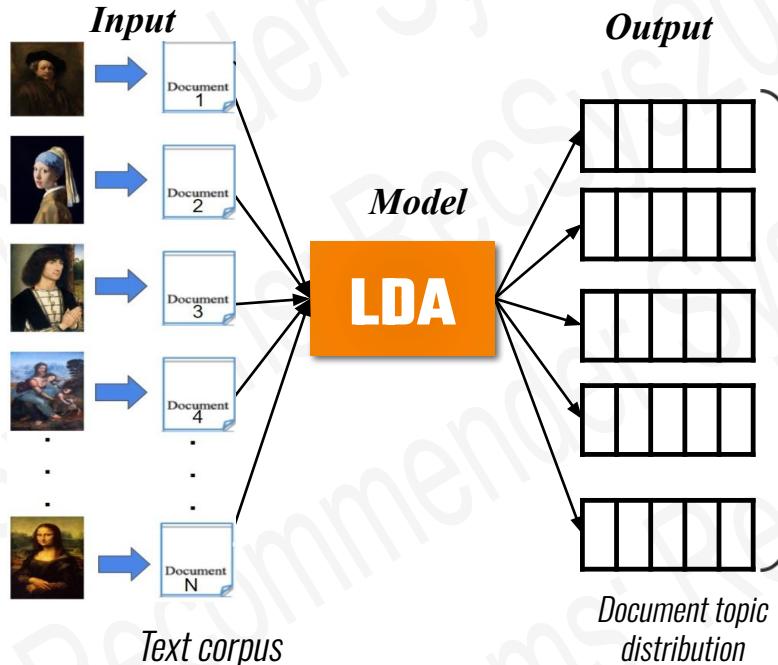


More on LDA → Notes on Dirichlet Processes by Timothy Hopper: <https://dp.tdhopper.com/>



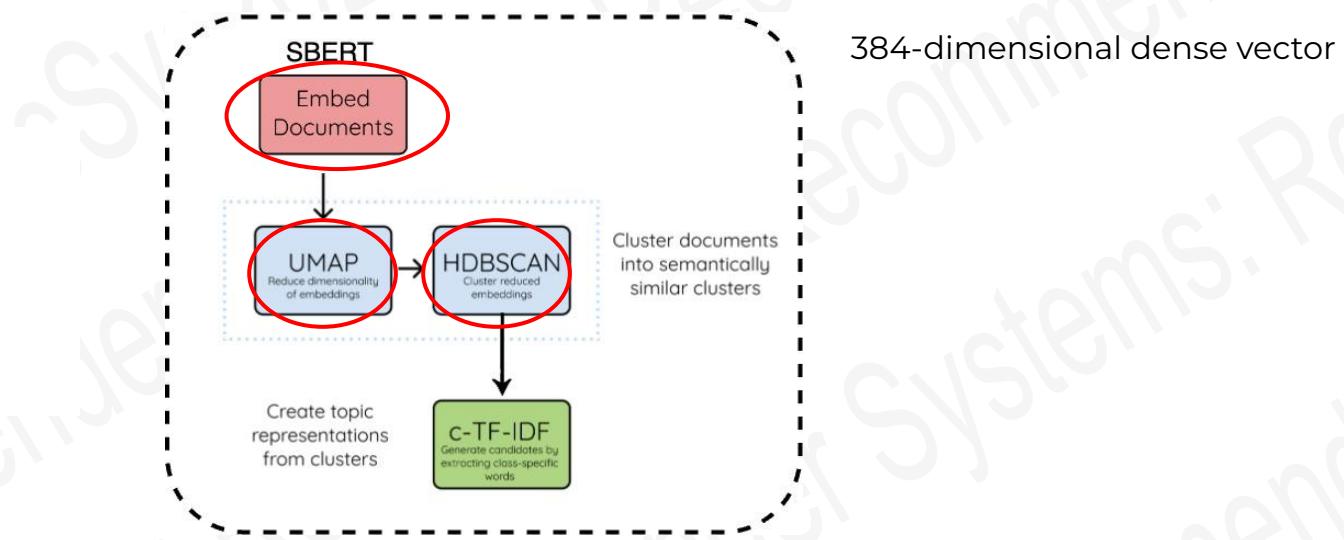
The HC RecSys pipeline: A case-study approach

LDA Painting Model:



The HC RecSys pipeline: A case-study approach

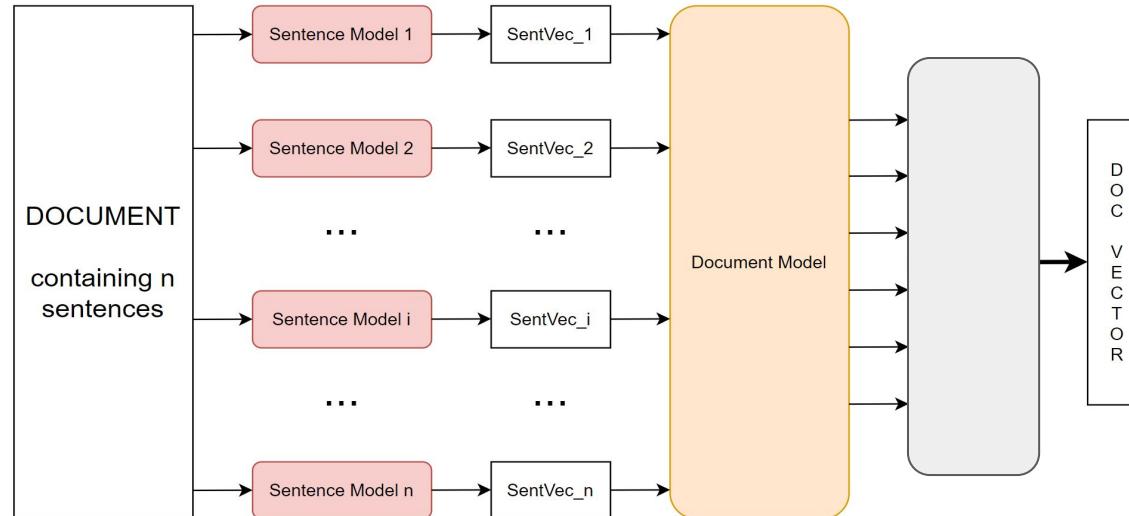
Pretrained Language model Sentence Transformers



Neural topic modeling with a class-based TF-IDF procedure. (Maartin Grootendorst 2022)

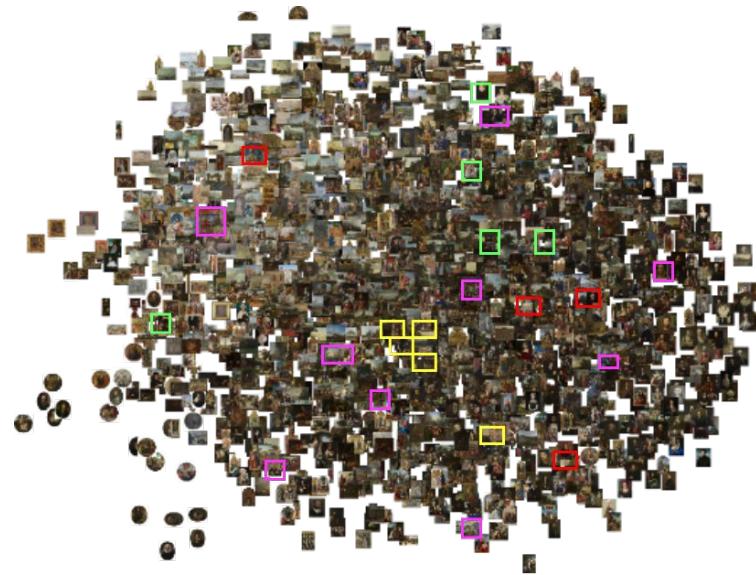
The HC RecSys pipeline: A case-study approach

Pretrained Language model Sentence Transformers

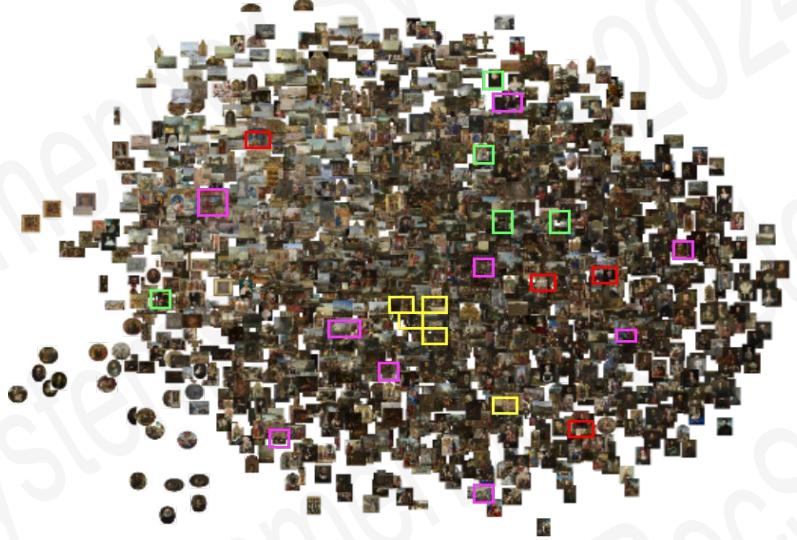




The HC RecSys pipeline: A case-study approach



The HC RecSys pipeline: A case-study approach



Latent Semantic Representation learning:

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	0.59	0.45	0.57	0.65	0.59	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	0.05	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	0.55	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	0.48
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

Similar paintings will be represented close to each other in the representation space

Data Pre-processing



Task
Personalised
Recommendation

Model Training

Post Processing

Input
(User rated paintings)

Weight (W^u) (P^u)

w^{u_1}
w^{u_2}
w^{u_3}
.
.
w^{u_y}



$S(P, U)$

Output
Score Dataset

$S(P, U)$

$S(P_1, U)$

$S(P_2, U)$

$S(P_3, U)$

.

.

.

.

$S(P_M, U)$

.

- The predicted Score $S(P_i, U)$ for a novel painting P_i with respect to an active user u is based on the weighted average score from all other paintings that have been rated by the active user.

$$S(P, U) = \frac{1}{N} \sum_{j=1}^N w_j * d(p_i, p_j)$$

- $d(p_i, p_j)$ is the similarity between p_i and p_j according to our model (LDA, BERT, ResNet..)
- Top K recommendation

Data
Pre-processing



Task
Personalised
Recommendation

Model
Training

Post
Processing

Evaluation

- Proxy for how relevant/ good are recommender systems.

1. Offline Experiment.

- Easiest to conduct
- Requires no interaction with users.

- Common evaluation protocols in ML, IR

2. User Studies

- Small group of Subjects
- Controlled setting
- Qualitative/quantitative

3. Online Experiments

- The most trustworthy
- A pool of real users (unaware of the experiment)



The HC RecSys pipeline: A case-study approach

Evaluation

A couple of basic guidelines in general experimental studies

1. Hypothesis:

What do you want to evaluate? Form a **concise** and **restrictive** Hypothesis.

E.g. Algorithm **A** better predicts rating than Algorithm **B**

→ **Predictive Accuracy** not other factors

Algorithm **A** generates diverse recommendations than Algorithm **B**

→ **Diversity** not other factors, etc.

Evaluation

A couple of basic guidelines in general experimental studies

2. **Controlling variables:** Variables that are not being tested should stay fixed.

E.g. Algorithm **A** better predicts rating than Algorithm **B** → **Predictive Accuracy**

Train A on NG dataset



Can not tell why $A > B$ or $B < A$

- Superior model?
- better input data?

Train both A & B on the same dataset.

Train B on Louvre dataset



Evaluation: Offline Experiments

Performed using a pre-collected dataset of users choosing or rating of items.

- Using this data we can simulate behaviour of users that interact with the a Recommender System: (assuming users will behave the same when the Recommender System is deployed.)
 - To make reliable decision.
- **Attractive & easy:**
 - Requires no interaction with real users.
 - We can compare wide range of candidate algorithms at low cost.



The HC RecSys pipeline: A case-study approach



Evaluation: Offline Experiments

- **Downside:** We can not measure the recommender's influence on user behavior.

Useful for :

- Filtering out inappropriate approaches, select candidate algorithms for more costly user studies/online experiments.
- Tuning parameters of algorithms.

Evaluation: User Studies

Conducted by recruiting a set of test subject, and asking them to perform several tasks requiring an interaction with the recommendation system.

- During interaction we observe and record their behaviour.

Quantitative measures: % of completed task, accuracy, time, etc.

Qualitative measures: pre/post interaction questions that are not directly observable.

- weather the subject enjoyed the UI
- weather the subject perceived the task easy, etc.

Evaluation: User Studies

Downsides:

- Expensive to conduct (large set of subjects, large set of tasks)
- Subjects (volunteers or employed)
 - Motivations (intrinsic/ extrinsic)--> quality of response
 - Budget
- Testing all possible scenarios can be challenging.
- Finding subjects that represent the entire population. (Bias)

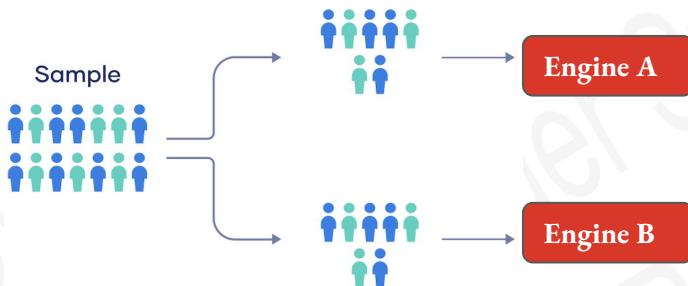
Pilot user studies: to test the systems for bugs and malfunctions.

Evaluation: User Studies

Between vs. Within Subjects

Few candidate approaches: each method must be tested on the same task.

1. Between Subjects (A-B testing)



- Easier to setup and analyse correctly
- No learning across conditions
- Test long term effects

2. Within Subjects



- More informative (superiority of methods)
- Can ask comparative questions about candidates



The HC RecSys pipeline: A case-study approach

Evaluation: Online Evaluation

Done with a set of real users unaware of the experiment.

- Many realistic RecSys applications wish to influence the behaviour of users.
(engagement, purchase)
- Measure the change in user behavior while interacting with recommendations.
 - Did the user follow recommendations? for how long?
 - Weather some utility gathered from users of system A exceeds the one from system B.
(which system is superior?)

Evaluation: Online Evaluation

Most reliable:

Real users with real needs in the context.

- The real effect of Recommendation systems depends on several factors
 - Users' intent
 - How specific are their needs?
 - How much novelty are they looking for?
 - How much risk are they willing to take?
 - Users' context
 - What items are they already familiar with ?
 - how much they trust the system?
 - The Recommendation interface



The HC RecSys pipeline: A case-study approach



Evaluation: Online Evaluation

Downsides:

- May discourage users from using the real system ever again.
- Financial risk in commercial applications.

To reduce such risks it is best to run an online evaluation last

- After an extensive Offline study followed by a user study provided evidence that the candidate approaches are reasonable.



The HC RecSys pipeline: A case-study approach



Evaluation: Drawing Reliable Conclusions

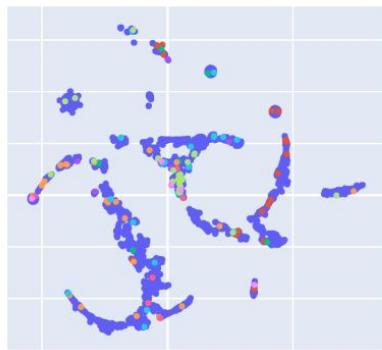
Even after a carefully conducted experiment Recsys might fail in unseen scenarios when deployed in real life.

To reduce such risks it is best to perform significance testing on the results.

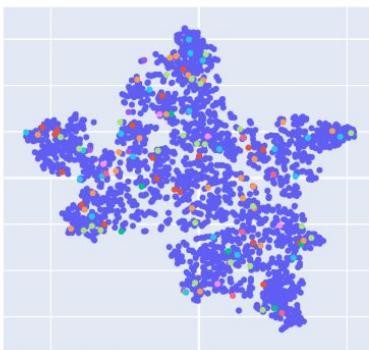
The Elements of Visual Art Recommendation

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

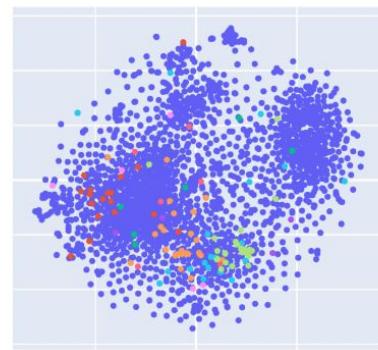
BERT



LDA



ResNet



Story groups

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

- We developed Visual art recommendation engines

BERT

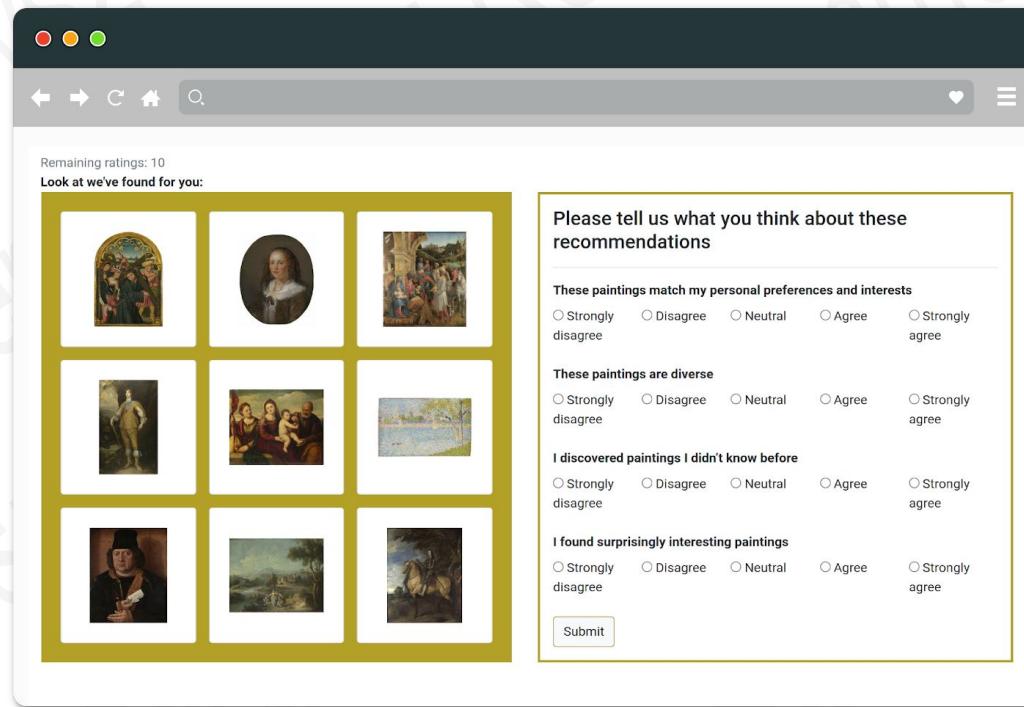
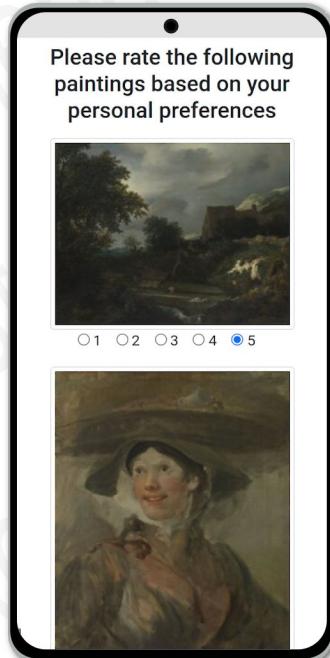
LDA

ResNet

The HC RecSys pipeline: A case-study approach

Evaluation: User Study

User-centric evaluation



A web browser window showing a user study interface. The title bar includes standard browser controls (back, forward, search, etc.). The main content area displays a grid of nine painting thumbnails under the heading "Look at we've found for you:". Below the grid, there is a section titled "Please tell us what you think about these recommendations" containing four sets of statements with radio button options for responses ranging from "Strongly disagree" to "Strongly agree".

Remaining ratings: 10

Look at we've found for you:

Please tell us what you think about these recommendations

These paintings match my personal preferences and interests

Strongly disagree Disagree Neutral Agree Strongly agree

These paintings are diverse

Strongly disagree Disagree Neutral Agree Strongly agree

I discovered paintings I didn't know before

Strongly disagree Disagree Neutral Agree Strongly agree

I found surprisingly interesting paintings

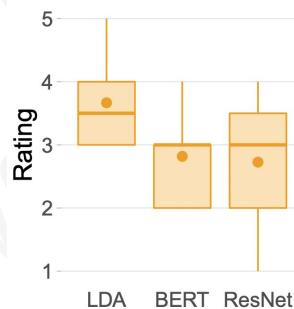
Strongly disagree Disagree Neutral Agree Strongly agree

Submit

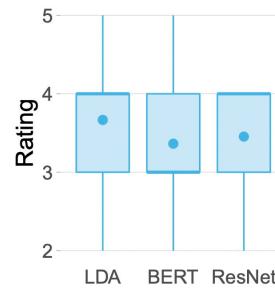
The HC RecSys pipeline: A case-study approach

Evaluation: User Study

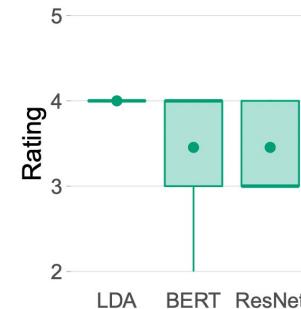
User-centric evaluation



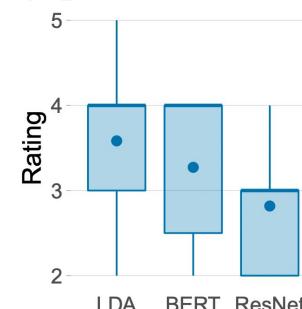
(a) Accuracy



(b) Diversity



(c) Novelty



(d) Serendipity

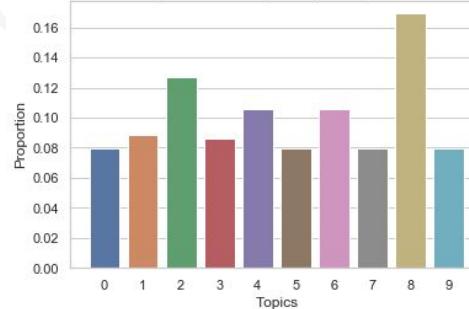
The HC RecSys pipeline: A case-study approach

Explaining Recommendations

Target painting



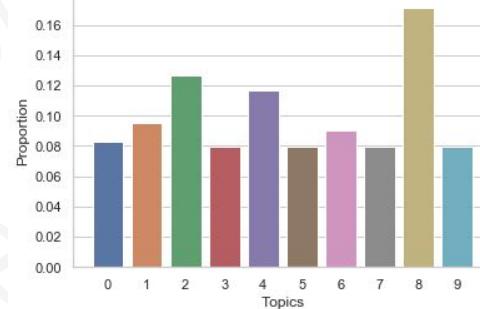
Proportions of the topics for painting n°2330



Most similar painting



Proportions of the topics for painting n°843



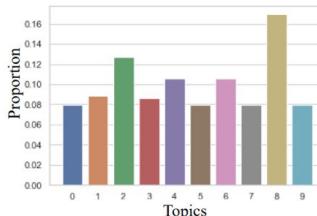
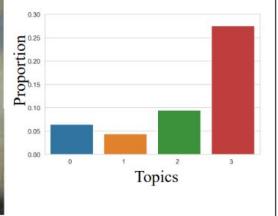
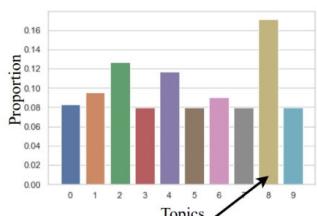
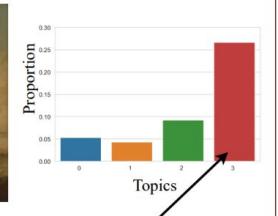
Topic 8
CHRIST
SAINT
JESUS
EVANGELIST
CROSS
CHURCH



Explainable recommendations have a positive impact on user experience.

The HC RecSys pipeline: A case-study approach

Explaining Recommendations

	LDA	BERT	ResNet																																
Target painting	  <table border="1"> <caption>LDA Topic Proportions for Target Painting</caption> <thead> <tr> <th>Topic</th> <th>Proportion</th> </tr> </thead> <tbody> <tr><td>0</td><td>0.08</td></tr> <tr><td>1</td><td>0.09</td></tr> <tr><td>2</td><td>0.13</td></tr> <tr><td>3</td><td>0.08</td></tr> <tr><td>4</td><td>0.10</td></tr> <tr><td>5</td><td>0.07</td></tr> <tr><td>6</td><td>0.10</td></tr> <tr><td>7</td><td>0.07</td></tr> <tr><td>8</td><td>0.16</td></tr> <tr><td>9</td><td>0.08</td></tr> </tbody> </table>	Topic	Proportion	0	0.08	1	0.09	2	0.13	3	0.08	4	0.10	5	0.07	6	0.10	7	0.07	8	0.16	9	0.08	  <table border="1"> <caption>BERT Topic Proportions for Target Painting</caption> <thead> <tr> <th>Topic</th> <th>Proportion</th> </tr> </thead> <tbody> <tr><td>0</td><td>0.04</td></tr> <tr><td>1</td><td>0.03</td></tr> <tr><td>2</td><td>0.08</td></tr> <tr><td>3</td><td>0.26</td></tr> </tbody> </table>	Topic	Proportion	0	0.04	1	0.03	2	0.08	3	0.26	
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(christ, saint, altarpiece, panel,
Jesus, new testament, evangelist,
cross, church crucification)

(landscape, oil, van, anchor,
17th_century, river, view, scene,
17th_century landscape)

The HC RecSys pipeline: A case-study approach

Explaining Recommendations



Beauty

Old Age

Time

Batoni intends to encourage considering the brevity of youth and the inevitable passing of time.

Semantic Gap



Mary Magdalene

precious ointment

Religious

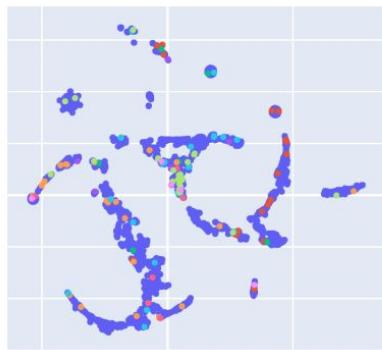
Time orders Old Age to destroy Beauty
by Pompeo Girolamo Batoni
18th century

The Donor and Saint Mary Magdalene
by Marten van Heemskerck.
16th century

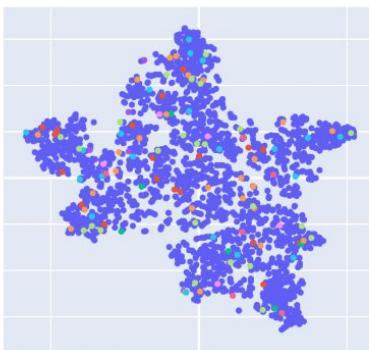
The Elements of Visual Art Recommendation

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

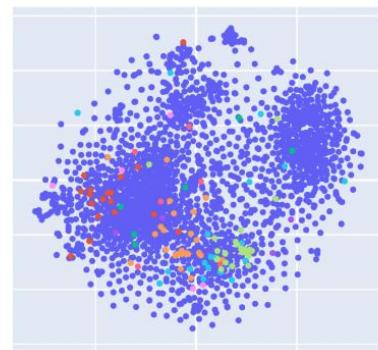
BERT



LDA



ResNet



Story groups

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

- We developed Visual art recommendation engines

BERT

LDA

ResNet

Reciprocal rank fusion

ResNet + BERT

ResNet + LDA

25%	75%	25%	75%
50%	50%	50%	50%
75%	25%	75%	25%

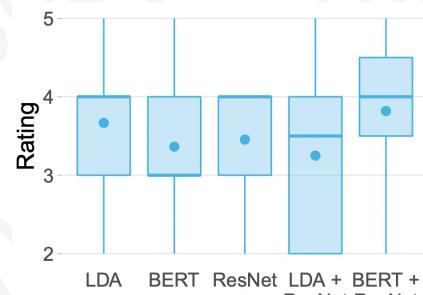
Late Fusion Results



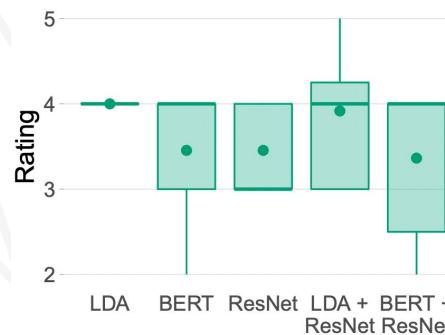
Evaluation: User Study



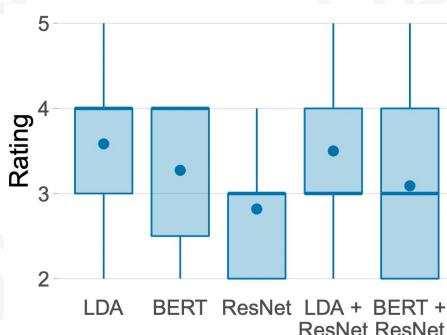
(a) Accuracy



(b) Diversity



(c) Novelty



(d) Serendipity

Yilma et al. (CHI23 The Elements of visual Art recommendation)

Late Fusion Results

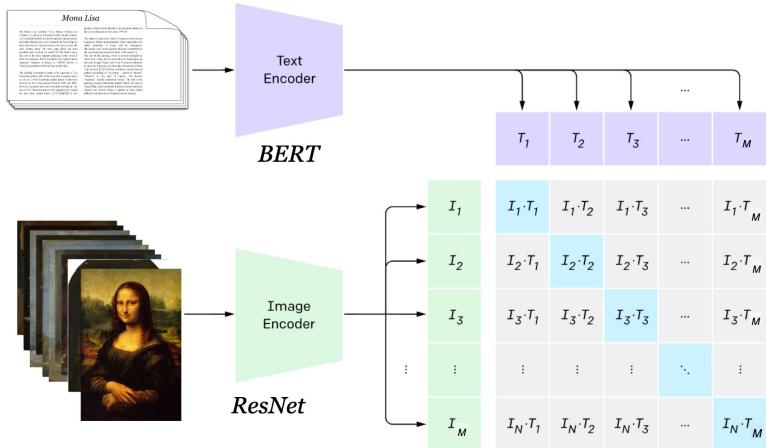


Evaluation: User Study

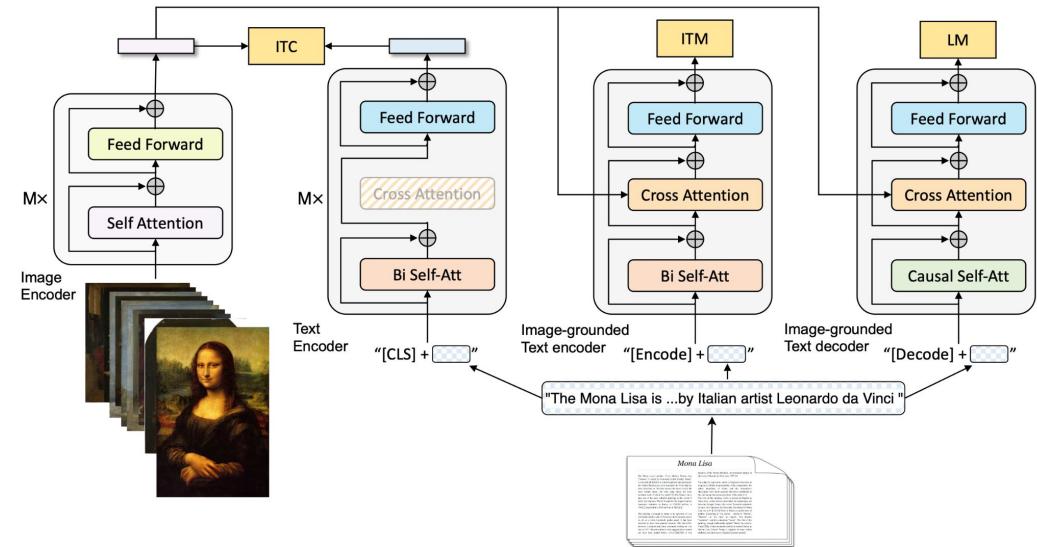
- Latent semantics inherent in visual arts are effectively captured through the fusion of modalities.
- Distinct modalities lead to varying degrees of exposition of latent semantics

Early Fusion

Can we jointly learn latent semantic representations of Paintings



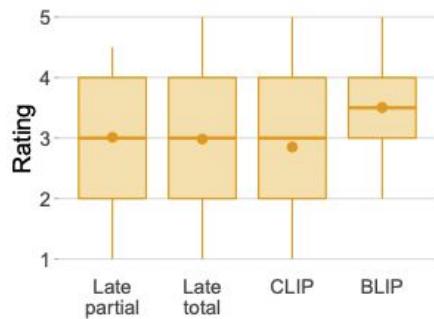
Contrastive Language-Image Pre-training (CLIP)



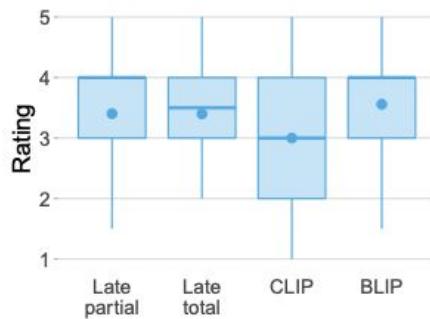
Bootstrapping Language-Image Pre-training (BLIP)

Distribution of user ratings

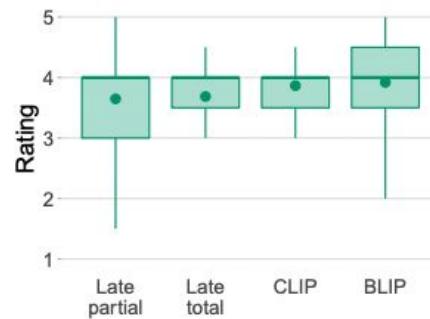
Dots denote mean values.



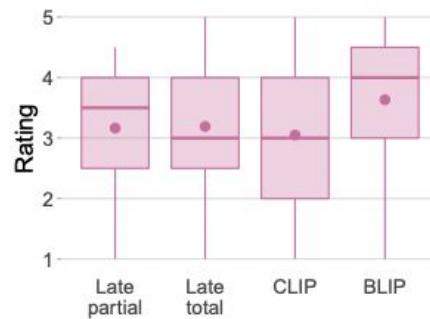
(a) Accuracy ratings



(b) Diversity ratings



(c) Novelty ratings



(d) Serendipity ratings



The HC RecSys pipeline: A case-study approach

Data
Pre-processing



Model
Training

Post
Processing

Evaluation



Next session:

- A Multi-Stakeholder aware RecSys
- How to formulate the RecSys Problem? →(A framework)



- Sort
- Filter
- Recommend





The HC RecSys pipeline: A case-study approach

Data
Pre-processing



Model
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Processing

Evaluation



- Sort
- Filter
- Recommend

