

Recommender Systems Challenge

DataQuest, May 2025



We aim to provide personalised offers across all interfaces to maximise the lifetime value of the relationship with all our customers.

Diverse, relevant and novel offers are part of a bigger customer journey that are personalised through context and executed across multiple interfaces.

Recommender System models are designed to solve this challenge well.

Examples of other companies who do this well are the personalised recommendations from Amazon, Netflix and Spotify.



Problem Statement

The delivery of personalised offers should be prioritised and ranked based on customer needs derived through contextual data points.

To deliver the best possible customer experience, you need to develop a recommender system model, that can recommend the most relevant offers to each customer.



Questions / Challenge

1. Train a recommender system machine learning model of your choice to solve this challenge, using the dataset provided.
2. Show a variety of accuracy and beyond-accuracy measures to motivate why your model is expected to work well.
3. Describe any additional considerations that you would expect if this system is used in a live/production environment.



Apply the above first on the *Kaggle e-Commerce* dataset, and then on the *FNB dataset*.

Dataset 1 – Kaggle

eCommerce



Kaggle E-Commerce Data

<https://www.kaggle.com/datasets/carrie1/ecommerce-data>

About Dataset

Context

Typically e-commerce datasets are proprietary and consequently hard to find among publicly available data. However, [The UCI Machine Learning Repository](#) has made this dataset containing actual transactions from 2010 and 2011. The dataset is maintained on their site, where it can be found by the title "Online Retail".

Content

"This is a transnational data set which contains all the transactions occurring between 01/12/2010 and 09/12/2011 for a UK-based and registered non-store online retail. The company mainly sells unique all-occasion gifts. Many customers of the company are wholesalers."

Acknowledgements

Per the UCI Machine Learning Repository, this data was made available by Dr Daqing Chen, Director: Public Analytics group. chend '@' lsbu.ac.uk, School of Engineering, London South Bank University, London SE1 0AA, UK.

Image from stocksnap.io.




Inspiration

Analyses for this dataset could include time series, clustering, classification and more.



Kaggle E-Commerce Data

<https://www.kaggle.com/datasets/carrie1/ecommerce-data>

▲ InvoiceNo	▲ StockCode	▲ Description	# Quantity	📅 InvoiceDate	# UnitPri
25900 unique values	4070 unique values	4224 unique values	 -80995 81.0k	 2010-12-01 2011-12-09	 -11.1k
536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55
536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39
536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75
536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39
536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39
536365	22752	SET 7 BABUSHKA NESTING BOXES	2	12/1/2010 8:26	7.65



References

E-Commerce Sales Forecast Data Analysis

<https://www.kaggle.com/code/allunia/e-commerce-sales-forecast>

Customer Segmentation Analysis

<https://www.kaggle.com/code/farzadnekouei/customer-segmentation-recommendation-system>



Dataset 2 – FNB

eCommerce



Dataset

idcol	interaction	int_date	item	page	tod	item_type	item_descrip	segment	beh_segment	active_ind
755	DISPLAY	17-Jan-23	NONE	Screen1	Afternoon	ALL		segment3	B01	Semi Active
4521	DISPLAY	27-Feb-23	NONE	Screen1	Afternoon	ALL		segment1	B07	Semi Active
4521	DISPLAY	18-Feb-23	NONE	Screen1	Afternoon	ALL		segment1	B07	Semi Active
4521	DISPLAY	30-Jan-23	NONE	Screen1	Morning	ALL		segment1	B07	Semi Active
4521	CLICK	5-Feb-23	IBAB	Screen1	Afternoon	INSURE	GENERIC MESSAGE	segment1	B07	Semi Active
4521	CHECKOUT	5-Feb-23	IBAB	Screen1	Afternoon	INSURE	GENERIC MESSAGE	segment1	B07	Semi Active
6145	DISPLAY	26-Feb-23	NONE	Screen1	Evening	ALL		segment3	B01	Cold Start
6145	DISPLAY	27-Jan-23	NONE	Screen1	Early	ALL		segment3	B01	Cold Start
6145	DISPLAY	10-Feb-23	NONE	Screen1	Morning	ALL		segment3	B01	Cold Start
6145	DISPLAY	10-Jan-23	NONE	Screen1	Afternoon	ALL		segment3	B01	Cold Start
7125	DISPLAY	18-Feb-23	NONE	Screen1	Morning	ALL		segment3	B01	Cold Start
8469	DISPLAY	5-Feb-23	NONE	Screen1	Morning	ALL		segment1	B01	Semi Active
8469	DISPLAY	14-Jan-23	NONE	Screen1	Afternoon	ALL		segment1	B01	Semi Active
8469	DISPLAY	21-Feb-23	NONE	Screen1	Morning	ALL		segment1	B01	Semi Active
13768	DISPLAY	2-Feb-23	NONE	Screen1	Morning	ALL		segment3	B01	Cold Start
14454	DISPLAY	9-Feb-23	NONE	Screen1	Morning	ALL		segment2	B01	Active
14454	CLICK	8-Feb-23	CAFM	Screen2	Morning	TRANSACT	FUSION MIGRATION	segment2	B01	Active
14454	CHECKOUT	8-Feb-23	CAFM	Screen2	Morning	TRANSACT	FUSION MIGRATION	segment2	B01	Active
15000	CLICK	31-Jan-23	CARF	Screen2	Morning	LEND	REVOLVING FACILITY	segment3	B01	Cold Start
15000	CHECKOUT	31-Jan-23	CARF	Screen2	Morning	LEND	REVOLVING FACILITY	segment3	B01	Cold Start

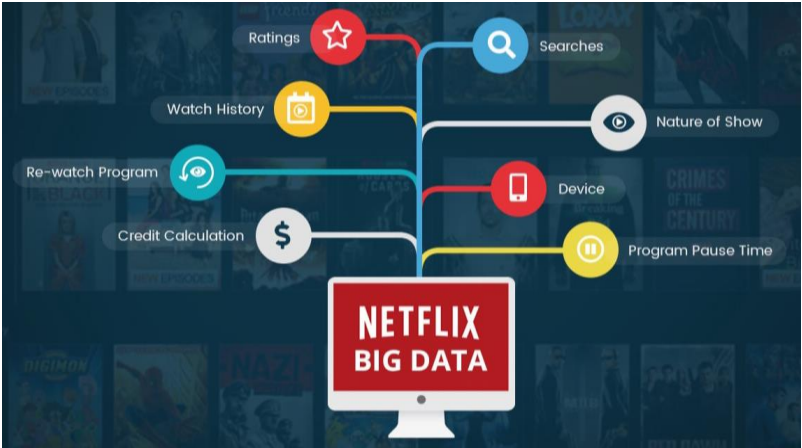
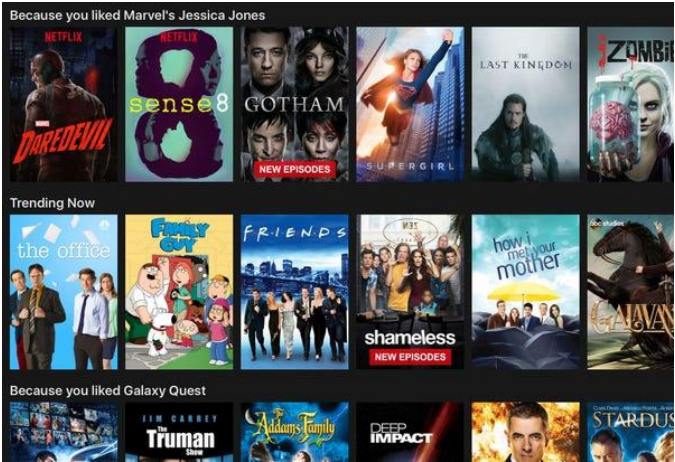
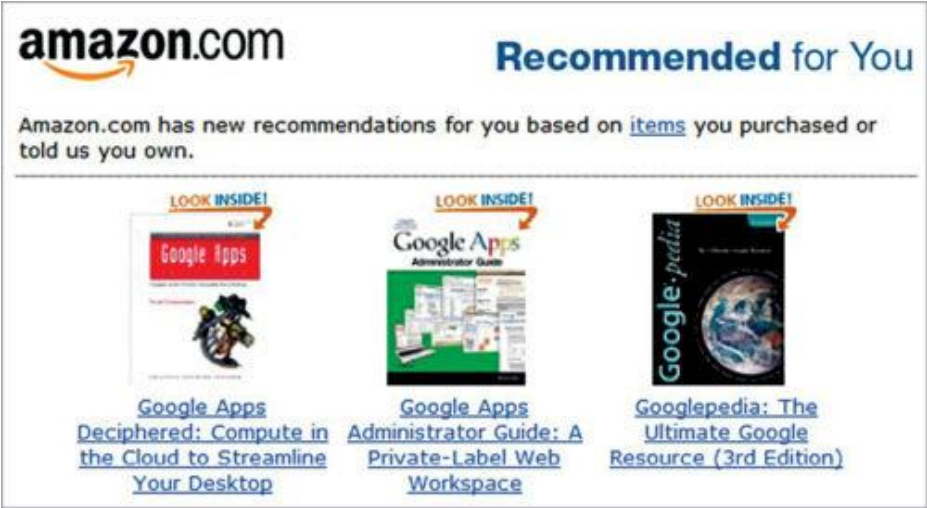


Introduction to Recommender Systems

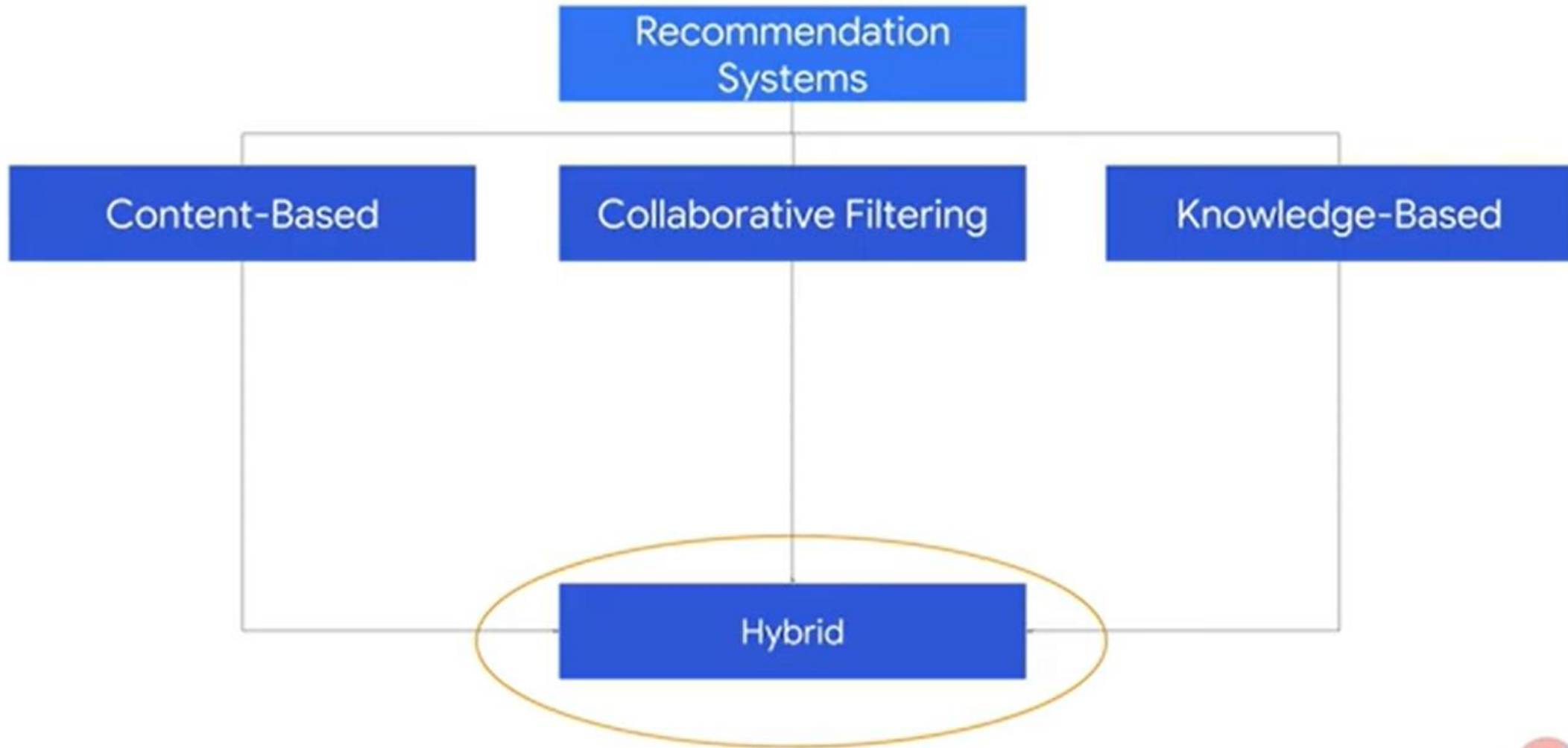
RecSys 101

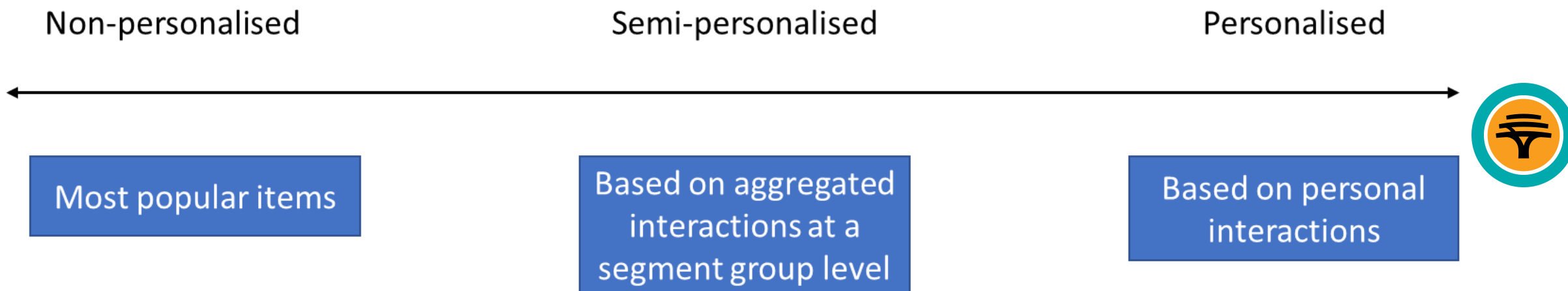


RecSys Introduction

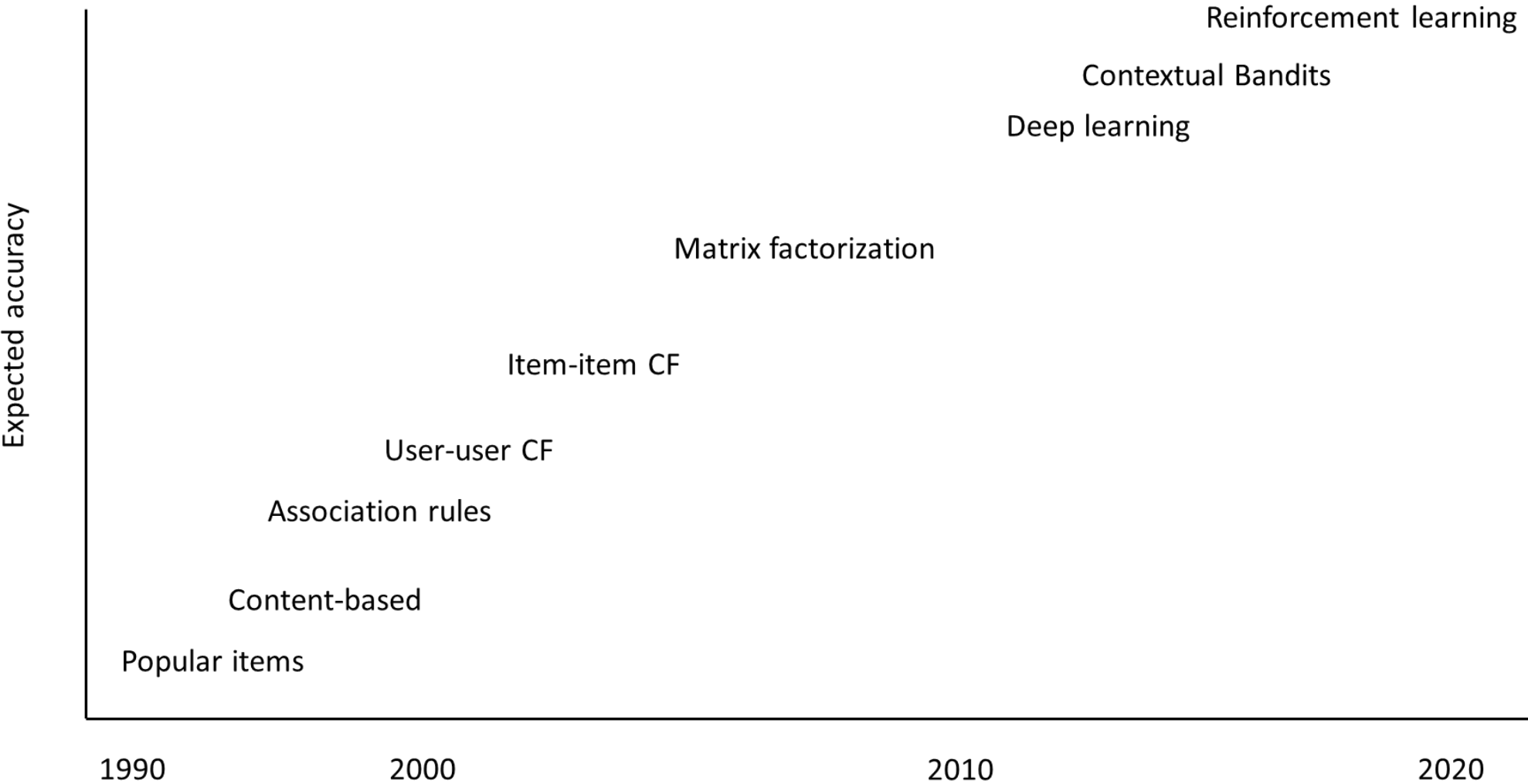


Real-world recommendation systems are a hybrid of three broad theoretical approaches






RecSys Introduction



Content-based filtering uses item features to recommend new items similar to what the user has liked in the past.

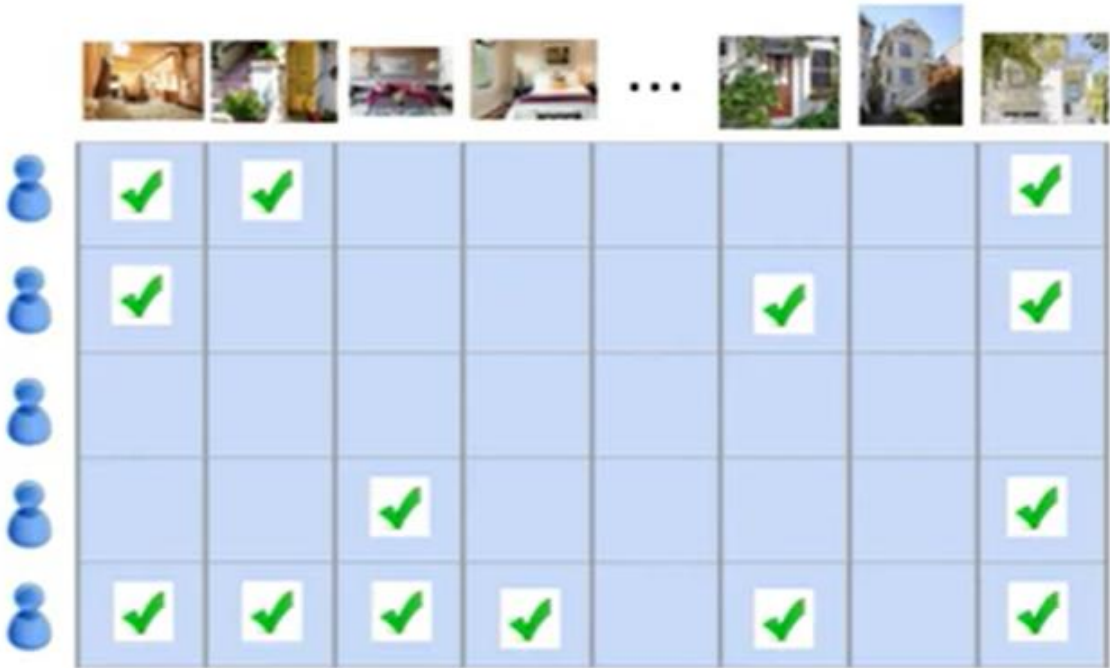
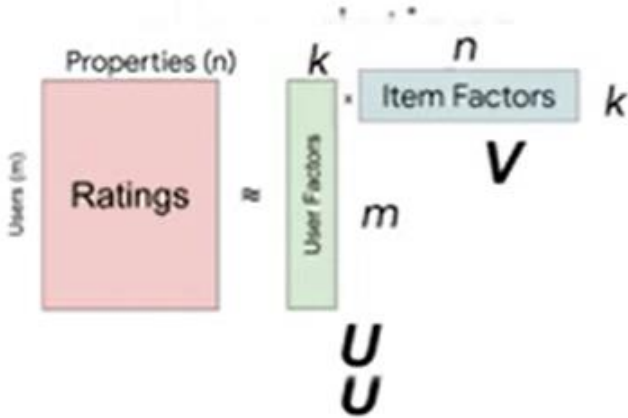


The diagram illustrates content-based filtering using a grid of user-item interactions. At the top, there are eight item images: a living room, a kitchen, a bedroom, a bathroom, an ellipsis, a house exterior, a house exterior, and a house exterior. To the left of the grid are five blue person icons representing users. The grid has 5 rows and 8 columns. Green checkmarks indicate interactions. The second row is highlighted in light blue. The first row has checkmarks in columns 1, 2, and 8. The second row has checkmarks in columns 1, 6, and 8. The third row is empty. The fourth row has checkmarks in columns 3 and 8. The fifth row has checkmarks in columns 1, 2, 3, 4, 6, and 8.

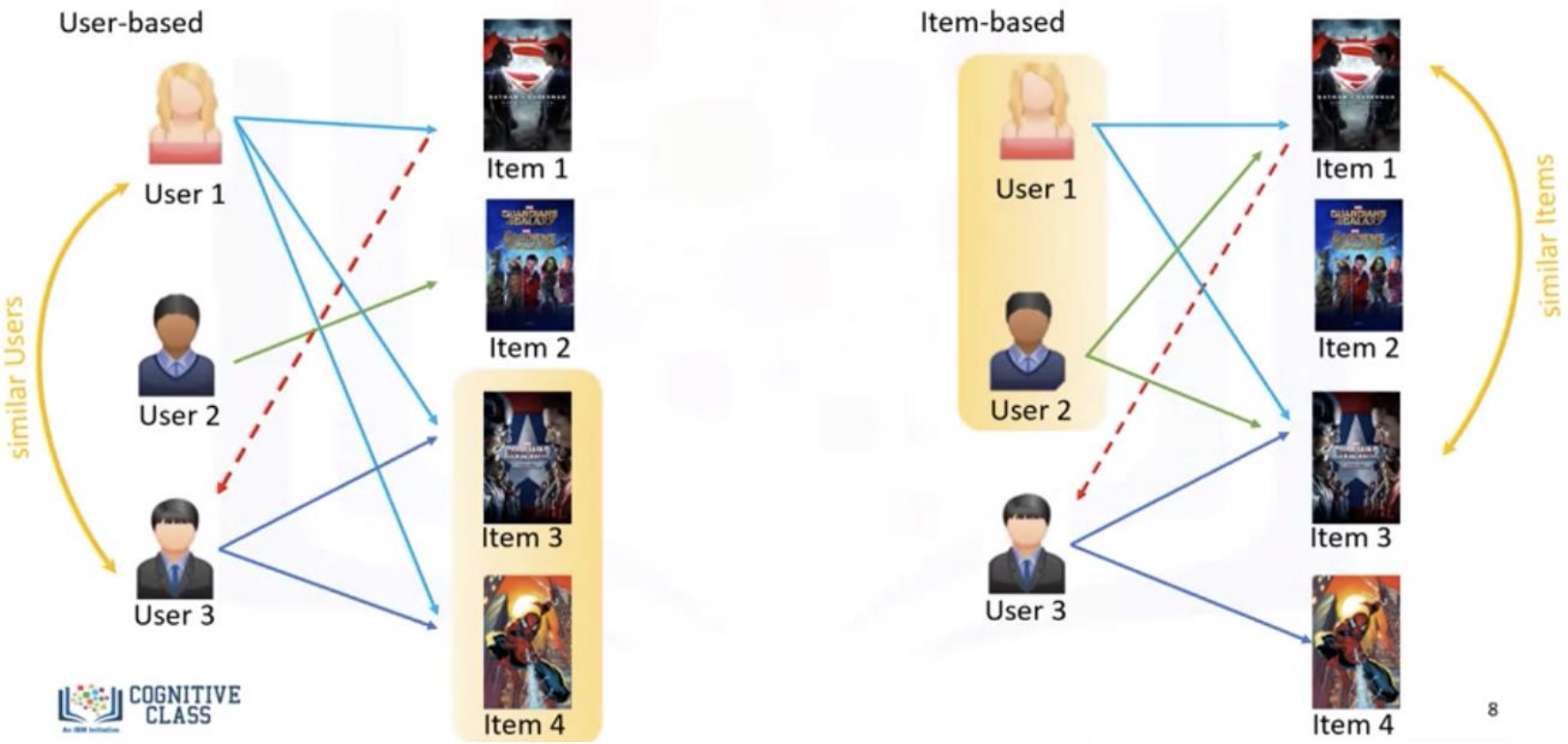
					...			
	✓	✓						✓
	✓					✓		✓
			✓					✓
	✓	✓	✓	✓		✓		✓



Collaborative Filtering uses similarities between users and items simultaneously to determine



Collaborative Filtering



8



References

What are recommendations systems machine learning

<https://www.analyticssteps.com/blogs/what-are-recommendation-systems-machine-learning>

Recommendation systems: Principles, methods and evaluation

<https://www.sciencedirect.com/science/article/pii/S1110866515000341>

<https://developers.google.com/machine-learning/recommendation>

Recommendation Systems on Google Cloud

https://www.cloudskillsboost.google/course_templates/39?catalog_rank=%7B%22rank%22%3A2%2C%22num_filters%22%3A0%2C%22has_search%22%3Atrue%7D&search_id=31637355

Content-Based Recommender

<https://analyticsindiamag.com/how-to-build-a-content-based-movie-recommendation-system-in-python/>



Thank you
Questions?

