

Recommender systems



Recommender systems





Prezi

What are they ?

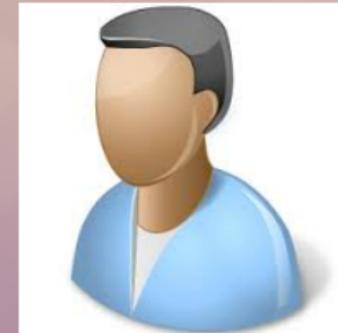
They are software tools and techniques providing suggestions for items to be of use to a user

How are they different from a search engine?

Information Retrieval
Information filtering and discovery

Goals of a Recommender System

Increase the number of items sold



Find some good items

Information overload

Complex search space

Express self

Influence others

Help other users

Just browsing

Sell more diverse items

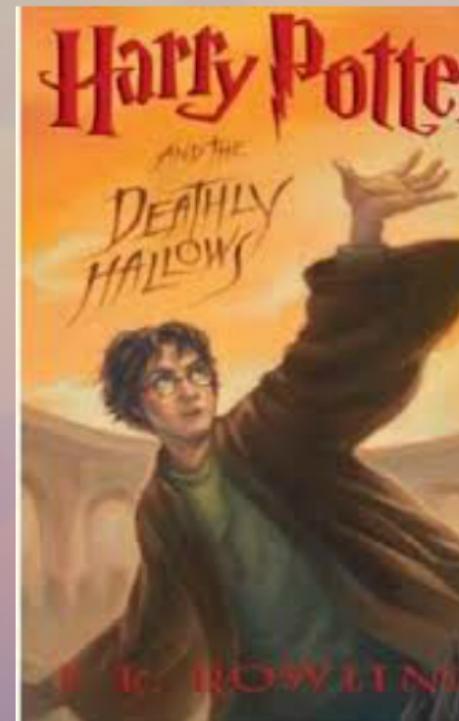
Increase user satisfaction

Increase user trust

Understand what the user wants

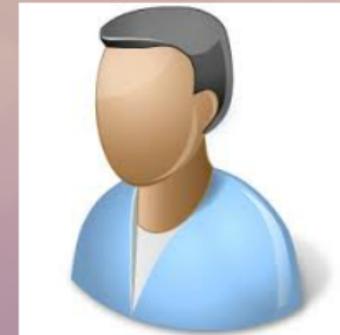


Large, difficult to navigate search spaces



Goals of a Recommender System

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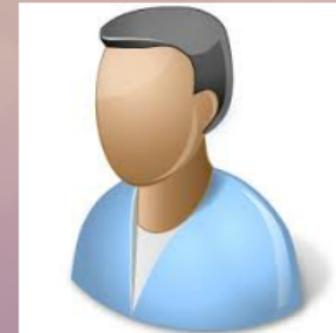
KEY FEATURES

effective mega-pixels in an APS-C sized CMOS sensor
fast continuous shooting at 8.3FPS
selectable Anti-Aliasing Filter
FOX11 Autofocus Module
real Time Scene Analysis with 86,000 pixel sensor
U, Eye-fi Wireless, and SDX Memory card compatibility
professional H.264 video
INTAX body-based Shake Reduction (SR)
Dual SD card slots
Prism Optical Viewfinder for 100% FOV and .95 magnification
Fully weather sealed
Multi-pattern white balance
ISO 51200 ISO
MI port
R Image Capture
Magnesium alloy body w stainless steel chassis



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How did it all begin?



John Riedl - A professor in University of Minnesota

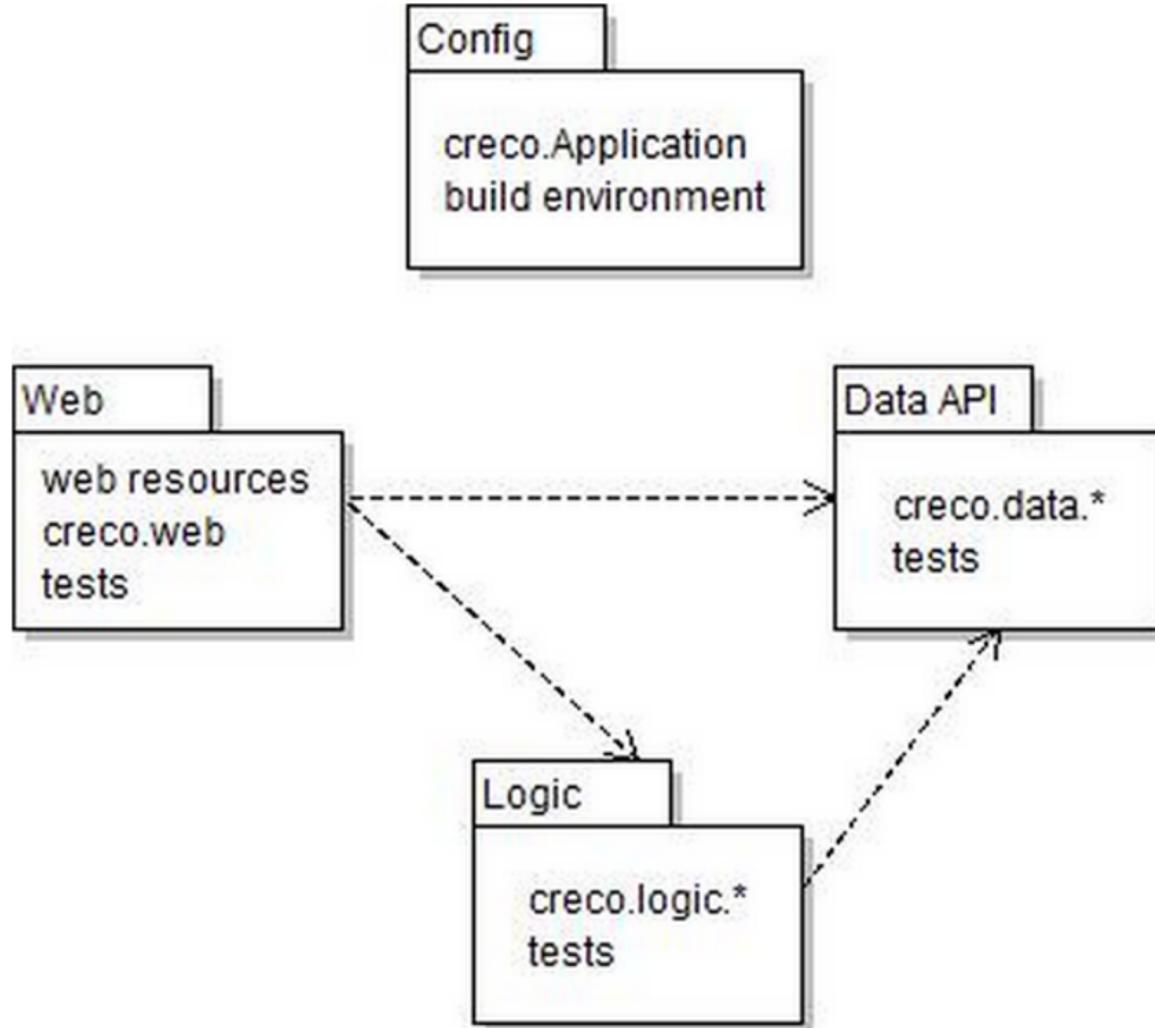
Pioneer in the field of recommender system research

Developed GroupLens

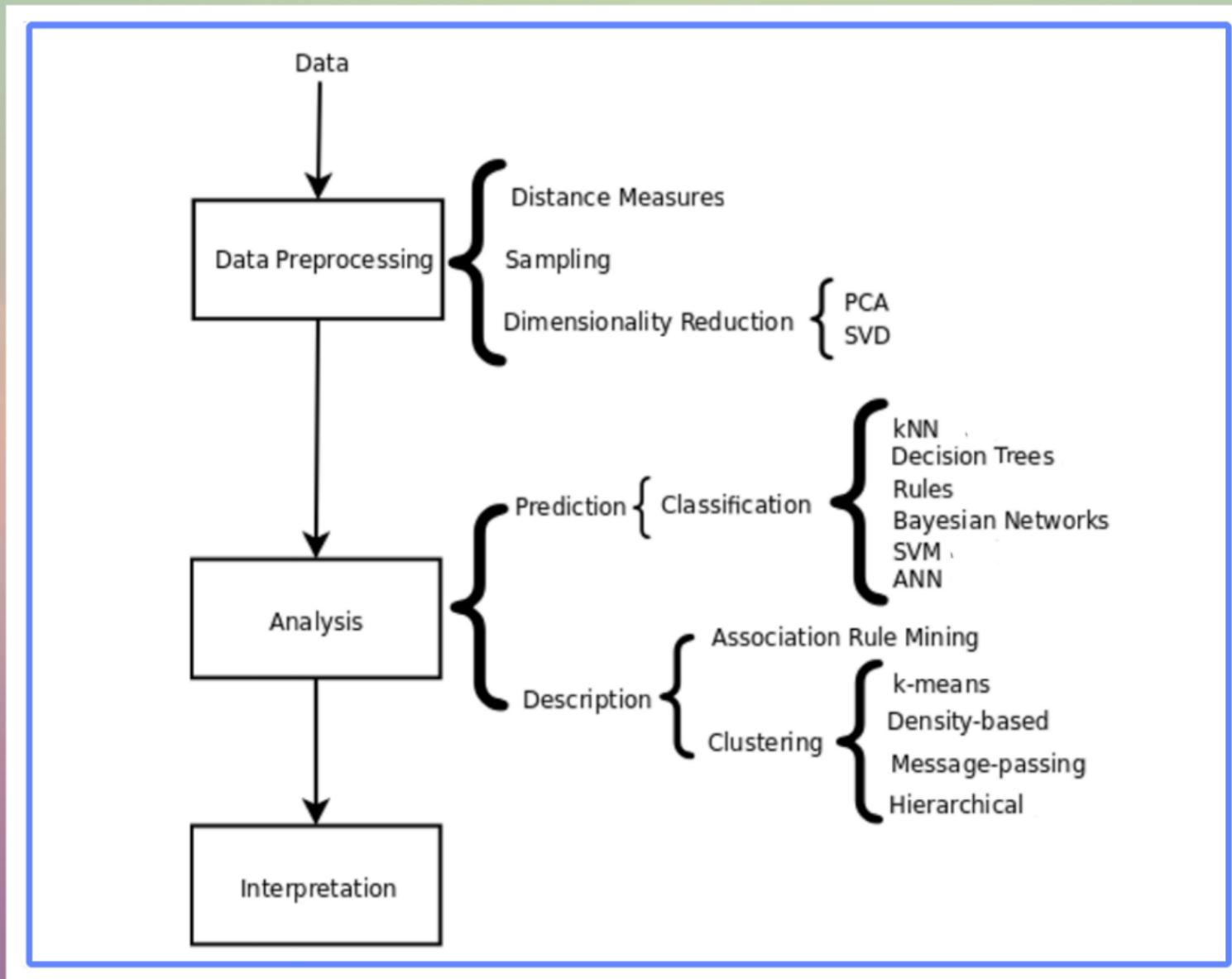
Built key data sets for recommendation research

Key paper cited over 4298 times

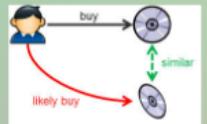
Structure of a Recommender System



Data for a RecSys



Source : Recommender Systems Handbook: Francesco Ricci et al.



Collaborative Filtering



Types of Recommender Systems

Content Based Recommender System
just users and items but context too.....



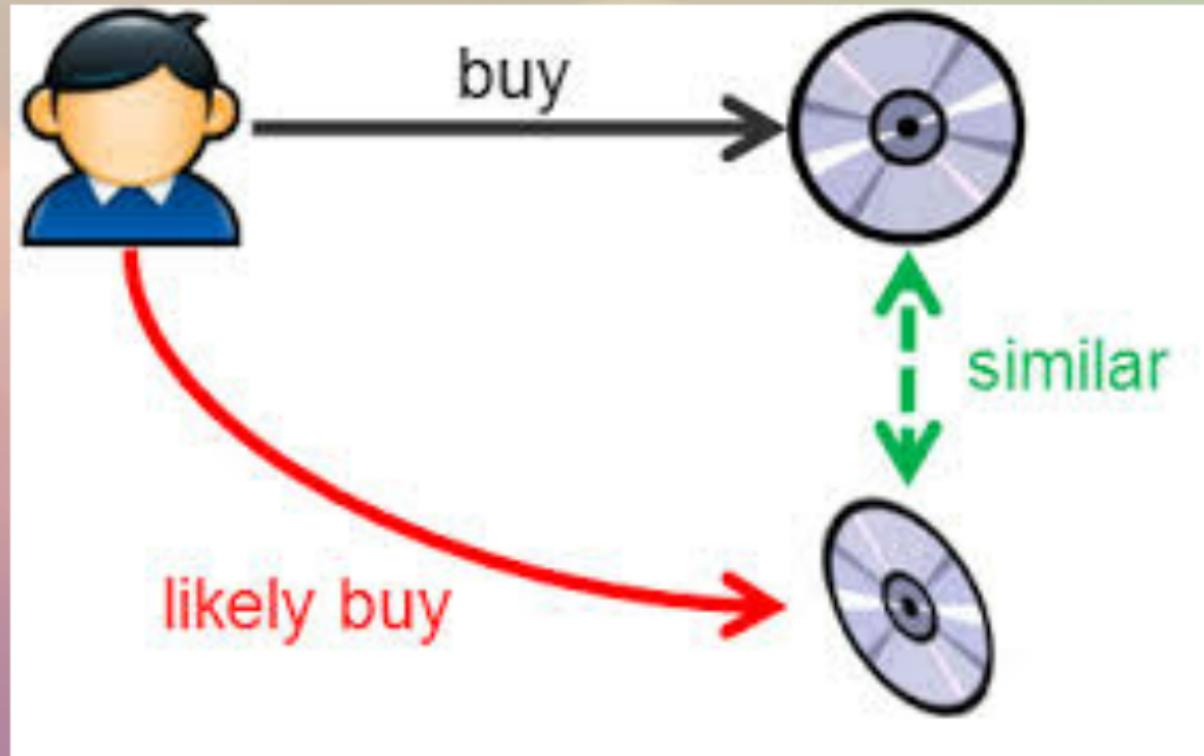
Critiquing Recommender

So far, we have this



Image Source : EBSeR 2013 Recommender Systems tutorial 12
karimzadehsefri_2013_recommender_systems.pdf

Content Based Recommenders



1) Analyze items previously rated by the user
2) Build a user profile based on the items rated by user
3) The recommendation process: Classify items the user would like based upon the attributes of similar users



Items



Features

	Item 1	Item 2	Item 3	Item 4
User 1	✓	✓	✓	✓
User 2	✓	✓	✓	✓
User 3	✓	✓	✓	✓
User 4	✓	✓	✓	✓

Classical problem

- 1) Keyword matching - TF-IDF
- 2) Aromatic feature extractors
- 3) Ontology-based approaches (Content-based matching)

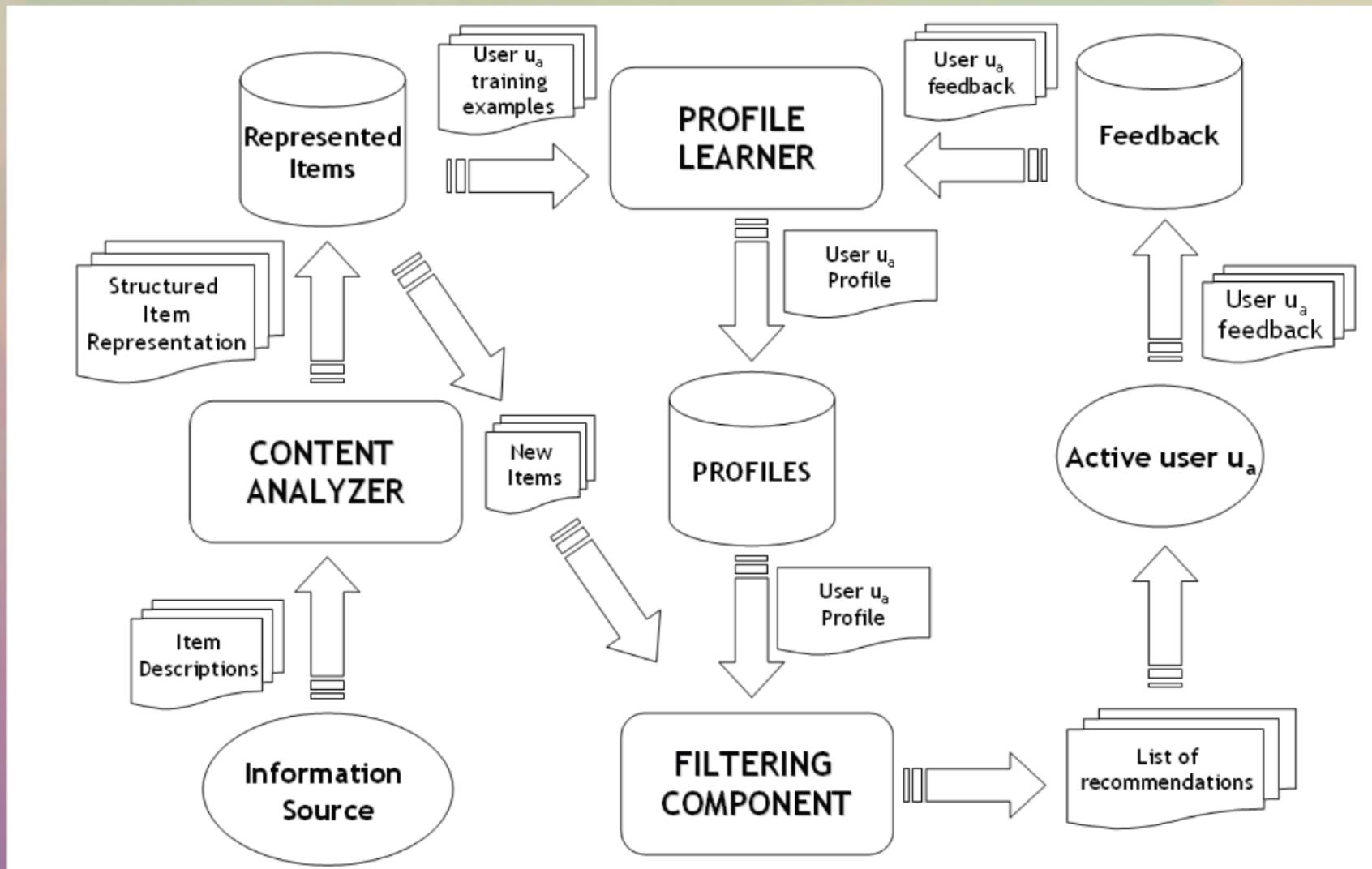
Advantages

- 1) Very robust and effective
- 2) Very efficient

Disadvantages

- 1) Cold start problem
- 2) User needs to provide feedback
- 3) More specialized

- 1) Analyze items previously rated by the user
- 2) Build a user profile based on the items rated by him
- 3) **Recommendation process** - Basically match the attributes of the user profile against the attributes of a content object.



Source : Recommender Systems Handbook: Francesco Ricci et al.

Items



Features



Feature Comparison Matrix Chart Template

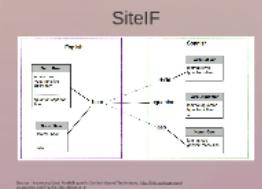
	Product 1	Product 2	Product 3	Product 4
Feature 1	✓	✓	✓	
Feature 2	✓		✓	✓
Feature 3	✓	✓	✓	✓
Feature 4		✓	✓	✓

Classical problem

1) Keyword matching - TF-IDF

2) Automatic feature extraction

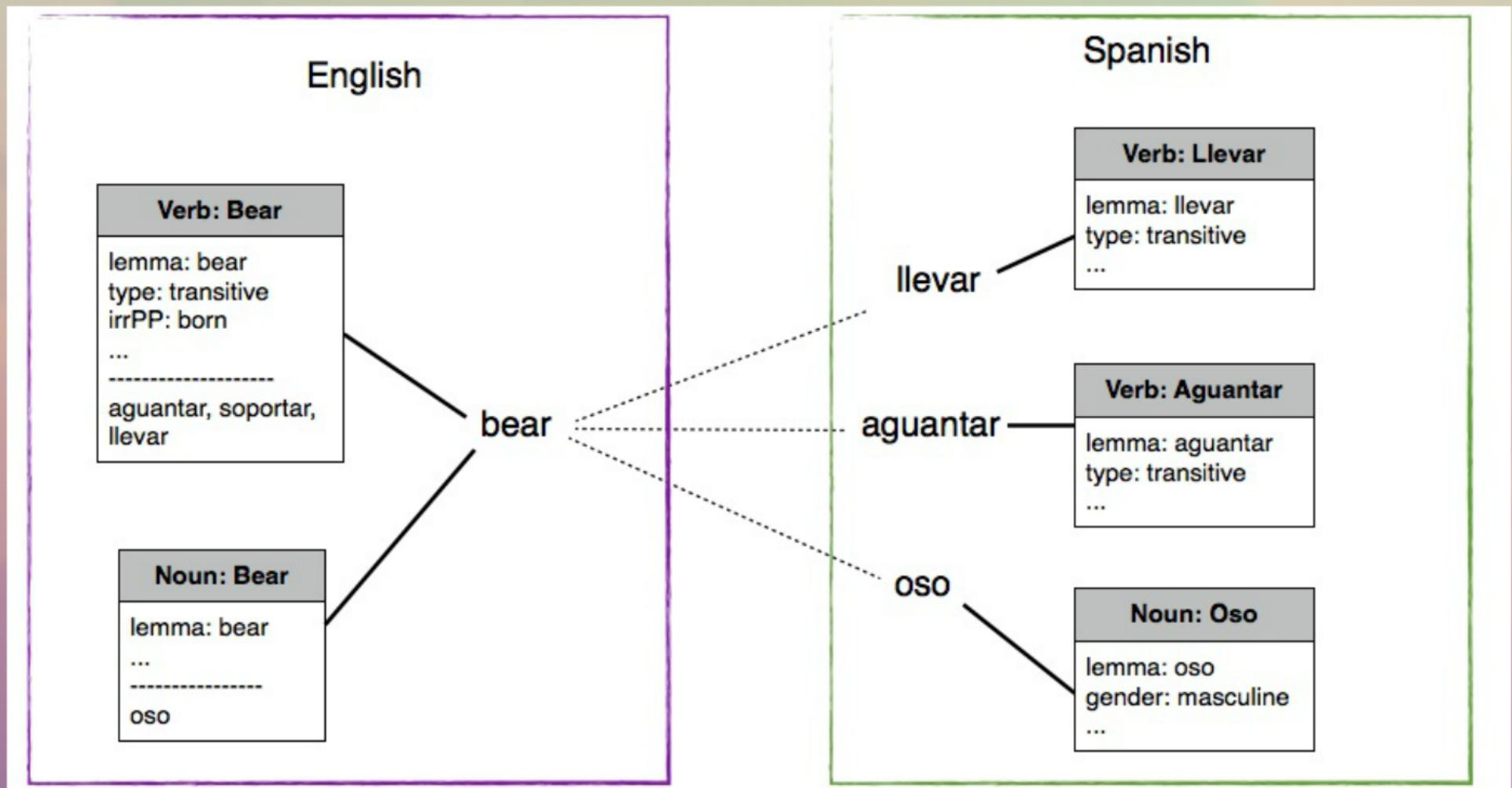
3) Ontology based approaches
(Context based matching)



Semantic web

- Term coined by Tim Berners Lee
- Led by world wide web consortium (W3C)
- Web of data that can be accessed by machines
- Make it accessible to bots, Active learning machines

SitelF



Semantic web

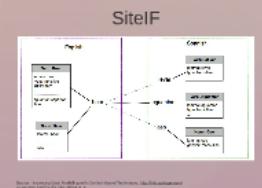
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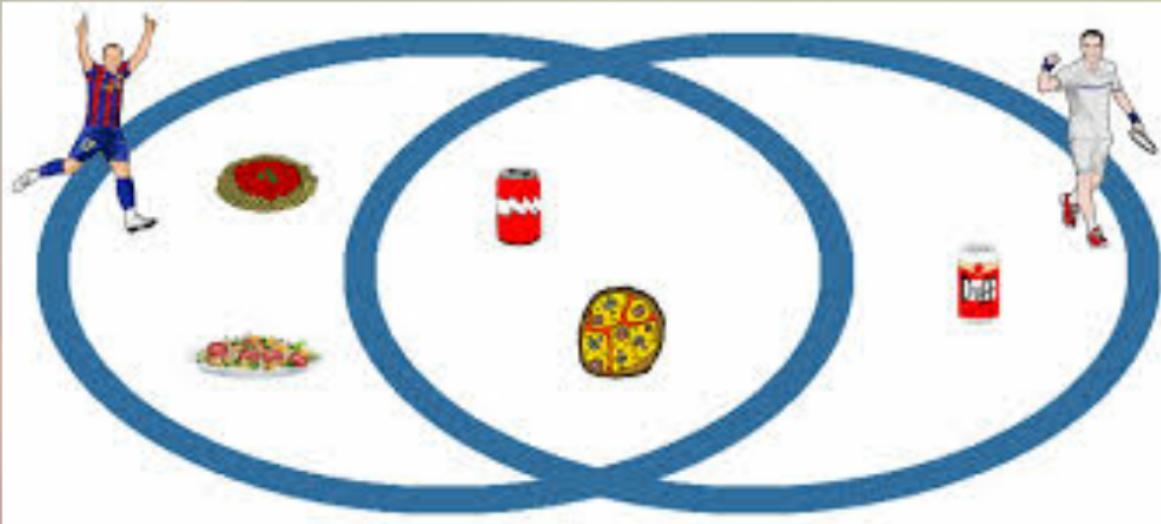
Advantages

- 1) Very personalized
- 2) Transparency

Disadvantages

- 1) Cold start problem
- 2) Limited content discovery
- 3) Over-specialization

Collaborative Filtering



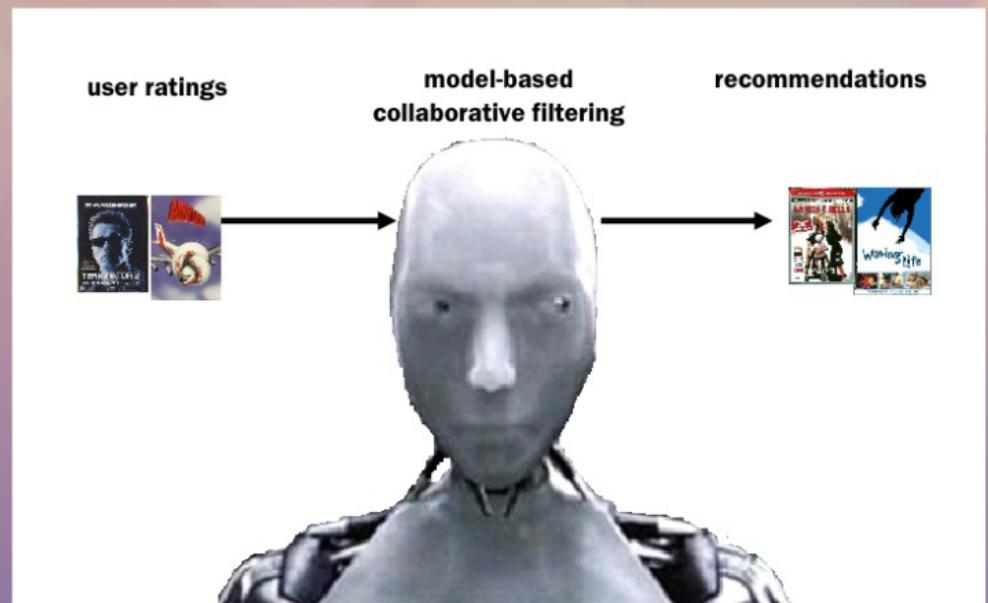
Memory Based



User Based:
- User by items used by target user
- User by the most similar users to target user
- Similarity
- Take those user to average and predict target user's ratings

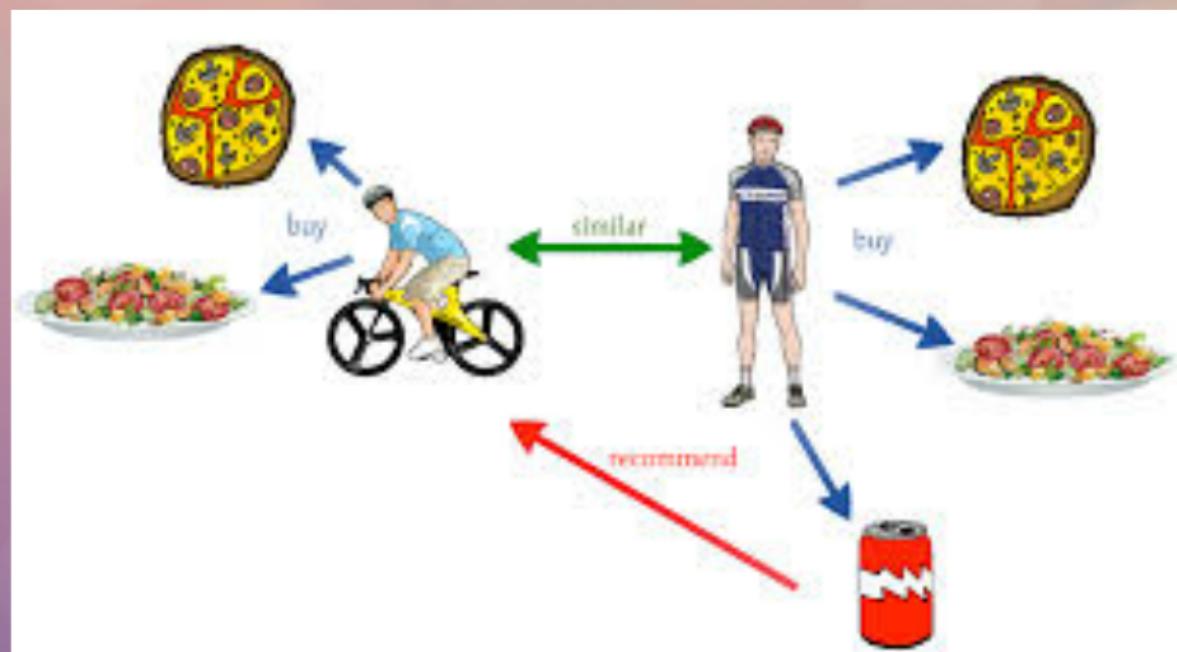
Item Based:
- Similar items used by target user
- Similar items used by the most similar users to target user
- Similarity
- Take those user to average and predict target user's ratings

Memory Based:
- User by items used by target user
- User by the most similar users to target user
- Similarity
- Take those user to average and predict target user's ratings



User Based

- Identify items rated by target user
- Identify the most similar users using Neighborhood methods
- Take those user's ratings and predict target user's ratings



Item Based

- 1) Identify users who have rated target item i
- 2) Identify which other items were rated by those users
- 3) Compute neighbours based on the similarity between these items
- 4) Predict ratings for the target item



Memory Based

ExampleSet (4 examples, 0 special attributes, 10 regular attributes)

Row No.	UserID	HP 1	HP 2	HP 3	TW 1	TW 2	TW 3	SW 4	SW 5	SW 6
1	A	4	5	5	1	?	?	?	?	?
2	B	2	?	?	3	2	?	3	?	?
3	C	3	?	?	5	4	4	?	?	?
4	D	?	?	?	3	2	2	4	5	4

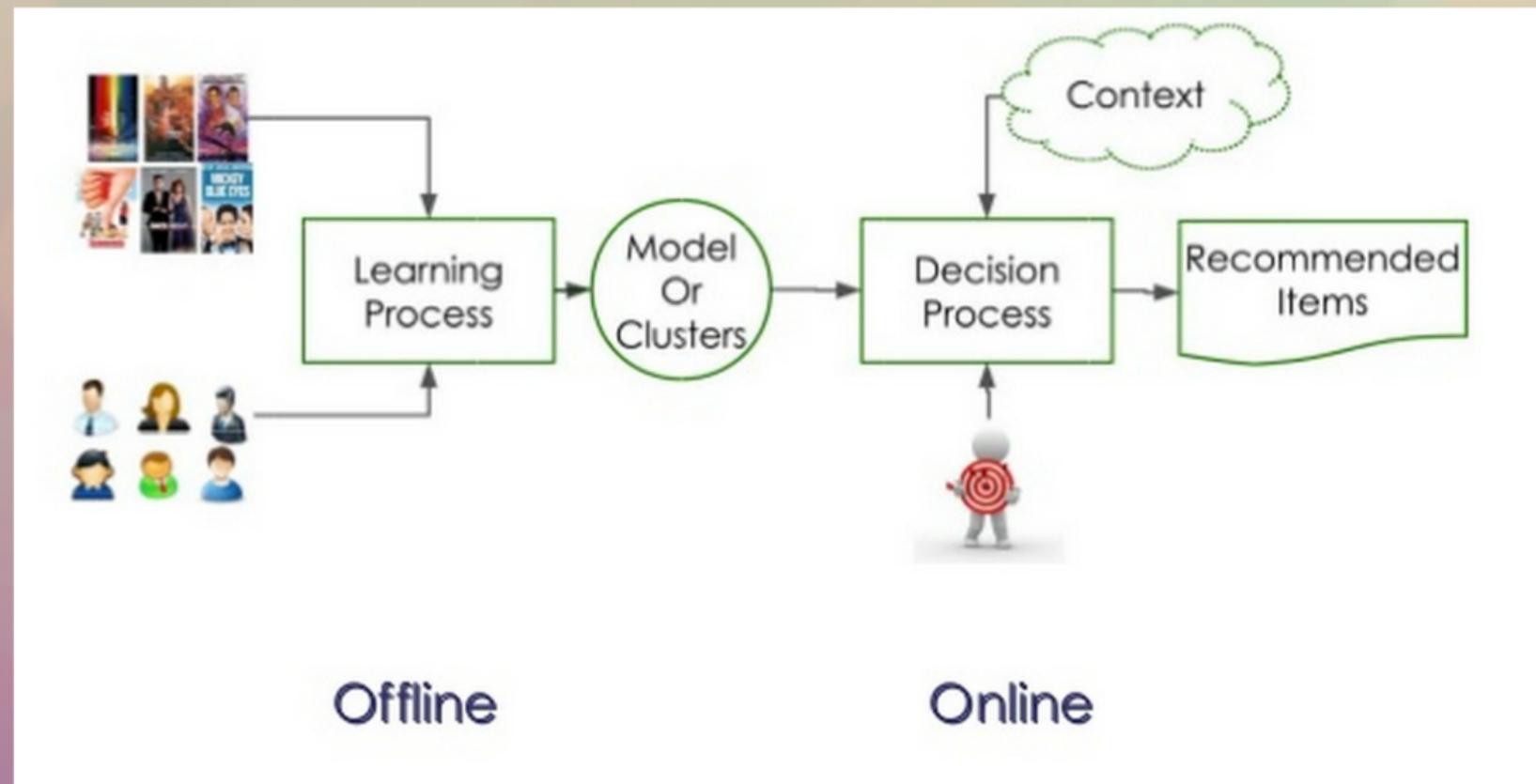
Item similarity: uses column vectors to compute cosine. $HP1=(4,2,3,0)$, $HP2=(5,0,0,0)$.
 $Similarity = HP1 \cdot HP2 / \|HP1\| \|HP2\|$

User similarity: uses row vectors to compute the cosine. $A=(4,5,5,1,0,0,0,0,0)$ $B=(2,0,0,3,2,0,3,0,0)$.
 $Similarity = A \cdot B / \|A\| \|B\|$

Item-Item vs User-User



Model Based Collaborative Filtering



Source : Factor in the Neighbors: Scalable and Accurate Collaborative Filtering, <http://acm.org/citation.cfm?id=1644874&dl=ACM&coll=DL&CFID=457612124&CFTOKEN=15805810>

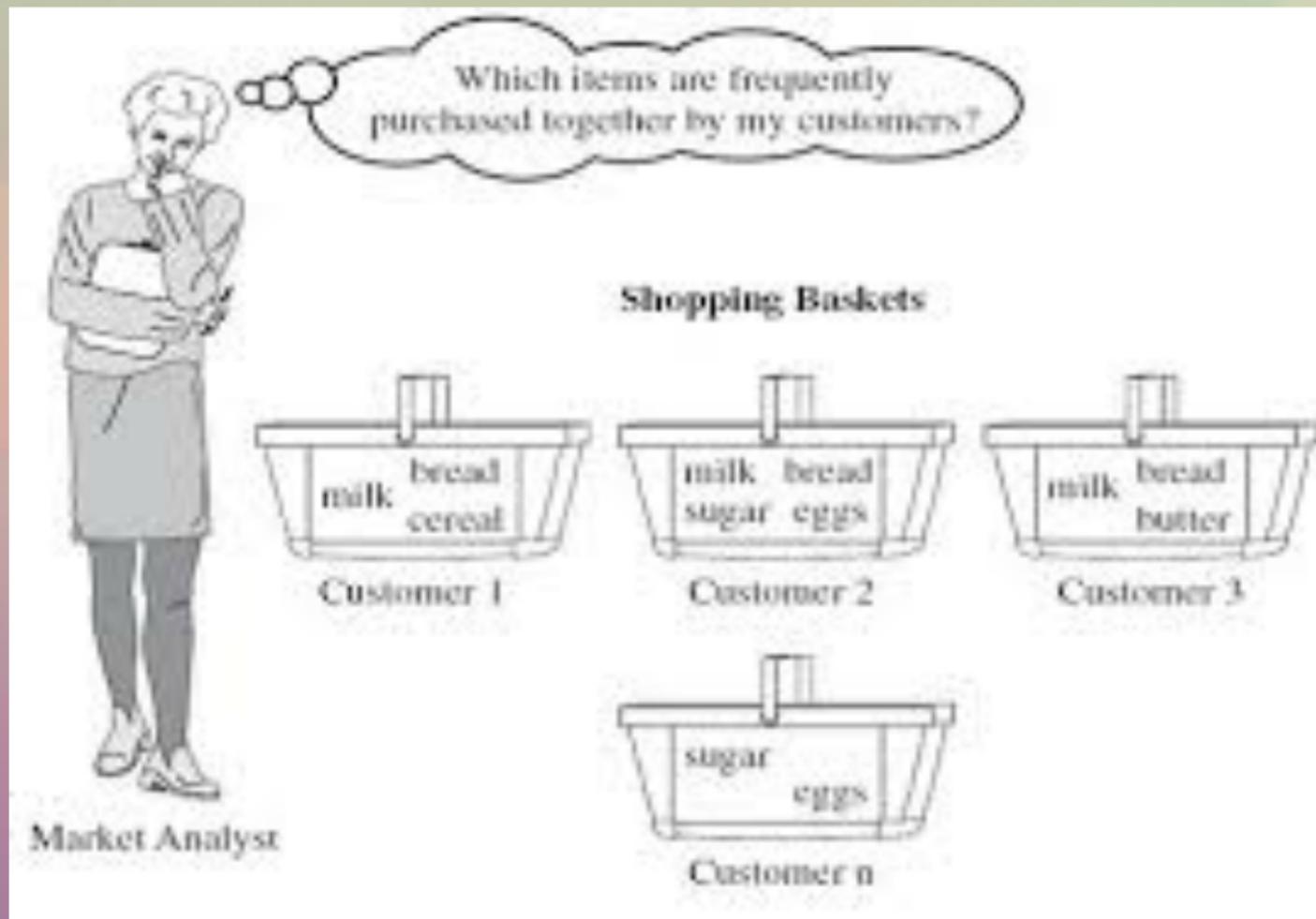
Clustering Models

Cluster users based on their preferences

	BOOK 1	BOOK 2	BOOK 3	BOOK 4	BOOK 5	BOOK 6
CUSTOMER A	X			X		
CUSTOMER B		X	X		X	
CUSTOMER C		X	X			
CUSTOMER D		X				X
CUSTOMER E	X			X		

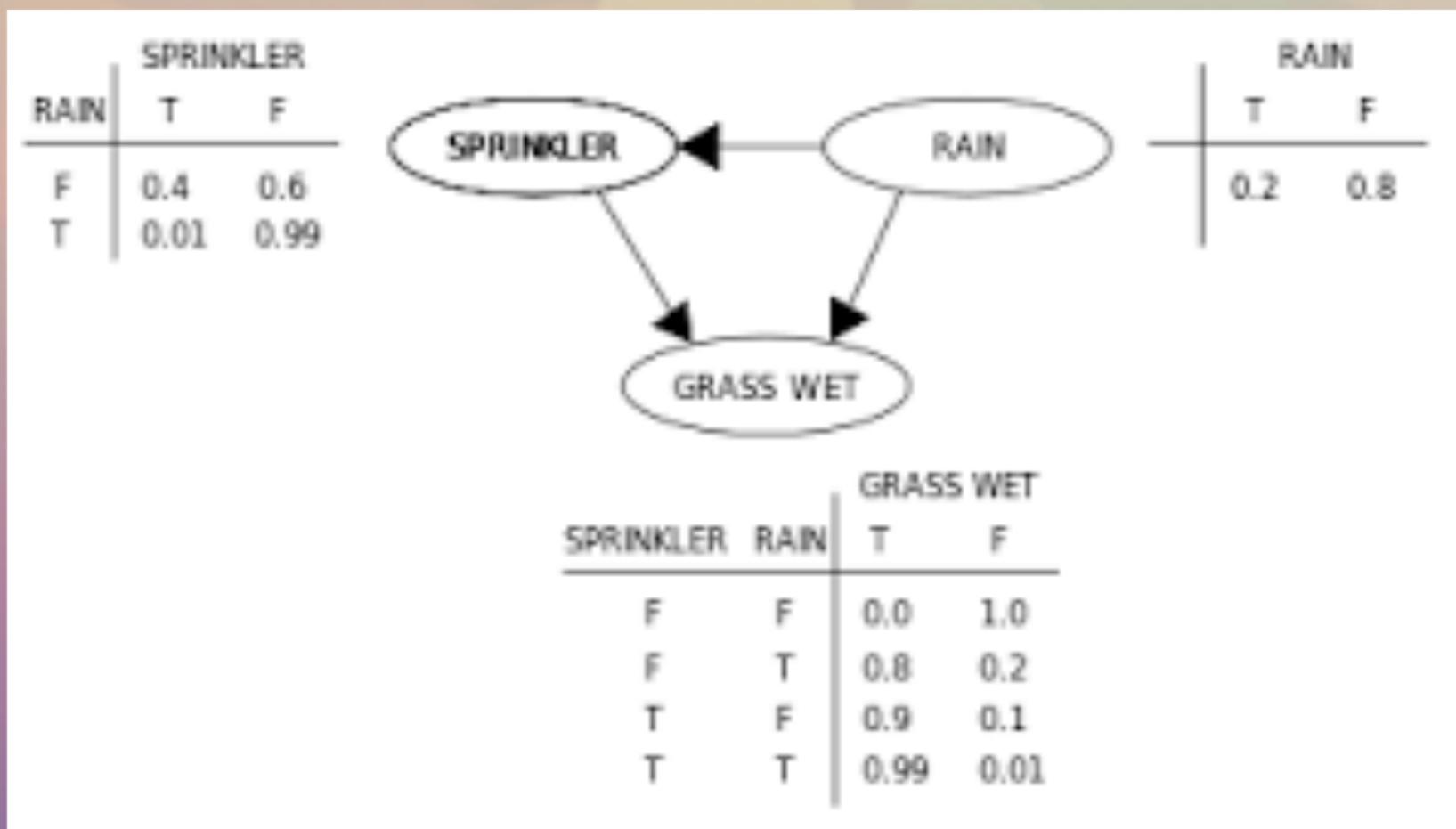
Image Source : ESSIR 2013 Recommender Systems tutorial, <http://www.slideshare.net/serveros99/essir-2013-recsysfinal-25957057>

Association Rule Mining



milk → bread
sugar → eggs

Bayesian Network



Limitations of CF

1) Requires data about users and items.

New users?

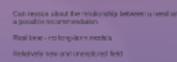
Users do not rate many items

2) Popularity bias

3) Unique taste users ?

Knowledge Based Recommender System

Not just users and items but context too.....



Life stages
of a customer

Intent to
purchase

What is context?

weather

companion

User * Item * Context -> Rating

Movie(MovieID, Title, Length, ReleaseYear, Director, Genre).

User(UserID, Name, Address, Age, Gender, Profession).

Also consider,

Theater(TheaterID, Name, Address, Capacity, City, State, Country).

Time(Date, DayOfWeek, TimeOfWeek, Month, Quarter, Year).

Source : Recommender Systems Handbook: Francesco Ricci et al.

Can reason about the relationship between a need and a possible recommendation

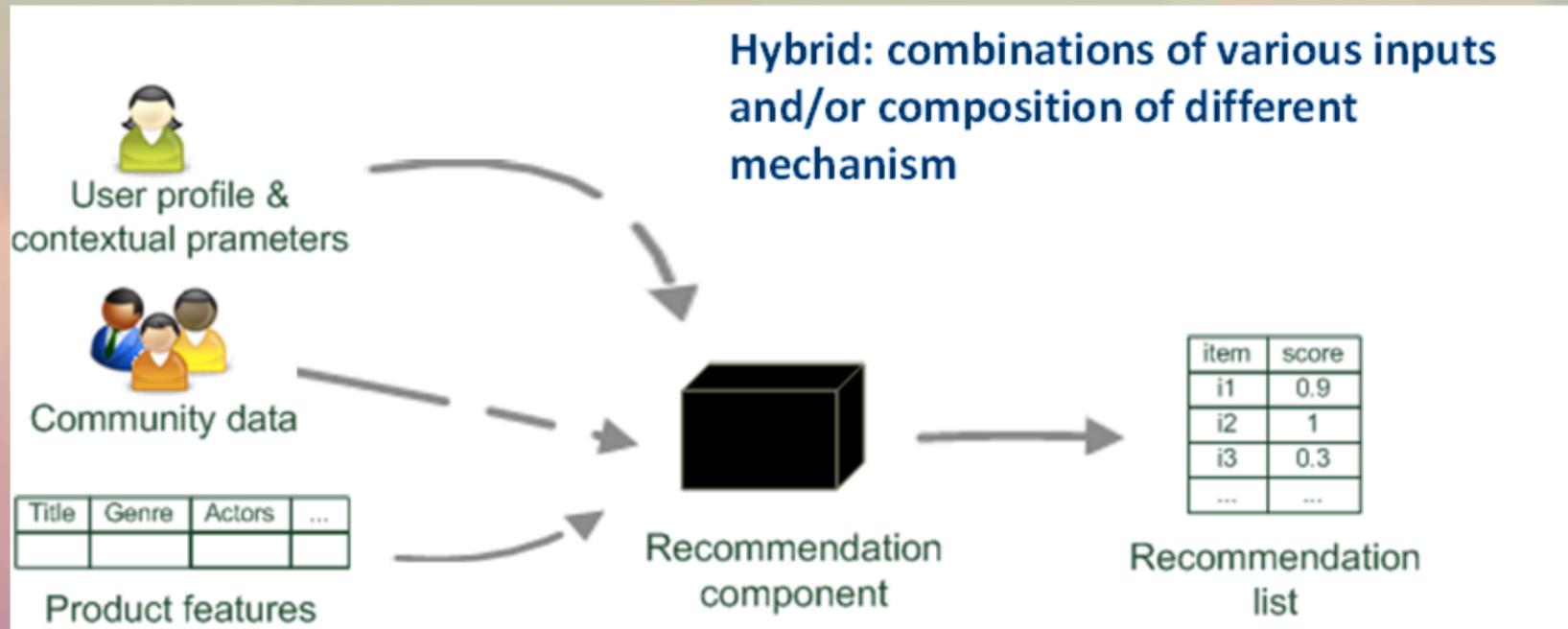
Real time - no long-term models

Relatively new and unexplored field

Pitfalls ?

- More complex to build
- Lots of data to store and process
- How to obtain context? (Social media, Ask user questions)
- How to generate generalized recommendations?(For a general set of users)

Hybrid Recommender System



Combine multiple methods in order to take advantage of different data and different models:
• **Ensemble**: Interactions of several recommendation techniques combined
• **Stacking**: One system takes multiple recommendation methods as input
• **Mixed**: Recommendation from several different mechanisms presented at the same time

Combine multiple methods in order to take advantage of strengths and alleviate drawbacks

- **Weighted**
scores/votes of several recommendation techniques combined together to produce a single recommendation
- **Switching**
system switches between recommendation techniques depending on the current situation
- **Mixed**
recommendations from several different recommenders presented at the same time

Critiquing Recommender System

So far, we have this



Image Source : ESSIR 2013 Recommender Systems tutorial, <http://www.slideshare.net/kerveros99/essir-2013-recsysfinal-25957057>



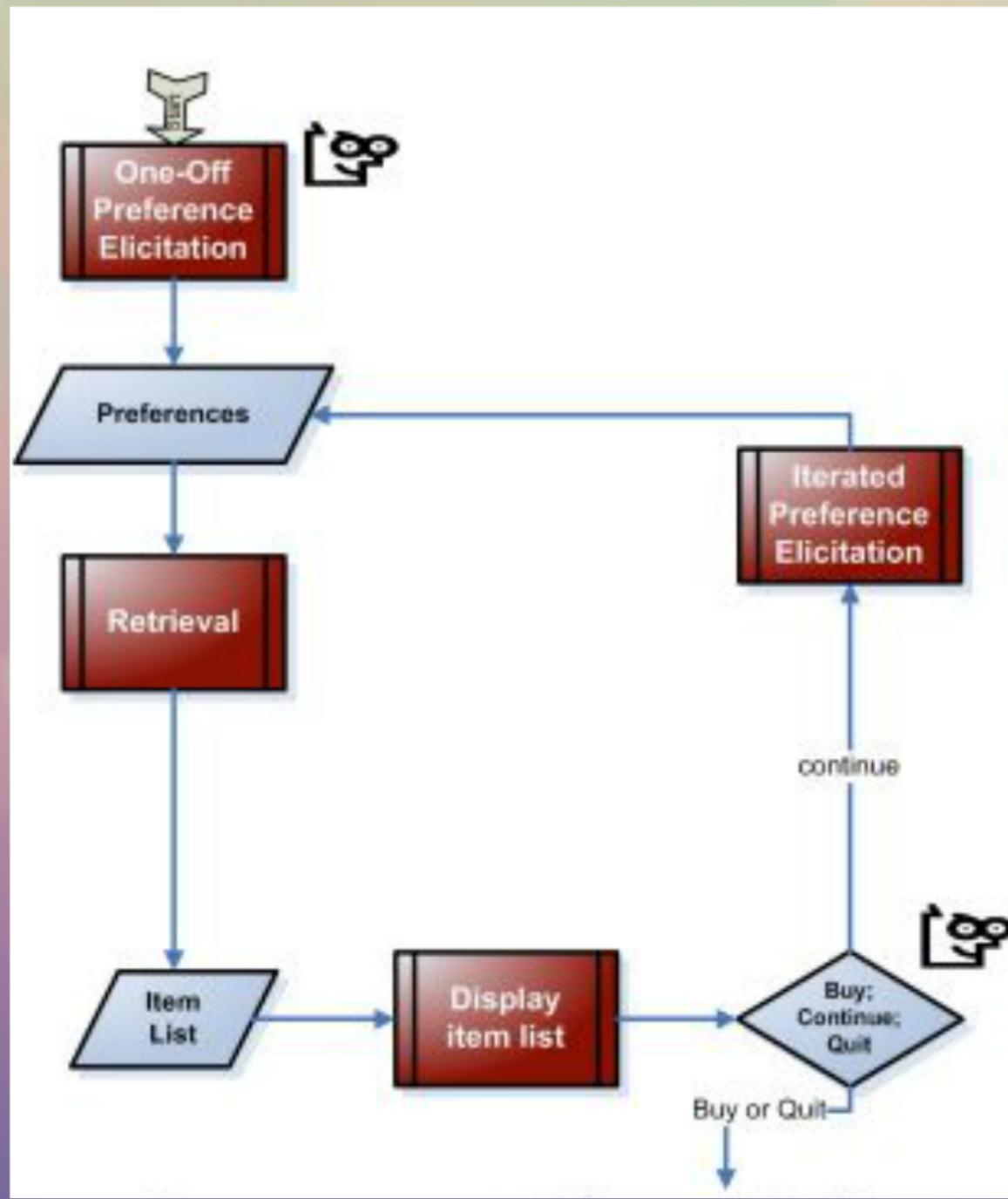
If no product of
interest in
recommended set,
start over with
reformulated
search?



“NARROWING”
PROBLEM

Image Source : ESSIR 2013 Recommender Systems tutorial, <http://www.slideshare.net/kerveros99/essir-2013-recsysfinal-25957057>

Conversational Recommenders



How to elicit user feedback?

Fundamental unit
- critique

Feedback is now a
part of the system

Unit Critiques

Nissan Altima

\$15600

150 Horsepower

0-60 in 9.4 sec.

E11 F004CO 21 City MPG

E11 F004CO 29 Highway MPG

2.4 litres

5 people

39.3 inches

42.6 inches

14.0 cubic feet

\$19000

180 Horsepower

0-60 in 8.8 sec.

20 City MPG

35 Highway MPG

3.7 litres

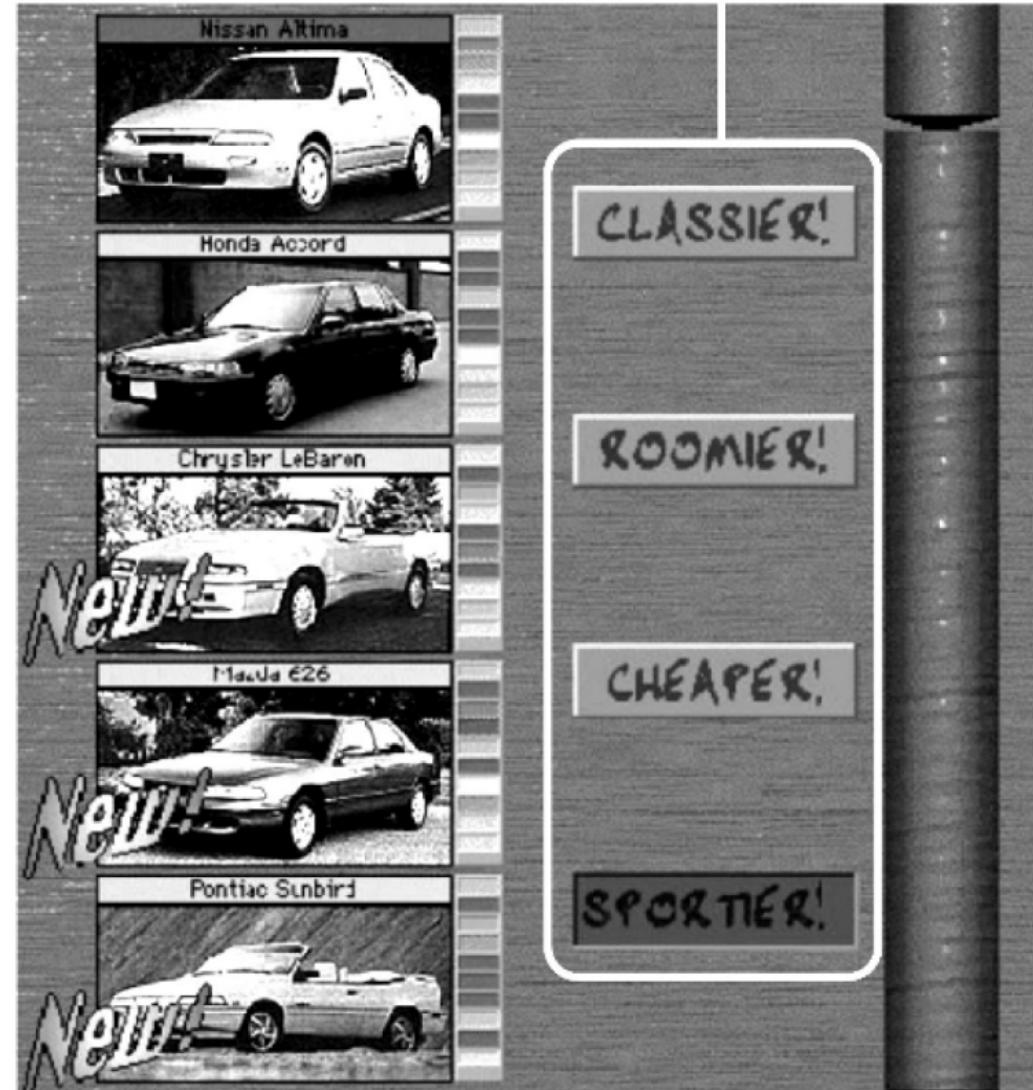
5 people

33.1 inches

45.4 inches

15.4 cubic feet

Compound Critiques



Conversational Recommenders

QWIKSHOP.COM

HOME : ABOUT THIS PROJECT : CONTACT

>> Digital Cameras

Shop for: ► Digital Cameras ► Computers ► Holidays



Product Found: Canon EOS 30

6.3 Megapixel CMOS sensor
7-point wide-area AF
High-performance DIGIC processor
100-1600 ISO speed range
Compatible with all Canon EF lenses and EX Speedlites
PictBridge, Canon Direct Print and Bubble Jet Direct compatible - no PC required

Adjust your preferences to find the right camera for you

Manufacturer	X	Canon	X
Optical Zoom	↓	7x	↑
Memory (MB)	↓	512	↑
Weight (Grams)	↓	780	↑
Resolution	↓	6.2 M Pixels	↑
Size	X	Large	X
Case	X	Magnesium	X
Price	↓	995	↑

Explain:

1. Less Memory and Lower Resolution and Cheaper

This Critique covers 153 other Digital Cameras

Less Memory
Current Value: 512 MB
Critique: Less Than
Remaining: (0 to 256 MB)

Lower Resolution
Current Value: 6.2 M Pixels
Critique: Less Than
Remaining: (1.4 to 5.9 M Pixels)

Cheaper
Current Value: 995 €
Critique: Less Than
Remaining: (75€ to 960€)

We have more matching cameras with the following:

1. Less Memory and Lower Resolution and Cheaper **EXPLAIN** **PICK** PICK
2. Different Manufacturer and Less Zoom and Lighter **EXPLAIN** **PICK**
3. Lighter and Smaller and Different Case **EXPLAIN** **PICK**

Source : Critiquing with



Prezi, http://link.springer.com/chapter/10.1007/11536406_34

Problems?

- Limited product space discovery
- Assumes that the user knows exactly what he wants
- Long winded ?



Evaluation of Recommender Systems

Recommendation System
Properties

Experimental
Settings

Prediction Accuracy

$$\text{accuracy} = \frac{\text{number of successful recommendations}}{\text{number of recommendations}}$$

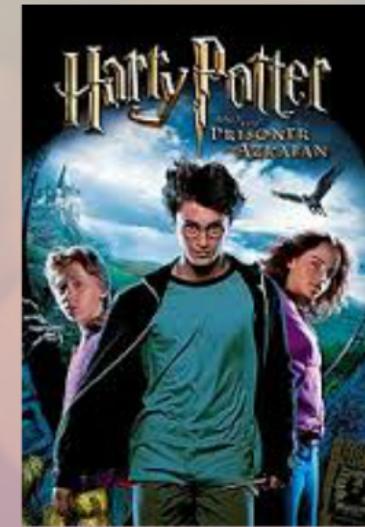
$$\text{accuracy} = \frac{\sum_{(\forall u,i/r(u,i)=1)} 1 - |p(u,i) - P(u,i)|}{R}$$

$p(u,i)$ Preferences of a user

$P(u,i)$ Predictions of a Recommender system

$R = \sum_{u,i} r(u,i)$ Number of recommended items shown to users





Good recommendation?

Serendipity



Solution : Systems that penalize for recommending popular items - since they are less novel.

Must be balanced with similarity !

Trust



Solution

- 1) Trust Network based RecSys
- 2) Social RecSys
- 3) Explanation Based

Why was this item recommended?
Increased user's trust in the system
More personal feel
Both
Not always easy to achieve
Not always necessary

Why was this item recommended?

- Increases user's trust in the system
- More personal feel

Pitfalls

- Not always easy to answer
- Not always necessary

User Interactiveness

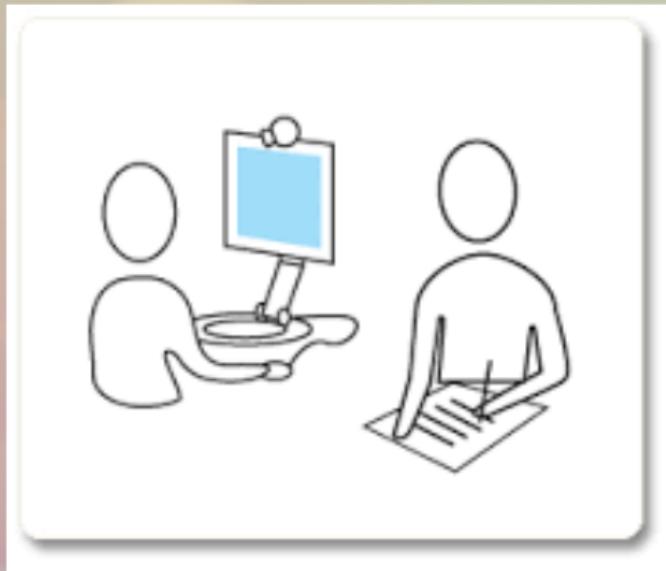
- Most important
 - Know your users (experienced, novice)
 - Is it easy to use
 - Is it visually appealing?
- HCI(Human Computer Interaction)
- Changing needs (Netflix)



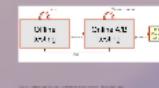
Other factors

- Confidentiality
- Privacy
- Maintainability
- Item space coverage

Under Experimental Settings

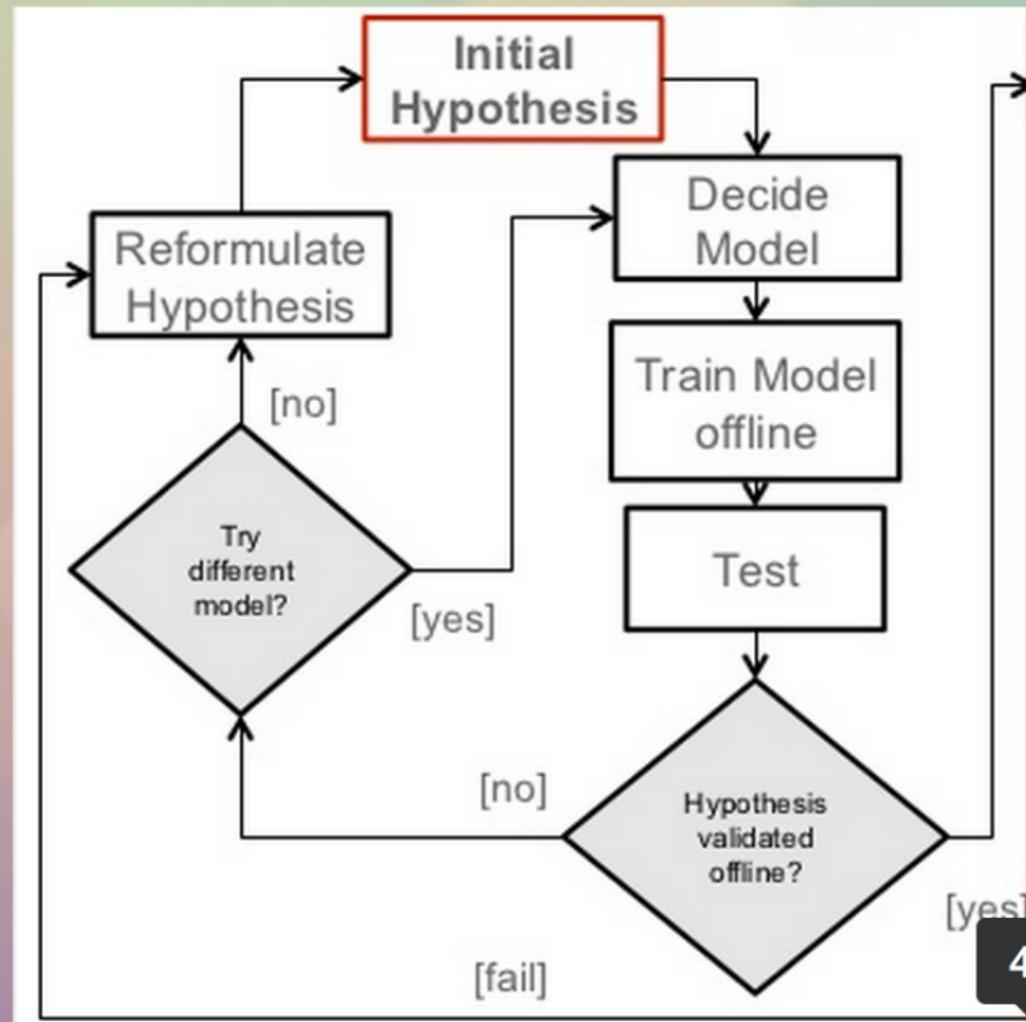


Offline Experiments



Online Testing

- Low cost
- Test a number of different approaches
- Minimal user interaction required
- Takes less time to generate user data (users to read news)
- Tests the core functionality of the application



4

Source : Building Large-scale Real-world Recommender Systems - Recsys2012 tutorial

<http://www.slideshare.net/xamat/building-largescale-realworld-recommender-systems-recsys2012-tutorial>

Offline Testing

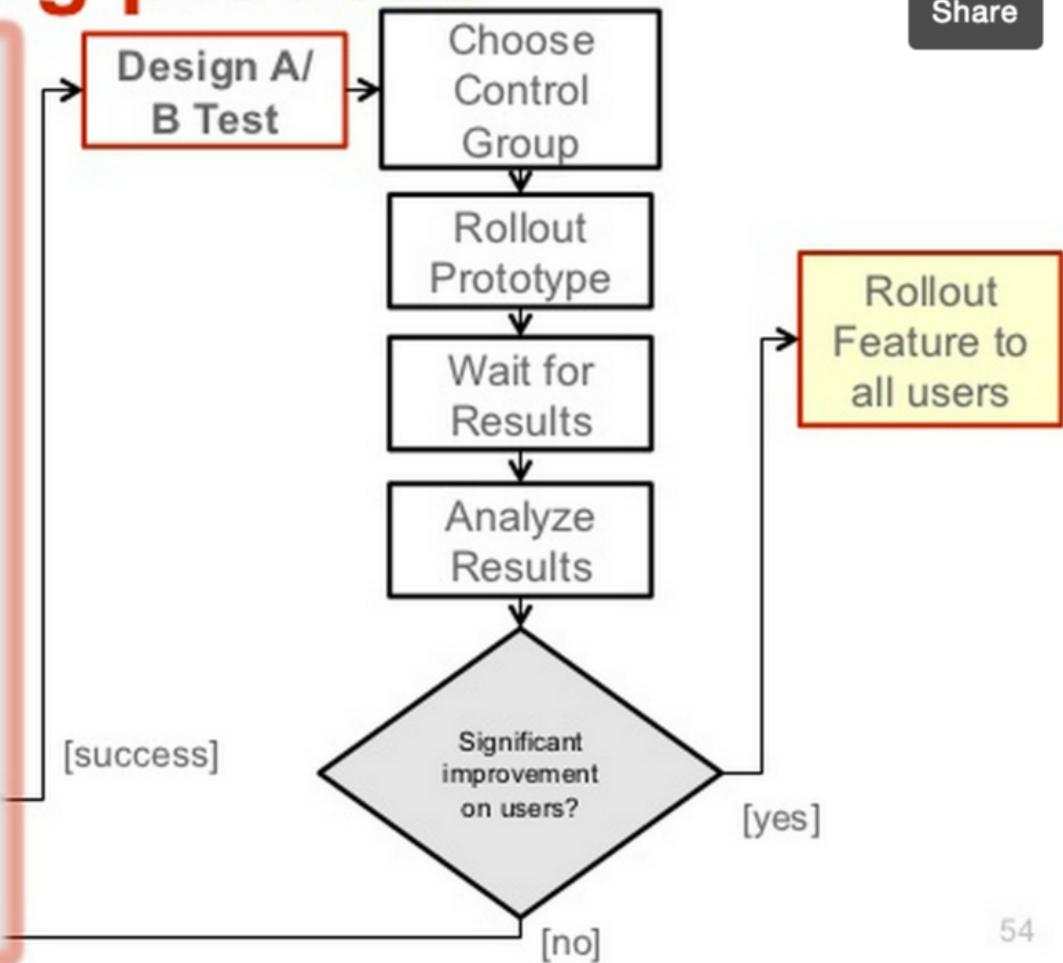
- Low cost.
- Test a number of different approaches
- Simulate user behavior. How?
 - 1)Take previous data (outdated?)
 - 2)Algorithm to generate user data (close to real world?)
- Test the core functionality of the recommender

Online A/B testing process



Share

Offline
testing

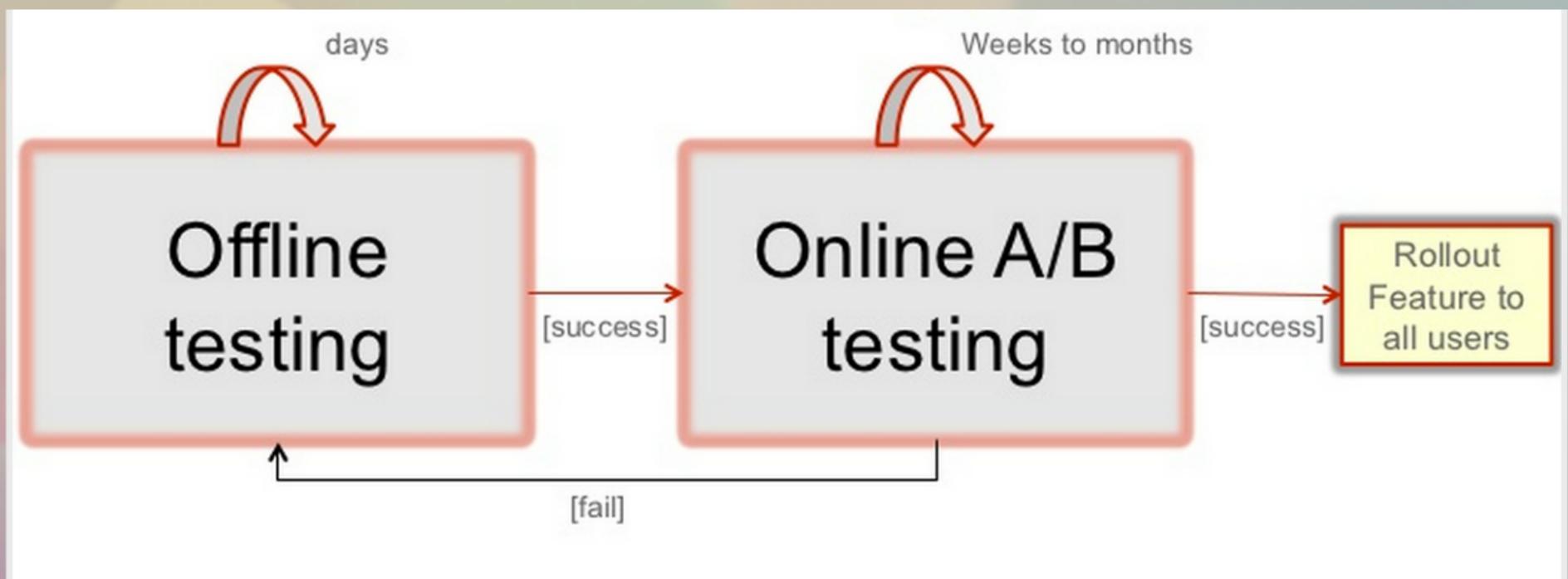


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Prezi



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Questions ?

Recommender systems

