Machine Learning
(IT3190E)

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The course's content:

- Introduction
- Performance evaluation of ML system
- Supervised learning
- **Unsupervised learning**
  - **Clustering problem**
  - **Partition-based clustering: k-Means**
  - **Hierarchical clustering: HAC**
  - **Recommender system and Collaborative filtering**
- Ensemble learning
- Reinforcement learning

Supervised vs. Unsupervised learning

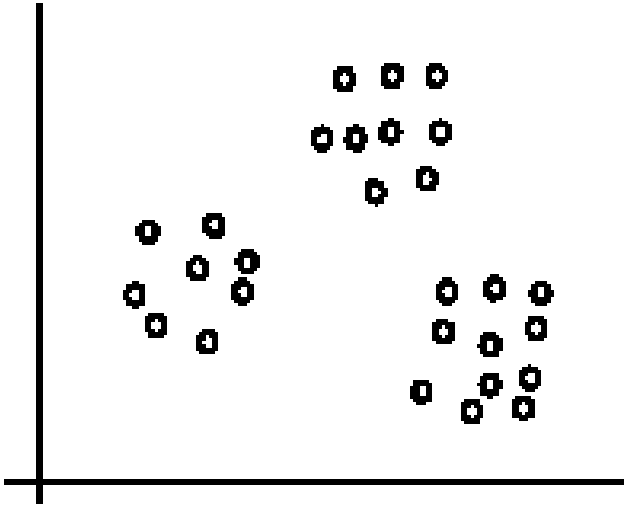
- **Supervised** learning
  - The training set is a set of examples, each associated **with a class/output value**
  - The goal is to learn (approximate) a hypothesis (e.g., a classification function, or a regression function) that fits the given **labelled** dataset
  - The learned hypothesis will then be used to classify/predict future (unseen) examples
- **Unsupervised** learning
  - The training set is a set of instances **with no class/output value**
  - The goal is to find some intrinsic groups/structures/relations

Clustering

- The most popular and important *unsupervised* learning method
  - There exist other unsupervised learning methods, such as *collaborative filtering*, association rules mining, etc.
- *Clustering*
  - Take as input an *unlabeled* dataset (i.e., a set of instances with no class/output value)
  - Group the instances in clusters
- A cluster is a set of instances that are
  - similar together (i.e., by some measure/meaning), and
  - dissimilar to the instances in other clusters

Clustering – Example

A clustering example, where the instances are grouped into three clusters



[Liu, 2006]

Clustering methods – Main components

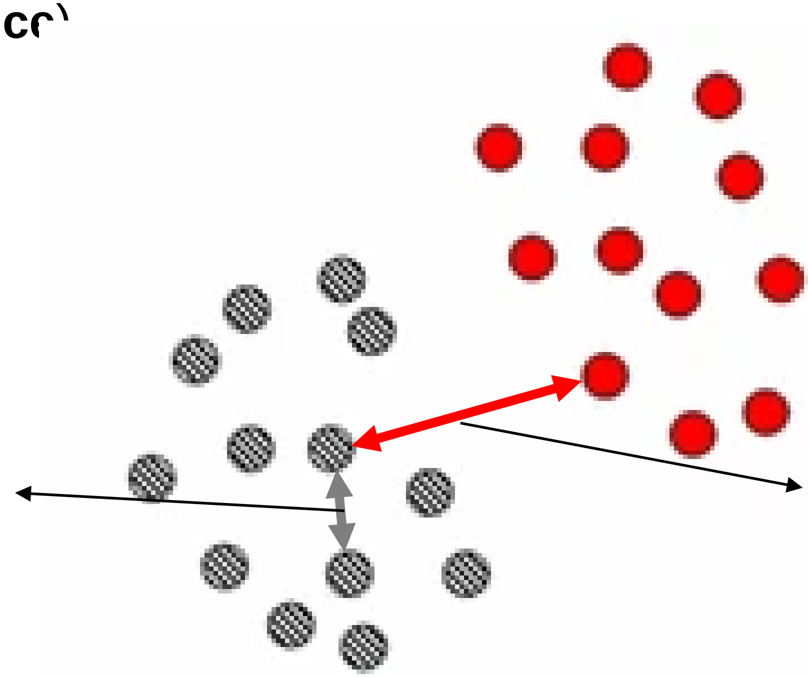
- A distance (or similarity, or dissimilarity) function
- A clustering algorithm
  - **Partition-based clustering**
  - **Hierarchical clustering**
  - Self-organizing map (SOM)
  - Mixture models
  - …
- Clustering quality measure
  - *Inter-cluster* distance/dissimilarity → To be maximized
  - *Intra-cluster* distance/dissimilarity → To be minimized

Clustering problem: Performance evaluation

- How to evaluate clustering efficiency?
  - *External evaluation*: Use additional external information (e.g., the class label of each example)
    - Example: Accuracy, Precision,…
  - *Internal evaluation*: Based on clustered examples only (without additional external information)
    - Very challenging!
    - <u>Is the focus to be presented next</u>

Internal evaluation: Principle

- **Compactness (coherence)**
  - Distance between examples in the same cluster (**intra-cluster distance**)
- **Separation**
  - The distance between the examples belongs to 2 different clusters (**inter-cluster distance**)



Distance between examples in the same cluster (**intra-cluster distance**)

The distance between the examples belongs to 2 different clusters (**inter-cluster distance**)

Internal evaluation: Metrics (1)

- **RMSSTD** (Root-mean-square standard deviation)
  - Evaluate the cohesion (compactness) of the obtained clusters
  - Expected that the **RMSSTD** value is *as small as possible*!

$$RMSSTD = \sqrt{\frac{\sum_{i=1}^{k} \sum_{x \in C_i} \|x - m_i\|^2}{P \sum_{i=1}^{k} (n_i - 1)}}$$

- k: The number of clusters
- C_i: Cluster i
- m_i: The center (centroid) of cluster C_i
- P: The number of dimensions (i.e., the number of attributes) used to represent examples
- n_i: The number of examples in cluster C_i

Internal evaluation: Metrics (2)

- **R-squared**
  - Evaluate the separation between the obtained clusters
  - Expected that the **R-squared** value is *as large as possible*!

$$R\text{-}squared = \frac{\sum_{x \in D} \|x - g\|^2 - \sum_{i=1}^{k} \sum_{x \in C_i} \|x - m_i\|^2}{\sum_{x \in D} \|x - g\|^2}$$

  - k: The number of clusters
  - C_i: Cluster i
  - m_i: The center (centroid) of cluster C_i
  - D: The entire set of examples
  - g: The center (centroid) of the entire set of examples

Internal evaluation: Metrics (3)

- **Dunn index**
  - ~ (Separation/Compactness): The ratio between the minimum inter-cluster distance and the maximum intra-cluster distance
  - Expected that the **Dunn index** is *as large as possible*!

$$Dunn - index = \frac{min_{1 \le i < j \le k} inter - distance(i, j)}{max_{1 \le h \le k} intra - distance(h)}$$

- *k*: The number of clusters
- *inter-distance(i,j)*: The distance between the 2 clusters *i* and *j*
- *intra-distance(h)*: The distance (dissimilarity) between the examples of cluster *h*

Internal evaluation: Metrics (4)

- **Davies-Bouldin index**
  - ~ (Compactness/Separation): The ratio of the average intra-cluster distance and the inter-cluster distance
  - Expected that the **Davies-Bouldin index** is *as small as possible*!

$$DB-index = \frac{1}{k}\sum_{i=1}^{k} max_{j\neq i} \frac{\frac{1}{n_i}\sum_{x\in C_i} d(x,m_i) + \frac{1}{n_j}\sum_{x\in C_j} d(x,m_j)}{d(m_i,m_j)}$$

- k: The number of clusters
- n_i, m_i: The number of examples and the centroid of cluster i
- n_j, m_j: The number of examples and the centroid of cluster j
- $d(m_i,m_j)$: The distance between the 2 cluster centroids m_i and m_j

k-means clustering

- The most popular method of partition-based clustering
- Let's call $D=\{x_1,x_2,\ldots,x_r\}$ the dataset
  - Where x_i is an instance (i.e., a vector in an *n*-dimensional vector space X)
- The k-means algorithm partitions the given dataset into k clusters
  - Each cluster has a cluster center, called **centroid**
  - k (i.e., the number of clusters) is pre-defined (i.e., decided by the system designer)

k-means algorithm – Main steps

Given a pre-defined value of k

- Step 1. Randomly choose k instances (i.e., **seeds**) to be the *initial centroids* (i.e., the *k* initial clusters)
- Step 2. For each instance, *assign it to the cluster* (among the k clusters) whose centroid is closest to the instance
- Step 3. For each cluster, *re-compute its centroid* based on the instances in that cluster
- Step 4. If the *convergence criterion* is satisfied, then stop; otherwise, go to Step 2

k-means(D, k)

D: The dataset

k: The number of clusters

```
Randomly select k instances in D as the initial centroids
while not CONVERGENCE
    for each instance x∈D
        Compute the distance from x to each centroid
        Assign x to the cluster whose centroid is closest to x
    end for
    for each cluster
        Re-compute its centroid based on its own instances
end while
return {The k clusters}
```

Convergence criterion

The clustering process stops if:

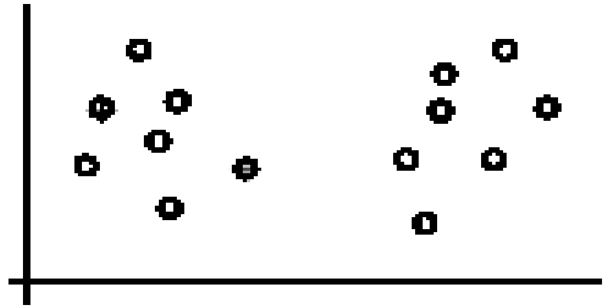
- no (or insignificant) re-assignment of instances to different clusters, or
- no (or insignificant) change of centroids, or
- insignificant decrease in the sum of squared error:

$$Error = \sum_{i=1}^{k} \sum_{\mathbf{x} \in C_i} d(\mathbf{x}, \mathbf{m_i})^2$$

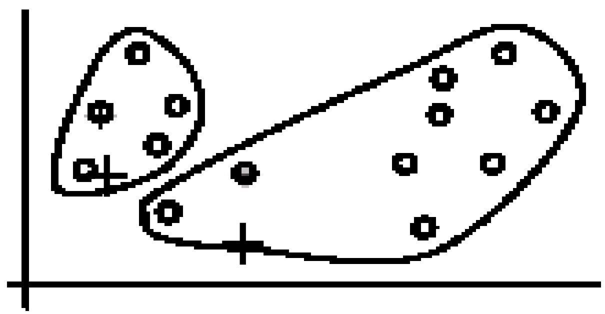
where

- C_i: The i-th cluster
- $\mathbf{m_i}$: The centroid of cluster C_i, and
- $d(\mathbf{x}, \mathbf{m}_i)$: The distance between instance $\mathbf{x}$ and centroid $\mathbf{m}_i$

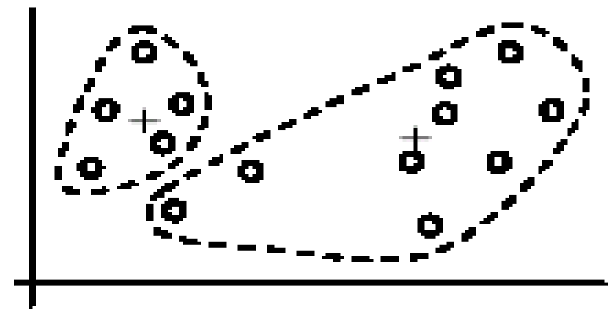
k-means algorithm – Illustration (1)



(A). Random selection of k centers



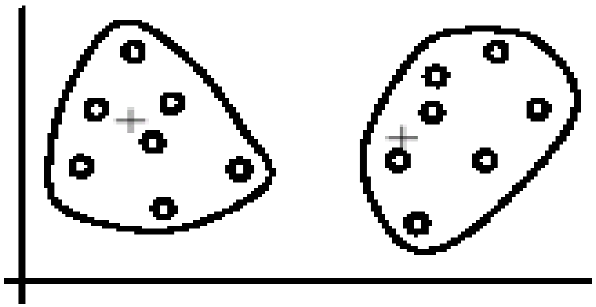
Iteration 1: (B). Cluster assignment



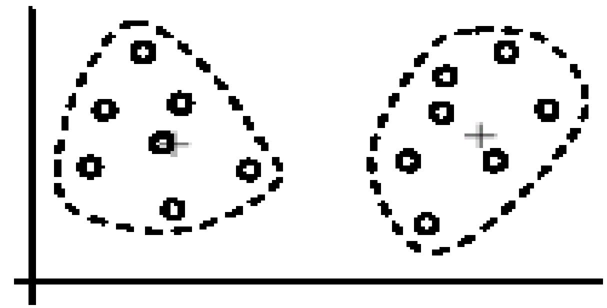
(C). Re-compute centroids

[Liu, 2006]

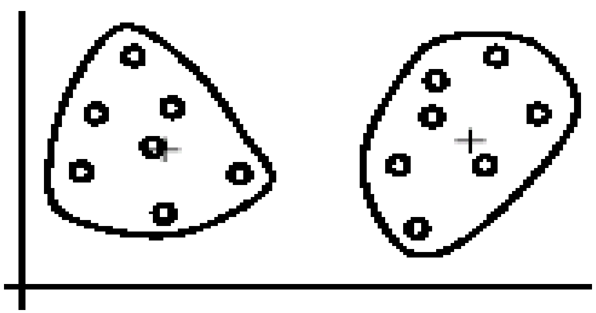
k-means algorithm – Illustration (2)



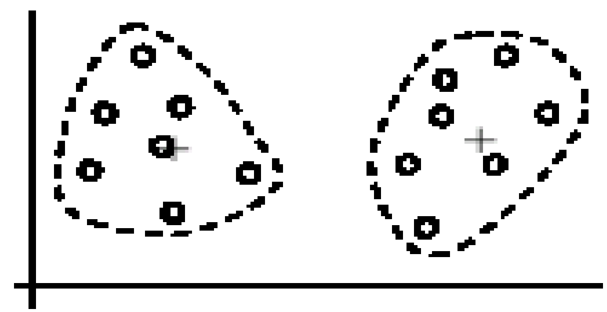
Iteration 2: (D). Cluster assignment



(E). Re-compute centroids



Iteration 3: (F). Cluster assignment



(G). Re-compute centroids

[Liu, 2006]

Centroid computation and Distance function

- Example of the centroid computation: *Mean centroid*

$$\mathbf{m_i} = \frac{1}{|C_i|} \sum_{\mathbf{x} \in C_i} \mathbf{x}$$

  - (vector) $\boldsymbol{m_i}$ is the centroid of cluster C_i
  - $|C_i|$ is the size of cluster C_i (i.e., the number of instances in C_i)

- Example of the distance function: *Euclidean distance*

$$d(\mathbf{x}, \mathbf{m_i}) = \|\mathbf{x} - \mathbf{m_i}\| = \sqrt{(x_1 - m_{i1})^2 + (x_2 - m_{i2})^2 + \ldots + (x_n - m_{in})^2}$$

  - (vector) $\boldsymbol{m_i}$ is the centroid of cluster C_i
  - $d(\boldsymbol{x},\boldsymbol{m_i})$ is the distance between instance $\boldsymbol{x}$ and centroid $\boldsymbol{m_i}$

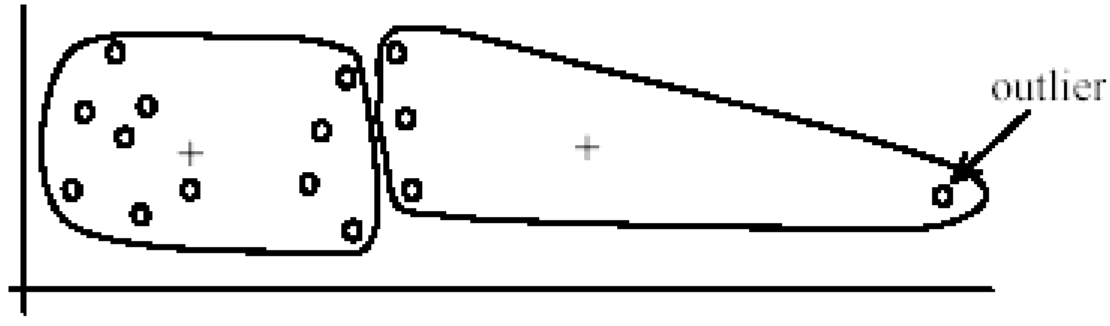
k-means algorithm – Strengths

- Simple
  - Easy to implement
  - Easy to understand
- Efficient
  - The time complexity ~ $O(rkt)$
    - r: The number of instances (i.e., the size of the dataset)
    - k: The number of clusters
    - t: The number of iterations
  - If both k and t are small, then k-means is considered as a linear algorithm
- k-means is the most popular clustering algorithm

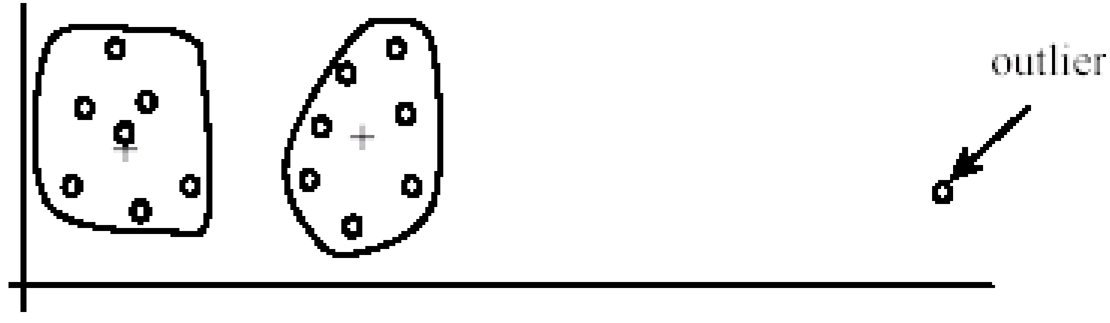
k-means algorithm – Weaknesses (1)

- The value of k (i.e., # of clusters) must be pre-defined
- The k-means algorithm needs the mean definition (in order to compute a cluster's centroid)
  - For nominal attributes, the centroid can be represented by the most frequent values of those attributes
- The k-means algorithm is sensitive to ***outliers***
  - Outliers are such instances that are (very) far away (dissimilar) from all the other instances
  - Outliers may be resulted by errors in the data recording/collection
  - Outliers may be special/abnormal instances with very different values

k-means algorithm – Outliers problem



(A): Undesirable clusters



(B): Ideal clusters

[Liu, 2006]

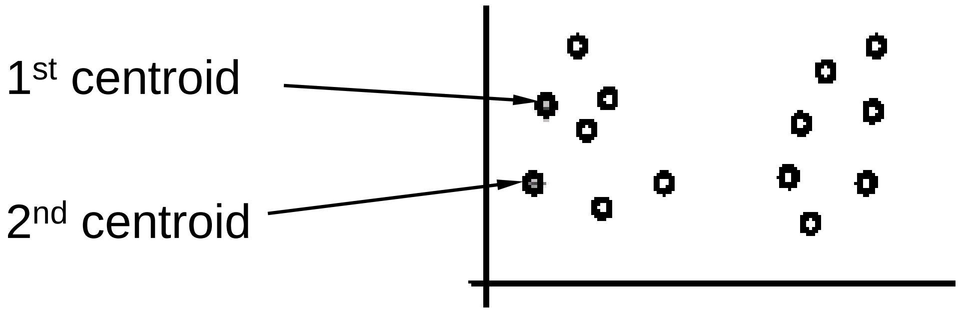
Solving the outliers problem

- Solution 1. To remove some instances in the clustering process that are much further away from the centroids than other instances
  - To be safe, track the outliers over a few (instead of only one) iterations

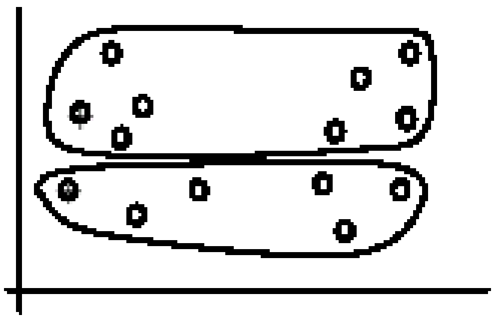
- Solution 2. To perform a random sampling
  - Since a sampling process selects only a small subset of the dataset, the chance of selecting an outlier is very small
  - Assign the rest of the dataset to the clusters by distance (or similarity) comparison

k-means algorithm – Weaknesses (2)

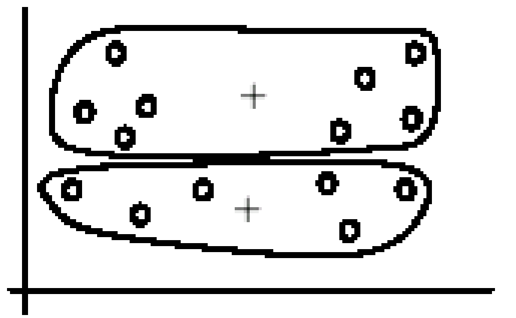
- The k-means algorithm is sensitive to the initial centroids



(A). Random selection of seeds (centroids)



(B). Iteration 1

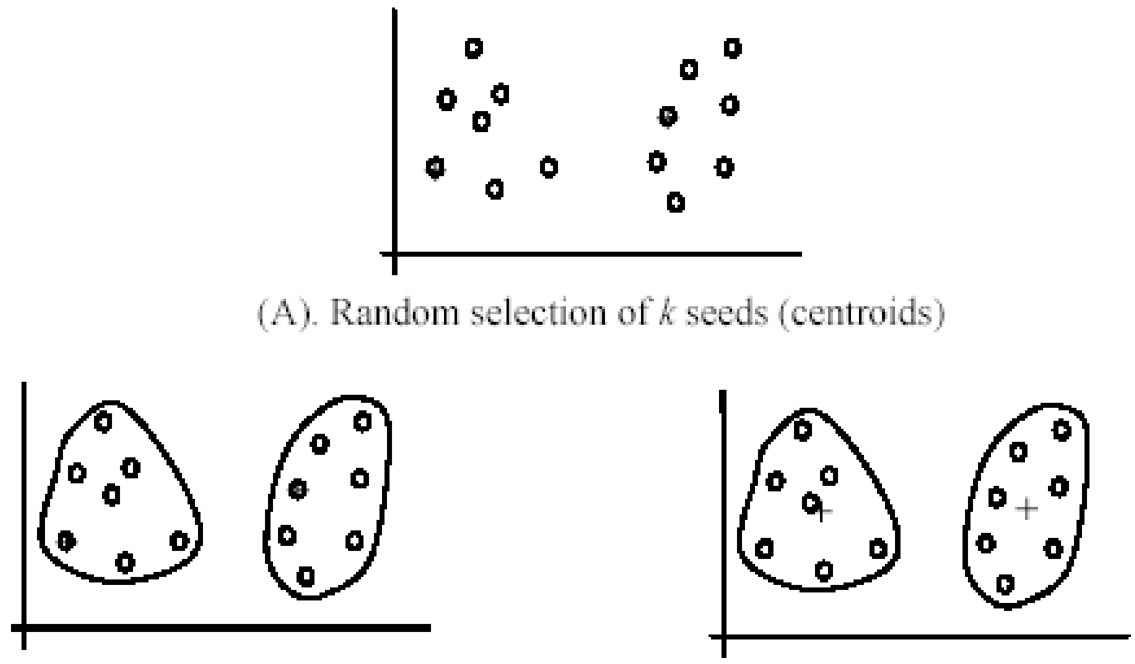


(C). Iteration 2

[Liu, 2006]

k-means algorithm – The initial seeds (1)

- To use different seeds → A better result!
  - Do many runs of k-means, each starting with different random initial seeds



(A). Random selection of k seeds (centroids)

(B). Iteration 1

(C). Iteration 2

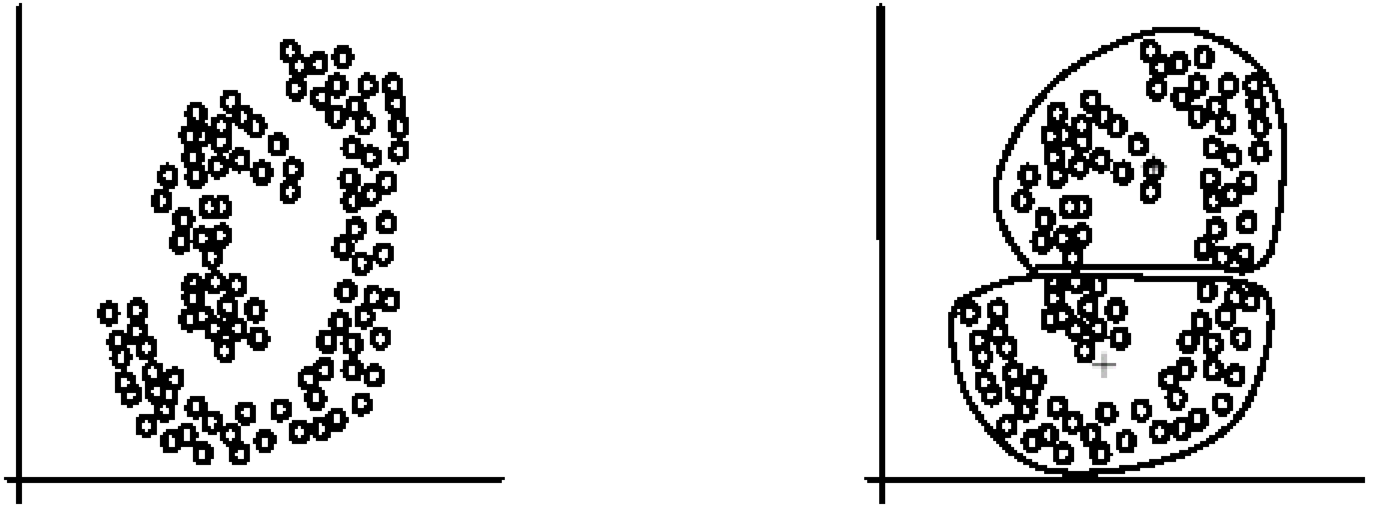
[Liu, 2006]

k-means algorithm – The initial seeds (2)

- Randomly select the first centroid ($\boldsymbol{m_1}$)
- Select a second centroid ($\boldsymbol{m_2}$) that is *as far away as possible* from the first one
- …
- Select the i-th centroid ($\boldsymbol{m_i}$) that is *as far away as possible* from the closest of $\{\boldsymbol{m_1}, \boldsymbol{m_2}, \dots, \boldsymbol{m_{i-1}}\}$
- ...

k-means algorithm – Weaknesses (3)

- The k-means algorithm is not suitable for discovering clusters that are not hyper-ellipsoids (or hyper-spheres)



(A): Two natural clusters

(B): k-means clusters

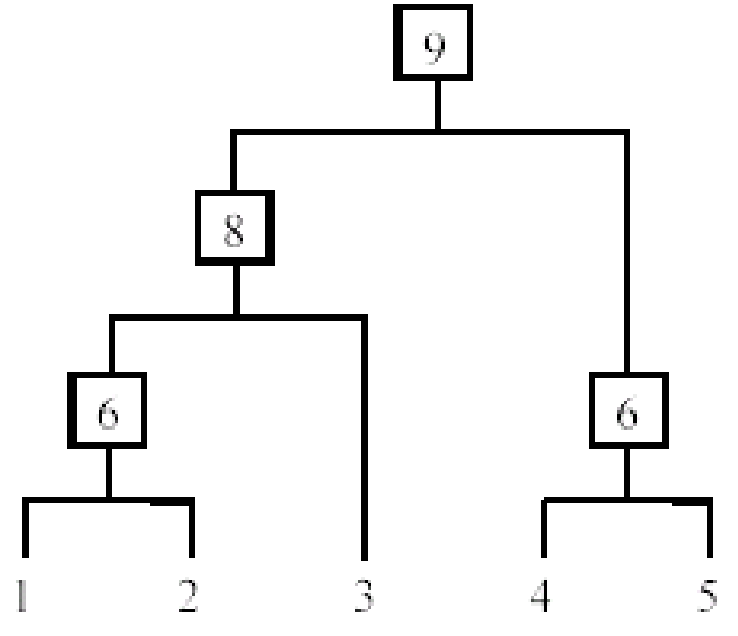
[Liu, 2006]

k-means algorithm – Summary

- Despite its weaknesses, k-means is still the most popular algorithm due to its simplicity and efficiency
  - Other clustering algorithms have also their own weaknesses
- No clear evidence that any other clustering algorithm performs better than k-means in general
  - Some clustering algorithms may be more suitable for some specific types of dataset, or for some specific application problems, than the others
- Comparing the performance of different clustering algorithms is a difficult task
  - No one knows the correct clusters!

Hierarchical agglomerative clustering (1)

- Produce a nested sequence of clusters - called **dendrogram**
  - Also called *taxonomy/hierarchy/tree* of instances

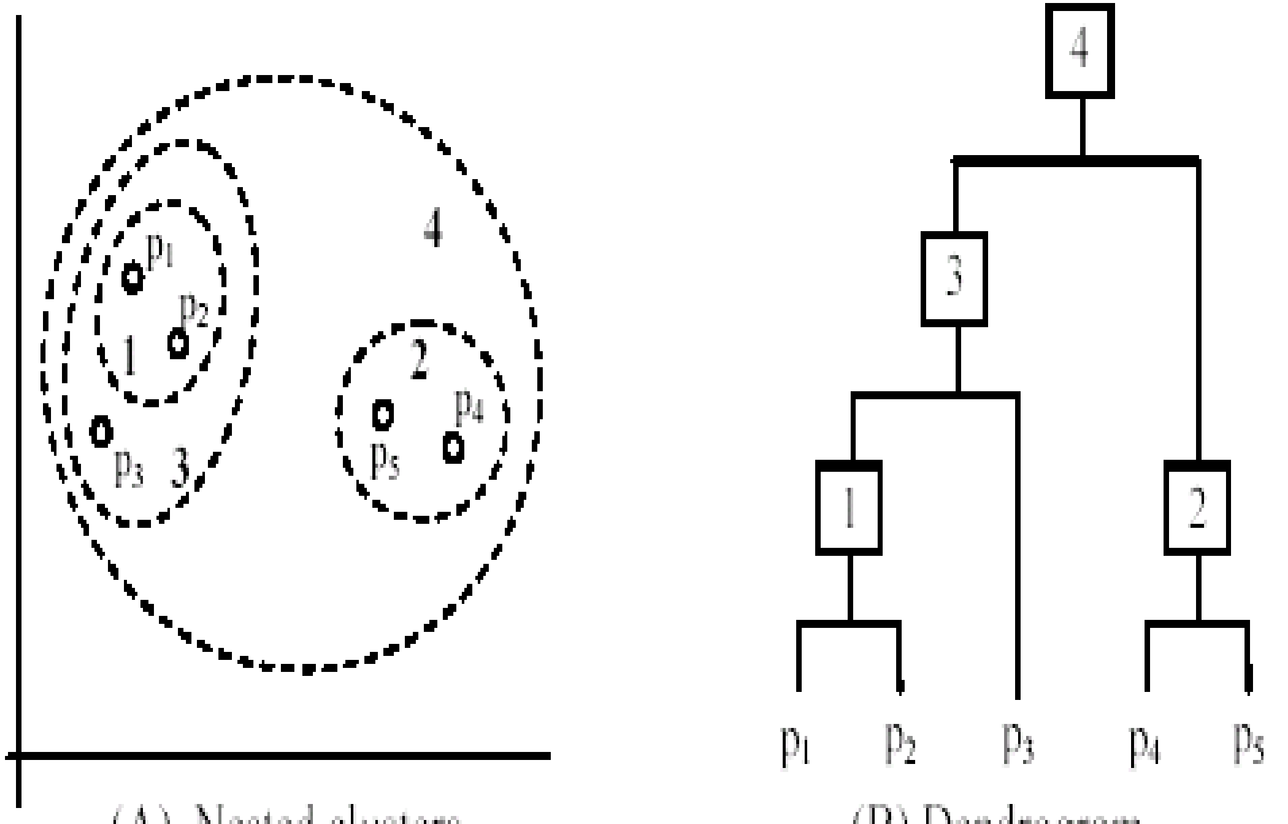


[Liu, 2006]

Hierarchical agglomerative clustering (2)

- Hierarchical agglomerative (bottom-up) clustering builds the dendrogram from the bottom level
- The algorithm:
  - At the beginning, each instance forms a cluster (also called a node)
  - Merge *the most similar* (nearest) pair of clusters
    - i.e., The pair of clusters that have *the least distance* among all the possible pairs
  - Continue the merging process
  - Stop when all the instances are merged into a single cluster (i.e., the *root* cluster)

HAC algorithm – Example



(A). Nested clusters
(Venn diagram)

(B) Dendrogram

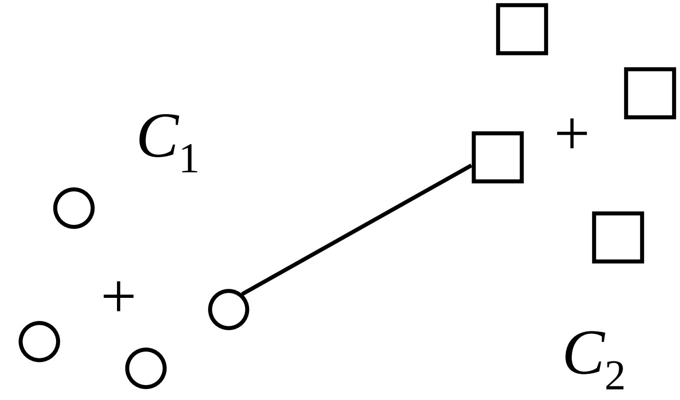
[Liu, 2006]

Distance of two clusters

- The HAC algorithm requires the computation of the distance between two clusters
  - Before the merging, for every possible pairs of clusters the distance between the two clusters is computed
- Different methods to measure the distances of two clusters (i.e., resulting in variations of the HAC algorithm)
  - Single link
  - Complete link
  - Average link
  - Centroid link
  - …

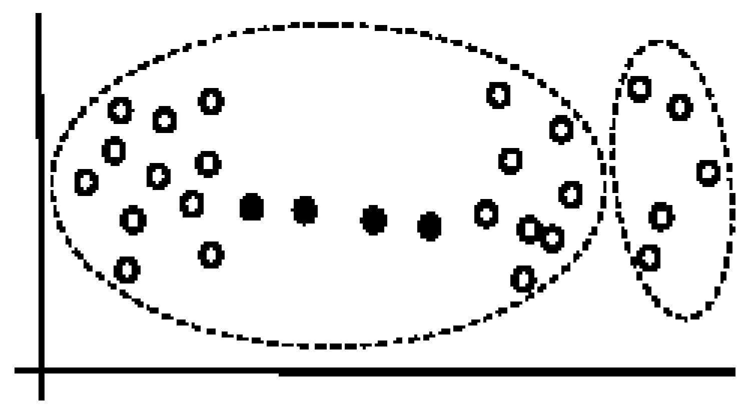
HAC – Single link

- The distance between two clusters is the **minimum distance** between the instances (members) of the two clusters



- Tend to generate "long chains"

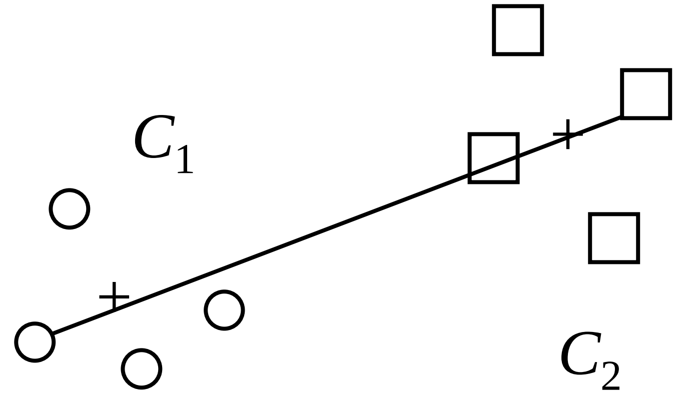
Two natural clusters are split into two

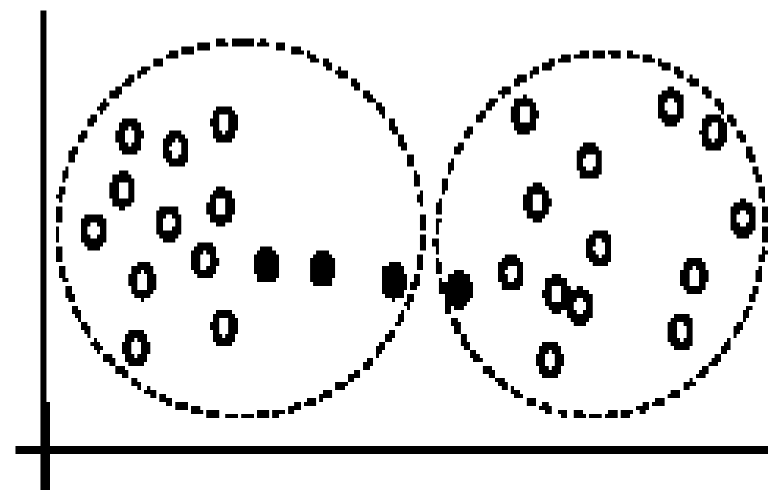


[Liu, 2006]

HAC – Complete link

- The distance between two clusters is the **maximum distance** between the instances (members) of the two clusters
- Sensitive to outliers





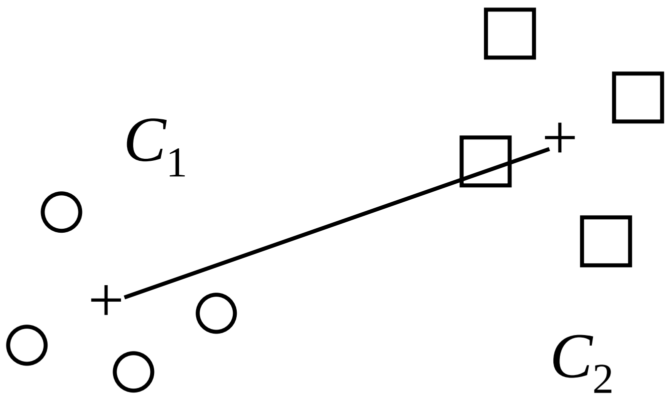
[Liu, 2006]

HAC – Average link

- Average-link distance is a compromise between complete-link and single-link distances
  - To reduce the sensitivity of complete-link clustering to outliers
  - To reduce the tendency of single-link clustering to form long chains (that do not correspond to the intuitive notion of clusters)
- The distance between two clusters is the average distance of all pairs of instances (one from each cluster)

HAC – Centroid link

- The distance between two clusters is the distance between their centroids



HAC algorithm – Complexity

- All the variations of the HAC algorithm have the complexity of at least $O(r^2)$
  - r: The number of instances (i.e., the size of the dataset)
- Single-link can be done in $O(r^2)$
- Complete-link and average-link can be done in $O(r^2 \log r)$
- Because of the complexity, the HAC algorithm is hard to use for large datasets

Clustering – Distance functions

- A key component to clustering
  - “similarity functions” and “dissimilarity functions” are also commonly used terms
- There are different distance functions for
  - Different types of data
    - Numeric data
    - Nominal data
  - Specific application problems

Distance functions for numeric attributes

- The family of geometry distance functions (Minkowski distance)
- Most commonly used functions
  - Euclidean distance and
  - Manhattan (a.k.a. city-block) distance
- Let's denote $d(\mathbf{x}_i, \mathbf{x}_j)$ the distance between the two instances (vectors) $\mathbf{x}_i$ and $\mathbf{x}_j$
- The general Minkowski distance (p is a positive integer)

$$d(\mathbf{x_i}, \mathbf{x_j}) = [(x_{i1} - x_{j1})^p + (x_{i2} - x_{j2})^p + \ldots + (x_{in} - x_{jn})^p]^{1/p}$$

Distance functions for binary attributes

- We use a confusion matrix to introduce the distance function
  - *a*: The number of attributes with value of 1 for both $\mathbf{x}_i$ and $\mathbf{x}_j$
  - *d*: The number of attributes with value of 0 for both $\mathbf{x}_i$ and $\mathbf{x}_j$
  - *b*: The number of attributes for which the value in $\mathbf{x}_i$ is 1 whereas the value in $\mathbf{x}_j$ is 0
  - *c*: The number of attributes for which the value in $\mathbf{x}_i$ is 0 whereas the value in $\mathbf{x}_j$ is 1

instance $\mathbf{x}_i$ \ instance $\mathbf{x}_j$	1	0
1	a	b
0	c	d

- **Simple matching coefficient**: The proportion of mismatches of the attribute values between the two examples $\mathbf{x}_i$ and $\mathbf{x}_j$

$$d(\mathbf{x}_i, \mathbf{x}_j) = \frac{b+c}{a+b+c+d}$$

Distance functions for nominal attributes

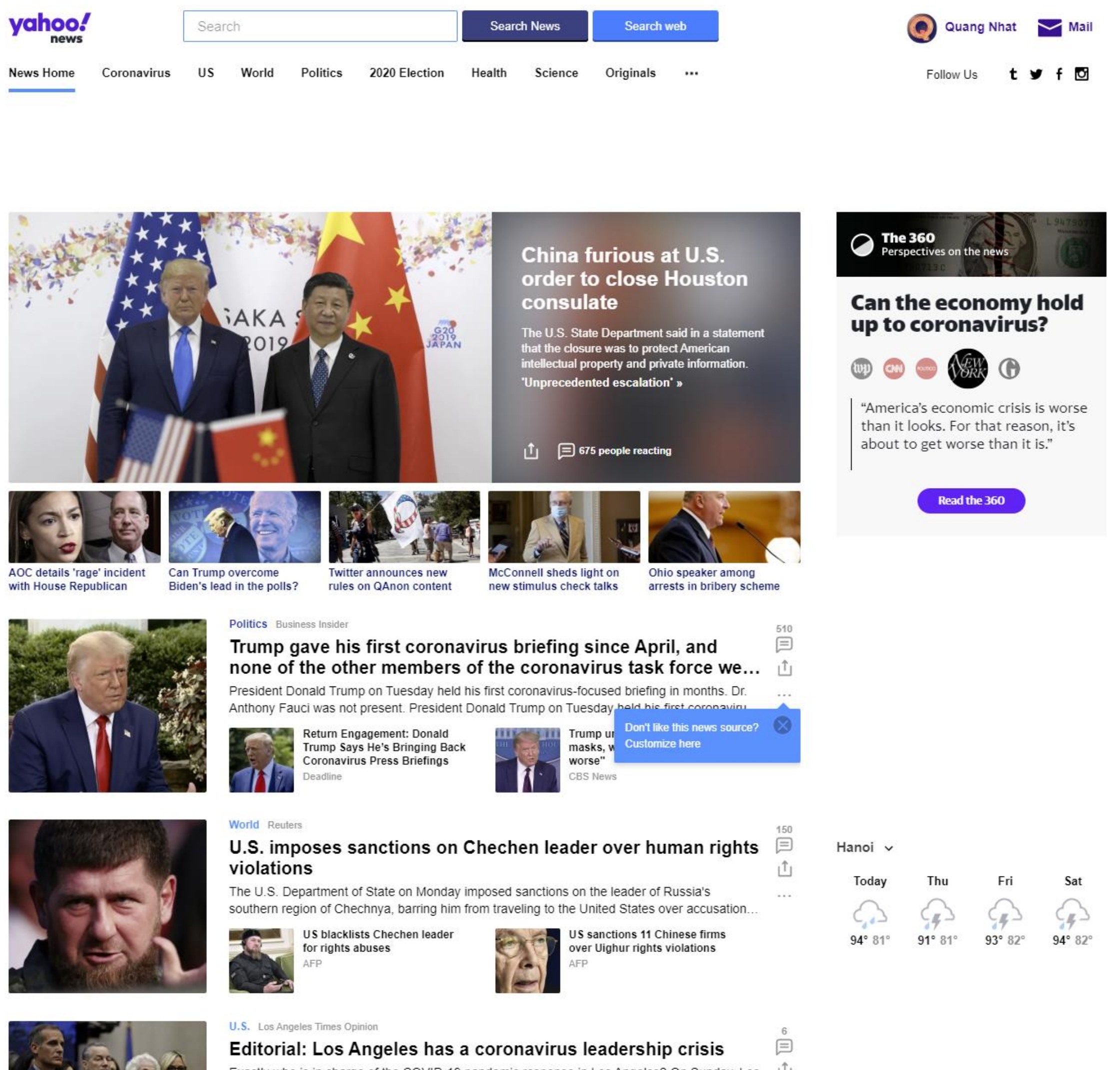
- The distance function is also based on the simple matching method
- Given two examples $\mathbf{x}_i$ and $\mathbf{x}_j$, let's denote *p* the number of attributes and *q* the number of attributes whose values are identical in $\mathbf{x}_i$ and $\mathbf{x}_j$

$$d(\mathbf{x_i}, \mathbf{x_j}) = \frac{p - q}{p}$$

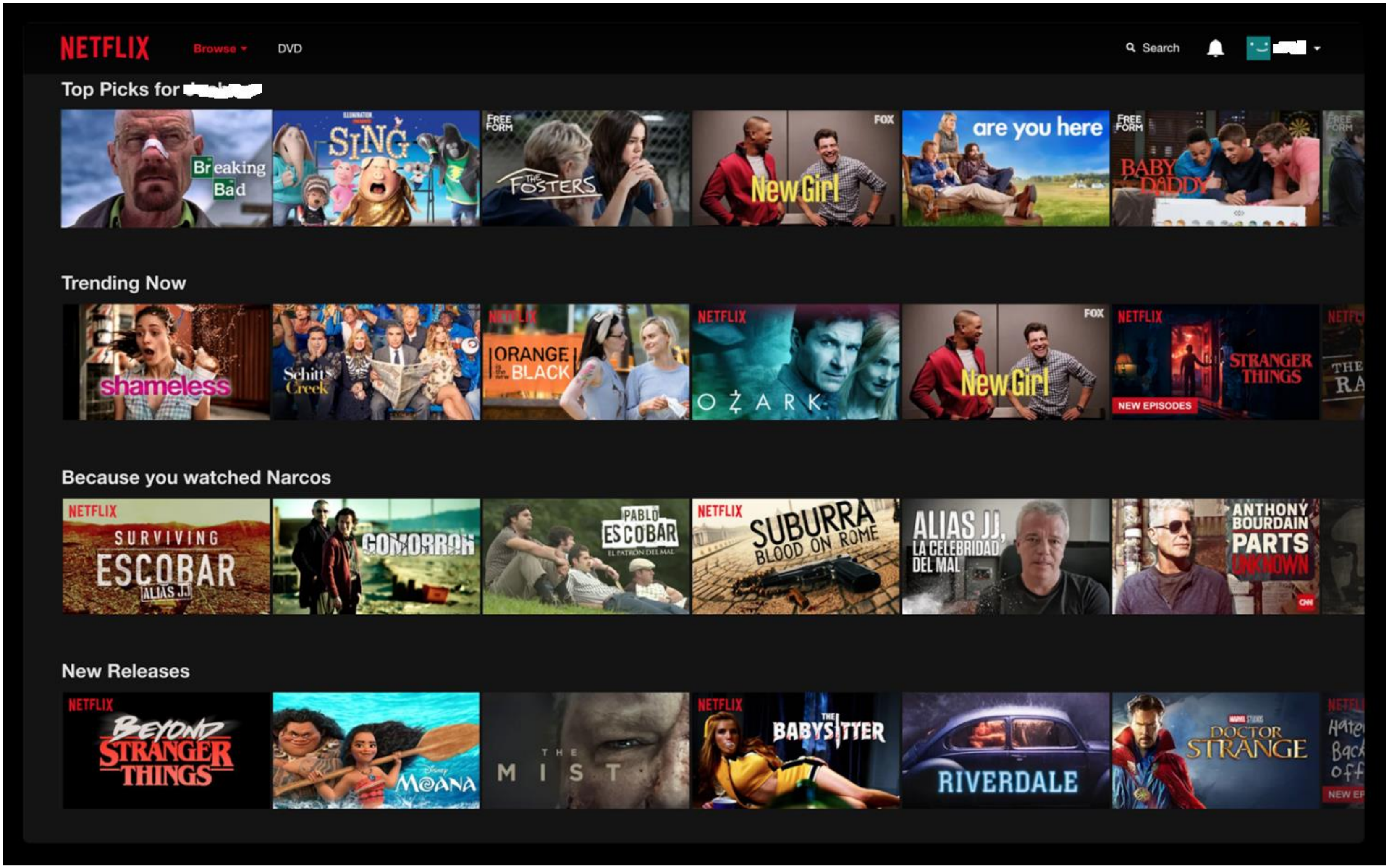
Recommender system: Information overload

- The problem of information overload
  - Too much information
  - Too many options of a certain product/service
- In many information search tasks (e.g., product selection) the user:
  - is not aware of the range of available options,
  - may not know exactly what he wants to search for,
  - if presented with some options, may not be able to choose
- It is (very) difficult for a user to make a decision
  - Not enough of time
  - Not enough of effort
  - Not enough of knowledge of the (product/service) domain

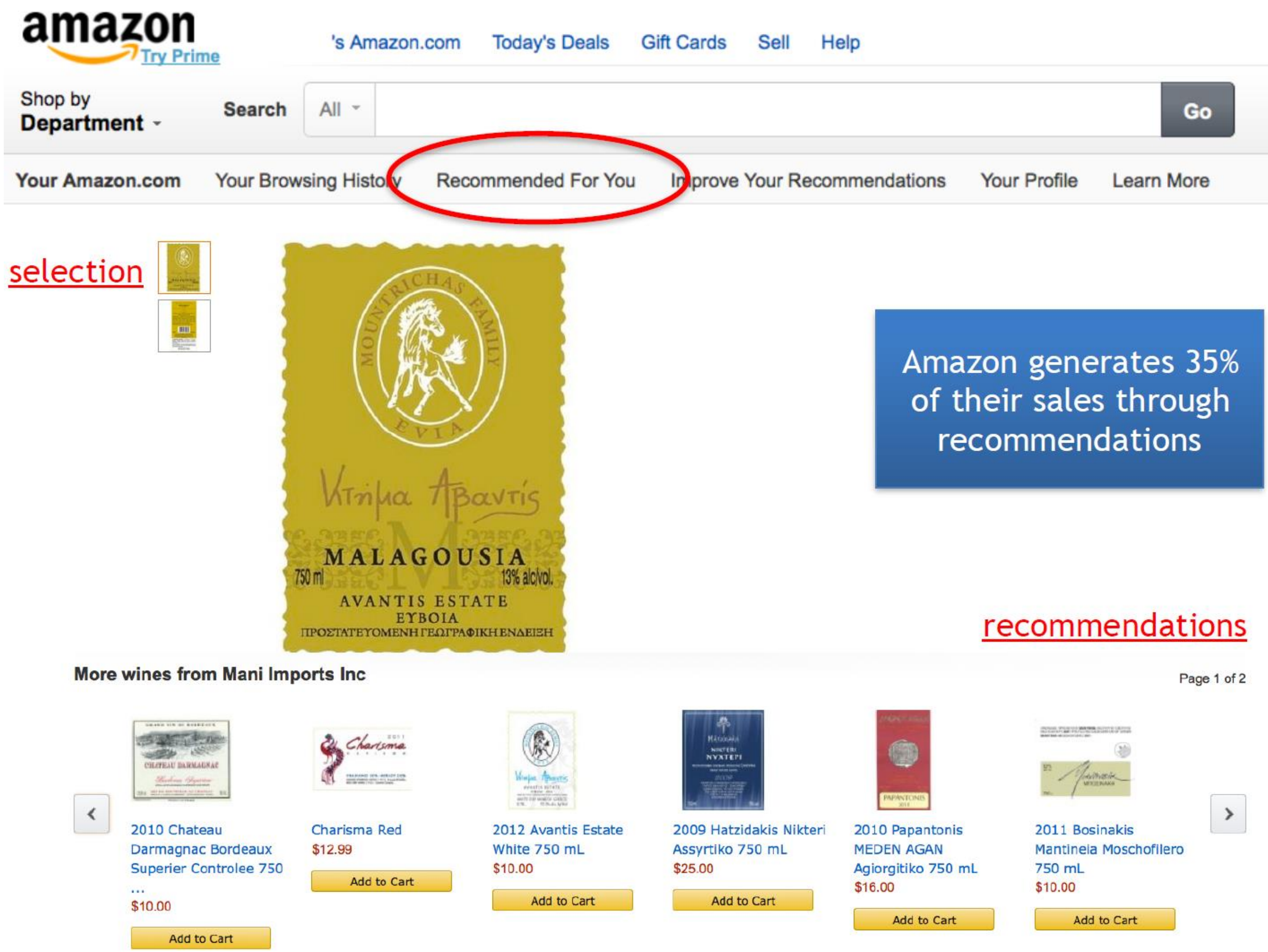
What news should I read?



What movie should I see?

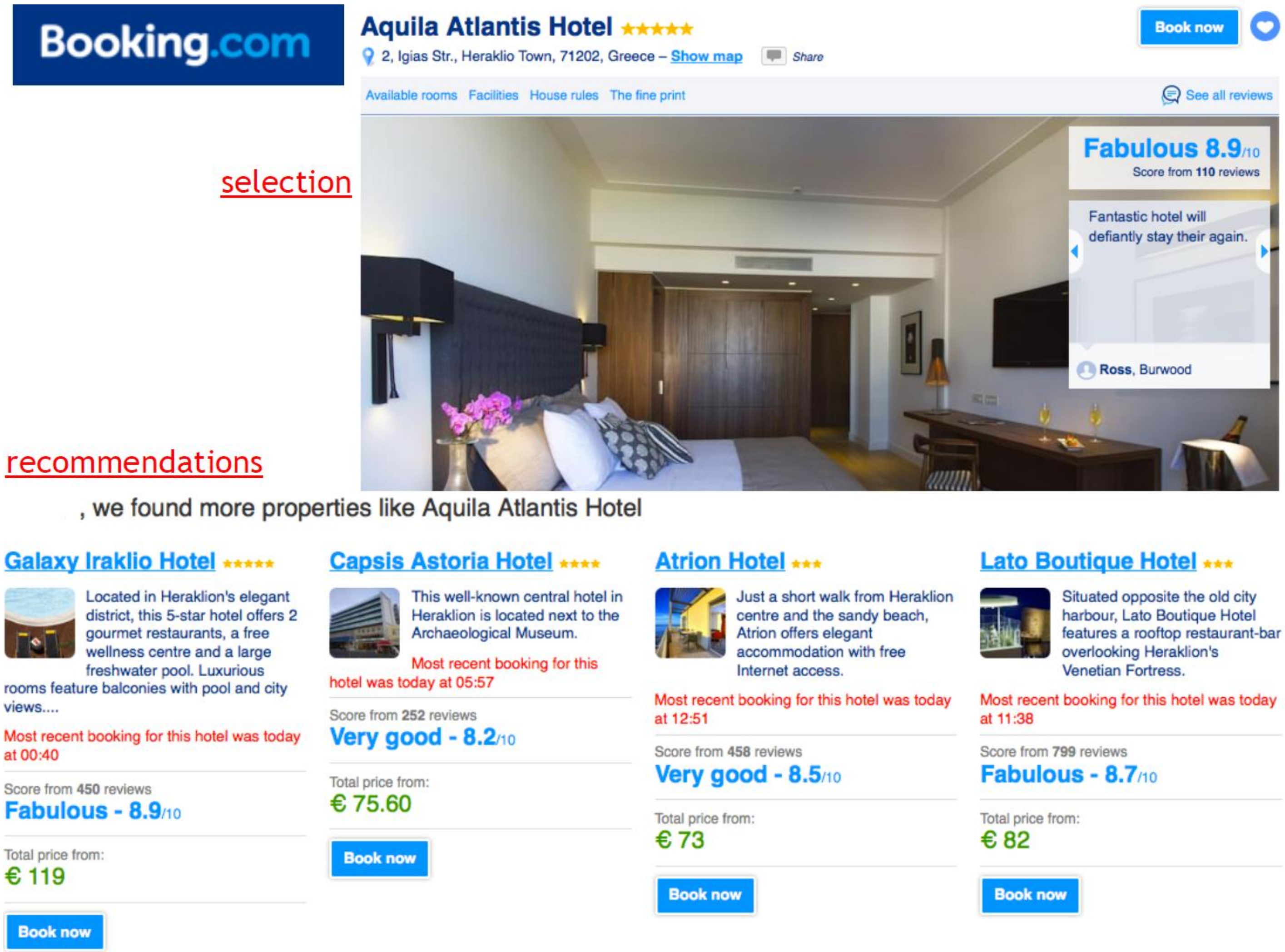


What book should I buy?

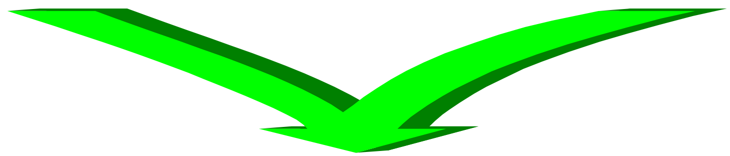


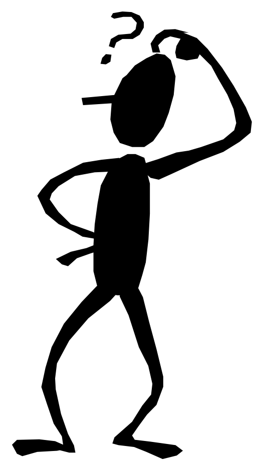
Amazon generates 35% of their sales through recommendations

What accommodation should I select ?



Information overload





Which one(s) should I select?

Which one(s) best suit for me?

Information search vs. discovery

- **Search** means to locate *known* objects in a content repository
- **Discovery** means to explore some promising space for *partially specified or unknown* objects
- There are many search tools, but few discovery environments

Recommender systems (RSs)

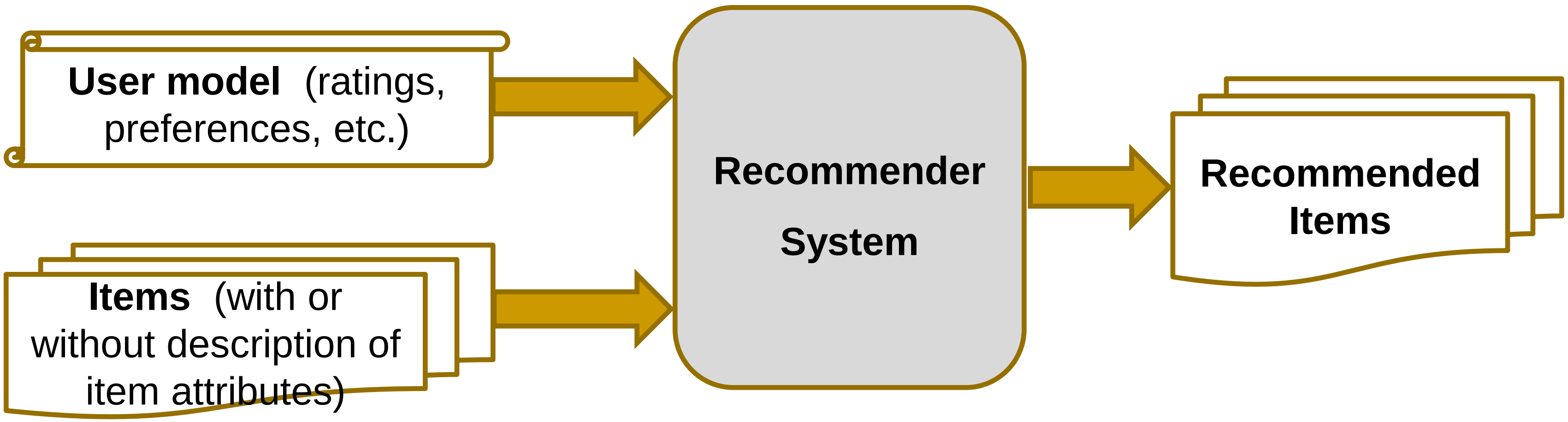
- **RSs** are **decision-making support tools**
  - Aimed at **addressing the information overload problem**
  - **Provide product and service recommendations** to a user
    - Personalized (adapted) to the user’s needs and preferences
    - Appropriate at the user’s request context
- Inspiration of RSs
  - In everyday life we rely on recommendations from other people (word of mouth, recommendation letters, reviews in newspapers, …)
- RSs are based on a number of technologies:
  - Information Filtering
  - Machine Learning
  - Adaptive and Personalized Systems,
  - User Modeling
  - …

Recommender systems (RSs)

- Successful application domains
  - E-Commerce, Entertainment, Travel and tourism, E-Learning, E-Health, Social network, etc.
- Examples on contribution of RSs in practice:
  - *Netflix*: 2/3 of all movies viewed by users are based on the recommendation function
  - *Google News*: The recommendation function helps increase the number of views by 38%
  - *Amazon*: 35% of total sales value is due to the recommendation function

Recommender systems (RSs)

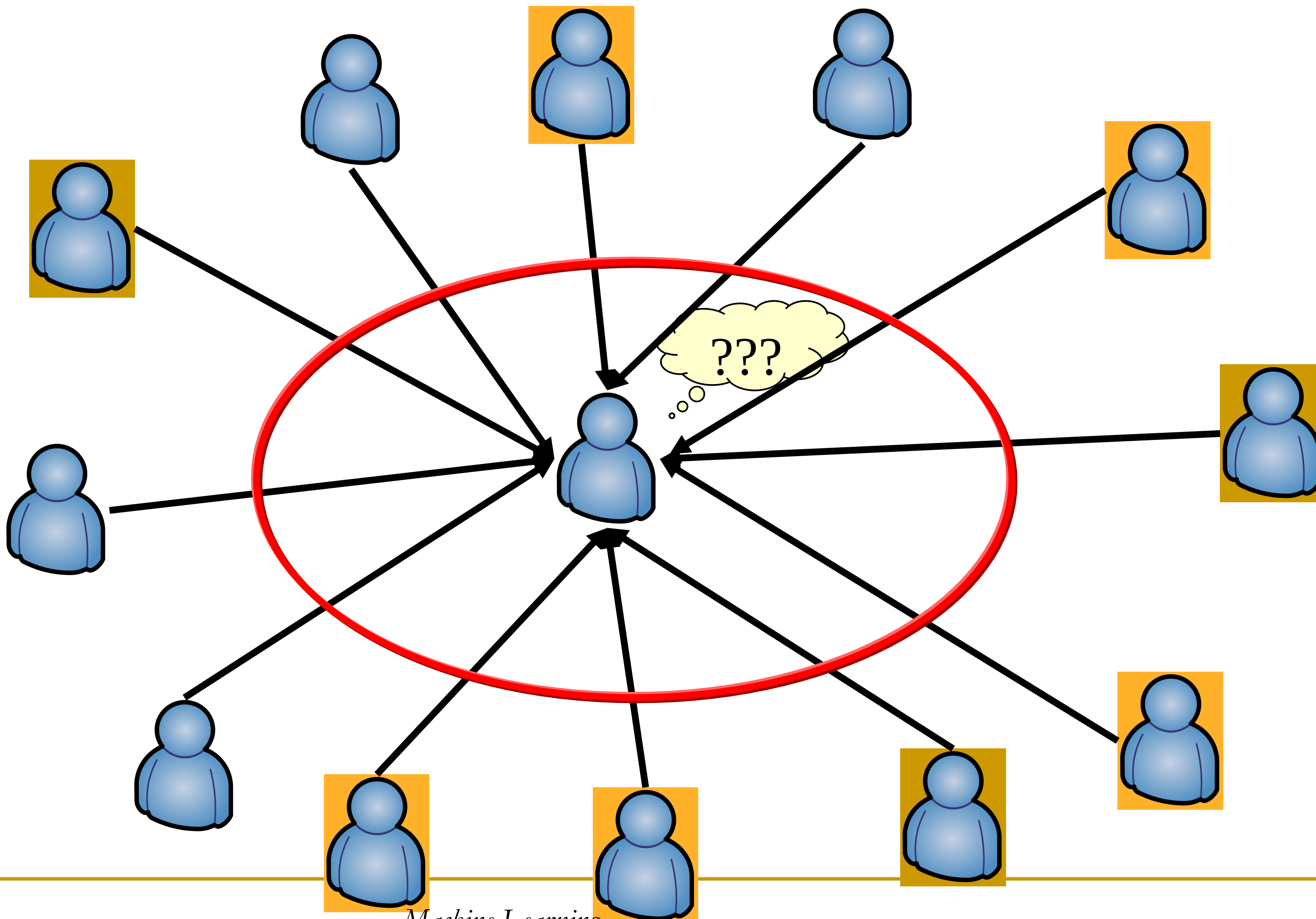
- Recommender System can be seen as a function
- Given:
  - User model (e.g., ratings, preferences, demographics, situational context, etc.)
  - Items (with or without description of item attributes)
- Find:
  - Relevance score. Used for ranking.



Traditional recommendation approaches

- **Collaborative filtering (a.k.a. Social filtering)**
  - *Assumption: Users who had similar tastes in the past will have similar tastes in the future*
- Content-based
- Knowledge-based

Social filtering



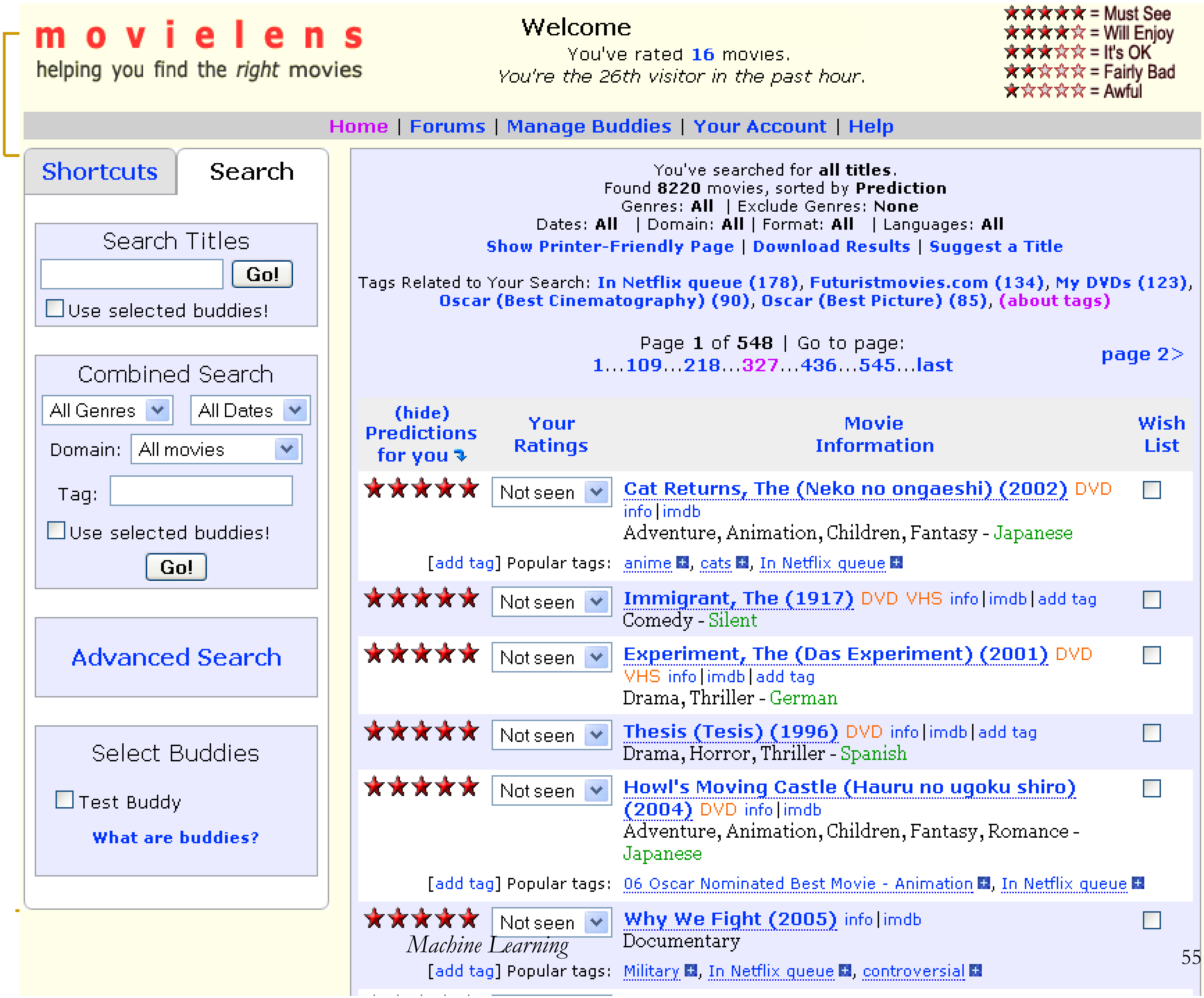
So far you have rated **0** movies.
MovieLens needs at least **15** ratings from you to generate predictions for you.
Please rate as many movies as you can from the list below.

next >

Your Rating		Movie Information
	3.0 stars	**Austin Powers: International Man of Mystery (1997)** Action, Adventure, Comedy
	4.0 stars	**Contact (1997)** Drama, Sci-Fi
???	Not seen	**Crouching Tiger, Hidden Dragon (Wu Hu Zang Long) (2000)** Action, Adventure, Drama, Fantasy, Romance
???	Not seen	**Demolition Man (1993)** Action, Comedy, Sci-Fi
???	Not seen	**Eraser (1996)** Action, Drama, Thriller
???	Not seen	**Maverick (1994)** Action, Comedy, Western
	4.5 stars	**Philadelphia (1993)** Drama
	3.5 stars	**Piano, The (1993)** Drama, Romance
???	Not seen	**Toy Story 2 (1999)** Adventure, Animation, Children, Comedy, Fantasy
	3.5 stars	**X-Men (2000)** Action, Adventure, Sci-Fi

next >

To get a new set of movies click the **next>** link.


movielens
helping you find the right movies
Welcome
You've rated 16 movies.
You're the 26th visitor in the past hour.
= Must See
= Will Enjoy
= It's OK
= Fairly Bad
= Awful
Home | Forums | Manage Buddies | Your Account | Help
Shortcuts
Search
Search Titles
Go!
Use selected buddies!
Combined Search
All Genres
All Dates
Domain: All movies
Tag:
Use selected buddies!
Go!
Advanced Search
Select Buddies
Test Buddy
What are buddies?
You've searched for all titles.
Found 8220 movies, sorted by Prediction
Genres: All | Exclude Genres: None
Dates: All | Domain: All | Format: All | Languages: All
Show Printer-Friendly Page | Download Results | Suggest a Title
Tags Related to Your Search: In Netflix queue (178), Futuristmovies.com (134), My DVDs (123), Oscar (Best Cinematography) (90), Oscar (Best Picture) (85), (about tags)
Page 1 of 548 | Go to page:
1...109...218...327...436...545...last
page 2>
(hide) Predictions for you
Your Ratings
Movie Information
Wish List
Not seen
Cat Returns, The (Neko no ongaeshi) (2002) DVD
info | imdb
Adventure, Animation, Children, Fantasy - Japanese
[add tag] Popular tags: anime, cats, In Netflix queue
Not seen
Immigrant, The (1917) DVD VHS info | imdb | add tag
Comedy - Silent
Not seen
Experiment, The (Das Experiment) (2001) DVD VHS info | imdb | add tag
Drama, Thriller - German
Not seen
Thesis (Tesis) (1996) DVD info | imdb | add tag
Drama, Horror, Thriller - Spanish
Not seen
Howl's Moving Castle (Hauru no ugoku shiro) (2004) DVD info | imdb
Adventure, Animation, Children, Fantasy, Romance - Japanese
[add tag] Popular tags: 06 Oscar Nominated Best Movie - Animation, In Netflix queue
Not seen
Why We Fight (2005) info | imdb
Documentary
[add tag] Popular tags: Military, In Netflix queue, controversial

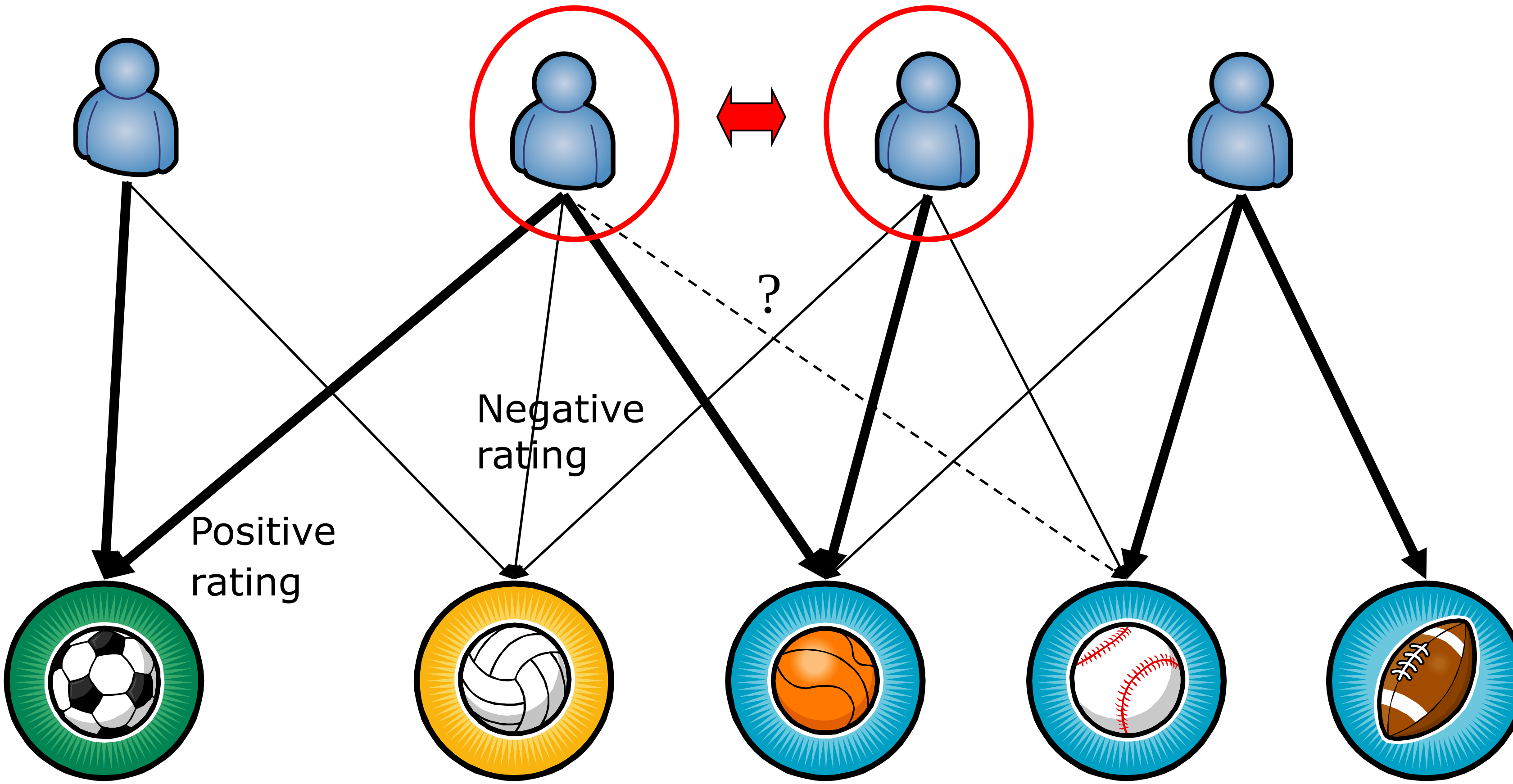
Matrix of ratings

Items

Users

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
a			1		4	5			4		3					2			4		2				
b			4							3							5	1		3					
c		5		4			4						3		5					4		5			
d								3				5				3			4		2			3	
e		3					5			4	5				5					1			5	4	
f			4				1		3	5		4	1		5	4	4		4				3		
g	2	4				4		2			5		1	4	5		4	2	4		5			4	
h			2		1		4		3	5		4	2		5	4	5						5		
i		1					3			5				5		4	4		5			4		3	
j			4			4				5			1		5		4		4				4		
k		5				4			2		5		1	5		4		2		4				2	
l					3			3				4	1		4		4	2	4					3	
m	5		3					5	3		5	4		5	5	3			4	4	5	4		4	
n			1		4	5				4	5		1	5		4		3		4		4	3		
o			4			4				5		4		5			4	2		5		5		3	
p				4			5								5	4		2	4	4	5	4		2	
q					3			3					1	5		4	4		4			4		3	
r		4			1	4		2					2		5		4				5	4		4	
s			2		4		4			5			1			4		2	4		4		5		
t		1		4			3					4		5	5		4			4				3	
u			2		1		4		3				1		5	4		2	4		5	4			
v					4	5				4	3		5			2					2			5	
w				2			2		3			5			4	5		4	2		3	4			
x	4			5				3		3				4	5					1					
y			1			3				2	3						3	3		5		4			

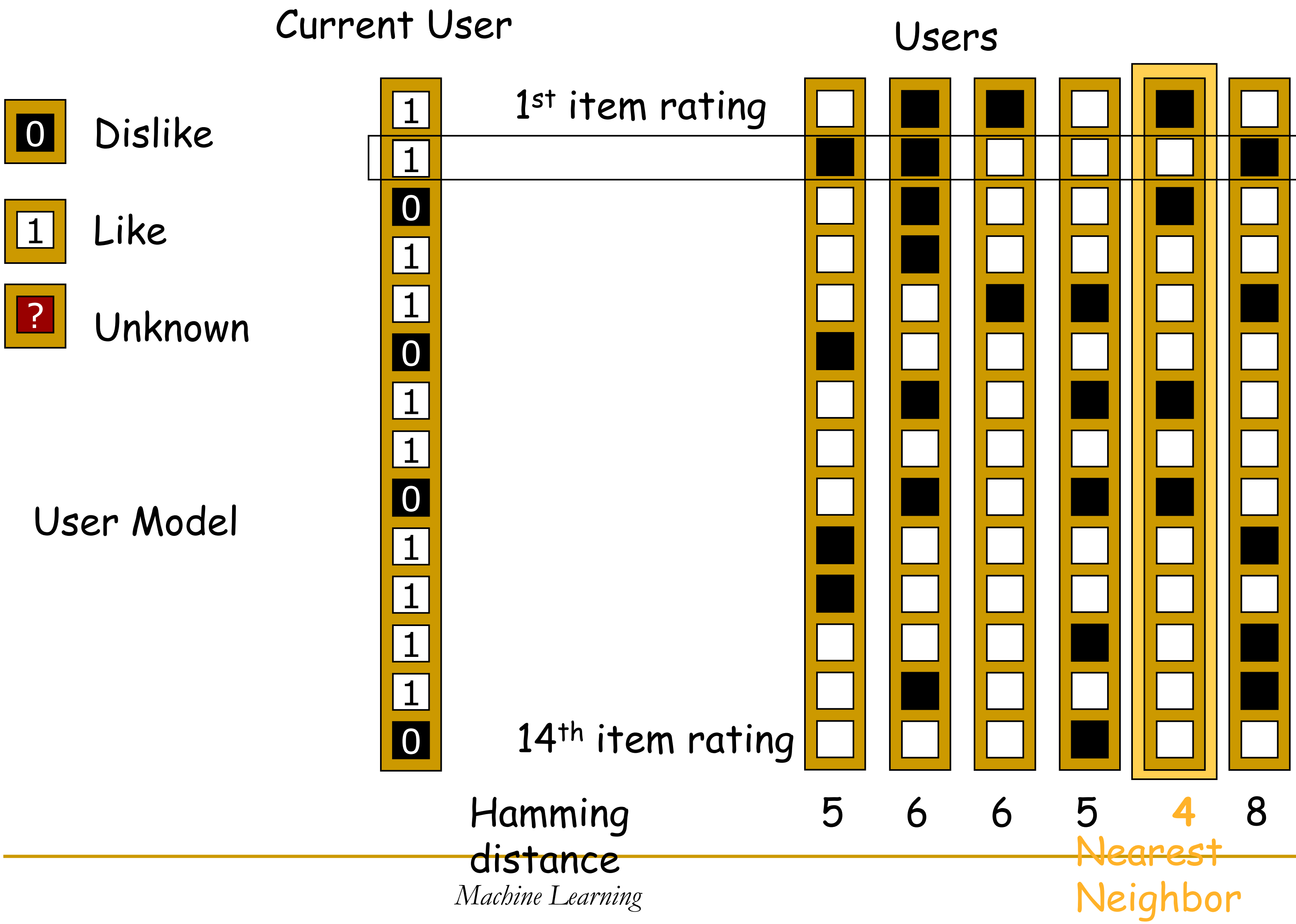
Collaborative filtering



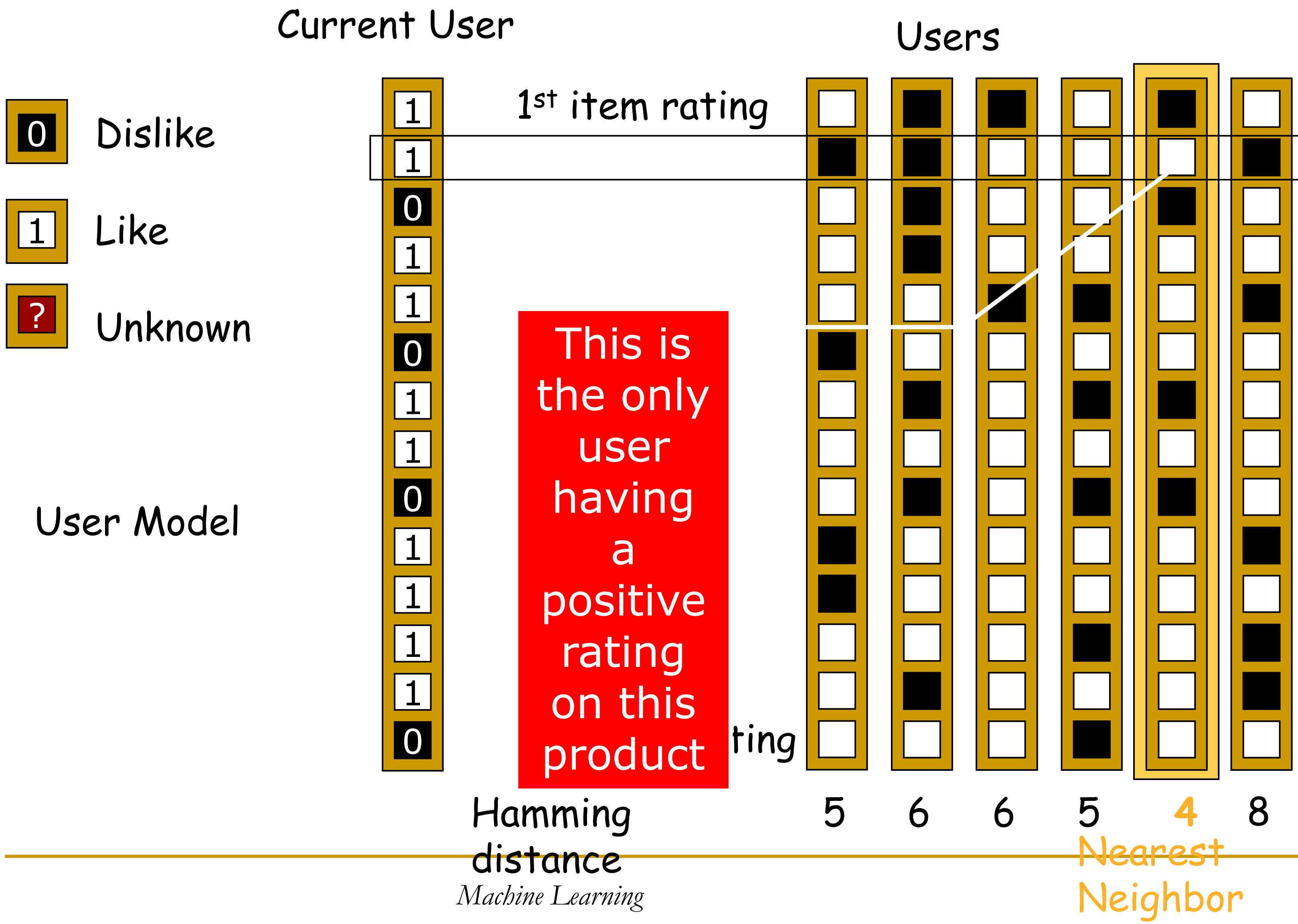
Collaborative filtering recommendation

- For a target user (i.e., to whom a recommendation is produced) the set of his **ratings** to the items are collected
- **Neighbor** formation. The users most similar to the target user (according to a **similarity function**) are identified
- The items selected (bought/interested) by these similar users are identified
- For each of these items, a prediction (i.e., the **estimated rating** that the target user may give to the item) is generated
- Based on these predicted ratings, a set of **top N items** (i.e., those with highest estimated ratings) are recommended

Nearest neighbor collaborative filtering



1-Nearest neighbor can be easily wrong



Collaborative filtering

- A collection of users u_i, $i=1, \ldots n$ and a collection of products p_j, $j=1, \ldots, m$
- An $n \times m$ matrix of ratings v_{ij} , with $v_{ij} = ?$ if user i has not rated product j
- A predicted rating of user i on product j is computed as:

$$v^*_{ij} = v_i + K \sum_{v_{kj} \neq ?} u_{ik} (v_{kj} - v_k)$$

- Where, v_i is the average rating of user i, K is a normalization factor such that the sum of u_{ik} is 1, and

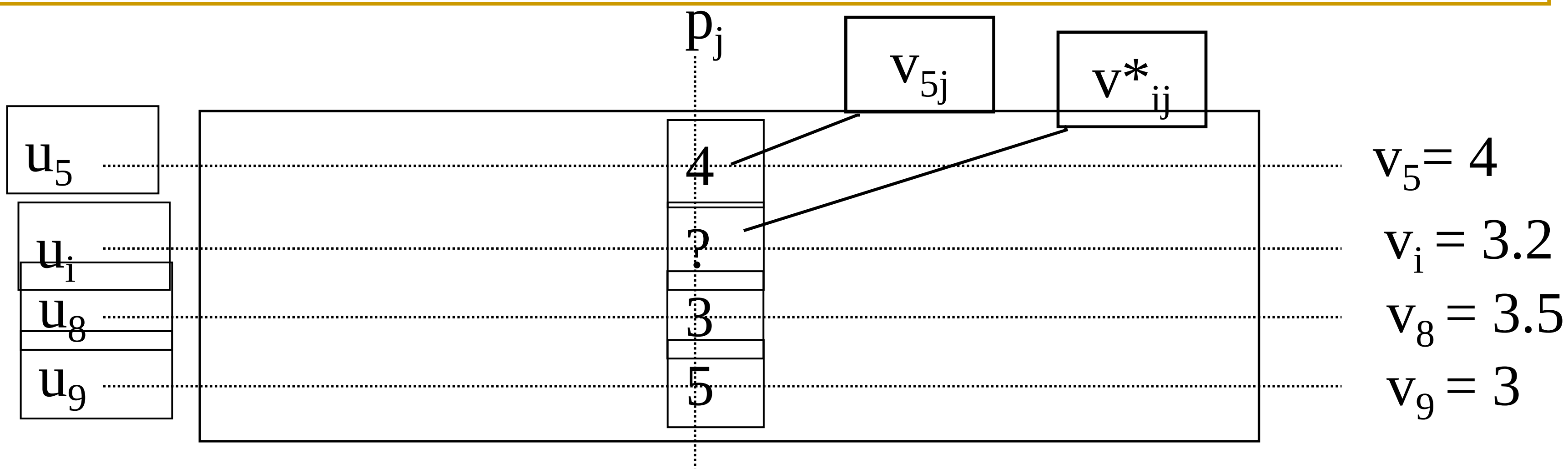
$$u_{ik} = \frac{\sum_l (v_{il} - v_i)(v_{kl} - v_k)}{\sqrt{\sum_l (v_{il} - v_i)^2 \sum_l (v_{kl} - v_k)^2}}$$

Pearson similarity of user i and user k

- Where the sums (and averages) are over products l, such that v_{il} and v_{kl} are not "?"

[Breese et al., 1998]

Example



Users' similarities: $u_{i5} = 0.5$, $u_{i8} = 0.5$, $u_{i9} = 0.8$

$$v^*_{ij} = v_i + K \sum_{v_{kj} \neq ?} u_{ik} (v_{kj} - v_k)$$

$v^*_{ij} = 3.2 + 1/(0.5+0.5+0.8) * [0.5 (4 - 4) + 0.5 (3 - 3.5) + 0.8 (5 - 3)$

$= 3.2 + 1/1.8 * [0 - 0.25 + 1.6] = 3.2 + 0.75 = 3.95$

More on ratings: Explicit ratings

- Probably the most precise ratings
- Most commonly used (1 to 5, 1 to 7 Likert response scales)
- Research topics
  - Optimal granularity of scale; indication that 10-point scale is better accepted in movie domain
  - An even more fine-grained scale was chosen in the joke recommender discussed by Goldberg et al. (2001), where a continuous scale (from −10 to +10) and a graphical input bar were used
  - Multi-dimensional ratings (multiple ratings per movie such as ratings for actors and sound)
- Main problems
  - Users not always willing to rate many items
    - Number of available ratings could be too small → Sparse rating matrices → Poor recommendation quality
  - How to stimulate users to rate more items?

More on ratings: Implicit ratings

- When a customer buys an item, for instance, many recommender systems interpret this behavior as a positive rating
- Clicks, page views, time spent on some page, demo downloads …
- Implicit ratings can be collected constantly and do not require additional efforts from the user
- Main problem
  - One cannot be sure whether the user behavior is correctly interpreted
  - For example, a user might not like all the books he or she has bought; the user also might have bought a book for someone else
- Implicit ratings can be used in addition to explicit ones; question of correctness of interpretation

Collaborative filtering issues

- Pros:
  - well-understood, works well in some domains, no knowledge engineering required
- Cons:
  - requires user community, sparsity problems, no integration of other knowledge sources, no explanation of results
- How to evaluate the prediction quality?
  - MAE / RMSE: What does an MAE of 0.7 actually mean?
  - Serendipity (novelty and surprising effect of recommendations)
    - Not yet fully understood
- What about multi-dimensional ratings?

References

- B. Liu. *Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data*. Springer, 2006.
- Dietmar Jannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich (2010). *Recommender Systems: An Introduction*. Cambridge University Press.