Universidade do Minho
Escola de Engenharia
Departamento de Informática

Mestrado Integrado em Engenharia Informática
Mestrado em Engenharia Informática
Aprendizagem e Extração de Conhecimento
2020/2021

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ISLab
Synthetic Intelligence Lab

AEC @ 2020/2021

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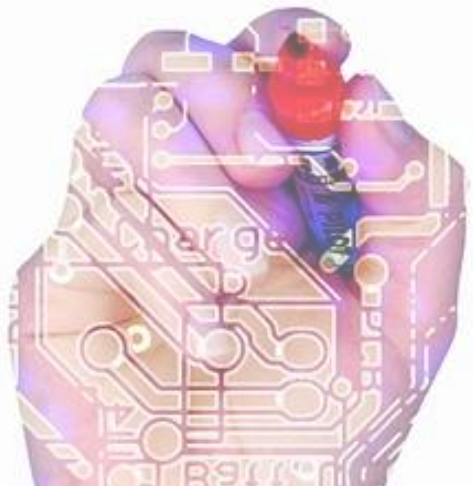
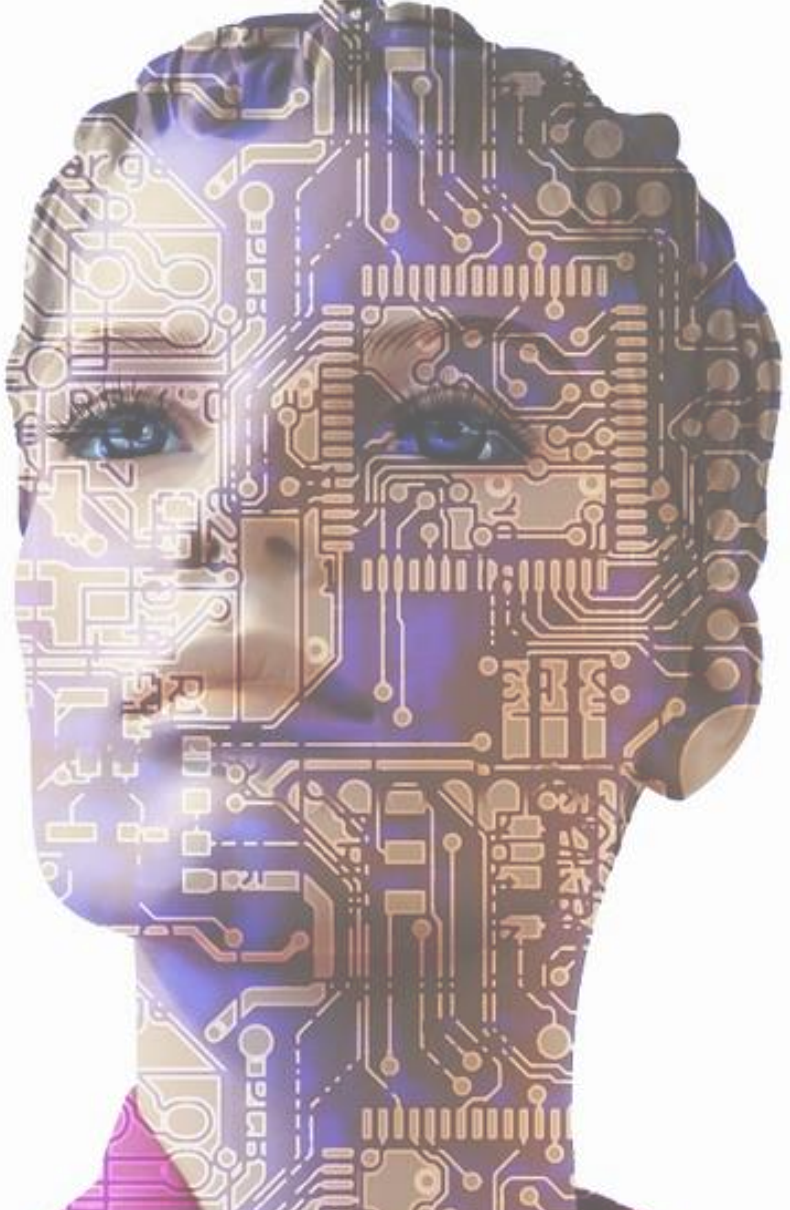
- Departamento de Informática
  Escola de Engenharia
  Universidade do Minho
- ISLab – (Synthetic Intelligence Lab)
- Centro ALGORITMI
  Universidade do Minho

K-Nearest Neighbor





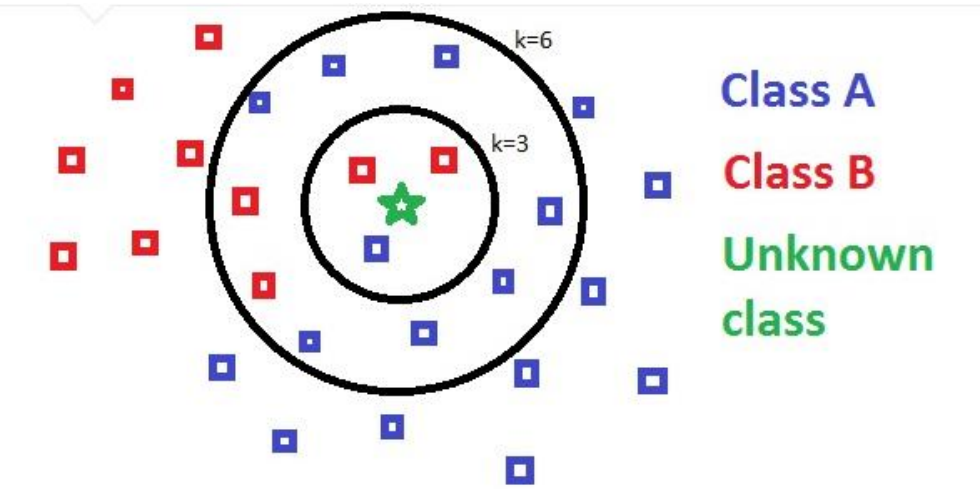
K-Nearest Neighbor (KNN)

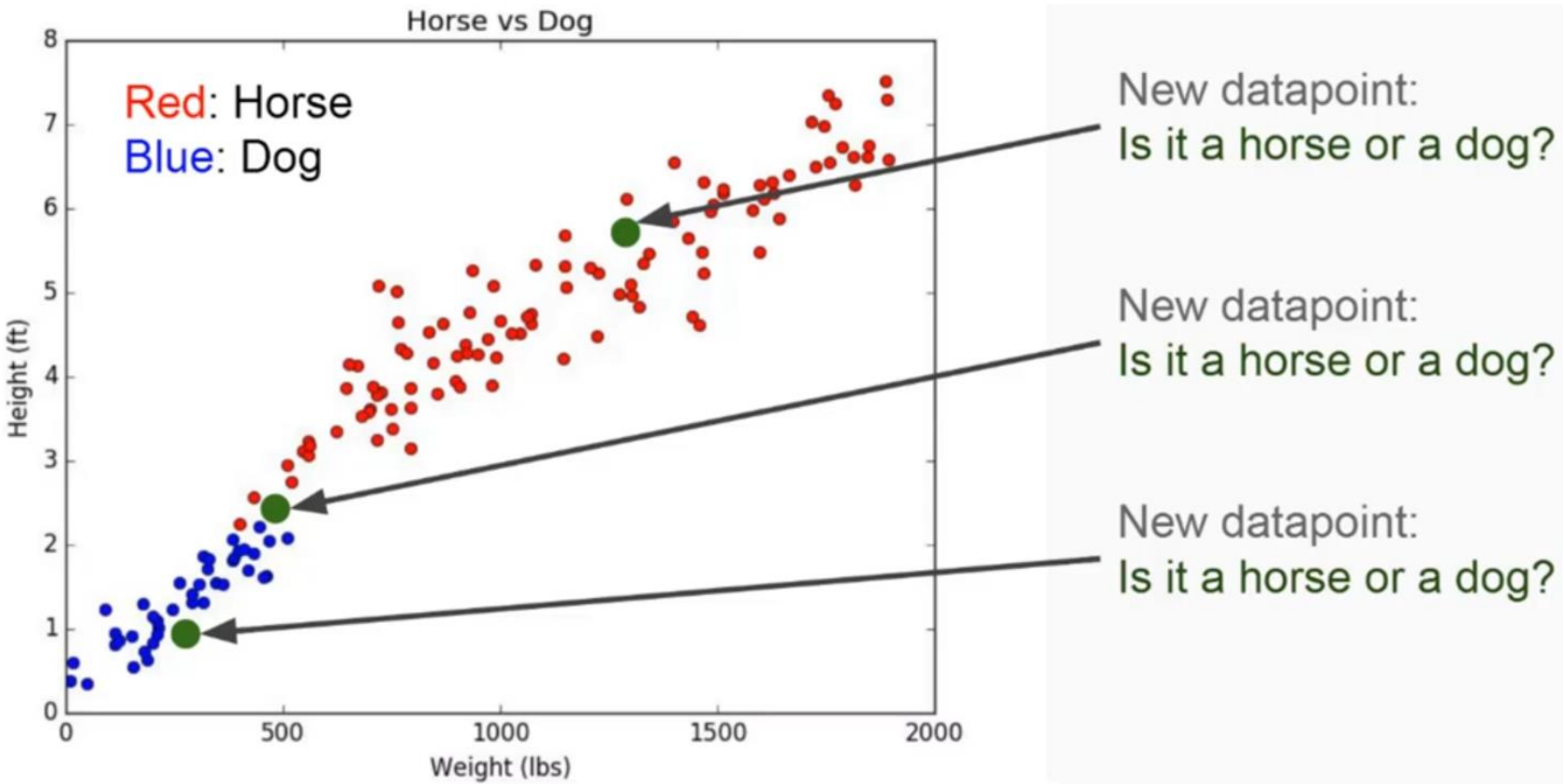
- One of the simplest machine learning models there is
  - Qualified as “supervised learning”
- Can be applied for detecting similarities between users / products
- Example:
  - Movie similarities based on metadata!

Customers Who Watched This Item Also Watched

K-Nearest Neighbor (KNN)

- Classification algorithm that operates on a very simple principle
- Best shown through the next example:
  - Image we had a dataset on Dogs and Horses, with heights and weights



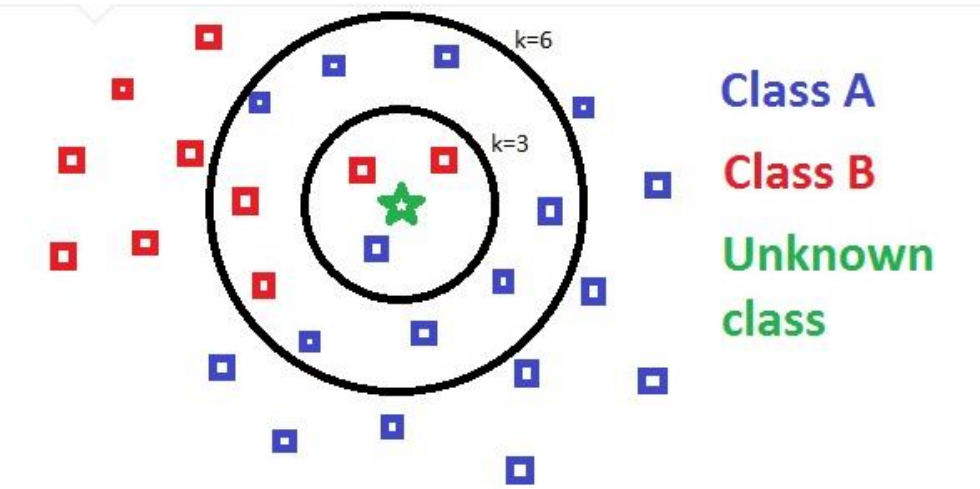

Horse vs Dog
Red: Horse
Blue: Dog
Height (ft)
Weight (lbs)
0
1
2
3
4
5
6
7
8
0
500
1000
1500
2000
New datapoint:
Is it a horse or a dog?
New datapoint:
Is it a horse or a dog?
New datapoint:
Is it a horse or a dog?

Training Algorithm:

- Store all the Data

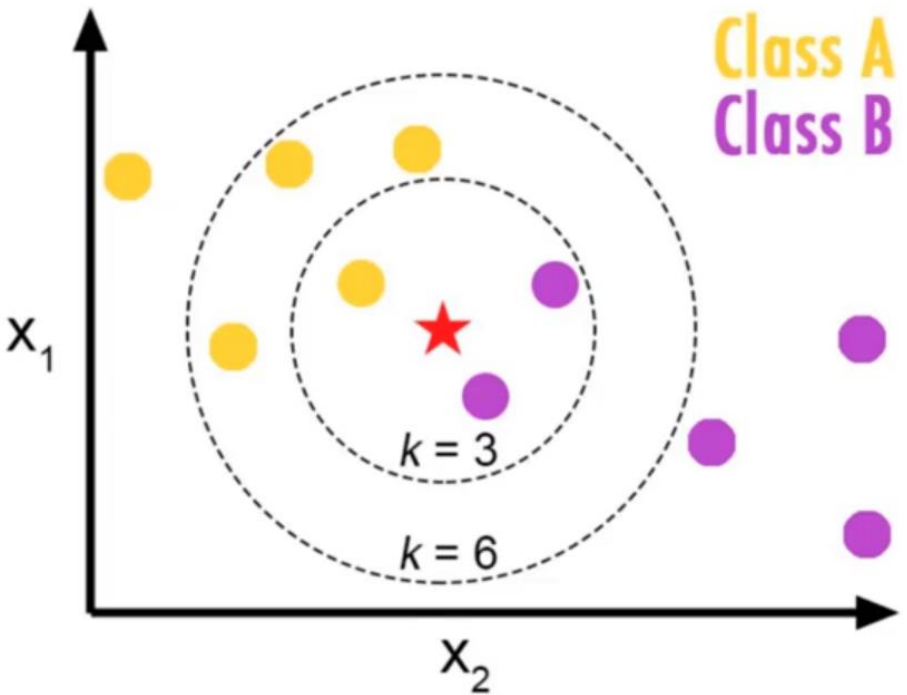
Prediction Algorithm:

- Calculate the distance from X (case to predict) to all points in your data
- Sort the points in your data by increasing distance from X
- Predict the majority label of the “k” closest points



K-Nearest Neighbor (KNN)

- Choosing a K will affect what class a new point is assigned to:



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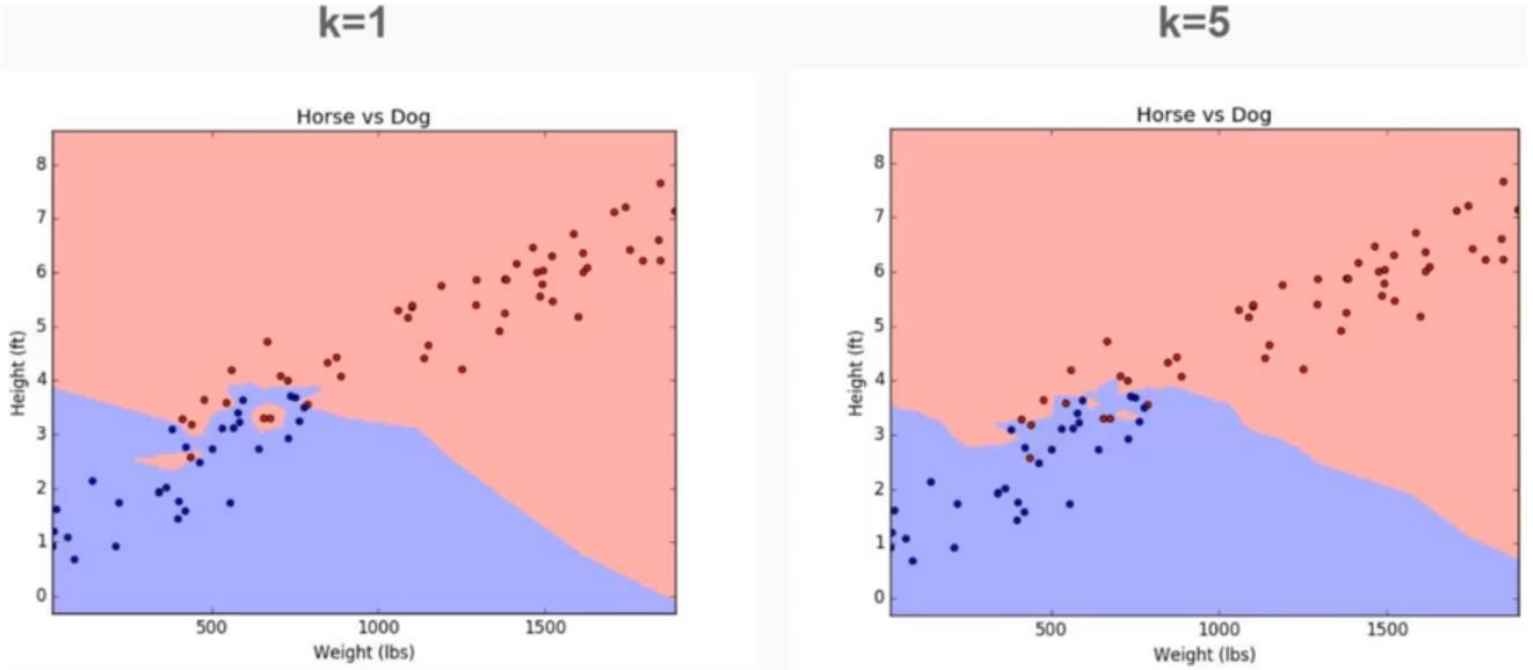

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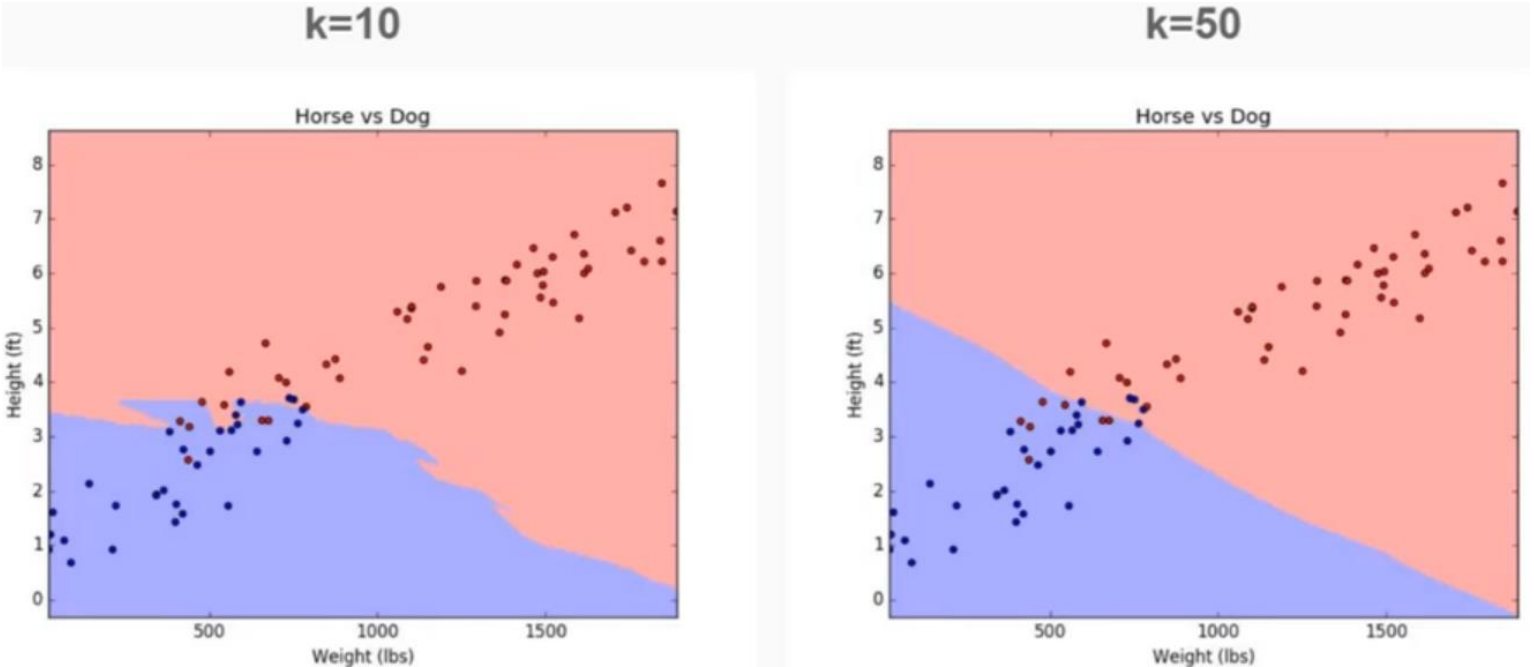
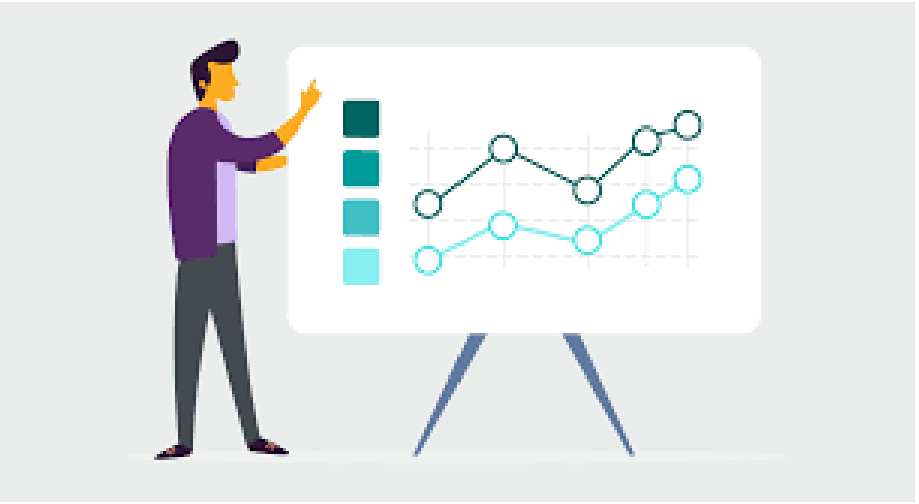


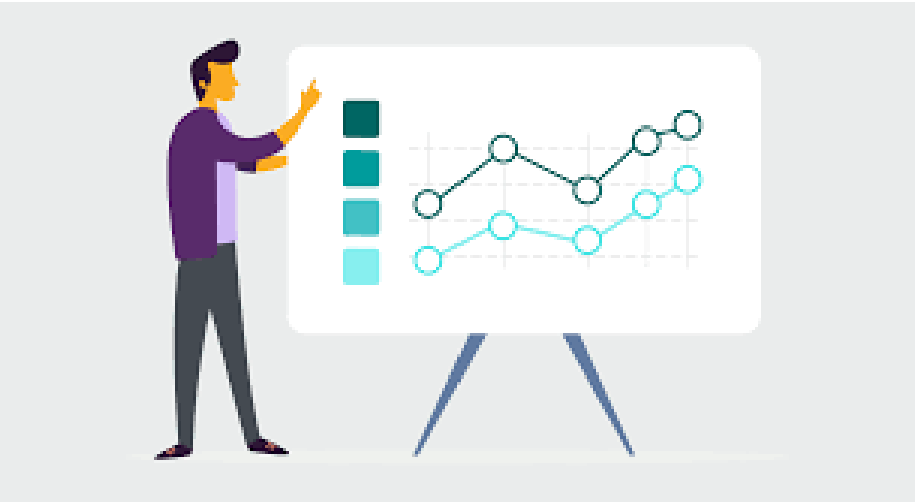
Pros:

- Very simple
- Training is trivial
- Works with any number of classes
- Easy to add more data
- Few parameters:
  - K
  - Distance Metric

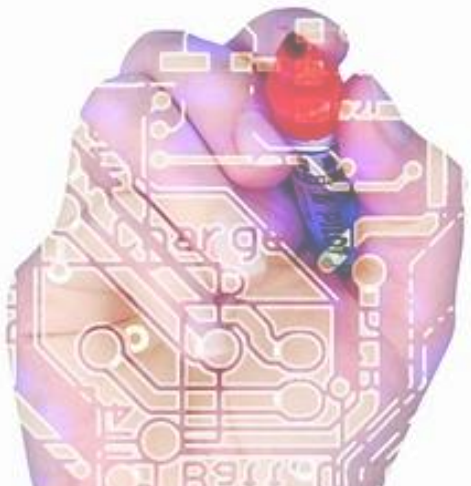


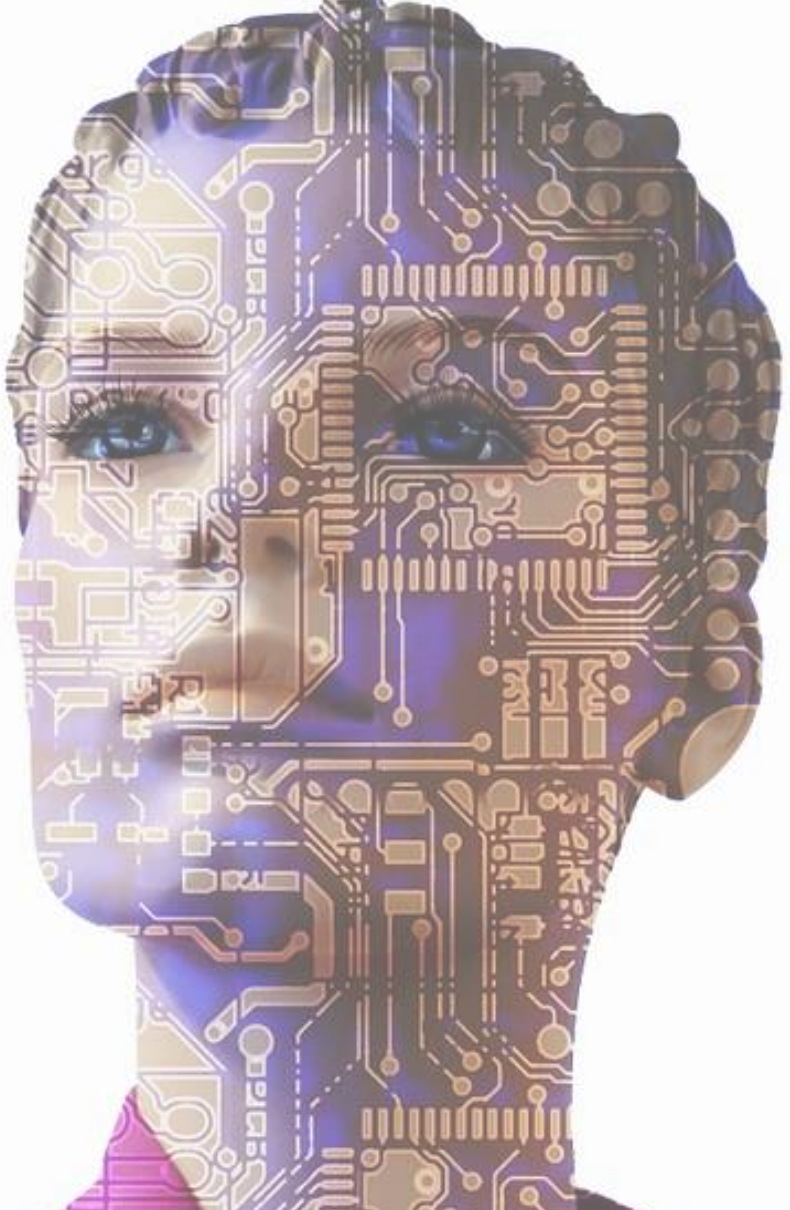
Cons:

- High Prediction Cost
  - Larger Data sets provides worse computational impact
- Not good with high dimensional data
- Categorical Features don't work well



Recommender Systems





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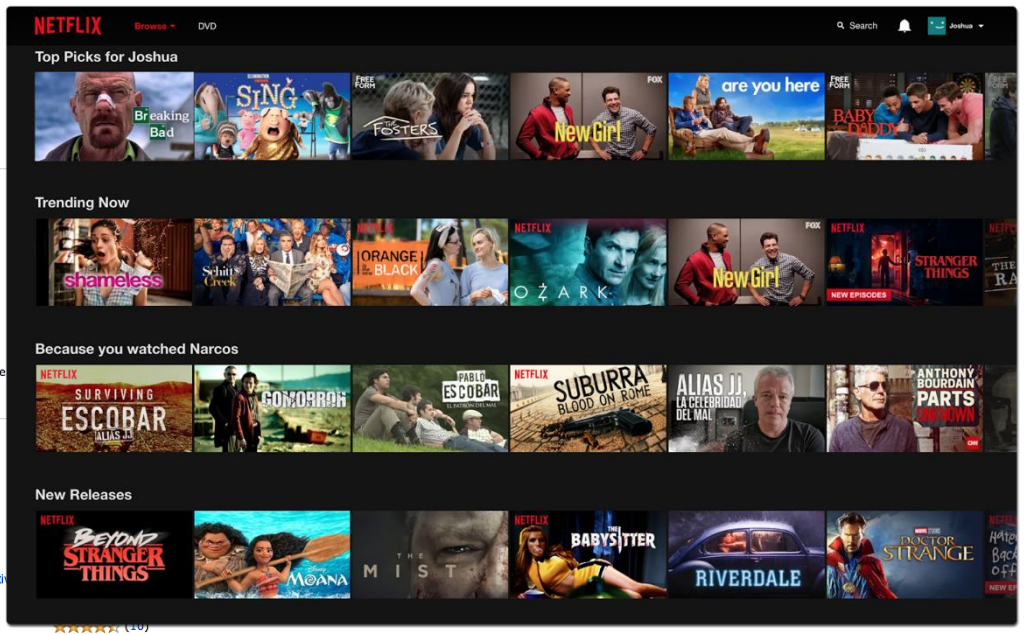
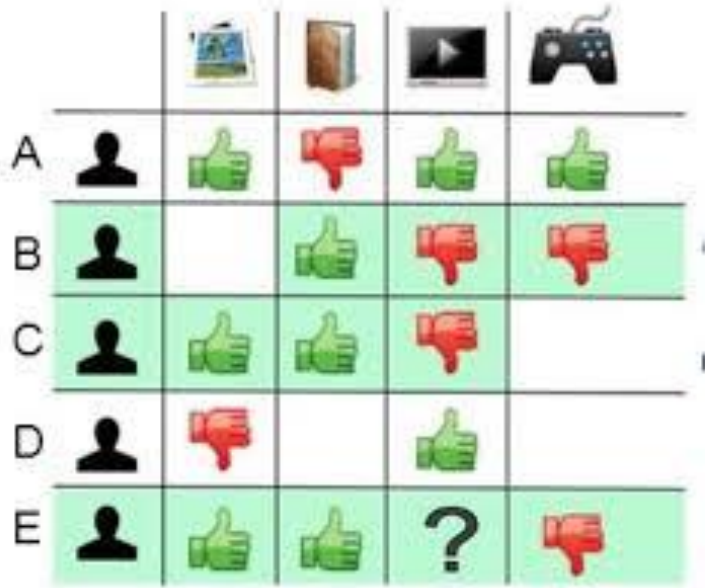
- What are recommender systems?



User-Based Collaborative Filtering

- Builds a matrix of products each user bought / viewed / rated
- Compute similarity scores between users & filter users with similar aspects (e.g., correlation based similarity, cosine-based similarity, KNN, etc.)
- Recomendation engine focuses on the users behaviours
- Recommends products past users bought / viewed / rated that the new user hasn't yet



User-Based Collaborative Filtering

Problems with User-Based CF

- New items or new users lack information about them to be compared with others.
- Users are fickle – tastes change
- There are usually many more users than products or the percentage of people who rate items is really low
    - Data sparsity problems
- People commit mistakes that may influence negatively the Recommendation Systems
- Harmful Bots may provide further negative impact
    - Define rule-based system to filter outliers / strange behaviours

What if we based recommendations on similarities between things instead of users?

- Technique called Item-Based Collaborative Filtering
    - Recomendation engine focused on similarity between items to make predictions
- Products don't present updates (contrary to user's ratings)
- There are usually fewer products than users (less computation to do)
- Harder to influence negatively the recommendation system

Item-Based Collaborative Filtering

- Analyse a product that was buyed / viewed / rated
- Measure the similarity of the respective ratings across all products (e.g., correlation based similarity, cosine-based similarity, KNN, etc.)
- Filter similar results and calculate their weighted sum

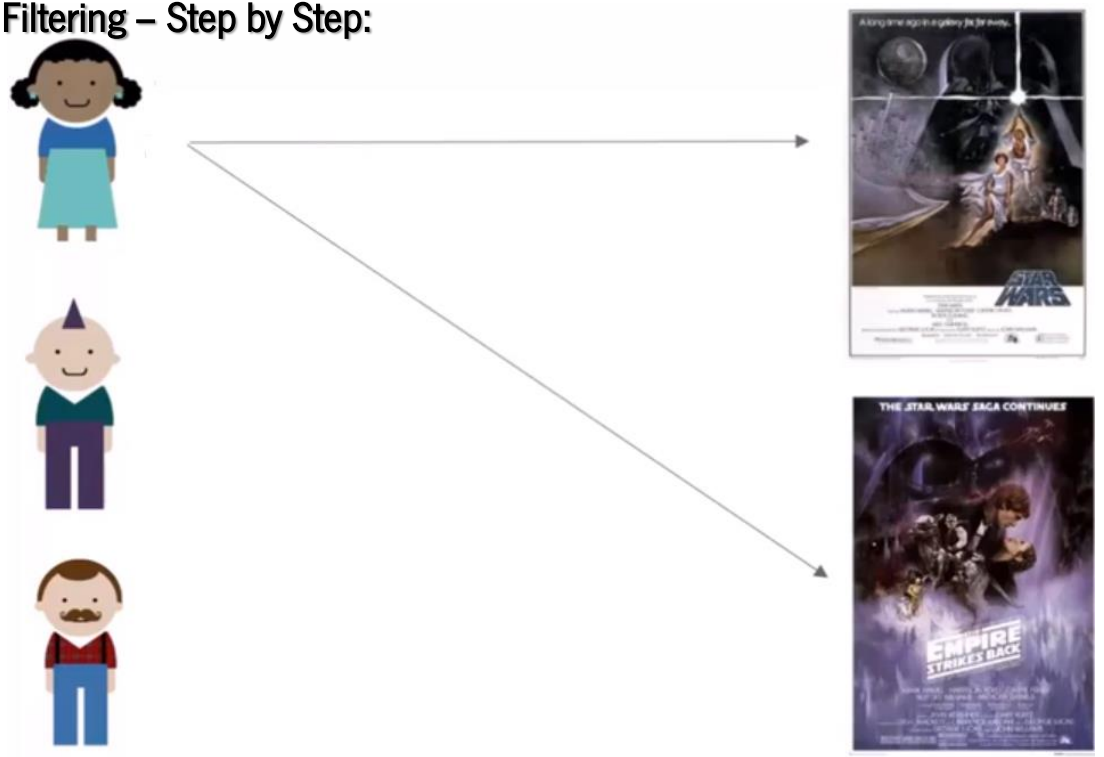
	Item 1	Item 2	Item 3	Item 4	Item 5
User 1 	8	1	?	2	7
User 2 	2	?	5	7	5
User 3 	5	4	7	4	7
User 4 	7	1	7	3	8
User 5 	1	7	4	6	?
User 6 	8	3	8	3	7

Item-Based Collaborative Filtering - Example:

- Look for items that are similar to Item5
- Take Alice's ratings for these items to predict the rating for Item5

	Item1	Item2	Item3	Item4	Item5
Alice	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

Item-Based Collaborative Filtering – Step by Step:



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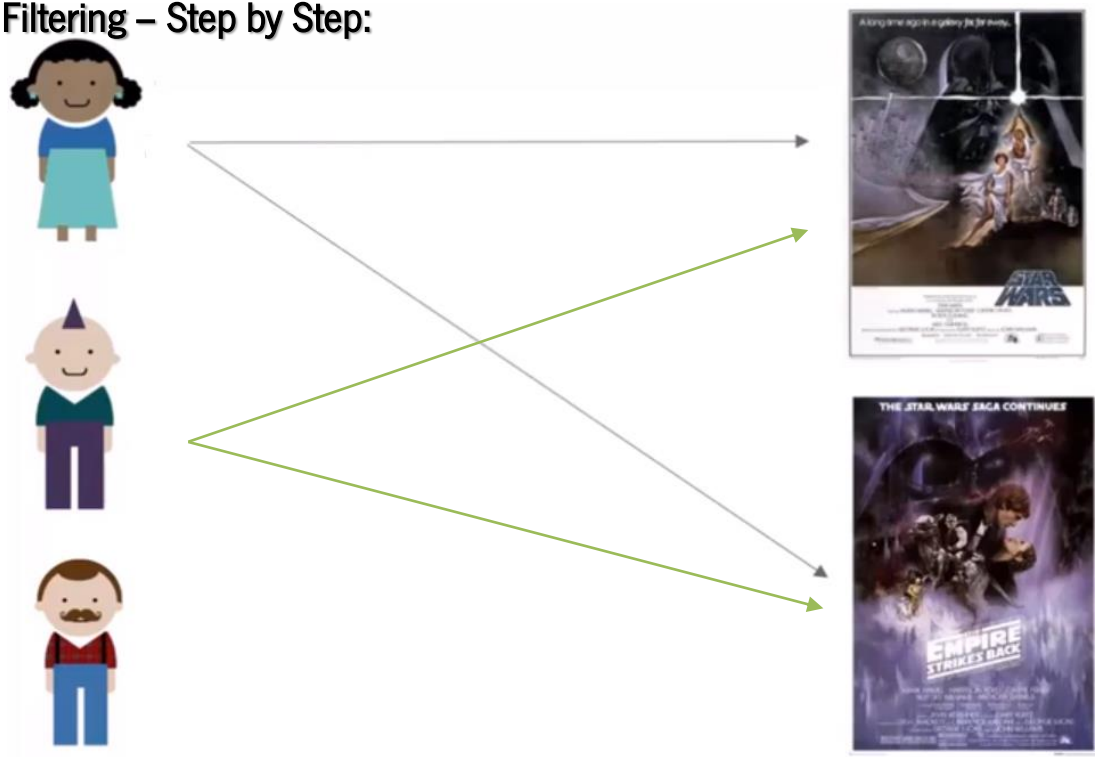

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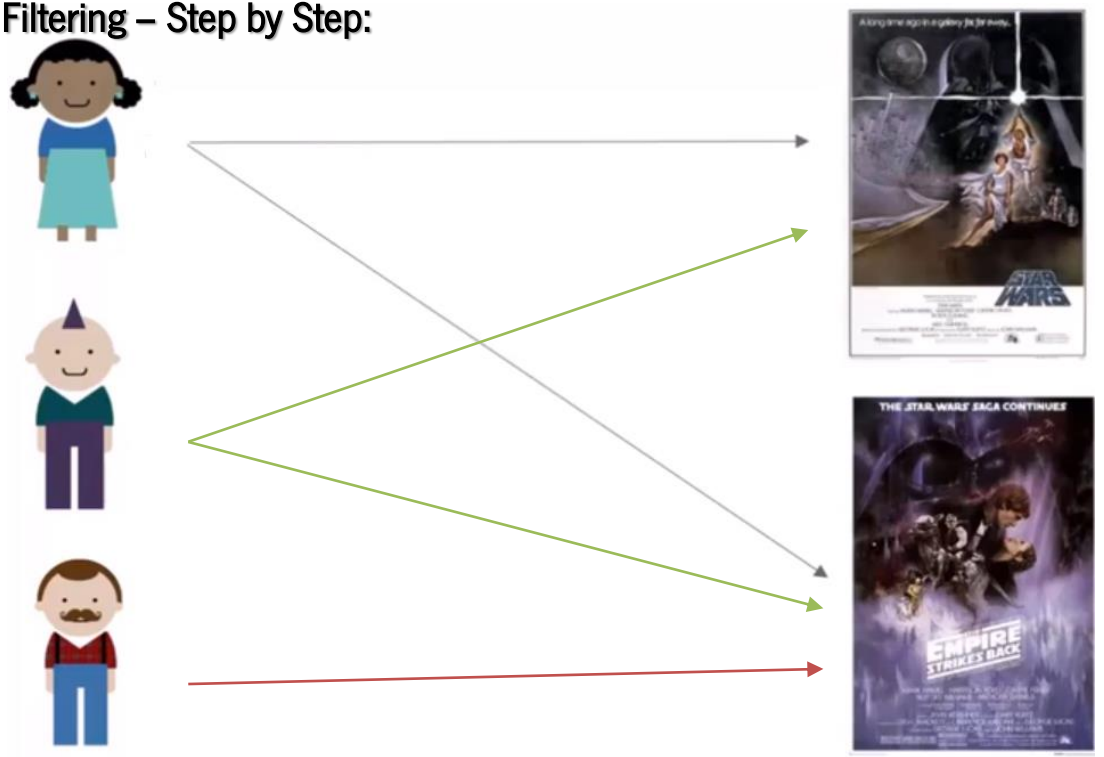

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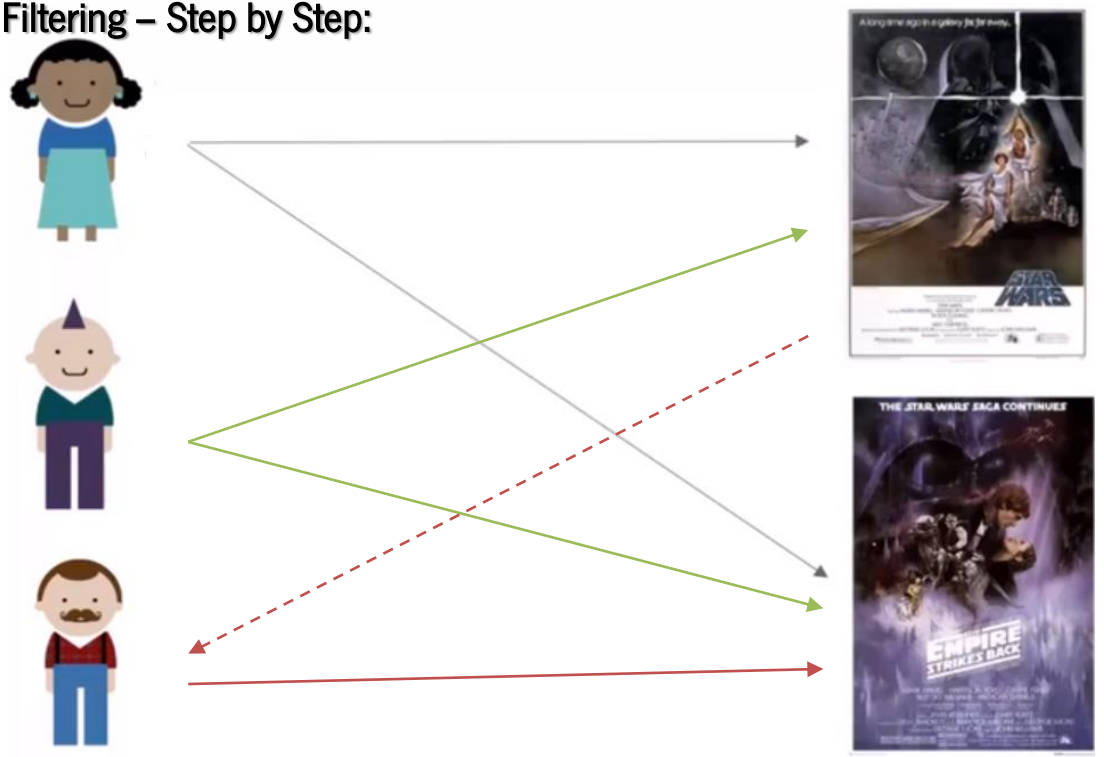
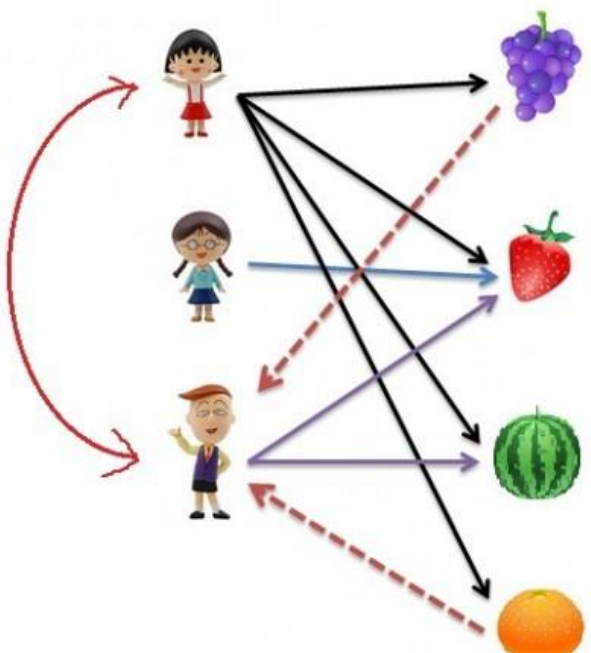
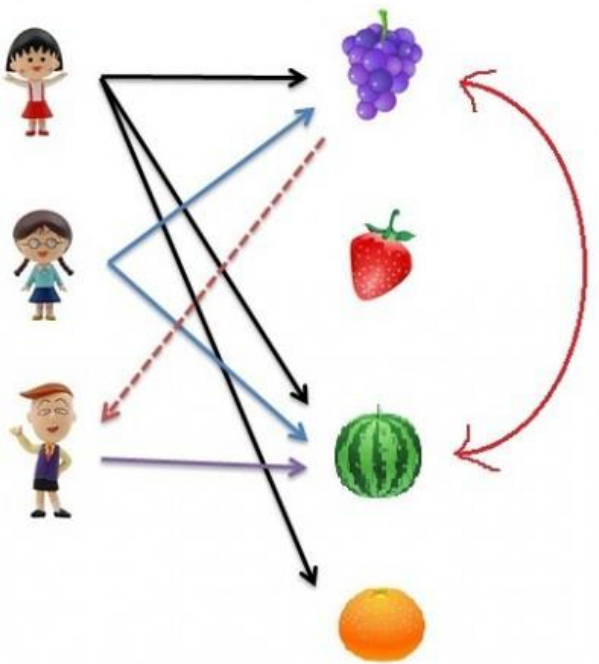


User-Based CF vs Item-Based CF:



User-based filtering



Item-based filtering

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