

# Tutorial 11

# Overview

## Recommender Systems

- Content-based Filtering
- Collaborative Filtering

## Multi-Dimensional Scaling

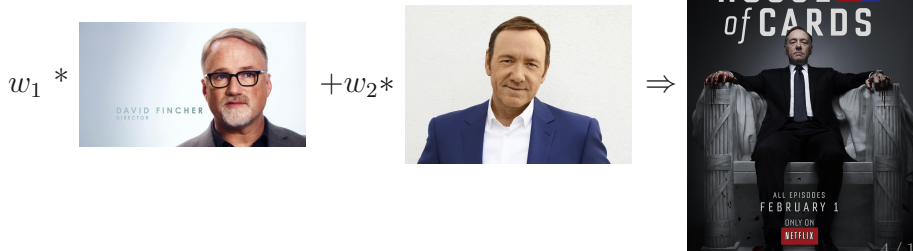
- Vanilla MDS
- MDS Variants
- ISOMAP Exercise

# Recommender Systems



# Content-based Filtering

- ▶ Supervised learning method (features & labels)
  - Features can describe users (e.g. “average amount of time spent watching netflix”) and/or items (e.g. “Romantic Comedy”, “Oscar winning”)
  - Labels are ratings
- ▶ Fit a model, then at test time recommend the item that would be rated the highest.



# Collaborative Filtering

## ► Unsupervised learning

- We are given users' ratings of items but no features of users or items
- Need to fill in the "user-item matrix"

$$Y = \begin{matrix} \text{user} & \left[ \begin{array}{cccccc} ? & 4 & 3 & 2 & 3 & 3 \\ 2 & 1 & ? & 5 & ? & 5 \\ ? & 1 & ? & 5 & 5 & 5 \\ ? & 3 & 3 & ? & ? & ? \end{array} \right] \end{matrix}$$

movie

"Green Lantern"

"Ryan Reynolds"

# Collaborative Filtering - Latent Factor Model

- ▶ Instead of prespecifying features like content-based filtering, we learn features to represent users and items

$$y_{ij} \approx w_j^T z_i$$
$$Y \approx Z_{n,k} W_{k,d}$$

- ▶  $z_i$  feature vector for each user
- ▶  $w_j$  feature vector for each movie
- ▶ Use a squared loss function with L2 regularization to train model over available ratings,  $R$

$$F(Z, W) = \sum_{(i,j) \in R} (w_j^T z_i - y_{ij})^2 + \frac{\lambda_1}{2} \|Z\|_F^2 + \frac{\lambda_2}{2} \|W\|_F^2$$

- ▶ Can also introduce bias for user, item, or both

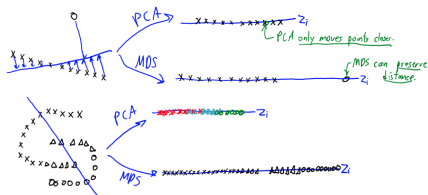
$$y_{ij} \approx w_j^T z_i + \beta + \beta_i + \beta_j$$

# Multi-Dimensional Scaling

- ▶ No latent factors, directly optimize the location of the  $z_i$  values
- ▶ Classic MDS cost function:

$$f(Z) = \sum_{i+1}^N \sum_{j=i+1}^N (\|z_i - z_j\| - \|x_i - x_j\|)^2$$

- ▶ PCA used latent factors,  $W$ , and represented the data as a **linear** combination of them
- ▶ MDS is non-parametric



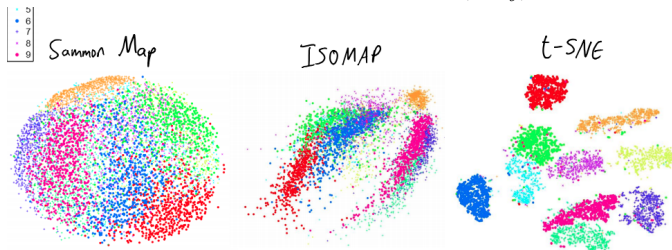
# MDS Variants

- ▶ General MDS cost function:

$$f(Z) = \sum_{i+1}^N \sum_{j=i+i}^N d_3(d_1(z_i, z_j), d_2(x_i, x_j))$$

- ▶  $d(\cdot, \cdot)$  can be
  - A norm (classic MDS)
  - Geodesic distance (ISOMAP,  $d_2$ )
    - ▶ Distance along graph formed by k-nearest neighbours
- ▶ Sammon's Mapping

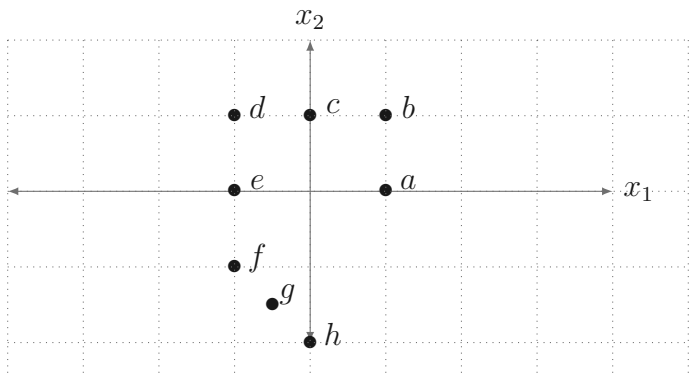
$$f(Z) = \sum_{i+1}^N \sum_{j=i+i}^N \frac{(d_1(z_i, z_j) - d_2(x_i, x_j))^2}{d_2(x_i, x_j)}$$





# ISOMAP Exercise

Create a distance matrix using geodesic distances, where  $k = 2$



## ISOMAP Exercise - Answer

	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
<i>a</i>	0	1	$\sqrt{2}$	$\sqrt{2} + 1$	$\sqrt{2} + 2$	$\sqrt{2} + 3$	$1.5\sqrt{2} + 3$	$2\sqrt{2} + 3$
<i>b</i>		0	1	2	3	4	$0.5\sqrt{2} + 4$	$\sqrt{2} + 4$
<i>c</i>			0	1	2	3	$0.5\sqrt{2} + 3$	$\sqrt{2} + 3$
<i>d</i>				0	1	2	$0.5\sqrt{2} + 2$	$\sqrt{2} + 2$
<i>e</i>					0	1	$0.5\sqrt{2} + 1$	$\sqrt{2} + 1$
<i>f</i>						0	$0.5\sqrt{2}$	$\sqrt{2}$
<i>g</i>							0	$0.5\sqrt{2}$
<i>h</i>								0