

How does this work ?

- You are an example $\mathbf{x}^{(i)}$, expressed as a vector of features
 - $\mathbf{x}_j^{(i)}$ is your "rating" for product j
- The number n of products is large
 - You have rated only a small fraction $n_i < n$
- You have *not* rated product j'
 - How can the system recommend j' to you ?

PCA to the rescue !

- Perform PCA on \mathbf{X} (m is number of users; n is number of products)
- The Principal Components are
 - "Concepts" that identify groups of products

We will

- Re-express your ratings of concrete product $\mathbf{x}^{(i)}$
- Into strength of concepts $\tilde{\mathbf{x}}^{(i)}$
- Find other users i' with similar strength of concepts
$$\tilde{\mathbf{x}}^{(i')} \approx \tilde{\mathbf{x}}^{(i)}$$
- Deduce that you (user i) have similar tastes to user i'
- Recommend to you (user i) any product j
 - where $\mathbf{x}_j^{i'}$ is high

This is roughly how Netflix recommendations work.

- Products are Movies
- Principal Components ("concepts") turn out to be Movie genres
 - Action, Comedy, Romance, Gender-specific

So if your movie preferences lean to Comedy, Netflix will recommend to you Comedy-type movies

Although this *seems* like a simple application of PCA

- There is a giant catch !
- \mathbf{X} is sparse (lots of empty entries)
 - How many of the thousands of movies in Netflix have *you* rated ?

How do we factor a matrix with undefined entries ?

Let's go to the [notebook section on Pseudo Matrix Factorization \(Unsupervised.ipynb#Recommender-Systems:-Pseudo-SVD\)](#).

Pseudo Matrix factorization wrap-up

The techniques in Pseudo factorization are a nice bridge between Classical ML and Deep Learning

- An interesting Loss function
- Not amenable to closed form solution (because of missing entries)
- But approximated using our generic optimization tool
 - Gradient Descent

This type of problem is very typical of those that we will encounter in Deep Learning.

Thus, it is a good transition.

In [4]: `print("Done")`

Done