

# From lasso to collaborative filtering and recommender systems

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MSc Data Science

## Collaborative filtering: basics

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# Collaborative filtering

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We assume that there exist an (unknown) matrix  $\mathbf{Z} \in \mathbb{R}^{m \times n}$ , which is the "true user-product matrix", that we want to recover given our observations. We therefore have

$$\forall (i, j) \in \Omega, x_{ij} = z_{ij},$$

or more realistically

$$\forall (i, j) \in \Omega, x_{ij} \approx z_{ij}.$$

**Exercise:** How could we model  $x_{ij} \approx z_{ij}$ ?

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**Exercise:** How could we model  $x_{ij} \approx z_{ij}$ ? For example, we could say that  $(x_{ij} - z_{ij})^2$  is minimised. A probabilistic approach would be

$$\forall (i, j) \in \Omega, x_{ij} = z_{ij} + \varepsilon_{ij}, \text{ with } \varepsilon_{ij} \sim \mathcal{N}(0, \sigma).$$

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This is clearly an ill-posed problem!(for now)

To be able to solve it, we need to assume that  $\mathbf{Z}$  has some sort of simple structure. We need a notion of "simple structure" for matrices. Any idea?

## Collaborative filtering

To be able to solve it, we **need to assume that  $Z$  has some sort of simple structure**. We need a notion of "simple structure" for matrices.

A first simple notion of simplicity is **a constant matrix**: all entries are identical. In a collaborative filtering context, it means all users have the exact same taste, and all products are equivalent... **This is clearly overly simple!**

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We can be a bit more general and maybe assume that **all columns (or rows) are proportional**.

The notion of **rank of a matrix** generalises these simple heuristics!

## What is the rank of a matrix?

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The **rank** is a measure of **complexity** for matrices. A matrix  $\mathbf{Z} \in \mathbb{R}^{n \times n}$  has rank  $r \in \{1, \dots, n\}$  if there exists two matrices  $\mathbf{U} \in \mathbb{R}^{n \times r}$  and  $\mathbf{V} \in \mathbb{R}^{r \times n}$  such that

$$\mathbf{Z} = \mathbf{U}\mathbf{V}^T.$$

Intuitively, it means that we can describe the matrix with only  $2nr$  coefficients, rather than  $n^2$ . So when  $r$  is small there is a huge gain...

An equivalent definition is that **the rank of  $\mathbf{Z}$  is the number of nonzero eigenvalues of  $\mathbf{Z}^T\mathbf{Z}$ .**

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- A matrix  $\mathbf{Z}$  of rank 1 can be written  $\mathbf{Z} = \mathbf{u}\mathbf{v}^T$ . This gives

$$\mathbf{Z} = \mathbf{u}(v_1, \dots, v_n) = (v_1\mathbf{u}, \dots, v_n\mathbf{u}),$$

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$$\mathbf{Z} = \mathbf{u}(v_1, \dots, v_n) = (v_1\mathbf{u}, \dots, v_n\mathbf{u}),$$

which means that **the columns of  $\mathbf{Z}$  are proportional**. Similarly, we can write

$$\mathbf{Z} = (u_1, \dots, u_n)^T \mathbf{v} = (u_1\mathbf{v}, \dots, u_n\mathbf{v})^T,$$

which means that **the rows of  $\mathbf{Z}$  are proportional**.

## Collaborative filtering with low-rank matrices

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A way to have a well posed problem: add the assumption that the "true matrix" should have low-rank  $k$ ! This makes sense because it means that there are just a few factors of variation. In particular, we recover the naive solutions of the previous slides.

$$\hat{\mathbf{Z}} \in \operatorname{argmin}_{\mathbf{Z} \in \mathbb{R}^{m \times n}} \sum_{(i,j) \in \Omega} (z_{ij} - x_{ij})^2 + \lambda \operatorname{rank}(\mathbf{Z}).$$

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is unfortunately a super hard combinatorial problem to solve, because the rank is the **number of non-zero singular values of  $Z$** .

**Exercise:** Can we replace this number of nonzeros by something smooth and convex?

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**Exercise:** Can we replace this number of nonzeros by something smooth and convex?

Yes! The  $\ell_1$  norm of the singular values, it's called the **nuclear norm**:

$$\|Z\|_* = \sum_{i=1}^{\min(n,m)} \lambda(Z)_i.$$

Like for the lasso, we replaced a **number of nonzero elements by a  $\ell_1$  norm**.

## Collaborative filtering with the nuclear norm

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The new problem is then:

$$\hat{\mathbf{Z}} \in \operatorname{argmin}_{\mathbf{Z} \in \mathbb{R}^{m \times n}} \sum_{(i,j) \in \Omega} (z_{ij} - x_{ij})^2 + \lambda \|\mathbf{Z}\|_*$$

It's convex and **very fast algorithms** exist!

We will use one called **softimpute** (Hastie, Mazumder, Lee, & Zadeh, JMLR 2015) in today's lab.