Session 2: Linear transformations and matrices

Optimization and Computational Linear Algebra for Data Science

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- 2. Operation on matrices
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- 4. Why do we care about all these things?

 Solving linear systems

Linear maps & matrices

Linear maps & matrices 1/22

Two sides of the s	ame coin
Linear map	Matrix
$L:\mathbb{R}^m o \mathbb{R}^n$	$L \in \mathbb{R}^{n \times m}$

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Linear maps & rnatrices

Two sides of the s	ame coin
Linear map	Matrix
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Linear maps & rnatrices

Rotations in \mathbb{R}^2

Let $\theta \in \mathbb{R}$. The rotation $R_{\theta} : \mathbb{R}^2 \to \mathbb{R}^2$ of angle θ about the origin is linear.

Exercise: what is the canonical matrix of R_{θ} ?

Operations on matrices

Operations on matrices 4/22

Addition and scalar multiplication

Sum of two matrices of the **same** dimensions:

$$\begin{pmatrix} a_{1,1} & \cdots & a_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,m} \end{pmatrix} + \begin{pmatrix} b_{1,1} & \cdots & b_{1,m} \\ \vdots & \ddots & \vdots \\ b_{n,1} & \cdots & b_{n,m} \end{pmatrix} = \begin{pmatrix} a_{1,1} + b_{1,1} & \cdots & a_{1,m} + b_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} + b_{n,1} & \cdots & a_{n,m} + b_{n,m} \end{pmatrix}$$

• Multiplication by a scalar λ :

$$\lambda \begin{pmatrix} a_{1,1} & \cdots & a_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,m} \end{pmatrix} = \begin{pmatrix} \lambda a_{1,1} & \cdots & \lambda a_{1,m} \\ \vdots & \ddots & \vdots \\ \lambda a_{n,1} & \cdots & \lambda a_{n,m} \end{pmatrix}$$

Operations on matrices 5/22

A new vector space!

Proposition

- $ightharpoonup \mathbb{R}^{n imes m}$ is a vector space.
- $\operatorname{dim}(\mathbb{R}^{n \times m}) =$

Proof.

Operations on matrices 6/22

Product of two matrices

Warning:

$$\begin{pmatrix} a_{1,1} & \cdots & a_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,m} \end{pmatrix} \times \begin{pmatrix} b_{1,1} & \cdots & b_{1,m} \\ \vdots & \ddots & \vdots \\ b_{n,1} & \cdots & b_{n,m} \end{pmatrix} \neq \begin{pmatrix} a_{1,1} \times b_{1,1} & \cdots & a_{1,m} \times b_{1,m} \\ \vdots & \ddots & \vdots \\ a_{n,1} \times b_{n,1} & \cdots & a_{n,m} \times b_{n,m} \end{pmatrix}$$

Operations on matrices

Matrix product

Let $L \in \mathbb{R}^{n \times m}$ and $M \in \mathbb{R}^{m \times k}$.

Definition (Matrix product)

The matrix product LM is the $n \times k$ matrix of the linear map $L \circ M$.

Matrix product

Theorem

The entries matrix product LM are given by

$$(LM)_{i,j} = \sum_{\ell=1}^m L_{i,\ell} M_{\ell,j}, \qquad \text{for } 1 \leq i \leq n \text{ and } 1 \leq j \leq k.$$

Rotations in \mathbb{R}^2

The R_a and R_b denote respectively the matrix of the rotation of angle a and b about the origin, in \mathbb{R}^2 .

Exercise: Compute the product R_aR_b .

Matrix product properties

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Operations on matrices

Kernel and image

Kernel and image 12/22

Definitions

Let $L: \mathbb{R}^m \to \mathbb{R}^n$ be a linear transformation.

Definition (Kernel)

The kernel $\mathrm{Ker}(L)$ (or nullspace) of L is defined as the set of all vectors $v \in \mathbb{R}^m$ such that L(v) = 0, i.e.

$$\operatorname{Ker}(L) \stackrel{\text{def}}{=} \{ v \in \mathbb{R}^m \, | \, L(v) = 0 \}.$$

Definition (Image)

The image $\operatorname{Im}(L)$ (or column space) of L is defined as the set of all vectors $u \in \mathbb{R}^n$ such that there exists $v \in \mathbb{R}^m$ such that L(v) = u.

Kernel and image 13/22

Pictu	Picture														

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Kernel and image

Remarks

Let $L: \mathbb{R}^m \to \mathbb{R}^n$ be a linear transformation.

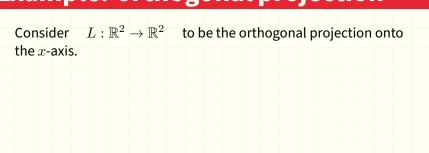
Proposition

- $ightharpoonup \operatorname{Ker}(L)$ is a subspace of \mathbb{R}^m .
- $ightharpoonup \operatorname{Im}(L)$ is a subspace of \mathbb{R}^n .

Remark: ${\rm Im}(L)$ is also the Span of the columns of the matrix representation of L.

Kernel and image 15/22

Example: orthogonal projection



Kernel and image

Why do we care about this?

Linear systems

Why do we care about this?

Assume that we given a dataset:

$$a_i = (a_{i,1}, \dots, a_{i,m}) \in \mathbb{R}^m, \quad y_i \in \mathbb{R}$$
 for $i = 1, \dots, n$.

 $x_1a_{i,1} + \dots + x_ma_{i,m} = y_i$

We would like to find $x \in \mathbb{R}^m$ such that

for all $i \in \{1, \ldots, n\}$.

Matrix notation

Why do we care about this?

Let us write			
$A = \begin{pmatrix} a_{1,1} & \cdots \\ \vdots & \ddots \\ a_{n,1} & \cdots \end{pmatrix}$	$ \begin{vmatrix} a_{1,m} \\ \vdots \\ a_{n,m} \end{vmatrix} \in \mathbb{R}^{n \times m} $	and	$y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \in \mathbb{R}^n.$

3 possible cases

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Why do we care about this?

 $A = \begin{pmatrix} 1 & -1 & 0 & 1 \\ 2 & 0 & 1 & -1 \\ -1 & 5 & 2 & 0 \end{pmatrix} \in \mathbb{R}^{n \times m} \quad \text{and} \quad y = \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix} \in \mathbb{R}^{n}.$

Why do we care about this?

Gaussian elimination

Gaussian elimination

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Questions?