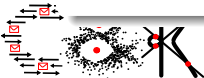
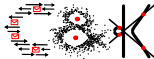


## Orthogonal projections

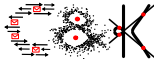
- If  $V \subseteq \mathbb{R}^d$ , then  $V^\perp := \{y \in \mathbb{R}^d \mid \forall x \in V : \langle y, x \rangle = 0\}$  is the orthogonal complement of  $V$





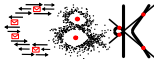
## Orthogonal projections

- If  $V \subseteq \mathbb{R}^d$ , then  $V^\perp := \{y \in \mathbb{R}^d \mid \forall x \in V : \langle y, x \rangle = 0\}$  is the orthogonal complement of  $V$
- $V \cap V^\perp = \{0\}$  and for all  $x \in \mathbb{R}^d$  there exist unique  $x' \in V, x'' \in V^\perp$  with  $x = x' + x''$



## Orthogonal projections

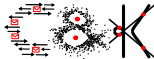
- If  $V \subseteq \mathbb{R}^d$ , then  $V^\perp := \{y \in \mathbb{R}^d \mid \forall x \in V : \langle y, x \rangle = 0\}$  is the orthogonal complement of  $V$
- $V \cap V^\perp = \{0\}$  and for all  $x \in \mathbb{R}^d$  there exist unique  $x' \in V, x'' \in V^\perp$  with  $x = x' + x''$
- $\pi_V : \mathbb{R}^d \rightarrow V, \pi_V(x) = x'$ , orthogonal projection onto  $V$ ,  $x''$  denoted  $\pi_V(x)^\perp$ .



## Orthogonal projections

- If  $V \subseteq \mathbb{R}^d$ , then  $V^\perp := \{y \in \mathbb{R}^d \mid \forall x \in V : \langle y, x \rangle = 0\}$  is the orthogonal complement of  $V$
- $V \cap V^\perp = \{0\}$  and for all  $x \in \mathbb{R}^d$  there exist unique  $x' \in V, x'' \in V^\perp$  with  $x = x' + x''$
- $\pi_V : \mathbb{R}^d \rightarrow V, \pi_V(x) = x'$ , orthogonal projection onto  $V$ ,  $x''$  denoted  $\pi_V(x)^\perp$ .
- If  $\dim(V) = 1, V = \text{span}(v)$ , then

$$\pi_V(x) = \frac{\langle x, v \rangle}{\langle v, v \rangle} v \quad \text{and} \quad \pi_V(x)^\perp = x - \frac{\langle x, v \rangle}{\langle v, v \rangle} v$$

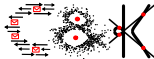


## Problem 5.1 ( $k$ -variance problem)

Given  $P \subset \mathbb{R}^d$ ,  $|P| = n$  and  $k \in \mathbb{N}$ , Find the  $k$ -dimensional subspace  $V_k$  that minimizes

$$D(P, V) := \sum_{p \in P} \|p - \pi_V(p)\|^2.$$

The subspace  $V_k$  is called the ( $k$ -dimensional) singular value decomposition of  $P$ .



## Lemma 5.2

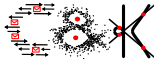
For all  $P \subset \mathbb{R}^d$

$$V_k = \operatorname{argmin}_{V: \dim(V)=k} \{D(P, V)\}$$

$$\Leftrightarrow V_k = \operatorname{argmax}_{V: \dim(V)=k} \left\{ \sum_{p \in P} \|\pi_V(p)\|^2 \right\}.$$

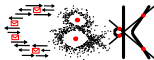
More generally, for every subspace  $V \subseteq \mathbb{R}^d$

$$D(P, V) = \sum_{q \in P} \|q\|^2 - \sum_{q \in P} \|\pi_V(q)\|^2.$$



## Theorem 5.3

*For every  $P \subset \mathbb{R}^d$  and  $k \in \mathbb{N}$  the subspace  $V_k$  minimizing  $D(P, V)$  can be computed efficiently.*



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## Lemma 5.4

*For every  $P \subset \mathbb{R}^d$  and  $k \in \mathbb{N}$*

$$D(P, V_k) \leq \text{opt}_k(P).$$





## Spectral algorithms

Given  $P \subset \mathbb{R}^d$ ,

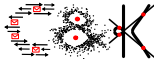
- 1** compute the singular value decomposition  $V_k$ , i.e. the subspace minimizing  $D(P, V)$ ,
- 2** solve your favorite clustering problem with your favorite algorithm on input  $\pi_{V_k}(P) := \{\pi_{V_k}(p) : p \in P\}$ ,
- 3** return the solution found in the previous step.



## Definition 5.5

Let  $V \subseteq \mathbb{R}^d$  be a  $k$ -dimensional subspace of  $\mathbb{R}^d$  and let  $B = \{v_1, \dots, v_k\}$  be a basis of  $V$ . Basis  $B$  is an orthonormal basis (ONB) of  $V$  if

- 1  $\|v_i\| = 1, i = 1, \dots, k$
- 2  $\langle v_i, v_j \rangle = 0$  for  $i \neq j, i, j = 1, \dots, n$ .



## Definition 5.5

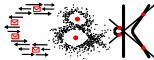
Let  $V \subseteq \mathbb{R}^d$  be a  $k$ -dimensional subspace of  $\mathbb{R}^d$  and let  $B = \{v_1, \dots, v_k\}$  be a basis of  $V$ . Basis  $B$  is an orthonormal basis (ONB) of  $V$  if

- 1  $\|v_i\| = 1, i = 1, \dots, k$
- 2  $\langle v_i, v_j \rangle = 0$  for  $i \neq j, i, j = 1, \dots, n$ .

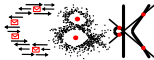
## Theorem 5.6

Every subspace  $V \subseteq \mathbb{R}^d$  has an orthonormal basis. Moreover, any orthonormal basis of  $V$  can be extended to an orthonormal basis of  $\mathbb{R}^d$ .

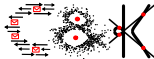
# Length-preserving linear maps



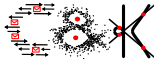
- $V \subseteq \mathbb{R}^d$  subspace with orthonormal basis  $B_V = \{v_1, \dots, v_k\}$ .



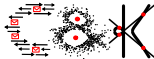
- $V \subseteq \mathbb{R}^d$  subspace with orthonormal basis  $B_V = \{v_1, \dots, v_k\}$ .
- $U \in \mathbb{R}^{k \times d}$  matrix with rows  $v_1^T, \dots, v_k^T$ .



- $V \subseteq \mathbb{R}^d$  subspace with orthonormal basis  $B_V = \{v_1, \dots, v_k\}$ .
- $U \in \mathbb{R}^{k \times d}$  matrix with rows  $v_1^T, \dots, v_k^T$ .
- $\Pi_V$  denotes function  $\Pi_V : \mathbb{R}^d \rightarrow \mathbb{R}^k, x \mapsto U \cdot x$



- $V \subseteq \mathbb{R}^d$  subspace with orthonormal basis  $B_V = \{v_1, \dots, v_k\}$ .
- $U \in \mathbb{R}^{k \times d}$  matrix with rows  $v_1^T, \dots, v_k^T$ .
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- $V \subseteq \mathbb{R}^d$  subspace with orthonormal basis  $B_V = \{v_1, \dots, v_k\}$ .
- $U \in \mathbb{R}^{k \times d}$  matrix with rows  $v_1^T, \dots, v_k^T$ .
- $\Pi_V$  denotes function  $\Pi_V : \mathbb{R}^d \rightarrow \mathbb{R}^k, x \mapsto U \cdot x$

## Theorem 5.7

*The linear function  $\Pi_V$  has the following properties:*

- 1  $\Pi_V$  is surjective.
- 2  $\Pi_V$  is length-preserving on  $V$ , i.e. for all  $x \in V : \|x\| = \|\Pi_V(x)\|$ .





## Spectral algorithms

Given  $P \subset \mathbb{R}^d$ ,

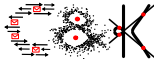
- 1** compute the singular value decomposition  $V_k$ , i.e. the subspace minimizing  $D(P, V)$ ,
- 2** solve your favorite clustering problem with your favorite algorithm on input  $\pi_{V_k}(P) := \{\pi_{V_k}(p) : p \in P\}$ ,
- 3** return the solution found in the previous step.



## Spectral algorithms

Given  $P \subset \mathbb{R}^d$ ,

- 1 compute the singular value decomposition  $V_k$ , i.e. the subspace minimizing  $D(P, V)$ ,
- 2 solve your favorite clustering problem with your favorite algorithm on input  $\pi_{V_k}(P) := \{\pi_{V_k}(p) : p \in P\}$ , i.e. compute an orthonormal basis for  $V_k$  and apply your favorite clustering algorithm on the set  $\Pi_{V_k}(\pi_{V_k}(P))$
- 3 return the solution found in the previous step.

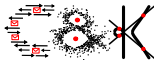


### Lemma 5.8

Let  $P \subset \mathbb{R}^d$  and let  $V$  be an arbitrary  $k$ -dimensional subspace of  $\mathbb{R}^d$ . Then

$$\text{opt}_k(\pi_V(P)) \leq \text{opt}_k(P),$$

where  $\text{opt}_k(P)$  denotes the cost of an optimal solution of  $k$ -means with input  $P$ .



## Lemma 5.9

Let  $P \subset \mathbb{R}^d$  and let  $V$  be an arbitrary  $k$ -dimensional subspace of  $\mathbb{R}^d$ . Assume  $\hat{\mathcal{C}} = \{\hat{C}_1, \dots, \hat{C}_k\}$  is a  $k$ -clustering of  $\pi_V(P)$  and denote by  $\mathcal{C} := \{C_1, \dots, C_k\}$  with  $C_i := \{p \in P : \pi_V(p) \in \hat{C}_i\}$ , the corresponding  $k$ -clustering of  $P$ . Then

$$\text{cost}(\pi_V(P), \hat{\mathcal{C}}) \leq \text{cost}(P, \mathcal{C}) \leq \text{cost}(\pi_V(P), \hat{\mathcal{C}}) + D(P, V).$$



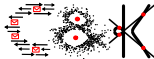
## Spectral algorithms

Given  $P \subset \mathbb{R}^d$ ,

- 1 compute the singular value decomposition  $V_k$ , i.e. the subspace minimizing  $D(P, C)$ ,
- 2 solve your favorite clustering problem with your favorite algorithm on input  $\pi_{V_k}(P) := \{\pi_{V_k}(p) : p \in P\}$ ,
- 3 return the solution found in the previous step.

## Theorem 5.10

*Let  $P \subset \mathbb{R}^d$  and let  $V_k$  be the  $k$ -dimensional subspace of  $\mathbb{R}^d$  minimizing  $D(P, V)$ . If  $\hat{C}$  is a  $\gamma$ -approximate  $k$ -clustering for  $\pi_{V_k}(P)$ , then the corresponding  $k$ -clustering  $C$  as defined in the previous lemma is a  $(\gamma + 1)$ -approximate  $k$ -clustering for  $P$ .*



---

## EXACT-K-MEANS( $P, k$ )

---

Compute the set  $K$  of sets of  $t$  hyperplanes with  $k \leq t \leq \binom{k}{2}$  where each hyperplane contains  $d$  affinely independent points from  $P$ ;

**for**  $S \in K$  **do**

    check that  $S$  defines an arrangement of exactly  $k$  cells;

**for** all assignments  $a_S$  of points of  $P$  on hyperplanes in  $S$  to cells **do**

**for** all cells **do**

            compute the centroid of points of  $P$  in the cell;

**end**

$C_{S, a_S} :=$  set of centroids computed in the previous step;

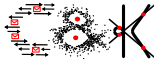
**end**

$C_S := \operatorname{argmin}_{C_{S, a_S}} \{D(P, C_{S, a_S})\}$ ;

**end**

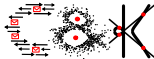
**return**  $\operatorname{argmin}_{C_S} \{D(P, C_S)\}$ ;

---



## Theorem 5.11

*Algorithm EXACT-K-MEANS solves the  $k$ -means problem optimally in time  $O(n^{dk^2/2})$ .*



---

SPECTRAL-K-MEANS( $P, k$ )

---

Compute  $V_k := \operatorname{argmin}_{V: \dim(V)=k} \{D(P, V)\}$ ;

$\bar{C} := \text{EXACT-K-MEANS}(\pi_{V_k}(P), k)$ ;

**return**  $\bar{C}$ ;

---





---

SPECTRAL-K-MEANS( $P, k$ )

---

Compute  $V_k := \operatorname{argmin}_{V: \dim(V)=k} \{D(P, V)\}$ ;

$\bar{C} := \text{EXACT-K-MEANS}(\pi_{V_k}(P), k)$ ;

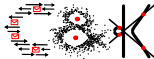
**return**  $\bar{C}$ ;

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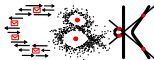
## Theorem 5.12

SPECTRAL-K-MEANS is an approximation algorithm for the  $k$ -means problem with running time  $O(n \cdot d^2 + n^{k^3/2})$  and approximation factor 2.

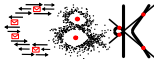
# Matrix representation of point sets



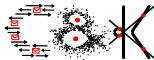
- $P = \{p_1, \dots, p_n\} \subset \mathbb{R}^d$



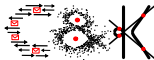
- $P = \{p_1, \dots, p_n\} \subset \mathbb{R}^d$
- matrix  $A \in \mathbb{R}^{d \times n}$  with columns  $p_i$  called *matrix representation* of  $P$



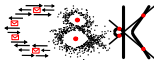
- $P = \{p_1, \dots, p_n\} \subset \mathbb{R}^d$
- matrix  $A \in \mathbb{R}^{d \times n}$  with columns  $p_i$  called *matrix representation* of  $P$
- rows of  $A^T \in \mathbb{R}^{n \times d}$  are  $p_i^T$



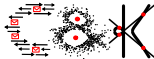
- $P = \{p_1, \dots, p_n\} \subset \mathbb{R}^d$
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- rows of  $A^T \in \mathbb{R}^{n \times d}$  are  $p_i^T$
- for every  $v \in \mathbb{R}^d$ :



- $P = \{p_1, \dots, p_n\} \subset \mathbb{R}^d$
- matrix  $A \in \mathbb{R}^{d \times n}$  with columns  $p_i$  called *matrix representation* of  $P$
- rows of  $A^T \in \mathbb{R}^{n \times d}$  are  $p_i^T$
- for every  $v \in \mathbb{R}^d$ :
  - $A^T \cdot v = (\langle p_1, v \rangle, \dots, \langle p_n, v \rangle)^T \in \mathbb{R}^n$



- $P = \{p_1, \dots, p_n\} \subset \mathbb{R}^d$
- matrix  $A \in \mathbb{R}^{d \times n}$  with columns  $p_i$  called *matrix representation* of  $P$
- rows of  $A^T \in \mathbb{R}^{n \times d}$  are  $p_i^T$
- for every  $v \in \mathbb{R}^d$ :
  - $A^T \cdot v = (\langle p_1, v \rangle, \dots, \langle p_n, v \rangle)^T \in \mathbb{R}^n$
  - $\|A^T \cdot v\|^2 = v^T \cdot A \cdot A^T \cdot v = \sum_{i=1}^n \langle p_i, v \rangle^2$

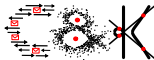


## Theorem 5.13

For every set of points  $P \subset \mathbb{R}^d$ ,  $|P| = n$ , with matrix representation  $A \in \mathbb{R}^{d \times n}$  :

$$\operatorname{argmax}_{V: \dim(V)=k} \left\{ \sum_{p \in P} \|\pi_V(p)\|^2 \right\} =$$
$$\operatorname{argmax}_{\text{ONB } B: |B|=k} \left\{ \sum_{v \in B} v^T \cdot A \cdot A^T \cdot v \right\}$$





## Definition 5.14

*Let  $M \in \mathbb{R}^{d \times d}$ ,  $\lambda \in \mathbb{R}$  and  $v \in \mathbb{R}^d$ ,  $v \neq 0$ . Then  $\lambda$  is called an eigenvalue of  $M$  to eigenvector  $v$  (and vice versa) if  $M \cdot v = \lambda \cdot v$ .*



## Definition 5.14

Let  $M \in \mathbb{R}^{d \times d}$ ,  $\lambda \in \mathbb{R}$  and  $v \in \mathbb{R}^d$ ,  $v \neq 0$ . Then  $\lambda$  is called an eigenvalue of  $M$  to eigenvector  $v$  (and vice versa) if  $M \cdot v = \lambda \cdot v$ .

## Theorem 5.15

For every  $A \in \mathbb{R}^{d \times n}$  the matrix  $M = A \cdot A^T \in \mathbb{R}^{d \times d}$  has non-negative eigenvalues  $\lambda_1 \geq \dots \geq \lambda_d \geq 0$ . Moreover, there is an orthonormal basis  $B = \{v_1, \dots, v_d\}$  such that  $\lambda_i$  is an eigenvalue of  $M$  to eigenvector  $v_i$ ,  $i = 1, \dots, d$ .

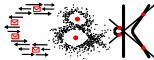


## Theorem 5.16

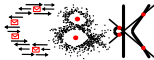
Let  $P \subset \mathbb{R}^d$  be a finite set of points with matrix representation  $A \in \mathbb{R}^{d \times n}$  and  $k \in \mathbb{N}$ . If  $A \cdot A^T$  has eigenvalues  $\lambda_1 \geq \dots \geq \lambda_d$  and  $B = \{v_1, \dots, v_d\}$  is an orthonormal basis consisting of eigenvectors, i.e.  $v_i$  is an eigenvector to eigenvalue  $\lambda_i$ ,  $i = 1 \dots, d$ , then

$$\text{span}\{v_1, \dots, v_k\} = \operatorname{argmin}_{V: \dim(V)=k} \{D(P, V)\}.$$

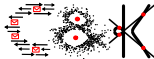
# Singular values and vectors



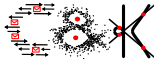
- $M \in \mathbb{R}^{n \times d}$ ,



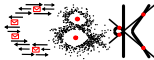
- $M \in \mathbb{R}^{n \times d}$ ,
- case  $d = n$ :  $v \in \mathbb{R}^d$  eigenvector to eigenvalue  $\sigma$  if  $M \cdot v = \sigma \cdot v$



- $M \in \mathbb{R}^{n \times d}$ ,
- case  $d = n$ :  $v \in \mathbb{R}^d$  eigenvector to eigenvalue  $\sigma$  if  
 $M \cdot v = \sigma \cdot v$
- generalization to  $n \neq d$ ?



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- case  $d = n$ :  $v \in \mathbb{R}^d$  eigenvector to eigenvalue  $\sigma$  if  $M \cdot v = \sigma \cdot v$
- generalization to  $n \neq d$ ?
- can one compute eigenvectors and eigenvalues of  $A \cdot A^T$  without computing the matrix product?



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- case  $d = n$ :  $v \in \mathbb{R}^d$  eigenvector to eigenvalue  $\sigma$  if  $M \cdot v = \sigma \cdot v$
- generalization to  $n \neq d$ ?
- can one compute eigenvectors and eigenvalues of  $A \cdot A^T$  without computing the matrix product?





- $M \in \mathbb{R}^{n \times d}$ ,
- case  $d = n$ :  $v \in \mathbb{R}^d$  eigenvector to eigenvalue  $\sigma$  if  $M \cdot v = \sigma \cdot v$
- generalization to  $n \neq d$ ?
- can one compute eigenvectors and eigenvalues of  $A \cdot A^T$  without computing the matrix product?

## Singular vectors and singular values

$\sigma \in \mathbb{R}$  is called singular value of  $M$  with corresponding singular vectors  $v \in \mathbb{R}^d, u \in \mathbb{R}^n$  if

- 1  $M \cdot v = \sigma \cdot u$
- 2  $u^T \cdot M = \sigma \cdot v^T.$



## Lemma 5.17

Let  $M \in \mathbb{R}^{n \times d}$ . Then  $\sigma \in \mathbb{R}$  is a singular value of  $M$  with corresponding singular vectors  $v \in \mathbb{R}^d$  and  $u \in \mathbb{R}^n$  if and only if

- 1  $\sigma^2$  is an eigenvalue of  $M^T \cdot M$ ,
- 2  $v$  is a right eigenvector of  $M^T \cdot M$  to eigenvalue  $\sigma^2$ ,
- 3  $u^T$  is a left eigenvector of  $M \cdot M^T$  to eigenvalue  $\sigma^2$ .