COMPSCI 514: ALGORITHMS FOR DATA SCIENCE

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University of Massachusetts Amherst. Spring 2020.

Lecture 14

Move Online:

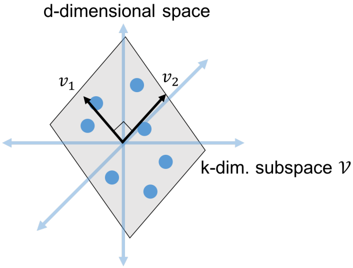
- Check out Piazza post for details about moving online.
- Lectures will be streamed and recorded. Feel free to ask questions using audio or by typing into chat. Mute when not talking.
- Feel free to turn on video, although it will be automatically off at the beginning of each lecture.
- Office hours will be over Zoom, after class on Tuesdays. `Different Zoom link.`
- Message me if you want to attend office hours but can't.
- Problem set rules will remain the same: you can submit in groups of up to three, but do not have to.

Midterm:

- Midterm grades are posted in Moodle. Average was a 30/37.
- Email me if you'd like to see your graded midterm.
- I won't release an answer key, but you can ask about midterm solutions in office hours or on Piazza.
- If you were not happy with your performance I'm happy to talk about it, and see if there are any adjustments we can make to get things on track.

LAST CLASS: EMBEDDING WITH ASSUMPTIONS

Set Up: Assume that data points $\vec{x}_1, \ldots, \vec{x}_n \in \mathbb{R}^d$ lie in some k-dimensional subspace $\mathcal{V}$ of $\mathbb{R}^d$.



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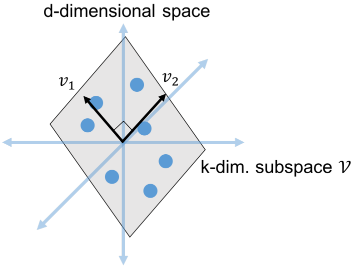

Let $\vec{v}_1, \ldots, \vec{v}_k$ be an orthonormal basis for $\mathcal{V}$ and $\mathbf{V} \in \mathbb{R}^{d \times k}$ be the matrix with these vectors as its columns.

$$\|\mathbf{V}^T\vec{x}_i - \mathbf{V}^T\vec{x}_j\|_2^2 = \|\vec{x}_i - \vec{x}_j\|_2^2.$$

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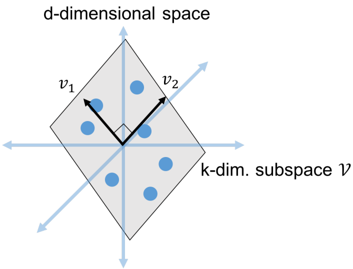

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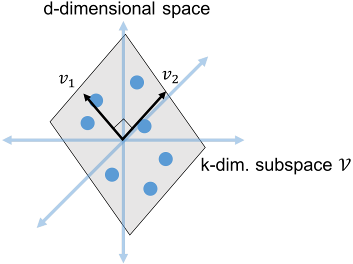
Letting $\tilde{x}_i = \mathbf{V}^T\vec{x}_i$, we have a perfect embedding from $\mathcal{V}$ into $\mathbb{R}^k$.

Main Focus of Today: Assume that data points $\vec{x}_1, \ldots, \vec{x}_n$ lie close to any k-dimensional subspace $\mathcal{V}$ of $\mathbb{R}^d$.



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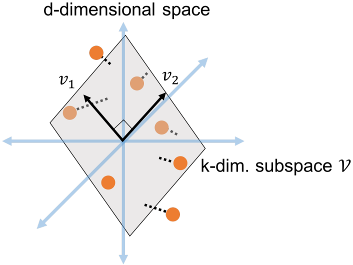

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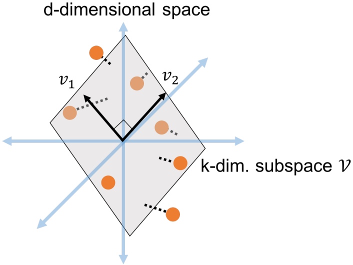

Letting $\vec{v}_1, \ldots, \vec{v}_k$ be an orthonormal basis for $\mathcal{V}$ and $\mathbf{V} \in \mathbb{R}^{d \times k}$ be the matrix with these vectors as its columns, $\mathbf{V}^T \vec{x}_i \in \mathbb{R}^k$ is still a good embedding for $x_i \in \mathbb{R}^d$.

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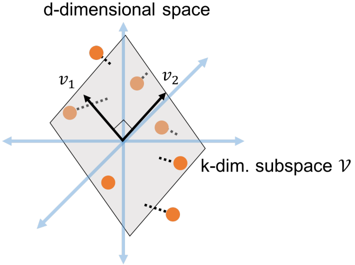

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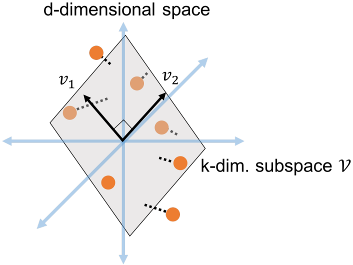

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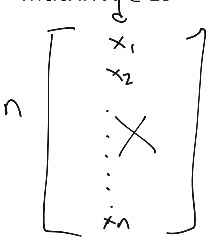
Why is this a reasonable assumption?

- How do we find $\mathcal{V}$ and $\mathbf{V}$?
- How good is the embedding?

Claim: $\vec{x}_1, \ldots, \vec{x}_n$ lie in a k-dimensional subspace $\mathcal{V} \Leftrightarrow$ the data matrix $\mathbf{X} \in \mathbb{R}^{n \times d}$ has rank $\leq k$.



(there are at most k linearly independent columns

- at most k linearly independent rows.

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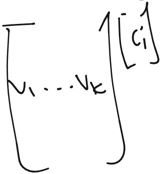
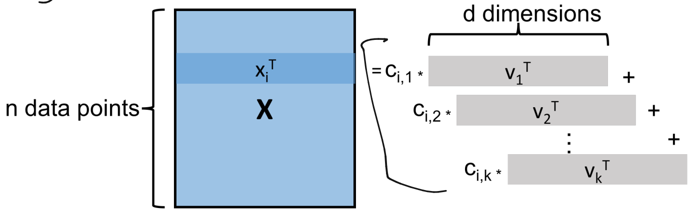


$$\vec{x}_i = \mathbf{V}\vec{c}_i = c_{i,1} \cdot \vec{v}_1 + c_{i,2} \cdot \vec{v}_2 + \ldots + c_{i,k} \cdot \vec{v}_k.$$



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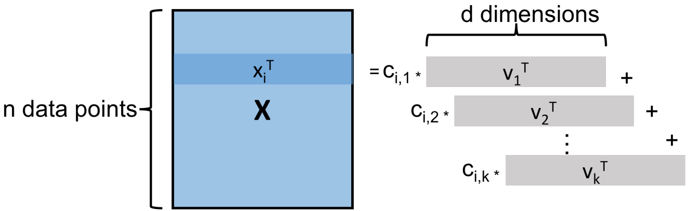
- So $\vec{v}_1, \ldots, \vec{v}_k$ span the rows of $\mathbf{X}$ and thus $\text{rank}(\mathbf{X}) \leq k$.



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- Every data point $\vec{x}_i$ (row of $\mathbf{X}$) can be written as $\vec{x}_i = \mathbf{V}\vec{c}_i = c_{i,1} \cdot \vec{v}_1 + \ldots + c_{i,k} \cdot \vec{v}_k$.

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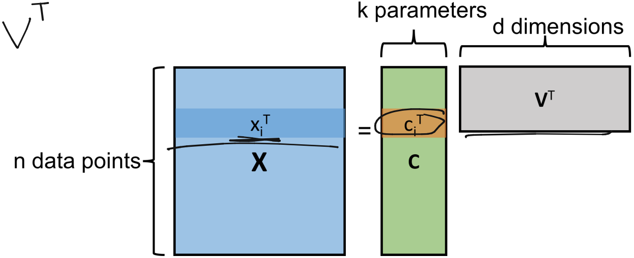
$x_i^T = c_i^T V^T$



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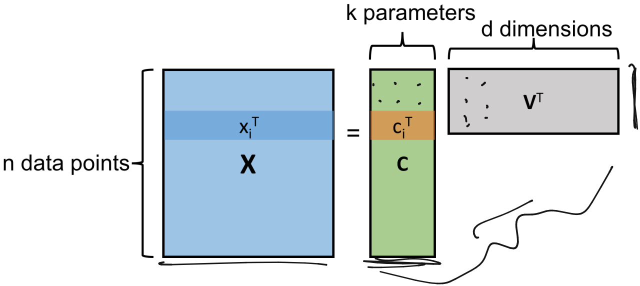

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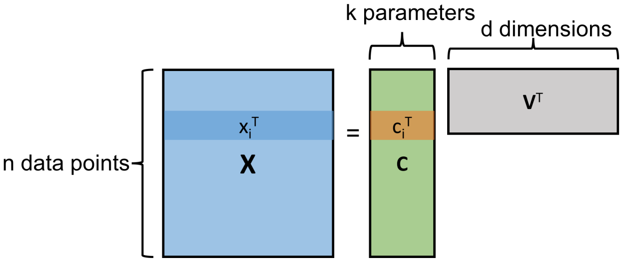
$X = CV^T$



- $\mathbf{X}$ can be represented by $(n + d) \cdot k$ parameters vs. $n \cdot d$.
- The rows of $\mathbf{X}$ are spanned by k vectors: the columns of $\mathbf{V} \implies$ the columns of $\mathbf{X}$ are spanned by k vectors: the columns of $\mathbf{C}$.

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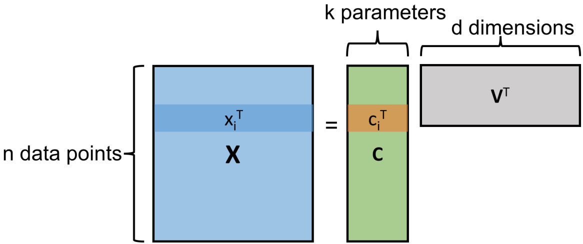

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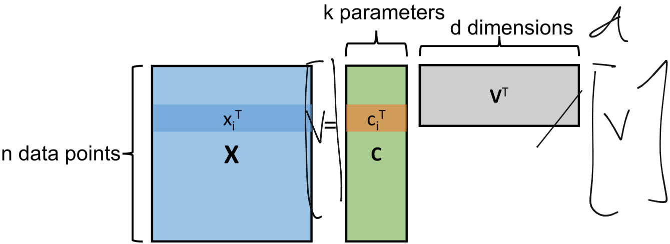

Exercise: What is this coefficient matrix $\mathbf{C}$? **Hint:** Use that $\mathbf{V}^T\mathbf{V} = \mathbf{I}$.

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LOW-RANK FACTORIZATION

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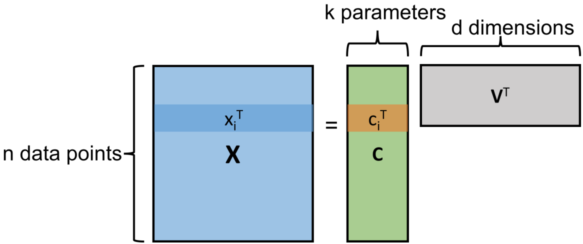

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- $\mathbf{X} = \mathbf{C}\mathbf{V}^T \implies \mathbf{X}\mathbf{V} = \mathbf{C}\mathbf{V}^T\mathbf{V}$ ($\mathbf{V}^T\mathbf{V} = I$ (because V is orthonormal))

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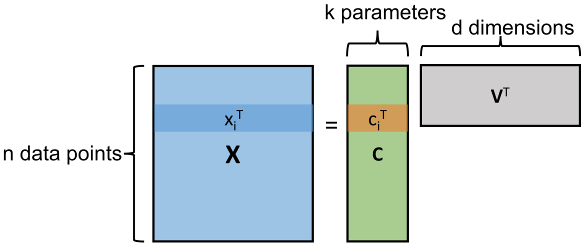

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- $\mathbf{V}^T\mathbf{V} = \mathbf{I}$, the identity (since $\mathbf{V}$ is orthonormal)

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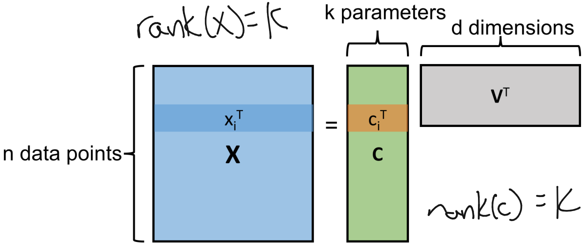

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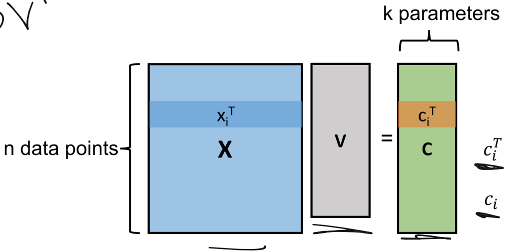
$X = BV^T$

columns of V: orthonormal
columns of C: ind.

$\tilde{x}_i = V^T x_i$



$c_i^T = x_i^T \boldsymbol{V} = \tilde{x}_i^T$

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PROJECTION VIEW

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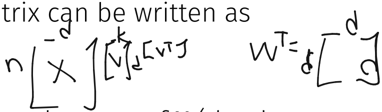

- $\mathbf{V}\mathbf{V}^T$ is a projection matrix, which projects the rows of $\mathbf{X}$ (the data points $\vec{x}_1, \ldots, \vec{x}_n$ onto the subspace $\mathcal{V}$.

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PROJECTION VIEW

Claim: If $\vec{x}_1, \ldots, \vec{x}_n$ lie in a k-dimensional subspace $\mathcal{V}$ with orthonormal basis $\mathbf{V} \in \mathbb{R}^{d \times k}$, the data matrix can be written as

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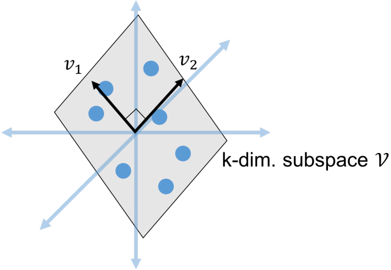

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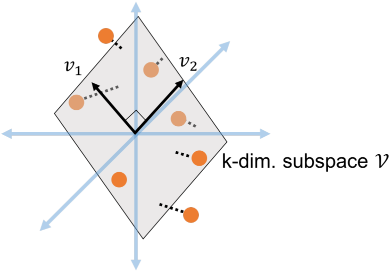

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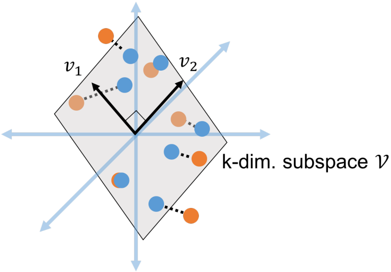

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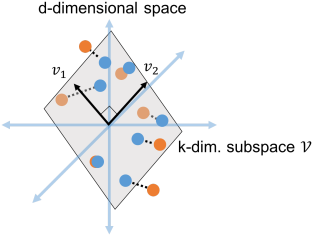
LOW-RANK APPROXIMATION

Claim: If $\vec{x}_1, \ldots, \vec{x}_n$ lie close to a k-dimensional subspace $\mathcal{V}$ with orthonormal basis $\mathbf{V} \in \mathbb{R}^{d \times k}$, the data matrix can be approximated as:

$$\mathbf{X} \approx \mathbf{X}\mathbf{V}\mathbf{V}^T$$



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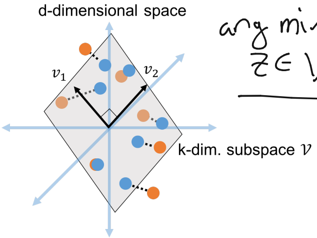
If $y \in V$ then $y = Vc$

$VV^Ty = VV^TVc = Vc = y$

For any $y \in \mathbb{R}^d$

$\arg\min_{z \in V} \|y - z\|_2^2 = VV^Ty$



Note: $\mathbf{X}\mathbf{V}\mathbf{V}^T$ has rank k. It is a low-rank approximation of $\mathbf{X}$.

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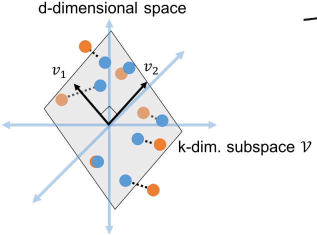
$$\|X - B\|_F^2 = \sum_{i=1}^{d} \|x_i - b_i\|_2^2$$

$$b_i = W^T x_i$$



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Frobenius norm

$$\mathbf{X}\mathbf{V}\mathbf{V}^\mathsf{T} = \underset{\mathbf{B} \text{ with rows in } \mathcal{V}}{\arg\min} \|\mathbf{X} - \mathbf{B}\|_F^2 = \sum_{i,j}^{n \cdot d} (\mathbf{X}_{i,j} - \mathbf{B}_{i,j})^2.$$

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— proj into subspace

This is the closest approximation to $\mathbf{X}$ with rows in $\mathcal{V}$ (i.e., in the column span of $\mathbf{V}$).

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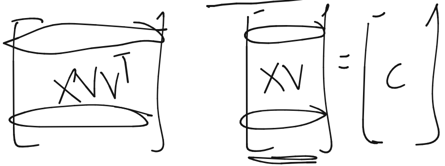

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- Can use $\mathbf{X}\mathbf{V} \in \mathbb{R}^{n \times k}$ as a compressed approximate data set.

$\mathbb{R}^d \to \mathbb{R}^k$

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Key question is how to find the subspace $\mathcal{V}$ and correspondingly $\mathbf{V}$.

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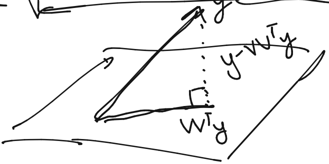
Quick Exercise: Show that $\mathbf{V}\mathbf{V}^T$ is idempotent. I.e., $(\mathbf{V}\mathbf{V}^T)(\mathbf{V}\mathbf{V}^T)\vec{y} = (\mathbf{V}\mathbf{V}^T)\vec{y}$ for any $\vec{y} \in \mathbb{R}^d$.

Why does this make sense intuitively?

Less Quick Exercise: (Pythagorean Theorem) Show that:

$$\|\vec{y}\|_2^2 = \|(\mathbf{V}\mathbf{V}^T)\vec{y}\|_2^2 + \|\vec{y} - (\mathbf{V}\mathbf{V}^T)\vec{y}\|_2^2.$$



Question: Why might we expect $\vec{x}_1, \ldots, \vec{x}_n \in \mathbb{R}^d$ to lie close to a k-dimensional subspace?

A STEP BACK: WHY LOW-RANK APPROXIMATION?

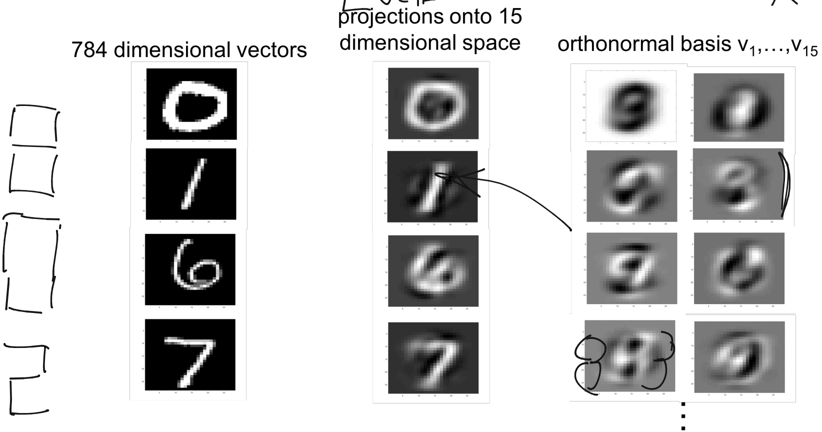
Question: Why might we expect $\vec{x}_1, \ldots, \vec{x}_n \in \mathbb{R}^d$ to lie close to a k-dimensional subspace?

- The rows of $\mathbf{X}$ can be approximately reconstructed from a basis of k vectors.

Question: Why might we expect $\vec{x}_1, \ldots, \vec{x}_n \in \mathbb{R}^d$ to lie close to a k-dimensional subspace?

- The rows of X can be approximately reconstructed from a basis of k vectors.

$\min_{V \in \mathbb{R}^{d \times k}} \|X - XVV^T\|_F^2$ X XVV^T



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DUAL VIEW OF LOW-RANK APPROXIMATION

Question: Why might we expect $\vec{x}_1, \ldots, \vec{x}_n \in \mathbb{R}^d$ to lie close to a k-dimensional subspace?

- Equivalently, the columns of **X** are approx. spanned by k vectors.

$$X \approx \underbrace{XV}_{C} V^T$$

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Linearly Dependent Variables:

	bedrooms	bathrooms	sq.ft.	floors	list price	sale price
home 1	2	2	1800	2	200,000	195,000
home 2	4	2.5	2700	1	300,000	310,000
⋮	⋮	⋮	⋮	⋮	⋮	⋮
home n	5	3.5	3600	3	450,000	450,000

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10000* bathrooms+ 10* (sq. ft.) ≈ list price

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If $\vec{x}_1, \ldots, \vec{x}_n$ are close to a k-dimensional subspace $\mathcal{V}$ with orthonormal basis $\mathbf{V} \in \mathbb{R}^{d \times k}$, the data matrix can be approximated as $\mathbf{X}\mathbf{V}\mathbf{V}^T$. $\mathbf{X}\mathbf{V}$ gives optimal embedding of $\mathbf{X}$ in $\mathcal{V}$.

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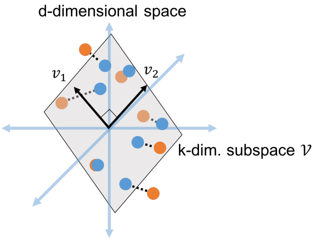

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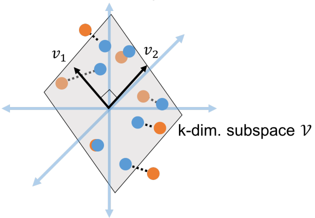

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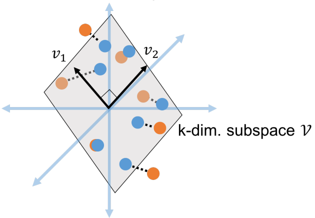

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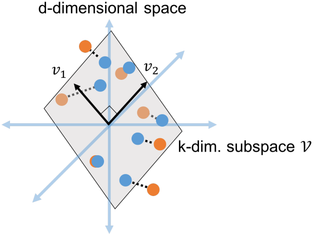

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BEST FIT SUBSPACE

$\mathbf{V}$ minimizing $\|\mathbf{X} - \mathbf{X}\mathbf{V}\mathbf{V}^T\|_F^2$ is given by:

$$\underset{\text{orthonormal } \mathbf{V} \in \mathbb{R}^{d \times k}}{\arg\max} \|\mathbf{X}\mathbf{V}\mathbf{V}^T\|_F^2 = \sum_{i=1}^{n} \|\mathbf{V}\mathbf{V}^T \vec{x}_i\|_2^2$$

$\vec{x}_1, \ldots, \vec{x}_n \in \mathbb{R}^d$: data points, $\mathbf{X} \in \mathbb{R}^{n \times d}$: data matrix, $\vec{v}_1, \ldots, \vec{v}_k \in \mathbb{R}^d$: orthogonal basis for subspace $\mathcal{V}$. $\mathbf{V} \in \mathbb{R}^{d \times k}$: matrix with columns $\vec{v}_1, \ldots, \vec{v}_k$.

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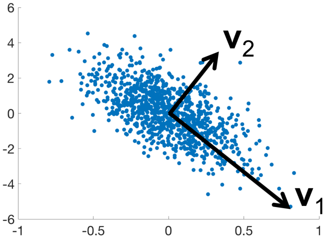

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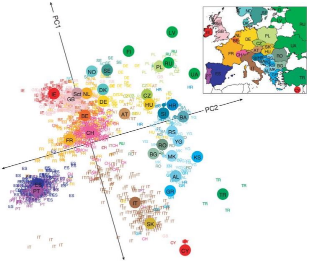

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- Can take advantage of this to do data-dependent linear dimensionality reduction (low-rank approximation.
- Dual view: both rows (data points) and columns (features) are approximated spanned by a small number of vectors.

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next class

- **Step 1:** Find this subspace by finding the directions of greatest variance in the data.
- **Step 2:** Get best approximation to the data points in this subspace via projection matrix $\mathbf{V}\mathbf{V}^T$. $\mathbf{V} \in \mathbb{R}^{d \times k}$ used as linear mapping from d-dimensional to k-dimensional space.