

EECS 16A
August 10, 2020
Lecture 7A
Grace Kuo

Today: ①
- Orthogonal Matching Pursuit (OMP)

Announcements:

- last lecture: tuesday
- last HW: 7A due wed., self grade due Thur.
- review sessions / OH
- exam format - free response

Overview:

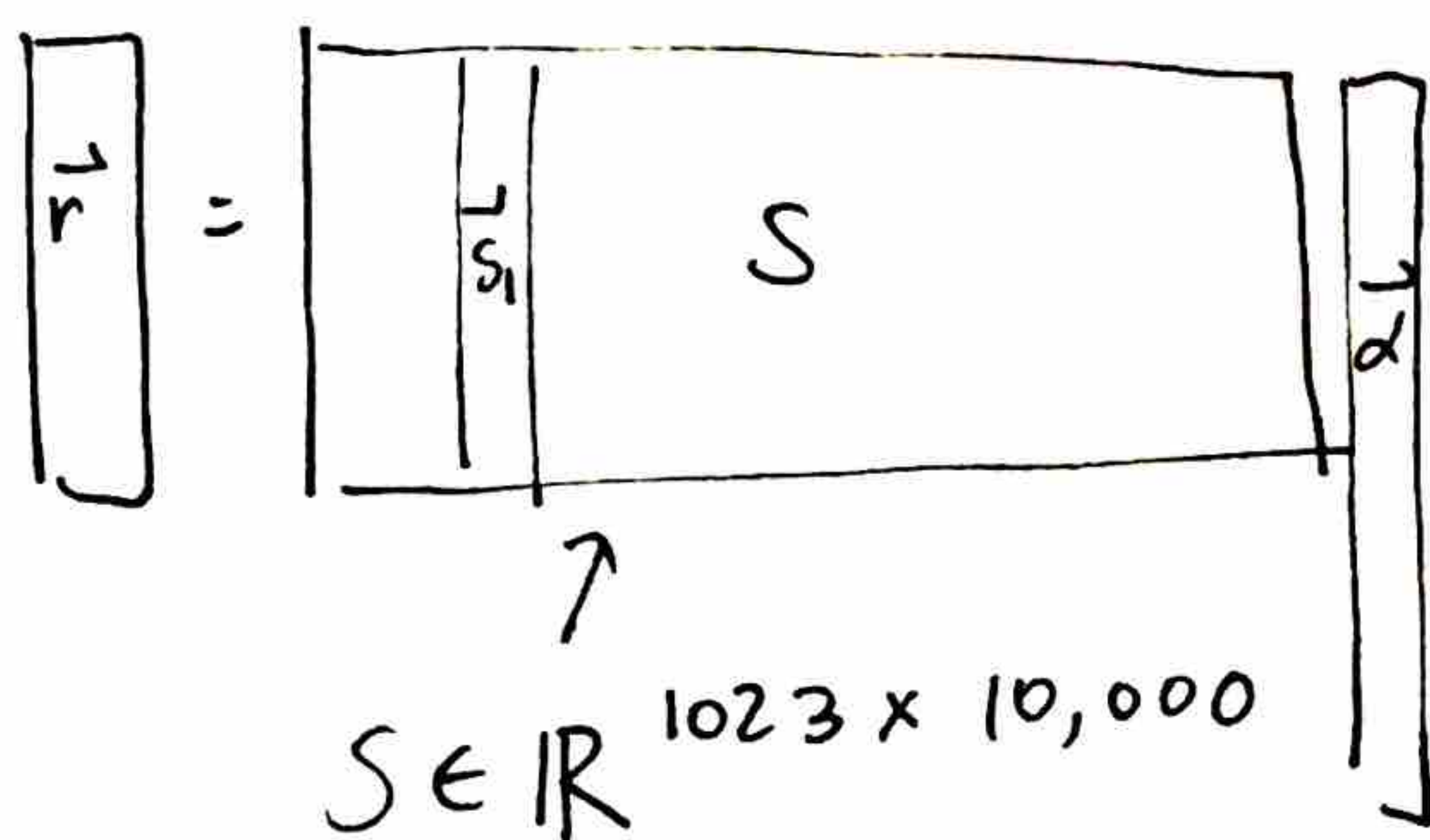
- Unique \leftarrow mod. 1, GE
- no solution \leftarrow least squares
- inf. solutions \leftarrow OMP

\uparrow "not enough information"

Application of OMP: smart city

$$\vec{r} = \alpha_1 \vec{s}_1 + \alpha_2 \vec{s}_2 + \dots + \alpha_n \vec{s}_n$$

$n = 10,000$
big number



messages \uparrow
device signature
"gold codes"
length 1023

\rightarrow we know that most devices transmit zero = α

$\hookrightarrow \vec{\alpha}$ is sparse

$\rightarrow \langle s_i, s_j \rangle \approx 0$ if $i \neq j$

OMP helps us solve problems of the form

(2)

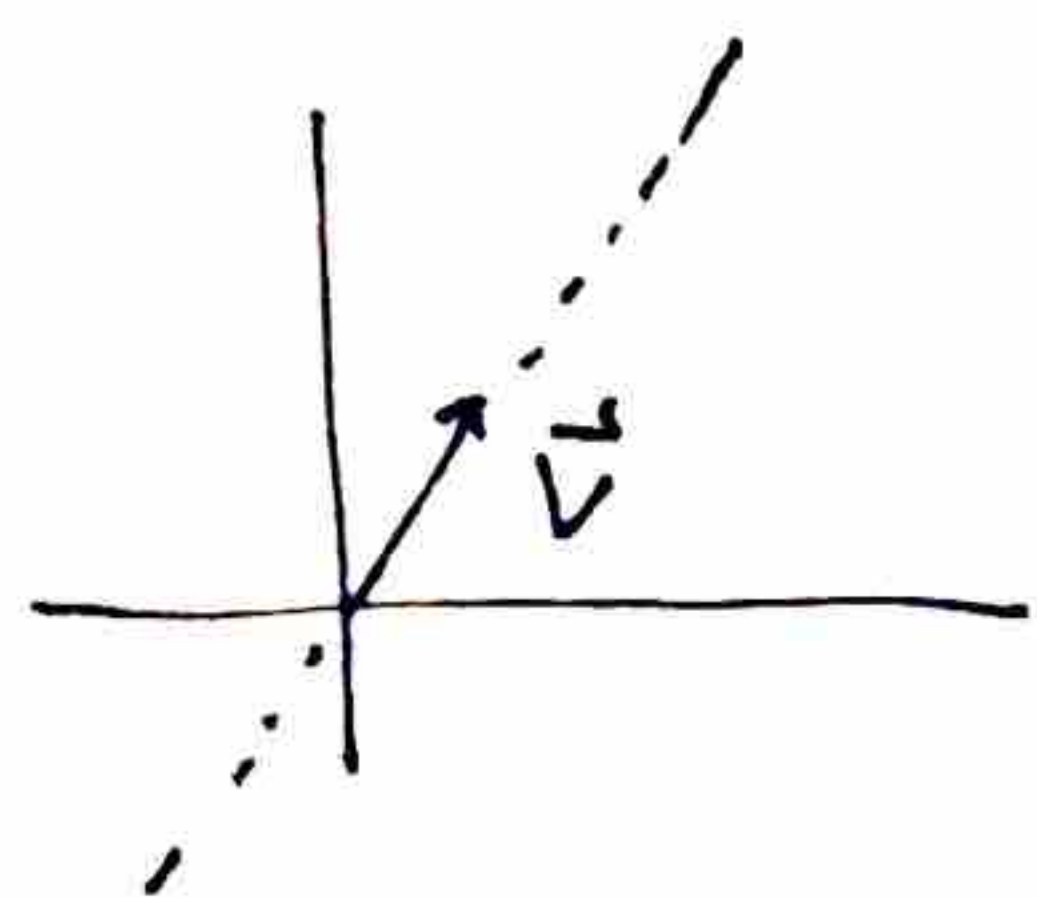
$$A\vec{x} = \vec{b} \quad A = [\vec{a}_1 \ \vec{a}_2 \ \dots \ \vec{a}_n] \quad A \in \mathbb{R}^{m \times n}$$

where

- $m < n$ ↙ not strict condition, case when most useful more columns than rows
- \vec{x} is sparse (mostly zeros)
- $\langle \vec{a}_i, \vec{a}_j \rangle \approx 0$ columns are "nearly" orthogonal
- $\|\vec{a}_1\| = \|\vec{a}_2\| = \dots = \|\vec{a}_n\|$

↙ already taken care of with gold codes

Aside: "Normalizing vectors"



$$\alpha \vec{v}$$
$$\|\alpha \vec{v}\| = |\alpha| \|\vec{v}\|$$
$$\alpha = \frac{1}{\|\vec{v}\|} \quad \|\alpha \vec{v}\| = \frac{\|\vec{v}\|}{\|\vec{v}\|} = 1$$

Back to smart city Example

$$\vec{r} = \alpha_{10} \vec{s}_{10} + \alpha_{200} \vec{s}_{200} + \alpha_5 \vec{s}_5$$

$$\begin{aligned} \text{Try } \langle \vec{r}, \vec{s}_1 \rangle &= \langle \alpha_{10} \vec{s}_{10} + \alpha_{200} \vec{s}_{200} + \alpha_5 \vec{s}_5, \vec{s}_1 \rangle \\ &= \langle \alpha_{10} \vec{s}_{10}, \vec{s}_1 \rangle + \langle \alpha_{200} \vec{s}_{200}, \vec{s}_1 \rangle + \langle \alpha_5 \vec{s}_5, \vec{s}_1 \rangle \\ &= \alpha_{10} \underbrace{\langle \vec{s}_{10}, \vec{s}_1 \rangle}_{\text{small}} + \alpha_{200} \underbrace{\langle \vec{s}_{200}, \vec{s}_1 \rangle}_{\text{small}} + \alpha_5 \underbrace{\langle \vec{s}_5, \vec{s}_1 \rangle}_{\text{small}} \end{aligned}$$

≈ 0 , small + close to zero

Try $\langle \vec{r}, \vec{s}_{10} \rangle = \alpha_{10} \underbrace{\langle \vec{s}_{10}, \vec{s}_{10} \rangle}_{\text{large, } 1023} + \alpha_{200} \underbrace{\langle \vec{s}_{200}, \vec{s}_{10} \rangle}_{\text{small}} + \alpha_5 \underbrace{\langle \vec{s}_5, \vec{s}_{10} \rangle}_{\text{small}}$

$= \text{large} \approx \alpha_{10} (1023)$

Let's design an algorithm

Plan:

\Rightarrow consider $\langle \vec{r}, \vec{s}_1 \rangle$
 \vdots
 $\langle \vec{r}, \vec{s}_{10,000} \rangle$ } Find max abs. value \rightarrow say we find $\langle \vec{r}, \vec{s}_{200} \rangle$ has the largest inner product

\downarrow
 Declare that device 200 is transmitting

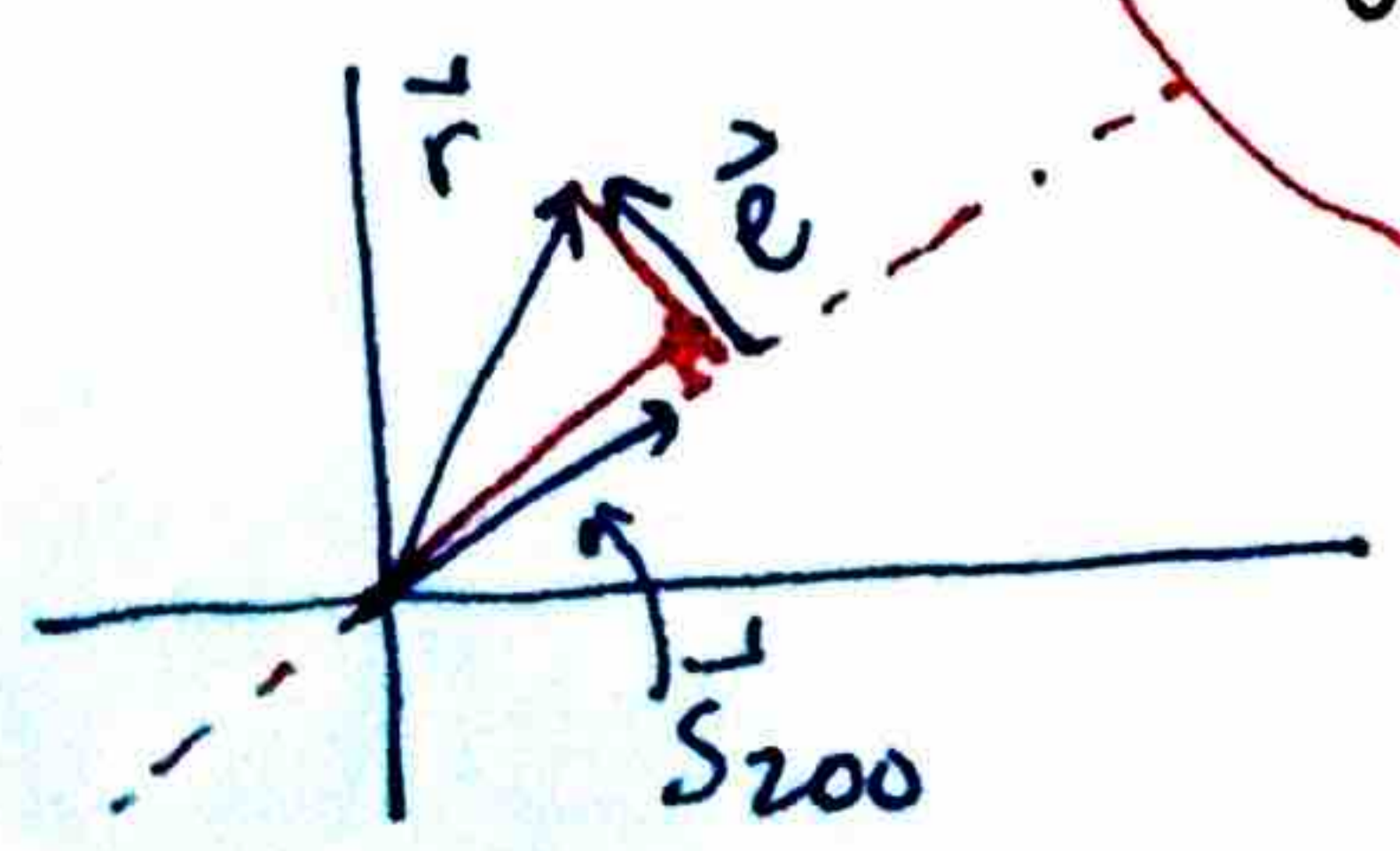
What if we get a large negative value?
 \rightarrow transmitting $-\alpha$

\Rightarrow Guess that only device 200 is transmitting
 ~~\vec{r}~~ $\vec{r} \approx \alpha_{200} \vec{s}_{200}$

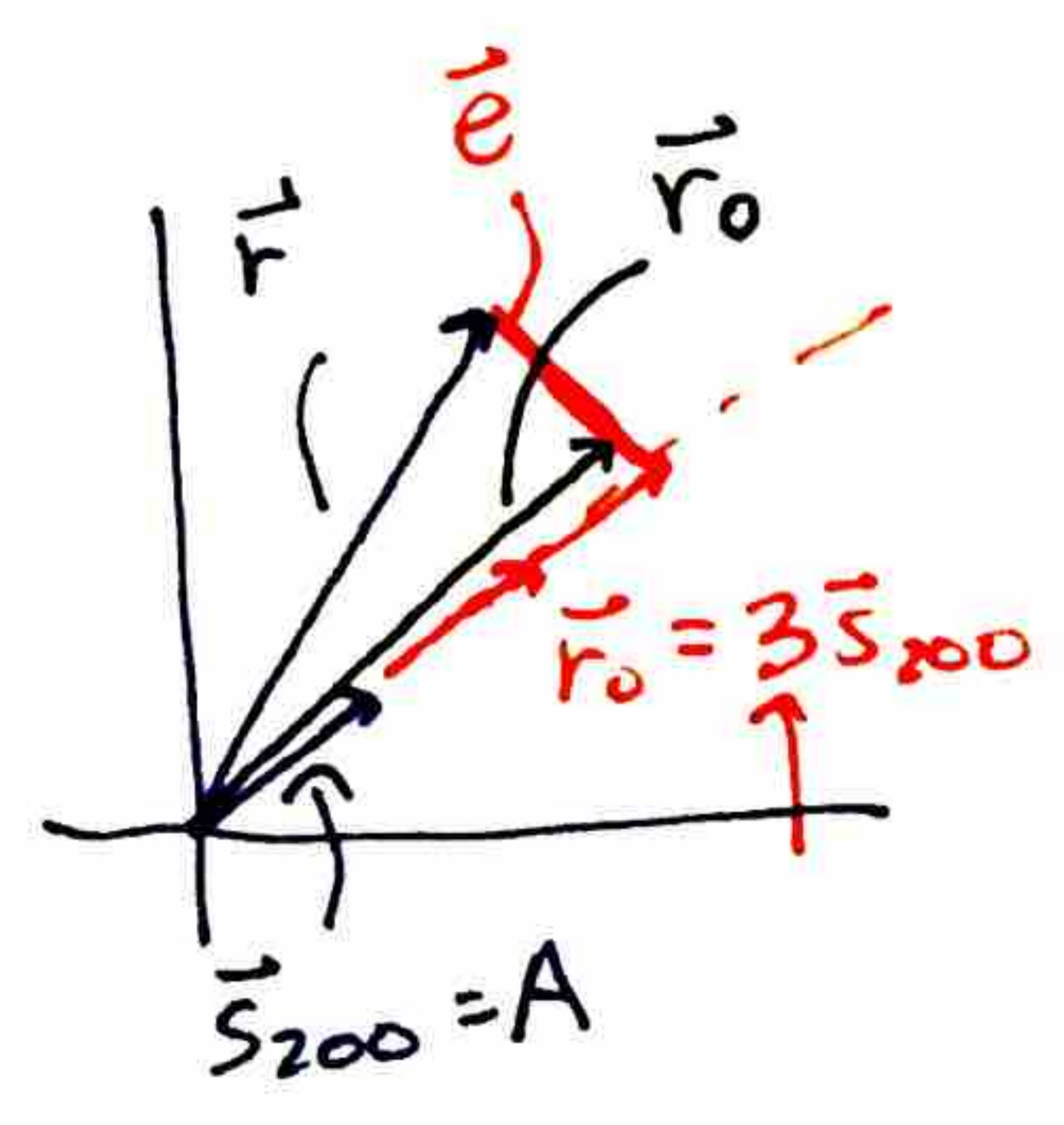
How do we find best fit α_{200} in this model?

A is 1023×1 $\rightarrow A = \begin{bmatrix} \vec{s}_{200} \end{bmatrix}$ $\vec{x} = [\alpha_{200}]$ $\vec{r} \approx A\vec{x}$

$\hat{x} = (A^T A)^{-1} A^T \vec{r} = \alpha_{200}$
 $\vec{r}_0 = A\hat{x} = A(A^T A)^{-1} A^T \vec{r}$



$\langle \vec{s}_{200}, \vec{s}_{200} \rangle^{-1} \langle \vec{s}_{200}, \vec{r} \rangle$
 $= \frac{\langle \vec{s}_{200}, \vec{r} \rangle}{\|\vec{s}_{200}\|^2}$



⇒ How well did we do?

look at error:

$$\vec{e} = \vec{r} - \vec{r}_0$$

$$\alpha_{10} \vec{s}_{10} + \alpha_{200} \vec{s}_{200} + \alpha_5 \vec{s}_5 \quad \vec{r}_0 \approx \begin{matrix} \alpha_{200} \vec{s}_{200} \\ \times A \end{matrix}$$

expect: $\vec{e} \approx \alpha_{10} \vec{s}_{10} + \alpha_5 \vec{s}_5$

go back and repeat using error vector!

ITERATION 2

⇒ consider

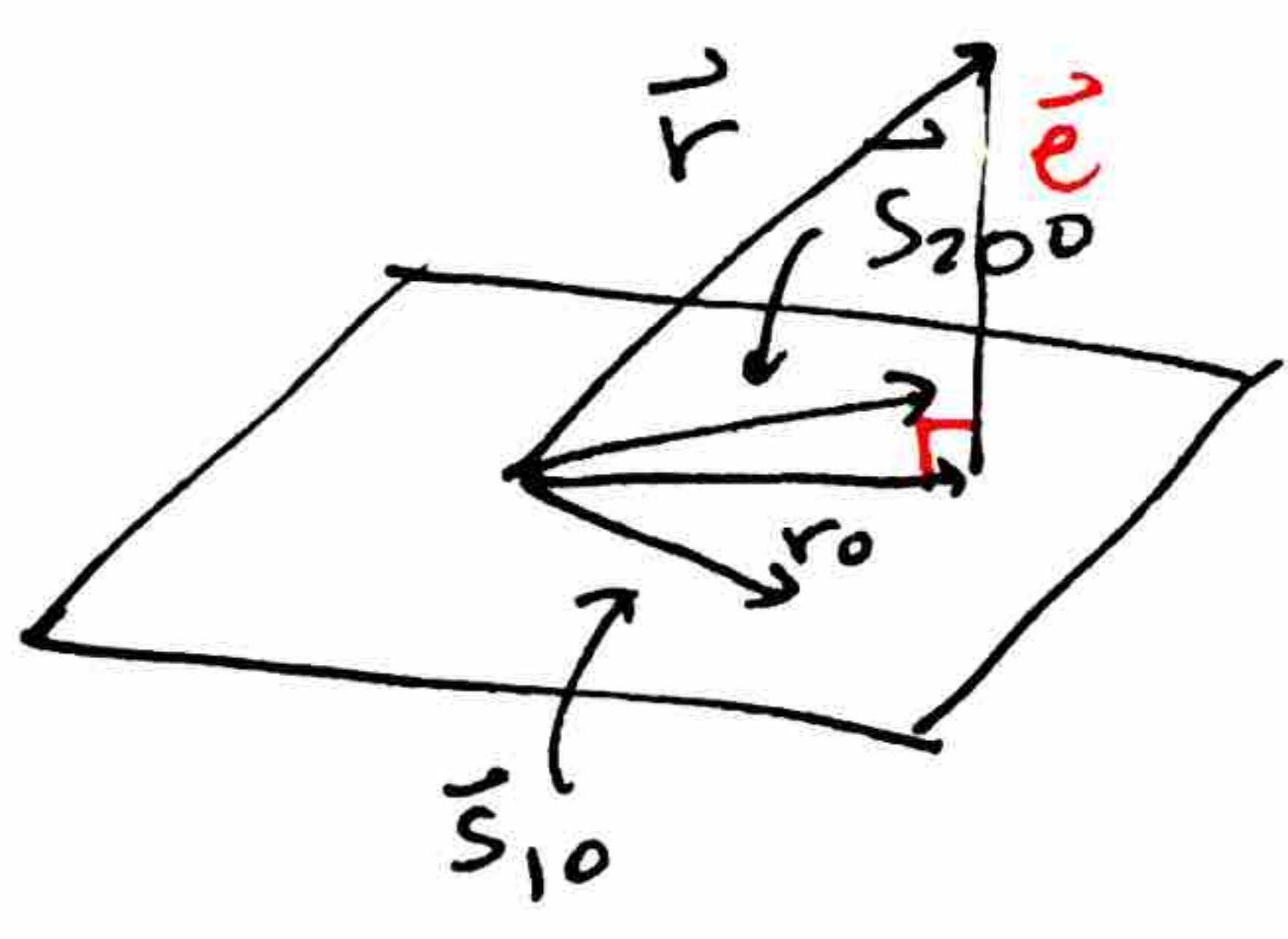
- $\langle \vec{e}, \vec{s}_1 \rangle$
- $\langle \vec{e}, \vec{s}_2 \rangle$
- ⋮
- $\langle \vec{e}, \vec{s}_{10,000} \rangle$

Find max abs. value → we find $\langle \vec{e}, \vec{s}_{10} \rangle$ is max

Declare that \vec{s}_{10} and \vec{s}_{200} are transmitting

⇒ GUESS:

$$\vec{r} \approx \alpha_{200} \vec{s}_{200} + \alpha_{10} \vec{s}_{10}$$



$$\vec{r} \approx \begin{bmatrix} | & | \\ \vec{s}_{200} & \vec{s}_{10} \\ | & | \end{bmatrix} \underbrace{\begin{bmatrix} \alpha_{200} \\ \alpha_{10} \end{bmatrix}}_{\vec{x}}$$

$$\hat{x} = (A^T A)^{-1} A^T \vec{r} \quad \text{not } \vec{e}$$

$$\vec{r}_0 = A \hat{x}$$

⇒ How did we do?

$$\vec{e} = \vec{r} - \vec{r}_0 \approx \alpha_5 \vec{s}_5$$

ITERATION 3

⇒ take all inner products

$\langle \vec{e}, \vec{s}_i \rangle \rightarrow$ find ~~the~~ \vec{s}_5 is largest $\langle \vec{e}, \vec{s}_5 \rangle$

⇒ Guess:

$$\vec{r} \approx \alpha_{200} \vec{s}_{200} + \alpha_{10} \vec{s}_{10} + \alpha_5 \vec{s}_5$$

$$\vec{r} = \underbrace{\begin{bmatrix} | & | & | \\ \vec{s}_{200} & \vec{s}_{10} & \vec{s}_5 \\ | & | & | \end{bmatrix}}_A \underbrace{\begin{bmatrix} \alpha_{200} \\ \alpha_{10} \\ \alpha_5 \end{bmatrix}}_{\vec{x}}$$

$$\hat{x} = (A^T A)^{-1} A^T \vec{r}$$

$$\vec{r}_0 = A \hat{x}$$

⇒ How did we do?

$$\vec{e} = \vec{r} - \vec{r}_0$$

← close to zero!
(exactly zero w/ no noise)

OMP Algorithm:

Problem: $S\vec{\alpha} = \vec{r}$
 $\vec{\alpha}$ is sparse

$$S = [\vec{s}_1 \dots \vec{s}_n]$$

$$\|\vec{s}_1\| = \|\vec{s}_2\| = \dots = \|\vec{s}_n\|$$

Algorithm:

initialize $\vec{e} = \vec{r}$, $A = []$, $\vec{x} = []$

on each iteration: (k)

① Take inner product of \vec{e} with every column of \vec{s} .

Find i such that $|\langle \vec{s}_i, \vec{e} \rangle|$ is maximized.

② Update matrix A and vector \vec{x}

$$A = [A \mid \vec{s}_i] \quad \vec{x} = \begin{bmatrix} \vec{x} \\ \alpha_i \end{bmatrix} \quad \vec{x} \in \mathbb{R}^k$$

$A \in 1023 \times k$ prior A new column

③ Find the best estimate of \vec{r} by projecting \vec{r} on to the column space of A

$$\vec{r} \approx A\vec{x} \quad \hat{x} = (A^T A)^{-1} A^T \vec{r}$$

$$\vec{r}_0 = A\hat{x}$$

④ Update the error:

$$\vec{e} = \vec{r} - \vec{r}_0$$

Repeat until ~~error~~ k iterations have passed
~~noise~~ is error is small enough
 $\|\vec{e}\| < \text{threshold}$