Online Generation of Locality Sensitive Hash Signatures

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Data Overload

- Our access to data is growing fast

Data Overload

- Our access to data is growing faster than our ability to process it

Data Overload

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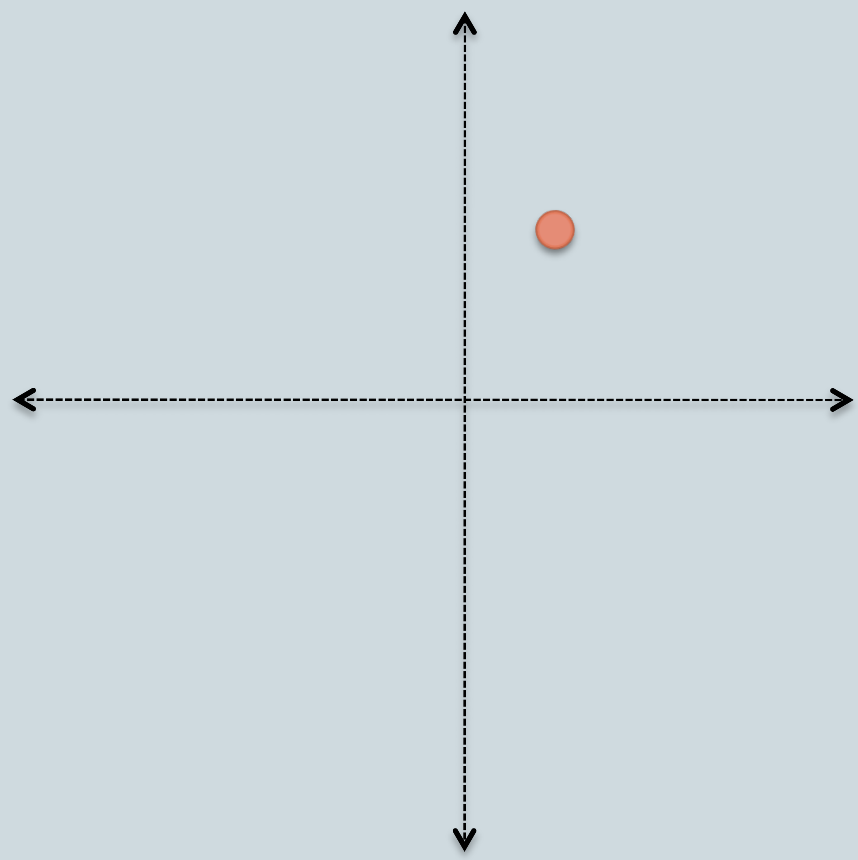
- Complementary solutions:
  - Distributed environments (e.g., MapReduce)
  - Streaming / Randomized Algorithms

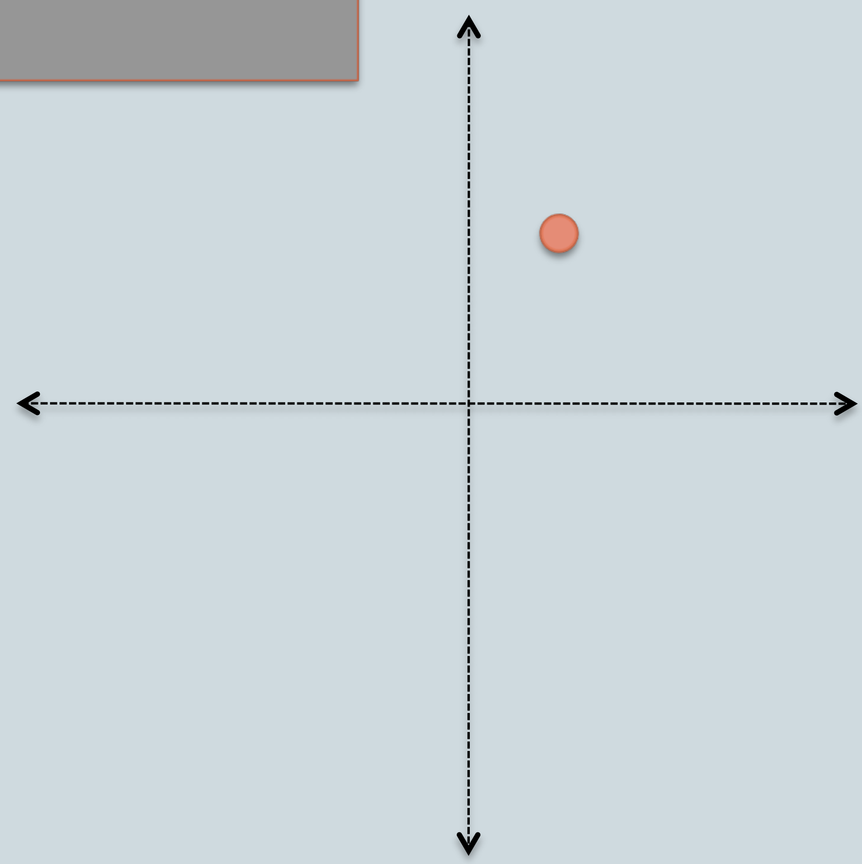
Locality Sensitive Hashing

- Goal: fast comparison between points in very high dimensional space
- Indyk & Motwani (‘98) => Charikar (’02)
  - Randomly project points to low dimensional *bit signatures* such that **cosine distance** is approximately preserved
- Example Applications in HLT
  - Noun clustering [Ravichandran *et al* ’05]
  - Topic Detection and Tracking (TDT) [Petrovic *et al* ‘10]

Locality Sensitive Hashing



Locality Sensitive Hashing



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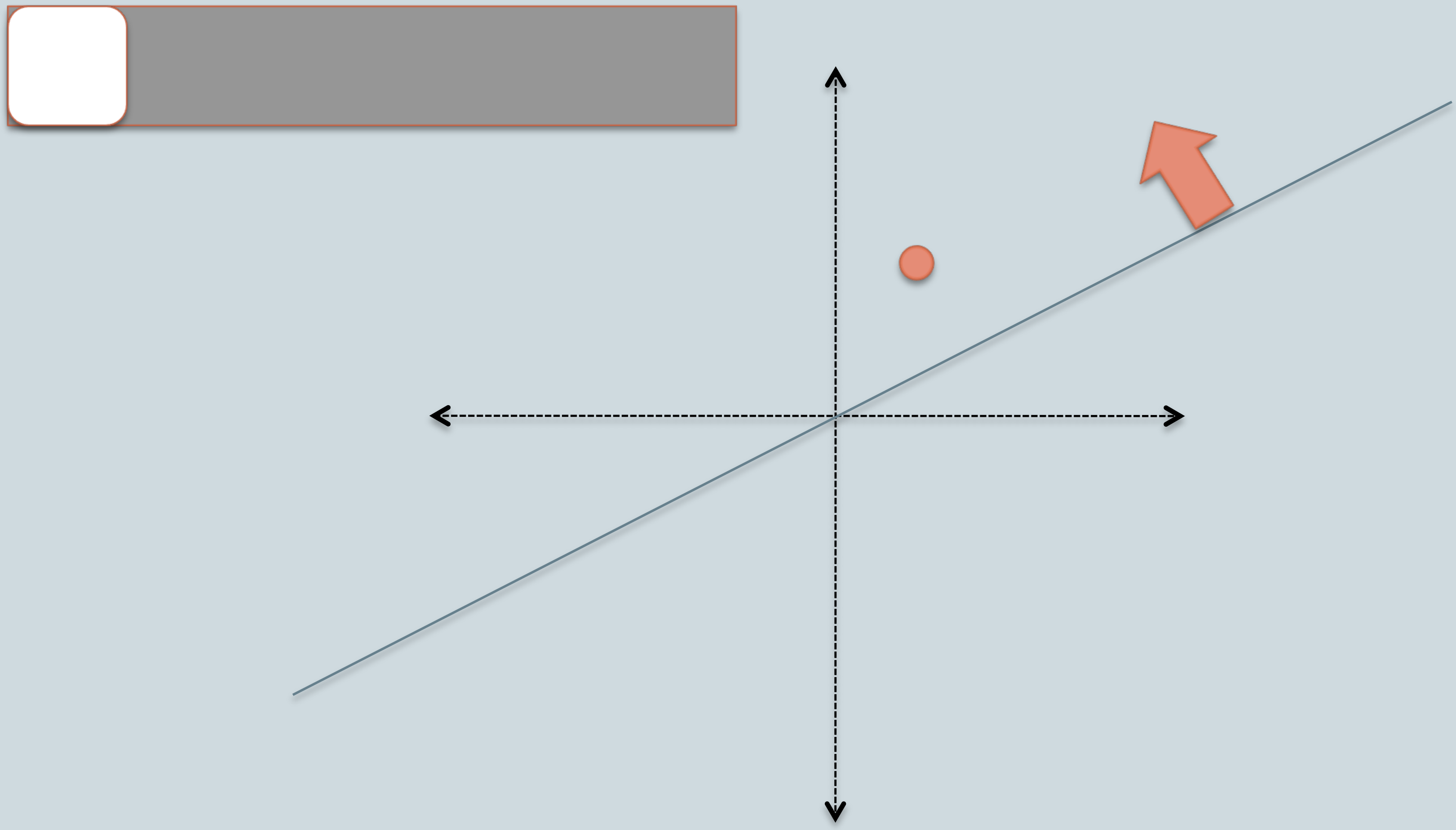

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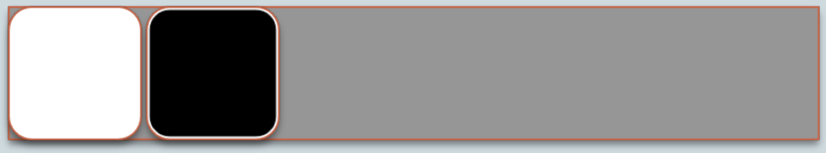

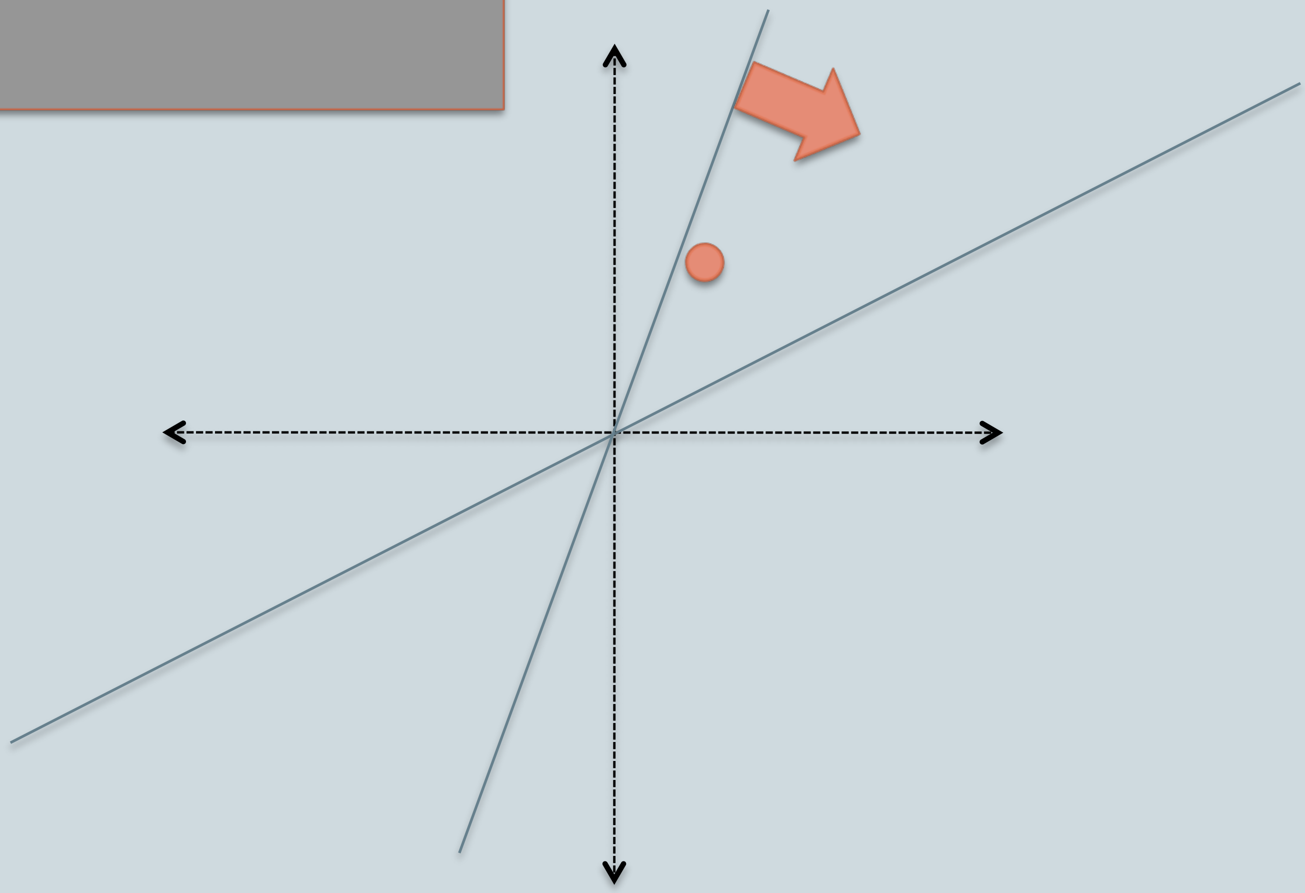

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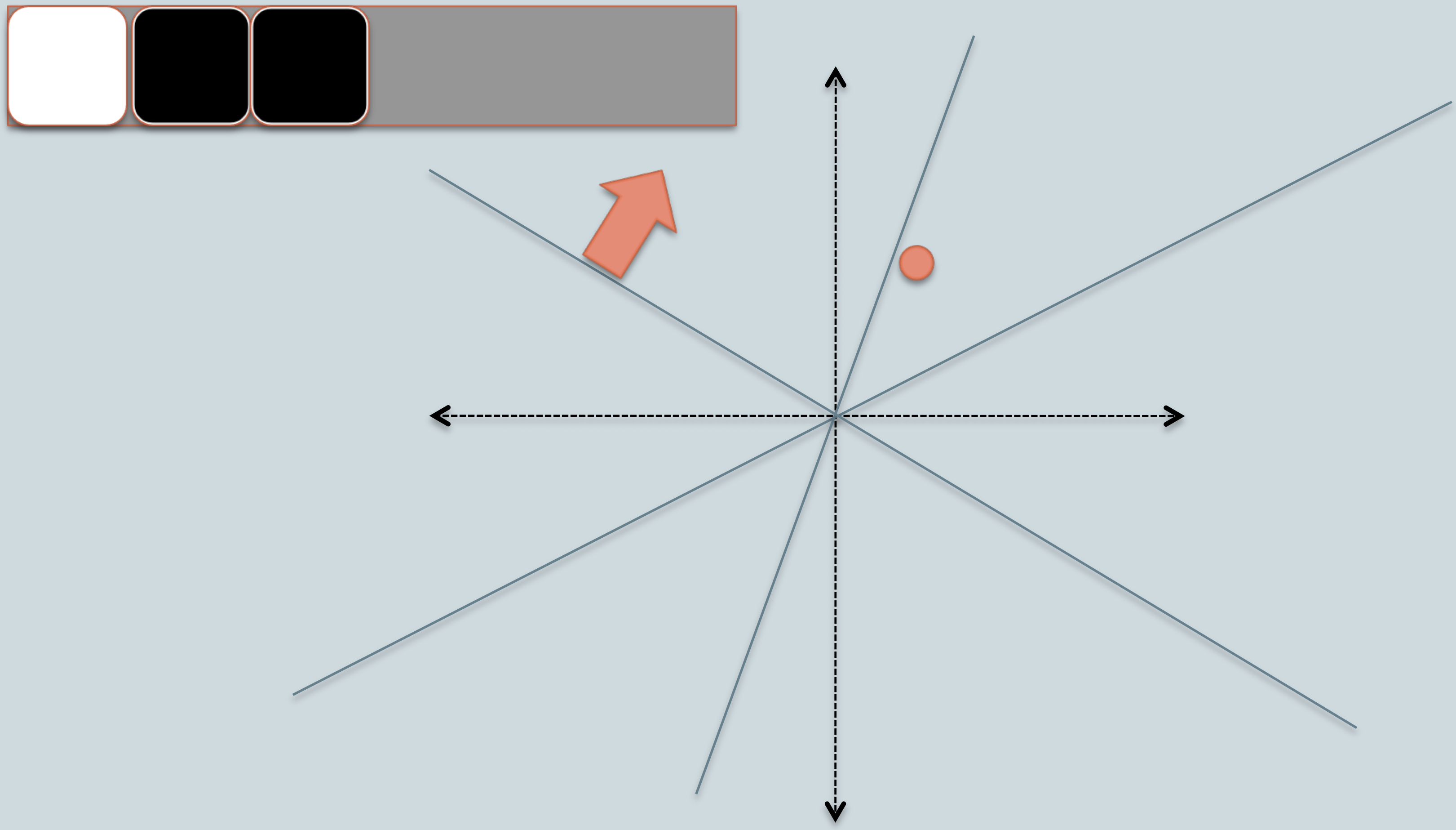

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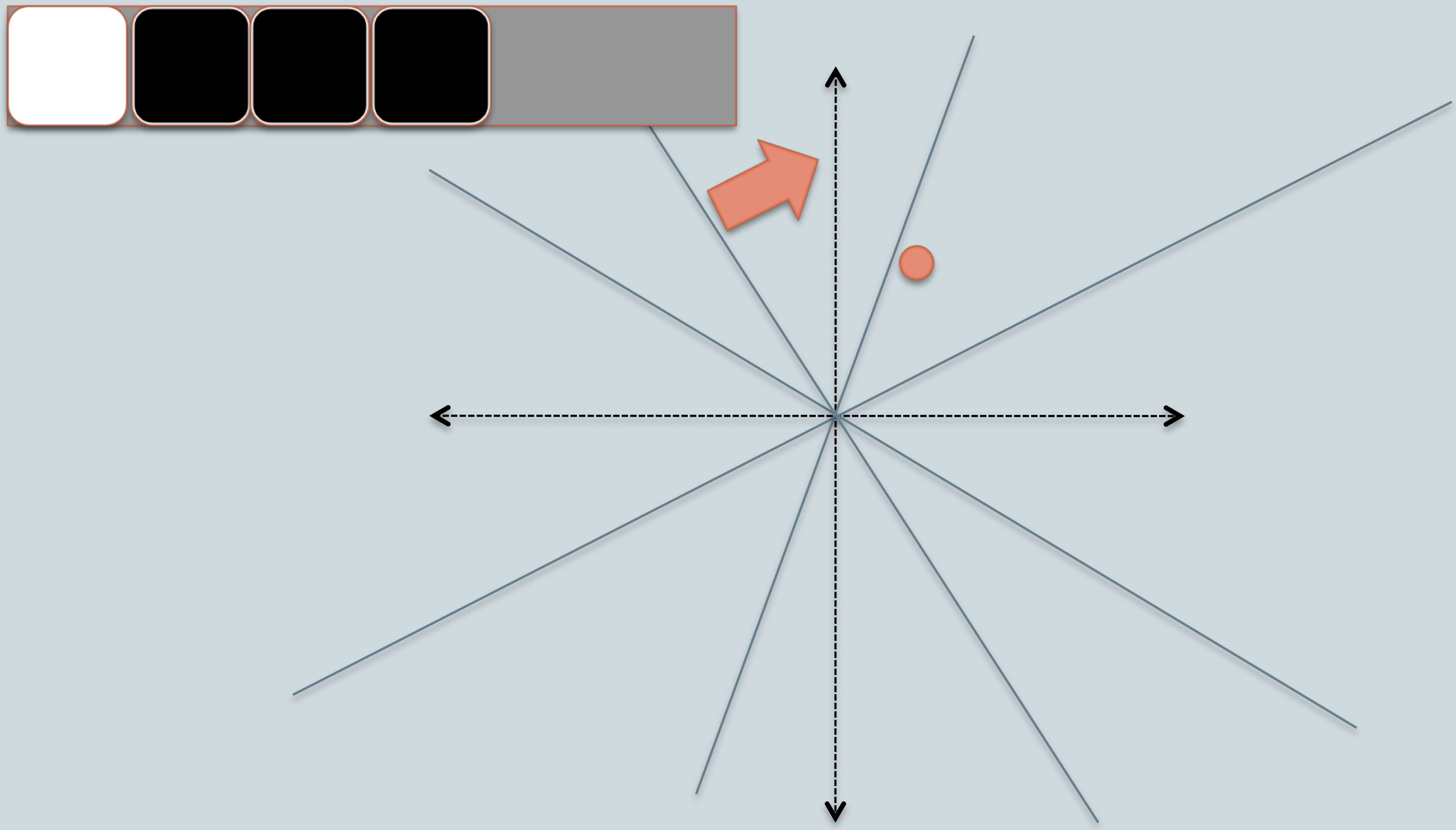

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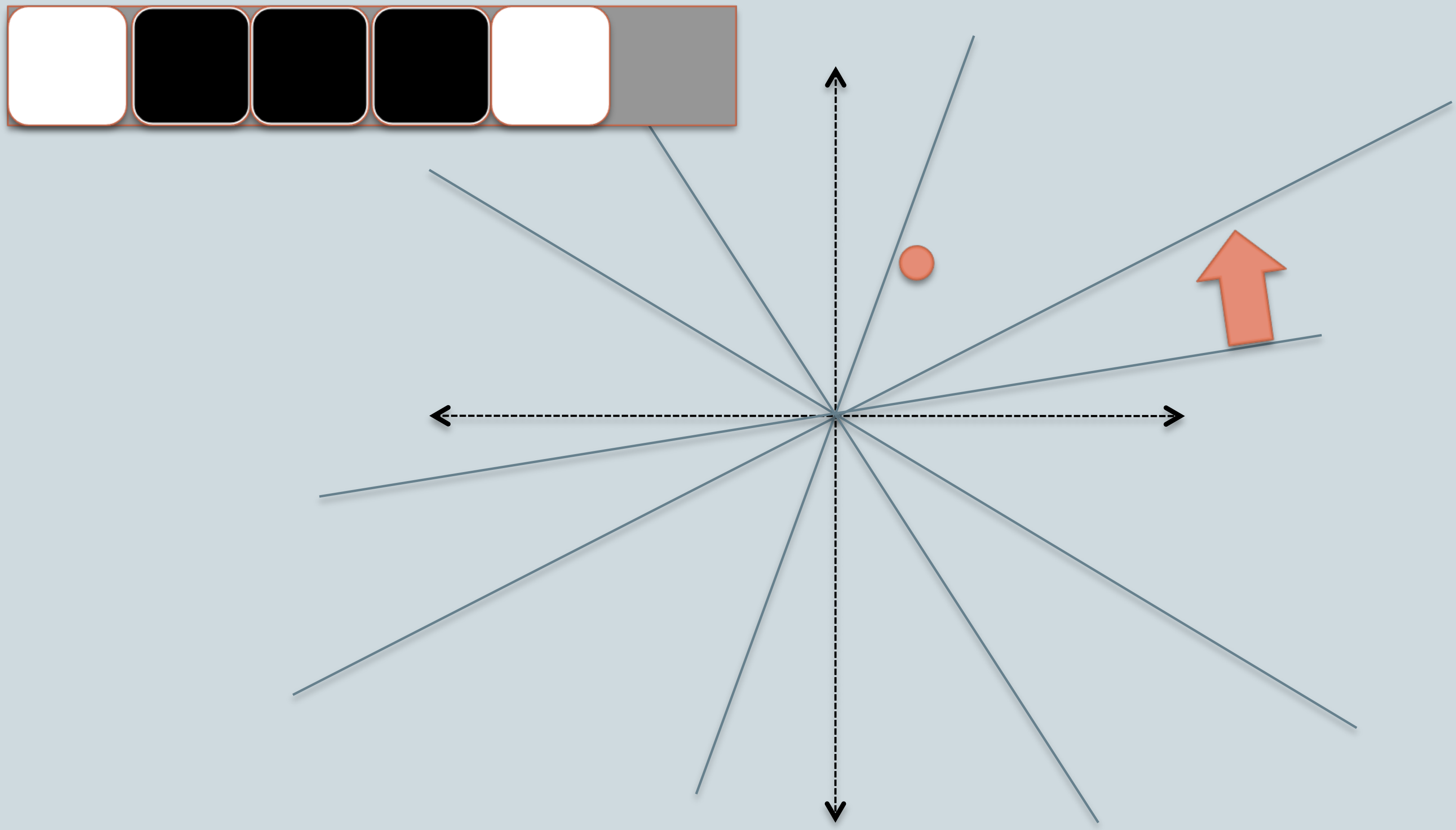

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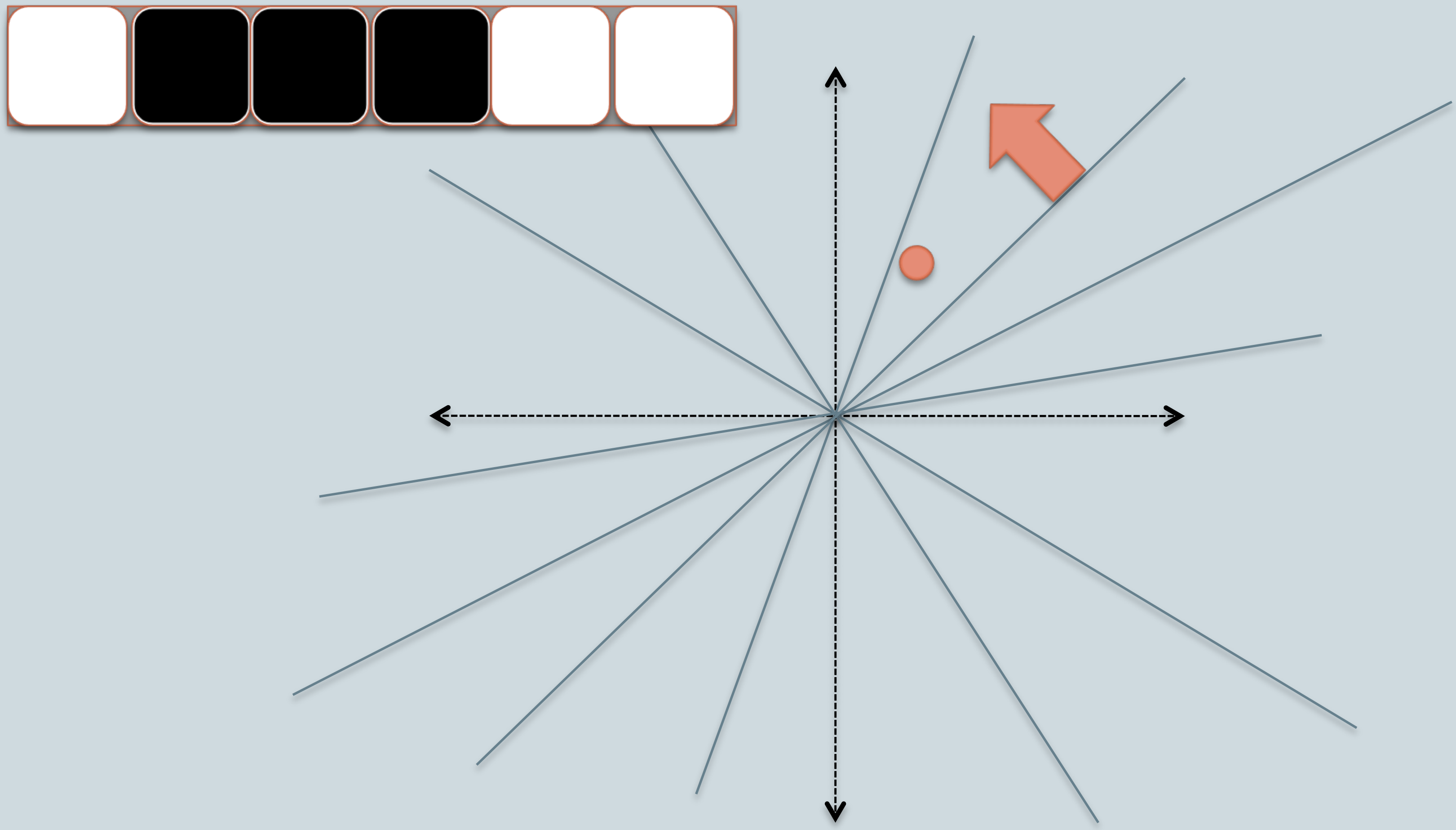

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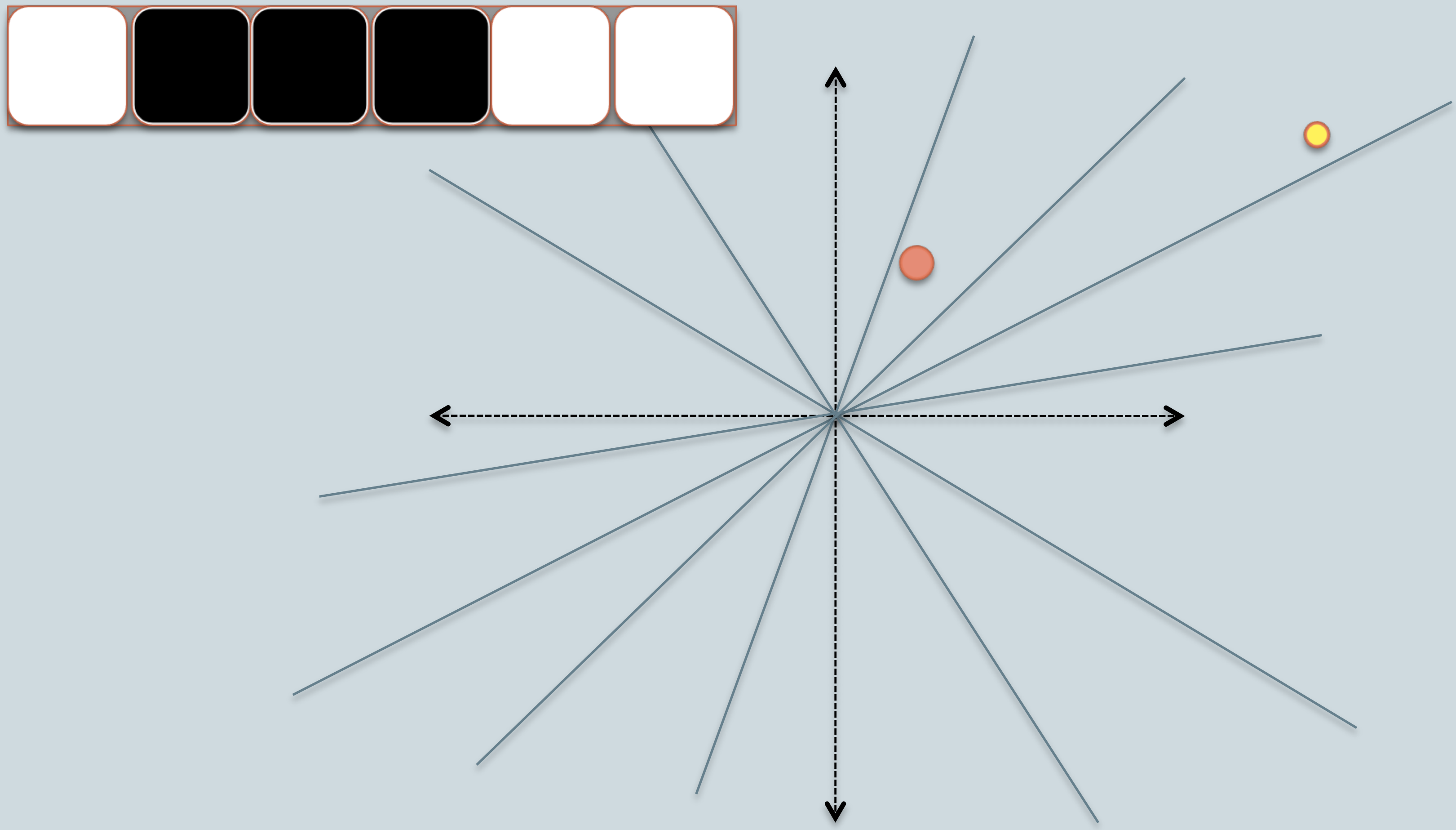

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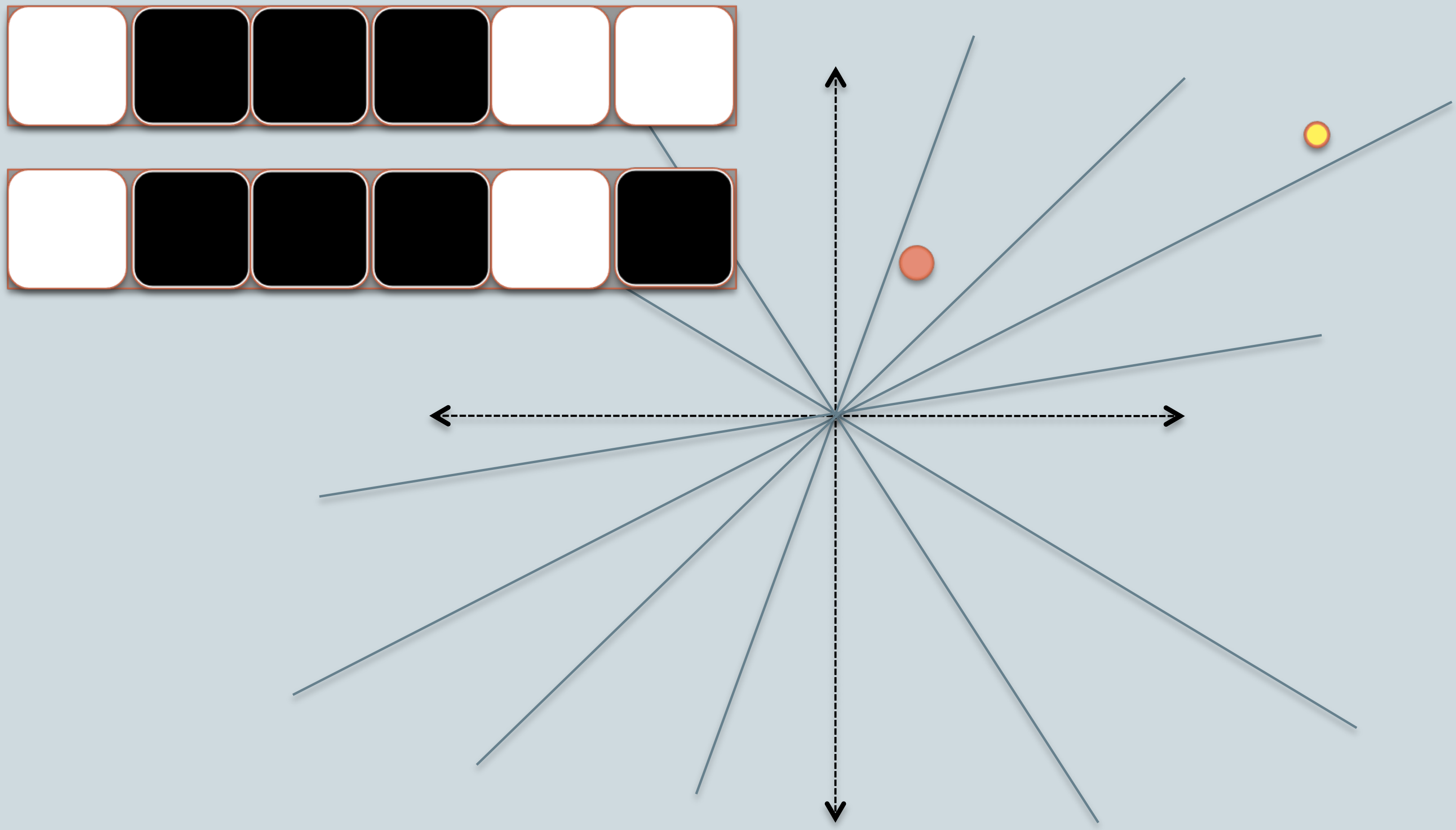

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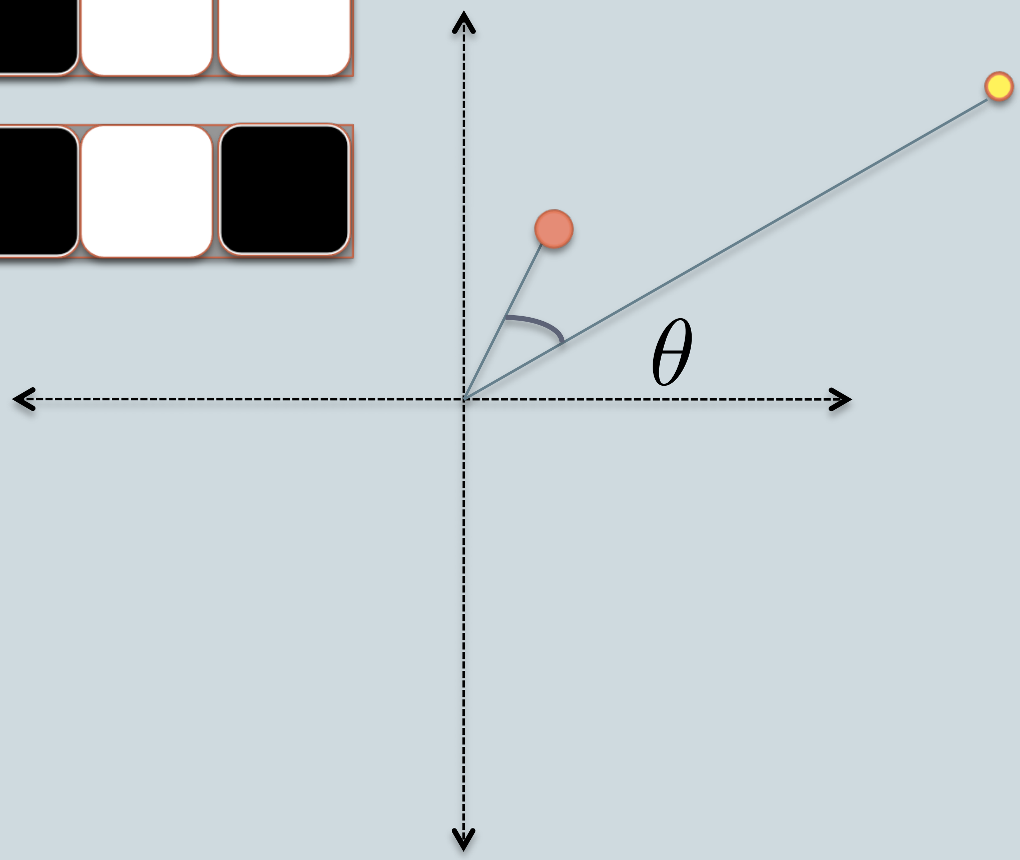

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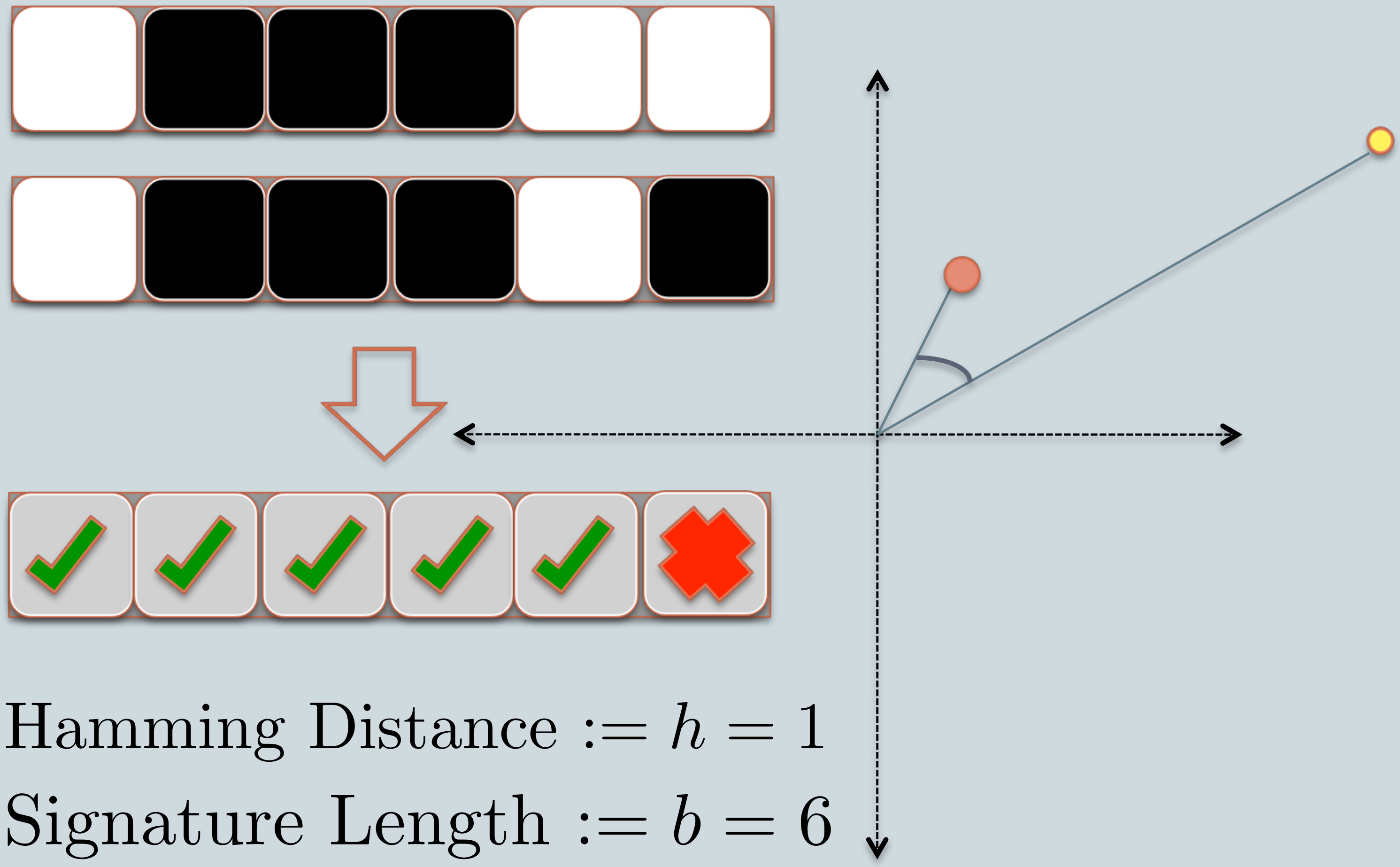
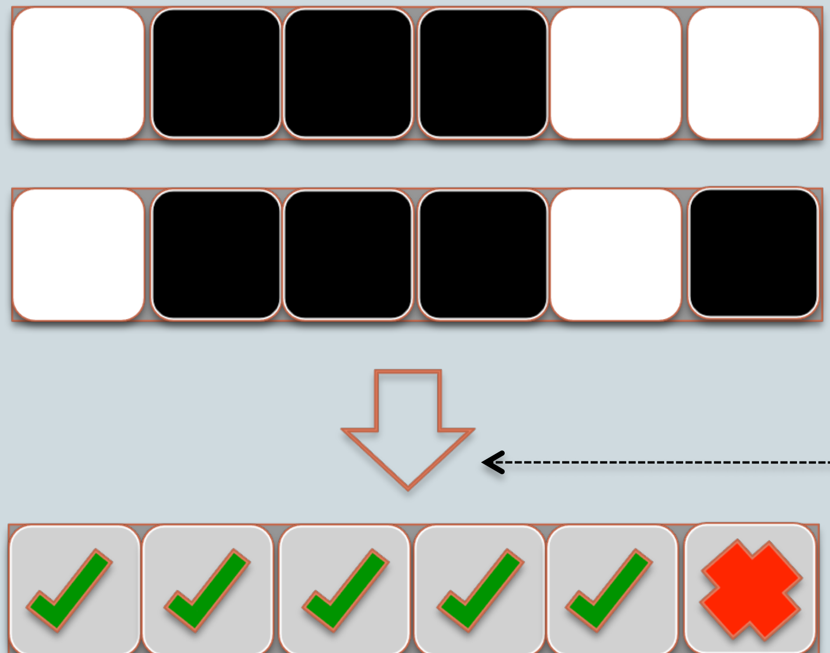
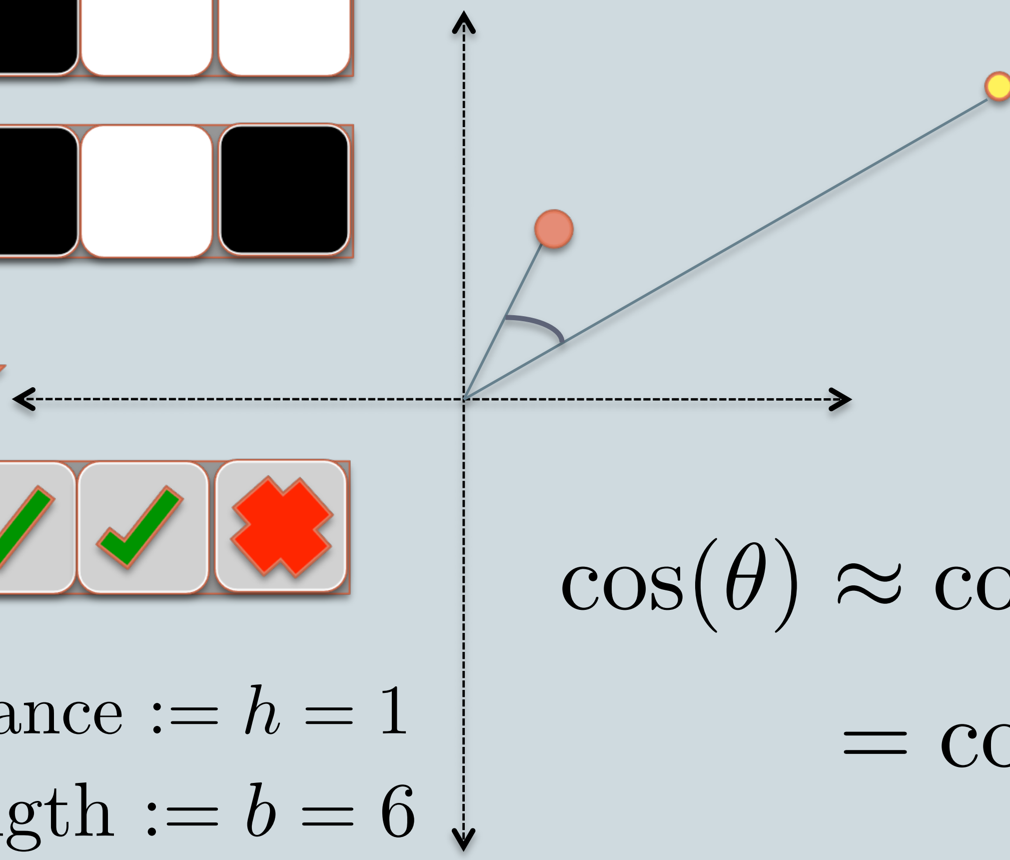


$$\text{Hamming Distance} := h = 1$$

$$\text{Signature Length} := b = 6$$

Locality Sensitive Hashing



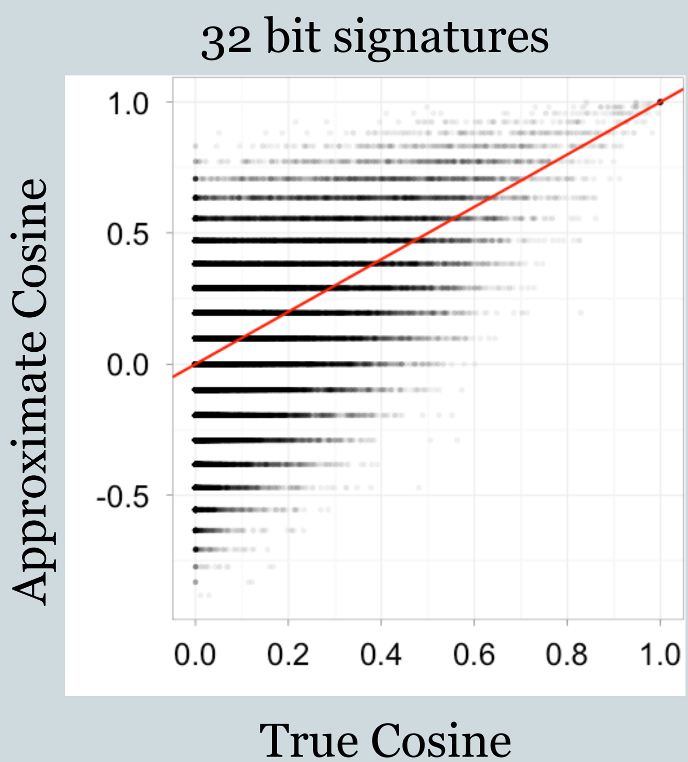


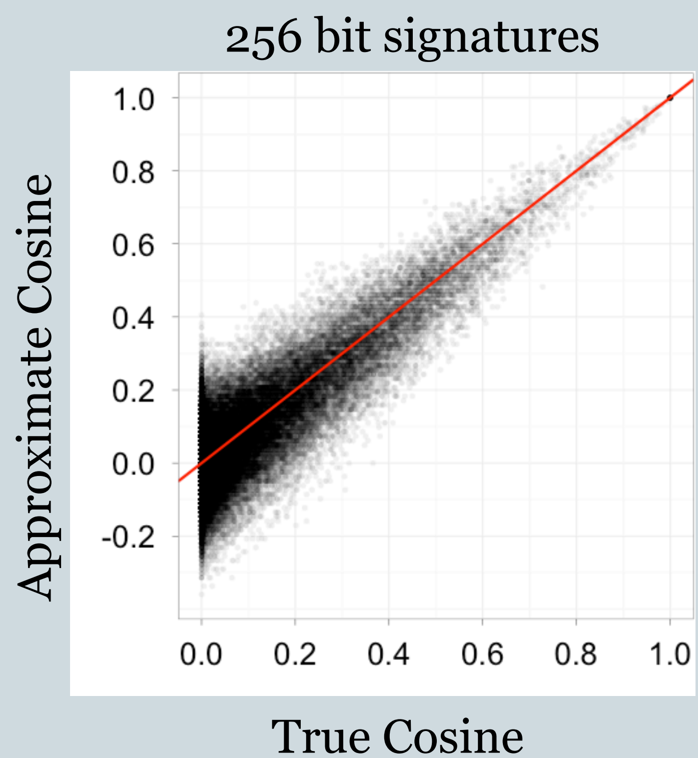
$$\cos(\theta) \approx \cos(\frac{h}{b}\pi)$$
$$= \cos(\frac{1}{6}\pi)$$

Hamming Distance $:= h = 1$

Signature Length $:= b = 6$

Accuracy as function of bit length





Cheap

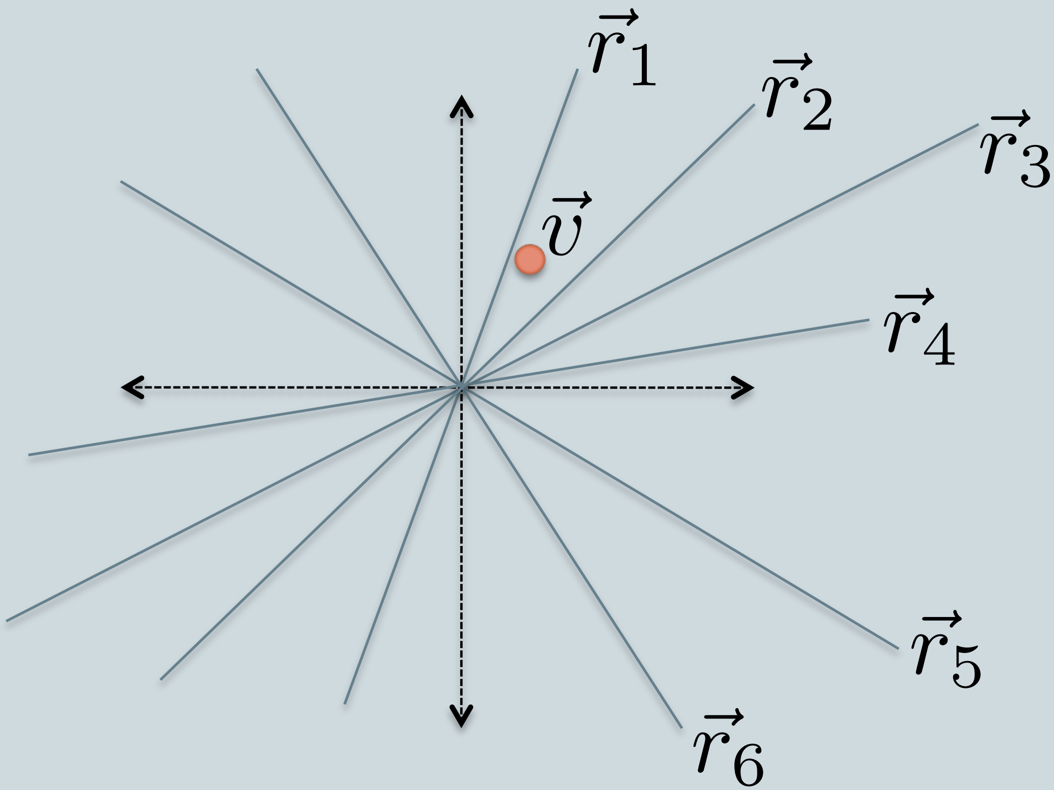
Accurate

Novel Points Here

1. Online hash function

2. Pooling trick

Online Hash Function



$$\vec{v} \in \mathbb{R}^d$$

$$\vec{r}_i \sim N(0,1)^d$$

Online Hash Function

$$\vec{v} \in \mathbb{R}^d$$

$$\vec{r}_i \sim N(0,1)^d$$

$$h_i(\vec{v}) = \begin{cases} 1 & \text{if } \vec{v} \cdot \vec{r}_i \geq 0, \\ 0 & \text{otherwise.} \end{cases}$$

Online Hash Function

$$\text{if } \vec{v} = \Sigma_j \vec{v}_j$$
$$\text{then } \vec{v} \cdot \vec{r}_i = \Sigma_j \vec{v}_j \cdot \vec{r}_i$$

Break into local products

Online Hash Function

$$h_i(\vec{v}) = \begin{cases} 1 & \text{if } \vec{v} \cdot \vec{r}_i \geq 0, \\ 0 & \text{otherwise.} \end{cases}$$

Offline

$$\text{if } \vec{v} = \Sigma_j \vec{v}_j$$
$$\text{then } \vec{v} \cdot \vec{r}_i = \Sigma_j \vec{v}_j \cdot \vec{r}_i$$

Online

$$h_{it}(\vec{v}) = \begin{cases} 1 & \text{if } \Sigma_j^t \vec{v}_j \cdot \vec{r}_i \geq 0, \\ 0 & \text{otherwise.} \end{cases}$$

The Pooling Trick

$$\vec{r}_i \sim N(0,1)^d$$

$$\begin{pmatrix} \vec{r}_1 \\ \dots \\ \vec{r}_b \end{pmatrix} = \begin{pmatrix} N(0,1) & \dots & N(0,1) \\ \dots & \dots & \dots \\ N(0,1) & \dots & N(0,1) \end{pmatrix}$$

The Pooling Trick

The random projection matrix can easily require gigabytes of memory

$$\begin{pmatrix} \vec{r}_1 \\ \ldots \\ \vec{r}_b \end{pmatrix} = \begin{pmatrix} N(0,1) & \ldots & N(0,1) \\ \ldots & \ldots & \ldots \\ N(0,1) & \ldots & N(0,1) \end{pmatrix}$$

The Pooling Trick

$$\vec{p} \sim N(0,1)^m$$

$$\vec{p} = \begin{pmatrix} N(0,1) & \ldots & N(0,1) \end{pmatrix}$$

$$\text{Define } \vec{r}_i[j] = \vec{p}\,[\mathrm{hash}(i,j)\ \mathrm{MOD}\ m]$$

$$m \ll b \times d$$

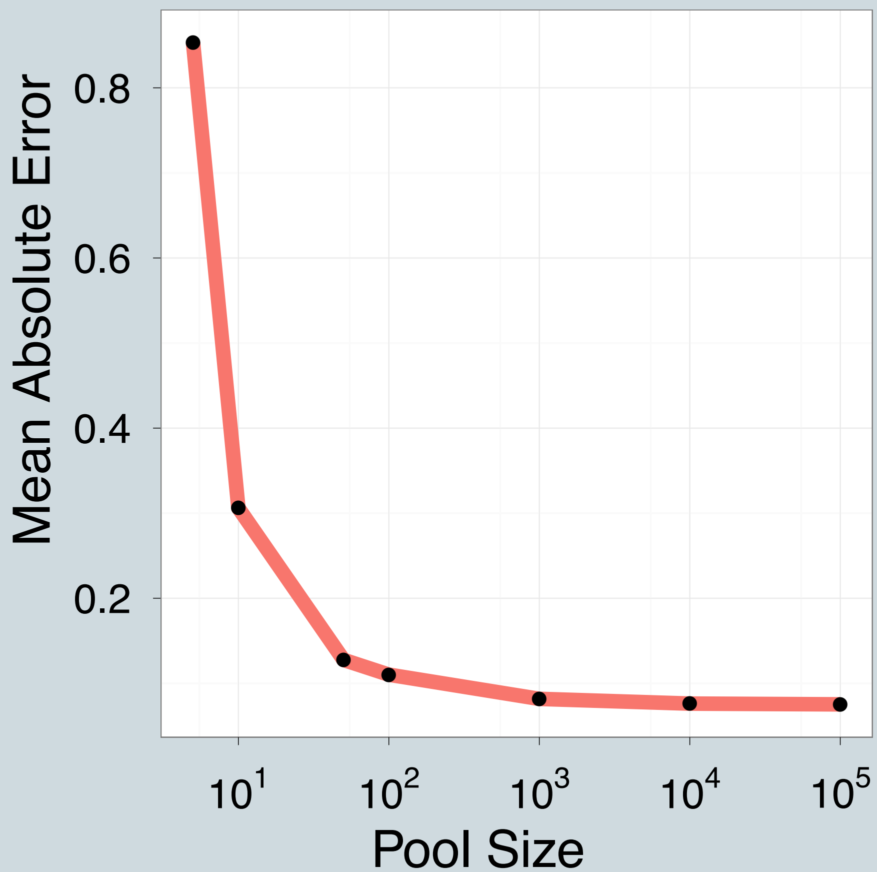
The Pooling Trick

$$\text{Define } \vec{r}_i[j] = \vec{p}\,[\text{hash}(i,j) \text{ MOD } m]$$

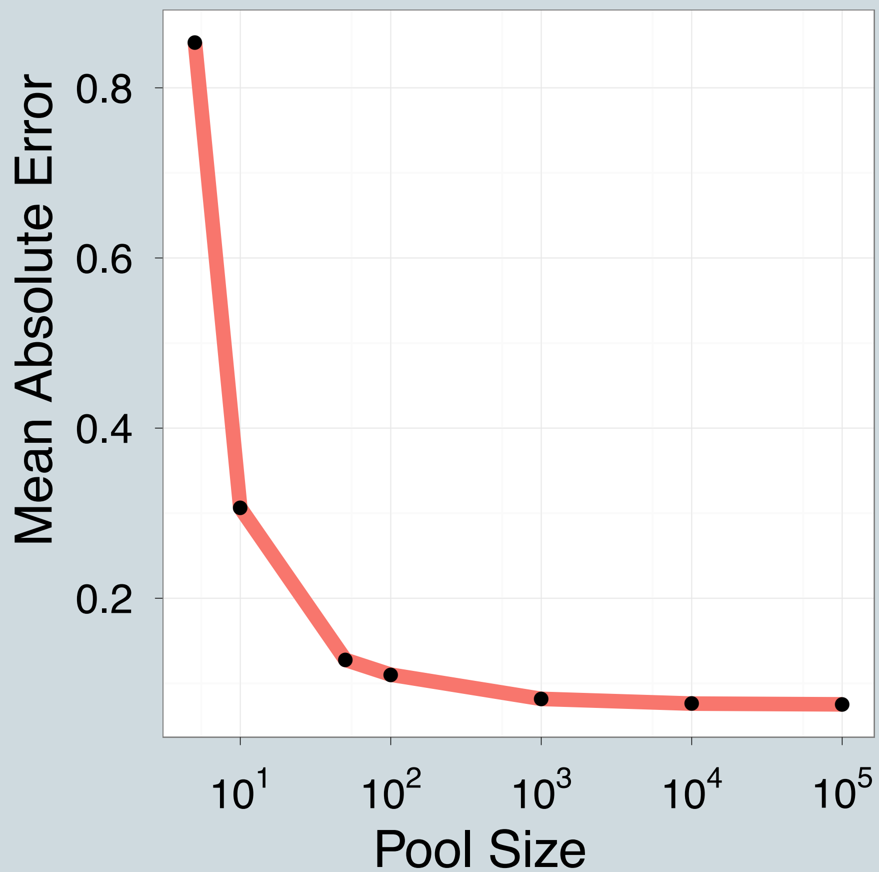
$$\begin{pmatrix} \ldots & \ldots & \ldots \\ \ldots & (i,j) & \ldots \\ \ldots & \ldots & \ldots \end{pmatrix}$$

$$\begin{pmatrix} N(0,1) & \ldots & N(0,1) \end{pmatrix}$$

The Pooling Trick



The Pooling Trick



That is 400 **kilobytes**

Example

London

Milan$_{.97}$, **Madrid**$_{.96}$, **Stockholm**$_{.96}$, **Manila**$_{.95}$, **Moscow**$_{.95}$
ASHER$_0$, Champaign$_0$, MANS$_0$, NOBLE$_0$, come$_0$
Prague$_1$, Vienna$_1$, suburban$_1$, synchronism$_1$, Copenhagen$_2$
Frankfurt$_4$, Prague$_4$, Taszar$_5$, Brussels$_6$, Copenhagen$_6$
Prague$_{12}$, Stockholm$_{12}$, Frankfurt$_{14}$, Madrid$_{14}$, Manila$_{14}$
Stockholm$_{20}$, Milan$_{22}$, Madrid$_{24}$, Taipei$_{24}$, Frankfurt$_{25}$

Accurate

Closest based on true cosine

London

Milan$_{.97}$, **Madrid**$_{.96}$, **Stockholm**$_{.96}$, **Manila**$_{.95}$, **Moscow**$_{.95}$

ASHER$_0$, Champaign$_0$, MANS$_0$, NOBLE$_0$, come$_0$

Prague$_1$, Vienna$_1$, suburban$_1$, synchronism$_1$, Copenhagen$_2$

Frankfurt$_4$, Prague$_4$, Taszar$_5$, Brussels$_6$, Copenhagen$_6$

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London

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Closest based on 32 bit sig.'s

Cheap

London

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Closest based on 256 bit sig.'s

Cheap-ish

No Questions.

See Poster.

Also: these algorithms distribute to the cloud.

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