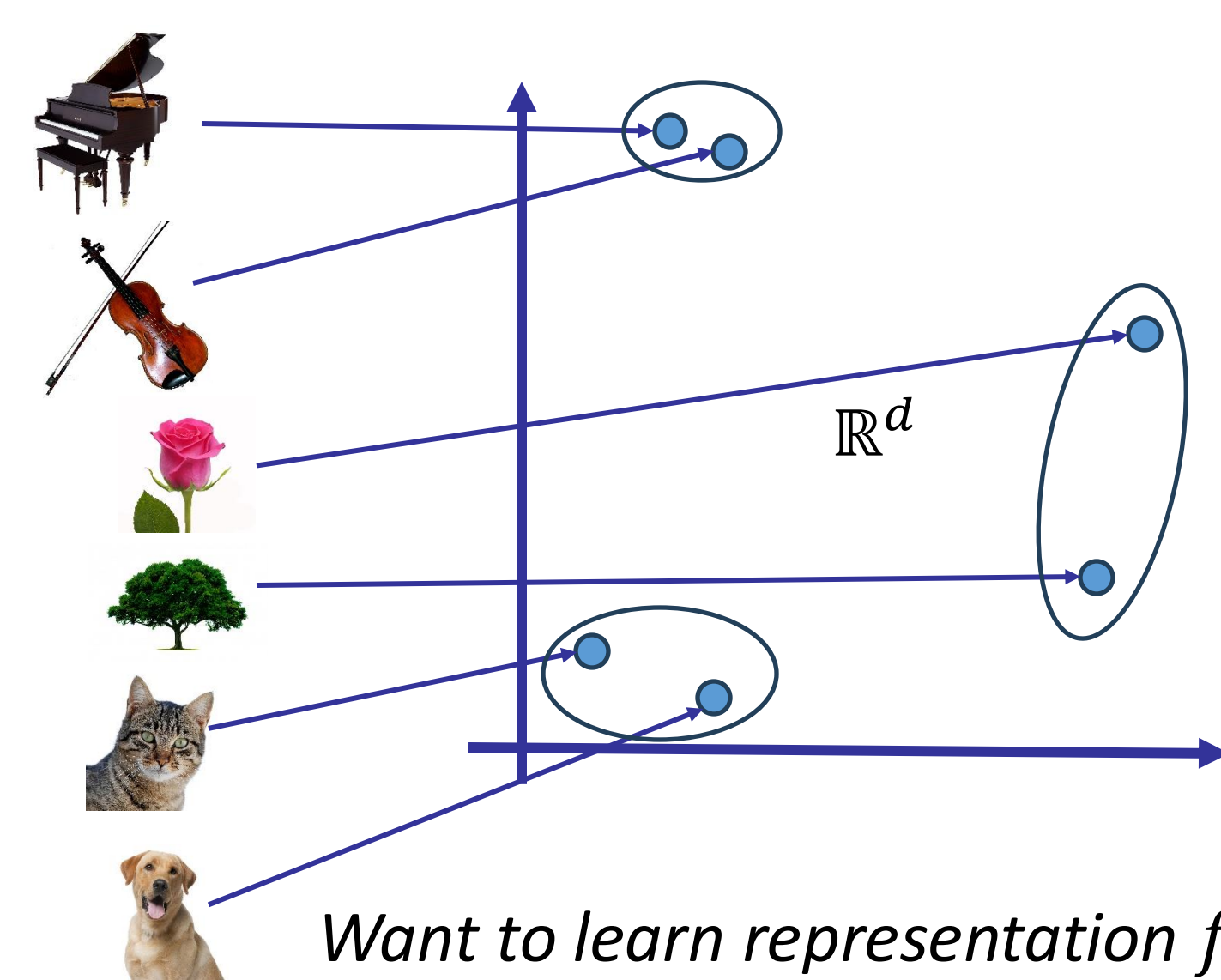


Embedding Dimension of Contrastive Learning and k -Nearest Neighbors

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REPRESENTATION LEARNING



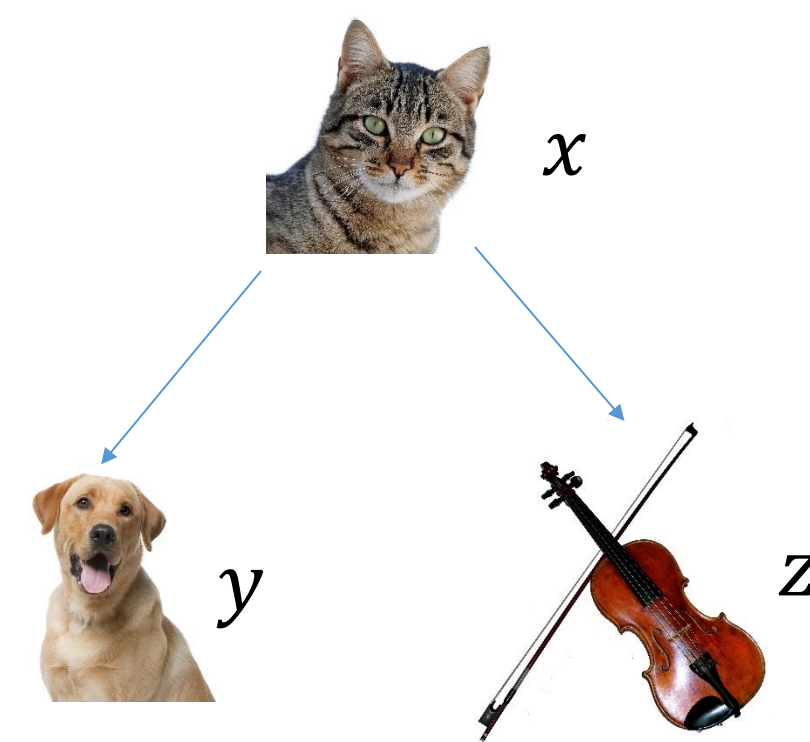
CONTRASTIVE LEARNING

Labeled Input

- Triplet (x, y^+, z^-)
- ❖ "Anchor" x
- ❖ "Positive" element y
- ❖ "Negative" element z

Interpretation

" x is more similar to y than to z "
 $\|f(x) - f(y)\| < \|f(x) - f(z)\|$



EMBEDDING DIMENSION

Question

Assume we have m contrastive constraints

What is the minimum dimension d required to satisfy all constraints?

E.g. a design choice when designing a neural network

k -NEAREST NEIGHBORS

For each point $x \in V$, know k points $y_1, \dots, y_k$ closest to x

- $\|f(x) - f(y_1)\| < \|f(x) - f(y_2)\| < \dots < \|f(x) - f(y_k)\|$
- $\|f(x) - f(y_k)\| < \|f(x) - f(z)\|$ for all other z

What is the minimum dimension d required to preserve k -NN for all points?

Previous work

[Alon et al.'24]: for a fixed dimension d , the VC-dimension of contrastive learning is $\tilde{O}(nd)$

[Chatziafratis, Indyk'23]:

- ❖ $d = \Theta(n)$ is necessary and sufficient to preserve all constraints
- ❖ $d = \Theta(k)$ to preserve orderings between k -NN, but not necessarily k -NN

OUR RESULT

CONTRASTIVE LEARNING

Consider a set of m non-contradictory constraints. There exists embedding into ℓ_p space satisfying all constraints if d is chosen as follows.

- ❖ $d \in \Theta(\sqrt{m})$ for $p = 2$
 - ❖ $O(\sqrt{m})$ always suffices, and some set of constraints require $\Omega(\sqrt{m})$
- ❖ $d \in O(m^{2/3}) \cap \Omega(\sqrt{m})$ for $p = \infty$
- ❖ $d \in O(m) \cap \Omega(\sqrt{m})$ for positive integer p

k -NN

For a positive integer p , there exists embedding into ℓ_p space of dimension $d = \text{poly}(k) \cdot \text{polylog}(n)$ preserving the k -nearest neighbors of each point.

- ❖ No polynomial dependence on n
 - ❖ Very surprising since k -NN information encodes $\Theta(n^2)$ constraints
- ❖ No dependence on p

MAIN TECHNIQUES

Intuition

For $m = \Theta(n^2)$, have $d = \Theta(n)$ [Chatziafratis, Indyk'23]

- ❖ Gives the $\Omega(\sqrt{m})$ lower bound

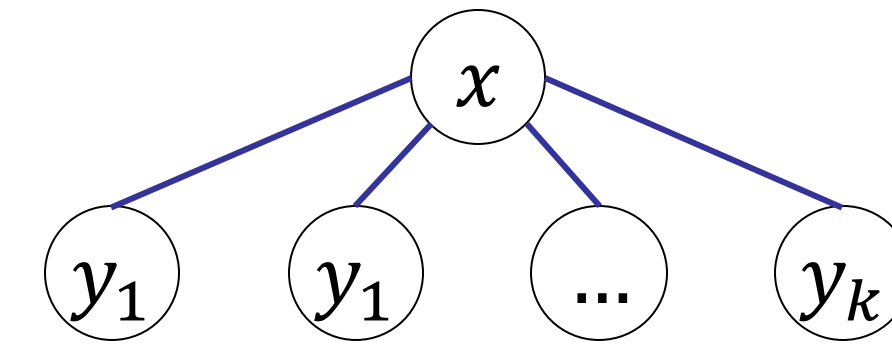
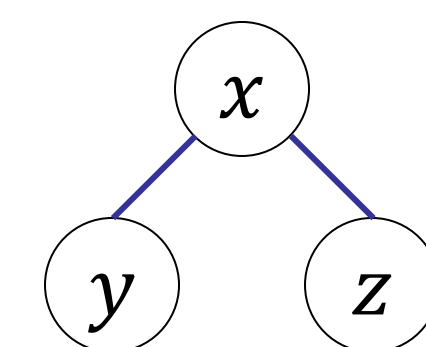
If there are $O(n)$ constraints:

- ❖ If the constraints are spread over all n points, $d = \Theta(1)$
- ❖ If these constraints are concentrated on $\sqrt{n}$ points, $d = \Theta(\sqrt{n})$.

The density seems to matter

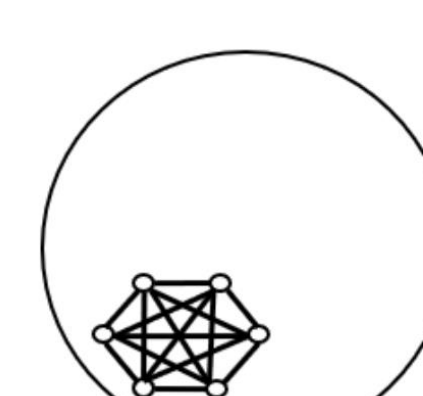
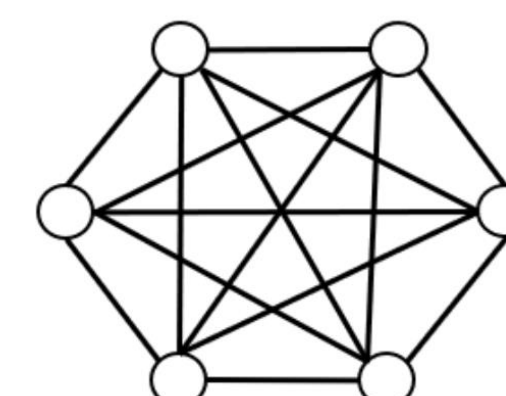
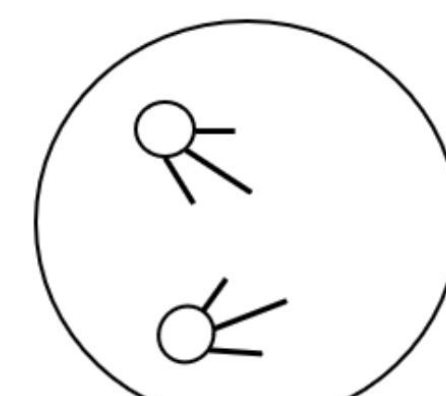
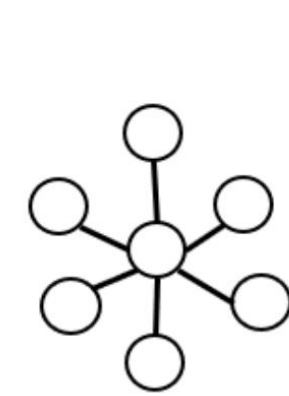
Constraint graph

Create edges for all constraints (contrastive learning) or points (k -NN)
 (x, y^+, z^-) x with its nearest neighbors $y_1, \dots, y_k$



Arboricity

- ❖ **Definition:** the minimum number of forests to cover the graph
- ❖ Measure of graph density



Low arboricity

High arboricity

Bounds on arboricity

- ❖ Clique has arboricity $\lceil \sqrt{m/2} \rceil$
- ❖ The $\lceil \sqrt{m/2} \rceil$ bound is tight

Why is arboricity useful?

Assume that the graph has arboricity r

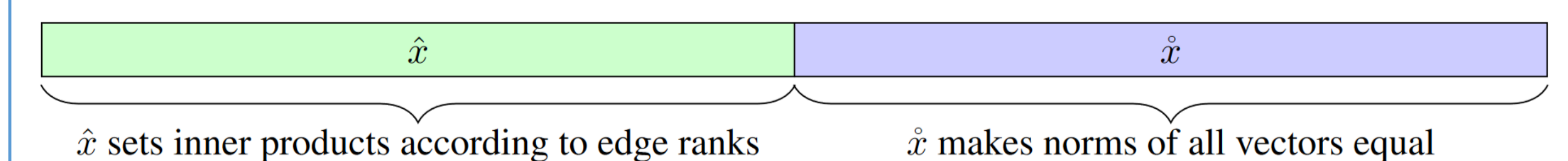
- ❖ ($2r$ -degeneracy) There is an order of vertices so that for any $x \in V$, the number of neighbors of x preceding x is at most $2r$
- ❖ The graph is $2r$ -vertex colorable

UPPER BOUND FOR CONTRASTIVE LEARNING IN ℓ_2 ($d = \Theta(\sqrt{m})$)

Outline

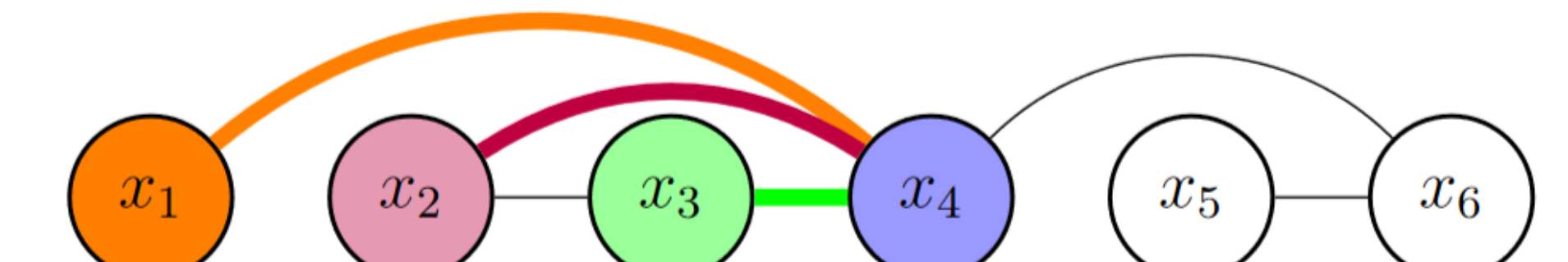
- ❖ Since constraints are non-contradictory, there exists a metric satisfying these constraints
- ❖ Let $w(x, y) \in \{1, \dots, 2m\}$ be the rank of edge (x, y) in the metric, starting from the heaviest edge
- ❖ We'll construct embedding f :
 $\|f(x) - f(y)\| - \|f(x) - f(z)\| = w(x, z) - w(x, y)$

$$\|f(x) - f(y)\|^2 = \underbrace{\|f(x)\|^2}_{\text{same}} + \underbrace{\|f(y)\|^2}_{\text{same}} - 2\underbrace{\langle f(x), f(y) \rangle}_{= w(x, y)}$$



CONSTRUCTION OF $\hat{x}$

- ❖ $\langle \hat{x}_1, \hat{x}_4 \rangle = w(\hat{x}_1, \hat{x}_4)$
- ❖ $\langle \hat{x}_2, \hat{x}_4 \rangle = w(\hat{x}_2, \hat{x}_4)$
- ❖ $\langle \hat{x}_3, \hat{x}_4 \rangle = w(\hat{x}_3, \hat{x}_4)$



Dimension?

- ❖ System of at most $2r$ linear equations over $\hat{x}_i$
- ❖ Add small noise to every vector
- ❖ If dimension is $2r$ – there is always a solution

CONSTRUCTION OF $\hat{x}$

Equalize vector norms

- ❖ Every vertex chooses one coordinate
- ❖ For each vertex, set its coordinate so that $\|f(x_1)\| = \|f(x_2)\| = \dots = \|f(x_n)\|$

How to preserve inner products?

- ❖ A vertex chooses a coordinate not used by any of preceding neighbors
 - ❖ Then, $\langle f(x), f(y) \rangle = \underbrace{\langle \hat{x}, \hat{y} \rangle}_{= 0} + \langle \hat{x}, \hat{y} \rangle$
- ❖ There are at most $2r$ preceding neighbors