# Nearest Neighbor Search for OT in High-Dimensional Spaces

**Setting**: Sparse distributions supported on

a high-dimensional Euclidean space  $\mathbb{R}^d$ .

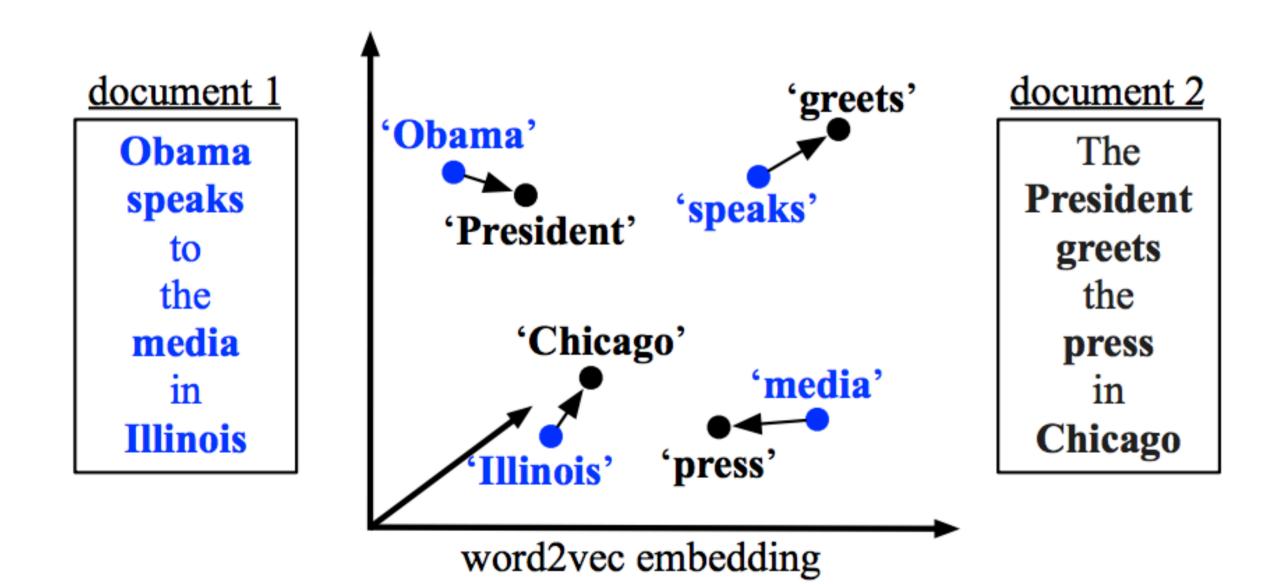
**Goal**: Given a collection of distributions

 $\mu_1, \ldots, \mu_n$ , and a query distribution  $\nu$ , find

the **nearest neighbor** of  $\nu$  in  $\mu_1, \dots, \mu_n$ .

#### **Example: Word-Mover Distance** between

text documents [Kusner et al. 2015]



**References:** 

Alexandr Andoni, Piotr Indyk, and Robert Krauthgamer. Earth mover distance over high-dimensional spaces. SODA 2008.

Arturs Backurs and Piotr Indyk. Better embeddings for planar Earth-Mover Distance over sparse sets. SoCG 2014.

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Marco Cuturi. Sinkhorn distances: Lightspeed computation of optimal transport. NeurIPS 2013.

Piotr Indyk and Nitin Thaper. Fast image retrieval via embeddings. International workshop on statistical and computational theories of vision, 2003.

Matt Kusner, Yu Sun, Nicholas Kolkin, and Kilian Weinberger. From word embeddings to document distances. ICML 2015.

▷ Tam Le, Makoto Yamada, Kenji Fukumizu, and Marco Cuturi. **Tree-sliced** approximation of wasserstein distances. NeurIPS 2019.

# Scalable Nearest Neighbor Search for Optimal Transport

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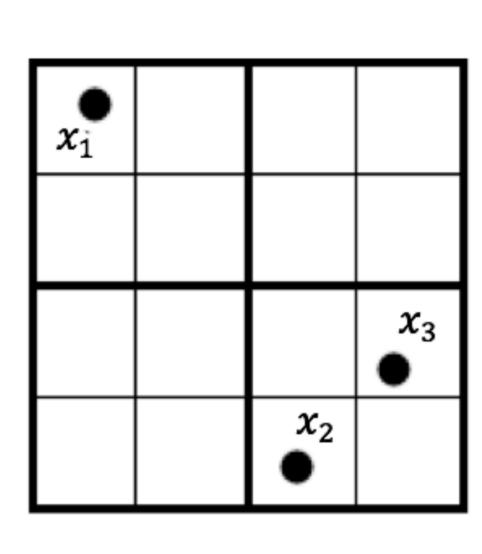
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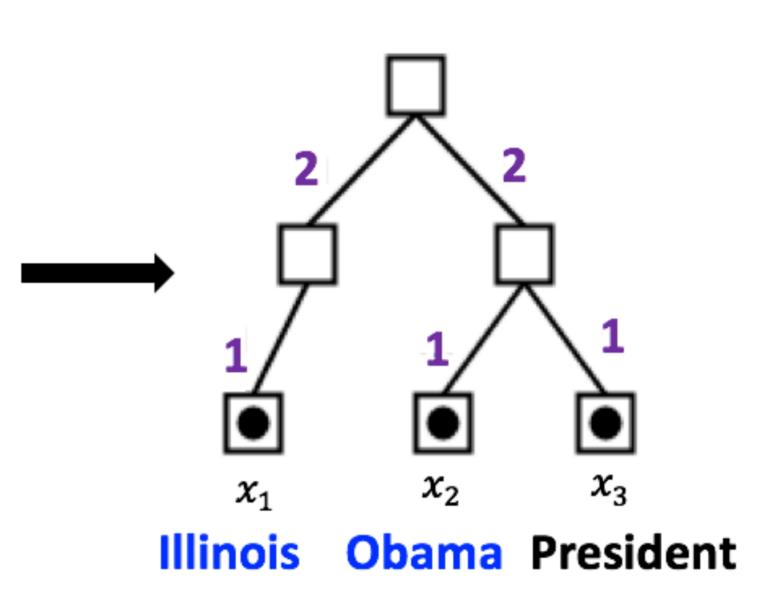
# Tree-based Methods for Fast OT

### **Classical method: Quadtree**

[Charikar 2002, Indyk & Thaper 2003, Le et al. 2019]

- 1. Embed support in tree of nested hypercubes.
- 2. Solve OT on the tree metric (linear time).





### **Our method: Flowtree**

Solve for the optimal flow on the tree, but compute its cost w.r.t. the original distance.

### **Taxonomy of fast approximate OT methods:**

- Coarse linear time: Mean [Kusner et al. 2015], **Overlap/TF-IDF**, Quadtree
- Fine quadratic time : **R-WMD** [Kusner et al. 2015], **Sinkhorn iterations** [Cuturi 2013]
- "Slower" linear time: Flowtree Nearly as accurate and much faster than quadratic time methods.

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Random input model <sub>5</sub>

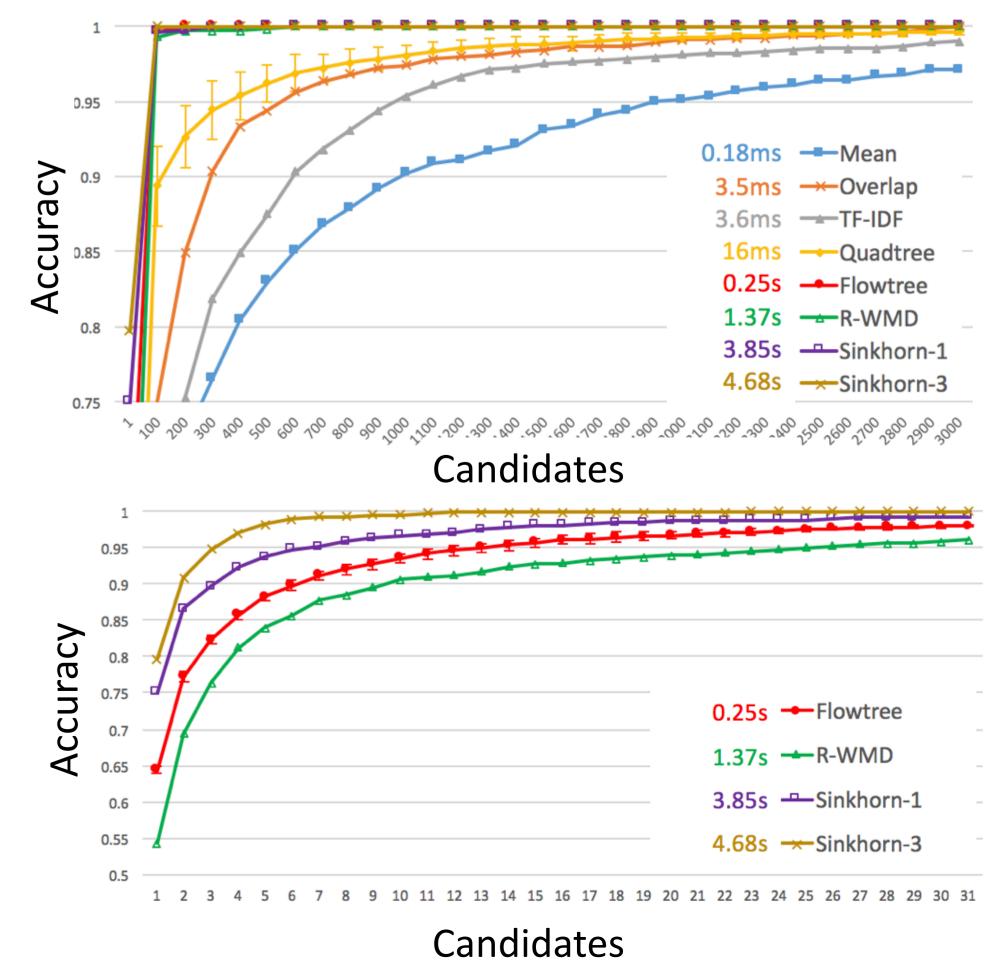
--Flowtree --Quadtree

Worst-case analysis: Based on [Andoni et al. 2008, Backurs & Indyk 2014]

**Theorem: Flowtree** finds an

In comparison, **Quadtree** finds an **O**(log(sn) ·  $log(d\Phi)$ )-approximate nearest neighbor, and the dependence on log *n* is necessary.

20newsgroups dataset:

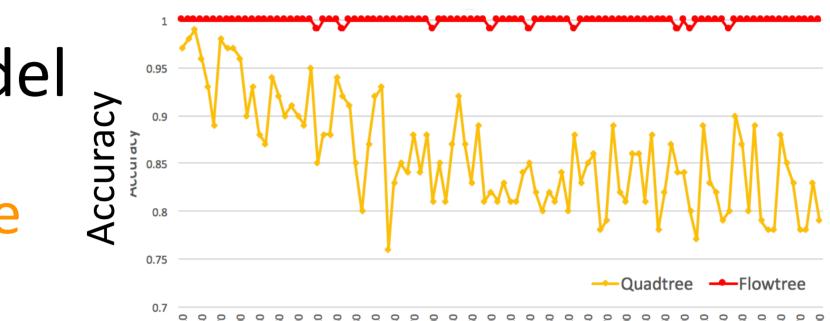


All methods:

High-accuracy methods:

## Results

### Flowtree, unlike Quadtree, does not degrade in NN-accuracy as the datasets size *n* grows.



Dataset size (*n*)

# $O(\min\{\log^2 s, \log s \cdot \log(d\Phi)\})$ -approximate nearest neighbor, where **s** is the max. support size, d is the dimension, $\Phi$ is the aspect ratio. Note: This is independent of the dataset size *n*.