Core-sets for Fair and Diverse Data Summarization

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Diversity Maximization

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Given a set of objects, how to pick a few of them while maximizing diversity?

Applications

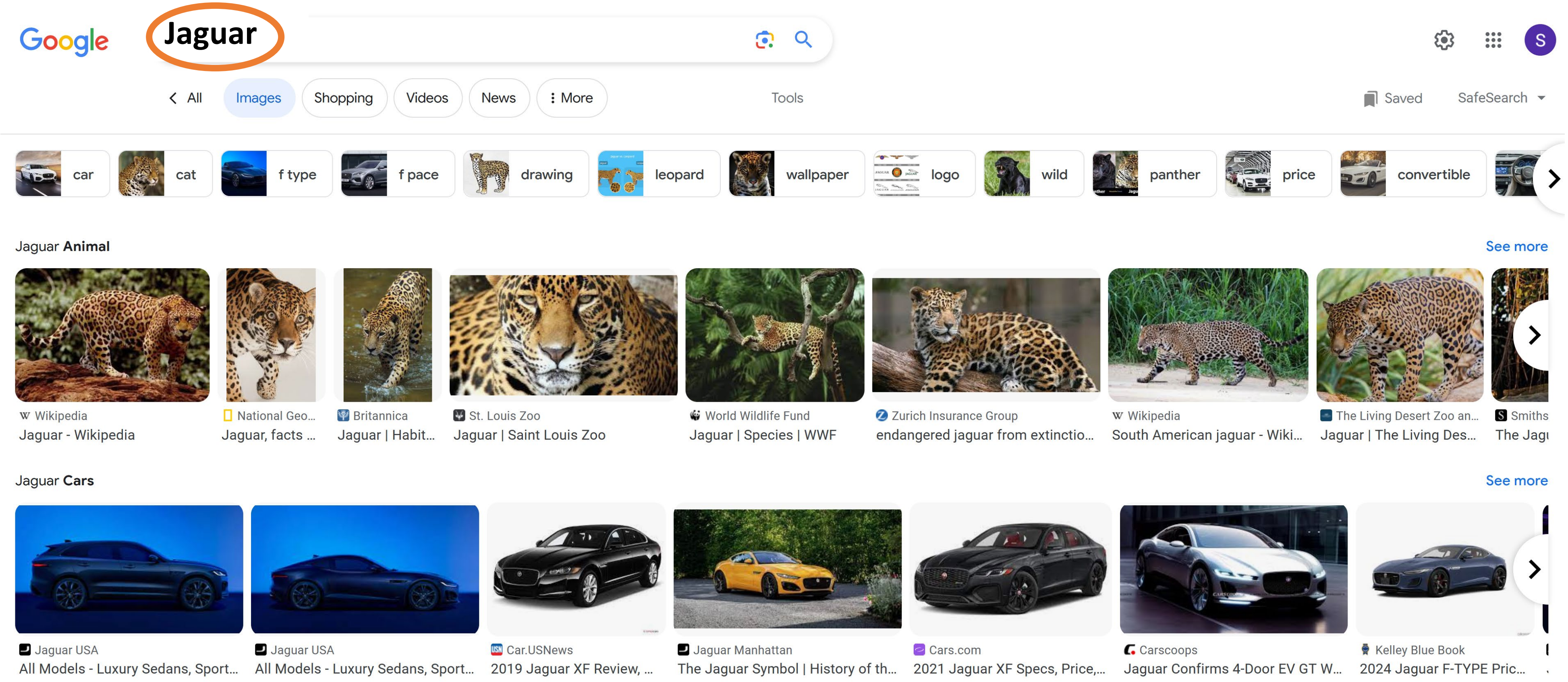
- **Summarization (e.g. User’s Feed, Video, Documents, Images)**

Applications

- **Summarization**
  - User’s feed Generation
    - A set of users
    - Each with a set of messages
      - People who they interact with
      - The channels they are part of
      - …
    - Which messages to show in their feed?
      - Relevant messages are shown to the users based on user’s likes and replies
      - Need to have diversity in the retrieved summary

Applications

- **Summarization (e.g. User's Feed, Documents, Images)**
- **Searching**



Applications

- **Summarization (e.g. User's Feed, Documents, Images)**
- **Searching**
- **Recommendation Systems**
  - **Movies, News articles**
  - **Shopping**
  - **Hiring Candidates e.g. for LinkedIn**

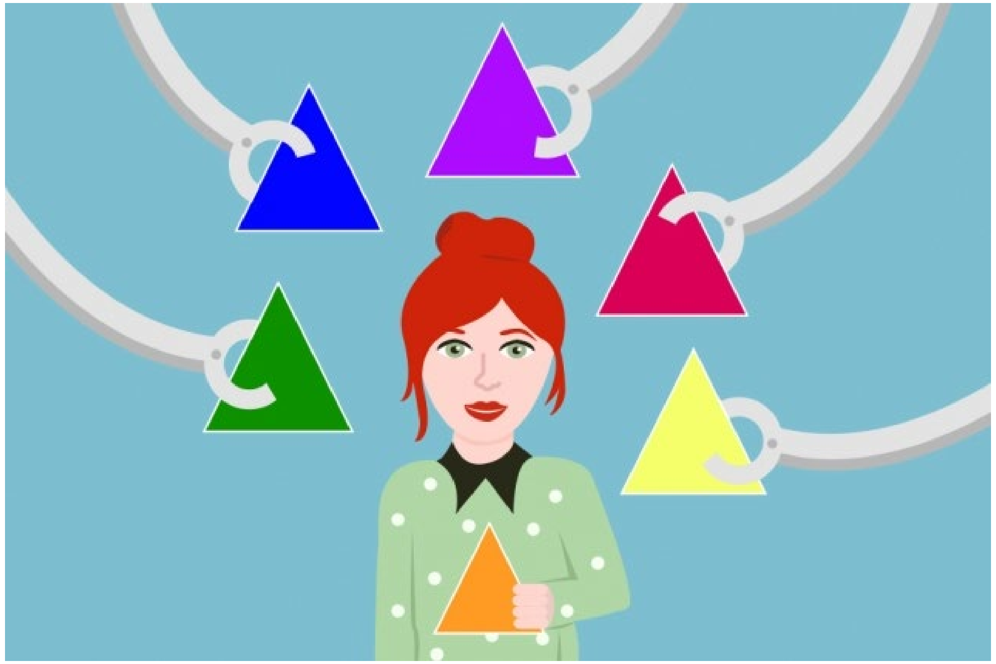


Image from: http://news.mit.edu/2017/better-recommendation-algorithm-1206

Applications

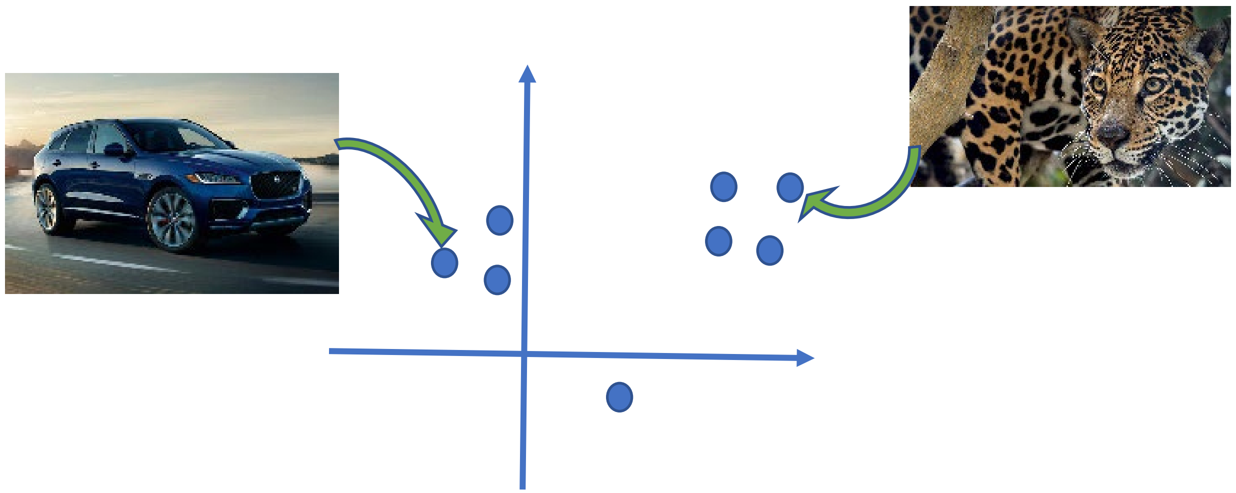
- **Summarization (e.g. User’s Feed, Documents, Images)**
- **Searching**
- **Recommendation Systems**
- **…**

Modeling the Objects

Objects
(documents, images, etc)

Feature Vectors

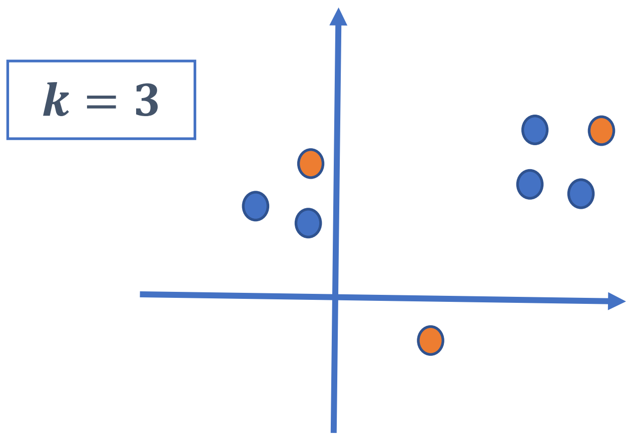
Points in a high dimensional space



The Diversity Maximization problem

Given: a set of n points P in a metric space and a parameter k,

Goal: pick a subset $S \subseteq P$ of k points while maximizing "diversity".



Diversity Notions

Diversity I: Minimum Pairwise Distance

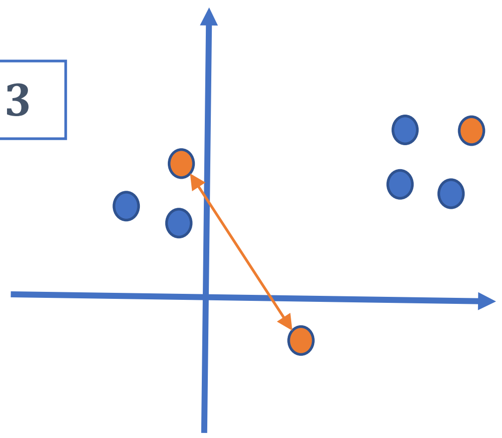
Input: a set of n vectors $\mathrm{P} \subset \mathbb{R}^d$ and a parameter $k \leq d$,

Goal: pick k points s.t. the **minimum pairwise distance** of the picked points is maximized.

$$\boldsymbol{min_{p,q \in S} dist(p, q)}$$

- **$O(1)$-approx Greedy Algorithm**
  [RRT'94]

$\boldsymbol{k = 3}$



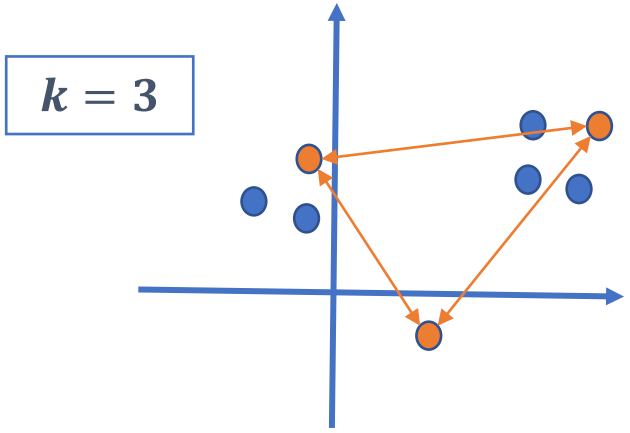
Diversity II: Sum of Pairwise Distances

Input: a set of n vectors $\mathrm{P} \subset \mathbb{R}^d$ and a parameter $k \leq d$,

Goal: pick k points s.t. the **sum pairwise distances** of the picked points is maximized.

$$\sum_{p,q \in S} dist(p, q)$$

- ❑ $O(1)$**-approx Local Search Algorithm** [HRT'97][AMT'13]

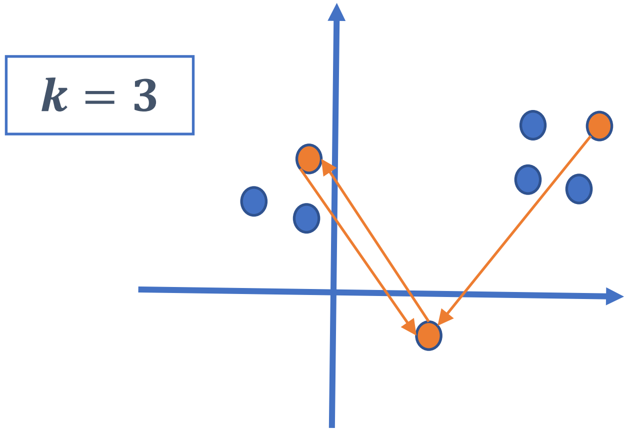


Diversity III: Sum of Nearest Neighbor Distances

Input: a set of n vectors $\mathrm{P} \subset \mathbb{R}^d$ and a parameter $k \leq d$,

Goal: pick k points s.t. the **sum of NN distances** of the picked points is maximized.

$$\sum_{p \in S} \min_{q \in S \setminus \{p\}} dist(p, q)$$



- ❑ Between Min-Pairwise Dist and Sum of Pairwise Dists

- ❑ $O(\log k)$-approx Alg [CH'01]
- ❑ $O(1)$-approx Alg [BGMS'16]

Diversity Notions

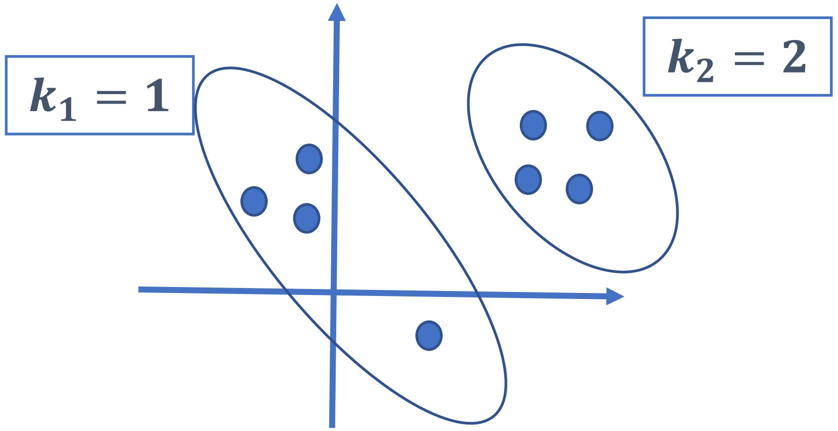
Diversity Notion		Offline
Min Pairwise Distance	$\boldsymbol{min_{p,q \in S} dist(p,q)}$	$\boldsymbol{\theta}(\mathbf{1})$ [Ravi et al 94]
Sum of Pairwise distances	$\boldsymbol{\sum_{p,q \in S} dist(p,q)}$	$\boldsymbol{\theta}(\mathbf{1})$ [Hassin et al 97]
Sum of NN Distances	$\boldsymbol{\sum_{p \in S} min_{q \in S \setminus \{p\}} dist(p,q)}$	$\boldsymbol{\theta}(1)$ [BGMS'16]
…	…	…

Constrained(Fair) Diversity Maximization

Constrained/Fair Diversity Maximization

Input:

- sets of vectors $P_1, \cdots, P_m$, $P = \bigcup_i P_i$
- and $k_1, \cdots, k_m$, $k = \sum_i k_i$

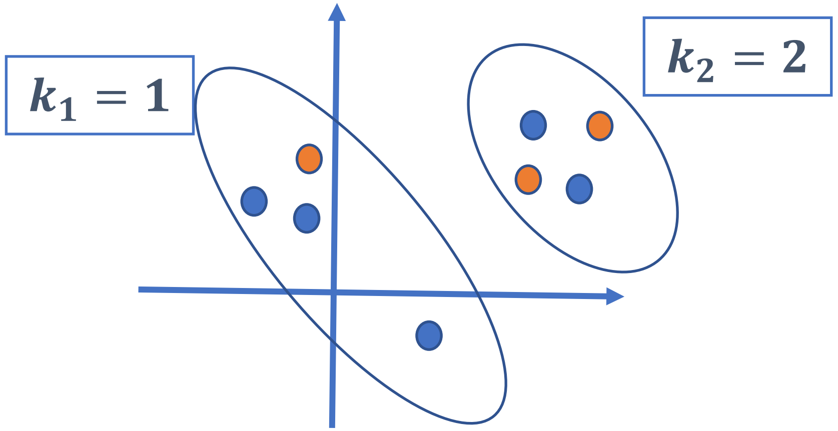


Constrained/Fair Diversity Maximization

Input:

- sets of vectors $P_1, \cdots, P_m$, $P = \bigcup_i P_i$
- and $k_1, \cdots, k_m$, $k = \sum_i k_i$

Goal: pick k_i points $S_i \subset P_i$ s.t. the diversity of the picked points $S = \bigcup_i S_i$ is maximized.



Prior Work: Fair Diversity Maximization

Diversity Notion	FDM
Min Pairwise Distance	$\boldsymbol{\theta}(m)$ [MMM20, AMMM'22]
Sum of Pairwise distances	$\boldsymbol{\theta}(\mathbf{1})$ [AMM'13]
Sum of NN Distances	$\boldsymbol{\theta}(\mathbf{1})$ [BGMS'16]

Application I: in User's Feed Generation

- Each message has a posted time
- Goal: show more recent messages and less old ones
- Still need diversity

- Modeling Recency
  - Divide the messages in a month into four groups based on the week they have been posted
  - Set k_i to be higher for more recent weeks
- Data Set: Reddit Messages
  - Messages of a single month (~21000 messages) and divide it into four groups based on the week they appear in

Application II: Movie Recommendation

- Task: Movie recommendation
- Goal: assign budgets for each genre, e.g. comedy, action, drama, …

- MovieLens Data Set
  - Collection of 4000 movies
  - Group based on the movie genre into 18 groups (e.g. “documentary”, “crime”, “drama”, “action”, …)

Experimental Results

1. **Need for FDM:** As expected, in the unconstrained version, the recency is not preserved

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2. **Price of Balancedness:** diversity loss by resorting to FDM
   - 1%, for sum-of-pairwise distances
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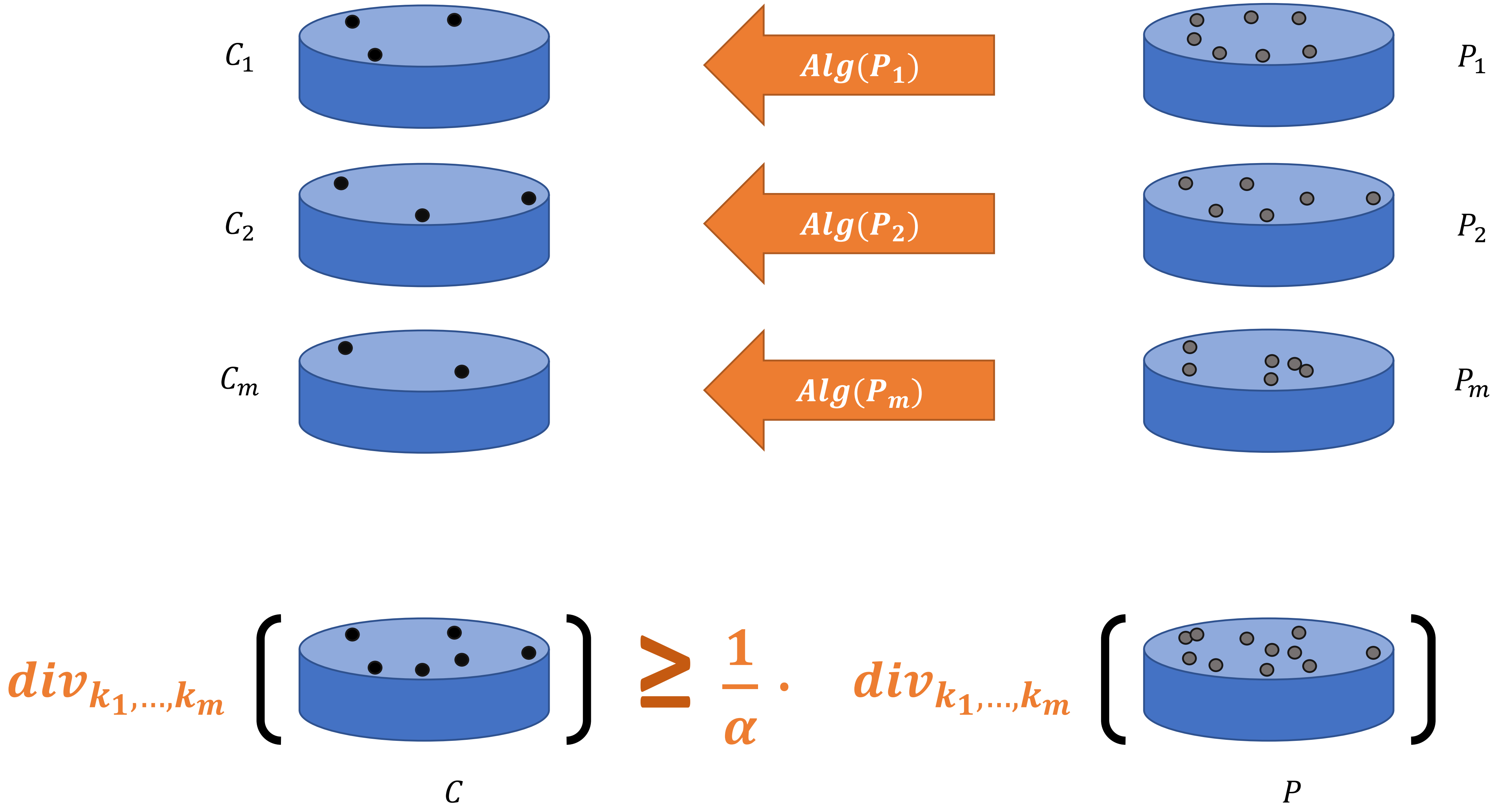
   - 50%, for minimum pairwise distance

FDM under Big Data Model: Coresets



C_1
$Alg(P_1)$
P_1
C_2
$Alg(P_2)$
P_2
C_m
$Alg(P_m)$
P_m
$div_{k_1,\dots,k_m}$
$\geq \frac{1}{\alpha} \cdot$
$div_{k_1,\dots,k_m}$
C
P

Theoretical Results

- ✓ Algorithms are simple to implement
- ✓ Show a new offline algorithm for FDM under Sum-of-NN-Distances

Diversity Notion	FDM	Coreset Setting		
		Approx.	Coreset Size	Reference
Min Pairwise Distance	$\boldsymbol{\theta}(m)$ [MMM20, AMMM'22]	$O(1)$	$O(k)$ *per group*	[MMM20]
Sum of Pairwise distances	$\boldsymbol{\theta}(\mathbf{1})$ [AMM13]	$(1+\epsilon)$	Depends on n or aspect ratio	[CPP18]
		$O(1)$	$O(k_i^2)$ per group	**[This work]**
Sum of NN Distances	$\boldsymbol{\theta}(\mathbf{1})$ [BGMS'16]	$O(m \cdot \log k)$	$O(k^2)$ per group	**[This work]**

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3. **Using Coresets**
   - The runtime of the algorithm improves by a factor of **100x**
   - The diversity is only lost by a **few precents**.
   - No **need to recompute the summary** of old messages.

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4. **Show superiority of our coreset construction algorithm over Prior work**

Summary

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- Algorithms are simple to implement
- Showed effectiveness of coresets

THANK YOU!