

Fairness and Explainability

TOP: Data Clustering 076/091

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Portland State University

Outline

- 1 Introduction
- 2 The Fair Model
- 3 An Algorithm
- 4 Explainability
- 5 Explainable Clustering

Factors of Importance

In ML/Algorithms, what are the most important factors that drive technological innovation?

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- Running time
- Query time
- Update time
- Storage and handling of big data
- Computational power of hardware
- Quality
- Privacy and security

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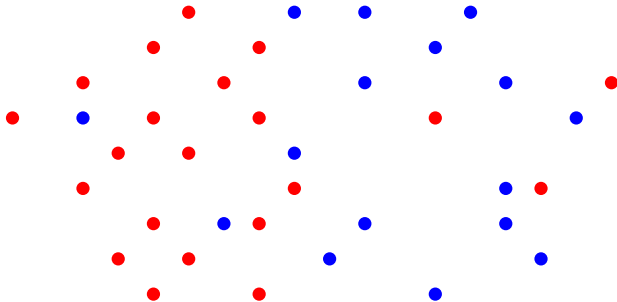
Recent challenges

- Fairness
- Explainability

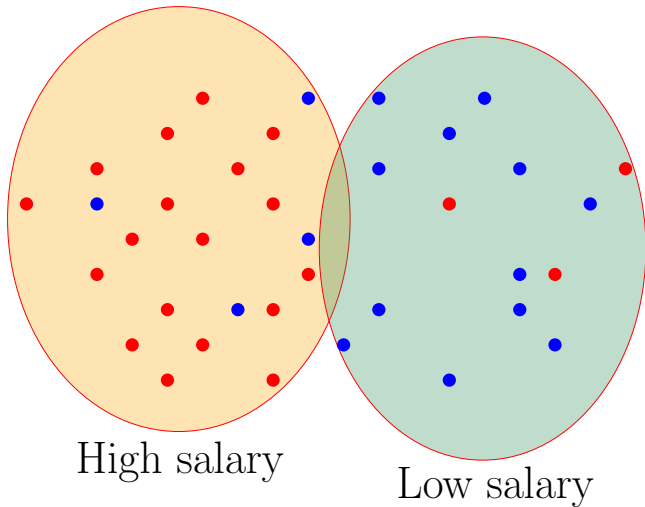
Recommendation of Jobs



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Recommendation of Jobs

DE GRUYTER OPEN

Proceedings on Privacy Enhancing Technologies 2015, 2015 (1):92–112

Amit Datta*, Michael Carl Tschantz, and Anupam Datta

Automated Experiments on Ad Privacy Settings

A Tale of Opacity, Choice, and Discrimination

ANITA BORG INSTITUTE
WOMEN TRANSFORMING TECHNOLOGY

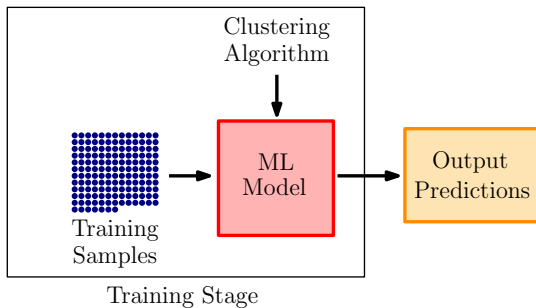
GRACE HOPPER
CELEBRATION OF WOMEN IN COMPUTING

Recommending Dream Jobs in a Biased Real World

Nadia FAWAZ

LinkedIn Corporation
nfawaz@linkedin.com

The ML Pipeline

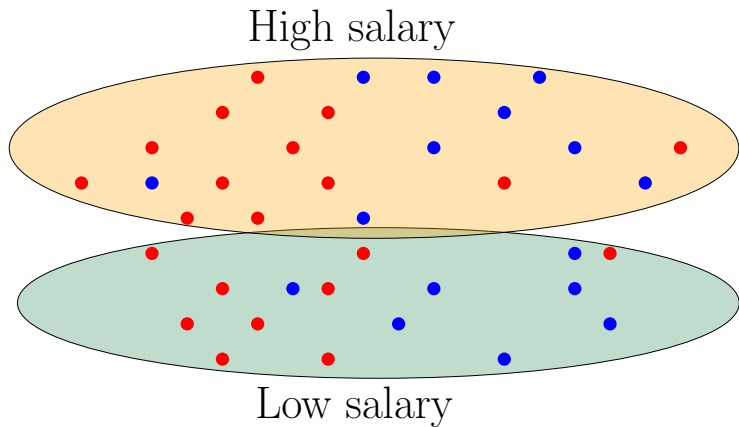


Training the classifier: feature engineering/labeling of samples

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Fair Clustering



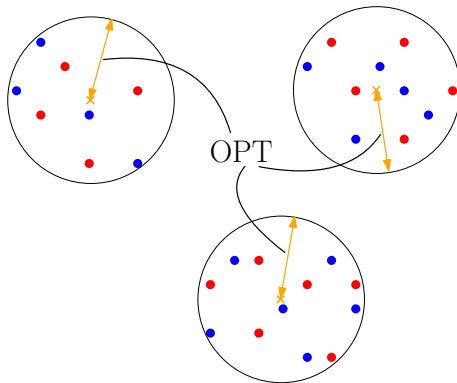
(Proportionally) Fair k -center Clustering

- Given colored points in \mathbb{R}^d
- Find a set C of k points (cluster centers) in \mathbb{R}^d that
 - minimizes $\text{cost}(C)$; and
 - each cluster is fair or color-balanced

Fair k -center Clustering

- Given n red and n blue points in \mathbb{R}^d
- Find a set C of k points (cluster centers) in \mathbb{R}^d that
 - minimizes $\max_{c \in C} \text{radius}(c)$; and
 - each cluster has equal number of red and blue points.

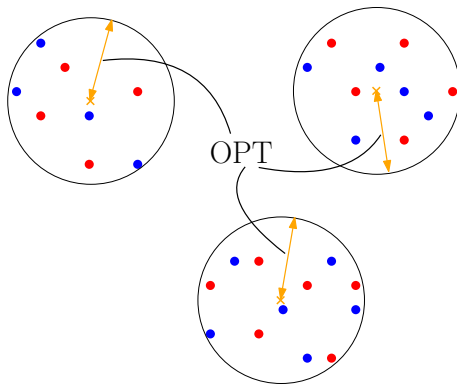
Fair Clustering



Outline

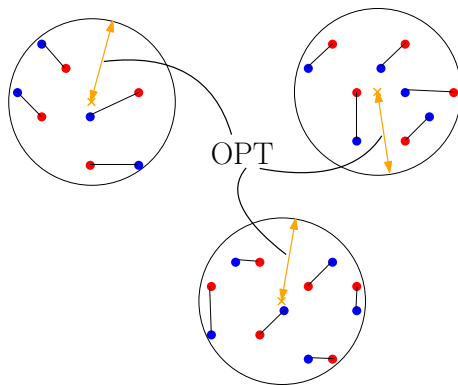
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How to address fairness?



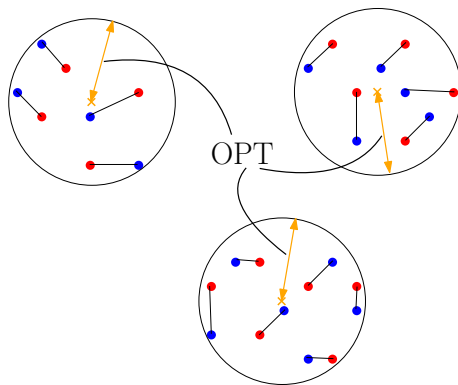
We know how to solve regular k -center problem

Observations



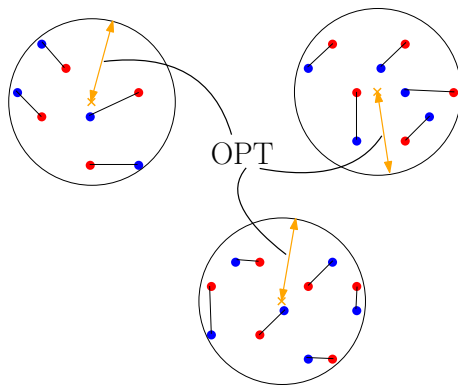
- Consider the bipartite graph between red and blue points (vertices)

Observations



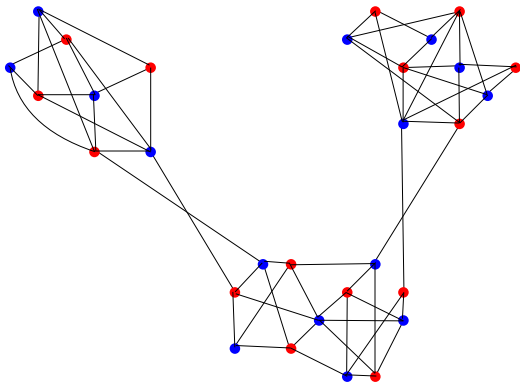
- Consider the bipartite graph between red and blue points (vertices)
- There is a perfect matching in this graph

Observations



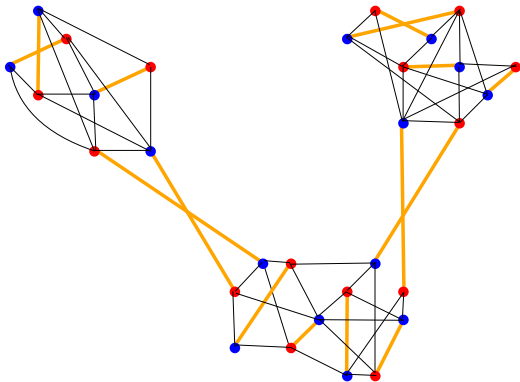
- Consider the bipartite graph between red and blue points (vertices)
- There is a perfect matching in this graph
- Each edge has length at most $2 \cdot \text{OPT}$

The Algorithm



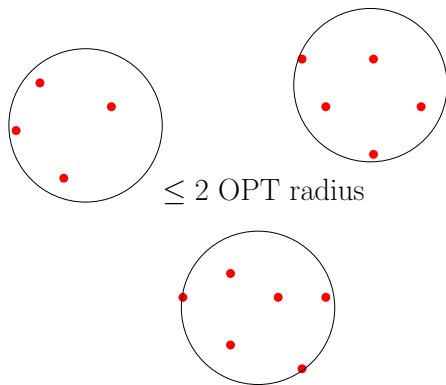
Compute a bipartite graph G between red and blue points (vertices) by adding edges of length at most $2 \cdot \text{OPT}$

The Algorithm



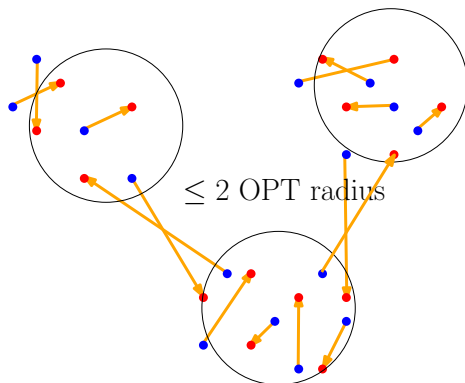
Compute a perfect matching in G (orange edges)

The Algorithm



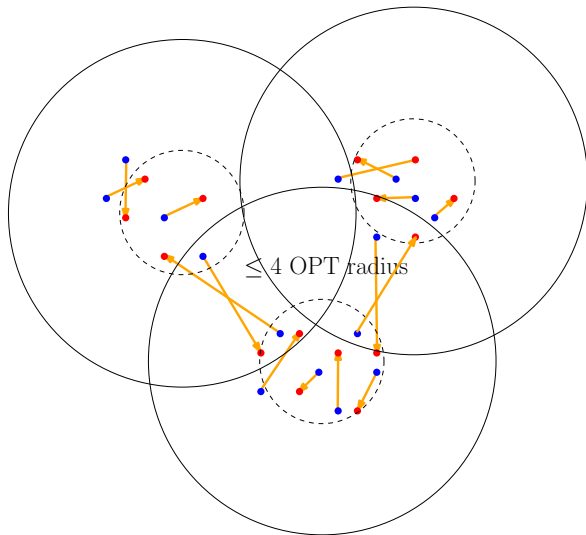
Compute a 2-approximate k -center clustering of the red points

The Algorithm



Assign each blue point to the cluster of the red point matched to it

The Algorithm

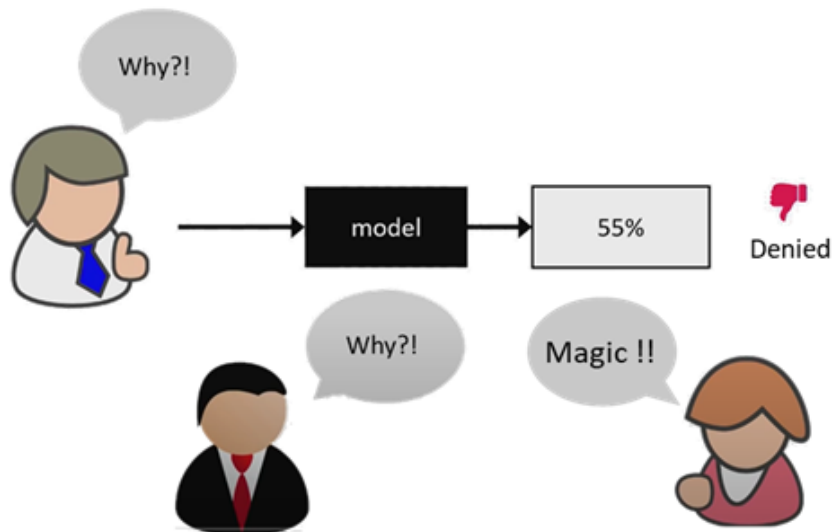


Expand each ball by 2OPT to cover all points assigned to the cluster

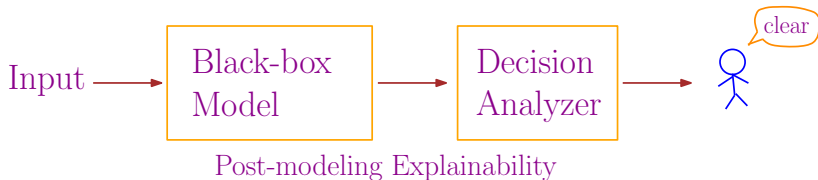
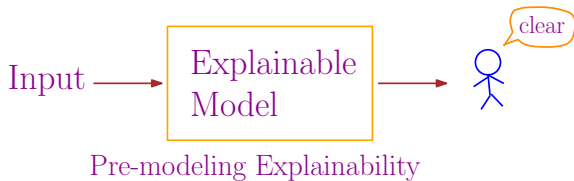
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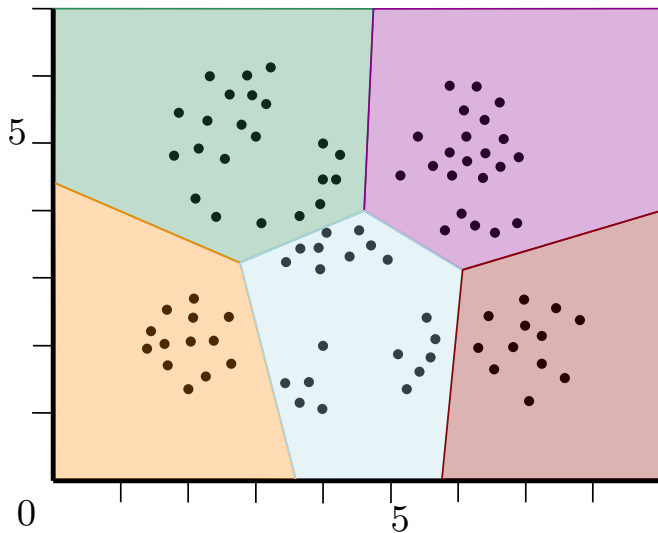
Black Magic of Black Boxes



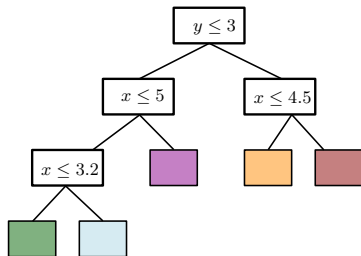
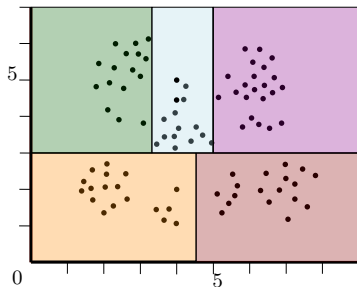
Explainable AI



Explaining a Clustering



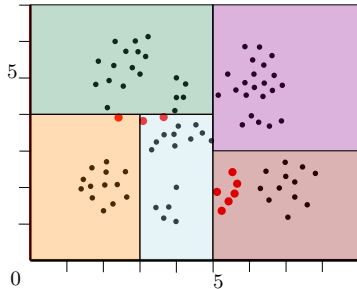
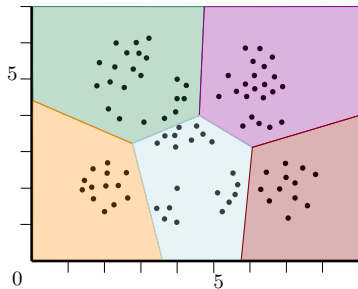
Pre-modeling Explainability¹



Inherent explainability via decision tree

¹Moshkovitz et al. ICML 2020

Post-modeling Explainability

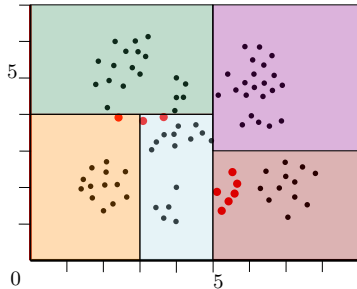
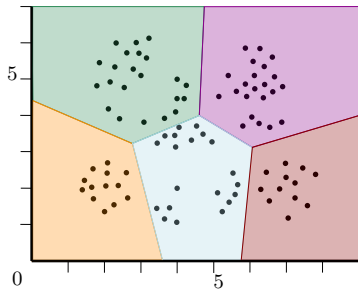


Remove a subset of points to explain the given clustering

Outline

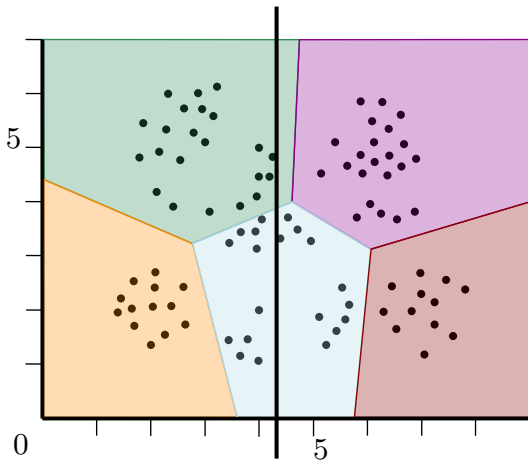
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Clustering Explanation



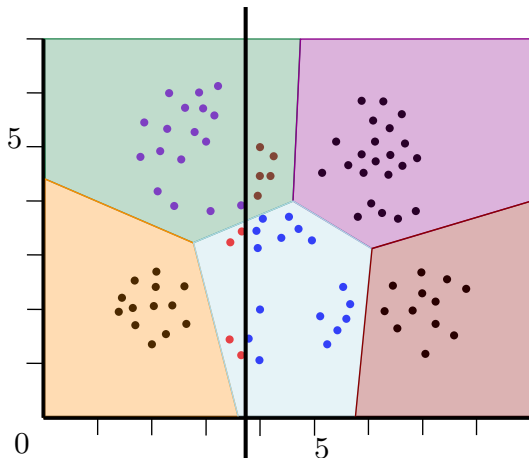
Remove 5 points to explain the given clustering

An Exact Algorithm for 2D



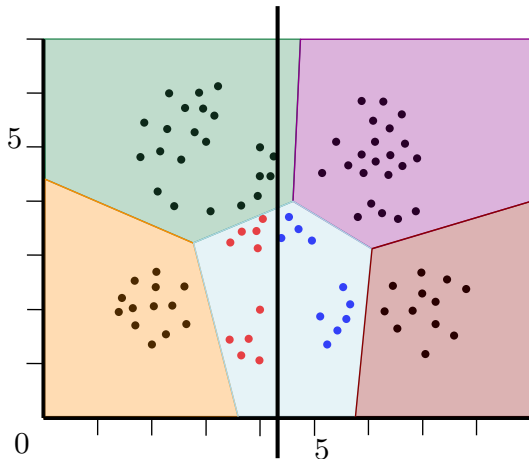
A cut might separate a cluster

An Exact Algorithm for 2D



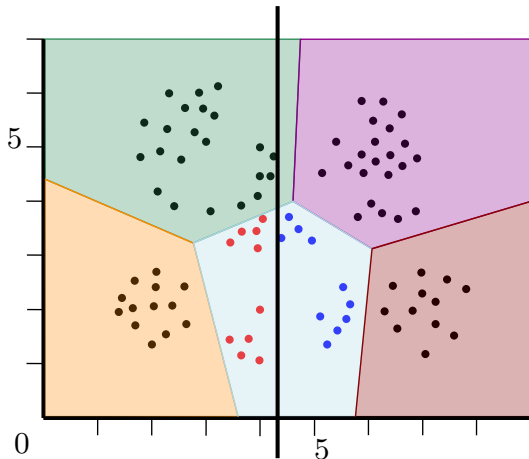
A cut might separate multiple clusters - 2^k choices to make

An Exact Algorithm for 2D



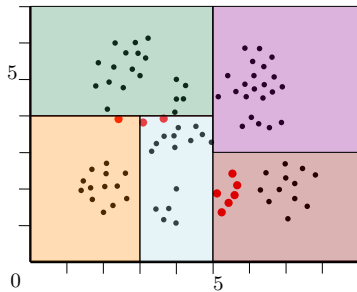
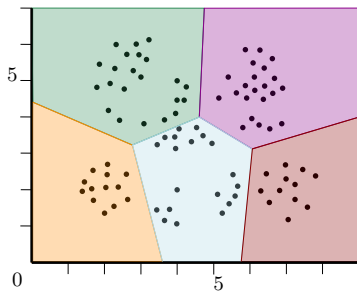
You have $2(n - 1)$ choices for vertical and horizontal cuts -

An Exact Algorithm for 2D



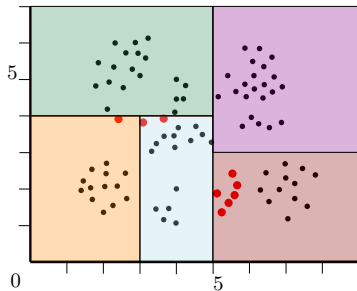
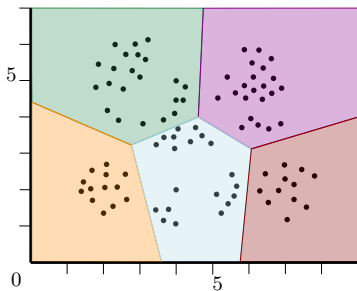
You have $2(n - 1)$ choices for vertical and horizontal cuts -
 $2(n - 1)2^k =$ choices for selecting the first cut

An Exact Algorithm for 2D



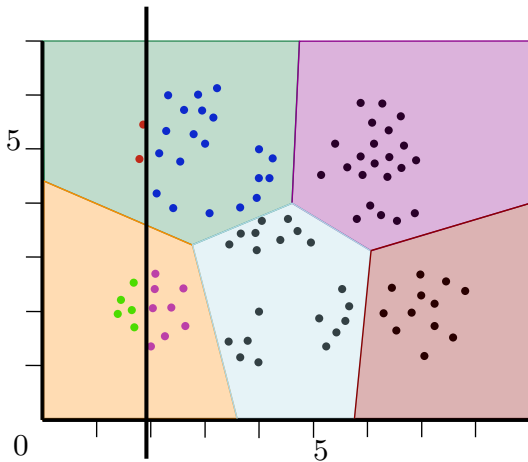
For k clusters, we need $k - 1$ cuts

An Exact Algorithm for 2D



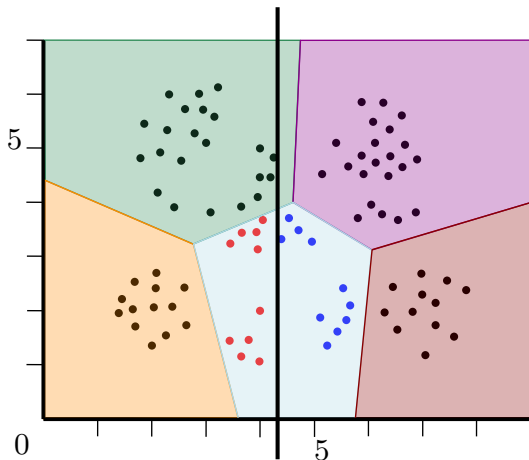
For k clusters, we need $k - 1$ cuts $\rightarrow (2(n - 1)2^k)^{k-1}$
 $= O(n^k 2^{k^2})$ choices in total

An Approximation Algorithm



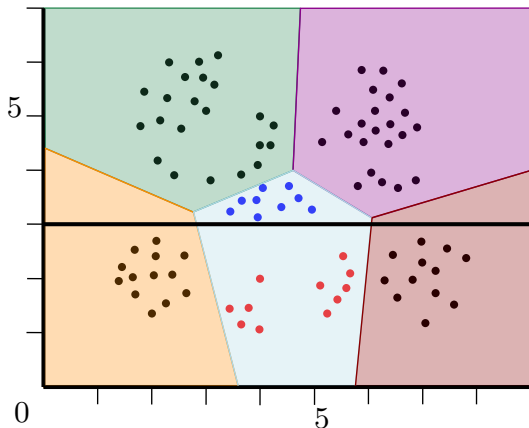
Several choices for cuts

An Approximation Algorithm



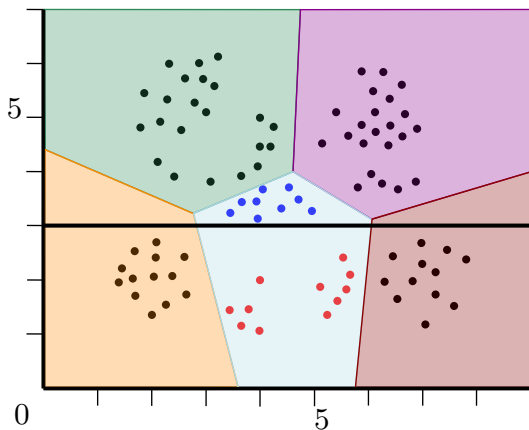
Several choices for cuts

An Approximation Algorithm



Greedly pick the cut that removes the minimum number of points: remove the smaller chunk for each cluster

An Approximation Algorithm



Runs in poly-time – $(k - 1)$ -approximation

