


Online and Consistent Correlation Clustering

Andreas Maggiori

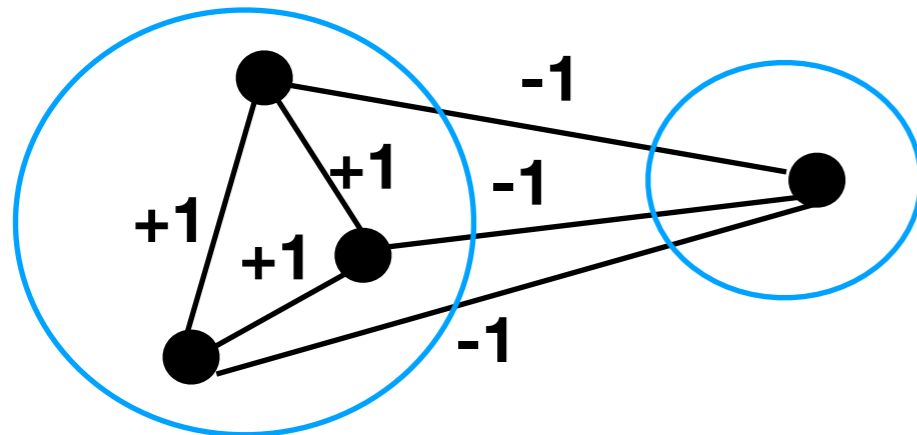
Vincent Cohen-Addad, Silvio Lattanzi, Nikos Parotsidis

EPFL

The Google logo is displayed in its characteristic multi-colored font (blue, red, yellow, blue, green, red) on a light pink rectangular background.

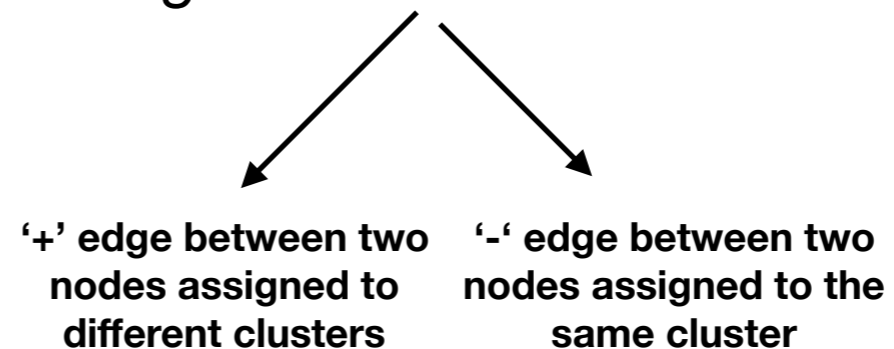
Correlation Clustering - Problem Statement

Input: a complete signed graph $G = (V, E, s)$ where $s(e) = '+'$ or $'-'$ for every edge e



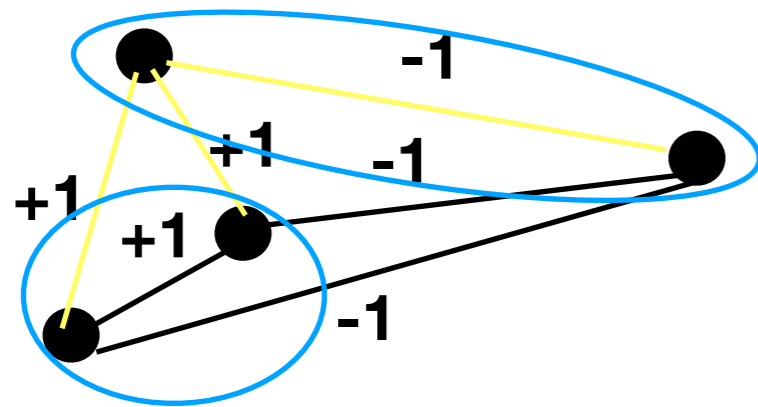
0 disagreements 😊

Goal: output a clustering which minimises *disagreements*



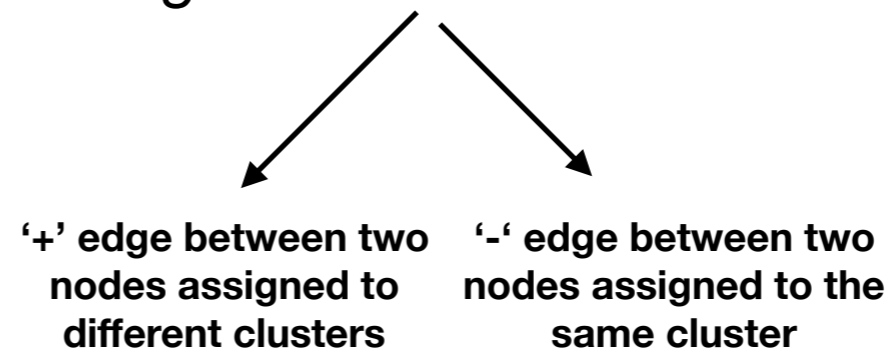
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3 disagreements 🤔

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Correlation clustering is well studied.

Offline setting

- Introduced by Bansal et al. 2004. The problem is NP-HARD.
- Pivot algorithm is a 3-approximation on expectation. (Ailon et al. 2008)
- LP based 2.06-approximation algorithm (Chawla et al 2015)

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Other settings

- Distributed: Chierichietti et al 2014, Ahi et al. 2015, Pan et al. 2015, Cohen-Addad et al. 2021
- Online: Mathieu et al. 2010

Online setting

- At each time t : a node arrives, revealing all its incident edges to previously arrived nodes.
- Clustering decisions are irrevocable:
 - create a new singleton cluster with the newly arrived node; or
 - Add that node to a preexisting cluster.
- Mathieu et al. proved that any online algorithm is $\Omega(n)$ -competitive.
Why: difficult to distinguish if an edge is a bridge between two cliques or it is part of a clique.



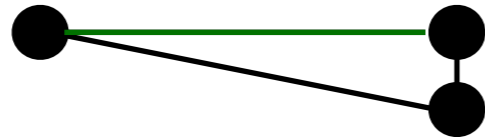
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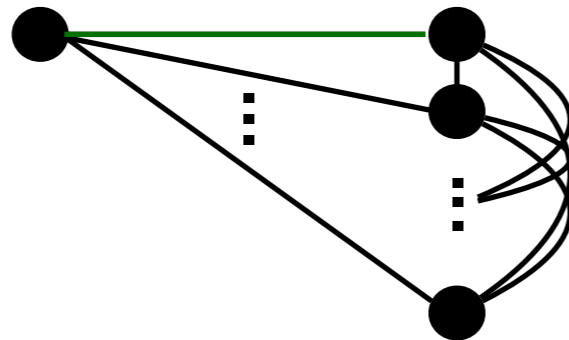
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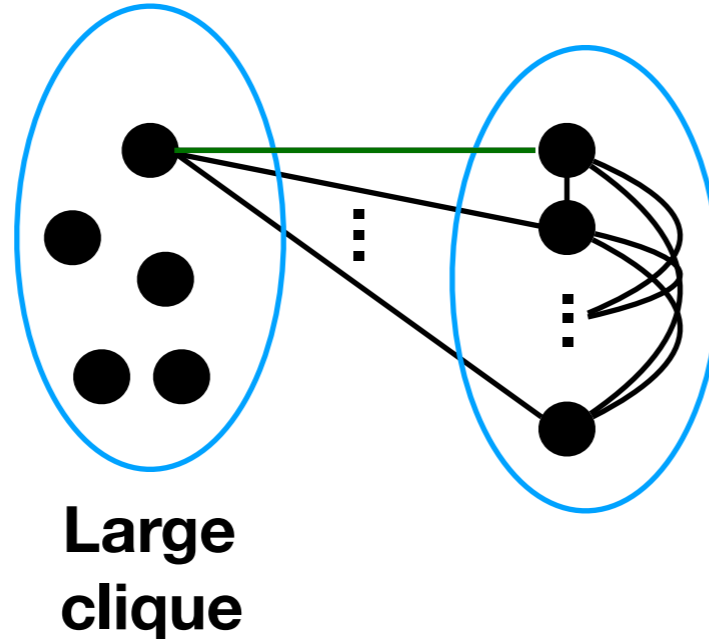
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Online setting with recourse

times a node changes cluster

- At each time t : a node arrives, revealing all its incident edges to previously arrived nodes.
- Clustering decisions are **NOT** irrevocable.
- Goal: having at all times a constant factor approximation while minimising the worst case recourse of a node.

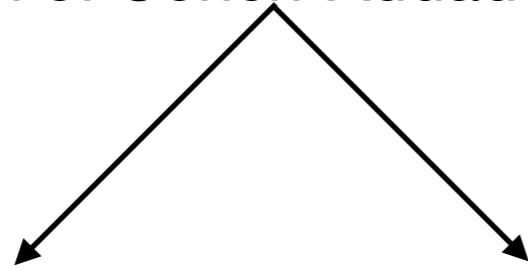


Contributions:

- A constant factor approximation algorithm which achieves worst case $\log(n)$ recourse per node.
- A matching lower bound.

Online setting with recourse

Agreement Algorithm of Cohen-Addad et al 2021 as a subroutine

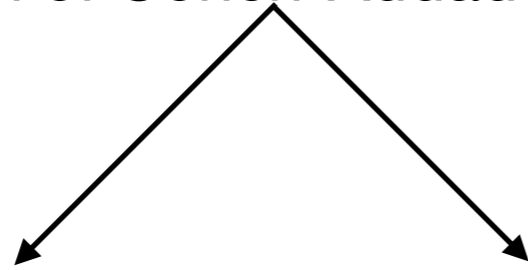


Creates dense clusters
with few outgoing edges

Constant factor approximation

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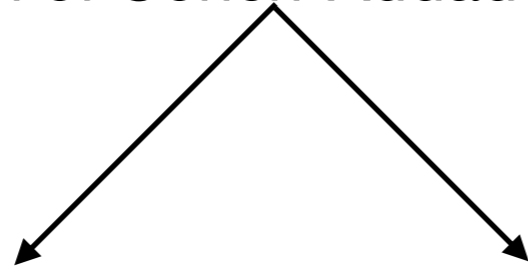
Constant factor approximation

Online Agreement Algorithm

1. Rerun the Agreement Algorithm

Online setting with recourse

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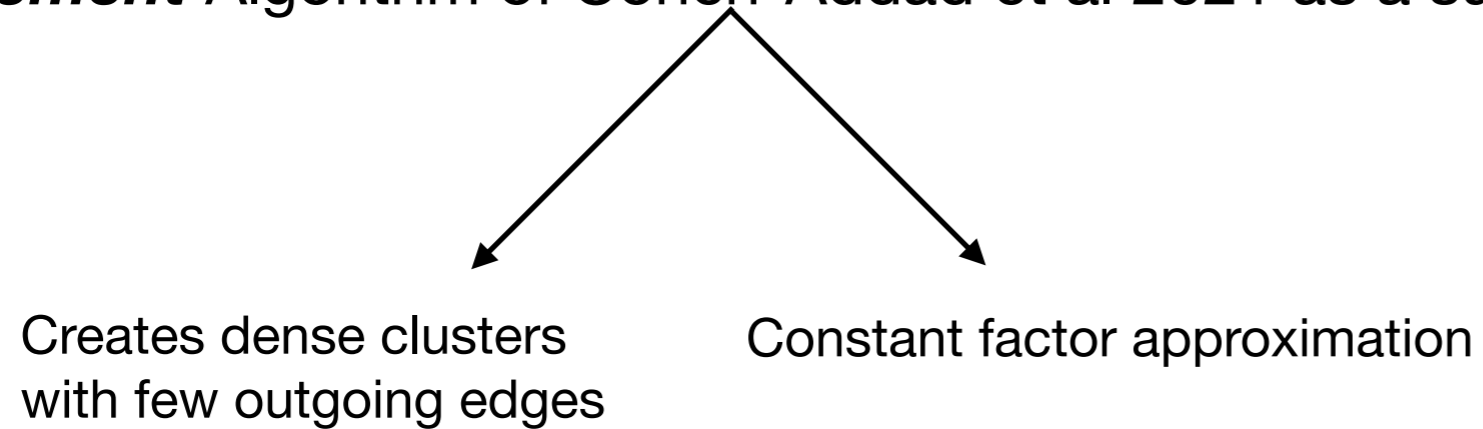
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Worst case linear recourse



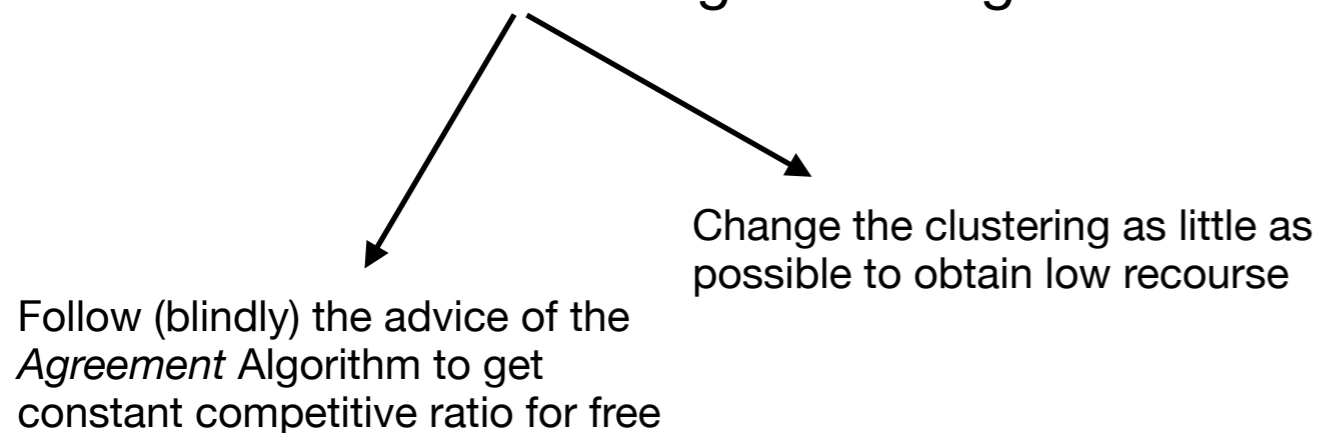
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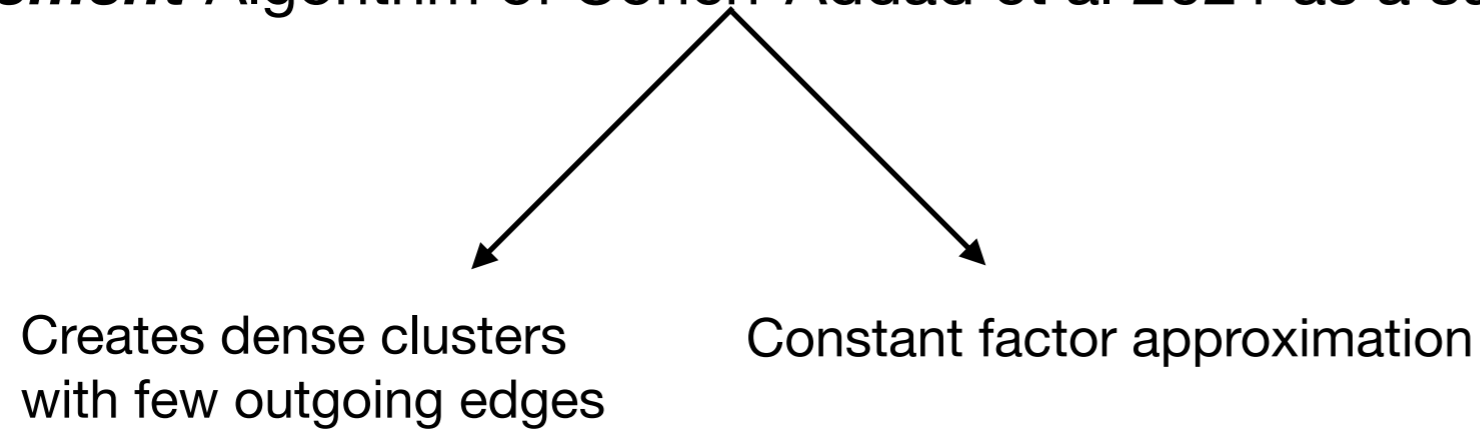
Online Agreement Algorithm

1. Rerun the Agreement Algorithm
2. Stabilize the resulting clustering



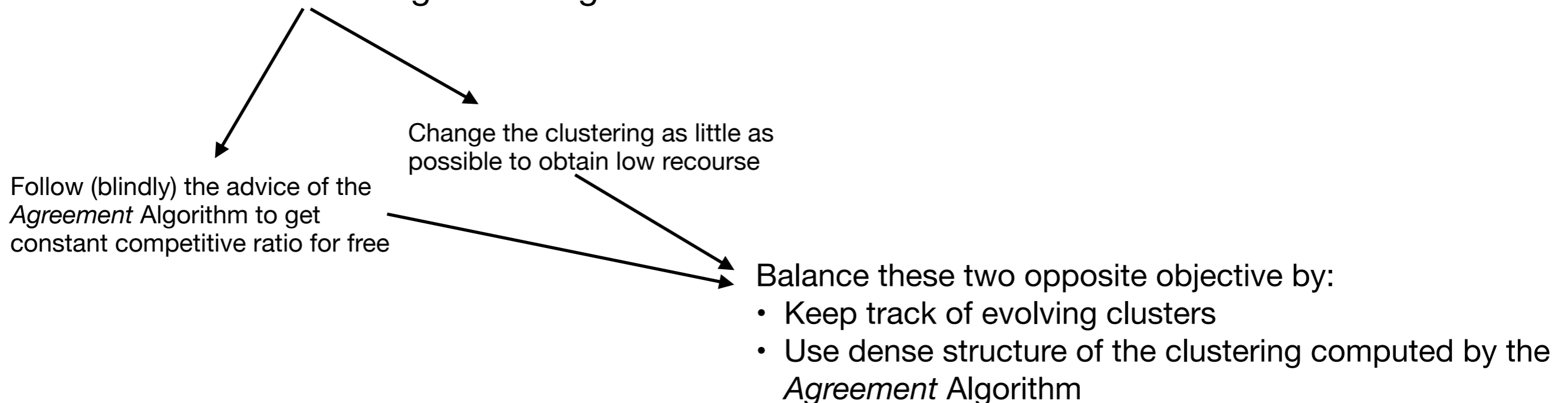
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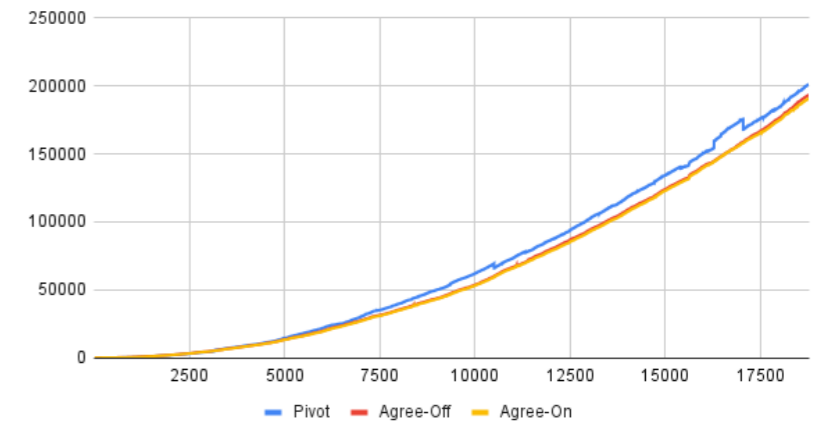
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Correlation Clustering Objective

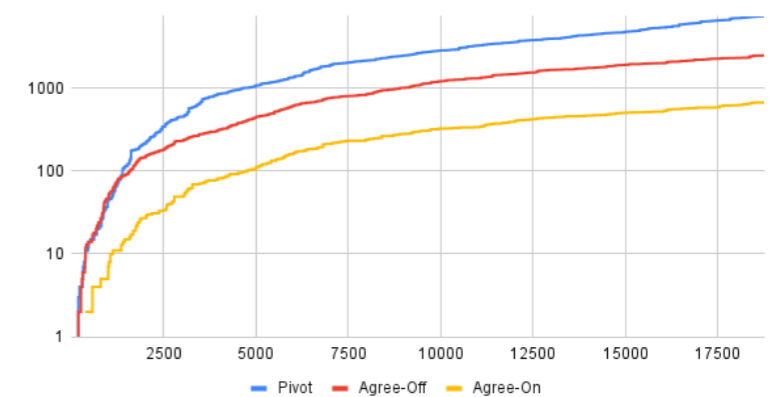


Online Agreement Algorithm

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Change the clustering as little as possible to obtain low recourse

Cumulative Recourse



Follow (blindly) the advice of the Agreement Algorithm to get constant competitive ratio for free

Balance these two opposite objective by:

- Keep track of evolving clusters
- Use dense structure of the clustering computed by the Agreement Algorithm

Thank you for your attention!