Primal-Dual Algorithms for Clustering and Feature Allocation

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Feature Allocation Problem

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Figure: http://examples.gurobi.com/facility-location

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- $y_i =$ indicator for whether facility i is open

Primal IP:

minimize $\sum_{i \in F, j \in C} c_{ij} x_{ij} + \sum_{i \in F} f_i y_i$ subject to $\forall j \in C : \sum x_{ij} \geq 1$, $i \in F$ $\forall i \in F, j \in C : y_i - x_{ij} > 0,$ $\forall i \in F, j \in C : x_{ij} \in \{0, 1\},\$ $\forall i \in F : y_i \in \{0, 1\}.$

 $c_{ij} = \text{distance}, f_i = \text{facility cost},$ $x_{ij} = \text{client connection}, y_i = \text{facility open}$

Primal LP Relaxation:

minimize $\sum_{i \in F, j \in C} c_{ij} x_{ij} + \sum_{i \in F} f_i y_i$ subject to $\forall j \in C : \sum x_{ij} \geq 1$, $i \in F$ $\forall i \in F, j \in C : y_i - x_{ij} \ge 0,$ $\forall i \in F, j \in C : x_{ij} > 0,$ $\forall i \in F : \mathbf{y}_i \geq \mathbf{0}.$

 $c_{ij} = \text{distance}, f_i = \text{facility cost},$ $x_{ij} = \text{client connection}, y_i = \text{facility open}$

Dual LP:

$$\begin{array}{ll} \text{maximize} & \sum\limits_{j \in C} \alpha_j \\ \text{subject to} & \forall i \in F, j \in C : \alpha_j - \beta_{ij} \leq c_{ij}, \\ & \forall i \in F, \sum\limits_{j \in C} \beta_{ij} \leq f_i, \\ & \forall j \in C : \alpha_j \geq 0, \\ & \forall i \in F, j \in C : \beta_{ij} \geq 0. \end{array}$$

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Facility *i* is *paid* for when $\sum_{j:\phi(j)=i} \beta_{ij} = f_i$

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 $\phi(j) = i$ denotes that client j is *connected* to facility iFacility i is *paid for* when $\sum_{j:\phi(j)=i} \beta_{ij} = f_i$

Total price paid by client $j: \alpha_j = \beta_{\phi(j)j} + c_{\phi(j)j}$

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Finish when all clients are connected

Running Time: $O(m \log m)$, where $m = |F| \cdot |C|$

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$$\sum_{i \in F, j \in C} c_{ij} x_{ij} + \sum_{i \in F} f_i y_i \le 3 \cdot \mathsf{OPT}$$

Primal-Dual Clustering

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LP relaxation and dual programs are similar
Algorithm is just Facility Location in the special case

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Compare with K-means

- At worst a 3-approximation algorithm
- As λ gets large, results converge to OPT
- Running time is $O(n^2 \log n)$ where n = |C|
 - \blacksquare Can run quicker for smaller values of λ
- Compare with K-means
 - PD approach takes a little longer, but can give better results

Examples: 1200 points

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K-means: 0.06 s, k=4 / PD: 0.77 s, $\lambda=7$

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K-means: 0.04 s, k=2 / PD: 0.59 s, $\lambda=3$

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K-means: 0.04 s, k=2 / PD: 0.54 s, $\lambda=2$

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K-means: 0.04 s, k=3 / PD: 0.83 s, $\lambda=5$

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K-means: 0.12 s, k=2 / PD: 1.15 s, $\lambda=10$

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LP relaxation and dual programs are the same

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- A client may contribute to more than one facility, and thus have multiple features

Example:



Example: $\lambda = 1$



Example: $\lambda = 2$



Example: $\lambda = 7$



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Example: $\lambda = 11$



Example: $\lambda = 15$



Compare with BP Means [BKJ]:



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- As λ gets large, the algorithm's result equals OPT
- Worst case approximation bound: ongoing work

Leaving Out λ

We require $\lambda \geq 0$

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Theorem: The smallest value of λ that allows all edges to go tight is $\lambda^* = \max_i \left(n \cdot \max_j (c_{ij}) - \sum_j c_{ij} \right)$

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Theorem: The smallest value of λ that allows all edges to go tight is $\lambda^* = \max_i \left(n \cdot \max_j (c_{ij}) - \sum_j c_{ij} \right)$ **Theorem**: For $\lambda \ge \lambda_* = \min_i \left(n \cdot \max_j (c_{ij}) - \sum_j c_{ij} \right)$, OPT = $\min_i \left(\sum_j c_{ij} \right) + \lambda$

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- \blacksquare Before the first facility gets paid for, the algorithm's computations are the same for each value of λ
- Branch computations for a particular \(\lambda\) when it reaches its first paid facility event
- Running PD algorithms without first choosing λ :
 - \blacksquare Algorithm chooses values of $\lambda \in [0,\lambda^*]$ to test

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Keep the best looking result?

Same strategies work for running both clustering and feature allocation together

- Keep the best looking result?
- Run clustering and feature allocation together, without λ!

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