CS880: Approximation and Online Algorithms

Lecture 9: Dual Fitting, Primal Dual Algorithms

9.1 Properties of Primal-Dual Linear Programming

$$\begin{array}{lll} \text{Primal} & \text{Dual} \\ \min \ c^T x \text{ s.t.} & \max \ b^T y \text{ s.t.} \\ Ax \geq b & \Longleftrightarrow & y \geq 0 & m \text{ constraints} \\ x \geq 0 & \Longleftrightarrow & A^T y \geq 0 & n \text{ constraints} \end{array}$$

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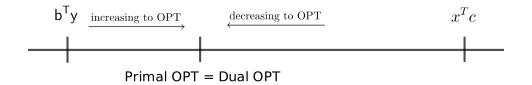


Figure 9.1.1: Primal-Dual Relationship

Theorem 9.1.1 Weak Duality

For every feasible x and y:

$$c^Tx \geq (A^Ty)^Tx = x^TA^Ty = (Ax)^Ty \geq b^Ty$$

Theorem 9.1.2 Strong Duality

For optimal solutions x^* and y^* :

$$x^{*T}c = b^T y^*$$

Theorem 9.1.3 Complementary Slackness

x and y are optimal iff:

(a)
$$\forall i$$
, either $x_i = 0$ or $(A^T y)_i = c_i$.

(b)
$$\forall j$$
, either $y_j = 0$ or $(Ax)_j = b_j$.

Theorem 9.1.4 Approximate version of complementary slackness

Given $\alpha, \beta > 1$:

(a)
$$\forall i, \text{, either } x_i = 0 \text{ or } (A^T y)_i \ge \frac{1}{\beta} c_i.$$

(b)
$$\forall j$$
, either $y_j = 0$ or $(Ax)_j \leq \alpha b_j$

Theorem 9.1.5 For all feasible x and y which satisfy conditions of $\alpha - \beta$ complementary slackness, x and y are $(\alpha\beta)$ -approximately optimal.

Proof:

$$c^T x \le \beta (A^T y)^T x = \beta (Ax)^T y \le (\beta \alpha) b^T y$$

9.2 Set Cover

We write a primal-dual program for set cover problem: Consider i as indexes of sets and e as index of elements. Then we have:

$$\begin{array}{lll} & & & & & & & \\ \min \ \Sigma_i c_i x_i \ \text{s.t.} & & \max \ \Sigma_e y_e \ \text{s.t.} \\ \forall e \Sigma_{S_i \ni e} x_i \ge 1 & & \forall e y_e \ge 0 \\ \forall i x_i \ge 0 & & \forall i \Sigma_{e \in S_i} y_e \le c_i \\ \text{covering constraints} & & \text{packing constraints} \end{array}$$

Fact 9.2.1 The dual presents variables which their values represent how much should be paid for each edge to be covered.

Consider the greedy algorithm below to solve set cover problem.[1]

Algorithm 1 Greedy Algorithm

- 1: Initialize $C \leftarrow \emptyset$
- 2: while $C \neq$ all elements do
- Let $i = \arg\min_{\overline{|S_i \setminus C|}} \frac{c_i}{|S_i \setminus C|}$
- Include S_i in solution
- For all $e \in S_i \setminus C$ set $y_e = \frac{c_i}{|S_i \setminus C|}$ $C \leftarrow C \cup S_i$ [i.e. set $x_i = 1$]
- 7: end while

Claim 9.2.2 x is feasible.

Proof: The algorithm works until all elements are covered and sets 1 for the corresponding variables. So the condition in primal linear program will hold in the end.

Claim 9.2.3
$$\Sigma_{i \in solution} c_i = \Sigma_i c_i x_i = \Sigma_e y_e$$
.

We only set x variables 1 which were included in the solution. This concludes the first Proof: equality.

Moreover, at each iteration which we found a new set to include in the solution, we set exactly $|S_i \setminus C|$ y variables as $\frac{c_i}{|S_i \setminus C|}$. This concludes the second equality.

Claim 9.2.4 If n is the number of elements, $\forall i : \Sigma_{e \in S_i} y_e \leq H_n c_i$.

Proof: Order elements in S_i in order of coverage. Consider j^{th} element.

For each element, cost of S_i when j was covered is less than or equal to $\frac{c_i}{|S_i|-j+1}$. Therefore $y_i \leq \frac{c_i}{|S_i|-j+1}$.

$$\Sigma_{e \in S_i} y_e = \Sigma_j \frac{c_i}{|S_i| - j + 1} = c_i \left[\frac{1}{|S_i|} + \frac{1}{|S_i| - 1} + \dots + 1 \right] \le c_i H_n$$

Implication 9.2.5 $\hat{y} = \frac{y}{H_n}$ is a feasible dual solution and $\Sigma_e \hat{y}_e \ge \frac{1}{H_n} \Sigma_i c_i x_i$. This means we have a H_n approximation factor in which $H_n = \sum_{i=1}^n \frac{1}{i} = \theta(\log n)$.

9.3 Primal Dual Algorithms

Basic Steps in a Primal-Dual Algorithm (in a minimization problem) is as follows:

Algorithm 2 Primal Dual Algorithm

- 1: **Initialize** Start with x = 0, y = 0. Always maintain dual feasibility.
- 2: while Primal is not feasible do
- 3: Raise some y's until some dual constraint goes tight.
- 4: Raise corresponding primal variables; freeze dual variables in the tight constraint. (Raise it enough to satisfy all constraints it is in.)
- 5: end while

Primal-Dual for set cover is as follows:

Algorithm 3 Primal Dual Algorithm for Set Cover Problem

- 1: **Initialize** Start with x = 0, y = 0.
- 2: Pick some uncovered e. Raise y_e until for some i, $\Sigma_{e \in S_i} y_e = c_i$.
- 3: Set $x_i = 1$. For all $e \in S_i$, freeze y_e .
- 4: If there exists any uncovered e, go to Step 2.

Claim 9.3.1 x and y are feasible.

Claim 9.3.2 If $x_i > 0$ then $\sum_{e \in S_i} y_e = c_i$.

Claim 9.3.3 $\Sigma_{i:S\ni e}x_i \leq F$ where F is the maximum frequency. (i.e. $F = \max_{\mathbf{e}} |\{i \in S_i \ni e\}|)$ This concludes a F-approximation factor for the problem.

9.4 Feedback Vertex Set

Assume G = (V, E) is a graph with costs c_v on vertices.

Goal: Remove the min cost set of vertices to make the graph acyclic.

This problem is NP-hard due to Karp. [2]

Here by C we mean any cycle in the graph. Primal-Dual algorithm for FVS is as follows: [3]

Algorithm 4 Primal Dual Algorithm for Set Cover Problem

- 1: **Initialize** Start with x = 0, y = 0.
- 2: Pick some uncovered cycle C with fewest vertices of degree greater than or equal to 3. Raise y_C until for some v, $\Sigma_{C\ni v}y_C=c_v$.
- 3: Set $x_v = 1$. For all $C \ni v$, freeze y_C .
- 4: If there exists any uncovered C, go to Step 2.

Claim 9.4.1 x and y are feasible.

Claim 9.4.2 If for some $v, x_v > 0$, then $\Sigma_{C \ni v} y_C = c_x$.

Claim 9.4.3 In each iteration, we can find an uncovered edge with less than or equal to $2 \log n$ vertices of degree greater than or equal to 3.

Claim 9.4.4 For all cycles C in which $y_C > 0$,

$$\sum_{v \in C} x_v \le 4 \log n$$

Proof: Before C is covered, $\Sigma_{v \in C} x_v = 0$.

C contains less than or equal to $2 \log n$ vertices of degree greater than or equal to 3 and between them there at less than or equal to $2 \log n$ segments that are paths over degree 2 vertices. (one per segment)

Therefore, we pick at most $2 \log n + 2 \log n = 4 \log n$ vertices during this algorithm.

Corollary 9.4.5 The above claim concludes a 4 log n-approximation factor for FVS.

Fact 9.4.6 We would not get a bounded result if we had chosen cycles arbitrarily during step 2 of primal-dual algorithm.

Remark 9.4.7 This analysis is nearly tight. The best approximation ratio for this problem is 2.

References

- [1] V. Chvatal. A greedy heuristic for the set-covering problem. *Mathematics of Operations Research*, 4(3):233–235, 1979.
- [2] Richard M. Karp. Reducibility among Combinatorial Problems, pages 85–103. Springer US, Boston, MA, 1972.

[3]				Shmoys. NY, US <i>l</i>			ion 2	Algorithms.	Cam-