Yale University CPSC 516, Spring 2023 Assignment 4

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P.1.

(a)

For the (i, j)-th entry of A, let us write it as

$$A_{ij} = \frac{a_{ij}}{b_{ij}}$$

for some coprime $a_{ij} \in \mathbb{Z}, b_{ij} \in \mathbb{Z}_+$. Then consider

$$M := \prod_{i,j} b_{ij} \in \mathbb{Z}$$

$$B := MA$$

By construction, $A = \frac{1}{M}B$ and since $b_{ij} \mid M$ for all i, j, we know that $A \in \mathbb{Z}^{m \times n}$. The bit complexity of M is

$$O\left(\log\prod_{i,j}b_{ij}\right) = O\left(\sum_{i,j}\log b_{ij}\right).$$

This is at most the bit complexity of A. The bit complexity of any B_{ij} is at most

$$O\left(\log a_{ij}\prod_{k,\ell}b_{k,\ell}\right) = O\left(\log a_{ij} + \sum_{k,\ell}\log b_{k,\ell}\right).$$

Once again, this is at most the bit complexity of A.

(b)

Suppose $C \in \mathbb{Q}^{p \times p}$. Write

$$D := MC \in \mathbb{Z}_{p \times p}.$$

The matrix norm is obtained by some unit-vector $x \in \mathbb{R}^p$. Thus

$$||C||_{2} = ||Cx||$$

$$= \sqrt{\sum_{i=1}^{p} (Cx)_{i}^{2}}$$

$$\leq \sum_{i=1}^{p} ||Cx|_{i}|| \qquad \sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$$

$$\leq \sum_{i=1}^{p} ||C^{(i)}|| \cdot ||x|| \qquad C^{(i)} \text{ } i\text{-th row}$$

$$= \sum_{i=1}^{p} ||C^{(i)}|| ||$$

$$\leq \sum_{i=1}^{p} \sum_{j=1}^{p} |C_{ij}| ||$$

$$= \frac{1}{M} \sum_{i=1}^{p} \sum_{j=1}^{p} |D_{ij}|.$$

The bit complexity of D^{ij} is at most L. Hence the value of the summation is at most $n^2 2^L$. Thus the operator norm is at most

 $2^{O(L \log n)}$

as desired.

Similarly, the inverse of the matrix norm is equivalent to

$$\min_{\|x\|=1} \|Cx\|.$$

Again, our analysis above holds since x was arbitrary. Thus the largest value the operator norm of the inverse can take is

 $2^{O(L\log n)}$

This concludes the proof.

(c)

Let x be a vertex of K and recall that it is uniquely determined by some invertible submatrix C of A so that $Cx = b^{-}$ where b^{-} is some subvector of b.

We know that

$$x = C^{-1}b^{=} = \frac{1}{\det C}\operatorname{adj}(C)b^{=}$$

where $\operatorname{adj} C$ is the adjugate matrix of C. But since all intermediaries are rational, x must be rational as well.

P.2.

(a)

Lemma 1:

If $f: J \subseteq \mathbb{R} \to \mathbb{R}, g: K \subseteq \mathbb{R}^m \to J$ are convex and f is non-decreasing, then $f \circ g$ is convex.

Proof: Lemma 1

Fix $\lambda \in [0,1]$ and $x, y \in K$.

$$f(g[(1-\lambda)x + \lambda y]) \le f([1-\lambda]g(x) + \lambda g(y))$$
 f non-decreasing, g convex
 $\le (1-\lambda)f(g(x)) + \lambda f(g(y)).$ f convex

Consider the function $\langle x, \mathbb{1}_M \rangle$. It is a linear function and is thus convex. Now, the exponential is convex and non-decreasing, so $\exp(\langle x, \mathbb{1}_M \rangle)$ is convex. Moreover, the sum of convex function is convex. So $\sum_M \exp(\langle x, \mathbb{1}_M \rangle)$ is convex. Finally, ln is non-decreasing and thus

$$f(x) = \ln \sum_{M} \exp(\langle x, \mathbb{1}_{M} \rangle)$$

is convex as desired.

(b)

Let us assume that G has bipartition V=(U,W) where |U|=|W|=n/2, or else $P=\varnothing$ and the problem is trivial.

We claim that P is equivalent to the following polytope Q

$$\sum_{v \sim u} x_{uv} = 1 \qquad \forall u \in V$$
$$x \ge 0.$$

If we let A be the vertex-edge incident matrix of G, then we can succinctly write this as

$$Ax = 1 \\ x > 0.$$

Note that for $x \in \{0,1\}^m$, $x \in Q$ if and only if $x = \mathbb{1}_M$ for some perfect matching M.

If we show P = Q then we are done, since we can just check in polynomial time whether any of the constraints are violated.

To see the claim, first note that $P \subseteq Q$. This is because any indicator vector for a matching $\mathbb{1}_M$ necessarily satisfies all the inequalities. But then all the convex combinations of indicator variables also satisfies the inequalities as well since the inequalities are linear.

It remains to show that $Q \subseteq P$. We argue that the extreme points of Q are integral, ie the extreme points of Q are indicator vectors of perfect matchings. This would complete the proof since Q is then the convex hull of some indicator vectors while P is the convex hull of all indicator vectors.

Lemma 2:

A is totally unimodular, ie every square submatrix of A has determinant taking values in $\{-1,0,1\}$.

Proof: Lemma 2

Without loss of generality, assume that G has bipartition V = (U, W) and the rows of A are such that the first n/2 correspond to U and the last n/2 correspond to W.

Let $B \in \{-1,0,1\}^{k \times k}$ be a square submatrix of A. We argue by induction on k.

The base case of k = 1 certainly holds.

Suppose inductively that this holds up to k-1. If B has any zero columns, then det(B) is zero and we are done. Otherwise, if B has any columns with a single non-zero entry 1, we can use cofactor expansion along that column to determine that

$$det(B) = \pm det(B')$$

where B' is a $(k-1) \times (k-1)$ submatrix of A. In this case, we are also done. Finally, suppose every column of B has exactly two non-zero entries. But since we assumed that A has the particular format, if we subtract the row of B corresponding to U and the rows of B corresponding to W, we get the zero vector and thus B is singular.

By induction, we conclude the proof.

To see why the lemma completes the proof, note that any extreme point x of Q is determined by some invertible square submatrix $A_{=}$ where the non-zero entries of x are given by

$$x_{=} = A_{=}^{-1} \mathbb{1}_{=} = \frac{1}{\det(A_{=})} \operatorname{adj}(A_{=}) \mathbb{1}_{=}.$$

But $\frac{1}{\det(A_{=})} \in \{\pm 1\}$ and $\operatorname{adj}(A_{=})$ is also integral, Hence $x_{=}$ must be integral as well.

(c)

Suppose we can evaluate f(1) in polynomial time. Then

$$\exp f(\mathbb{1}) = \sum_{M \in \mathcal{M}} \exp(\langle \mathbb{1}, \mathbb{1}_M \rangle)$$
$$= \sum_{M \in \mathcal{M}} \exp(n/2)$$
$$= |\mathcal{M}| \exp(n/2)$$
$$|\mathcal{M}| = \frac{\exp f(\mathbb{1})}{\exp(n/2)}.$$

Thus we can count the number of perfect matching within G in polynomial time.

P.3.

By computation,

$$\nabla f(x) = \sum_{S} \frac{\exp\langle x, \mathbb{1}_{S} \rangle}{\sum_{T} \exp\langle x, \mathbb{1}_{T} \rangle} \mathbb{1}_{S}$$

$$\nabla_{i} f(x) = \sum_{S \ni i} \frac{\exp\langle x, \mathbb{1}_{S} \rangle}{\sum_{T} \exp\langle x, \mathbb{1}_{T} \rangle}$$

$$\frac{\partial \nabla_{i} f(x)}{\partial x_{j}} = \sum_{S \ni i, j} \frac{\exp\langle x, \mathbb{1}_{S} \rangle}{\sum_{T} \exp\langle x, \mathbb{1}_{T} \rangle} - \nabla_{i} f(x) \nabla_{j} f(x).$$

Note that when we take a quadratic form, the second term in $\nabla^2 f(x)$ is non-positive.

Lemma 3:

If f is convex, then ∇f is L-Lipschitz if

$$y^T \nabla^2 f(x) y \le L \|y\|^2$$

for all $y \in \mathbb{R}^n$.

Proof: Lemma 3

By Taylor's theorem,

$$f(y) - f(x) = \nabla f(x)^{T} (y - x) + \frac{1}{2} (y - x)^{T} \nabla^{2} f(\xi) (y - x) \qquad \xi \in [x, y]$$

$$f(y) - f(x) = \nabla f(y)^{T} (x - y) + \frac{1}{2} (x - y)^{T} \nabla^{2} f(\eta) (x - y) \qquad \eta \in [x, y]$$

$$[\nabla f(x) - \nabla f(y)]^{T} (y - x) = -\frac{1}{2} (y - x)^{T} \nabla^{2} f(\xi) (y - x) - \frac{1}{2} (x - y)^{T} \nabla^{2} f(\eta) (x - y)$$

$$\geq -L ||x - y||^{2}. \qquad \text{assumption}$$

Now, the LHS is at most $\|\nabla f(x) - \nabla f(y)\| \cdot \|x - y\|$. Dividing by $-\|x - y\|$ yields the proof.

By the lemma, is suffices to bound $y^T \nabla^2 f(x) y$.

$$\sum_{i,j} y_i y_j \nabla_{i,j}^2 f(x) \leq \sum_{i,j} y_i y_j \sum_{S \ni i,j} \frac{\exp\langle x, \mathbb{1}_S \rangle}{\sum_T \exp\langle x, \mathbb{1}_T \rangle}$$

$$\leq \sum_{i,j} y_i y_j \cdot 1$$

$$\leq n^2 ||y||_{\infty}^2$$

$$\leq n^2 ||y||_2^2.$$

By the lemma, ∇f is n^2 -Lipschitz as desired.