## Formula Sheet for Math 340, Section 101, Fall 2015 December 2015 Joel Friedman, UBC

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This is a list of formulas that you will be given with your final exam. You are responsible to know what these formulas mean.

DualityGap = (ValueBettyAnnouncesPure) - (ValueAliceAnnouncesPure)

If A is a  $2 \times 2$  matrix, then either (1) the duality gap is zero, or (2) Alice and Betty have mixed strategies where the values are balanced, e.g.,

$$[x_1 \ 1 - x_1]A = [v \ v]$$

for Alice.

LP standard form: maximize  $\vec{c} \cdot \vec{x}$ , subject to  $A\vec{x} \leq \vec{b}, \vec{x} \geq \vec{0}$ .

Unbounded LP: A variable enters, but nothing leaves.

2-phase method: (1) introduce  $x_0$  on right, (2) pivot  $x_0$  into the basis for a feasible dictionary, and try to maximize  $w = -x_0$ , (3) if w reaches 0, pivot  $x_0$  out of dictionary and eliminate all  $x_0$ ; e.g.,

 $\begin{array}{rcl} x_4 = & -7 + \dots + x_0 \\ x_9 = & -8 + \dots + x_0 \end{array} \quad x_0 \text{ enters, } x_9 \text{ leaves} \end{array}$ 

The formulas for simplex method dictionaries (in standard form) is

$$\vec{x}_B = A_B^{-1}\vec{b} - A_B^{-1}A_N\vec{x}_N$$
$$z = \vec{c}_B^{\rm T}A_B^{-1}\vec{b} + (\vec{c}_N^{\rm T} - \vec{c}_B^{\rm T}A_B^{-1}A_N)\vec{x}_N$$

In the computation above, we compute  $\vec{c}_B^{\mathrm{T}} A_B^{-1} A_N$  by first computing  $\vec{c}_B^{\mathrm{T}} A_B^{-1}$ , and then multiplying the result (a row vector) times  $A_N$ ; it would be more expensive to first compute  $A_B^{-1} A_N$ .

For the  $A_B^{-1}$  of the i-1-th and i-th dictionaries we have

$$A_{B_i}^{-1} = E_i^{-1} A_{B_{i-}}^{-1}$$

where  $E_i$  is an eta matrix, equal to the identity except in one column. This formula can be applied recursively to get

$$A_{B_{i+k}}^{-1} = E_{i+k}^{-1} E_{i+k-1}^{-1} \cdots E_i^{-1} A_{B_{i-1}}^{-1}.$$

Let the *b*-th row in a matrix game be  $\vec{f}(b)$ . If  $\vec{f}$  is a convex function (i.e., concave up), then Alice has an optimal strategy that is some combination of the smallest and largest values of *b* (i.e., the top and bottom rows). If  $\vec{f}$  is concave down, then Alice has an optimal strategy this is some combination of two adjacent rows. (These combinations can be 100% of one row in certain cases.)