5.3 Strong Duality

$P = \max\{c^T x \mid Ax \leq b, x \geq 0\}$

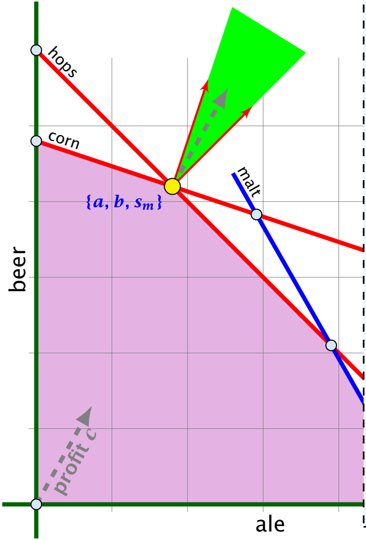
n_A: number of variables, m_A: number of constraints

We can put the non-negativity constraints into A (which gives us unrestricted variables): $\bar{P} = \max\{c^T x \mid \bar{A}x \leq \bar{b}\}$

$n_{\bar{A}} = n_A$, $m_{\bar{A}} = m_A + n_A$

Dual $D = \min\{\bar{b}^T y \mid \bar{A}^T y = c, y \geq 0\}$.

5.3 Strong Duality



If we have a conic combination y of c then $b^T y$ is an upper bound of the profit we can obtain (weak duality):

$$c^T x = (\bar{A}^T y)^T x = y^T \bar{A} x \le y^T \bar{b}$$

If x and y are optimal then the duality gap is 0 (strong duality). This means

$$\begin{aligned} 0 &= c^T x - y^T \bar{b} \\ &= (\bar{A}^T y)^T x - y^T \bar{b} \\ &= y^T (\bar{A} x - \bar{b}) \end{aligned}$$

The last term can only be 0 if y_i is 0 whenever the i-th constraint is not tight. This means we have a conic combination of c by normals (columns of $\bar{A}^T$) of *tight* constraints.

Conversely, if we have x such that the normals of tight constraint (at x) give rise to a conic combination of c, we know that x is optimal.

The profit vector c lies in the cone generated by the normals for the hops and the corn constraint (the tight constraints).

Strong Duality

Theorem 2 (Strong Duality)

Let P and D be a primal dual pair of linear programs, and let z^* and w^* denote the optimal solution to P and D, respectively. Then

$$z^* = w^*$$

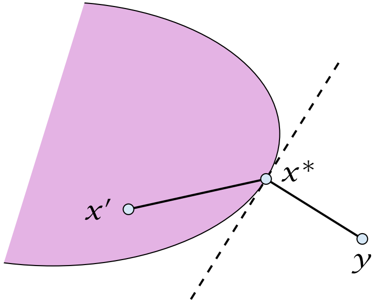
Lemma 3 (Weierstrass)

Let X be a compact set and let $f(x)$ be a continuous function on X. Then $\min\{f(x) : x \in X\}$ exists.

(without proof)

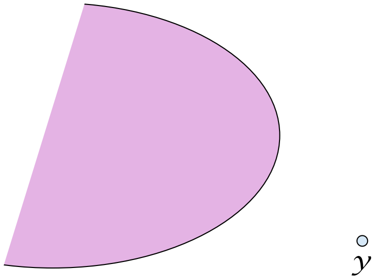
Lemma 4 (Projection Lemma)

Let $X \subseteq \mathbb{R}^m$ be a non-empty convex set, and let $y \notin X$. Then there exist $x^* \in X$ with minimum distance from y. Moreover for all $x \in X$ we have $(y - x^*)^T(x - x^*) \leq 0$.



Proof of the Projection Lemma

- Define $f(x) = \|y - x\|$.
- We want to apply Weierstrass but X may not be bounded.
- $X \neq \emptyset$. Hence, there exists $x' \in X$.
- Define $X' = \{x \in X \mid \|y - x\| \leq \|y - x'\|\}$. This set is closed and bounded.
- Applying Weierstrass gives the existence.



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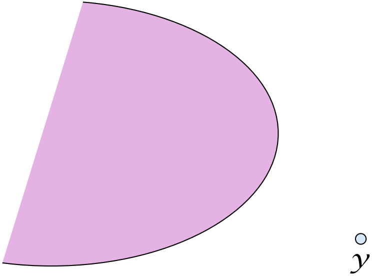

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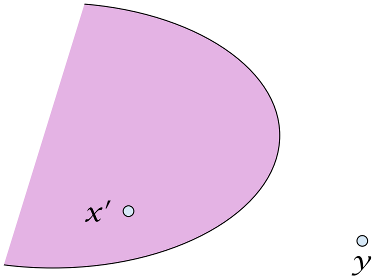

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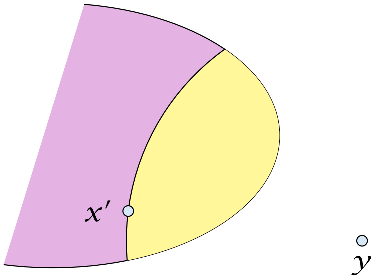

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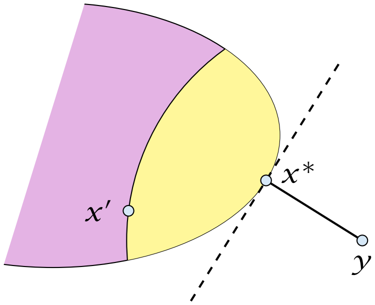

Proof of the Projection Lemma (continued)

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$$\|y - x^*\|^2 \le \|y - x^* - \epsilon(x - x^*)\|^2$$

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$$\begin{aligned} \|y - x^*\|^2 &\leq \|y - x^* - \epsilon(x - x^*)\|^2 \\ &= \|y - x^*\|^2 + \epsilon^2\|x - x^*\|^2 - 2\epsilon(y - x^*)^T(x - x^*) \end{aligned}$$

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Hence, $(y - x^*)^T(x - x^*) \leq \frac{1}{2}\epsilon\|x - x^*\|^2$.

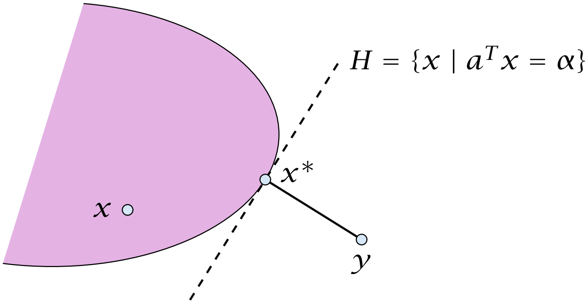
Letting $\epsilon \to 0$ gives the result.

Theorem 5 (Separating Hyperplane)

Let $X \subseteq \mathbb{R}^m$ be a non-empty closed convex set, and let $y \notin X$. Then there exists a separating hyperplane $\{x \in \mathbb{R} : a^T x = \alpha\}$ where $a \in \mathbb{R}^m$, $\alpha \in \mathbb{R}$ that separates y from X. ($a^T y < \alpha$; $a^T x \geq \alpha$ for all $x \in X$)

Proof of the Hyperplane Lemma

- Let $x^* \in X$ be closest point to y in X.
- By previous lemma $(y - x^*)^T(x - x^*) \leq 0$ for all $x \in X$.
- Choose $a = (x^* - y)$ and $\alpha = a^T x^*$.
- For $x \in X : a^T(x - x^*) \geq 0$, and, hence, $a^T x \geq \alpha$.
- Also, $a^T y = a^T(x^* - a) = \alpha - \|a\|^2 < \alpha$



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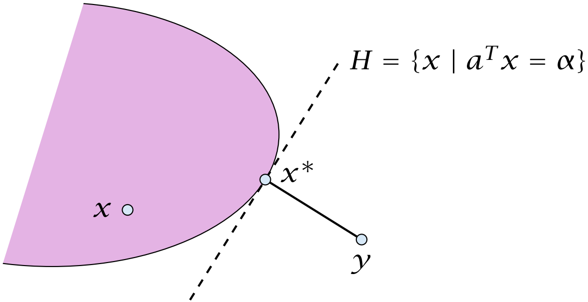

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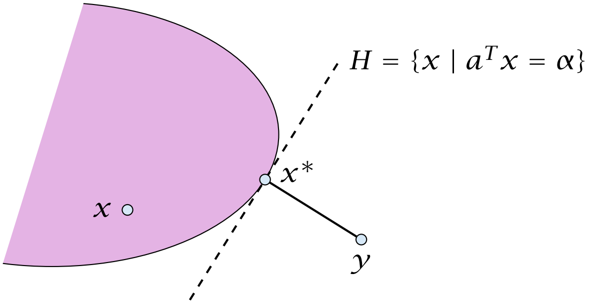

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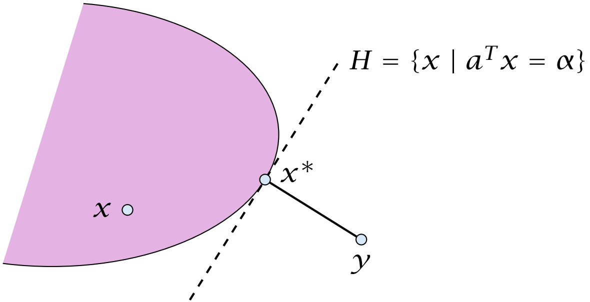

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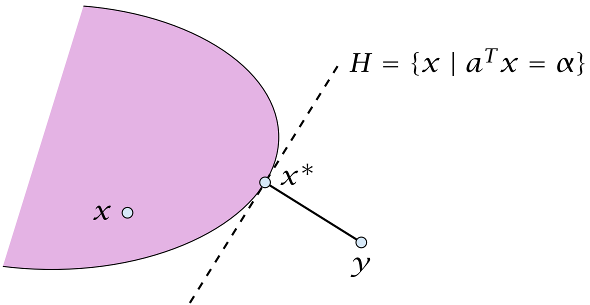

Lemma 6 (Farkas Lemma)
Let A be an $m \times n$ matrix, $b \in \mathbb{R}^m$. Then exactly one of the following statements holds.

1. $\exists x \in \mathbb{R}^n$ *with* $Ax = b$, $x \geq 0$
2. $\exists y \in \mathbb{R}^m$ *with* $A^T y \geq 0$, $b^T y < 0$

Assume $\hat{x}$ satisfies 1. and $\hat{y}$ satisfies 2. Then

$$0 > y^T b = y^T A x \geq 0$$

Hence, at most one of the statements can hold.

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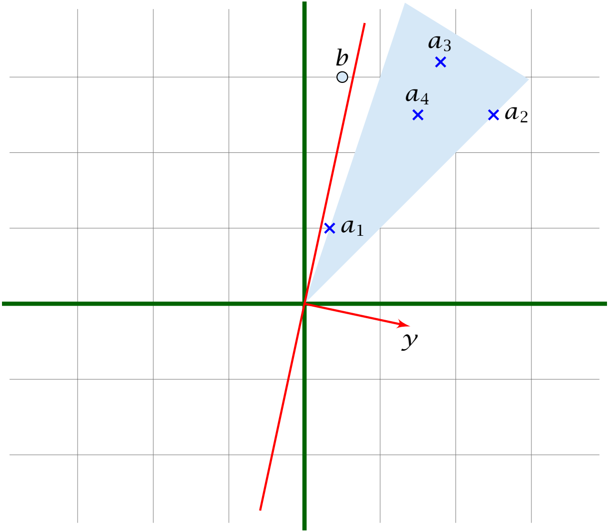
Farkas Lemma



If b is not in the cone generated by the columns of A, there exists a hyperplane y that separates b from the cone.

Proof of Farkas Lemma

Now, assume that 1. does not hold.

Consider $S = \{Ax : x \geq 0\}$ so that S closed, convex, $b \notin S$.

We want to show that there is y with $A^T y \geq 0$, $b^T y < 0$.

Let y be a hyperplane that separates b from S. Hence, $y^T b < \alpha$ and $y^T s \geq \alpha$ for all $s \in S$.

$0 \in S \Rightarrow \alpha \leq 0 \Rightarrow y^T b < 0$

$y^T Ax \geq \alpha$ for all $x \geq 0$. Hence, $y^T A \geq 0$ as we can choose x arbitrarily large.

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We want to show that there is y with $A^Ty \geq 0$, $b^Ty < 0$.

Let y be a hyperplane that separates b from S. Hence, $y^Tb < \alpha$ and $y^Ts \geq \alpha$ for all $s \in S$.

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Lemma 7 (Farkas Lemma; different version)

Let A be an $m \times n$ matrix, $b \in \mathbb{R}^m$. Then exactly one of the following statements holds.

1. $\exists x \in \mathbb{R}^n$ *with* $Ax \le b$, $x \ge 0$
2. $\exists y \in \mathbb{R}^m$ *with* $A^T y \ge 0$, $b^T y < 0$, $y \ge 0$

Rewrite the conditions:

1. $\exists x \in \mathbb{R}^n$ with $\begin{bmatrix} A & I \end{bmatrix} \cdot \begin{bmatrix} x \\ s \end{bmatrix} = b$, $x \ge 0$, $s \ge 0$
2. $\exists y \in \mathbb{R}^m$ with $\begin{bmatrix} A^T \\ I \end{bmatrix} y \ge 0$, $b^T y < 0$

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Proof of Strong Duality

P: $z = \max\{c^T x \mid Ax \le b, x \ge 0\}$

D: $w = \min\{b^T y \mid A^T y \ge c, y \ge 0\}$

Theorem 8 (Strong Duality)

Let P and D be a primal dual pair of linear programs, and let z and w denote the optimal solution to P and D, respectively (i.e., P and D are non-empty). Then

$$z = w \ .$$

Proof of Strong Duality

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$z \leq w$: follows from weak duality

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Proof of Strong Duality

$\boldsymbol{z} \leq \boldsymbol{w}$: follows from weak duality

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We show $z < \alpha$ implies $w < \alpha$.

Proof of Strong Duality

$z \leq w$: follows from weak duality

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$$\begin{array}{lrcl} \exists x \in \mathbb{R}^n & & & \\ \text{s.t.} & Ax & \leq & b \\ & -c^T x & \leq & -\alpha \\ & x & \geq & 0 \end{array}$$

Proof of Strong Duality

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$$\begin{array}{lrcl} \exists y \in \mathbb{R}^m; v \in \mathbb{R} & & & \\ \text{s.t.} & A^T y - cv & \geq & 0 \\ & b^T y - \alpha v & < & 0 \\ & y, v & \geq & 0 \end{array}$$

Proof of Strong Duality

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From the definition of α we know that the first system is infeasible; hence the second must be feasible.

Proof of Strong Duality

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If the solution y, v has $v = 0$ we have that

$$\begin{array}{rrcl} \exists y \in \mathbb{R}^m & & & \\ \text{s.t.} & A^T y & \geq & 0 \\ & b^T y & < & 0 \\ & y & \geq & 0 \end{array}$$

is feasible.

Proof of Strong Duality

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is feasible. By Farkas lemma this gives that LP P is infeasible. Contradiction to the assumption of the lemma.

Proof of Strong Duality

Hence, there exists a solution y, v with $v > 0$.

We can rescale this solution (scaling both y and v) s.t. $v = 1$.

Then y is feasible for the dual but $b^T y < \alpha$. This means that $w < \alpha$.

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Questions:

- Is LP in NP?
- Is LP in co-NP? yes!
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- Given a primal maximization problem P and a parameter α. Suppose that $\alpha > \text{opt}(P)$.
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