Definition 1.6. A point \mathbf{x} is an *extreme point* of a convex set C if there exist no two distinct points \mathbf{x}_1 and $\mathbf{x}_2 \in C$ such that $\mathbf{x} = \lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2$ for some $\lambda \in (0, 1)$.

Geometrically, extreme points are just the corner points of C.

Example 1.2. \mathbb{R}^n is convex. Let W be a subspace of \mathbb{R}^n and $\mathbf{x}_1, \mathbf{x}_2 \in W$. Thus any linear combination of \mathbf{x}_1 and \mathbf{x}_2 is also in W, in particular the linear combination $\lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2 \in W$ for $\lambda \in [0, 1]$. This shows that W is convex.

Example 1.3. The n dimensional open ball centered at x_0 with radius r is defined as

$$B_r(\mathbf{x}_0) = \{ \mathbf{x} \mid |\mathbf{x} - \mathbf{x}_0| < r \}.$$

The n dimensional closed ball centered at \mathbf{x}_0 with radius r is defined as

$$\overline{B_r(\mathbf{x}_0)} = \{\mathbf{x} \mid |\mathbf{x} - \mathbf{x}_0| < r\}.$$

Both the open ball and the closed ball are convex. We prove it for the open ball. Let $\mathbf{x}_1, \mathbf{x}_2 \in B(\mathbf{x}_0)$ and $\lambda \in [0, 1]$. Then

$$\begin{aligned} |(\lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2) - \mathbf{x}_0| &= |\lambda(\mathbf{x}_1 - \mathbf{x}_0) + (1 - \lambda)(\mathbf{x}_2 - \mathbf{x}_0)| \\ &\leq \lambda |\mathbf{x}_1 - \mathbf{x}_0| + (1 - \lambda)|\mathbf{x}_2 - \mathbf{x}_0| \\ &\leq \lambda r + (1 - \lambda)r = r. \end{aligned}$$

Let S be a subset of \mathbb{R}^n . A point x is a boundary point of S if every open ball centered at x contains both a point in S and a point in $\mathbb{R}^n - S$. Note that a boundary point can either be in S or not in S. The set of all boundary points of S, denoted by ∂S , is the boundary of S. A set S is closed if $\partial S \subset S$. A set S is open if its complement $\mathbb{R}^n - S$ is closed. Note that a set that is not closed is not necessarily open; and a set that is not open is not necessarily closed. There are sets that are neither open nor closed. The closure of a set S is the set $\overline{S} = S \cup \partial S$. The interior of a set S is the set $S^\circ = S - \partial S$. A set S is closed if and only if $S = \overline{S}$. A set S is open if and only if $S = S^\circ$.

Example 1.4. \mathbb{R}^n is both open and closed. The empty set \emptyset is both open and closed.

Example 1.5. The hyperplane $P = \{\mathbf{x} \mid \mathbf{c}^T \mathbf{x} = z\}$ is closed in \mathbb{R}^n . In fact we will show that $P \subseteq \partial P$. Without loss of generality we may assume $|\mathbf{c}| = 1$. Let $\mathbf{x} \in P$ and $B_r(\mathbf{x})$ is an open ball centered at \mathbf{x} with radius r. Since $\mathbf{x} \in B_r(\mathbf{x})$ it remains to show that $B_r(\mathbf{x})$ contains a point not in P. Let

$$\mathbf{y} = \mathbf{x} + \frac{r}{2}\mathbf{c}$$

then

$$\mathbf{c}^T \mathbf{y} = \mathbf{c}^T \mathbf{x} + \frac{r}{2} \mathbf{c}^t \mathbf{c} = z + \frac{r}{2} > z.$$
herefore $\mathbf{y} \in B_r(\mathbf{x})$.

Hence $\mathbf{y} \notin P$. But $|\mathbf{y} - \mathbf{x}| = \frac{r}{2}$ therefore $\mathbf{y} \in B_r(\mathbf{x})$.

Example 1.6. The half spaces

$$\partial P \subseteq P \qquad X_1 = \{ \mathbf{x} \mid \mathbf{c}^T \mathbf{x} \le z \} \quad \text{and} \quad X_2 = \{ \mathbf{x} \mid \mathbf{c}^T \mathbf{x} \ge z \} \qquad \mathcal{T} \geqslant \mathcal{T}$$

are closed in \mathbb{R}^n . In fact we have $\partial X_1 = \partial X_2 =$ the hyperplane $P = \{\mathbf{x} \mid \mathbf{c}^T \mathbf{x} = z\}$. We will show that $\partial X_1 = P$, the proof for $\partial X_2 = P$ is similar.

$$(P \subset \partial X_1)$$
 Let $\mathbf{x} \in P$. For any $r > 0$, let

$$\mathbf{y}_1 = \mathbf{x} + \frac{r}{2|\mathbf{c}|}\mathbf{c}, \quad \mathbf{y}_2 = \mathbf{x} - \frac{r}{2|\mathbf{c}|}\mathbf{c}.$$

We see that $|\mathbf{x} - \mathbf{y}_1| = \frac{r}{2} = |\mathbf{x} - \mathbf{y}_2|$ so both $\mathbf{y}_1, \mathbf{y}_2 \in B_r(\mathbf{x})$. Moreover

$$\mathbf{c}^T \mathbf{y}_1 = \mathbf{c}^T \mathbf{x} + \frac{r}{2|\mathbf{c}|} \mathbf{c}^T \mathbf{c} = r + \frac{r}{2} > r$$

and therefore $y_1 \notin X_1$. On the other hand

$$\mathbf{c}^T \mathbf{y}_2 = \mathbf{c}^T \mathbf{x} - \frac{r}{2|\mathbf{c}|} \mathbf{c}^T \mathbf{c} = r - \frac{r}{2} < r$$

so $y_2 \in X_1$. This shows $x \in \partial X_1$.

 $(\partial X_1 \subset P)$ Suppose $\mathbf{x} \notin P$. If $\mathbf{c}^T \mathbf{x} = z_1 < z$ then let $r = \frac{z-z_1}{2} > 0$. The open ball $B_r(\mathbf{x})$ lies entirely in X_1 . So $B_r(\mathbf{x})$ contains no point outside of X_1 , hence $\mathbf{x} \notin \partial X_1$. If $\mathbf{c}^T \mathbf{x} = z_1 > z$ then let $r = \frac{z_1-z_2}{2} > 0$. The open ball $B_r(\mathbf{x})$ lies entirely outside of X_1 . So $B_r(\mathbf{x})$ contains no point of X_1 , hence $\mathbf{x} \notin \partial X_1$. In either case $\mathbf{c} \notin \partial X_1$.

Lemma 1.1. (a) All hyperplanes are convex.

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(b) The closed half-space $\{\mathbf{x} \mid \mathbf{c}^T \mathbf{x} \leq z\}$ and $\{\mathbf{x} \mid \mathbf{c}^T \mathbf{x} \geq z\}$ are convex.

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- (c) The open half-space $\{\mathbf{x} \mid \mathbf{c}^T \mathbf{x} < z\}$ and $\{\mathbf{x} \mid \mathbf{c}^T \mathbf{x} > z\}$ are convex.
- (d) Any intersection of convex sets is still convex.
- (e) The set of all feasible solutions to a linear programming problem is a convex set.

Proof. (a) Let $X = \{\mathbf{x} \mid \mathbf{c}^T \mathbf{x} = z\}$ be our hyperplane. For all $\mathbf{x}_1, \mathbf{x}_2 \in X$ and $\lambda \in [0, 1]$, we have

$$\mathbf{c}^T[\lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2] = \lambda \mathbf{c}^T \mathbf{x}_1 + (1 - \lambda)\mathbf{c}^T \mathbf{x}_2 = \lambda z + (1 - \lambda)z = z.$$

Thus $\lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2 \in X$. Hence X is convex.

- (b) and (c) can be proved similarly by replacing the equality signs in (a) by the corresponding inequality signs.
- (d) Let $C = \bigcap_{\alpha \in I} C_{\alpha}$, where C_{α} are convex for all α in the index set I. Then for all $\mathbf{x}_1, \mathbf{x}_2 \in C$, we have $\mathbf{x}_1, \mathbf{x}_2 \in C_{\alpha}$ for all $\alpha \in I$. Hence for all $\lambda \in [0, 1]$,

$$\lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2 \in C_{\alpha}$$

for all $\alpha \in I$. Thus $\lambda \mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2 \in C$, and C is convex.

(e) For any LP problem, the constraints can be written as $\mathbf{a}_i \mathbf{x} \leq b_i$ or $\mathbf{a}_i \mathbf{x} = b_i$ etc. The set of points that satisfy any one of these constraints is thus a half space or a hyperplane. By (a), (b) and (c), they are convex. By (d), the intersection of all these sets, which is defined to be the set of feasible solutions, is a convex set.

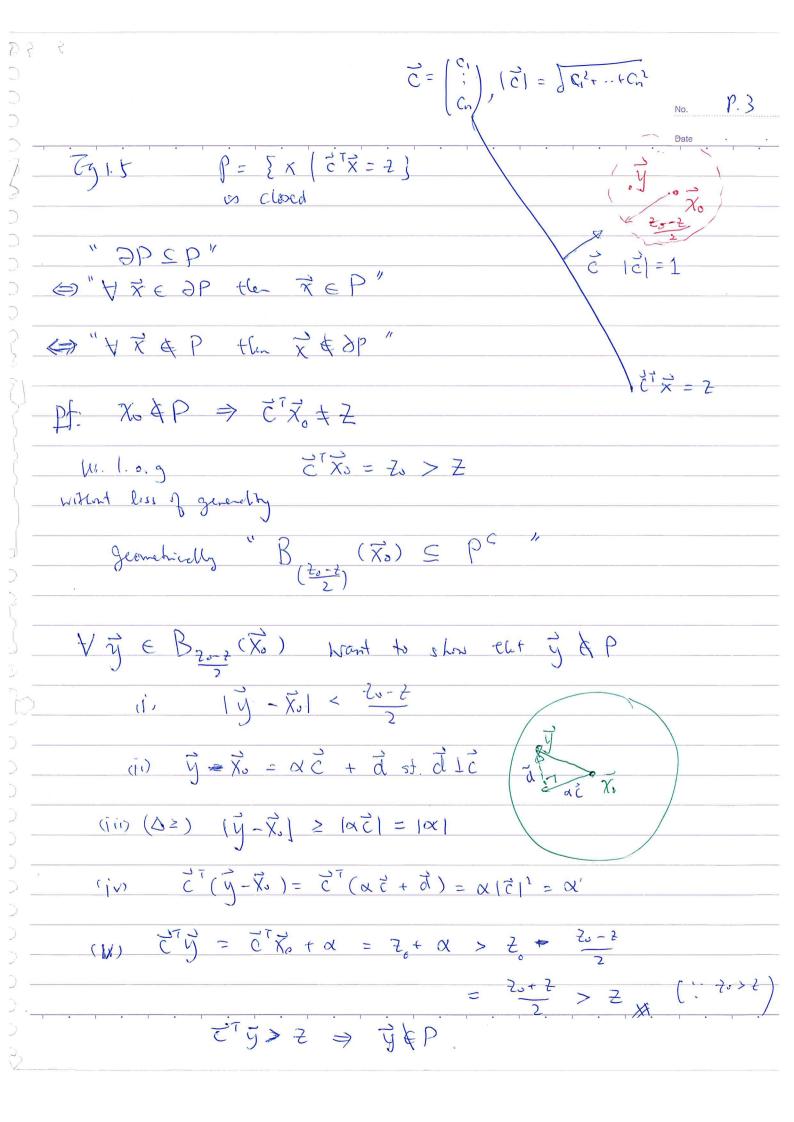
Definition 1.7. Let $\{x_1, \dots x_k\}$ be a set of given points. Let

$$\mathbf{x} = \sum_{i=1}^{k} M_i \mathbf{x}_i$$

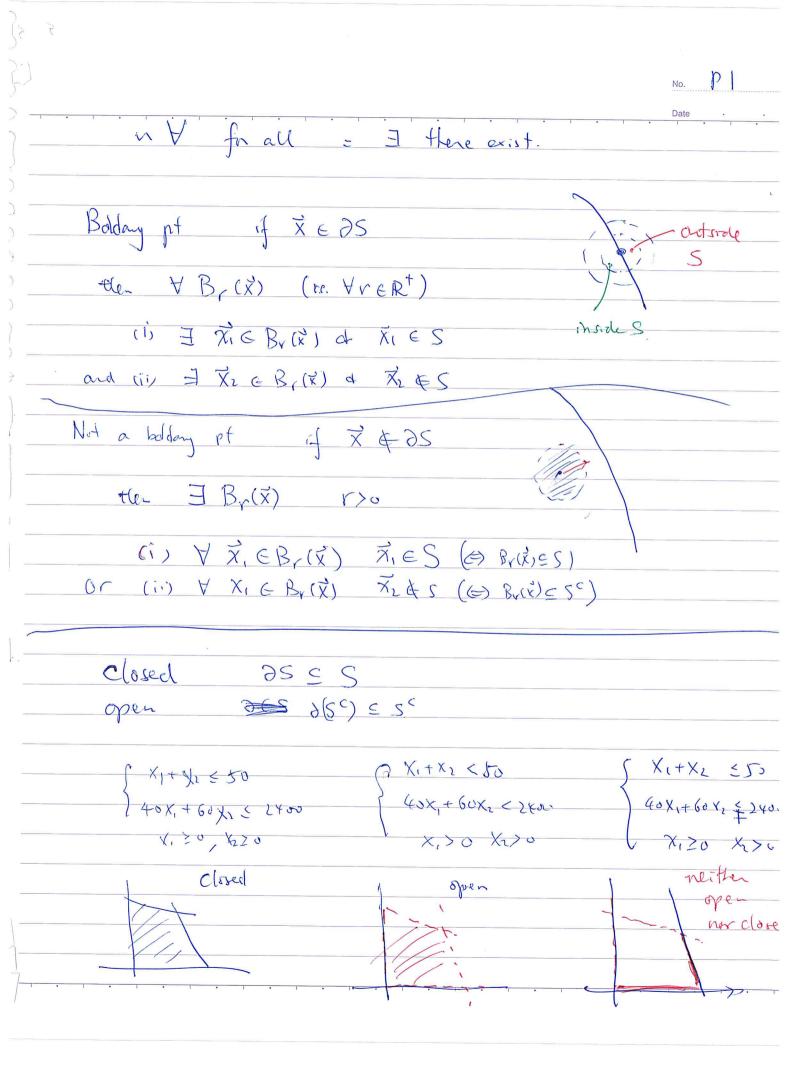
where $M_i \geq 0$ for all i and $\sum_{i=1}^k M_i = 1$. Then \mathbf{x} is called a *convex combination* of the points $\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_k$.

Example 1.7. Consider the triangle on the plane with vertices \mathbf{x}_1 , \mathbf{x}_2 , \mathbf{x}_3 . Then any point \mathbf{x} in the triangle is a convex combinations of $\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3\}$. In fact, let \mathbf{y} be the extension of the line segment

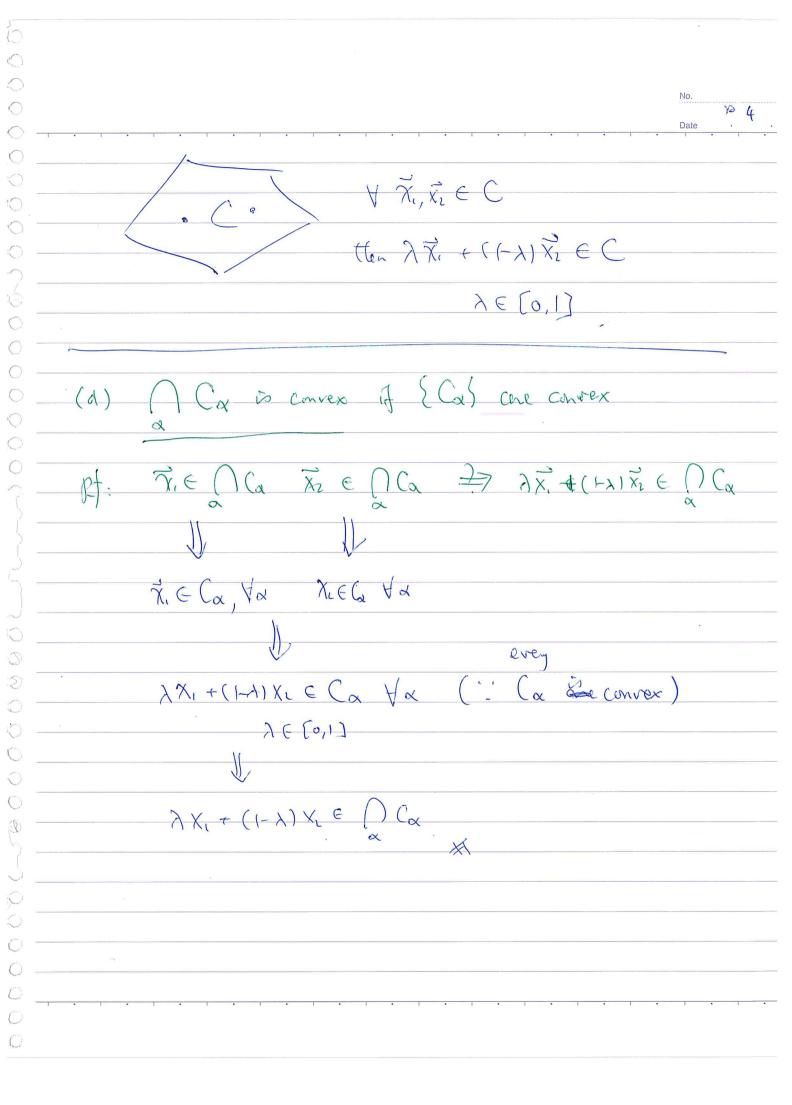
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