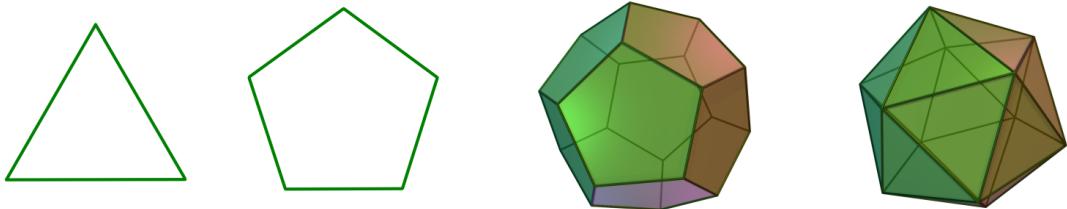


1 Polyhedral Geometry

1.a Real Vector Spaces

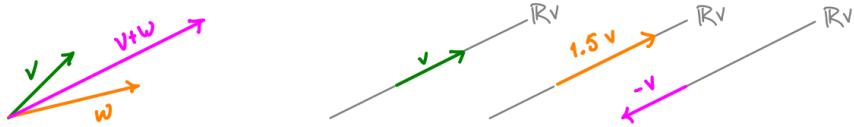
You've all seen polygons and polytopes before, maybe one of these is your favorite:



(Images from Wikipedia)

These are examples of polyhedra. To describe polyhedra carefully, we first have to say where they live – namely, we have to described “real vector spaces”. We’ll give a rough idea first, and then a more careful definition.

Idea: A real vector space is a space where we can add points together and rescale points by any real number.



Careful version: A *real vector space* is a set V with an addition operation

$$\begin{aligned} + : V \times V &\rightarrow V \\ (v, w) &\mapsto v + w \end{aligned}$$

and a real scalar multiplication

$$\begin{aligned} \cdot : \mathbb{R} \times V &\rightarrow V \\ (r, v) &\mapsto r \cdot v \end{aligned}$$

satisfying the following conditions. For all $u, v, w \in V$ and $r, s \in \mathbb{R}$:

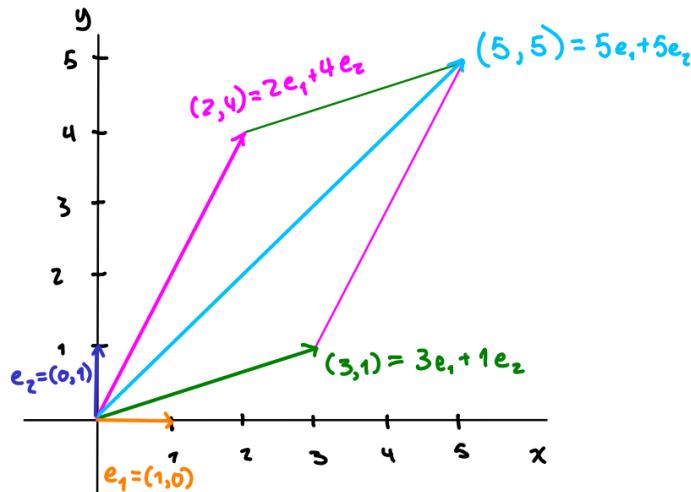
- $u + (v + w) = (u + v) + w$
(Associativity of Vector Addition)
- $v + w = w + v$
(Commutativity of Vector Addition)

- There is an element $\mathbf{0} \in V$ with $\mathbf{0} + v = v$.
(Identity Element of Vector Addition)
- There is an element $-v \in V$ with $v + (-v) = \mathbf{0}$.
(Inverse Elements of Vector Addition)
- $r \cdot (s \cdot v) = (rs) \cdot v$
(Compatibility of Scalar Multiplication with Multiplication in \mathbb{R})
- For the element $1 \in \mathbb{R}$, we have $1 \cdot v = v$.
(Identity Element of Scalar Multiplication)
- $r \cdot (v + w) = r \cdot v + r \cdot w$
(Distributivity of Scalar Multiplication with Respect to Vector Addition)
- $(r + s) \cdot v = r \cdot v + s \cdot v$
(Distributivity of Scalar Multiplication with Respect to Addition in \mathbb{R})

Notation: Usually, we will just write rv for $r \cdot v$.

Question: Does \mathbb{R} itself have the structure of a vector space?

Question: What about \mathbb{R}^2 with head-to-tail/ componentwise addition? What would change if we replaced \mathbb{R}^2 with \mathbb{R}^n ?



When we talk about “componentwise” addition, we are using a *basis* for our vector space.

Idea: A *basis* of V is a subset $B \subset V$ such that every element $v \in V$ can be written as a finite \mathbb{R} -linear combination of elements of B in exactly one way.

Careful version: A *basis* B of a real vector space V is a subset of V satisfying:

- for every finite subset $\{\mathbf{e}_1, \dots, \mathbf{e}_m\}$ of B , we can only have an equality $c_1\mathbf{e}_1 + \dots + c_m\mathbf{e}_m = \mathbf{0}$ if $c_1 = \dots = c_m = 0$.
(Linear Independence)
- for every $v \in V$, there is a finite subset $\{\mathbf{e}_1, \dots, \mathbf{e}_m\}$ of B and associated scalars $c_1, \dots, c_m \in \mathbb{R}$ such that $v = c_1\mathbf{e}_1 + \dots + c_m\mathbf{e}_m$.
(Spanning Property)

Next, given a pair of real vector spaces V and W , a map

$$f : V \rightarrow W$$

is *linear* if for every $u, v \in V$ and $r \in \mathbb{R}$:

- $f(u + v) = f(u) + f(v)$
- $f(r \cdot v) = r \cdot f(v)$

(Note that the operations on the left hand side occur in V , while those on the right hand side occur in W .)

On Homework 1, you will investigate linear maps from \mathbb{R}^2 to \mathbb{R} and show that this collection of maps is itself a real vector space. Once again, we could replace \mathbb{R}^2 with \mathbb{R}^n without meaningfully changing any arguments.

The space of linear maps from a real vector space V to \mathbb{R} is called the *dual vector space*. It's denoted V^* .

Fact: In finite dimensions, there is a natural identification between $(V^*)^*$ and V .

This lets us treat V and V^* on equal footing – we can equally well start with V^* and think of V as the dual vector space.

We have a canonical pairing, the “evaluation pairing”, between these two vector spaces:

$$\langle \cdot, \cdot \rangle : V \times V^* \rightarrow \mathbb{R}$$

$$(v, \omega) \mapsto \omega(v) = v(\omega).$$

↑ ↑

Here we view v as
an element of V .

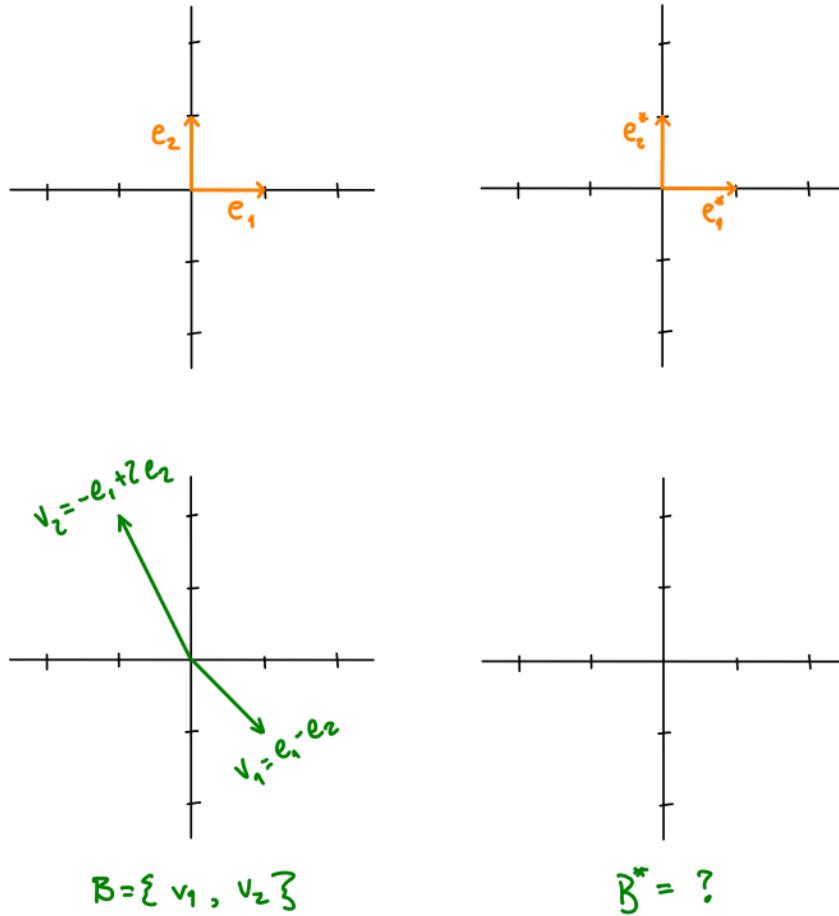
Here we view v as
an element of $(V^*)^*$.

If we have already fixed a basis $B = \{\mathbf{v}_1, \mathbf{v}_2, \dots\}$ of V , we can use this pairing to give V^* a basis $B^* = \{\mathbf{v}_1^*, \mathbf{v}_2^*, \dots\}$ as well. We define \mathbf{v}_i^* to be the unique element of V^* satisfying:

- $\langle \mathbf{v}_i, \mathbf{v}_i^* \rangle = 1$
- $\langle \mathbf{v}_j, \mathbf{v}_i^* \rangle = 0$ if $i \neq j$.

We generally abbreviate this as $\langle \mathbf{v}_j, \mathbf{v}_i^* \rangle = \delta_{ij}$. The function “ δ_{ij} ” is called the *Kronecker delta*. It is 1 if $i = j$ and 0 if $i \neq j$.

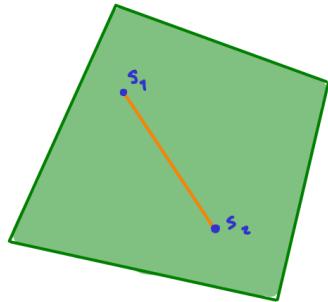
Example:



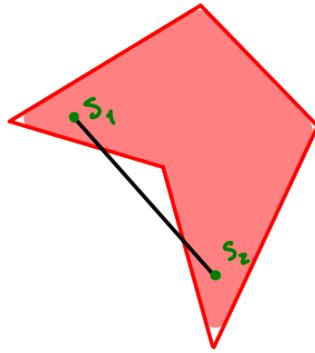
1.b Convex Polyhedra

Definition: Let S be a subset of a real vector space V . We say S is *convex* if for every pair of points s_1, s_2 in S , the line segment $\overline{s_1 s_2}$ is contained in S .

Example:

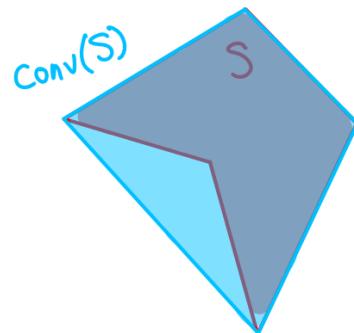


Non-example:



Definition: Let S be a subset of a real vector space V . The *convex hull* of S , denoted $\text{conv}(S)$, is the smallest convex set containing S . In other words, $\text{conv}(S)$ is the intersection of all convex sets containing S .

Example:



Question: Is a union of two convex sets necessarily convex?

Question: Is an intersection of two convex sets necessarily convex?

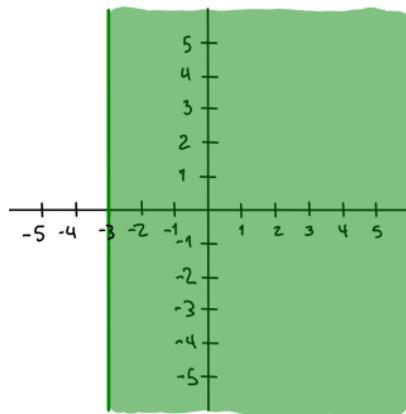
Definition: Let $w \in V^*$, with $w \neq \mathbf{0}$, and let $r \in \mathbb{R}$. The *half-space* $H_{w,r}^+$ is the subset of V defined by

$$H_{w,r}^+ := \{v \in V \mid \langle v, w \rangle \geq r\}.$$

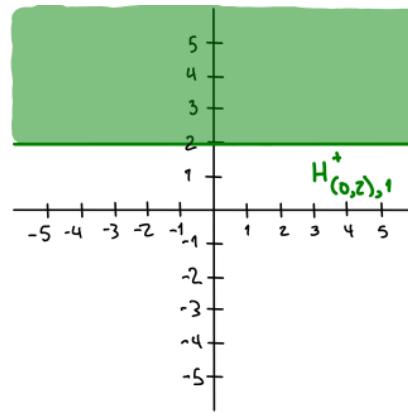
Its boundary is the *hyperplane*

$$H_{w,r} := \{v \in V \mid \langle v, w \rangle = r\}.$$

Examples:

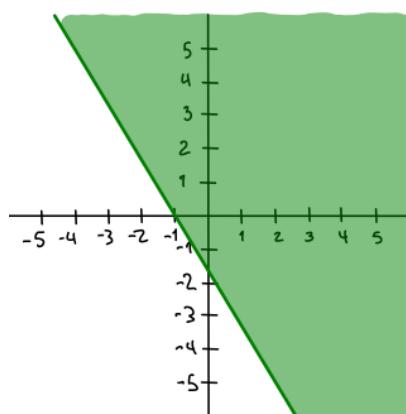


$$H_{(1,0), -3}^+$$

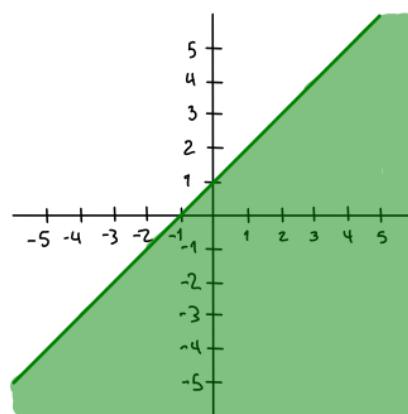


$$H_{(0,2), 1}^+$$

Can you think of
any other way to
write this?



$$H_{(5,3), -5}^+$$



$$H_{(1,-1), -1}^+$$

Question: Why have I insisted that $w \neq \mathbf{0}$? What would $H_{0,1}^+$ and $H_{0,-1}^+$ look like if we dropped this non-zero condition?

Question: Is a half-space convex?

Question: Is a hyperplane convex?

This next question isn't essential for the discussion that follows, but it's a good check that you understand the material we've covered so far.

Question: Is $H_{w,r}^+$ or $H_{w,r}$ a vector subspace of V ? Can you add some condition that will ensure one of them becomes a vector subspace?

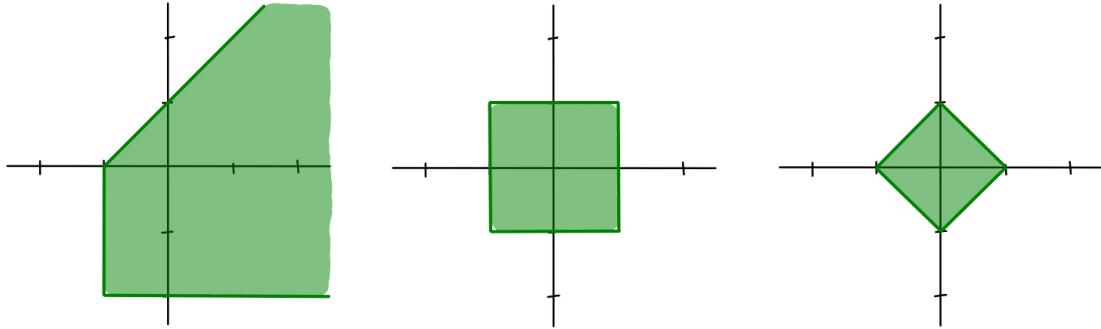
Now we are ready to introduce polyhedra and polytopes.

Definition: A *polyhedron* P in V is a subset of the form

$$P = \bigcap_{i \in I} H_{w_i, r_i}^+,$$

where I is some finite indexing set, each w_i is a non-zero element of V^* and each r_i is in \mathbb{R} .

Question: Can you describe the following polyhedra as intersections of half-spaces?



Definition: A subset P of V is called a *polytope* if it is a bounded polyhedron. Equivalently, a subset P of V is called a *polytope* if

$$P = \text{conv} (v_j \mid j \in J),$$

where J is some finite indexing set and each v_j is an element of V .

You should try to think about these two equivalent definitions and convince yourself that they really are describing the same subsets of V . Once you've internalized the definitions, this equivalence should feel “obviously true”. I'd argue that it genuinely *is* obviously true, but this is one of those obvious statements that take a surprising amount of work to prove. The usual proof makes use of a concept called *duality* or *polarity* which we haven't introduced yet.

So, we can describe a polytope $P \subset V$ as either

$$P = \bigcap_{i \in I} H_{w_i, r_i}$$

or as

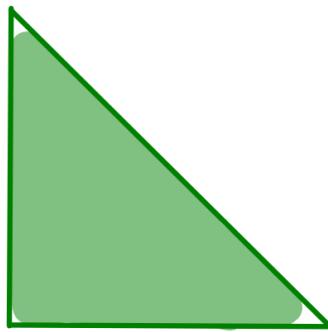
$$P = \text{conv} (v_j \mid j \in J).$$

The former is called the *half-space representation* of P and the latter is called the *vertex representation* of P . On the next homework, you'll describe polytopes in terms of both.

1.c Faces of Polyhedra

Definition: Let P be a polyhedron in V . We say that a subset F of P is a *face* if there is a half-space $H_{w,r}^+$ in V with $P \subset H_{w,r}^+$ such that $F = P \cap H_{w,r}$. That is, F is a face of P if it is the intersection of P with the boundary of some half-space containing P .

Example: Describe each face of the following polygon in \mathbb{R}^2 .



There are a couple of tricky points to consider in the above example. First, I specifically stated that the polygon was in \mathbb{R}^2 . Why? Would your answer change if we instead took it to lie in \mathbb{R}^3 , for instance if it were lying in the xy -plane ($z = 0$) of \mathbb{R}^3 ?

Next, is the empty set \emptyset a face of the polygon? Why?

Definition: We say a face F of P is a *proper face* if $F \notin \{\emptyset, P\}$.

Definition: We call the 0-dimensional faces of P *vertices*, the 1-dimensional faces of P *edges*, and the codimension 1 faces of P *facets*.

Question: If F is a face of a polyhedron P , is F itself a polyhedron?

Observation: Let $\mathcal{F}(P)$ be the set of faces of a polyhedron P . Then “ \subseteq ” is a partial order on $\mathcal{F}(P)$ and $(\mathcal{F}(P), \subseteq)$ is a poset. In fact, this poset has additional structure as well, which we will discuss soon. First, a few questions about the poset structure:

Question: Can you represent diagrammatically the poset $(\mathcal{F}(T), \subseteq)$ for a tetrahedron T ?

Question: Given an arbitrary polyhedron P , does $(\mathcal{F}(P), \subseteq)$ have a least element?

Question: Does $(\mathcal{F}(P), \subseteq)$ have a greatest element in general? When does it have a greatest element?

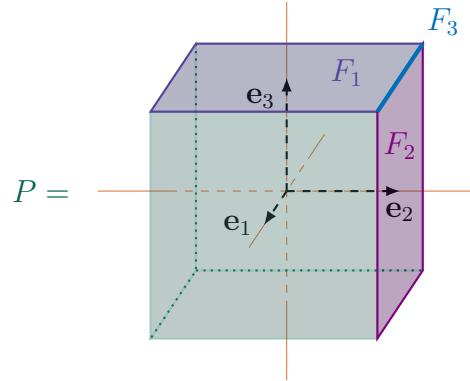
Question: If P is full dimensional, what are the maximal elements of $(\mathcal{F}(P), \subseteq)$?

Now on to the additional structure $\mathcal{F}(P)$ enjoys – it satisfies:

- If $F_1 \in \mathcal{F}(P)$ and $F_2 \in \mathcal{F}(F_1)$, then $F_2 \in \mathcal{F}(P)$. (*A face of a face is a face.*)
- If $F_1, F_2 \in \mathcal{F}(P)$, then $(F_1 \cap F_2) \in (\mathcal{F}(F_1) \cap \mathcal{F}(F_2))$. (*The intersection of two faces is a face of both.*)

That is to say, $\mathcal{F}(P)$ forms a *polyhedral complex*. We call it the *face complex* of P .

Example: Let P be the cube shown below, and F_1 , F_2 , and F_3 the indicated polytopes at the boundary of P . Note that F_1 and F_2 are *facets* of P . Meanwhile, $F_3 = (F_1 \cap F_2)$ is a facet of both F_1 and F_2 , and a face of P .

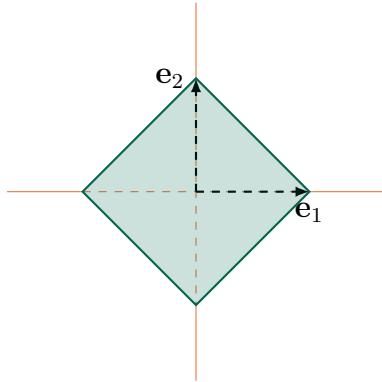


1.d Duality for Polytopes and Faces

Definition: Given a polytope P in a real vector space V , the *dual* of P is

$$P^\circ := \{w \in V^* \mid \langle v, w \rangle \geq -1 \text{ for all } v \in P\}.$$

Question: Let P be the square shown below. Can you draw P° ?



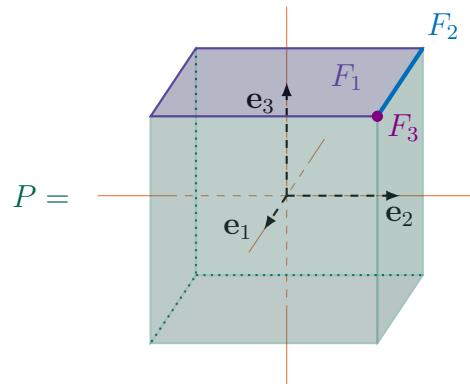
We also have a notion of duality for faces. Note that faces are themselves polytopes, and the definitions differ, so we should always try to be clear about which version of *dual* we are considering.

Definition: The *dual of a face* F of a polytope P in V is

$$\check{F} := \{w \in P^\circ \mid \langle v, w \rangle = -1\}.$$

Fact: If F is a face of P , then \check{F} is a face of P° .

Question: Let P be the cube shown below, and F_1 , F_2 , and F_3 its indicated faces. What are P° , \check{F}_1 , \check{F}_2 , and \check{F}_3 ?



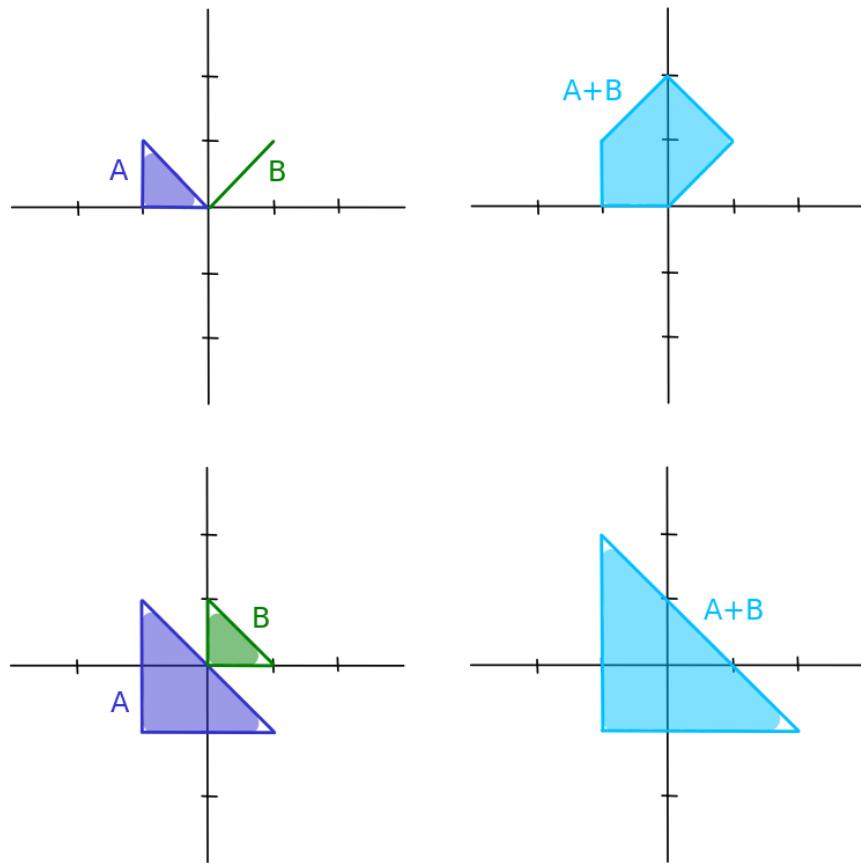
This question will be the start of your polyhedral geometry project, which will be an exploration of dual polytopes and their face complexes.

1.e Minkowski Sum

Definition: Let A and B be a pair of subsets of a vector space V . The *Minkowski sum* of A and B is

$$A + B := \{a + b \mid a \in A \text{ and } b \in B\}.$$

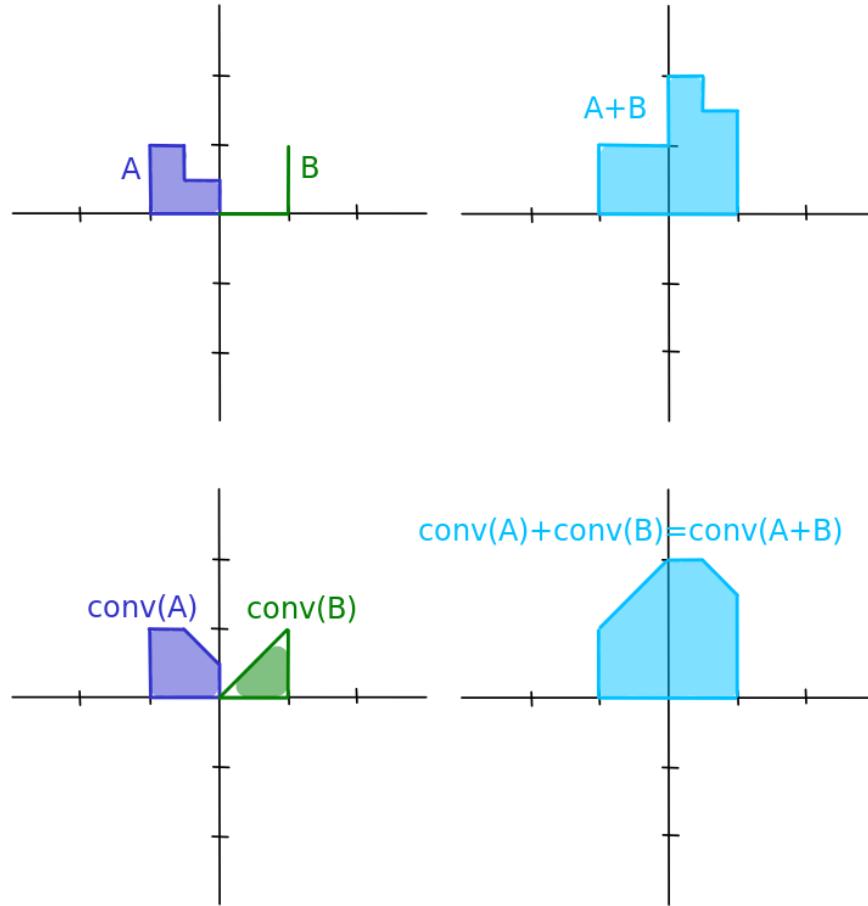
Examples:



Theorem:

$$\text{conv}(A + B) = \text{conv}(A) + \text{conv}(B)$$

Example:



1.f Convex Functions

Definition: A function $\varphi : V \rightarrow \mathbb{R}$ is *convex* if for all $u, v \in V$ and $t \in [0, 1]$, we have

$$\varphi((1-t)u + tv) \geq (1-t)\varphi(u) + t\varphi(v).$$

Warning: I'm making a non-standard choice of convention here – it's more common to have the inequality in the opposite direction. The inequality convention I've chosen is more convenient in my research area, and for a topic we'll discuss soon.

Question: What sort of function would we have if we replaced the inequality with an equality?

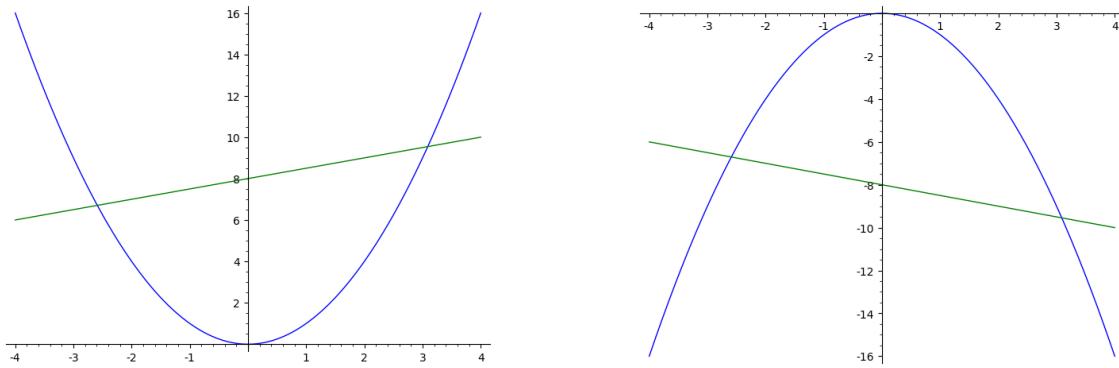
Here's an equivalent characterization of convex functions – since they are equivalent, you can use whichever version you prefer.

Theorem: (*Jensen's Inequality*) A function $\varphi : V \rightarrow \mathbb{R}$ is convex if and only if for all $v_1, v_2, \dots, v_n \in V$ and $a_1, a_2, \dots, a_n \in \mathbb{R}_{\geq 0}$, not all 0, we have

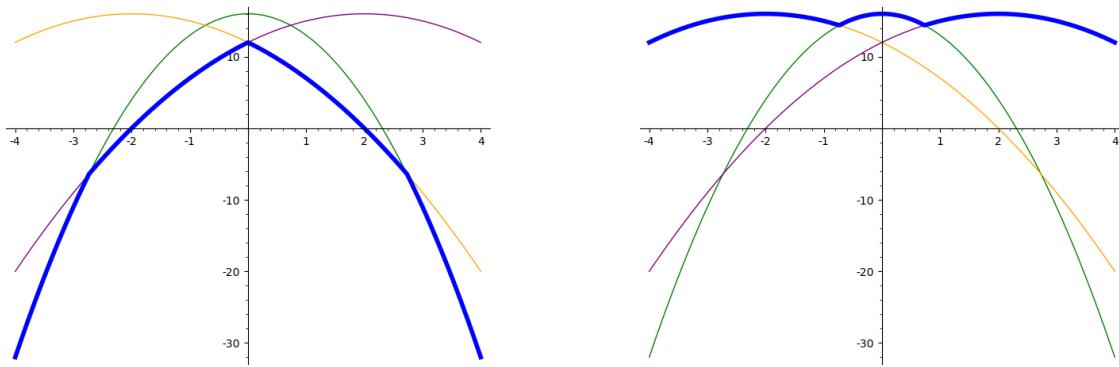
$$\varphi\left(\frac{\sum_{i=1}^n a_i v_i}{\sum_{i=1}^n a_i}\right) \geq \frac{\sum_{i=1}^n a_i \varphi(v_i)}{\sum_{i=1}^n a_i}.$$

Note that left hand side of Jensen's Inequality is φ applied to the weighted average of the v_i 's, where the a_i 's are the weights, while the right hand side is the weighted average of the $\varphi(v_i)$'s.

Question: Let $V = \mathbb{R}$, and let $f(x) = x^2$ and $g(x) = -x^2$. Which function f or g is convex?



Question: Let V be any real vector space, and let f and g be convex functions on V . Which function $\min(f, g)$ or $\max(f, g)$ is convex?



We can compare the equivalent characterization of convex functions described above to an equivalent characterization of the convex hull of a set and in turn of convex sets:

Theorem: Let S be a subset of a real vector space V . Then $\text{conv}(S)$ is the set of weighted averages of points in S . A set is convex if and only if it is equal to its convex hull.

This leads to a nice little relationship between convex functions and convex sets.

Theorem: Let $\varphi : V \rightarrow \mathbb{R}$ be a convex function. Then

$$\Xi_{\varphi,c} := \{v \in V \mid \varphi(v) \geq c\}.$$

is convex.

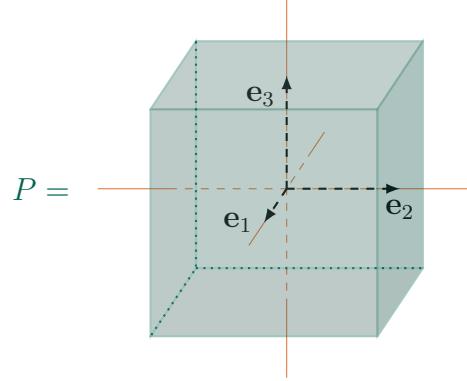
Question: Let $\varphi : V \rightarrow \mathbb{R}$ be the linear function $\langle \cdot, w \rangle$, where $w \in V^*$. Then $\Xi_{\varphi,c}$ has another name – it's a set we've described previously. What is it?

We can use this to describe the dual P° of a polytope P as well. Denote the set of vertices of P by $\text{Vert}(P)$ and let

$$\varphi = \min_{v \in \text{Vert}(P)} \langle v, \cdot \rangle.$$

Then $P^\circ = \Xi_{\varphi,-1}$.

Question: Can you describe the cube P shown below as $\Xi_{\varphi,-1}$ for some φ ?



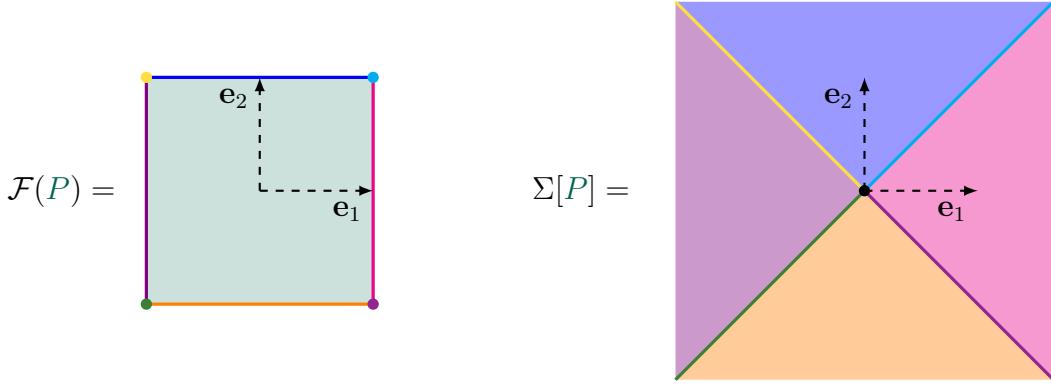
Let's now consider a full-dimensional polytope $P \subset V$ containing the origin in its interior.

Definition: Given a face F of P , the *cone of F* is $\sigma_F := \mathbb{R}_{\geq 0} \cdot F$. The *face-fan* of P , denoted $\Sigma[P]$, is

$$\Sigma[P] := \{\sigma_F \mid F \text{ is a face of } P\} \cup \{0\}.$$

We can think of σ_F as the set we get by taking rays from the origin through the points of F .

Example:



Definition: A function $\varphi : V \rightarrow \mathbb{R}$ is $\Sigma[P]$ -*piecewise linear* if $\varphi|_\sigma$ is linear for each cone $\sigma \in \Sigma[P]$.

This means that $\varphi|_\sigma = \langle \cdot, w_\sigma \rangle$ for some $w_\sigma \in V^*$. If we can take each of these w_σ 's to be lattice points of V^* , we say φ is an *integral* $\Sigma[P]$ -piecewise linear function.

Question: Can you come up with any convex integral $\Sigma[P]$ -piecewise linear functions for $\Sigma[P]$ the face-fan shown in the previous example?

1.g Nef Partitions

The final topic we will discuss is a fascinating duality discovered by Lev Borisov in 1993. This section is based on his paper *Towards the Mirror Symmetry for Calabi-Yau Complete Intersections in Gorenstein Toric Fano Varieties*.

Definition: Let P be a reflexive polytope in V . A decomposition of the vertices of P as a disjoint union

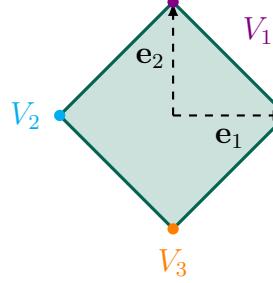
$$\text{Vert}(P) = V_1 \sqcup V_2 \sqcup \cdots \sqcup V_k$$

is a *nef partition* if there is a collection $\varphi_1, \varphi_2, \dots, \varphi_k$ of convex integral $\Sigma[P]$ -piecewise linear functions with

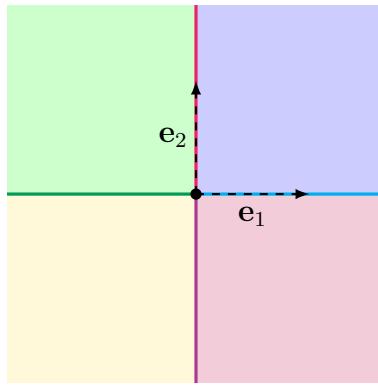
$$\varphi_i(v) = \begin{cases} -1 & \text{if } v \in V_i \\ 0 & \text{if } v \in V_j \text{ for } i \neq j. \end{cases}$$

This may look like a strange thing to define, and a weird name for it. Both the motivation and the name come from algebraic geometry – we're just exploring the polyhedral geometry part of a much deeper story with connections between several different fields of geometry.

Example: Consider the polytope P and decomposition of its vertices $\text{Vert}(P) = V_1 \sqcup V_2 \sqcup V_3$ shown below.



The face-fan of P is:



Now consider the following functions:

- $\varphi_1 = \min(\langle \cdot, -\mathbf{e}_1^* - \mathbf{e}_2^* \rangle, \langle \cdot, -\mathbf{e}_1^* \rangle, \langle \cdot, -\mathbf{e}_2^* \rangle, \langle \cdot, \mathbf{0} \rangle)$
- $\varphi_2 = \min(\langle \cdot, \mathbf{e}_1^* \rangle, \langle \cdot, \mathbf{0} \rangle)$
- $\varphi_3 = \min(\langle \cdot, \mathbf{e}_2^* \rangle, \langle \cdot, \mathbf{0} \rangle)$

Let's first check that

$$\varphi_i(v) = \begin{cases} -1 & \text{if } v \in V_i \\ 0 & \text{if } v \in V_j \text{ for } i \neq j. \end{cases}$$

We want $\varphi_1(\mathbf{e}_1) = \varphi_1(\mathbf{e}_2) = -1$ and $\varphi_1(-\mathbf{e}_1) = \varphi_1(-\mathbf{e}_2) = 0$.

$$\begin{aligned} \varphi_1(\mathbf{e}_1) &= \min(\langle \mathbf{e}_1, -\mathbf{e}_1^* - \mathbf{e}_2^* \rangle, \langle \mathbf{e}_1, -\mathbf{e}_1^* \rangle, \langle \mathbf{e}_1, -\mathbf{e}_2^* \rangle, \langle \mathbf{e}_1, \mathbf{0} \rangle) \\ &= \min(-1, -1, 0, 0) \\ &= -1 \end{aligned}$$

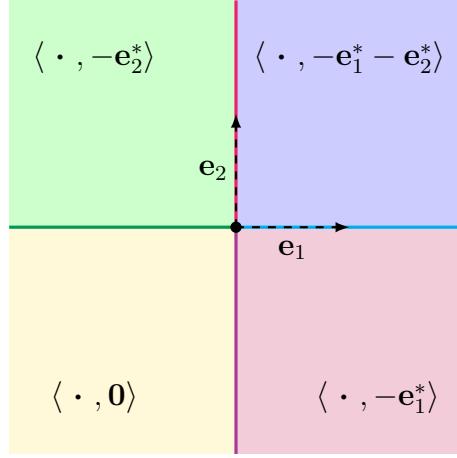
$$\begin{aligned}
\varphi_1(\mathbf{e}_2) &= \min (\langle \mathbf{e}_2, -\mathbf{e}_1^* - \mathbf{e}_2^* \rangle, \langle \mathbf{e}_2, -\mathbf{e}_1^* \rangle, \langle \mathbf{e}_2, -\mathbf{e}_2^* \rangle, \langle \mathbf{e}_2, \mathbf{0} \rangle) \\
&= \min(-1, 0, -1, 0) \\
&= -1
\end{aligned}$$

$$\begin{aligned}
\varphi_1(-\mathbf{e}_1) &= \min (\langle -\mathbf{e}_1, -\mathbf{e}_1^* - \mathbf{e}_2^* \rangle, \langle -\mathbf{e}_1, -\mathbf{e}_1^* \rangle, \langle -\mathbf{e}_1, -\mathbf{e}_2^* \rangle, \langle -\mathbf{e}_1, \mathbf{0} \rangle) \\
&= \min(1, 1, 0, 0) \\
&= 0
\end{aligned}$$

$$\begin{aligned}
\varphi_1(-\mathbf{e}_2) &= \min (\langle -\mathbf{e}_2, -\mathbf{e}_1^* - \mathbf{e}_2^* \rangle, \langle -\mathbf{e}_2, -\mathbf{e}_1^* \rangle, \langle -\mathbf{e}_2, -\mathbf{e}_2^* \rangle, \langle -\mathbf{e}_2, \mathbf{0} \rangle) \\
&= \min(1, 0, 1, 0) \\
&= 0
\end{aligned}$$

You can check that φ_2 and φ_3 have the desired values on the vertices of P as well.

Next, since each φ_i is a minimum of convex functions, each φ_i is convex. Moreover, the convex functions appearing in the minimum are all integral linear functions, so φ_i is an integral piecewise linear function. We just have to check that it is $\Sigma[P]$ -piecewise linear – that is, we want the domains of linearity of φ_i to be unions of cones in $\Sigma[P]$. Morally, we don't want half of one cone to lie in one domain of linearity and the other half in another. The restriction of φ_1 to each maximal cone of $\Sigma[P]$ is shown below.



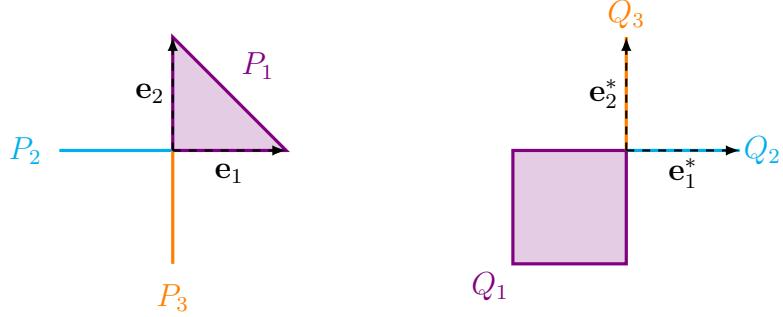
You can check that φ_2 and φ_3 are also $\Sigma[P]$ -piecewise linear. We do indeed have a nef partition.

Now define the following polytopes:

$$P_i := \text{conv}(\{0\} \cup V_i)$$

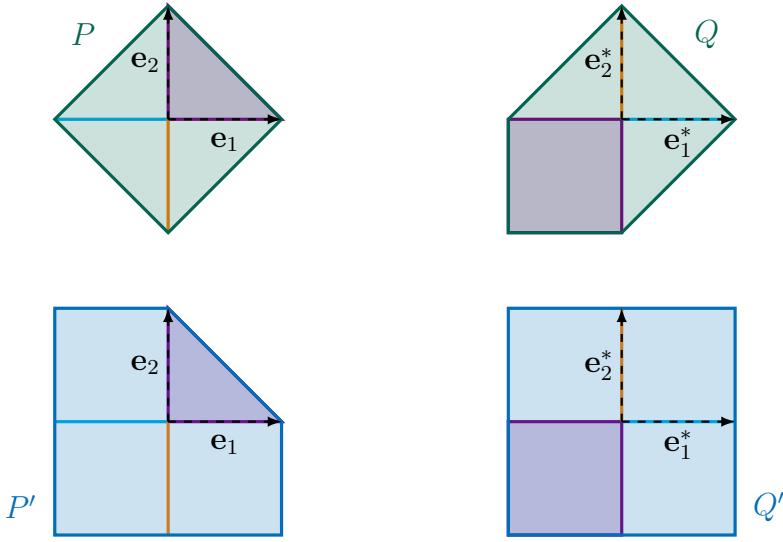
$$\begin{aligned}
Q_i &:= \{w \in V^* \mid \langle u, w \rangle \geq \varphi_i(u) \text{ for all } u \in V\} \\
&= \{w \in V^* \mid \langle v, w \rangle \geq -1 \text{ if } v \in V_i, \text{ and } \langle v, w \rangle \geq 0 \text{ if } v \in V_{j \neq i}\}
\end{aligned}$$

Example: Using the nef partition of the previous example, we have



Theorem: The four polytopes $P = \text{conv}(P_1 \cup P_2 \cup \dots \cup P_k)$, $Q = \text{conv}(Q_1 \cup Q_2 \cup \dots \cup Q_k)$, $P' = P_1 + P_2 + \dots + P_k$, and $Q' = Q_1 + Q_2 + \dots + Q_k$ are all reflexive. Moreover, the Q_i 's define a nef partition of $\text{Vert}(Q)$ – called the *dual nef partition* – and we have the polytope dualities $P^\circ = Q'$ and $Q^\circ = P'$. The double-dual nef partition is the original nef partition, so roles may be swapped in this picture.

Example: Continuing with our running example, we have:



Note that each of these four polytopes are reflexive – P and Q' are dual lattice polytopes as are P' and Q . What is the dual nef partition? What about the associated convex integral piecewise linear functions?