

# Kinetic Description of Hamilton-Jacobi PDE IV

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UC Berkeley

PDE/Probability Student Seminar

# Outline

Discrete Gauss Curvature and Alexandrov Maps

Optimal Transport Formulation and Monge-Kantorovich Duality

Hamilton-Jacobi Dynamics: Free Motion, Coagulation, and Collision

Hamilton-Jacobi Dynamics: Directed Secondary Polytope

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# Dual Tessellations/Legendre Transform

Given a finite  $P$  and a map  $f : P \rightarrow \mathbb{R}$ , we define two piecewise linear convex functions:

$$u(x) = f^*(x) = \sup_{\rho \in P} (x \cdot \rho - f(\rho))$$

$$u^*(\rho) = f^{**}(\rho) = \sup_x (x \cdot \rho - u(x)) = f^o(\rho) = \text{convex hull of } f.$$

Domains of the linearity of  $u$  yield a **Laguerre tessellation**:

$$\mathbf{X}(f) := \{X(\rho) : \rho \in \mathbb{R}^d\}, \quad X(\rho) = \partial u^*(\rho).$$

Domains of the linearity of  $u^*$  yield a **weighted Delaunay tessellation**:

$$\mathbf{P}(f) := \{P(x) : x \in \mathbb{R}^d\}, \quad P(x) = \partial u(x).$$

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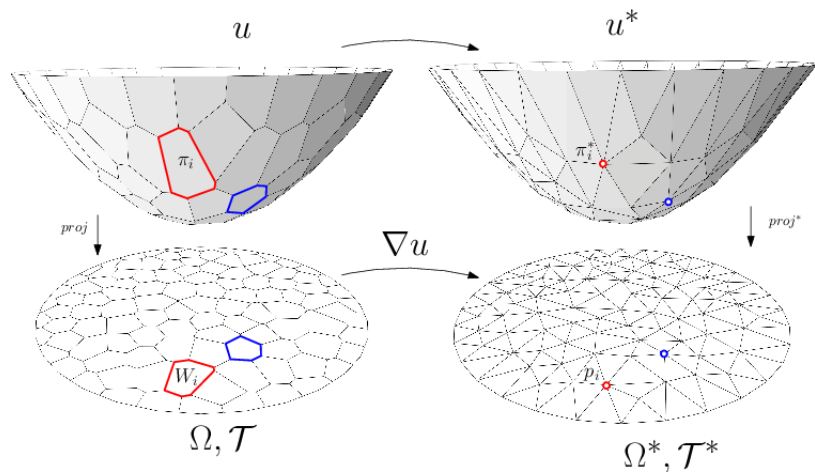
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# Legendre Transform

For generic  $f$ :



(Courtesy of N. Lei, W. Chen, Z. Luo, X. Gu 2019)

# Alexandrov Map I

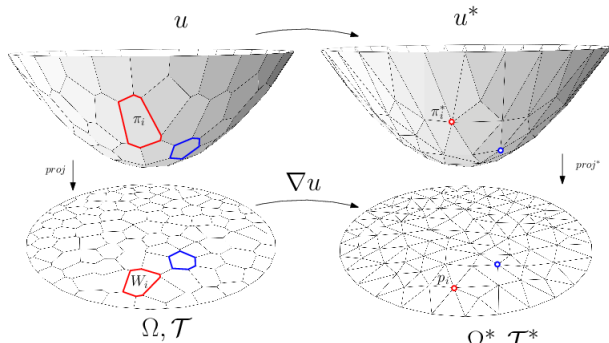
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$$\nu(\rho) = |X(\rho) \cap \Omega|.$$

$X(\rho)$  is the set of slopes of subgradients (generalized tangents) to the graph of  $u^*$  at  $\rho$ .

If  $\nu$  is known, then we can recover  $f$  (and hence  $u$ ) from it in  $\Omega$ .

**Alexandrov Map I** The inverse map  $\nu \mapsto u$ .



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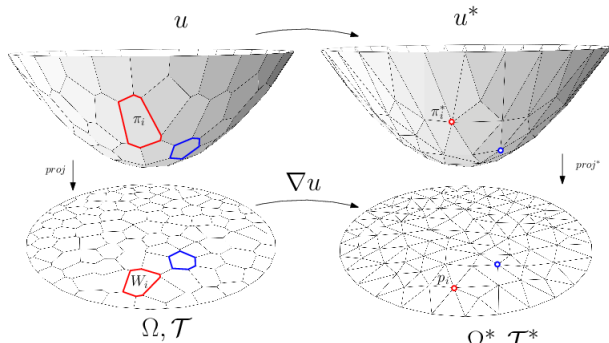
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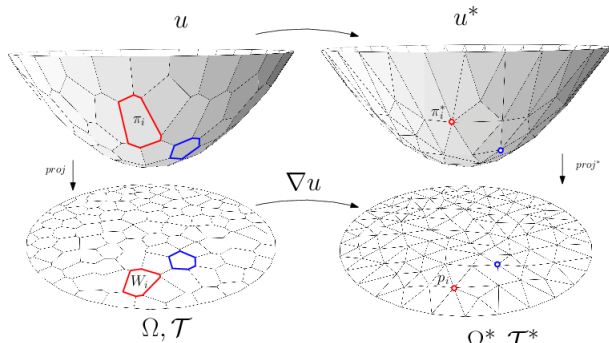
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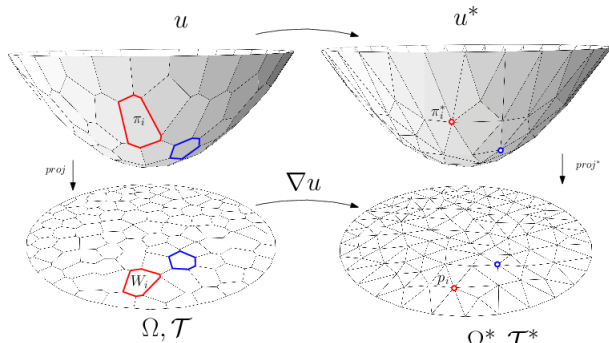
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# Discrete Gauss Curvature

Let  $x \in X(\rho)$ , then

$$N(x) = (1 + |x|^2)^{-1/2}(x, -1),$$

is normal to a face of the graph.

Define

$$\hat{X}(\rho) = \{N(x) : x \in X(\rho) \cap \Omega\} \subset \mathbb{S}_-^d.$$

Think of  $\rho \mapsto \hat{X}(\rho)$  as a discrete Gauss map. Define

$$\alpha(\rho) = \sigma(\hat{X}(\rho)),$$

where  $\sigma$  is the  $d$ -dimensional (surface) area on the sphere.

When  $\Omega = \mathbb{R}^d$ , then  $\alpha(\rho)$  is our candidate for the **Gauss curvature** at  $\rho$ .

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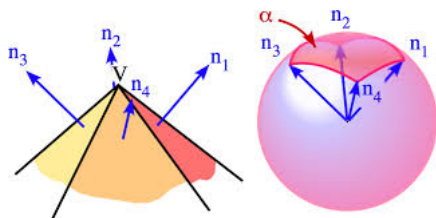
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## Alexandrov Map II

If  $\alpha$  is known, then we can recover  $f$  (and hence  $u$ ) from it in  $\Omega$ .

Alexandrov Map II The inverse map  $\alpha \mapsto u$ .



Write  $\lambda_1$  for the Lebesgue measure on  $\Omega$ .

Write  $\lambda_2$  for the pull back of  $\sigma$  with respect to  $x \mapsto N(x)$ .

Important Observation

1. The locally constant  $\rho = \nabla u$  pushes forward  $\lambda_1$  to

$$\mu_1 = \sum_{\rho \in P} \nu(\rho) \delta_\rho.$$

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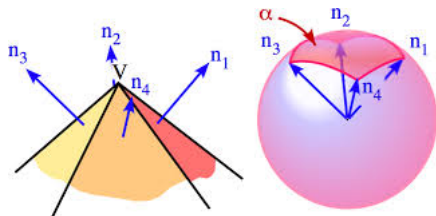
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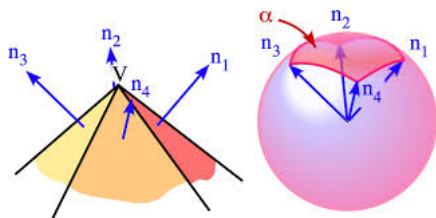
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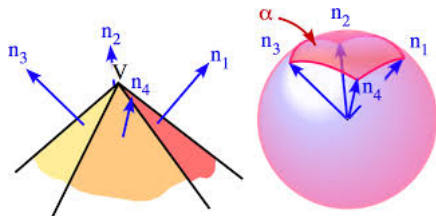
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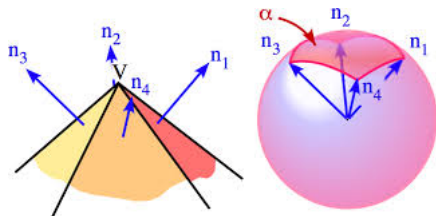
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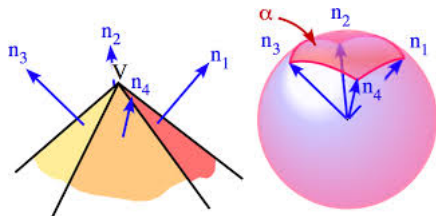
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# Monge-Kantorovich Problem and Duality

**Brenier:** Given two measures  $\lambda$  and  $\mu$ , there exists a unique (modulo a constant) convex function  $u : \Omega \rightarrow \mathbb{R}$  such that  $\rho = \nabla u$  pushes forward  $\lambda$  to  $\mu$ .

Moreover  $\rho$  is a minimizer in

$$I(\mu) (= I(\lambda, \mu)) := \inf \frac{1}{2} \int_{\Omega} |x - \rho(x)|^2 \lambda(dx).$$

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## Dual Problem

$$I(\mu) = \sup \left\{ \int \phi(x) \lambda(dx) + \int \psi(\rho) \mu(d\rho) \right\},$$

where the supremum is over pairs  $(\phi, \psi)$  such that

$$\varphi(x) + \psi(\rho) \leq \frac{1}{2}|x - \rho|^2 \text{ for all } (x, \rho).$$

For each pair  $(\varphi, \psi)$ , we define  $(u, v)$  as

$$u(x) = \frac{1}{2}|x|^2 - \varphi(x), \quad v(\rho) = \frac{1}{2}|\rho|^2 - \psi(\rho).$$

We then define

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These optimization problems are equivalent:

$$I(\mu) = \hat{I}(\mu) + \int \frac{1}{2}|x|^2 \lambda(dx) + \int \frac{1}{2}|\rho|^2 \mu(d\rho).$$

The maximizing pair  $(u, \nu)$  satisfies  $u = \nu^*$ , and  $u$  is the desired convex function.

This suggests a functional

$$E(\nu) = \int \nu^*(x) \lambda(dx),$$

which is convex. In terms of this functional,

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In summary the inverse of the map  $f \mapsto \nu$  is given by  $\nu = -\nabla E(f)$ .

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## Dual Problem

These optimization problems are equivalent:

$$I(\mu) = \hat{I}(\mu) + \int \frac{1}{2}|x|^2 \lambda(dx) + \int \frac{1}{2}|\rho|^2 \mu(d\rho).$$

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We are interested in the PDE  $u_t = H(u_x)$  with  $u(x, 0)$  convex and piecewise linear.

Write  $\mathcal{C}(P)$  for the set of functions of the form  $u = f^*$  where  $f : P \rightarrow \mathbb{R}$ .

Write  $\Phi_t$  for the flow associated with the PDE:

$$\Phi_t u(\cdot, 0) = u(\cdot, t).$$

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Without loss of generality we may assume that  $P$  is finite.

(Speed of propagation is finite.)

**Main Theorem:** There are times

$$t_0 = 0 < t_1 < \cdots < t_k < t_{k+1} = \infty,$$

such that

1. In  $(t_i, t_{k=1})$ , we have a **free motion**.
2. At transition

$$t_{i-} \rightarrow t_{i+},$$

we either have a **coagulation** or **collision**.

3. For  $t > t_k$ , the triangulation associated with  $f^t$  is very special (**stable**). We call it **anti- $H$  triangulation**.

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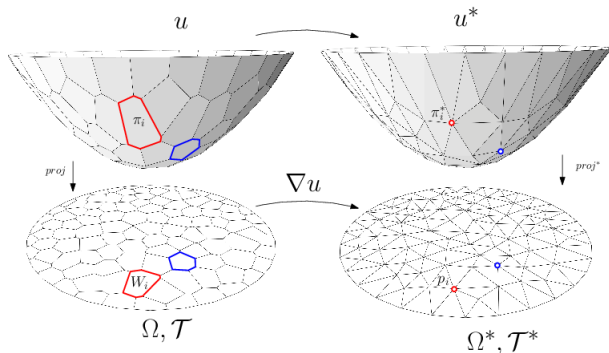
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# Hamilton-Jacobi Dynamics: Free Motion

During a free motion interval:

$u^*$ : The triangulation (domains of linearity of  $u^*$ )  $\mathbf{T}_t$  stays put, but the slopes of the graph of  $u^*$  change linearly with a velocity that will be described shortly.

$u$ : The slopes of the graph stay put. The vertices of  $\mathbf{X}_t$  travel according to their velocities. If  $t, t'$  are two times in the interval, then the corresponding faces in  $\mathbf{X}_t$  and  $\mathbf{X}_{t'}$  are parallel. Angles do not change.

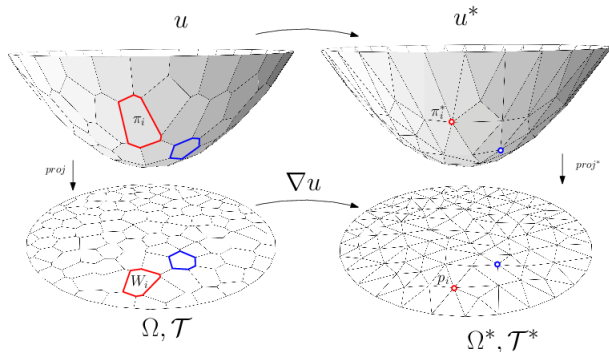


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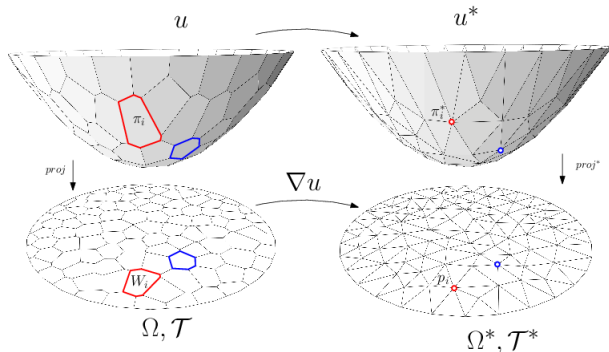


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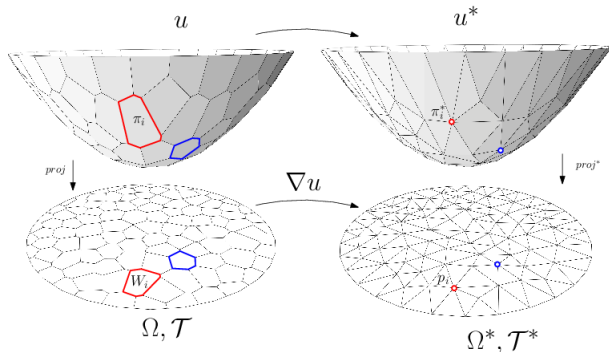


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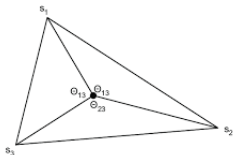
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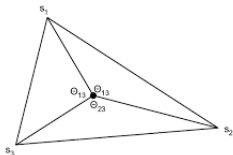


After  $t_j$  the  $d + 1$  simplexes are replaced with one simplex (their union).

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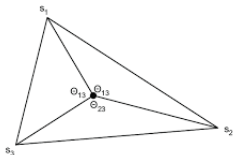


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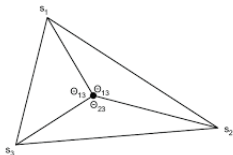


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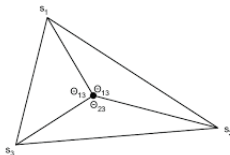


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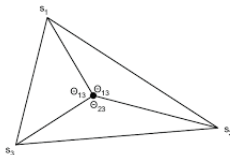


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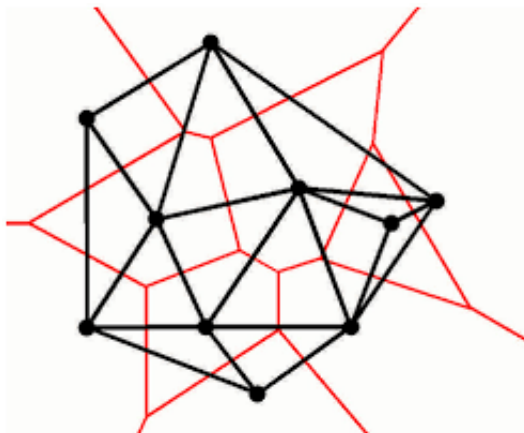


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The red triangle shrinks: Triangles in  $\mathbf{X}_t$  can only shrink (not true for other type of cells).





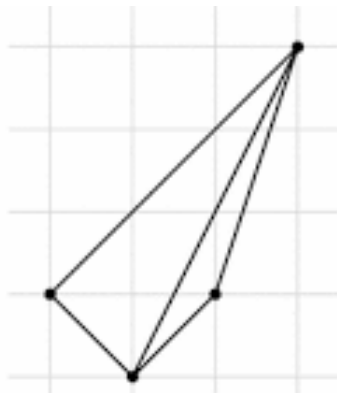
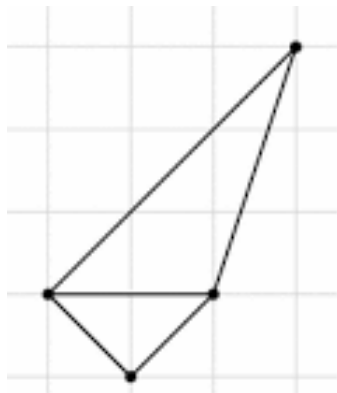
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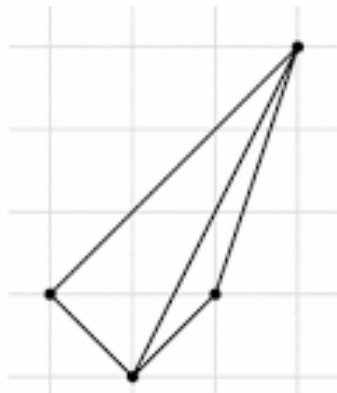
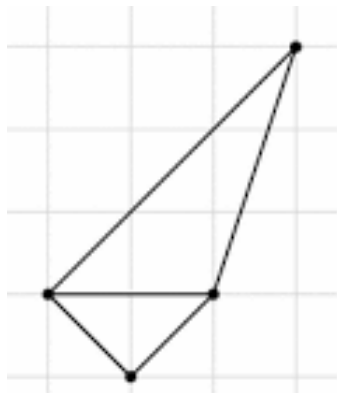
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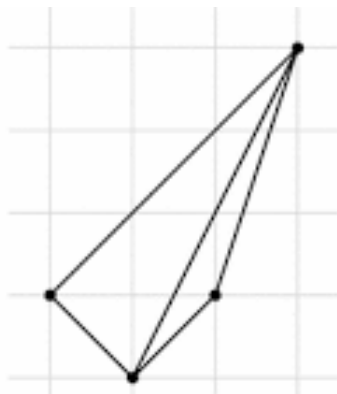
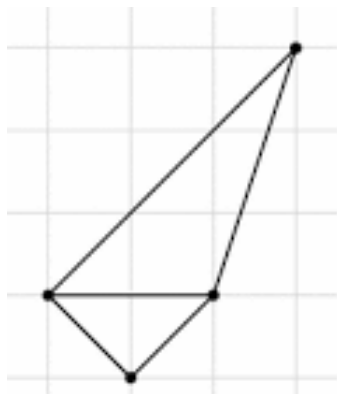
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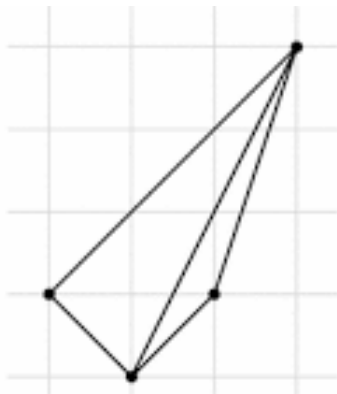
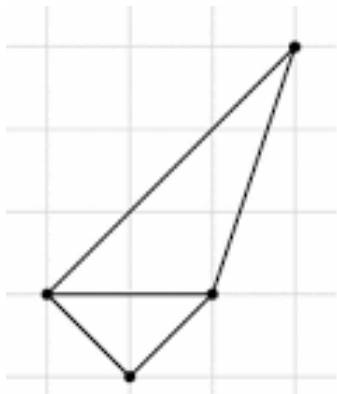
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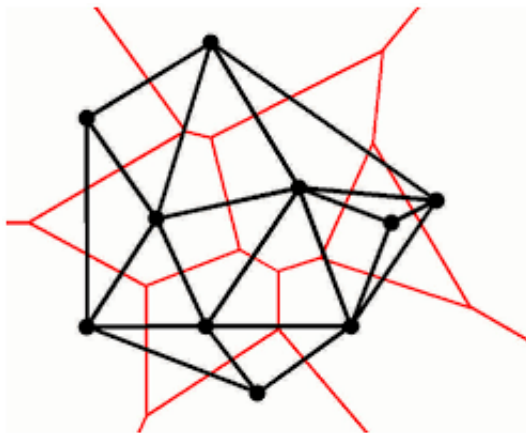
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# Hamilton-Jacobi Dynamics: Collision

Two red vertices may get closer or move away from each other.



# Hamilton-Jacobi Dynamics: Velocities

## Remarks

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The vector  $\rho - \rho' \perp X(\rho) \cap X(\rho')$  (In dimension one this is known as Rankine-Hugoniot Formula).

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**Moral:**  $v$  is a vertex in the tessellation  $\mathbf{X}(H)$ .

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1.  $X(\rho) \cap X(\rho')$  is a common face of  $X(\rho)$  and  $X(\rho')$ . The vector  $\rho - \rho' \perp X(\rho) \cap X(\rho')$  (In dimension one this is known as Rankine-Hugoniot Formula). It points from  $X(\rho')$  side to  $X(\rho)$  side (this is entropy condition/viscosity criteria).
2. If  $T$  is a triangle/simplex in the triangulation, then it is associated with a vertex  $x^t(T) = x^t(T)$  that is uniquely determined from solving

$$x^t(T) \cdot (\rho - \rho') = f^t(\rho) - f^t(\rho'), \quad \rho, \rho' \in T.$$

3. The velocity of  $x^t(T)$  is  $-v(T)$ , where  $v(T)$  is the unique solution of the linear system

$$v(T) \cdot (\rho - \rho') = H(\rho) - H(\rho'), \quad \rho, \rho' \in T.$$

**Moral:**  $v$  is a vertex in the tessellation  $\mathbf{X}(H)$ .



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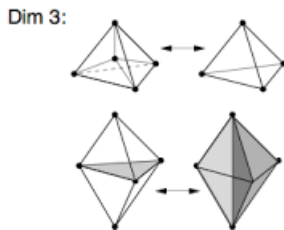
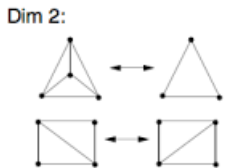
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# Hamilton-Jacobi Dynamics: Circuits

If  $R$  is a circuit, then there exists a function  $c : R \rightarrow (0, \infty)$  and a decomposition  $R = R^- \cup R^+$  such that

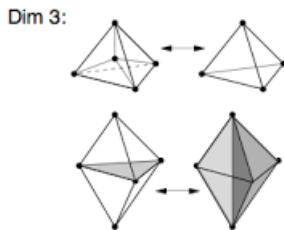
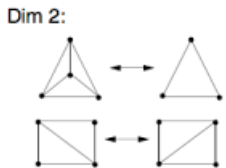
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# Hamilton-Jacobi Dynamics: Positive Edges

There are two triangulations:

$$\mathbf{T}^\pm(R) = \{R \setminus \{m\} : m \in R^\mp\}.$$

Choose  $\pm$  so that

$$\hat{H}(R) = \sum_{m \in R^+} c(m)H(m) - \sum_{m \in R^-} c(m)H(m) \geq 0.$$

In this way the restriction of  $H$  to  $R$  is associated with the triangulation  $\mathbf{T}^-(R)$ .

If two triangulations  $\mathbf{T}$  and  $\mathbf{T}'$  are vertices of an edge of the secondary polytope, then they differ only on a circuit  $R$ .

We call the edge positive if  $\mathbf{T} \rightarrow \mathbf{T}'$  means switching from  $\mathbf{T}^-(R)$  to  $\mathbf{T}^+(R)$ .

In the HJ dynamics we can only jump across a positive edge at  $t_j$ .

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# Hamilton-Jacobi Dynamics: Coagulation/Collision

1. The time of a coagulation of a shrinking  $f : R \rightarrow \mathbb{R}$ :

$$\tau = \frac{\hat{f}(R)}{\hat{H}(R)}.$$

2. If  $f : R \rightarrow \mathbb{R}$ , and  $\hat{f}(R) < 0$ , then the triangulation induced by  $f$  is  $\mathbf{T}^+(R)$  and there will be no collision.
3. If  $f : R \rightarrow \mathbb{R}$ , and  $\hat{f}(R) > 0$ , then the triangulation induced by  $f$  is  $\mathbf{T}^-(R)$ , and collision occurs at

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