

# Central Swaths

(a generalization of the central path)

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- $p: \mathbb{R}^d \rightarrow \mathbb{R}$  homogeneous polynomial of degree  $n$
- $p(e) > 0$

**Defn:** The polynomial  $p$  is

“hyperbolic in direction  $e$ ”

if for all  $x \in \mathbb{R}^d$ , the univariate polynomial  $t \mapsto p(te + x)$   
has only real roots.

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$\lambda \mapsto p(\lambda e - x)$

Roots:  $\lambda_{1,e}(x) \leq \lambda_{2,e}(x) \leq \dots \leq \lambda_{n,e}(x)$

“eigenvalues of  $x$  (in direction  $e$ )”

LP:

- $p(x) = x_1 \cdots x_n$

- $e > 0$

$$\lambda \mapsto p(\lambda e - x) = (\lambda e_1 - x_1) \cdots (\lambda e_n - x_n)$$

Eigenvalues of  $x$  in direction  $e$ :  $\frac{x_1}{e_1}, \dots, \frac{x_n}{e_n}$

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SDP:

- $p(x) = \det(x)$

- $e \succ 0$

$$\lambda \mapsto \det(\lambda e - x) = \det(e) \det(\lambda I - e^{-1/2} x e^{-1/2})$$

Eigenvalues of  $x$  in direction  $e$

= traditional eigenvalues of  $e^{-1/2} x e^{-1/2}$

$$\lambda_{1,e}(x) \leq \lambda_{2,e}(x) \leq \cdots \leq \lambda_{n,e}(x) \quad \text{roots of } \lambda \mapsto p(x - \lambda e)$$

Hyperbolicity Cone:

$$\Lambda_{++} := \{x : \lambda_{1,e}(x) > 0\}$$

= connected component of  
 $\{x : p(x) > 0\}$  containing  $e$

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**Gårding** (1959):  $p$  is hyperbolic in direction  $e$  for all  $e \in \Lambda_{++}$

Corollary:  $\Lambda_{++}$  is a convex cone

Corollary:  $x \mapsto \lambda_{n,e}(x)$  is a convex function

## Bauschke, Güler, Lewis & Sendov:

If  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is a convex and permutation-invariant  
then  $x \mapsto f(\vec{\lambda}_e(x))$  is convex

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## Helton-Vinnikov Theorem:

Assume  $e \in \Lambda_{++}$  and  $x, y \in \mathbb{R}^d$ .

There exist  $n \times n$  symmetric matrices  $X$  and  $Y$  satisfying

$$(r, s, t) \mapsto p(rx + sy + te) = p(e) \det(rX + sY + tI) .$$

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*Is every hyperbolicity cone a slice of a PSD cone?*

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**Chua:** Every homogeneous cone is a slice of a PSD cone.

*The literature on hyperbolic polynomials is relatively small,  
but its growth is accelerating,  
its quality in general is distinctly impressive,  
and its reach is surprisingly broad.*

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L. Gurvits, Van der Waerden/Schrijver-Valiant like conjectures  
and stable (aka hyperbolic) homogeneous polynomials,  
Elec. Jour. of Comb. (2008)

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F.R. Harvey and H.B. Lawson Jr.,  
Hyperbolic polynomials and the Dirichlet problem, arXiv (2009)

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J. Borcea and P. Brändén, Pólya-Schur master theorems for  
circular domains and their boundaries, Ann. of Math. (2009)

$\phi$  a univariate polynomial

If  $\phi$  has only real roots then:

- $\phi'$  has only real roots.
- Roots are interlaced:  $\lambda_1 \leq \lambda'_1 \leq \lambda_2 \leq \cdots \leq \lambda'_{n-1} \leq \lambda_n$

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$p$  a multivariate polynomial

$p'_e(x) := \langle \nabla p(x), e \rangle$  (directional derivative)

If  $p$  is hyperbolic in direction  $e$  then:

- $p'_e$  is hyperbolic in direction  $e$ .
- $\Lambda_+ \subseteq \Lambda'_{e,+}$

Inductively:  $p_e^{(i+1)}(x) = \langle \nabla p_e^{(i)}(x), e \rangle$

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LP:  $p(x) := x_1 x_2 \cdots x_n, \quad e > 0$

$$p_e^{(i)}(x) = i! p(e) \sum_{j_1 < j_2 < \cdots < j_{n-i}} \left( \frac{x_{j_1}}{e_{j_1}} \right) \left( \frac{x_{j_2}}{e_{j_2}} \right) \cdots \left( \frac{x_{j_{n-i}}}{e_{j_{n-i}}} \right)$$

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In general:  $p_e^{(i)}(x) = i! p(e) E_{n-i}(\vec{\lambda}_e(x))$

where  $E_k$  = elementary symmetric polynomial of degree  $k$



$$\Lambda_+ = \Lambda_{e,+}^{(0)} \subseteq \Lambda_{e,+}^{(1)} \subseteq \dots \subseteq \Lambda_{e,+}^{(n-1)} = \text{a halfspace}$$

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$$\begin{aligned} \Lambda_{e,++}^{(i)} &= \text{connected component of} \\ &\quad \{x : p_e^{(i)}(x) > 0\} \text{ containing } e \\ &= \{x : p_e^{(k)}(x) > 0 \text{ for } k = i, \dots, n\} \end{aligned}$$

## Computing $p_e^{(i)}(x)$ , $\nabla p_e^{(i)}(x)$ , $\nabla^2 p_e^{(i)}(x)$

Univariate interpolation using a primitive root of unity  $\omega$ :

$$\text{If } \phi(t) := \sum_{i=0}^n a_{n-i} t^i \text{ then } a_i = \frac{1}{n} \sum_{j=1}^n \omega^{ij} \phi(\omega^j)$$

Letting  $\phi(t) := p(x + te)$  gives

$$p_e^{(i)}(x) = \frac{i!}{n} \sum_{j=1}^n \omega^{ij} p(x + \omega^j e)$$

Differentiating both sides wrt  $x$ :

$$\nabla p_e^{(i)}(x) = \frac{i!}{n} \sum_{j=1}^n \omega^{ij} \nabla p(x + \omega^j e)$$

$$\nabla^2 p_e^{(i)}(x) = \frac{i!}{n} \sum_{j=1}^n \omega^{ij} \nabla^2 p(x + \omega^j e)$$

Hyperbolic Program (HP):

$$\begin{array}{ll} \min & \langle \mathbf{c}, \mathbf{x} \rangle \\ \text{s.t.} & \mathbf{Ax} = \mathbf{b} \\ & \mathbf{x} \in \Lambda_+ \end{array}$$

Introduced by Güler (mid-90's) in context of ipm's.

“Central Path” =  $\{\mathbf{x}(\eta) : \eta > 0\}$   
where  $\mathbf{x}(\eta)$  solves

$$\begin{array}{ll} \min & \eta \langle \mathbf{c}, \mathbf{x} \rangle - \ln p(\mathbf{x}) \\ \text{s.t.} & \mathbf{Ax} = \mathbf{b} \end{array}$$

$O(\sqrt{n}) \log(1/\epsilon)$  iterations suffice

to reduce  $\alpha := \langle \mathbf{c}, \mathbf{x} \rangle - \langle \mathbf{b}, \mathbf{y} \rangle$  to  $\epsilon \alpha$

## Hyperbolic Program relaxation:

$$\underbrace{\begin{array}{ll} \min & \langle c, x \rangle \\ \text{s.t.} & Ax = b \\ & x \in \Lambda_+ \end{array}}_{\text{HP}} \quad \xrightarrow{\text{relax}} \quad \underbrace{\begin{array}{ll} \min & \langle c, x \rangle \\ \text{s.t.} & Ax = b \\ & x \in \Lambda_{e,+}^{(i)} \end{array}}_{\text{HP}_e^{(i)}}$$

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Defn: The “ $i^{\text{th}}$  central swath” is the set of directions  $e$  satisfying

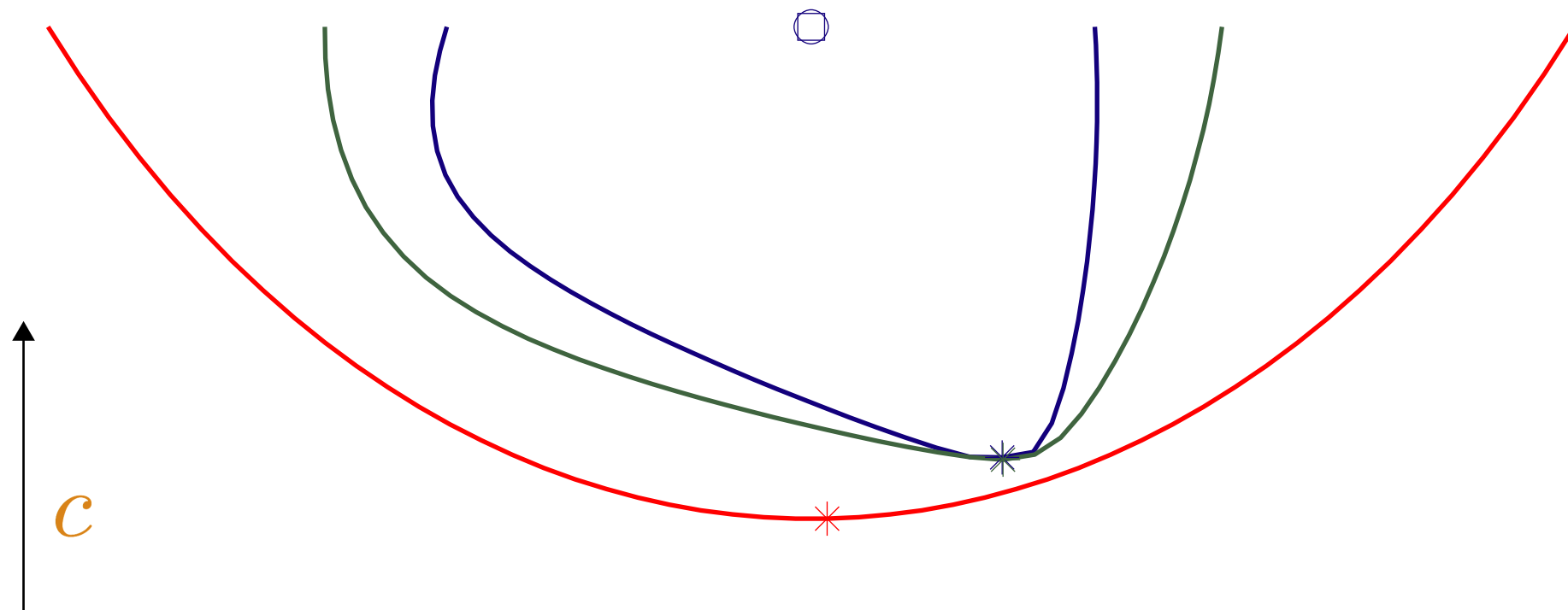
- $Ae = b$ ,  $e \in \Lambda_{e,++}^{(i)}$  (strict feasibility)
- $\text{HP}_e^{(i)}$  has an optimal solution

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Thm: central path =  $(n - 1)^{\text{th}}$  central swath

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## How might solving $HP_e^{(i)}$ help in solving $HP$ ?

$z(e)$ : optimal solution for  $HP_e^{(i)}$

– assume we know  $z(e)$  exactly

Obtaining a derivative direction with  
better objective value is easy:

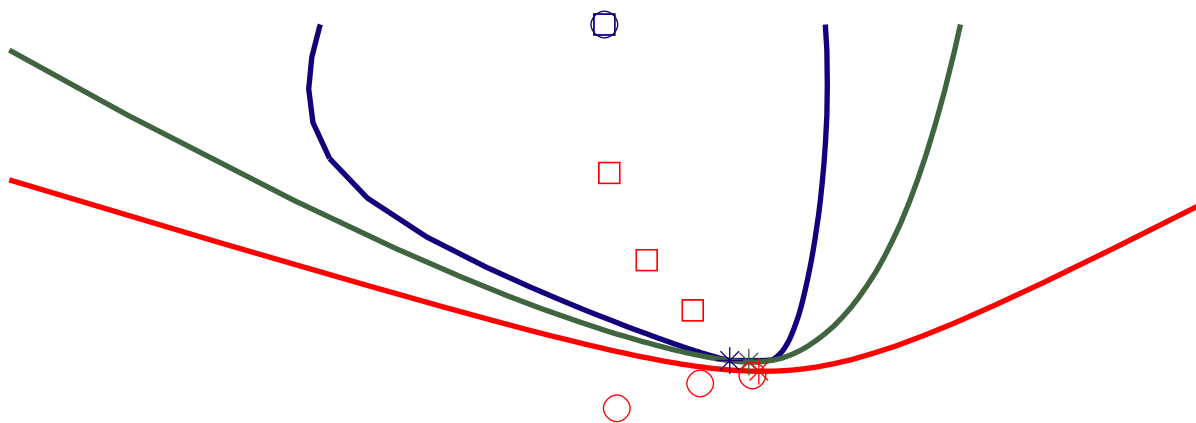
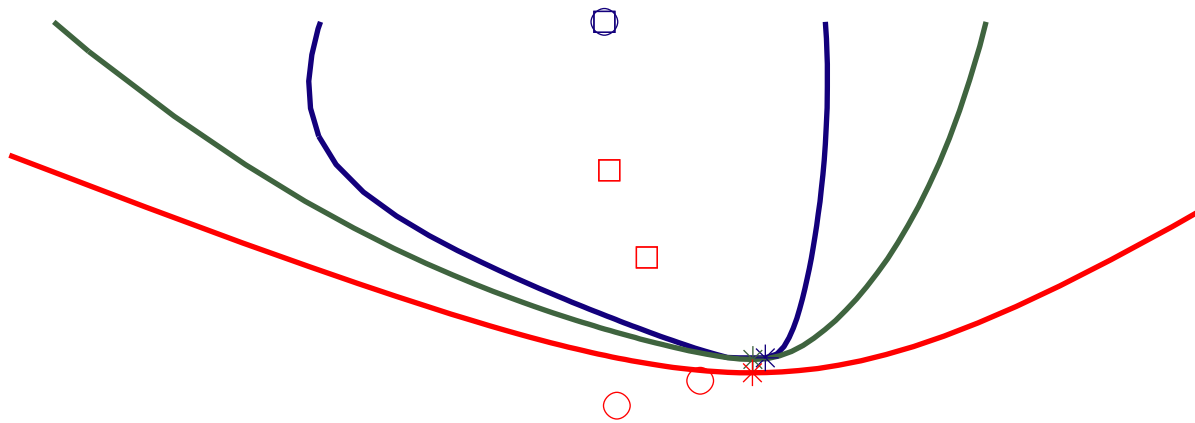
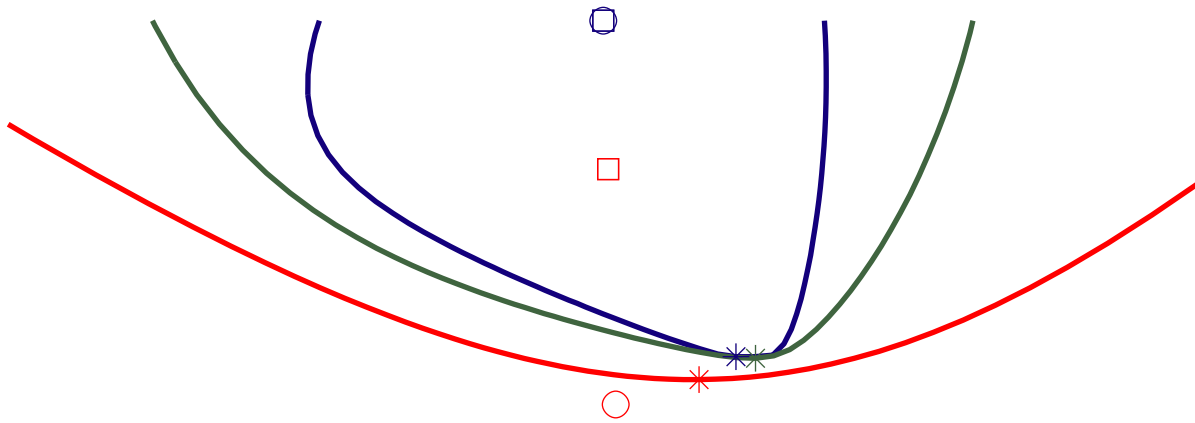
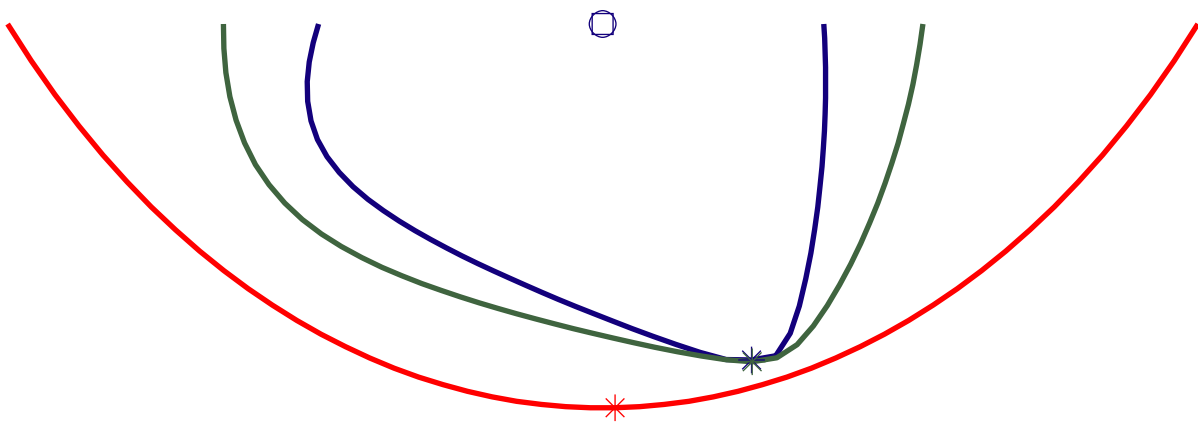
Just move  $e$  towards  $z(e)$

Dynamics on  $e$  :  $\dot{e} = z(e) - e$

Of course  $z(e)$  then changes dynamically, too.

Are the dynamics well-defined?

If so, where do they lead?





## How might solving $\text{HP}_e^{(i)}$ help in solving $\text{HP}$ ?

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$$\begin{array}{ll}
 \min & \langle c, x \rangle \\
 \text{s.t.} & Ax = b \\
 & x \in \Lambda_+
 \end{array}
 \xrightarrow{\text{relax}}
 \begin{array}{ll}
 \min & \langle c, x \rangle \\
 \text{s.t.} & Ax = b \\
 & x \in \Lambda_{e,+}^{(i)}
 \end{array}$$

Recall:  $\text{Swath}(i) = \{e \in \Lambda_{++} : Ae = b \text{ and } \text{Opt}_e^{(i)} \neq \emptyset\}$

Define  $\text{Core}(i) = \{e \in \text{Swath}(i) : \text{Opt}_e^{(i)} = \text{Opt}\}$

**Thm:** Assume  $1 \leq i \leq n - 2$ .

For  $e \in \text{Swath}(i) \setminus \text{Core}(i)$ ,

$\text{Opt}_e^{(i)} = \{z(e)\}$  (a single point)

and  $e \mapsto z(e)$  is analytic.

In other words, the dynamics are well-defined.

*Another reason for appropriateness*

*of the terminology “central swaths”:*

Thm: If  $i = n - 2$  and  $e(0)$  is on the central path  
then  $e(t)$  traces the central path.

$e(0) \in \text{Swath}(i) \setminus \text{Core}(i)$

$\{e(t) : 0 \leq t < T\}$  maximal trajectory

$T$  finite means trajectory leaves  $\text{Swath}(i) \setminus \text{Core}(i)$  at time  $T$

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**Main Thm (Part I):**

Assume  $1 \leq i \leq n - 2$  and  $\text{Opt}$  is nonempty and bounded.

**A)** If  $T = \infty$  then all limit points of  $\{e(t)\}$  are in  $\text{Opt}$ .

**B)** If  $T < \infty$  then  $\{e(t)\}$  has a unique limit point,  
and the point is in  $\text{Core}(i)$ .

Moreover, the path  $\{z(e(t))\}$  is then bounded,  
and each of its limit points lies in  $\text{Opt}$ .

$$\underbrace{\begin{array}{l} \min \quad \langle c, x \rangle \\ \text{s.t.} \quad Ax = b \\ \quad \quad x \in \Lambda_+ \end{array}}_{\text{HP}}$$

relax  
→

$$\underbrace{\begin{array}{l} \min \quad \langle c, x \rangle \\ \text{s.t.} \quad Ax = b \\ \quad \quad x \in \Lambda_{e,+}^{(i)} \end{array}}_{\text{HP}_e^{(i)}}$$

$z(e)$  optimal solution of  $\text{HP}_e^{(i)}$

**Thm:**  $z(e)$  also is the unique optimal solution for

$$\begin{array}{l} \min_x \quad -\ln \langle c, e - x \rangle - \frac{p_e^{(i)}(x)}{p_e^{(i+1)}(x)} \\ \text{s.t.} \quad Ax = b, \end{array}$$

a linearly-constrained optimization problem

with convex objective function.

More generally ...

$$\begin{array}{ll} \min & \langle c, x \rangle \\ \text{s.t.} & Ax = b \\ & x \in \Lambda_+ \end{array}$$

⏟  
HP

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**Thm:** The optimal solutions of **HP** satisfying  $z \notin \partial \Lambda'_{e,+}$  are precisely the optimal solutions for

$$\begin{array}{ll} \min_x & -\ln \langle c, e - x \rangle - \frac{p(x)}{p'_e(x)} \\ \text{s.t.} & Ax = b, \end{array}$$

a linearly-constrained optimization problem  
with convex objective function.

**Thm:** If  $p$  is hyperbolic in direction  $e$

then  $p/p'_e$  is a concave function on  $\Lambda'_{e,++}$

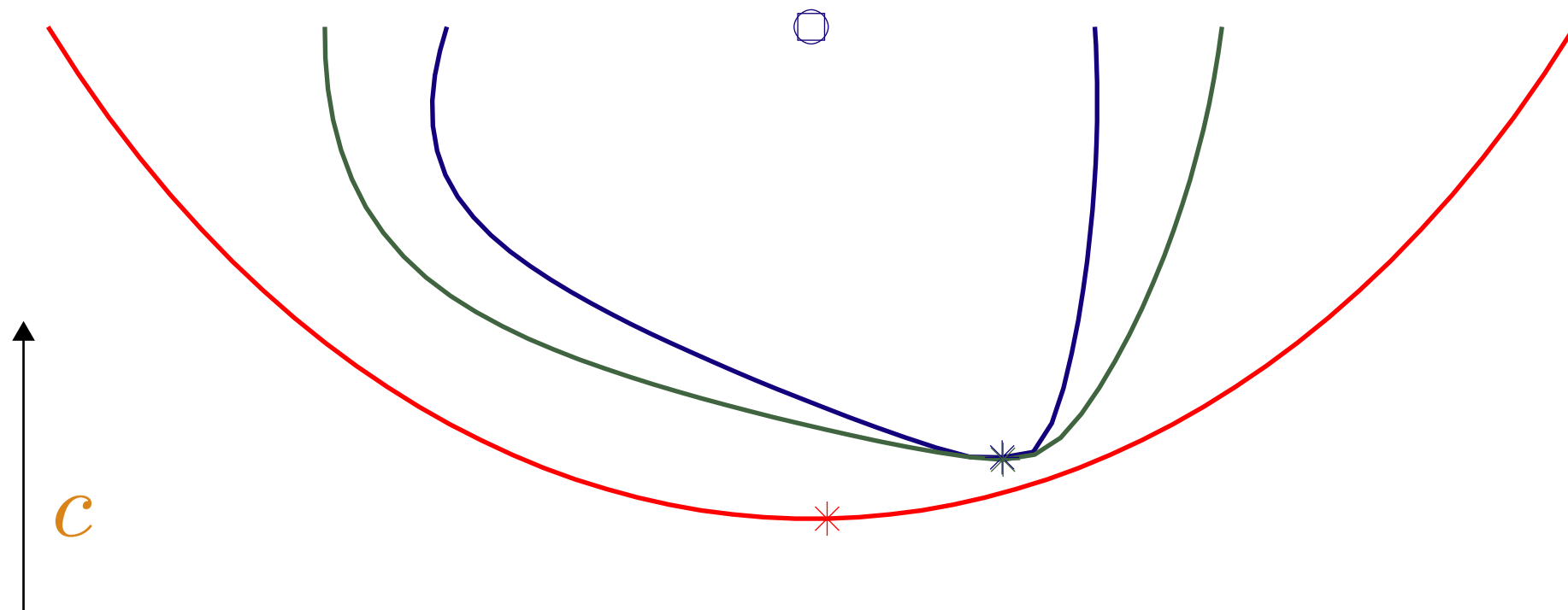
**Pf:**

- $P(x, t) := tp(x)$  is hyperbolic in direction  $(e, 1)$
- Hence,  $P'_{(e,1)}$  is hyperbolic in direction  $(e, 1)$
- Hyperbolicity cone of  $P'_{(e,1)}$  is epigraph of

$$x \mapsto -p(x)/p'_e(x)$$

$$\begin{aligned} \min \quad & \langle c, x \rangle \\ \text{s.t.} \quad & Ax = b \\ & x \in \Lambda_+ \end{aligned}$$

$$\begin{aligned} \min \quad & \langle c, x \rangle \\ \text{s.t.} \quad & Ax = b \\ & x \in \Lambda_{+,e}^{(i)} \end{aligned}$$





$$\begin{array}{l} \min \quad \langle c, x \rangle \\ \text{s.t.} \quad Ax = b \\ \quad \quad x \in \Lambda_+ \end{array}$$

HP

$$\begin{array}{l} \max \quad \langle b, y \rangle \\ \text{s.t.} \quad A^*y + s = c \\ \quad \quad x \in \Lambda_+^* \end{array}$$

HP\*

Let  $s(e) := \frac{\langle c, e-z \rangle}{p_e^{(i+1)}(z)} \nabla p_e^{(i)}(z)$  where  $z := z(e)$   
 and let  $y(e)$  solve  $A^*y + s(e) = c$

### Main Thm (Part II):

The path  $t \mapsto (y(e(t)), s(e(t)))$

is strictly feasible for HP\* and bounded.

Moreover,  $t \mapsto \langle b, y(e(t)) \rangle$  converges monotonically  
 to the optimal value for HP\*.