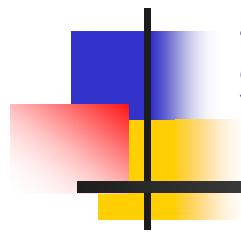


# The Method of Moments

4th International Conference on Frontiers in Global Optimization  
Santorini, June 8-12, 2003

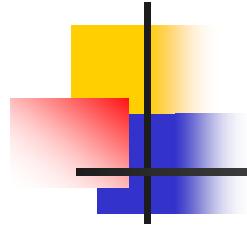


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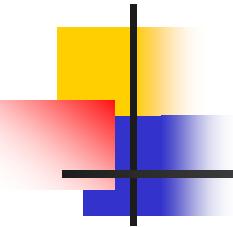


# General Mathematical Program

$$\min_{t \in \Omega} f(t)$$

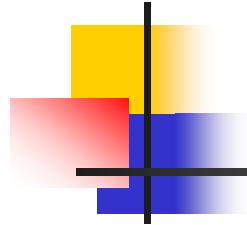
$f$  continuous and bounded from below

$$\Omega \subset R^n$$



# Convex Envelopes

$$\min f_c = \text{global } \min f$$



# Caratheodory's Theorem

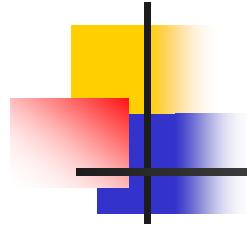
$$f_c(t) = \min \sum_{k=1}^{n+1} \lambda_k f(t_k)$$

s.a

$$t = \sum_{k=1}^{n+1} \lambda_k t_k$$

$$1 = \sum_{k=1}^{n+1} \lambda_k$$

$$\lambda_k \geq 0 \quad \forall k = 1, \dots, n+1$$

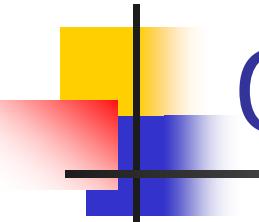


# Convex Analysis

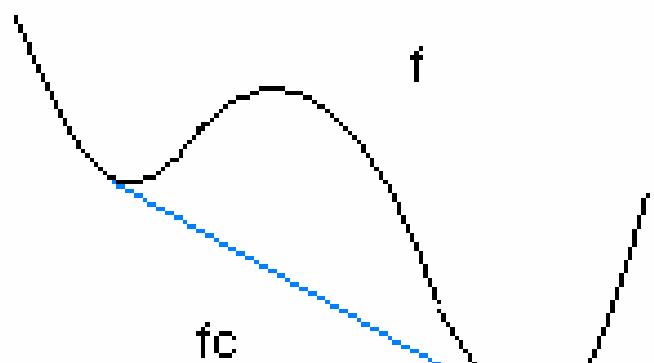
$$Epi(f_c) = \overline{co(Epi(f))}$$

*co* : convex hull

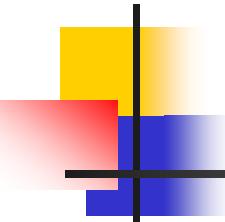
*bar* : closure



# Graphical Illustration



- Function
- Convex Envelope



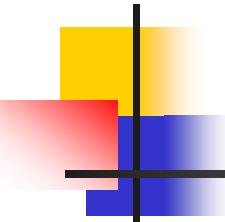
# Probability

---

- Caratheodory's Theorem
- Convex Combinations as Discrete Probability Distributions

$$\sum_{k=1}^{n+1} \lambda_k f(t_k) = \sum_{k=1}^m \lambda_k f(t_k)$$

$$\sum_{k=1}^m \lambda_k f(t_k) = \int_{\Omega} f(s) d\nu(s)$$

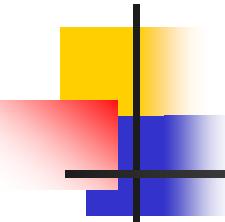


# Measure

---

- Discrete Distributions  
approximate any  
Regular Borel Measures

$$\sum_{k=1}^m \lambda_k f(t_k) \rightarrow \int_{\Omega} f(s) d\nu(s)$$



# Convex Envelopes

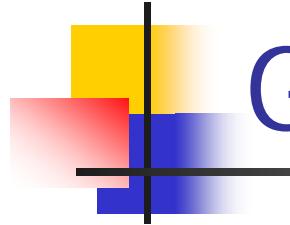
## Alternative Estimation with Measures

$$f_c(t) = \min_{\Omega} \int f(s) d\nu(s)$$

s.t.

$$t = \int_{\Omega} s d\nu(s)$$

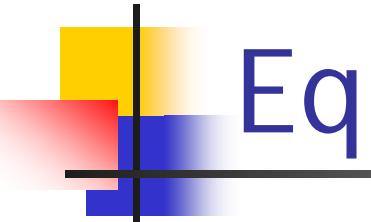
$\nu \in P(\Omega)$ : set of probability measures in  $\Omega$



# Global Optimization

$$\text{global min}_{t \in \Omega} f(t) = \min_{t \in \Omega} f_c(t)$$

$$\text{global min}_{t \in \Omega} f(t) = \min_{\nu \in P(\Omega)} \int_{\Omega} f(s) d\nu(s)$$



# Equivalent Problem

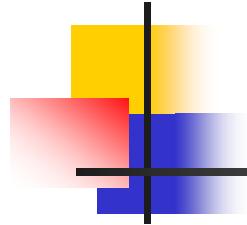
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$$\min_{v \in P(\Omega)} \langle f, v \rangle$$

where

$$\langle f, v \rangle = \int_{\Omega} f(s) dv(s)$$

is a linear objective function  
defined in a convex feasible set  $P(\Omega)$



# Theorem 1

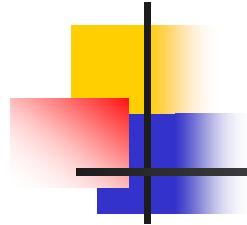
$$\langle f, v^* \rangle = \min_{v \in P(\Omega)} \langle f, v \rangle$$

if and only if

$$v^* \in P(G)$$

$G$ : set of global minima of  $f$  in  $\Omega$

$P(G)$ : set of probability measures supported in  $G$



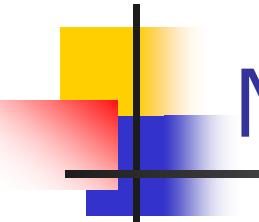
# Decomposition in Moments

$$f(t) = \sum_{i=1}^k c_i \psi_i(t)$$

$\psi_1, \dots, \psi_k$  : basis of continuous functions in  $\Omega$

$$\langle f, v \rangle = \sum_{i=1}^k c_i m_i$$

$(m_1, \dots, m_k)$ : vector of generalized moments in  $R^k$

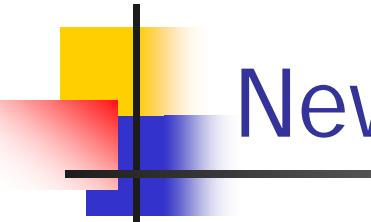


# New Convex Program Equivalent

- Linear objective function
- Convex Feasible Set

$$\langle f, v \rangle = \sum_{i=1}^k c_i m_i = c \cdot m \quad : \text{dot product in } R^k$$

$$v \rightarrow \langle (\psi_1, \dots, \psi_k), v \rangle \quad : P(\Omega) \rightarrow R^k \quad \text{linear}$$

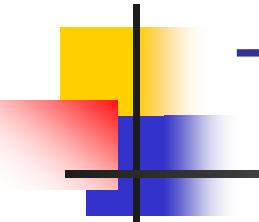


## New Convex Program Equivalent

$$\min_{m \in \bar{V}} c \cdot m$$

$$\bar{V} \subset R^k$$

$\bar{V}$ : convex feasible set



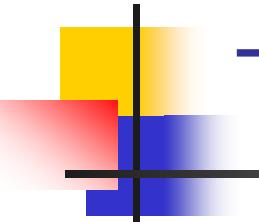
## Theorem 2

---

- Every solution of the equivalent program  
(1) is linked with a global minima of the non convex global optimization program (2)

$$(1) \quad \min_{\bar{V}} c \cdot m$$

$$(2) \quad \min_{\Omega} f(t)$$



## Theorem 3

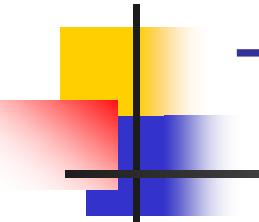
$$t^* \in G$$

when

$$(\psi_1(t^*), \dots, \psi_k(t^*)) = (m_1^*, \dots, m_k^*)$$

and  $m^*$  is an extreme point of the solution set of

$$\min_{\bar{V}} c \cdot m$$



## Theorem 4

- Every solution  $m^*$  of the convex program (1) is characterized by the following equality

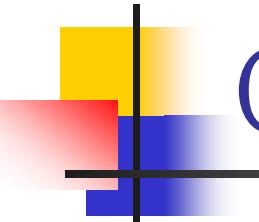
$$m_i^* = \lambda_1 \psi_i(t_1^*) + \cdots + \lambda_{k+1} \psi_i(t_{k+1}^*)$$

$$i = 1, \dots, k$$

$$1 = \lambda_1 + \cdots + \lambda_{k+1}$$

$$\lambda_i \geq 0$$

$$t_i^* \in G$$



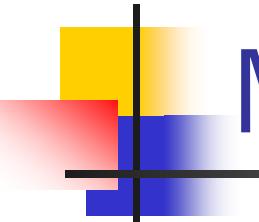
# Convex Combination

- Notice the convex combination form in the previous equation

$$m^* = \lambda_1 \Psi(t^*_1) + \dots + \lambda_{k+1} \Psi(t^*_{k+1})$$

*where*

$$\Psi = (\psi_1, \dots, \psi_k)$$

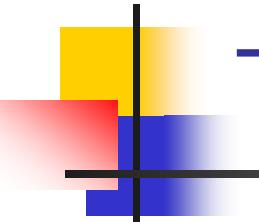


# Moments Form

- Notice the moments form of the previous equation

$$m^*_i = \int_{\Omega} \psi_i(s) d\nu(s) \quad i = 1, \dots, k$$

$$\nu = \sum_{i=1}^{k+1} \lambda_i \delta_{t_i^*}$$

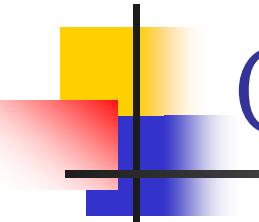


## Theorem 5

- Every solution  $m^*$  of the Program (1) can be solved as a Problem of Moments by a discrete measure supported in  $G$ .

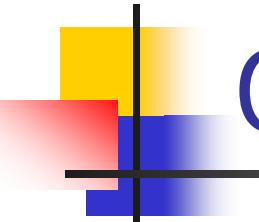
$$m^* = \int_{\Omega} \Psi(s) d\nu(s) \quad i = 1, \dots, k$$

$\nu$  discrete in  $P(G)$



# Classical Moment Problems

- Hamburger  $1, t, \dots, t^k$
- Stieltjes  $R, [0, \infty), [a, b]$
- Hausdorff  $e^{-jkt}, \dots, e^{jkt}$
- Trigonometric  $[0, 2\pi]$



# General Solution

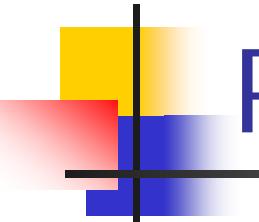
$$M = \left\{ \int_{\Omega} \Psi(s) d\nu(s) : \nu \text{ medida positiva en } \Omega \right\}$$

*cono momentos*

$$P = \left\{ c \in R^k : \sum_{i=1}^k c_i \psi_i(t) \geq 0 \text{ en } \Omega \right\}$$

*cono de funciones positivas*

$$\overline{M} = P^*$$



# Particular Solutions

- Hamburger

*Positive Semidefinite Hankel Form*

$$k = 2n$$

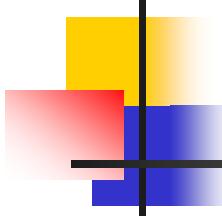
$$H = (m_{i+j})_{i,j=0,\dots,n}$$

- Trigonometric

*Positive Semidefinite Toeplitz Form*

$$k = n$$

$$H = (m_{i-j})_{i,j=0,\dots,n}$$



# Classical Characterizations of Positive Polynomials

- Algebraic

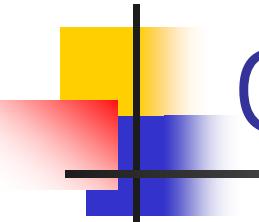
$q(t) \geq 0$  in  $R$ , if and only if

$$q(t) = \left( \sum_{i=0}^n a_i t^i \right)^2 + \left( \sum_{i=0}^n b_i t^i \right)^2$$

- Trigonometric

$q(t) \geq 0$  in  $[0, 2\pi]$ , if and only if

$$q(t) = \left| \sum_{j=0}^n a_j e^{ijt} \right|^2$$



# Quadratic forms

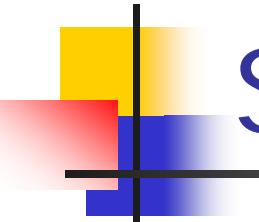
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- Algebraic

$$q(t) = \sum_{i=0}^n \sum_{j=0}^n a_i a_j t^{i+j} + \sum_{i=0}^n \sum_{j=0}^n b_i b_j t^{i+j}$$

- Trigonometric

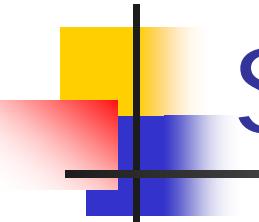
$$q(t) = \sum_{j=0}^n \sum_{j'=0}^n a_j \overline{a_{j'}} e^{i(j-j')t}$$



# Semidefinite Relaxations

- Algebraic

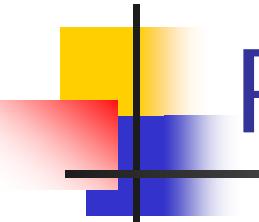
$$\min_R \sum_{i=0}^{2n} c_i t^i \text{ equivalent to}$$
$$\min \sum_{i=0}^{2n} c_i m_i \text{ s.t. } (m_{i+j})_{i,j=0,\dots,n} \geq 0 \text{ and } m_0 = 1$$



# Semidefinite Relaxations

- Trigonometric

$$\min_{S^1} \sum_{i=-n}^n c_i z^i \text{ equivalent to}$$
$$\min \sum_{i=-n}^n c_i m_i \text{ s.t. } (m_{i-j})_{i,j=0,\dots,n} \geq 0 \text{ and } m_0 = 1$$



# Recovering Global Minima

Seminidefinite Program

$$\begin{aligned} \min & \sum_{i=0}^{2n} c_i m_i \\ \text{s.t. } & (m_{i+j})_{i,j=0,\dots,n} \geq 0 \text{ and } m_0 = 1 \end{aligned}$$

*solution*  $m^*$

$$roots\ of\ p(t) = \begin{vmatrix} m_0^* & m_1^* & \cdots & m_j^* \\ & & \cdots & \\ m_{j-1}^* & m_j^* & \cdots & m_{2j-1}^* \\ 1 & t & \cdots & t^j \end{vmatrix}$$

$$\text{are global minima of } q(t) = \sum_{i=0}^{2n} c_i t^i$$