

Convex Optimization

A Journey of 60 Years

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History and Prehistory

- **Prehistory:** Early 1900s - 1949.
 - Caratheodory, Minkowski, Steinitz, Farkas.
 - Properties of convex sets and functions.

- **Fenchel - Rockafellar era:** 1949 - mid 1980s.
 - Duality theory.
 - Minimax/game theory (von Neumann).
 - (Sub)differentiability, optimality conditions, sensitivity.

- **Modern era - Paradigm shift:** Mid 1980s - present.
 - Nonsmooth analysis (a theoretical/esoteric direction).
 - Algorithms (a practical/high impact direction).
 - A change in the assumptions underlying the field.

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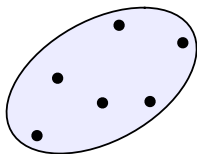
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Duality

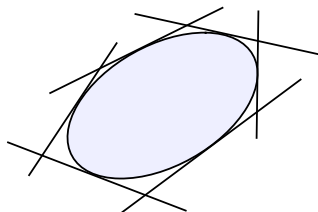
- Two different views of the same object.
- Example: Dual description of signals.



- Dual description of **closed** convex sets



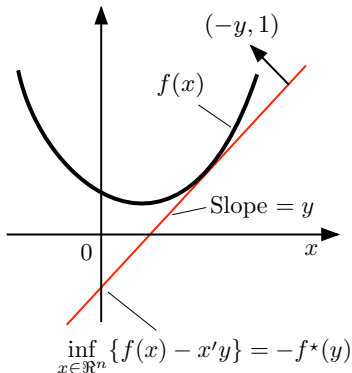
A union of points



An intersection of halfspaces

Dual Description of Convex Functions

- Define a closed convex function by its epigraph.
- Describe the epigraph by hyperplanes.
- Associate hyperplanes with crossing points (the **conjugate function**).



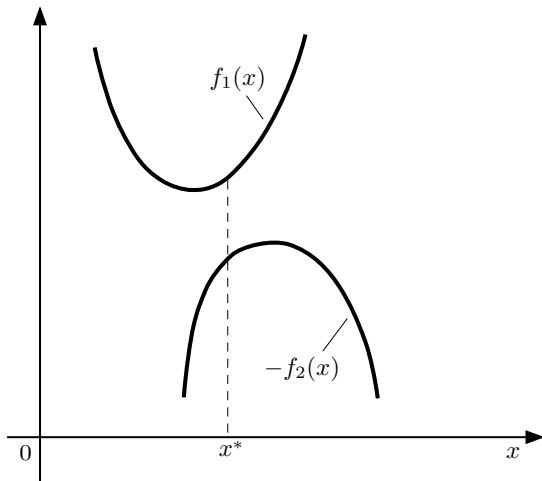
Primal Description

Values $f(x)$

Dual Description

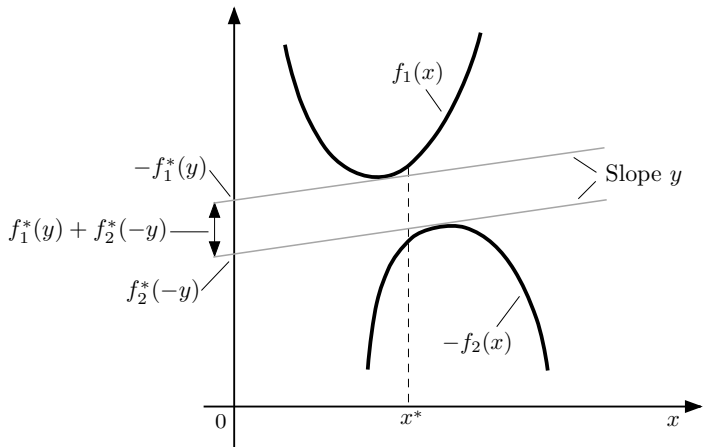
Crossing points $f^*(y)$

Fenchel Duality Framework



$$\min_x \{f_1(x) + f_2(x)\}$$

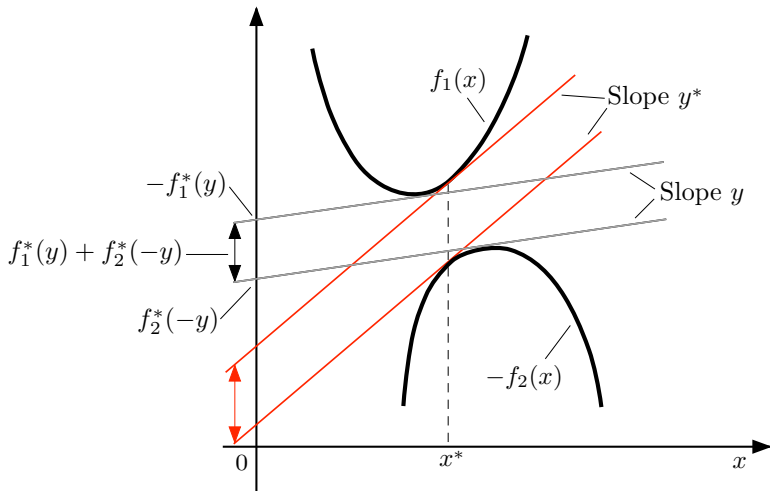
Fenchel Primal and Dual Problem Descriptions



Primal Description
Vertical Distances

Dual Description
Crossing Point Differentials

Fenchel Duality



$$\min_x \{f_1(x) + f_2(x)\} = \max_y \{f_1^*(y) + f_2^*(-y)\}$$

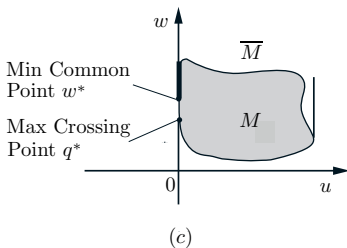
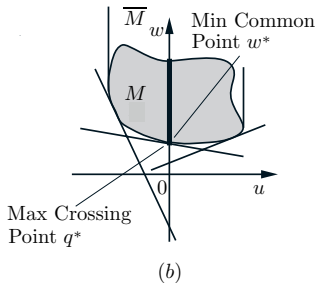
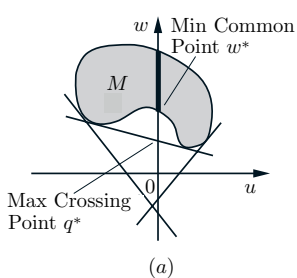
A More Abstract View of Duality

- Back to the **primal and dual description of a set M** .
- **Two simple prototype problems** dual to each other.

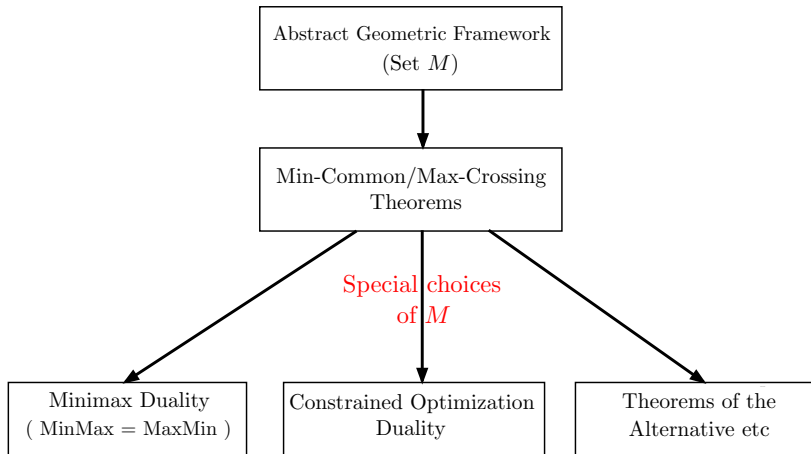
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Min-Common/Max-Crossing Duality



Abstract Framework for Duality Analysis



The Modern Era: Duality Coupled with Algorithms

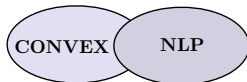
- **Traditional view:** Pre 1990s

- LPs are solved by simplex method (G. Dantzig view).
- NLPs are solved by gradient/Newton methods (M. Powell view).
- Convex programs are special cases of NLPs.



Simplex

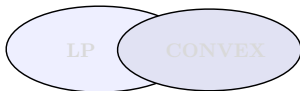
Duality



Gradient/Newton

- **Modern view:** Post 1990s

- LPs are often solved by nonsimplex/convex methods.
- Convex problems are often solved by the same methods as LPs.
- "Key distinction is not Linear-Nonlinear but Convex-Nonconvex" (Rockafellar)



Simplex

Duality
Cutting plane
Interior point
Subgradient



Gradient/Newton

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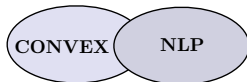
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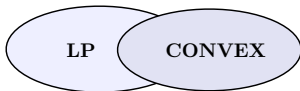
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Methodological Trends

- Convex programs and LPs connect around **duality** and **large-scale piecewise linear** problems.
- **New methods**, renewed interest in old methods
 - Interior point methods
 - Subgradient methods
 - Polyhedral approximation/cutting plane methods
 - Regularization/proximal methods
- Renewed emphasis on **complexity analysis**
 - Nesterov, Nemirovski, and others ...
 - Extrapolated gradient methods

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Synergy Between Duality, Algorithms, and Applications

- **Duality-based decomposition**

- Large-scale resource allocation
 - Lagrangian relaxation, discrete optimization
 - Stochastic programming

- **Conic programming**

- Robust optimization
 - Semidefinite programming

- **Machine learning**

- Support vector machines
 - l_1 regularization/Robust regression/Compressed sensing
 - Incremental methods

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Speculation - What's Next?

- **Very large problems/new applications.**
Problems with network overlays (e.g., smart grids).
Huge data sets in machine learning.
- **New approaches to large size and complexity.**
Approximate dynamic programming paradigm (e.g., LP-based dynamic programming).
Reduced space approximations.
Sampling mechanisms.
- **Better hardware/better algorithms multiplier effect?**
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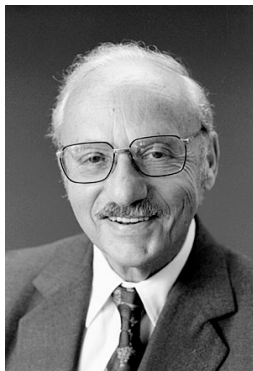
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Fenchel, Dantzig, Rockafellar



Werner Fenchel



George Dantzig



Terry Rockafellar

Paul Tseng, 1959-2009

