Institute of Communications Engineering
National Chiao Tung University

Thursday 1:30-2:30 pm

Instructor:	Prof. Ching-Yi Lai
Office:	ED926
Office hours:	~~Tuesday 3:20-4:30pm~~ (or by appointment)
email:	cylai@nctu.edu.tw

Lectures: 2EF4D-EE102

Tuesday

TA: Ping-Rui Tsai-office:ED909, office hour:15:30 17:00, mail:m30253333.cm07g@nctu.edu.tw
Po-Wen Chen-office:ED909, office hour:15:30 17:00, mail:chenkevin8520.cm07g@nctu.edu.tw
Kai-Lun Chen-office:ED909, office hour:15:30 17:00, mail:a0970960600@gmail.com

Text: *Convex Optimization*, Stephen Boyd and Lieven Vandenberghe (Cambridge, 2004)
(online available) `http://web.stanford.edu/~boyd/cvxbook/bv_cvxbook.pdf`

Reference:
1. *Convex Optimization for Signal Processing and Communications: From Fundamentals to Applications*, Chong-yung Chi, Wei-chiang Li, Chia-hsiang Lin (CRC Press, 2017)
2. CVX: Matlab software `http://cvxr.com/cvx/`

Course grade:

Homework (25%):	seven to eight problem sets will be assigned at 1-2 week intervals
Midterm Exam (35%):	November 5, Tuesday 1:20-3:20 pm
Final Exam (40%):	January 7, Tuesday 1:20-3:20 pm

Required preparation: a basic understanding of probability theory and advanced analysis and a good knowledge of linear algebra

Learning Objectives

Convex optimization is a class of mathematical optimization problems, which includes least-square and linear programming problems that can be solved efficiently and arise in a variety of applications. The idea is to extend known tools for these two problems to a larger class of convex optimization problems, such as semidefinite programming. Convex optimization has found applications in many areas, such as estimation and signal processing, communications and networks, machine learning, circuit design, analysis, statistics, and finance, where it is used to find optimal or approximate solutions. The goal of this course is to develop a working knowledge for recognizing or formulating a problem as a convex optimization problem, which can then be reliably and efficiently solved by well developed numerical analysis tools.


HUA TUNG
華通書坊
HUATUNG.com
回到首頁
熱賣新書專區
超值特價叢書
購物袋
會員登入
聯絡我們
QuickSearch
請選擇分類
書名
GO
純文字模式
圖文列表
列出現有庫存書籍
關於華通
會員專區
購買方式
熱賣新書
RESULTS: 1-30
若店內無庫存顯示之書籍
Book Name Description
Author
OurPrice
Status
Buy
電子電機 Electronics 類
Convex Optimization for Signal Processing and Communications: From Fundamentals to Applications 2017 (CRC)
C.Y.CHI
$1,880
In Stock
BUY
Convex Optimization & Euclidean Distance Geometry 2008
Dattorro
$4,830
Out of Stock
訂購
Convex Optimization in Signal Processing and Communications 2010 0-521-76222-7
Palomar
$3,473
Out of Stock
訂購
數學 Mathematics 類
Convex Optimization 2004 0-521-83378-7
S.BOYD
$1,600
In Stock
BUY
RESULTS: 1-30

Computation

$\mathbb{R}$: the set of real numbers

Big-O notation

Let $f: \mathbb{R}^n \to \mathbb{R}$, $g: \mathbb{R}^n \to \mathbb{R}$

We say that $f(x) = O(g(x))$ as $x \to \infty$ if and only if there exists $M \in \mathbb{R}$ and $x_0 \in \mathbb{R}$ such that

$$|f(x)| \le M g(x) \quad \forall x \ge x_0.$$

Ex. $p(n) = 4n^2 - 2n + 5 \le 5n^2 \quad \forall n \ge 2$

M $\quad$ x_0.

$\Rightarrow \quad p(n) = O(n^2)$

$p(n) = O(n^2)$

$O(n^3)$

$g(n) = e^{2n}$. $p(n) = O(e^{2n})$

$n = 10 \quad e^{2n} = e^{20} \simeq 2.7^{20}$

$4n^2 = \underline{400}$

Big Θ - notation characterizes both the upper & lower bounds.

- Usually an algorithm that takes a polynomial amount of computation time is considered efficient.

$p(n)$, where n is the size of the input.

Ex. multiplication of two n-bit strings.

$$
\begin{array}{rcccl}
 & a_n & a_{n-1} & \cdots & a_1 \qquad a_i \in \{0,1\} \\
 & b_n & b_{n-1} & \cdots & b_1 \\
\hline
 & a_n b_1 & a_{n-1} b_1 & \cdots & a_1 b_1 \\
 & \vdots & \vdots & & \vdots \\
+ \; a_n b_n & a_{n-1} b_n & \cdots & a_1 b_n & \\
\hline
\end{array}
$$

n^2 bit-multiplication

n terms in addition.

n^2 additions.

$\Rightarrow$ $O(n^2)$ for multiplication

Example, Factoring an integer N of k bits

$$2^{k-1} < N \le 2^k$$

$\boxed{\text{Trivially we can try}}$

$2, 3, \ldots, \sqrt{N}$ in sequence

to test whether they are factors of N.

We say a is a factor of N

if $N = a \times b$ for some b.

$a, N, b \in \mathbb{Z}$ = the set of integers.

$$\sqrt{N} = O(\sqrt{N}) = O(\sqrt{2^k}) = O(1.414^k)$$

We need at most $O(\sqrt{N})$ test,

each of which needs a division

in polynomial time.

Best known classical algorithm $\quad O\left(\exp\left(\sqrt[3]{\frac{64}{9}\, n (\log n)^2}\right)\right)$

$\Rightarrow$ Factoring is hard for large N

Quantum computer: $\quad O(n^3)$

The largest integer that can be factored has 768-bits

It takes 10^{20} operations.

1 GHz $\quad 10^{11}$ seconds

applications in RSA cryptography

$n = 768 \quad O(n^3) \sim 10^{9}$

Quantum algorithms and lower bounds for convex optimization

Shouvanik Chakrabarti, Andrew M. Childs, Tongyang Li, Xiaodi Wu

Sep 07 2018 quant-ph cs.DS math.OC arXiv:1809.01731v2

Scite! 63 PDF

While recent work suggests that quantum computers can speed up the solution of semidefinite programs, little is known about the quantum complexity of more general convex optimization. We present a quantum algorithm that can optimize a convex function over an n-dimensional convex body using $\tilde{O}(n)$ queries to oracles that evaluate the objective function and determine membership in the convex body. This represents a quadratic improvement over the best-known classical algorithm. We also study limitations on the power of quantum computers for general convex optimization, showing that it requires $\tilde{\Omega}(\sqrt{n})$ evaluation queries and $\Omega(\sqrt{n})$ membership queries.

Convex optimization using quantum oracles

Joran van Apeldoorn, András Gilyén, Sander Gribling, Ronald de Wolf

Sep 05 2018 quant-ph cs.DS math.OC arXiv:1809.00643v3

Scite! 55 PDF

We study to what extent quantum algorithms can speed up solving convex optimization problems. Following the classical literature we assume access to a convex set via various oracles, and we examine the efficiency of reductions between the different oracles. In particular, we show how a separation oracle can be implemented using $\tilde{O}(1)$ quantum queries to a membership oracle, which is an exponential quantum speed-up over the $\Omega(n)$ membership queries that are needed classically. We show that a quantum computer can very efficiently compute an approximate subgradient of a convex Lipschitz function. Combining this with a simplification of recent classical work of Lee, Sidford, and Vempala gives our efficient separation oracle. This in turn implies, via a known algorithm, that $\tilde{O}(n)$ quantum queries to a membership oracle suffice to implement an optimization oracle (the best known classical upper bound on the number of membership queries is quadratic). We also prove several lower bounds: $\Omega(\sqrt{n})$ quantum separation (or membership) queries are needed for optimization if the algorithm knows an interior point of the convex set, and $\Omega(n)$ quantum separation queries are needed if it does not.

A Short Path Quantum Algorithm for Exact Optimization

M. B. Hastings

Mar 01 2018 quant-ph arXiv:1802.10124v3

Scite! 54 PDF

We give a quantum algorithm to exactly solve certain problems in combinatorial optimization, including weighted MAX-2-SAT as well as problems where the objective function is a weighted sum of products of Ising variables, all terms of the same degree D; this problem is called weighted MAX-ED-LIN2. We require that the optimal solution be unique for odd D and doubly degenerate for even D; however, we expect that the algorithm still works without this condition and we show how to reduce to the case without this assumption at the cost of an additional overhead. While the time required is still exponential, the algorithm provably outperforms Grover's algorithm assuming a mild condition on the number of low energy states of the target Hamiltonian. The detailed analysis of the runtime dependence on a tradeoff between the number of such states and algorithm speed: fewer such states allows a greater speedup. This leads to a natural hybrid algorithm that finds either an exact or approximate solution.

Machine learning \& artificial intelligence in the quantum domain

Vedran Dunjko, Hans J. Briegel

Sep 11 2017 quant-ph cs.AI cs.CV arXiv:1709.02779v1

Scite! 51 PDF

Quantum information technologies, and intelligent learning systems, are both emergent technologies that will likely have a transforming impact on our society. The respective underlying fields of research -- quantum information (QI) versus machine learning (ML) and artificial intelligence (AI) -- have their own specific challenges, which have hitherto been investigated largely independently. However, in a growing body of recent work, researchers have been probing the question to what extent these fields can learn and benefit from each other. QML explores the interaction between quantum computing and ML, investigating how results and techniques from one field can be used to solve the problems of the other. Recently, we have witnessed breakthroughs in both directions of influence. For instance, quantum computing is finding a vital application in providing speed-ups in ML, critical in our "big data" world. Conversely, ML already permeates cutting-edge technologies, and may become instrumental in advanced quantum technologies. Aside from quantum speed-up in data analysis, or classical ML optimization used in quantum experiments, quantum enhancements have also been demonstrated for interactive learning, highlighting the potential of quantum-enhanced learning agents. Finally, works exploring the use of AI for the very design of quantum experiments, and for performing parts of genuine research autonomously, have reported their first successes. Beyond the topics of mutual enhancement, researchers have also broached the fundamental issue of quantum generalizations of ML/AI concepts. This deals with questions of the very meaning of learning and intelligence in a world that is described by quantum mechanics. In this review, we describe the main ideas, recent developments, and progress in a broad spectrum of research investigating machine learning and artificial intelligence in the quantum domain.

Quantum gradient descent for linear systems and least squares

Iordanis Kerenidis, Anupam Prakash

Apr 18 2017 quant-ph arXiv:1704.04992v4

Scited 50 PDF

Quantum machine learning and optimization are exciting new areas that have been brought forward by the breakthrough quantum algorithm of Harrow, Hassidim and Lloyd for solving systems of linear equations. The utility of classical linear system solvers extends beyond linear algebra as they can be leveraged to solve optimization problems using iterative methods like gradient descent. In this work, we provide the first quantum method for performing gradient descent when the gradient is an affine function. Performing τ steps of the gradient descent requires time $O(\tau C_S)$ for weighted least squares problems, where C_S is the cost of performing one step of the gradient descent quantumly, which at times can be considerably smaller than the classical cost. We illustrate our method by providing two applications: first, for solving positive semidefinite linear systems, and, second, for performing stochastic gradient descent for the weighted least squares problem with reduced quantum memory requirements. We also provide a quantum linear system solver in the QRAM data structure model that provides significant savings in cost for large families of matrices.

Chapter 1 Introduction

A mathematical optimization problem has the form

$$\text{minimize} \quad f_0(x)$$

← objective function

$$\text{subject to} \quad f_i(x) \le b_i, \quad i=1,\dots,m$$

where $x \in \mathbb{R}^n$ is the variable.

$(\mathbb{C}^n)$

constraint functions

$$f_i(x) : \mathbb{R}^n \to \mathbb{R}$$

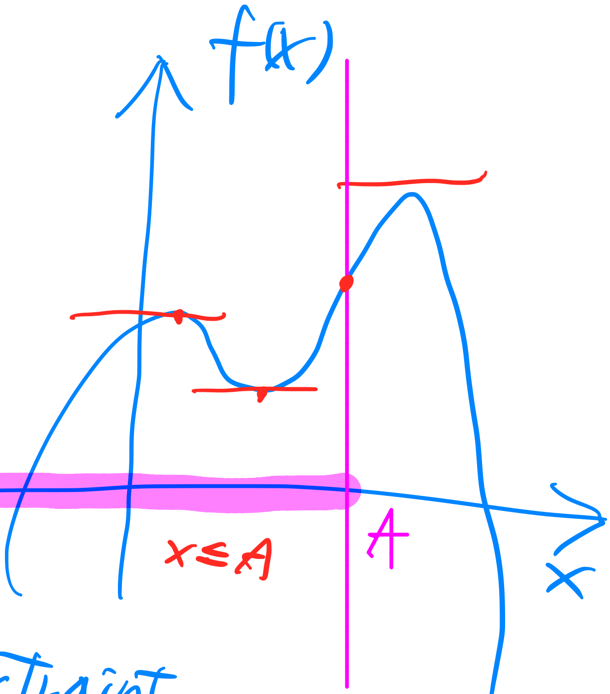
x^* is optimal if $f_0(x^*) \le f_0(z)$

$\forall z$ with $f_i(z) \le b_i$, $i=1,\dots,m$.

such z is called feasible.

Ex.

$$f(x) = ax^4 + bx^3 + cx^2 + dx$$



max $f(x)$

check x : $f'(x) = 0$.

What if we add a constraint that $x \le A$?

Convex Optimization

The objective function $f_0(x)$ and the constraint functions $f_i(x), i=1,\dots,m$ are convex.

We say $f(x)$ is convex if

$$f(\alpha x+\beta y) \leq \alpha f(x)+\beta f(y)$$

where $x, y \in \mathbb{R}^n$, $0 \leq \alpha, \beta \leq 1$

$\alpha+\beta=1$.

ch. 2. convex sets.

ch. 3. convex functions.

ch. 4. convex optimization problems.

Ch. 5. duality.

Lagrange multiplier.

Ch. 6, 7, 8. Applications

Ch. 9, 10, 11 Algorithms.

In general, no analytical solutions

Interior-point method (Ch. 11).

it takes $O(n^3, n^2 m, F)$

where F is the cost of evaluating the first & second derivatives of the objective & constraint functions.

reliable: solve $10^3 \sim 10^4$ variables/constraints easily.

Two special cases.

$\begin{cases} \text{least-squares problem} \\ \text{linear programming problem} \end{cases}$

Least-squares Problems

ℓ_2-norm

$$\text{Minimize } f_0(x) = \|Ax-b\|_2^2 \quad x \in \mathbb{R}^n$$

where $A = \begin{bmatrix} — a_1^T — \\ \vdots \\ — a_k^T — \end{bmatrix} \in \mathbb{R}^{k\times n}$, $b = \begin{pmatrix} b_1 \\ \vdots \\ b_k \end{pmatrix} \in \mathbb{R}^k$

$$f_0(x) = \sum_{i=1}^{k} (a_i^T x - b_i)$$

Example. data-fitting

Given $(x_1, f(x_1)), (x_2, f(x_2)), \ldots, (x_k, f(x_k))$.

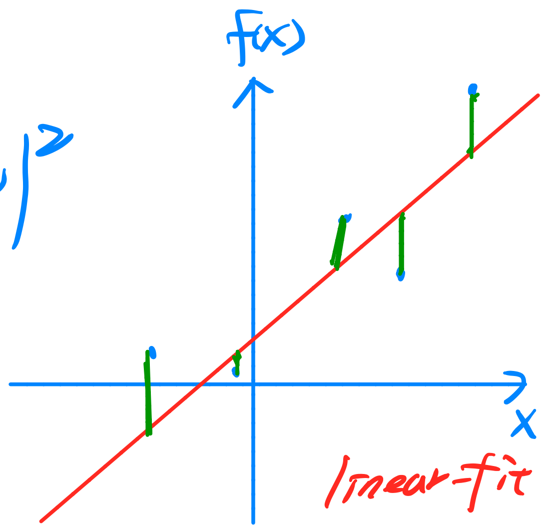
$x_i \in \mathbb{R}$. $f: \mathbb{R} \to \mathbb{R}$.

find $\hat{f}(x)$ such that

$$\min \sum_i |\hat{f}(x_i) - f(x_i)|^2$$

$\hat{f}(x) = ax+b$

ax^2+bx+c



Linear Programming (LP)

f_i are linear.

$f_i(\alpha x+\beta y) = \alpha f_i(x) + \beta f_i(y)$

$\Rightarrow \quad f_i(x) = a^T x.$

$$\begin{cases} \text{variable } x \in \mathbb{R}^n. \\ \text{minimize } c^T x \\ \text{subject to } \underline{a_i^T x \le b_i \ , i=1,\dots,m.} \end{cases}$$

$\underset{(m\times n)}{A}\, x \le \underset{(m\times 1)}{b}$.

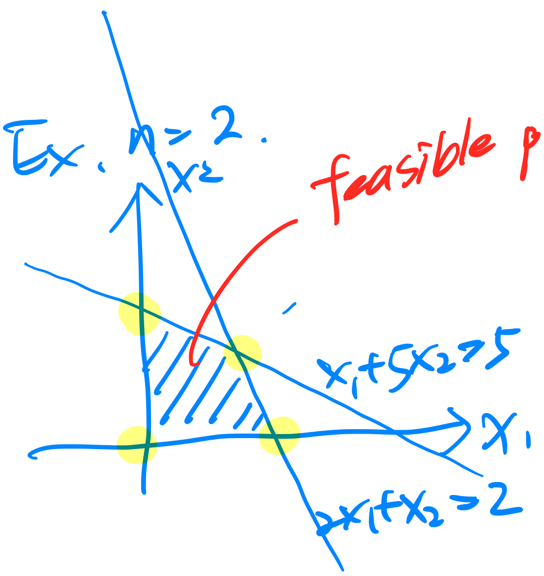
componentwise

~~Definition~~

$(a_1, a_2, \dots, a_n) \le (b_1, b_2, \dots, b_n)$

$\Rightarrow \quad a_1 \le b_1$
$a_2 \le b_2$
$\vdots$
$a_n \le b_n.$

Ex. $n=2$.



$$\begin{cases} x_1 \ge 0 \quad x_2 \ge 0 \\ x_1+5x_2 \le 5 \\ 2x_1+x_2 \le 2. \end{cases}$$

maximize x_1+x_2

LP solvers are available.

$\left\{ \begin{array}{l} \text{Dantzig's simplex method} \\ \text{interior-point method} \end{array} \right.$ $\sim O(n^2 m)$ $m \ge n$

If we can formulate a practical problem as a convex optimization problem, then we can solve it efficiently.

Challenge:
recognizing & formulating the problem.

Ex. Chebyshev approximate problem.

$$\text{minimize} \quad \max_{i=1,\dots,k} \left| a_i^T x - b_i \right|$$

$$x \in \mathbb{R}^n.$$

$\Rightarrow$ minimize t. such that

$$|a_i^T x - b_i| \le t \quad \forall\, i=1,\dots,k.$$

$$\begin{cases} a_i^T x - b_i \le t \\ -(a_i^T x - b_i) \le t \end{cases}$$

linear constraints.

$$|a| \le b \iff \begin{array}{l} a \le b \\ -a \le b \end{array}$$