

# TTK4135 – Optimization and Control

Spring 2023

Lecturer: Lars Imsland

Teaching Assistant: Trym Arve Lund Gabrielsen

6 Student Assistants

### **Learning Objectives**

- Optimization important concepts and theory
- Formulating an engineering problem as a mathematical optimization problem (modeling for optimization)
- Solving an optimization problem numerically:
  - What type is the optimization problem?
  - What is the right algorithm/the right software?
  - Basics for implementation of algorithms

for some important classes of optimization problems

Applications of optimization in control engineering – model predictive control

Numerical optimization is an incredibly versatile tool across most engineering domains



### **Course Information: General**

- Description:
  - All course information is provided through Blackboard
  - Course description: <a href="http://www.itk.ntnu.no/emner/ttk4135">http://www.itk.ntnu.no/emner/ttk4135</a>
- Assignments and assessment (More information on Blackboard):
  - Exercises: 7 of 10 assignments must be approved
    - No extra assignments will be given, deadlines are absolute
    - Pay attention and make sure your delivered assignments are approved
    - Do not copy (kok)!
  - Helicopter lab: must be approved
    - For approval: Must score 70% on lab report
  - Matlab assessments
    - 6 Matlab assessments, each counts 3.3% towards grade (pass/no pass)
  - Final exam ("school exam")
    - Evaluation weighted 80% towards grade

### Matlab assessments

- Completed "inside" Blackboard
- You must implement and submit yourself, but you are allowed to cooperate, discuss and seek help
- Unlimited attempts

- The problems might seem more complex at a first glance, than they actually are
  - You only have to program a few lines inside a template

### **Course Information: Course Material**

#### Lectures:

- Will not cover the full curriculum in lectures
- Will focus on difficult parts and build intuition
- Will be recorded, and video/PDF made available afterwards

#### Course Material:

- Numerical Optimization, J. Nocedal and S. J Wright, 2nd ed.,
   Springer (ISBN-10: 0-387-30303-0 or ISBN-13: 987-0387-30303-1).
   Download <u>here</u> from campus or through VPN.
- Errata on Blackboard
- Note on Merging Optimization and Control,
   B. Foss and T. A. Heirung (Blackboard)
- Note on Matrix Calculus, T. A. Heirung (Blackboard)





### **Course Information: Practical**

- Grading
  - Final exam: 80%
  - Matlab assessments: 20% (6 individual tasks)
- Timetable

Lectures: Tuesday 14:15 – 16:00 EL5

Friday 08:15 - 10:00 A2

Assignment Sessions: Monday 17:15 - 18:00 EL5

- Exam: Written exam, June 8, 09:00 13:00
- Reference group!

### **Expected Background**

- Linear algebra and real analysis
  - Quick recap next time (Also: Note on Blackboard + Exercise 0)
- Some numerical analysis (Newton's method)
- Basic control theory:
  - TTK4105 Control engineering
  - Advantage: TTK4115 Linear system theory



### **Tentative lecture schedule**

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	TTK4135 Plan for Spring 2023						
	The state of the s						
Week no.	Lectures Tuesday 14:15-16:00	Lectures Friday 8:15-10:00	Helicopter project	Matlab assessment	Exercise out (Mon 15:00)	Help session Monday 17:15-18:00	Exercise in (Thu 23:59)
	Lecture 1 Introduction on optimization - N&W	Lecture 2 Optimality conditions - N&W Ch. 12.1-					
2	Ch.1	12.2			0: Matrix Calculus, 1: KKT		
_	Lecture 3 Optimality conditions and linear algebra				0.15		
3	- N&W Ch.12.3, 12.5 (12.8, 12.9) Lecture 5 Linear Programming - N&W Ch.13.1-	Lecture 4 Linear Programming - N&W Ch.13.1-13.5 Lecture 6 Quadratic programming - N&W Ch.15.3-		Assessment 1 out	2: LP	0, 1, 2	
4	13.5	15.5. 16.1-2.4-5		Assessment 1 in	3: LPQP	2. 3	0. 1
4	Lecture 7 Quadratic Programming - N&W	Lecture 8 Open loop dynamic optimization - MPC		Assessment I in	3: LPQP	2, 3	0, 1
5	Ch.15.3-15.5, 16.1-2,4-5		Helicopter Lab week	Assessment 2 out	4: QP	3. 4	2
	Lecture 9 Linear quadratic control - MPC note	Lecture 10 Model predictive control - MPC note	Tremedpter Edb Week	7 to occoment 2 out	7. 01	0, 4	
6	Ch.4.3.2-4.4		Helicopter Lab week	Assessment 2 in	5: OLMPC	4. 5	3
	Lecture 11 Model predictive control - MPC note	Lecture 12 Linear quadratic control - MPC note				,, -	
7	Ch.4.2.2-4.3.1	repetition and 4.6	Helicopter Lab week	Assessment 3 out	6: MPCLQR	5	4
			<u>'</u>				
8	No lecture	No lecture	Helicopter Lab week	Assessment 3 in		5, 6	
	Lecture 13 Unconstrained optimization - N&W						
9	Ch.2.1-2.2	No lecture	Helicopter Lab week	Assessment 4 out	7: RICATTI	6, 7	5
		Lecture 14 Line search methods - N&W Ch.3-3.1,					
10	No lecture Lecture 15 Quasi Newton methods - N&W Ch.6-	3.4, 3.5	Helicopter Lab week	Assessment 4 in	8: UNCON	7, 8	6
	Lecture 15 Quasi Newton methods - N&W Ch.6- 6.1, 8-8.1	Lecture 16 Derivative free optimization - Ch.9, 9.5		4	0.007410	8. 9	_
11	Lecture 17 Newton's method for nonlinear	Lecture 16 Derivative free optimization - Cn.9, 9.5	Helicopter Lab week	Assessment 5 out	9: OPTALG	8, 9	7
12	equations - N&W 11-11.1. 11.2	Excursion?	Helicopter Lab week	Assessment 5 in	10: SQP		8
12	equations - Navv 11-11.1, 11.2	Excursion?	Helicopter Lab week	Assessment 5 III	10. SQF		•
13	Excursion	Excursion					
- 10	Execusion	Execusion					
14	Easter vacation						
		Lecture 18 Sequential quadratic programming					
15	Easter vacation	(SQP) - N&W Ch.18-18.2					
	Lecture 19 Sequential quadratic programming	Lecture 20 Summing up + Nonlinear MPC - MPC					
16	(SQP) - Ch.18.3-18.4, 15.4, 15.5	note 4.5/4.6		Assessment 6 out		9, 10	
17		End of lecturing		Assessment 6 in		10	9
18							10
	Submit heli report	21.04.2022. 23:59					
	Submit neil report	21.04.2022, 23.03		+	1	1	
	Q&A before exam						
	action of the state of the stat						
	Final written exam	08.06.2023 (?)					

• Updated schedule will be available on Blackboard



# Norwegian University of Science and Technology

# TTK4135 – Lecture 1 Optimization: What and Why?

Spring 2022 Lecturer: Lars Imsland

## **Purpose of Lecture**

- Brief Timeline & Motivation
- Formulation of optimization problems, classes of optimization problems
- Definition of important terms
  - Convexity and non-convexity
  - Global vs. local solution
  - Constrained vs. unconstrained problems
  - Feasible set

Reference: Chapter 1 Nocedal & Wright

### **Brief Timeline**

~1600 BC	Ancient Geometry: Babylonian method for solving $x^2 + bx = c$
~300 BC	Ancient Geometry: Euclid's minimal distance between point and line
~200s	Iterative approaches: Han Dynasty methods for solving $\sum_{i=0}^3 a_i x^i = 0$
~900s	Modern algebra and arithmetics: Muhammad Al-Khwarizmi ("Algorismi") gives various root solving methods
1600s	Basis of Calculus of Variations: Newton's Body of minimal resistance, Bernoulli's Brachistochrone problem
1700s	Calculus of Variations and combinatorial optimization: Maupertius' Principle of Least Action, Samuel König's optimal honeycomb
1800s	First "Optimization algorithms": Hamilton-Jacobi Equation, Extreme Value Theorem, Rolle's Theorem, Cauchy's Gradient Descent
1900-1957	Rigorous theory and applications: Minkowski's Convex Sets, Hancock's Theory of Minima and Maxima, Kantorevich's Linear Optimization Problems, Dantzig's Simplex method, Neumann and Morgenstern's Dynamic Programming, Karush-Kuhn-Tucker's Optimality Conditions, Bellman's Optimality principle, Pontryagin's Maximum Principle
1950+	Optimization is applied to economics, agriculture, space travel, social media, robots, manufacturing, art and everything in between



### **Examples of optimization problems**

#### In finance

- How to best invest NOK 500 000?
  - To maximize return
  - To minimize risk
  - No more than 20% of money in one stock
  - Return rate > 4%

#### In control engineering

- How to drive an autonomous vehicle from A to B?
  - To minimize fuel consumption
  - To minimize travel time
  - Distance to closest obstacle > 2 meters
  - Speed < 50 km/h.</li>
  - Path needs to be smooth (no sudden changes in direction)

#### In machine learning

- How to assign likelihoods to transactions being fraudulent?
  - To minimize probability of a false negative
  - To penalize overfitting on training set
  - Probability of false positive < .15</li>
  - Misclassification error on training set < 5%</li>

The question is **not** 

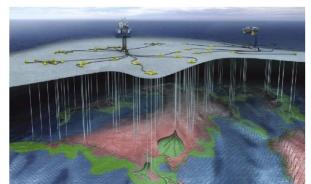
which problems are optimization problems (since all are),

but

which optimization problems can we solve!



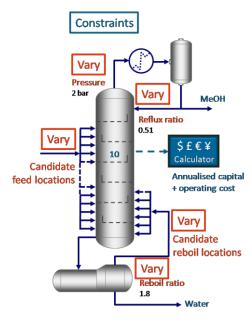
#### **Control Applications: Model Predictive Control for all domains**





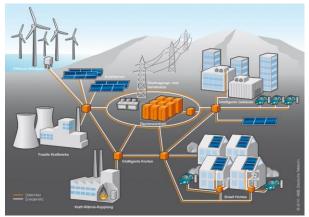




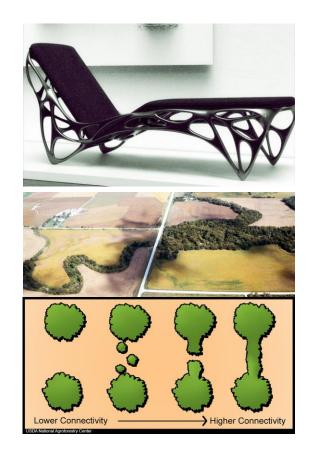




### Lots of other applications



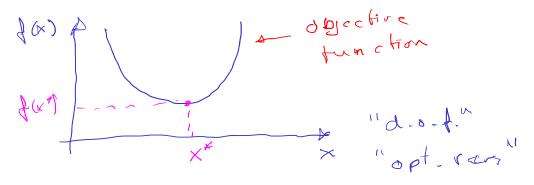






### What is optimization?

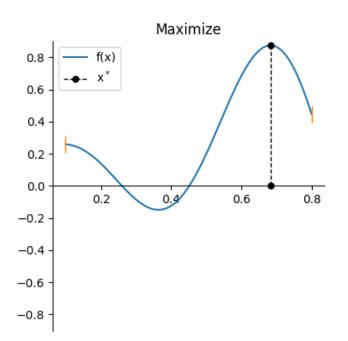
Search for the best so hution

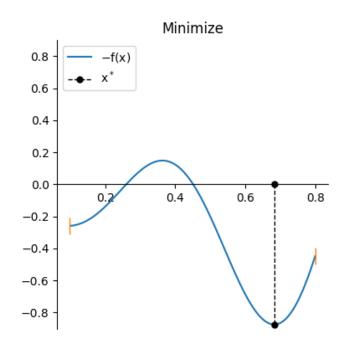


Math; min p cxs

[unconstrained opt.]

### Minimization or Maximization?





Convention this course: Minimization!



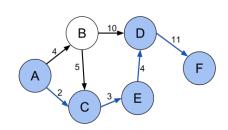
### What characterizes an optimum?

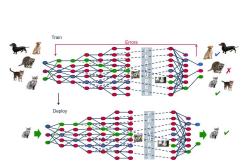
Optimization – A recurring friend

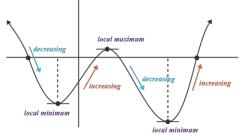
Finding max and min of a function (Calc 1)

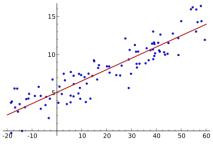
- The Lagrange Method (Calc 2)
- Algorithms course (Shortest path, dynamic programming, max flow, travelling salesman, etc)
- Statistics (Least-squares, data fitting)

- Machine Learning (Gradient descent)
- (And many applications in control...)

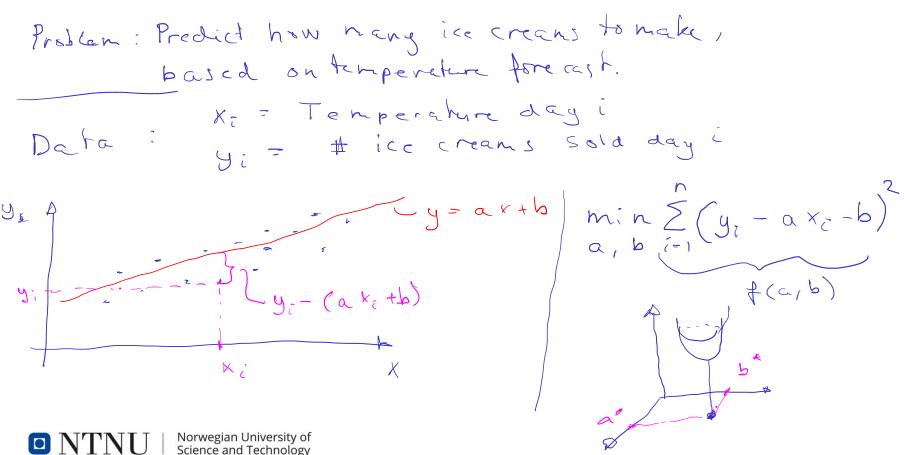






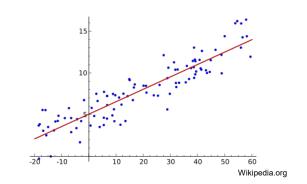


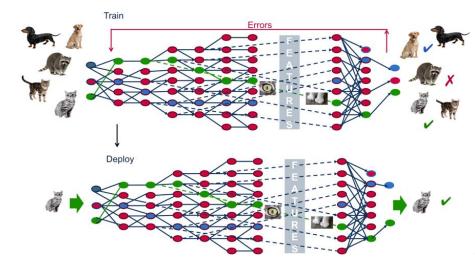
### **Example optimization problem: Least Squares**



### **Example: Machine Learning**

- Learn, and make predictions, from data
- Linear regression is the most basic ML algorithm, solved using optimization
  - Linear least squares: Explicit solution
  - Nonlinear least squares: Ch. 10, N&W
- In a similar fashion: ML, neural networks, deep learning etc. are "trained" using "gradient descent" algorithms
  - Gradient descent topic of Ch. 2-10, N&W







### **Constrained optimization problems**

min f(x)

Unconstrained Constrained opt.

min 
$$f(x)$$

with  $f(x)$ 

xell

s.t.  $C_i(x) = 0$ ,  $i \in \mathbb{Z}$ 

Feosible set
$$\Omega = \{ x \in \mathbb{R}^n \mid C_i(x) = 0 \mid i \in \mathcal{E} \}$$

$$C_i(x) > 0, i \in \mathcal{I} \}$$

### **General Constrained Optimization Problem**

 $\min_{\mathbf{x} \in \mathbb{R}^n} f(\mathbf{x}) \qquad \text{subject to} \qquad \begin{aligned} c_i(\mathbf{x}) &= 0, & i \in \mathcal{E}, \\ c_i(\mathbf{x}) &\geq 0, & i \in \mathcal{I}. \end{aligned}$ 

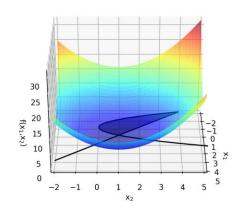
E= (1,2)

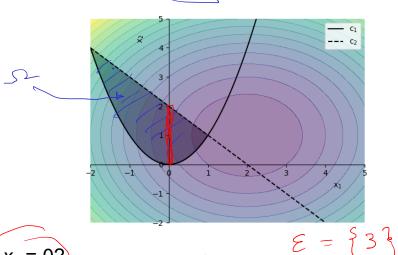
Example:

$$\min (x_1 - 2)^2 + (x_2 - 1)^2$$

subject to 
$$x_1^2 - x_2 \le 0$$

$$(2(x) = 2 - x_1 - y_2 > 6$$





What if we add equality-constraint  $x_1 = 0$ ?

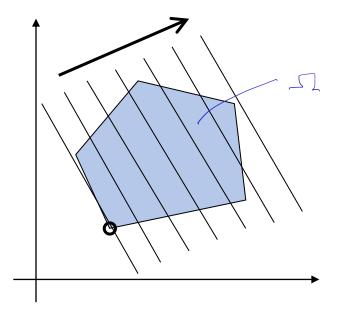
(3) = X = S



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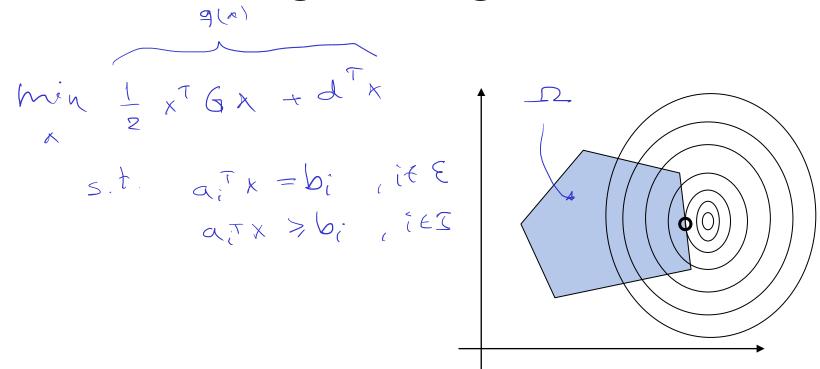
### **Linear Programming**

min 
$$C^T \times$$
 $X$ 
 $X = bi, i \in \mathcal{E}$ 
 $A_i^T \times b_i, i \in \mathcal{T}$ 





### **Quadratic Programming**



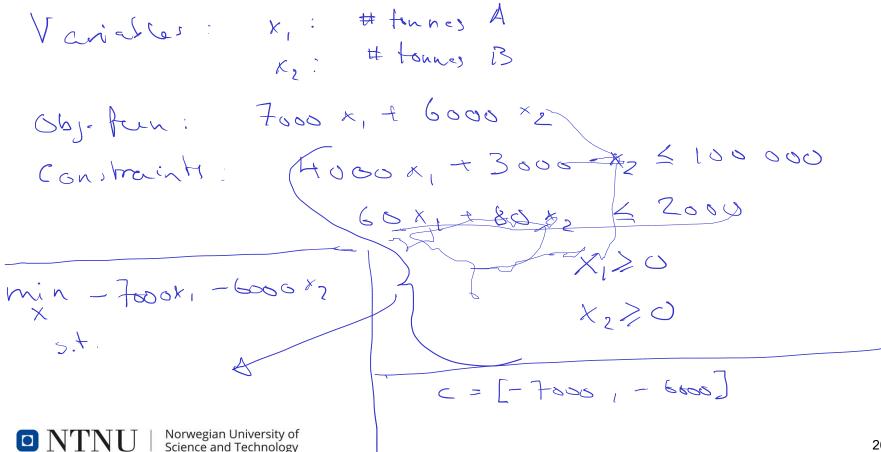
### LP Example: Farming

- A farmer wants to grow apples (A) and bananas (B)
- He has a field of size 100 000 m<sup>2</sup>
- Growing 1 tonne of A requires an area of 4 000 m<sup>2</sup>, growing 1 tonne of B requires an area of 3 000 m<sup>2</sup>

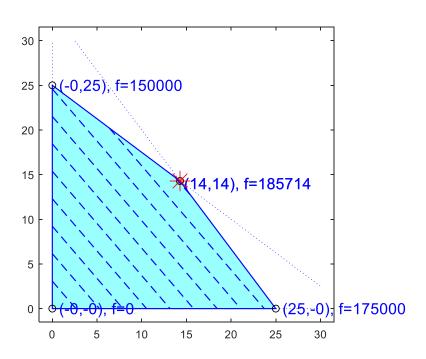


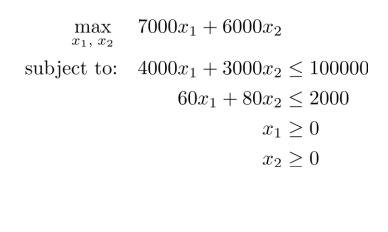
- A requires 60 kg fertilizer per tonne grown, B requires 80 kg fertilizer per tonne grown
- The profit for A is 7000 per tonne (including fertilizer cost), the profit for B is 6000 per tonne (including fertilizer cost)
- The farmer can legally use up to 2000 kg of fertilizer
- The farmer wants to maximize his profits

### Formulating a LP optimization problem



# Farming Example: Geometric Interpretation and Solution





### Matlab linprog input



### Convexity

Convex set: A set S is convex if:  

$$x,y \in S \Rightarrow \alpha x + (1-\alpha)y \in S, \alpha = [0,1]$$

### Convexity

Conver function: The function f: 5 -> IR is convex it Siraconvea set, and  $f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y)$  $\alpha \in [0,1]$ 



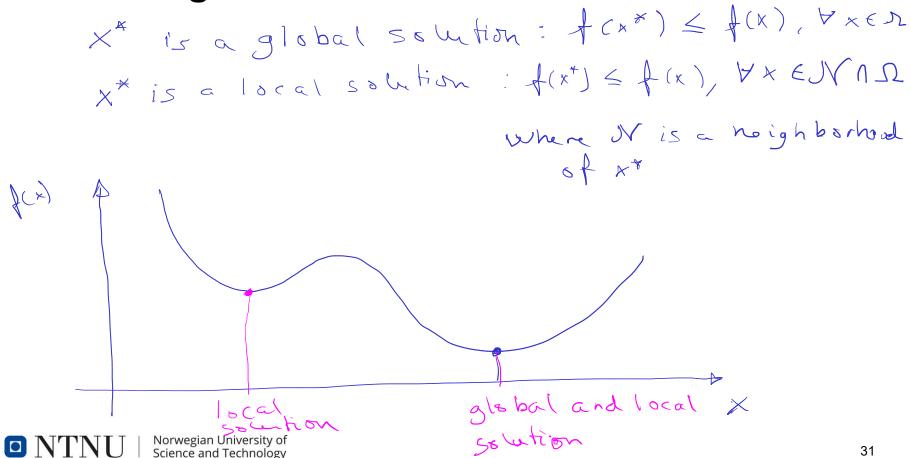
### **Convex optimization problems**

$$\min_{x \in \mathbb{R}^n} f(x) \quad \text{subject to} \quad \begin{cases} c_i(x) = 0, & i \in \mathcal{E} \\ c_i(x) \ge 0, & i \in \mathcal{I} \end{cases}$$

- An optimization problem is convex if
  - 1. f(x) is a convex function, and
  - the feasible set is a convex set



### Local and global solutions



## Importance of convexity

#### Facts:

- Finding local solution: "easy"
- Finding global solution: "hard"

- Convex problems: All local solutions are global!
  - Consequence: Convex problems are "easy"

# **Optimization Taxonomy**

Con	vex	Non-convex	Solution algorithms	
Linear	Non	-linear	Solution algorithms	
Linear programming			Simplex, interior point	
	Quadratic programming		Active set, interior point	
	Semi-definite programming (LMI, second-order cone p.)		Interior point	
	F-7	Non-linear programming	SQP	
		Mixed-integer programming		

