Multiple Constraints and Non-regular Solution in Deep Declarative Network

Suikei Wang

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Except where otherwise indicated, this thesis is my own original work.

Suikei Wang
9 October 2020

to my parents, yyy (yyy is the people you want to dedicated this thesis to.)

Acknowledgments

The past two years at the Australian National University have been an invaluable experience for me. When I started my Master of Machine Learning and Computer Vision at the beginning of 2019, I could barely understand lectures, knew little about the country, and had never heard of the term "convex optimization". It is unbelievable that I have been doing a research project on this topic for a whole year. ANU has the top tier research group in this realm and how honored I am to be a postgraduate student here.

First and foremost, I would like to express my deep and sincere gratitude to my supervisor, Stephen Gould. I knew Stephen before the admission of the program and how privileged I am to work and learn with one of the most brilliant minds in our field. He always has an insightful and high-level view on this topic. More importantly, Stephen is extremely kind and patient as he is always willing to discuss and share ideas with us during the weekly meetings. Although sometimes I am stuck in some problems he used to give me constructive suggestions.

I would like to thank Dylan Campbell and Miaomiao Liu – another two giants of the Australian Centre for Robotic Vision – for offering my supervision and being my second examiner on my thesis. Dylan

Abstract

Put your abstract here.

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Chapter 1

Introduction

1.1 Motivation

Deep learning models composed with multiple parametrized processing layers can learn different levels of features and representations of data through the directed graph structure.

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You have to rewrite your thesis!!!

1.2 Thesis Outline

How many chapters you have? You may have Chapter 2, Chapter **??**, Chapter **??**, Chapter 6, and Chapter 7.

1.3 Contribution

Part I

Deep Declarative Network: Multiple Constrained Declarative Nodes

Chapter 2

An Overview of Numerical Optimization

In this chapter, we aim to provide readers with an overview of numerical optimization. We begin with the theory of optimization (Section 2.1), from the existence of optimizers, to the optimality conditions for both unconstrained and constrained problems with duality. As the theoretical background of optimization, this field provides a solid solution for the algorithm.

We then formally define the optimization of unconstrained and constrained problems in Section 2.2 and describe the general regular solution for these problems based on the gradient calculation.

Next, we discuss briefly the bi-level optimization, which is a lower-level optimization problem embedded within an upper-level problem sharing the same variables. (Section 2.3). Finally, we give a summary of the numerical optimization in constrained problems in Section 2.4.

2.1 Theory of Optimization

2.1.1 Existence of Optimizers

In optimization, a basic question is to determine the existence of a global minimizer for a given function f. There are several sufficient conditions on f to guarantee the existence, and the optimizer falls in the feasible set of solutions. For a feasible set, some related definitions are following:

Definition 2.1. A subset $\Omega \in \mathbb{R}^n$ is called

- *bounded* if there is a constant $R > 0$ such that $\|x\| \leq R$ for all $x \in \Omega$
- *closed* if the limit point of any convergent sequence in Ω always lies in Ω
- *compact* if any sequence $\{x_k\}$ in Ω contains a subsequence that converges to a point in Ω

The following result gives a characterization of compact sets in $\mathbb{R}$. When we find the minimum or maximum solution for the problem, there exists a lower bound or upper bound but not necessarily an optimal solution. Therefore, we have some additional requirements.

Firstly, we give the definition of compact sets in Lemma 2.2. [Oman, 2017] gives a brief proof.

Lemma 2.2 (Bolzano-Weierstrass theorem)**.** A subset Ω in $\mathbb{R}^n$ is *compact* if and only if it is bounded and closed.

We also assume that the function f is continuous and "$+\infty$ at infinity". More precisely, $f(x) \to +\infty$ if $|x| \to +\infty$. Such a function is called *inf-compact* or *coercive*. [Nocedal and Wright, 2006] Then the problem can be restricted to a bounded set and existence of a global minimum x^* is guaranteed: a continuous function has a minimum on a compact set. This theorem is defined as follows and the proof is given in Appendix A.1.1.

Theorem 2.3. *[Nocedal and Wright, 2006] If f is a continuous function defined on a compact set Ω in $\mathbb{R}$, then f has a global minimizer x^* on Ω i.e. there exists $x^* \in \Omega$ such that $f(x^*) \leq f(x)$ for all $x \in \Omega$*

More general, based on the definition of coercive function f, we can give following theorem. Proof is given in Appendix A.1.2.

Theorem 2.4. *[Nocedal and Wright, 2006] If $f : \mathbb{R}^n \to \mathbb{R}$ is a continuous coercive function, then f has at least one global minimizer.*

Theorem 2.4 requires the continuity of f which is somewhat restrictive for applications. However, we can replace it by the lower semi-continuity of f which is a rather weaker condition.

Definition 2.5. Let $f : \mathbb{R}^n \to \mathbb{R} \cup \{\pm\infty\}$. Then f is called *lower semi-continuous* at a point $x_0 \in \mathbb{R}^n$ if for any sequence $f(x_k)$ converging to x_0 here holds $f(x_0) \leq \lim_{k\to\infty} f(x_k)$. f is called *lower semi-continuous* if f is lower semi-continuous at every point.

Recall our assumptions on function f, it is a continuous function, which is always lower semi-continuous. However, lower semi-continuous functions are not necessarily continuous. For instance, a binary function equals to 0 when $x \leq 0$ and equals to 1 when $x > 0$ is not continuous at $x_0 = 0$. However, since it is greater than 0 for all x and $f(0) = 0$, we have $f(0) = 0 \leq \liminf_{x\to 0} f(x)$ and it is lower semi-continuous at $x_0 = 0$.

The theorem of the existence of the optimizer of lower semi-continuous function is given as follows and the proof is given in Appendix A.1.3

Theorem 2.6. *[Nocedal and Wright, 2006] Let $f : \mathbb{R}^n \to \mathbb{R}$ be a lower semi-continuous function. If f has a nonempty, compact sublevel set $D := \{x \in \mathbb{R}^n : f(x) \leq \alpha\}$, then f achieves a global minimizer on $\mathbb{R}$*

Also, we introduce the definition of convex function and convex set which are important in regular optimization problems.

Definition 2.7. A function f is convex when

$$f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y) \quad \text{for all } x, y, \text{ and } \alpha \in]0,1[$$

A set $C \subset \mathbb{R}^n$ is convex when

$$\alpha x + (1-\alpha)y \in C \quad \text{for all } x, y \text{ in } C, \text{ and } \alpha \in]0,1[$$

The problem we are going to discuss in this part is convex and regular, which means its gradient can be computed and the solution exists. However, although the existence of the optimizer is sufficient, for different problems, the optimality conditions are different. In the next two sections, we will give necessary and sufficient conditions for both unconstrained and constrained problems.

2.1.2 Optimality Conditions for Unconstrained Problems

Firstly, we consider the unconstrained minimization problem

$$\min_{\mathbf{x} \in \mathbb{R}^n} f(x), \tag{2.1}$$

where f is given function on $\mathbb{R}^n$.

In order to determine the minimizer, it is important to understand what can happen at a minimizer, and at what condition a point must be a minimizer. Now we have to recognize the optimum point. There are two necessary conditions and one sufficient condition given below [Nocedal and Wright, 2006]. The proof is given in Appendix A.1.4.

Theorem 2.8. *Necessary and Sufficient Conditions. Let $f : \Omega \to \mathbb{R}$ be a funcion defined on a set $\Omega \subset \mathbb{R}^n$ and let x^* be an interior point of Ω that is a local minimizer of f.*
Necessary conditions:

- *(NC1) If f is differentiable at x^*, then x^* is a critical point of f, i.e. $\nabla f(x^*) = 0$.*
- *(NC2) If f is twice continuous differentiable on Ω, then the Hessian $\nabla^2 f(x^*)$ is positive semidefinite.*

Sufficient condition (SC1): if x^* is such that $\nabla f(x^*) = 0$ and $\nabla^2 f(x^*)$ is positive definite, then x^* is a local minimum. (i.e. $f(x) \geq f(x^*)$ for x close to x^*)

Any point satisfying (NC1) as the minimizer of f is called a *critical* or *stationary* point of f. In the objective function f is convex, (NC1) is also the sufficient condition for the global minimum of the solution.

Let us see an example of unconstrained minimization problem. Supposed we have to determine the minimization of function

$$f(x, y) = x^4 - 4xy + y^4$$

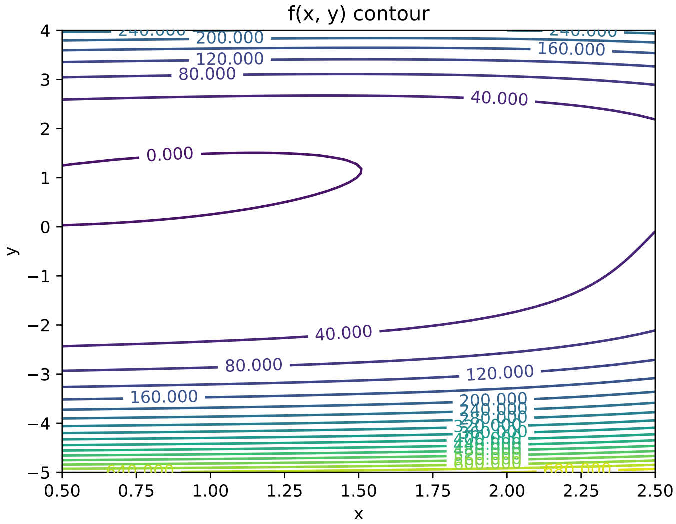


Figure 2.1: Contour Graph of $f(x,y) = x^4 - 4xy + y^4$

From the definition of function f, it is clear that f is continuous. Then we can expand f by writing

$$f(x,y) = \left(x^4 + y^4\right)\left(1 - \frac{4xy}{x^4 + y^4}\right)$$

we can see f is coercive. Also, we give the contour graph of function f in Figure 2.1. Therefore f has global minimizers which are critical points. Now according to (NC1), we can find the global minimizer through solving the derivative of f equaling to zero:

$$0 = \nabla f(x,y) = \begin{pmatrix} 4x^3 - 4y \\ -4x + 4y^3 \end{pmatrix}$$

Thus, $y = x^3$ and $x = y^3$. Consequently $y = y^9$, i.e.

$$0 = y - y^9 = y\left(1 - y^8\right) = y\left(1 - y^4\right)\left(1 + y^4\right) = y(1-y)(1+y)\left(1 + y^2\right)\left(1 + y^4\right)$$

This implies $y = 0, 1, -1$. Thus f has three critical points $(0,0), (1,1), (-1,-1)$. Then we can evaluate f as these points since they may be local minimizer:

$$f(0,0) = 0, \quad f(1,1) = -2, \quad f(-1,-1) = -2$$

It achieves the same global minimum value on $(1,1)$ and $(-1,-1)$. Therefore, they are both global minimizers of f. Figure 2.2 shows the function $f(x,y)$ at these two optimal points.

From this example, we verify that through (NC1), we can find the global minimizer. However, not all continuous functions with critical points have any maximizer

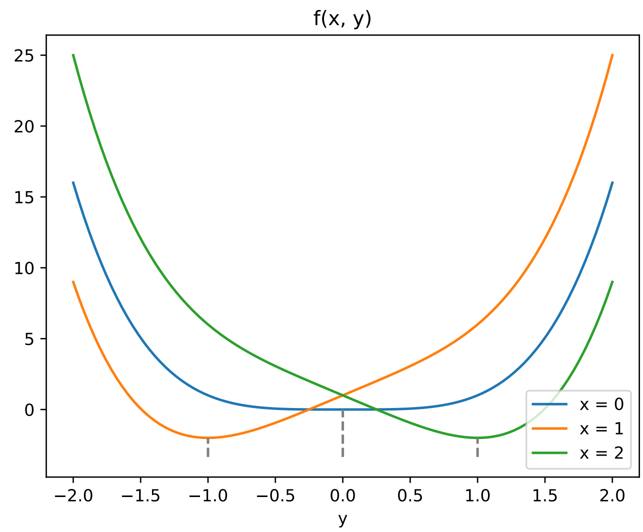


Figure 2.2: Function $f(x,y)$ at $x=0$, $x=-1$ and $x=1$

or minimizer. If the function goes to infinity along its axes or a line, it does not have any maximizer or minimizer although it has a critical point. The condition of the minimizer as the critical point is that the function f should be a convex function with continuous first partial derivatives.

Let us move to the sufficient condition (SC1). The result obtained under this theorem is best possible for general functions. Specifically, for a convex function f is defined on a convex set $\Omega \subset \mathbb{R}^n$, any local minimizer of f is also a global minimizer. Moreover, if a function f is strictly convex, it has at most one global minimizer.

2.1.3 Optimality Conditions for Constrained Problems

A general formulation for constrained optimization problems is as follows:

$$\begin{aligned}&\text{minimize } f(x)\\ &\text{subject to } \begin{cases} c_i(x)=0 & \text{for } i=1,\cdots,m_e,\\ c_i(x)\le 0 & \text{for } i=m_e+1,\cdots,m\end{cases}\end{aligned} \tag{2.2}$$

where f and c_i are smooth real-valued functions on $\mathbb{R}^n$, and m_e and m are nonnegative integers with $m_e < m$. We set

$$\mathcal{E} := \{1,\cdots,m_e\} \quad \text{and} \quad \mathcal{I} := \{m_e+1,\cdots,m\}$$

as index sets of equality constraints and inequality constraints, respectively.

Here, f is so-called the objective function, and $c_i, i \in \mathcal{E}$ and $\mathcal{I}$ are equality constraints and inequality constraints respectively.

To solve the optimization problem (2.2), we define the feasible set of it to be

$$\mathscr{F} := \{x \in \mathbb{R}^n : c_i(x) = 0 \text{ for } i \in \mathscr{E} \text{ and } c_i(x) \leq 0 \text{ for } i \in \mathscr{I}\}$$

Any point $x \in \mathscr{F}$ is called a feasible point of (2.2) and we call (2.2) infeasible if $\mathscr{F} = 0$. Also, in this feasible set, a feasible point $x^* \in \mathscr{F}$ is called a local minimizer of (2.2) if it is the minimum solution in a neighborhood (strict local minimizer if it is the only one minimum solution). The definition of the global minimizer and strict global minimizer is similar, whose neighborhood is the whole feasible set.

Let us move to the constraints in this problem. For equality constraints, they are strictly equivalent. However, for inequality constraints, there are some exceptions. Let x^* be a local minimizer of (2.2). If there is an index $i \in \mathscr{I}$ such that $c_i(x^*) < 0$, then, x^* is still the local minimizer of the problem obtained by deleting i-th constraint. In this situation, we say that the i-th constraint is inactive at x^* since it does not have any effect on the solution. A general definition of active and inactive inequality constraints is as follows:

Definition 2.9. At a feasible point $x \in \mathscr{F}$, the index $i \in \mathscr{I}$ is said to be *active* if $(x) = 0$ and *inactive* if $c_i(x) < 0$.

In the next chapter, we will give different processes for different cases of active or inactive inequality constraints in the deep declarative nodes. In this chapter, we only focus on the necessary and sufficient conditions for a feasible point x to be a local minimizer of (2.2). These conditions will be derived by considering the change of f on the feasible set along with certain directions. We give the lemma for the condition of local minimizer $x^* \in \mathscr{F}$ as follows, which can be proved through Taylor's formula in Appendix A.1.5.

Lemma 2.10. If $x^* \in \mathscr{F}$ is a local minimizer of (2.2), then

$$d^T \nabla f\,(x^*) \geq 0 \quad \text{for all } d \in T_{x^*}\mathscr{F}$$

where $T_{x^*}\mathscr{F}$ is the set of all vectors tangent to $\mathscr{F}$.

However, we may not be able to extract useful results from this lemma, since $T_{x^*}\mathscr{F}$ depends only on the geometry of $\mathscr{F}$ but not on the constraints functions c_i. Not all local minimum falls on the boundary of the constraint function, which is a part of $T_{x^*}\mathscr{F}$. Therefore, it is necessary to introduce linearized feasible directions to give a characterization of $T_{x^*}\mathscr{F}$ in terms of c_i.

Definition 2.11. Given $x \in \mathscr{F}$, we define

$$\mathrm{LFD}(x) := \left\{d \in \mathbb{R}^n : d^T \nabla c_i(x) = 0 \text{ for } i \in \mathscr{E}; d^T \nabla c_i(x) \leq 0 \text{ for } i \in \mathscr{I} \cap \mathscr{A}(x)\right\}$$

and call it the set of linearized feasible directions of $\mathscr{F}$ at x.

Heuristically, for $i \in \mathscr{E}$ we should travel along directions d with $d^T \nabla c_i(x) = 0$ in order to stay on the curve $c_i(x) = 0$; for $i \in \mathscr{I}$ we should travel along directions with

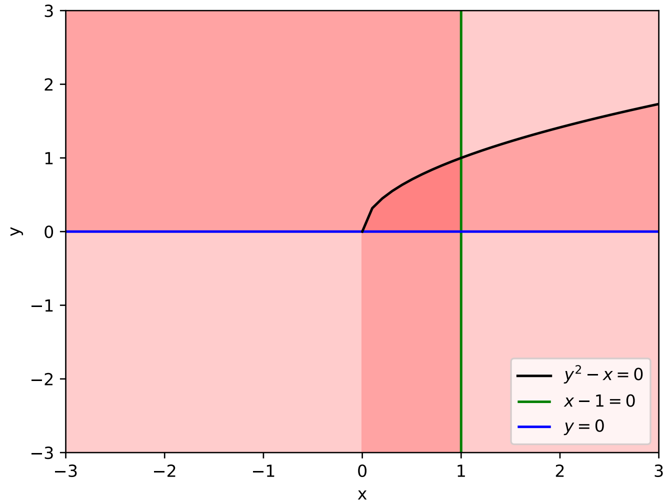


Figure 2.3: Feasible set of constraints c_1, c_2 and c_3

$d^T \nabla c_i(x) \leq 0$ in order to stay in the region $c_i(x) \leq 0$. Let us see an example of the linearized feasible directions and the tangent. Supposed we are considering a set $\mathscr{F}$ with variables $(x, y) \in \mathbb{R}^2$ and three inequality constraints functions:

$$\begin{aligned}
c_1(x, y) &= x - 1 \leq 0 \\
c_2(x, y) &= -y \leq 0 \\
c_3(x, y) &= y^2 - x \leq 0
\end{aligned}$$

We can illustrate the feasible set of constriants c_1, c_2 and c_3 in Fig 2.3. The active set of $0 = (0, 0)$ is $\{2, 3\}$, since $c_1(0) = -1 < 0$, which is inactive. And we can get the derivative of c_2 and c_3 at 0:

$$\nabla c_2(0) = (0, -1)^T \quad \text{and} \quad \nabla c_3(0) = (-1, 0)^T$$

Then we have the linearized feasible directions on $x = 0$:

$$\begin{aligned}
\text{LFD}(0) &= \left\{ d \in \mathbb{R}^2 : d^T \nabla c_2(0) \leq 0 \text{ and } d^T \nabla c_3(0) \leq 0 \right\} \\
&= \left\{ d \in \mathbb{R}^2 : d \geq 0 \right\}
\end{aligned}$$

which equals to the set of all vectors tangent to the feasible set $T_0\mathscr{F}$.

Unlike the unconstrained optimization problem, the first order necessary condition of the existence of the optimizer is different since we should consider its linearized feasible directions and constraints feasibility. This is so-called the Karush-Kuhn-Tucker theorem:

Theorem 2.12 (Karush-Kuhn-Tucker Theorem)**.** *Let $x^* \in \mathscr{F}$ be a local minimizer of* *problem (2.2). If*

$$T_{x^*}\mathscr{F} = \mathrm{LFD}(x^*),$$

then there exists $\lambda^* = (\lambda_1^*, \cdots, \lambda_m^*)^T \in \mathbb{R}^m$ *such that*

$$\nabla f(x^*) + \sum_{i \in \mathscr{E} \cup \mathscr{I}} \lambda_i^* \nabla c_i(x^*) = 0, \quad (\textit{Lagrangian stationary})$$

$$\left.\begin{array}{ll} c_i(x^*) = 0 & \textit{for all } i \in \mathscr{E}, \\ c_i(x^*) \leq 0 & \textit{for all } i \in \mathscr{I}, \end{array}\right\} \quad (\textit{primal feasibility})$$

$$\lambda_i^* \geq 0 \quad \textit{for alli} \in \mathscr{I}, \quad (\textit{dual feasibility})$$

$$\lambda_i^* c_i(x^*) = 0 \quad \textit{for alli} \in \mathscr{E} \cup \mathscr{I}. \quad (\textit{complementary slackness})$$

This set of equations are Karush-Kuhn-Tucker (KKT) conditions and a point x^* *is called a KKT point if there exists* λ^* *such that* (x^*, λ^*) *satisfies the KKT conditions.*

For constrained optimization problem, the classic solution is using Lagrange multipliers [Bertsekas, 2014]. This introduces the function

$$\mathscr{L}(x, \lambda) := f(x) + \sum_{i \in \mathscr{E} \cup \mathscr{I}} \lambda_i c_i(x)$$

which is called the Lagrange function. x is the primal variables and $\lambda_i, i = 1, \ldots, m$ are the Lagrange multipliers or the dual variables. According to the Lagrange multipliers method, we can solve this problem through the gradient of the Lagrange function:

$$\nabla_x \mathscr{L}(x, \lambda) = \nabla f(x) + \sum_{i \in \mathscr{E} \cup \mathscr{I}} \lambda_i \nabla c_i(x)$$

Therefore, the first equation in KKT conditions can be written as

$$\nabla_x \mathscr{L}(x^*, \lambda^*) = 0$$

2.2 Solution of Unconstrained and Constrained Optimization Problems

According to the sufficient conditions for unconstrained optimization problems, we can easily compute the optimality through the first and second derivative of the objective function. For equality and inequality constrained problems, the introduction of Lagrangian $\mathcal{L}$ is useful for their closed-form solution. Gould et al. [2016] collect both argmin and argmax bi-level optimization results with and without constraints, which also provide insightful examples of these cases. Amos and Kolter [2017] also present a solution for exact, constrained optimization within a neural network. In this thesis, we only focus on argmin problems, but the argmax problems have similar results.

In this section, we are going to provide some background for the solution of both unconstrained and constrained optimization problems, which is based on the gradient of the regular point.

2.2.1 Unconstrained Optimization

For unconstrained optimization problems, the solution is easy to obtain since we only need to focus on the optimality of the objective function. We consider an objective function $f : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}$:

$$y(x) \in \operatorname{argmin} f(x, y)$$

The derivative of $y(x)$ with respect to x is

$$\frac{dy(x)}{dx} = -[\frac{\partial^2 f}{\partial y(x)^2}]^{-1} \frac{\partial^2 f}{\partial x \partial y(x)} \tag{2.3}$$

which can be proved through differentiating and chain rule. [A.2.1]

A very classic example of the unconstrained minimization problem based on a closed convex nonempty set is the L2 norm $\|\cdot\|_2$. Let $\Omega \in \mathbb{R}^n$ be a closed convex nonempty set. For any $x \in \mathbb{R}^n$, the minimization problem is defined as follows:

$$\min_{y \in \Omega} \|y - x\|_2^2$$

This problem has a unique minimizer, which can be denoted by $P_\Omega(x)$, the Euclidean projection of x onto Ω.

Proof. Let $m := \inf_{y \in \Omega} \|y - x\|_2^2$. Since $\Omega \neq \emptyset$, we have $0 \leq m < \infty$. Let $\{y_k\} \subset \Omega$ be a minimizing sequence such that $\|y_k - x\|_2^2 \to m$ as $k \to \infty$. Thus $\|y_k - x\|_2^2 \leq m + 1$ for large k which implies that $\|y_k\|_2 \leq \|x\|_2 + \sqrt{m+1}$ for large k. Therefore $\{y_k\}$ is a bounded sequence. Consequently $\{y_k\}$ has a convegent subsequence $\{y_{k_l}\}$ with limit y^*. Since Ω is closed, we have $y^* \in \Omega$, Thus

$$m = \lim_{l \to \infty} \|y_{k_l} - x\|_2^2 = \|y^* - x\|_2^2$$

which means that m is achieved at y^*, i.e. the given minimization problem has a solution.

Next we show that the given minimization problem has a unique solution by contradiction. If the solution is not unique, let y_0 and y_1 be two distinct solutions. Then for $0 < t < 1$ we set $y_t = ty_1 + (1-t)y_1$. Since Ω is convex, we have $y_t \in \Omega$.

Thus

$$
\begin{aligned}
\|y_0 - x\|_2^2 = \|y_1 - x\|_2^2 \leq \|y_t - x\|_2^2 = {} & \|t\,(y_1 - x) + (1-t)\,(y_0 - x)\|_2^2 \\
= & t^2 \|y_1 - x\|_2^2 + (1-t)^2 \|y_0 - x\|_2^2 + 2t(1-t)\,\langle y_1 - x, y_0 - x\rangle \\
= & t\,\|y_1 - x\|_2^2 + (1-t)\,\|y_0 - x\|_2^2 - \left(t - t^2\right)\|y_1 - x\|_2^2 \\
& - \left(1 - t - (1-t)^2\right)\|y_0 - x\|_2^2 + 2t(1-t)\,\langle y_1 - x, y_0 - x\rangle \\
= & t\,\|y_1 - x\|_2^2 + (1-t)\,\|y_0 - x\|_2^2 \\
& - t(1-t)\left(\|y_1 - x\|_2^2 + \|y_0 - x\|_2^2 - 2\,\langle y_1 - x, y_0 - x\rangle\right) \\
= & \|y_0 - x\|_2^2 - t(1-t)\,\|y_1 - y_0\|_2^2
\end{aligned}
$$

where $\langle \cdot, \cdot \rangle$ denotes the inner product on $\mathbb{R}^n$. Therefore $t(1-t)\,\|y_1 - y_0\|_2^2 \leq 0$ for $0 < t < 1$ and thus $\|y_1 - y_0\|_2^2 \leq 0$. So $y_1 = y_0$ which is a contradiction.

Overall, the minimization problem defined above has a unique minimizer. □

There are many different methods to solve the unconstrained optimization problem since generally, we treat this kind of problem as basic one. There are two most classical methods, Newton method [Newton and Colson, 1736] and the Method of Steepest Descent [Debye, 1909]. The former one, Newton method starts from an initial guess x_0 and defines a sequence $\{x_k\}$ iteratively according to some rule. It uses the tangent line of the objective function f at x_k to replace f and uses the root of $L(x) = 0$, where $L(x)$ is the updated $f(x)$ as the next iterate x_{k+1}. Finally, the iteration is terminted as long as the difference between x_k and x_{k+1} less than a preassigned small number. The later one, steepest descent is a basic gradient method, which decreases the value of the objective function in a direction of most rapid change. The change rate of a function f at x in the direction u, a unit vector in $\mathbb{R}$ is determined by the directional derivative. Therefore, at x the value of f decrease fastest in the direction $u = -\nabla f(x)/\|\nabla f(x)\|$, which leads to the gradient method: we update the x through the direction with the step length.

2.2.2 Equality Constrained Optimization

Constrained problems are usually more complicated since the solution is restricted on a boundary or in a feasible region. For equality constraints, the basic case is the linear equality constraints $A\boldsymbol{y} = \boldsymbol{b}$. Again, we consider an objective function $f : \mathbb{R}^n \to \mathbb{R}$. Let $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^m$. A is a set of m linear equations as constraints $A\boldsymbol{y} = \boldsymbol{b}$. The problem is defined as follows:

$$
\begin{aligned}
y(x) \in \arg\min\nolimits_{y \in \mathbb{R}^m} \quad & f(x, y) \\
\text{subject to} \quad & A\boldsymbol{y} = \boldsymbol{b}
\end{aligned}
$$

The derivative of $y(x)$ with respect to x is

$$\frac{dy(x)}{dx} = \left(H^{-1}A^T \left(AH^{-1}A^T \right)^{-1} AH^{-1} - H^{-1} \right) B \tag{2.4}$$

where $H = \partial^2 f(x,y)/\partial y(x)^2$ and $B = \partial^2 f(x,y)/\partial x \partial y(x)$.

The solution in 2.4 can be proved through the Lagrange multipliers [Bertsekas, 2014] in A.2.2.

2.2.3 Inequality Constrained Optimization

2.3 Bi-level Optimization

2.4 Summary

Summary what you discussed in this chapter, and mention the story in next chapter. Readers should roughly understand what your thesis takes about by only reading words at the beginning and the end (Summary) of each chapter.

Chapter 3

Deep Declarative Network

Same as the last chapter, introduce the motivation and the high-level picture to readers, and introduce the sections in this chapter.

3.1 An Overview of Deep Declarative Network

3.1.1 Structure

3.1.2 Declarative Nodes

3.2 Learning

3.3 Back-propagation Through Declarative Nodes

3.3.1 Unconstrained

3.3.2 Equality Constrained

3.3.3 Inequatlity Constrained

3.4 Examples of Declarative Nodes

3.4.1 Unconstrained

3.4.2 Equality Constrained

3.4.3 Inequatlity Constrained

3.5 Summary

Same as the last chapter, summary what you discussed in this chapter and be the bridge to next chapter. s

Chapter 4

The Future of Declarative Nodes

Same as the last chapter, introduce the motivation and the high-level picture to readers, and introduce the sections in this chapter.

Part II

Deep Declarative Network: Non-regular Solution

Chapter 5

An Overview of Regular and Non-regular Solution

5.1 Problems in Regular Deep Declarative Nodes

5.2 Related Work in Non-regular Solution

5.2.1 Overdetermined System

5.2.2 Rand Deficiency

5.2.3 Non-convex Problems

Table 5.1 shows how to include tables and Figure 5.1 shows how to include codes.

Architecture	Pentium 4	Atom D510	i7-2600
Model	P4D 820	Atom D510	Core i7-2600
Technology	90nm	45nm	32nm
Clock	2.8GHz	1.66GHz	3.4GHz
Cores $\times$ SMT	2×2	2×2	4×2
L2 Cache	1MB $\times$ 2	512KB $\times$ 2	256KB $\times$ 4
L3 Cache	none	none	8MB
Memory	1GB DDR2-400	2GB DDR2-800	4GB DDR3-1066

Table 5.1: Processors used in our evaluation.

```
int main(void)
{
  printf("Hello␣World\n");
  return 0;
}
```

(a)

```
void main(String[] args)
{
  System.out.println("Hello␣World");
}
```

(b)

Figure 5.1: Hello world in Java and C.

Chapter 6

Solutions of Non-regular Point

6.1 Overdetermined System

6.1.1 Least-Squared Method

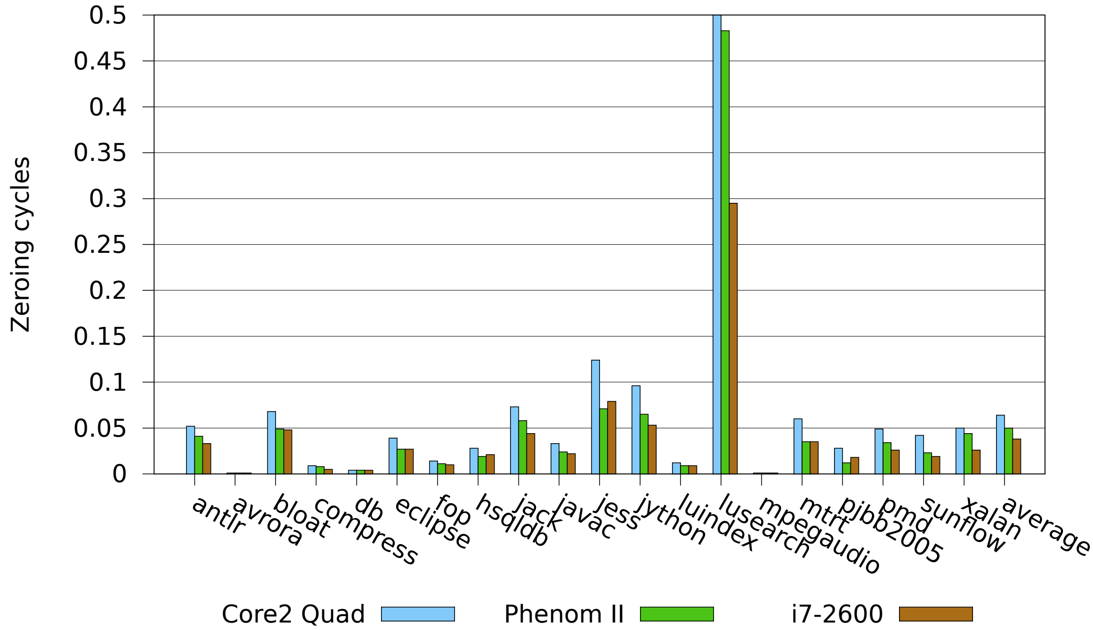
6.2 Conjugate Gradient and Preconditioning

6.3 Rank Deficiency

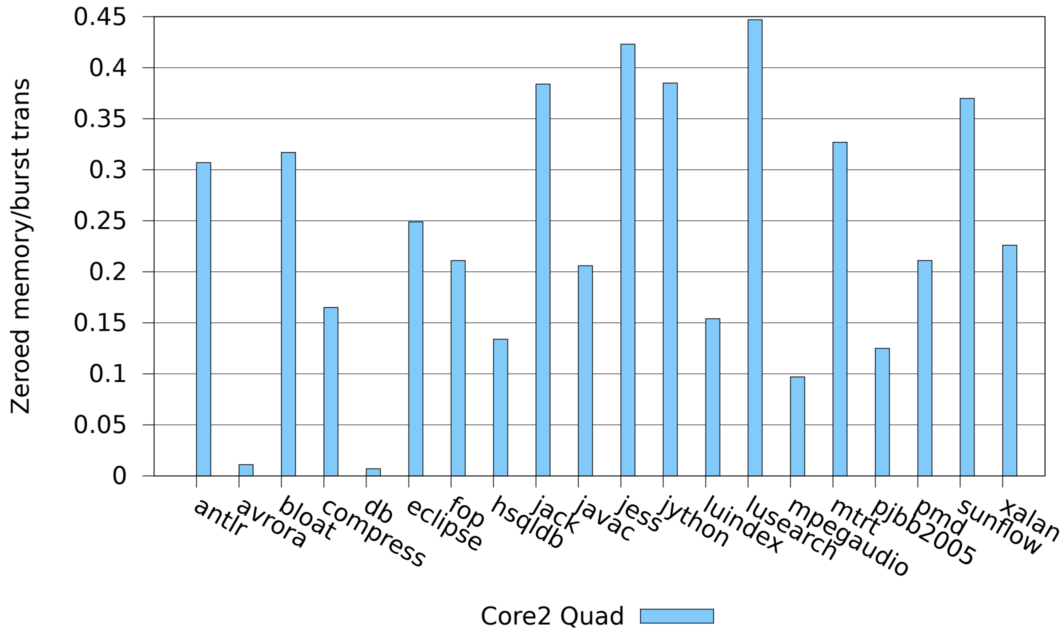
6.4 Non-convex Problems

Here is the example to show how to include a figure. Figure 6.1 includes two subfigures (Figure 6.1(a), and Figure 6.1(b));

6.5 Summary



(a) Fraction of cycles spent on zeroing



(b) BytesZeroed / BytesBurstTransactionsTransferred

Figure 6.1: The cost of zero initialization

Chapter 7

Conclusion

Summary your thesis and discuss what you are going to do in the future in Section 7.1.

7.1 Future Work

Good luck.

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Appendix

A An Overview of Numerical Optimization

A.1 Theory of Optimization

A.1.1 Proof of Theorem 2.3

Proof. Let

$$m := \inf\{f(x) : x \in \Omega\}$$

By the definition of m we may pick a sequence $\{x_k\} \subset \Omega$ with $f(x_k) \to m$ as $k \to \infty$. Because Ω is compact, we can extract a convergent subsequence $\left\{x_{k_j}\right\}$ from $\{x_k\}$. Let $x^* \in \Omega$ denote the limit point of $\left\{x_{k_j}\right\}$. Since f is continuous, $f(x^*) = \lim_{j\to\infty} f\left(x_{k_j}\right) = m$. Thus m is finite and x^* is a global minimizer of f on Ω.
When $\Omega = \mathbb{R}^n$, we need to impose conditions on f at infinity to guarantee the existence of a global minimizer. □

A.1.2 Proof of Theorem 2.4

Proof. Let $m := \inf\{f(x) : x \in \mathbb{R}^n\}$, and take a sequence $\{x_k\}$ such that

$$f(x_k) \to m \quad \text{as } k \to \infty.$$

Since f is coervice, $\{x_k\}$ must be bounded; otherwise it has a subsequence $\left\{x_{k_j}\right\}$ with $\left\|x_{k_j}\right\| \to \infty$ as $j \to \infty$, and hence $m = \lim_{j\to\infty} f\left(x_{k_j}\right) = +\infty$, a contradition. Thus there is $r > 0$ such that

$$\{x_k\} \subset \{x \in \mathbb{R}^n : \|x_k\| \le r\}.$$

Because $\{x \in \mathbb{R}^n : \|x\| \leq r\}$ is compact, $\{x_k\}$ has a convergent subsequence $\left\{x_{k_j}\right\}$ with $x_{k_j} \to x^*$ as $j \to \infty$. In view of the continuity of f, we have

$$f(x^*) = \lim_{j \to \infty} f\left(x_{k_j}\right) = m$$

Therefore m is finite and f achieves its minimum on $\mathbb{R}^n$ at x^* □

A.1.3 Proof of Theorem 2.6

Proof. We may assume that $\alpha > f_* := \inf\{f(x) : x \in \mathbb{R}^n\}$. Let $\{x_k\}$ be a minimizing sequence for f, i.e.

$$f(x_k) \to f_* \quad \text{as } k \to \infty$$

Then there is an N such that $f(x_k) \leq \alpha$ for all $k \geq N$, that is, $x_k \in D$ for all $k \geq N$. Since D is compact, $\{x_k\}_{k=N}^{\infty}$ has a convergent subsequence $\left\{x_{k_j}\right\}$ with $x_{k_j} \to x_* \in D$ as $j \to \infty$. In view of the lower semi-continuity of f, we have

$$f(x_*) \leq \lim_{j \to \infty} f\left(x_{k_j}\right) = f_*$$

By the definition of f_* we must have $f(x_*) = f_*$. Therefore f achieves its minimum on $\mathbb{R}$ at x_*. □

A.1.4 Proof of Theorem 2.8

Proof. (NC1): First recall that for any $v \in \mathbb{R}^n$ there holds

$$v^T \nabla f(x^*) = D_v f(x^*) = \lim_{t \searrow 0} \frac{f(x^* + tv) - f(x^*)}{t}.$$

Since x^* is a local minimizer, we have

$$f(x^* + tv) - f(x^*) \geq 0 \quad \text{for small } |t|.$$

Therefore

$$v^T \nabla f(x^*) \geq 0 \quad \text{for all } v \in \mathbb{R}^n.$$

In particular this implies $(-v)^T \nabla f(x^*) \geq 0$ and thus

$$v^T \nabla f(x^*) \leq 0 \quad \text{for all } v \in \mathbb{R}^n.$$

Therefore $v^T \nabla f(x^*) = 0$ for all $v \in \mathbb{R}^n$. Taking $v = \nabla f(x^*)$ gives $\|\nabla f(x^*)\|^2 = 0$ which shows that $\nabla f(x^*) = 0$ □

Proof. (NC2): Recall that for any $v \in \mathbb{R}^n$ and small $t > 0$ there is $0 < s < 1$ such that

$$f(x^* + tv) = f(x^*) + tv^T \nabla f(x^*) + \frac{1}{2} t^2 v^T \nabla^2 f(x^* + stv) v.$$

Since x^* is a local minimizer of f, we have $f(x^* + tv) \geq f(x^*)$ and $\nabla f(x^*) = 0$ by (NC1). Therefore

$$\frac{1}{2}t^2 v^T \nabla^2 f(x^* + stv)\, v = f(x^* + tv) - f(x^*) \geq 0.$$

This implies that

$$v^T \nabla^2 f(x^* + stv)\, v \geq 0.$$

Taking $t \to 0$ gives

$$v^T \nabla^2 f(x^*)\, v \geq 0 \quad \text{for all } v \in \mathbb{R}^n$$

i.e. $\nabla^2 f(x^*)$ is semi-definite. □

Proof. (SC1): Since $\nabla^2 f(x$ is continuous and $\nabla^2 f(x^*) \geq 0$, we can find $r > 0$ such that

$$B_r(x^*) \subset \Omega \quad \text{and} \quad \nabla^2 f(x) > 0 \text{ for all } x \in B_r(x^*).$$

By Taylor's formula we have

$$f(x) = f(x^*) + \nabla f(x^*) \cdot (x - x^*) + \frac{1}{2}(x - x^*)^T \nabla^2 f(\hat{x})(x - x^*)$$

where $\hat{x} := x^* + t(x - x^*)$ for some $0 < t < 1$. It is clear that $\hat{x} \in B_r(x^*)$ and hence $\nabla^2 f(\hat{x}) > 0$ which implies that

$$(x - x^*)^T \nabla^2 f(\hat{x})(x - x^*) > 0 \quad \text{for } x \neq x^*$$

Consequently

$$f(x) > f(x^*) + \nabla f(x^*) \cdot (x - x^*)$$

for all $x \in B_r(x^*)$ with $x \neq x^*$. Since $\nabla f(x^*) = 0$, we can obtain $f(x) > f(x^*)$ for all $x \in B_r(x^*)$ with $x \neq x^*$. □

A.1.5 Proof of Lemma 2.10

Proof. For $d \in T_{x^*}\mathscr{F}$, we have $z_k \subset \mathscr{F}$ and t_k such that

$$z_k \to x^*, \quad 0 < t_k \to 0 \quad \text{and} \quad \frac{z_k - x^*}{t_k} \to d$$

as $k \to \infty$. As $f(x^*) \leq f(z_k)$, by Taylor's formula we have

$$\begin{aligned} f(x^*) &\leq f(z_k) = f(x^* + (z_k - x^*)) \\ &= f(x^*) + (z_k - x^*)^T \nabla f(x^*) + \frac{1}{2}(z_k - x^*)^T \nabla^2 f(\hat{z}_k)(z_k - x^*) \end{aligned}$$

where $\hat{z}_k$ is a point on the line segment joining x^* and z_k. This implies that

$$0 \leq \left(\frac{z_k - x^*}{t_k}\right)^T \nabla f\left(x^*\right) + \frac{1}{2}\left(z_k - x^*\right)^T \nabla^2 f\left(\hat{z}_k\right)\left(\frac{z_k - x^*}{t_k}\right)$$

Letting $k \to \infty$ gives $d^T \nabla f\left(x^*\right) \geq 0$ □

A.2 Solution of Unconstrained and Constrained Optimization Problems

A.2.1 Proof of Equation 2.3

Proof. Firstly, for any optimal y, according to the first-order optimality condition, we have

$$\frac{df(x,y)}{dy} = \mathbf{0} \in \mathbb{R}^{1\times m}$$

Then from the implicit function theorem, rearranging and differentiating both sides we have

$$\begin{aligned} \mathrm{D}(\frac{df(x,y)}{dy})^T &= \mathbf{0} \in \mathbb{R}^{m\times n} \\ &= \frac{\partial^2}{\partial x \partial y} f(x,y) + \frac{\partial^2}{\partial y^2} f(x,y) \frac{dy(x)}{dx} \\ \frac{dy(x)}{dx} &= -[(\frac{\partial^2}{\partial y^2}) f(x,y)]^{-1} (\frac{\partial^2}{\partial x \partial y}) f(x,y) \end{aligned}$$

□

A.2.2 Proof of Equation 2.4

Proof. According to the definition of Lagrange multipliers, we can define the Lagrangian:

$$\mathcal{L}(x,y,\lambda) = f(x,y) - \sum_{i=1}^{p} \lambda_i (A_i y - b)$$

□