Deep Learning

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note For reading

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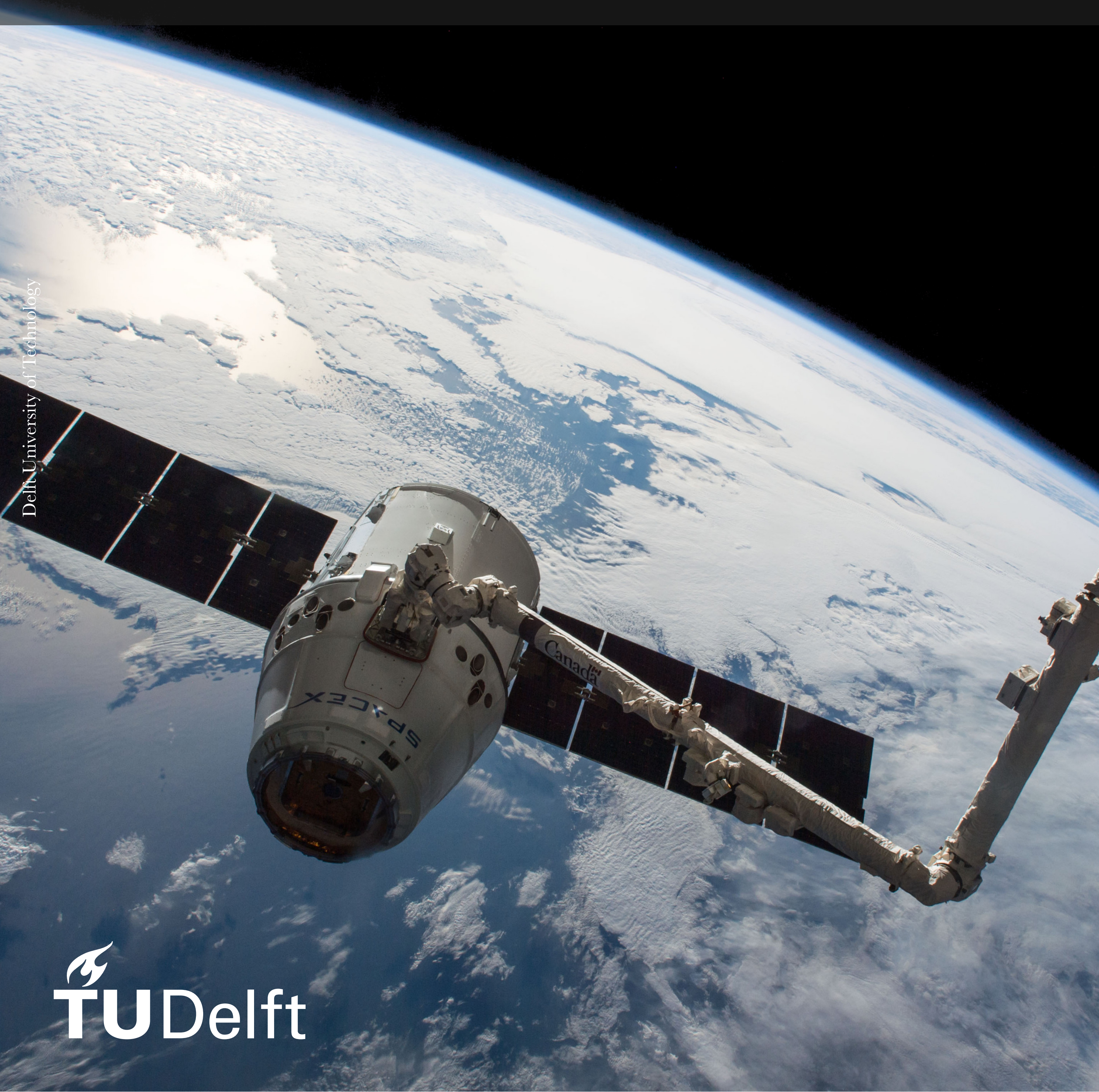

Delft University of Technology

TU Delft

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by

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Project Duration:	Month, Year - Month, Year
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Preface

A preface...

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Delft, August 2024

Summary

A summary...

目录

Nomenclature

If a nomenclature is required, a simple template can be found below for convenience. Feel free to use, adapt or completely remove.

Abbreviations

Abbreviation	Definition
ISA	International Standard Atmosphere
...	

Symbols

Symbol	Definition	Unit
V	Velocity	[m/s]
...		
ρ	Density	[kg/m^3]
...		

Chapter 1

Linear Nerual Network

1.1. Practice 1: 线性回归

Question 1: 假设有一些数据 $x_1, \cdots, x_n \in \mathbb{R}$。找使得 $\sum_i (x_i - b)^2$ 最小化的解析解，这个问题以及其解和正态分布有什么关系？

令 $\mathcal{L}(b) = \sum_i (x_i - b)^2$，则

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial b} &= -\sum_i 2(x_i - b) = 0 \\ \Rightarrow b &= \frac{x_1 + \cdots, x_n}{n}\end{aligned} \tag{1.1}$$

即令解析解最小化的 b 刚好是数据集 $x_1, \cdots, x_n$ 的均值。

Question 2: 推导使用平方误差的线性回归优化问题的解析解。

1. 用向量表示法写出优化问题；
2. 计算损失对 ω 的梯度；
3. 通过将梯度设为 0、求解矩阵方程来找到解析解；
4. 什么时候可能比使用**随机梯度下降**更好？这种方法何时会失效？

首先对于数据矩阵为 $X = (x_1, x_2, \cdots, x_n)^T \in \mathbb{R}^{m \times n}$，其中 $x_i = (x_{1i}, x_{2i}, \cdots, x_{ni})$ 写成线性回归问题为

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{1.2}$$

因此回归问题写成

$$\hat{y} = \omega^T X \tag{1.3}$$

其中 $\omega = (\omega_1, \cdots, \omega_n)^T$，$\hat{y} \in \mathbb{R}^n$。假设 $y \in \mathbb{R}^n$ 是标签向量，则优化问题写成

$$\omega = \arg\min \|y - \hat{y}\|_2^2 = \arg\min \|y - \omega^T X\|^2 \tag{1.4}$$

因此损失函数为

$$\mathcal{L}(\omega) = \|y - \omega^T X\|^2 \tag{1.5}$$

求损失函数的梯度

$$\nabla_\omega \mathcal{L} = \tag{1.6}$$

Question 3: 假定控制附加噪声 ε 的噪声模型是指数分布：$p(\omega) = \frac{1}{2}exp(-|\varepsilon|)$，

1. 写出模型 $-log\ P(y|X)$ 下数据的负对数似然函数；
2. 试着写解析解；
3. 提出一种 *SGD* 算法来解决这个问题，那里可能出错？（当我们不断更新参数时，在驻点处会发生什么？）

1.2. Practice 2: 线性回归从零实现

Question 4: 如果我们将权重初始化为零，会发生什么？

Question 5: 假设试图为电压和电流关系建立一个模型，自动唯微分可以用来学习模型的参数吗？

Question 6: 能基于普朗克定律使用广谱能量密度来确定物体的温度么？

Question 7: 计算二阶导数时可能会遇到什么问题？

Question 8: 为什么在 *squared_loss* 函数中需要使用 *reshape* 函数

Question 9: 尝试使用不同的学习率，观察损失函数值下降的快慢

Question 10: 如果样本个数不能被批量整除，*data_iter* 函数的行为会有什么变化

References

[1] I. Surname, I. Surname, and I. Surname. “The Title of the Article”. In: *The Title of the Journal* 1.2 (2000), pp. 123–456.

Chapter A

Source Code Example

Adding source code to your report/thesis is supported with the package `listings`. *An example can be found below. Files can be added using* `\lstinputlisting[language=<language>]{<filename>}`.

```python
"""
ISA Calculator: import the function, specify the height and it will return a
list in the following format: [Temperature,Density,Pressure,Speed of Sound].
Note that there is no check to see if the maximum altitude is reached.
"""

import math
g0 = 9.80665
R = 287.0
layer1 = [0, 288.15, 101325.0]
alt = [0,11000,20000,32000,47000,51000,71000,86000]
a = [-.0065,0,.0010,.0028,0,-.0028,-.0020]

def atmosphere(h):
    for i in range(0,len(alt)-1):
        if h >= alt[i]:
            layer0 = layer1[:]
            layer1[0] = min(h,alt[i+1])
            if a[i] != 0:
                layer1[1] = layer0[1] + a[i]*(layer1[0]-layer0[0])
                layer1[2] = layer0[2] * (layer1[1]/layer0[1])**(-g0/(a[i]*R))
            else:
                layer1[2] = layer0[2]*math.exp((-g0/(R*layer1[1]))*(layer1[0]-layer0[0]))
    return [layer1[1],layer1[2]/(R*layer1[1]),layer1[2],math.sqrt(1.4*R*layer1[1])]
```

Chapter B

Task Division Example

If a task division is required, a simple template can be found below for convenience. Feel free to use, adapt or completely remove.

表 **B.1:** Distribution of the workload

	Task	Student Name(s)
	Summary	
Chapter 1	Introduction	
Chapter 2		
Chapter 3		
Chapter *		
Chapter *	Conclusion	
	Editors	
	CAD and Figures	
	Document Design and Layout	

Chapter C

矢量求导

C.1. 多元泰勒展开

一元函数 $f(x)$ 在 x_0 处的泰勒展开表示为

$$f(x_0) = f(x_0) + \frac{f'(x)}{1!}(x - x_0) \tag{C.1}$$