# **Q&A ASSIGNMENT 1**

REINFORCEMENT LEARNING KU - WINTER 2023/24

Ozan Özdenizci, Thomas Wedenig (+homas.wedenig @ tugraz.at)
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Institute of Theoretical Computer Science Graz University of Technology, Austria

## TABLE OF CONTENTS



1. Mathematical Preliminaries

2. Banach's Fixed Point Theorem





#### Definition

Let  $\mathcal V$  be a vector space. Then the function  $\|\cdot\|:\mathcal V\to\mathbb R$  is called a **norm on**  $\mathcal V$  if it satisfies the following properties:

- 1.  $\|\mathbf{x}\| \ge 0$ ,  $\forall \mathbf{x} \in \mathcal{V}$  and  $\|\mathbf{x}\| = 0$  iff  $\mathbf{x} = \mathbf{0}$  (non-negativity)
- 2.  $\|\lambda \mathbf{x}\| = |\lambda| \cdot \|\mathbf{x}\|, \quad \forall \mathbf{x} \in \mathcal{V}, \forall \lambda \in \mathbb{R}$  (positive homogeneity)
- 3.  $\|\mathbf{x} + \mathbf{y}\| \le \|\mathbf{x}\| + \|\mathbf{y}\|, \quad \forall \mathbf{x}, \mathbf{y} \in \mathcal{V}$  (triangle inequality)



## **IMPORTANT NORMS**



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For  $\mathbf{x} = (x_1, \dots, x_n)^T \in \mathbb{R}^n$ , we define

- The  $\ell_2$  norm  $\|\mathbf{x}\|_2 = \sqrt{\sum_{i=1}^n x_i^2}$
- The  $\ell_1$  norm  $\|\mathbf{x}\|_1 = \sum_{i=1}^n |x_i|$
- The  $\ell_{\infty}$  norm  $\|\mathbf{x}\|_{\infty} = \max_{i} |x_{i}|$

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# $\ell_{\scriptscriptstyle D}$ Norms

$$\|\mathbf{x}\|_{p} = \left(\sum_{i=1}^{n} |x_{i}|^{p}\right)^{1/p} \text{ with } p \ge 1$$

· Actually,  $\|\mathbf{x}\|_{\infty} = \lim_{p \to \infty} \|\mathbf{x}\|_{p}$ 



## **Important Norms**

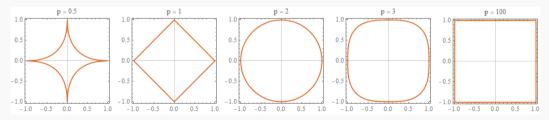
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https://ekamperi.github.io/machine%20learning/2019/10/19/norms-in-machine-learning.html



## Definition

Let  $(\mathcal{V}, \|\cdot\|)$  be a **normed vector space** and  $(v_n; n \geq 0)$  be a sequence of vectors in  $\mathcal{V}$ . Then  $v_n$  is called a **Cauchy Sequence** if

$$\forall \varepsilon > 0 \ \exists N \in \mathbb{N} \ \text{such that} \ \forall i, j \geq N : \ \|v_i - v_j\| < \varepsilon$$



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 $(\mathcal{V},\|\cdot\|)$  is **complete** if every Cauchy sequence in  $\mathcal{V}$  converges to an element in  $\mathcal{V}$ .



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A complete, normed vector space is called a Banach Space.



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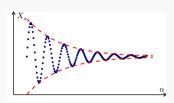
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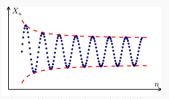
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# **Banach Space**

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https://en.wikipedia.org/wiki/File: Cauchy\_sequence\_illustration.svg



https://en.wikipedia.org/wiki/File: Cauchy\_sequence\_illustration2.svg

#### **LIPSCHITZ FUNCTIONS**



#### Definition

Let  $(\mathcal{V}, \|\cdot\|)$  be a **normed vector space**. A function

 $\mathcal{T}:\mathcal{V}\to\mathcal{V}$  is called L-Lipschitz if for any  $x,y\in\mathcal{V}$ 

$$\|T(x) - T(y)\| \le L\|x - y\|$$

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## **Fixed Point**

 $x \in \mathcal{V}$  is a fixed point of T if T(x) = x.



#### Definition

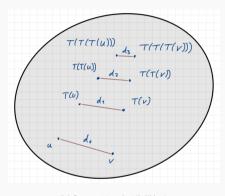
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If L < 1, T is a contraction.

#### **Fixed Point**

 $x \in V$  is a fixed point of T if T(x) = x.



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BANACH'S FIXED POINT THEOREM

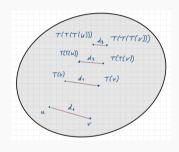
## BANACH'S FIXED POINT THEOREM



# Theorem !!

Let  $(\mathcal{V}, \|\cdot\|)$  be a **Banach space** and  $T: \mathcal{V} \to \mathcal{V}$  be a contraction. Then,

- 1. T has a unique fixed point  $x^*$  (i.e.,  $T(x^*) = x^*$ )
- 2. Iterating T, i.e.,  $T(\cdots T(T(x_0)))$ , converges to the fixed point  $x^*$  for any  $x_0$ .



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Numerical Demo in python

$$f(x) = \frac{1}{2}x + 1$$

$$|f(x) - f(y)| \le L \cdot |x - y|$$
  
 $|\frac{1}{2}x + 1 - (\frac{1}{2}y + 1)| \le L \cdot |x - y|$   
 $|\frac{1}{2}(x - y)| \le L \cdot |x - y|$   
 $|\frac{1}{2}(x - y)| \le L \cdot |x - y|$ 

$$f(x) = \frac{1}{2}x^{*} + 1 = x^{*}$$

$$1 = \frac{1}{2}x^{*}$$

$$2 = x^{*}$$

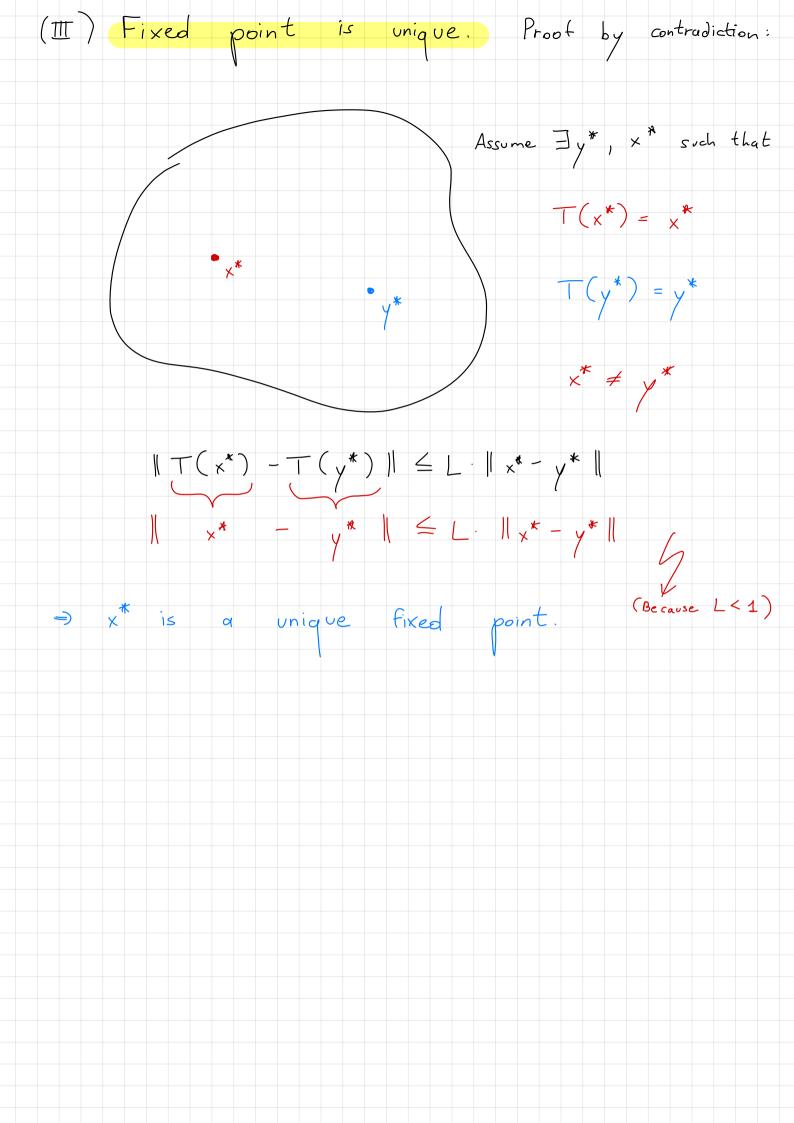


Proof of Banach's Fixed Point Theorem

```
Assume T is a contraction, i.e.,
         \|T(x)-T(y)\|\leq L\cdot \|x-y\|
                                                         Yx, y E R^
                                                                      \alpha_{1} = x_{0}
\alpha_{2} = T(x_{0})
 (I) \times_{o}, T(\times_{o}), T(T(\times_{o})),
   To show: (a_n)_{n \in \mathbb{N}} is (a_n)_{n \in \mathbb{N}}
                                                                    a_n = T(a_{n-1}), a_n = x_0
   \| T^{i+1}(x_0) - T^i(x_0) \| \leq L \cdot \| T^i(x_0) - T^{i-1}(x_0) \|
  \leq L^{2} \cdot \| T^{i-1}(x_{0}) - T^{i-2}(x_{0}) \|
                                        \leq L \parallel T(x_0) - x_0 \parallel
 \|T^{i+1}(x_0)-T^i(x_0)\leq L^i\|T(x_0)-x_0\|
  Assume i > j
\left( \begin{array}{c} e.g. \\ a_{4} - a_{1} \end{array} \right) = \left( \begin{array}{c} a_{4} - a_{3} + (a_{3} - a_{2}) + (a_{2} - a_{1}) \end{array} \right)
  \|a_{i} - a_{j}\| = \|(a_{i} - a_{i-1}) + (a_{i-1} - a_{i-2}) + (a_{i-2} - ) + (a_{j+1} - a_{j})\|
               \Delta-ineq.

\leq \|\alpha_{i} - \alpha_{i-1}\| + \|\alpha_{i-1} - \alpha_{i-2}\| + \ldots + \|\alpha_{j+1} - \alpha_{j}\|
```

$$\begin{cases} (1) & \leq L^{1-\alpha} \cdot \|T(x_0) - x_0\| + L^{1-2} \cdot \|T(x_0) - x_0\| + \dots + L^{d} \|T(x_0) - x_0\| \\ & = \|T(x_0) - x_0\| \cdot \sum_{k=0}^{d-1} L^k \\ & = \|T(x_0) - x_0\| \cdot \sum_{k=0}^{d-1} L^k \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \sum_{k=0}^{d} L^k \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \sum_{k=0}^{d} L^k \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) - x_0\| \cdot \frac{\Lambda}{\Lambda - L} < E \\ & = L^{d} \cdot \|T(x_0) -$$



# **ASSIGNMENT 1 QUESTIONS**

# REFERENCES I