

# $Ax=b$ : A Familiar Setup, Axioms and An Open Question

*Karthik P. N.*

*Joint work with Prof. Rajesh Sundaresan*

An example

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- Consider a problem of image reconstruction

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$$f = \sum_{j=1}^n x_j f_j, \quad f_j = \text{indicator of the } j\text{th pixel}$$



- *Measurements*



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🔍  $x$

$b$  ✓

- Goal: Recover  $x = (x_1, \dots, x_n)^T$  from the measurements

Criterion for / goodness of  
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# Criterion for / goodness of recovery

- Typically, one first defines a cost function

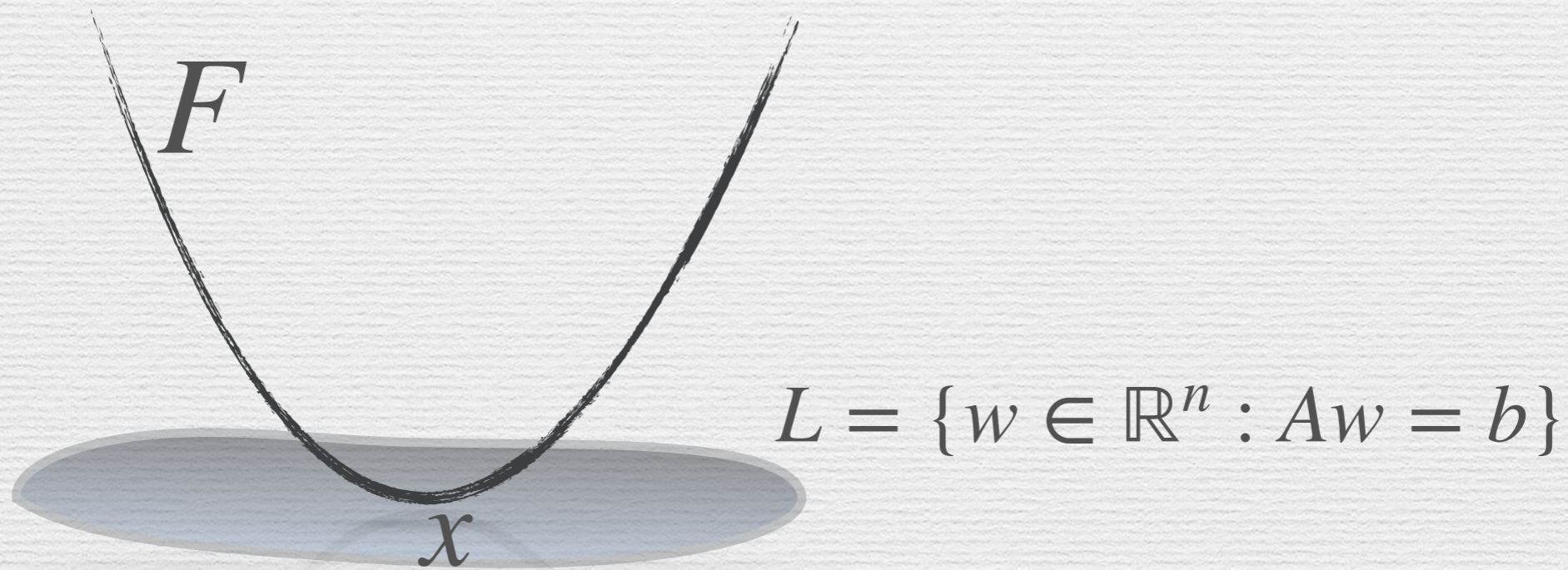


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$$L = \{w \in \mathbb{R}^n : Aw = b\}$$

$$x = \arg \min_{w \in L} F(w)$$

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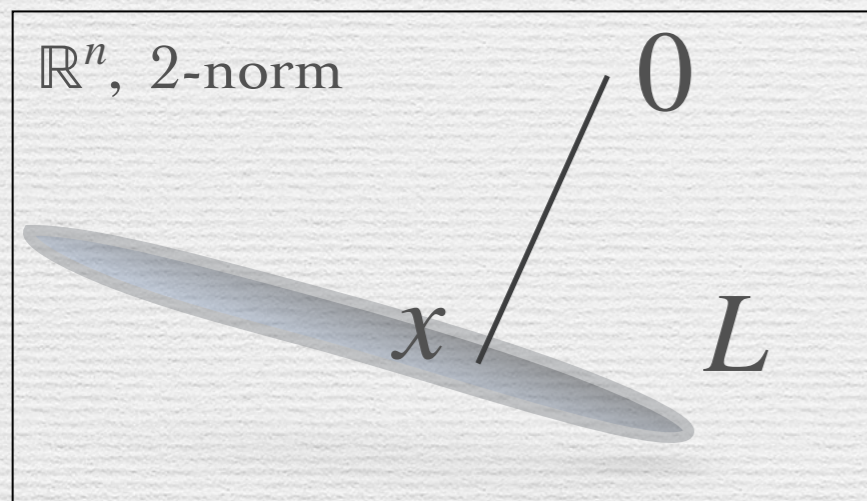
$$x = \arg \min_{w \in L \cap \mathbb{R}_+^n} \sum_{i=1}^n w_i \log \frac{w_i}{x_i^\star} - w_i + x_i^\star$$

# Function-minimisation approach

- The aforementioned methods are examples of “projection rules” that involve updating some prior guess

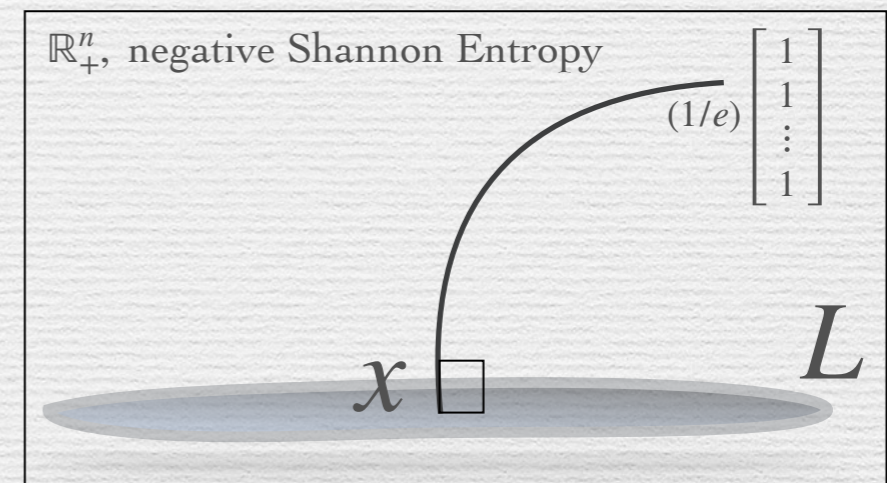
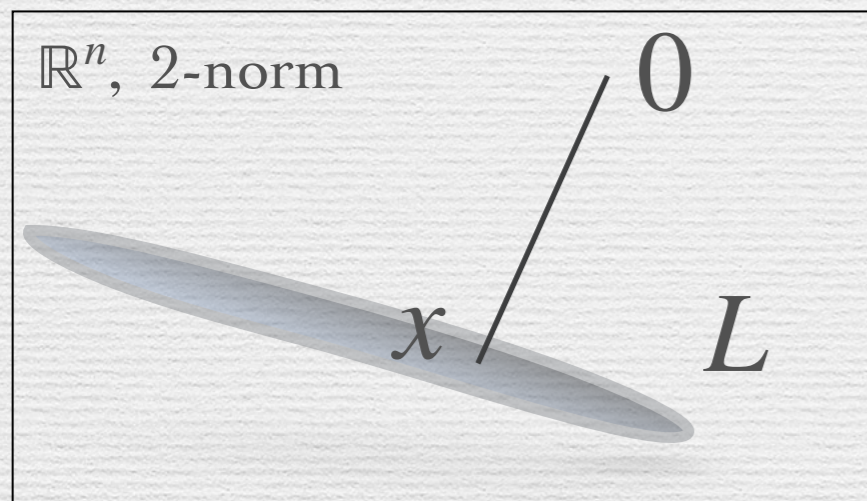
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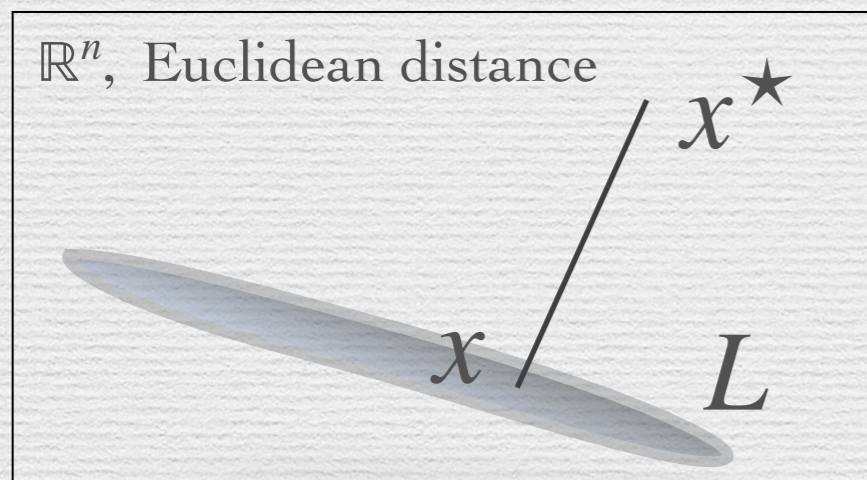
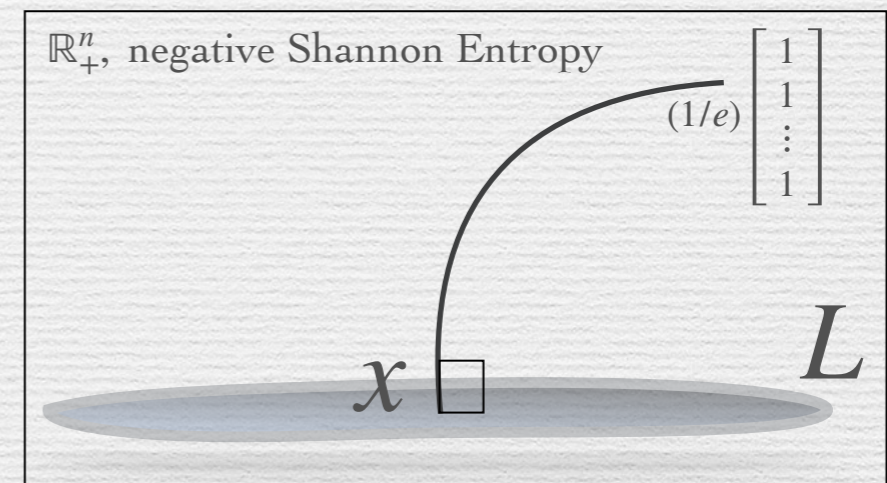
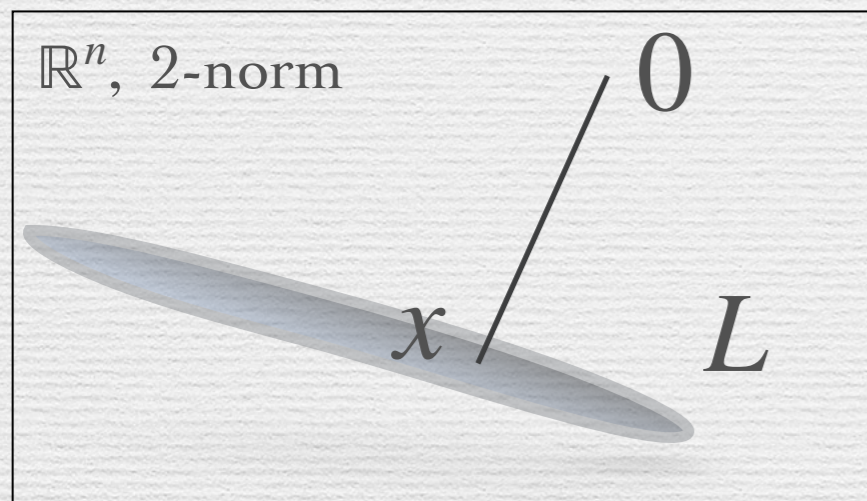
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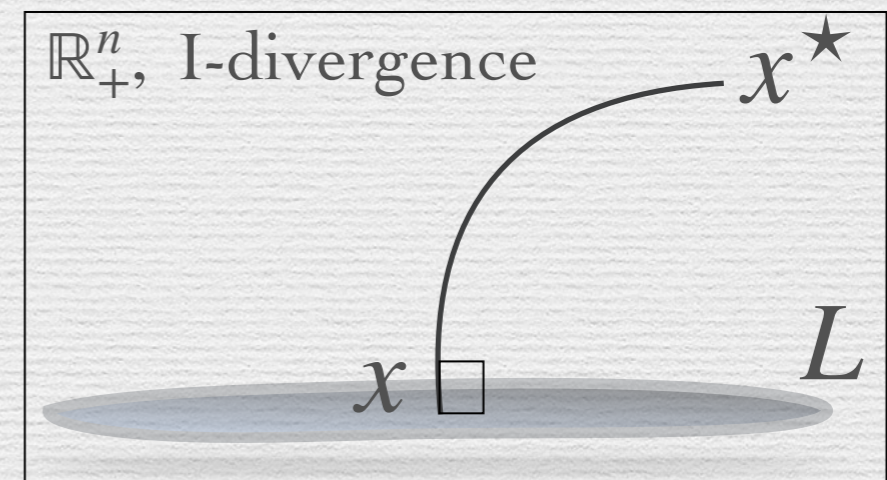
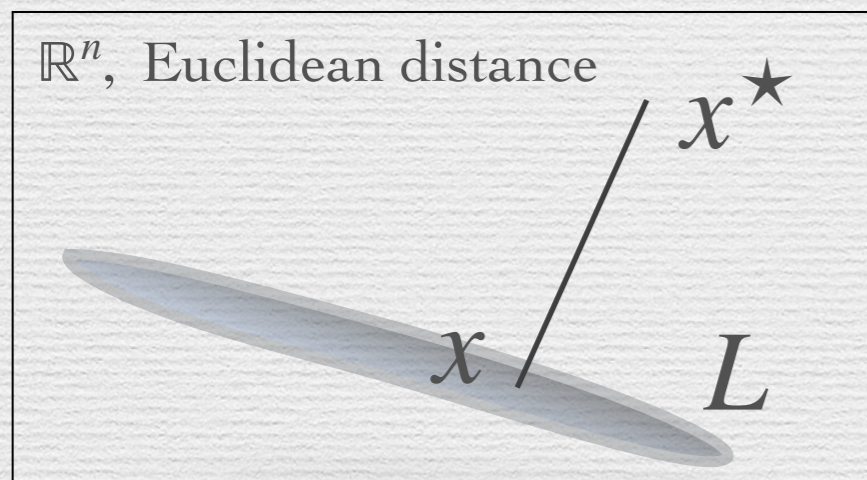
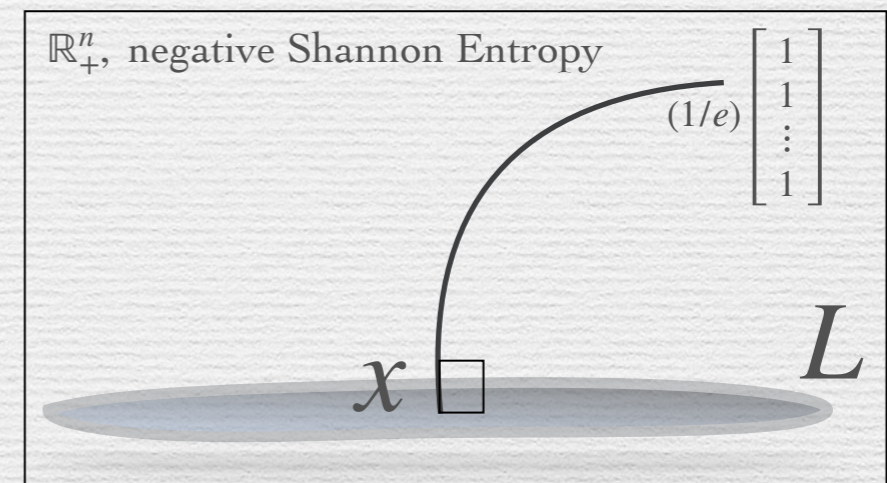
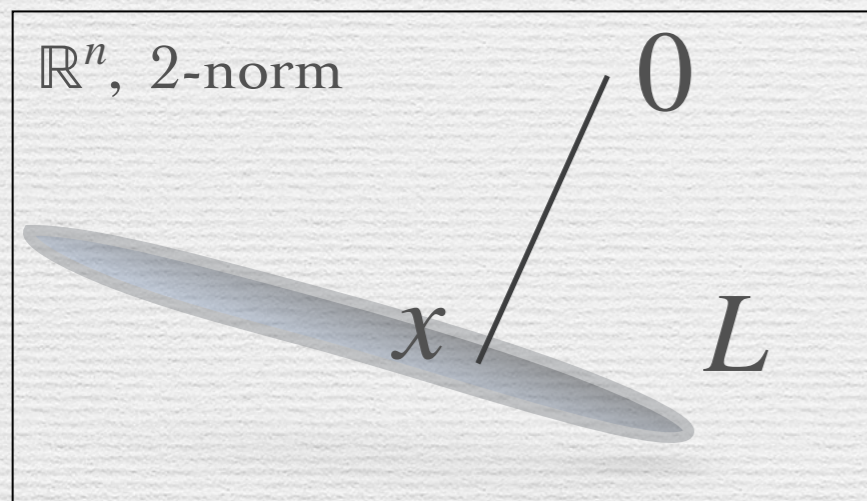
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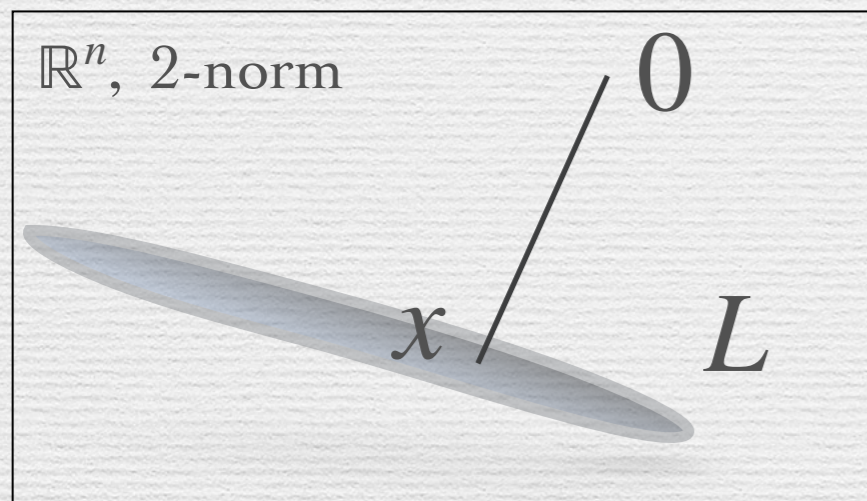
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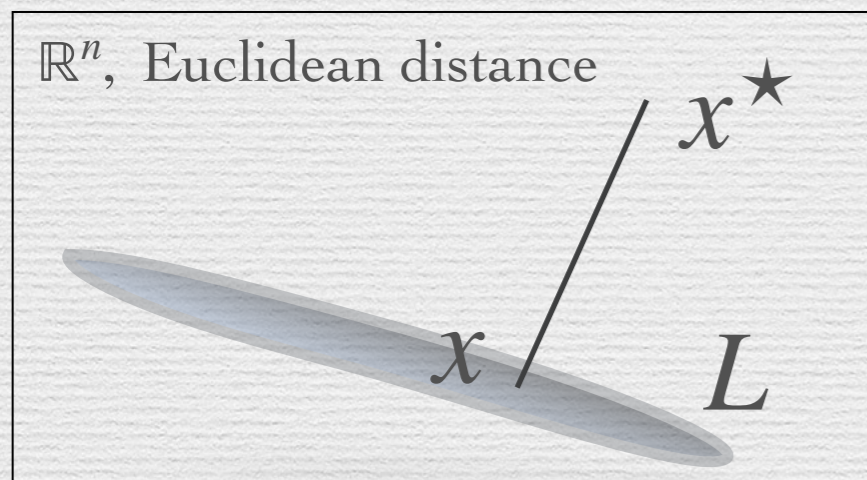
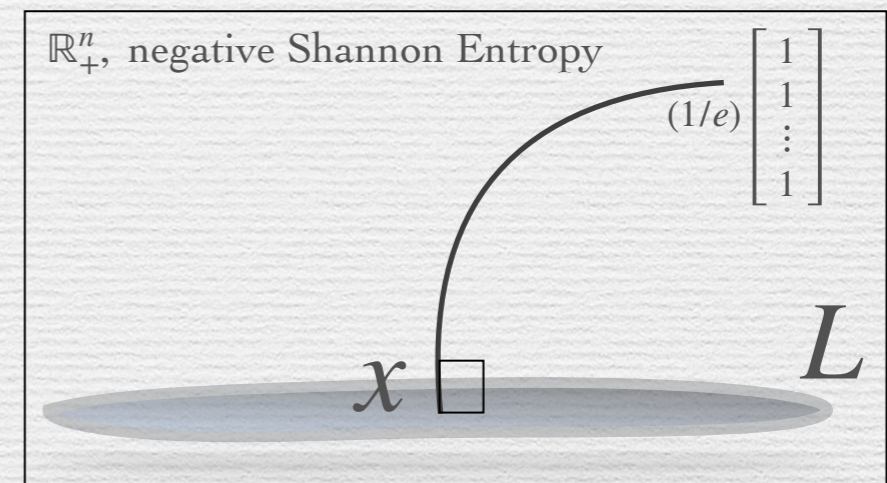


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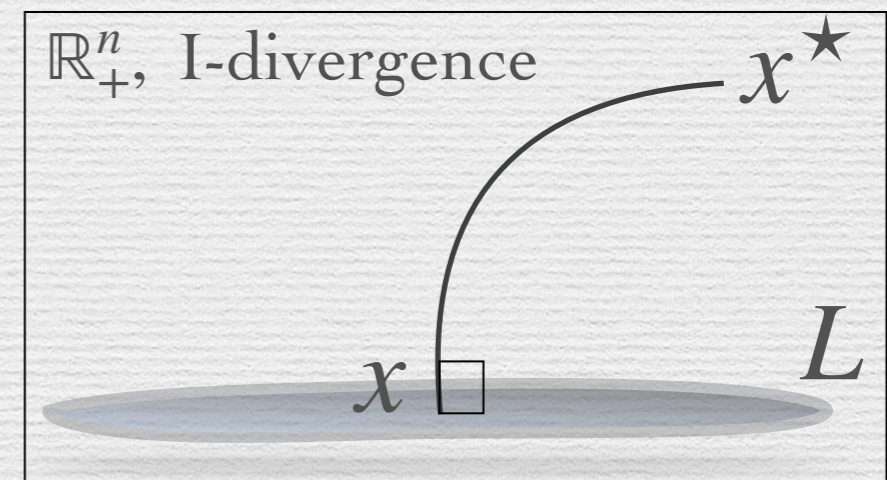
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Thus,  
function-  
minimisation



defines a  
projection  
rule



# Projection rules: formal definition

- Let

$$\mathcal{L} = \left\{ L = \{w \in \mathbb{R}^n : Aw = b\} : A \text{ is a } k \times n \text{ matrix having rank } k, b \in \mathbb{R}^k \right\}$$

where  $k = 0, 1, 2, \dots, n$

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Definition:  $\Pi$  is generated by  $F$ , if

$$\Pi(L | x^\star) = \arg \min_{w \in L} F(w | x^\star)$$

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*The Annals of Statistics*  
1991, Vol. 19, No. 4, 2032–2066

## **WHY LEAST SQUARES AND MAXIMUM ENTROPY? AN AXIOMATIC APPROACH TO INFERENCE FOR LINEAR INVERSE PROBLEMS<sup>1</sup>**

BY IMRE CSISZÁR

*Mathematical Institute of the Hungarian Academy of Sciences*

An attempt is made to determine the logically consistent rules for selecting a vector from any feasible set defined by linear constraints, when either all  $n$ -vectors or those with positive components or the probability vectors are permissible. Some basic postulates are satisfied if and only if the selection rule is to minimize a certain function which, if a “prior guess” is available, is a measure of distance from the prior guess. Two further natural postulates restrict the permissible distances to the author’s  $f$ -divergences and Bregman’s divergences, respectively. As corollaries, axiomatic characterizations of the methods of least squares and minimum discrimination information are arrived at. Alternatively, the latter are also characterized by a postulate of composition consistency. As a special case, a derivation of the method of maximum entropy from a small set of natural axioms is obtained.

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Axioms satisfied by a projection rule	Nature of the function generating the projection rule
<b>Regularity</b> + Locality	$F(w   x^\star) = \sum_{i=1}^n f_i(w_i   x_i^\star)$ , $f_i$ continuously differentiable and strictly convex
<b>Regularity</b> + Locality + Subspace Transitivity	$F(w   x^\star) =$ Bregman's divergence
<b>Regularity</b> + Locality + Subspace Transitivity + Statistical	$F(w   x^\star) =$ I-divergence
<b>Regularity</b> + Locality + Subspace Transitivity + Location Invariance + Scale Invariance	$F(w   x^\star) =$ Euclidean distance



# The axiom of regularity

$$\mathcal{M} = \left\{ \{w \in \mathbb{R}^n : a^T w = b\}, a \in \mathbb{R}^n, a \neq 0, b \in \mathbb{R} \right\}$$

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$\Pi : \mathcal{L} \times \mathbb{R}^n \rightarrow \mathbb{R}^n$  projection rule

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$\Pi$  satisfies regularity if, for all  $x^\star \in \mathbb{R}^n$ ,

Regularity

(Consistency)

$$L' \subset L, \Pi(L|x^\star) \in L' \implies \Pi(L'|x^\star) = \Pi(L|x^\star)$$

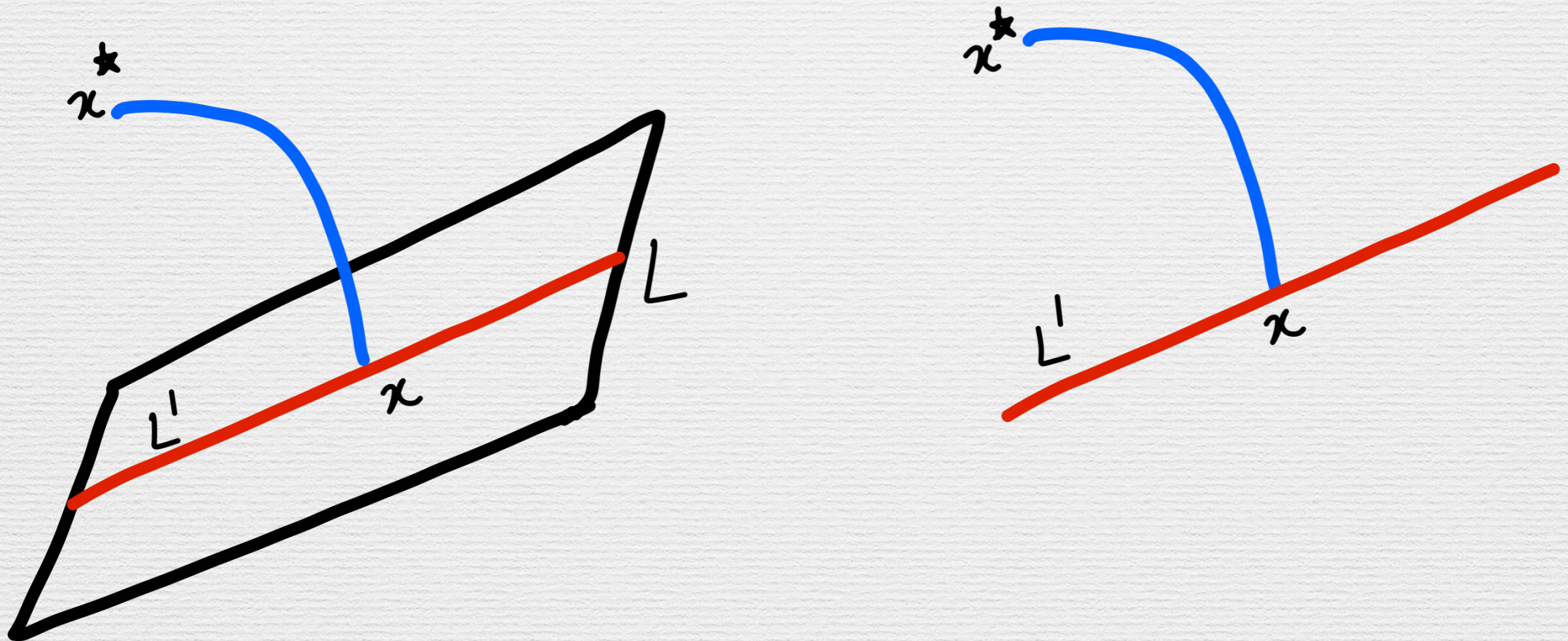
(Distinctness)

$$L, \tilde{L} \in \mathcal{M}, L \neq \tilde{L}, x^\star \notin L \cap \tilde{L} \implies \Pi(L|x^\star) \neq \Pi(\tilde{L}|x^\star)$$

(Continuity)

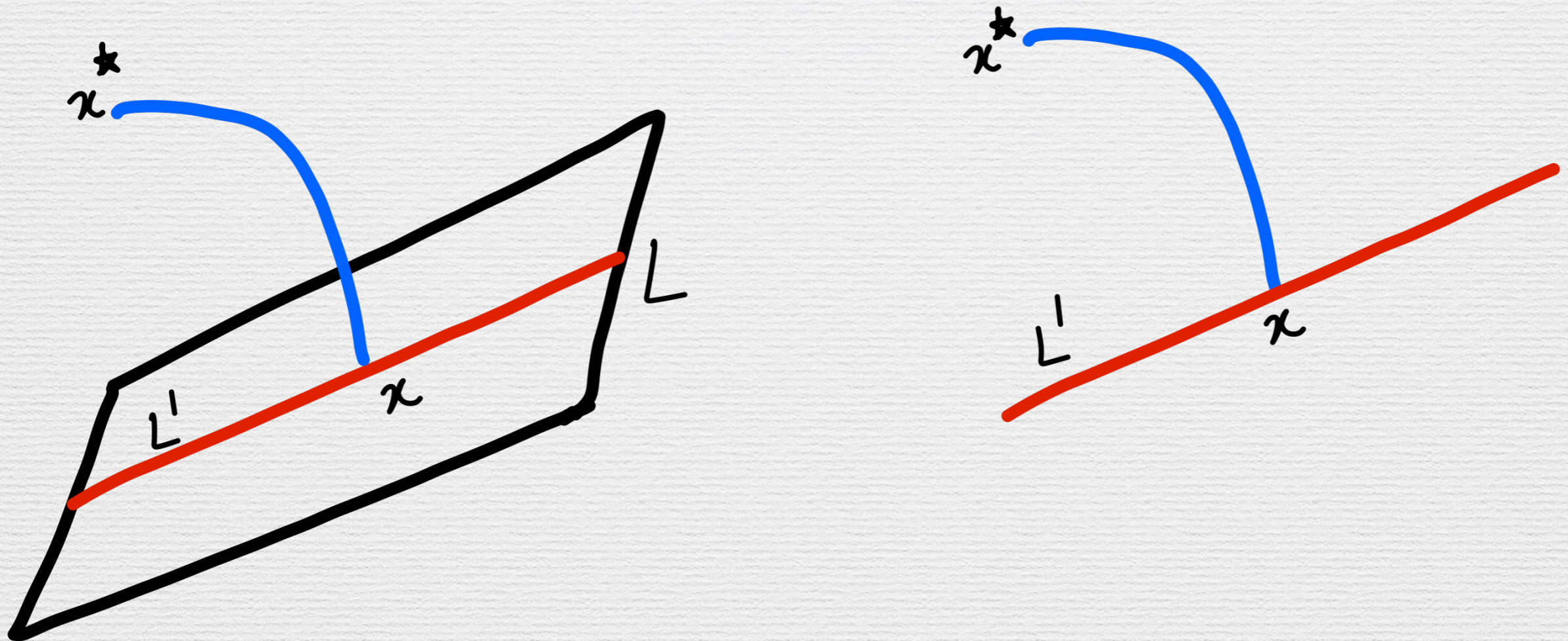
$\Pi(\cdot | x^\star)$  restricted to any fixed dimension is continuous

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$$L' \subset L, \Pi(L|x^*) \in L' \implies \Pi(L'|x^*) = \Pi(L|x^*)$$

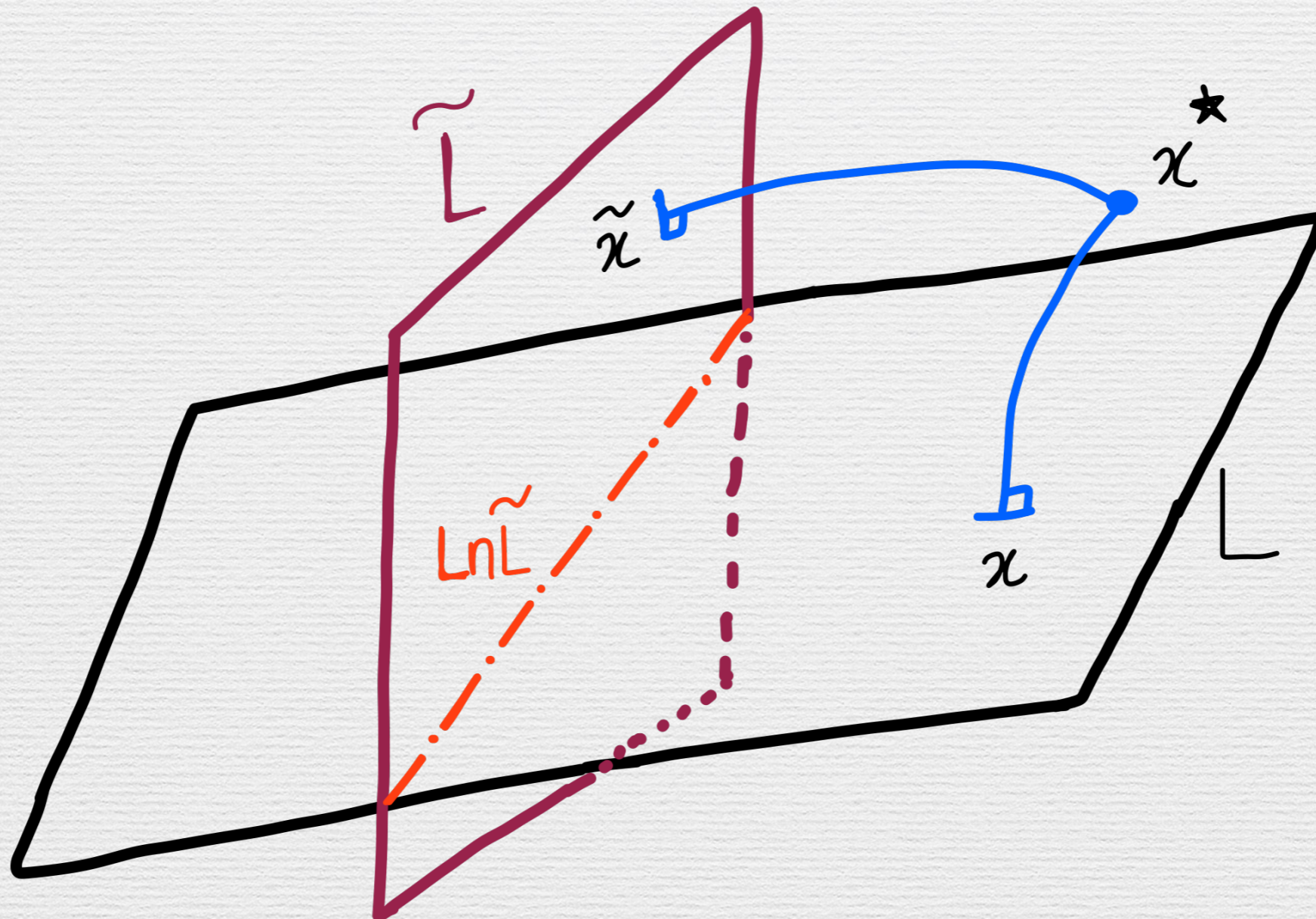
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Additional observations do not give a reason to change the original selection

# The axiom of distinctness



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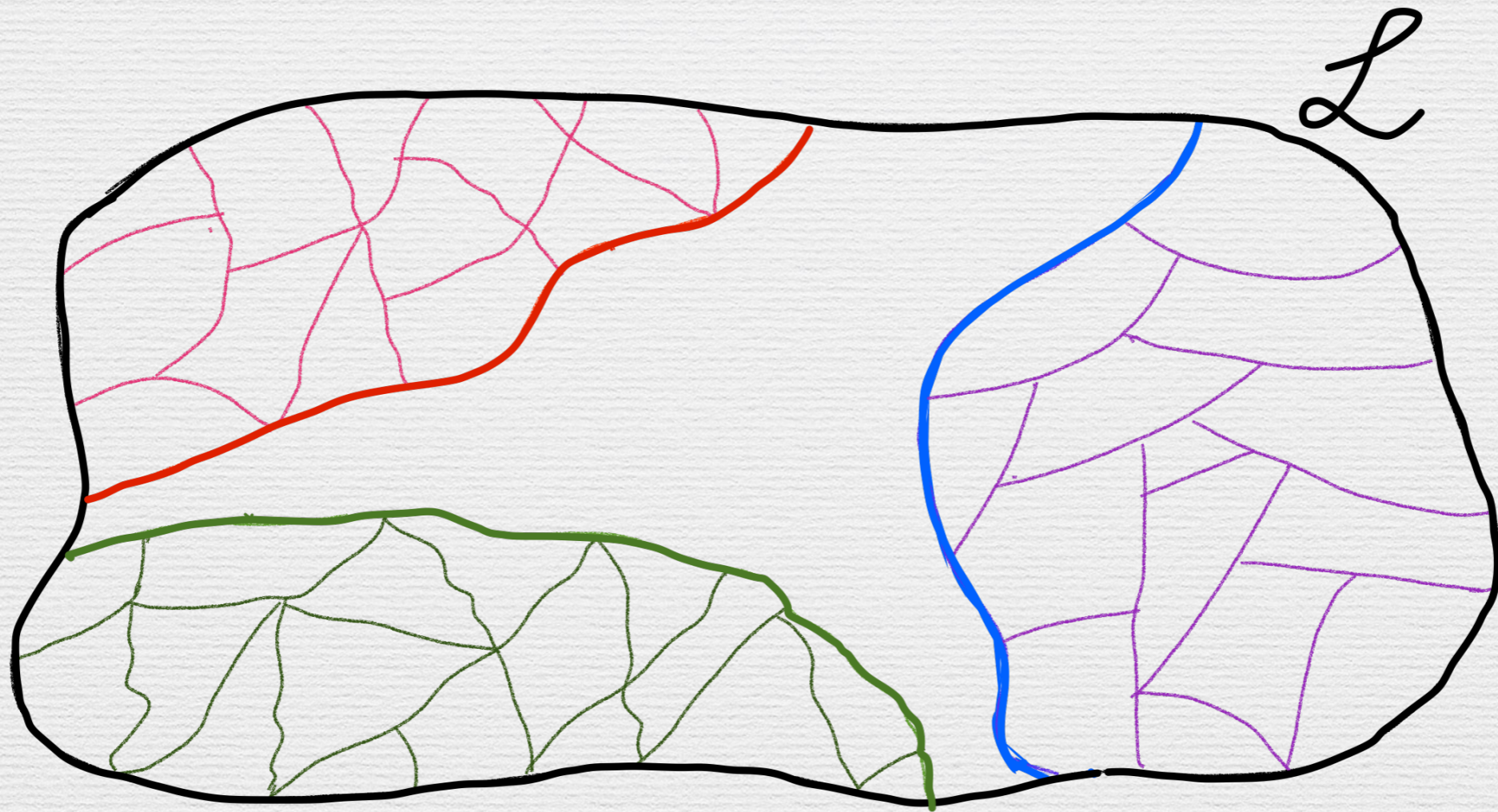
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- Topology on  $Y$  is the quotient topology derived out of the Euclidean topology on  $X$

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collection of all  $(n - 2)$ -dimensional sets

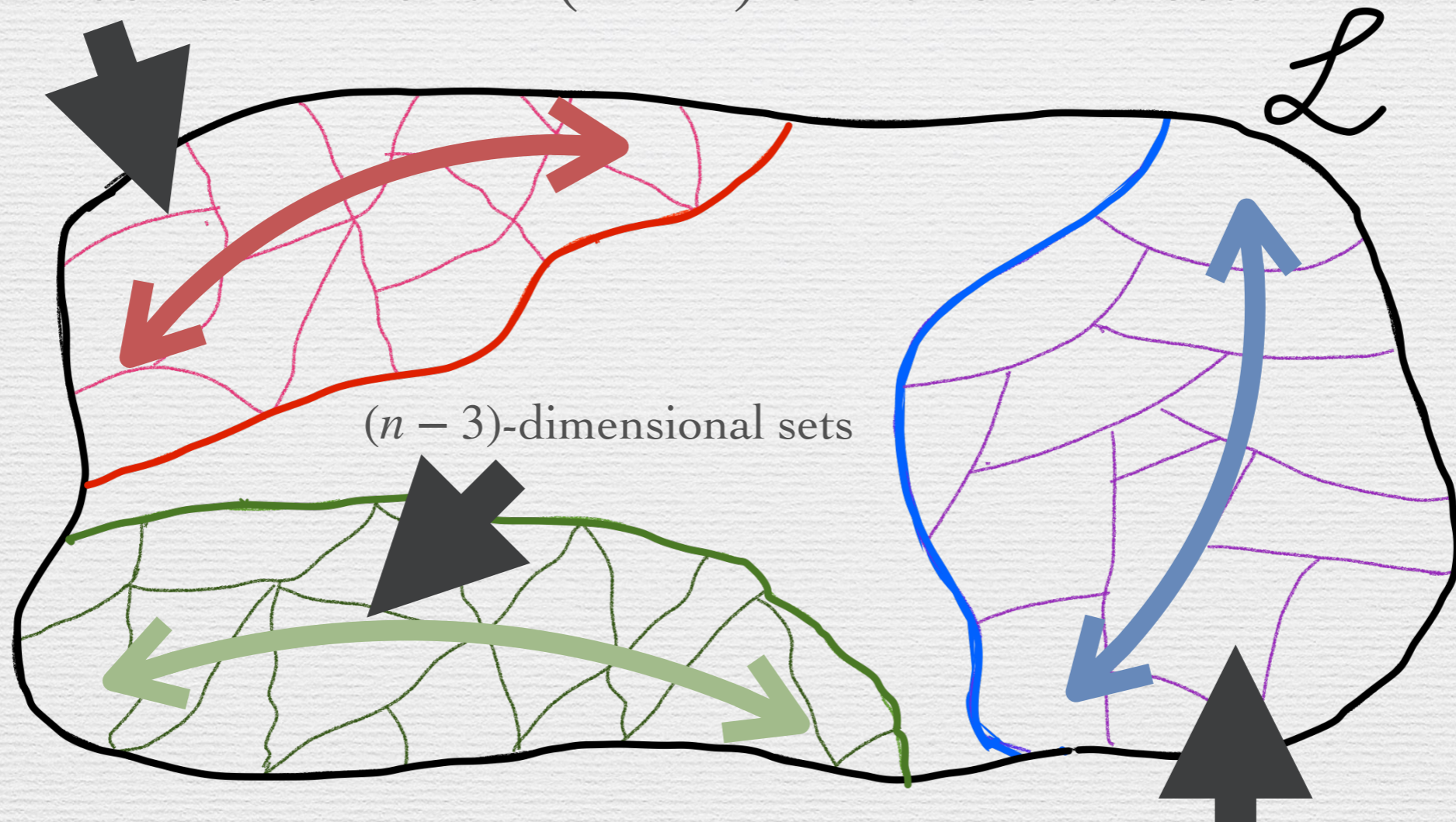


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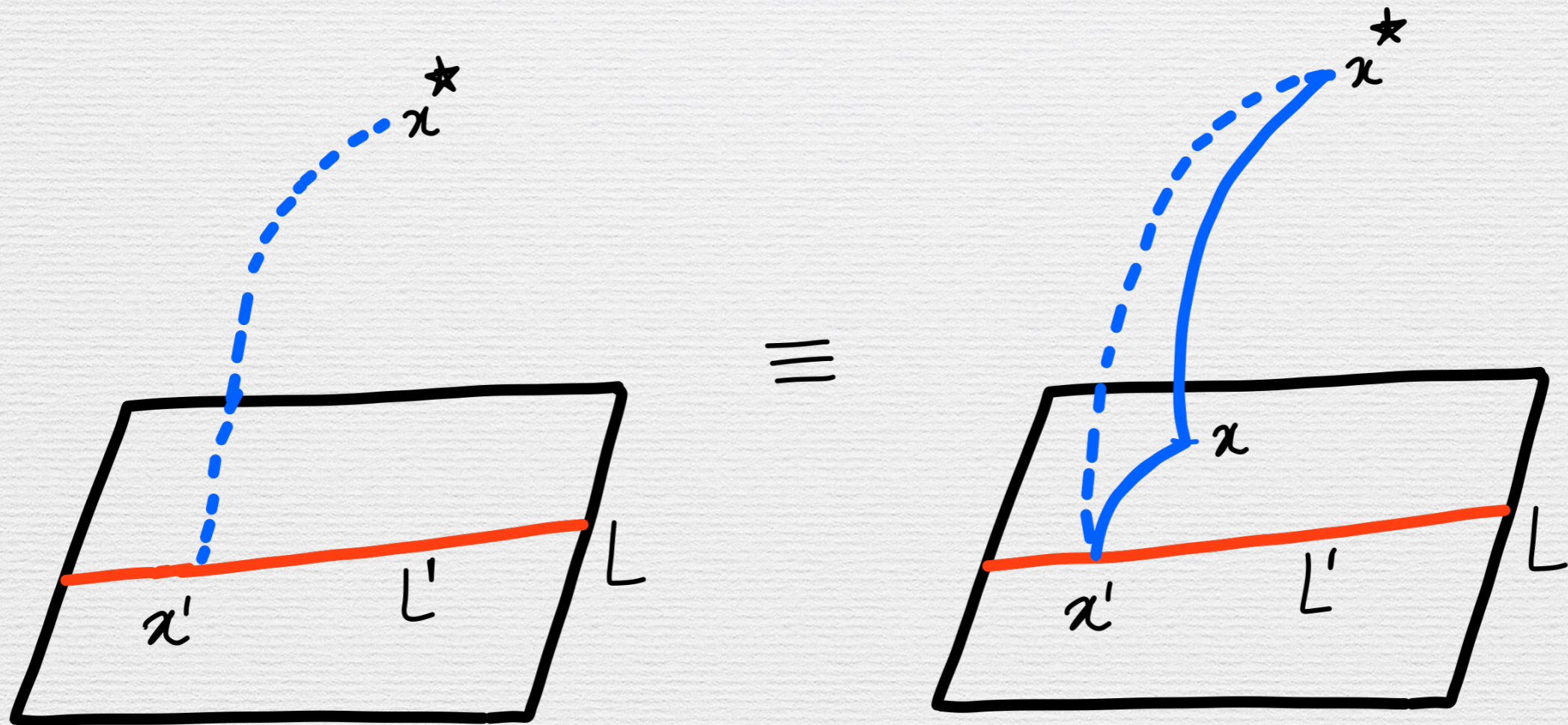
collection of all  $(n - 2)$ -dimensional sets



$\mathcal{M} =$  collection of all  $(n - 1)$ -dimensional sets

$\Pi(\cdot | x^*)$  restricted to any fixed dimension is continuous

# Axiom of subspace transitivity



$$L' \subset L \implies \Pi(L' | x^*) = \Pi(\Pi(L | x^*) | x^*)$$

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- These projection rules are generated by a divergence known as Sundaresan's divergence (relative  $\alpha$ -entropy)



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$$\mathcal{F}_\alpha(w, x) = \frac{\alpha}{1 - \alpha} \log \left( \sum_{i=1}^n \frac{w_i}{\|w\|} \left( \frac{x_i}{\|x\|} \right)^{\alpha-1} \right),$$

$$\text{where } \|x\| = \left( \sum_{i=1}^n x_i^\alpha \right)^{1/\alpha}, \quad \alpha > 0, \alpha \neq 1$$

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$$\text{where } \|x\| = \left( \sum_{i=1}^n x_i^\alpha \right)^{1/\alpha}, \quad \alpha > 0, \alpha \neq 1$$

- This is not a Bregman's divergence. Hence, the corresponding projection rule is not local

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Remainder of the talk is about regularity, and more....



# What we want to know about regularity

- Csiszár's results provide a necessary and sufficient axiomatic characterisation of many projection rules

Regularity + Locality  $\longleftrightarrow$  Projection rule generated by  $F(w | x^\star) = \sum_{i=1}^n f_i(w_i | x_i^\star)$

Regularity + Locality  
+ Subspace  
Transitivity  $\longleftrightarrow$  Projection rule generated by Bregman's divergence

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Regularity



Projection rule generated by ???

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$$\mathcal{L}^0(x^\star) = \left\{ L \in \mathcal{L} : \Pi(L | x^\star) = x^\star \right\}, \quad x^\star \in \mathbb{R}^n$$

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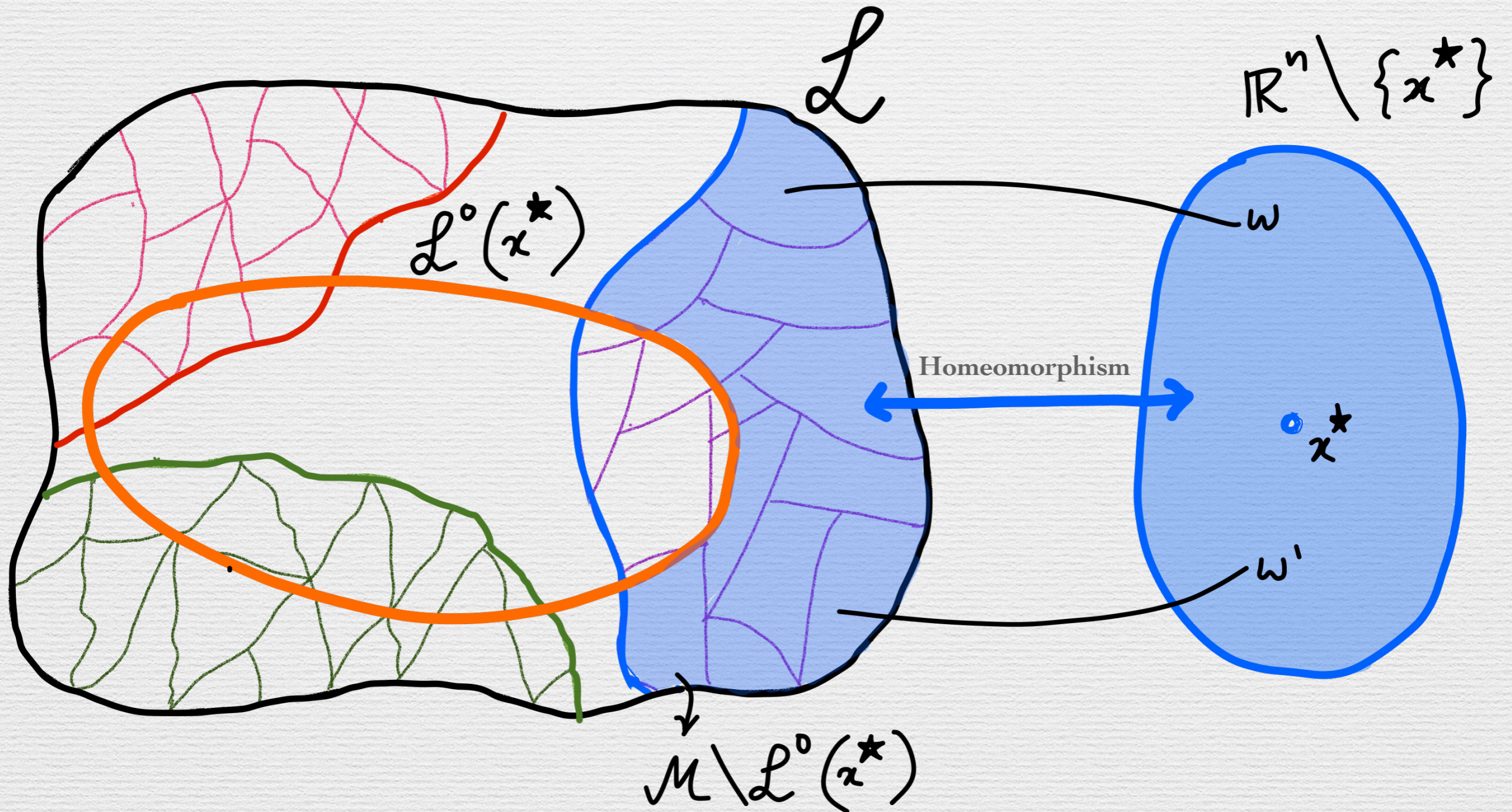
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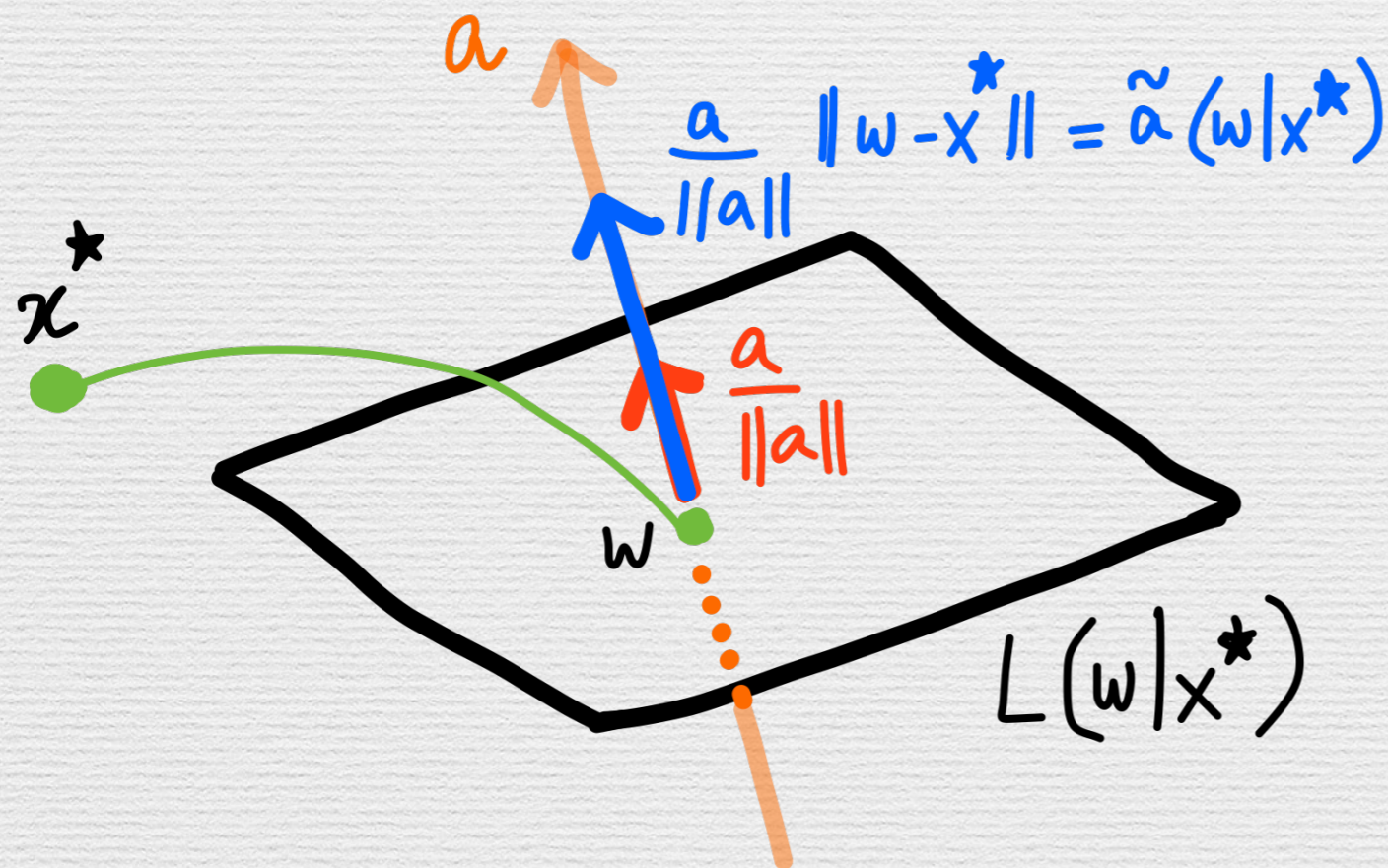


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This means that for every  $w \neq x^\star$ ,  
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$$\begin{aligned} L(w | x^*) &= \{y \in \mathbb{R}^n : a^T y = b\} \\ &= \{y \in \mathbb{R}^n : a^T y = a^T w\} \\ &= \left\{y \in \mathbb{R}^n : \frac{a^T}{\|a\|} (y - w) = 0\right\} \\ &= \left\{y \in \mathbb{R}^n : \tilde{a}(w | x^*)^T (y - w) = 0\right\} \end{aligned}$$

# Regularity and vector fields

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$$\tilde{a}(\cdot | x^\star) : \mathbb{R}^n \rightarrow \mathbb{R}^n$$

$\tilde{a}(\cdot | x^\star)$  continuous

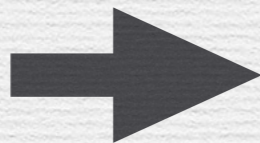
$$\tilde{a}(x^\star | x^\star) = 0,$$

$\tilde{a}(w | x^\star) \neq 0$  for all  $w \neq x^\star$

# Csiszár's results and vector fields

- The proof of Theorem 1 in Csiszár's paper reveals the following:

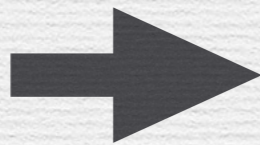
Regularity  
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There exists a smooth function

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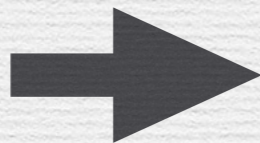
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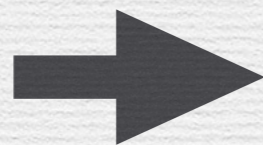


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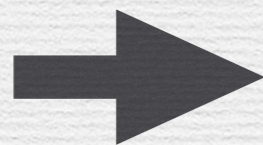
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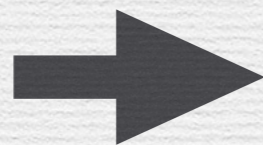
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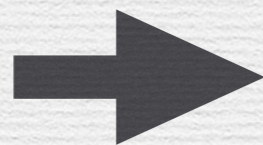
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**This particular form is due to locality axiom**

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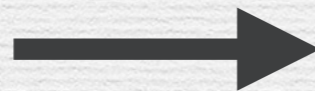
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Does there exist a nonzero scaling  $\lambda(\cdot | x^\star)$

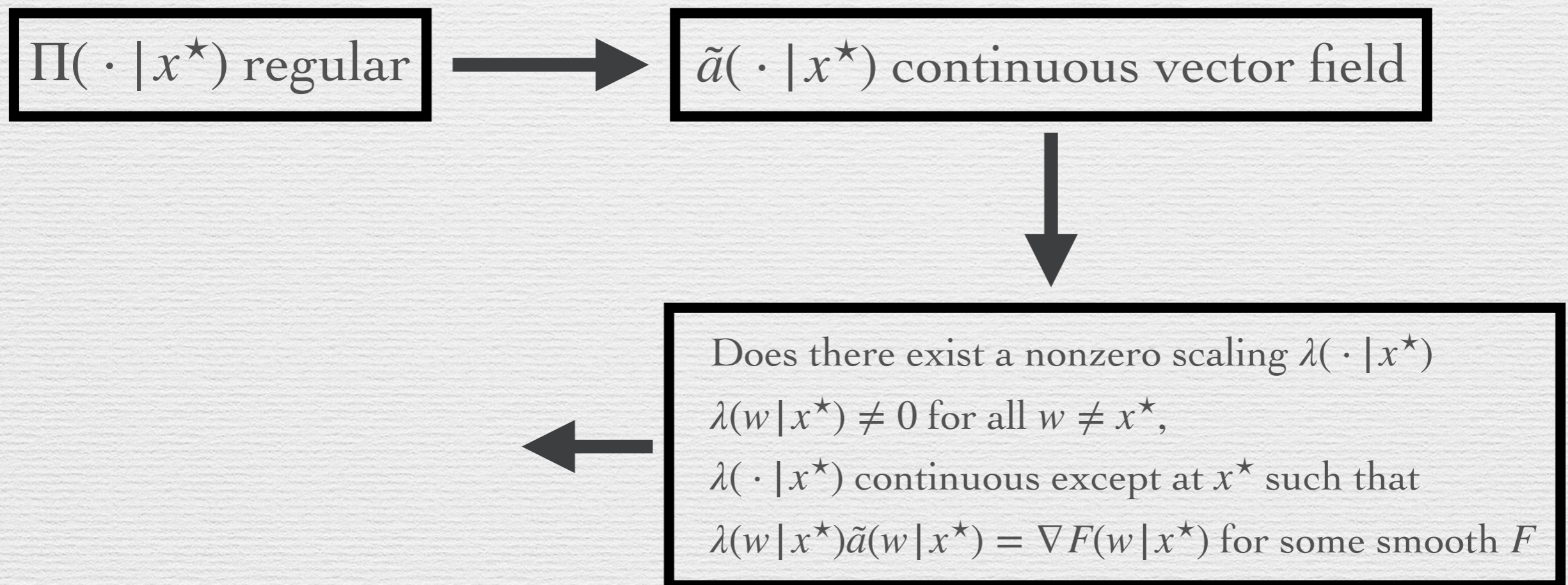
$\lambda(w | x^\star) \neq 0$  for all  $w \neq x^\star$ ,

$\lambda(\cdot | x^\star)$  continuous except at  $x^\star$  such that

$\lambda(w | x^\star)\tilde{a}(w | x^\star) = \nabla F(w | x^\star)$  for some smooth  $F$

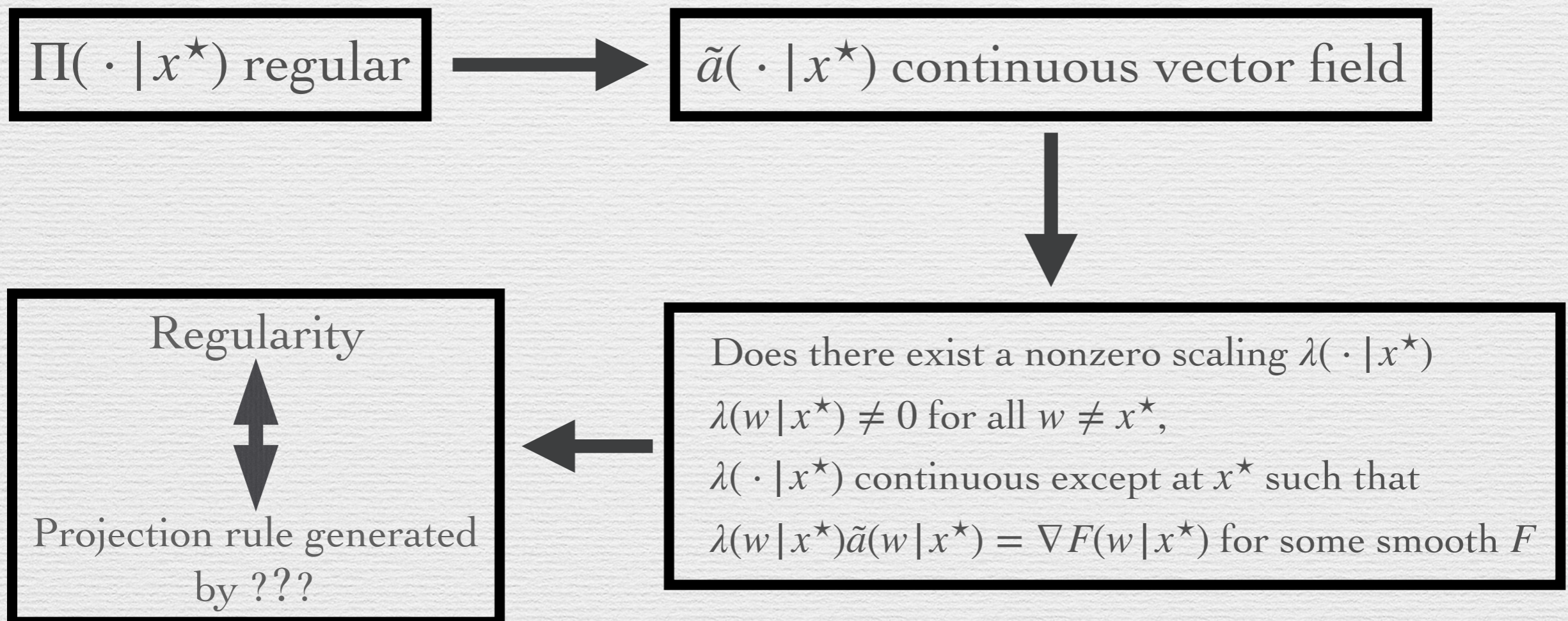
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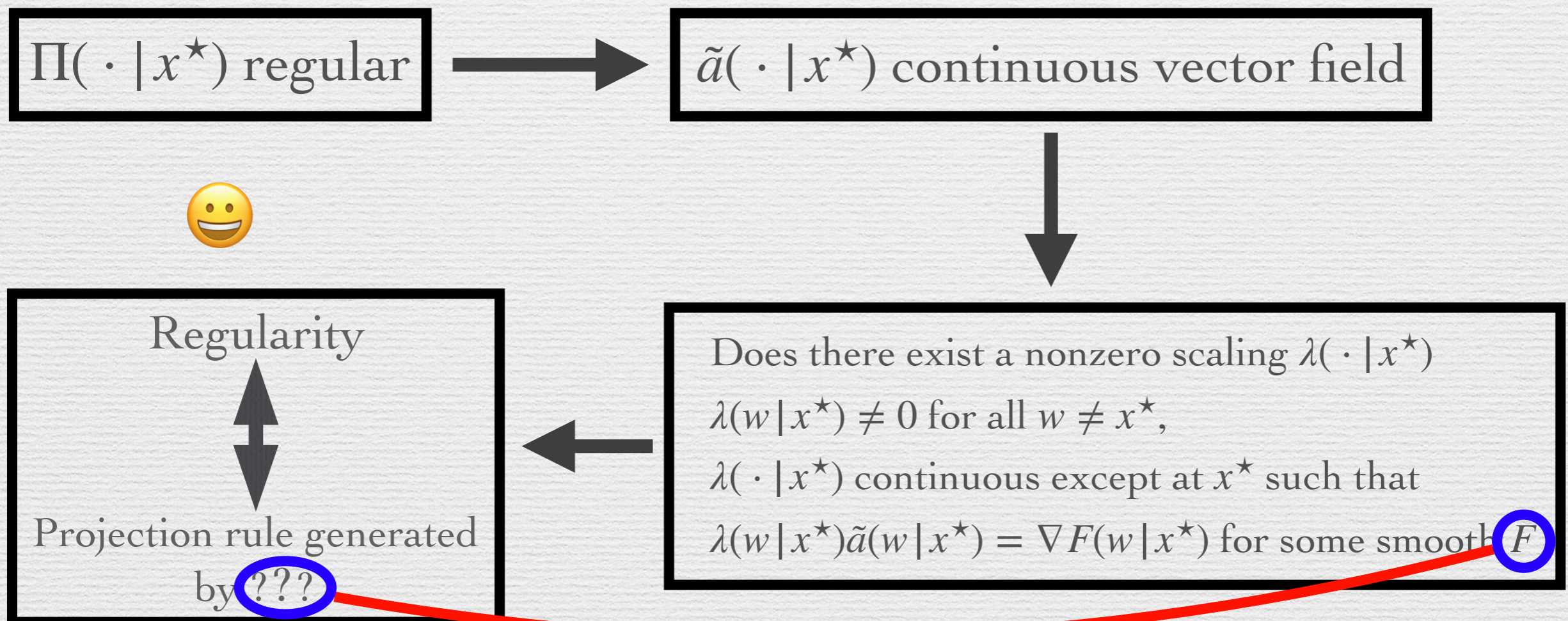
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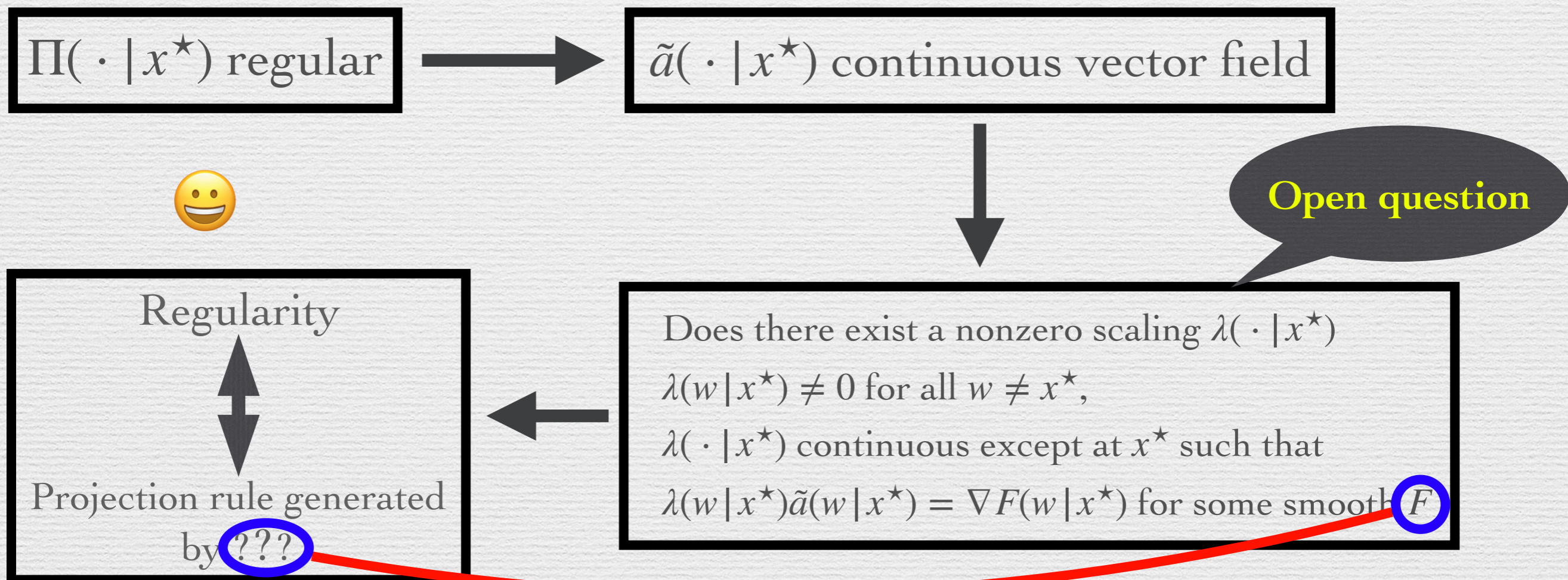
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$$a : \mathbb{R}^n \rightarrow \mathbb{R}^n \text{ continuous}$$

$$\lambda : \mathbb{R}^n \rightarrow \mathbb{R} \text{ continuous}$$

$$\lambda \cdot a = \nabla F?$$

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# Summary

- Axiomatic characterisation of projection rules
- Regularity: a fundamental axiom
- Regularity has connections with conservative vector fields
- Given a continuous vector field that is not necessarily conservative, is there a continuous scaling that can make the product vector field conservative? Open!

Thank you



# The axiom of locality

- Consider two sets  $L$  and  $\tilde{L}$  of the form

$$L = \{w \in \mathbb{R}^n : w_J \in L_0, w_{J^c} \in L'\}$$

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where  $J \subset \{1, 2, \dots, n\}$  is arbitrary

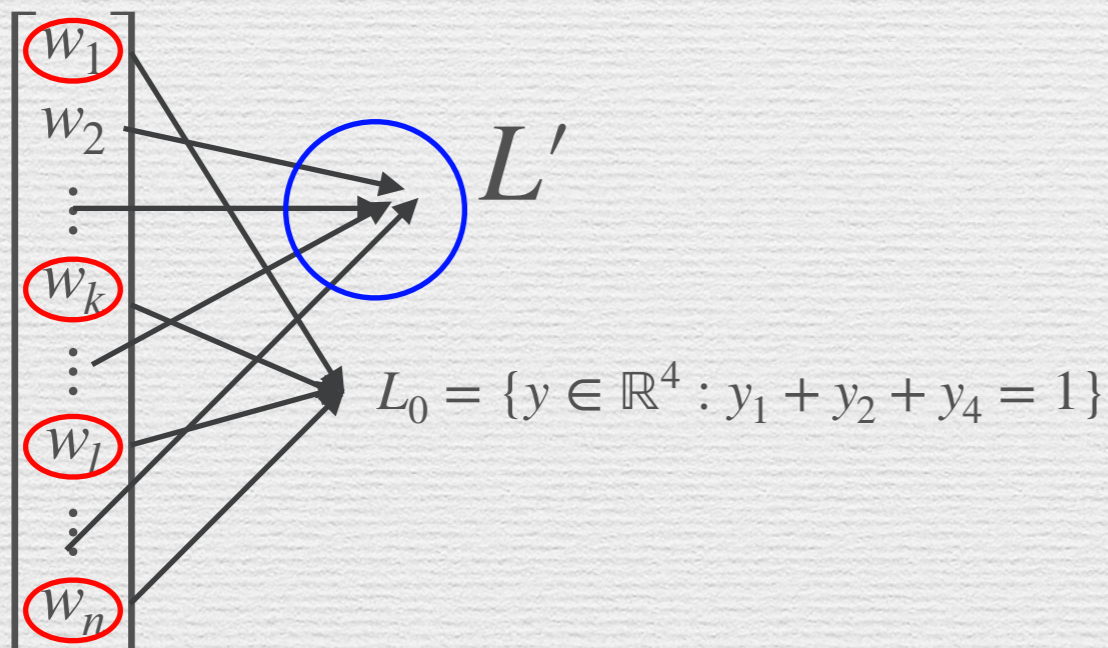
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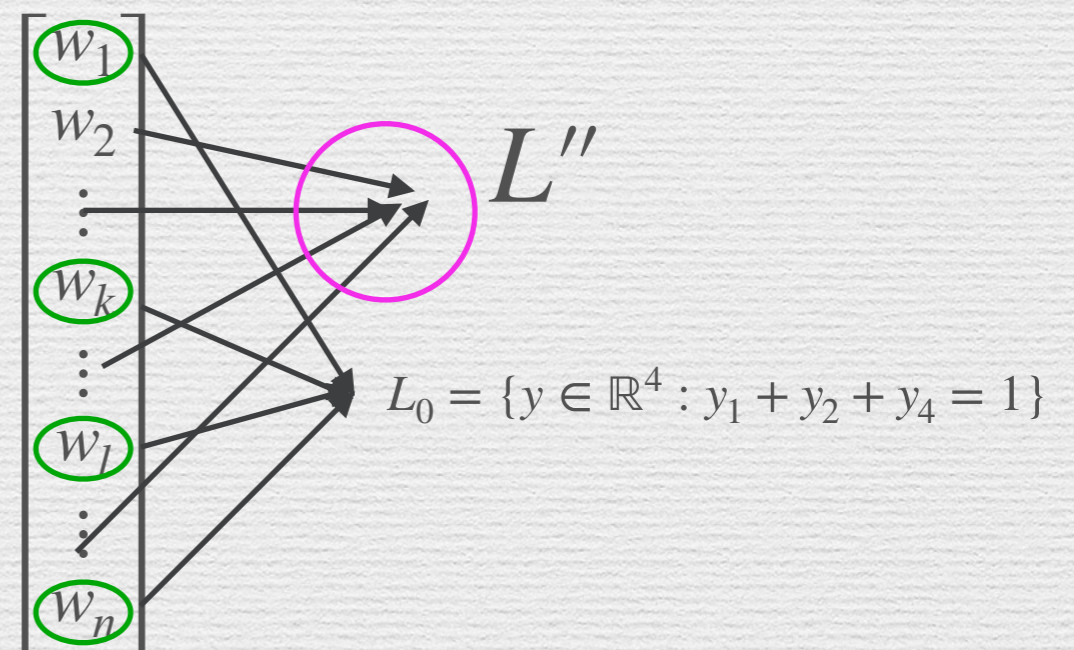
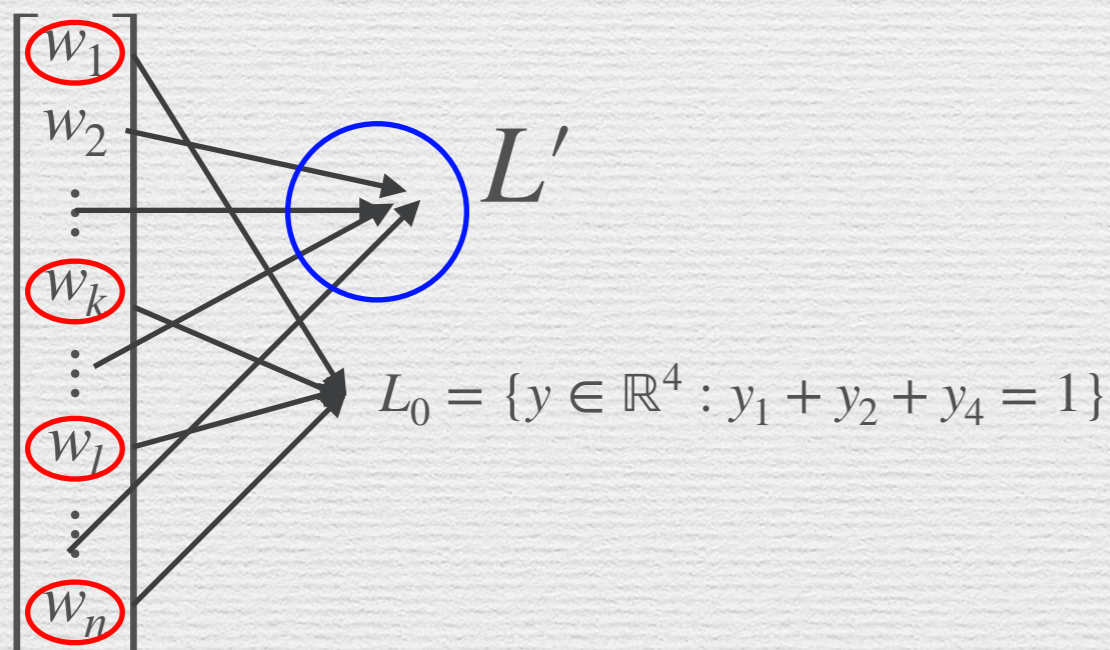
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$$\text{Then, } (\Pi(L | x^\star))_J = (\Pi(\tilde{L} | x^\star))_J$$

