

THE PERSISTENCE OF A SELF-MAP

HERBERT EDELSBRUNNER

IST AUSTRIA

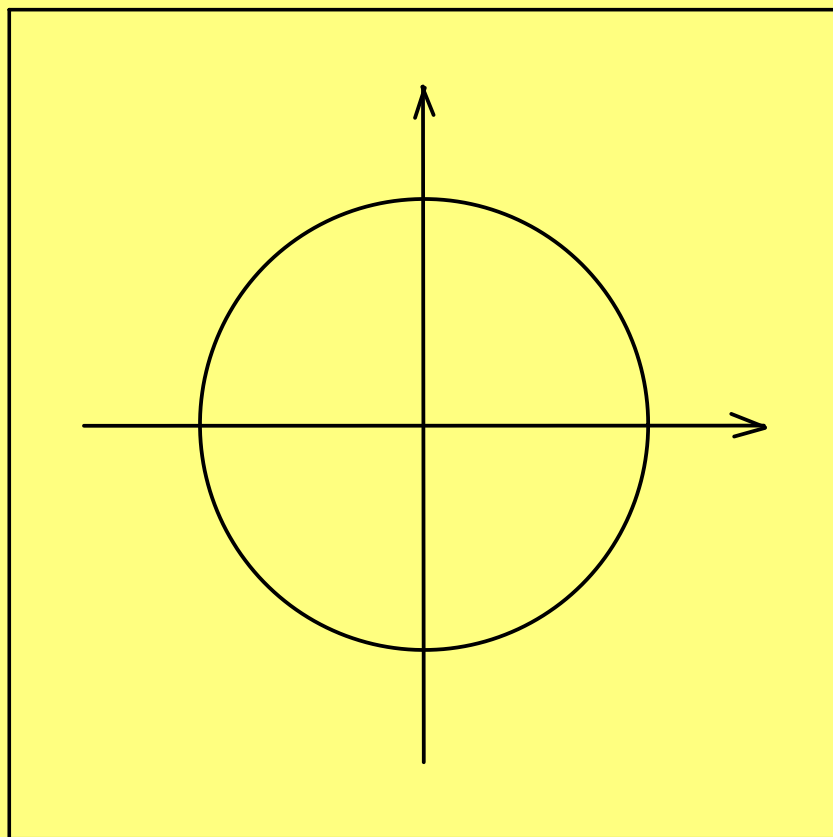
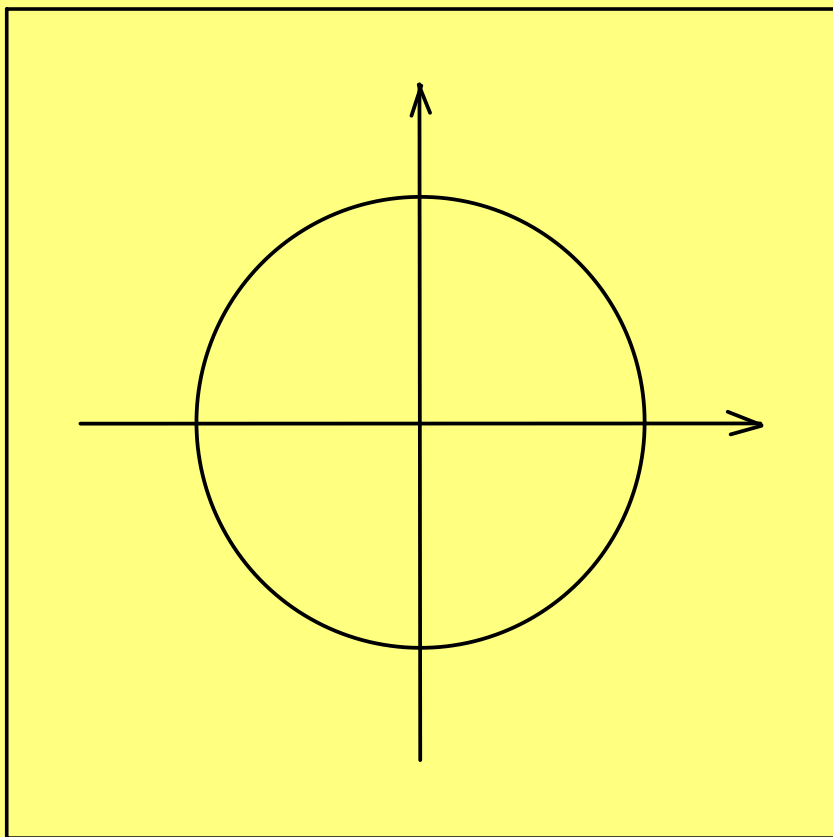
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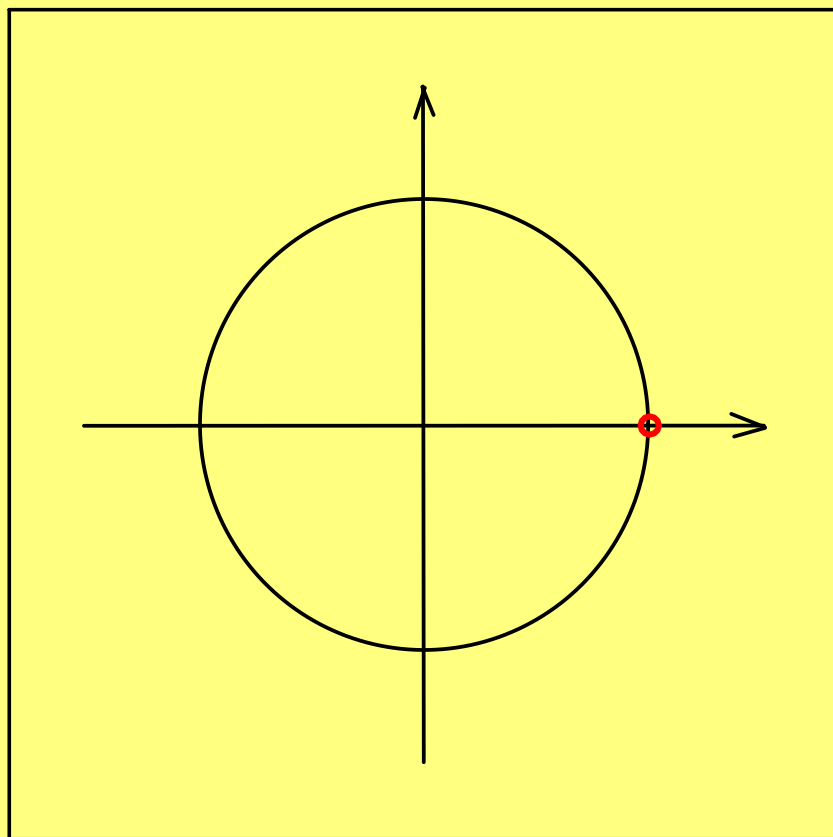
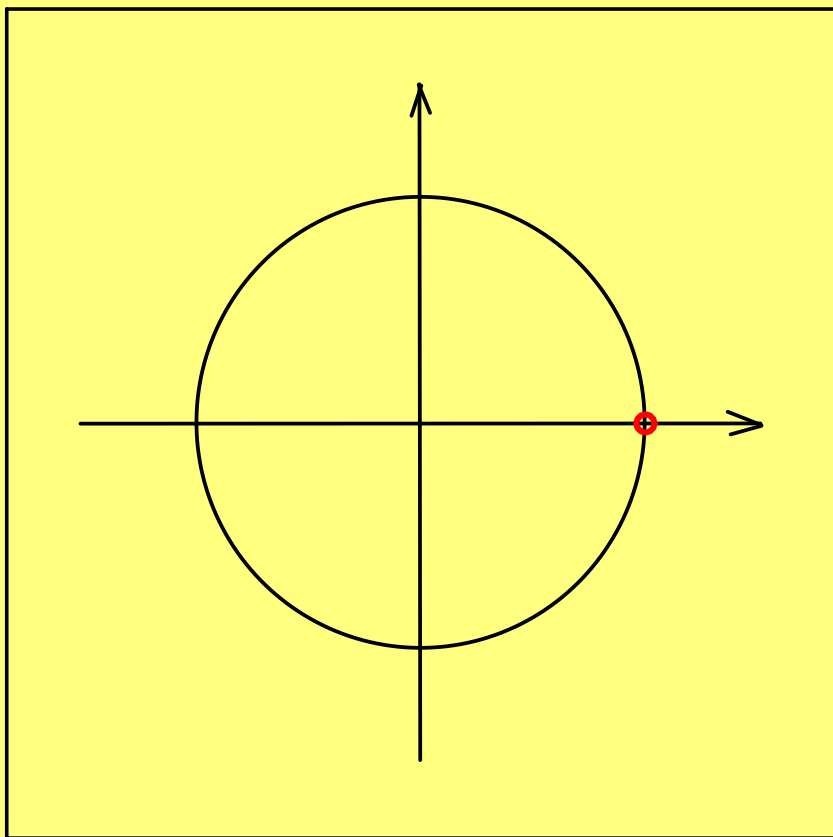
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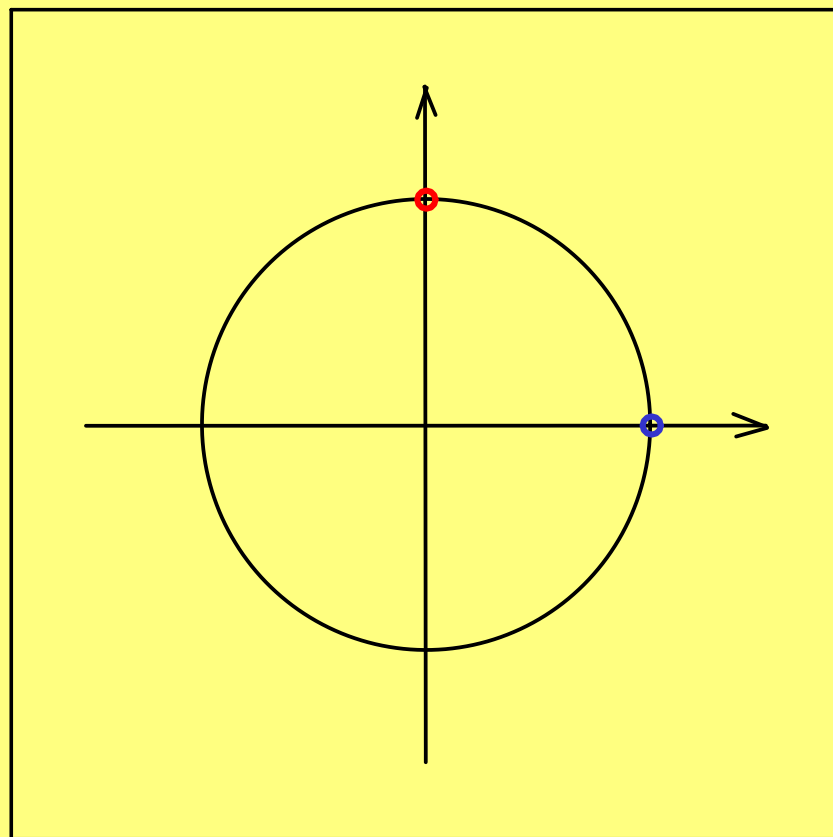
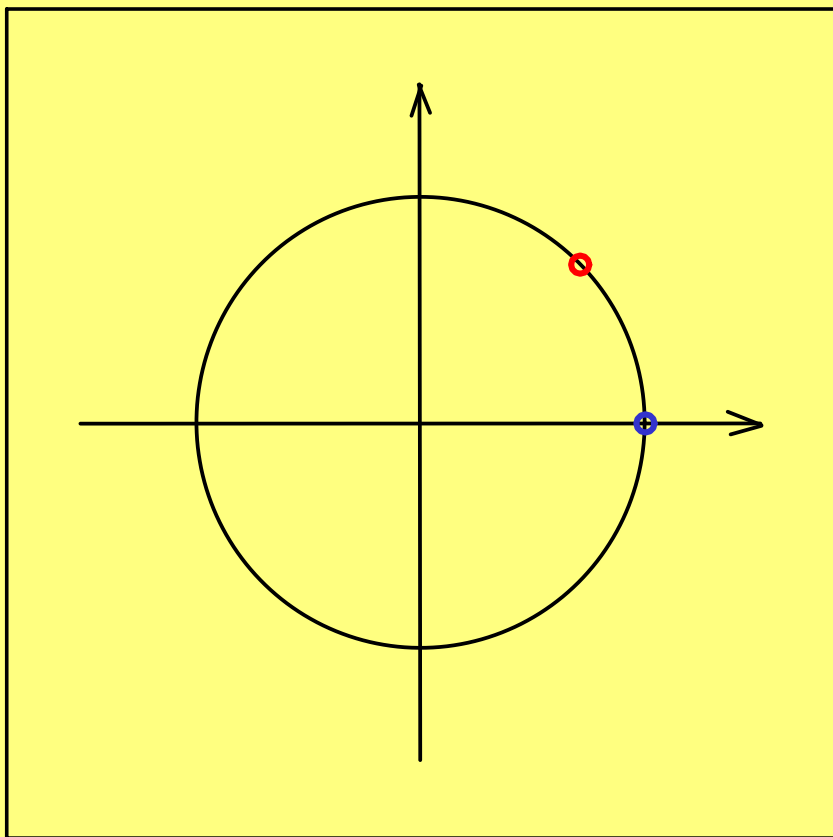
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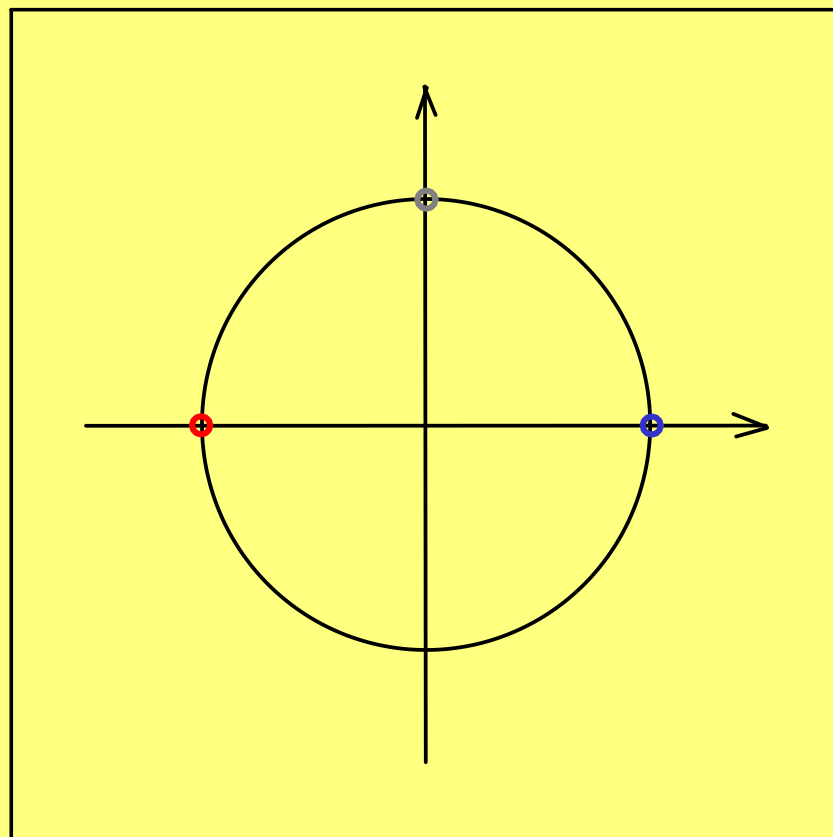
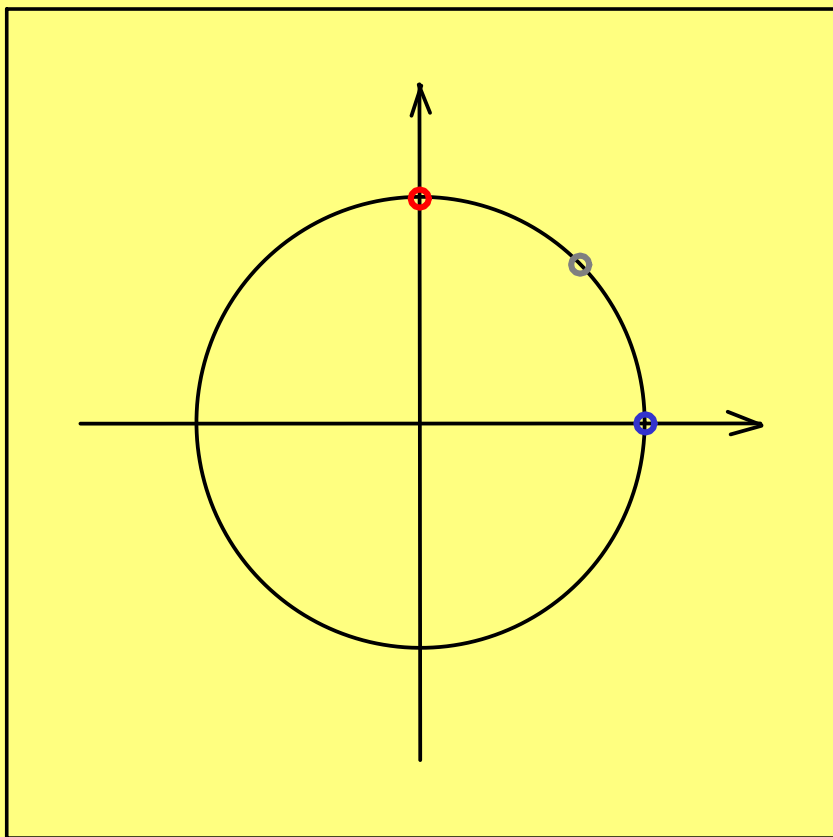
with GRZEGORZ JABŁOŃSKI and MARIAN MROZEK

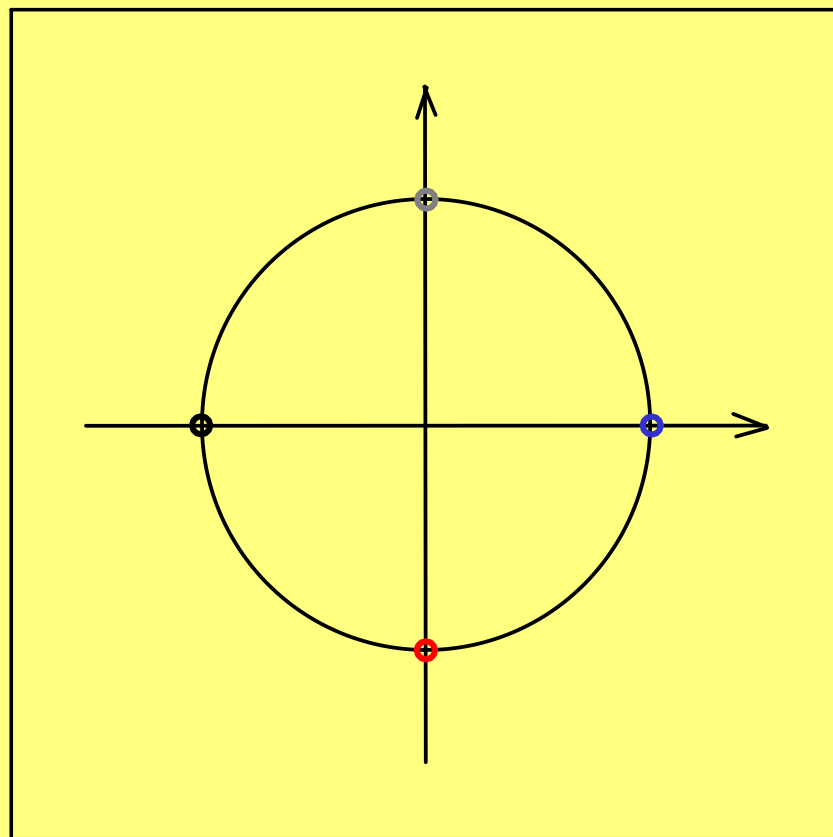
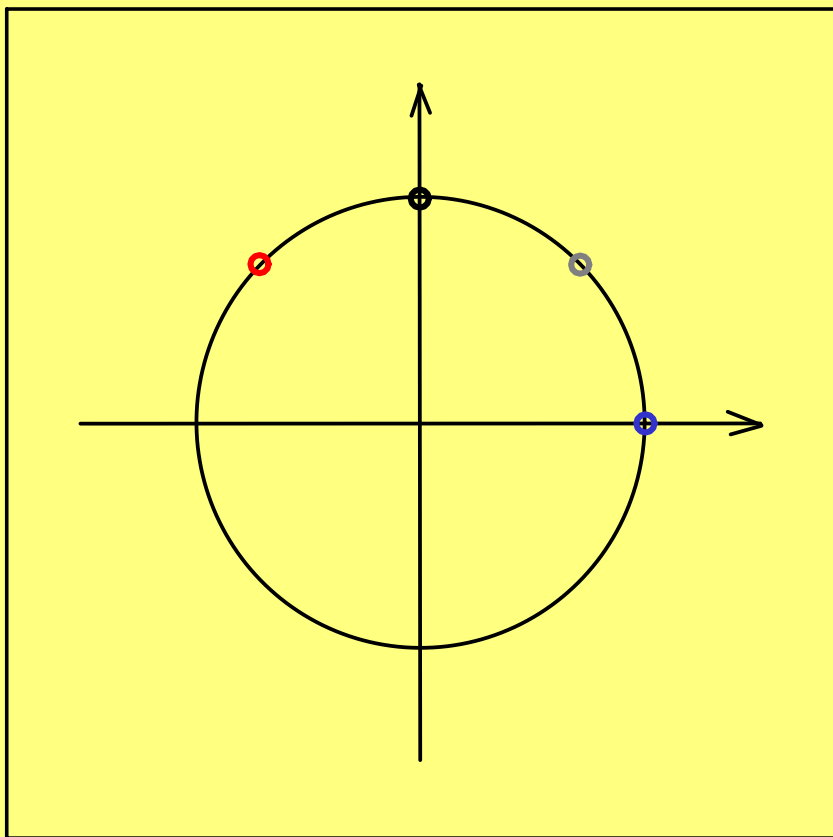
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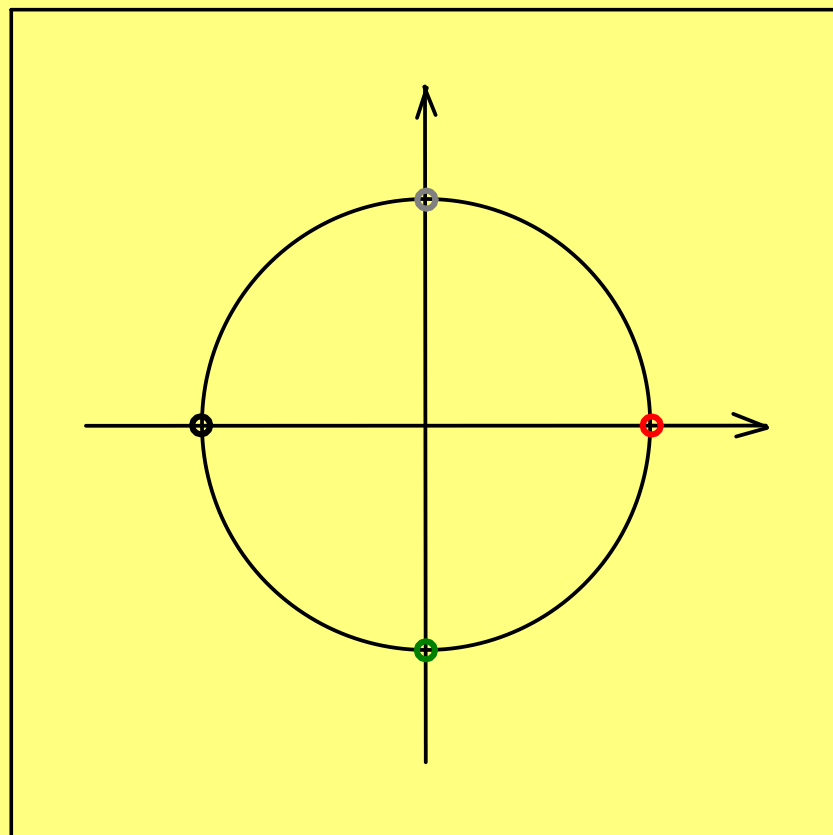
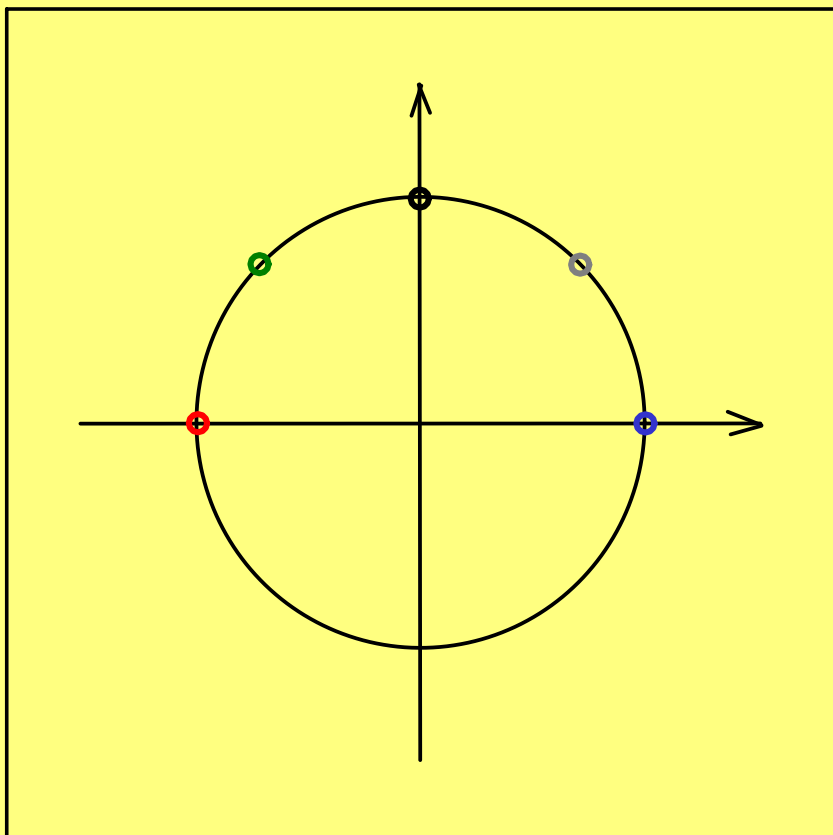


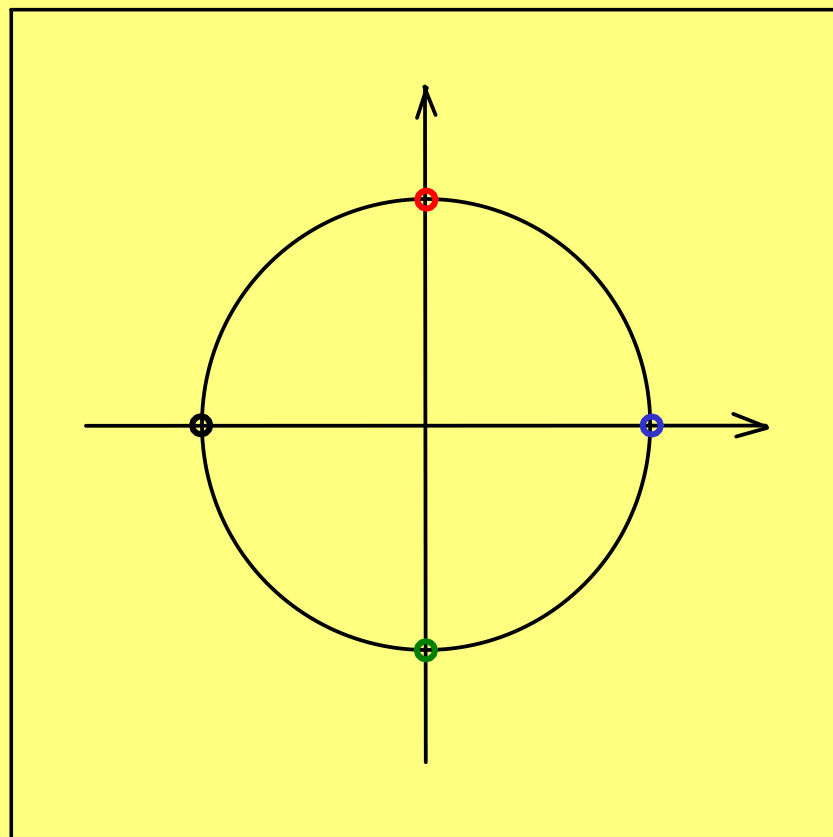
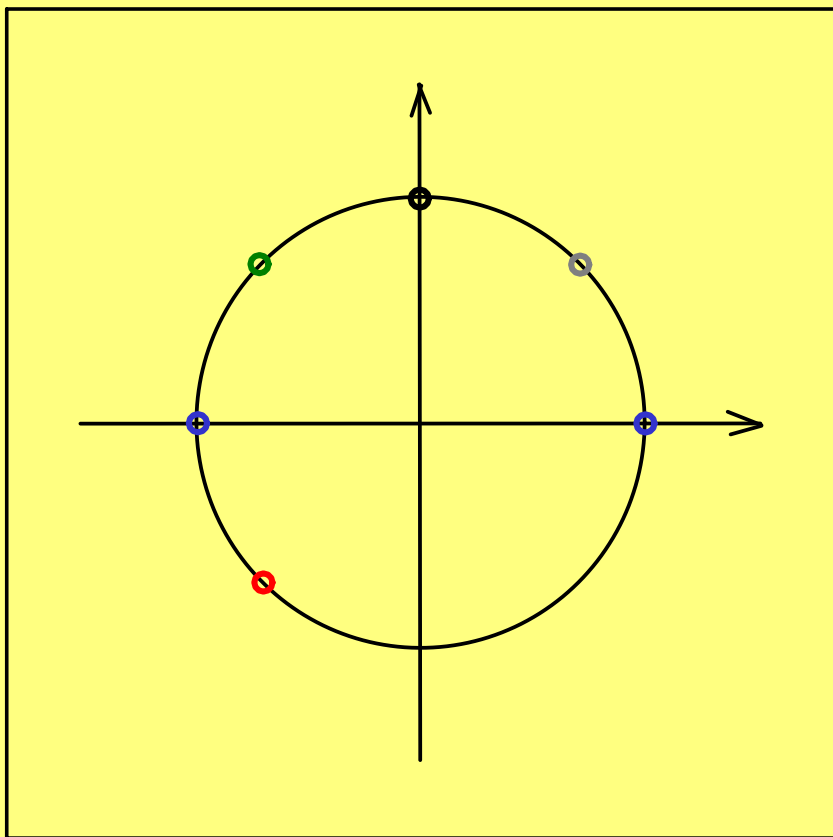


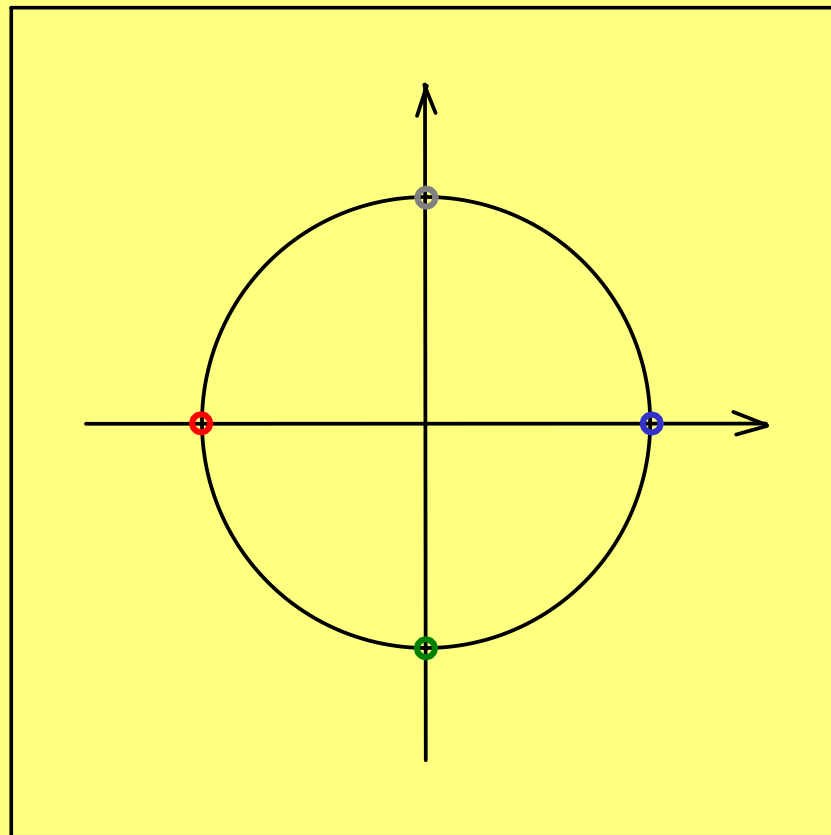
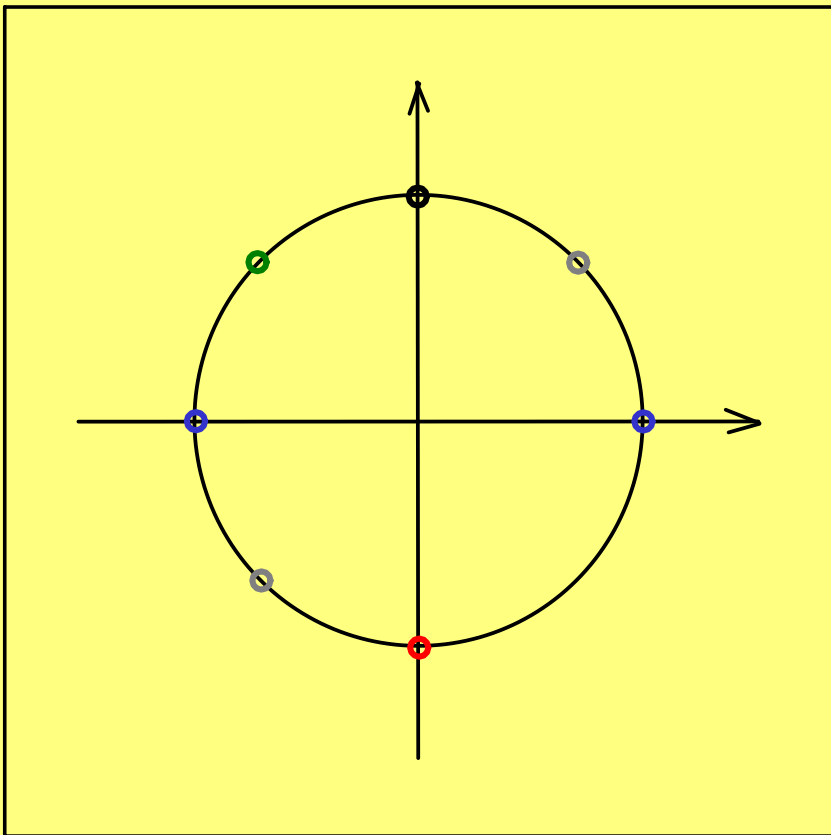


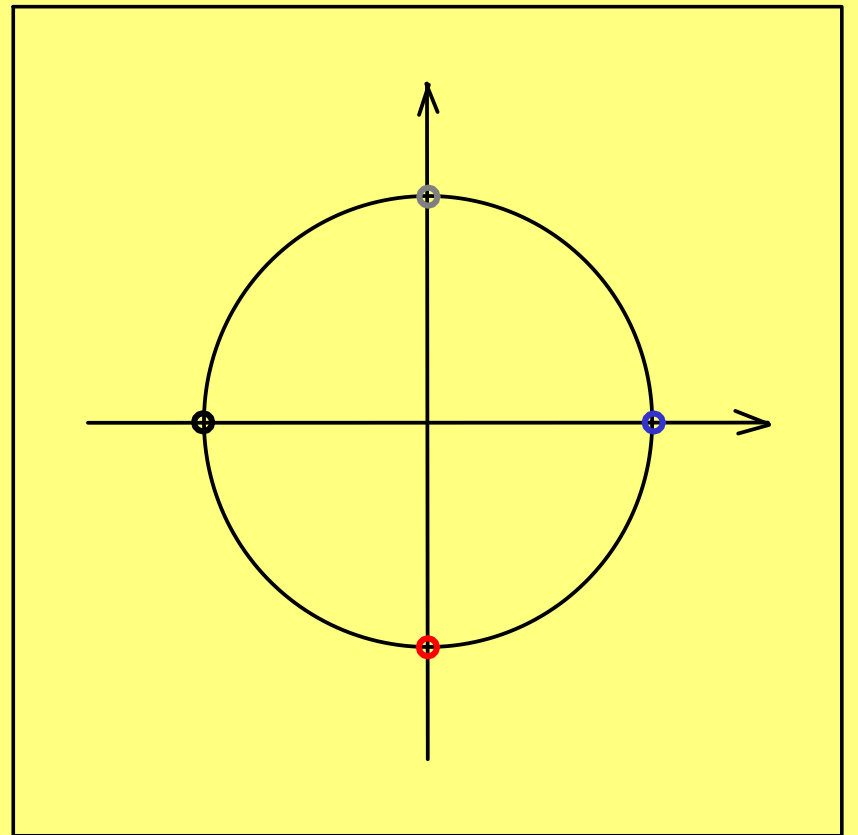
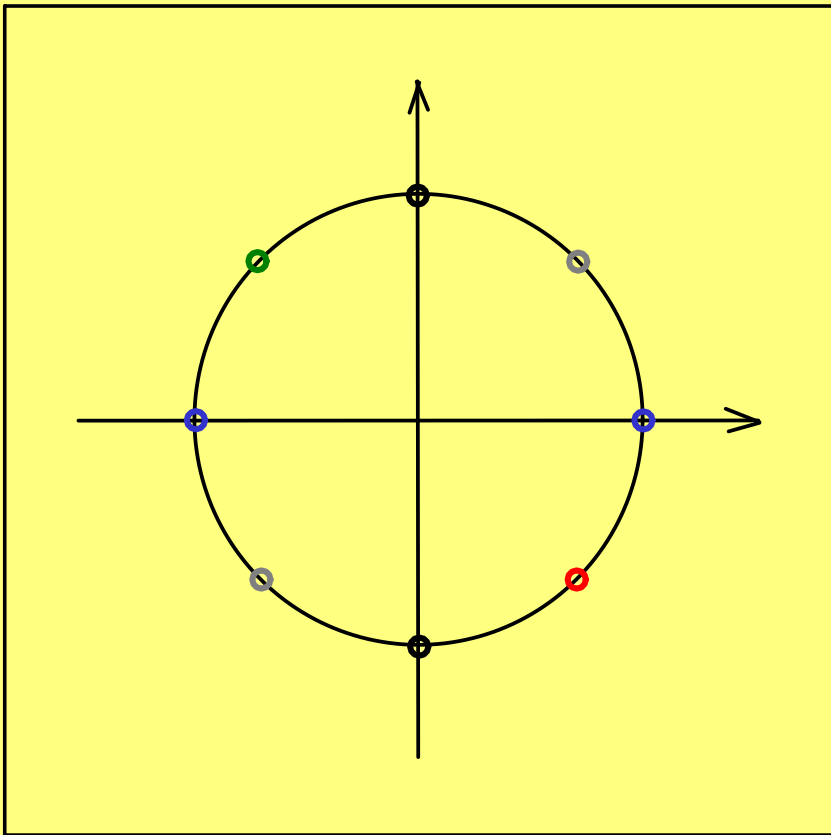


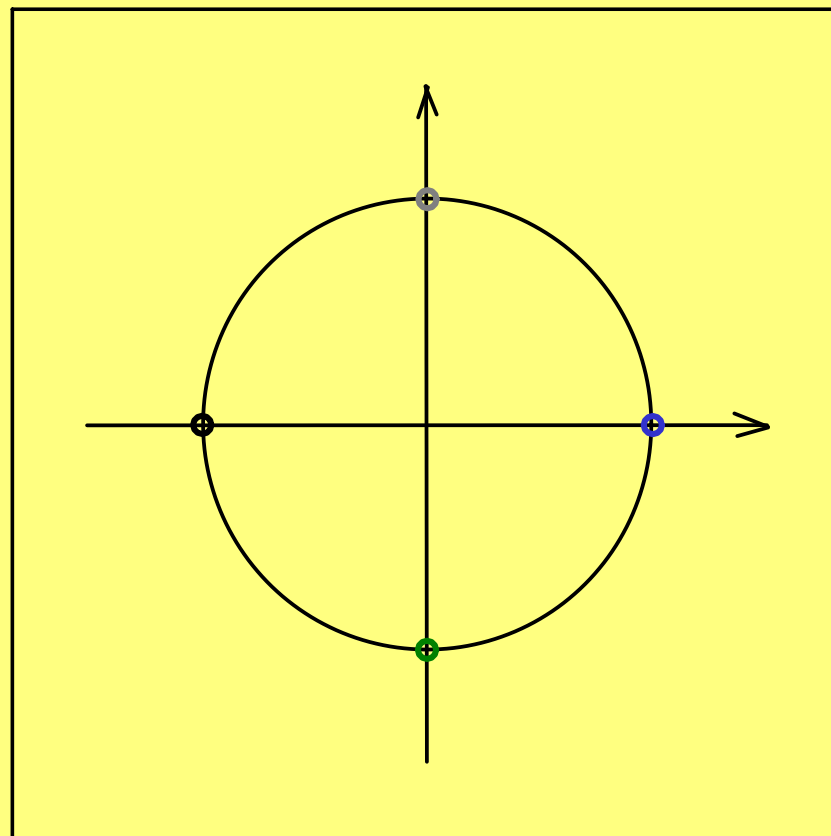
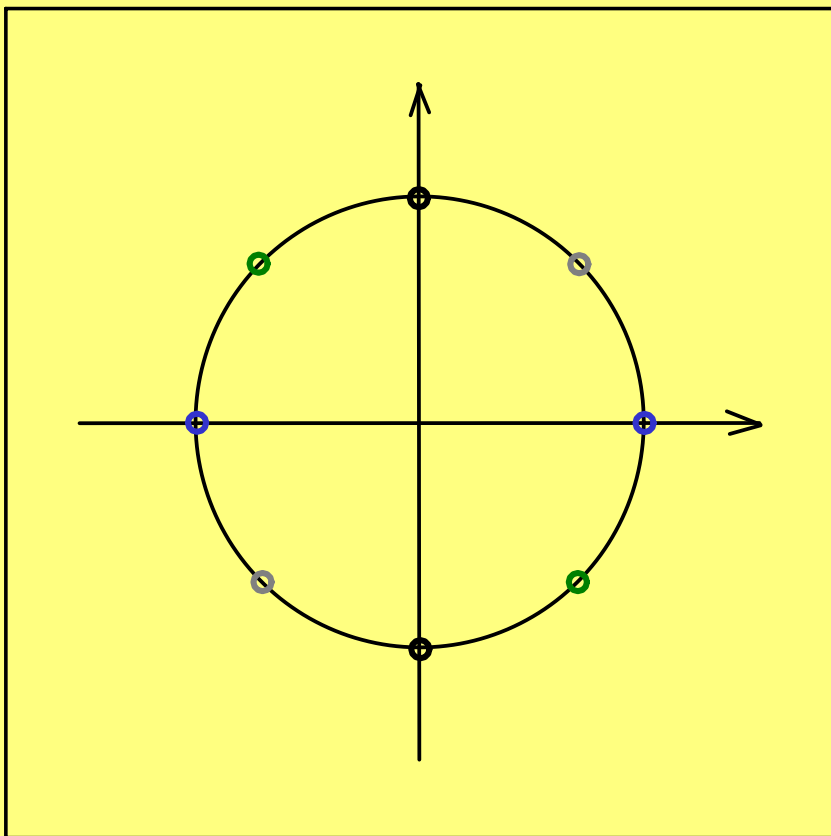








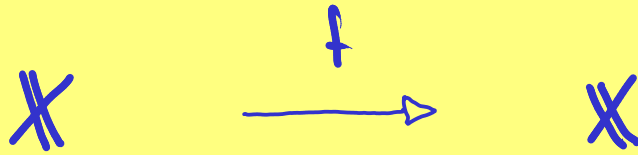




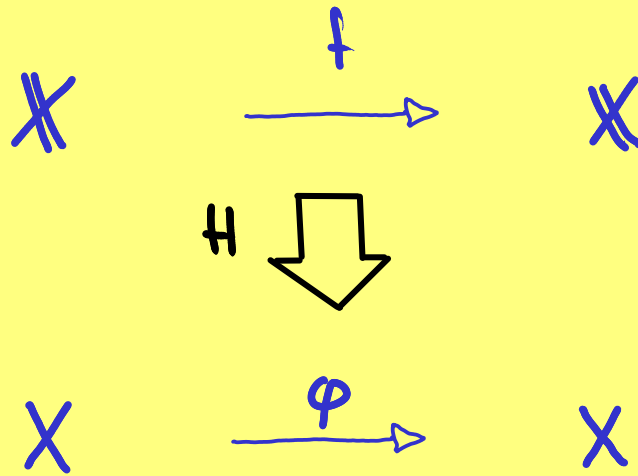
$f: \mathbb{S} \rightarrow \mathbb{S}$ defined by $f(x) = x^2$

THE PROBLEM

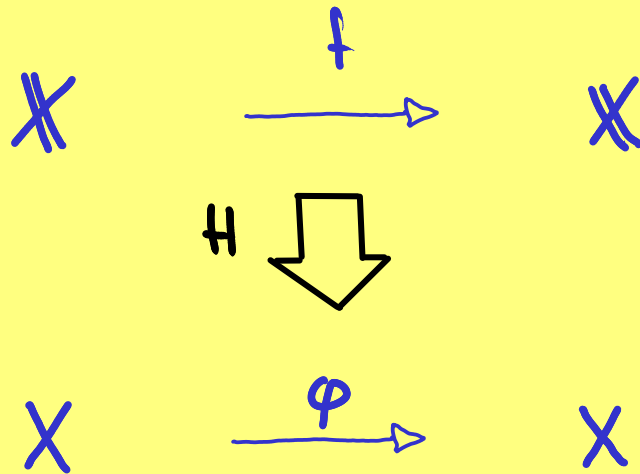
THE PROBLEM



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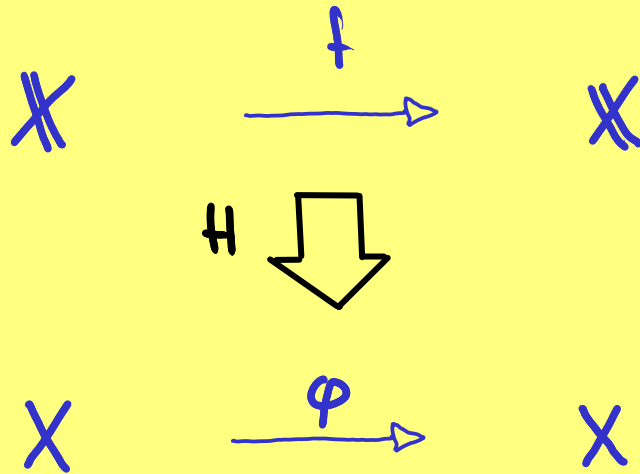


THE PROBLEM



eigenvalue $t \in \mathbb{R}_k$, eigenvector $\varphi(x) = tx$

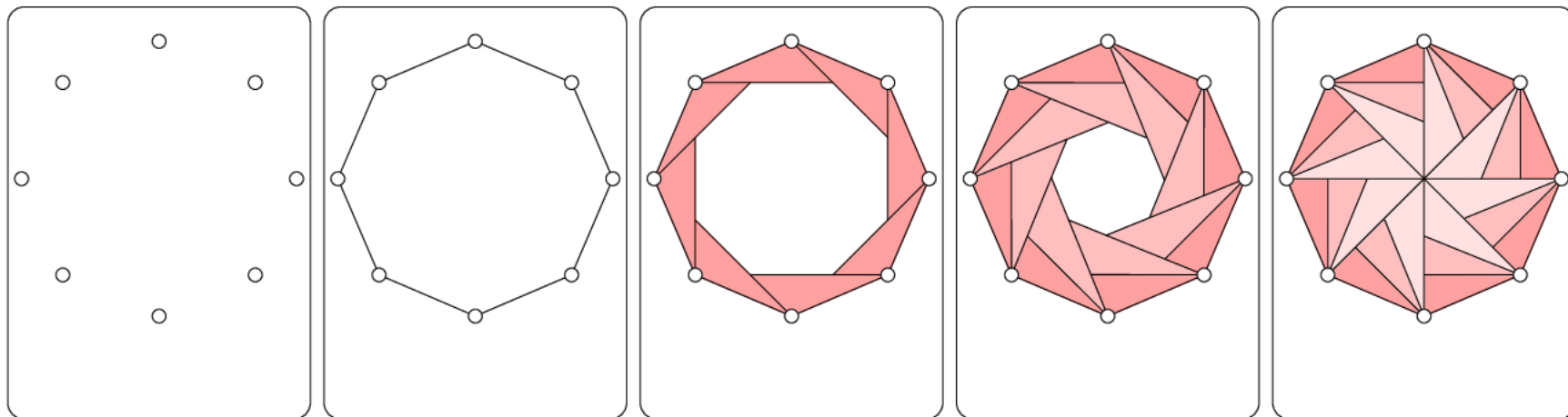
THE PROBLEM



eigenvalue $t \in \mathbb{Z}_k$, eigenvector $\varphi(x) = tx$

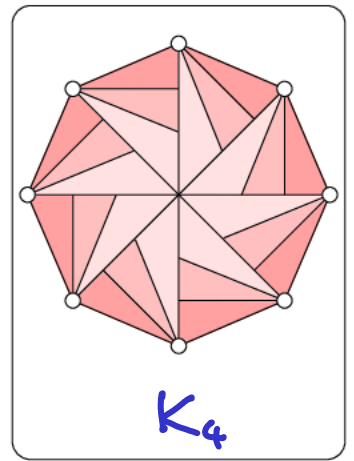
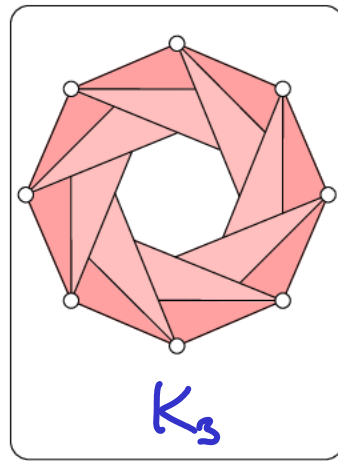
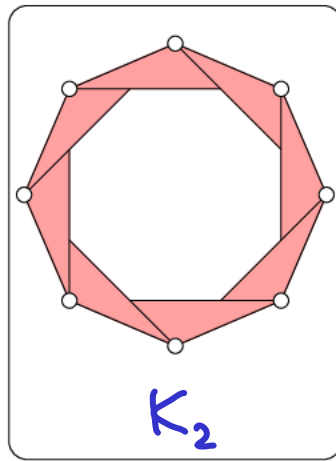
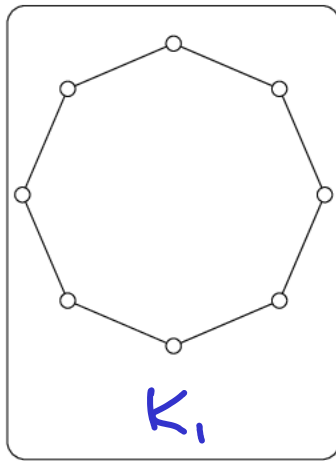
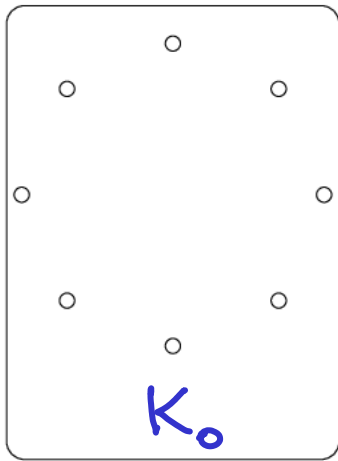
QUESTION: Can we compute the eigen-values and -vectors from a finite sample of f ?

$f: \mathcal{S} \rightarrow \mathcal{S}$ defined by $f(x) = x^2$



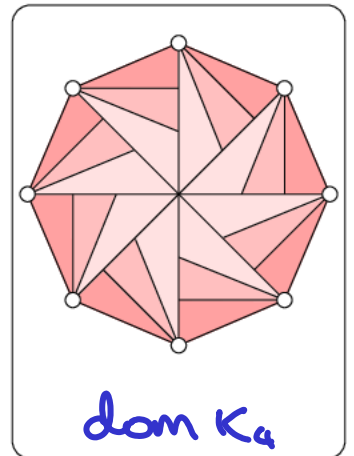
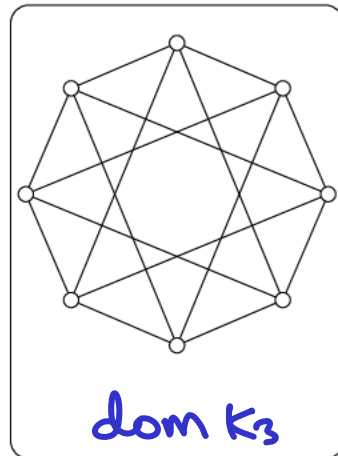
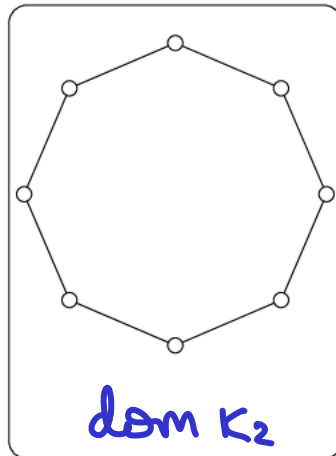
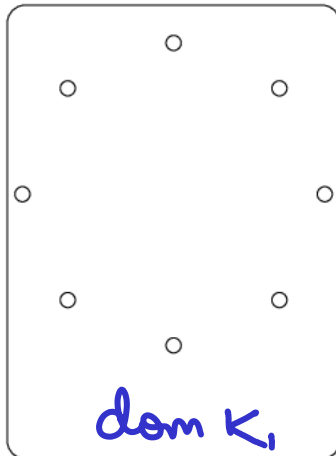
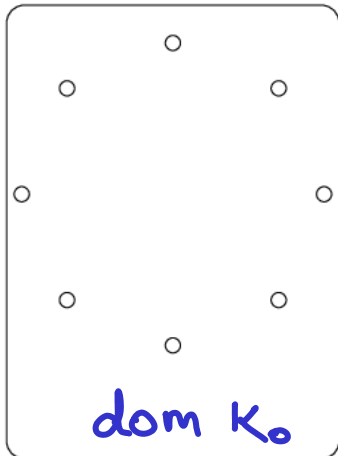
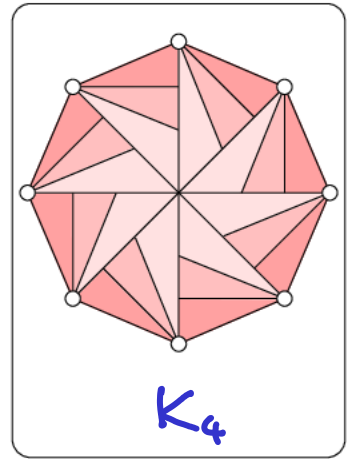
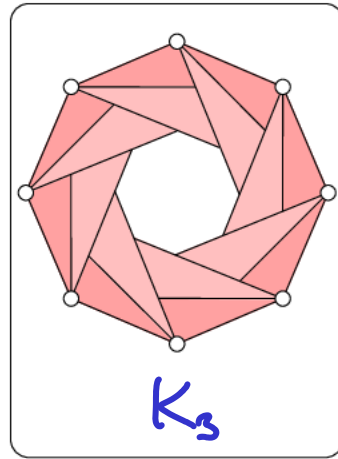
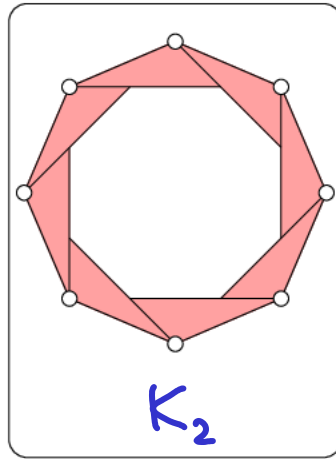
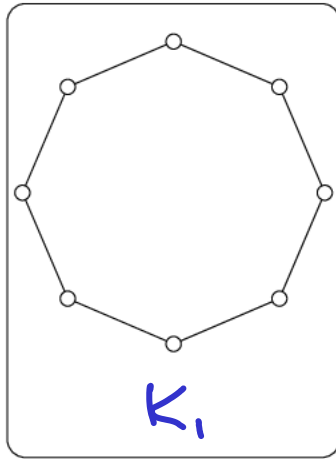
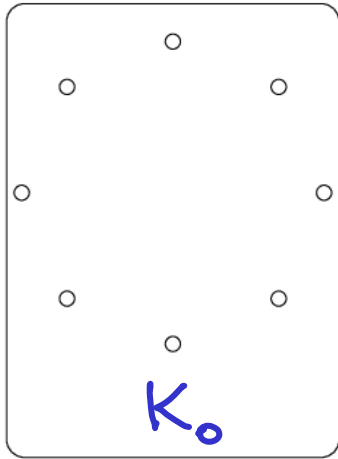
Vietoris-Rips complex K_i

$f: \mathbb{S} \rightarrow \mathbb{S}$ defined by $f(x) = x^2$



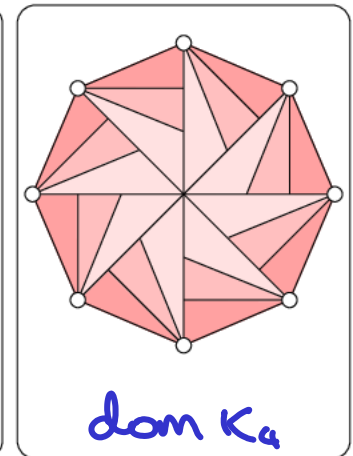
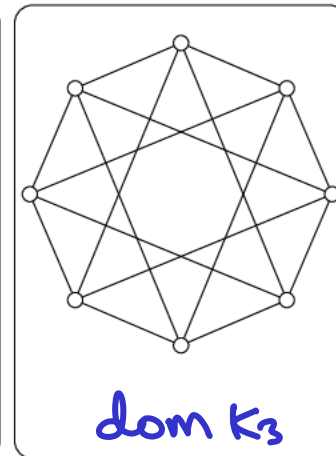
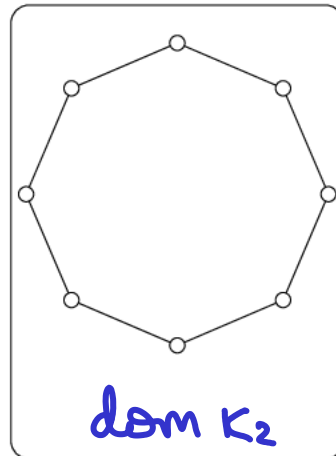
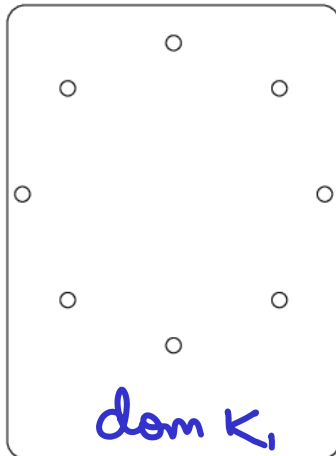
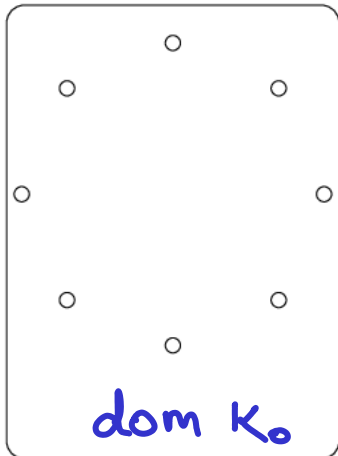
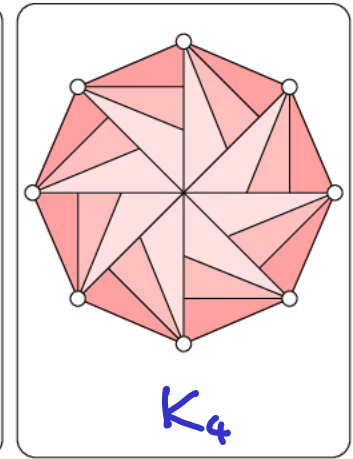
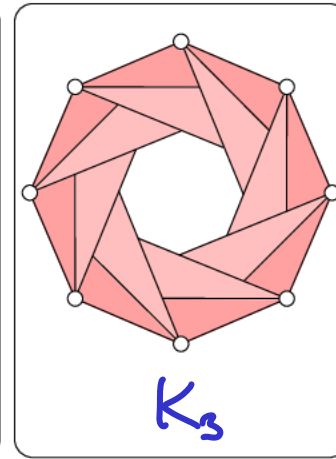
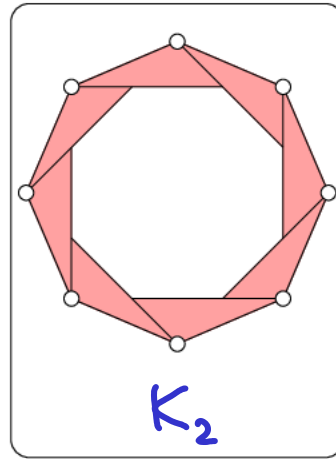
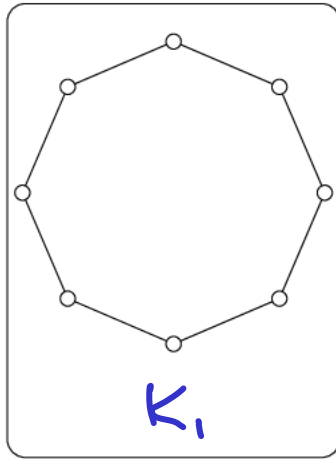
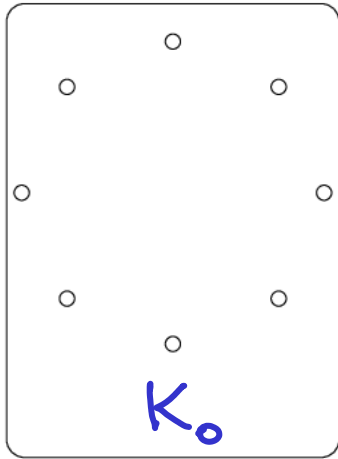
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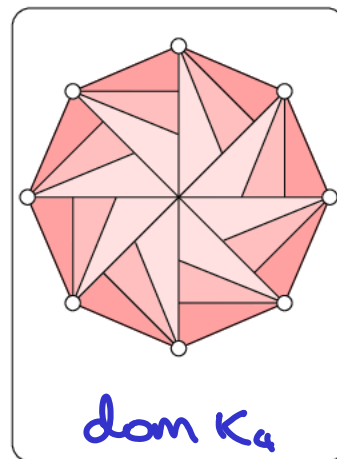
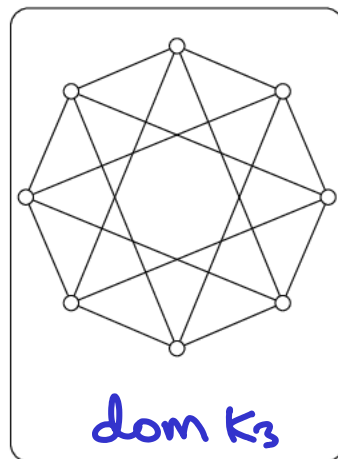
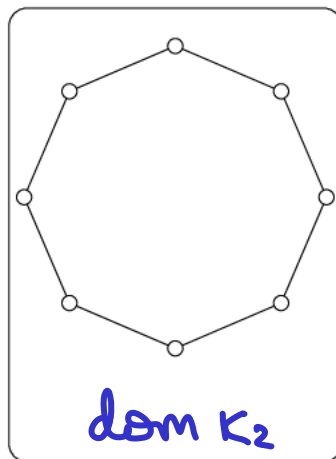
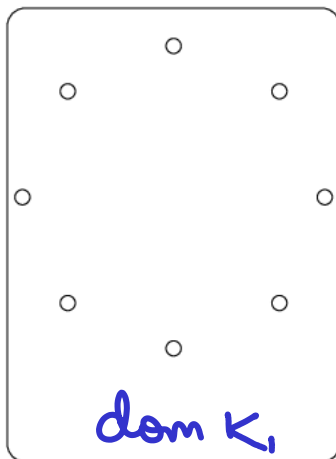
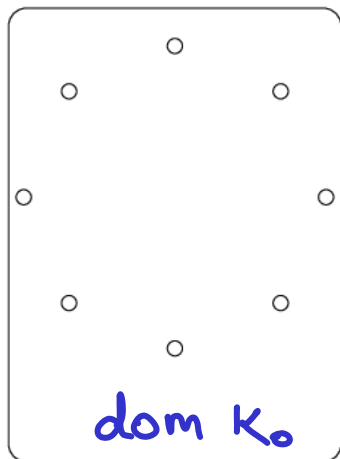
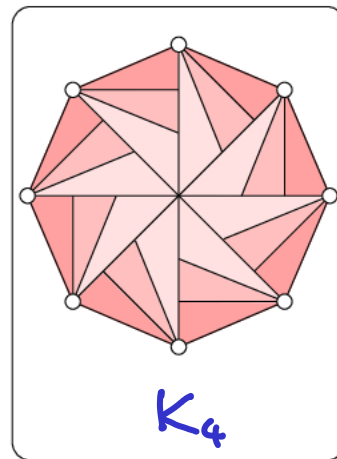
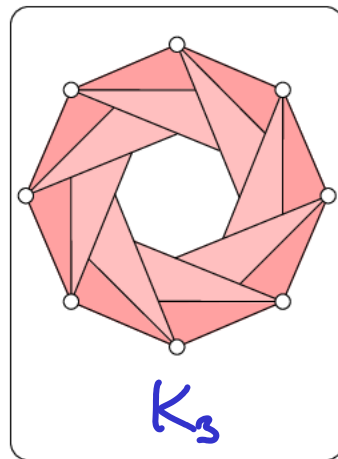
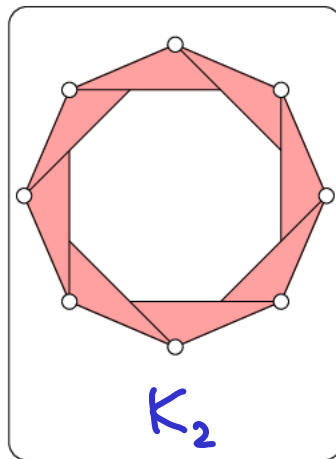
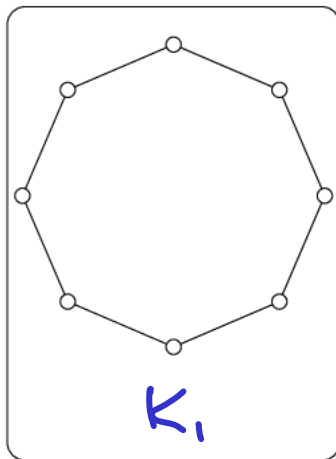
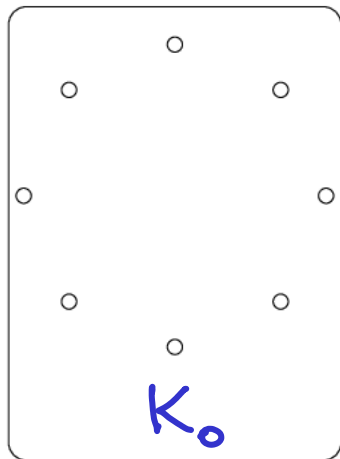
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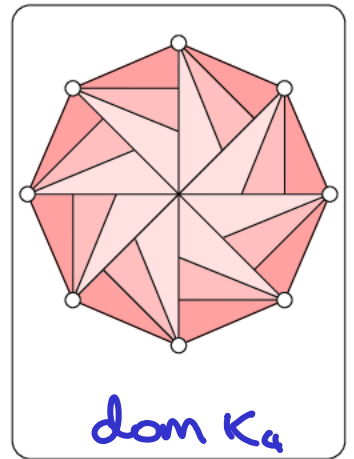
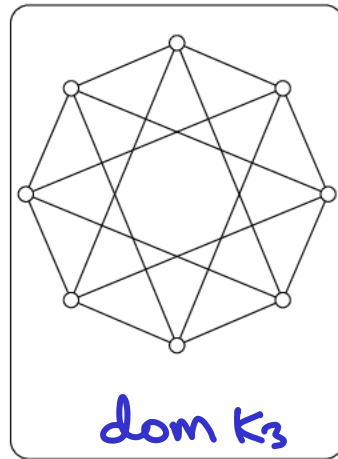
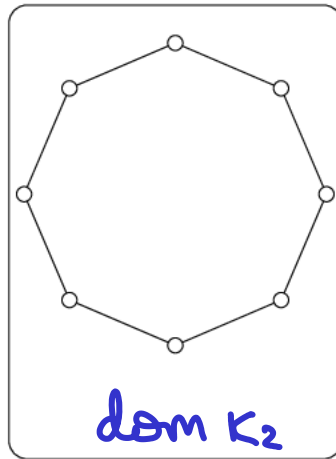
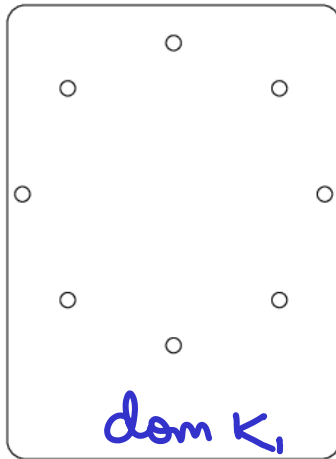
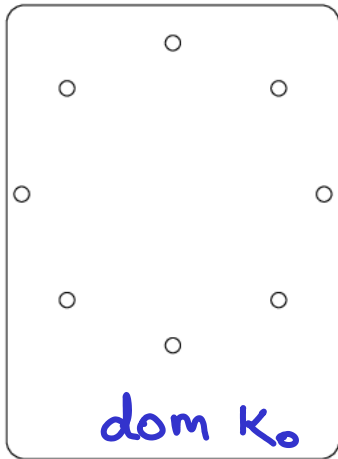
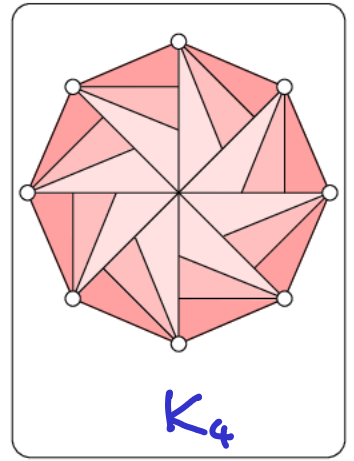
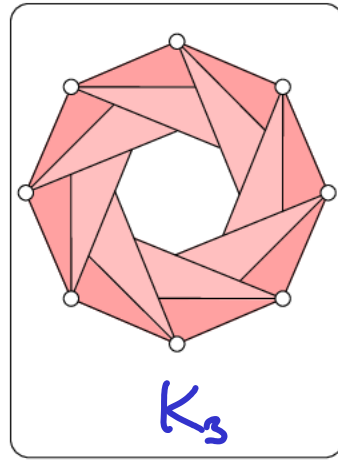
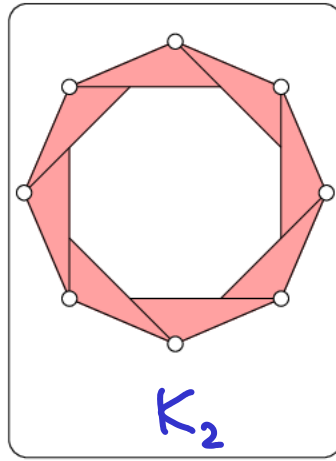
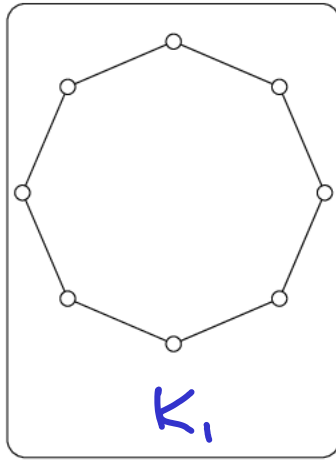
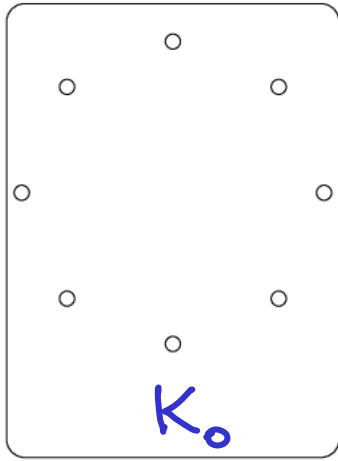
$K_i : K_i \rightarrow K_i$

$\text{dom } K_i$ is preimage of K_i



compare restriction $\text{dom } K_j \rightarrow K_j$

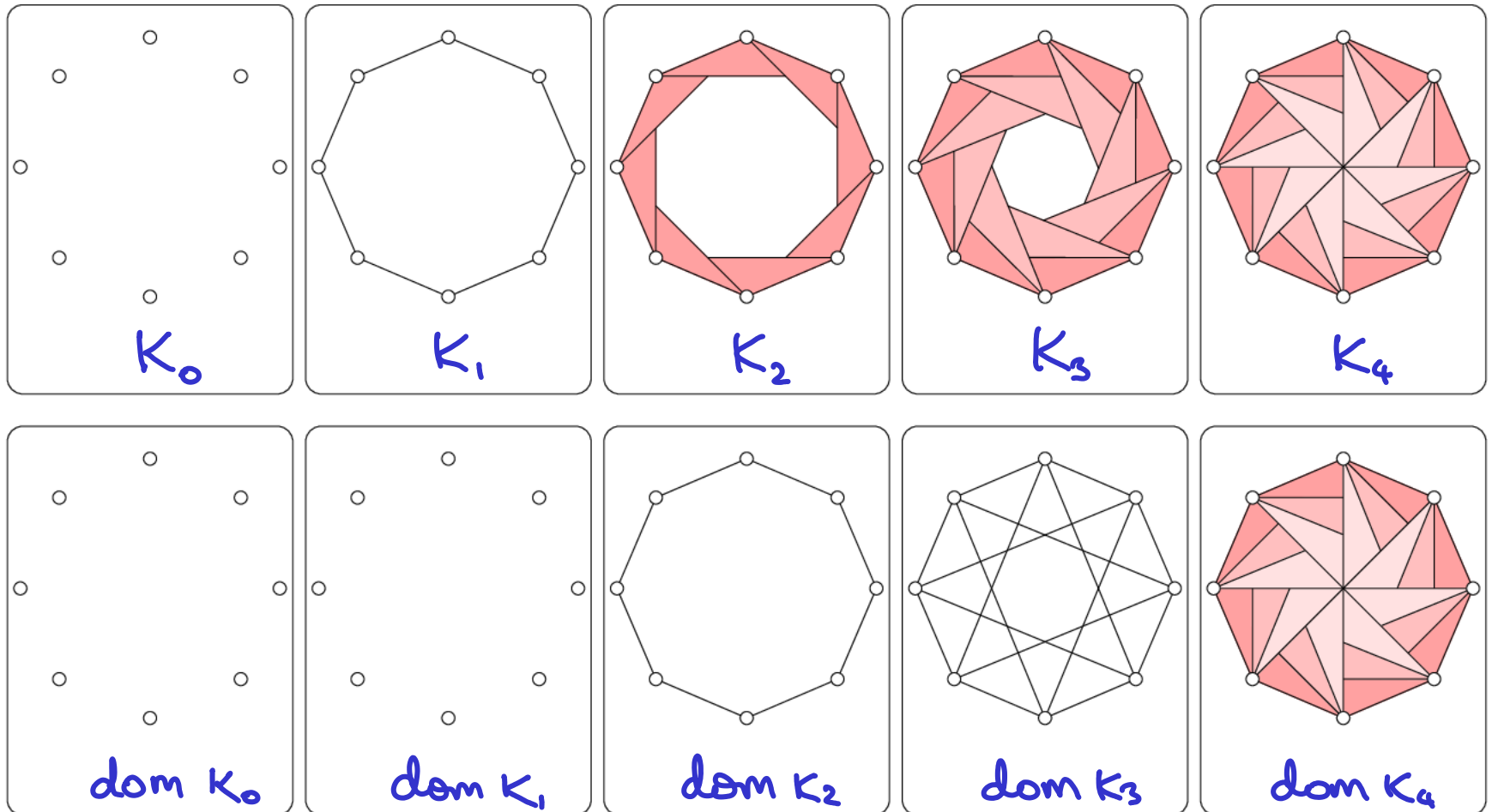
with inclusion $\text{dom } K_j \rightarrow K_j$



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For 1-dim. homology, we get eigenvalue $t=2$ for $j=2,3$.



I. CATEGORIES

II. LINEAR MAPS

III. ALGORITHM

IV. ANALYSIS

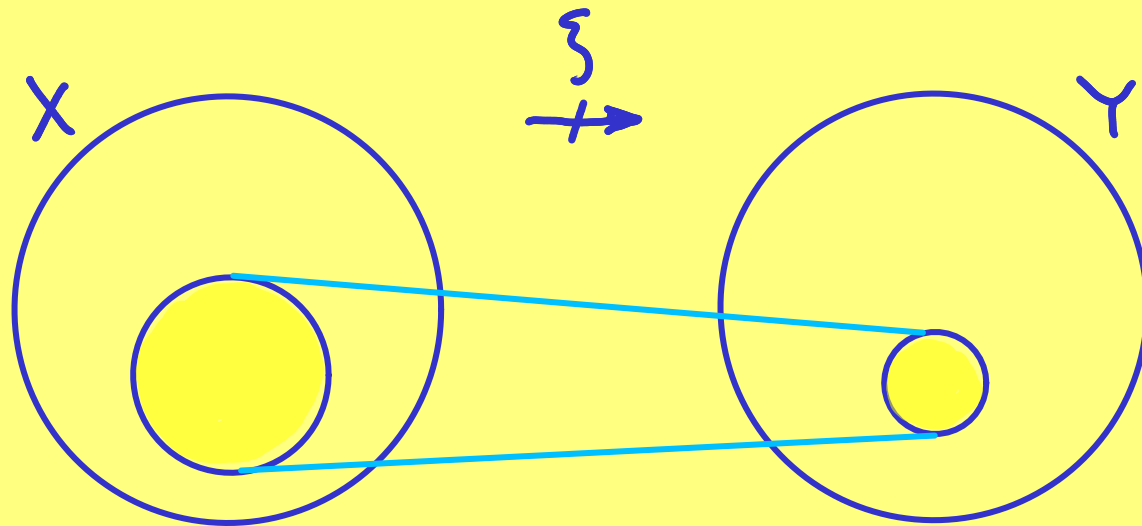
I.1 PARTIAL FUNCTIONS

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$f: X \rightarrow Y$ is partial function if every $x \in X$ maps to no or one element of Y .

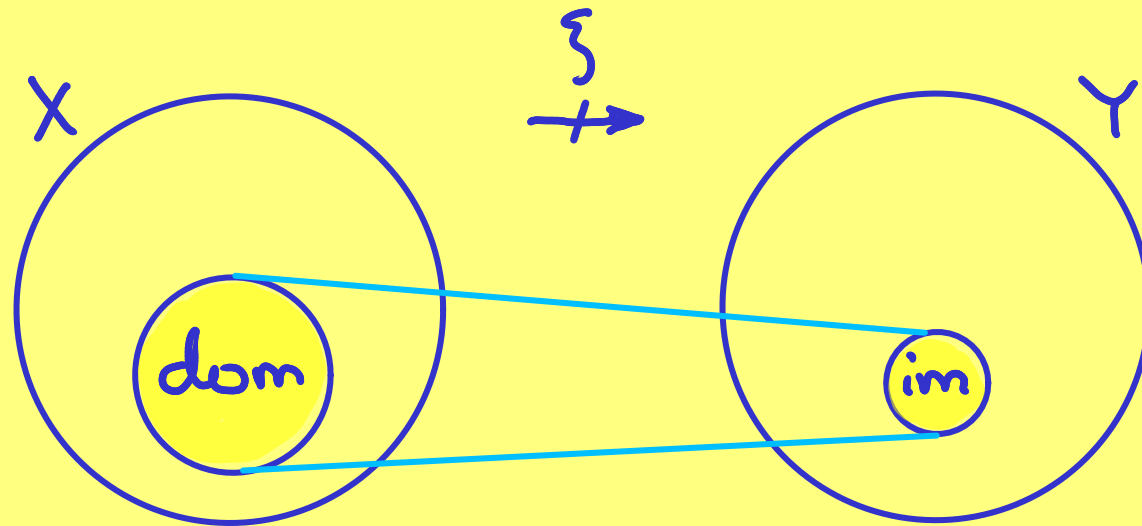
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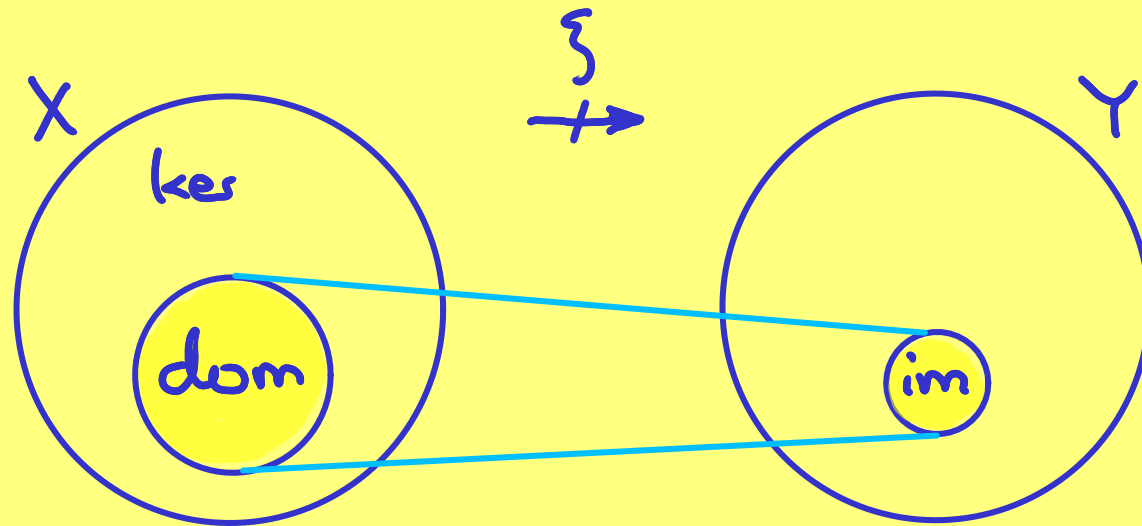
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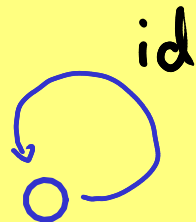
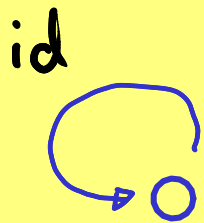
I.2 CATEGORY Part

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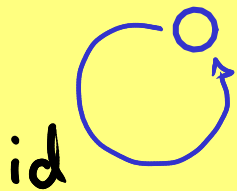
... objects are finite sets,
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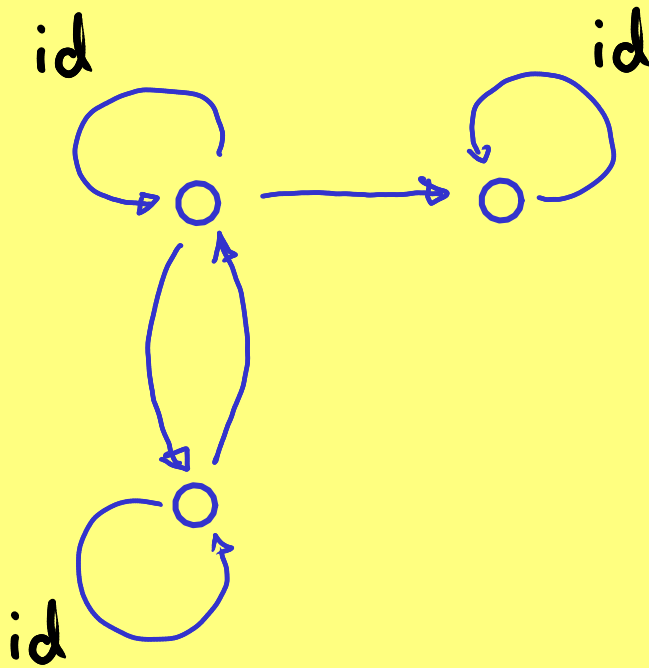


• identity arrows exist



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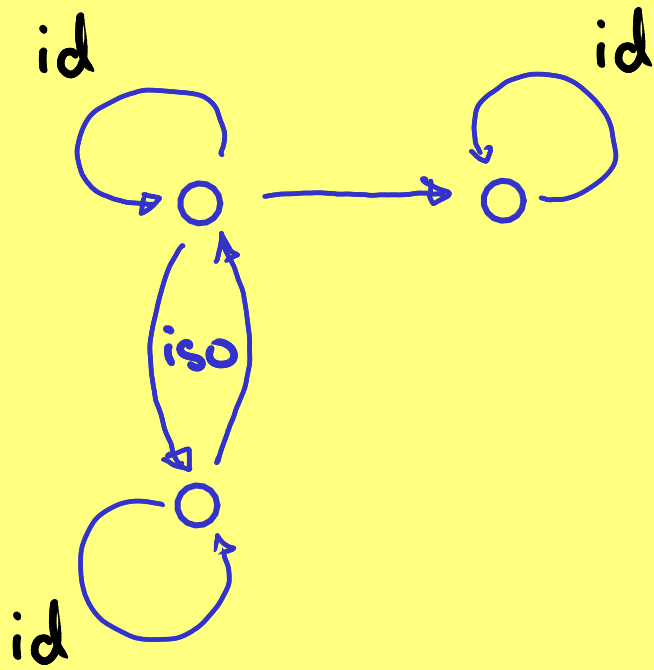
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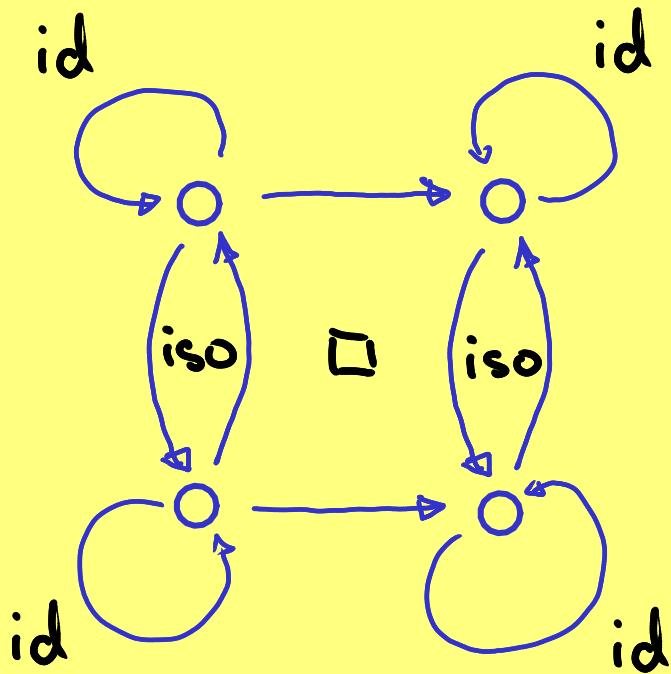
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- identity arrows exist
- arrows compose associatively
- objects are **isomorphic** if connected by invertible arrows
- arrows are **conjugate** if connected by commuting isos.

I.3 CATEGORY Mch

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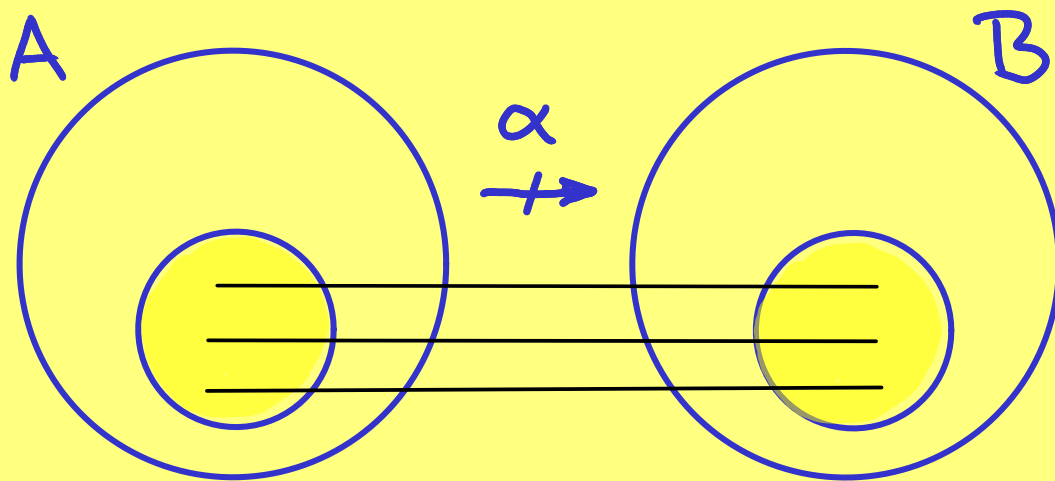
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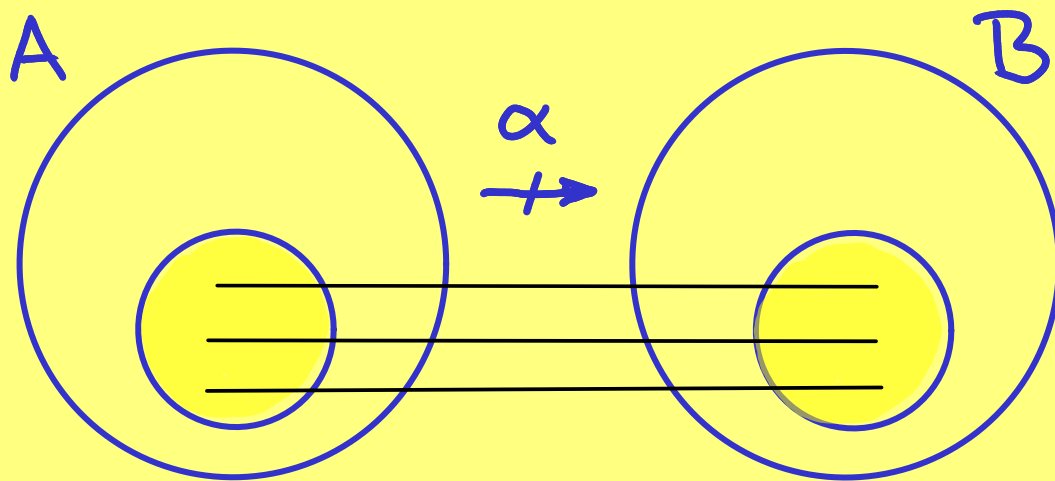
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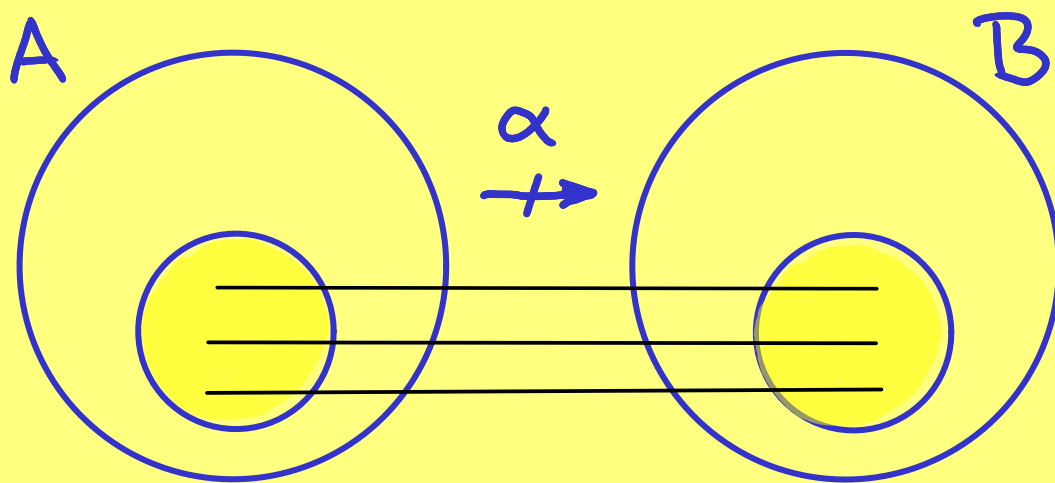


	0	
0	1	0
	0	

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$$\text{rank } \alpha = \#\text{dom } \alpha = \#\text{im } \alpha$$

	0	
0	1	0
	0	

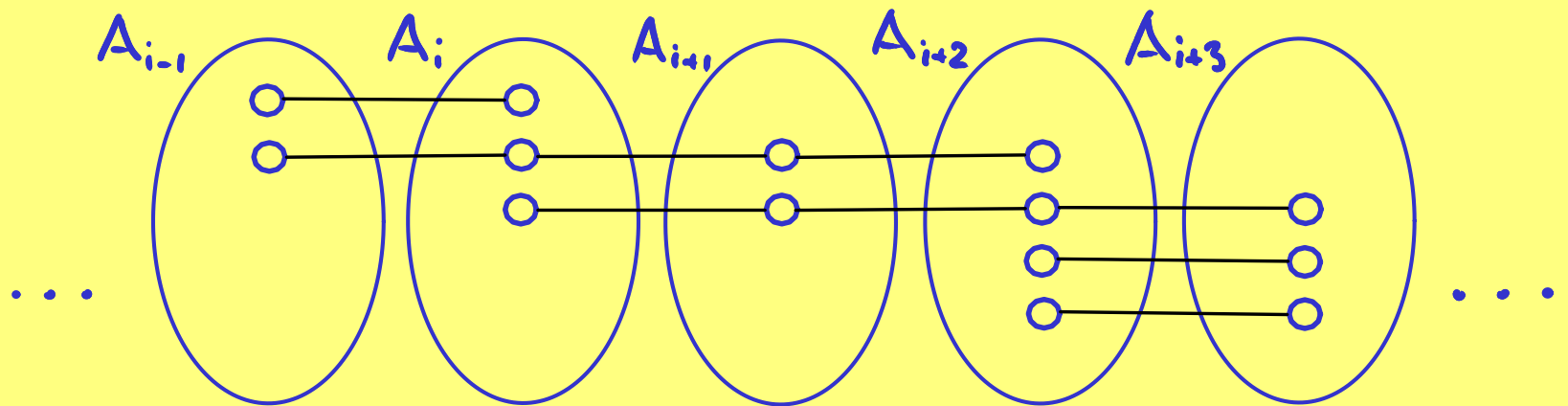
I.4 TOWER OF MATCHINGS

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A **tower** is a path with finitely many non-zero objects in a category.

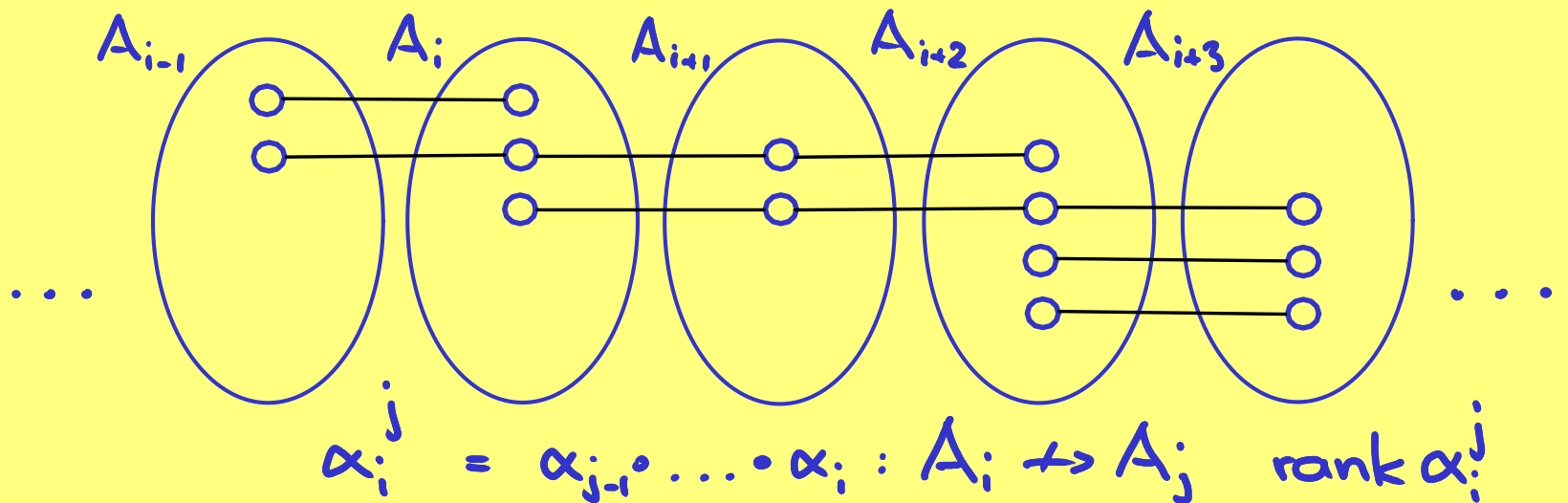
I.4 TOWER OF MATCHINGS

A **tower** is a path with finitely many non-zero objects in a category.



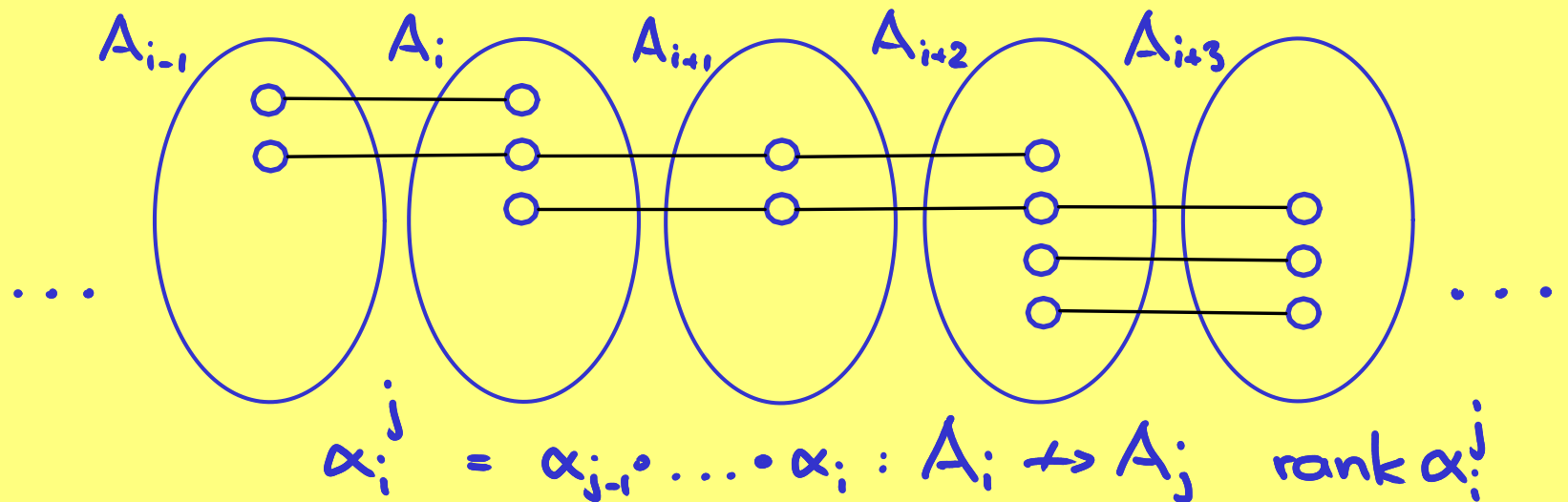
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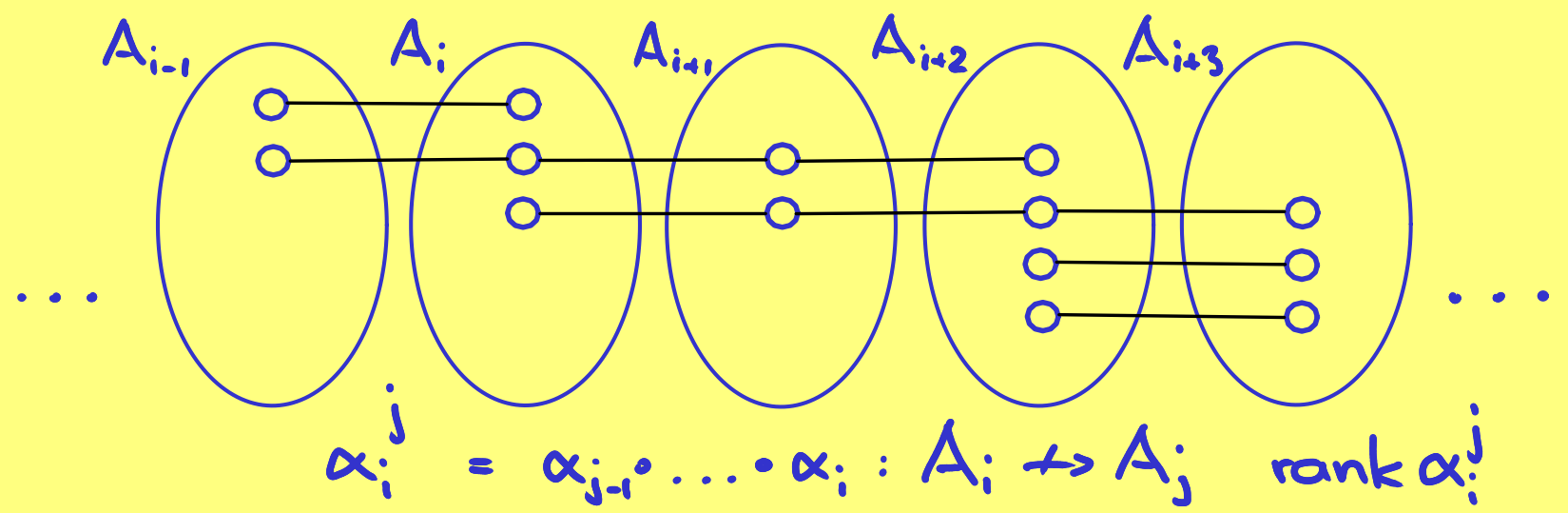
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THM. Towers in Mch are isomorphic

I.4 TOWER OF MATCHINGS

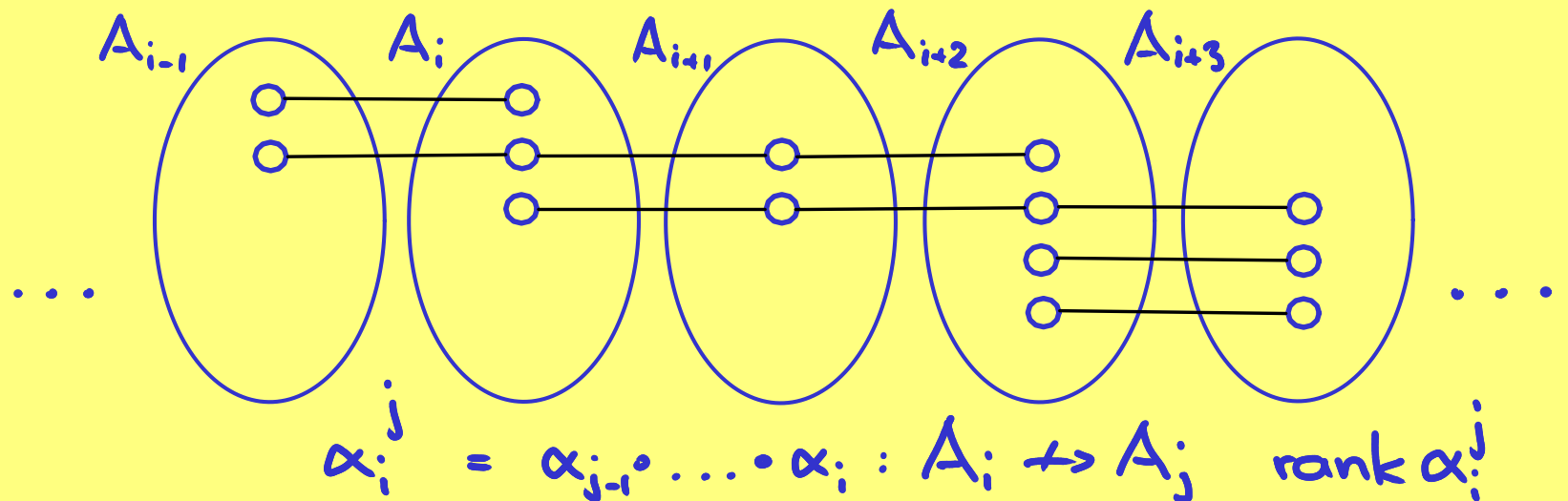
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THM. Towers in Mch are isomorphic

- \Leftrightarrow they have the same rank functions
- \Leftrightarrow their persistence diagrams are the same.

I. CATEGORIES

II. LINEAR MAPS

III. ALGORITHM

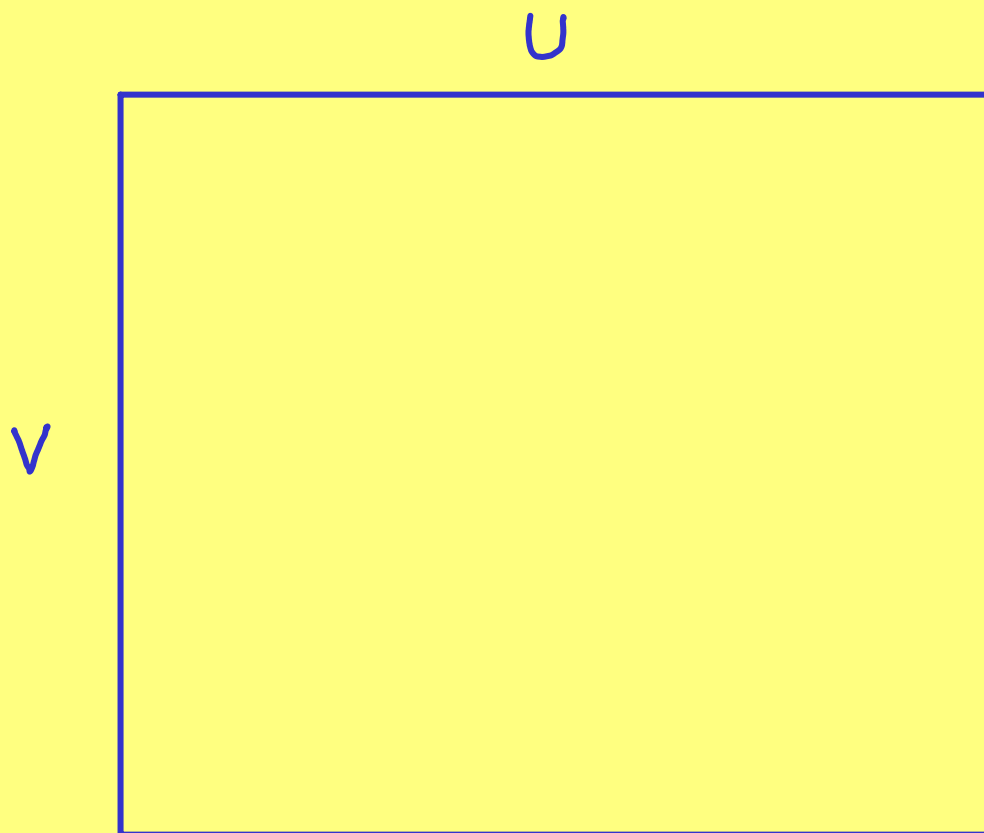
IV. ANALYSIS

II.1 CATEGORY Vect

$$v : U \rightarrow V$$

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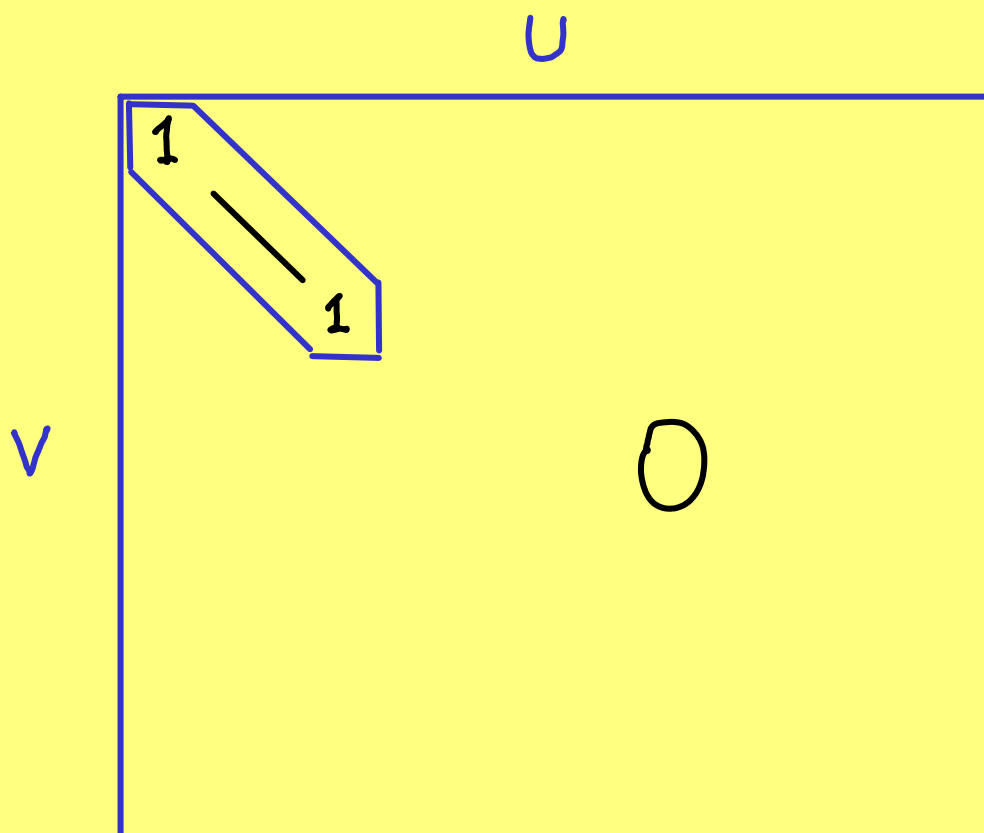
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$$\text{rank } \sigma = \dim \text{im } \sigma$$

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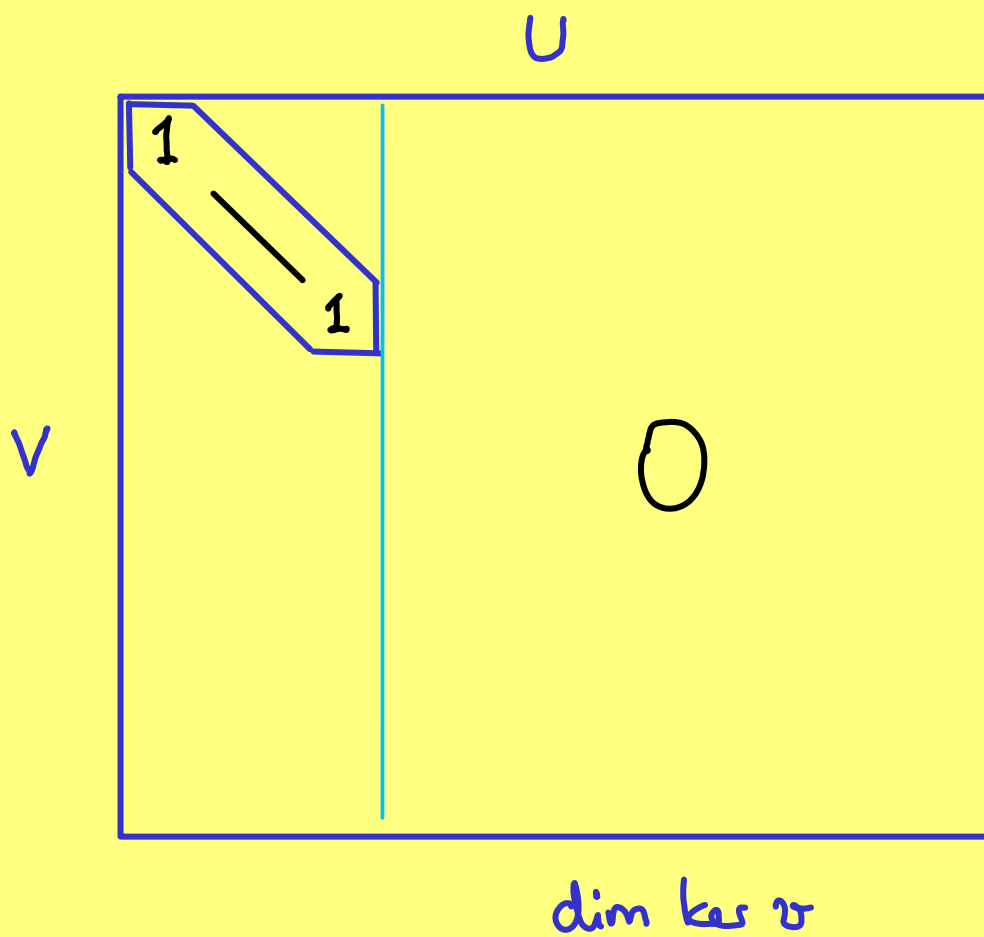
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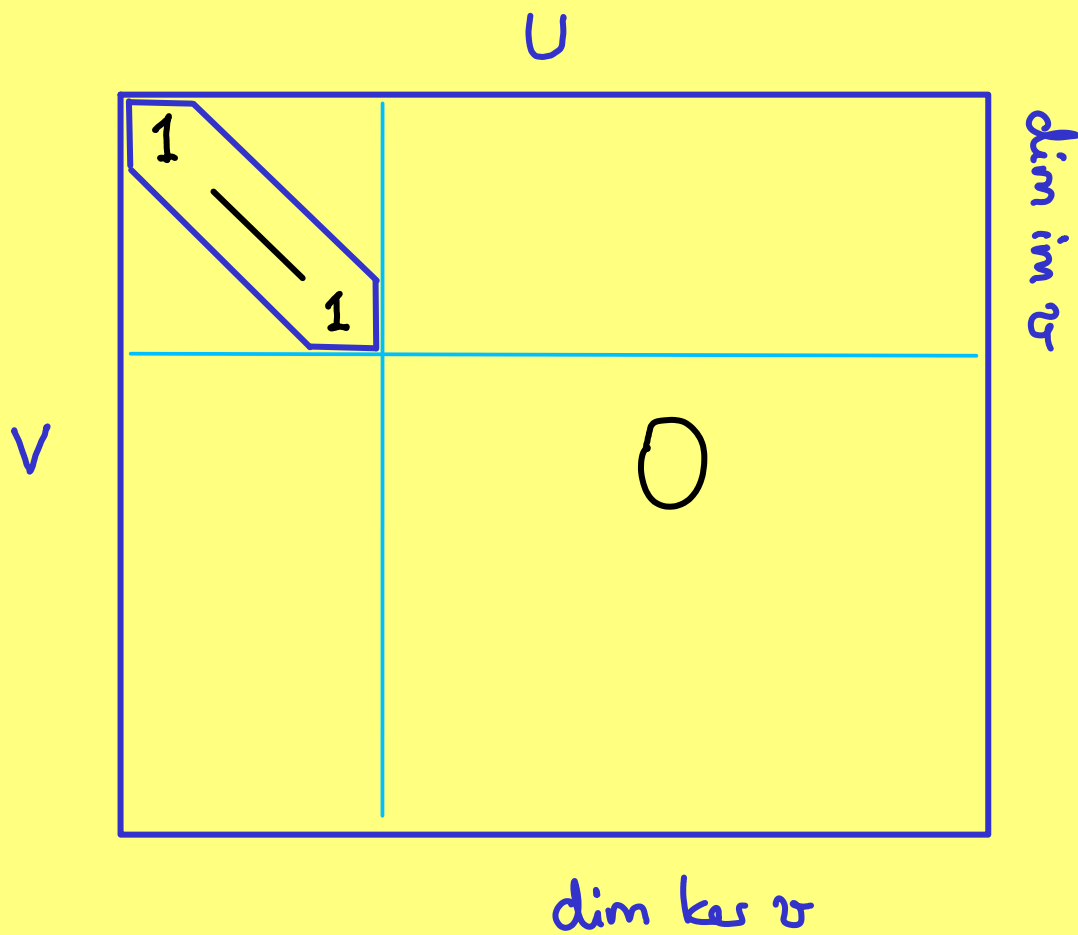
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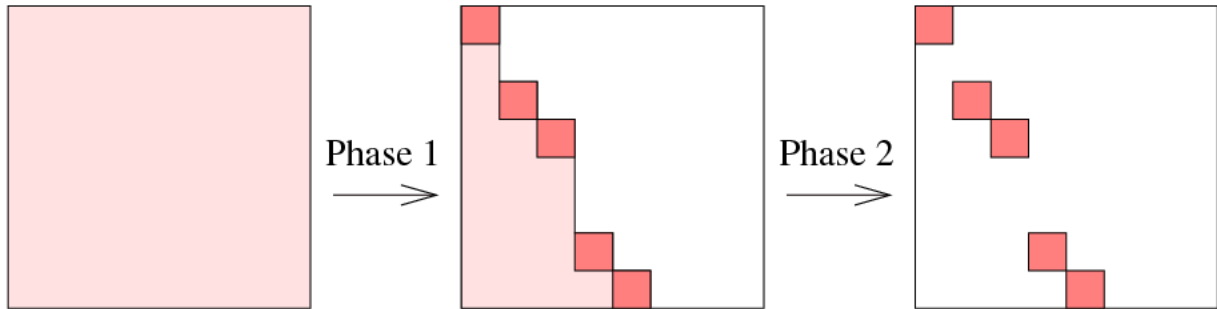
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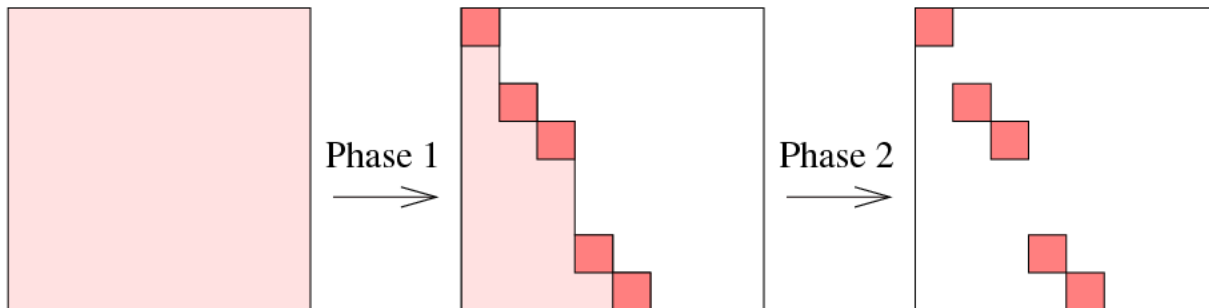
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I.2 BASIS ALGORITHM



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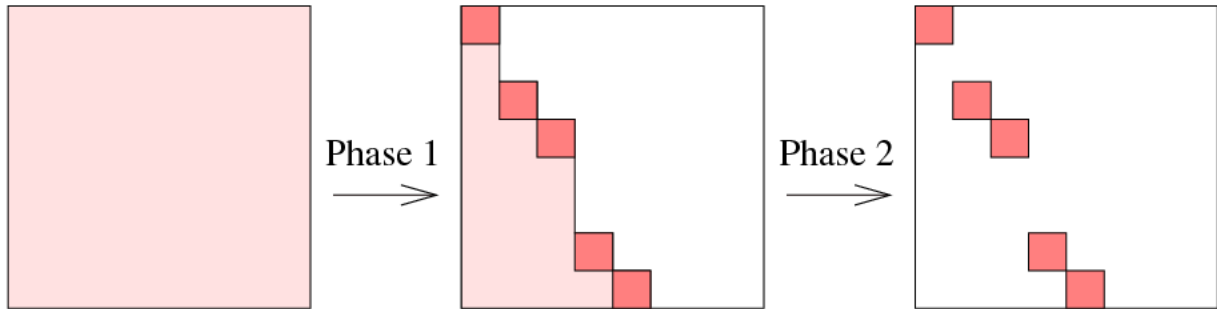
$$U_0 \xrightarrow{v_0} U_1 \xrightarrow{v_1} U_2 \xrightarrow{v_2} \dots \xrightarrow{v_{n-1}} U_n.$$



I.2 BASIS ALGORITHM

$$U_0 \xrightarrow{\sigma_0} U_1 \xrightarrow{\sigma_1} U_2 \xrightarrow{\sigma_2} \dots \xrightarrow{\sigma_{n-1}} U_n.$$

DEF. $A_0 \xrightarrow{\alpha_0} A_1 \xrightarrow{\alpha_1} A_2 \xrightarrow{\alpha_2} \dots \xrightarrow{\alpha_{n-1}} A_n$ is a basis if α_i is a matching and $\text{rank } \alpha_i = \text{rank } \sigma_i$, for $0 \leq i < n$.

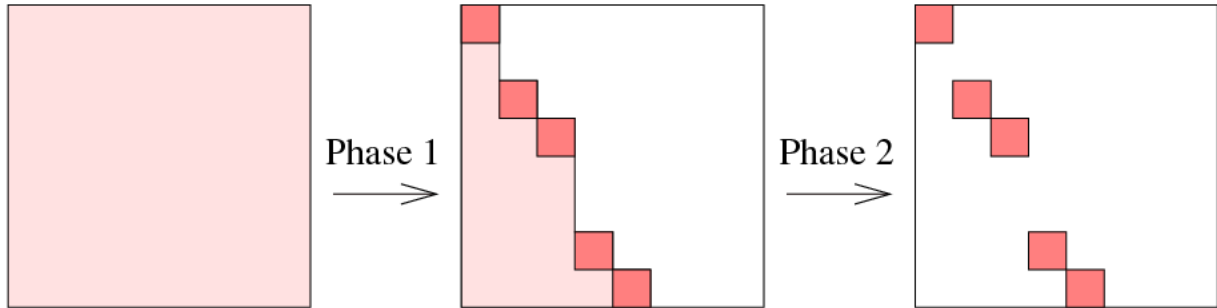


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THM. A basis exists but is generally not unique.

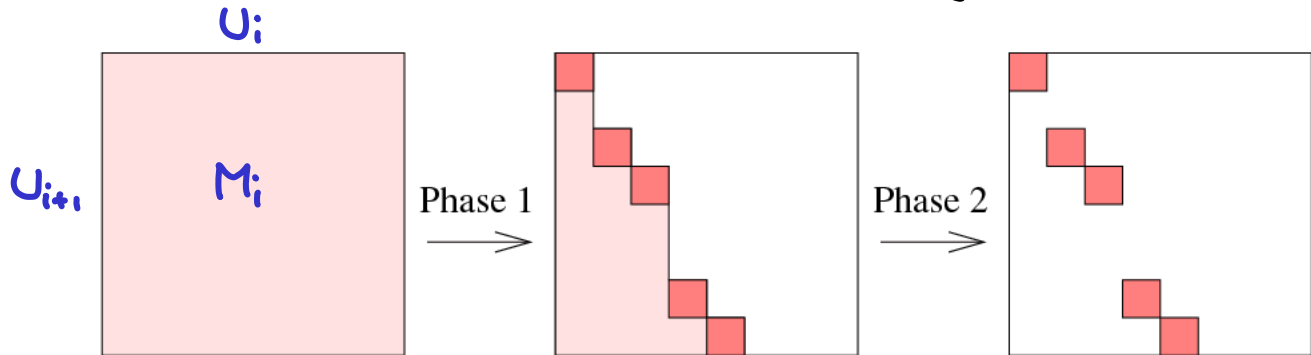


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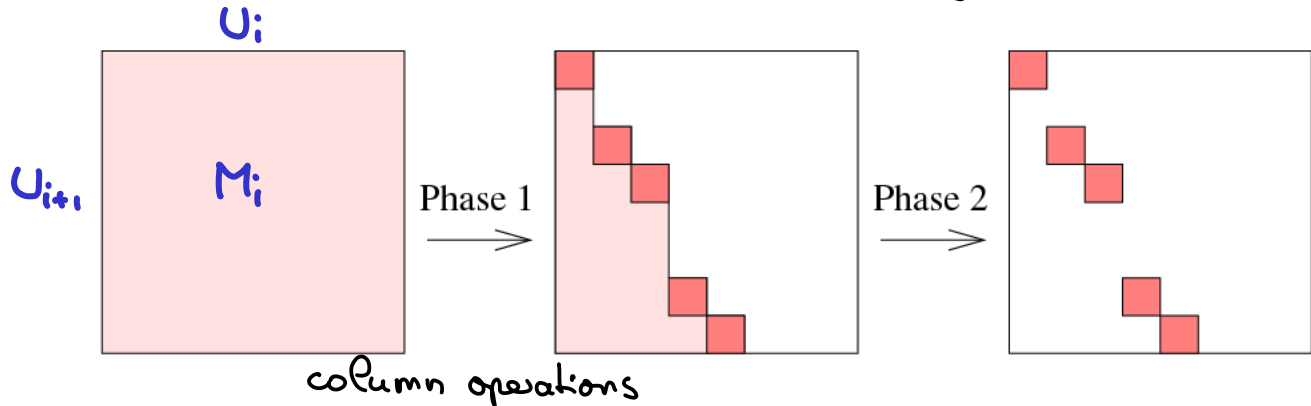


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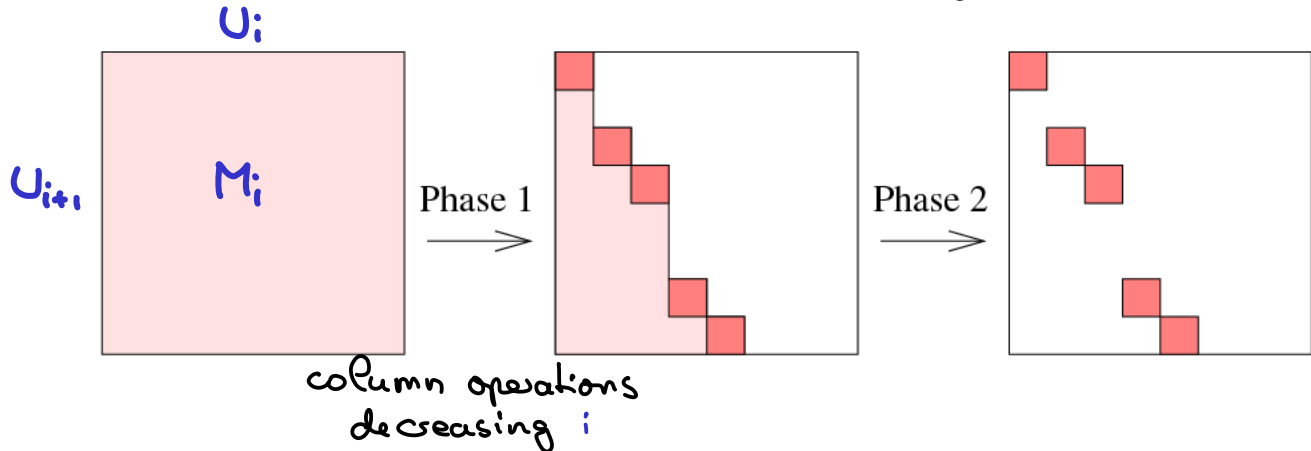


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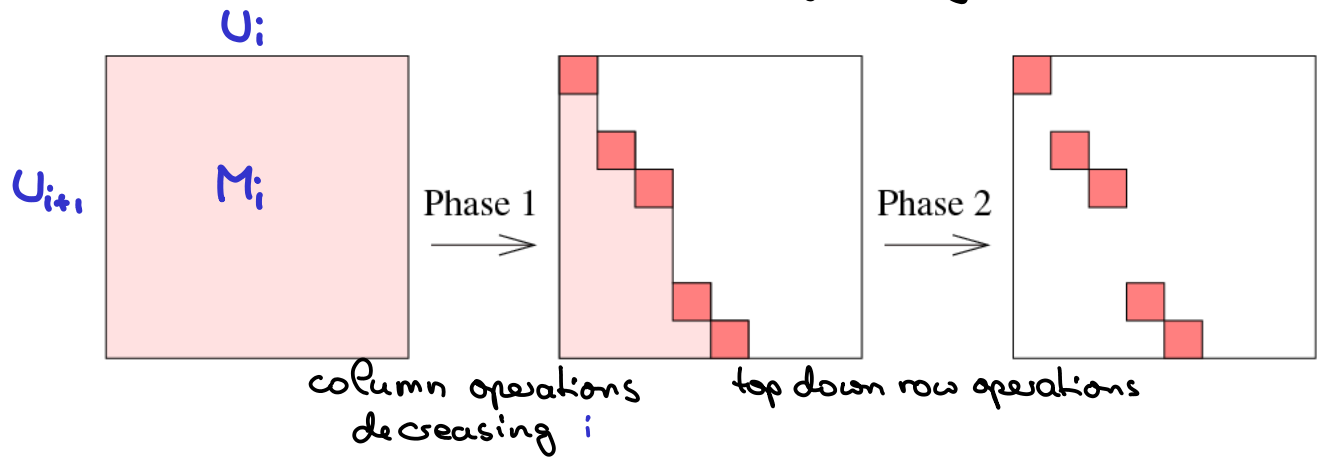


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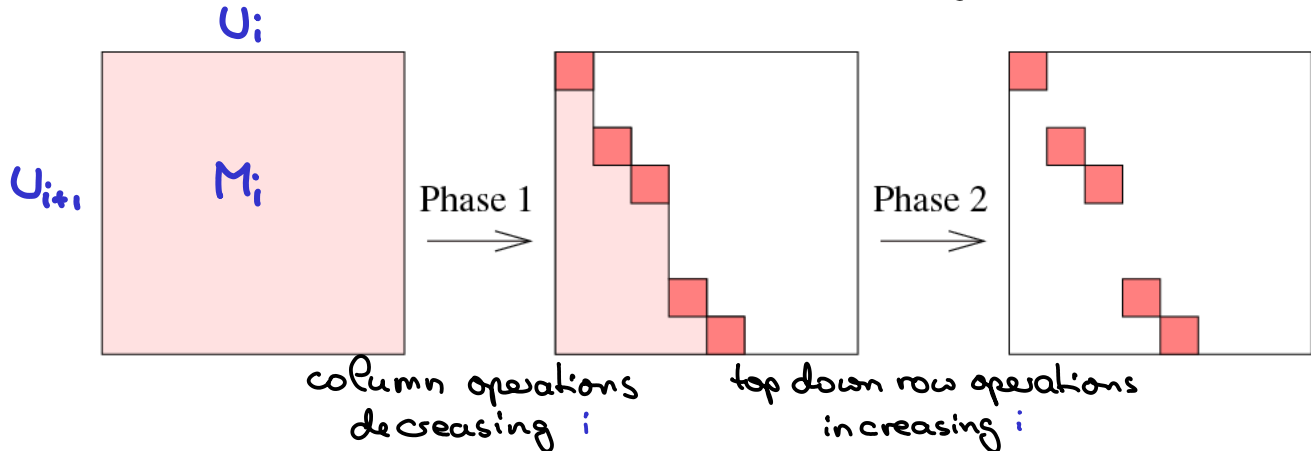


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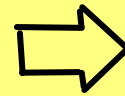
II.3 EIGENSPACES

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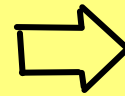
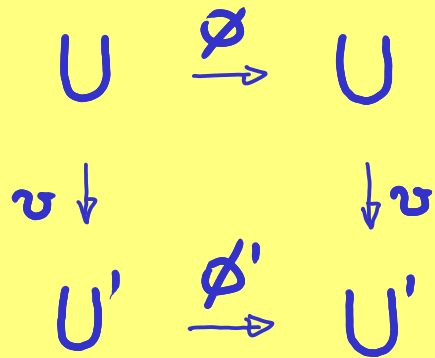
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$$\{u \mid \phi(u) = tu\}$$

"
 $E_t(\phi)$

II.3 EIGENSPACES



$$\begin{array}{c} \{u \mid \phi(u) = tu\} \\ \text{"} \\ E_t(\phi) \\ \downarrow \\ E_t(\phi') \end{array}$$

II.3 EIGENSPACES

$$\begin{array}{ccc} U & \xrightarrow{\phi} & U \\ \downarrow \nu & & \downarrow \nu \\ U' & \xrightarrow{\phi'} & U' \end{array}$$

functor E_t from $\{u \mid \phi(u) = tu\}$
 \downarrow
 $E_t(\phi)$
 \downarrow
 $E_t(\phi')$

\Rightarrow

Endo(Vect) to Vect

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$$\downarrow$$

$$E_t(\phi')$$

$$\begin{array}{ccccc}
 V & \xleftarrow{\varphi} & U & \xrightarrow{\tau} & V \\
 \downarrow & & \downarrow & & \downarrow \\
 V' & \xleftarrow{\varphi'} & U' & \xrightarrow{\tau'} & V'
 \end{array}$$

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$$E_t(\phi)$$

\downarrow

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$$\begin{array}{ccccc}
 V & \xleftarrow{\varphi} & U & \xrightarrow{\gamma} & V \\
 \downarrow & & \downarrow & & \downarrow \\
 V' & \xleftarrow{\varphi'} & U' & \xrightarrow{\gamma'} & V'
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\Rightarrow

$$E_t(\varphi, \gamma)$$

\downarrow

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$$\begin{array}{ccc}
 U & \xrightarrow{\phi} & U \\
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$$\{u \mid \phi(u) = tu\}$$

$$\cong E_t(\phi)$$

\downarrow

$$E_t(\phi')$$

$$\{u \mid \phi(u) = t\psi(u)\} / \ker\phi \cap \ker\psi$$

$$\begin{array}{ccccc}
 V & \xleftarrow{\phi} & U & \xrightarrow{\psi} & V \\
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 V & \xleftarrow{\phi} & U & \xrightarrow{\psi} & V \\
 \downarrow & & \downarrow & & \downarrow \\
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 \end{array}$$

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 \Downarrow
 $E_t(\phi, \psi)$
 \Downarrow
 $E_t(\phi', \psi')$

functor E_t from $\underline{\text{Pairs}}(\underline{\text{Vect}})$ to $\underline{\text{Vect}}$

I. CATEGORIES

II. LINEAR MAPS

III. ALGORITHM

IV. ANALYSIS

III.1 SETTING

$f: X \rightarrow X$ is continuous self-map

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General approach:

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4. get persistence.

III.2 RESULTS for $f(x) = x^2$

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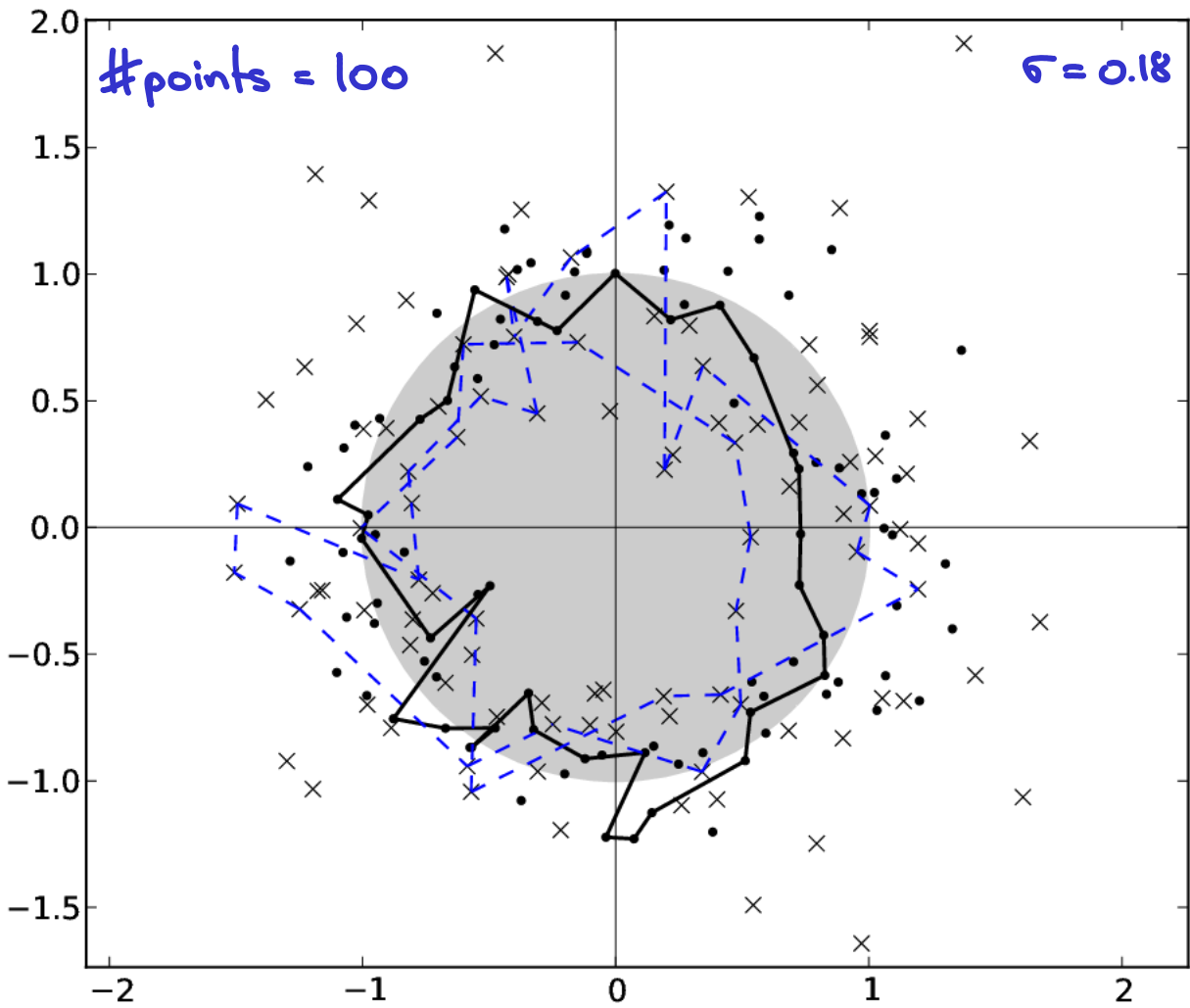
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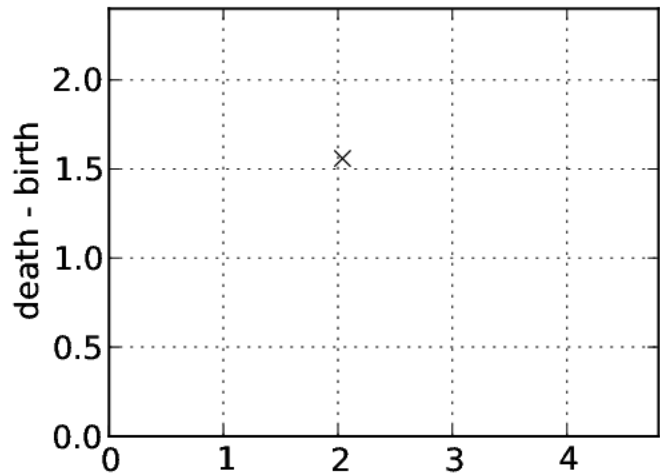
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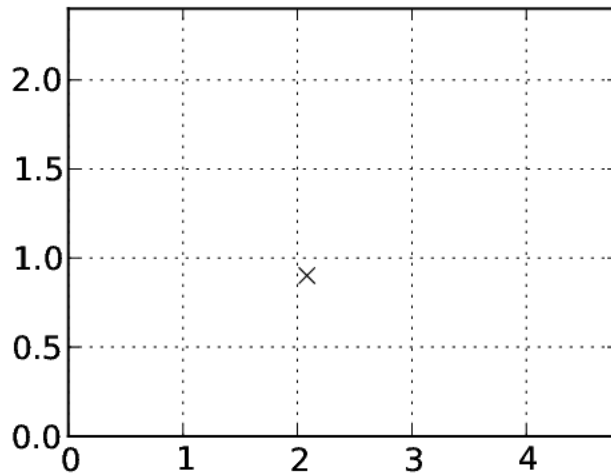
pick m points z_j equally spaced on \mathcal{S}' ;
choose the point x_j in nbhd. of z_j , with
isotropic Gaussian noise of width σ ;
set $f(x_j)$ equal to x_i nearest to x_j^2 .



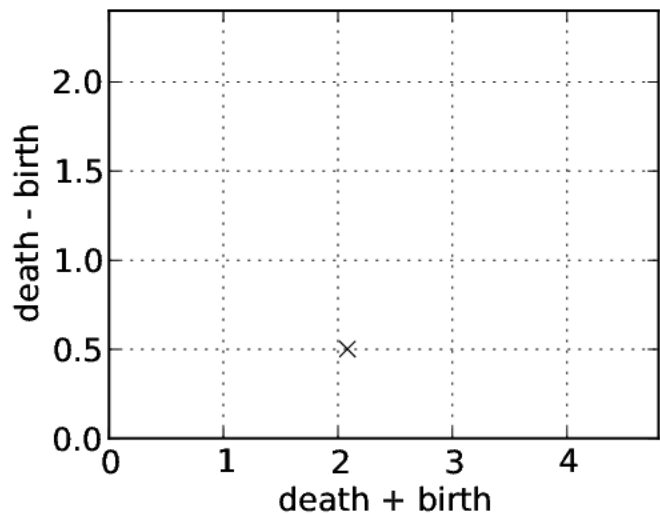
$\sigma=0$



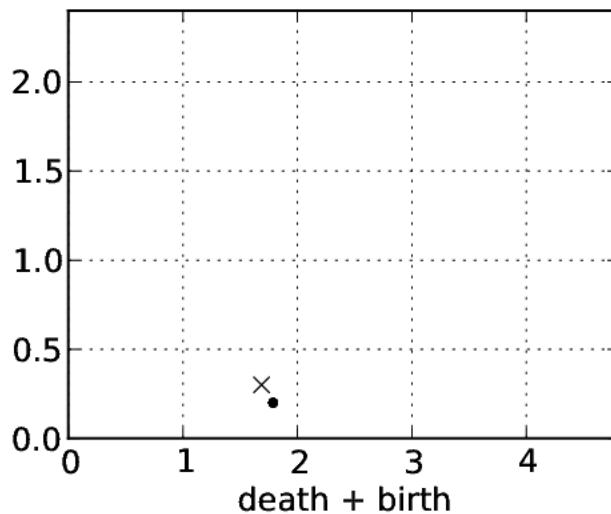
$\sigma=0.09$



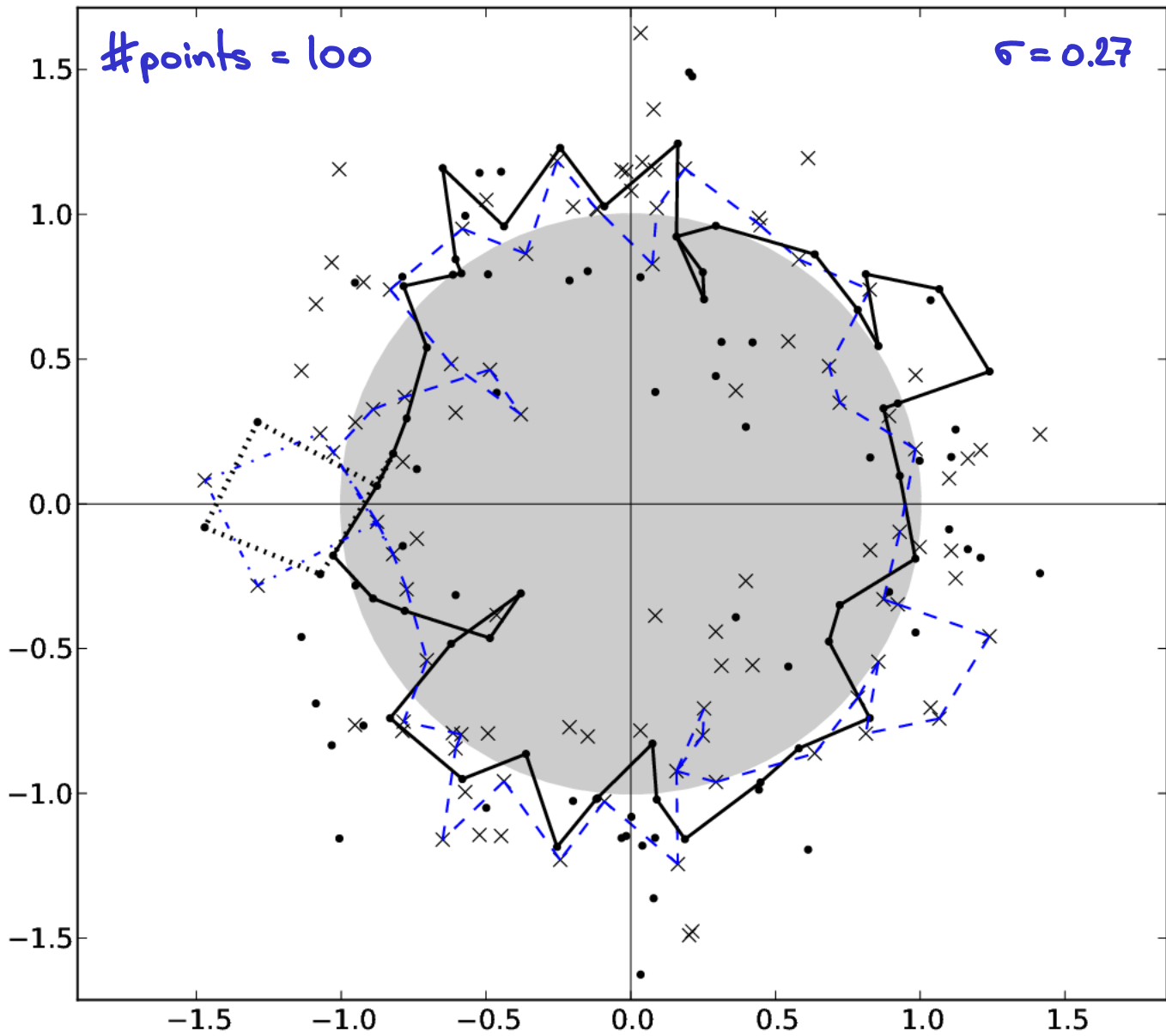
$\sigma=0.18$



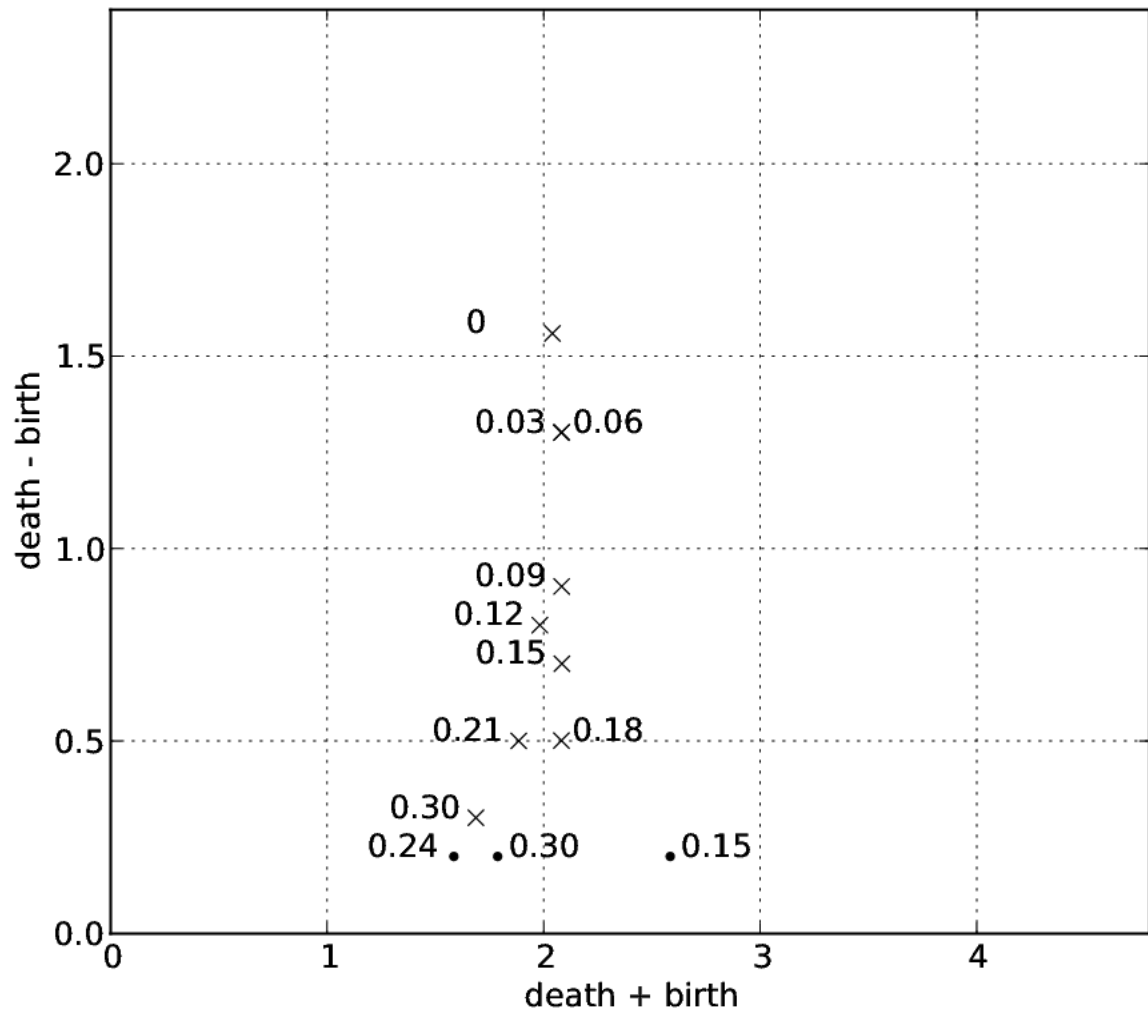
$\sigma=0.30$



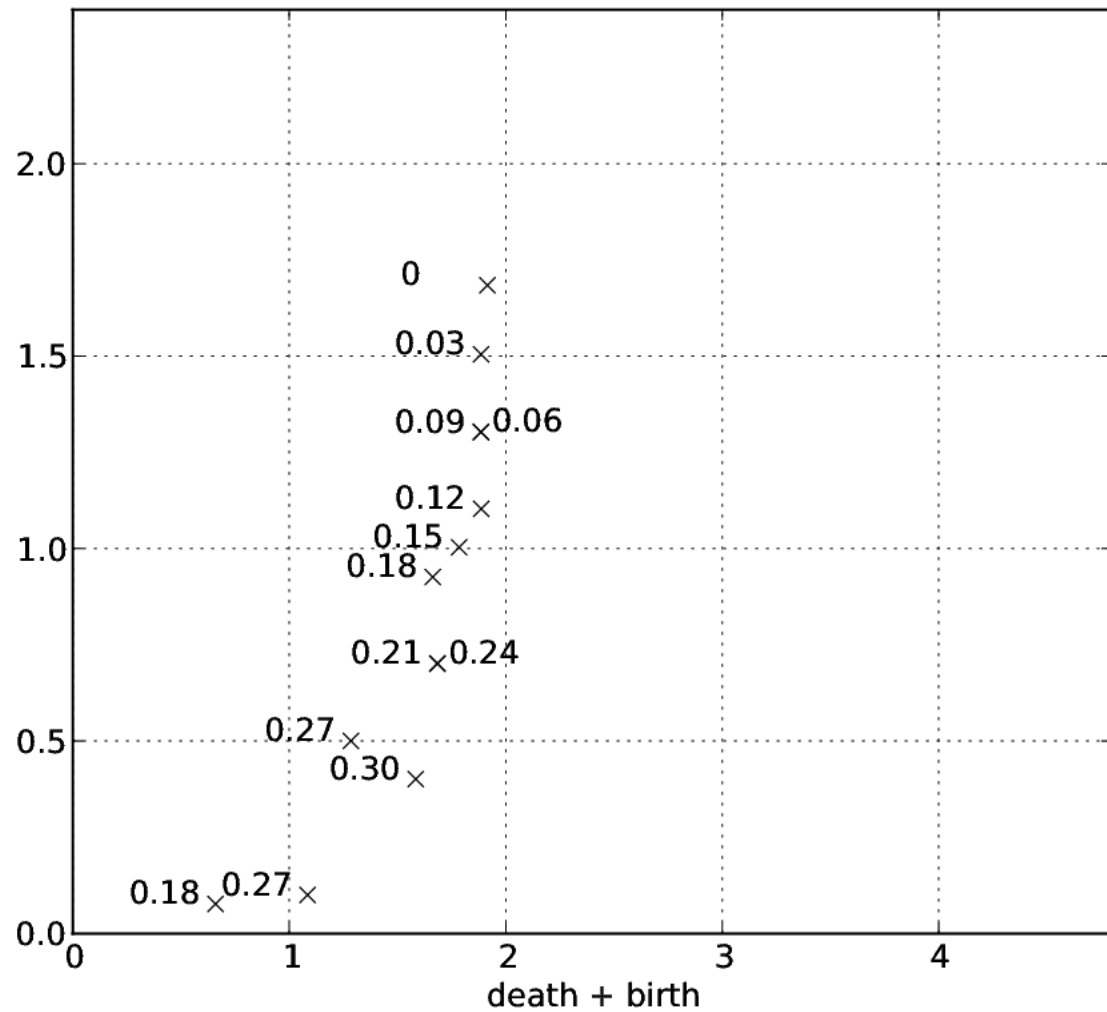
III.3 RESULTS for $f(x) = \bar{x}$



$$z \mapsto z^2$$



$$z \mapsto \bar{z}$$



I. CATEGORIES

II. LINEAR MAPS

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IV. ANALYSIS

IV.1 GRAPHS AND DISTANCES

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distance functions $d_X, d_S: \mathbb{R}^p \rightarrow \mathbb{R}$

$d_{G_f}, d_{G_g}: \mathbb{R}^p \times \mathbb{R}^p \rightarrow \mathbb{R}$

if $\epsilon \geq \text{Hdf}(G_f, G_g)$ then sublevel sets satisfy

$X_r \subseteq S_{r+\epsilon} \subseteq X_{r+2\epsilon}$ and $G_{f,r} \subseteq G_{g,r+\epsilon} \subseteq G_{f,r+2\epsilon}$.

IV.2 INTERLEAVING

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$$\begin{array}{ccccc} U_r & \leftarrow & Gh_r & \rightarrow & U_r \\ \downarrow & & \downarrow & & \downarrow \\ V_{r'} & \leftarrow & Gk_{r'} & \rightarrow & V_{r'} \end{array}$$

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H
→

E_t
→

$$\begin{array}{c} \epsilon_{t,r'}^r: E_t(\psi_{r'}, \psi_r) \\ \downarrow \\ E_t(u_{r'}, v_{r'}) \end{array}$$

IV.2 INTERLEAVING

$$\begin{array}{ccc}
 U_r \leftarrow G h_r \rightarrow U_r & \xrightarrow{H} & E_t \xrightarrow{\epsilon_{t,r}'} E_t(\varphi_{r_1}, \psi_r) \\
 \downarrow & & \downarrow \\
 V_{r'} \leftarrow G k_{r'} \rightarrow V_{r'} & \xrightarrow{\quad} & E_t(v_{r_1}, v_{r_1})
 \end{array}$$

INTERLEAVING LEMMA A. Let $U, V \subseteq \mathbb{R}^p$ and $h: U \rightarrow U, k: V \rightarrow V$ with tame distance functions.

IV.2 INTERLEAVING

$$\begin{array}{ccc}
 U_r \leftarrow Gh_r \rightarrow U_r & & E_t \\
 \downarrow & \downarrow & \downarrow \\
 V_{r'} \leftarrow Gk_{r'} \rightarrow V_{r'} & \xrightarrow{H} & E_t(\varphi_{r'}, \psi_r) \\
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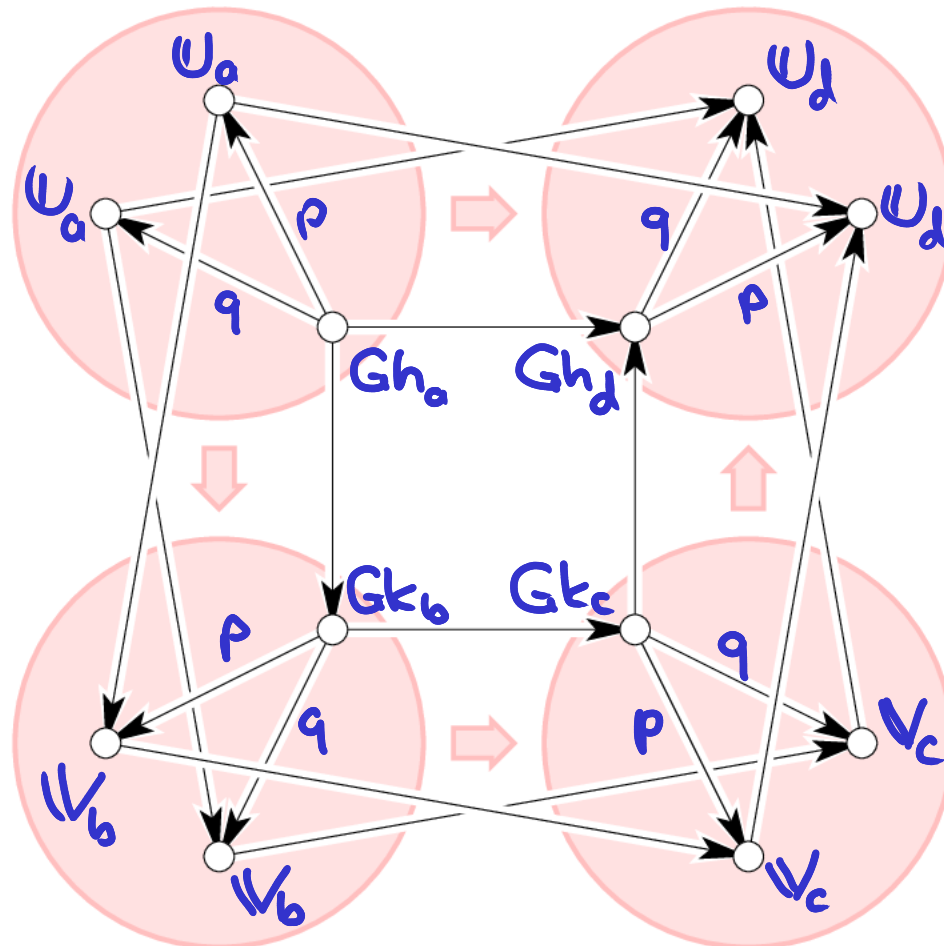
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 U_r \leftarrow Gh_r \rightarrow U_r & \xrightarrow{H} & E_t \\
 \downarrow & & \downarrow \\
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 & & \downarrow \\
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INTERLEAVING LEMMA A. Let $U, V \subseteq \mathbb{R}^p$ and $h: U \rightarrow U, k: V \rightarrow V$ with tame distance functions. Set $\varepsilon = \text{Hdft}(Gh, Gk)$. If $a + \varepsilon \leq b \leq c \leq d - \varepsilon$, then

$$\begin{array}{ccc}
 E_t(\varphi_a, \psi_a) & \rightarrow & E_t(\varphi_b, \psi_b) \\
 \downarrow & & \uparrow \\
 E_t(v_b, v_b) & \rightarrow & E_t(v_c, v_c) \quad \text{commutes.}
 \end{array}$$

PROOF



IV.3 CONVERGENCE

INFERENCE THM. Let $X \subseteq \mathbb{R}^p$ be a compact absolute neighborhood retract, $S \subseteq X$ finite, and $f: X \rightarrow X$ a map such that the distance functions for X and Gf are tame. Then any map $g: S \rightarrow S$ satisfies

$$\dim E_f(\emptyset) = \text{rank } E_{f, \varepsilon}^{3\varepsilon}$$

for all $\text{Hdf}(Gf, Gg) < \varepsilon < \frac{1}{4} \min \{ \text{hfs}(X), \text{hfs}(Gf) \}$.

IV.4 STABILITY

STABILITY THM. Let $U, V \in \mathbb{R}^l$, and $h: U \rightarrow U$, $k: V \rightarrow V$ such that the associated distance functions are tame. Then

$$\text{Bot}(D_{\text{gm}}(\mathcal{E}_t), D_{\text{gm}}(\mathcal{F}_t)) \leq \text{Hdf}(G_h, G_k),$$

where \mathcal{E}_t and \mathcal{F}_t are eigenspace towers defined by h and by k .

THANK YOU