# Identifying engineering (im)possibilities with geometry and topology<sup>1</sup>

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Identifying engineering (im)possibilities for:

Deep neural network autoencoders

Applied Koopman operator methods

Feedback stabilizability

## Identifying engineering (im)possibilities for:

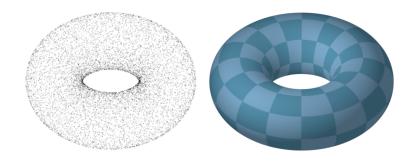
### Deep neural network autoencoders

They should not work, and yet they do: resolving the paradox Training implications:  $L^2$  but not  $L^\infty$  error can be made small

Applied Koopman operator methods

Feedback stabilizability

## Dimensionality reduction of data

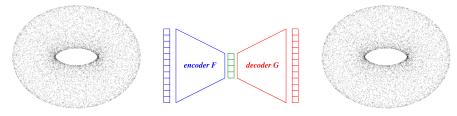


The "manifold hypothesis" postulates that a data set in  $\mathbb{R}^n$  lies on some k-dimensional submanifold  $K \subset \mathbb{R}^n$ .

 $\implies$  data can be parametrized locally by k < n real numbers.

Classical approaches like PCA to learn these parameters work well when K is linear, but not when K is nonlinear.

# Autoencoding as a nonlinear dimensionality reduction approach (and why it should not work)



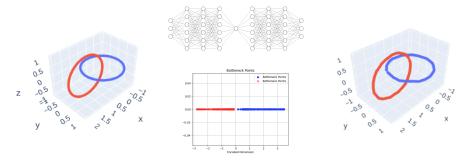
Popular nonlinear approach: seek **autoencoder**  $G \circ F$ , where the output of the **encoder**  $F : \mathbb{R}^n \to \mathbb{R}^k$  is the desired k parameters,  $G : \mathbb{R}^k \to \mathbb{R}^n$  is the **decoder**, and F, G are continuous.

Often F, G are artificial neural network functions.

**Ideal autoencoder**: G(F(x)) = x for all  $x \in K$ .

These **do not usually exist!** Existence  $\implies K$  is homeomorphic to a subset of  $\mathbb{R}^k$ , which is not true of most k-dimensional K.

If autoencoding should not work, how does it?<sup>2</sup> Example:



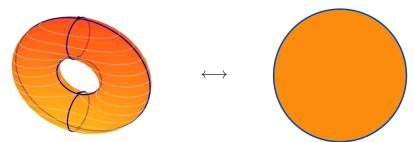
K = a pair of circles in  $\mathbb{R}^3$ , after thickening then deleting small intervals, is diffeomorphic to a pair of disjoint intervals in  $\mathbb{R}$ .

**Encoder**  $F: \mathbb{R}^3 \to \mathbb{R} =$  any extension of this diffeomorphism. **Decoder**  $G: \mathbb{R} \to \mathbb{R}^3 =$  any extension of inverse diffeomorphism.

Such small intervals disjoint from the data set always exist.

<sup>&</sup>lt;sup>2</sup>MDK and E D Sontag. *Why should autoencoders work?* Transactions on Machine Learning Research (2024).

## If autoencoding should not work, how does it? In general:



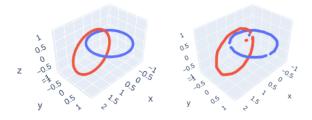
K= a union of  $\leq k$ -dimensional compact submanifolds of  $\mathbb{R}^n$ , after thickening then deleting the codimension >0 "steepest ascent disks" of a polar Morse function,<sup>3</sup> is diffeomorphic to a subset of  $\mathbb{R}^k$ .

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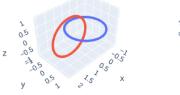
Can always find such a "codim > 0 set" disjoint from the data.

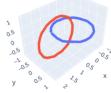
<sup>&</sup>lt;sup>3</sup>A navigation function, in the parlance of Rimon and Koditschek (1990).

## Note: training sometimes yields disconnected "good" sets



In practice, random initialization/training leads to random outcomes, even those with disconnected "good sets", despite the fact that arbitrarily large connected "good sets" (disks) exist.





## Semi-global autoencoders always exist<sup>4</sup>

Let  $\mathcal{F}^{\ell,m}$  be dense in the space of continuous functions  $\mathbb{R}^\ell \to \mathbb{R}^m$ , e.g., the collection of possible neural network outputs.

**Theorem 1 (MDK and E D Sontag).** Let  $K \subset \mathbb{R}^n$  be finitely many disjoint compact  $\leq k$ -dimensional submanifolds with(out) boundary, and let  $\mu$ ,  $\partial \mu$  be any smooth measures on K,  $\partial K$ . For each  $\delta > 0$  and finite set  $S \subset K$ , there is a closed set  $K_0 \subset K$  s.t.

- $K_0 \cap S = \emptyset$ ,  $\mu(K_0) < \delta$ ,  $\partial \mu(K_0 \cap \partial K) < \delta$ ;
- ▶  $M \setminus K_0$  is connected for each component M of K;
- ▶ For each  $\varepsilon > 0$  there are functions  $F \in \mathcal{F}^{n,k}$ ,  $G \in \mathcal{F}^{k,n}$  such that

$$\sup_{x\in K\setminus K_0}\|G(F(x))-x\|<\varepsilon.$$

 $\implies$  data S can be reconstructed to order  $\varepsilon$ , and generalization error will also be uniformly smaller than  $\varepsilon$  with probability  $1 - \delta$ .

<sup>&</sup>lt;sup>4</sup>MDK and E D Sontag. Why should autoencoders work? Transactions on Machine Learning Research (2024).

## Almost-global autoencoders do not generally exist

**Theorem 2 (MDK and EDS).** Let  $K \subset \mathbb{R}^n$  be a k-dimensional compact submanifold without boundary. For any continuous functions  $F: \mathbb{R}^n \to \mathbb{R}^k$  and  $G: \mathbb{R}^k \to \mathbb{R}^n$ ,

$$\sup_{x\in K}\|G(F(x))-x\|\geq \underbrace{r_K}_{\text{reach}}>0.$$

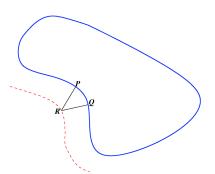


Figure: The **reach**  $r_K > 0$  of K is the largest number such that any  $x \in \mathbb{R}^n$  satisfying  $\text{dist}(x, K) < r_K$  has a unique nearest point on K. Both line segments shown have length  $r_K$ .

## Almost-global autoencoders do not generally exist<sup>5</sup>

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$$\sup_{x \in K} \|G(F(x)) - x\| \ge \underbrace{r_K}_{\text{reach}} > 0.$$
 (2)

#### **Proof:**

▶  $N := \{x \in \mathbb{R}^n : \operatorname{dist}(x, K) < r_K\}$  contains line segment from  $x \in N$  to nearest  $\rho(x) \in N$ ;  $\rho$  is continuous.

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- But this contradicts

$$0 = \deg_2(\rho \circ G \circ F|_K) = \deg_2(\rho \circ G|_{F(K)}) \underbrace{\deg_2(F|_K)}_{\rho}.$$

<sup>&</sup>lt;sup>5</sup>MDK and E D Sontag. *Why should autoencoders work?* Transactions on Machine Learning Research (2024).

## Example: K = 2 unit circles; max error > reach $r_K = 1$

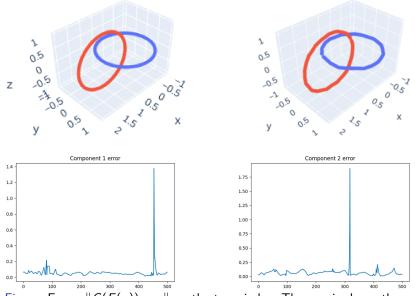


Figure: Errors ||G(F(x)) - x|| on the two circles. The *x*-axis shows the index *k* representing the *k*-th evenly-spaced point on the respective circle.

In fact, true min-max error is usually bigger than the reach<sup>6</sup>



Red reach = 1 but green reach =  $\varepsilon \ll 1$ , so previous min max error "reach" is conservative. But green "dewrinkled reach" =  $1 - \varepsilon$ .

**Corollary (MDK and EDS).** Let  $K \subset \mathbb{R}^n$  be a k-dimensional compact submanifold without boundary. For any continuous functions  $F \colon \mathbb{R}^n \to \mathbb{R}^k$  and  $G \colon \mathbb{R}^k \to \mathbb{R}^n$ ,

$$\sup_{\mathbf{x} \in K} \|G(F(\mathbf{x})) - \mathbf{x}\| \ge \underbrace{r_{K,k}^*}_{\text{dewrinkled reach}} := \sup_{L \in \mathcal{M}_{n,k}, T \in C(L \to K)} \{r_L - \delta(T)\}.$$

<sup>&</sup>lt;sup>6</sup>MDK and E D Sontag. Why should autoencoders work? Transactions on Machine Learning Research (2024).

## Implications for autoencoder training error<sup>7</sup>

Theorem 1  $\implies$  F, G always exist making the  $L^2(\mu)$  loss

$$\int_{K} \|G(F(x)) - x\|^{2} d\mu(x) < \varepsilon$$

$$\left( = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} G(F(x_{i})) - x_{i}\|^{2} \right)$$

**arbitrarily small** (any G can be modified off of  $F(K \setminus K_0)$  to make the autoencoder error smaller than a certain  $C_K > 0$  on  $K_0$ .)

**However**, Theorem 2  $\Longrightarrow$  for many K, the  $L^{\infty}$  loss

$$\max \|G(F(x)) - x\| > r_K > 0$$

is uniformly big, independent of F, G.

<sup>&</sup>lt;sup>7</sup>We thank Dr. Joshua Batson for suggesting these observations.

## Summary

**Main representation result**: data lying in a submanifold K of dimension k can be encoded through a bottleneck layer of the same dimension k, up to an arbitrarily small reconstruction error  $\varepsilon$ .

Moreover, the generalization error will also be uniformly smaller than  $\varepsilon$  with arbitrarily high probability  $1-\delta$ .

**Main necessity result:** for many K (including all K without boundary), there is a geometric lower bound on the global reconstruction error.

**Training implications:**  $L^2$  error can always be made arbitrarily small;  $L^{\infty}$  error cannot.

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Applied Koopman operator methods

Feedback stabilizability

## Identifying engineering (im)possibilities for:

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## Applied Koopman operator methods

Many assume the dynamical system is globally linearizable Which ones are?

1-parameter subgroups of torus actions with asymptotic phase

Feedback stabilizability

## "Applied Koopmanism"

"A central focus of modern Koopman analysis is to find a finite set of nonlinear measurement functions, or coordinate transformations, in which the dynamics appear linear."

— Brunton, Budišić, Kaiser, and Kutz. "Modern Koopman Theory for Dynamical Systems." SIAM Review, 64.2 (2022)

They seek nonlinear measurements that separate points, to be able to invert / not to lose information. Also want measurements / inverse to be continuous for practical reasons.

More formally, they seek *embeddings* of *nonlinear* dynamical systems into *linear* ones as invariant subsets, so that existing theoretical and algorithmic linear tools can be utilized.

## Linearizing embeddings

Let f be a locally Lipschitz vector field on a manifold M. Consider

$$\dot{x} = \frac{d}{dt}x = f(x),$$

assume this ODE's solutions  $x(t) = \Phi^t(x_0)$  are defined for all time.

 $F \colon M \to \mathbb{R}^n$  is a **topological embedding** if F is a one-to-one continuous map with a continuous inverse  $F^{-1} \colon F(M) \to M$ , and is a **smooth embedding** if additionally F,  $F^{-1}$  are smooth.

Such an embedding F is **linearizing** if  $F \circ \Phi^t = e^{Bt} \circ F$  for some  $n \times n$  matrix B. In the smooth case, y = F(x) satisfies  $\dot{y} = By$ .

**Fundamental question**: when is  $(M, \Phi)$  linearizable in this sense?

# When is a dynamical system $(M, \Phi)$ globally linearizable?

- Not when M is connected, forward  $\Phi$ -trajectories are precompact, and  $\Phi$  has a countable number  $\geq 2$  of omega limit sets (Liu, Ozay, Sontag 2023).
- Not when M is connected and  $\Phi$  has a non-global compact attractor  $A \neq \emptyset$ , since its open basin of attraction would also be closed (by the Jordan normal form theorem), hence empty.

Thus, we study linearizability of the restriction  $(S, \Phi)$  of  $\Phi$  to

- 1. compact invariant sets S, and
- 2. basins S of compact attractors A.

For these 2 cases we obtain **necessary and sufficient conditions** for global linearizability of  $(S, \Phi)$  by an embedding, for the 2 cases of topological and smooth embeddings (4 cases total).<sup>8</sup>

<sup>&</sup>lt;sup>8</sup>MDK and P. Arathoon, Linearizability of flows by embeddings (2023).

## Torus preliminaries

The *n*-torus  $T = T^n$  is (Lie group) isomorphic to  $(\mathbb{R}/\mathbb{Z})^n$ , vectors with *n* real entries but with addition defined elementwise modulo 1.

A **torus action** on S is a map  $\Theta \colon T \times S \to S$  satisfying  $\Theta^{\tau_1 + \tau_2}(s) = \Theta^{\tau_1} \circ \Theta^{\tau_2}(s)$  for all  $s \in S$  and  $\tau_1, \tau_2 \in T$ .

The flow  $(S, \Phi)$  is a **1-parameter subgroup of a torus action** if  $\Phi^t = \Theta^{\omega t \mod 1}$  for some torus action  $\Theta$  on  $S, \omega \in \mathbb{R}^n$ .

## The linearizability theorem, case 1: compact, smooth

**Observation:** If  $(S, \Phi)$  is linearizable with S compact, the Jordan normal form theorem implies  $(S, \Phi)$  embeds into the flow on  $\mathbb{C}^n$  of a diagonal imaginary matrix, so  $(S, \Phi)$  is a 1-parameter subgroup of restriction of standard torus action of  $T^n$  on  $\mathbb{C}^n$  to a subtorus.

This gives one implication below; the *Mostow-Palais equivariant* embedding theorem gives the other.

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This gives one implication below; the *Mostow-Palais equivariant embedding theorem* gives the other.

**Theorem (MDK and P. Arathoon).** If S is a compact embedded submanifold,  $(S, \Phi)$  is linearizable by a smooth embedding  $\iff$   $(S, \Phi)$  is a 1-parameter subgroup of a smooth torus action.

We use this theorem to construct examples of smoothly linearizable  $(S, \Phi)$  having isolated equilibria with e.g. S = a sphere, torus, Klein bottle. On the other hand, regarding *non*linearizability...

## Topological implications for case 1 (compact, smooth)

If  $(S,\Phi)$  is a 1-parameter subgroup of a smooth torus action, Bochner's linearization theorem yields an  $n\times n$  skew matrix  $B_e$  and a system of local coordinates on a neighborhood of each equilibrium  $e\in S$  such that  $\Phi^t\approx e^{B_e t}$ . Hence if e is isolated then  $B_e$  is invertible,  $n=\dim S$  is even, and the Hopf index of e is +1.

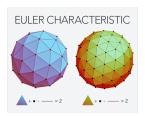
**Corollary (MDK and PA).** If S is an odd-dimensional connected compact submanifold with at least one isolated equilibrium, then  $(S,\Phi)$  cannot be linearized by a smooth embedding.

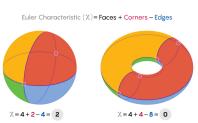
**Corollary (MDK and PA).** If S is a compact submanifold containing at most finitely many equilibria such that  $(S, \Phi)$  is linearizable by a smooth embedding,  $\chi(S) = \#\{\text{equilibria}\} \ge 0$ .

<sup>&</sup>lt;sup>9</sup>Apply the Poincaré-Hopf theorem.

## A primer on the Euler characteristic 10

Goes back to Francesco Maurolico (1537), Leonhard Euler (1758).





**Notation**:  $\chi(Y) := \text{Euler characteristic of } Y$ .

**Examples**: 
$$\chi(\bullet) = 1$$
,  $\chi(\mathbb{S}^1) = 0$ ,  $\chi(\mathbb{S}^2) = 2$ ,  $\chi(\Sigma_g) = 2 - 2g$ 







 $\Sigma_g$  for g=1,2,3 (not linearizable for g>1 if finite equilibria).

<sup>&</sup>lt;sup>10</sup>Figures from Quanta Magazine and Wikipedia.

## The linearizability theorem, case 2: compact, continuous

The theorem for case 2 is similar for case 1, but an additional assumption is needed to rule out a pathology not possible in case 1.

**Theorem (MDK and PA).** If S is compact,  $(S, \Phi)$  is linearizable by a topological embedding  $\iff (S, \Phi)$  is a 1-parameter subgroup of a continuous torus action with finitely many orbit types.

A torus action has **finitely many orbit types** if there are only finitely many subgroups  $H \subset T$  such that  $H = \{\tau \in T : \Theta^{\tau}(s) = s\}$  is the fixed point set of some  $s \in S$ .

## Another point of view: quasiperiodic pinched torus families



Figure: examples of quasiperiodic pinched torus families

**Proposition (MDK and PA).** If S is compact,  $(S, \Phi)$  is linearizable by a topological embedding  $\iff (S, \Phi)$  is a quasiperiodic pinched torus family.

**Definition.** P is a **pinched torus family** if there are  $m, n \in \mathbb{N}$ , closed subsets  $C_1, \ldots, C_n \subset B \subset T^m$ , and a continuous group homomorphism  $F \colon T^n \to T^m$  such that P is the quotient of  $F^{-1}(B)$  by collapsing the j-th  $(\mathbb{R}/\mathbb{Z})$ -factor of  $F^{-1}(C_j) \subset T^n$  for all j. A pinched torus family P is **quasiperiodic** if it is equipped with the induced flow generated by any  $\omega \in \mathbb{R}^n$  with  $\mathsf{T}F(\omega) = 0$ .

## The linearizability theorem, case 3: basin, continuous

If S is the basin of an asymptotically stable compact set  $A \subset S$ , A has continuous (smooth) **asymptotic phase**<sup>11</sup> if there is a continuous (smooth) **asymptotic phase map**  $P: S \to A$ , i.e.,

$$P|_A = \mathrm{id}_A, \qquad P \circ \Phi^t|_S = \Phi^t \circ P \quad \text{for all } t \in \mathbb{R}.$$

**Theorem (MDK and PA).**  $(S, \Phi)$  is linearizable by a topological embedding  $\iff$  A has continuous asymptotic phase and  $(A, \Phi)$  is a 1-parameter subgroup of a continuous torus action with finitely many orbit types.

**Example.** The basin of an asymptotically stable limit cycle is linearizable by a topological embedding  $\iff$  the cycle has continuous asymptotic phase. This is not always the case, but it is the case if  $\Phi \in C^1$  and the cycle is hyperbolic.

<sup>&</sup>lt;sup>11</sup>This notion has roots in oscillator theory and more generally NHIM theory.

## The linearizability theorem, case 4: basin, smooth

**Theorem (MDK and PA).**  $(S, \Phi)$  is linearizable by a smooth embedding  $\iff$  A is an embedded submanifold with smooth asymptotic phase,  $(A, \Phi)$  is a 1-parameter subgroup of a smooth torus action, and for some open  $U \supset A$ ,  $(U, \Phi)$  embeds in a reducible linear flow covering  $\Phi$  on some vector bundle over A.

When does the final condition hold? Classical linearization theorems and recent linearizing semiconjugacy theorems (MDK and Revzen, 2023) give answers in the special cases that A is an equilibrium or periodic orbit, and some things are known if A is quasiperiodic, but the general case seems to be an open problem.

A necessary condition for A to satisfy all conditions of the theorem is that A be a (eventually relatively  $\infty$ -)normally hyperbolic invariant manifold. See Eldering, MDK, Revzen (2018) for related results on asymptotic phase and linearizability.

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Brockett's necessary condition and beyond A homotopy theorem beyond the Coron/Mansouri tests Periodic orbits can be easier to stabilize than equilibria

## Two fundamental problems of control theory

Consider

$$\frac{dx}{dt} = f(x, u),\tag{1}$$

where  $M \ni x$  is a smooth manifold and f is smooth.

1. **Controllability problem**: Given  $a, b \in M$ , find u(t) s.t. x(T) = b if x(0) = a for some T > 0.

2. **Stabilizability problem**: Given a compact subset  $A \subset M$ , find smooth u(x) s.t. A is **asymptotically stable**<sup>12</sup> for the **closed-loop vector field** F(x) = f(x, u(x)).

 $<sup>^{12}</sup>$ For every open  $W \supset A$  there is an open  $V \supset A$  s.t. all forward F-trajectories initialized in V are contained in W and converge to A.

## The stabilization conjecture and Brockett's solution

Often  $A = \{x_*\}$  is a point,  $M = \mathbb{R}^n$  in the stabilization problem.

**Stabilization conjecture (pre-1983)**: a reasonably strong form of controllability implies smooth stabilizability of a point.

**Example:** the "Heisenberg system" or "nonholonomic integrator"

$$\begin{vmatrix} \dot{x} & = u \\ \dot{y} & = v \\ \dot{z} & = yu - xv \end{vmatrix} = f(\mathbf{x}, \mathbf{u}).$$

is controllable in every sense imaginable. But Brockett (1983) showed that no point is stabilizable, refuting the conjecture. How?

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**Theorem (Brockett).** If a point is stabilizable, then image(f) is a neighborhood of 0. (In the example,  $(0,0,\varepsilon) \notin image(f)$ .)

## Other stabilizability work

- Exponential (Gupta, Jafari, Kipka, Mordukhovich 2018; Christopherson, Mordukhovich, Jafari 2022),
- ▶ global (Byrnes 2008, Baryshnikov 2023),
- time-varying (Coron 1992), and
- discontinuous (Clarke, Ledyaev, Sontag, Subbotin 1997)

variants of the stabilization problem are not considered here.

### Coron's and Mansouri's obstructions

Krasnosel'skiĭ and Zabreĭko (1984) obtained a necessary condition for asymptotic stability of an equilibrium of a vector field.

Using this, Coron introduced a homological obstruction sharper than Brockett's, and Mansouri generalized. Define

$$\Sigma := \{(x, u) \in \mathbb{R}^n \times \mathbb{R}^m \colon f(x, u) \neq 0\}.$$

**Theorem (Coron 1990).** If n > 1 and a point is stabilizable,

$$f_*(H_{n-1}(\Sigma)) = H_{n-1}(\mathbb{R}^n \setminus \{0\})$$
 (\(\approx \mathbb{Z}\).

**Theorem (Mansouri 2010).** If a closed codimension > 1 submanifold  $A \subset \mathbb{R}^n$  with Euler characteristic  $\chi(A)$  is stabilizable,

$$f_*(H_{n-1}(\Sigma)) \supset \chi(A) \cdot H_{n-1}(\mathbb{R}^n \setminus \{0\}) \qquad (\cong \chi(A) \cdot \mathbb{Z}).$$

#### Limitations of these results

The results of Brockett, Coron, Mansouri rely on parallelizability of  $\mathbb{R}^n$  to view vector fields and control systems as  $\mathbb{R}^n$ -valued.

Furthermore, they apply only to the special case that A is a point or a closed submanifold of  $\mathbb{R}^n$  with  $\chi(A) \neq 0$ .

But sometimes one wants to stabilize more general subsets of more general spaces: robot gaits, safe behaviors for self-driving cars, etc.

How to test for stabilizability in such general settings?<sup>13</sup>

- ► **Generalization of Brockett's test** (MDK and Daniel E. Koditschek, J Geometric Mechanics, 2022).
- ► Generalization of Coron's and Mansouri's tests (MDK, SIAM J Control and Optimization, 2023).

 $<sup>^{13}</sup>$ An exposition of all stabilizability results here is in 2023 book *Topological Obstructions to Stability and Stabilization* by W. Jongeneel and E. Moulay.

### A primer on the Euler characteristic 14

Goes back to Francesco Maurolico (1537), Leonhard Euler (1758).



**Notation**:  $\chi(Y) := \text{Euler characteristic of } Y$ .

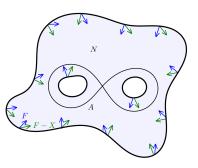
**Examples**: 
$$\chi(\bullet) = 1$$
,  $\chi(\mathbb{S}^1) = 0$ ,  $\chi(\mathbb{S}^2) = 2$ ,  $\chi(\text{figure 8}) = -1$ 

**Theorem (Poincaré, Hopf)**: if N is a compact smooth manifold with boundary  $\partial N$ , then  $\chi(N) = 0 \iff$  there exists a nowhere-zero smooth vector field on N pointing inward at  $\partial N$ .

<sup>&</sup>lt;sup>14</sup>Figures from Quanta Magazine.

### Generalization of Brockett's test

**Theorem (MDK & Koditschek 2022)**: Let  $A \subset M$  be compact & stabilizable. Then  $\chi(A)$  is well-defined. If  $\chi(A) \neq 0$ , then for any sufficiently small vector field X,  $\chi(x_0) = f(x_0, u_0)$  for some  $x_0, u_0$ .



**Proof**: Assume  $\exists$  stabilizing u(x) and define F(x) := f(x, u(x)). Lyapunov function theory  $\Longrightarrow \exists$  compact smooth domain  $N \supset A$  s.t. F points inward at  $\partial N$  and  $\chi(A) = \chi(N) \neq 0$ . Continuity  $\Longrightarrow F - X$  points inward at  $\partial N$  if X is small  $\Longrightarrow F - X$  has a zero by Poincaré-Hopf  $\Longrightarrow \exists x_0 \text{ s.t. } X(x_0) = F(x_0) = f(x_0, u(x_0))$ .

### **Examples**

#### Heisenberg system

#### Kinematic differential drive robot

$$\dot{x} = u$$
  $\dot{x} = u \cos \theta$   
 $\dot{y} = v$  (2)  $\dot{y} = u \sin \theta$  (3)  
 $\dot{z} = yu - xv$   $\dot{\theta} = v$ 

The right side of  $(2) \neq X_{\varepsilon} := (0,0,\varepsilon)$  for any  $\varepsilon > 0$ .

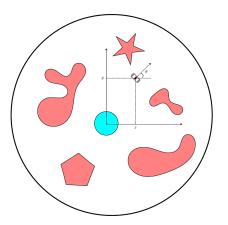
The right side of (3)  $\neq X_{\varepsilon} := (\varepsilon \sin \theta, -\varepsilon \cos \theta, 0)$  for any  $\varepsilon > 0$ .

Thus, our result  $\implies$  A is not stabilizable if  $\chi(A) \neq 0$ . E.g., if A is a stabilizable compact submanifold, A is a union of circles and tori.

**Other applications**: any stabilizable compact set has zero Euler characteristic for satellite orientation with  $\leq 2$  thrusters, for nonholonomic dynamics with  $\geq 1$  global constraint 1-form,...

### Safety application

Our Brockett generalization implies an obstruction to a control system operating safely, i.e., ensuring trajectories initialized on the boundary of some "bad" set immediately enter some "good" set.



E.g., impossible for this differential drive robot to aim within  $\pm 179$  degrees of the origin while "strictly" avoiding obstacles via u(x).

### Homotopy theorem & generalized Coron, Mansouri tests

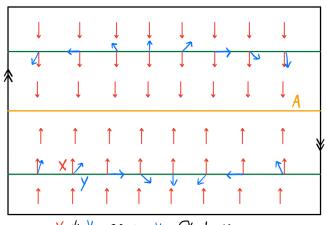
**Homotopy theorem (MDK 2023)**. Let X, Y be smooth vector fields on a manifold M with a compact set  $A \subset M$  asymptotically stable for both. There is an open set  $U \supset A$  such that  $X|_{U \setminus A}$ ,  $Y|_{U \setminus A}$  are homotopic through nowhere-zero vector fields.

 $\implies$  **Theorem (MDK 2023).** Let the compact set  $A \subset M$  be asymptotically stable for *some* smooth vector field Y on M. If A is stabilizable for  $\dot{x} = f(x, u)$ , then for all small enough open  $U \supset A$ ,

$$H_{\bullet}(T(U \setminus A) \setminus 0) \supset \underbrace{f_*H_{\bullet}(\Sigma) \supset Y_*H_{\bullet}(U \setminus A)}_{\text{cf. Coron, Mansouri}}.$$

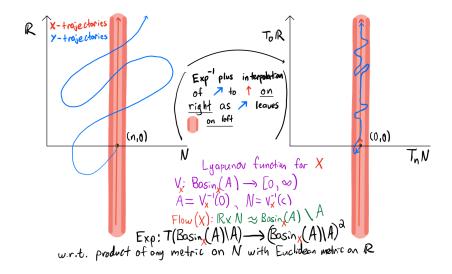
These are stronger than all preceding results: there is an example (MDK 2023) for which non-stabilizability is detected by each of these theorems but not by any of the preceding theorems.

# Möbius strip example



 $X \neq Y$  Since Y C' twice around  $\bigcirc$  W.r.t. X while X C' zero times W.r.t.  $X \Rightarrow A$  is not asymptotically stable for Y by the homotopy theorem.

## Proof of the homotopy theorem



## Can these results detect stabilizability of periodic orbits?

If A is the image of a periodic orbit with the same orientation for X and Y, the straight-line homotopy over a sufficiently small open  $U \supset A$  satisfies the homotopy theorem's conclusion regardless of whether A is attracting, repelling, or neither for X or Y.

⇒ homotopy theorem gives no information on stability or stabilization of periodic orbits. Since this is the strongest result, preceding results also give no information.

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...Could it be that periodic orbits might be "easy" to stabilize?

Periodic orbits are sometimes easier to stabilize

Indeed, at least sometimes:

Theorem (Anthony M. Bloch & MDK, in preparation). For a broad class of control systems including Heisenberg's and the differential-drive robot, any periodic orbit that can be created can be stabilized—even though no equilibrium that can be created can be stabilized for the mentioned examples!

## Identifying engineering (im)possibilities for:

Deep neural network autoencoders

Applied Koopman operator methods

#### Feedback stabilizability

Brockett's necessary condition and beyond A homotopy theorem beyond the Coron/Mansouri tests Periodic orbits can be easier to stabilize than equilibria



## Identifying engineering (im)possibilities for:

#### Deep neural network autoencoders

They should not work, and yet they do: resolving the paradox Training implications:  $L^2$  but not  $L^{\infty}$  error can be made small

#### Applied Koopman operator methods

Many assume the dynamical system is globally linearizable Which ones are?

1-parameter subgroups of torus actions with asymptotic phase

#### Feedback stabilizability

Brockett's necessary condition and beyond A homotopy theorem beyond the Coron/Mansouri tests Periodic orbits can be easier to stabilize than equilibria