

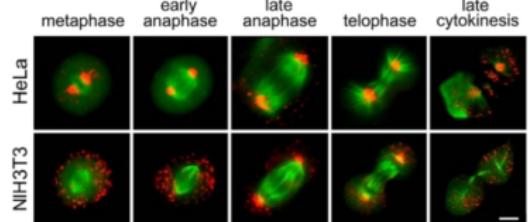
Utilizing Topological Data Analysis to Detect Periodicity

Elizabeth Munch

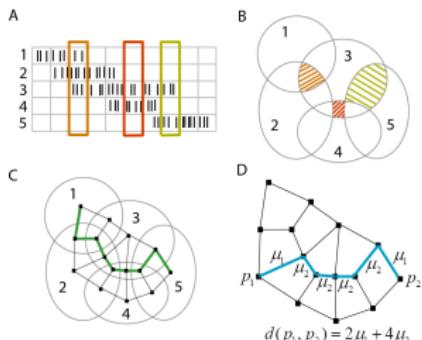
University at Albany - SUNY :: Department of Mathematics & Statistics

Oct 2, 2016

Time series in biology



Mitosis
Kredel et al. PLoS One 2009



Neuron Spike Trains
Curto et al. PLoS One 2008

	L5	JTK	DL	PH
Yeast Cell Cycle	ACP4 ✓✓✓✓✓	SRP1 ✓✓✓✓✓	HTA2 ✓✓✓✓✓	MET18 ✓✓✓✓✓
	SK07 ✓✓✓✓✓	SKP1 ✓✓✓✓✓	NRM1 ✓✓✓✓✓	RAD161 ✓✓✓✓✓
	TP03 ✓✓✓✓✓	SKP2 ✓✓✓✓✓	CLB1 ✓✓✓✓✓	NPI100 ✓✓✓✓✓
	YLR001W ✓✓✓✓✓	ECM32 ✓✓✓✓✓	SIM1 ✓✓✓✓✓	RAD60 ✓✓✓✓✓
	YDR239C ✓✓✓✓✓	PLB1 ✓✓✓✓✓	SRL1 ✓✓✓✓✓	POP ✓✓✓✓✓
Mammal Cytosol	Elev3 ✓✓✓✓✓	Elev3 ✓✓✓✓✓	Tub62B2 ✓✓✓✓✓	Sdg34 ✓✓✓✓✓
	Tar3 ✓✓✓✓✓	Brnp3 ✓✓✓✓✓	App1a ✓✓✓✓✓	Nmp1 ✓✓✓✓✓
	Gys2 ✓✓✓✓✓	Stgag5 ✓✓✓✓✓	Eka3 ✓✓✓✓✓	Sdg35 ✓✓✓✓✓
	Scd2 ✓✓✓✓✓	Namp1 ✓✓✓✓✓	Arnl ✓✓✓✓✓	Adm1b ✓✓✓✓✓
	ATG362950 ✓✓✓✓✓	ATG008620 ✓✓✓✓✓	RNS2 ✓✓✓✓✓	PBC1 ✓✓✓✓✓
	FAR7 ✓✓✓✓✓	CRP21 ✓✓✓✓✓	ATG012424 ✓✓✓✓✓	AT1028400 ✓✓✓✓✓
	AT1G00826 ✓✓✓✓✓	ATG015944 ✓✓✓✓✓	PKT3 ✓✓✓✓✓	DER ✓✓✓✓✓
	AT4015944 ✓✓✓✓✓	269207_s_at ✓✓✓✓✓	UNES ✓✓✓✓✓	AT1063310 ✓✓✓✓✓
	ATG011319 ✓✓✓✓✓	244917_at ✓✓✓✓✓	KCR1 ✓✓✓✓✓	AT2020960 ✓✓✓✓✓
Yeast Metabolism	SSA3 ✓✓✓✓✓	SWI5 ✓✓✓✓✓	SWI5 ✓✓✓✓✓	GUT1 ✓✓✓✓✓
	SIP18 ✓✓✓✓✓	BUD6 ✓✓✓✓✓	PTF2 ✓✓✓✓✓	EFT1 EFT2 ✓✓✓✓✓
	MPR135 ✓✓✓✓✓	ACE2 ✓✓✓✓✓	YGL044W-A ✓✓✓✓✓	ADE17 ✓✓✓✓✓
	GRE2 ✓✓✓✓✓	SRL1 ✓✓✓✓✓	SRL1 ✓✓✓✓✓	AAH1 ✓✓✓✓✓
	GND2 ✓✓✓✓✓	CHS2 ✓✓✓✓✓	HBT1 ✓✓✓✓✓	GLY1 ✓✓✓✓✓

Yeast gene expression
Deckard et al., Bioinformatics 2013



ECG
Goldberg et al. 2000

Our definition of time series

Definition

A time series is a function

$$f : \mathbb{R}_{\geq 0} \longrightarrow D$$

for some topological space D .

Our definition of time series

Definition

A time series is a function

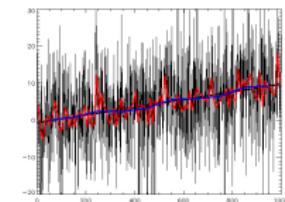
$$f : \mathbb{R}_{\geq 0} \longrightarrow D$$

for some topological space D .

Choice for D

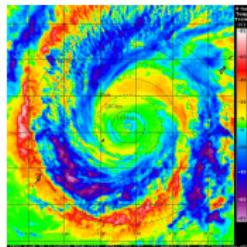
- \mathbb{R} - Classical time series analysis
- $\mathbb{R}^{m \times n}$ - \mathbb{R} -valued $m \times n$ matrices (movies)
- Pers - Persistence diagram valued time series (vineyards)

Commonly used tools



\mathbb{R} -valued TS

Takens Embedding

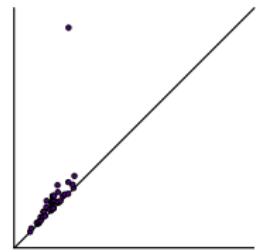


$\mathbb{R}^{m \times n}$ -valued TS

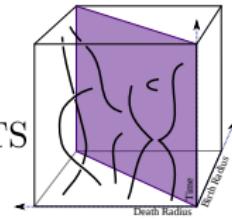
Sub/Sublevel-set
persistence

Pers

Persistence of
persistence



Pers-valued TS



Common questions

- Classification/Clustering
 - ▶ Is this signal Type A or Type B?

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 - ▶ Which pieces of this signal come from similar systems?

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Idea:

Persistent homology and other TDA tools
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This talk:

- Mechanical engineering
 - ▶ Firas Khasawneh
 - ▶ Jose Perea
- Atmospheric science
 - ▶ Bill Dong
 - ▶ Kristen Corbosiero
 - ▶ Jason Dunion
 - ▶ Ryan Torn

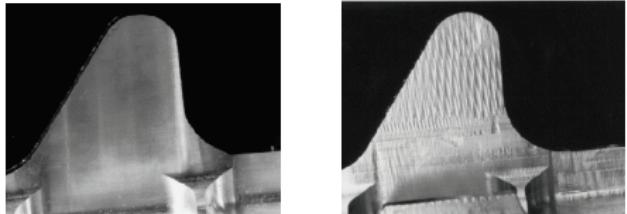
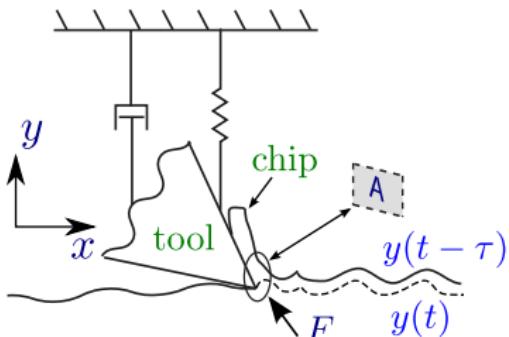
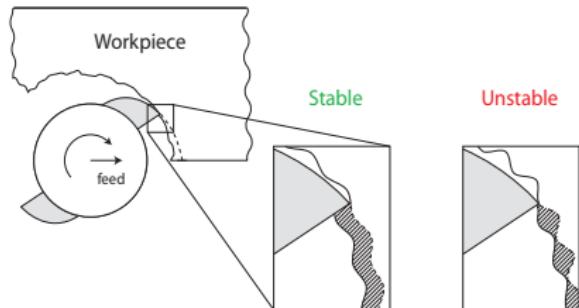
1 Classification and Machining Dynamics

2 Periodicity and Hurricanes

1 Classification and Machining Dynamics

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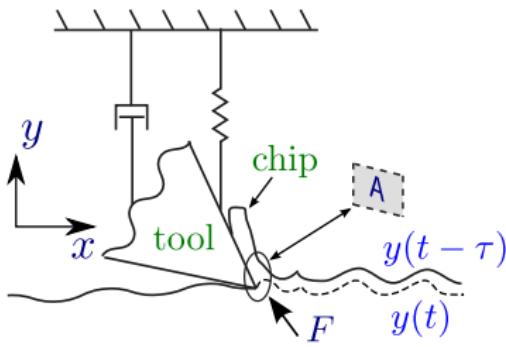
Machining Dynamics



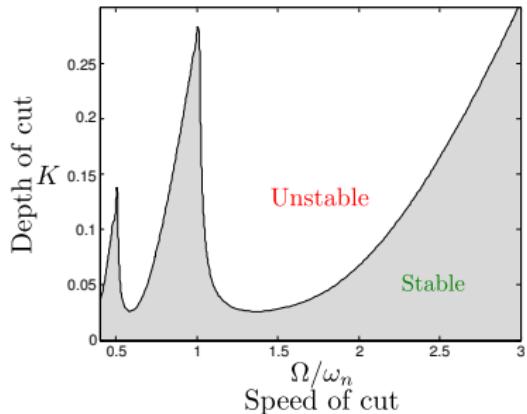
Images courtesy Firas Khasawneh, SUNYIT; and Boeing.

Deterministic model:

$$\ddot{y} + 2\zeta\dot{y} + y = K\rho^{\alpha-1}(1 + y(t-\tau) - y(t))^\alpha$$

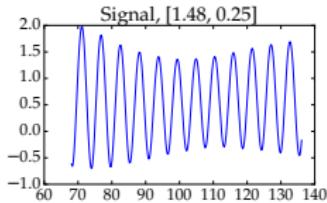
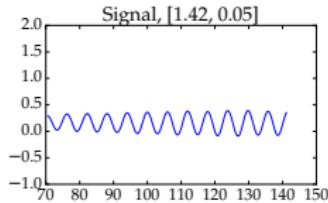
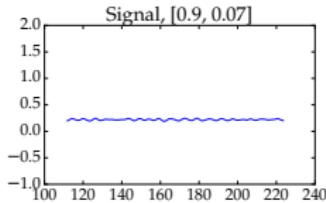
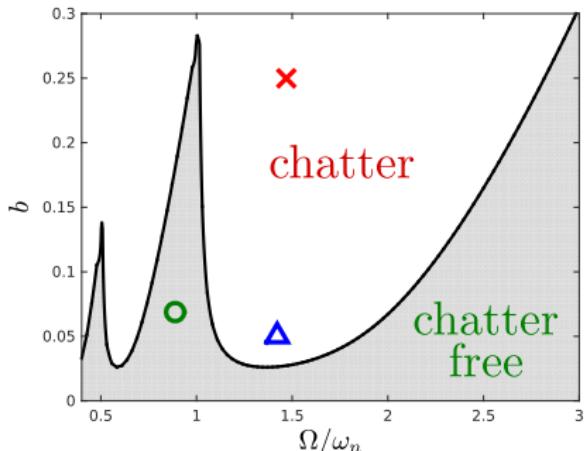


- Left side: standard linear oscillator
- Right side: input based on cutting forces



Khasawneh, F.A. & Mann, B. P. A spectral element approach for the stability of delay systems, International Journal for Numerical Methods in Engineering, 2011, 87, 566-592

Chatter

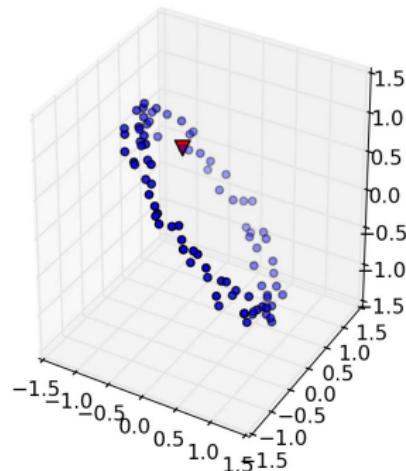
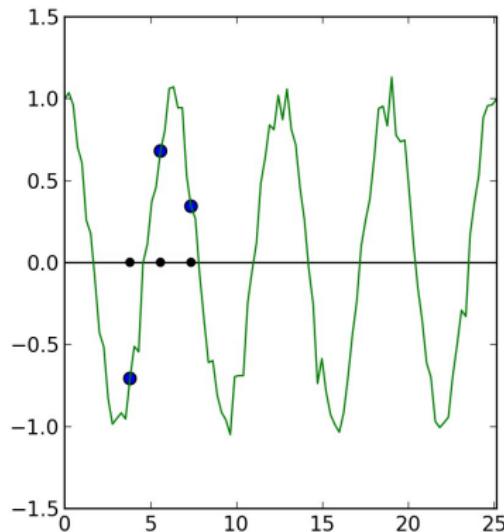


Takens embedding

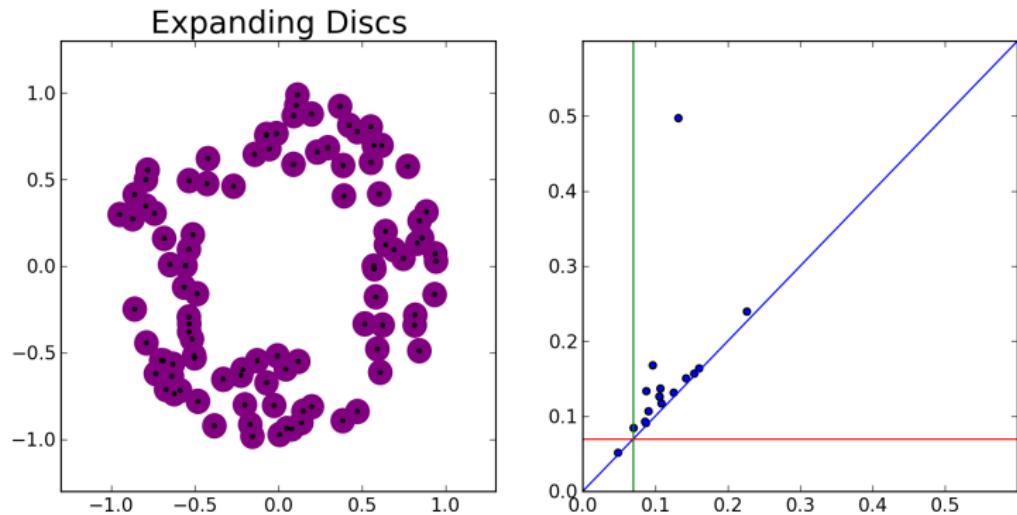
Definition

Given a time series $X(t)$, the Takens embedding is

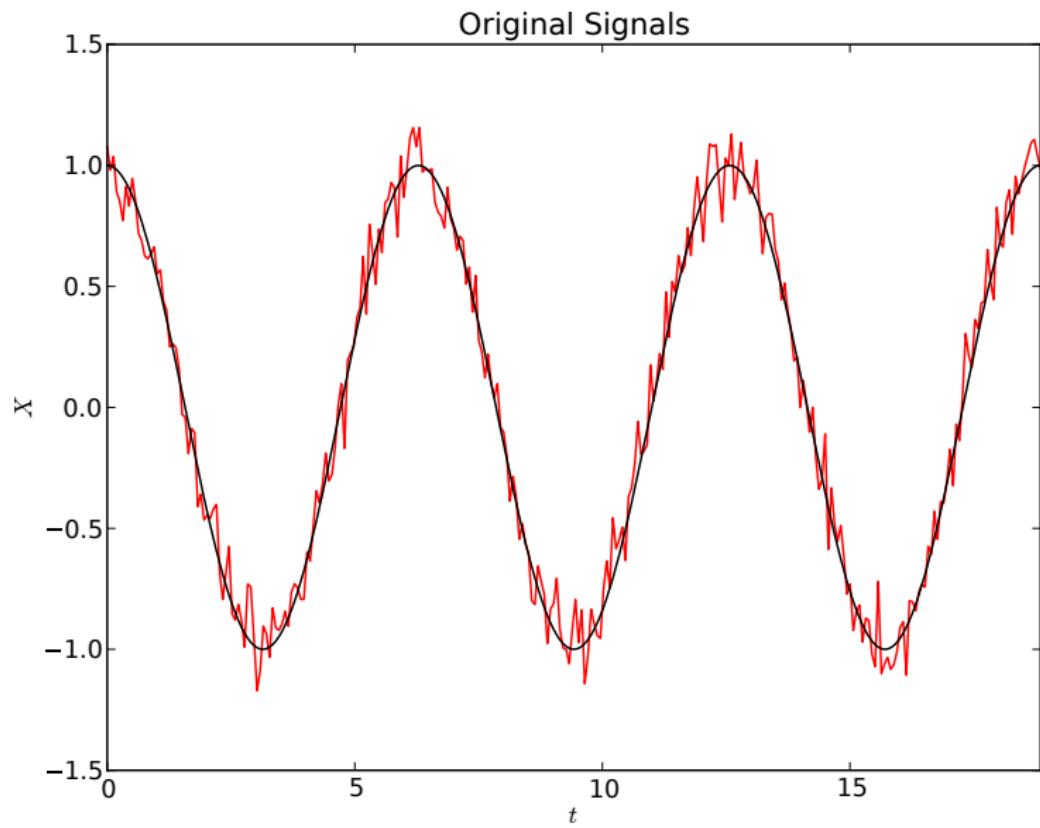
$$\psi_\eta^m : t \longmapsto (X(t), X(t + \eta), \dots, X(t + (m - 1)\eta)).$$



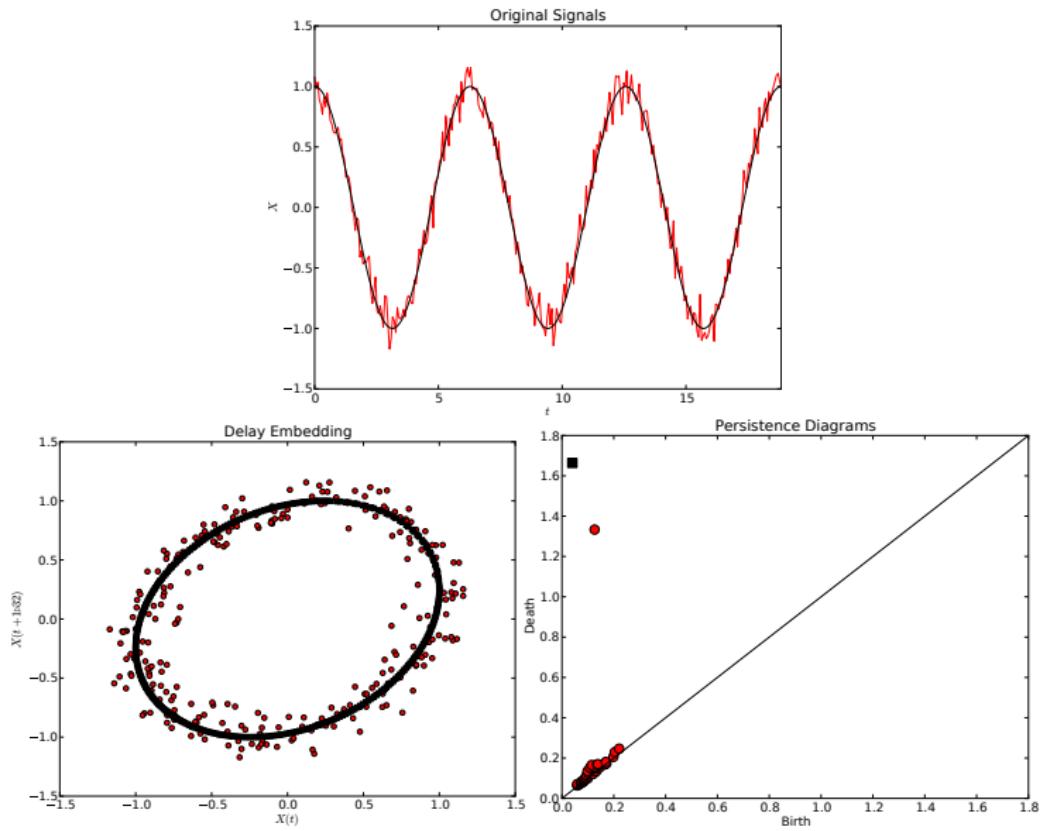
Persistent Homology of Point Cloud



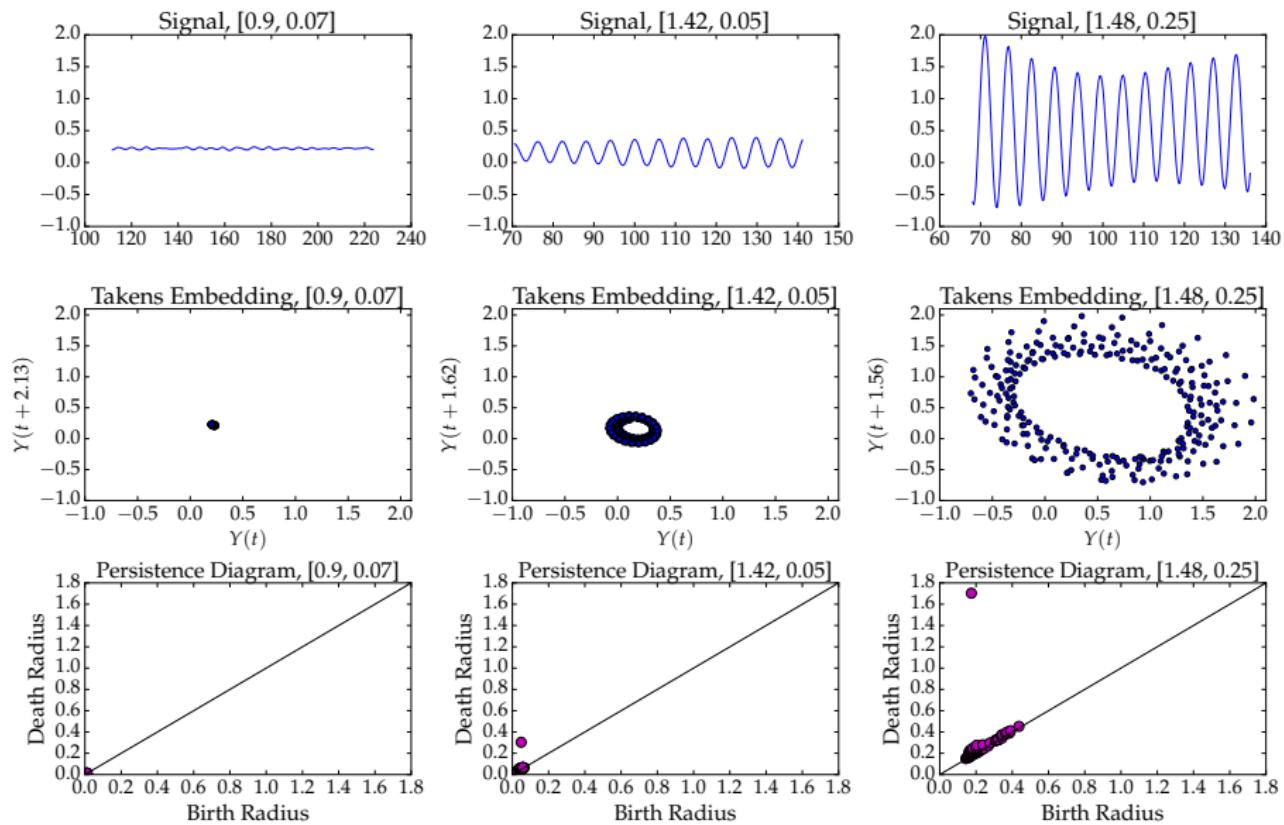
Noise resilience



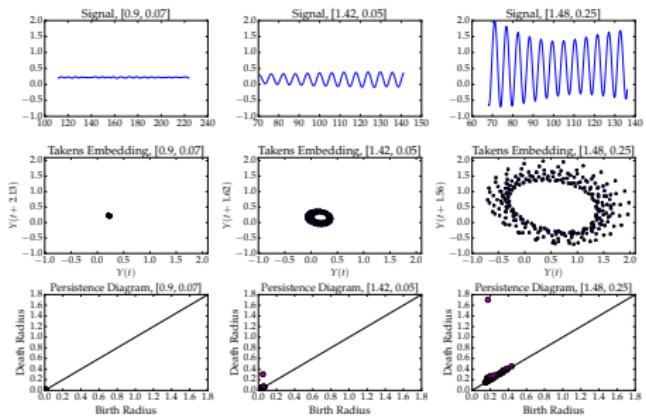
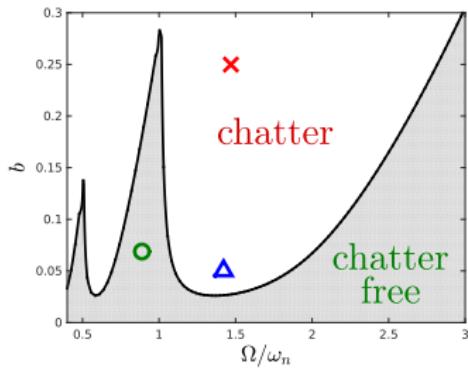
Noise resilience



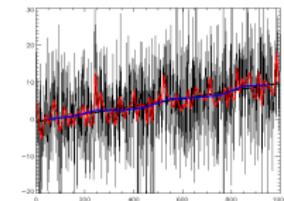
Comparing signals using persistence



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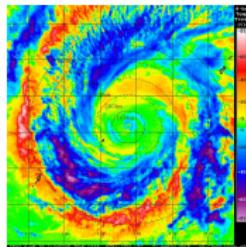


Overview



\mathbb{R} -valued TS

Takens Embedding

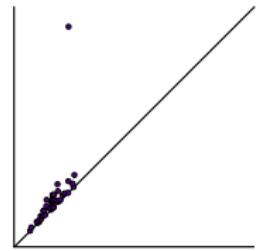


$\mathbb{R}^{m \times n}$ -valued TS

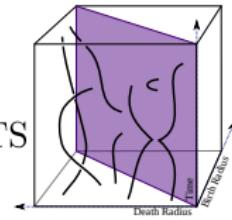
Sub/Superset
persistence

Pers

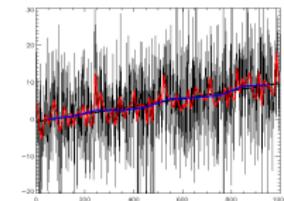
Persistence of
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Pers-valued TS

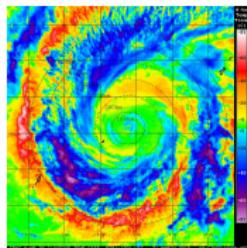


Overview



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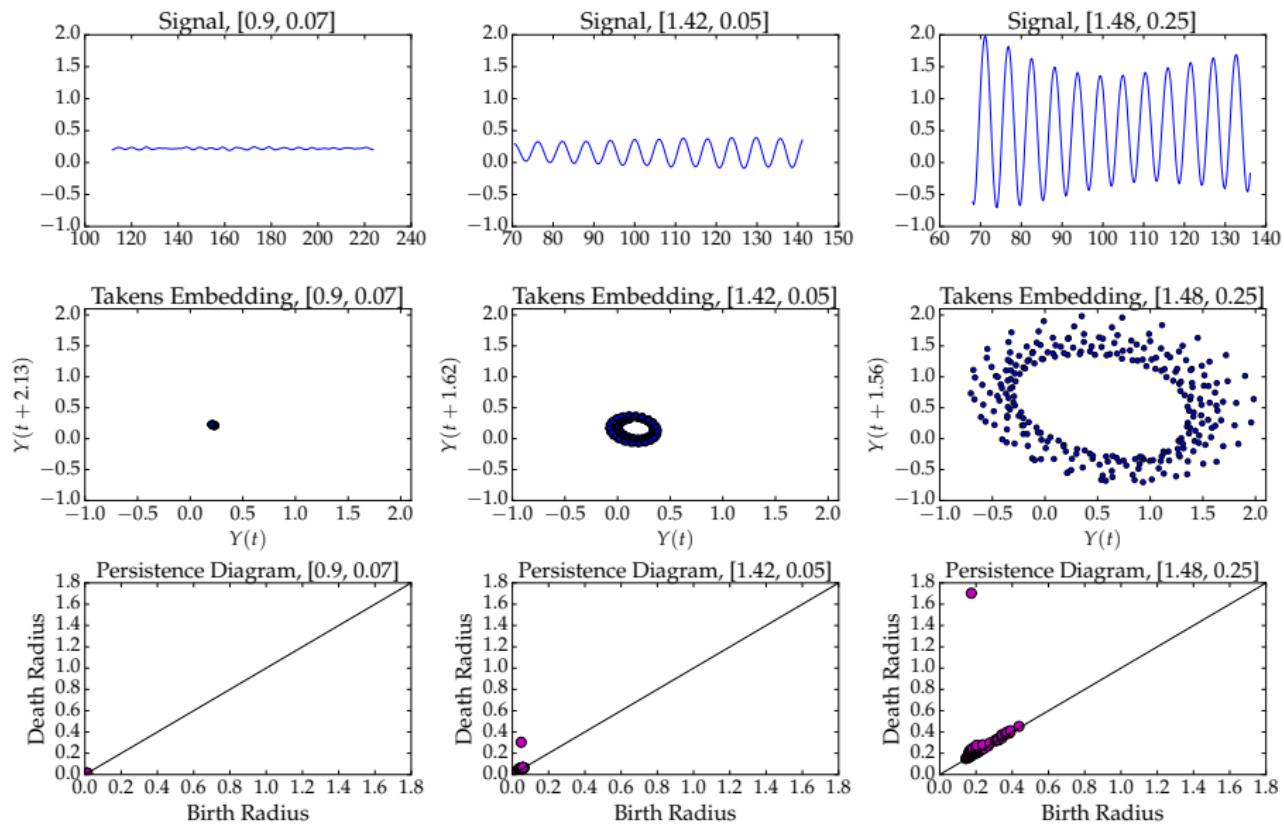
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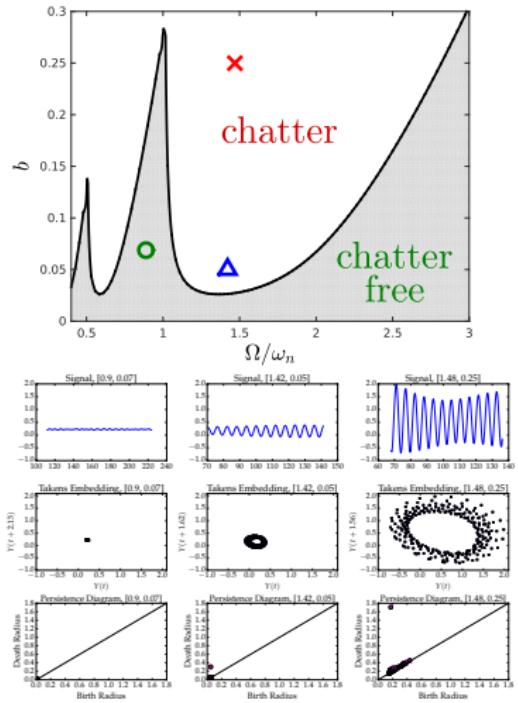
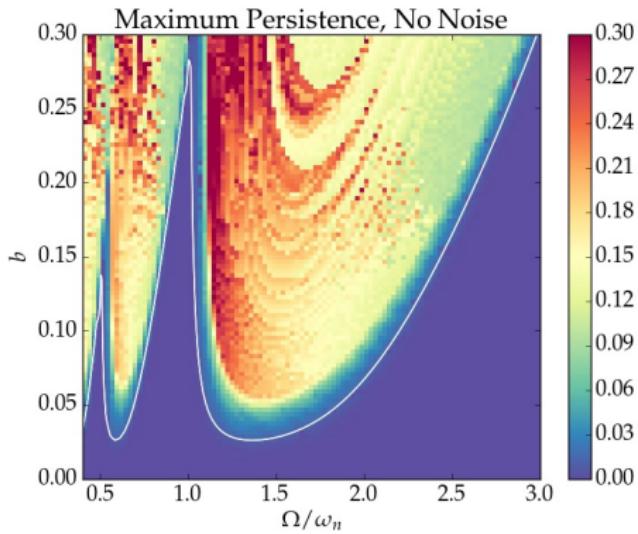
Persistence of
persistence



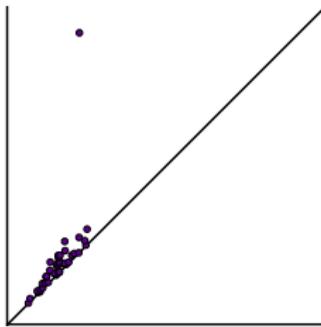
Differentiation by Max Persistence



Turning Model



Machine Learning

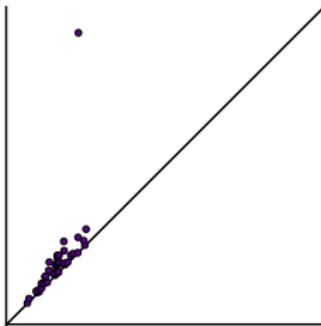


Adcock et al. Coordinates

Diagrams 0 and 1-dimensional of the form $\{(x_i, y_i)\}$

- $\sum x_i(y_i - x_i)$
- $\sum(y_{max} - y_i)(y_i - x_i)$
- $\sum x_i^2(y_i - x_i)^4$
- $\sum(y_{max} - y_i)^2(y_i - x_i)^4$
- $\max\{(y_i - x_i)\}$

Machine Learning



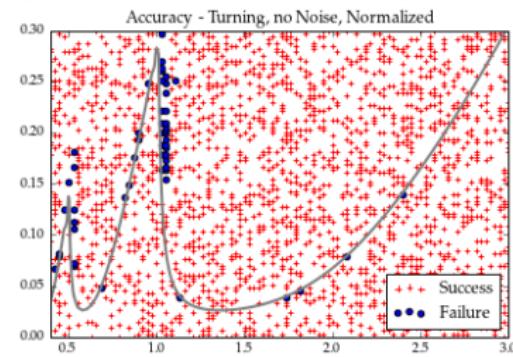
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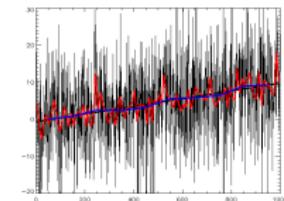
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Results (Khasawneh, M, Perea)

- Theoretical stability boundary for training
- Standard logistic classifier
- 97% accuracy

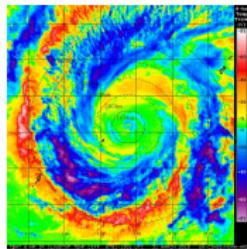


Overview



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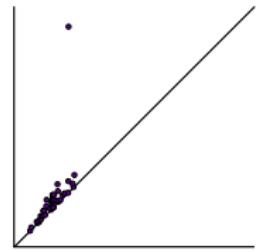


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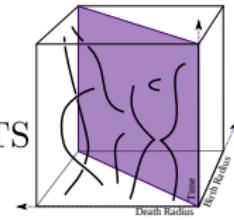
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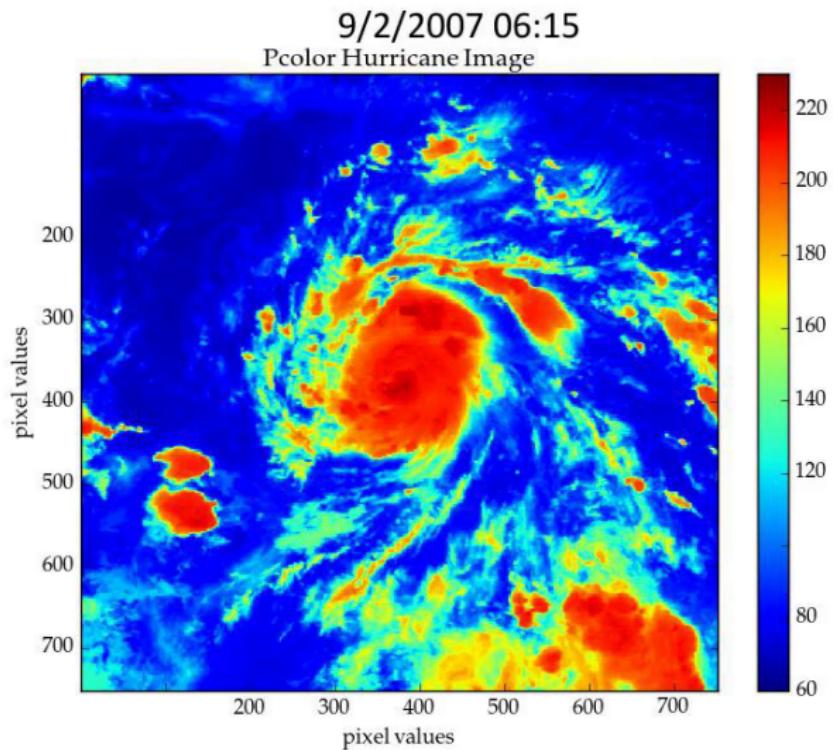
1 Classification and Machining Dynamics

2 Periodicity and Hurricanes

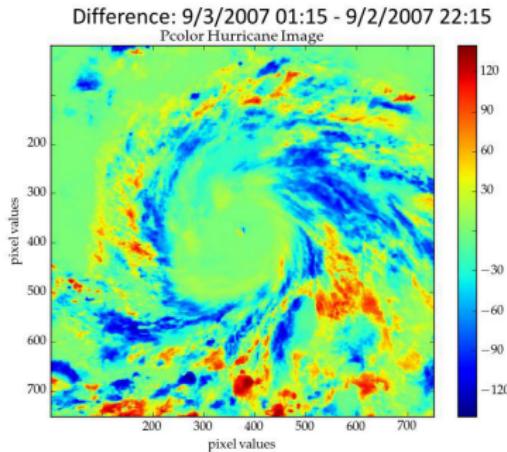
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Hurricane Felix



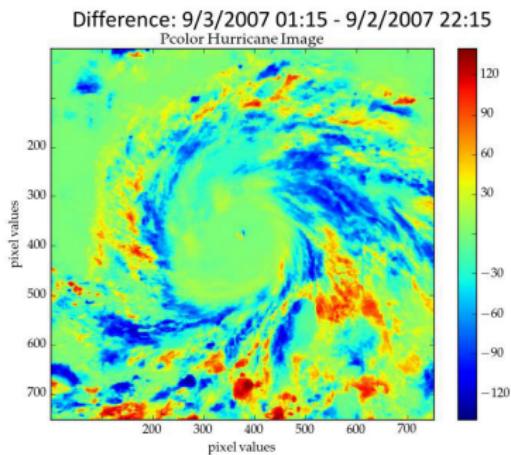
Diurnal cycle



3 hour difference

- $N(t)$ is IR matrix at time t
- $N(t) - N(t - 3 \text{ hrs})$

Diurnal cycle



3 hour difference

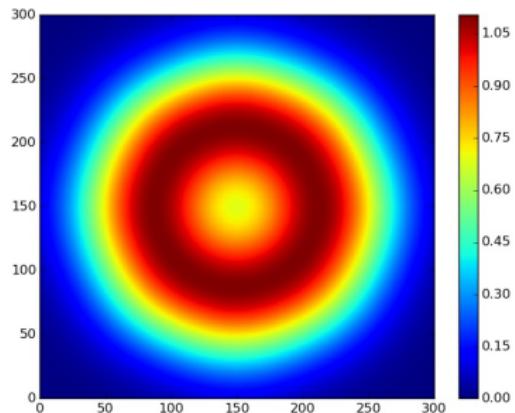
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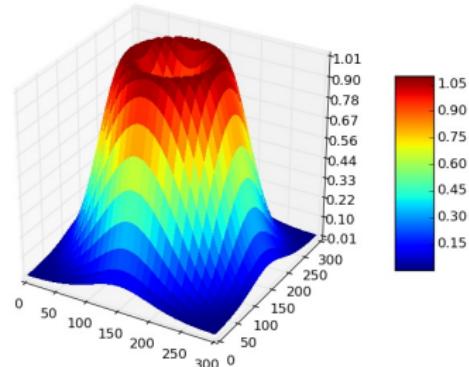
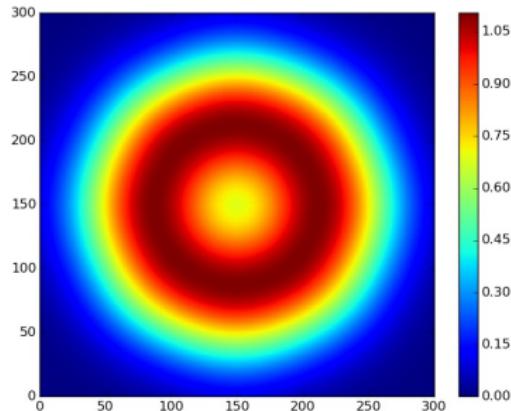
- Sunset: cold ring,
“diurnal pulse”
- Starts with radius $\leq 150\text{km}$,
spreads outward
- Warm ring forms behind this
pulse and spreads outward

Dunion et al. *The Tropical Cyclone Diurnal Cycle of Mature Hurricanes*.
Monthly Weather Review, 2014.

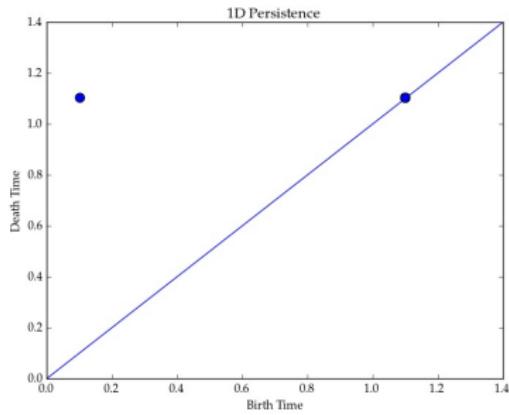
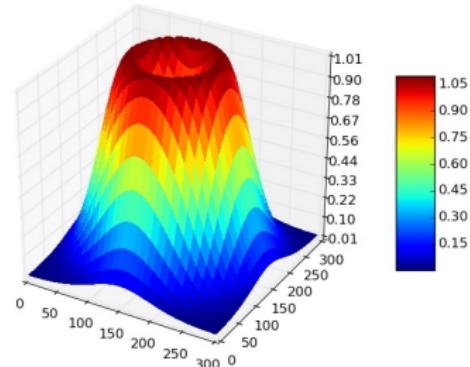
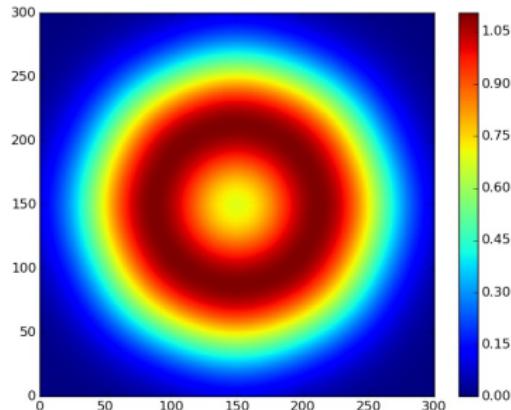
Sublevel Set Persistence



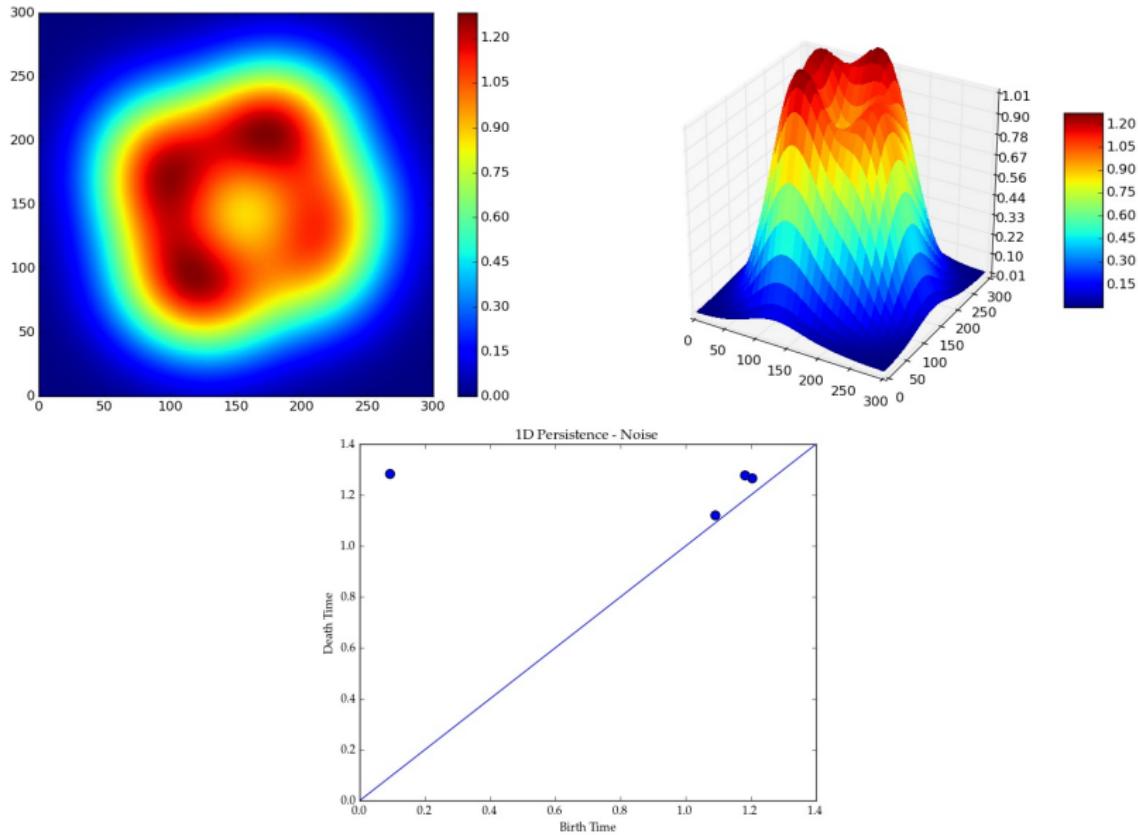
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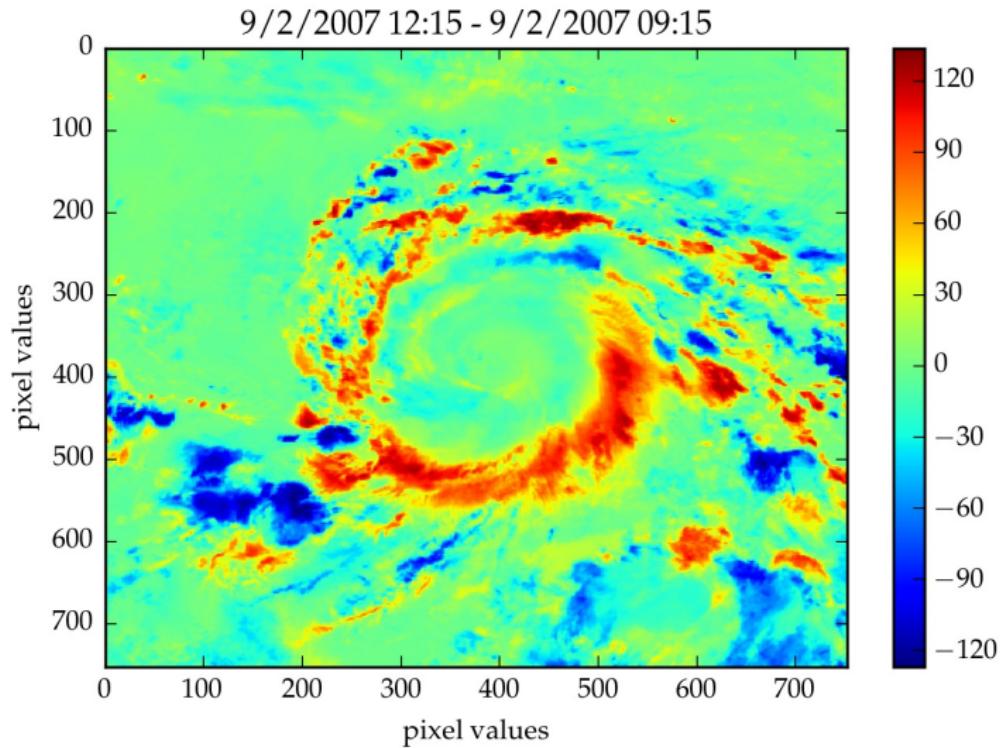
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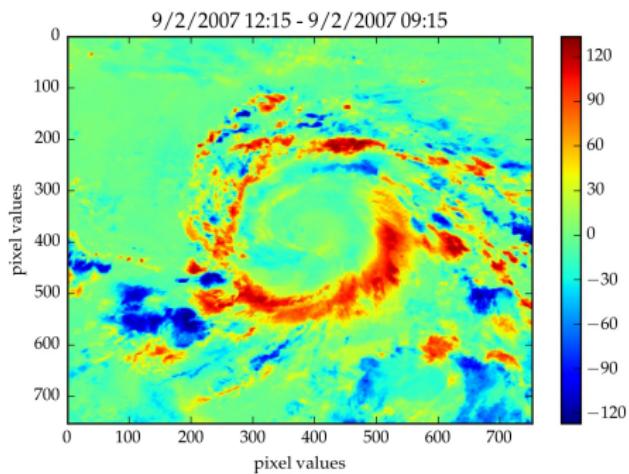
Sublevel Set Persistence



Why the obvious thing doesn't work



Plan B



Definition

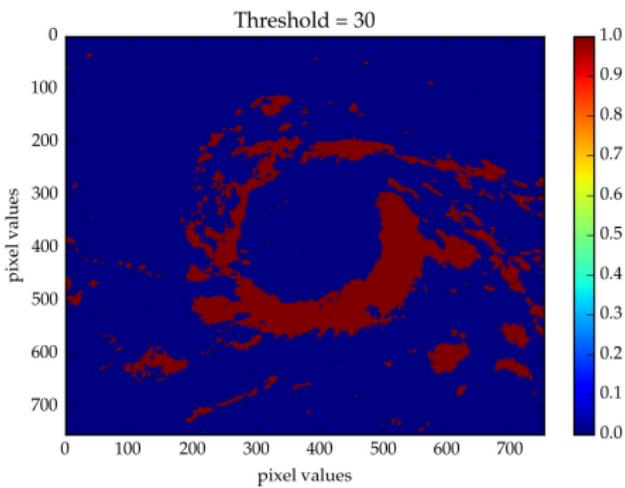
Let $K_{m \times n} = K$ be the $m \times n$ grid cubical complex.

Definition

Given $M \in \mathbb{R}^{m \times n}$, let

- $M : K \rightarrow \mathbb{R}$
- $M^\mu \subset K$ with function value $\geq \mu$.
- $S : K \rightarrow \mathbb{R}$ defined by $S(\sigma) = d(\sigma, M^\mu)$ for $\dim(\sigma) = 2$

Plan B



Definition

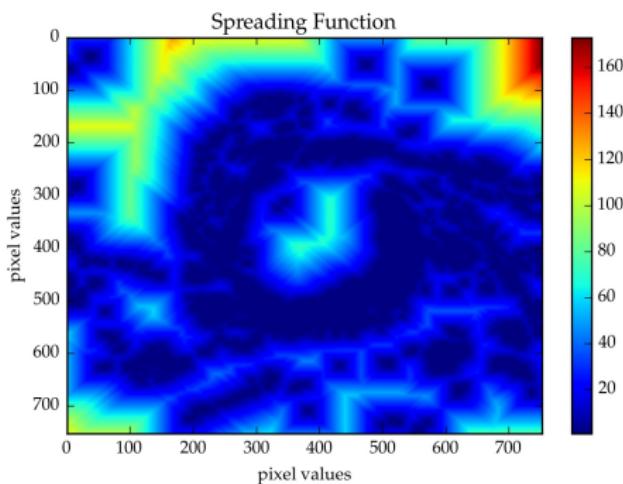
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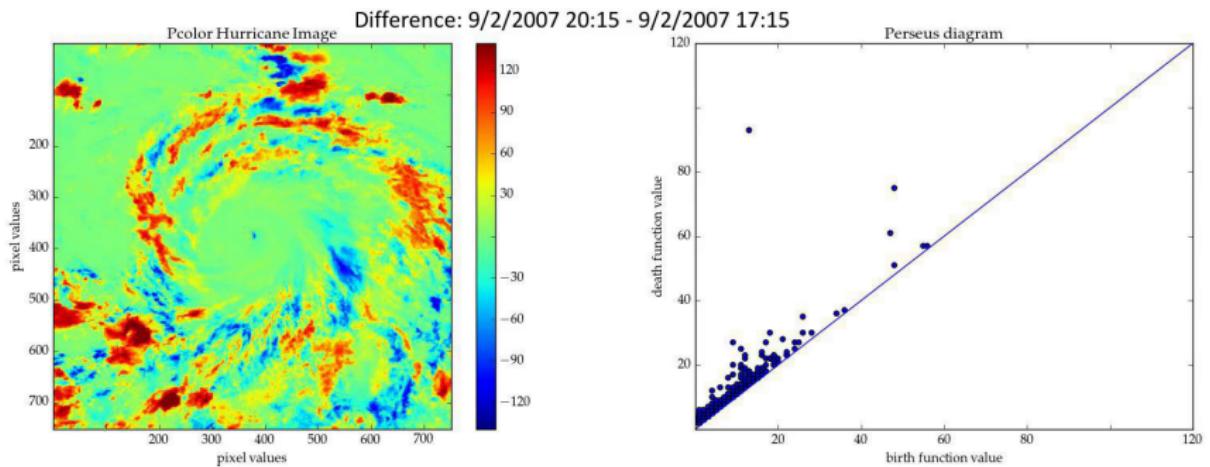
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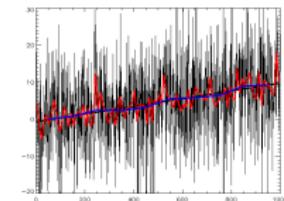
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Resulting persistence diagrams

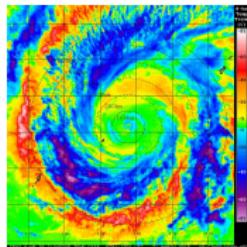


Overview



\mathbb{R} -valued TS

Takens Embedding



$\mathbb{R}^{m \times n}$ -valued TS

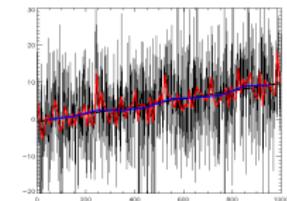
Sub/Superset
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Persistence of
persistence

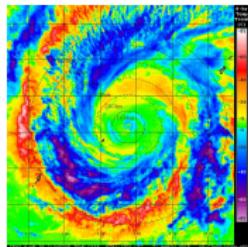


Overview



\mathbb{R} -valued TS

Takens Embedding



$\mathbb{R}^{m \times n}$ -valued TS

Sub/Superset
persistence

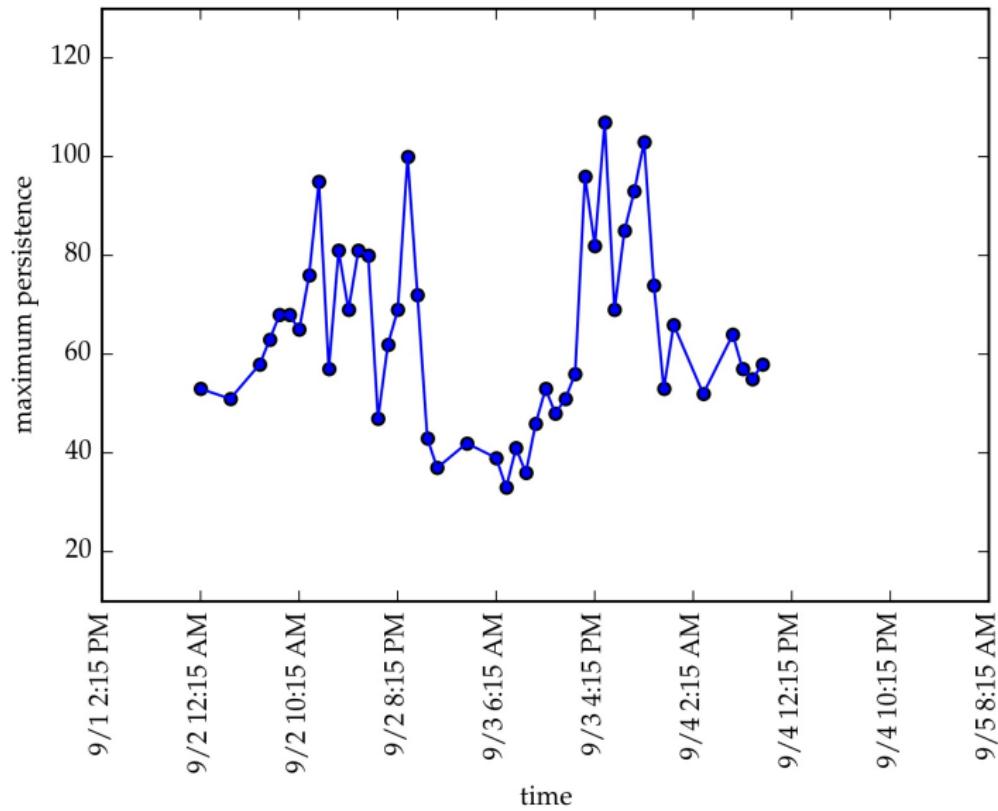
Pers

Persistence of
persistence

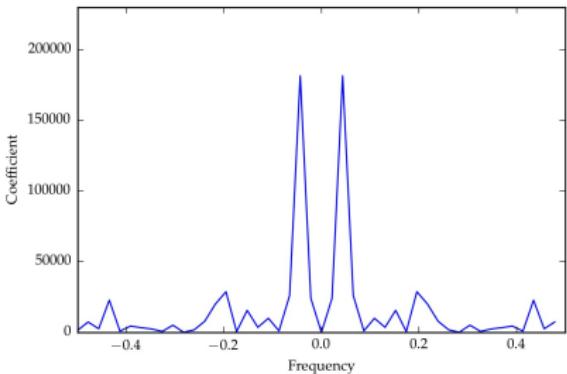
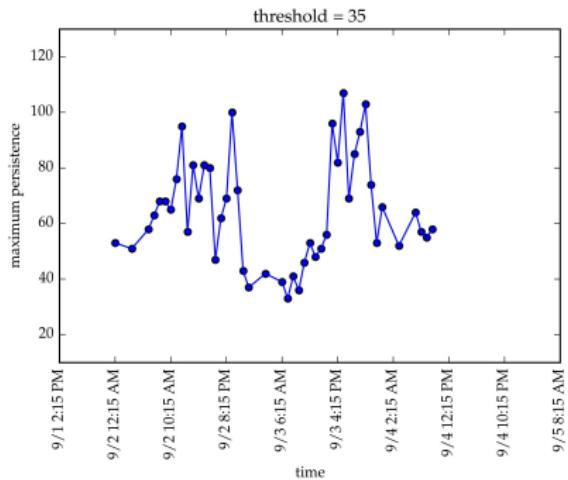
Pers-valued TS

Fourier spectrum of threshold

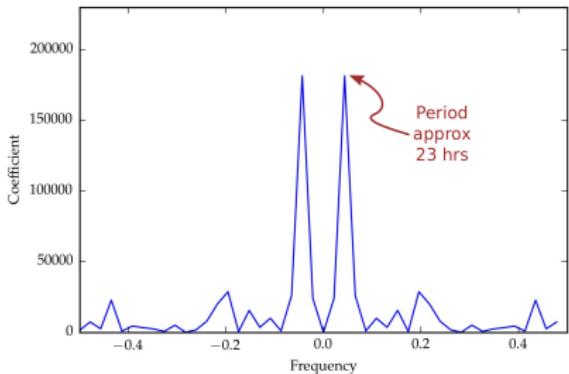
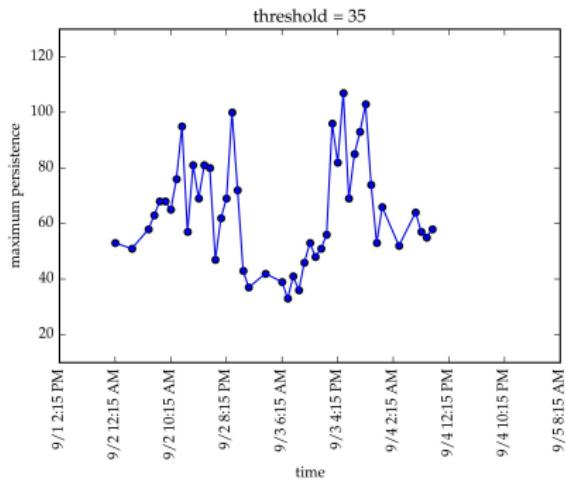
threshold = 35



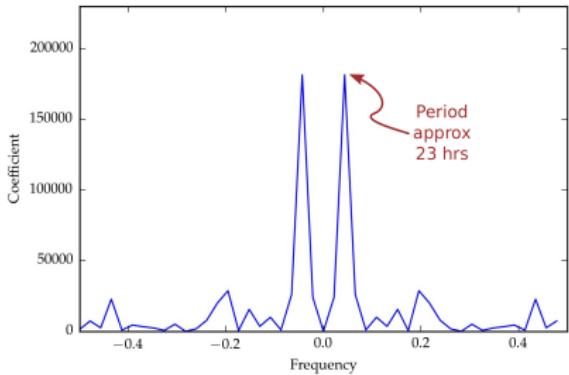
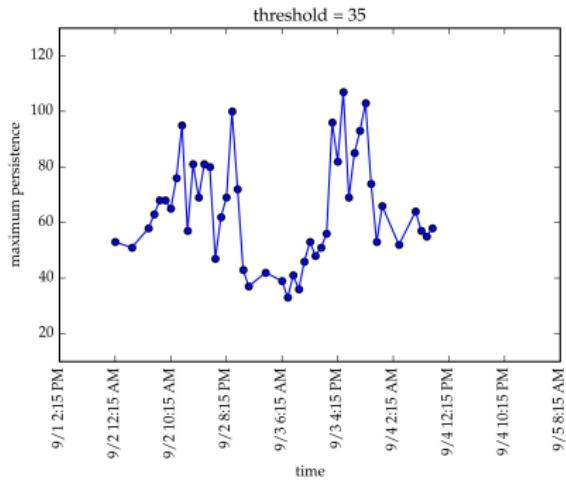
Fourier spectrum of threshold



Fourier spectrum of threshold



Fourier spectrum of threshold



Results

- 23 hour day?

General tools for TSA with TDA

- Takens embedding → persistence
 - ▶ Real-valued time series
 - ▶ Can do classification, segmentation using persistence diagrams

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 - ▶ Persistence of persistence
(Kramar, Levanger, et al. 2015 arXiv:1505.06168)

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(Kramar, Levanger, et al. 2015 arXiv:1505.06168)
- Structures and behaviors that are easy to tease out
 - ▶ Circles/holes
 - ▶ Periodicity

Thank you!

Hurricanes

Kristen Corbosiero (Albany)

Jason Dunion (Albany)

Bill Dong (Guilderland High School)

Ryan Torn (Albany)

Machining Dynamics

Firas Khasawneh (SUNY Poly)

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FK and EM. *Chatter detection in turning using persistent homology*. Mechanical Systems and Signals Processing, 2016.

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