Interpreting and Explaining Deep Neural Networks: A Perspective on Time Series Data – Part 3/3

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Some slides courtesy of Eamonn Keogh

Interpreting and Explaining Deep Neural Networks: A Perspective on Time Series Data

Agenda (150 min)

Overview to Explainable Artificial Intelligence (XAI) – 15 min Input Attributions Methods for Deep Neural Networks – 35 min Interpreting Inside of Deep Neural Networks – 50 min

Explainable Models for Time Series Data – 50 min

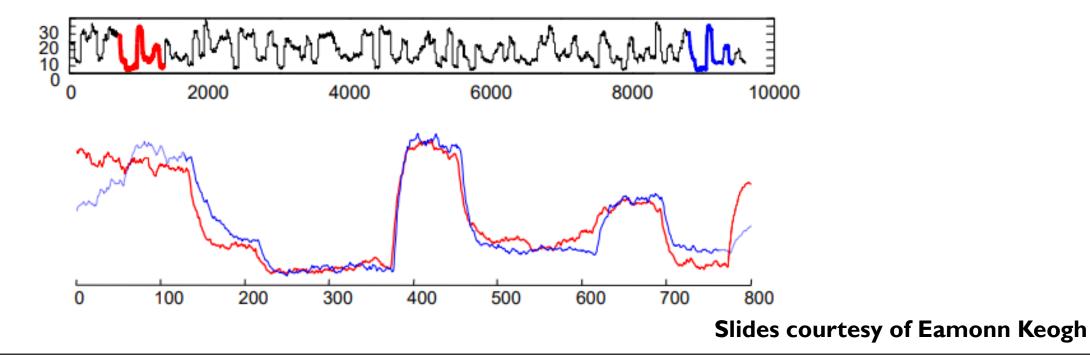
- Important Questions on Mining and Learning Time Series Data
- Visualizing Deep Temporal Neural Networks
- Clustered Pattern of Highly Activated Period (CPHAP)
- Automatic Statistician/Relational Automatic Statistician (Bayesian Approaches)

- 1. Have we ever seen a pattern that looks just like this?
- 2. Are there any repeated patterns in my data?
- 3. What are the three most unusual days in this three month long dataset?
- 4. Is there any pattern that is common to these two time series?
- 5. How do these two time series differ in terms of alignment?
- 6. Find the most conserved pattern that happens at least once every two days in this two week long dataset.
- 7. If you had to summarize this long time series with just two shorter examples, what would they be?
- 8. Are there any patterns that appear as time reversed versions of themselves in my data?
- 9. When does the regime change in this time series?
- 10. How can I compare these time series of different lengths?
- 11. Are there any patterns that repeat in my data, but at two distinct lengths?
- 12. Have we ever seen a multidimensional pattern that looks just like this?
- 13. How do I quickly search this long dataset for this pattern, if an approximate search is acceptable?
- 14. How can I optimize similarity search in a long time series?
- 15. What is most likely to happen next?
- 16. What is the right length for motifs in this dataset?
- 17. I need to find motifs faster! Part I
- 18. I need to find motifs faster! Part II
- 19. Have we ever seen a pattern that looks just like this, but possibly at a different length?
- 20. How can I know which of these two classification approaches is best for time series?
- 21. Are there any evolving patterns in this dataset (time series chains)
- 22. (pending)

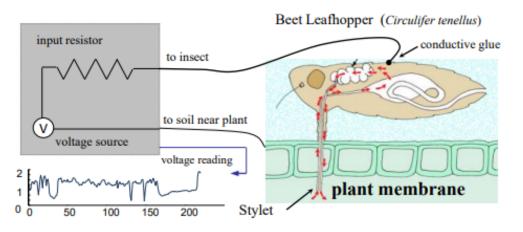
Slides courtesy of Eamonn Keogh

100 Time Series Data Mining Questions

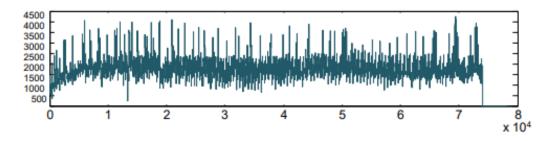
Find the subsequences having very high similarity to each other.



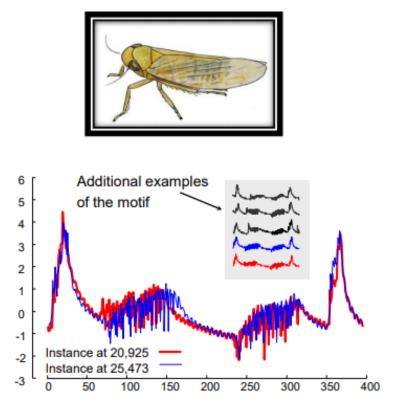
Time Series Motif



The **electrical penetration graph** or **EPG** is a system used by biologists to study the interaction of insects with plants.



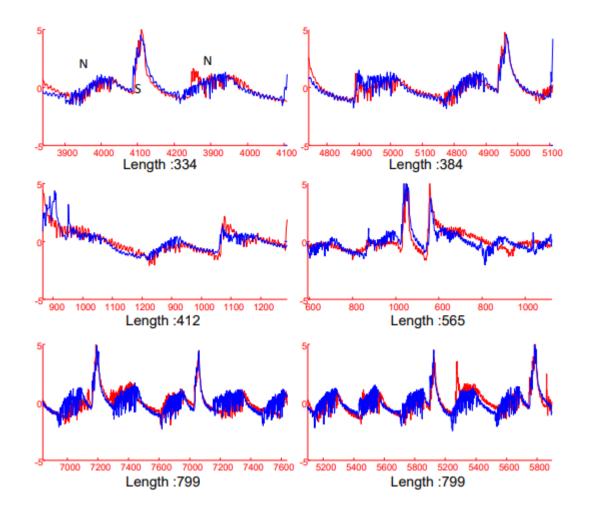
15 minutes of EPG recorded on Beet Leafhopper



As a bead of sticky secretion, which is byproduct of sap feeding, is ejected, it temporarily forms a highly conductive bridge between the insect and the plant.

Slides courtesy of Eamonn Keogh

Time Series Motif – An Example: Insect Behavior Analysis

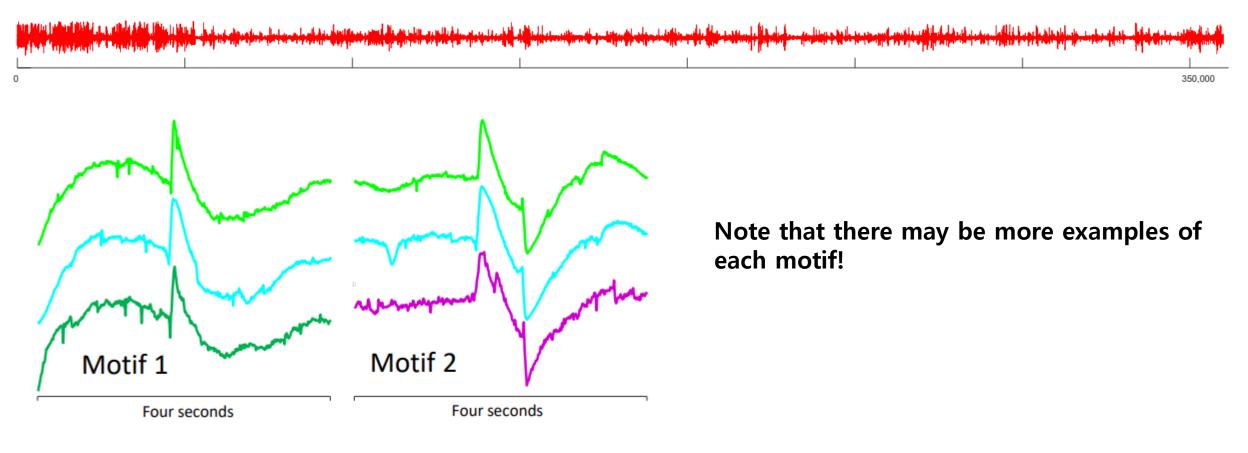


More motifs reveal different feeding patterns of Beet Leafhopper.

Slides courtesy of Eamonn Keogh

Time Series Motif – An Example: Insect Behavior Analysis

The dataset is an hour of EOG (eye movement) data of a sleeping patient, sampled at 100 Hz.

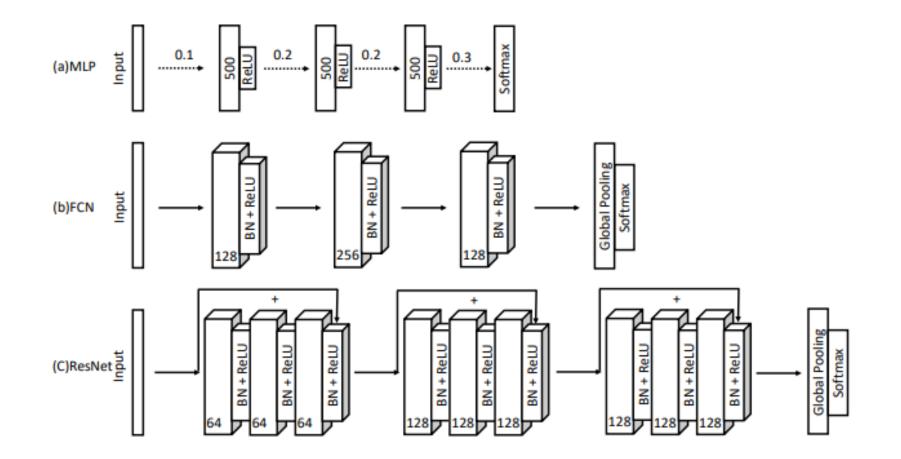


Slides courtesy of Eamonn Keogh

Are there any repeated patterns in my data? - Motif Search

Here, we are interested in finding **Temporal Motifs** Trained in **Deep Temporal Neural Networks**

Motif in Deep Temporal Neural Networks



Temporal Neural Networks: MLP vs FCN vs ResNet

Wang, Z. et al., Time Series Classification from Scratch with Deep Neural Networks: A Strong Baseline, arXiv:1611.06455, 2016.

	Err Rate	DTW	COTE	MCNN	BOSSVS	PROP	BOSS	SE1	TSBF	MLP	FCN	ResNet
	Adiac	0.396	0.233	0.231	0.302	0.353	0.22	0.373	0.245	0.248	0.143	0.174
	Beef	0.390	0.233	0.251	0.302	0.355	0.22	0.373	0.243	0.167	0.25	0.233
	CBF	0.003	0.001	0.002	0.001	0.002	0.2	0.01	0.009	0.107	0.25	0.006
Ch	lorineCon	0.352	0.314	0.203	0.345	0.36	0.34	0.312	0.336	0.128	0.157	0.172
	ECGTorso	0.349	0.064	0.058	0.13	0.062	0.125	0.021	0.262	0.158	0.187	0.229
	Coffee	0	0	0.036	0.036	0	0	0	0.004	0	0	0
	CricketX	0.246	0.154	0.182	0.346	0.203	0.259	0.297	0.278	0.431	0.185	0.179
	CricketY	0.256	0.167	0.154	0.328	0.156	0.208	0.326	0.259	0.405	0.208	0.195
	CricketZ	0.246	0.128	0.142	0.313	0.156	0.246	0.277	0.263	0.408	0.187	0.187
Dia	atomSizeR	0.033	0.082	0.023	0.036	0.059	0.046	0.069	0.126	0.036	0.07	0.069
	GFiveDays	0.232	0	0	0	0.178	0	0.055	0.183	0.03	0.015	0.045
	FaceAll	0.192	0.105	0.235	0.241	0.152	0.21	0.247	0.234	0.115	0.071	0.166
	FaceFour	0.17	0.091	0	0.034	0.091	0	0.034	0.051	0.17	0.068	0.068
1	FacesUCR	0.095	0.057	0.063	0.103	0.063	0.042	0.079	0.09	0.185	0.052	0.042
	50words	0.31	0.191	0.19	0.367	0.18	0.301	0.288	0.209	0.288	0.321	0.273
	fish	0.177	0.029	0.051	0.017	0.034	0.011	0.057	0.08	0.126	0.029	0.011
	GunPoint	0.093	0.007	0	0	0.007	0	0.06	0.011	0.067	0	0.007
	Haptics	0.623	0.488	0.53	0.584	0.584	0.536	0.607	0.488	0.539	0.449	0.495
I	inlineSkate	0.616	0.551	0.618	0.573	0.567	0.511	0.653	0.603	0.649	0.589	0.635
	ItalyPower	0.05	0.036	0.03	0.086	0.039	0.053	0.053	0.096	0.034	0.03	0.04
	Lightning2	0.131	0.164	0.164	0.262	0.115	0.148	0.098	0.257	0.279	0.197	0.246
	Lightning7	0.274	0.247	0.219	0.288	0.233	0.342	0.274	0.262	0.356	0.137	0.164
	MALLAT	0.066	0.036	0.057	0.064	0.05	0.058	0.092	0.037	0.064	0.02	0.021
Medi	icalImages	0.263	0.258	0.26	0.474	0.245	0.288	0.305	0.269	0.271	0.208	0.228
	MoteStrain	0.165	0.085	0.079	0.115	0.114	0.073	0.113	0.135	0.131	0.05	0.105
Nonl	nvThorax1	0.21	0.093	0.064	0.169	0.178	0.161	0.174	0.138	0.058	0.039	0.052
Nonl	nvThorax2	0.135	0.073	0.06	0.118	0.112	0.101	0.118	0.13	0.057	0.045	0.049
	OliveOil	0.167	0.1	0.133	0.133	0.133	0.1	0.133	0.09	0.60	0.167	0.133
	OSULeaf	0.409	0.145	0.271	0.074	0.194	0.012	0.273	0.329	0.43	0.012	0.021
SonyA	IBORobot	0.275	0.146	0.23	0.265	0.293	0.321	0.238	0.175	0.273	0.032	0.015
SonyAll	BORobotII	0.169	0.076	0.07	0.188	0.124	0.098	0.066	0.196	0.161	0.038	0.038
StarLi	ightCurves	0.093	0.031	0.023	0.096	0.079	0.021	0.093	0.022	0.043	0.033	0.029
Sw	vedishLeaf	0.208	0.046	0.066	0.141	0.085	0.072	0.12	0.075	0.107	0.034	0.042
	Symbols	0.05	0.046	0.049	0.029	0.049	0.032	0.083	0.034	0.147	0.038	0.128
Synthe	eticControl	0.007	0	0.003	0.04	0.01	0.03	0.033	0.008	0.05	0.01	0
	Trace	0	0.01	0	0	0.01	0	0.05	0.02	0.18	0	0
Two	LeadECG	0	0.015	0.001	0.015	0	0.004	0.029	0.001	0.147	0	0
T	woPatterns	0.096	0	0.002	0.001	0.067	0.016	0.048	0.046	0.114	0.103	0
	UWaveX	0.272	0.196	0.18	0.27	0.199	0.241	0.248	0.164	0.232	0.246	0.213
	UWaveY	0.366	0.267	0.268	0.364	0.283	0.313	0.322	0.249	0.297	0.275	0.332
	UWaveZ	0.342	0.265	0.232	0.336	0.29	0.312	0.346	0.217	0.295	0.271	0.245
	wafer	0.02	0.001	0.002	0.001	0.003	0.001	0.002	0.004	0.004	0.003	0.003
Word	Synonyms	0.351	0.266	0.276	0.439	0.226	0.345	0.357	0.302	0.406	0.42	0.368
	yoga	0.164	0.113	0.112	0.169	0.121	0.081	0.159	0.149	0.145	0.155	0.142
	Win	3	8	7	5	4	13	4	4	2	18	8
AVG Arithmet		8.205	3.682	3.932	7.318	5.545	4.614	7.455	6.614	7.909	3.977	4.386
AVG geometr	ric ranking	7.160	3.054	3.249	5.997	4.744	3.388	6.431	5.598	6.941	2.780	3.481
	MPCĚ	0.0397	0.0226	0.0241	0.0330	0.0304	0.0256	0.0302	0.0335	0.0407	0.0219	0.0231

Experimental Results on UCR dataset

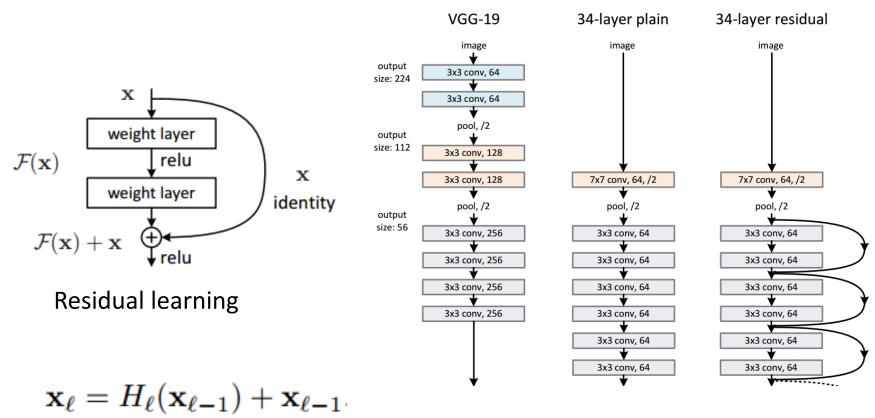
Wang, Z. et al., Time Series Classification from Scratch with Deep Neural Networks: A Strong Baseline, arXiv:1611.06455, 2016.

Err Rate	DTW	COTE	MCNN	BOSSVS	PROP	BOSS	SE1	TSBF	MLP	FCN	ResNet
Win	3	8	7	5	4	13	4	4	6.941	18	8
AVG Arithmetic ranking	8.205	3.682	3.932	7.318	5.545	4.614	7.455	6.614		3.977	4.386
AVG geometric ranking	7.160	3.054	3.249	5.997	4.744	3.388	6.431	5.598		2.780	3.481
MPCE	0.0397	0.0226	0.0241	0.0330	0.0304	0.0256	0.0302	0.0335		0.0219	0.0231

https://github.com/cauchyturing/UCR_Time_Series_Classification_Deep_Learning_Baseline

Experimental Results

Wang, Z. et al., Time Series Classification from Scratch with Deep Neural Networks: A Strong Baseline, arXiv:1611.06455, 2016.



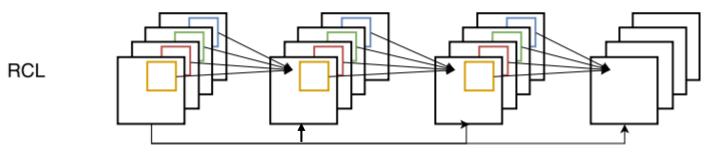
Comparison of Resnet

3.6% of error in ImageNet Challenge, 2015

Residual Network [ResNet, He et. al., 2015]

He et. al., 2015

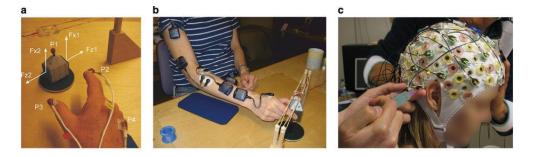


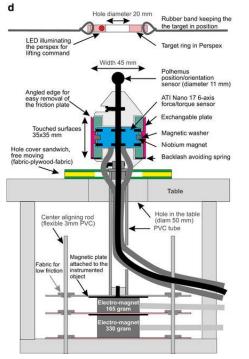


Recurrent Convolutional Layer (RCL)

 $x_{l} = x_{l-1} + H_{l}(x_{l-1}) + H_{l}(H_{l}(x_{l-1})) + H_{l}(H_{l}(H_{l}(x_{l-1})))$

Recurrent Convolutional Neural Layers [RCNN, Liang and Hu, 2015] Liang and Hu, 2015





Hand Start

First Digit Touch

Lift off

Replace

Both Released

* Joint work with Azamatbek Akhmedov

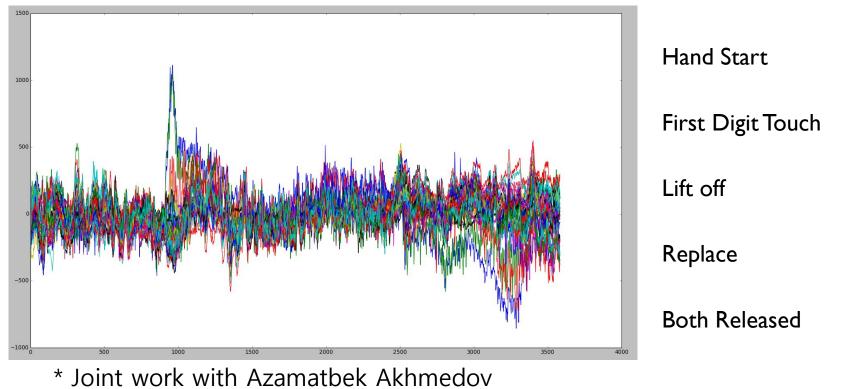
RCNN on EEG Analysis

Luciw et. al., 2014



Completed • \$10,000 • 379 teams Grasp-and-Lift EEG Detection Mon 29 Jun 2015 - Mon 31 Aug 2015 (4 months ago)

One chunk: Data: 3584,32



Convolutional Layer:(1,3584)

Max pooling

Applying RCL

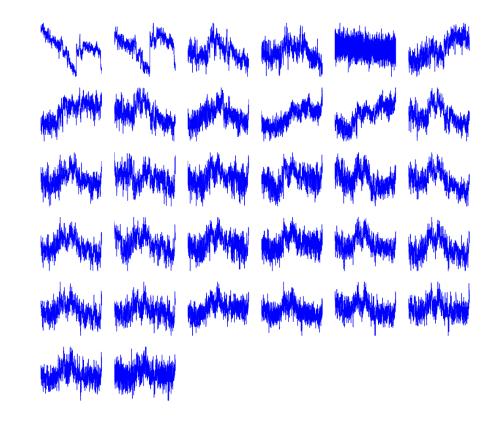
Max pooling	
RCL:(1,896)	
Max pooling	
RCL:(1,224)	
Max pooling	
RCL:(1,56)	
Max pooling	
RCL:(1,14)	
Max pooling (1,7)	
Fully Connected (6)	

Layer type	Size	Output shape
Convolutional	256 1×9 filters	(64, 256, 1, 3584)
Max pooling	Pool size 4, stride 4	(64, 256, 1, 896)
RCL	256 1×1 feed-forward filters, 256 1×9 filters, 3 iterations	(64, 256, 1, 896)
Max pooling	Pool size 4, stride 4	(64, 256, 1, 224)
RCL	256 1×1 feed-forward filters, 256 1×9 filters, 3 iterations	(64, 256, 1, 224)
Max pooling	Pool size 4, stride 4	(64, 256, 1, 56)
RCL	256 1×1 feed-forward filters, 256 1×9 filters, 3 iterations	(64, 256, 1, 56)
Max pooling	Pool size 4, stride 4	(64, 256, 1, 14)
RCL	256 1×1 feed-forward filters, 256 1×9 filters, 3 iterations	(64, 256, 1, 14)
Max pooling	Pool size 2, stride 2	(64, 256, 1, 7)
Fully connected	1792×6	(64, 6)

97.687%

256 Ix9 filters

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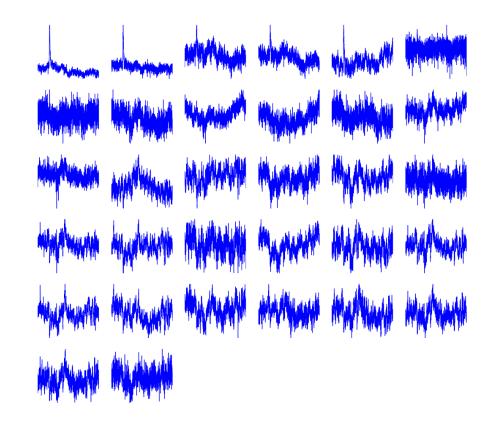
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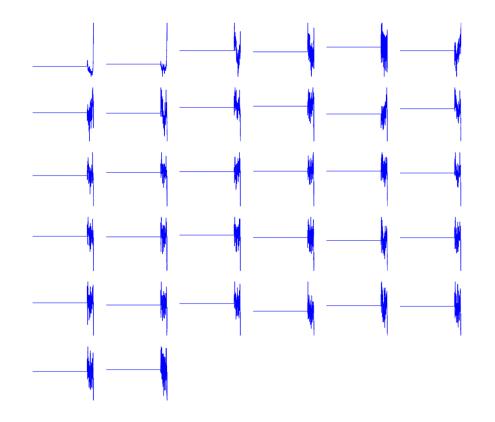
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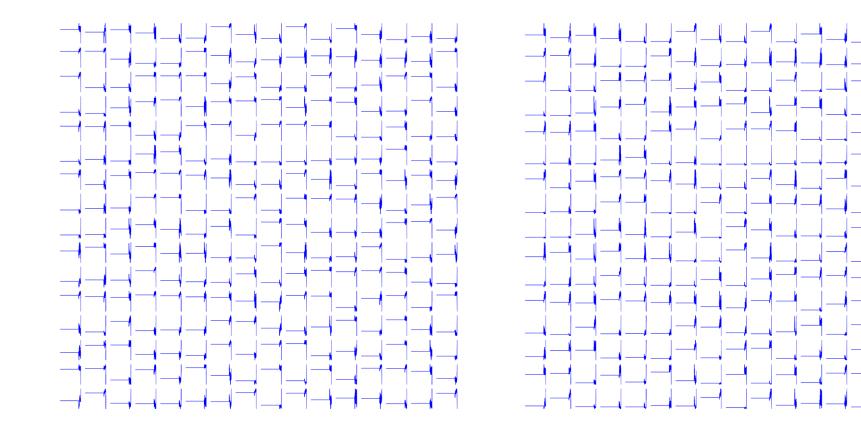
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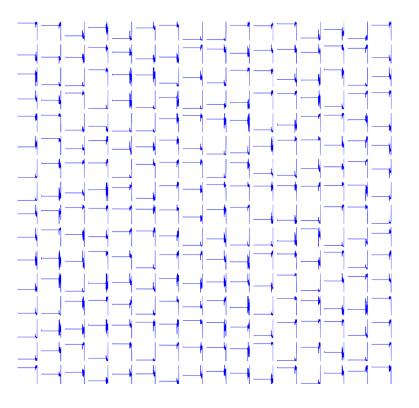
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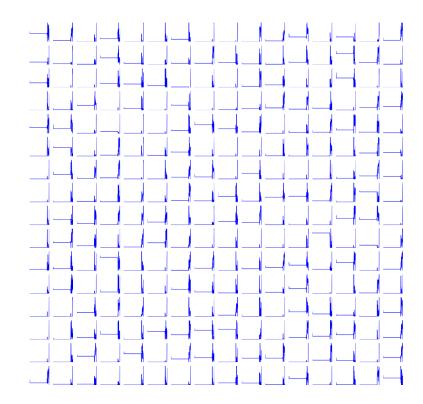
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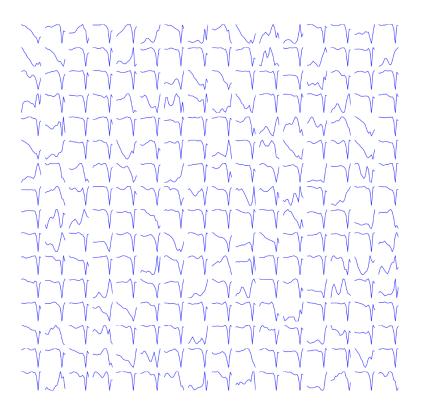
www.www.www.www.www. m m m /VV \ I WI MIMMIN NEMANA ~ ~ ~ ~ A ha $1 \sim 10^{\circ}$ \sim m w [W] Λ Λ Λ Λ Λ Λ Λ Λ Λ Λ NMALATINA INTO MININA $M_{M_{A}} M_{A} M_{A}$ $M_{M}/M_{A} \propto M/_{A} M_{A} M_{A} \sim 1$

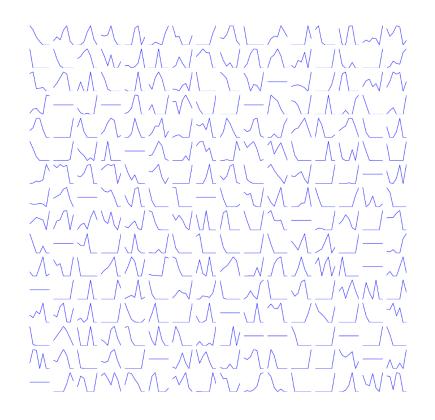








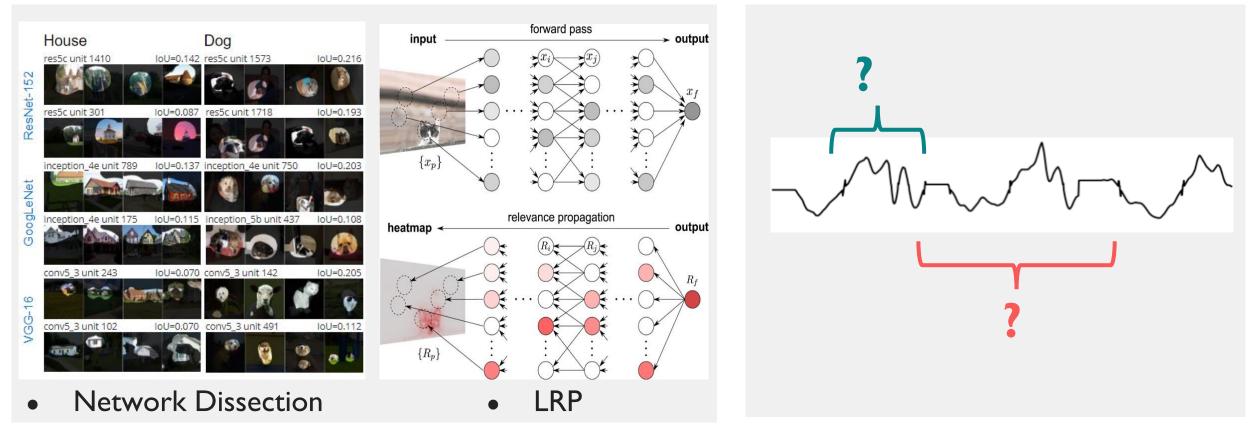




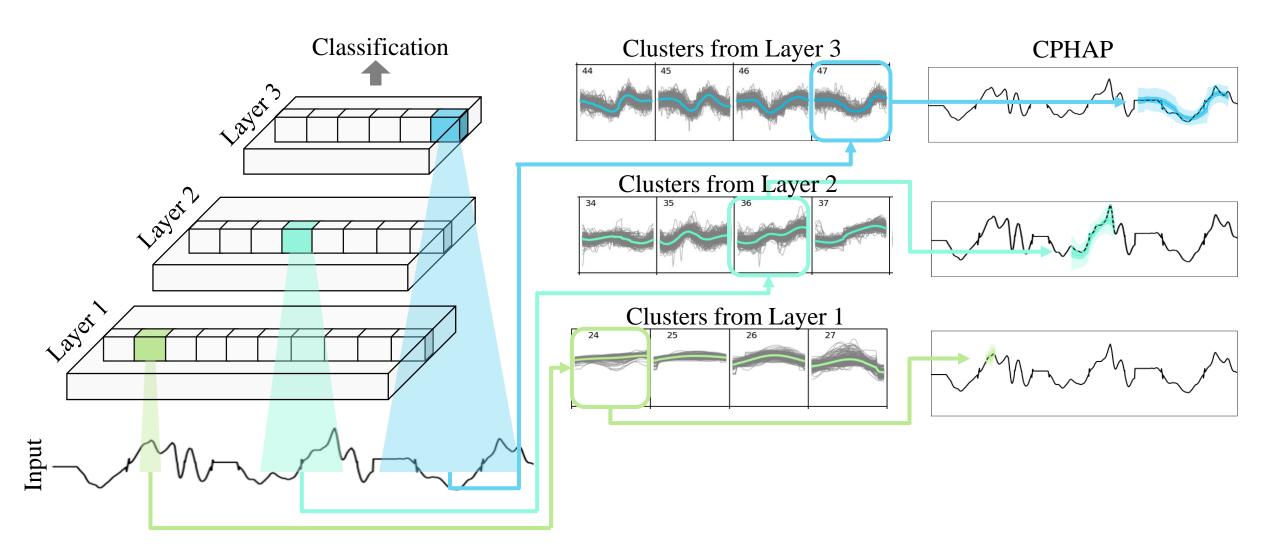
 How can we separate time series data into semi-global representative parts without hand-crafted segmentation labels for interpreting?

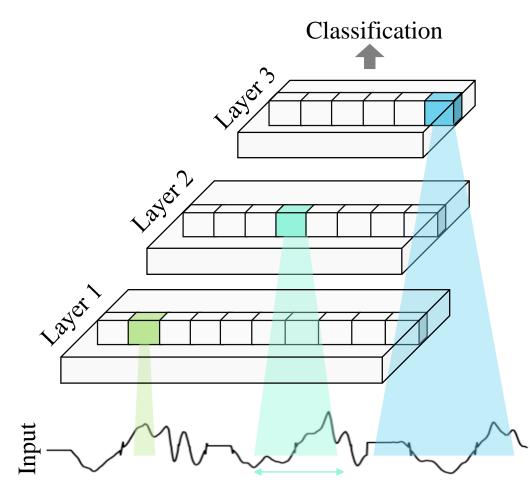
Image dataset

Time Series dataset



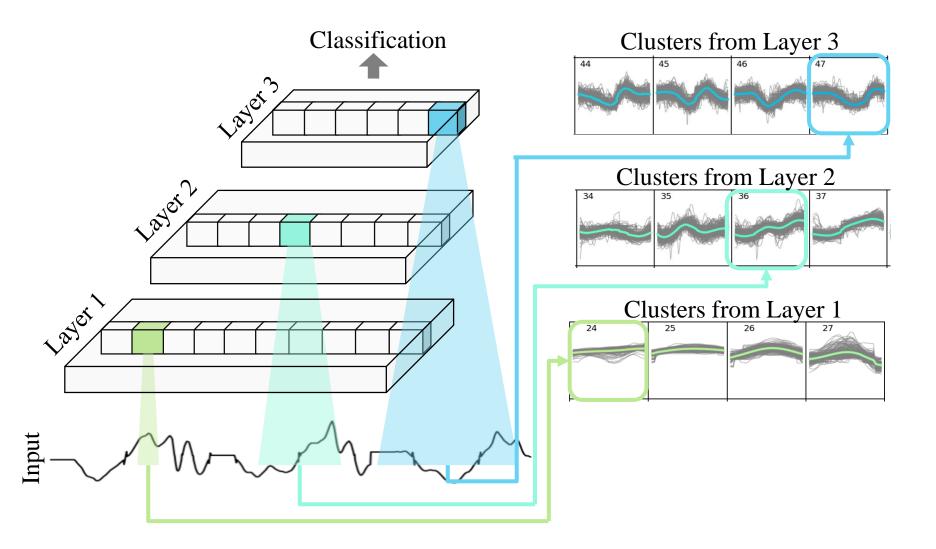
Clustered Pattern of Highly Activated Period: Motivation

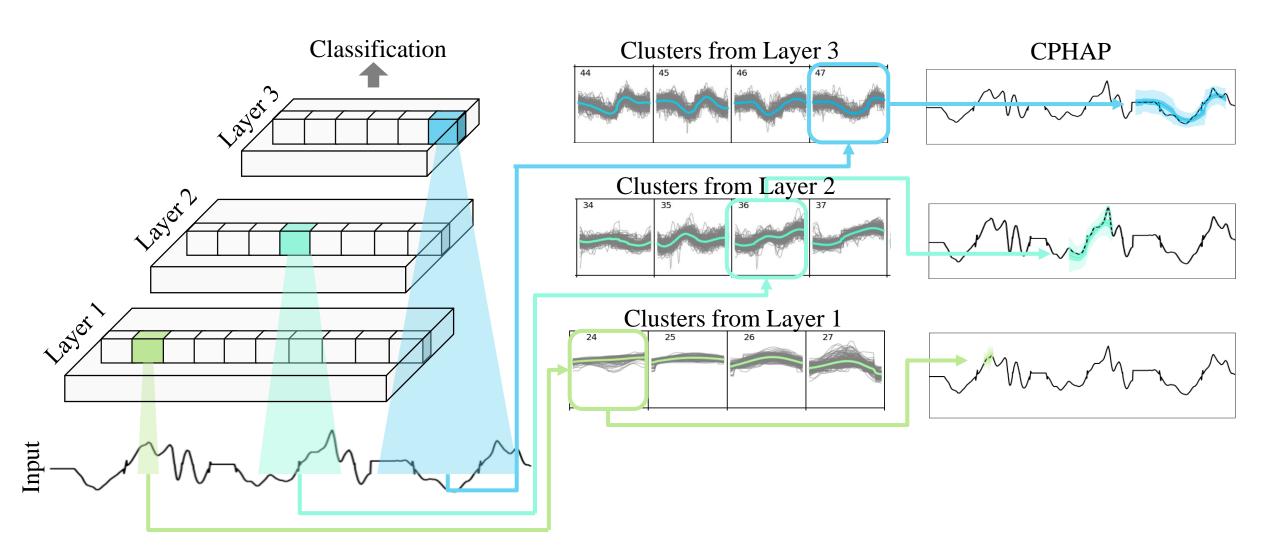


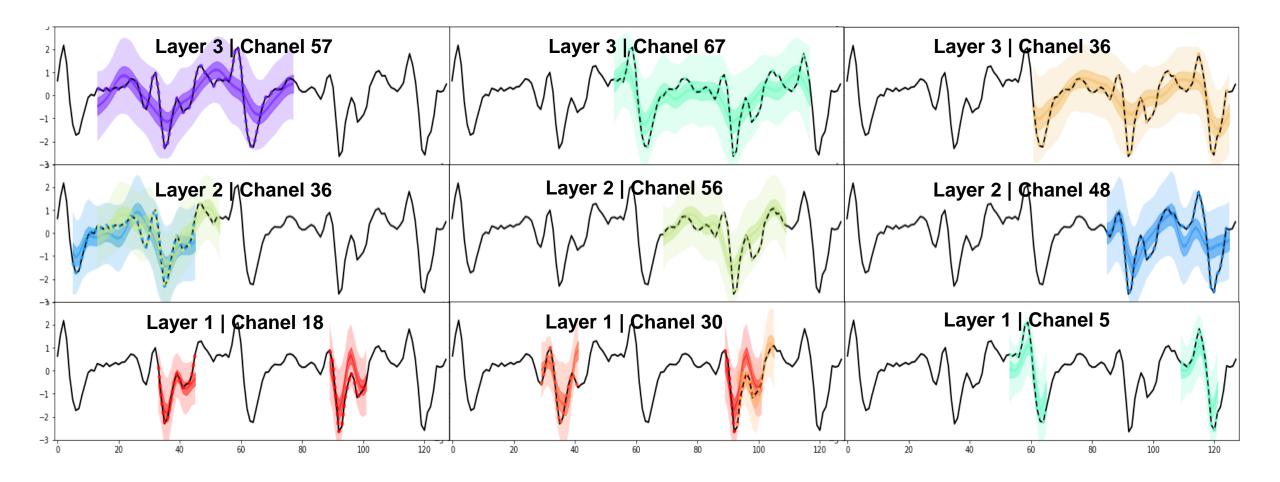


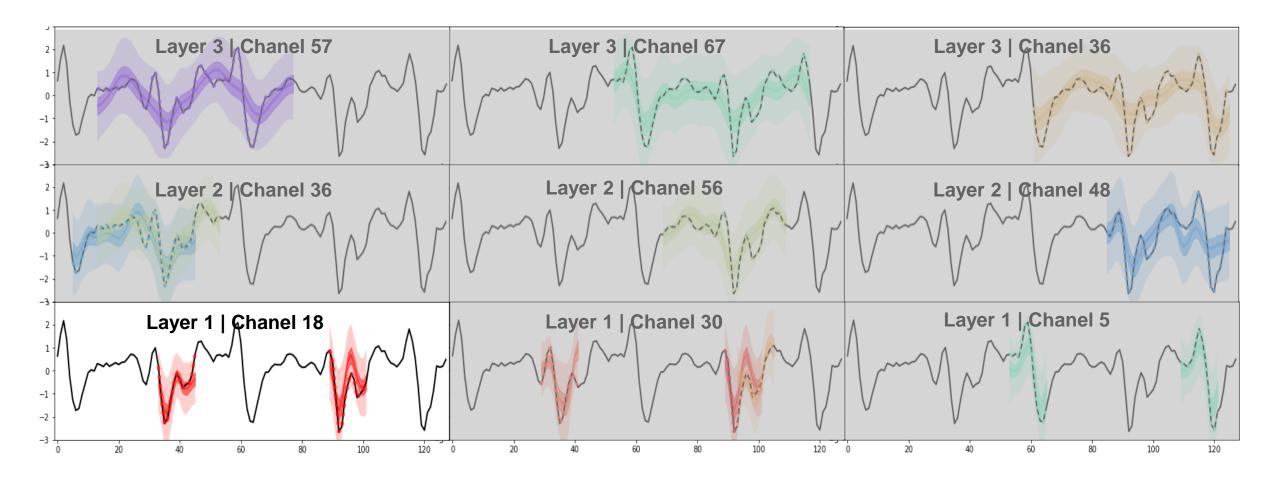
Highly Activated Period (HAP)

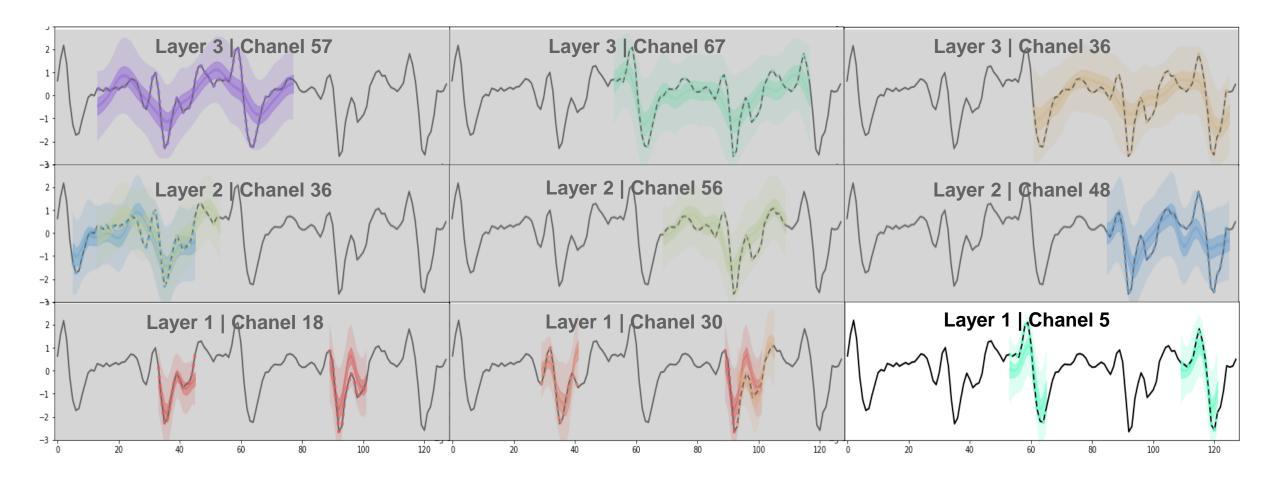
Clustered Pattern of Highly Activated Period

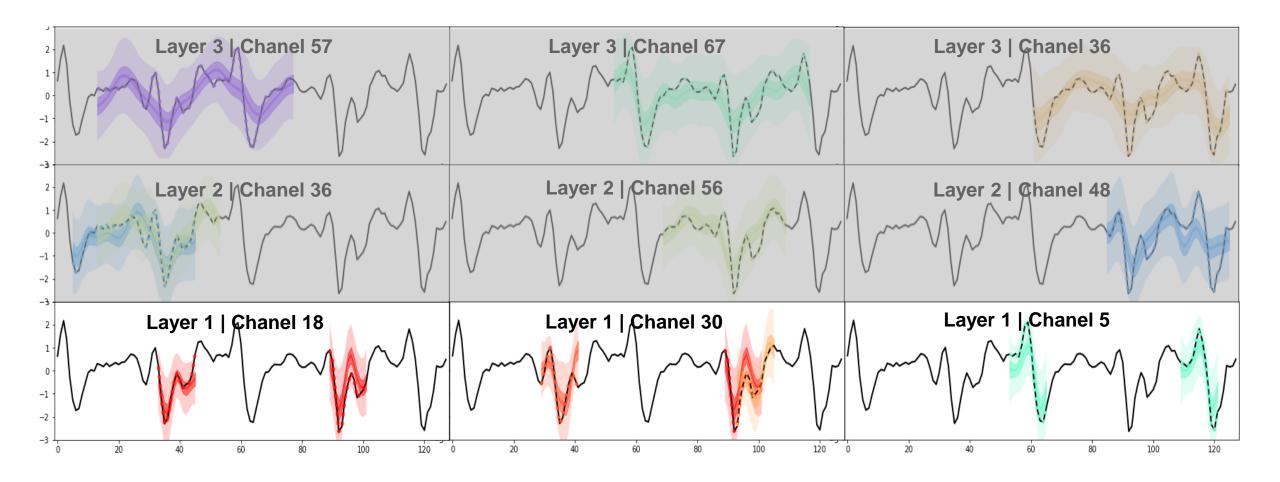


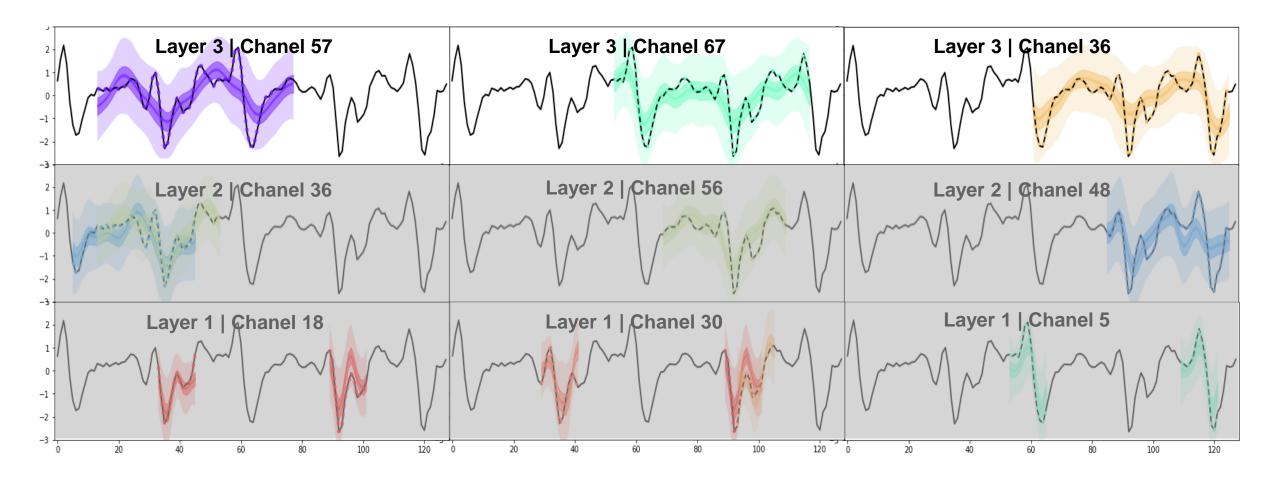


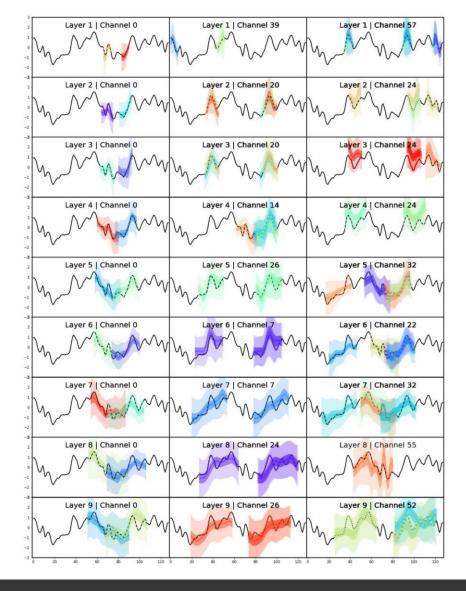


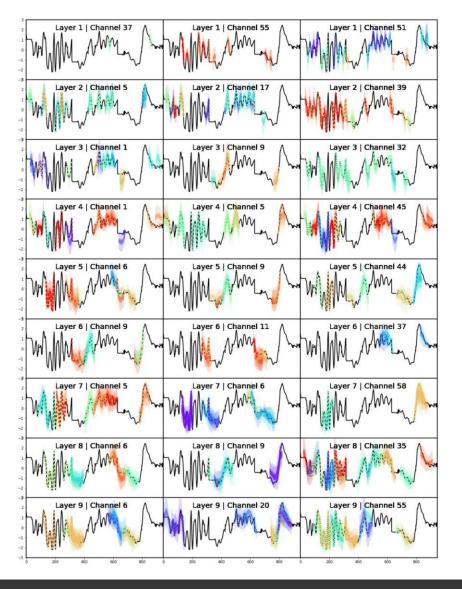




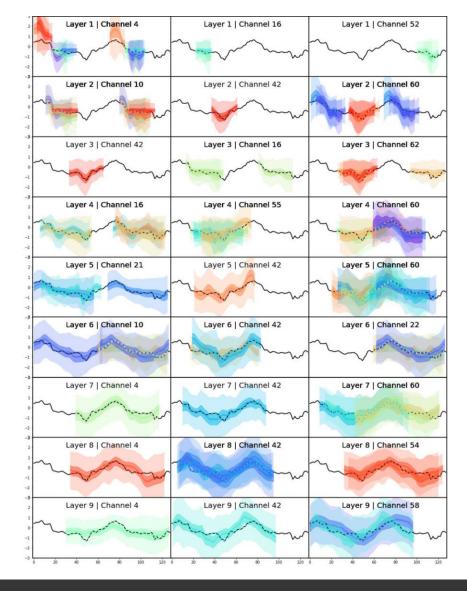


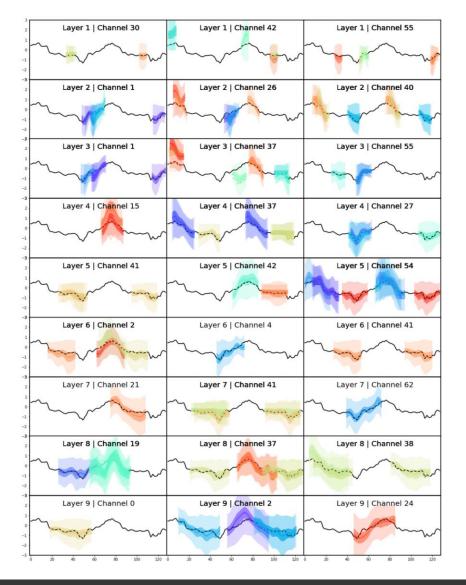




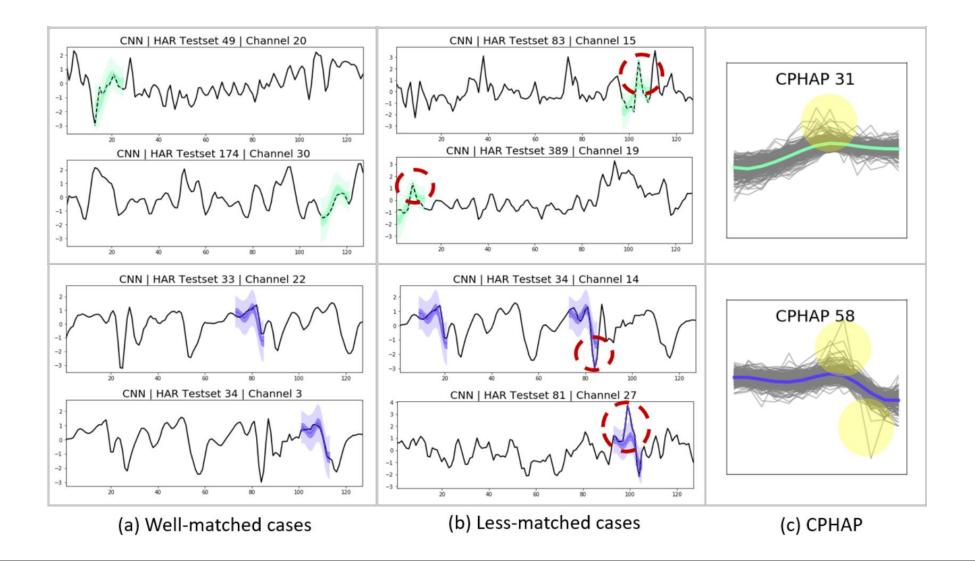


Experiment I : Different Network Structure (ResNet)

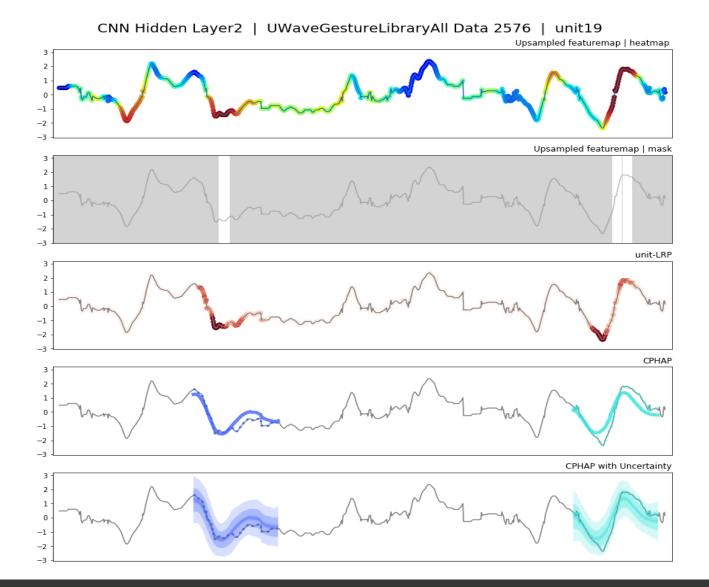




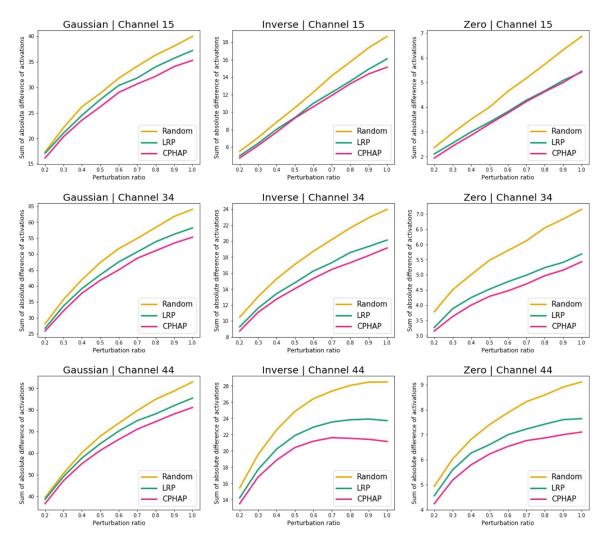
Experiment 2 : Different Filter Size



Experiment 3 : Sequences of test data with CPHAP of train data



Experiment 4 : Visual Comparison among XAI methods

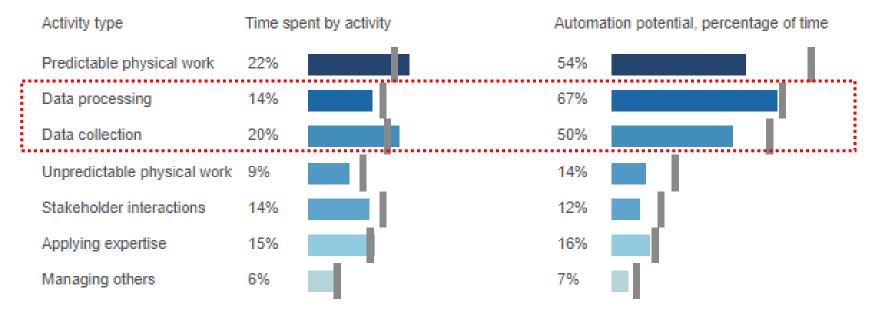


https://clusteredpattern.github.io/pages/

Experiment 5 : Perturbating with unimportant area

Work activity summary: Finance and insurance

Grey lines represent average per activity across all sectors.



SOURCE: <u>https://public.tableau.com/profile/mckinsey.analytics#!/vizhome/AutomationBySector/WhereMachinesCanReplaceHumans</u>

Automation of Knowledge Work

Finance and Insurance, McKinsey 2016

Adobe beats Street 3Q forecasts



Associated Press September 20, 2017

. . .

SAN JOSE, Calif. (AP) _ Adobe Systems Inc. (ADBE) on Tuesday reported fiscal third-quarter profit of \$419.6 million.

The San Jose, California-based company said it had profit of 84 cents per share. Earnings, adjusted for one-time gains and costs, were \$1.10 per share.

Adobe shares have climbed 52 percent since the beginning of the year. In the final minutes of trading on Tuesday, shares hit \$156.61, an increase of 57 percent in the last 12 months.

Automated Narrative Generation

This story was generated by Automated Insights (http://automatedinsights.com/ap) using data from Zacks Investment Research



Sonoma County Little Leagues (Falcons vs Mustangs)

Anthony T got it done on the bump on the way to a win. He allowed two runs over 2-1/3 innings. He struck out four, walked two, and surrendered no hits.

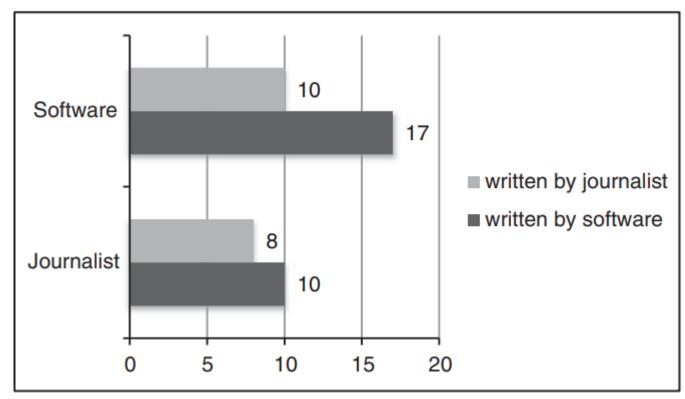
Anders Mathison ended up on wrong side of the pitching decision, charged with the loss. He lasted just two innings, walked two, struck out one, and allowed four runs.

Automated generated by Quill, Narrative Science

Automated Narrative Generation

Each of 45 respondents read a game recap article and decide

whether or not the text had been written by a journalist or by a computer.



Turing Test? Software vs Journalist

Automated Insights is acquired by Vista for \$80 million (Feb. 2015).

Narrative Science get funded \$43.4 million, so far.

 $\bullet \bullet \bullet$

Big Success in Funding

Adobe beats Street 3Q forecasts



Associated Press September 20, 2017

. . .

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An Old-School Al Strategy: Template



Sonoma County Little Leagues (Falcons vs Mustangs)

Anthony T got it done on the bump on the way to a win. He allowed two runs over 2-1/3 innings. He struck out four, walked two, and surrendered no hits.

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Generated by Quill, Narrative Science

An Old-School AI Strategy: Template

The deeper challenge lies not in generating copy, but in finding the most pertinent meaning in a given dataset.

"It's not just about converting numbers to language."

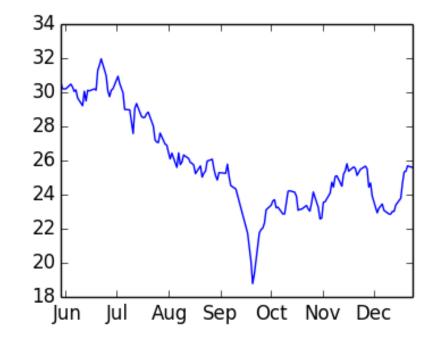
"Those numbers need context"

Challenges in Algorithmic Authors



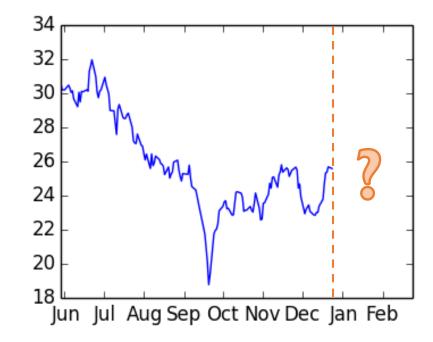
Finding Context in Time Series Data

Descriptive prediction of time series

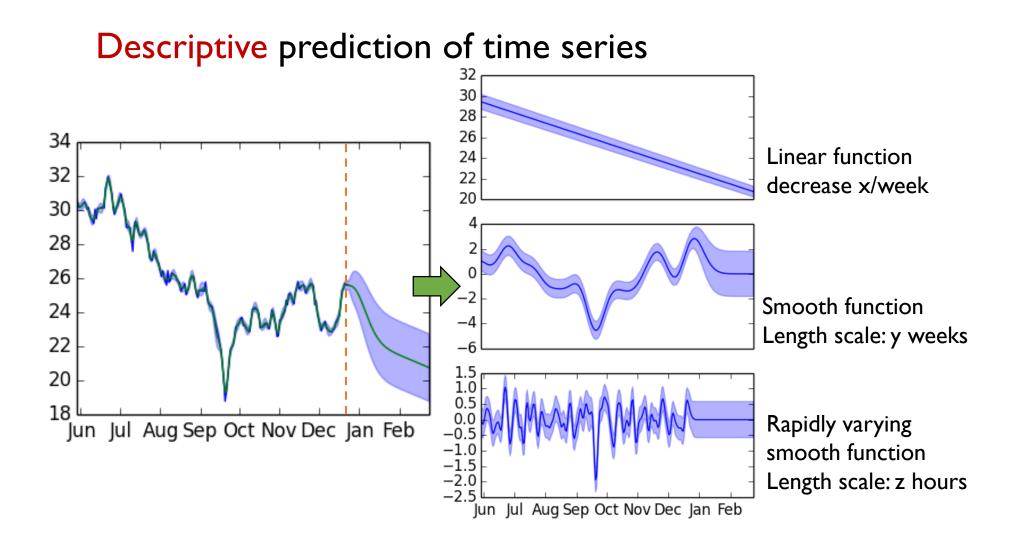


Problem

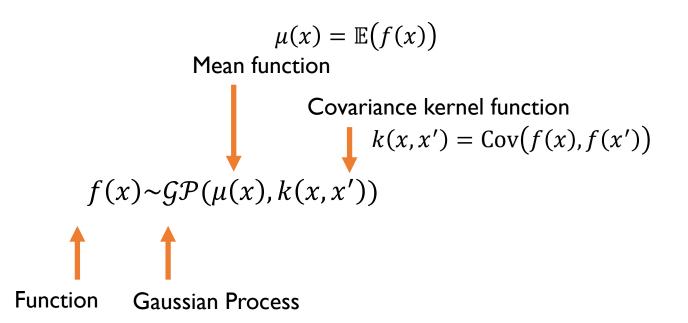
Descriptive prediction of time series



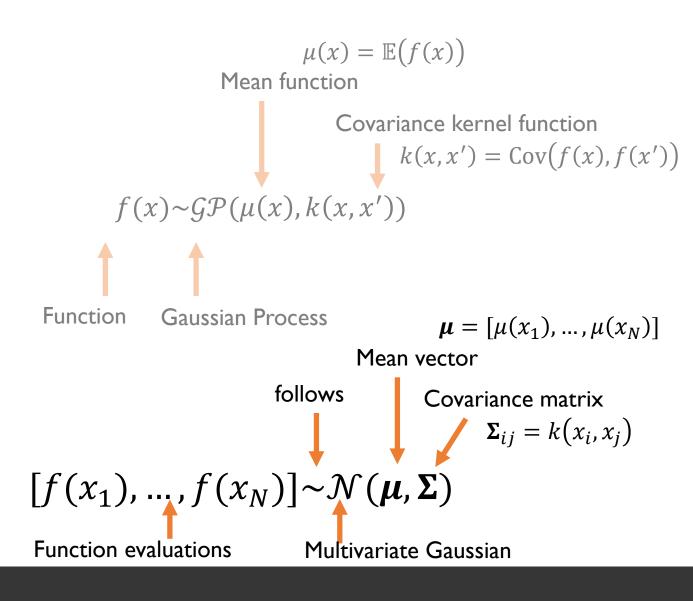
Problem



Problem

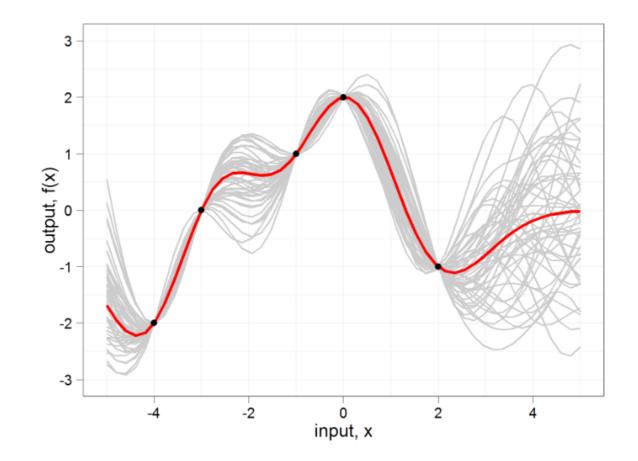




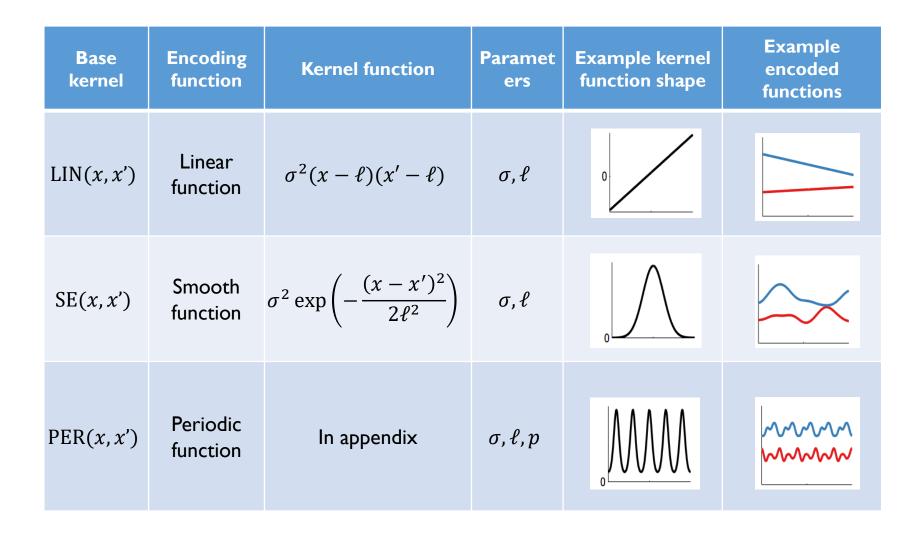


Gaussian Processes (GP)

$f(x) \sim \mathcal{GP}(\mu(x), k(x, x'))$



GP Examples



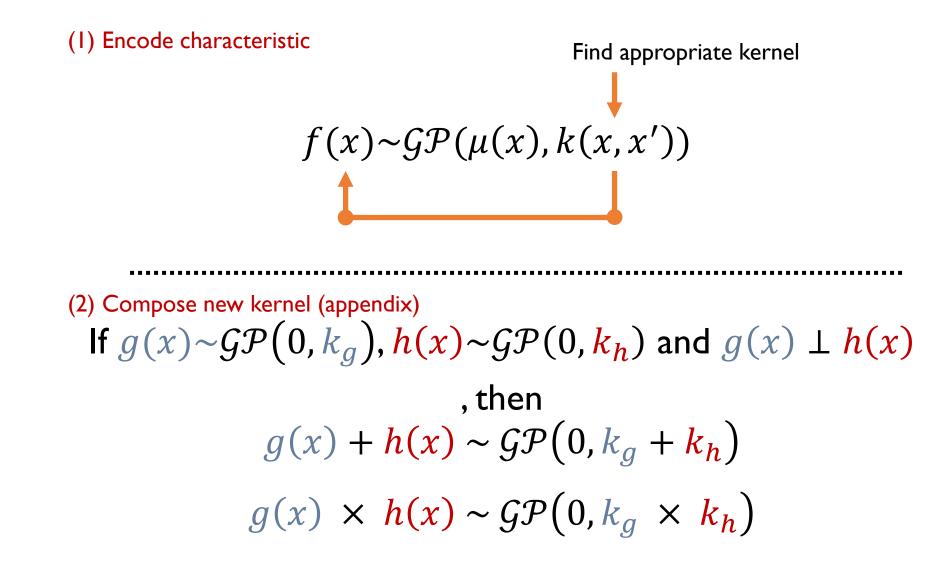
GP Base Kernels



Find appropriate kernel

 $f(x) \sim \mathcal{GP}(\mu(x), k(x, x'))$

Multi-kernel Learning



The Automatic Statistician

*Automatic Bayesian Covariance Discovery (http://www.automaticstatistician.com/)

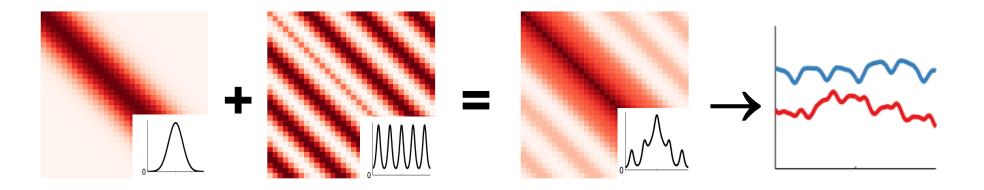
Ghahramani, 2015

Ор.	Concept	Params	Example	Example kernel function shape	Example encoded functions
+	Addition Superposition OR operator	N/A	SE + PER		~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
			LIN + PER	مر مر	-
×	Multiplication AND operator	N/A	$SE \times PER$	₀	

The Automatic Statistician: Kernel Composition

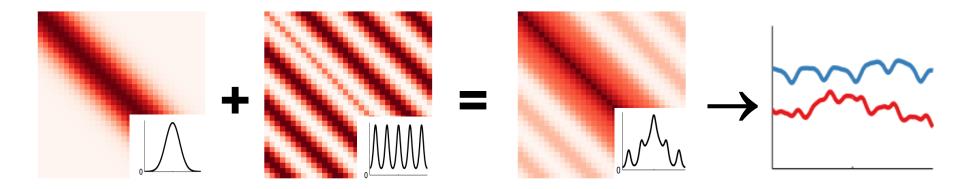
Grosse et. al., 2012

Kernel Composition: Generate Data from Models

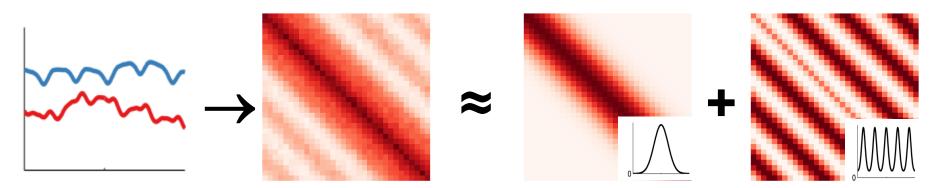


Kernel Composition & Covariance Decomposition

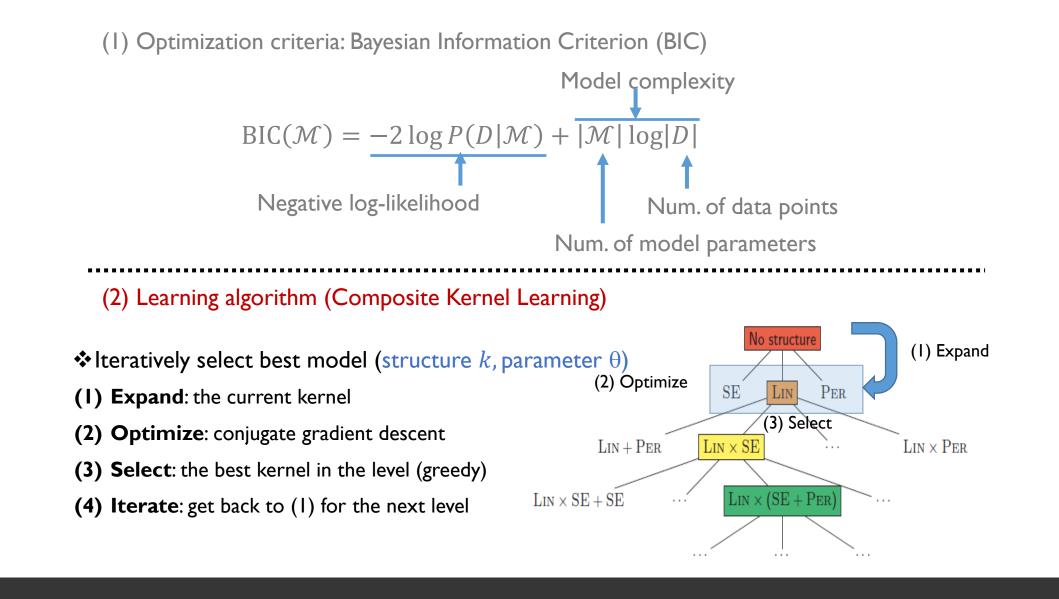
Kernel Composition: Generate Data from Models



Covariance Decomposition: Learn Explainable Models from Data

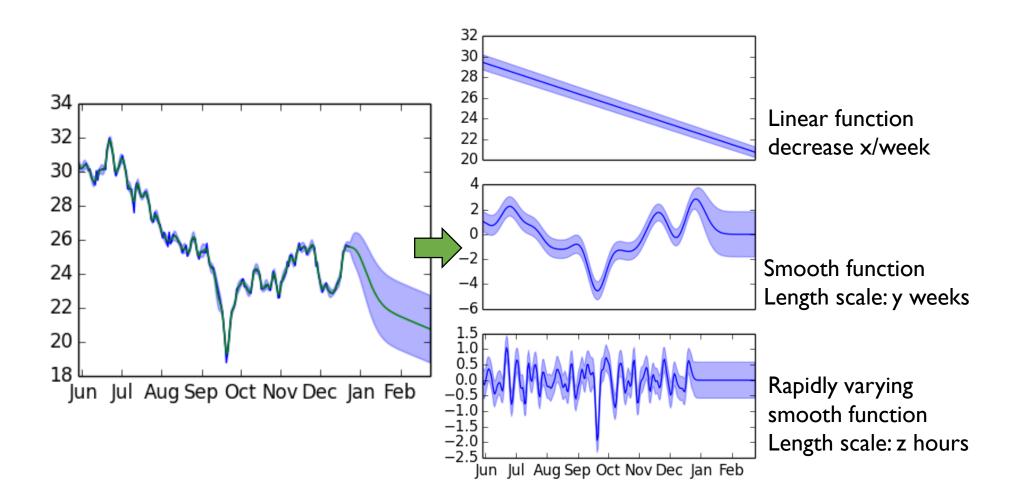


Kernel Composition & Covariance Decomposition



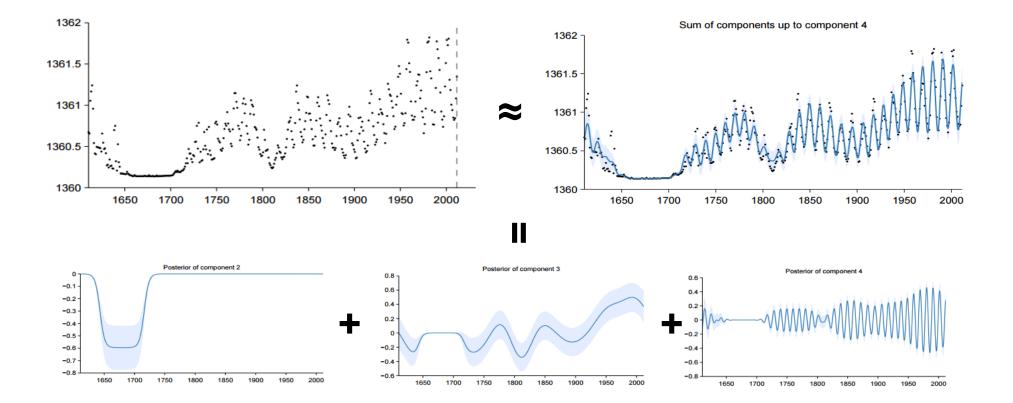
The Automatic Statistician: Greedy Kernel Search

Duvenaud et. al., 2014



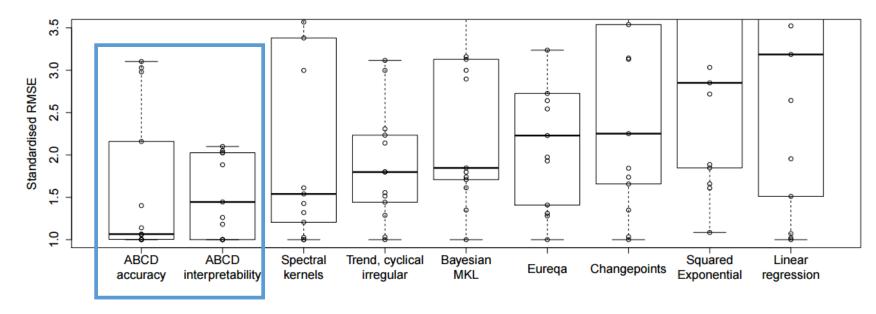
The Automatic Statistician: A Sample Report

Lloyd et. al., 2014



The Automatic Statistician: A Sample Report

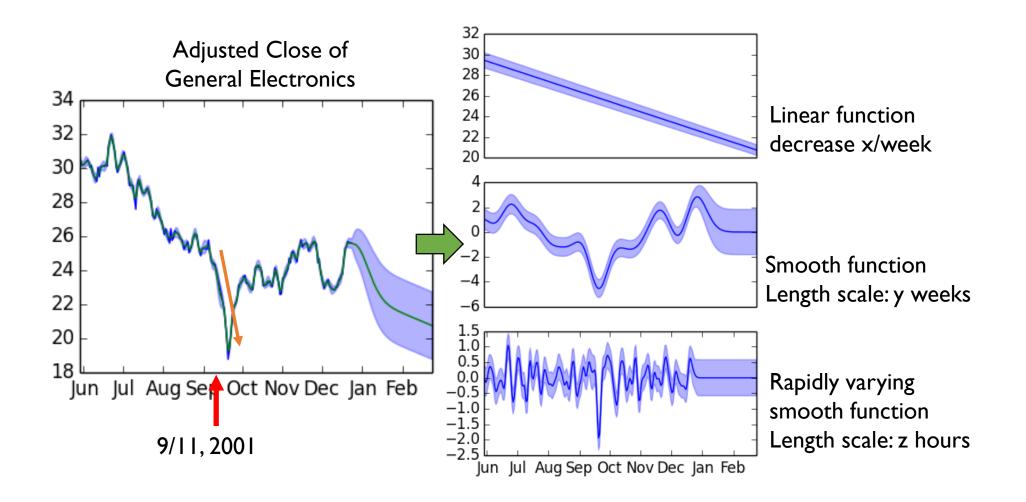
Lloyd et. al., 2014



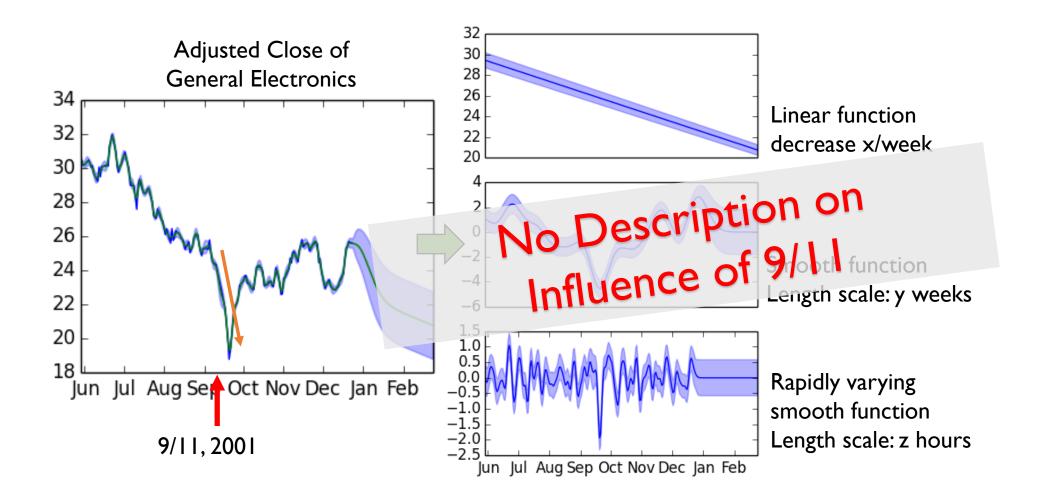
13 regression datasets

The Automatic Statistician: Extrapolation Performance

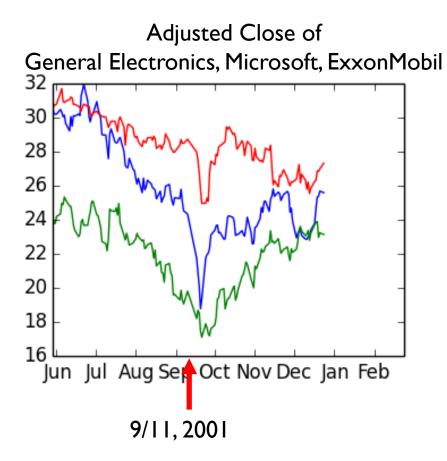
Lloyd et. al., 2014



Challenge: The Automatic Statistician Incorporating Global Changes

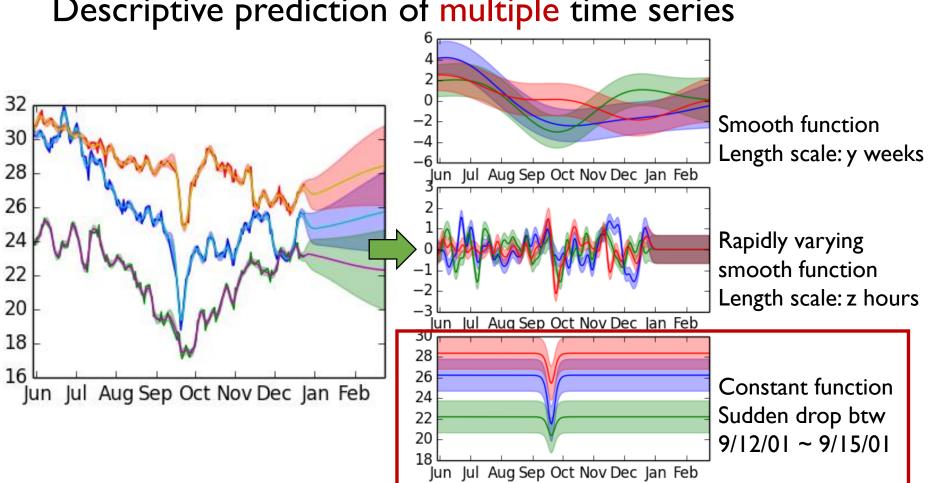


Challenge: The Automatic Statistician Incorporating Global Changes



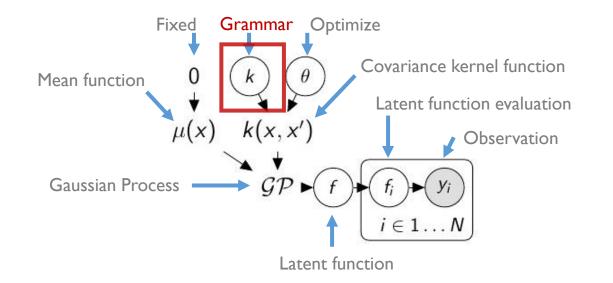
- Exploit multiple time series
- Find global descriptions
- Hope better predictive performance

Challenge: The Automatic Statistician Q: How about handling multiple time series?



Descriptive prediction of multiple time series

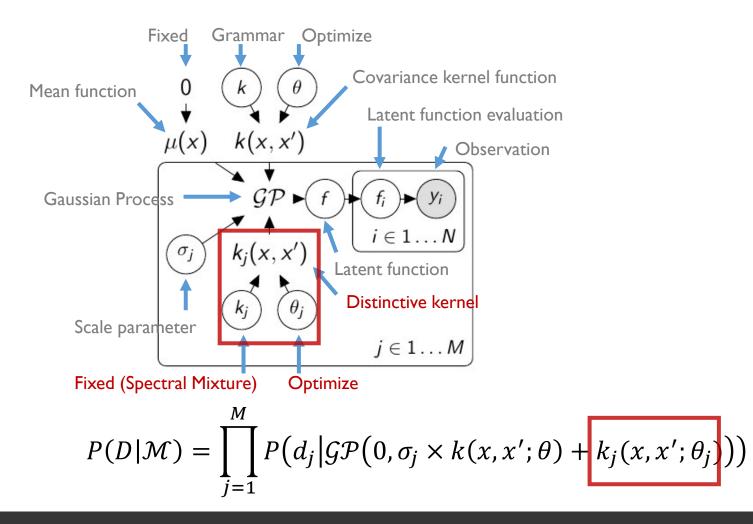
Problem (Our research)



A Generalized Multi Kernel Learning

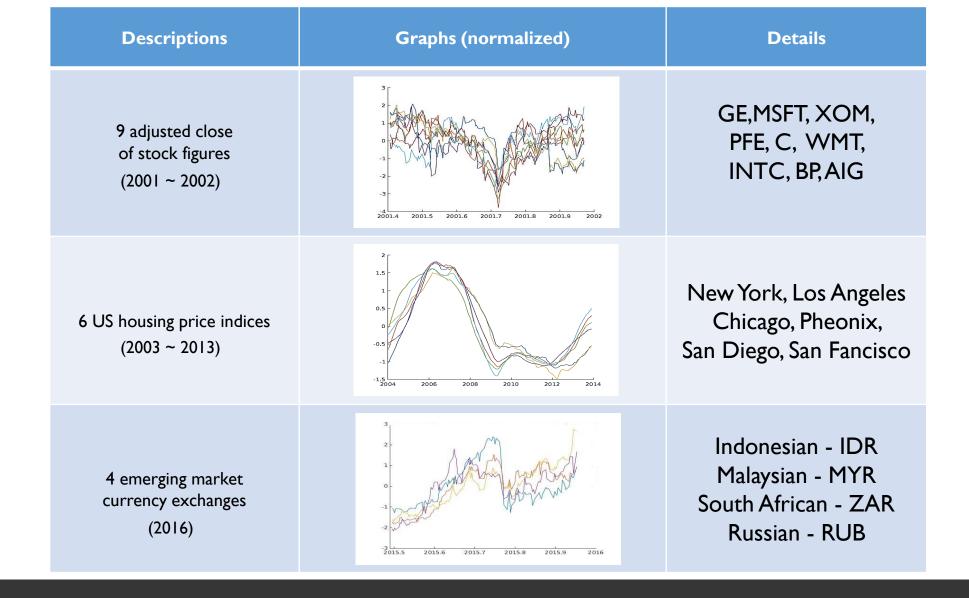
$$P(D|\mathcal{M}) = P(D|\mathcal{GP}(0, k(x, x'; \theta)))$$

Model: Composite Kernel Learning (The Automatic Statistician)

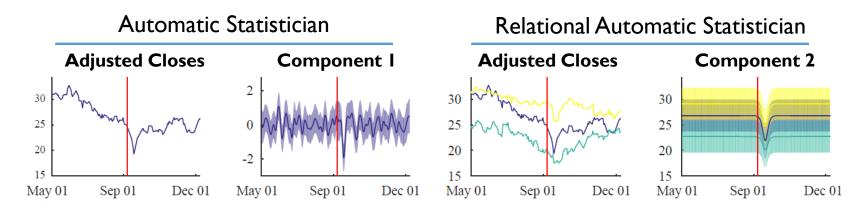


Model: Semi-Relational Kernel Learning

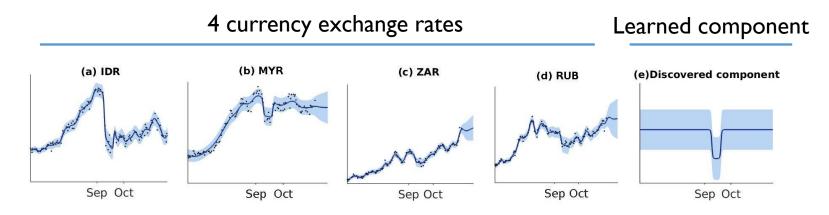
Hwang et al., 2016



Experiments on Financial Data Sets

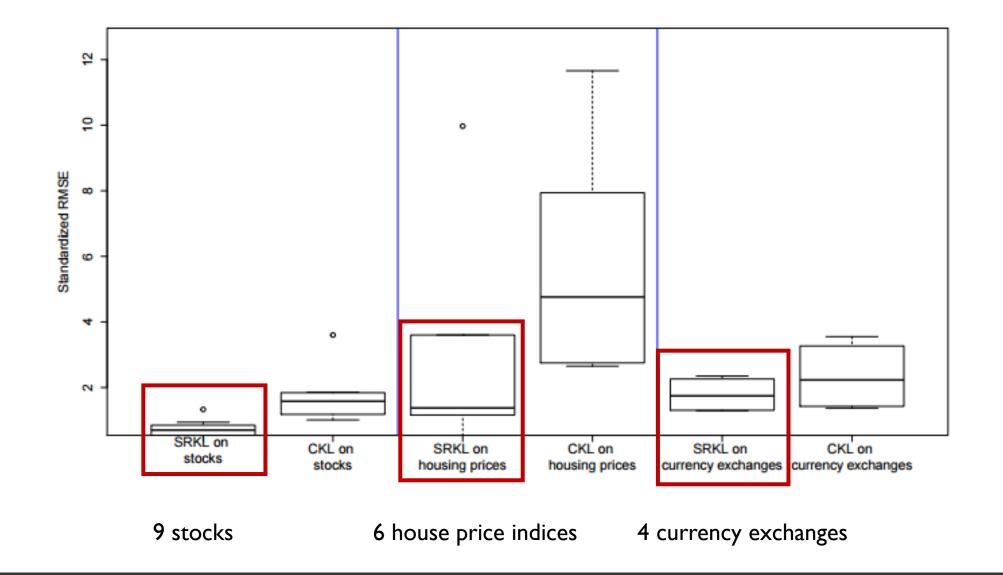


US stock market values suddenly drop after US 9/11 attacks.



Currency exchange is affected by FED's policy change in interest rates around middle Sep 2015.

Qualitative Results



Quantitative Results

Hwang et al., 2016

	Negative log likelihood			Bayesian Information Criteria			Root mean square error		
Data set	CKL	RKL	SRKL	CKL	RKL	SRKL	CKL	RKL	SRKL
STOCK3	332.75	311.84	304.05	750.65	665.09	1251.62	0.40	0.78	0.38
STOCK6	972.00	1007.09	988.14	2219.71	2066.18	3333.21	3.69	5.75	1.22
STOCK9	1776.31	1763.96	1757.11	3985.03	3626.00	5633.33	8.35	9.77	4.85
HOUSE2	264.69	304.29	310.38	634.00	634.76	905.76	6.58	2.75	3.12
HOUSE4	594.79	586.81	1249.82	1424.18	1221.88	3326.94	5.84	3.66	2.22
HOUSE6	849.64	891.09	1495.40	2100.62	1876.47	4339.54	7.96	5.33	3.10
CURRENCY4	578.35	617.77	693.76	1165.82	1291.77	2269.17	330.00	282.24	201.56

STOCK3 = {GE, MSFT, XOM} STOCK6= STOCK3 + {PFE, C, WMT} HOUSE2 = $\{NY, LA\}$

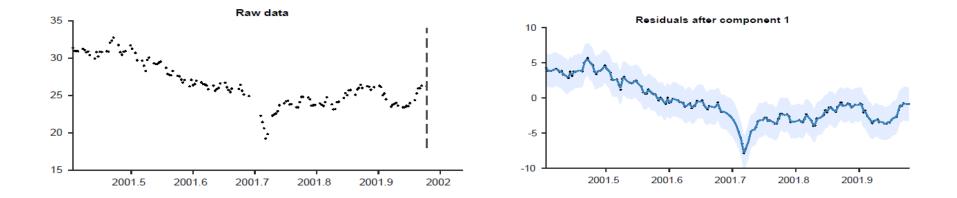
HOUSE4 = HOUSE2 + {Chicago, Pheonix}

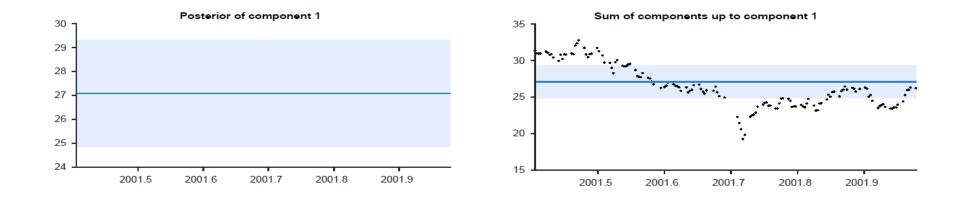
STOCK9 = STOCK6 + {INTC, BP, AIG}

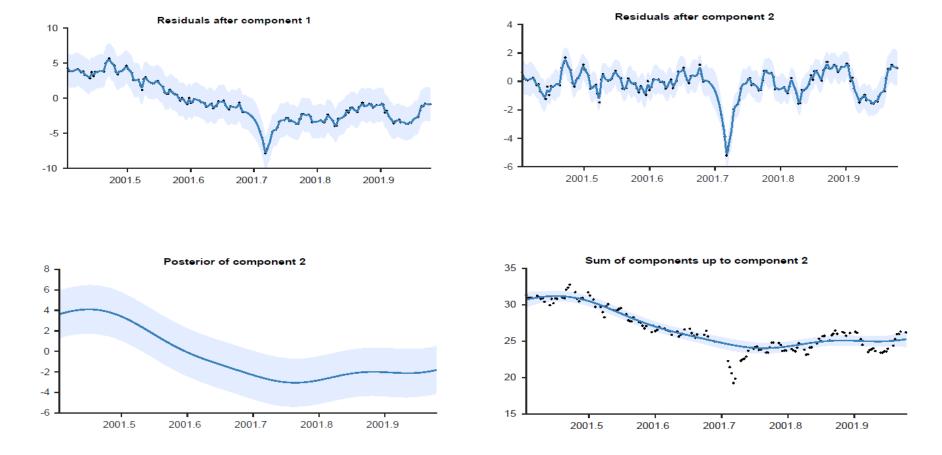
HOUSE6 = HOUSE4 + {San Diego, San Francisco}

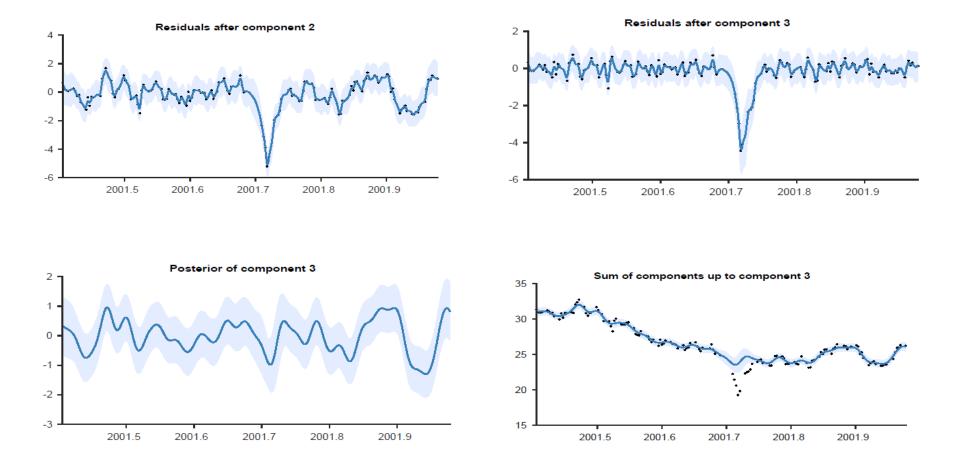
Quantitative Results

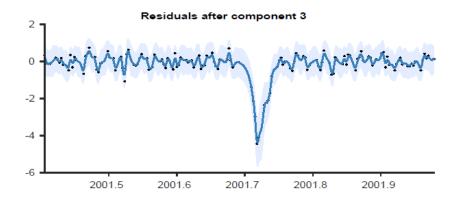
CURRENCY4 = {IDR, MYR,ZAR,RUB}

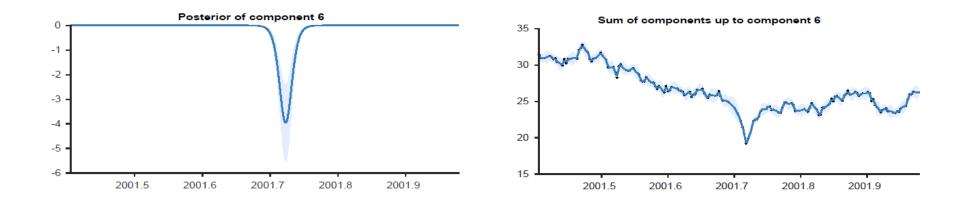


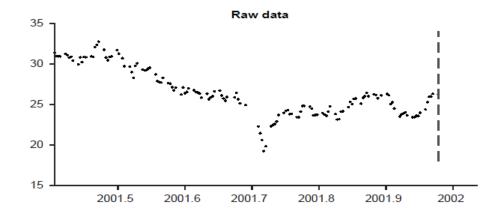




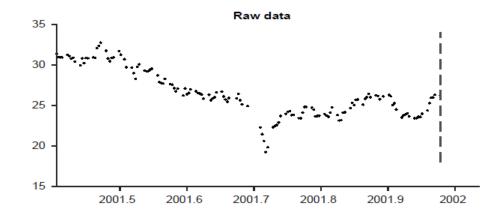




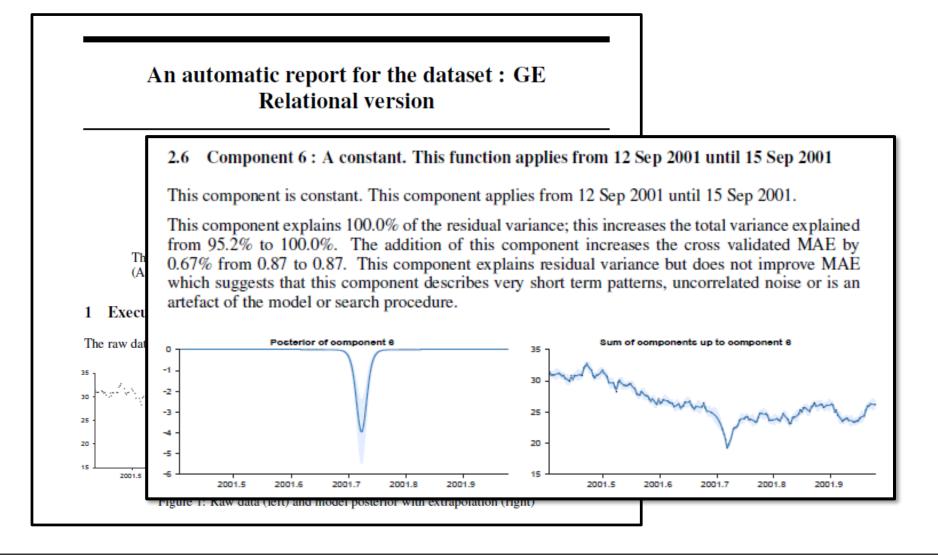


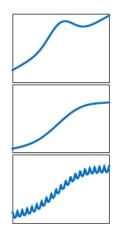




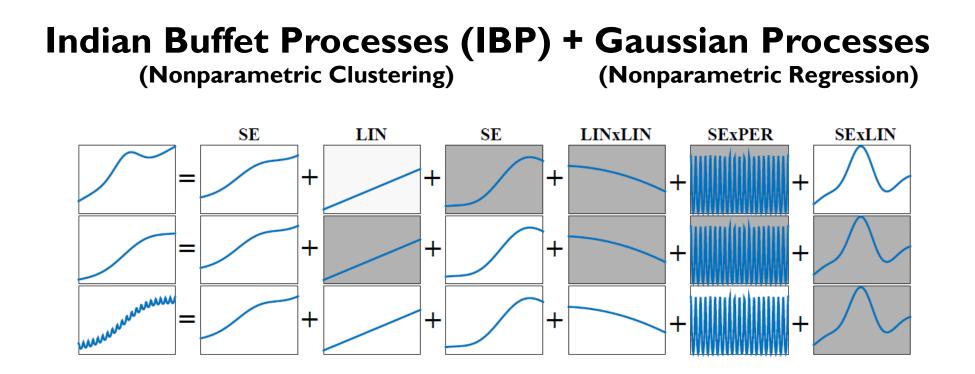






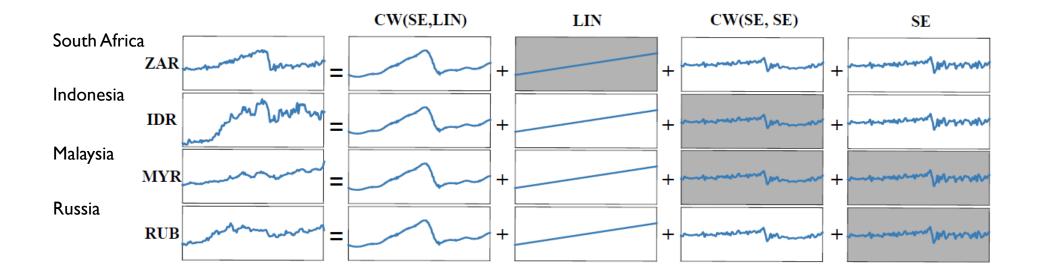


Challenges: Selective Kernel Search Q: Can we selectively search over time series?



Discovering Explainable Latent Covariance Structures for Multiple Time Series

Tong, Choi, 2018



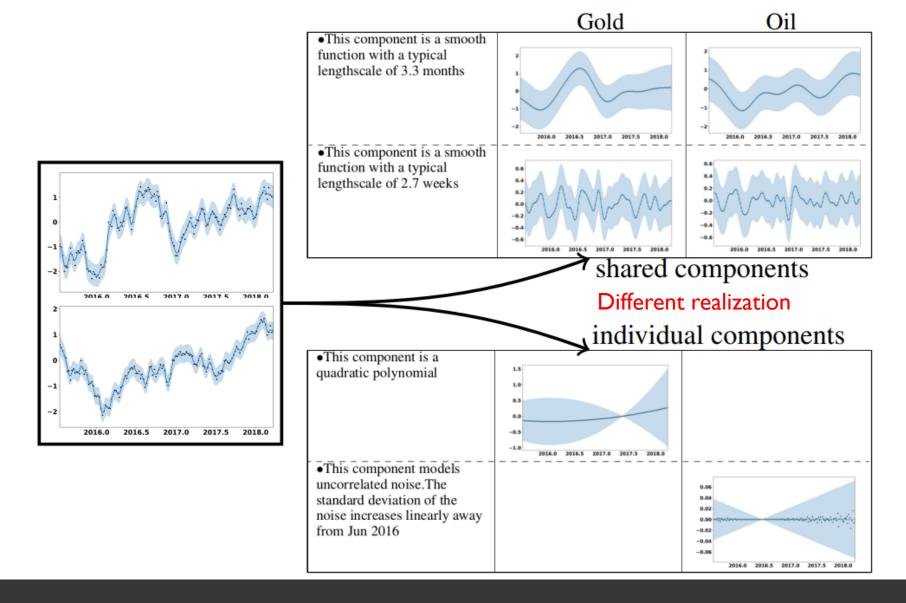
South African Rand and Indonesian Rupiah and Malaysian Ringgit and Russian Rouble share the following properties

 \rightarrow This component is a smooth function with a typical lengthscale of 6.4 days. This component applies until Sep. 15th 2015 and from Sep. 17th 2015 onwards.

Indonesian Rupiah and Malaysian Ringgit and Russian Rouble share the following properties \rightarrow This component is linearly increasing.

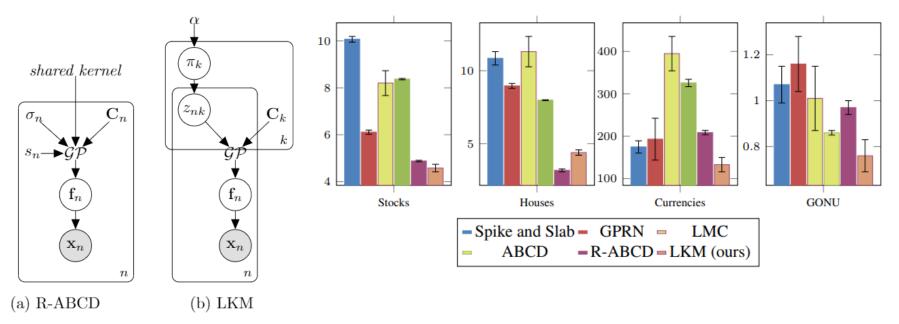
Discovering Explainable Latent Covariance Structures for Multiple Time Series – Version 1

Tong, Choi, 2018



Discovering Explainable Latent Covariance Structures for Multiple Time Series – Version II

Tong et al., 2018

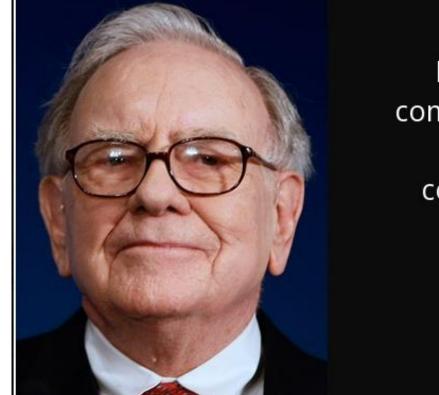


initial ν converged ν											
	9 stocks		6 houses		4 curren	cies	GONU				
	RMSE	MNLP	RMSE	MNLP	RMSE	MNLP	RMSE	MNLP			
Spike and Slab	10.07±0.12	$2.87 {\pm} 0.05$	10.85±0.46	$6.92 {\pm} 0.09$	174.71±14.52	$4.09 {\pm} 0.10$	1.07 ± 0.08	$2.36{\pm}0.11$			
GPRN	6.11±0.09	$2.78 {\pm} 0.14$	8.96±0.17	$6.64{\pm}0.46$	193.13 ± 49.40	$4.24{\pm}0.20$	$1.16{\pm}0.12$	$2.46 {\pm} 0.28$			
LMC	8.20 ± 0.53	2.24 ± 0.23	11.31 ± 1.04	$5.90 {\pm} 0.46$	394.83 ± 40.54	$4.90 {\pm} 0.15$	1.01 ± 0.14	$1.43{\pm}0.11$			
ABCD	8.37 ± 0.03	2.58 ± 0.05	7.98 ± 0.03	5.61 ± 0.05	325.58 ± 8.64	$4.47 {\pm} 0.04$	$0.86 {\pm} 0.01$	2.21 ± 0.03			
R-ABCD	4.88 ± 0.03	$1.95{\pm}0.05$	3.17±0.10	$6.07 {\pm} 0.09$	208.32 ± 5.02	$3.62{\pm}0.03$	$0.97{\pm}0.03$	$2.01{\pm}0.10$			
LKM	4.58±0.16	$1.87{\pm}0.10$	4.37±0.16	5.54±0.40	133.00±16.92	3.61±0.16	0.76±0.07	$1.90{\pm}0.25$			

Discovering Explainable Latent Covariance Structures for Multiple Time Series

I read annual reports of the company I'm looking at and I read the annual reports of the competitors - that is the main source of material.

Future: Toward Reading/Explaining Reports Beyond Chart-based Analysis

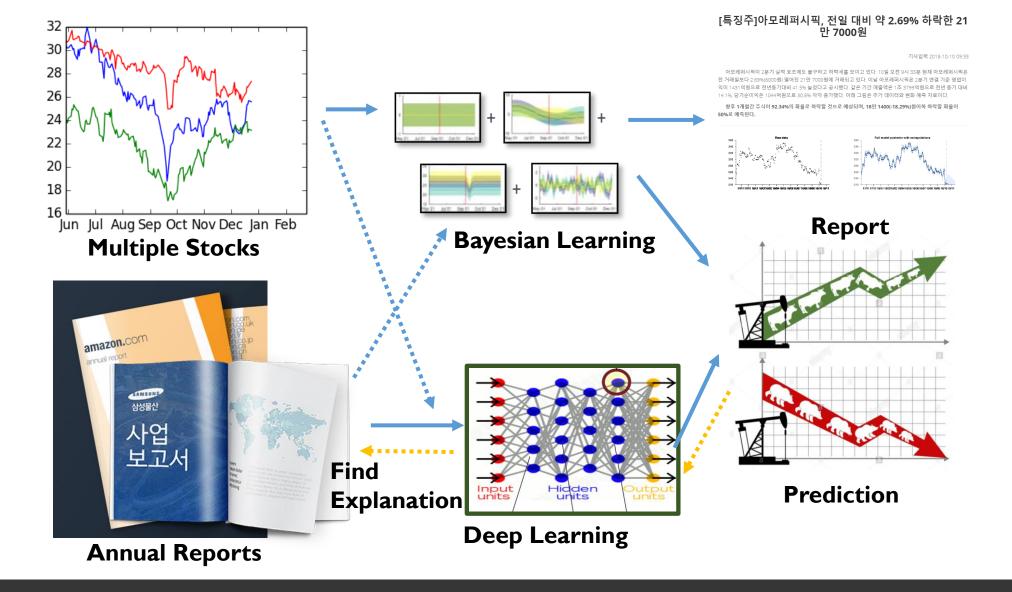


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— Warren Buffett —

AZQUOTES

Future: Toward Reading/Explaining Reports Beyond Chart-based Analysis



Future: Finding Explanation from Reports Read the Report and Explain It

- Automated data collection and processing soon will change our daily life.
- Automated narrative generation methods/frameworks may ha ve widespread applications such as finance and media.
- Compositions of explainable models would generate more hu man understandable descriptions of data.
- Reading and Explaining Articles (e.g., Annual Report) would gr eatly help to improve the prediction accuracy in the future.

Conclusions