# 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**

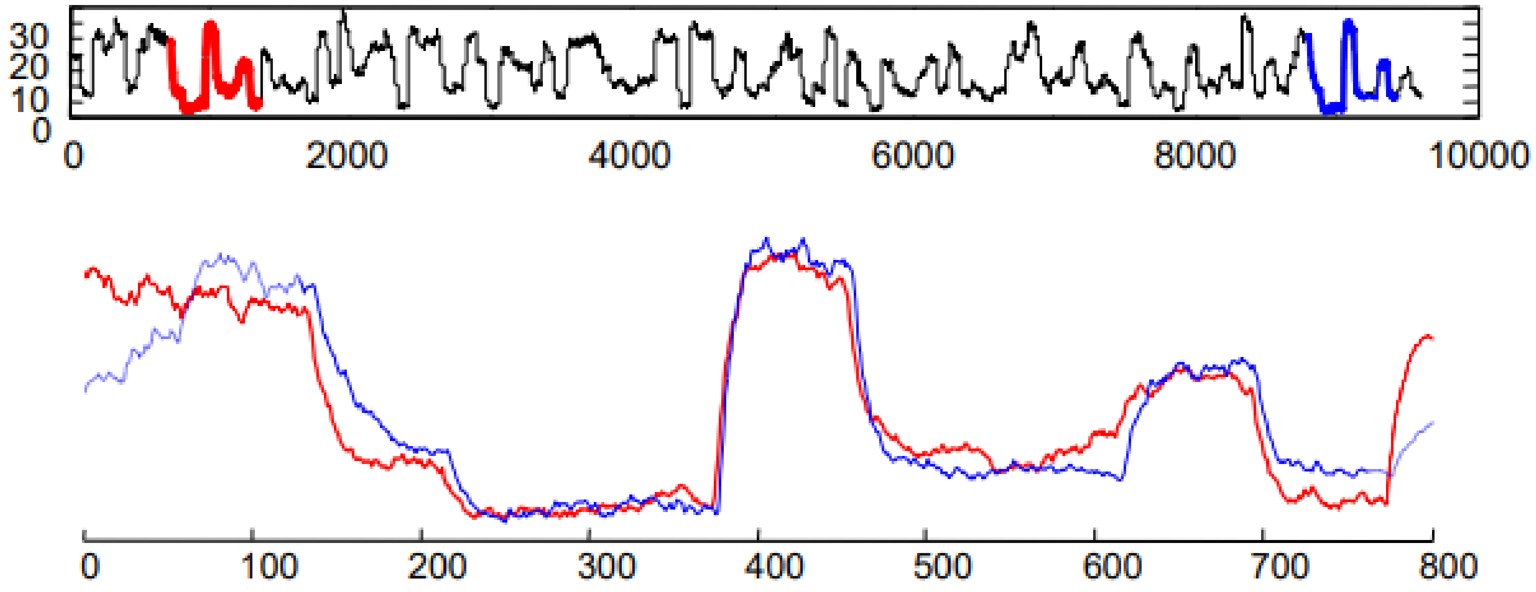
- **Important Questions on Mining and Learning Time Series Data**
- **Visualizing Deep Temporal Neural Networks**
- **Clustered Pattern of Highly Activated Period (CPHAP)**
- **Automatic Statistician/Relational Automatic Statistician (Bayesian Approaches)**

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**

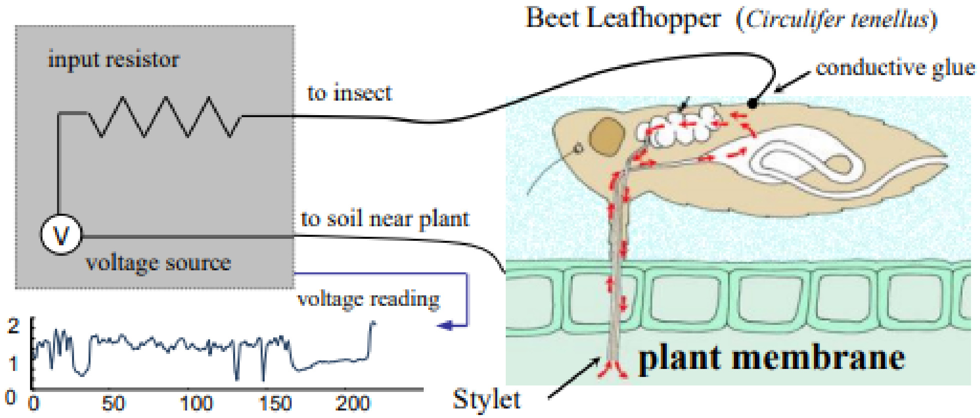
# 100 Time Series Data Mining Questions

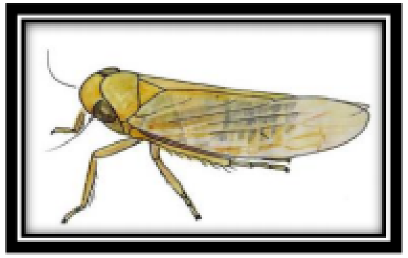
# Find the subsequences having very high similarity to each other.



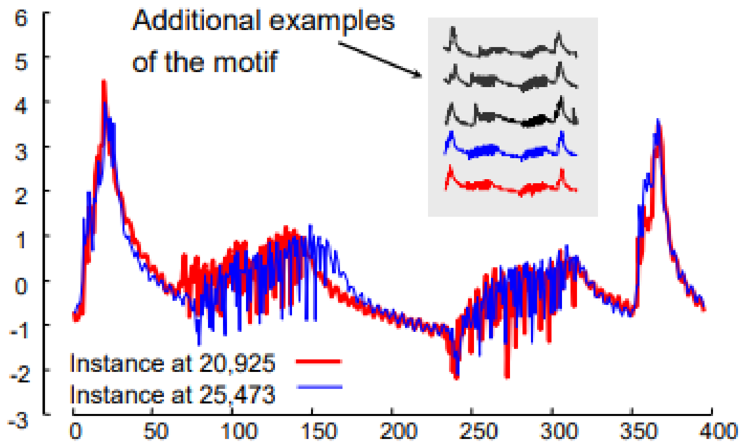

**Slides courtesy of Eamonn Keogh**

## Time Series Motif

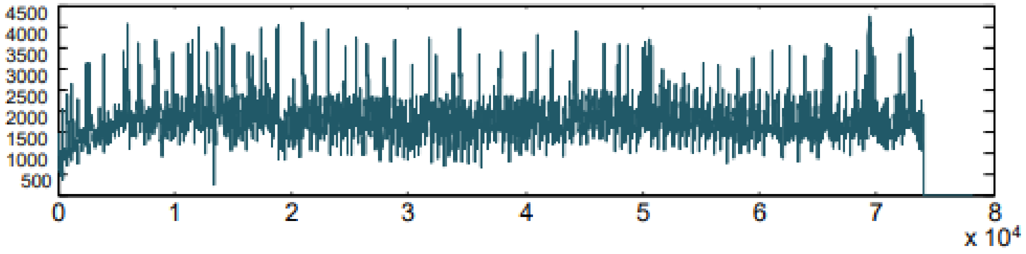


The **electrical penetration graph** or **EPG** is a system used by biologists to study the interaction of insects with plants.



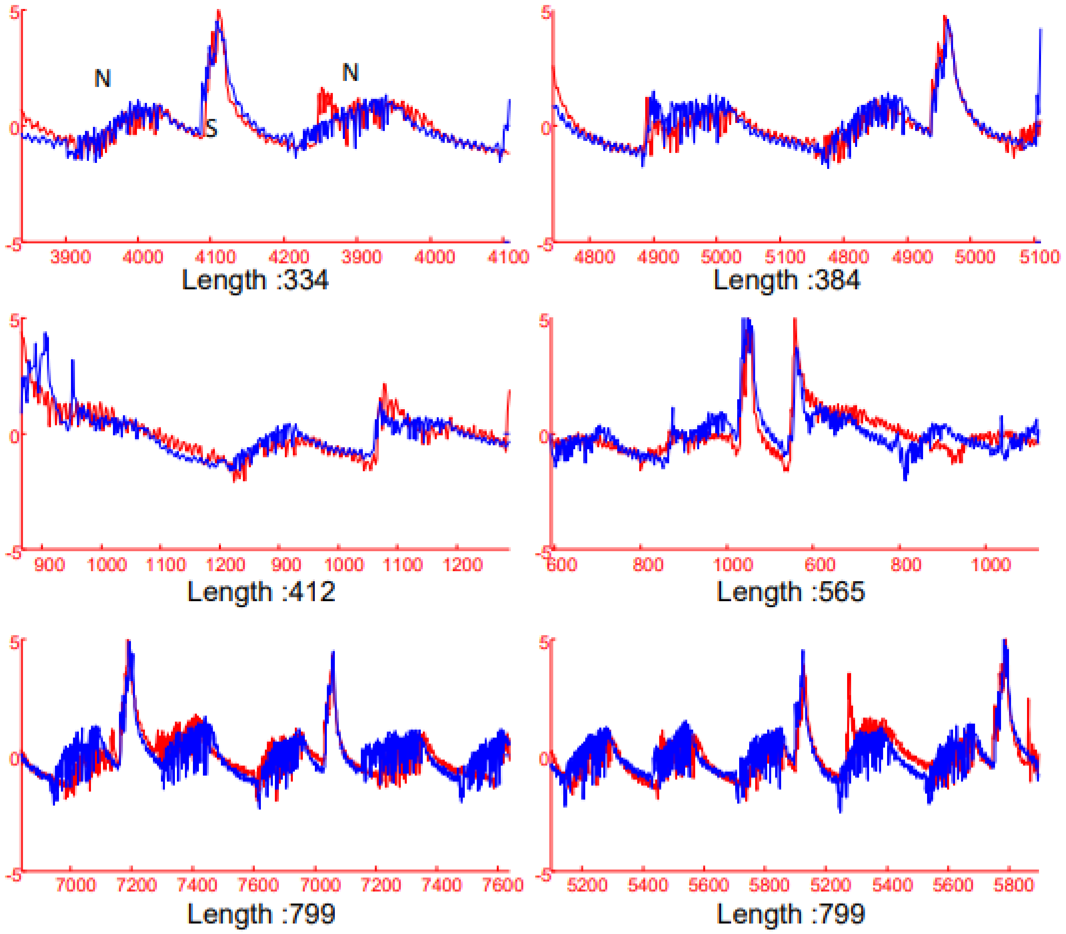

As a bead of sticky secretion, which is by-product of sap feeding, is ejected, it temporarily forms a highly conductive bridge between the insect and the plant.




15 minutes of EPG recorded on Beet Leafhopper

**Slides courtesy of Eamonn Keogh**

# Time Series Motif – An Example: Insect Behavior Analysis

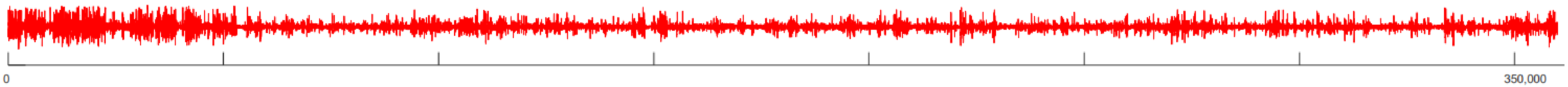


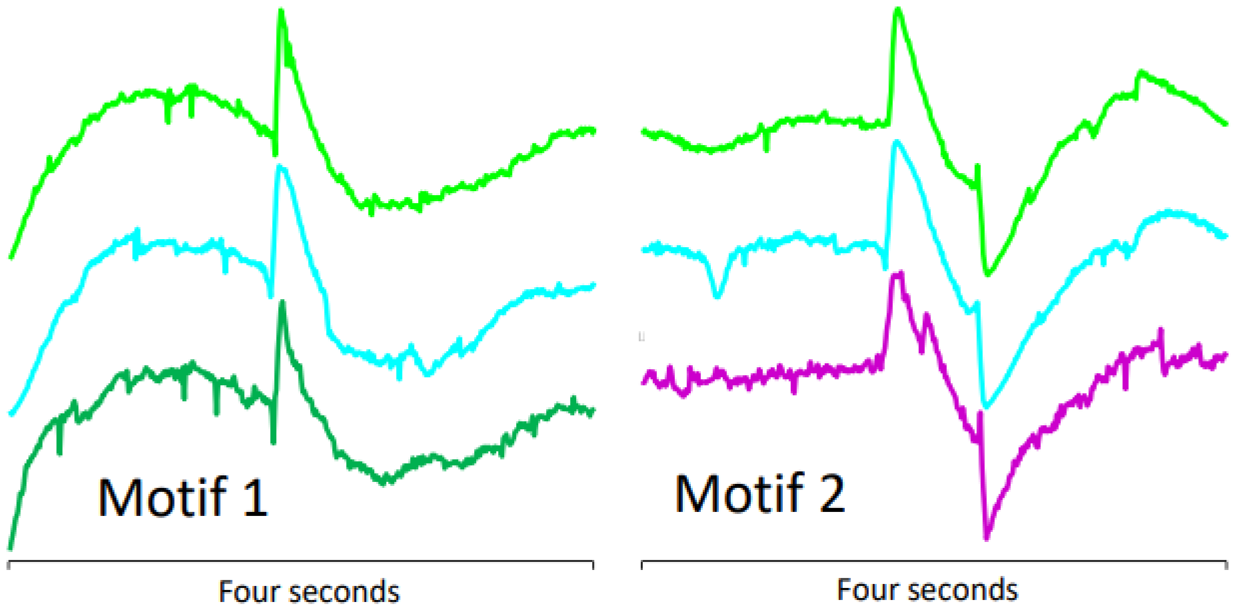

More motifs reveal different feeding patterns of Beet Leafhopper.

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.



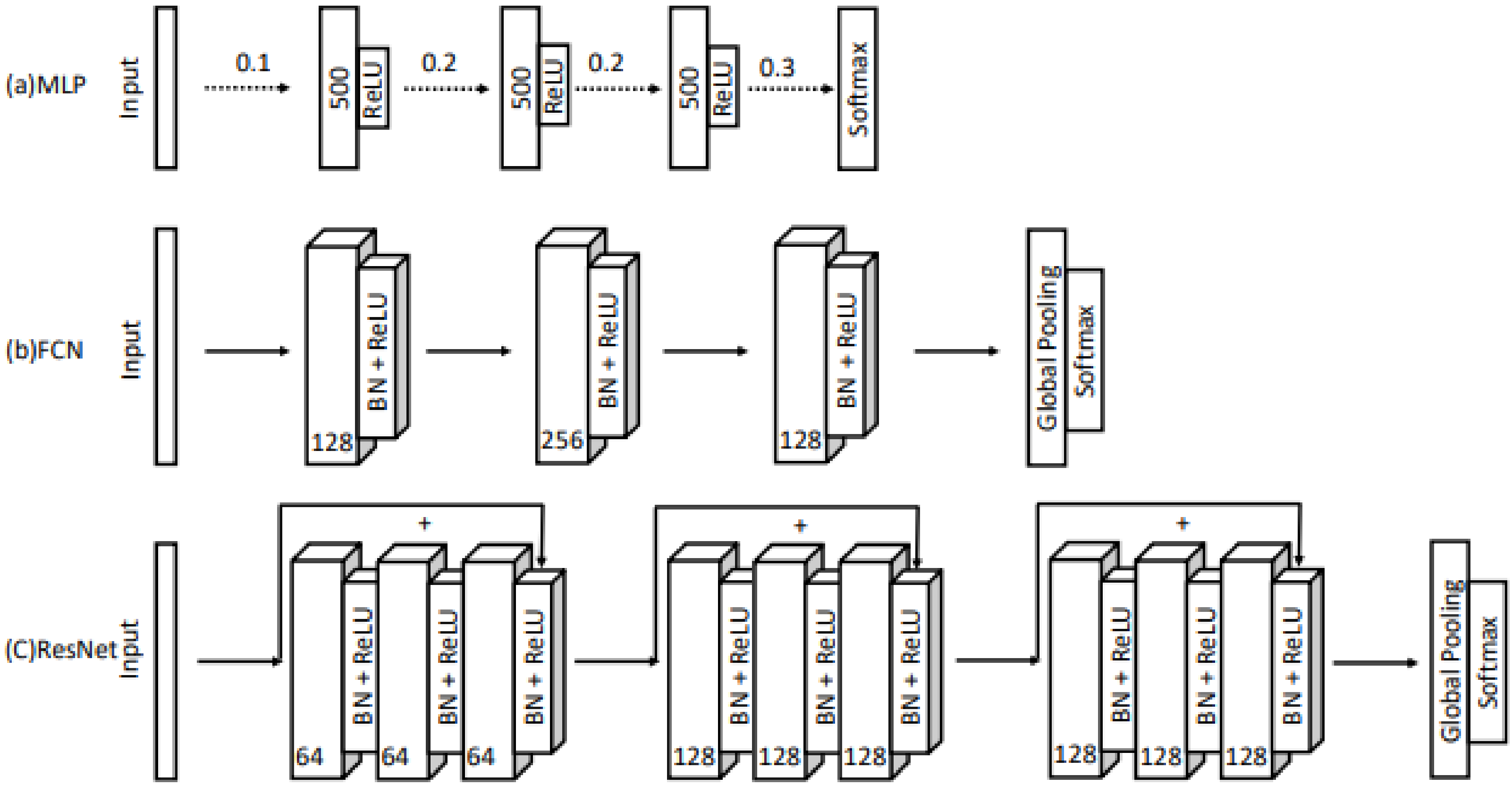

**Note that there may be more examples of each motif!**

**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 | 0.367 | **0.133** | 0.367 | 0.267 | 0.367 | 0.2 | **0.133** | 0.287 | 0.167 | 0.25 | 0.233 |
| CBF | 0.003 | 0.001 | 0.002 | 0.001 | 0.002 | **0** | 0.01 | 0.009 | 0.14 | **0** | 0.006 |
| ChlorineCon | 0.352 | 0.314 | 0.203 | 0.345 | 0.36 | 0.34 | 0.312 | 0.336 | **0.128** | 0.157 | 0.172 |
| CinCECGTorso | 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 |
| DiatomSizeR | 0.033 | 0.082 | **0.023** | 0.036 | 0.059 | 0.046 | 0.069 | 0.126 | 0.036 | 0.07 | 0.069 |
| ECGFiveDays | 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 |
| 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 |
| 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 |
| MedicalImages | 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 |
| NonInvThorax1 | 0.21 | 0.093 | 0.064 | 0.169 | 0.178 | 0.161 | 0.174 | 0.138 | 0.058 | **0.039** | 0.052 |
| NonInvThorax2 | 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 |
| SonyAIBORobot | 0.275 | 0.146 | 0.23 | 0.265 | 0.293 | 0.321 | 0.238 | 0.175 | 0.273 | 0.032 | **0.015** |
| SonyAIBORobotII | 0.169 | 0.076 | 0.07 | 0.188 | 0.124 | 0.098 | 0.066 | 0.196 | 0.161 | **0.038** | **0.038** |
| StarLightCurves | 0.093 | 0.031 | 0.023 | 0.096 | 0.079 | **0.021** | 0.093 | 0.022 | 0.043 | 0.033 | 0.029 |
| SwedishLeaf | 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 |
| SyntheticControl | 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** |
| TwoLeadECG | **0** | 0.015 | 0.001 | 0.015 | **0** | 0.004 | 0.029 | 0.001 | 0.147 | **0** | **0** |
| TwoPatterns | 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 |
| WordSynonyms | 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 Arithmetic ranking | 8.205 | **3.682** | 3.932 | 7.318 | 5.545 | 4.614 | 7.455 | 6.614 | 7.909 | 3.977 | 4.386 |
| AVG geometric ranking | 7.160 | 3.054 | 3.249 | 5.997 | 4.744 | 3.388 | 6.431 | 5.598 | 6.941 | **2.780** | 3.481 |
| MPCE | 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 |
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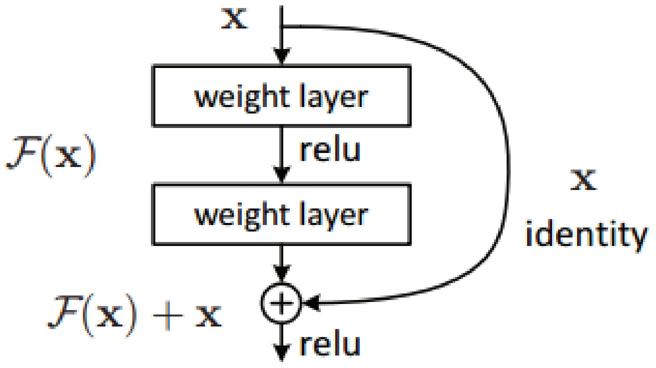
| MPCE | 0.0397 | 0.0226 | 0.0241 | 0.0330 | 0.0304 | 0.0256 | 0.0302 | 0.0335 | 0.0407 | **0.0219** | 0.0231 |

https://github.com/cauchyturing/UCR_Time_Series_Classification_Deep_Learning_Baseline

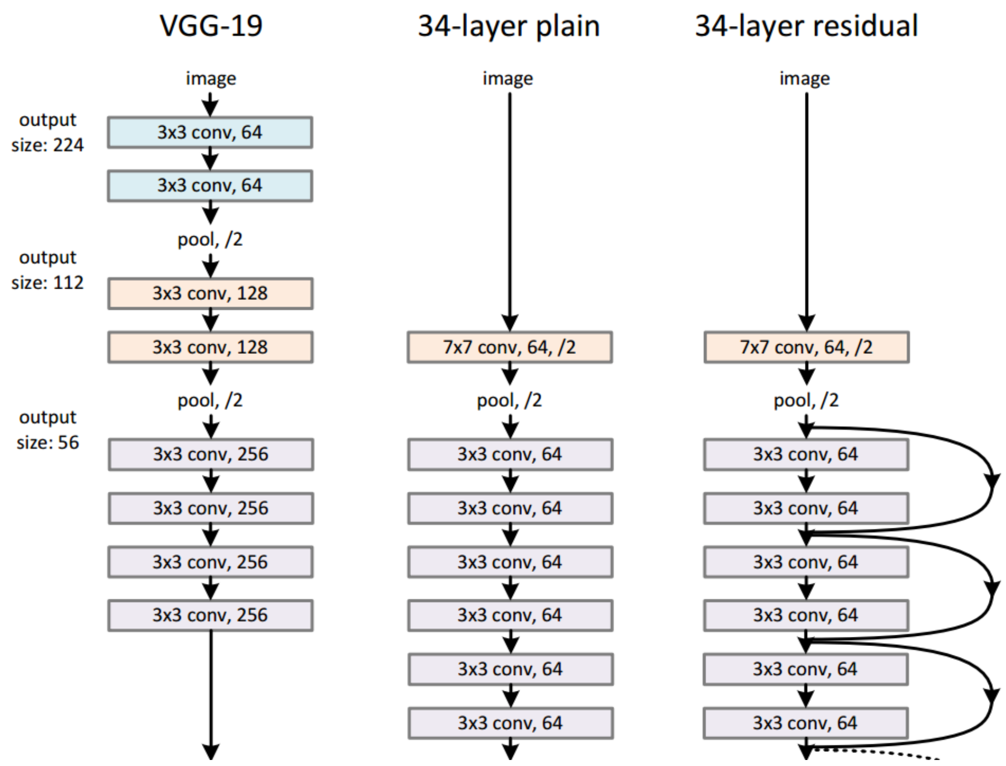
## Experimental Results

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




Residual learning

$$\mathbf{x}_\ell = H_\ell(\mathbf{x}_{\ell-1}) + \mathbf{x}_{\ell-1}.$$

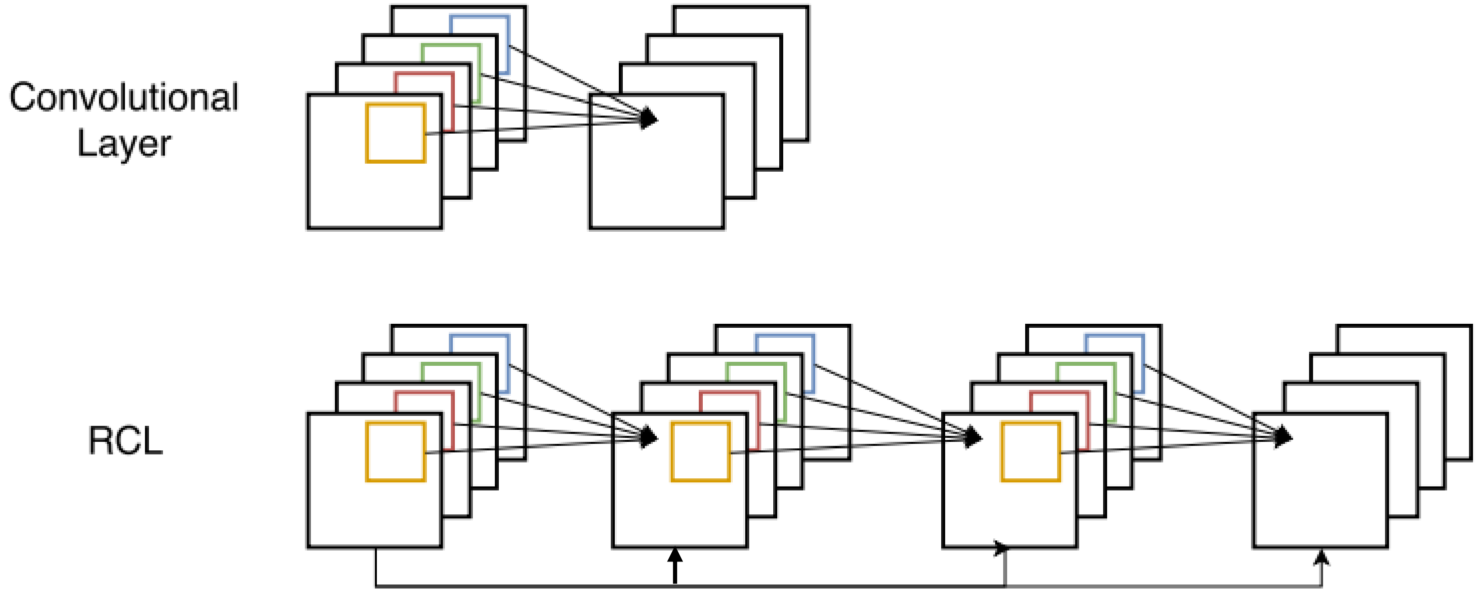



Comparison of Resnet

3.6% of error in ImageNet Challenge, 2015

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

He et. al., 2015

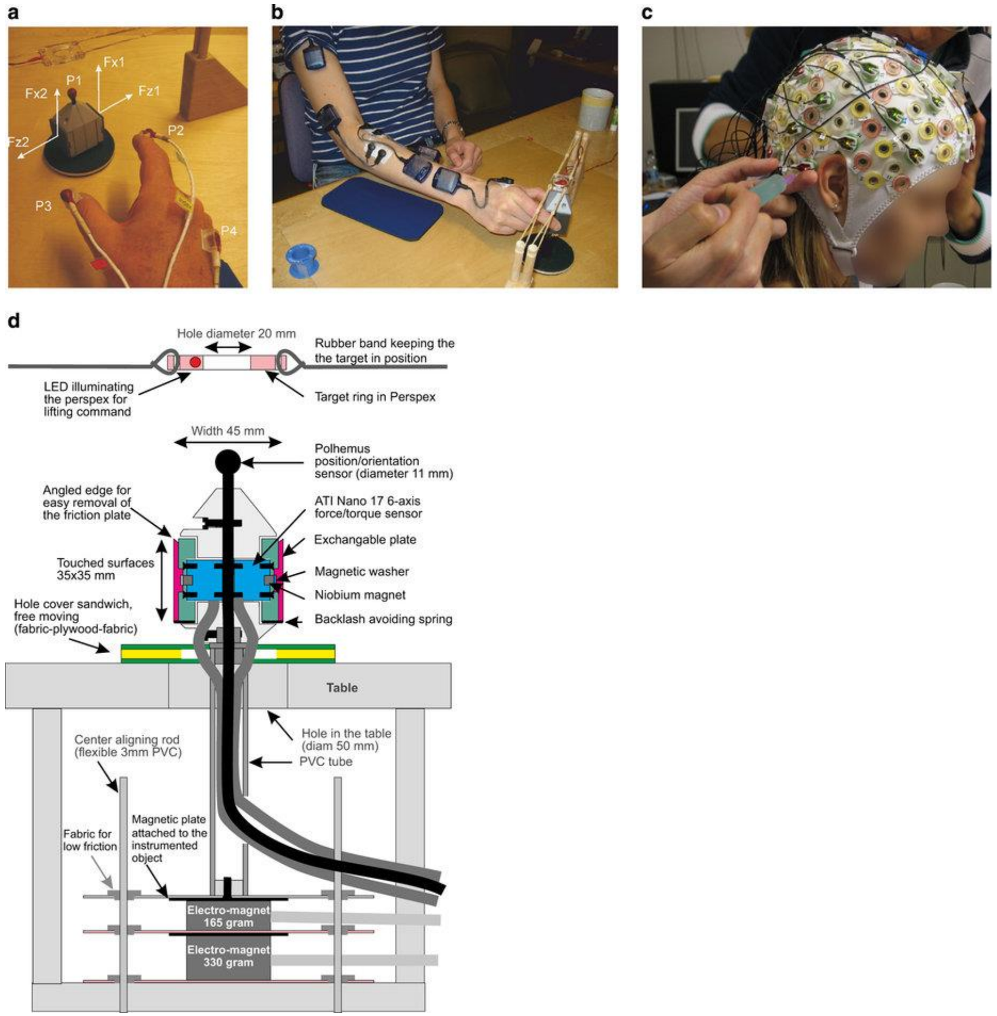



Recurrent Convolutional Layer (RCL)

$$x_l = x_{l-1} + H_l(x_{l-1}) + H_l(H_l(x_{l-1})) + H_l(H_l(H_l(x_{l-1})))$$

# 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

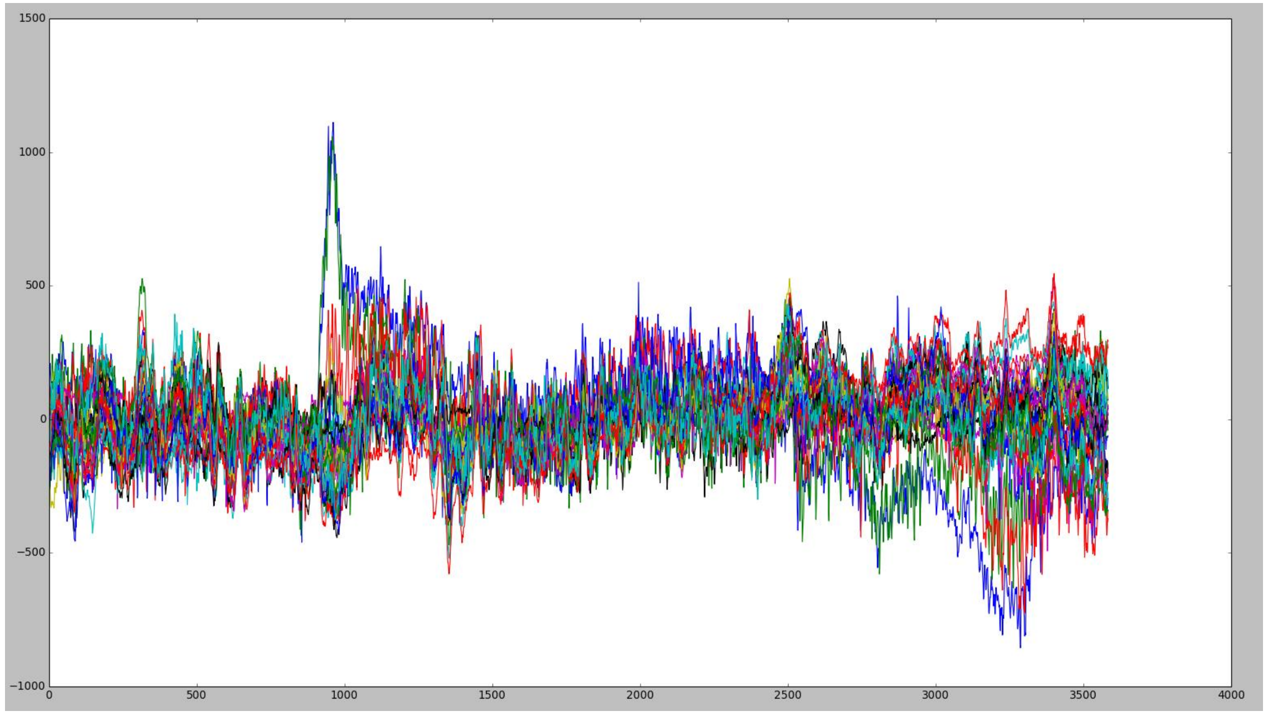
Luciw et. al., 2014

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

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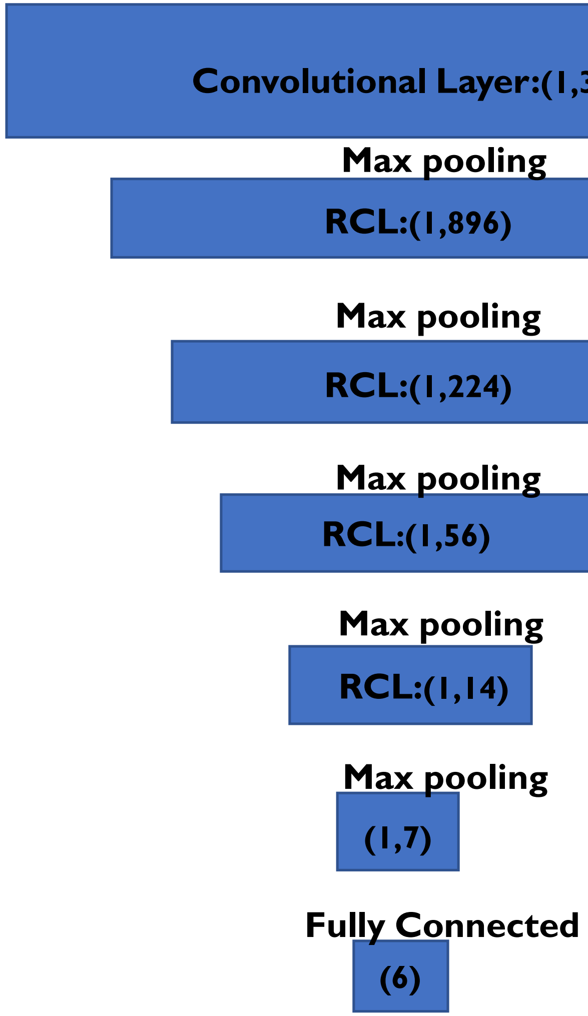
# RCNN on EEG Analysis

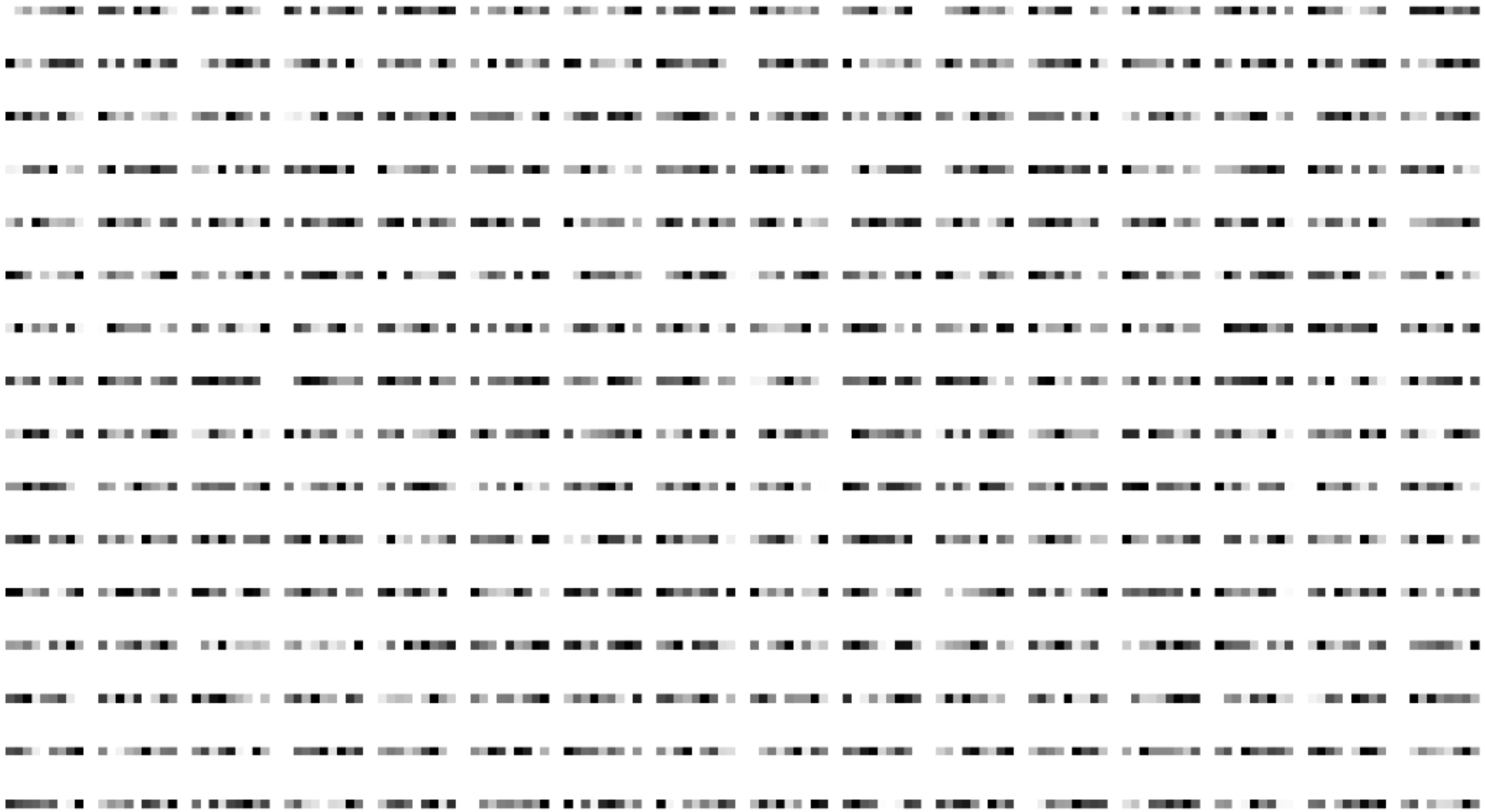
# Applying RCL




| 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) |

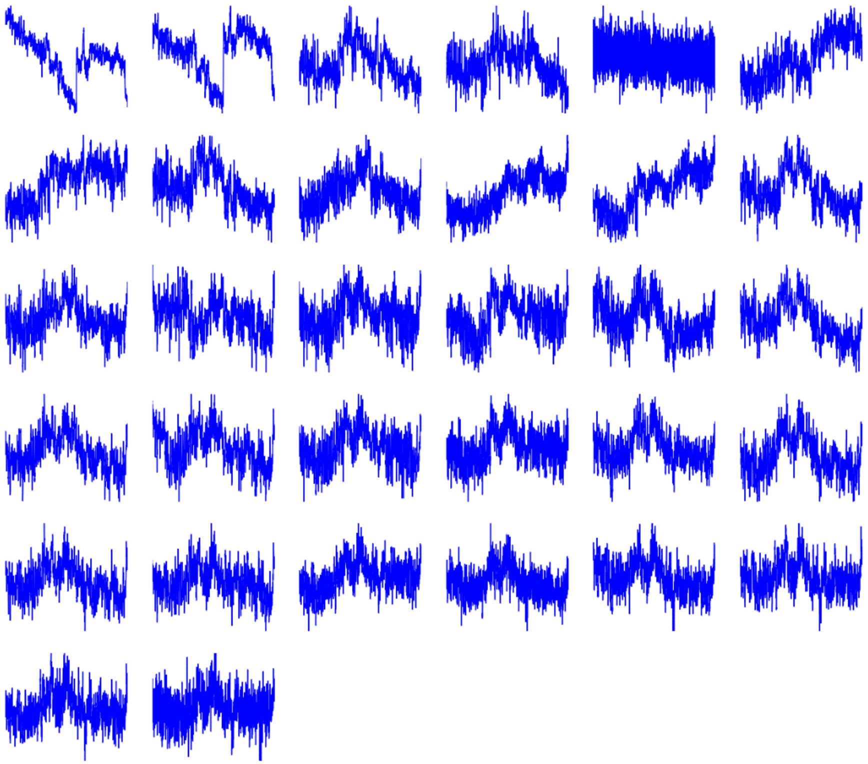
**97.687%**

# 256 1x9 filters



RCNN on EEG Analysis

# Example: Hand Start



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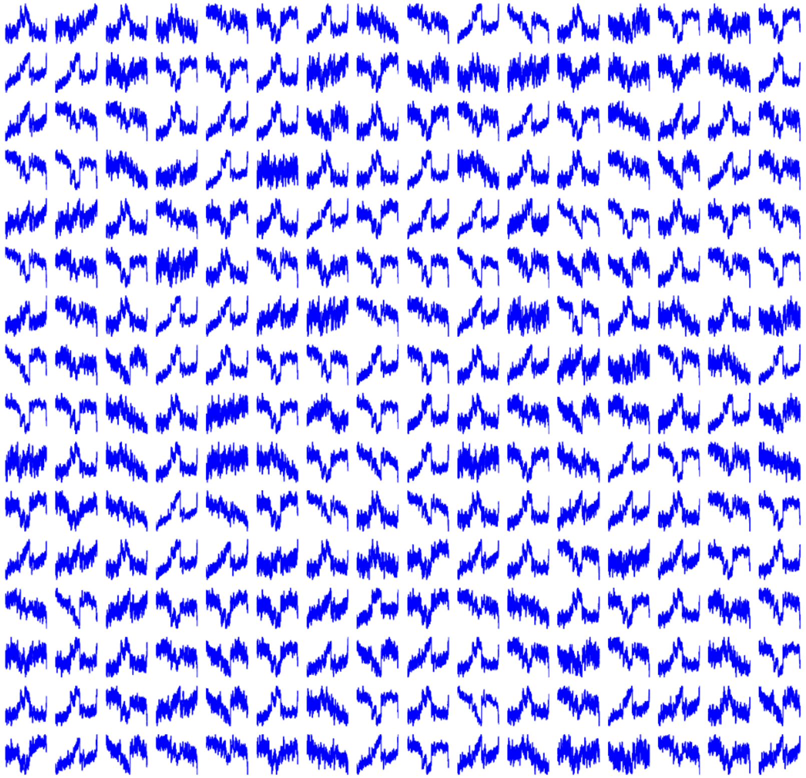
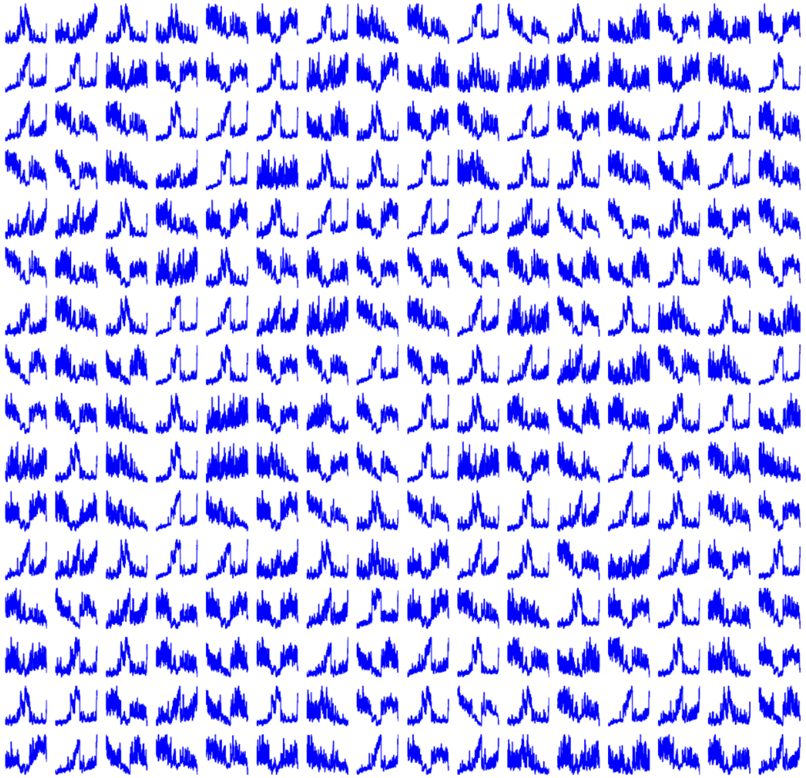
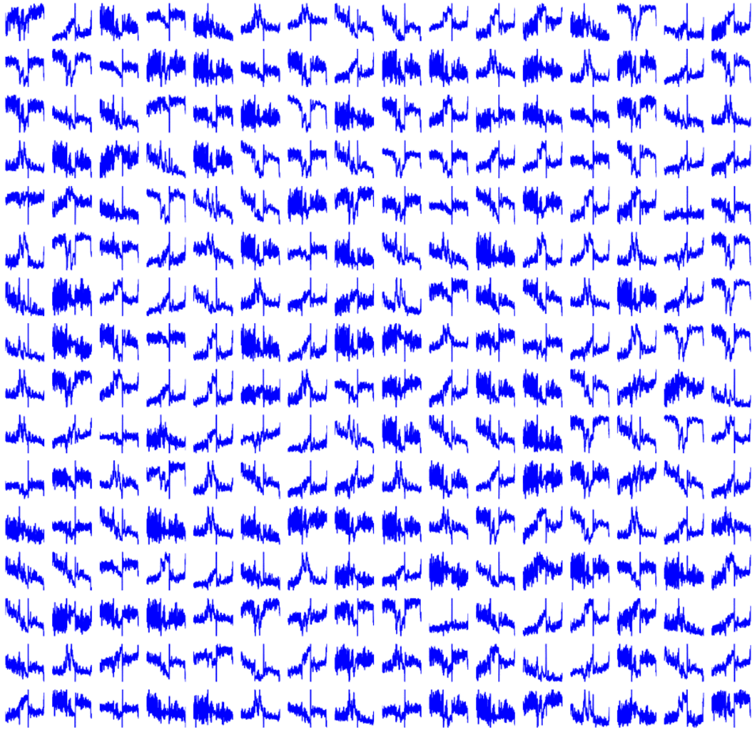
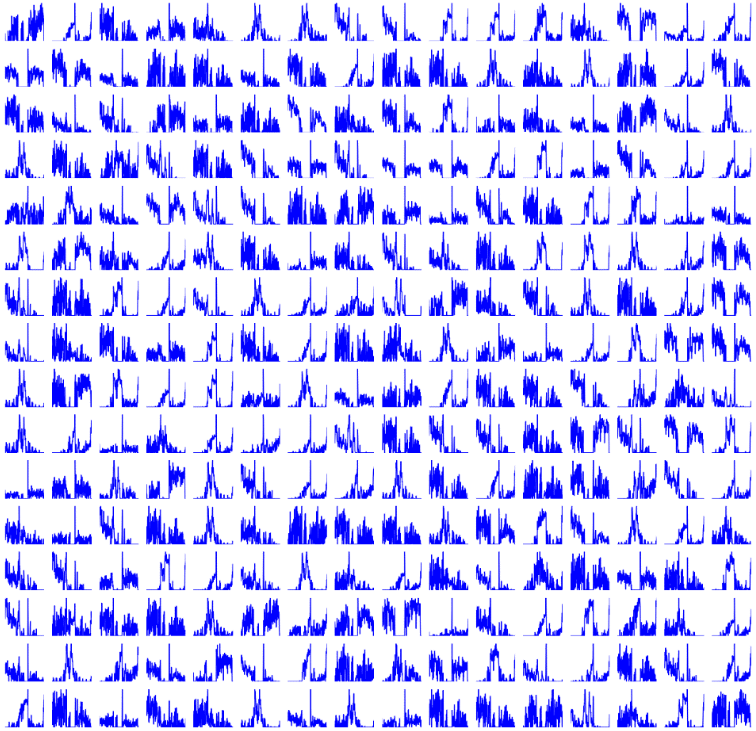




RCNN on EEG Analysis

# Example: Hand Start





RCNN on EEG Analysis

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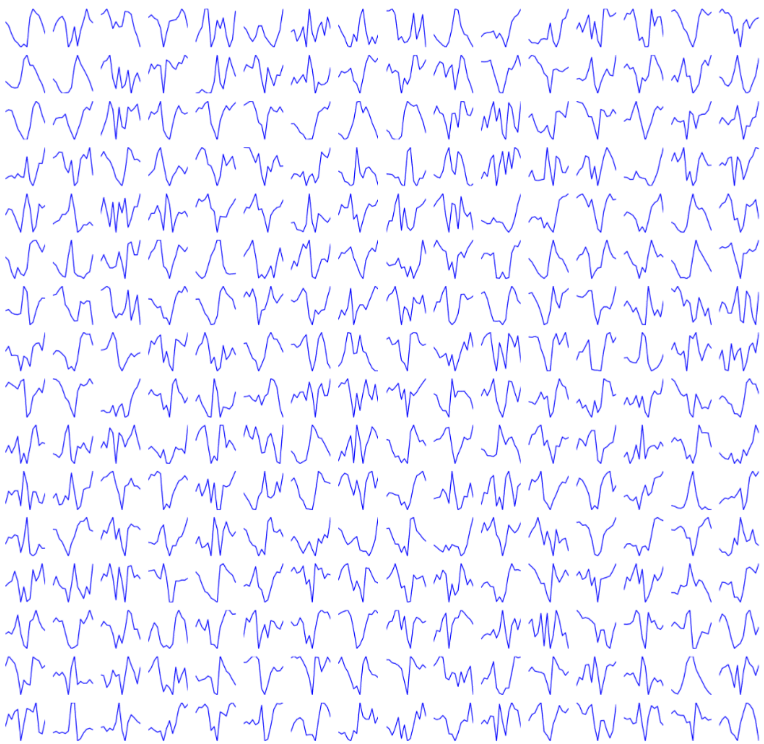
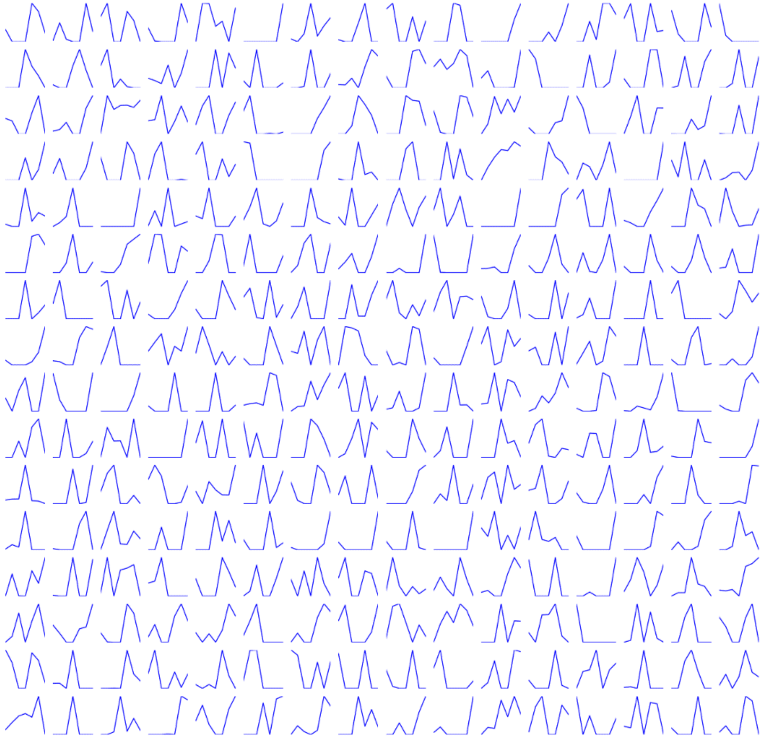
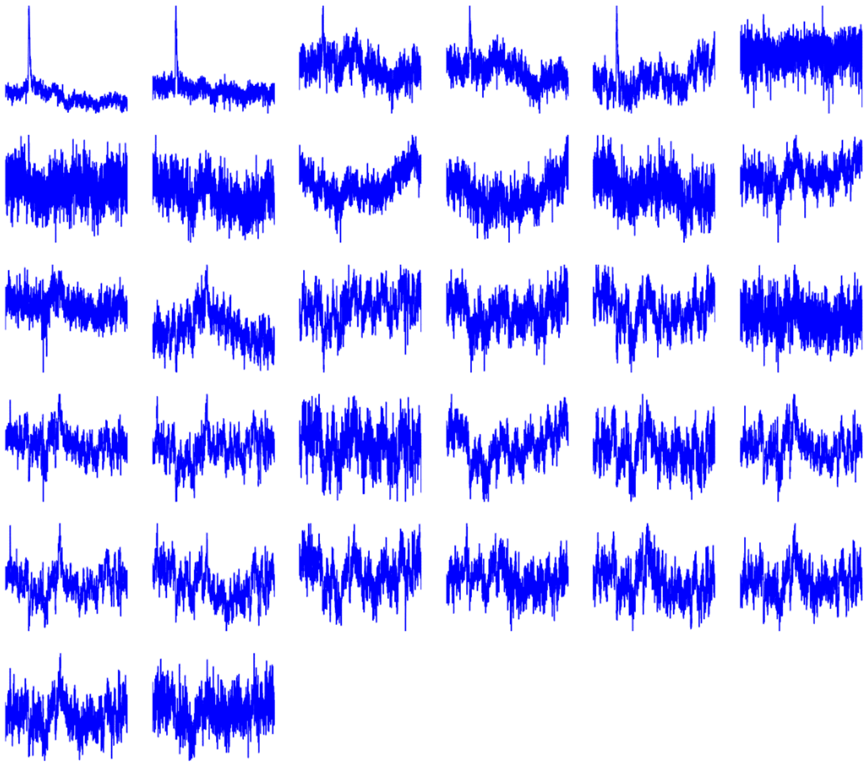


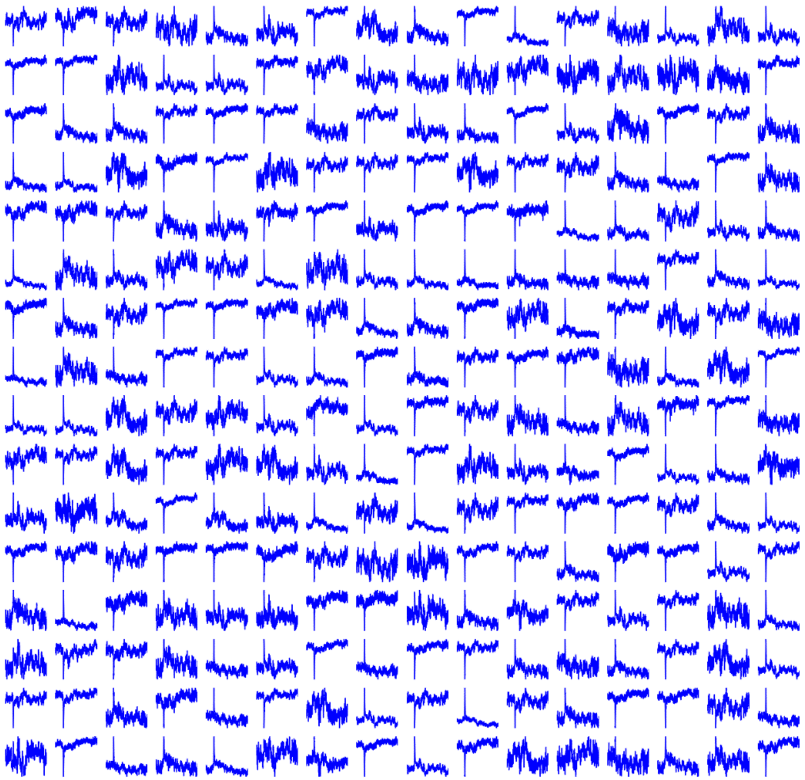


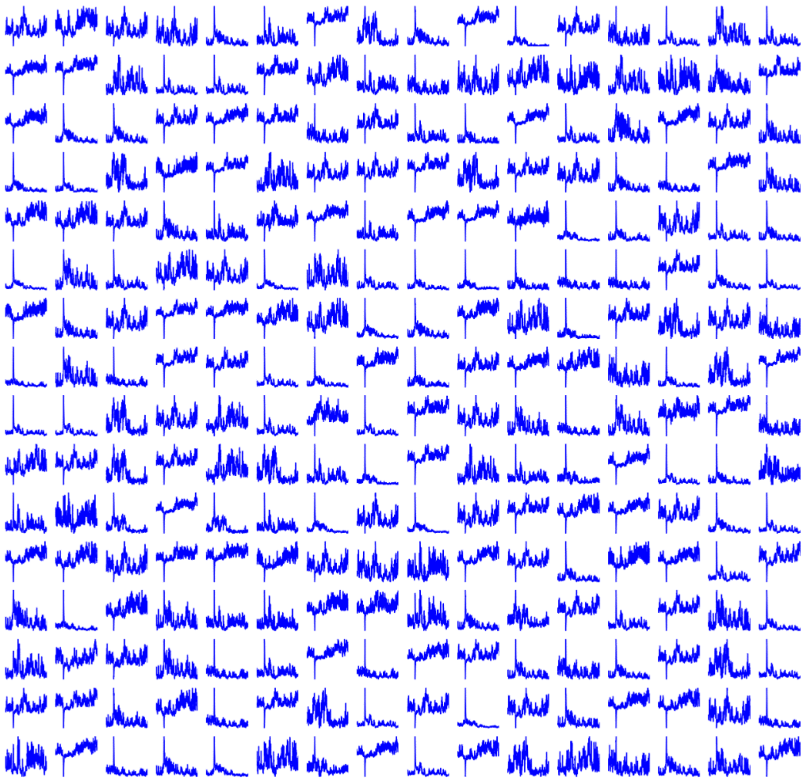
RCNN on EEG Analysis

# Example: First Digit Touch



# Example: First Digit Touch





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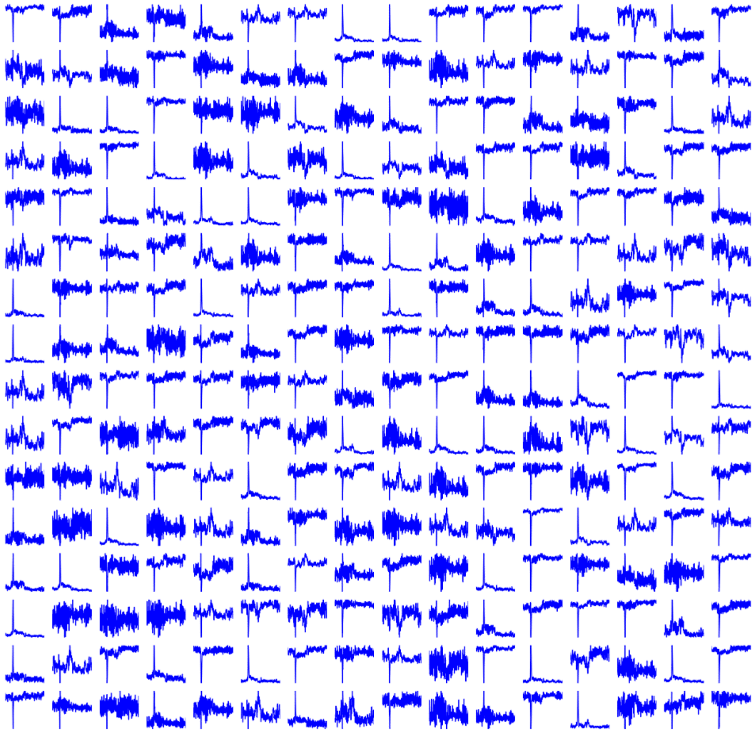

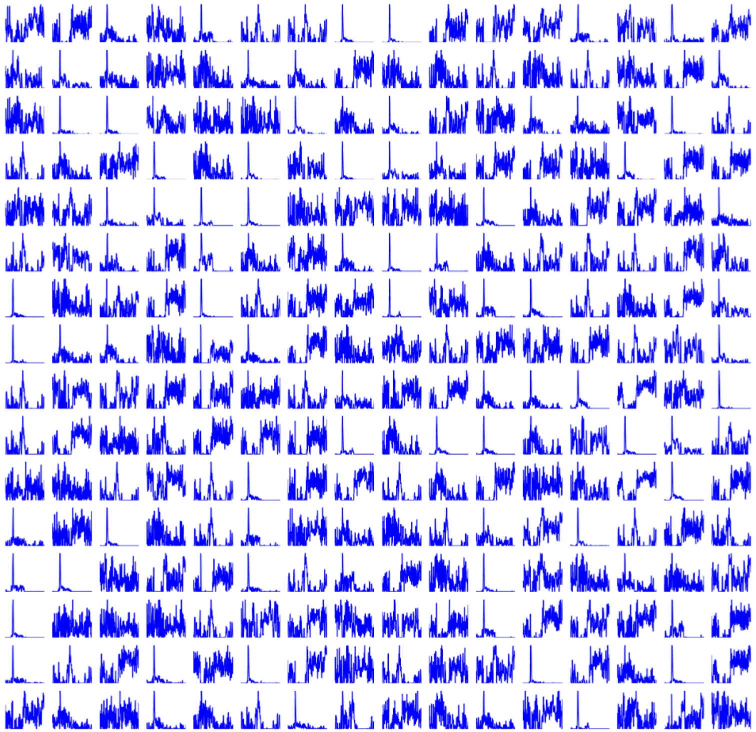

RCNN on EEG Analysis

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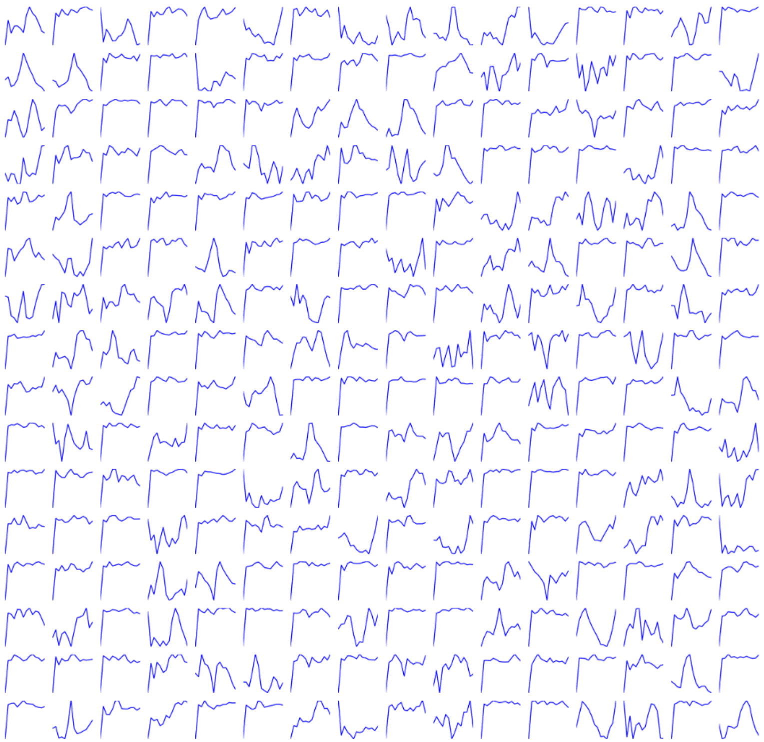
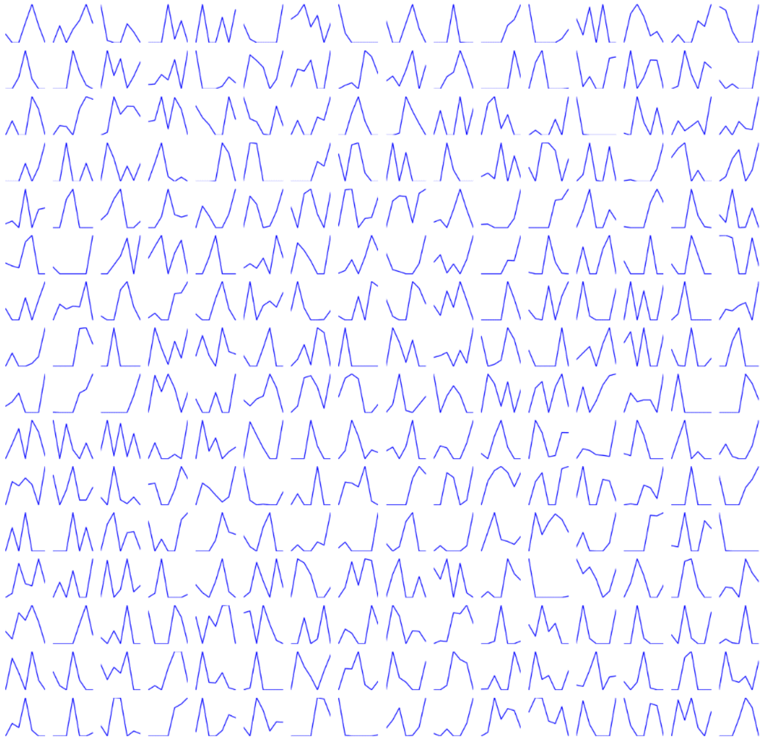
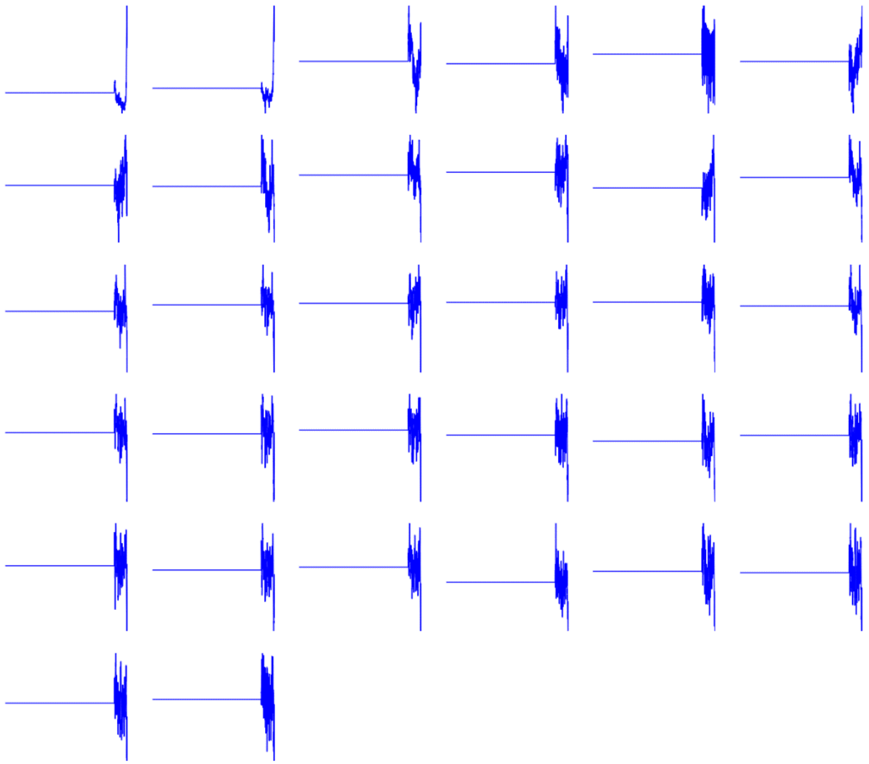


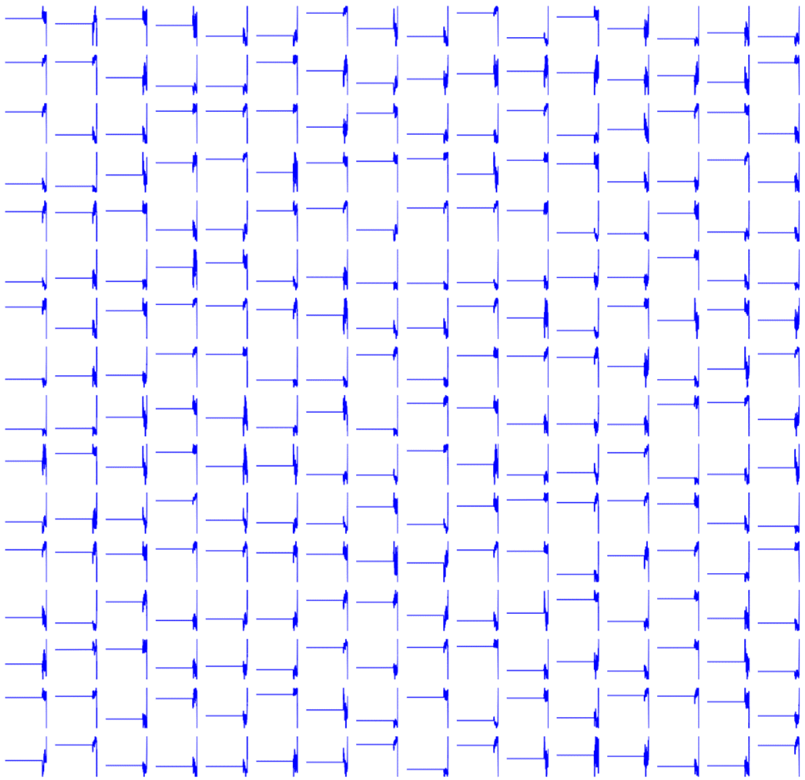


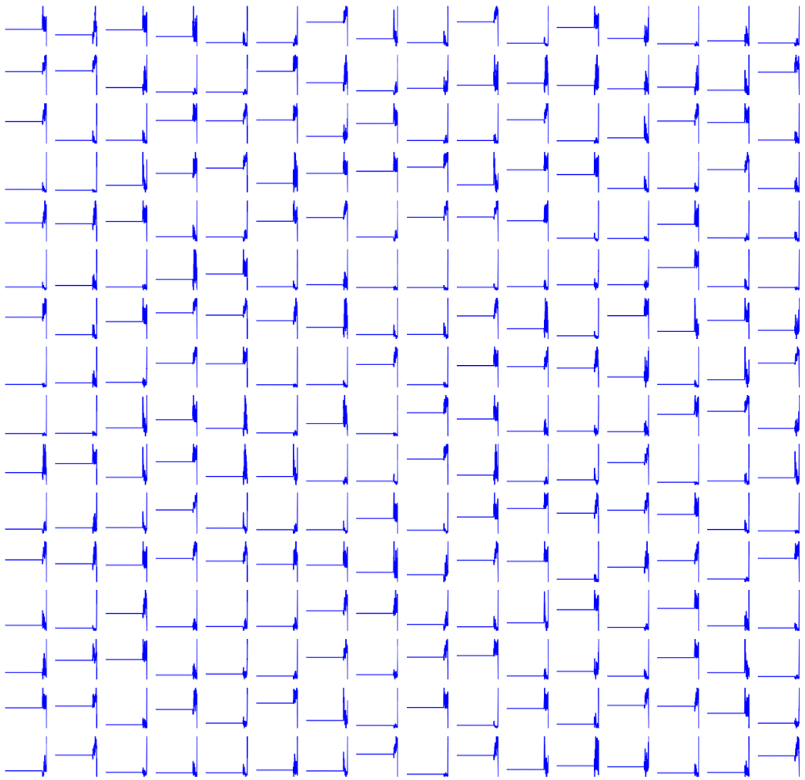
# Example: Replace



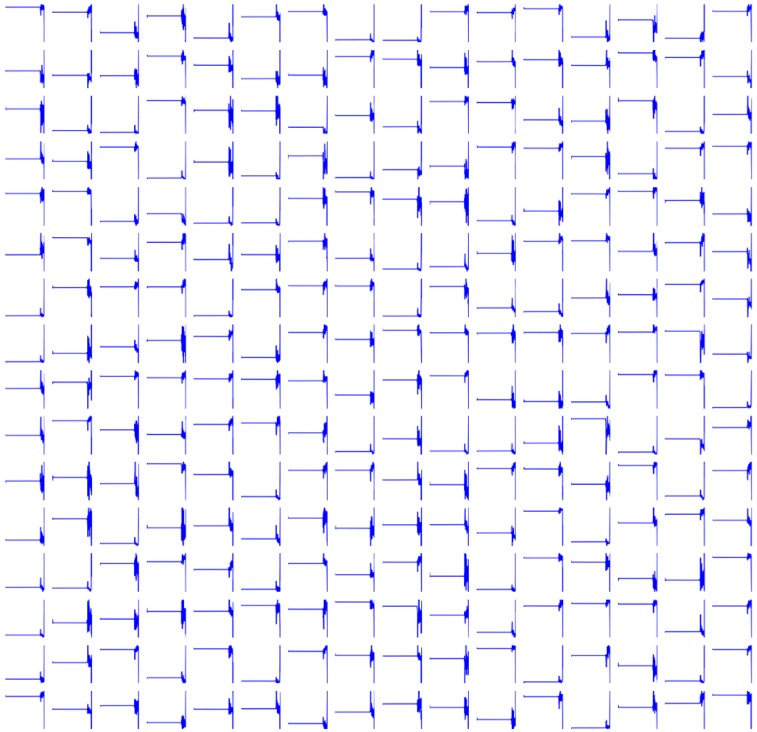
RCNN on EEG Analysis

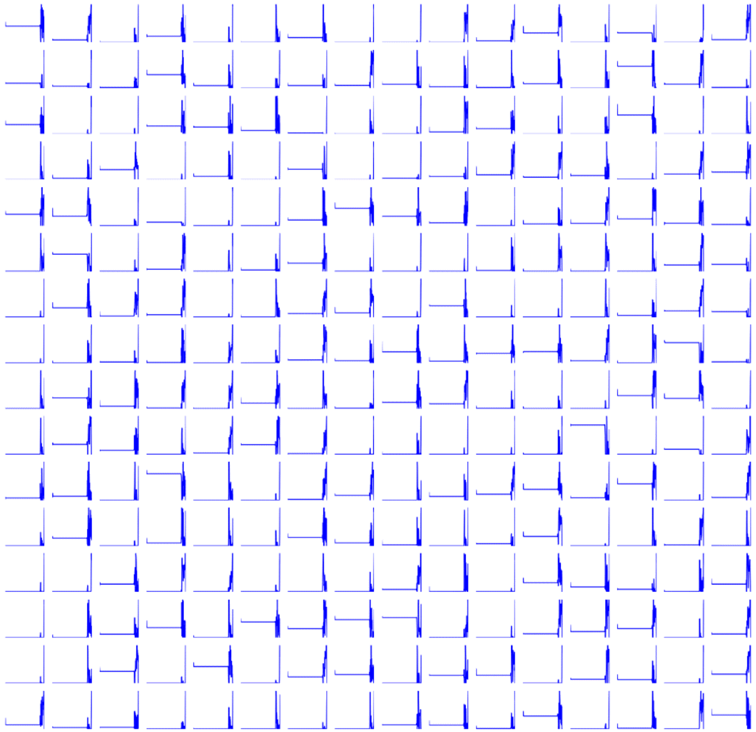
# Example: Replace



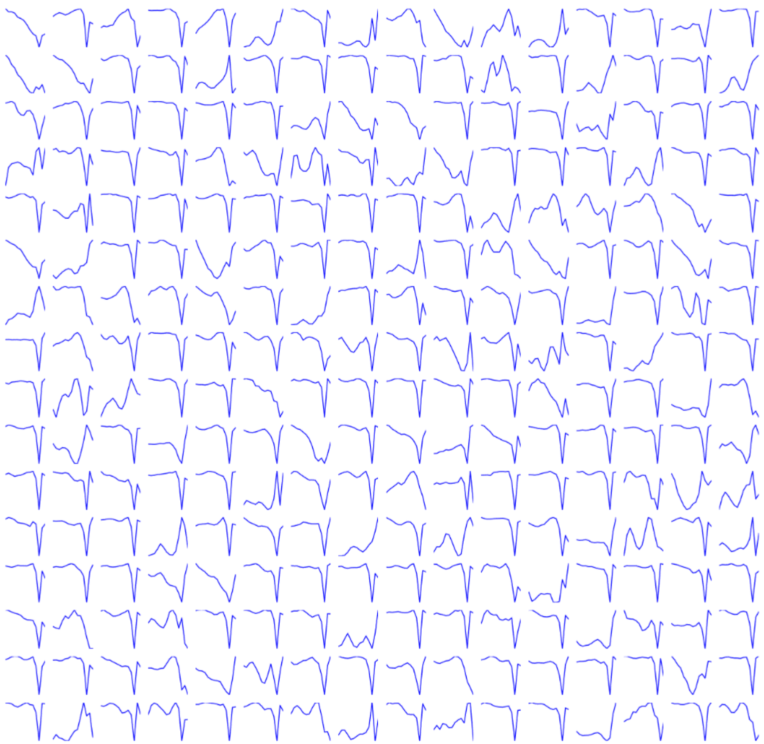


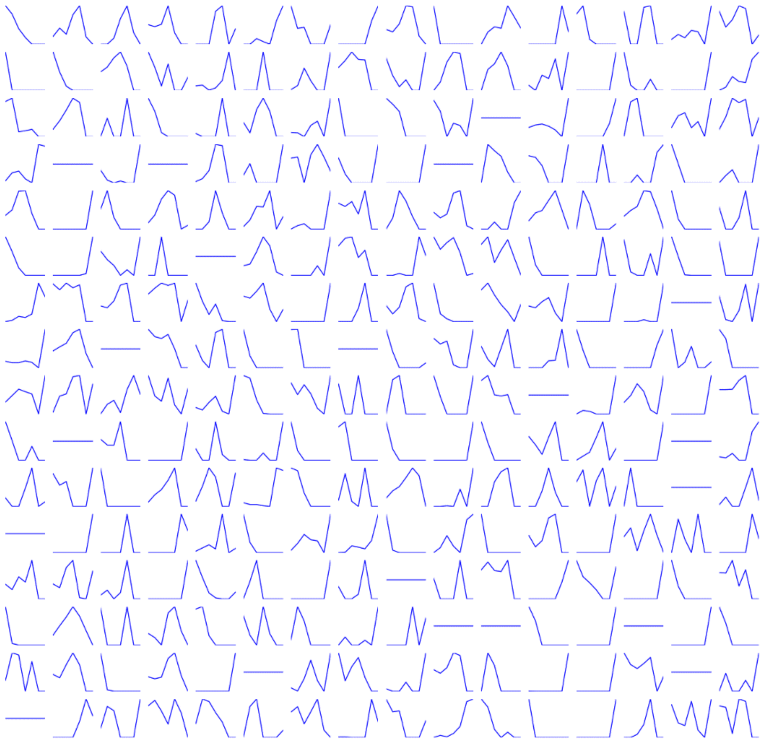
# Example: Replace





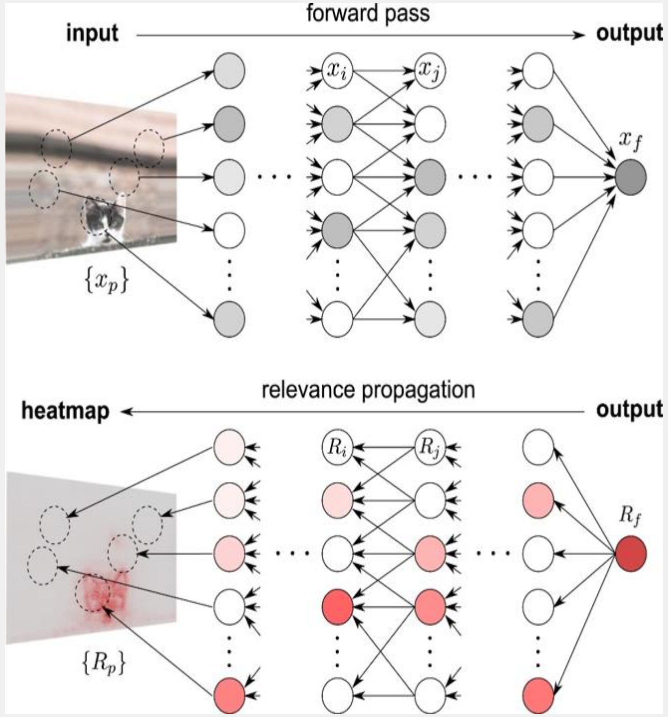
# Example: Replace





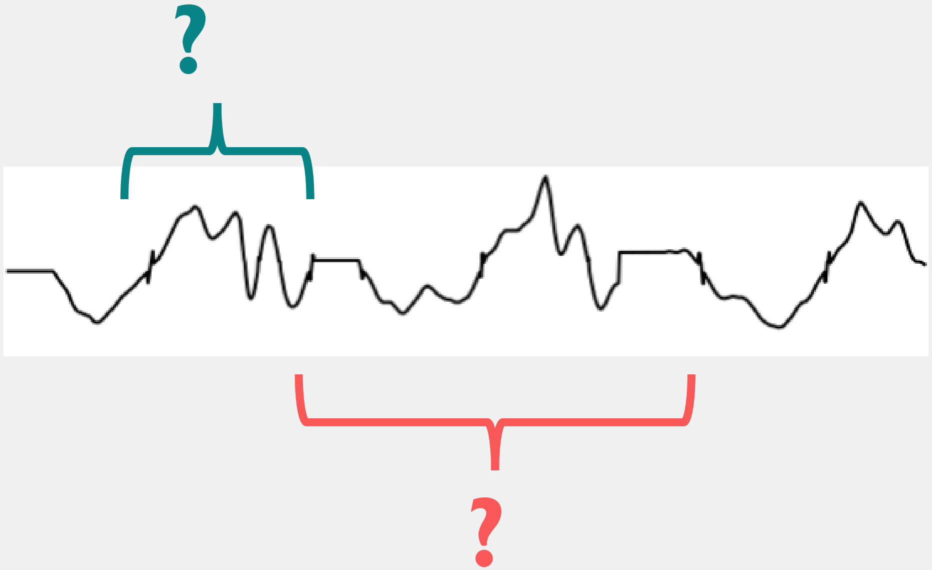
- **How can we separate time series data into semi-global representative parts without hand-crafted segmentation labels for interpreting?**

**Image dataset**

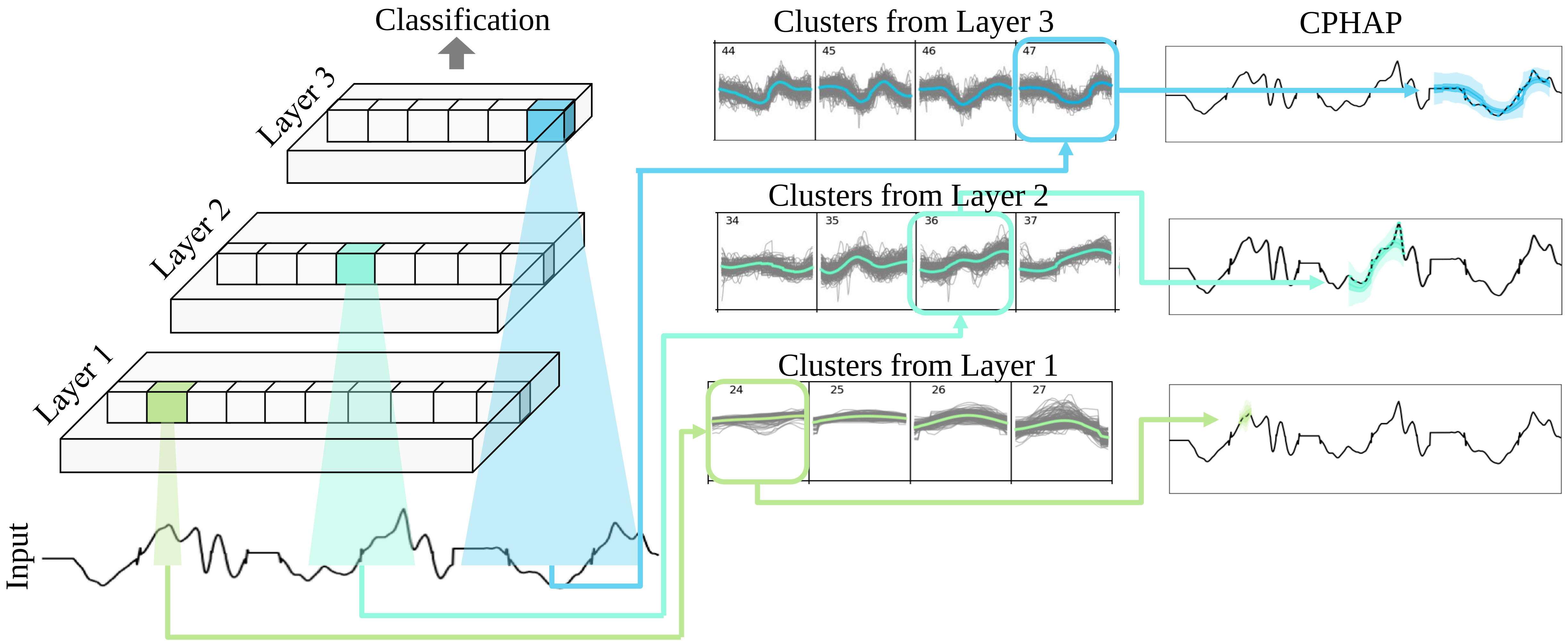

- Network Dissection
- LRP

**Time Series dataset**



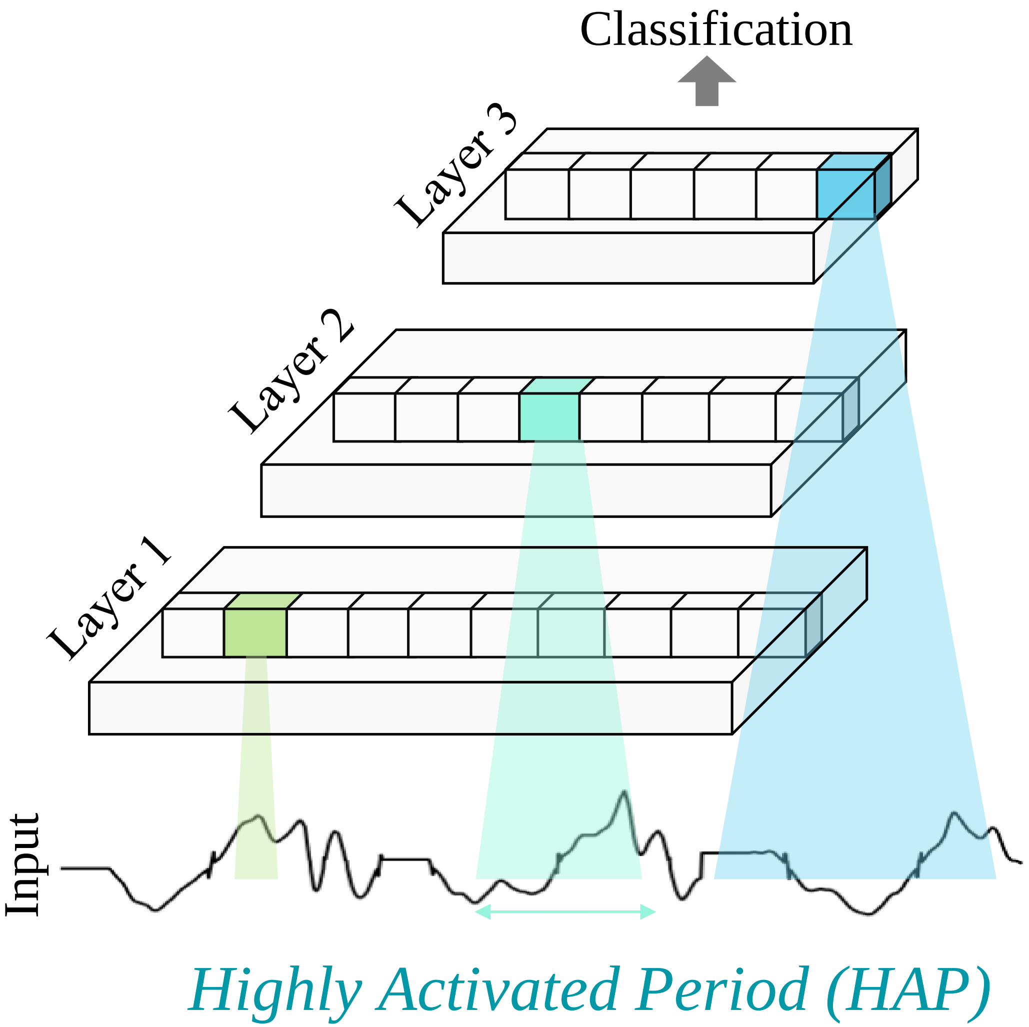

## Clustered Pattern of Highly Activated Period: Motivation

S. Cho et al., 2020



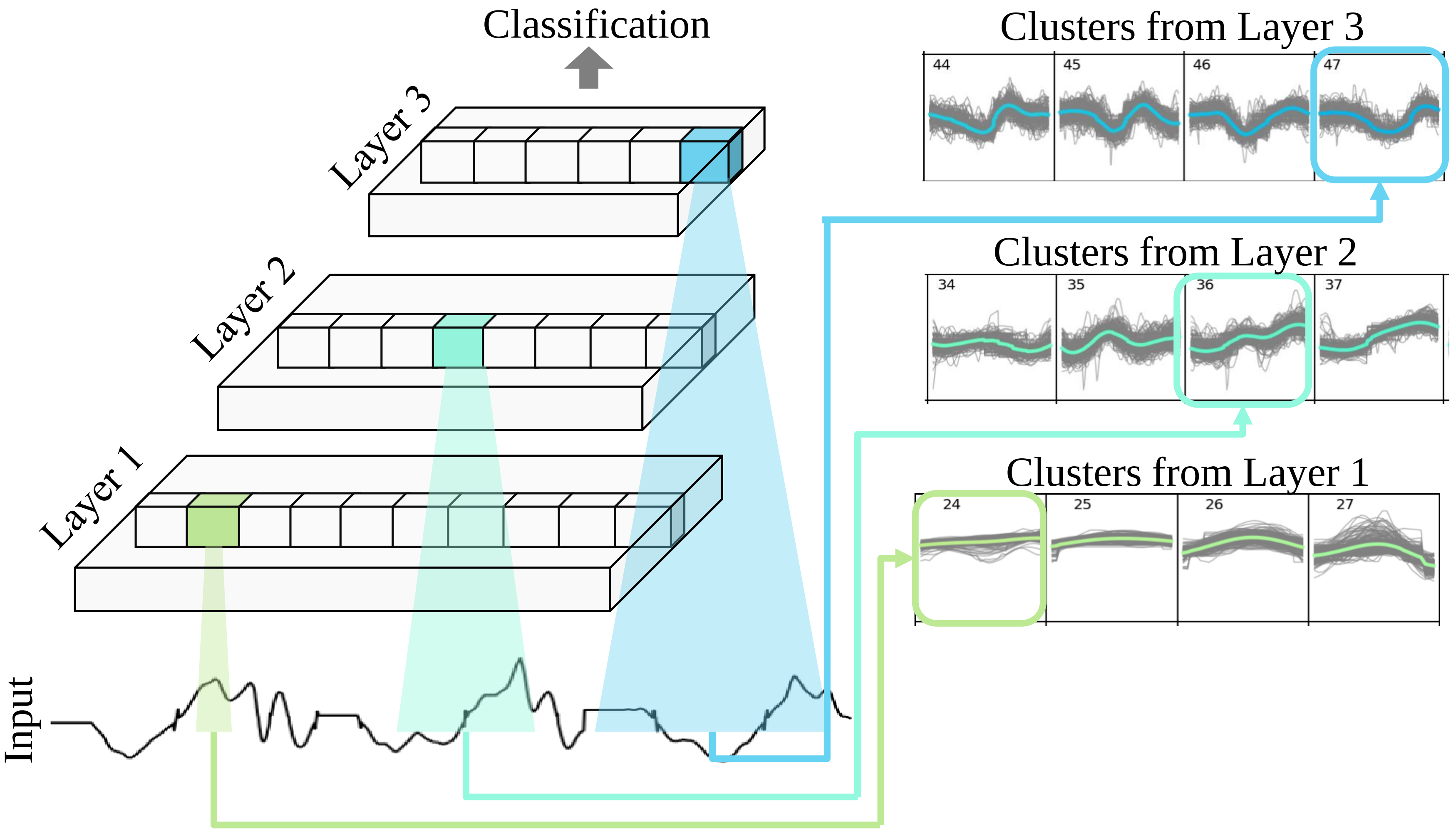

# Clustered Pattern of Highly Activated Period

S. Cho et al., 2020



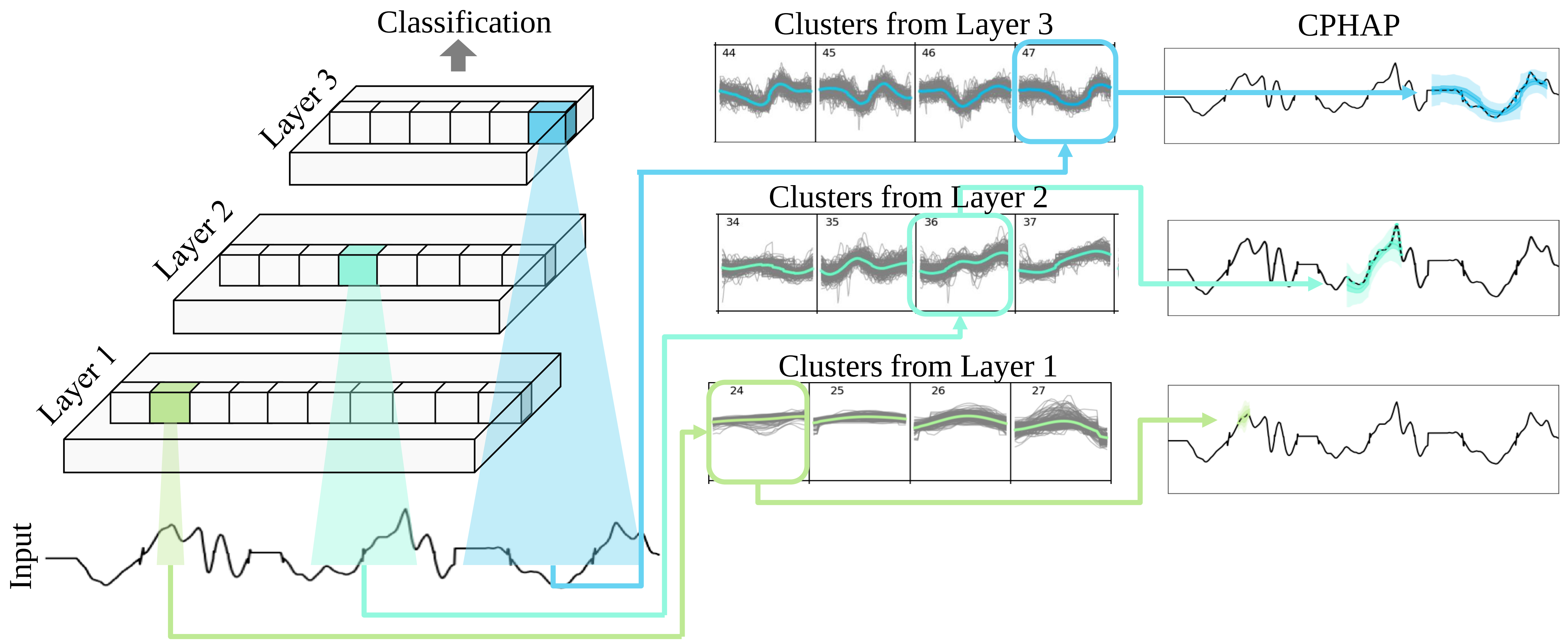

# Clustered Pattern of Highly Activated Period

S. Cho et al., 2020



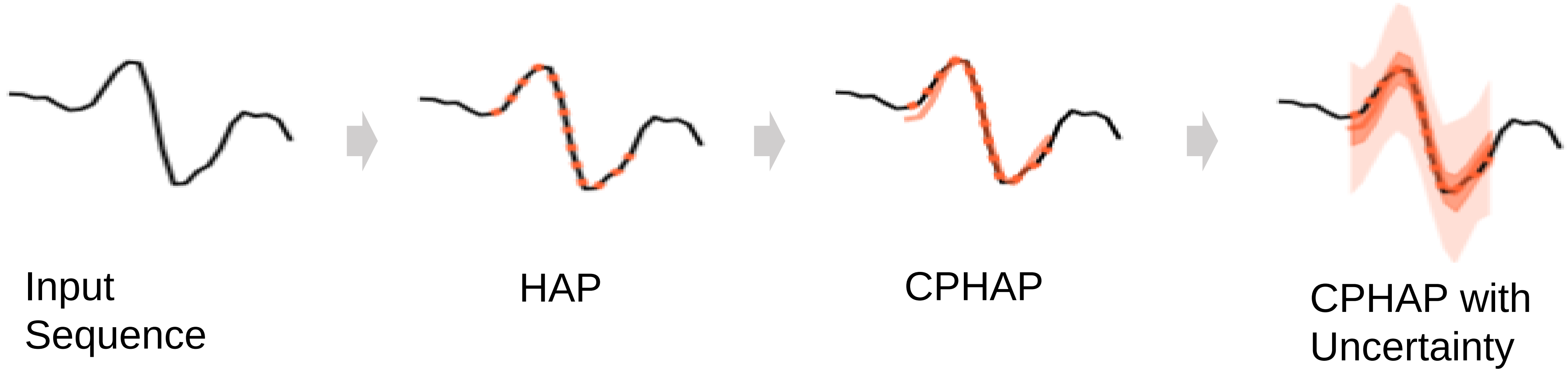

# Clustered Pattern of Highly Activated Period

S. Cho et al., 2020




# Clustered Pattern of Highly Activated Period

S. Cho et al., 2020

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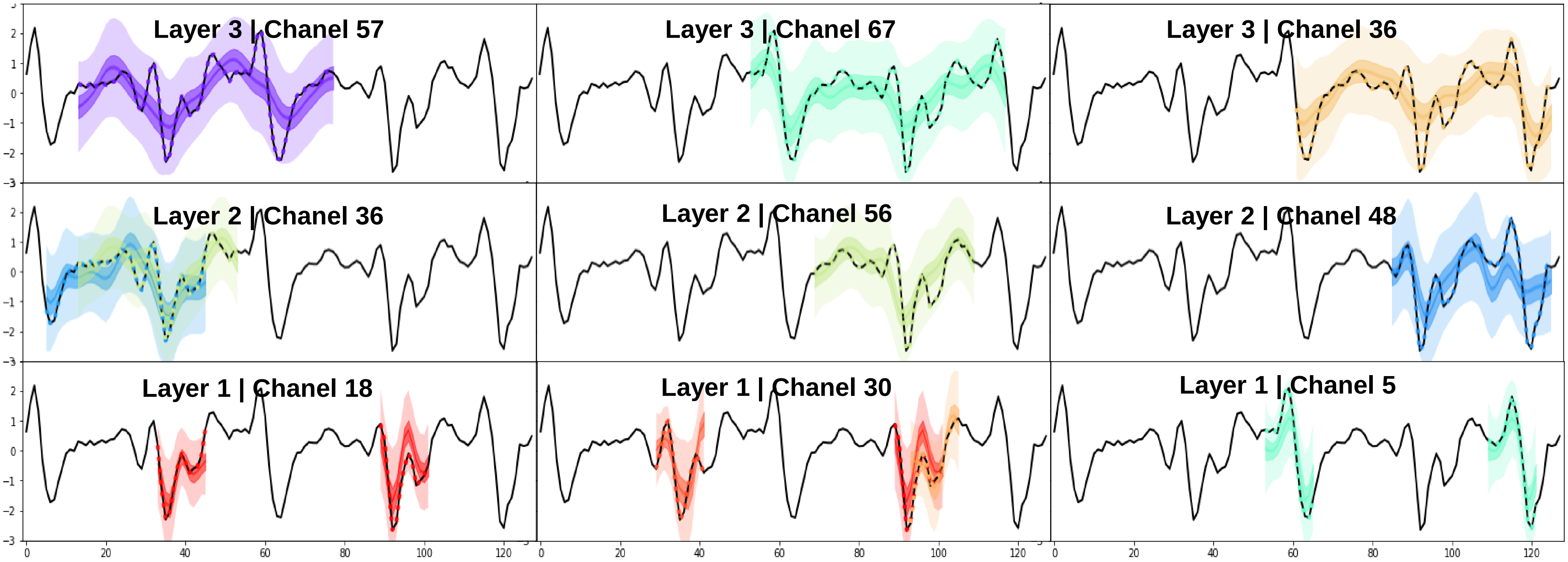
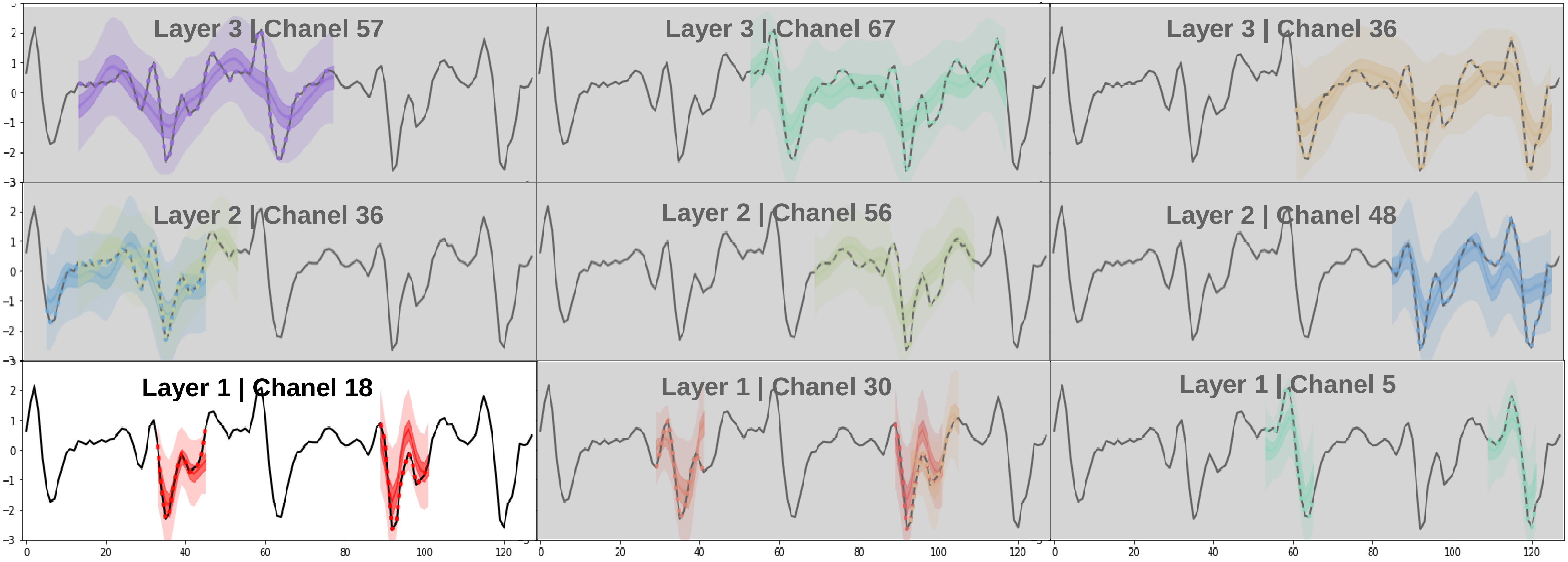
S. Cho et al., 2020



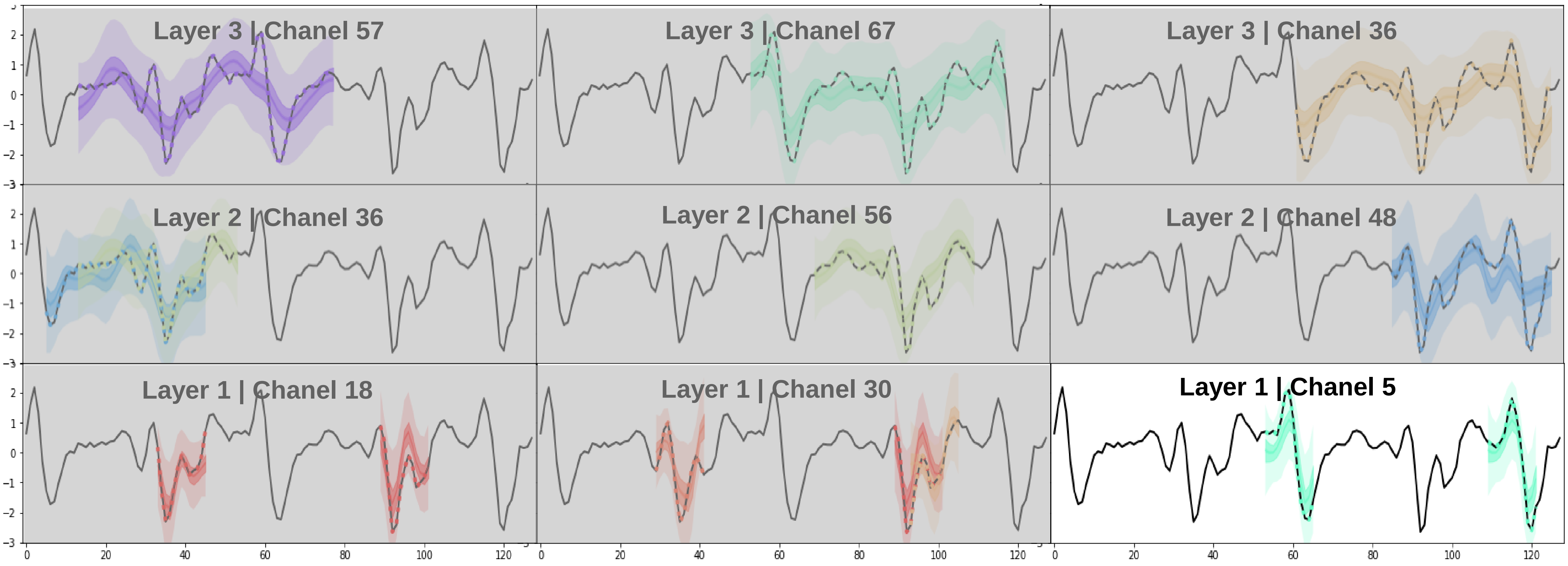

# Clustered Pattern of Highly Activated Period: Results

S. Cho et al., 2020



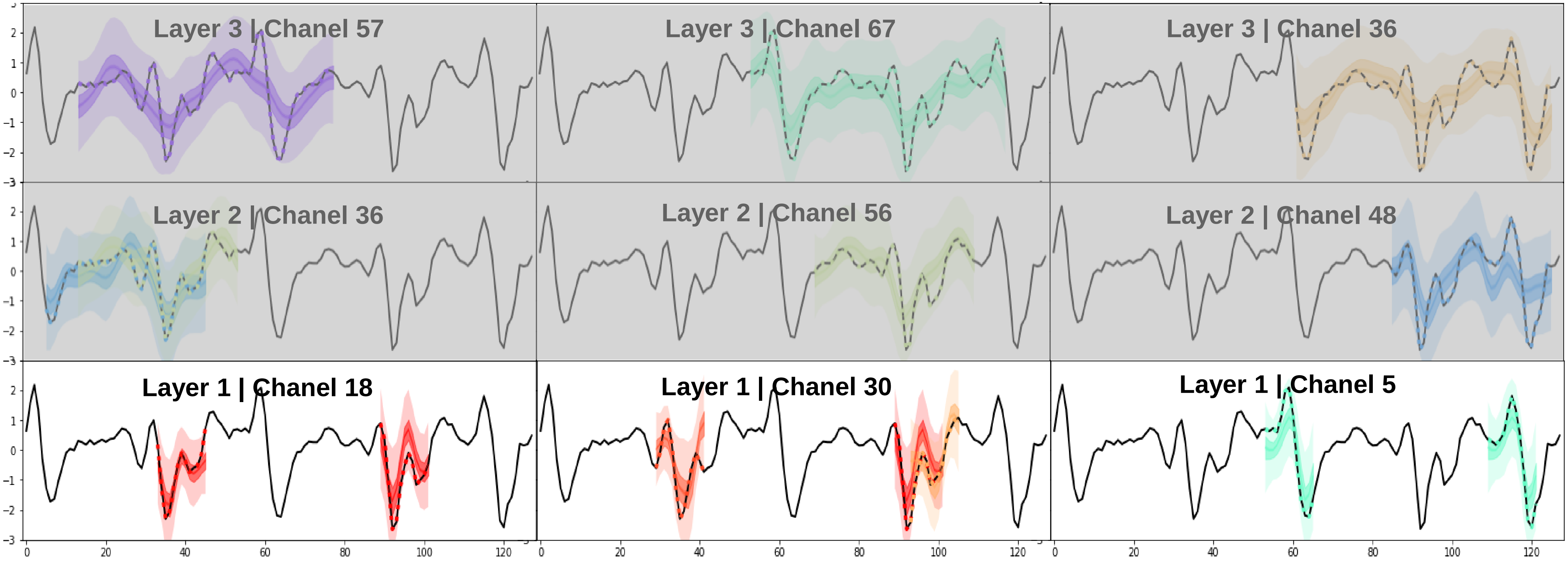

# Clustered Pattern of Highly Activated Period: Results

S. Cho et al., 2020



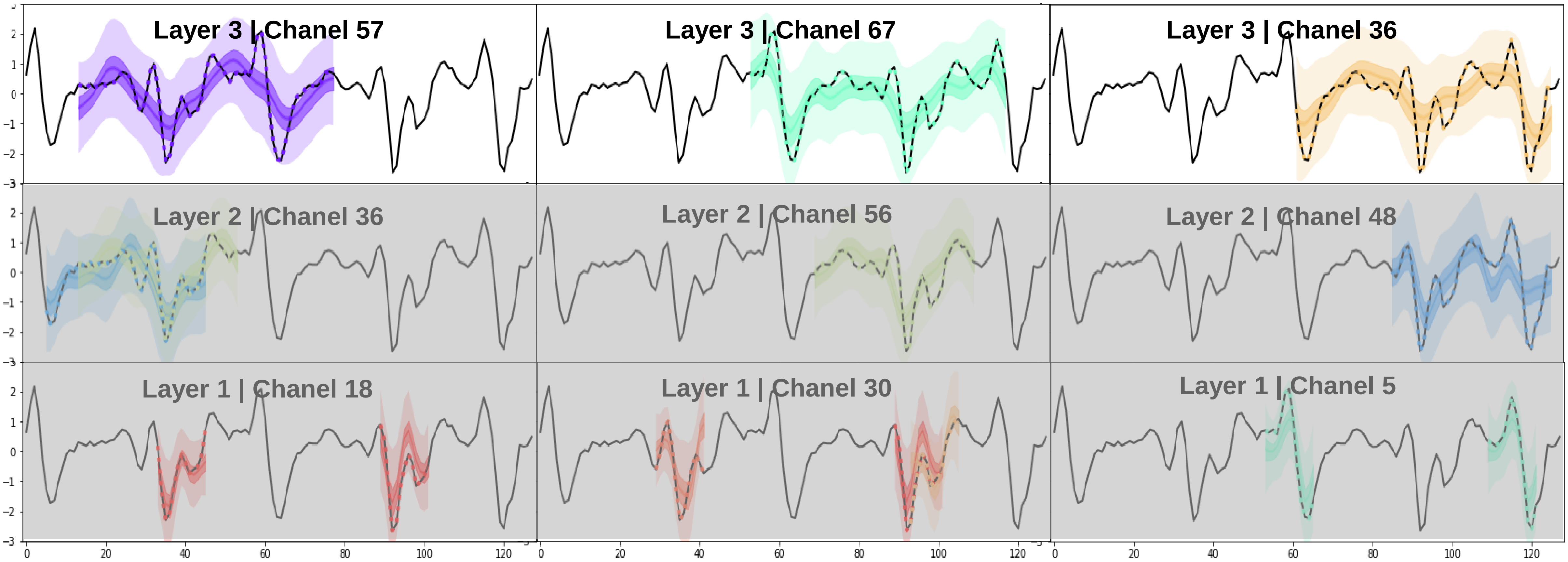

# Clustered Pattern of Highly Activated Period: Results

S. Cho et al., 2020



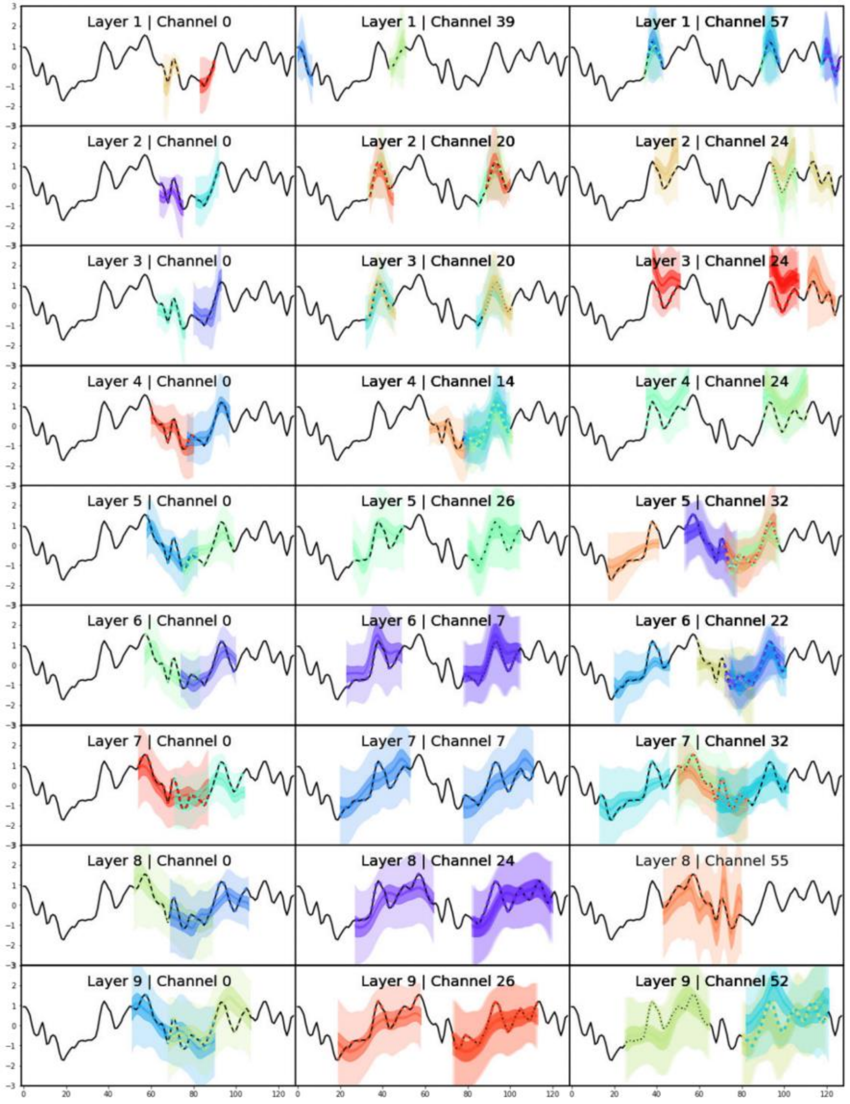

# Clustered Pattern of Highly Activated Period: Results

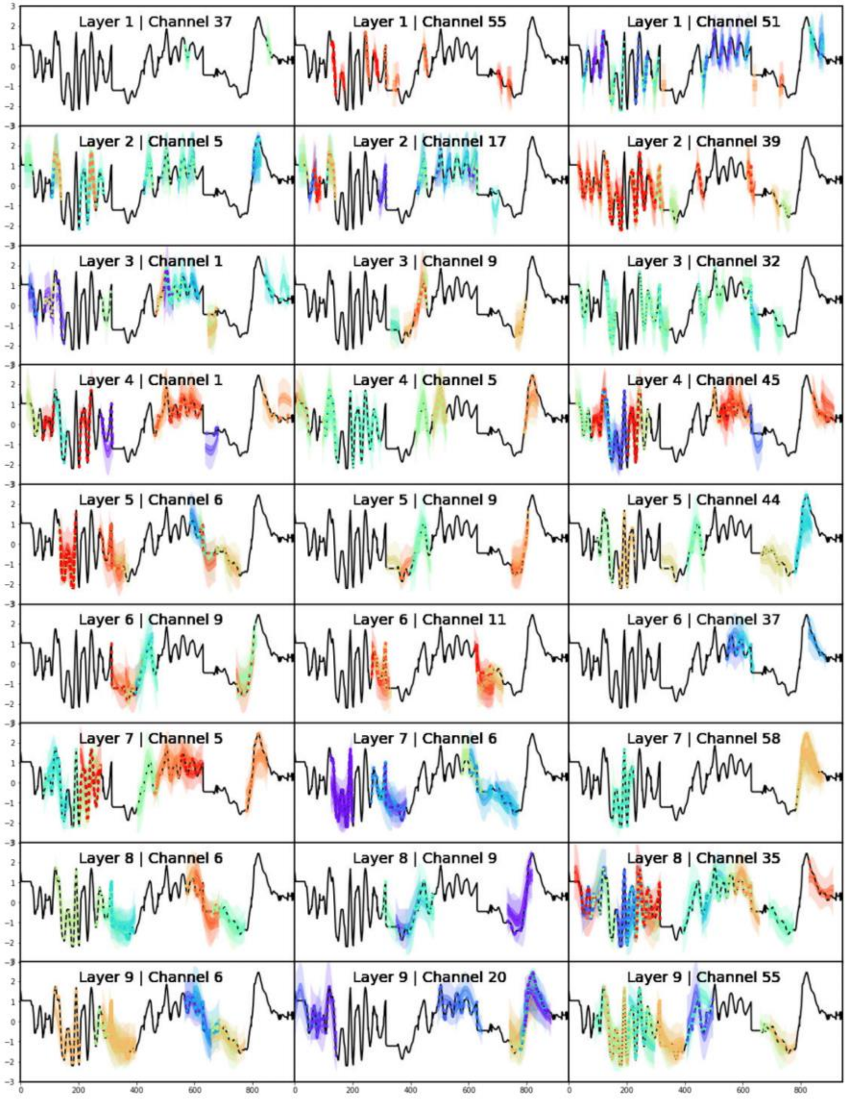
S. Cho et al., 2020




# Clustered Pattern of Highly Activated Period: Results

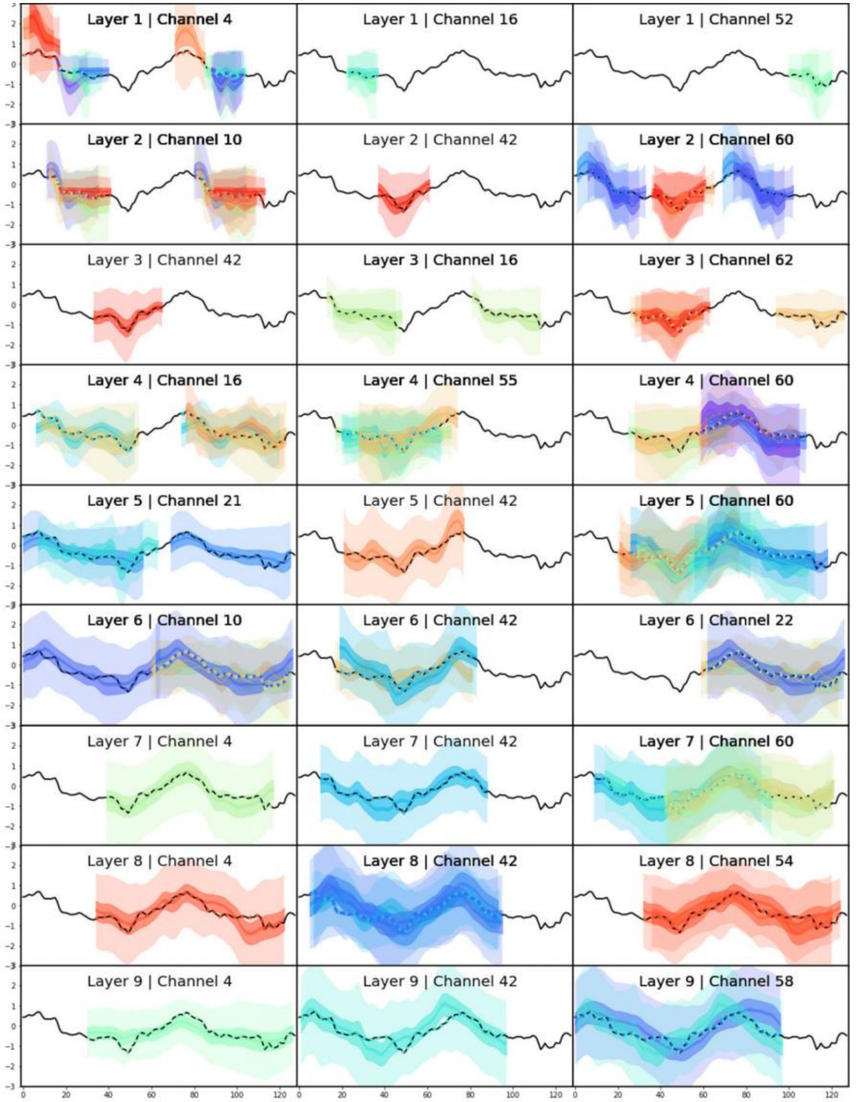
S. Cho et al., 2020

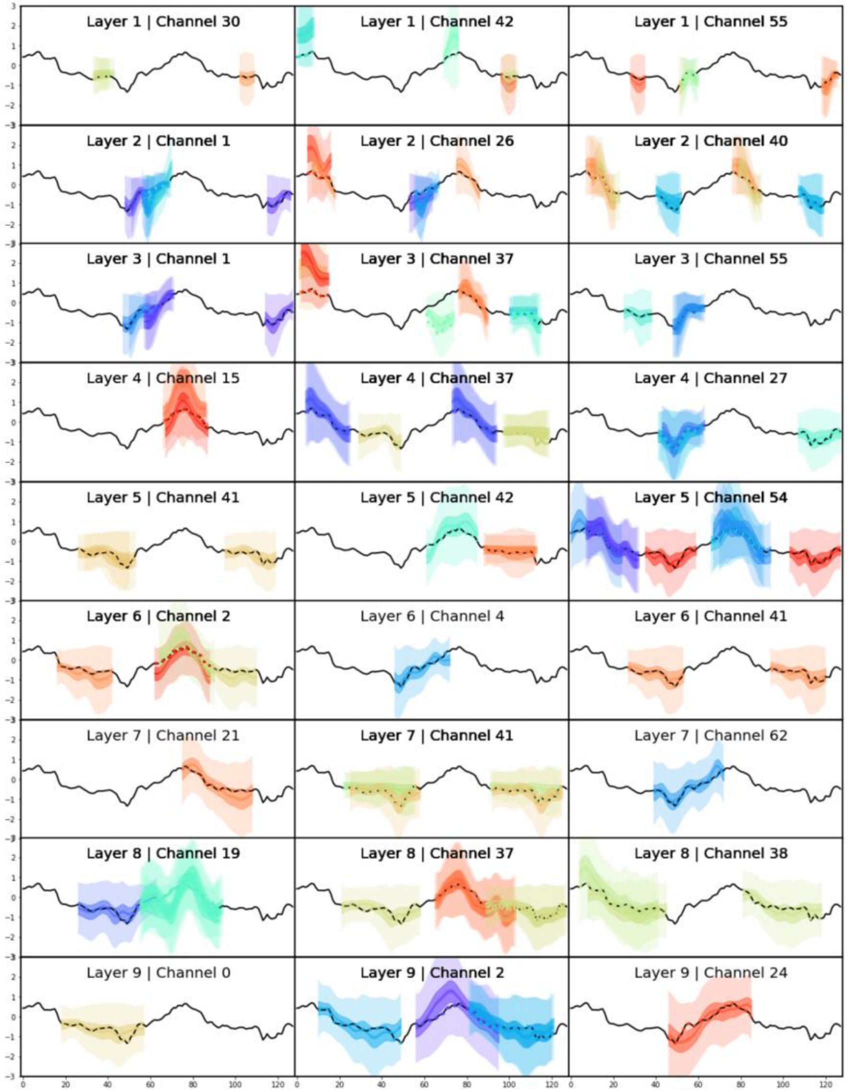



# Experiment 1 : Different Network Structure (ResNet)

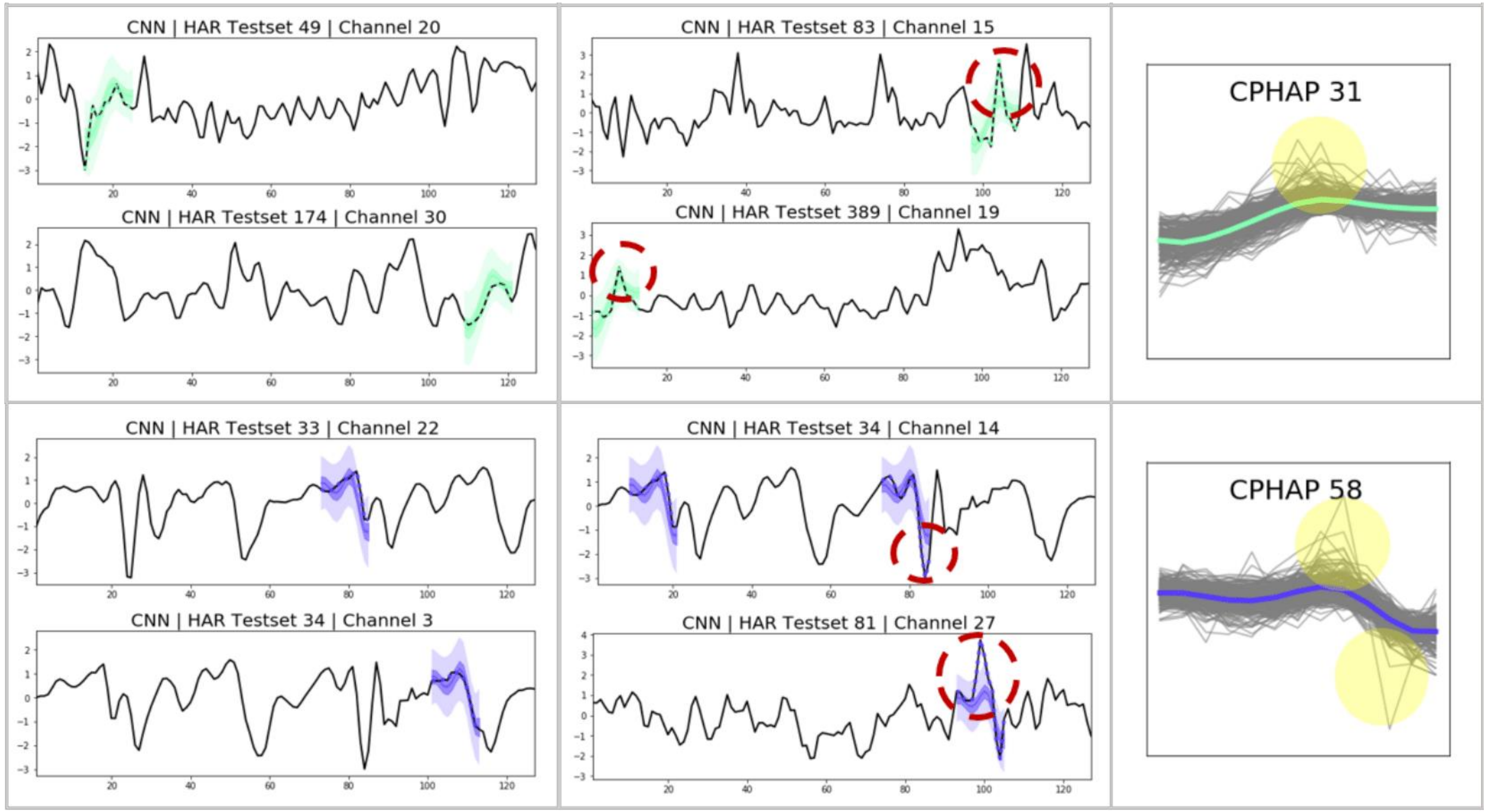
S. Cho et al., 2020




# Experiment 2 : Different Filter Size

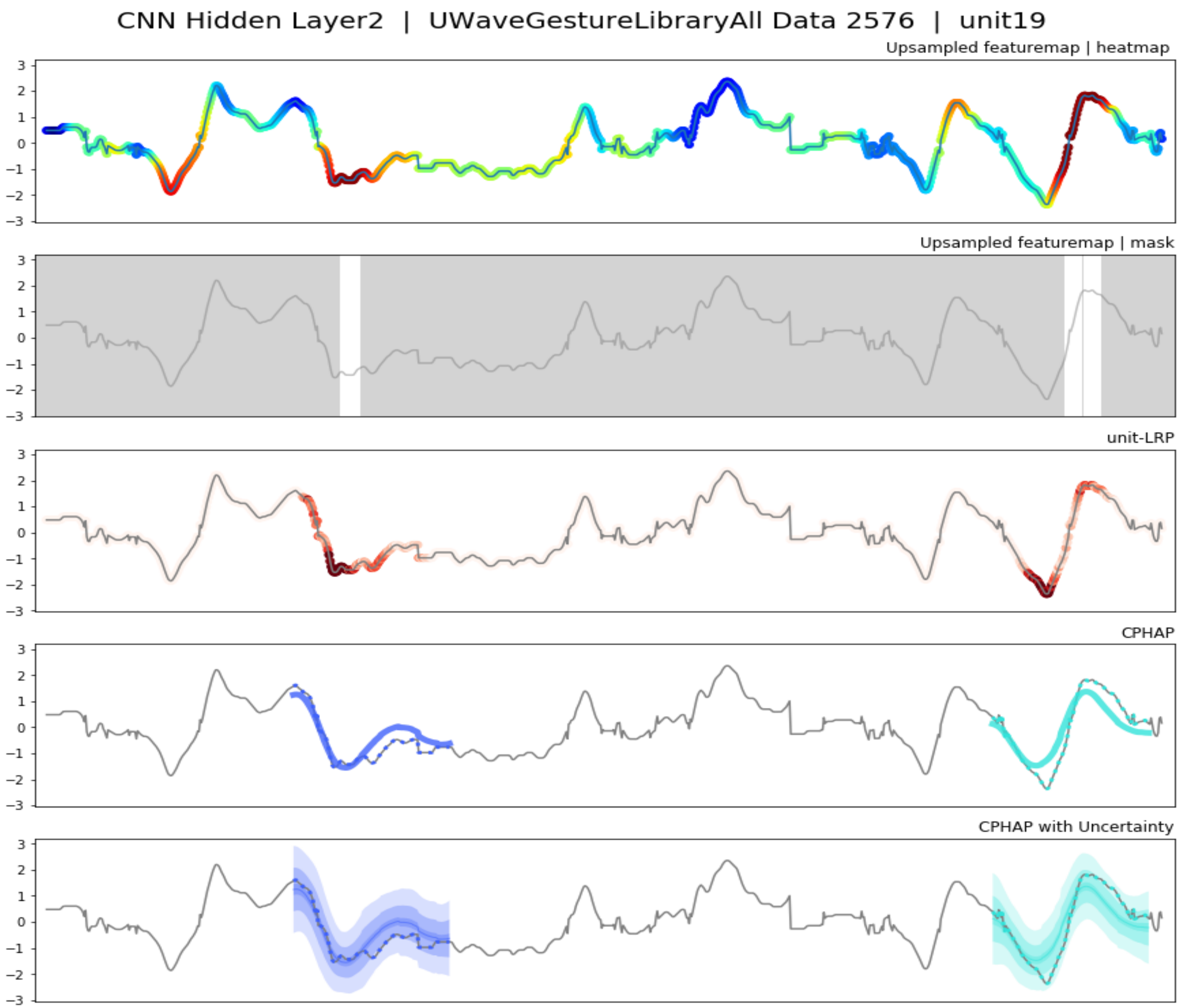
S. Cho et al., 2020




(a) Well-matched cases (b) Less-matched cases (c) CPHAP

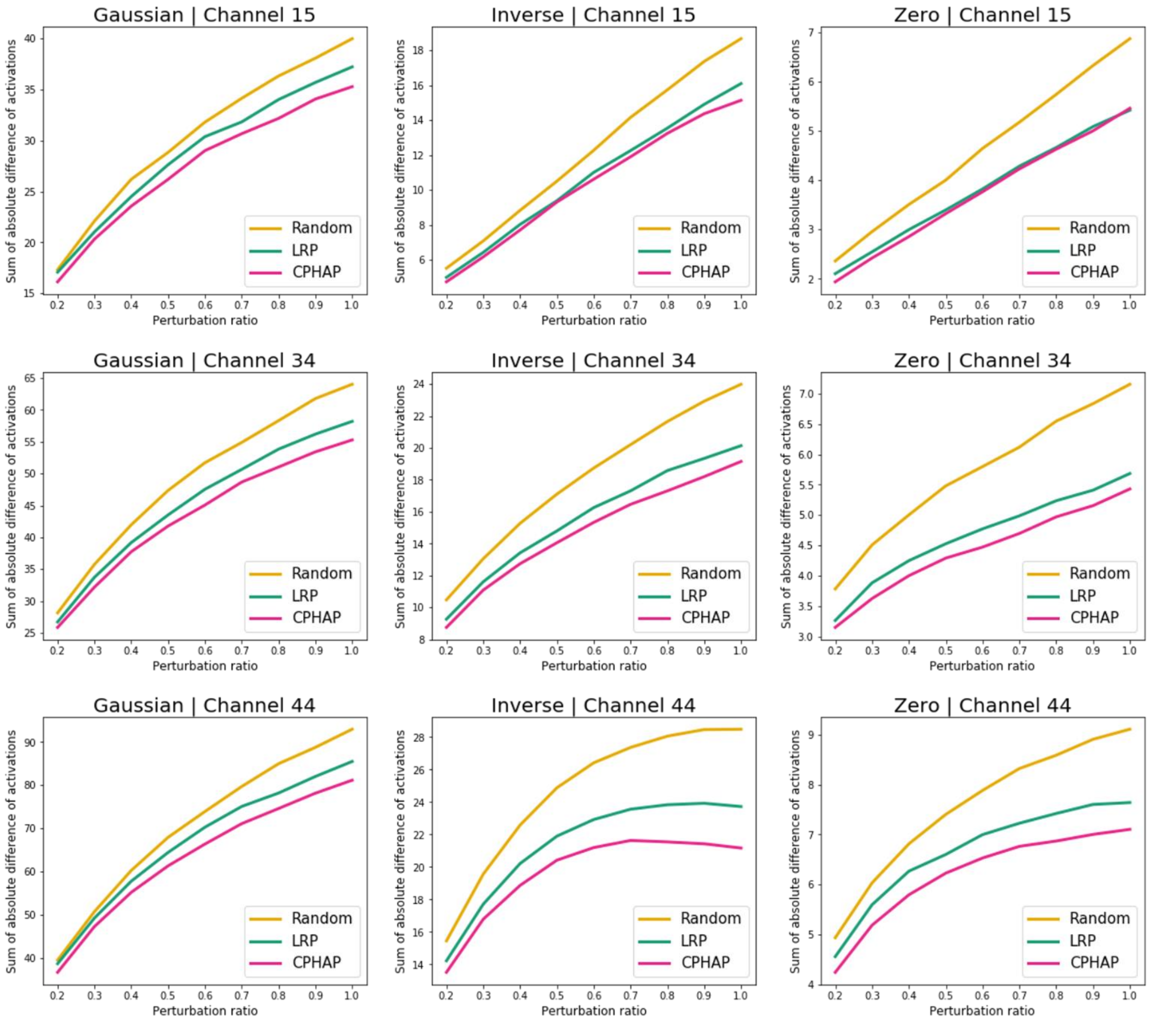
# Experiment 3 : Sequences of test data with CPHAP of train data

S. Cho et al., 2020




# Experiment 4 : Visual Comparison among XAI methods

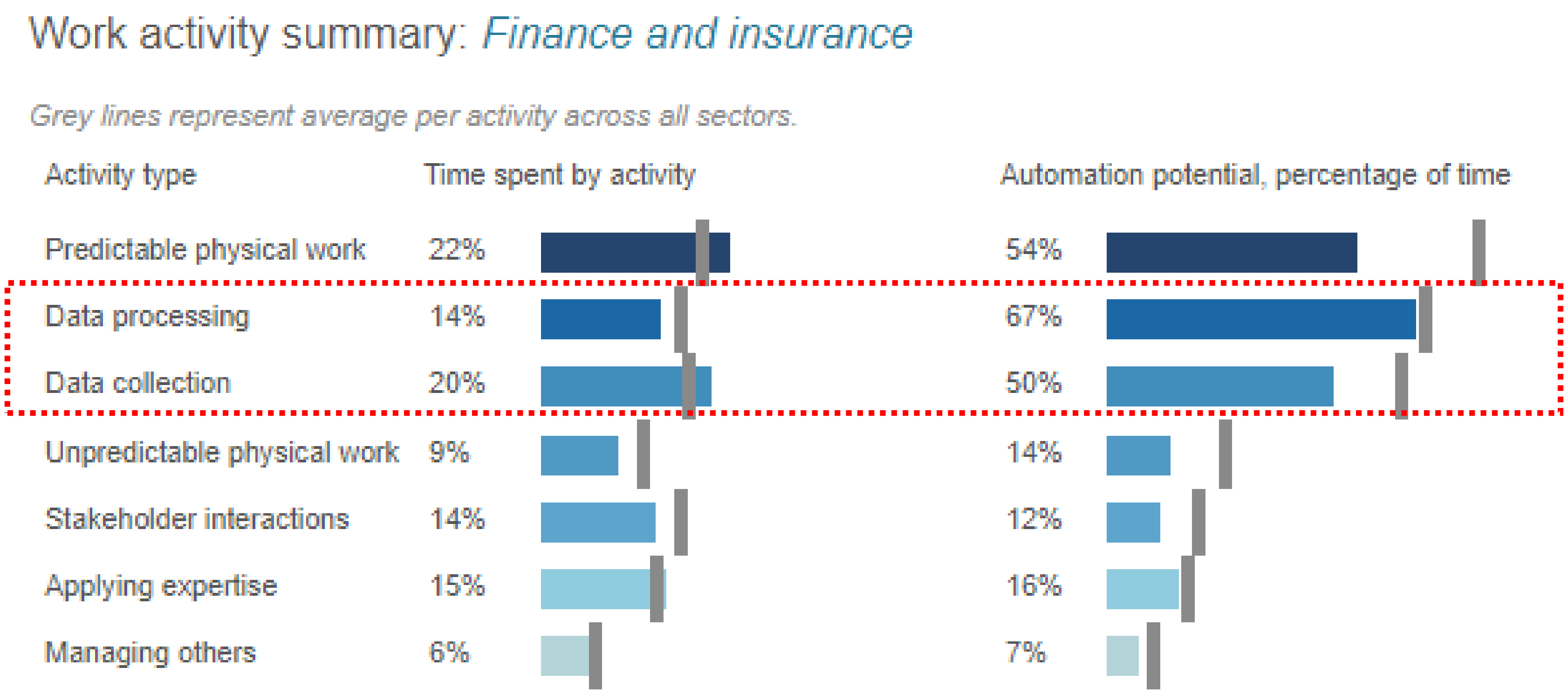
S. Cho et al., 2020




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

# Experiment 5 : Perturbating with unimportant area

S. Cho et al., 2020




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

# Automation of Knowledge Work

Finance and Insurance, McKinsey 2016

## Adobe beats Street 3Q forecasts

Associated Press September 20, 2017

AUTOMATED INSIGHTS

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.

______

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

## Automated Narrative Generation

narrative science

**Sonoma County Little Leagues (Falcons vs Mustangs)**

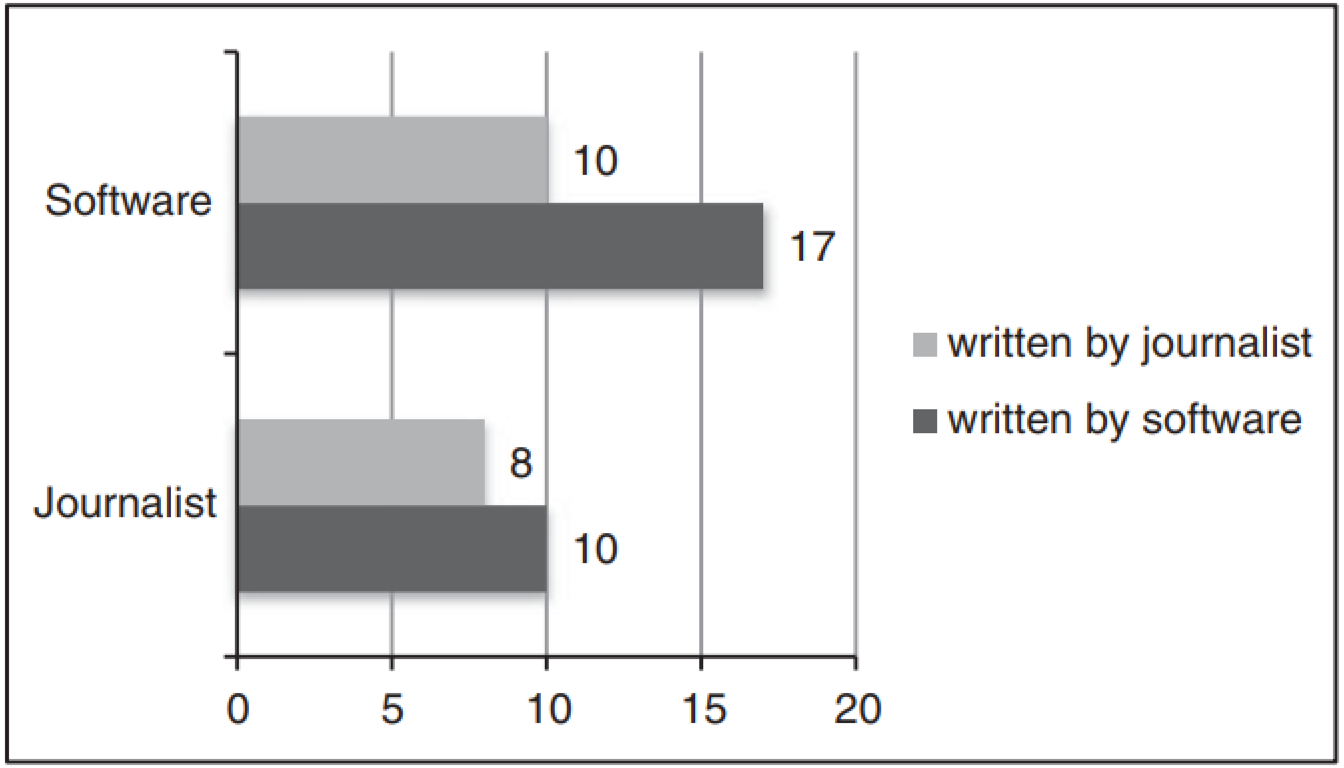
Anthony T got it done on the bump on the way to a win. He allowed two runs over 2-1/3 innings. He struck out four, walked two, and surrendered no hits.

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

Clerwall, Journalism Practice, 2014

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

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

**…**

## Big Success in Funding

# 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.
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______

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## An Old-School AI Strategy: Template

## Sonoma County Little Leagues (Falcons vs Mustangs)

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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.

Generated by Quill, Narrative Science

## An Old-School AI Strategy: Template

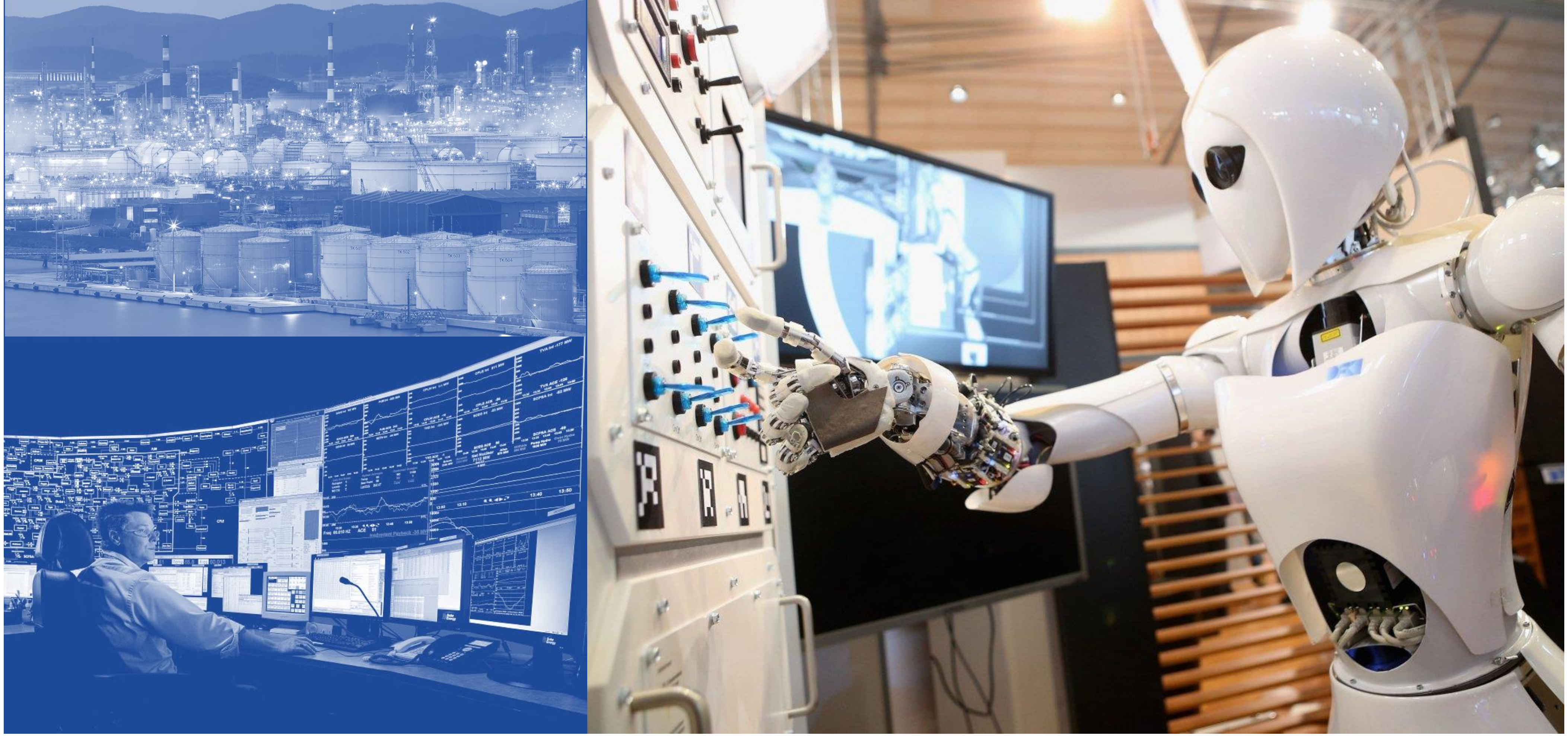
**The deeper challenge lies not in generating copy, but in finding the most pertinent meaning in a given dataset.**

**“It’s not just about converting numbers to language.”**

**“Those numbers need context”**

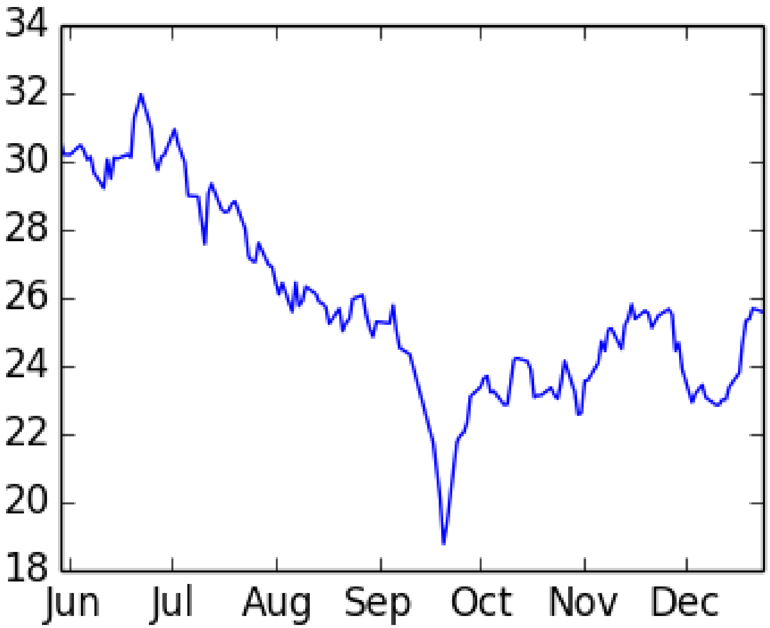
## Challenges in Algorithmic Authors

Wright et. al., 2015



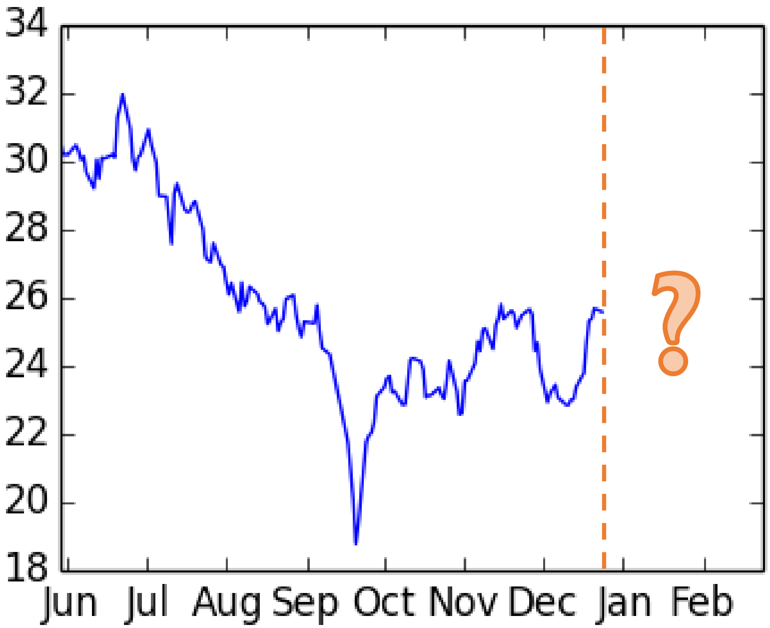
# Finding Context in Time Series Data

# Descriptive prediction of time series



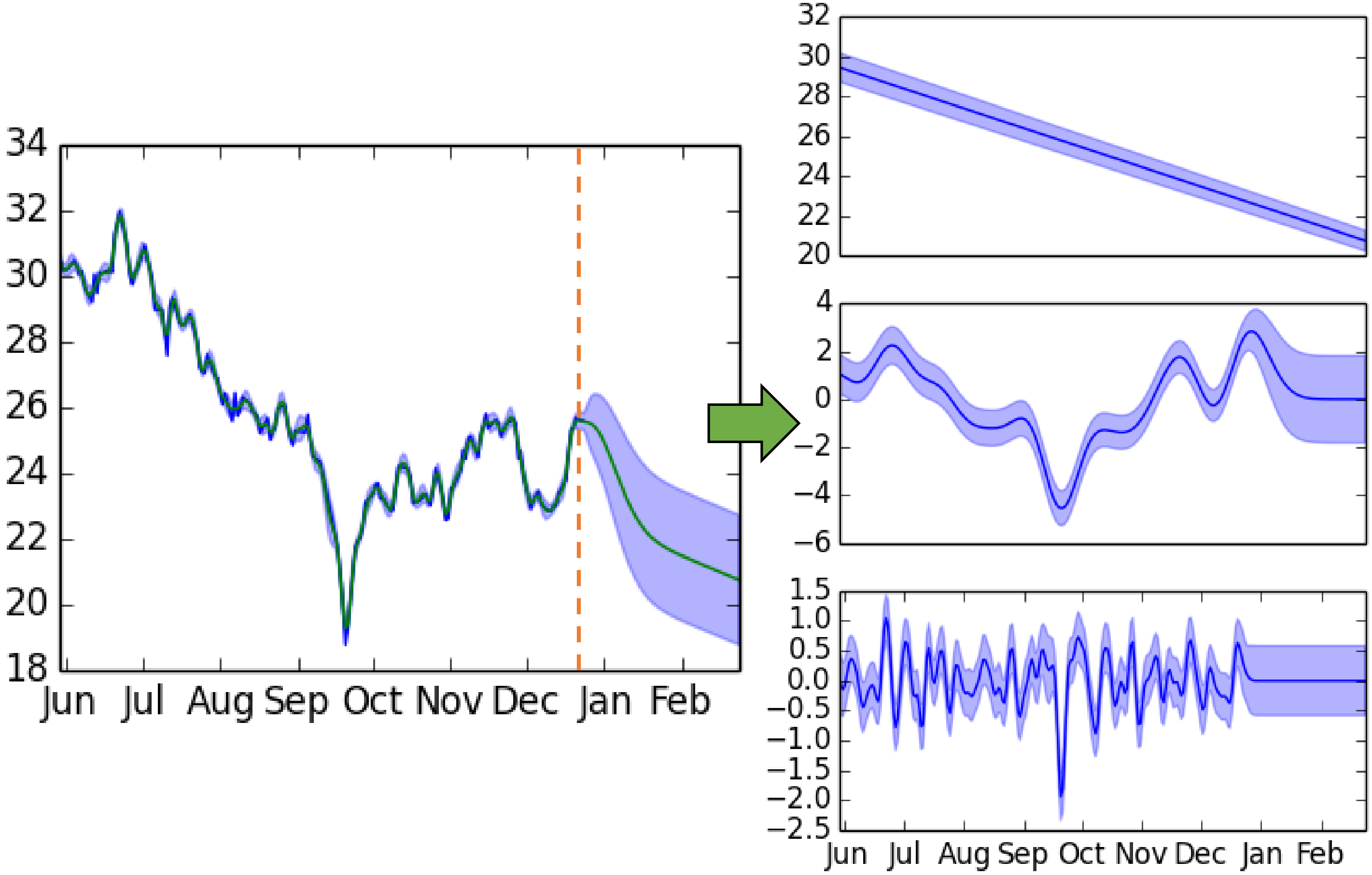

**Problem**

# Descriptive prediction of time series




**Problem**

# Descriptive prediction of time series




Linear function
decrease x/week

Smooth function
Length scale: y weeks

Rapidly varying
smooth function
Length scale: z hours

**Problem**

$$\mu(x) = \mathbb{E}\big(f(x)\big)$$

Mean function

Covariance kernel function

$$k(x, x') = \mathrm{Cov}\big(f(x), f(x')\big)$$

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

Function

Gaussian Process

# Gaussian Processes (GP)

$\mu(x) = \mathbb{E}(f(x))$

Mean function

Covariance kernel function

$k(x, x') = \mathrm{Cov}(f(x), f(x'))$

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

Function

Gaussian Process

$\boldsymbol{\mu} = [\mu(x_1), \ldots, \mu(x_N)]$

Mean vector

follows

Covariance matrix

$\boldsymbol{\Sigma}_{ij} = k(x_i, x_j)$

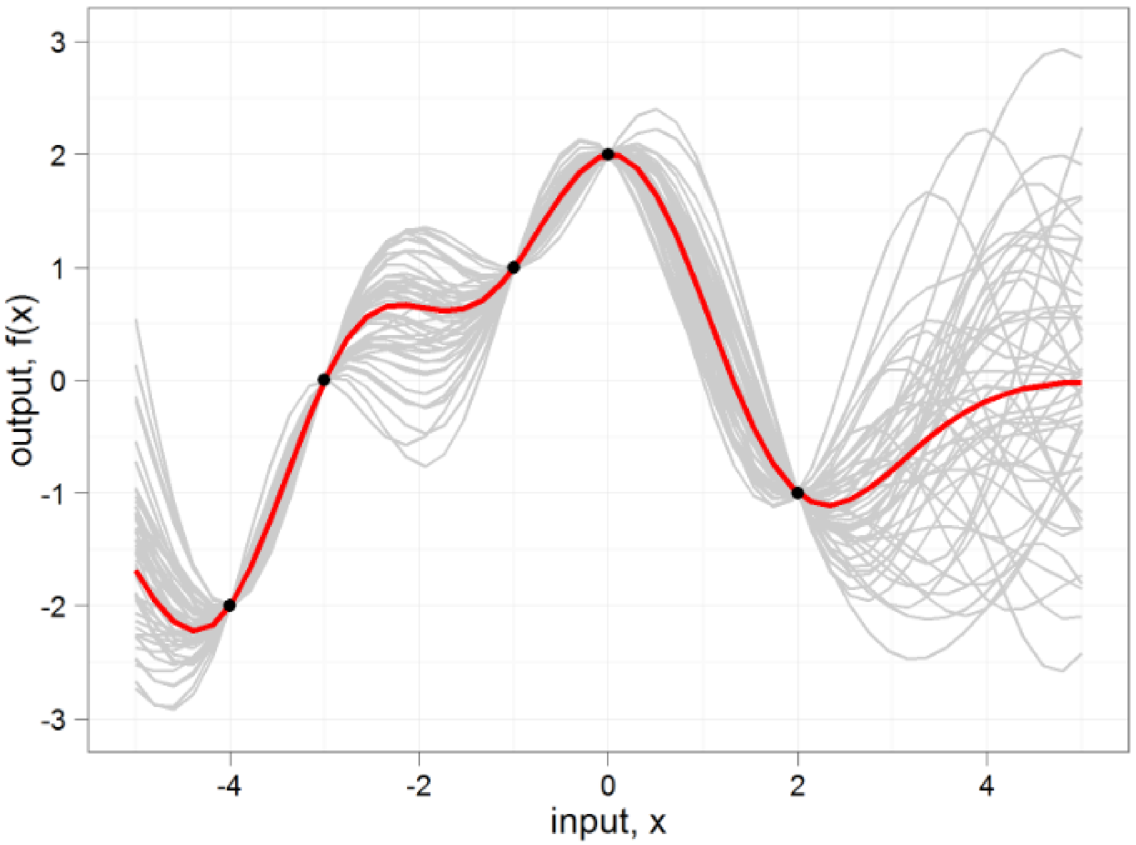
$$[f(x_1), \ldots, f(x_N)] \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

Function evaluations

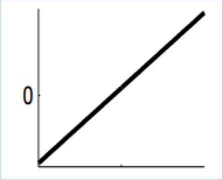
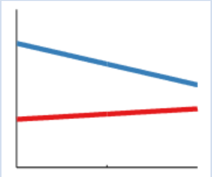
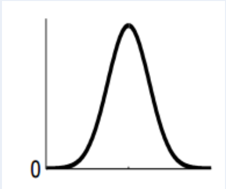
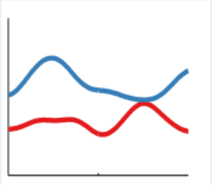
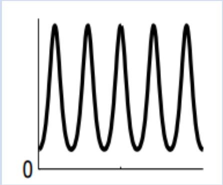
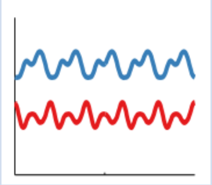
Multivariate Gaussian

# Gaussian Processes (GP)

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




# GP Examples

| Base kernel | Encoding function | Kernel function | Parameters | Example kernel function shape | Example encoded functions |
|---|---|---|---|---|---|
| $\mathrm{LIN}(x, x')$ | Linear function | $\sigma^2(x-\ell)(x'-\ell)$ | $\sigma, \ell$ |  |  |
| $\mathrm{SE}(x, x')$ | Smooth function | $\sigma^2 \exp\left(-\frac{(x-x')^2}{2\ell^2}\right)$ | $\sigma, \ell$ |  |  |
| $\mathrm{PER}(x, x')$ | Periodic function | In appendix | $\sigma, \ell, p$ |  |  |

# GP Base Kernels

(1) Encode characteristic

Find appropriate kernel

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

**Multi-kernel Learning**

(1) Encode characteristic

Find appropriate kernel

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

(2) Compose new kernel (appendix)

If $g(x) \sim \mathcal{GP}(0, k_g)$, $h(x) \sim \mathcal{GP}(0, k_h)$ and $g(x) \perp h(x)$

, then

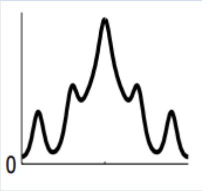
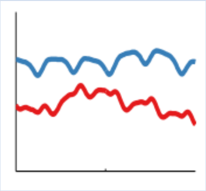
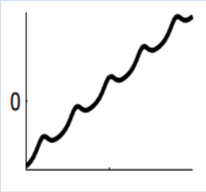
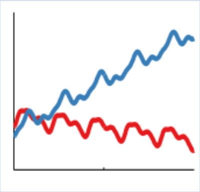
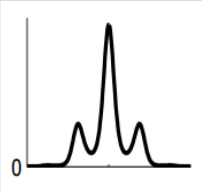
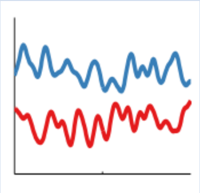
$$g(x) + h(x) \sim \mathcal{GP}(0, k_g + k_h)$$

$$g(x) \times h(x) \sim \mathcal{GP}(0, k_g \times k_h)$$

## The Automatic Statistician

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

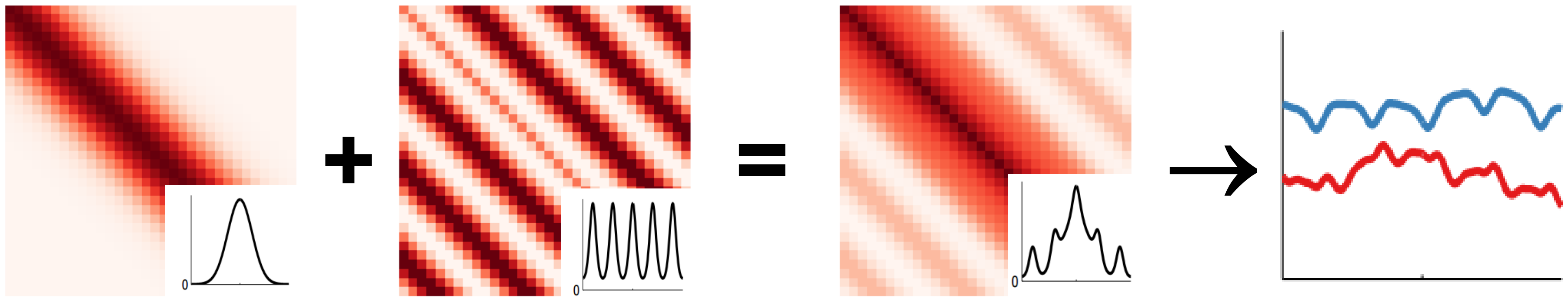
Ghahramani, 2015

| Op. | Concept | Params | Example | Example kernel function shape | Example encoded functions |
|---|---|---|---|---|---|
| + | Addition<br>Superposition<br>OR operator | N/A | SE + PER |  |  |
| | | | LIN + PER |  |  |
| × | Multiplication<br>AND operator | N/A | SE × PER |  |  |

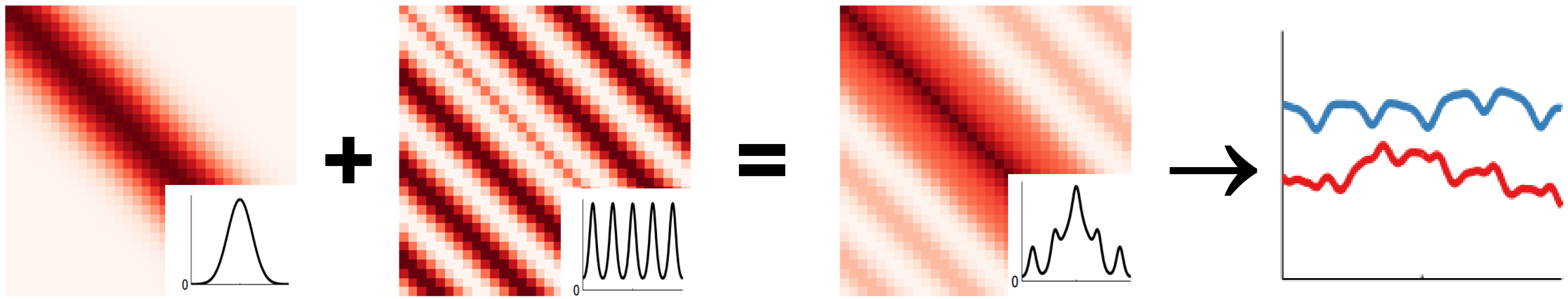
# The Automatic Statistician: Kernel Composition

Grosse et. al., 2012

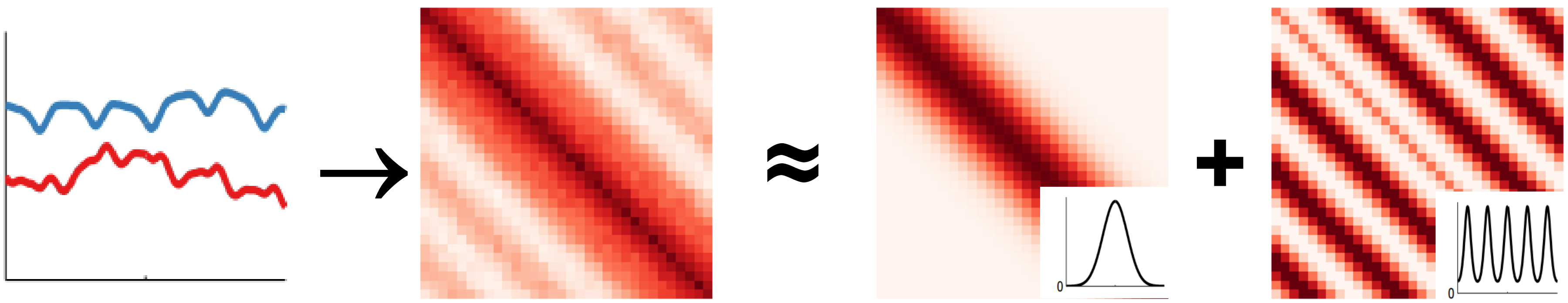
## Kernel Composition: Generate Data from Models



## Kernel Composition: Generate Data from Models



## Covariance Decomposition: Learn Explainable Models from Data



# Kernel Composition & Covariance Decomposition

(1) Optimization criteria: Bayesian Information Criterion (BIC)

$$\mathrm{BIC}(\mathcal{M}) = \underbrace{-2\log P(D|\mathcal{M})}_{\text{Negative log-likelihood}} + \overbrace{\underbrace{|\mathcal{M}|}_{\text{Num. of model parameters}}\log\underbrace{|D|}_{\text{Num. of data points}}}^{\text{Model complexity}}$$

(2) Learning algorithm (Composite Kernel Learning)

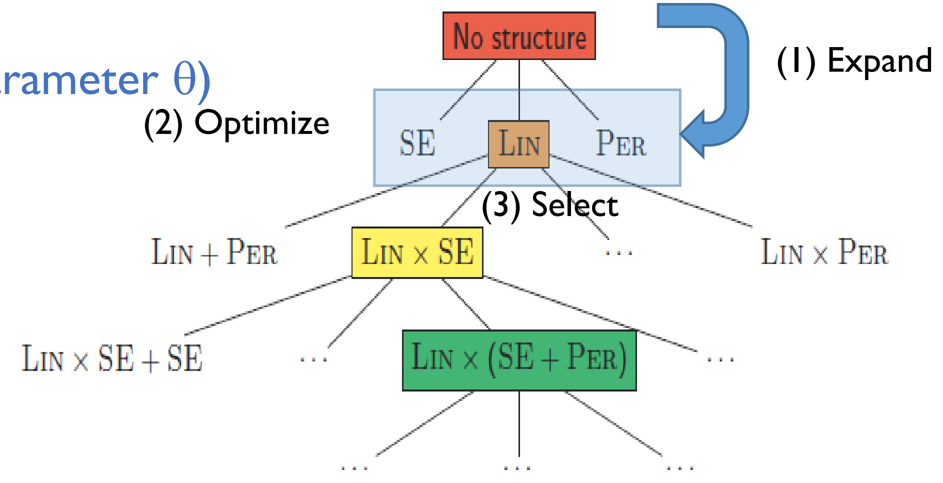
❖ Iteratively select best model (structure $k$, parameter $\theta$)

**(1) Expand**: the current kernel

**(2) Optimize**: conjugate gradient descent

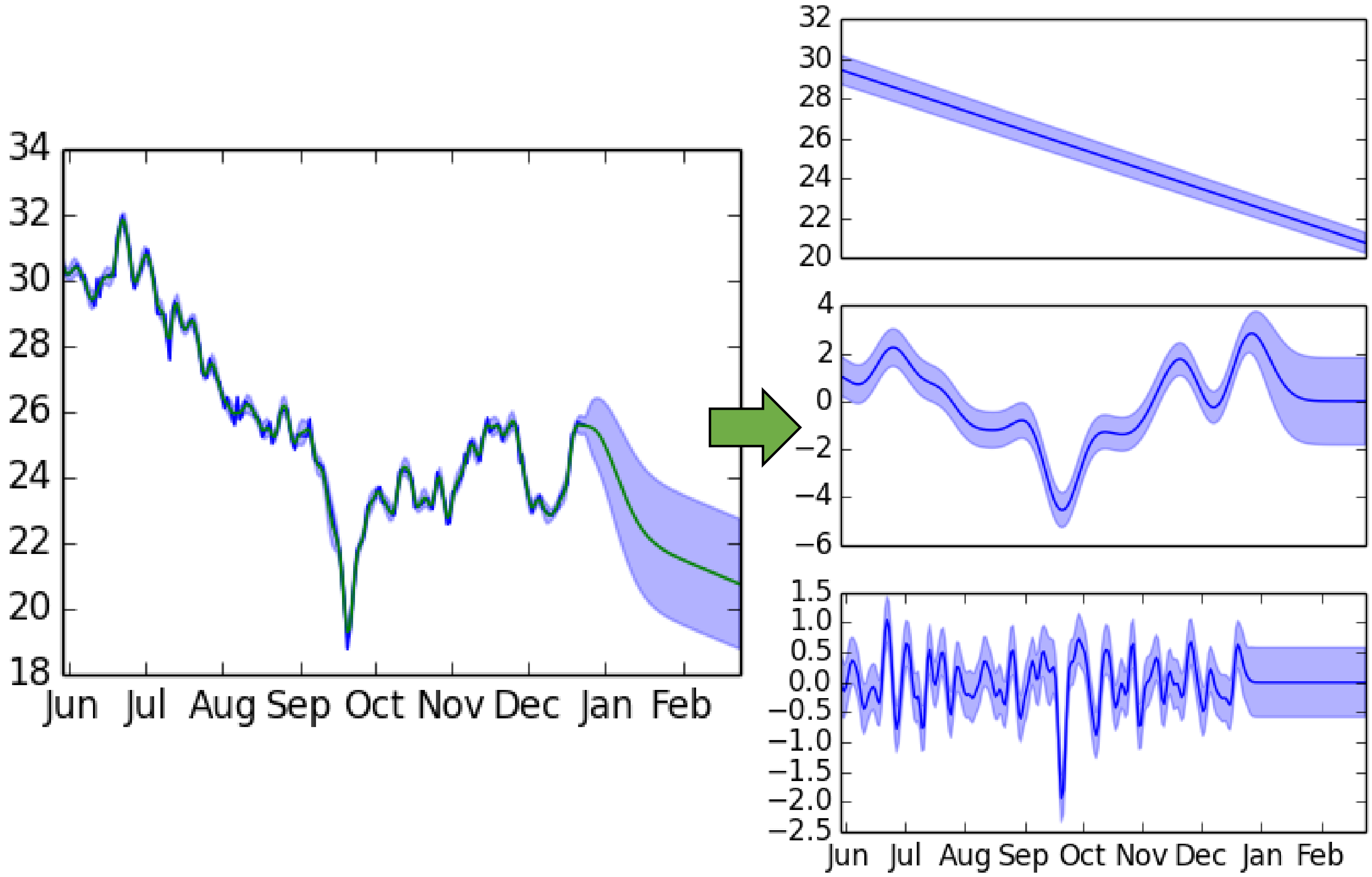
**(3) Select**: the best kernel in the level (greedy)

**(4) Iterate**: get back to (1) for the next level




# The Automatic Statistician: Greedy Kernel Search

Duvenaud et. al., 2014



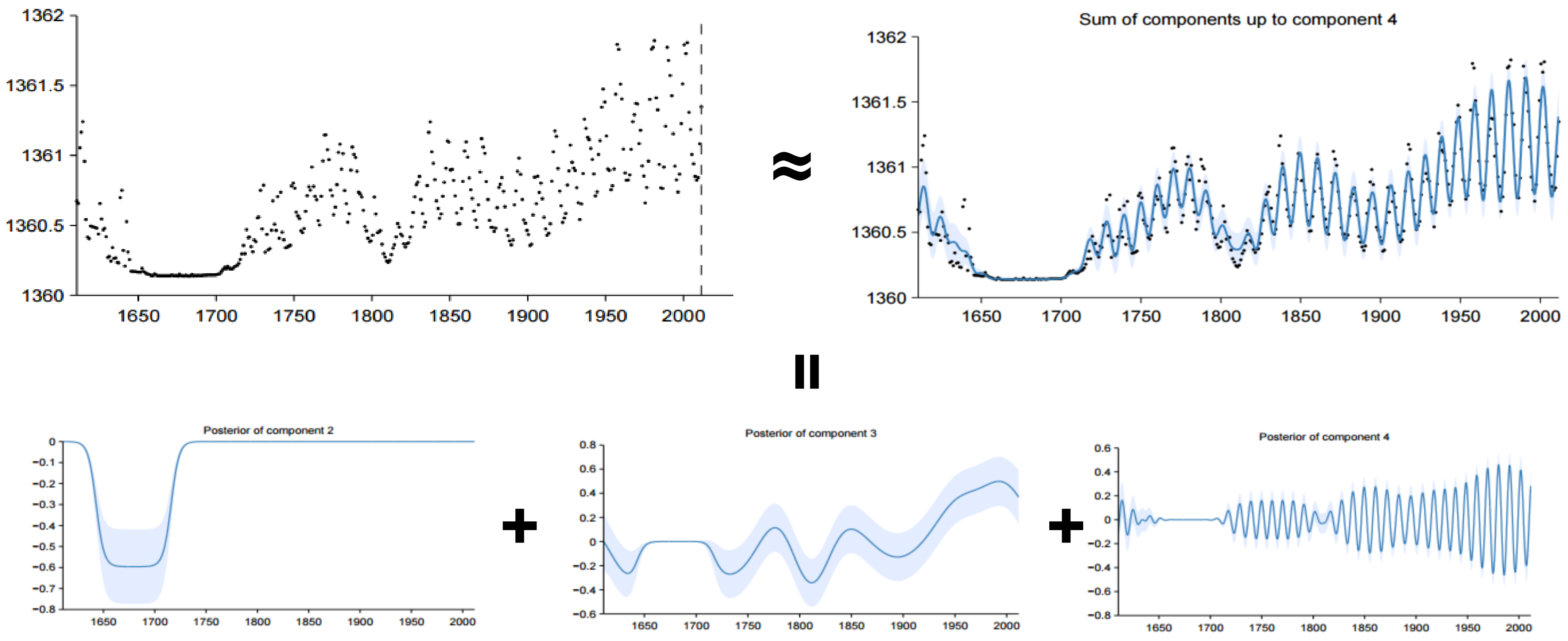

Linear function
decrease x/week

Smooth function
Length scale: y weeks

Rapidly varying
smooth function
Length scale: z hours

# The Automatic Statistician: A Sample Report

Lloyd et. al., 2014

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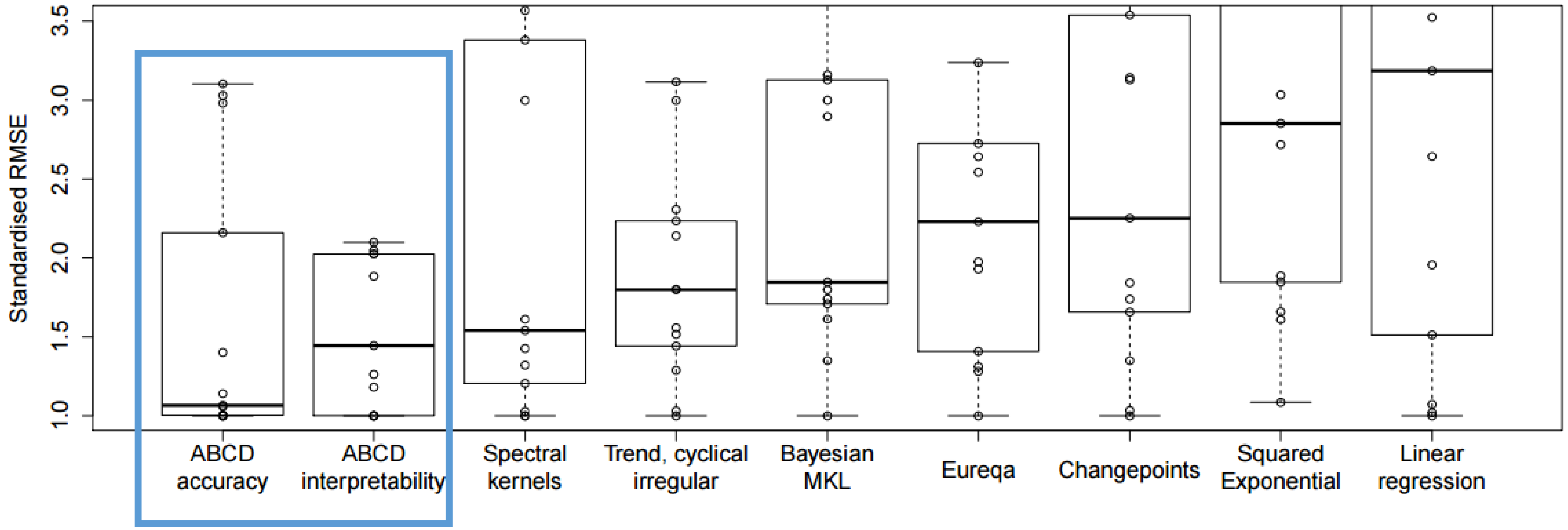
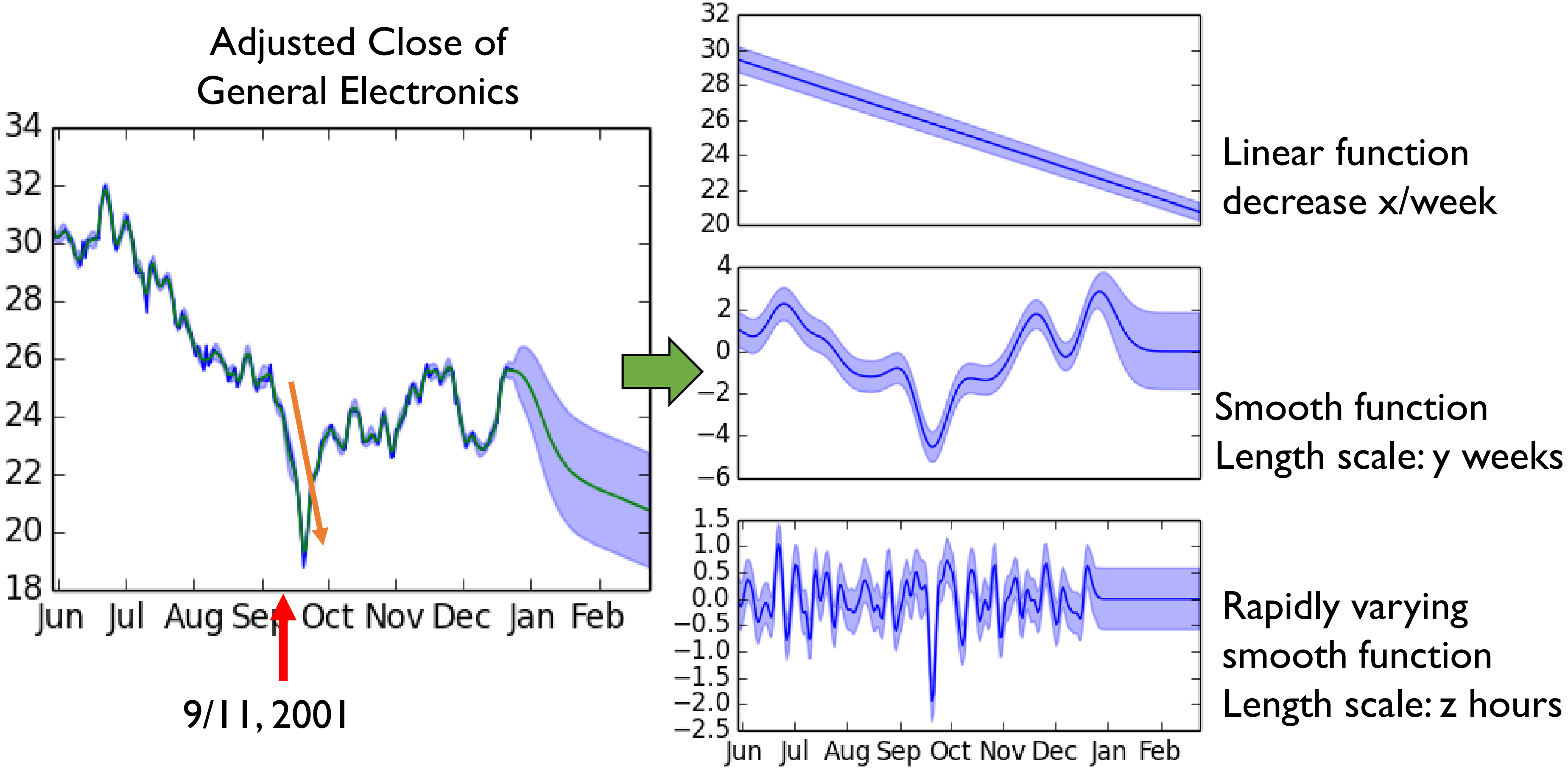
Lloyd et. al., 2014




**13 regression datasets**

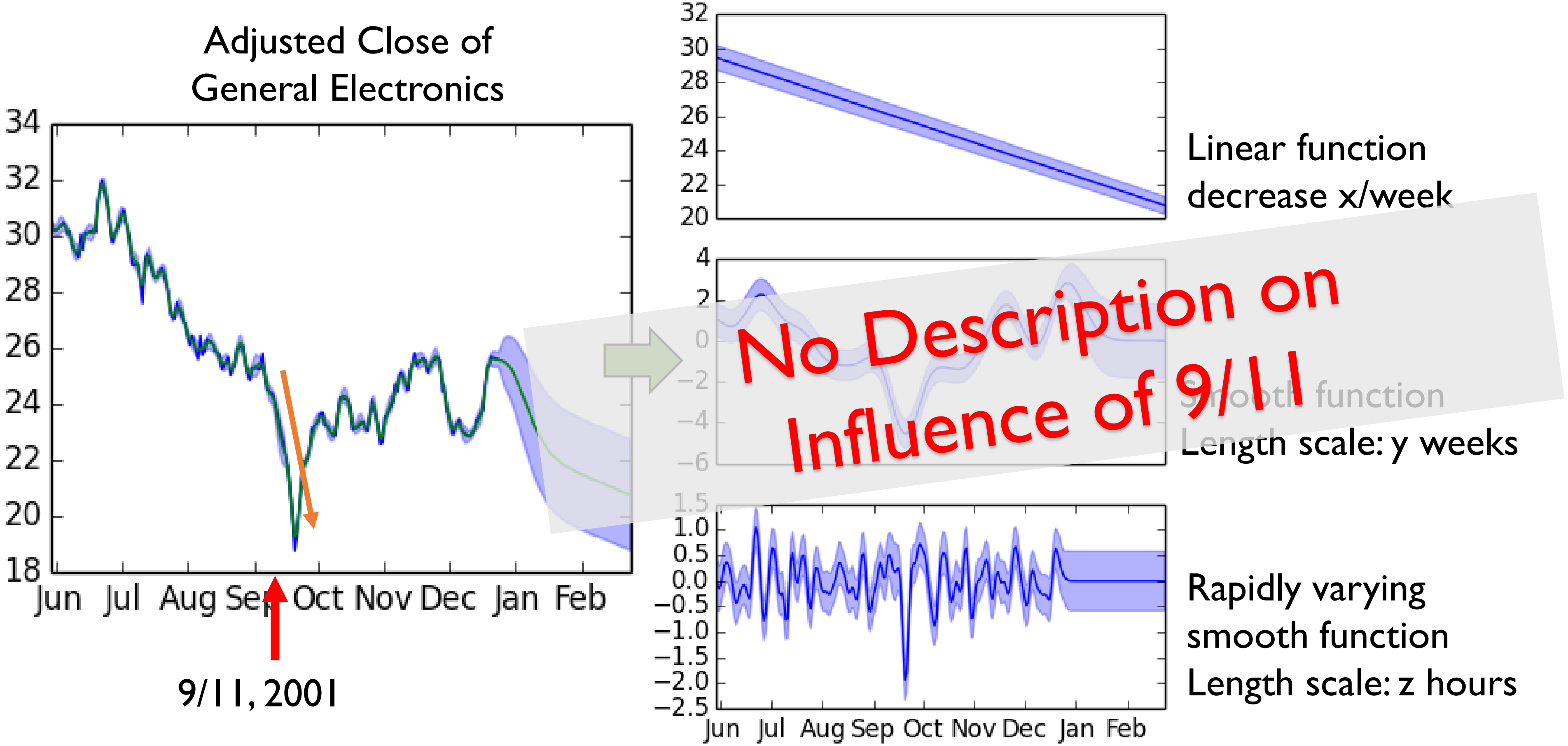
# The Automatic Statistician: Extrapolation Performance

Lloyd et. al., 2014



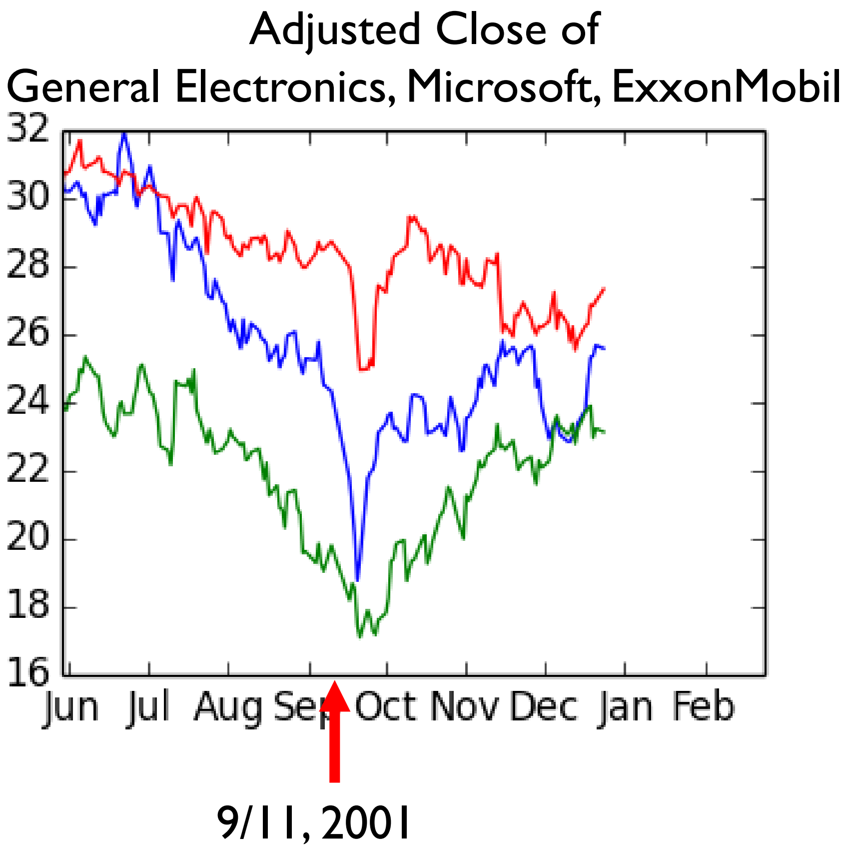

# Challenge: The Automatic Statistician

## Incorporating Global Changes




## Challenge: The Automatic Statistician

### Incorporating Global Changes

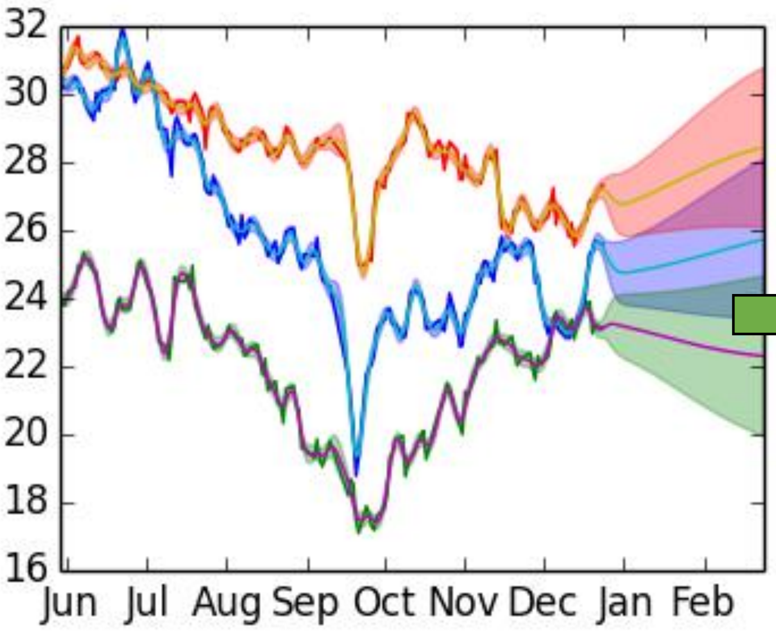


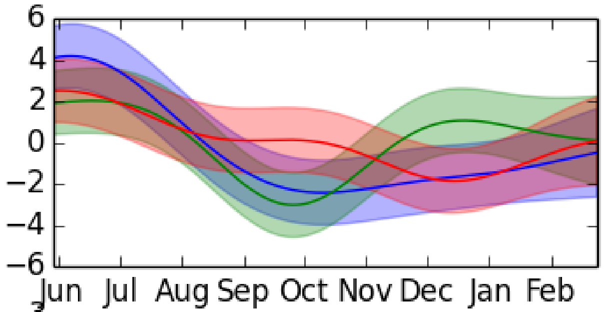

- Exploit multiple time series
- Find global descriptions
- Hope better predictive performance

**Challenge: The Automatic Statistician**

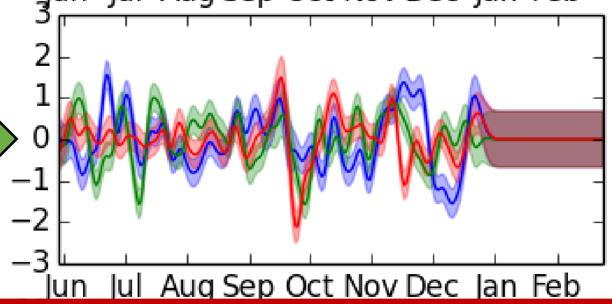
**Q: How about handling multiple time series?**

# Descriptive prediction of multiple time series

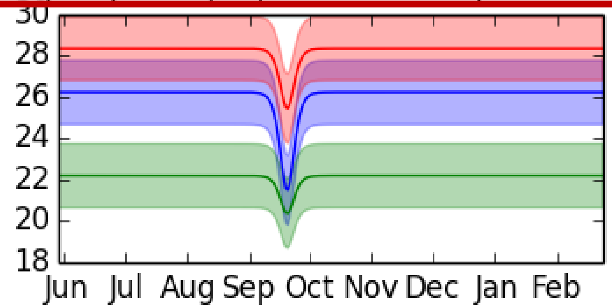



Smooth function
Length scale: y weeks

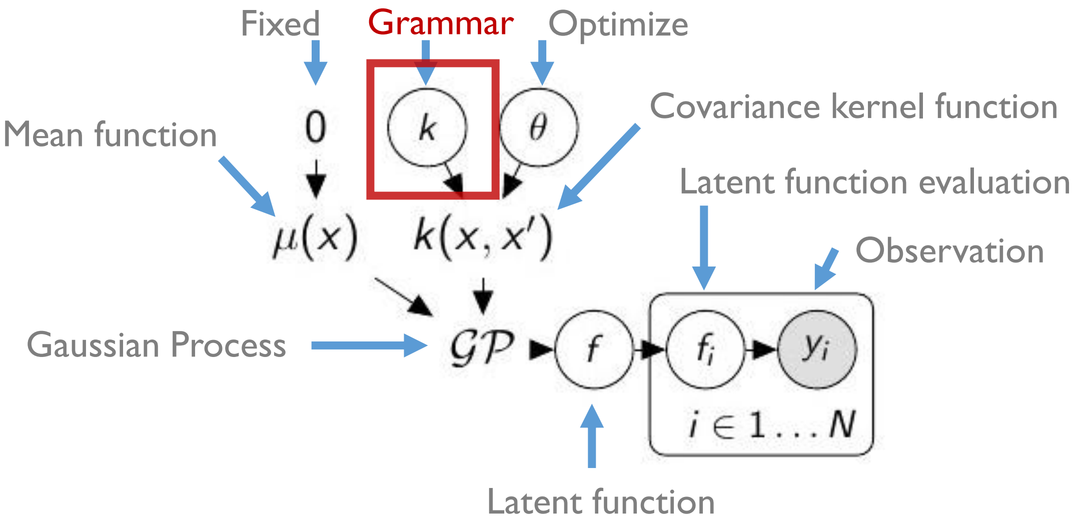



Rapidly varying
smooth function
Length scale: z hours




Constant function
Sudden drop btw
9/12/01 ~ 9/15/01

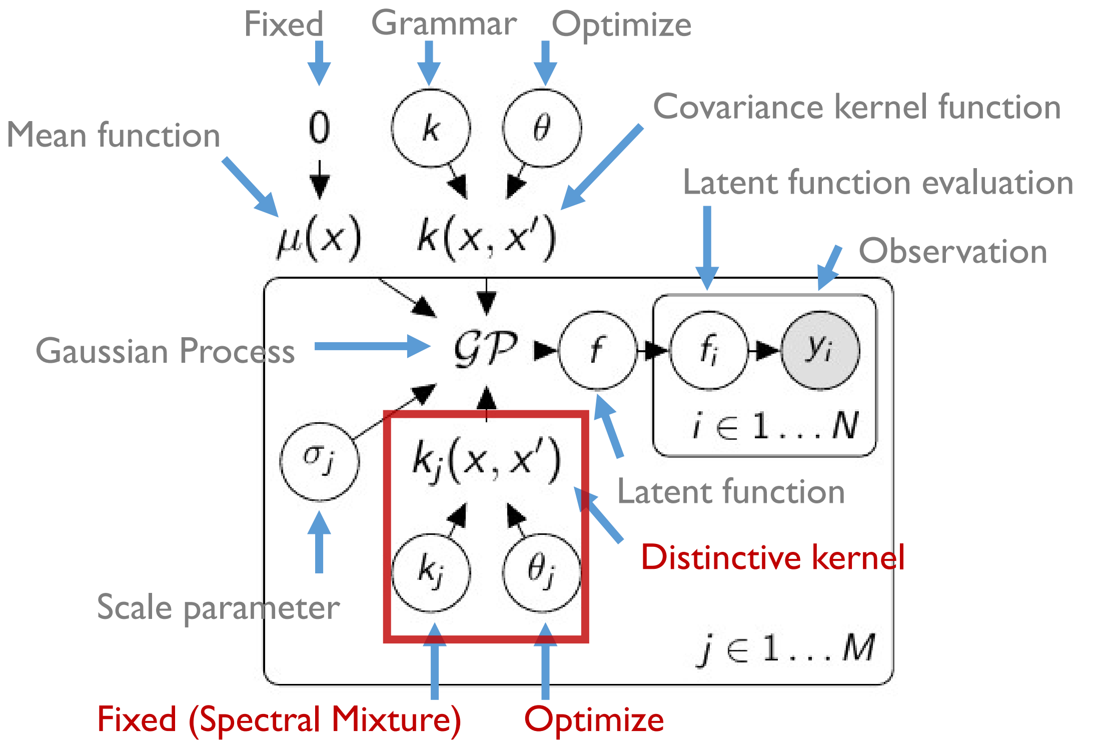
**Problem (Our research)**




A Generalized Multi Kernel Learning

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

# Model: Composite Kernel Learning (The Automatic Statistician)

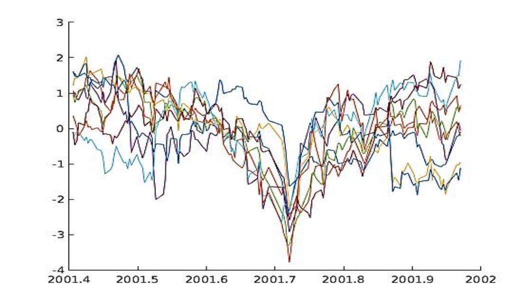
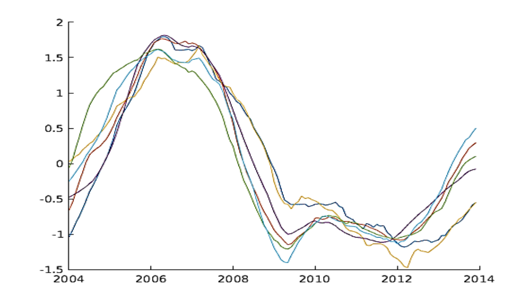
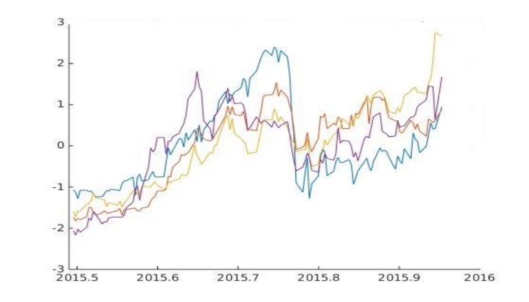



$$P(D|\mathcal{M}) = \prod_{j=1}^{M} P\left(d_j \middle| \mathcal{GP}\left(0, \sigma_j \times k(x, x'; \theta) + \boxed{k_j(x, x'; \theta_j)}\right)\right)$$

# Model: Semi-Relational Kernel Learning

Hwang et al., 2016

# Experiments on Financial Data Sets

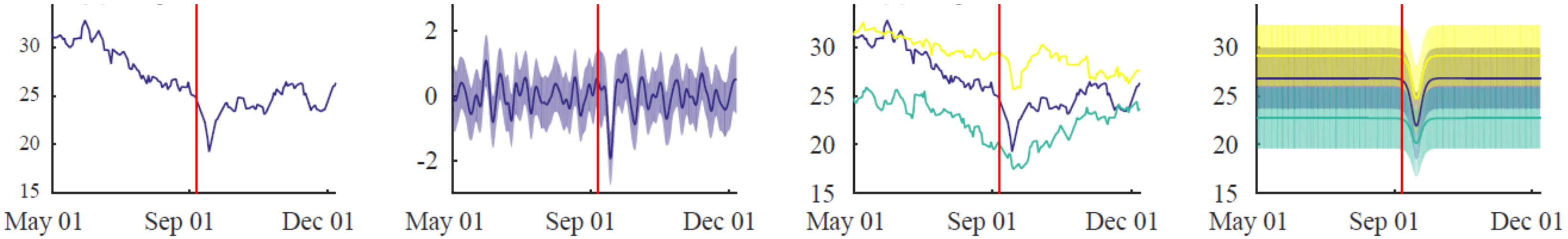
| Descriptions | Graphs (normalized) | Details |
|---|---|---|
| 9 adjusted close of stock figures (2001 ~ 2002) |  | GE,MSFT, XOM, PFE, C, WMT, INTC, BP, AIG |
| 6 US housing price indices (2003 ~ 2013) |  | New York, Los Angeles Chicago, Pheonix, San Diego, San Fancisco |
| 4 emerging market currency exchanges (2016) |  | Indonesian - IDR Malaysian - MYR South African - ZAR Russian - RUB |

Hwang et al., 2016

Automatic Statistician

Relational Automatic Statistician

Adjusted Closes | Component 1 | Adjusted Closes | Component 2




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

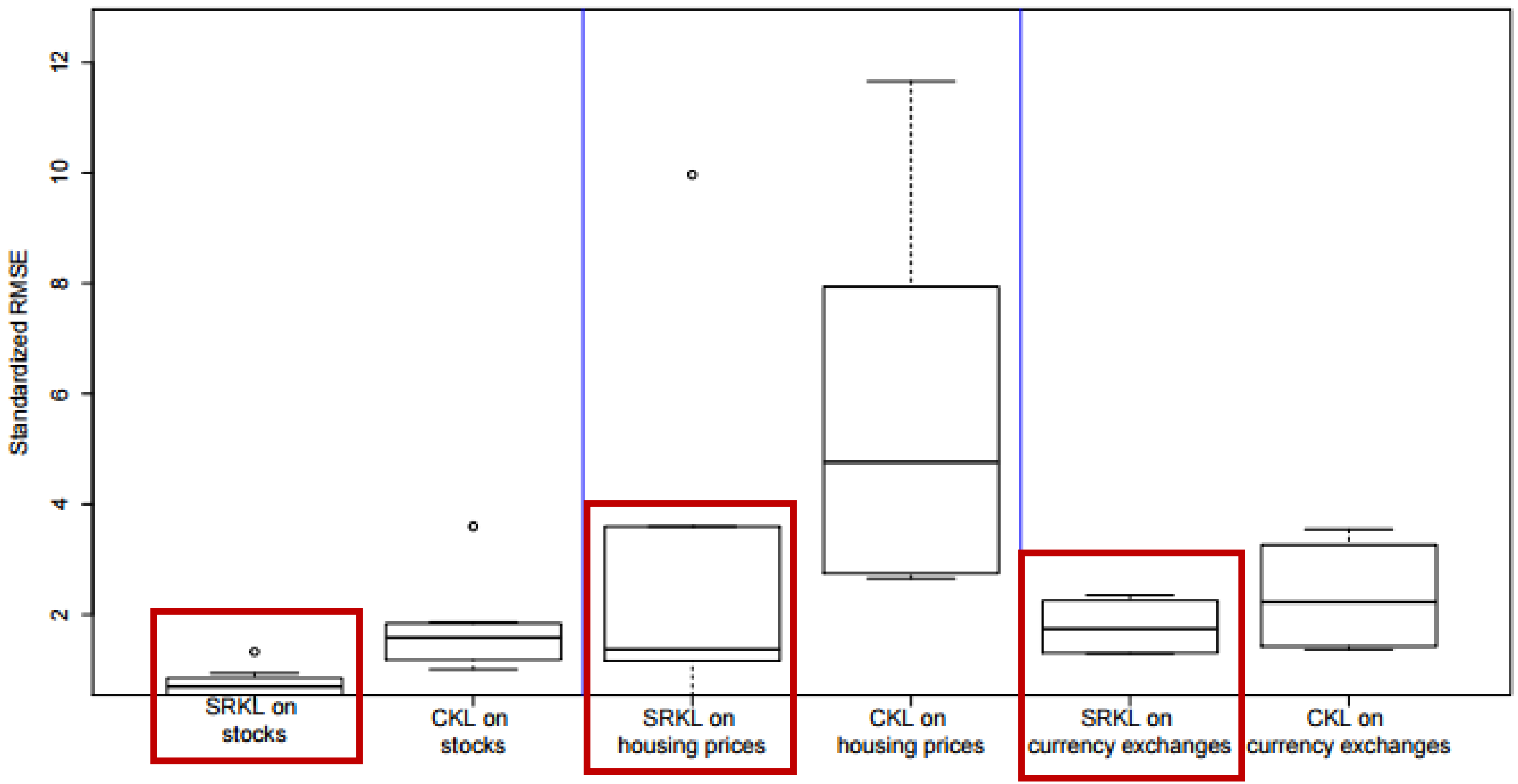
4 currency exchange rates

Learned component


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

# Qualitative Results

Hwang et al., 2016




9 stocks  6 house price indices  4 currency exchanges

# 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}

STOCK9 = STOCK6 + {INTC, BP, AIG}

HOUSE2 = {NY, LA}

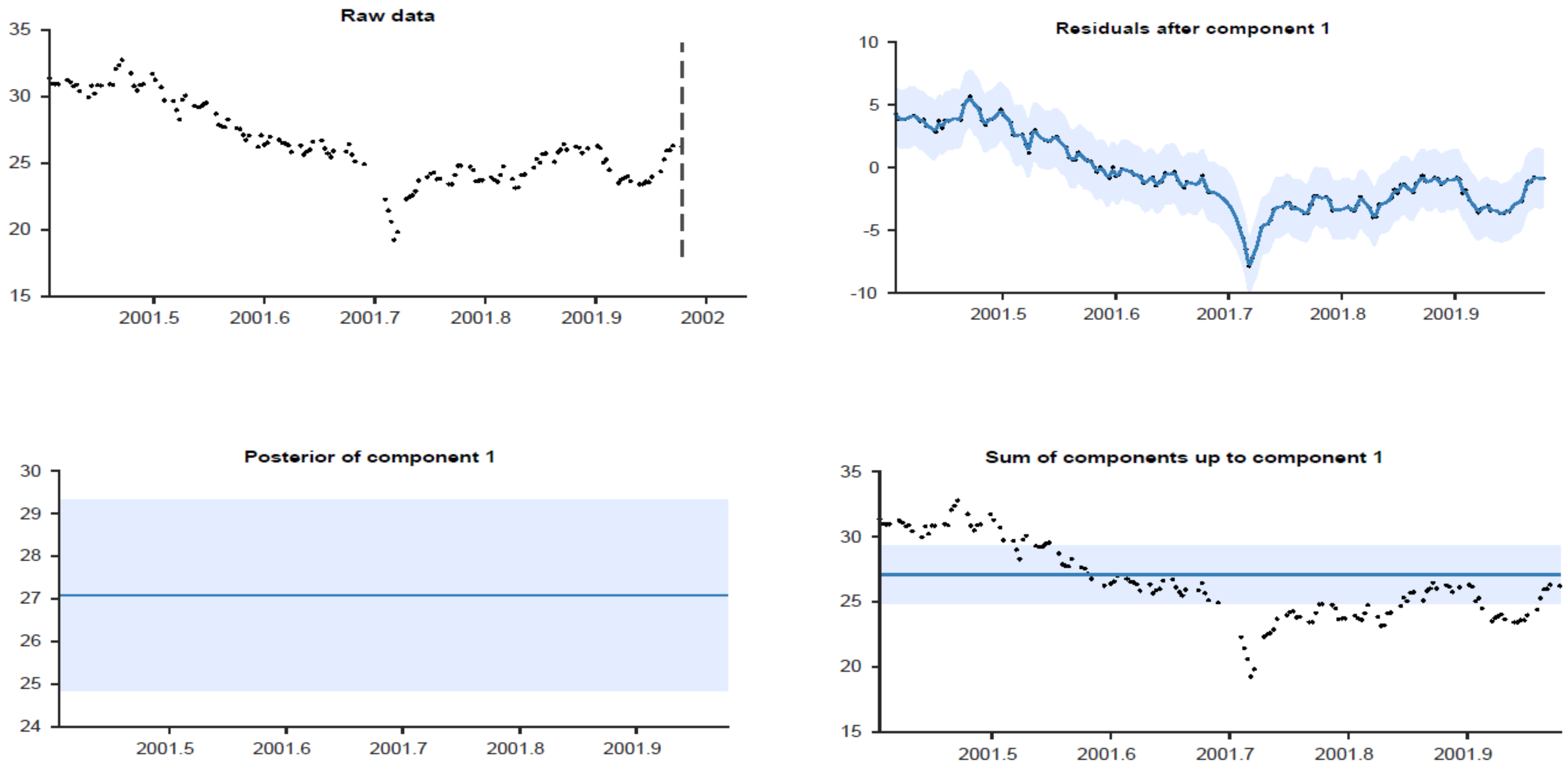
HOUSE4 = HOUSE2 + {Chicago, Pheonix}

HOUSE6 = HOUSE4 + {San Diego, San Francisco}

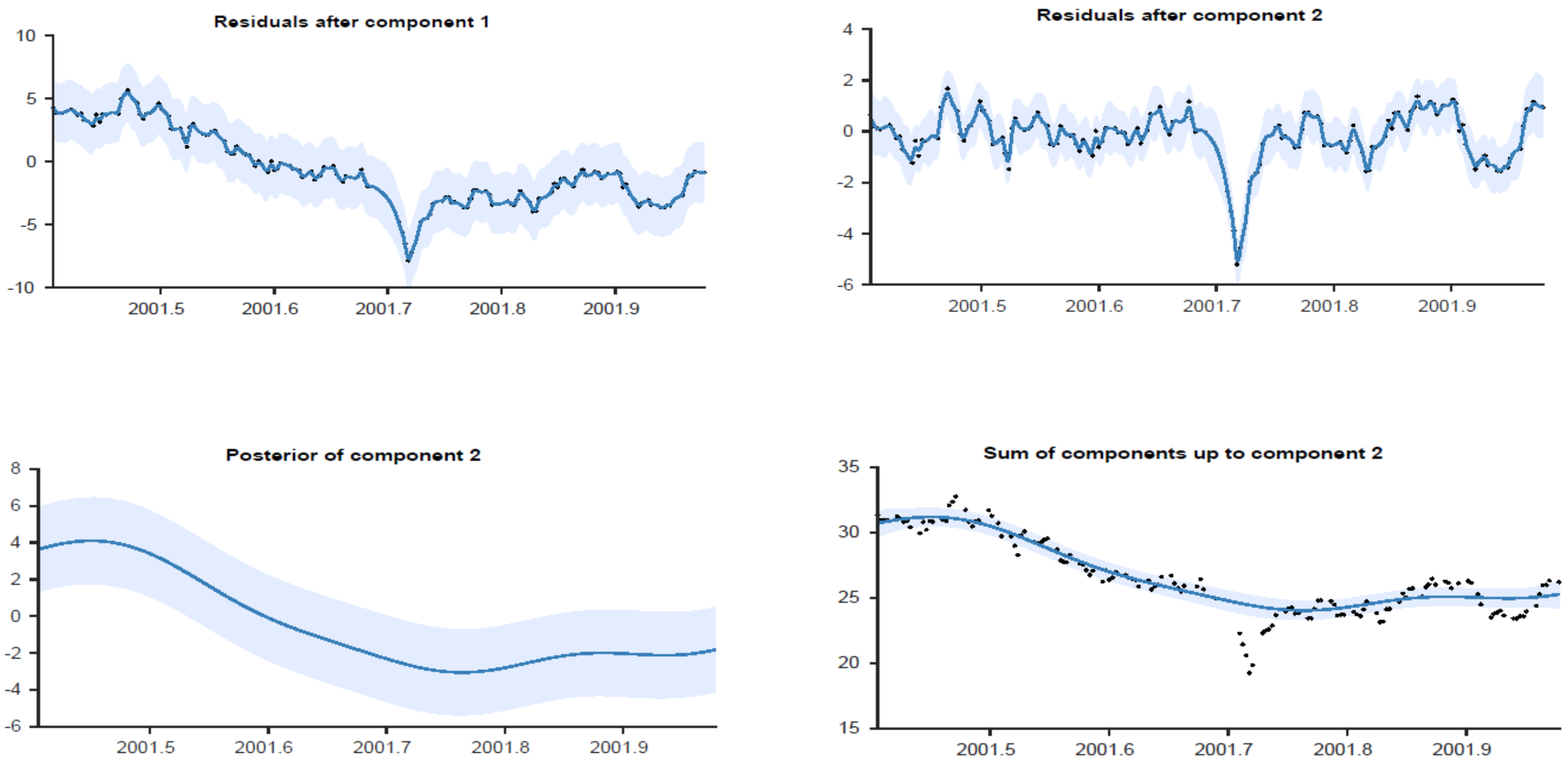
CURRENCY4 = {IDR, MYR,ZAR,RUB}

# Quantitative Results

Hwang et al., 2016

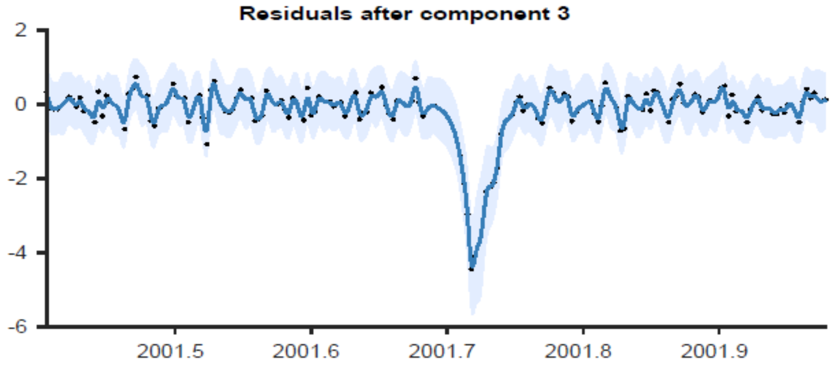


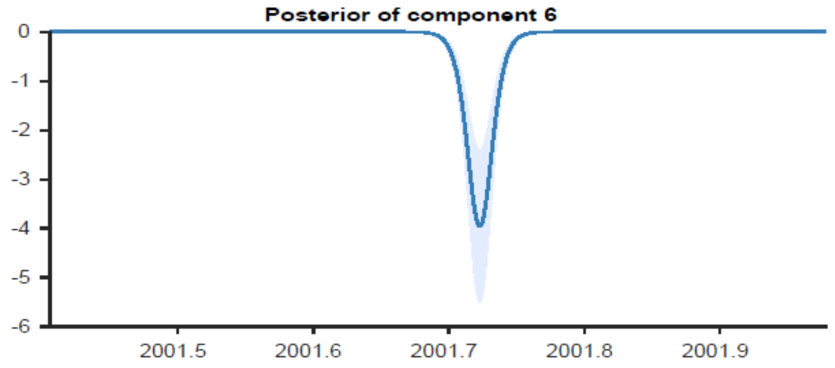

# An Automatically Generated Report




# An Automatically Generated Report

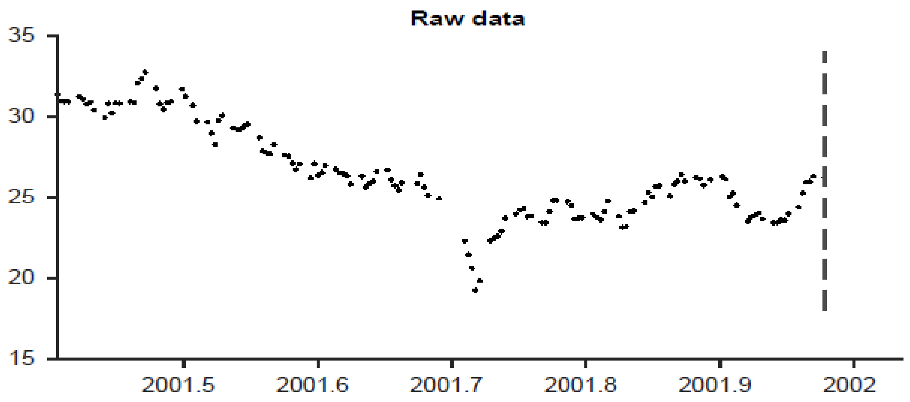

# An Automatically Generated Report

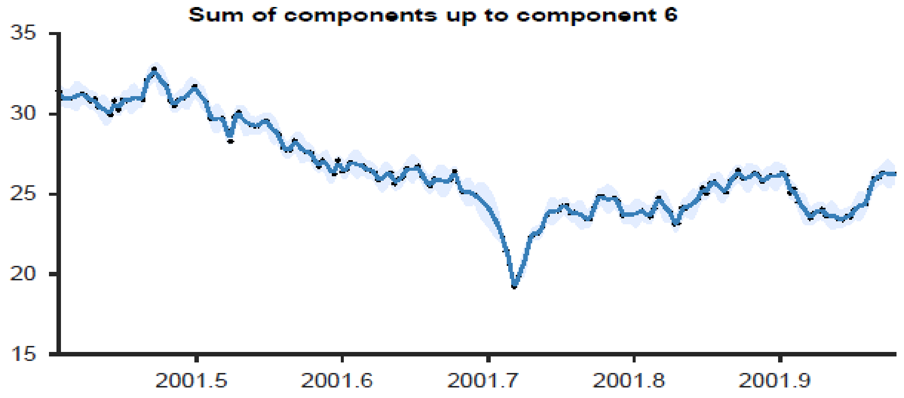


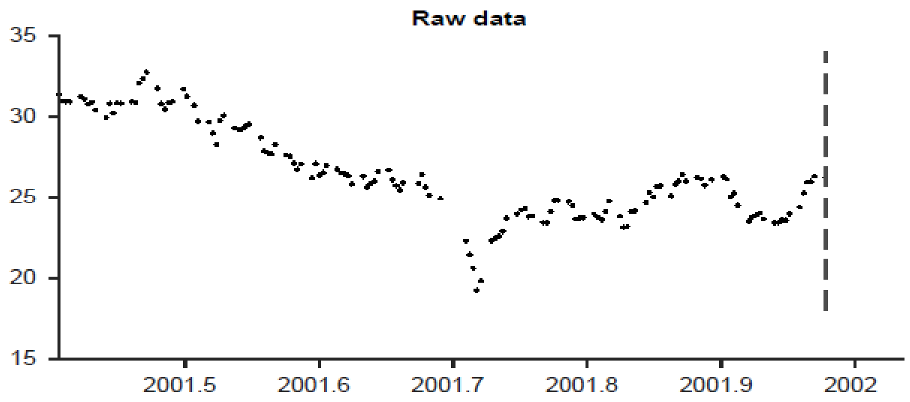


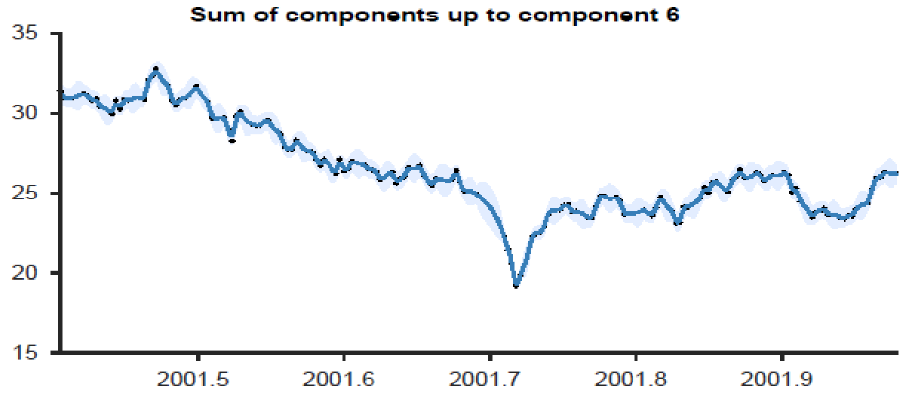
# An Automatically Generated Report



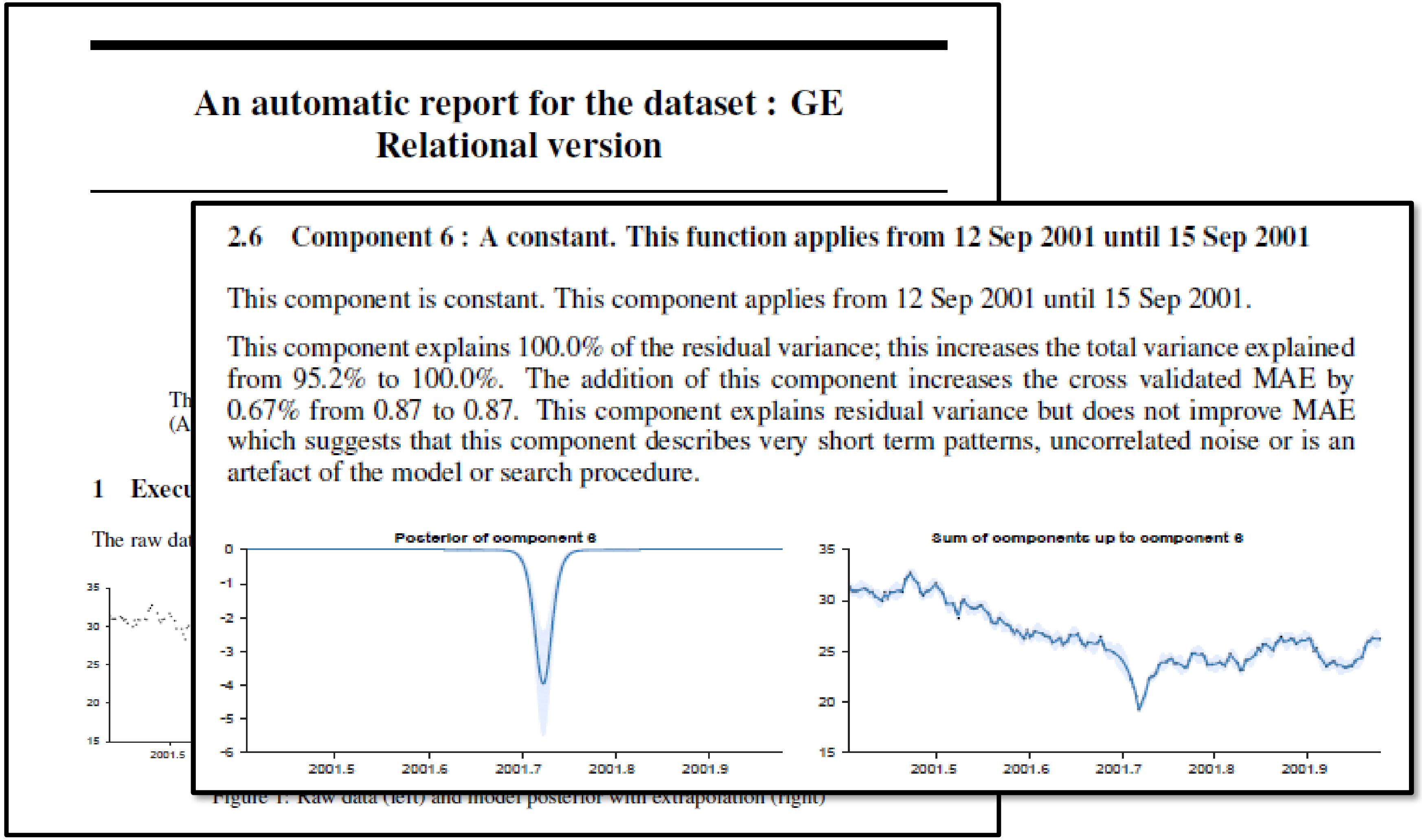




# An Automatically Generated Report




# An Automatically Generated Report


An automatic report for the dataset : GE
Relational version

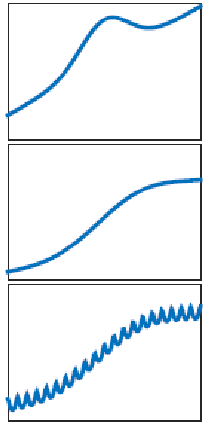
2.6 Component 6 : A constant. This function applies from 12 Sep 2001 until 15 Sep 2001

This component is constant. This component applies from 12 Sep 2001 until 15 Sep 2001.

This component explains 100.0% of the residual variance; this increases the total variance explained from 95.2% to 100.0%. The addition of this component increases the cross validated MAE by 0.67% from 0.87 to 0.87. This component explains residual variance but does not improve MAE which suggests that this component describes very short term patterns, uncorrelated noise or is an artefact of the model or search procedure.



# An Automatically Generated Report

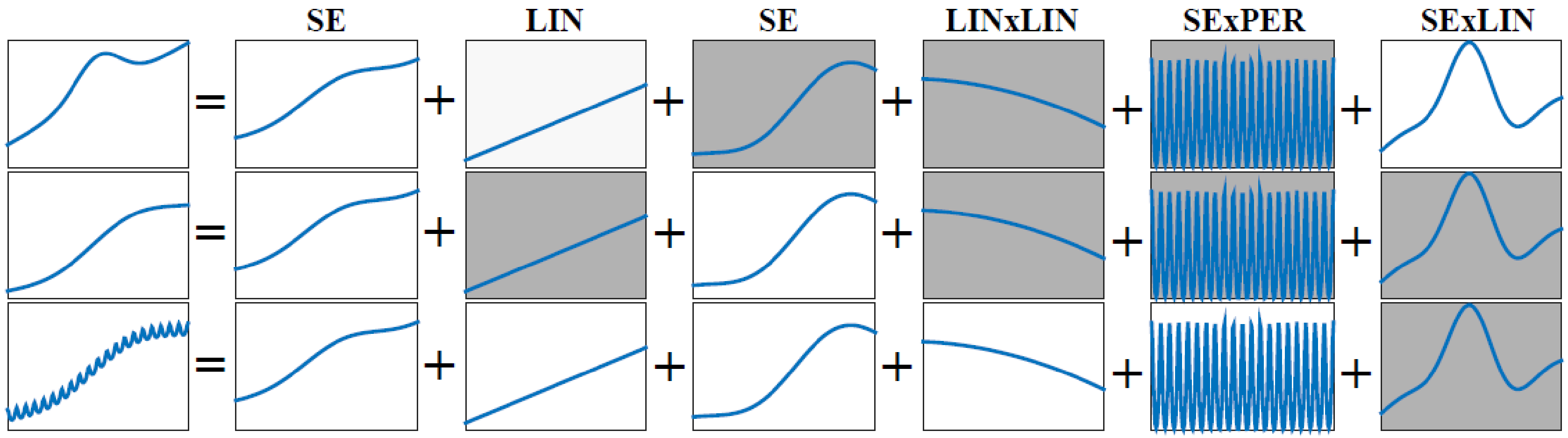


## Challenges: Selective Kernel Search

### Q: Can we selectively search over time series?

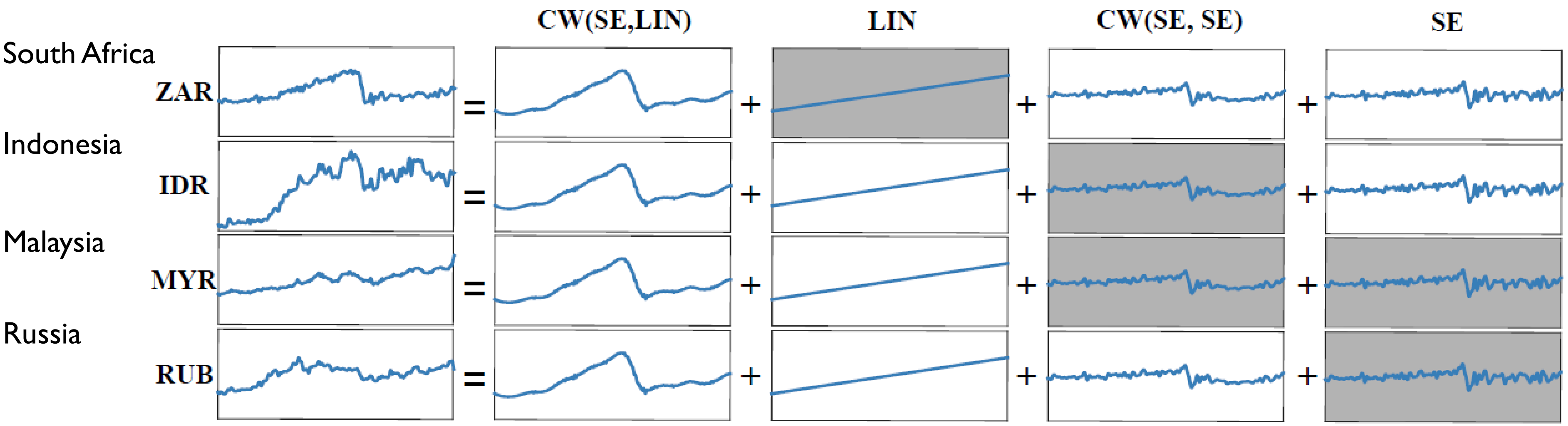
# Indian Buffet Processes (IBP) + Gaussian Processes

(Nonparametric Clustering) (Nonparametric Regression)




## Discovering Explainable Latent Covariance Structures for Multiple Time Series

Tong, Choi, 2018



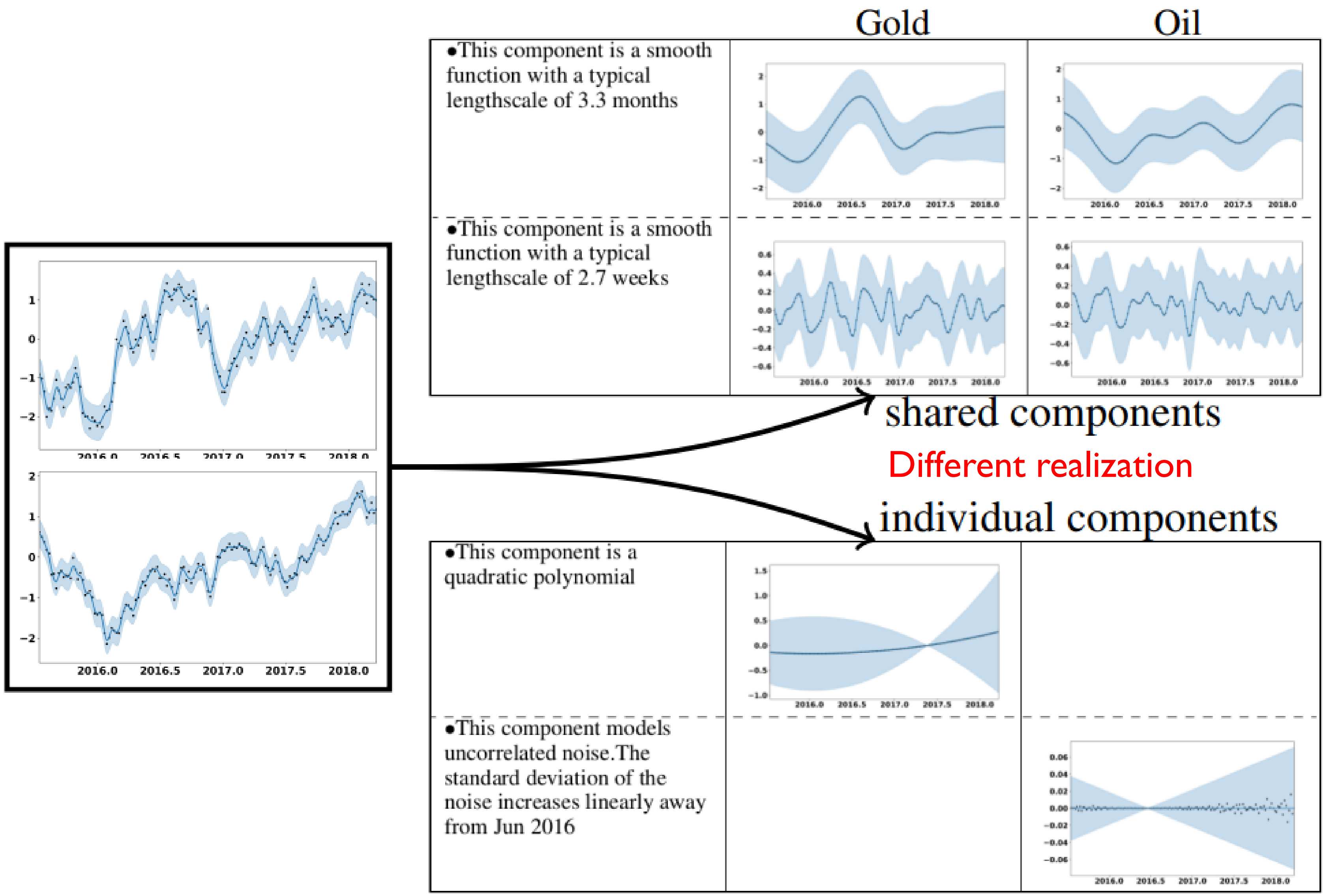

South African Rand and Indonesian Rupiah and Malaysian Ringgit and Russian Rouble share the following properties

→ 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
→ This component is linearly increasing.

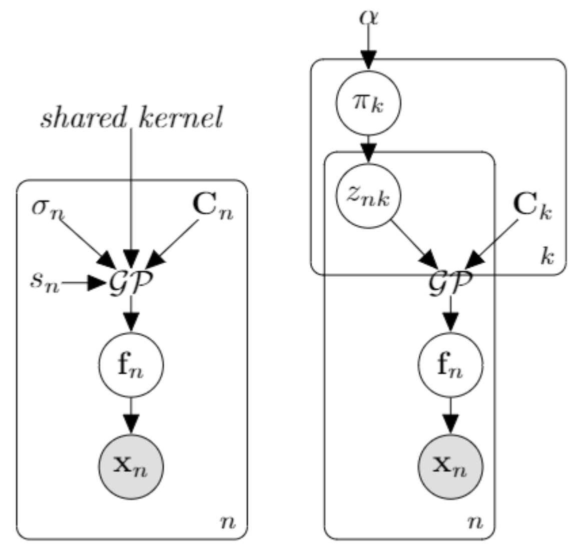
**Discovering Explainable Latent Covariance Structures for Multiple Time Series – Version 1**

Tong, Choi, 2018

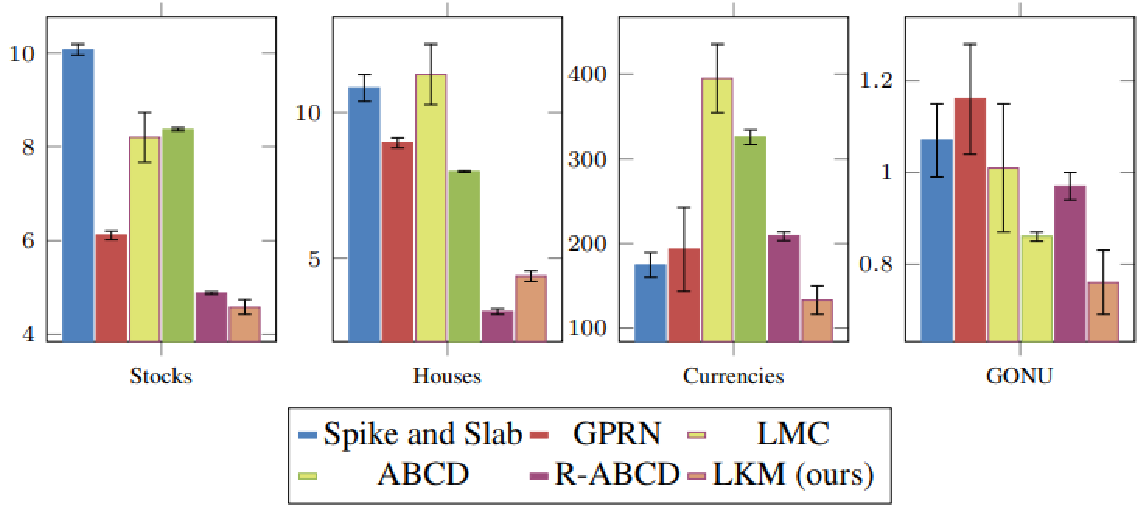


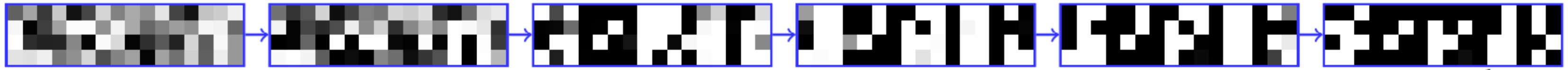

# Discovering Explainable Latent Covariance Structures for Multiple Time Series – Version II

Tong et al., 2018




(a) R-ABCD (b) LKM



initial $\boldsymbol{\nu}$ converged $\boldsymbol{\nu}$

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

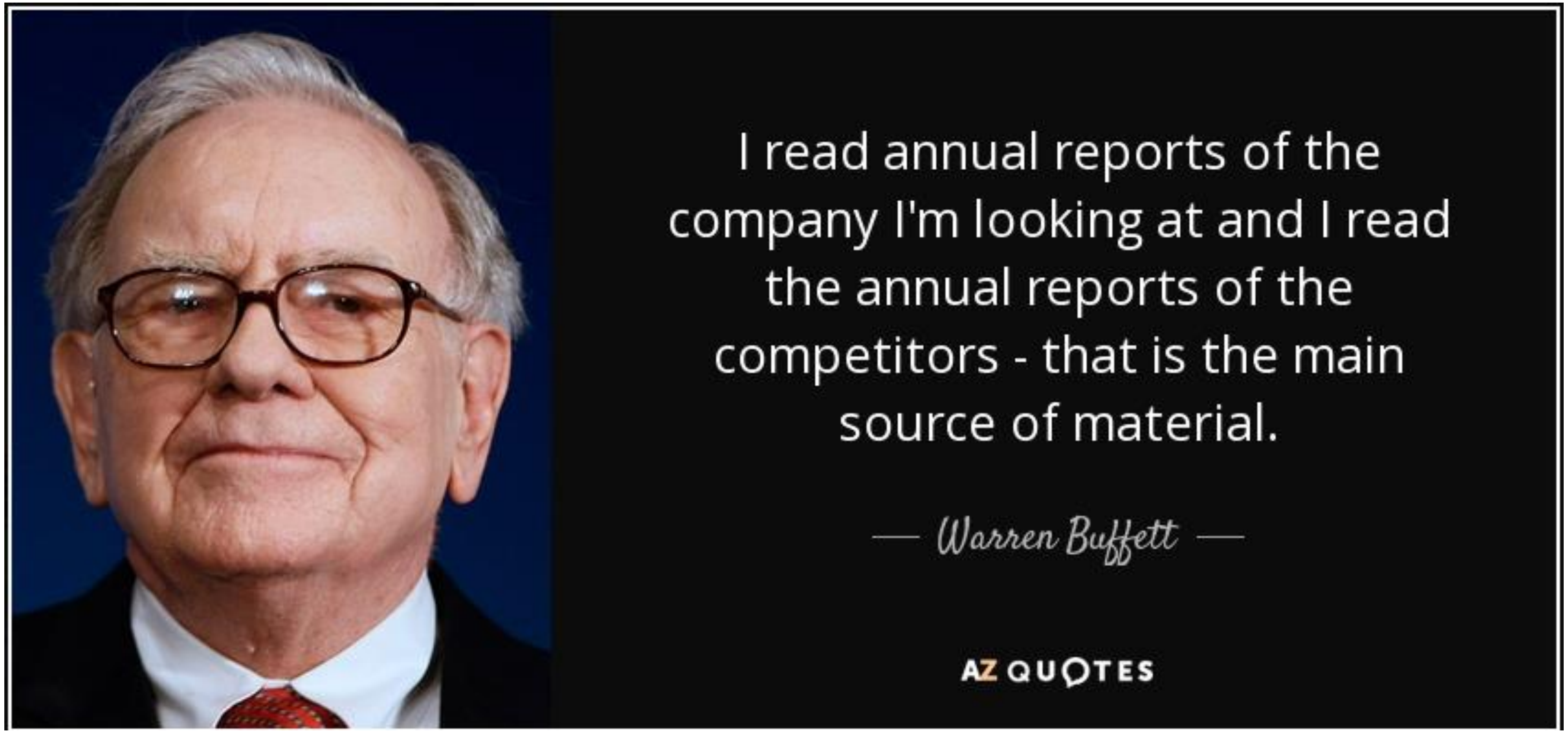
# Discovering Explainable Latent Covariance Structures for Multiple Time Series

Tong et al., 2018

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.

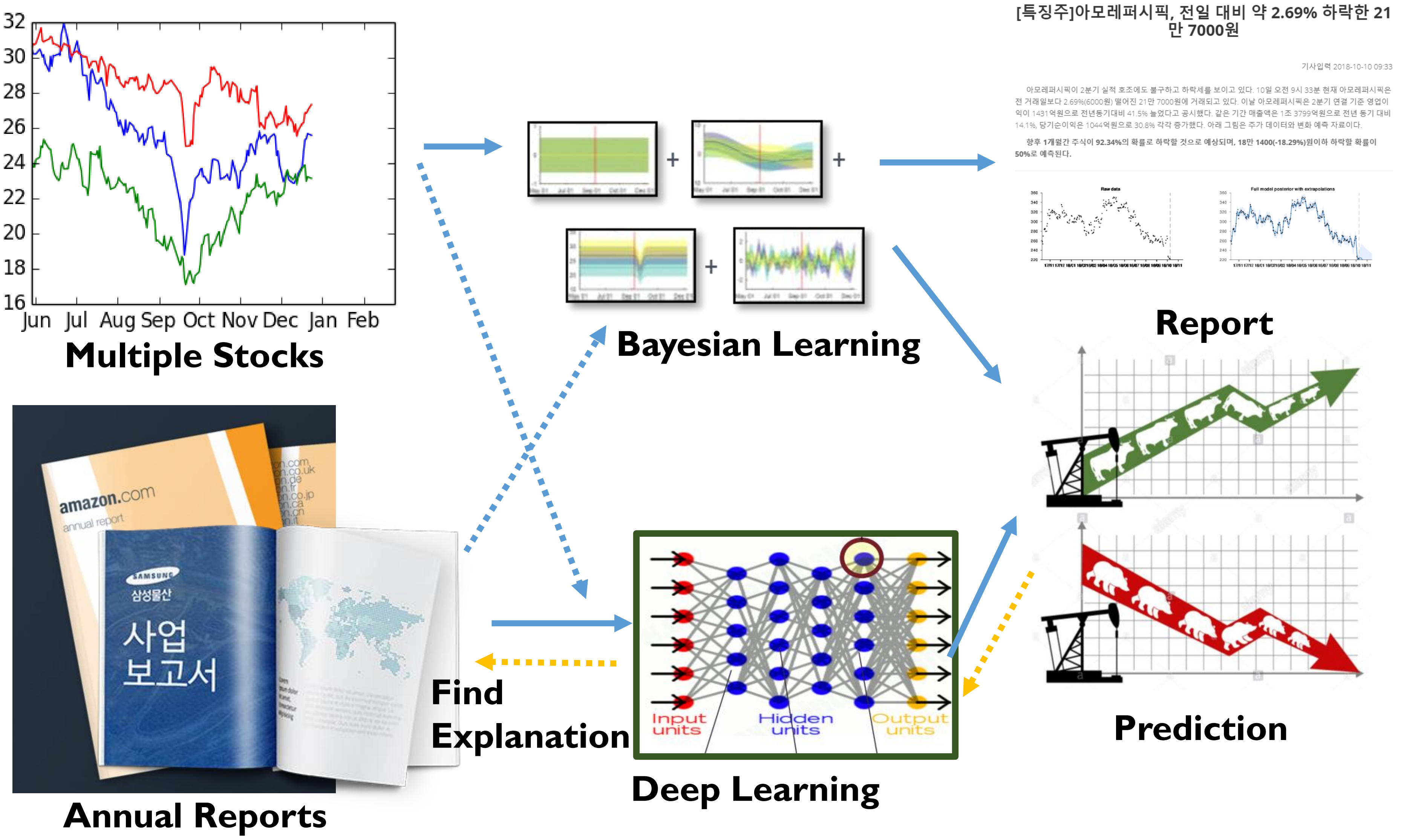
## Future: Toward Reading/Explaining Reports

**Beyond Chart-based Analysis**




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