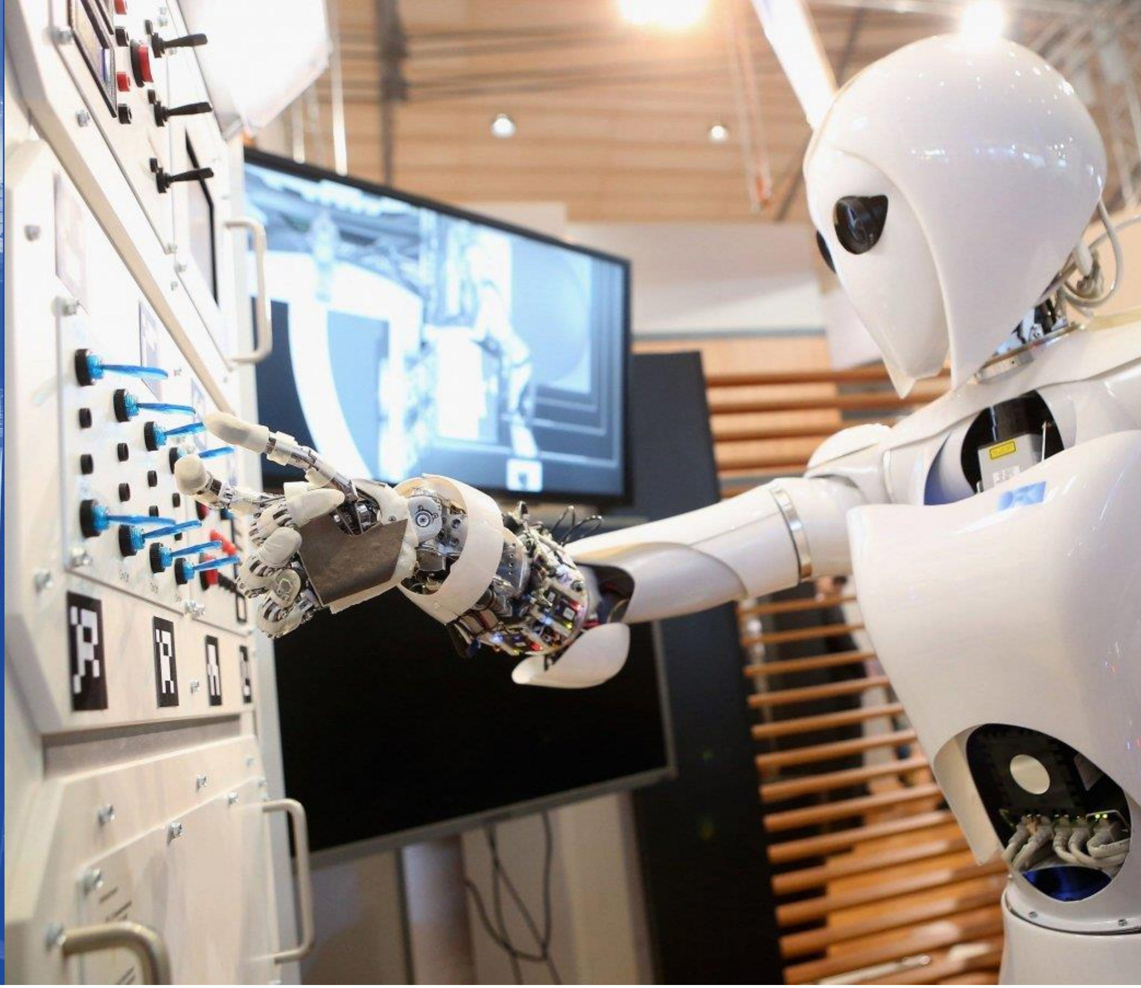
Explainable Artificial Intelligence for Financial Time Series*

UNIST

Jaesik Choi

Joint work with Anh Tong, Rafael Lima, Yeeun Chun, Eunji Bang and Yunseong Hwang



What is Explainable **A.I.**?

Artificial Intelligence

Finance

EU General Data Protection Regulation will be enforced (May. 2018)

- logic behind the automated algorithmic decision should be explained

US Equal Credit Opportunity Act/Fair Housing Act

- Reasons of decision on housing loan and credit decision should be explained

AI based credit rating systems

Pros	Cons
It is possible to find **hidden qualified clients** with deliberated analysis	The AI system may not be approved since it may not **clearly suggest the reasons of decisions.**

Issues

AI algorithms should be able to provide explanations of decisions

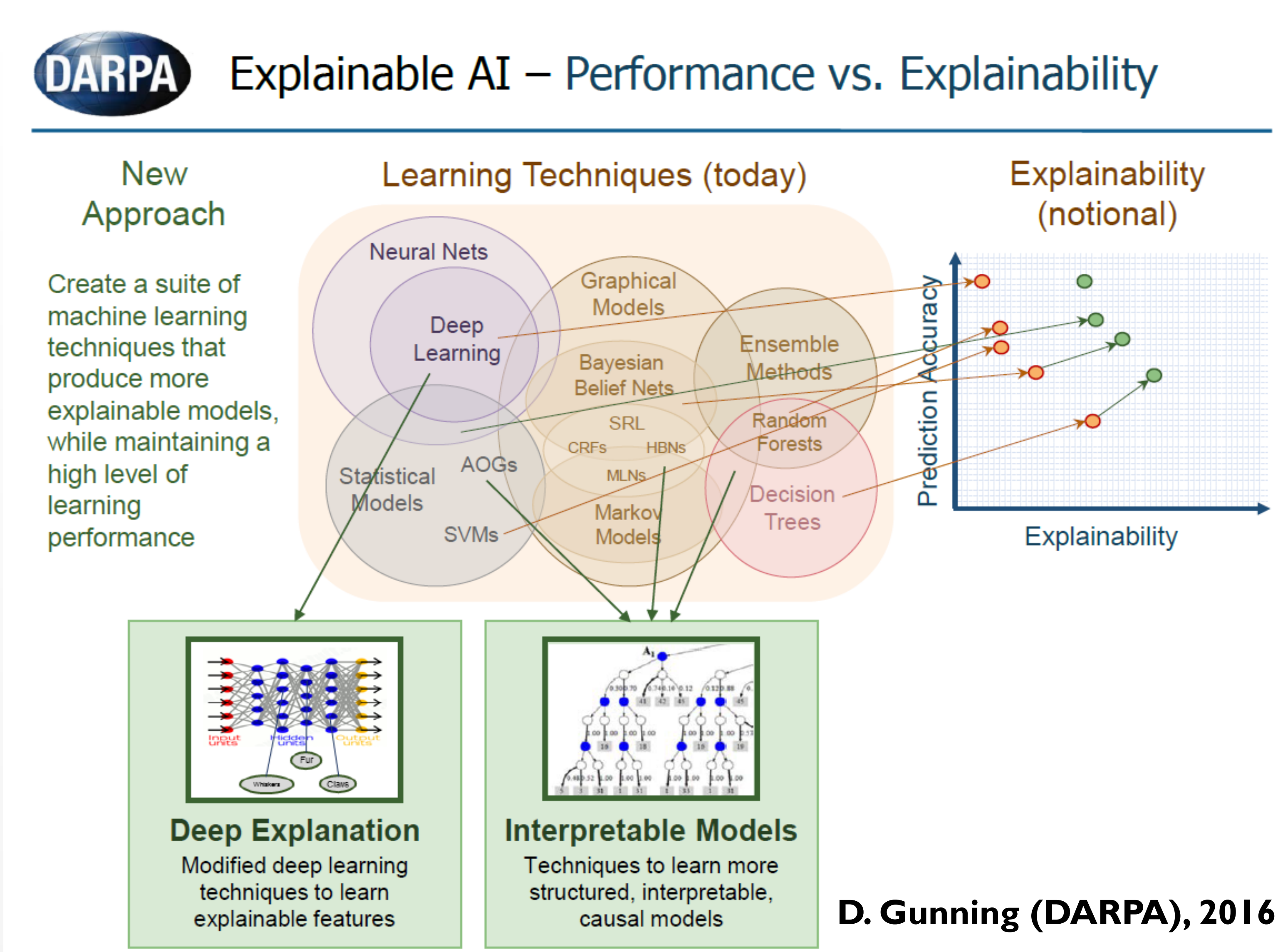
https://www.americanbanker.com/news/is-ai-making-credit-scores-better-or-more-confusing

Explainable Artificial Intelligence

EU General Data Protection Regulation

Article	Contents
17. Right to be forgotten	**An individual to have certain data deleted** so that third persons can no longer trace them
22. Automated individual decision making	The data **subject** shall **have the right not to be subject** to a decision based solely on **automated processing (including profiling)**.
13-14. **Right to explanation**	A data subject has the right to "**meaningful information about the logic involved**."
EU administration	When violated **4% of global revenue** will be fined.
Enact	**May 28th, 2018**

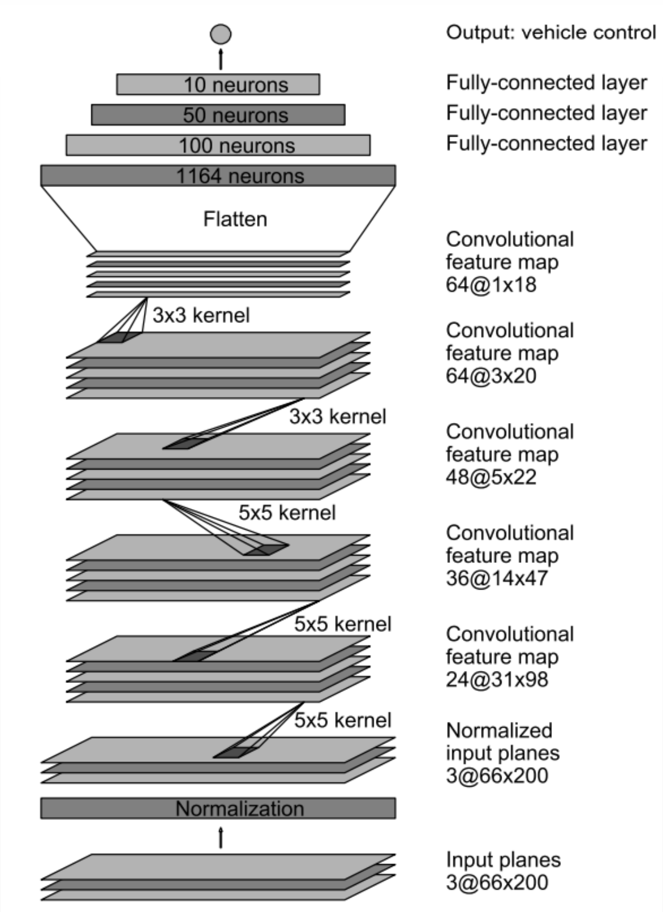
EU General Data Protection Regulation



DARPA Explainable AI

[D. Gunning (DARPA), 2016]

Explaining the decision of NVIDIA PilotNet (Automatic Driving)

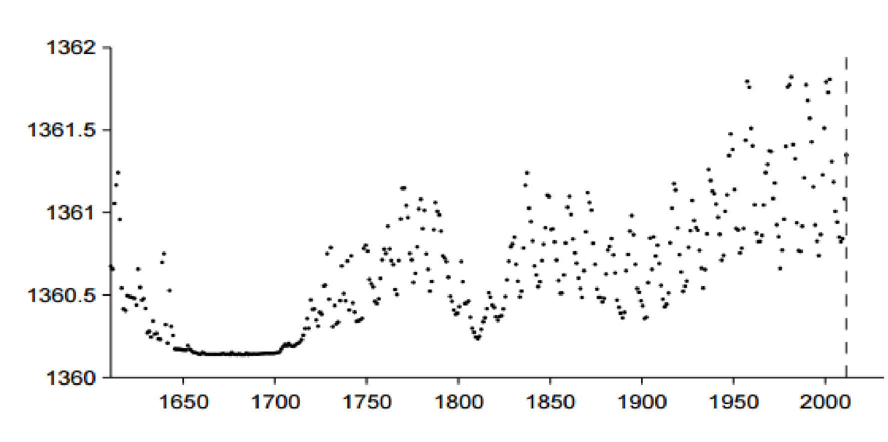


PilotNet architecture

Highlighting the parts of images which affect turning steering wheel

Explainable Deep Neural Networks
[NVIDIA & Google , 2017]

Activity of sunspots



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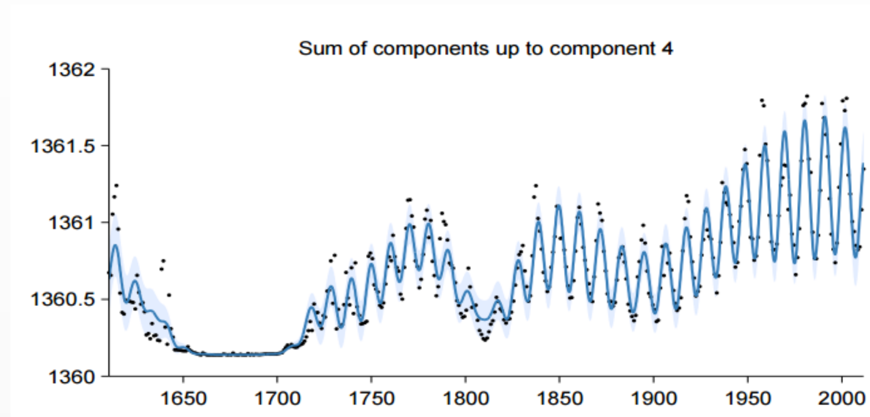

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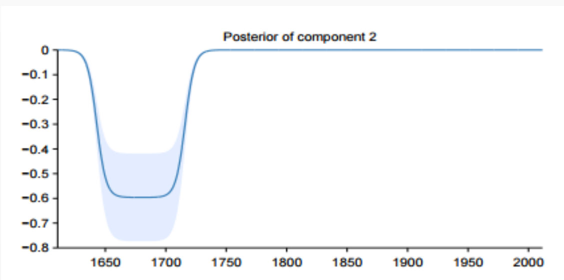

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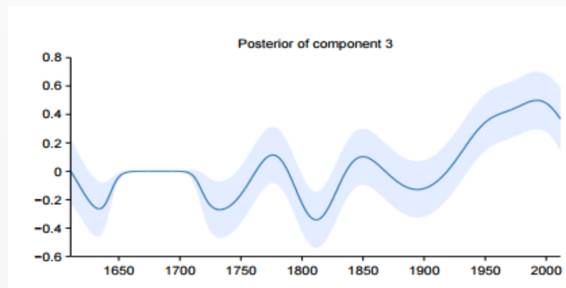

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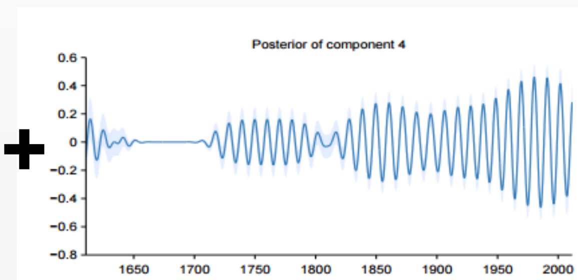
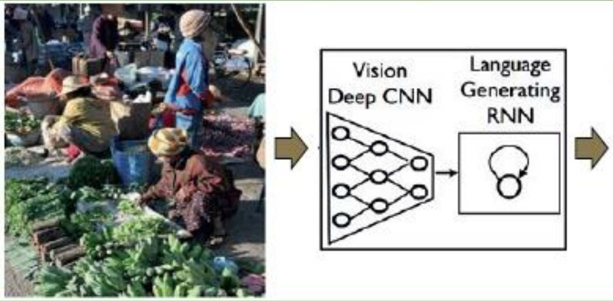


The Automatic Statistician

[Z. Ghahramani’ group (Cambridge), J. Tenenbaum’s group (MIT), 2014)]

Generating Image Captions

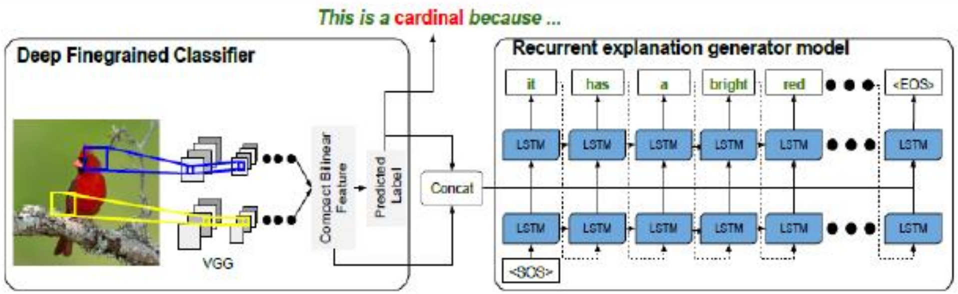


A group of people shopping at an outdoor market

There are many vegetables at the fruit stand

- A CNN is trained to recognize objects in images
- A language generating RNN is trained to translate features of the CNN into words and captions.

Generating Visual Explanations



Researchers at UC Berkeley have recently extended this idea to generate explanations of bird classifications. The system learns to:

- Classify bird species with 85% accuracy
- Associate *image descriptions* (discriminative features of the image) with *class definitions* (image-independent discriminative features of the class)

Example Explanations

This is a Kentucky warbler because this is a yellow bird with a black cheek patch and a black crown.

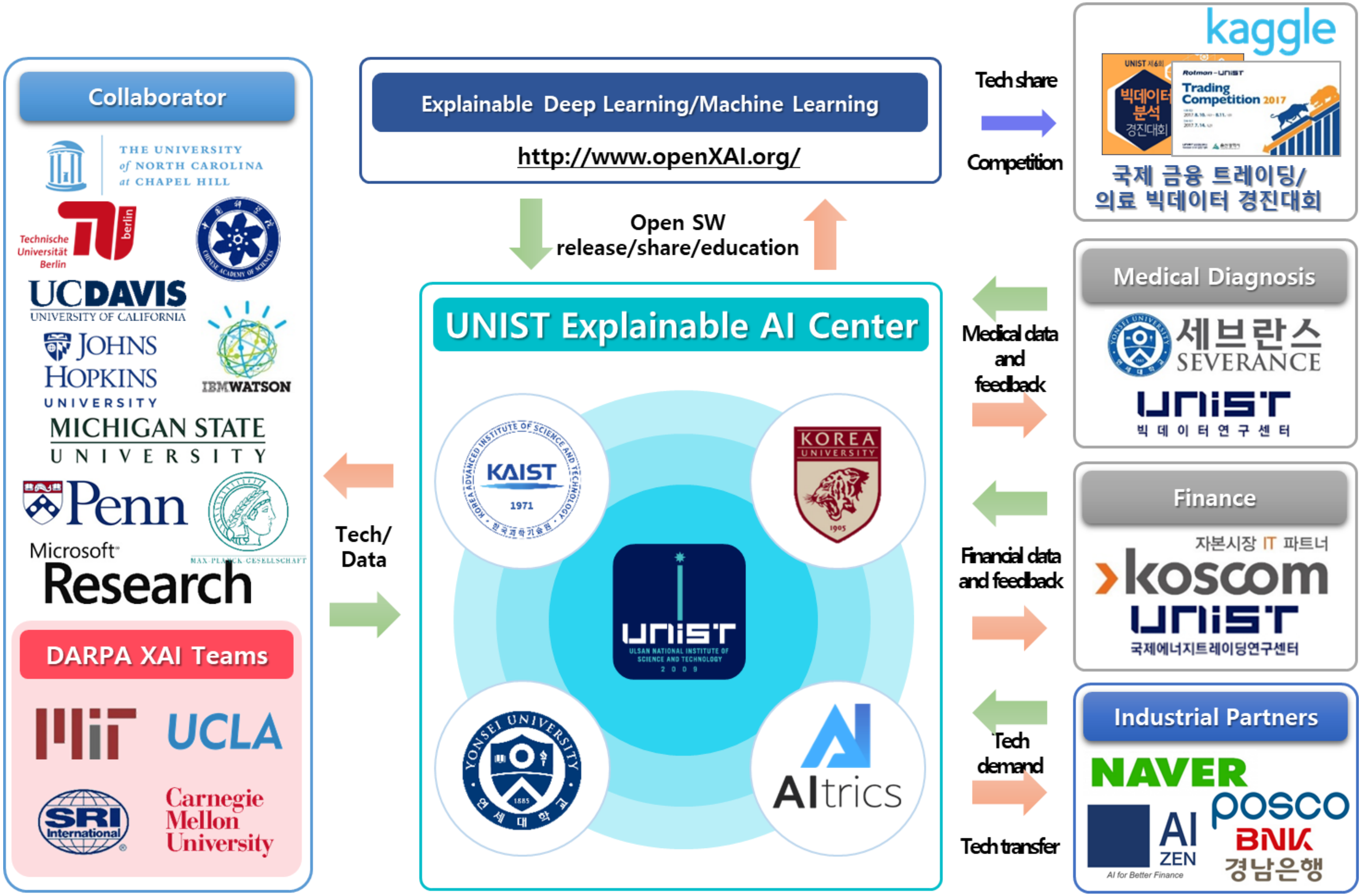
This is a pied billed grebe because this is a brown bird with a long neck and a large beak.

Limitations

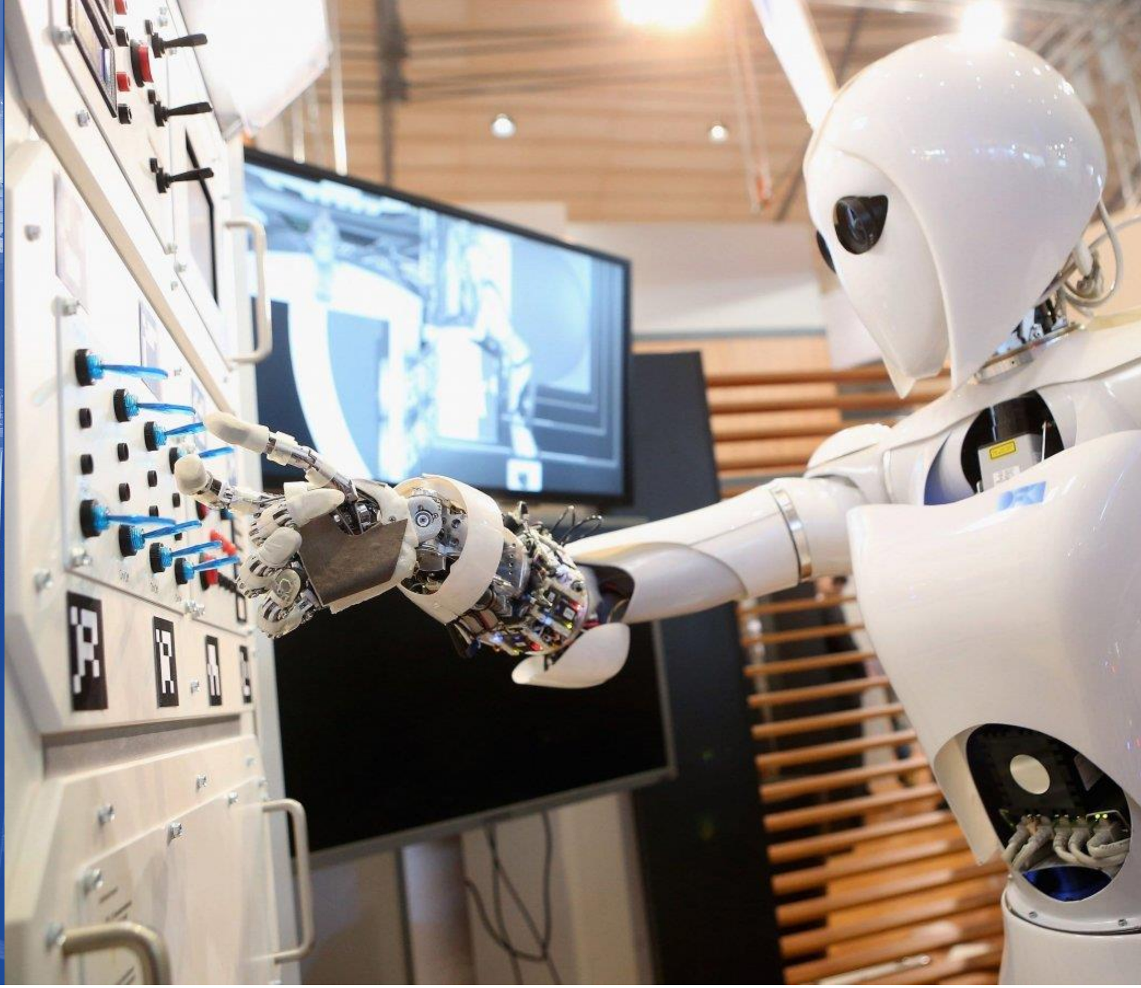
- Limited (indirect at best) explanation of internal logic
- Limited utility for understanding classification errors

Explaining object detection in images

[T. Darrell's group (Berkeley), B. Schiele's group (Max Planck), 2016]

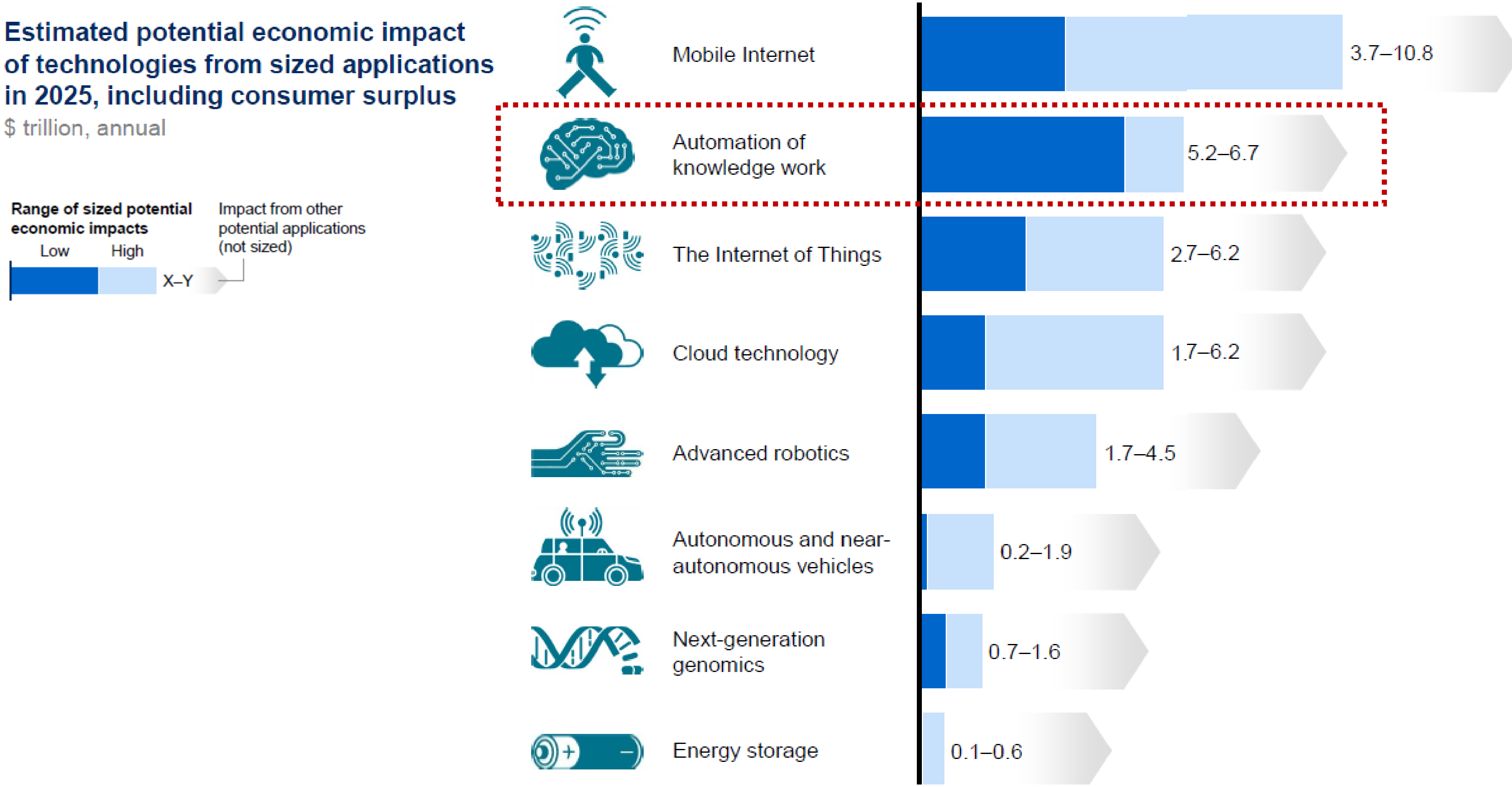


UNIST Explainable AI Center



Motivation: What is the future of **A.I.**?

Artificial Intelligence



Estimated Economic Impact of Disruptive Technology

[McKinsey 2013]

The technical potential for automation in the US

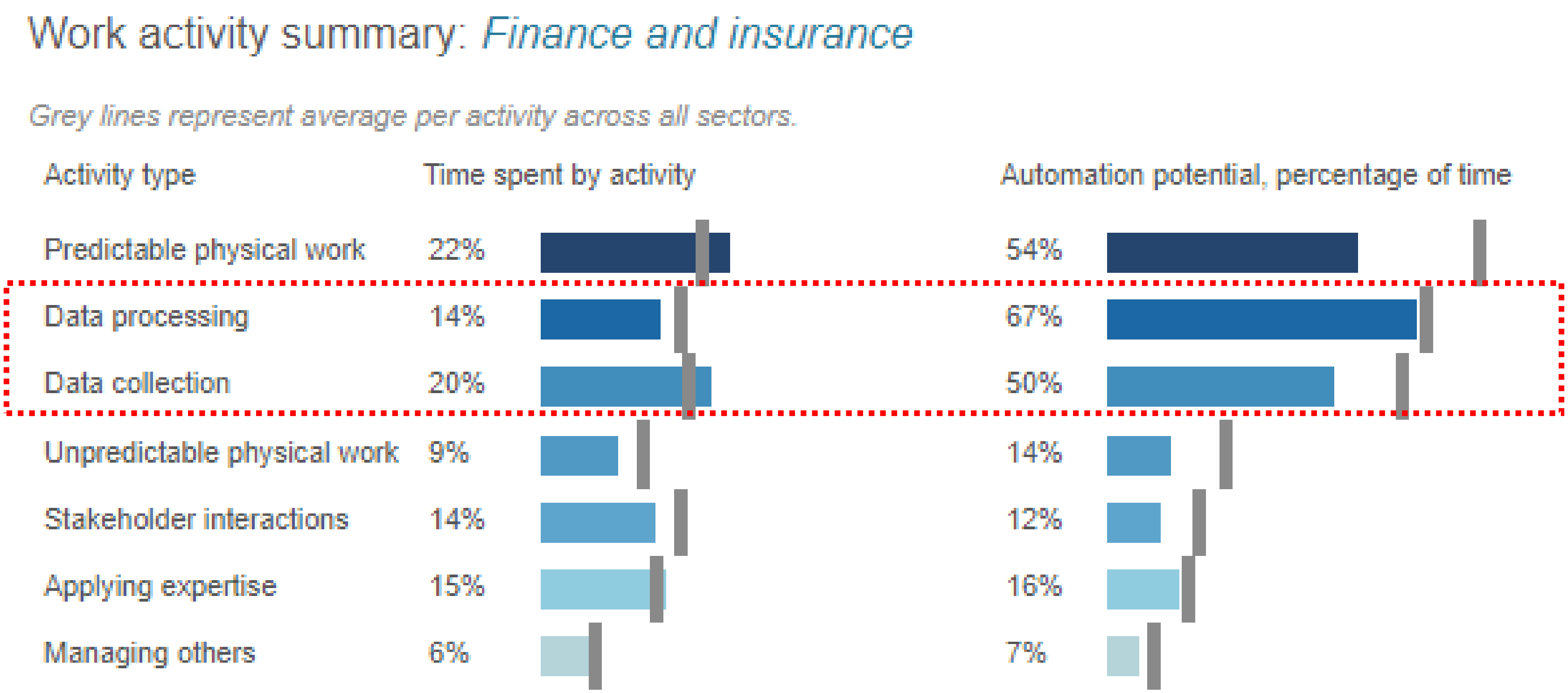
Many types of activities in industry sectors have the technical potential to be automated, but that potential varies significantly across activities.

Technical feasibility: % of time spent on activities that can be automated by adapting currently demonstrated technology

0 50 100

Automation of Knowledge Work

[McKinsey 2013]



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

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

[Automated Insights, 2017]

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.

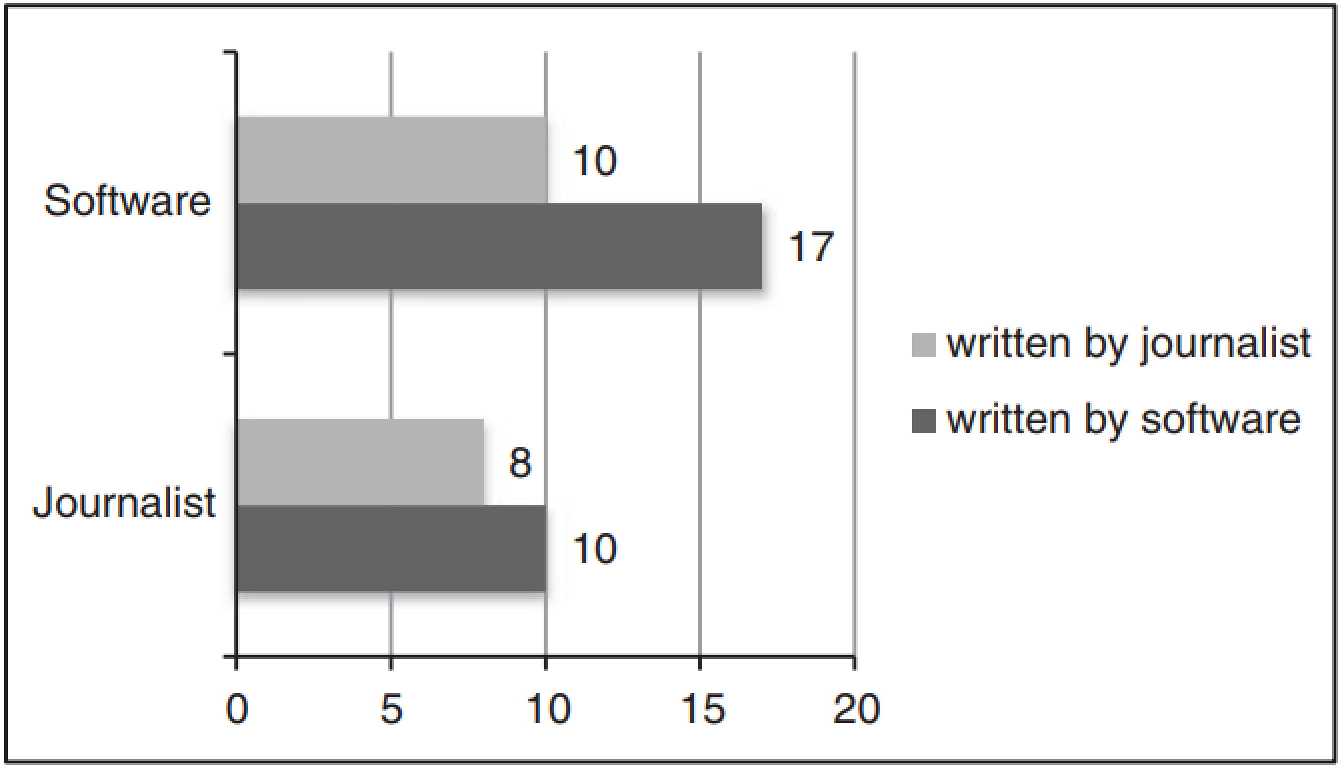
Anders Mathison ended up on wrong side of the pitching decision, charged with the loss. He lasted just two innings, walked two, struck out one, and allowed four runs.

Automated generated by Quill, Narrative Science

Automated Narrative Generation

[Narrative Science, 2015]

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.

…

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An Old-School AI Strategy: Template

[Automated Insights, 2017]

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Generated by Quill, Narrative Science

An Old-School AI Strategy: Template

[Narrative Science, 2015]

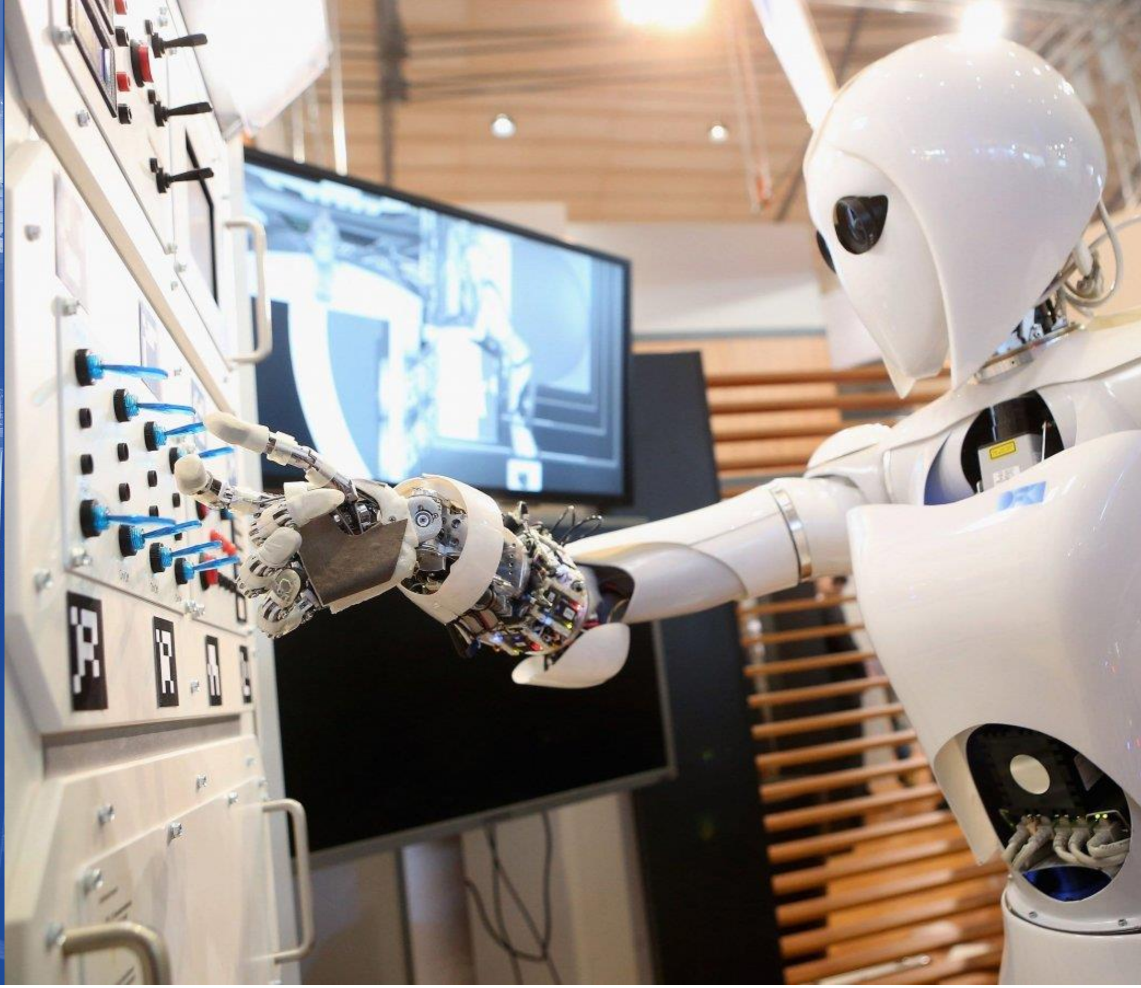
The deeper challenge lies not in generating copy, but in finding the most pertinent meaning in a given dataset.

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

"Those numbers need context"

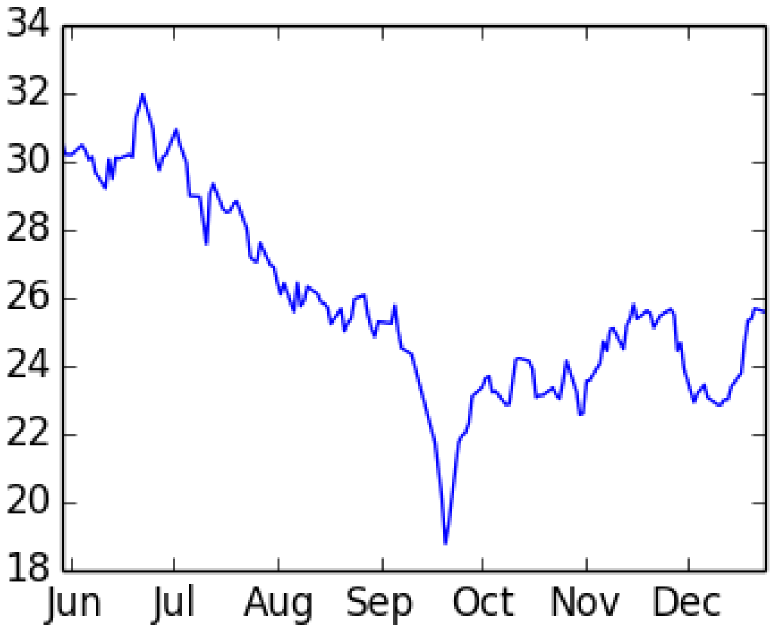
Challenges in Algorithmic Authors

[Wright, CACM, 2015]



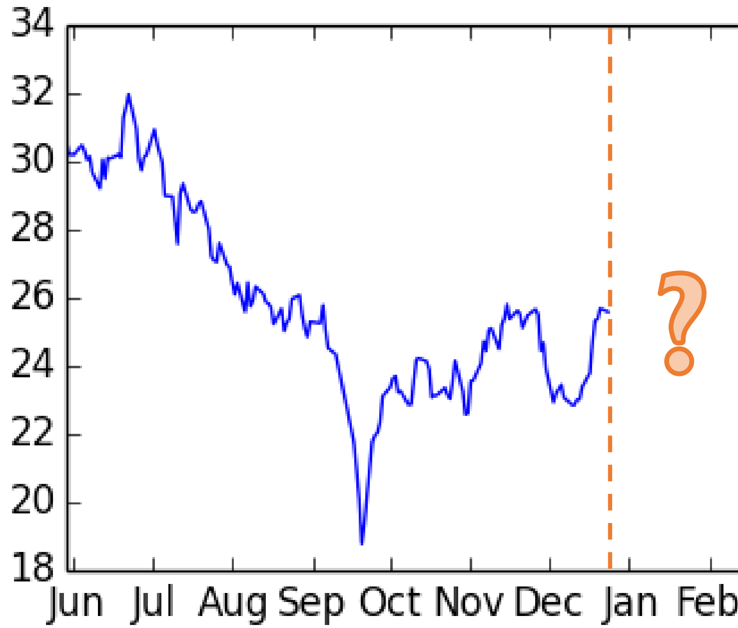
Finding Context in Time Series Data

Descriptive prediction of time series



Problem

Descriptive prediction of time series



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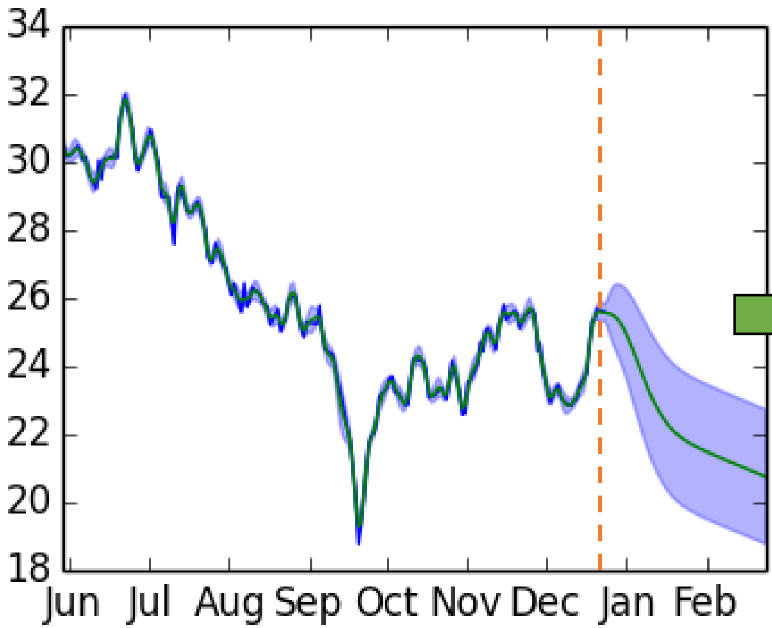
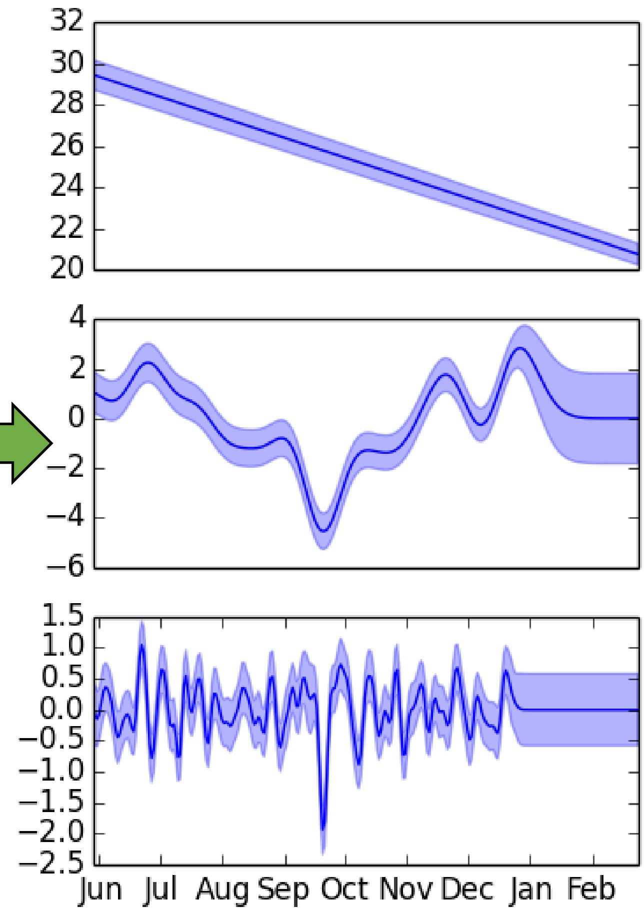
Descriptive prediction of time series





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

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

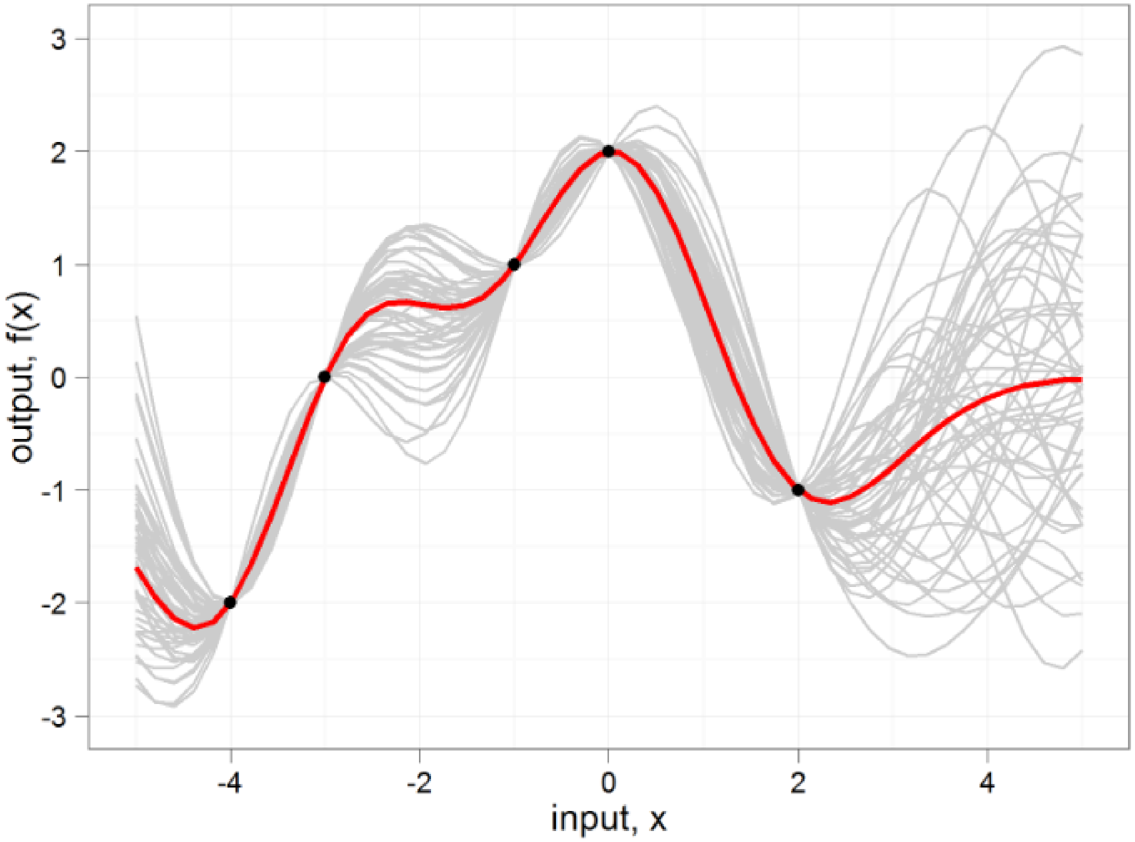
$$[f(x_1), \ldots, f(x_N)] \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

Function evaluations

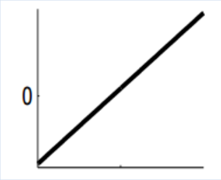
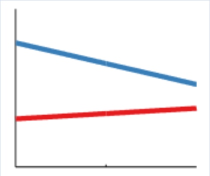
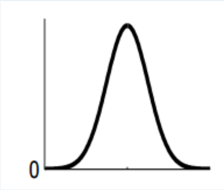
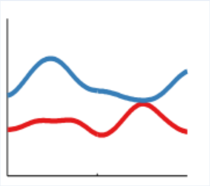
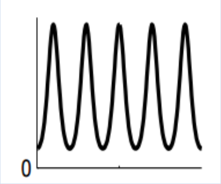
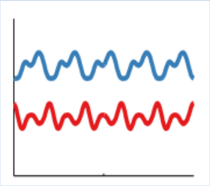
Multivariate Gaussian

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	$\sigma^2(x-\ell)(x'-\ell)$	σ, ℓ		
$\mathrm{SE}(x, x')$	Smooth function	$\sigma^2 \exp\left(-\frac{(x-x')^2}{2\ell^2}\right)$	σ, ℓ		
$\mathrm{PER}(x, x')$	Periodic function	In appendix	σ, ℓ, 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

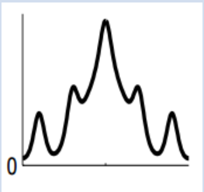
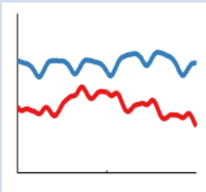
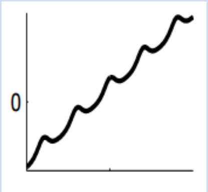
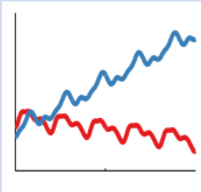
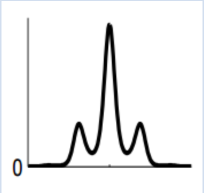
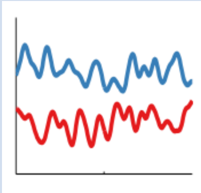
$$g(x) + h(x) \sim \mathcal{GP}(0, k_g + k_h)$$

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

The Automatic Statistician

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

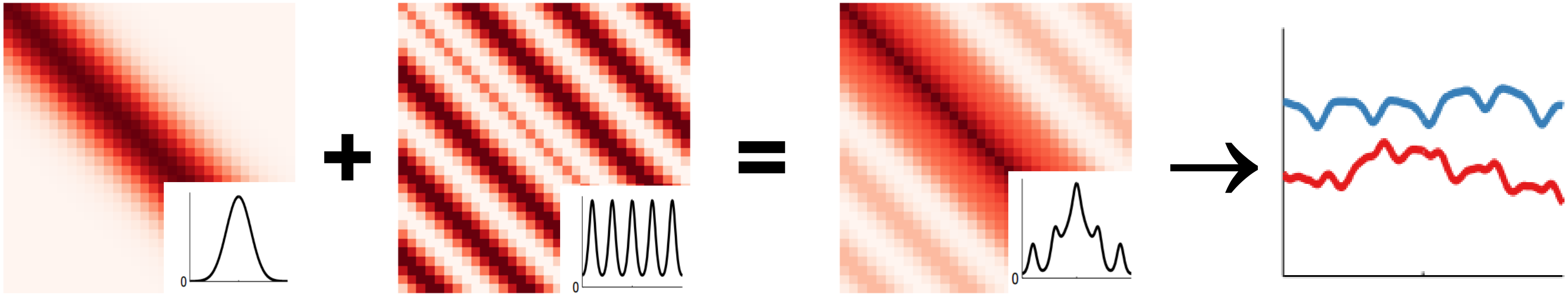
[Ghahramani. Nature. 2015.]

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

The Automatic Statistician – Kernel Composition

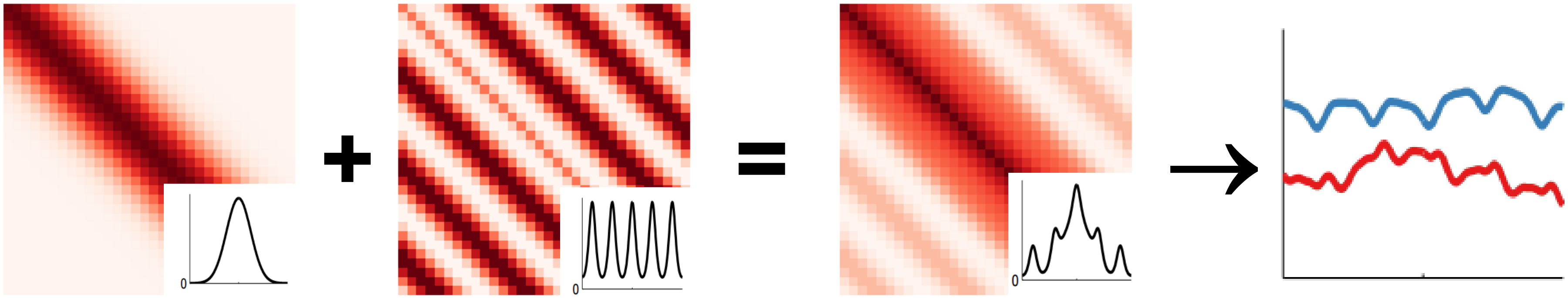
[Grosse et. al. UAI. 2012.]

Kernel Composition: Generate Data from Models

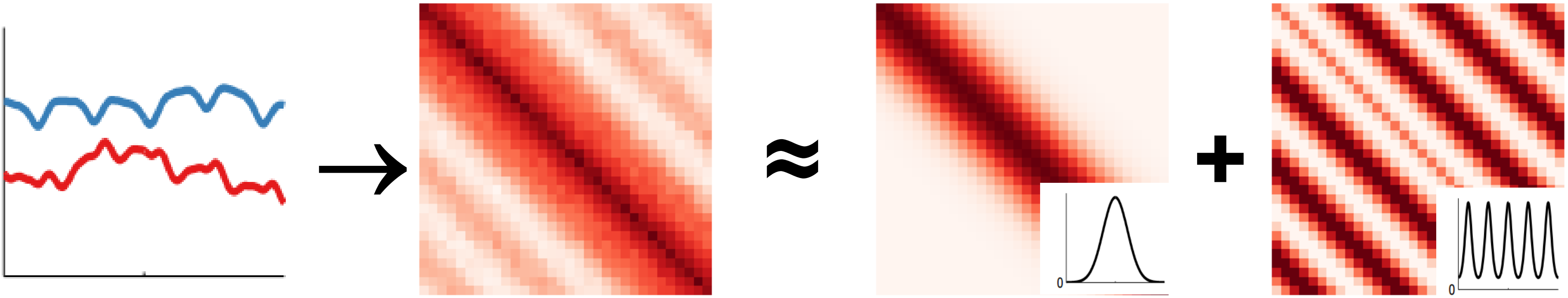


Kernel Composition & Covariance Decomposition

Kernel Composition: Generate Data from Models



Covariance Decomposition: Learn Explainable Models from Data



Kernel Composition & Covariance Decomposition

(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)

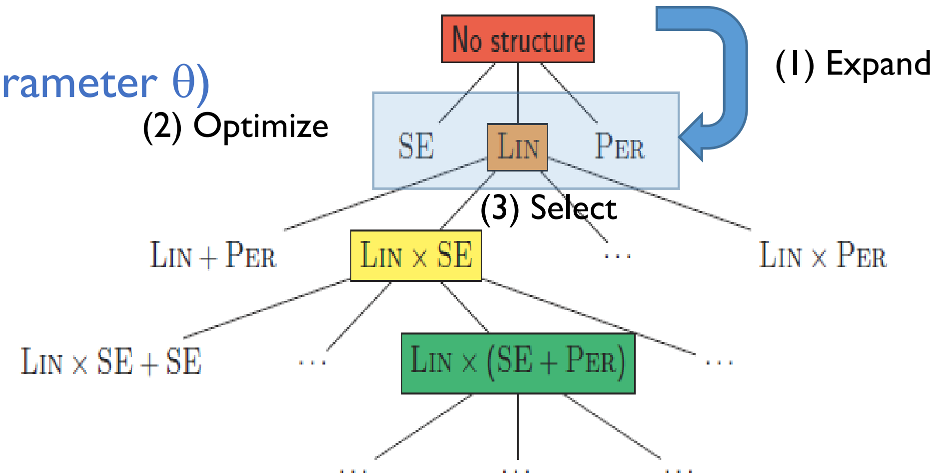
❖ Iteratively select best model (structure k, parameter θ)

(1) Expand: the current kernel

(2) Optimize: conjugate gradient descent

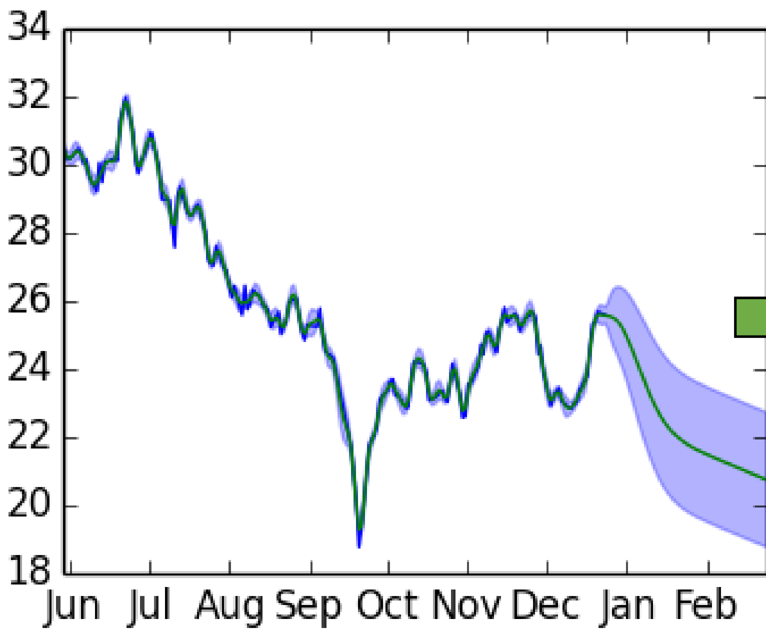
(3) Select: the best kernel in the level (greedy)

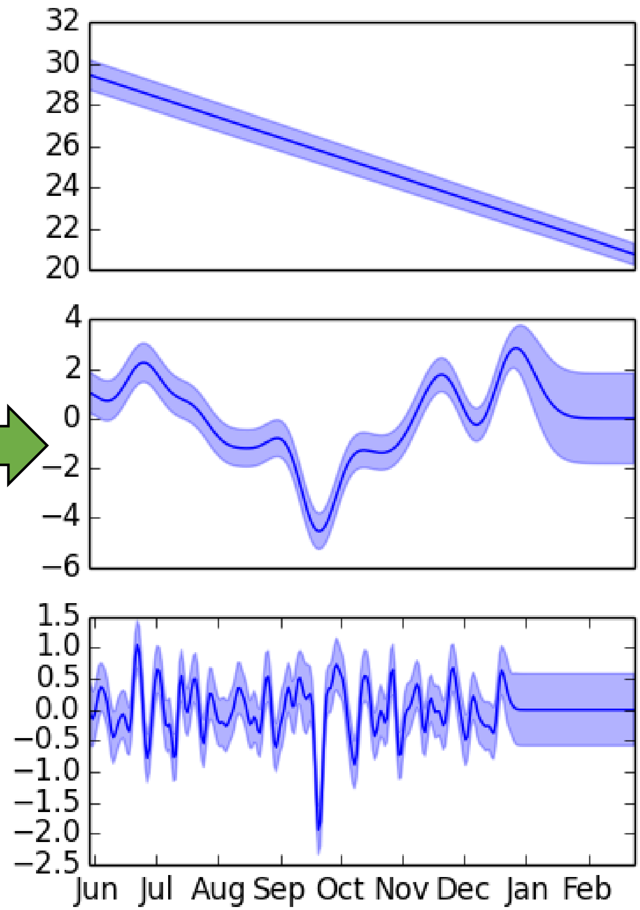
(4) Iterate: get back to (1) for the next level



The Automatic Statistician – Greedy Kernel Search

[Duvenaud et. al. UAI. 2012.]





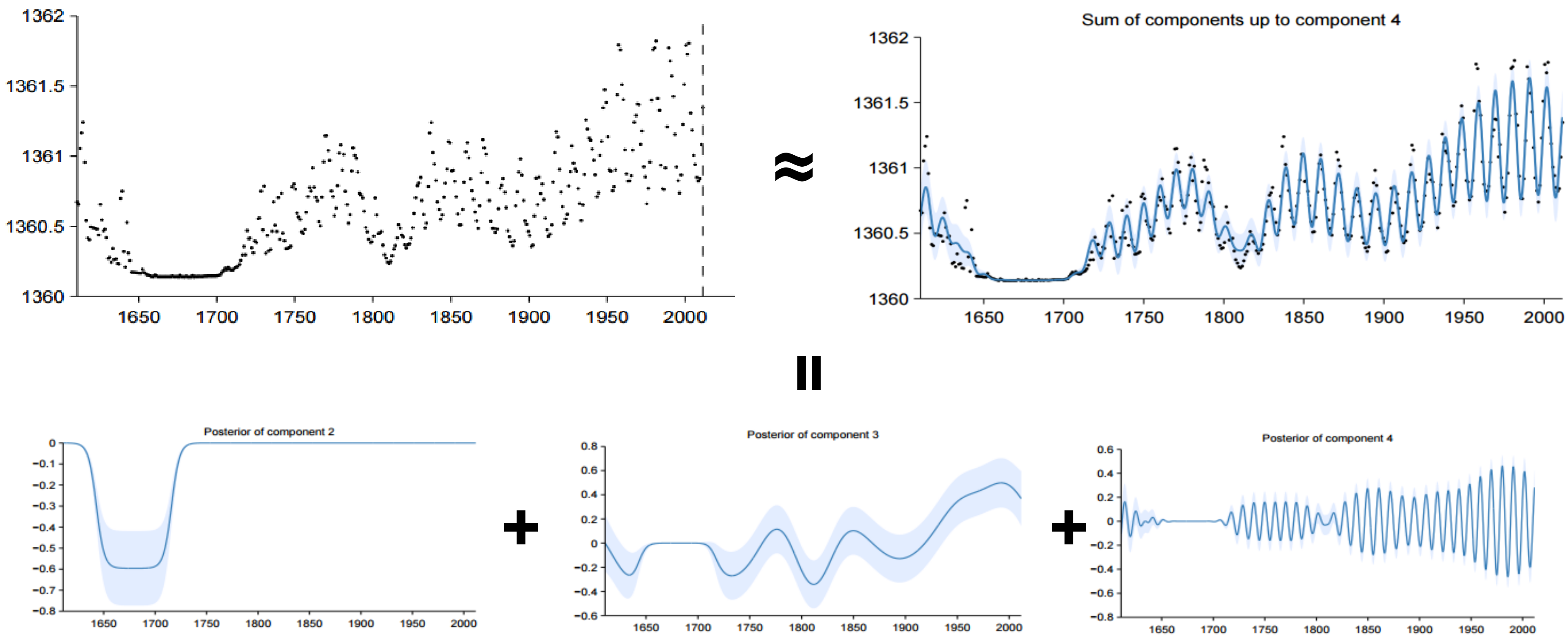
Linear function
decrease x/week

Smooth function
Length scale: y weeks

Rapidly varying
smooth function
Length scale: z hours

The Automatic Statistician – A Sample Report

[Lloyd et, al. AAAI. 2014.]



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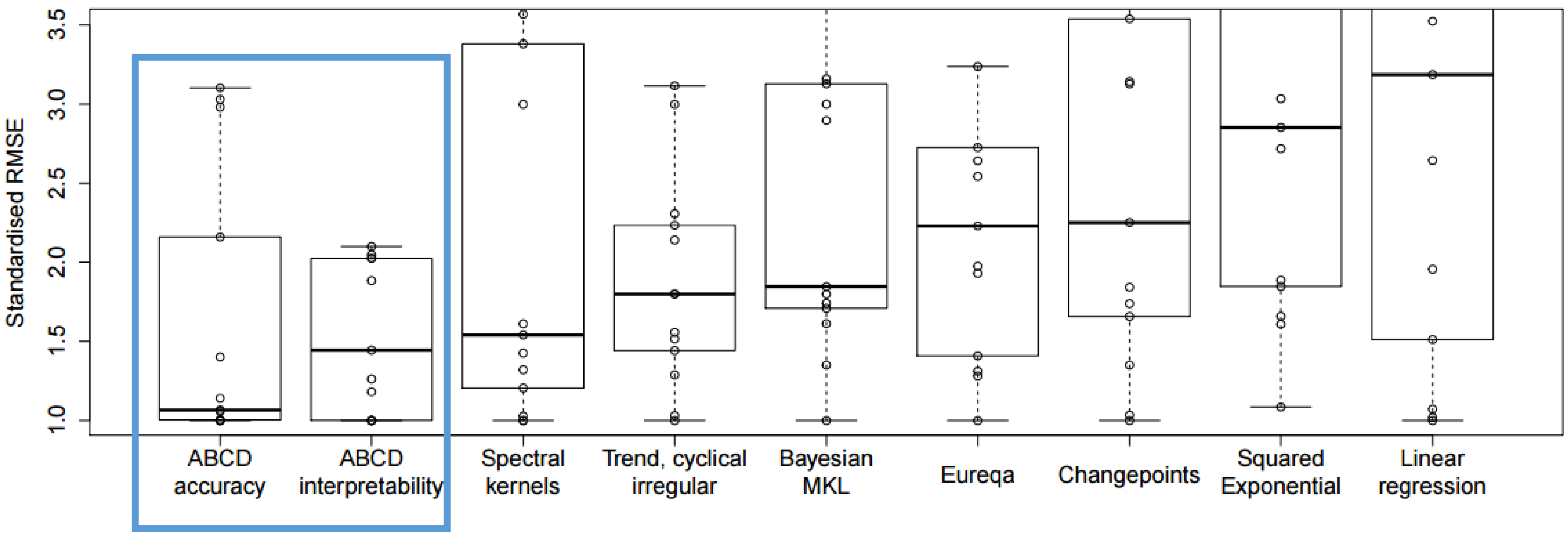
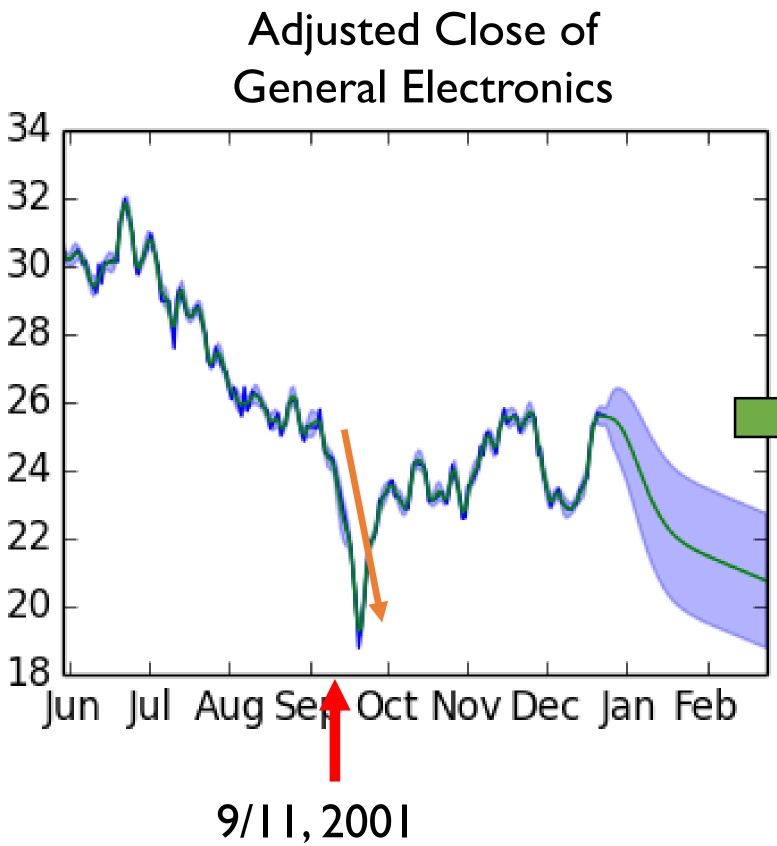
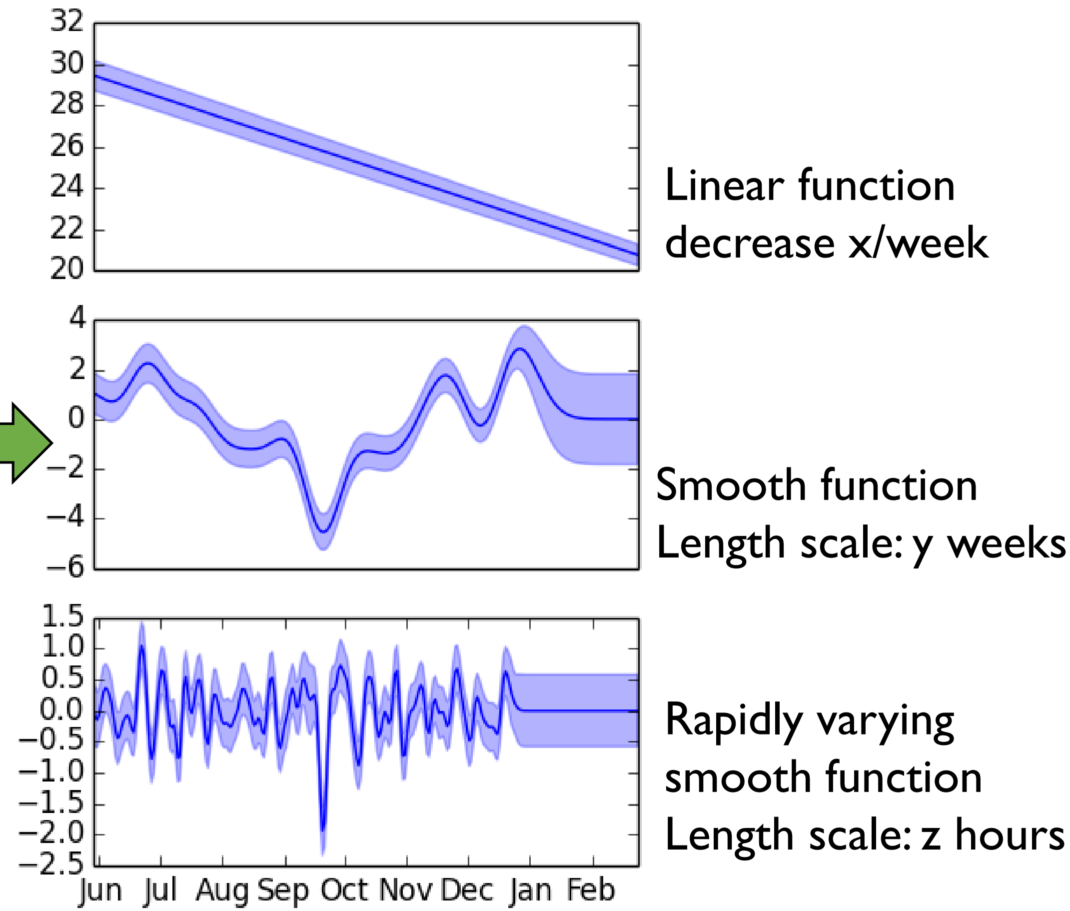


13 regression datasets

The Automatic Statistician – Extrapolation Performance

[Lloyd et, al. AAAI. 2014.]

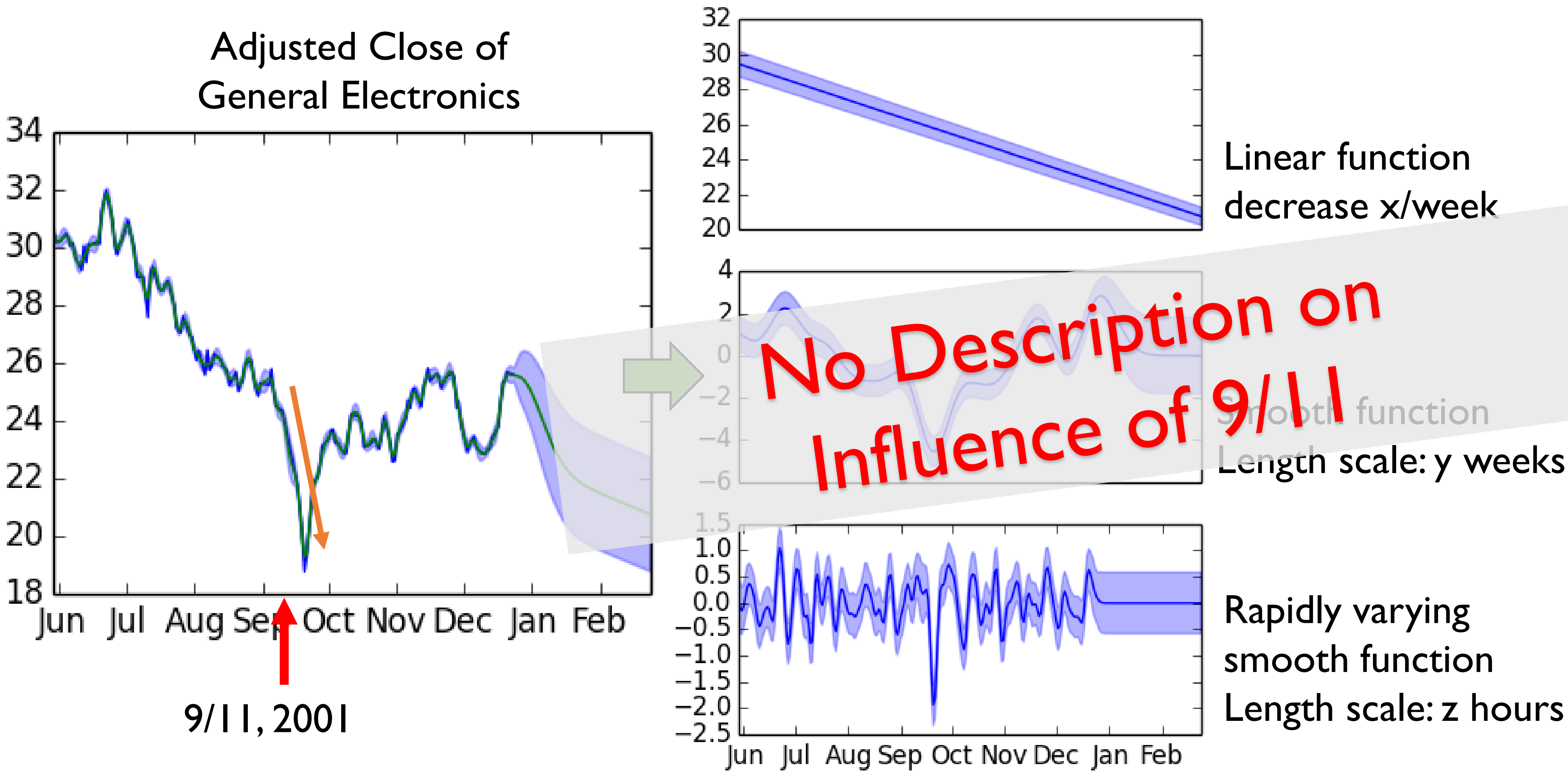




Challenge: The Automatic Statistician

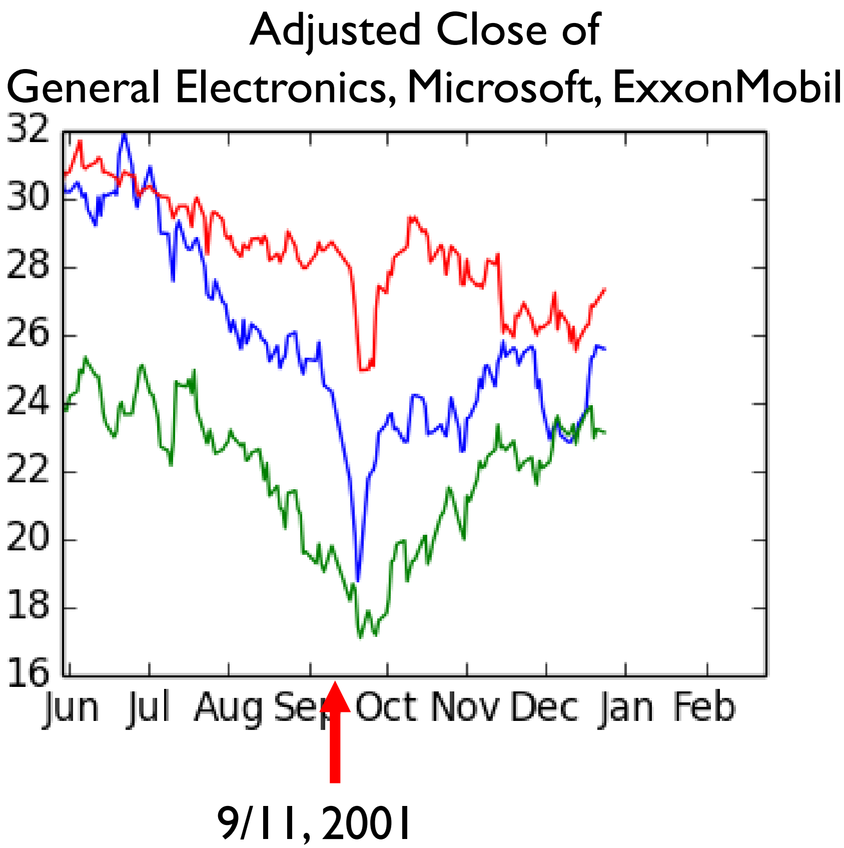
Incorporating Global Changes

Adjusted Close of General Electronics



Challenge: The Automatic Statistician

Incorporating Global Changes

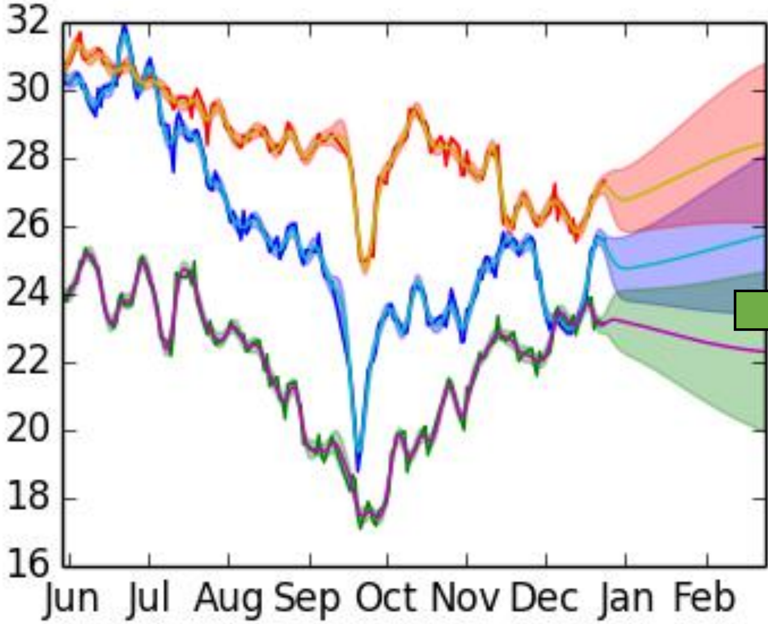


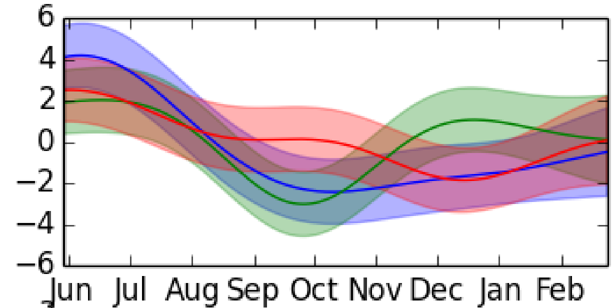
- Exploit multiple time series
- Find global descriptions
- Hope better predictive performance

Challenge: The Automatic Statistician

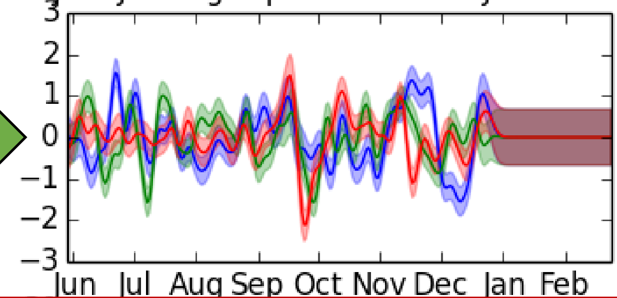
Q: How about handling multiple time series?

Descriptive prediction of multiple time series

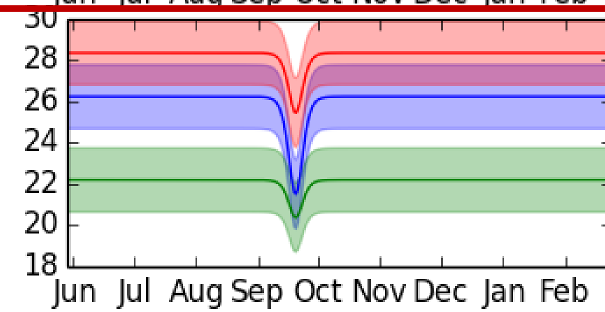




Smooth function
Length scale: y weeks

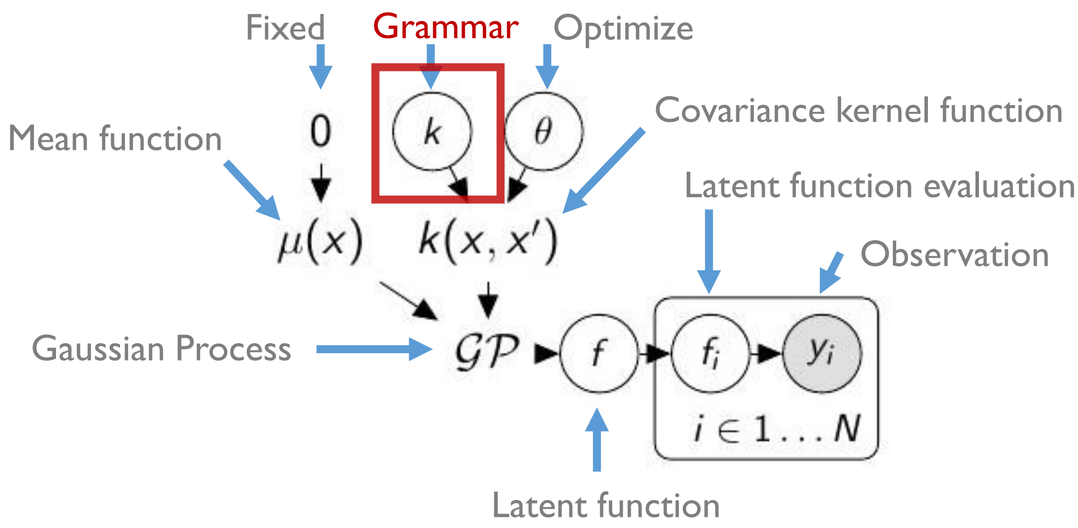


Rapidly varying
smooth function
Length scale: z hours



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

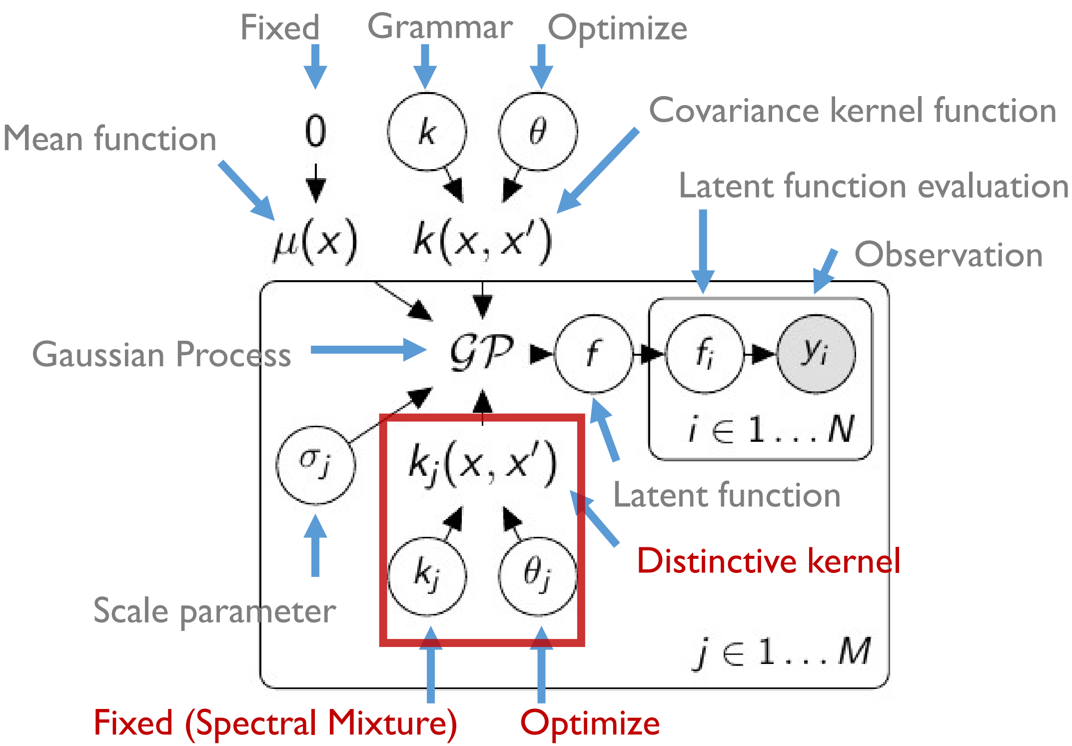
Problem (Our research)



A Generalized Multi Kernel Learning

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

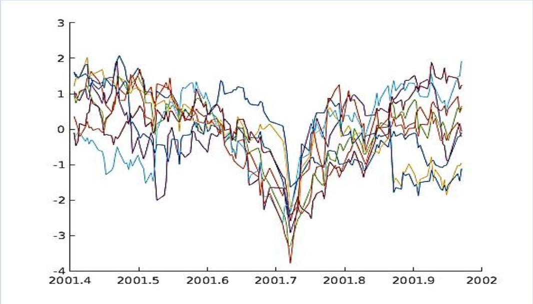
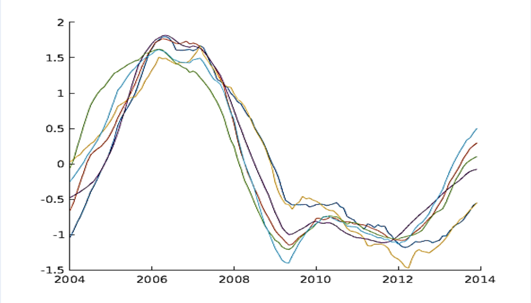
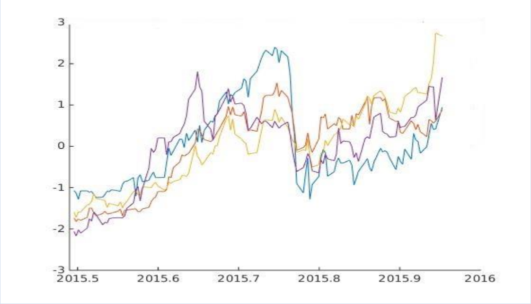
Model: Composite Kernel Learning
(The Automatic Statistician)



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

Model: Semi-Relational Kernel Learning

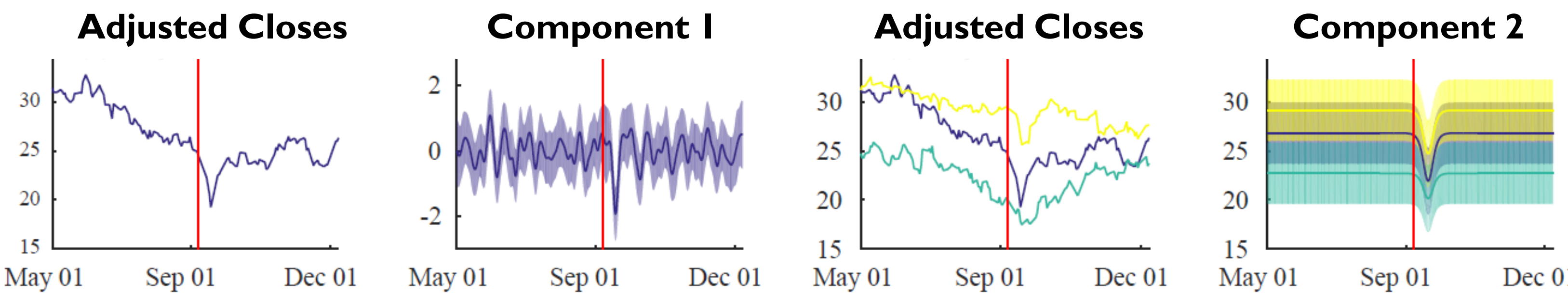
[Hwang; Tong; Choi. ICML. 2016]

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

Experiments on Financial Data Sets

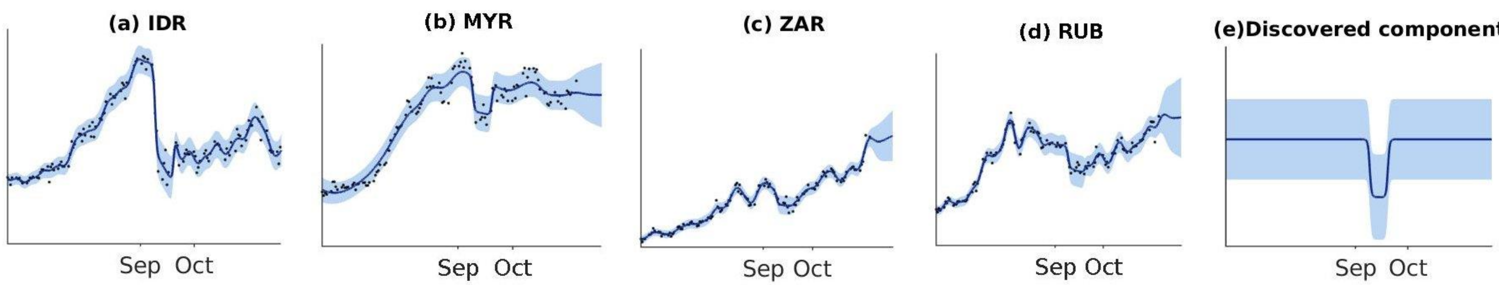
[Hwang; Tong; Choi. ICML. 2016]

Automatic Statistician | Relational Automatic Statistician



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

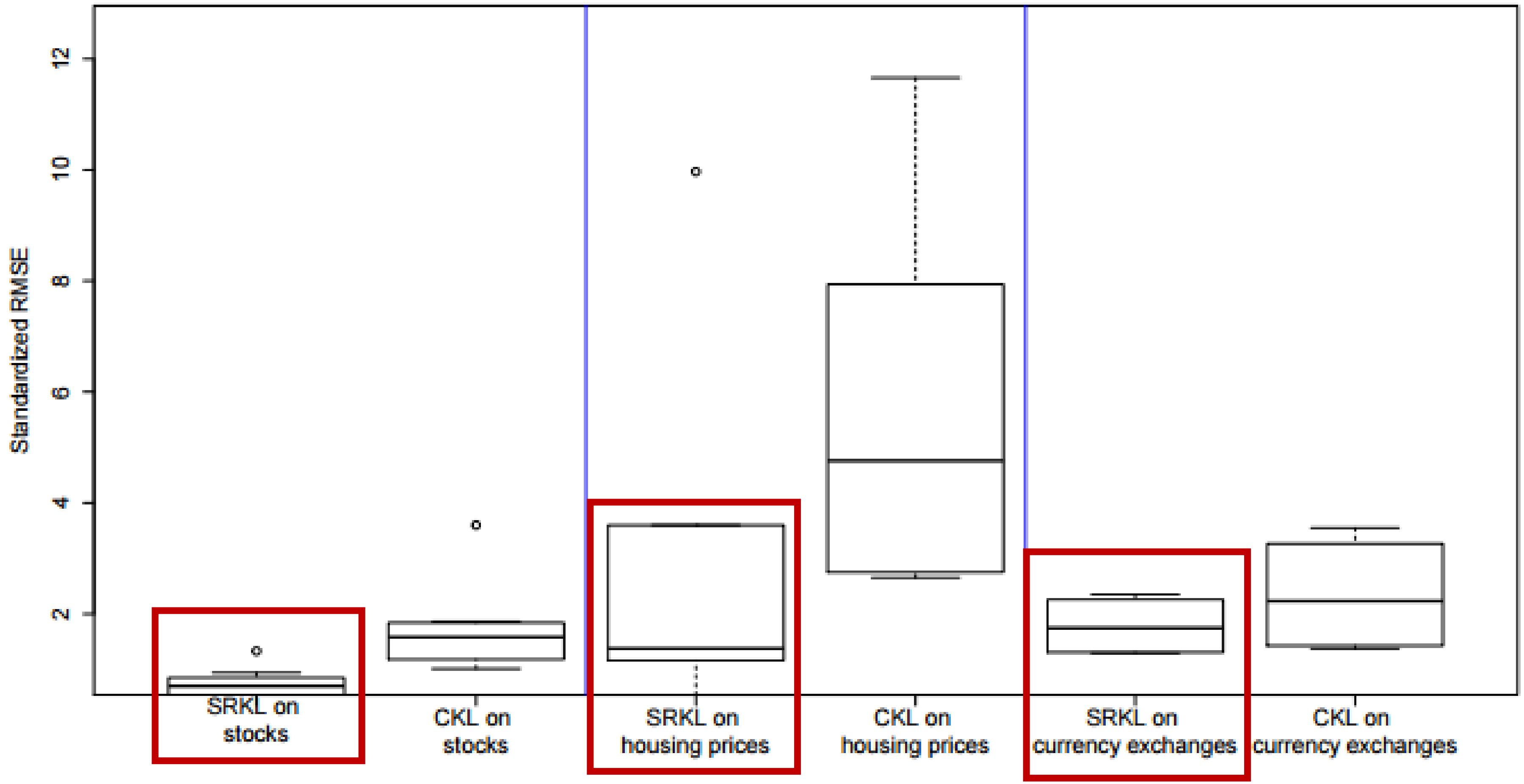
4 currency exchange rates | Learned component



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

Qualitative Results

[Hwang; Tong; Choi. ICML. 2016]



9 stocks

6 house price indices

4 currency exchanges

Quantitative Results

[Hwang; Tong; Choi. ICML. 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}

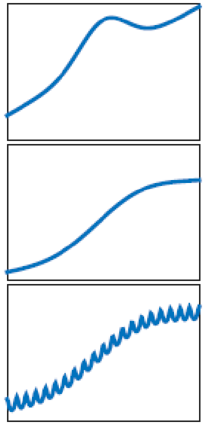
HOUSE4 = HOUSE2 + {Chicago, Pheonix}

HOUSE6 = HOUSE4 + {San Diego, San Francisco}

CURRENCY4 = {IDR, MYR, ZAR, RUB}

Quantitative Results

[Hwang; Tong; Choi. ICML. 2016]

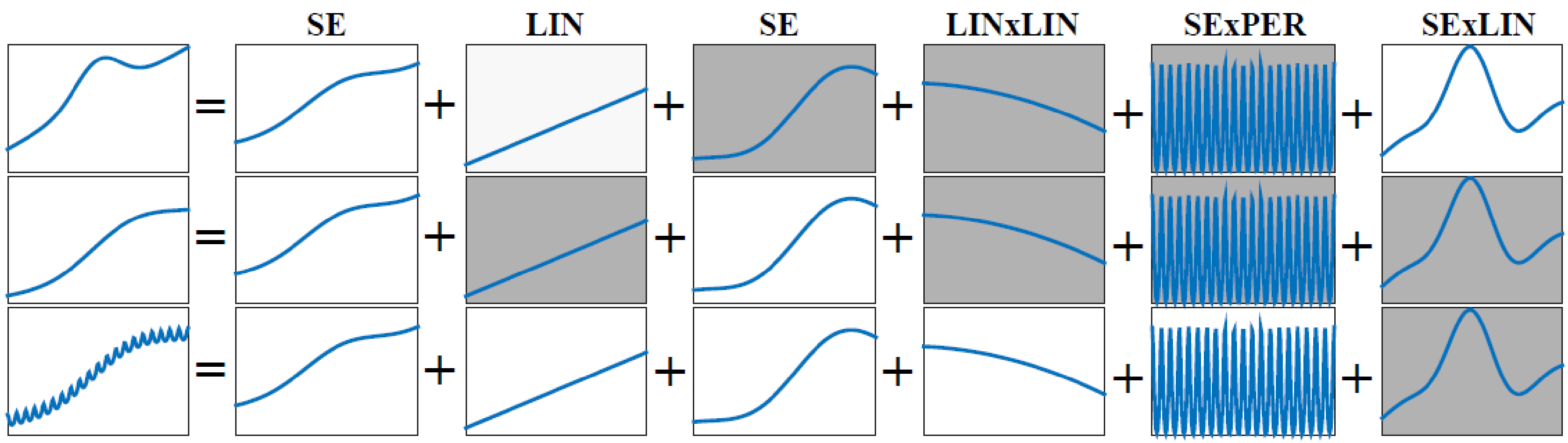


Challenges: Selective Kernel Search

Q: Can we selectively search over time series?

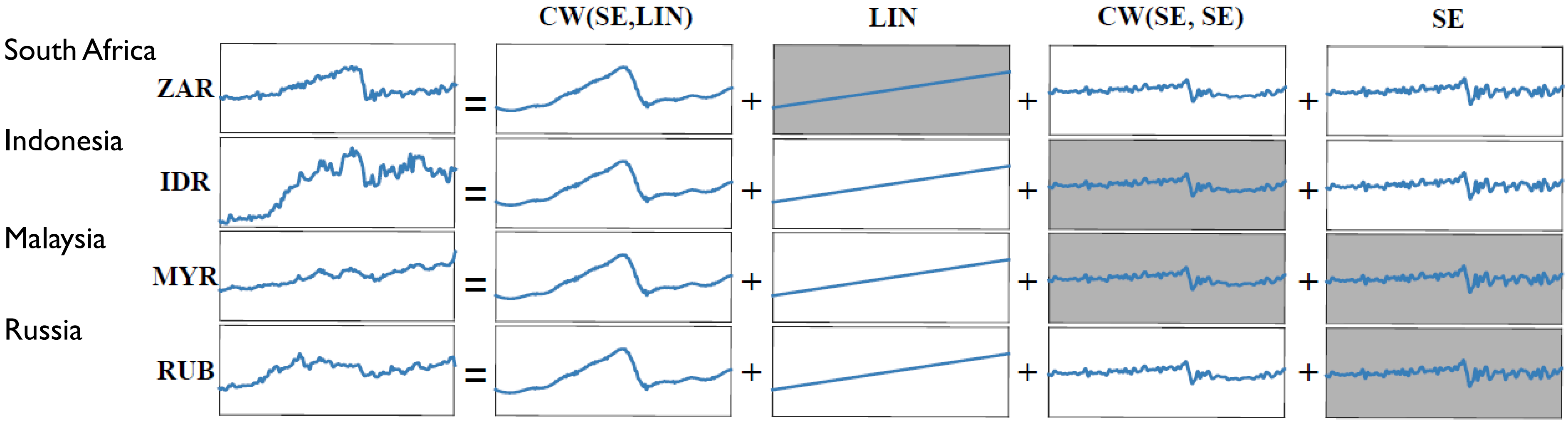
Indian Buffet Processes (IBP) + Gaussian Processes

(Nonparametric Clustering) **(Nonparametric Regression)**



Explainable Nonparametric Clustering and Regression

[Tong; Choi. Arxiv. 2017]



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

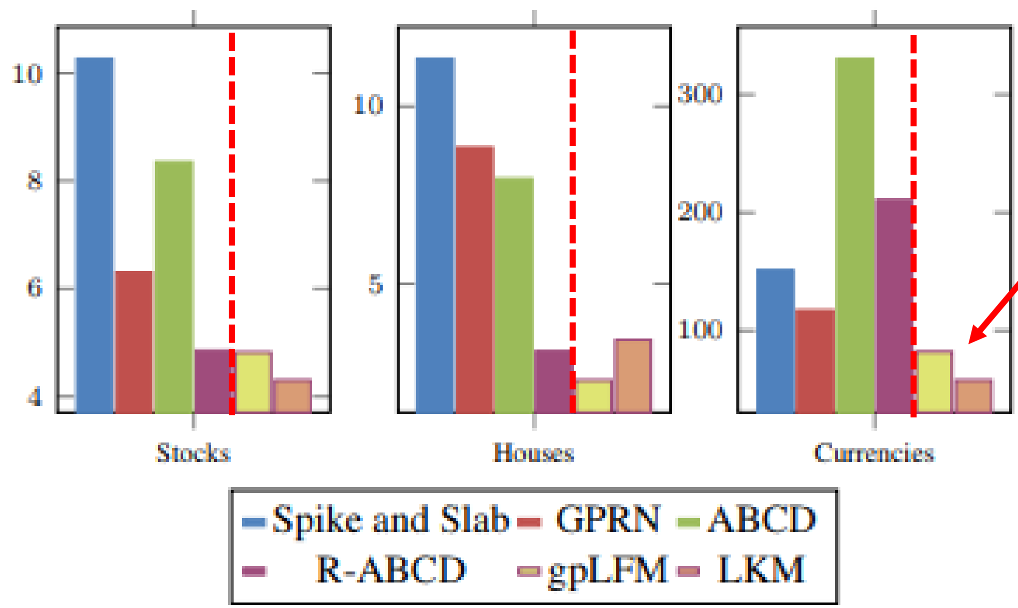
→ This component is linearly increasing.

Explainable Regression with Nonparametric Clustering

[Tong; Choi. Arxiv. 2017]

	9 stocks	6 houses	4 currencies
Spike and Slab	10.26	11.33	151.37
GPRN	6.30	8.84	117.05
ABCD	8.35	7.96	330.00
R-ABCD	4.85	3.10	210.56
gpLFM	**4.82**	**2.28**	**81.98**
LKM	**4.30**	3.42	**57.74**

IBP + GP methods



Explainable Regression with Nonparametric Clustering

[Tong; Choi. Arxiv. 2017]

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.

…

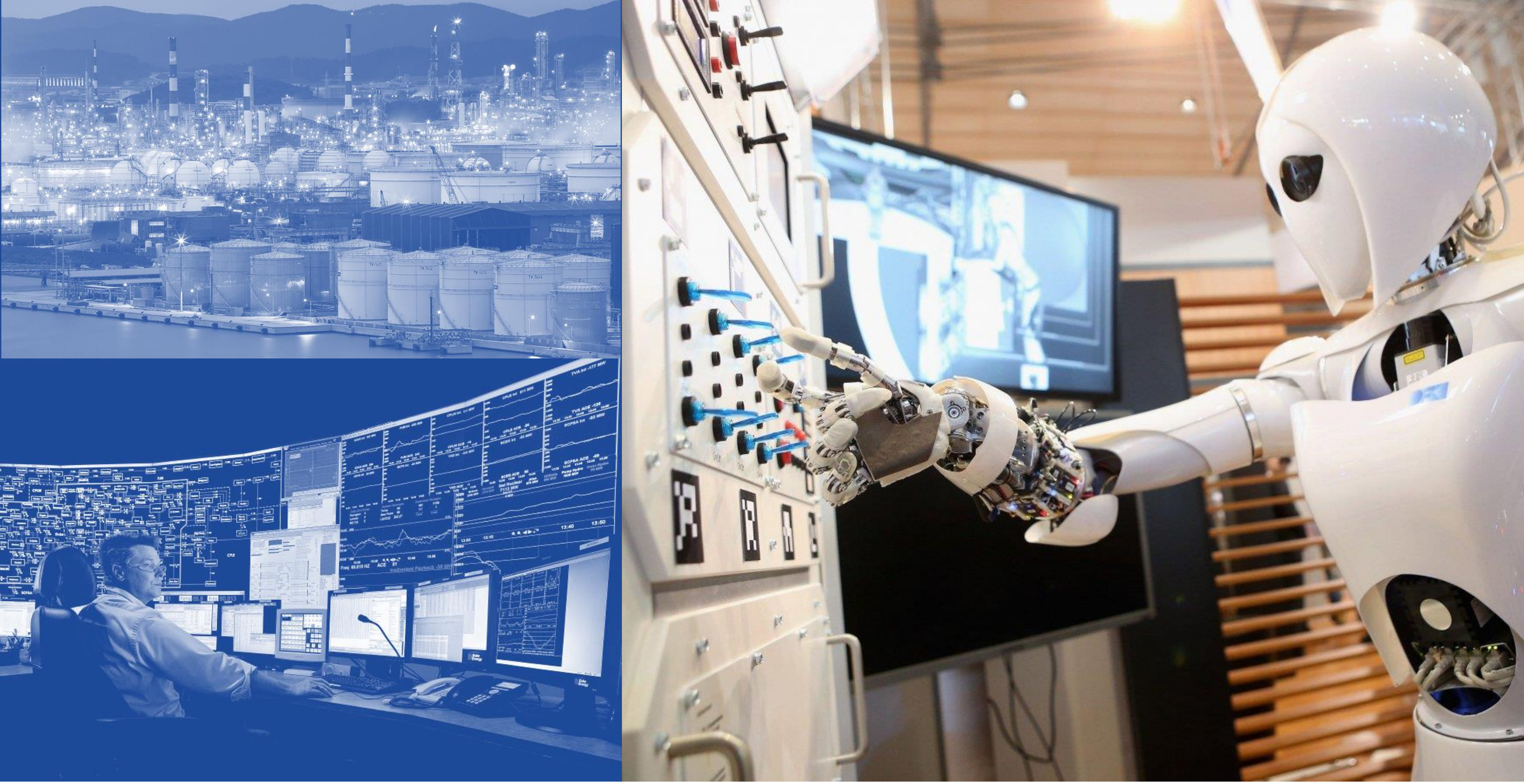
Adobe shares have climbed 52 percent since the beginning of the year. In the final minutes of trading on Tuesday, shares hit $156.61, an increase of 57 percent in the last 12 months.

…

In coming months, Adobe shares are expected to increase since Adobe is one of selected Silicon-based SW companies showing linearly increase trends.

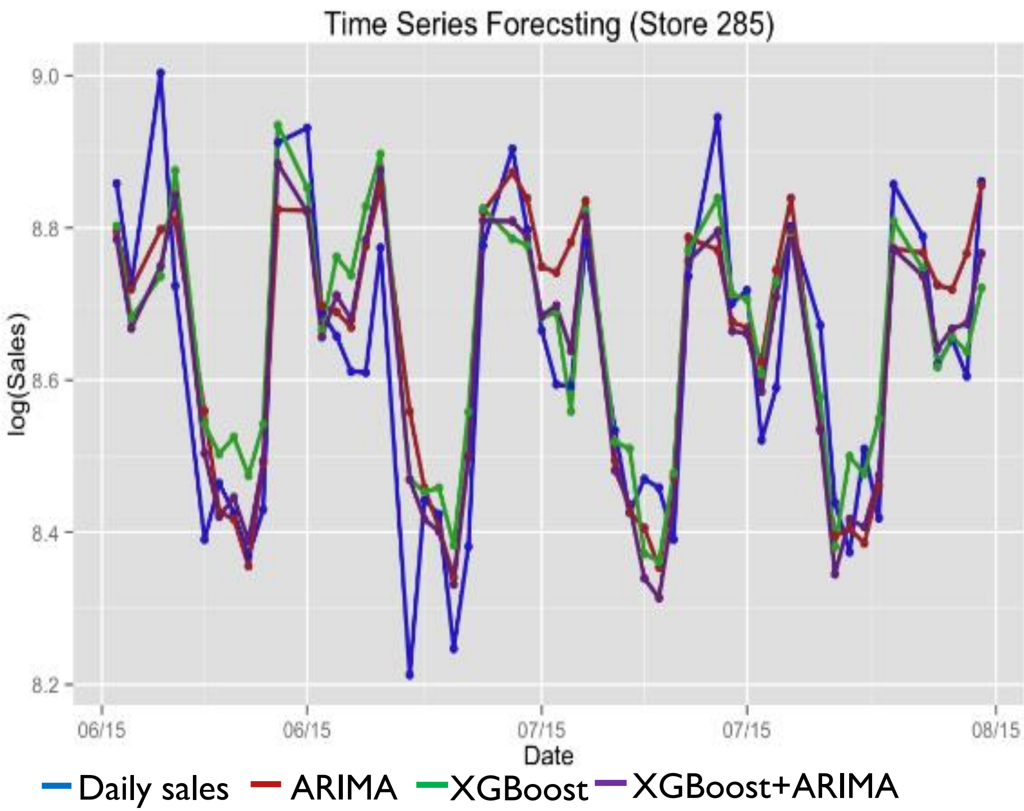
This story was generated by Automated Insights and Relational Automatic Statistician.

Toward Automated Narrative Generation Beyond Finite Templates



Machine Learning in Financial Analysis

Prediction of daily sales at Rossmann stores (six weeks ahead)



	RMSE
XGBoost+ARIMA	**0.093**
XGBoost	0.107
ARIMA	0.110

INPUT

Historical sales data

Stores, Sales, Customers, Competition distance, Store type, ….

Prediction Model

OUTPUT

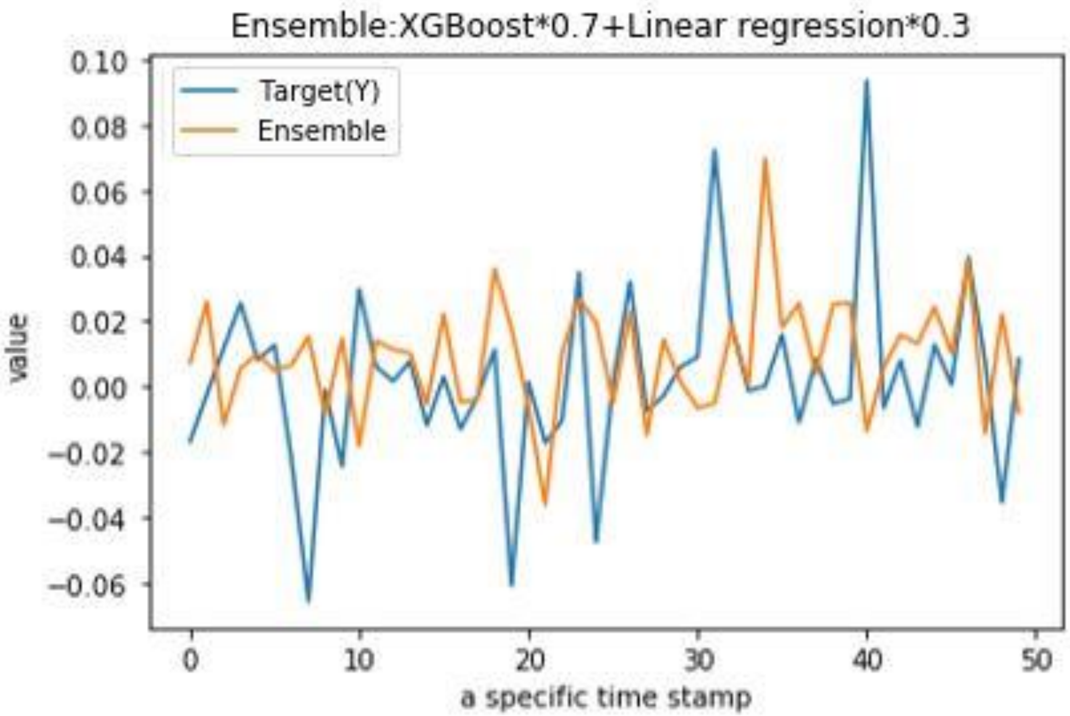
Sales data forecast

Future store sales prediction

Rossmann store daily sales at Kaggle

[http://www.Kaggle.com, 2015]

Prediction of unknown financial assets



	R-square
XGBoost (1st)	**0.0382**
Extra trees (2nd)	0.0369
Linear Regression	0.0219

INPUT

Anonymized features

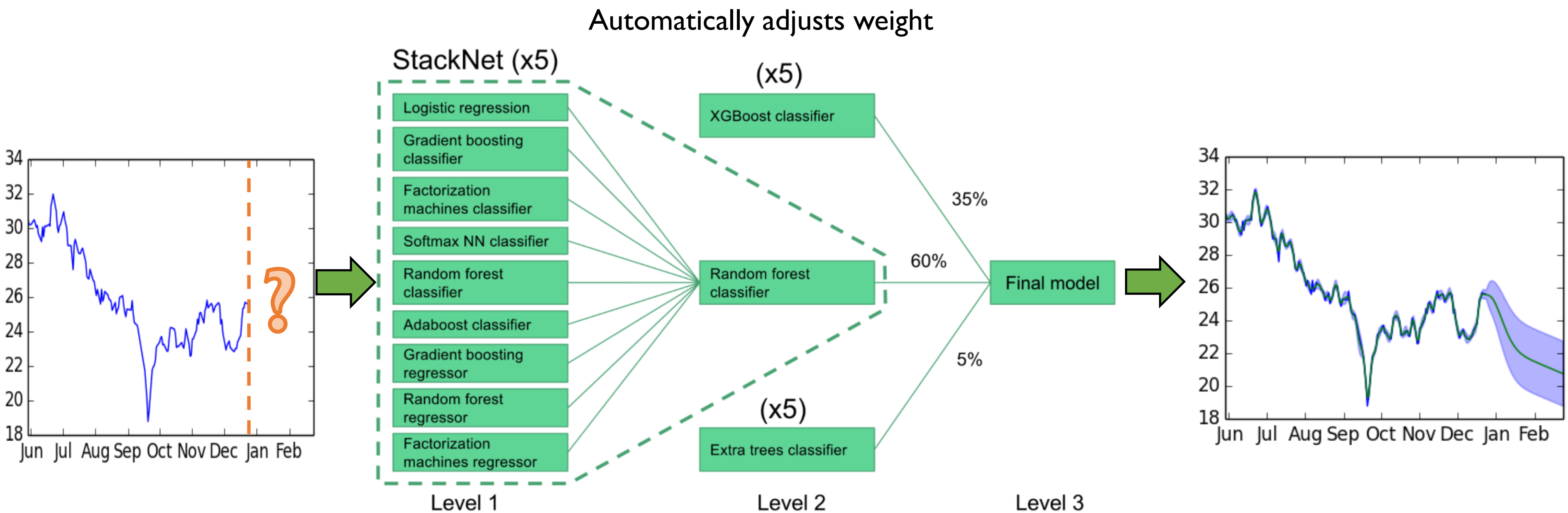
Time-varying value for a financial instrument
Containing missing value

→ **Prediction Model** →

OUTPUT

Predict anonymous 'Y'

Two Sigma Financial Modeling at Kaggle
[http://www.Kaggle.com, 2017]



A Typical Stacked Ensemble Model at Kaggle

- Automated data collection and processing soon will change our daily life.

- Automated narrative generation methods/frameworks may have widespread applications such as finance and media.

- Compositions of explainable models would generate more human understandable descriptions of data.

Conclusions

Thank you

jaesik@unist.ac.kr

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