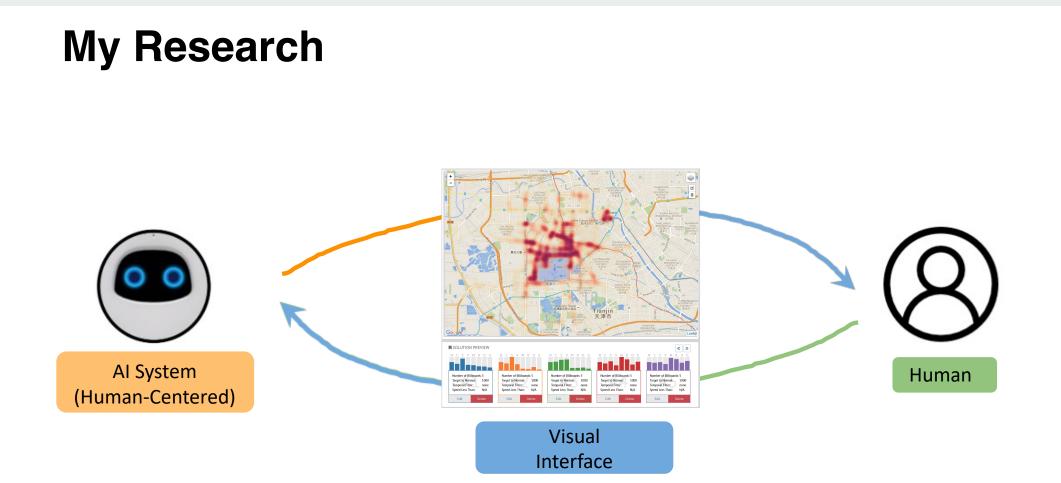
Signal Intelligence: Human-AI Teaming for Time Series Analytics

Dongyu Liu

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AI (ML)

The term is coined by Prof. John McCarthy in 1950s

"The science and engineering of making intelligent machines"

Intelligence might be defined as the ability to learn and perform suitable techniques to solve problems and achieve goals, appropriate to the context in an uncertain, ever-varying world. A fully pre-programmed factory robot is flexible, accurate, and consistent but not intelligent.

Artificial Intelligence (AI), a term coined by emeritus Stanford Professor John McCarthy in 1955, was defined by him as "the science and engineering of making intelligent machines". Much research has humans program machines to behave in a clever way, like playing chess, but, today, we emphasize machines that can learn, at least somewhat like human beings do.

Autonomous systems can independently plan and decide sequences of steps to achieve a specified goal without micro-management. A hospital delivery robot must autonomously navigate busy corridors to succeed in its task. In AI, autonomy doesn't have the sense of being self-governing common in politics or biology.

Machine Learning (ML) is the part of AI studying how computer agents can improve their perception, knowledge, thinking, or actions based on experience or data. For this, ML draws from computer science, statistics, psychology, neuroscience, economics and control theory.

In **supervised learning**, a computer learns to predict human-given labels, such as dog breed based on labeled dog pictures; **unsupervised learning** does not require labels, sometimes making its own prediction tasks such as trying to predict each successive word in a sentence; **reinforcement learning** lets an agent learn action sequences that optimize its total rewards, such as winning games, without explicit examples of good techniques, enabling autonomy.

Deep Learning is the use of large multi-layer (artificial) neural networks that compute with continuous (real number) representations, a little like the hierarchically organized neurons in human brains. It is currently the most successful ML approach, usable for all types of ML, with better generalization from small data and better scaling to big data and compute budgets.

An **algorithm** lists the precise steps to take, such as a person writes in a computer program. Al systems contain algorithms, but often just for a few parts like a learning or reward calculation method. Much of their behavior emerges via learning from data or experience, a sea change in system design that Stanford alumnus Andrej Karpathy dubbed **Software 2.0**.

Narrow AI is intelligent systems for one particular thing, e.g., **speech** or **facial recognition**. **Human-level AI**, or **Artificial General Intelligence (AGI)**, seeks broadly intelligent, context-aware machines. It is needed for effective **social chatbots** or **human-robot interaction**.

Human-Centered Artificial Intelligence is AI that seeks to augment the abilities of, address the societal needs of, and draw inspiration from human beings. It researches and builds effective partners and tools for people, such as a robot helper and companion for the elderly.

Text by Professor Christopher Manning, September 2020

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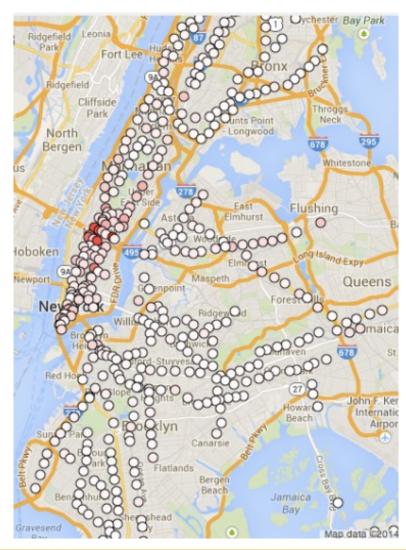
Text by Professor Christopher Manning, September 2020

Data visualization

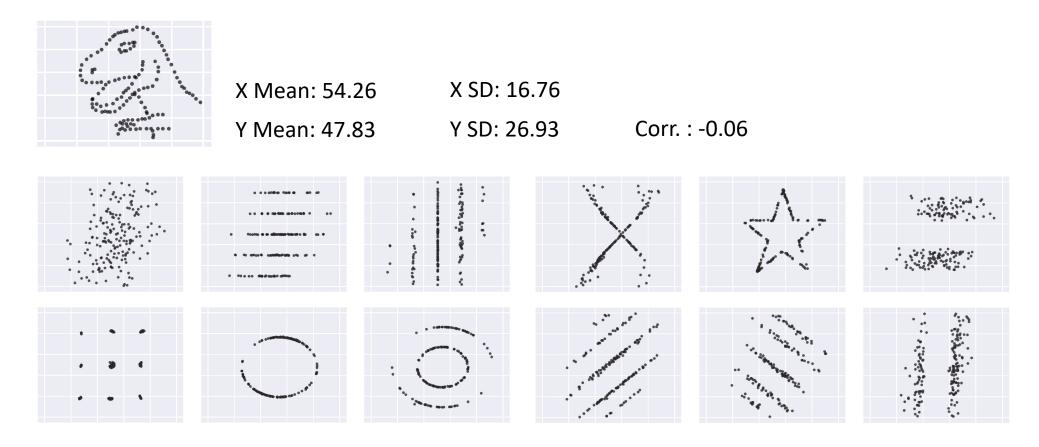
 "Data Visualization is the creation and study of the visual representation of data" - wiki

Input	<u>data</u>
Output	visual form
Goal	<u>insight</u>

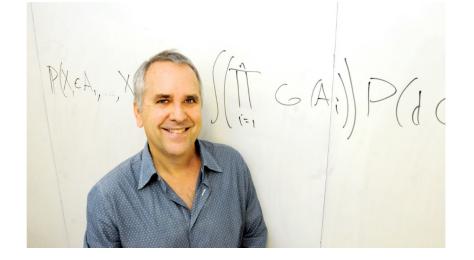
MTA FARE @ NY City



Same stats, different graphs



Matejka, and Fitzmaurice. Same stats, different graphs: generating datasets with varied appearance and identical statistics through simulated annealing. CHI 2017.



Harvard Data Science Review • Issue 1.1, Summer 2019

Artificial Intelligence—The Revolution Hasn't Happened Yet

Michael I. Jordan^{1,2,3}

¹Berkeley Artificial Intelligence Research Lab, Department of Electrical Engineering and Computer Sciences, University of California Berkeley, Berkeley, California, United States of America,

²Department of Electrical Engineering and Computer Sciences, University of California Berkeley, Berkeley, California, United States of America,

³Department of Statistics, University of California Berkeley, Berkeley, California, United States of America

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Whether or not we come to understand 'intelligence' any time soon, we do have a major challenge on our hands in bringing together computers and humans in ways that enhance human life. While some view this challenge as subservient to the creation of artificial intelligence, another more prosaic, but no less reverent, viewpoint is that it is the creation of **a new branch of** engineering. Much like civil engineering and chemical engineering in decades past, this new discipline aims to corral the power of a few key ideas, bringing new resources and capabilities to people, and to do so safely. Whereas civil engineering and chemical engineering built upon physics and chemistry, this new engineering discipline will build on ideas that the preceding century gave substance to, such as information, algorithm, data, uncertainty, computing, inference, and optimization. Moreover, since **much** of the focus of the new discipline will be on data from and about humans, its development will require perspectives from the social sciences and humanities.

AFOSR-3223

Summary Report

AUGMENTING HUMAN INTELLECT: A CONCEPTUAL FRAMEWORK

Prepared for:

DIRECTOR OF INFORMATION SCIENCES AIR FORCE OFFICE OF SCIENTIFIC RESEARCH WASHINGTON 25, D.C.

CONTRACT AF 49(638)-1024

RI

×

By: D. C. Engelbart

STANFORD RESEARCH INSTITUTE

MENLO PARK, CALIFORNIA

J.C.R. Licklider March 1960

Douglas C. Engelbart October 1962

Human Users

Three **functional roles** for AI systems:

- AI performs functions alongside the human
- AI performs functions when the human encounters high cognitive overload
- AI performs functions in lieu of a human





THE NATIONAL ARTIFICIAL INTELLIGENCE RESEARCH AND DEVELOPMENT STRATEGIC PLAN: 2019 UPDATE

A Report by the SELECT COMMITTEE ON ARTIFICIAL INTELLIGENCE of the NATIONAL SCIENCE & TECHNOLOGY COUNCIL

JUNE 2019

Augmenting human intelligence with AI

- Perception
- Attention
- Memory
- Language
- Reasoning
- Problem-solving
- Decision-making
- Creativity



Fine-grained image recognition

http://www.weixiushen.com/project/Awesome_FGIA/Awesome_FGIA.html

Augmenting human intelligence with Al

- Perception
- Attention
- Memory
- Language
- Reasoning
- Problem-solving
- Decision-making
- Creativity



Language Translation

https://www.michigandaily.com/statement/google-translate-and-end-language/

Augmenting human intelligence with Al

- Perception
- Attention
- Memory
- Language
- Reasoning
- Problem-solving
- Decision-making
- Creativity



Art Design

https://www.animaapp.com/blog/design/ai-generated-art-for-product-designers/

Augmenting human intelligence with AI

- Perception
- Attention
- Memory
- Language
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- Problem-solving
- Decision-making
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Clinical decision support

Human Users

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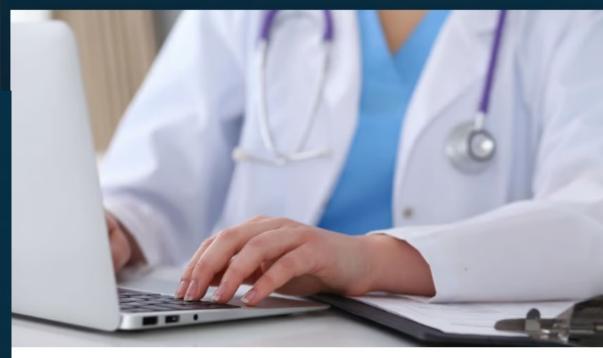
JUNE 2019

Nearly half of U.S. doctors say they are anxious about using AIpowered software: survey

By Heather Landi • Apr 25, 2019 10:55am



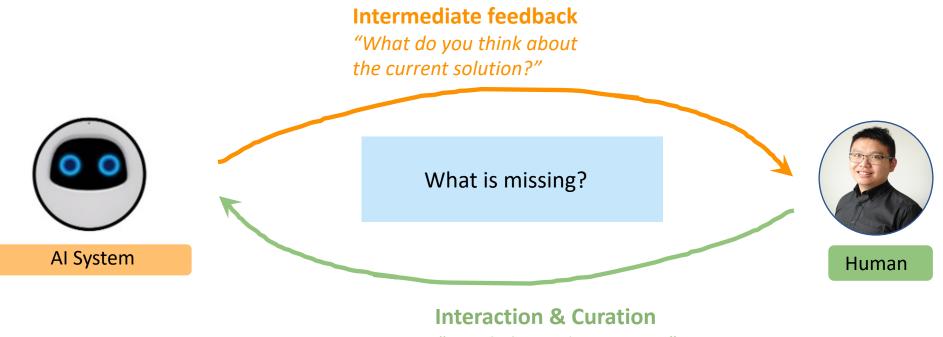
Al is promising, but ...



https://www.fiercehealthcare.com/practices/nearly-half-u-s-doctors-say-theyare-anxious-about-using-ai-powered-software-survey

A new physician survey indicates artificial intelligence applications are still in their infancy and have not affected mainstream physician practice at scale. (Getty/andrei_r)

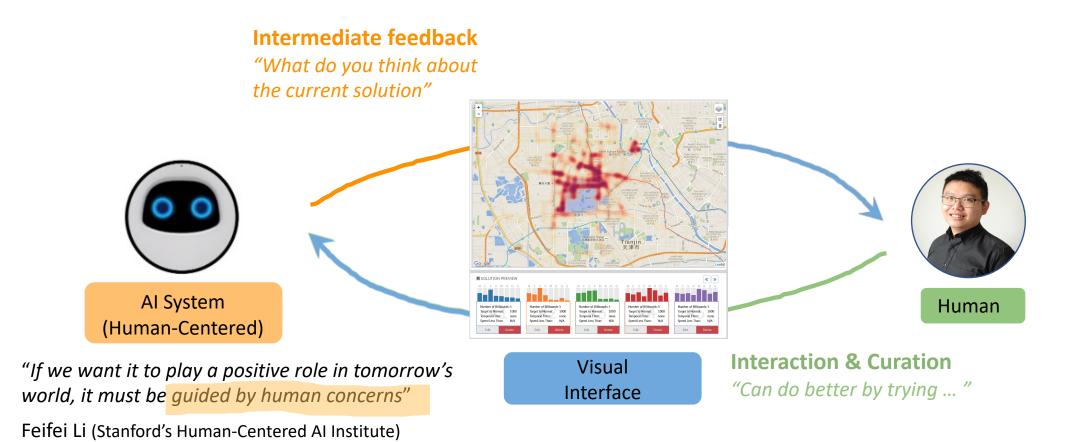
A general blueprint of Human-Al teaming



"Can do better by trying ... "

General blueprint for a human-in-the-loop interactive AI system. Image modified from: https://hai.stanford.edu/news/humans-loop-design-interactive-ai-systems

Visualization-powered teaming workflow



Human-Al teaming is essential, when

Al requires significant human knowledge to enhance its performance -> Ability to learn





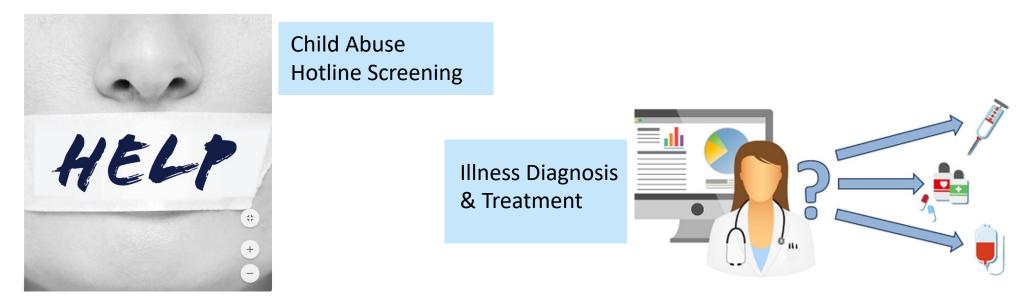
Large Devices Health Monitoring

Liu, et al., MTV: Visual Analytics for Detecting, Investigating, and Annotating Anomalies in Multivariate Time Series, CSCW 2022.

Human-AI teaming is essential, when

Al requires significant human knowledge to enhance its performance

Decisions being made are high-stakes -> Transparency



Zytek, **Liu**, et al., Sibyl: Understanding and Addressing the Usability Challenges of Machine Learning In High-Stakes Decision Making, TVCG (VIS'21).

Cheng, **Liu**, et al., VBridge: Connecting the Dots Between Features and Data to Explain Healthcare Models, TVCG (VIS'21). Best Paper Honorable Mention.

Human-Al teaming is essential, when

Al requires significant human knowledge to enhance its performance

Decisions being made are high-stakes

Decision-making involves multiple criteria and is heavily influenced by the context -> Steerability



Advertising Campaign Planning

Liu, et al, SmartAdP: Visual Analytics of Large-scale Taxi Trajectories for Selecting Billboard Locations, TVCG (VAST'16).



Store Operation Optimizing

Liu, et al., TPFlow: Progressive Partition and Multidimensional Pattern Extraction for Large-scale Spatio-temporal Data Analysis, TVCG (VAST'18), Best Paper Award.

Sintel

<u>Signal Intelligence</u>

(ability to learn)

Human-AI teaming for time series data analytics



https://sintel.dev/

Featurization

Featurize time series with domain knowledge encoded for machine learning uses.

Forecasting

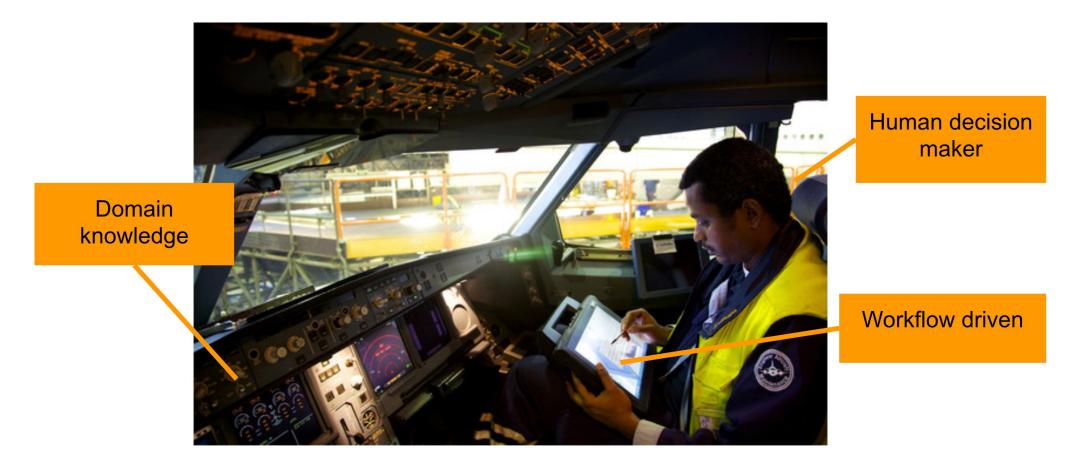
Predict future values by analyzing past trends.

Anomaly Detection

Identify anomalous time series segments.

Classification

Classify time series segments into particular categories.



Human-in-the-loop workflow to transfer insights into actions in minutes

Motivation

Wind turbines

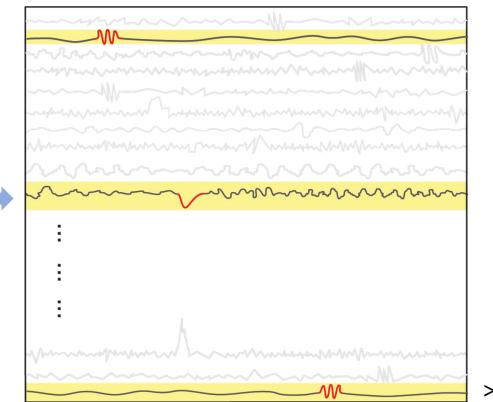


Satellites



Air quality monitors





How can we effectively monitor and analyze **anomalies** facing such massive amount of data?

```
> 30k signals
```

What is time series anomaly detection?

- Given a time series
$$X = (x^1, x^2, \dots, x^T)$$

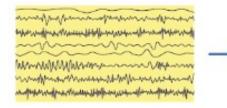
• Find
$$A_{seq} = \{\mathbf{a}_{seq}^1, \mathbf{a}_{seq}^2, ..., \mathbf{a}_{seq}^k\}$$
, where \mathbf{a}_{seq}^i is a continuous sequence of

data points over time that show anomalous or unusual behavior.

 \sim

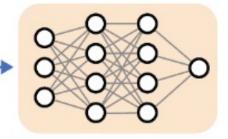
The problem we want to solve

Machine Learning (ML) Models



Time series data

100 PM 060 PM 070 PM 100 PM PM 200 PM 200 PM 200







Event ID	t _l	t ₂	Rank
127	June 10th, 2018 - 9:43 am	June 10th, 2018 - 12:50 pm	1/
202	June 11th, 2018 - 7:06 pm	June 12th, 2018 - 11:18 am	2
631	 Aug 12th, 2018 - 1:12 pm	 Aug 13th, 2018 - 4:50 pm	 k





Prioritize which events to investigate first



Users ask for details of the event and tag it

The problem we want to solve

Wind turbines

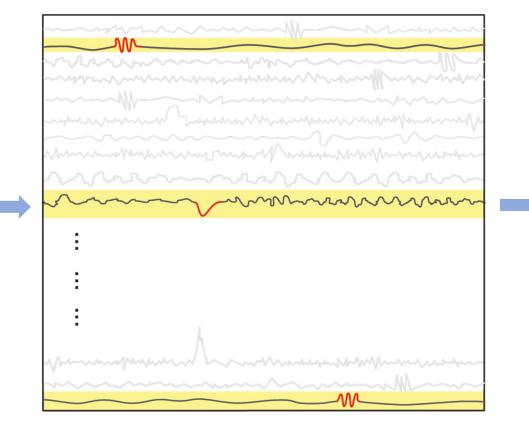


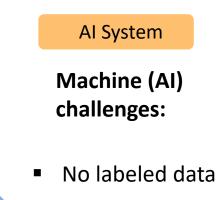
Satellites



Air quality monitors



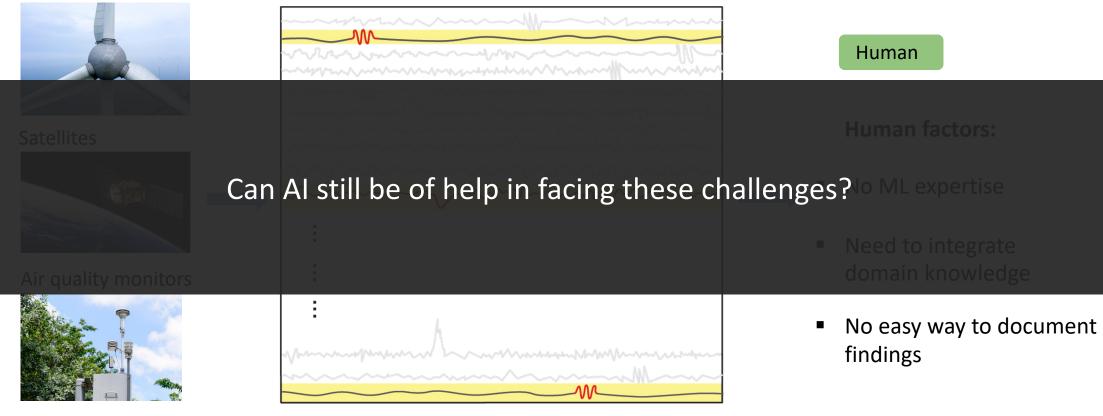




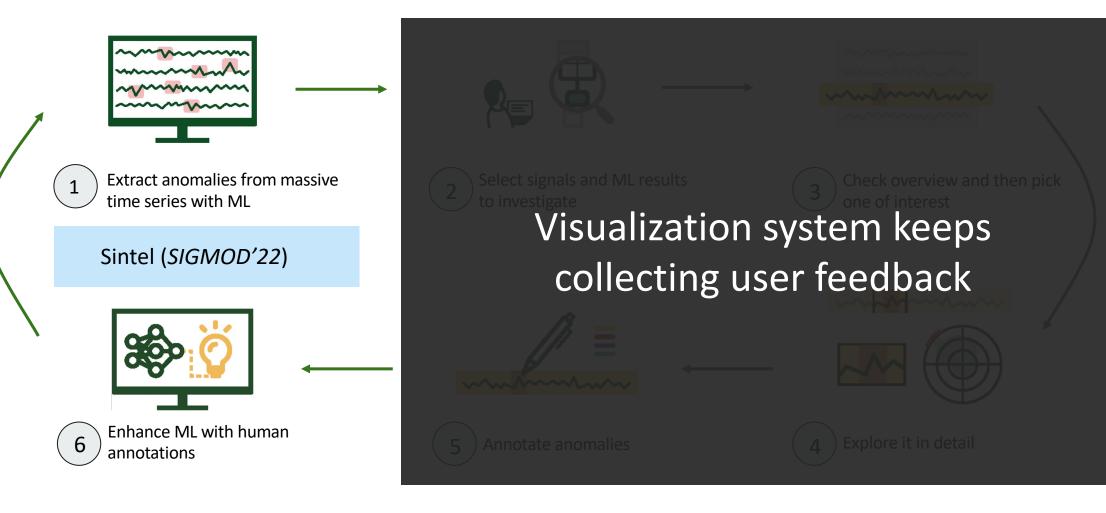
No normal baselines

The problem we want to solve

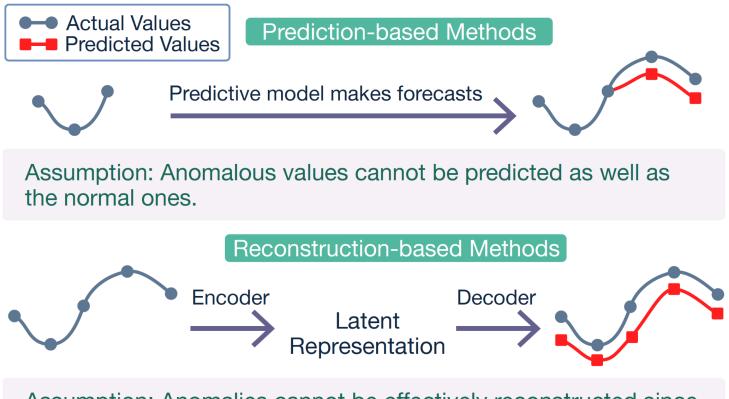
Wind turbines



Human-AI teaming workflow

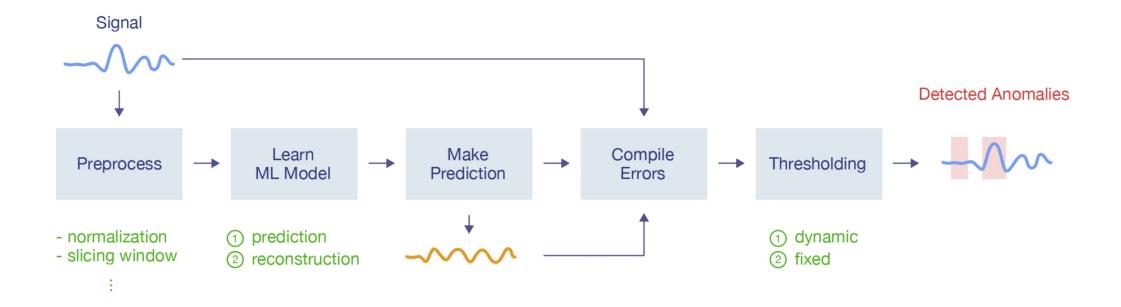


Unsupervised anomaly detection



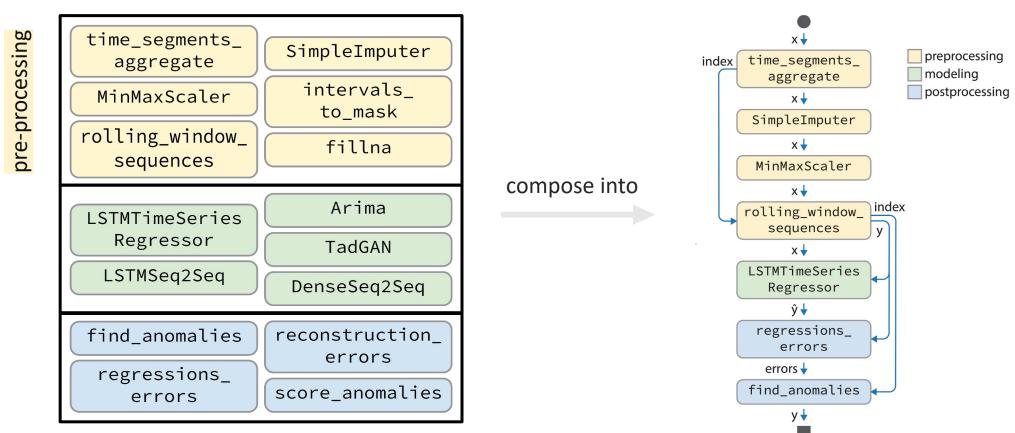
Assumption: Anomalies cannot be effectively reconstructed since information is lost in the mapping to the latent dimensions.

Use Sintel for anomaly detection



Primitives and Pipelines

Collection of Primitives



Pipeline

Alnegheimish, Liu, et al., Sintel: A Machine Learning Framework to Extract Insights from Signals, SIGMOD 2022.

modeling

What does Sintel achieve?

Integrate domain expertise

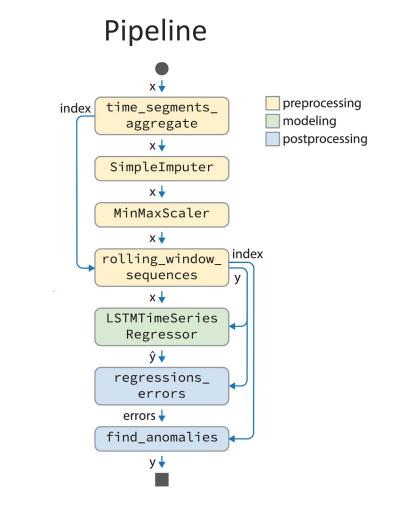
pre-processing

Satellite experts:

Use zero-order hold to impute missing values instead of mean

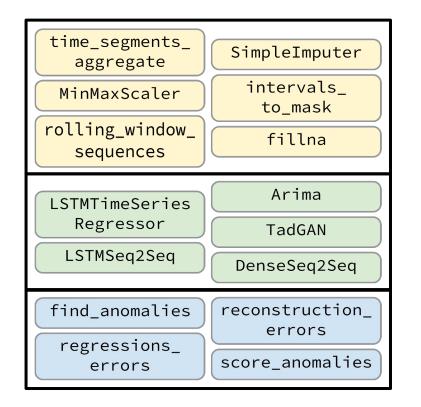
Wind turbine experts:

 Need domain specific aggregation and transformation methods (e.g., *fft*)



What does Sintel achieve?

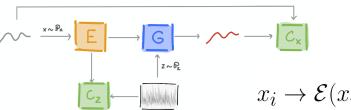
Develop better models



We now have in total 9 different models integrated:



Liu*, Geiger*, et al., TadGAN: Time Series Anomaly Detection Using Generative Adversarial Networks, IEEE BigData 2020



 $x_i \to \mathcal{E}(x_i) \to \mathcal{G}(\mathcal{E}(x_i)) \approx \hat{x}_i$

AER

ri-1 Yi:i+n-1 fi+n

Wong, **Liu**, et al., AER: Auto-Encoder with Regression for Time Series Anomaly Detection, IEEE BigData 2022

$$Loss = \frac{\gamma}{2} V_{pred}(t_{i-1}, r_{i-1}) + \frac{\gamma}{2} V_{pred}(t_{i+n}, f_{i+n}) + (1-\gamma) V_{rec}(t_{i:i+n-1}, y_{i:i+n-1})$$

Alnegheimish, Liu, et al., Sintel: A Machine Learning Framework to Extract Insights from Signals, SIGMOD 2022.

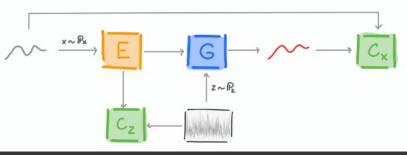
modeling

TadGAN



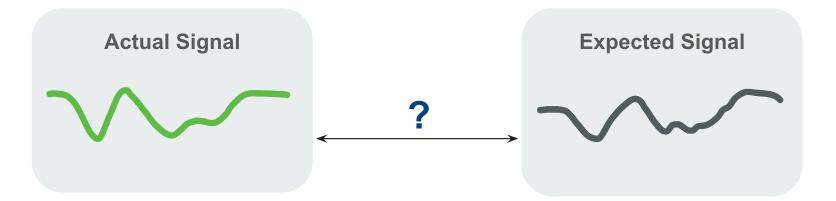
hods

$$x_i \to \mathcal{E}(x_i) \to \mathcal{G}(\mathcal{E}(x_i)) \approx \hat{x}_i$$



Liu*, Geiger*, et al., TadGAN: Time Series Anomaly Detection Using Generative Adversarial Networks, IEEE BigData 2020

Measure the discrepancies



- 1. **Reconstruction Error**: finding how much deviation there is between the real and the reconstructed signal.
- 2. **Critic score**: leveraging the trained critic to distinguish between real and reconstructed samples.

Measure the discrepancies

1. Convex combination.

$$\mathbf{a}(x) = \alpha Z_{RE}(x) + (1 - \alpha) Z_{\mathcal{C}_x}(x)$$

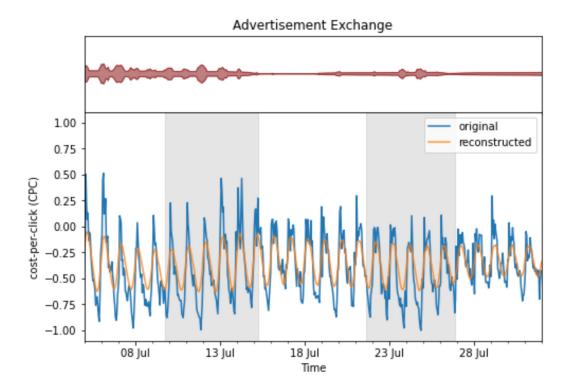
where α controls the relative importance of the two terms (by default alpha = 0.5).

2. Multiplication.

$$\mathbf{a}(x) = \alpha Z_{RE}(x) \odot Z_{\mathcal{C}_{x}}(x)$$
 where α defaults to 1.

Measure the discrepancies

Identify anomalous intervals with **locally adaptive thresholding**

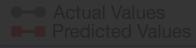


https://arxiv.org/pdf/1802.04431.pdf

Hundman, K., Constantinou, V., Laporte, C., Colwell, I. and Soderstrom, T., 2018, July. **Detecting spacecraft anomalies using lstms and nonparametric dynamic thresholding**. In *Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining* (pp. 387-395).

Dongyu Liu @ UCDavis

AER



Prediction-based Methods

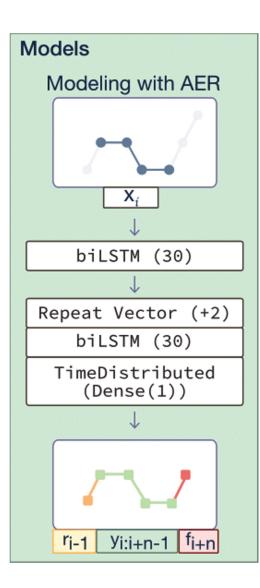
Predictive model makes forecasts

Objective Function

$$Loss = \frac{\gamma}{2} V_{pred}(t_{i-1}, r_{i-1}) + \frac{\gamma}{2} V_{pred}(t_{i+n}, f_{i+n}) + (1 - \gamma) V_{rec}(t_{i:i+n-1}, y_{i:i+n-1})$$

Assumption: Anomalies cannot be effectively reconstructed since information is lost in the mapping to the latent dimensions.

Wong, Liu, et al., AER: Auto-Encoder with Regression for Time Series Anomaly Detection, IEEE BigData 2022



Develop better models

 One single call to benchmark algorithms and know which one is the best

```
from sintel import benchmark
pipelines = ['arima', 'lstm_dynamic_threshold', '...']
datasets = ['NAB', 'NASA', '...']
metrics = ['f1', 'accuracy', '...']
benchmark(pipelines=pipelines,
         datasets=datasets,
         metrics=metrics.
         rank='f1')
# >>>
#
                pipeline rank accuracy elapsed
                                                     f1
                                                               precision
                                                                           recall
    lstm_dynamic_threshold 1 0.986993 915.958132 0.846868
                                                                0.879518
                                                                           0.816555
#
# 1
                     arima 2 0.962160 319.968949 0.382637
                                                               0.680000
                                                                            0.266219
```

Develop better models

Comparing against ARIMA whose roots are

In: Box, George; Jenkins, Gwilym (1970). *Time Series Analysis: Forecasting and Control*

TadGAN achieves the best overall improvement with an over 15% improvement.

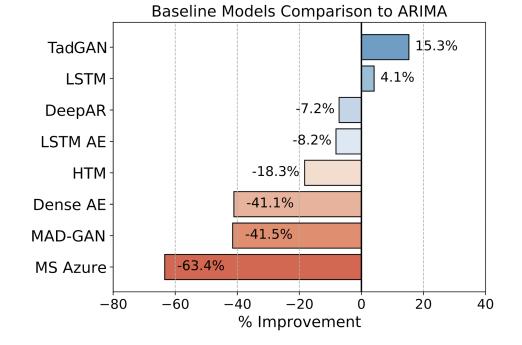


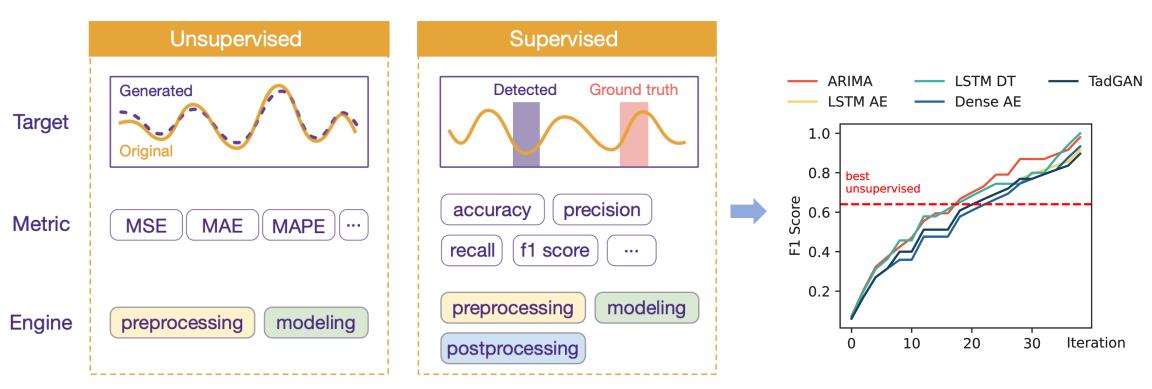
Fig. 3. Comparing average F1-Scores of baseline models across all datasets to ARIMA. The x-axis represents the percentage of improvement over the ARIMA score by each one of the baseline models.

Develop better models

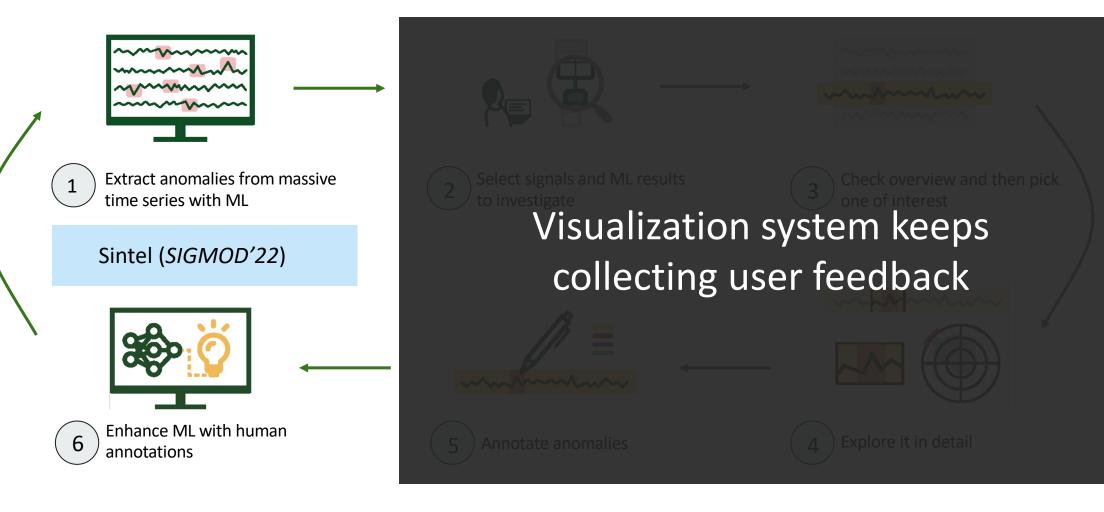
Models	NASA		УАНОО				NAB					UCR	Avg. F1 ($\mu \pm \sigma$)	
widers	MSL	SMAP	A1	A2	A3	A4	Art	AdEx	AWS	Traffic	Tweets	UCR	Avg. F1 $(\mu \pm 0)$	
ARIMA	0.442	0.333	0.733	0.807	0.818	0.700	0.353	0.518	0.741	0.500	0.567	0.124	0.553 ± 0.21	
LSTM-DT	0.515	0.707	0.721	0.980	0.744	0.638	0.400	0.513	0.741	0.667	0.580	0.391	0.633 ± 0.16	
LSTM-AE	0.500	0.705	0.610	0.866	0.420	0.253	0.545	0.750	0.692	0.457	0.483	0.314	0.550 ± 0.17	
LSTM-VAE	0.526	0.653	0.575	0.823	0.432	0.240	0.667	0.700	0.643	0.483	0.590	0.317	0.554 ± 0.16	
TadGAN	0.584	0.617	0.533	0.842	0.391	0.297	0.571	0.677	0.720	0.581	0.588	0.162	0.547 ± 0.18	
AER*	0.541	0.772	0.772	0.959	0.896	0.722	0.615	0.635	0.621	0.606	0.585	0.470	0.683 ± 0.14	

The latest and full results can be found here: https://bit.ly/orion-benchmark

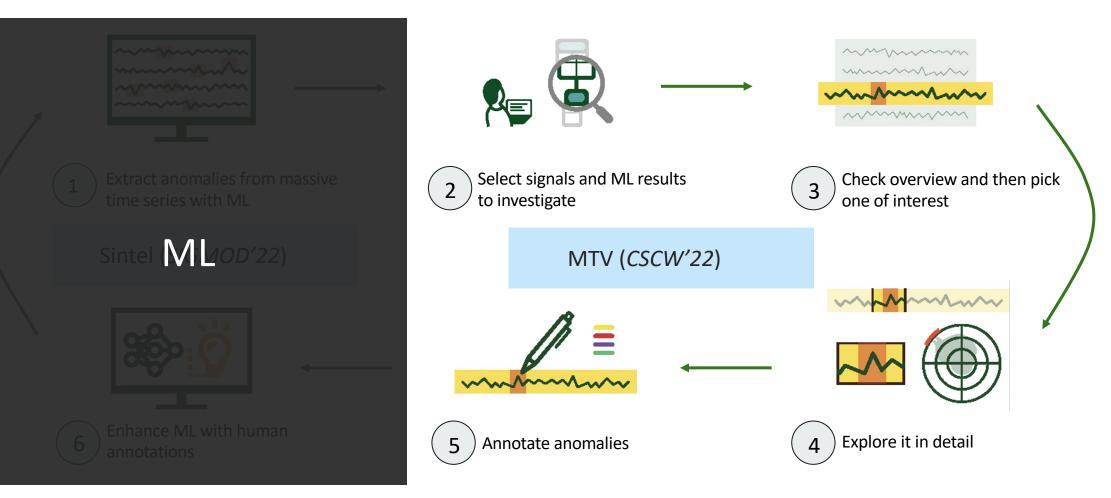
Improve over time



Human-AI teaming workflow



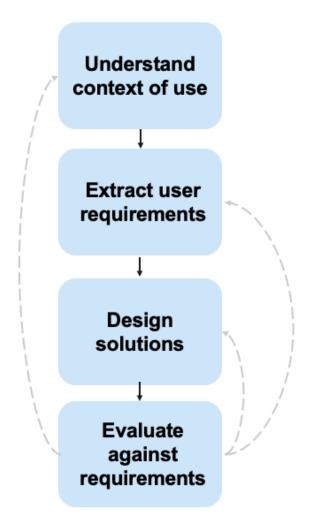
Human-Al teaming workflow



Working with domain experts

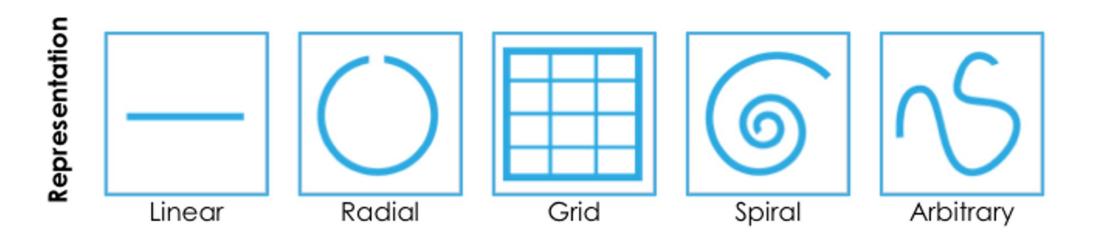
- Collaborated with 9 experts
 - □ 6 from a satellite operations company
 - **3** from a renewable energy company

- Followed an iterative user-centered design process
 - **G** design requirements



Liu, et al., MTV: Visual Analytics for Detecting, Investigating, and Annotating Anomalies in Multivariate Time Series, CSCW 2022.

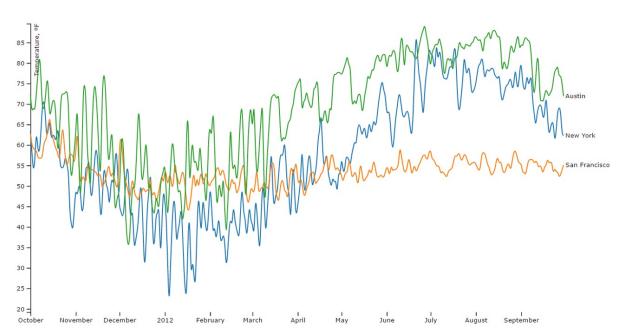
Time Representation



Brehmer, Matthew, et al. "Timelines revisited: A design space and considerations for expressive storytelling." TVCG 23.9 (2016): 2151-2164.

Linear Time

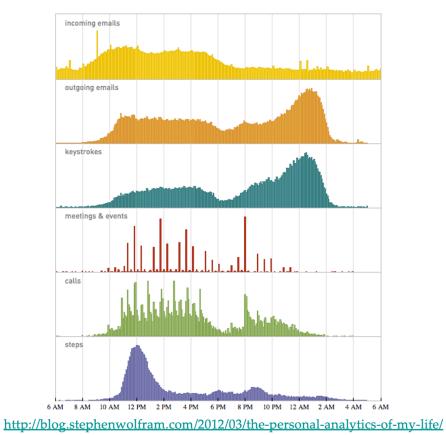
- Present time data as a 2D line graph and
 - Time on x-axis
 - The other variable on y-axis





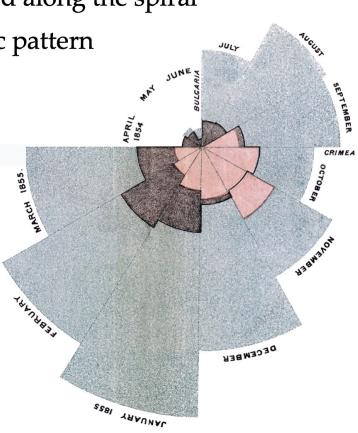
Linear Time

• Stephen Wolfram's Personal Data Visualization Report

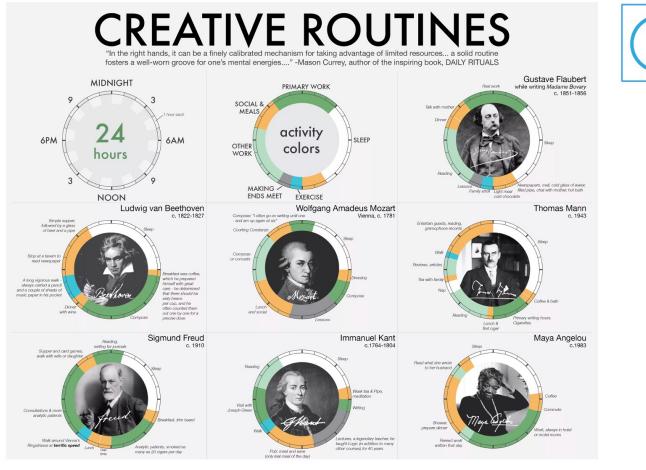


Radial Time

- Data distributed along the spiral
- To reveal cyclic pattern JUNE



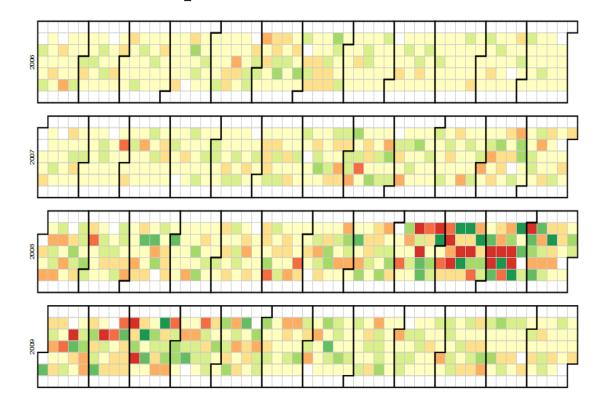
Radial Time



https://infowetrust.com/project/routines

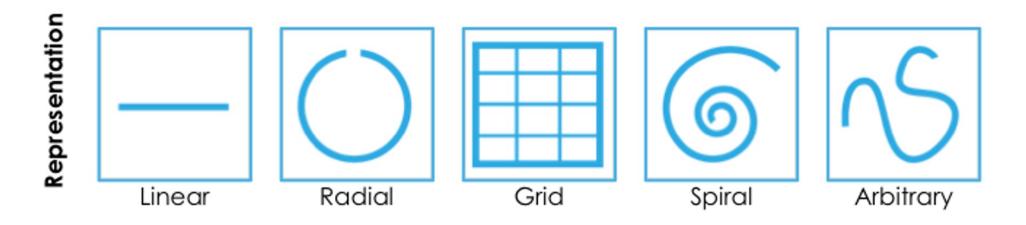
Grid Time

• Dow Jones stock price from 2006 to 2009



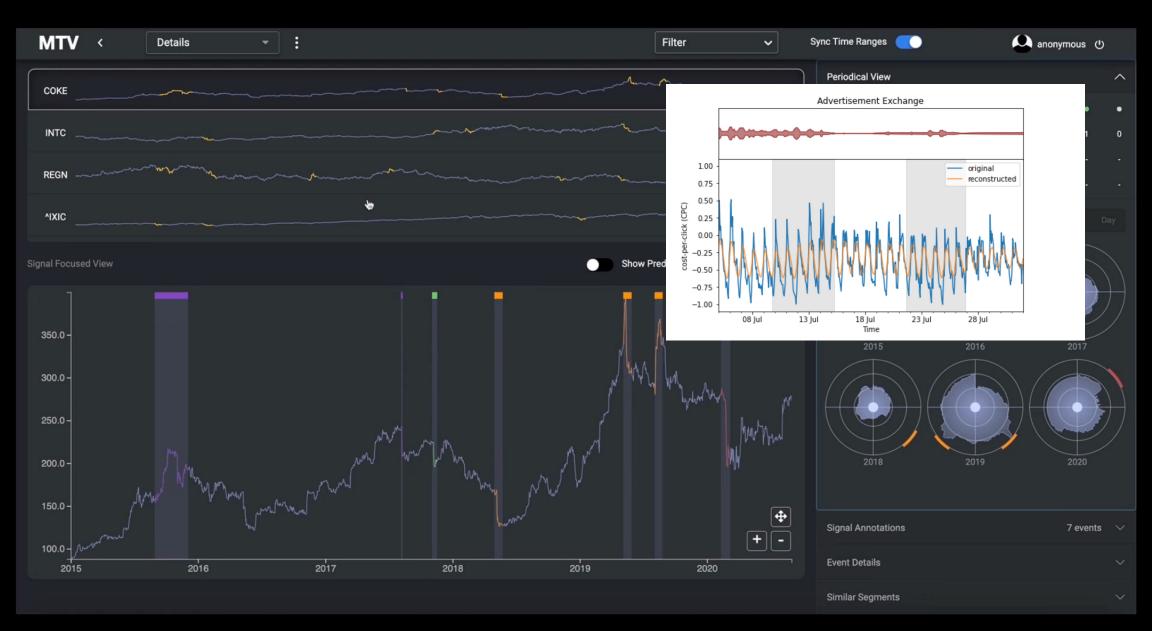
http://mbostock.github.io/d3/talk/20111018/calendar.html

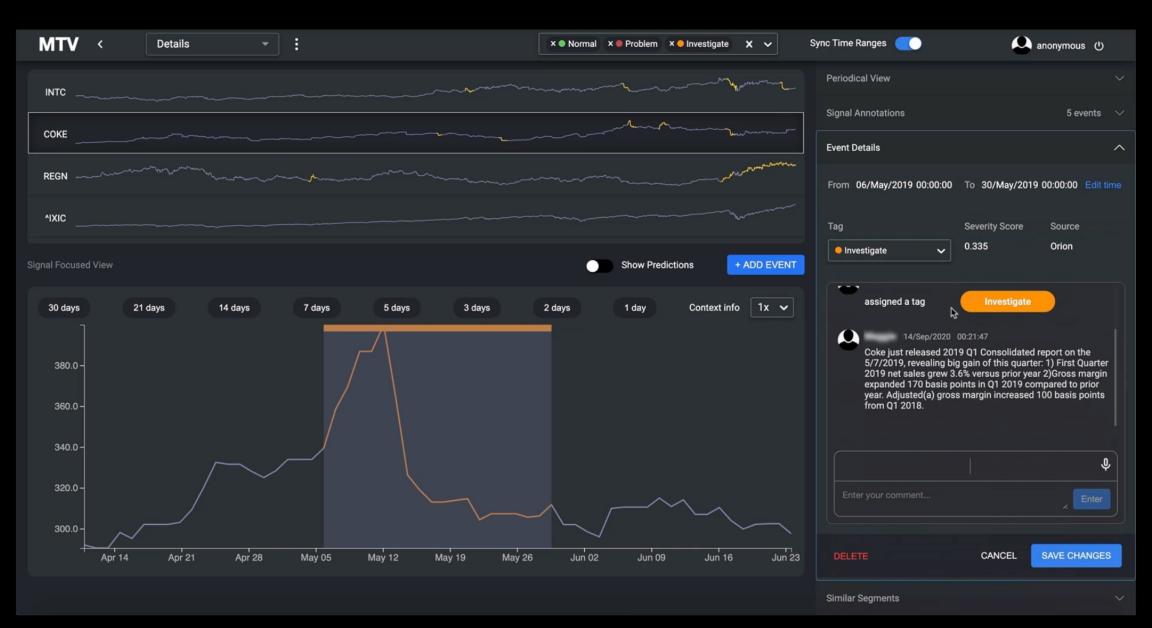
Time Representation

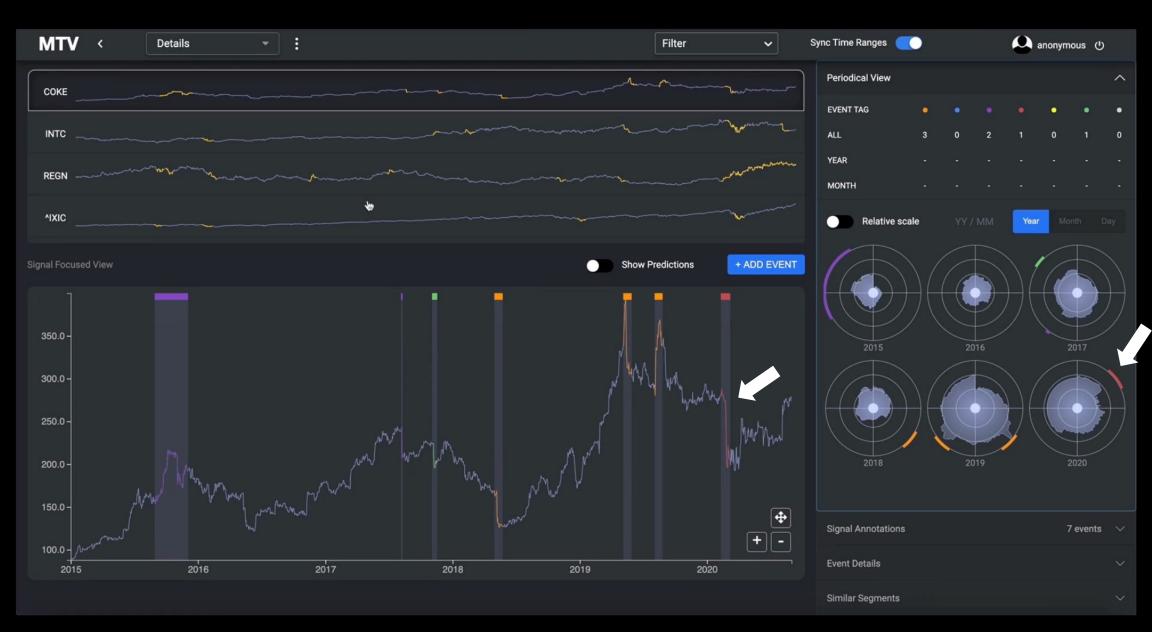


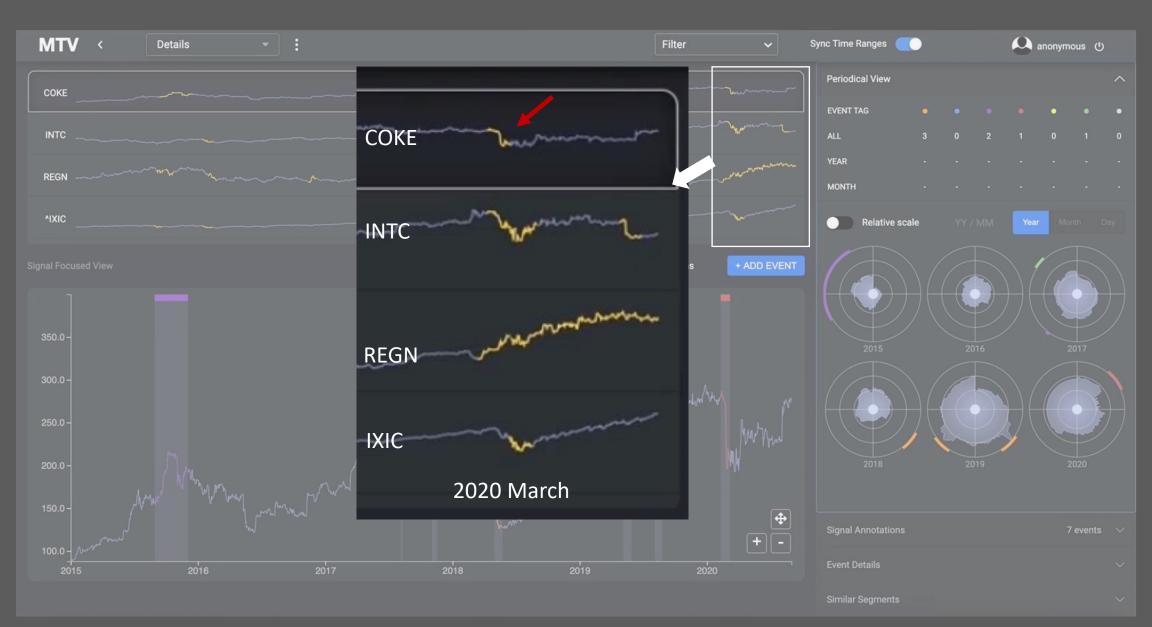
• Among the above four types, <u>linear time representation</u> <u>is more popular</u>

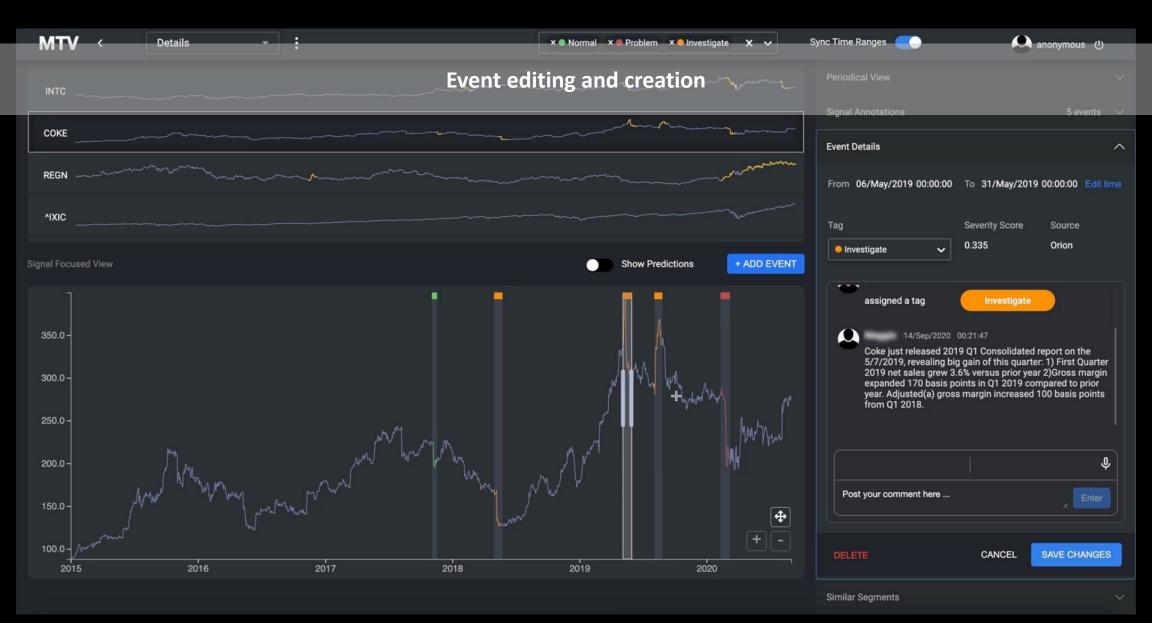


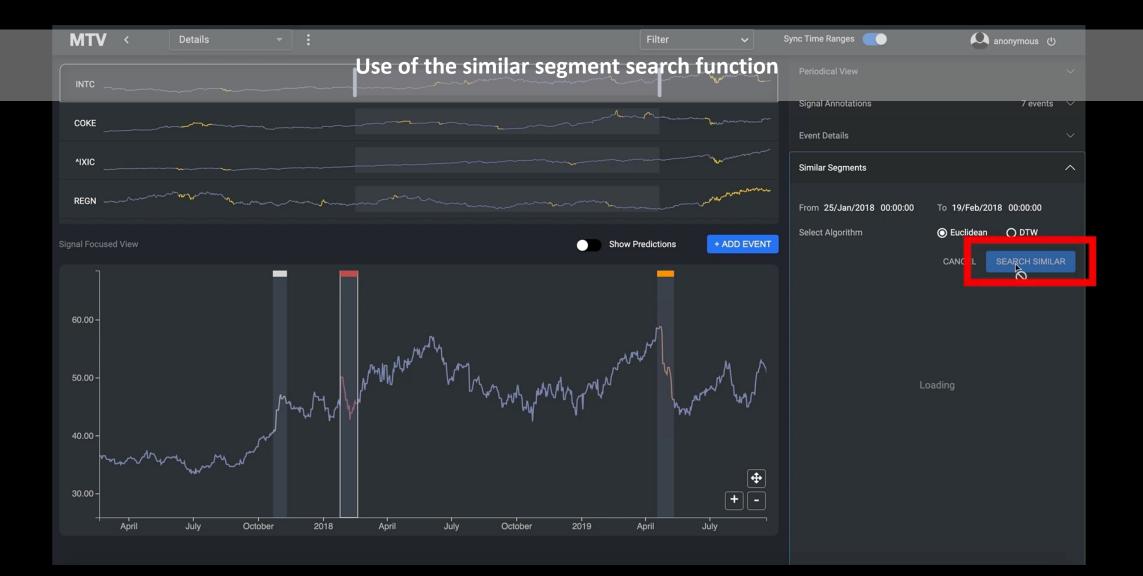






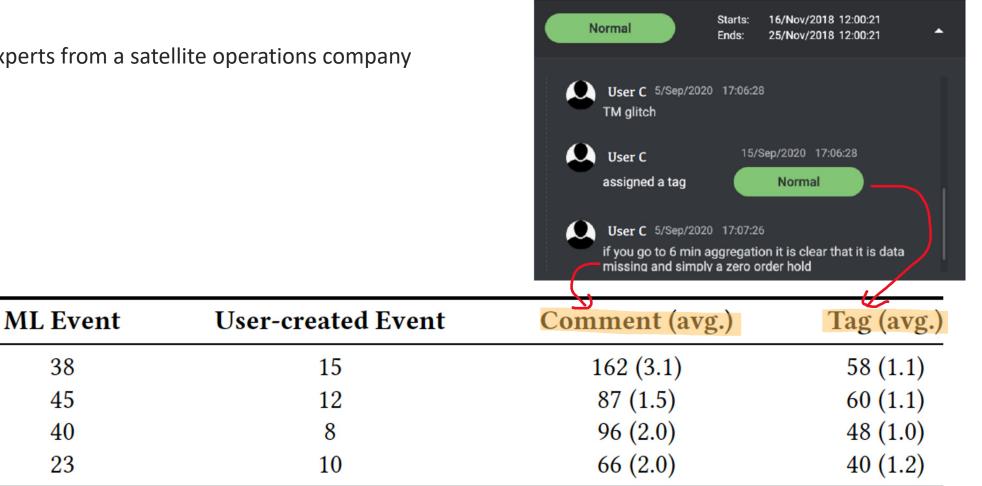






System evaluation

6 experts from a satellite operations company

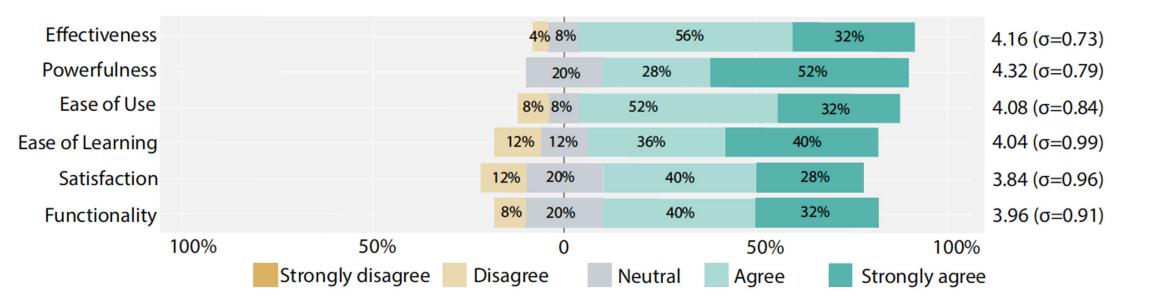


Liu, et al., MTV: Visual Analytics for Detecting, Investigating, and Annotating Anomalies in Multivariate Time Series, CSCW 2022.

Case

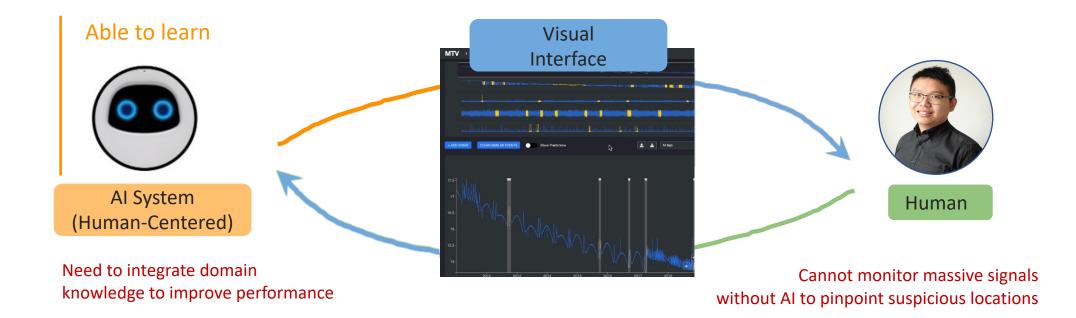
System evaluation

- 6 experts from a satellite operations company
- 25 general users using stock data



Liu, et al., MTV: Visual Analytics for Detecting, Investigating, and Annotating Anomalies in Multivariate Time Series, CSCW 2022.

Human-Al teaming workflow



Alnegheimish, Liu, et al., Sintel: A Machine Learning Framework to Extract Insights from Signals, SIGMOD 2022.

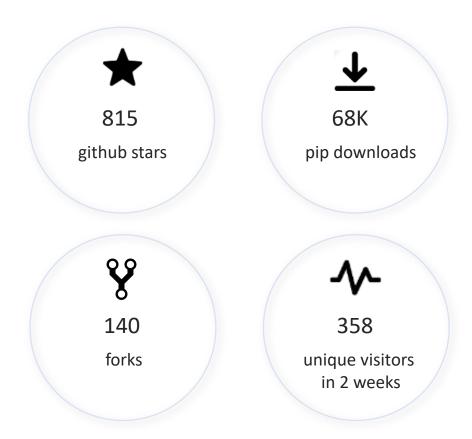
Liu, et al., MTV: Visual Analytics for Detecting, Investigating, and Annotating Anomalies in Multivariate Time Series, CSCW 2022.

Sintel

		MS Azure [30]	ADTK ²	Luminaire [6]	TODS [21]	Telemanom [17]	NAB [1]	EGADS [22]	Stumpy [24]	GluonTS [2]	Sintel
Users	End User		1	1	Х	X	Х	Х	1	Х	 ✓
	System Builder	1	X	X	X	X	Х	X	X	X	1
	ML Researcher	X	X	X	1	1	1	1	X	1	1
Engine	Preprocessing	X	1	1	1	Х	Х	Х	1	1	 ✓
	Modeling	1	✓	1	1	1	1	1	X	1	1
	Postprocessing	X	✓	1	1	X	X	X	1	X	1
Modular		X	1	1	1	X	Х	X	1	1	✓
Ċ.	Evaluation	Х	1	Х	X	1	Х	Х	Х	Х	
Comp.	Benchmark	X	X	X	1	X	1	X	X	✓	1
	Database	1	X	X	X	X	X	X	X	X	1
API	lang. specific		1	1	1	Х	1	Х	1	1	
	RESTful	1	X	X	X	X	Х	X	X	X	1
HIL		X	×	Х	X	Х	Х	Х	X	X	

Anomaly Detection

Orion repository metrics (as of 7/20/23) https://github.com/sintel-dev/Orion





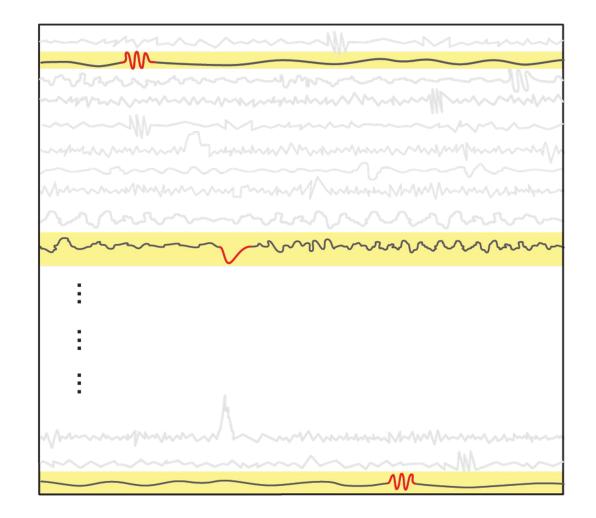
Sintel Signal Intelligence

Analyze massive time series (signal) data; enable human-in-the-loop analytics workflow; and transfer insights into actionable decisions.

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Project website: https://sintel.dev/

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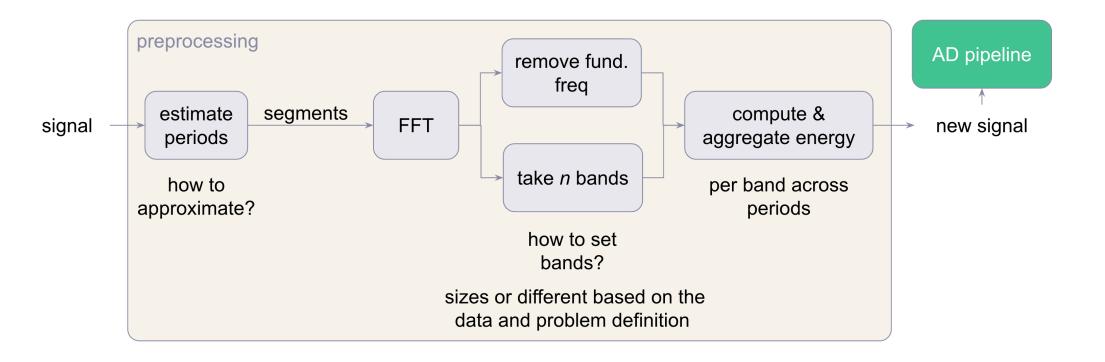


- Priority
- Group analysis

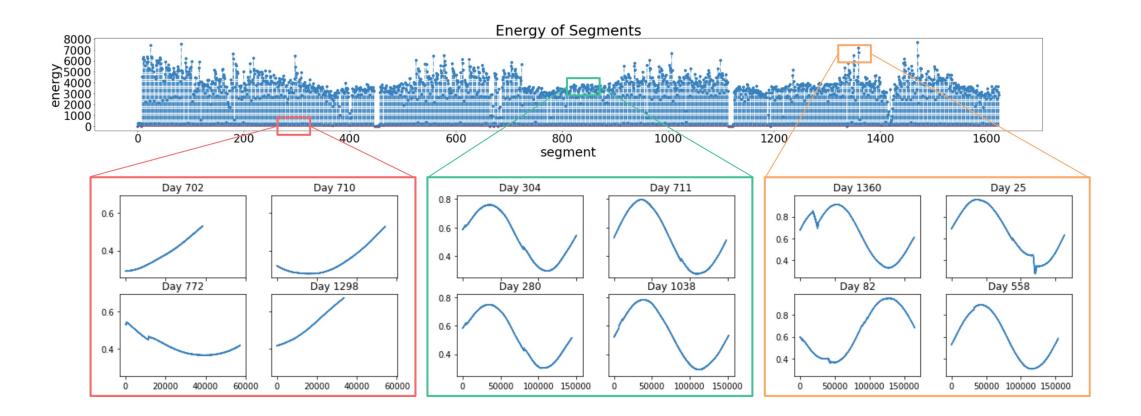
- Propagate / Predict / Suggest Annotations
- Few shot learning



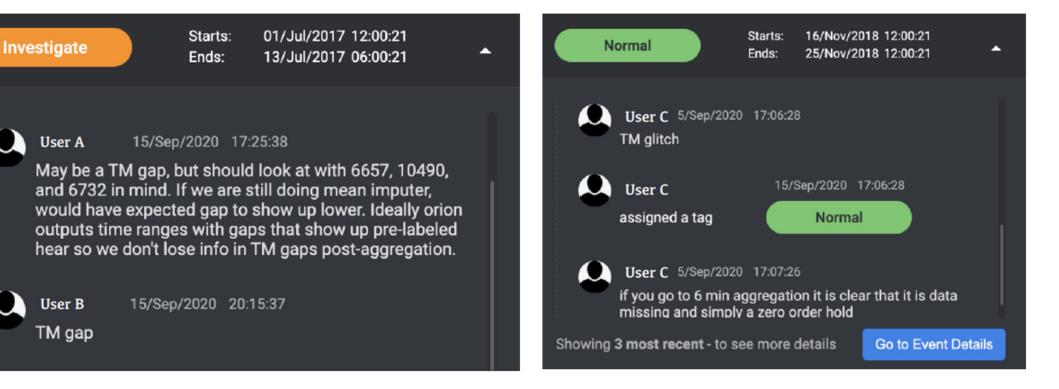
• Is ML necessary?



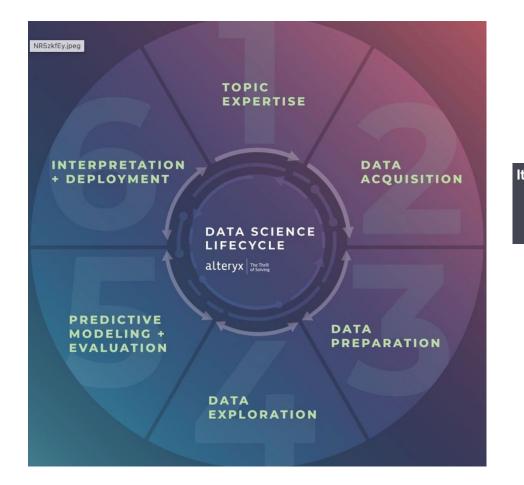
• Is ML necessary?



Actionable decisions



Data science life cycle



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• After deployment, new questions, challenges, or insights can emerge, leading to refinements or entirely new cycles of analysis.