Predictive Demand Disruption Signals for Supply Chain Networks

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IPIC 2024

Physical Internet Center

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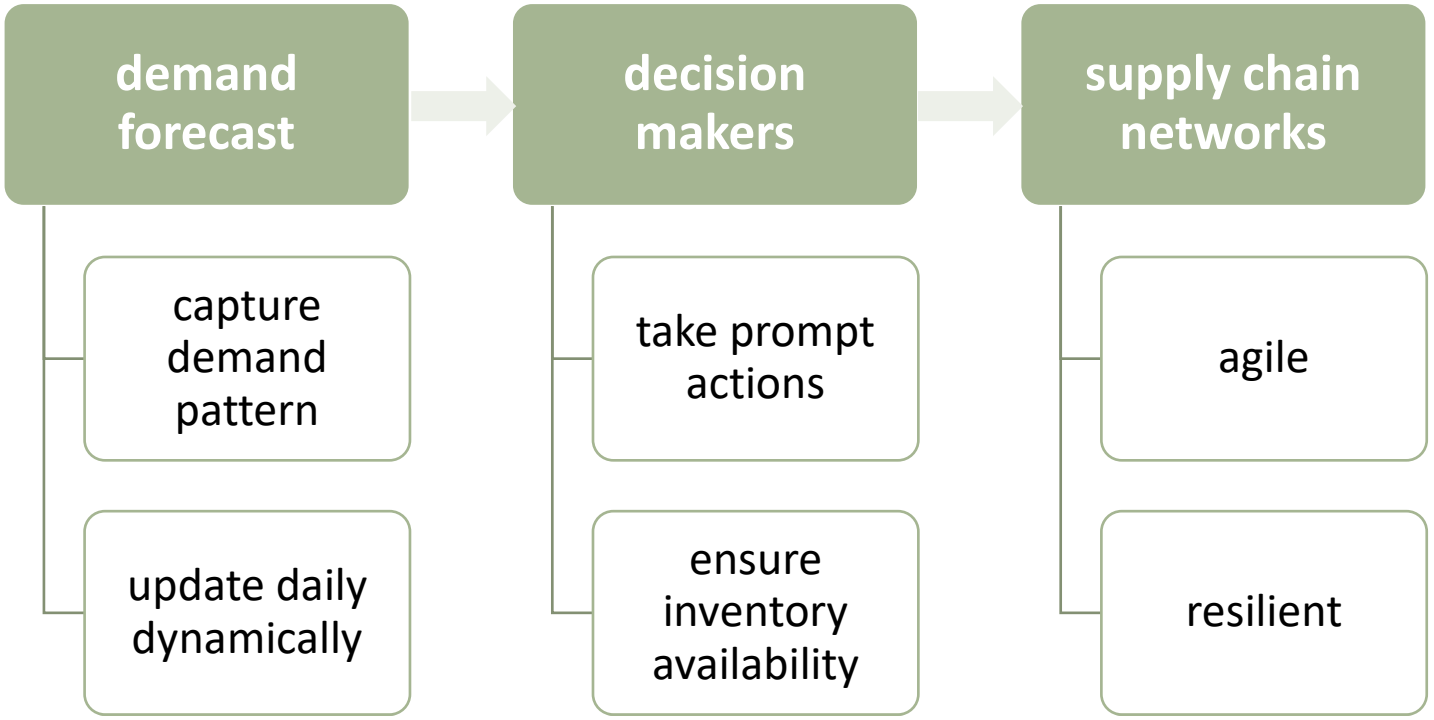
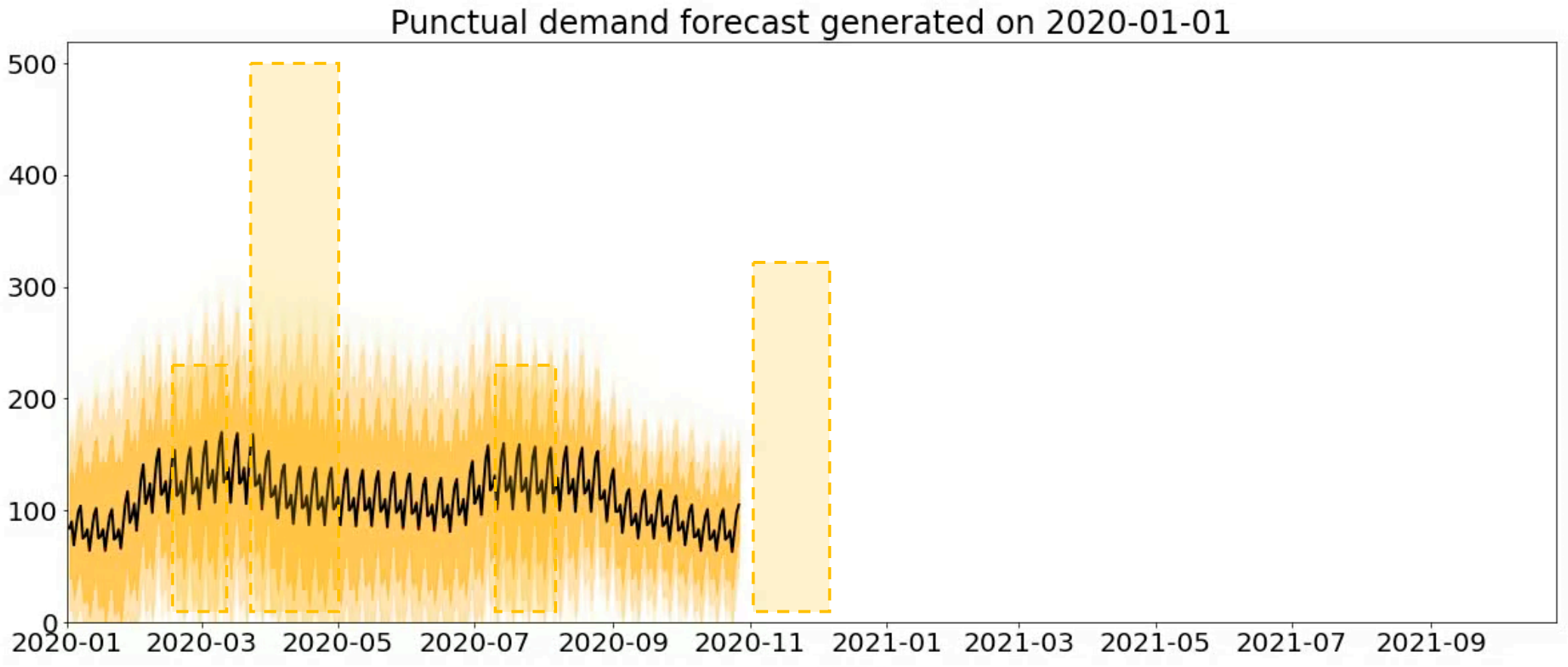
Purpose of Generating Demand Disruption Signals



Dynamic Update of Demand Forecasts

(e-commerce-based manufacturer, top-selling product category, forecasts updated daily for next 365 days)



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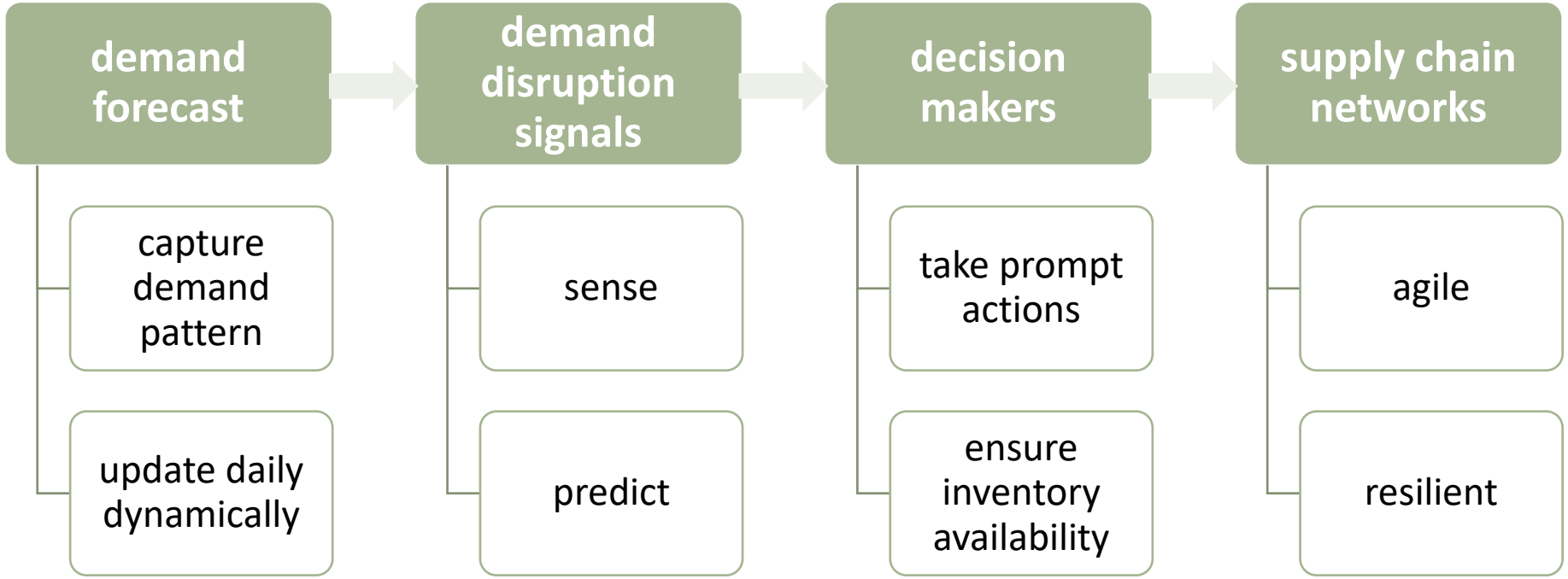

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Literature Review for Early Warning Signals

Early warning signals in different real-world fields

Early Warning Signals (EWSs) could be used to identify upcoming collapse of populations in marine ecosystems (Clements, et al., 2019), upcoming financial market downturns and upturns in stock market (Ismail, et al., 2022), and upcoming disease transition in disease detection (Southall, et al., 2021) at the early stage

Early warning signals in supply chain networks

Demand disruption signals have sensing capabilities (Pattanayak et al., 2023), demand insights that connect with present and future demand, and offer advanced information on demand, such as future planning and scheduling on demand (Hillman & Hochman, 2007)

Methods used to identify early warning signals

Change point *detection algorithms use a binary classifier, which are used for identification of pattern changes and release early warning signals in the demand process (Aminikhanghahi & Cook, 2017);* ***tracking signals*** *have been utilized for automatic update of forecasts (Snyder & Koehler, 2009), validation of the proposed forecasting methods (Saroha et al., 2021), and monitoring of forecast results (Rizki et al., 2021)*

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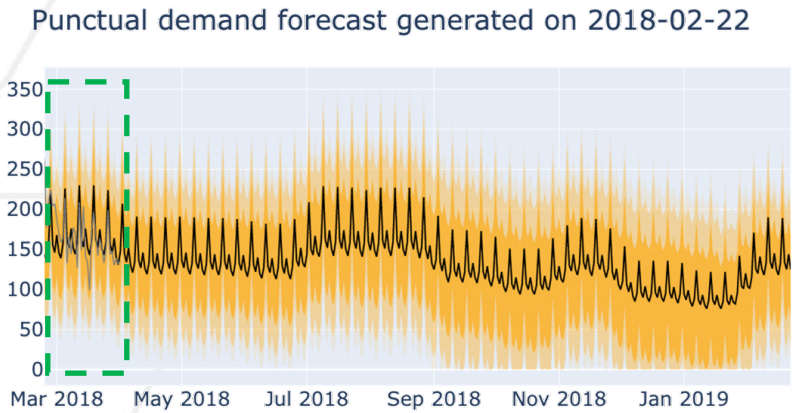
Introduction of Forecast Bias

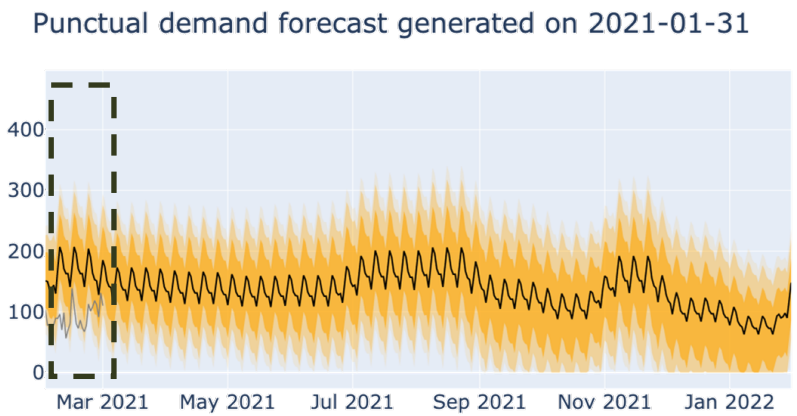
- Forecast bias is used to evaluate forecast on day t
- Formula: $b_t = \sum_{i=1}^{l}(d_{t+i} - f_{t+i,t})$
- Three classes of forecast bias:
  - No bias - $y = 0$, else
  - Negative bias - $y = -1$, if $b_t < Q_1$ and $d_{t+i} < f_{t+i,t}$
  - Positive bias - $y = 1$, if $b_t > Q_3$ and $d_{t+i} > f_{t+i,t}$

labels

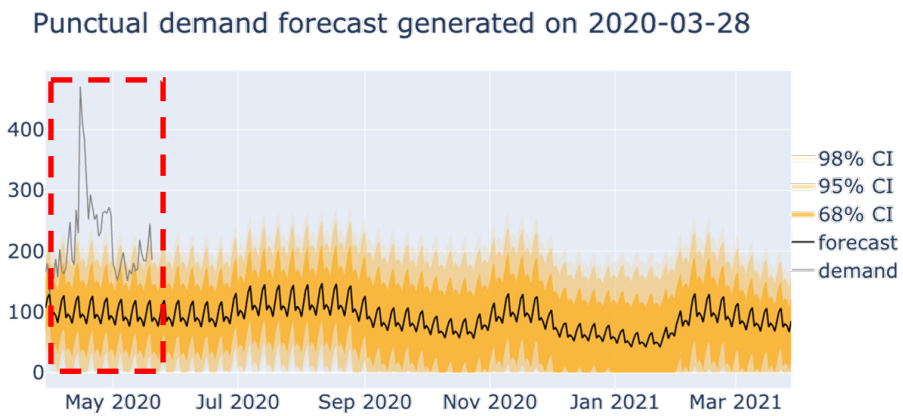
Notation	Definition
b_t	forecast bias using forecast generated on day t
d_{t+i}	estimated demand on day $t+i$ (future realizations)
$f_{t+i,t}$	demand forecast generated on day t for day $t+i$



No bias



Negative bias

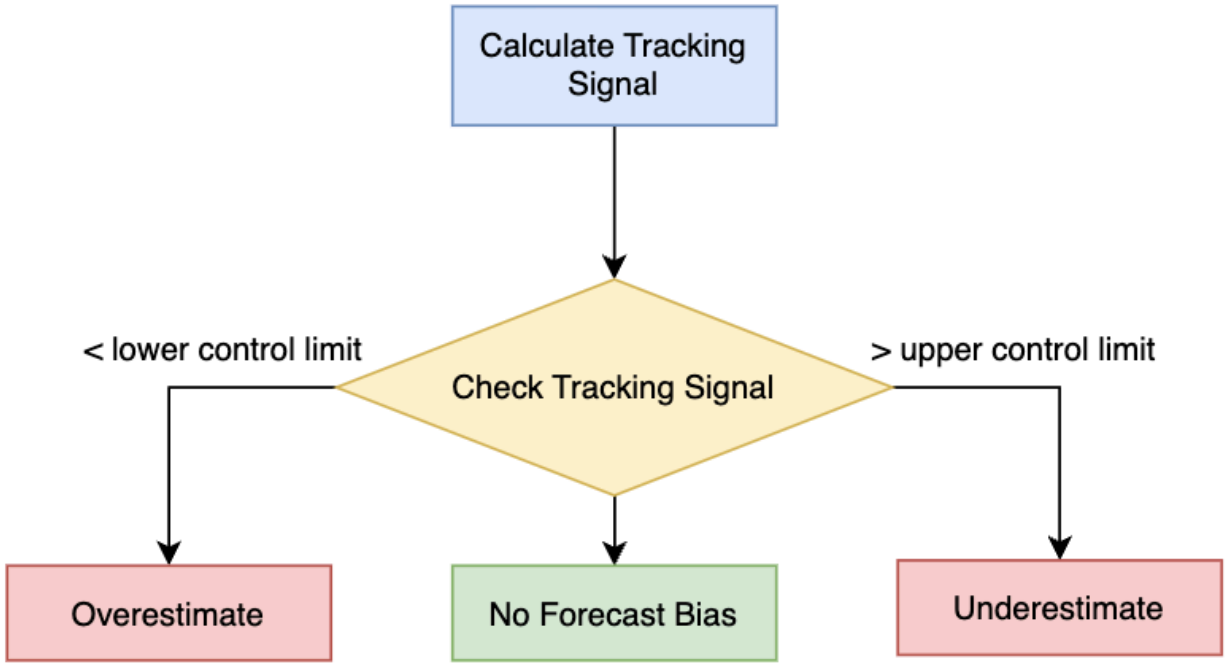


Positive bias

We consider upcoming 14 days to calculate forecast bias as we aim to capture disruptions in the short term in this study

Introduction of Tracking Signal

$$\text{Tracking Signal} = \frac{\Sigma(\text{Actual} - \text{Forecast})_t}{\text{Mean Absolute Deviation}}$$

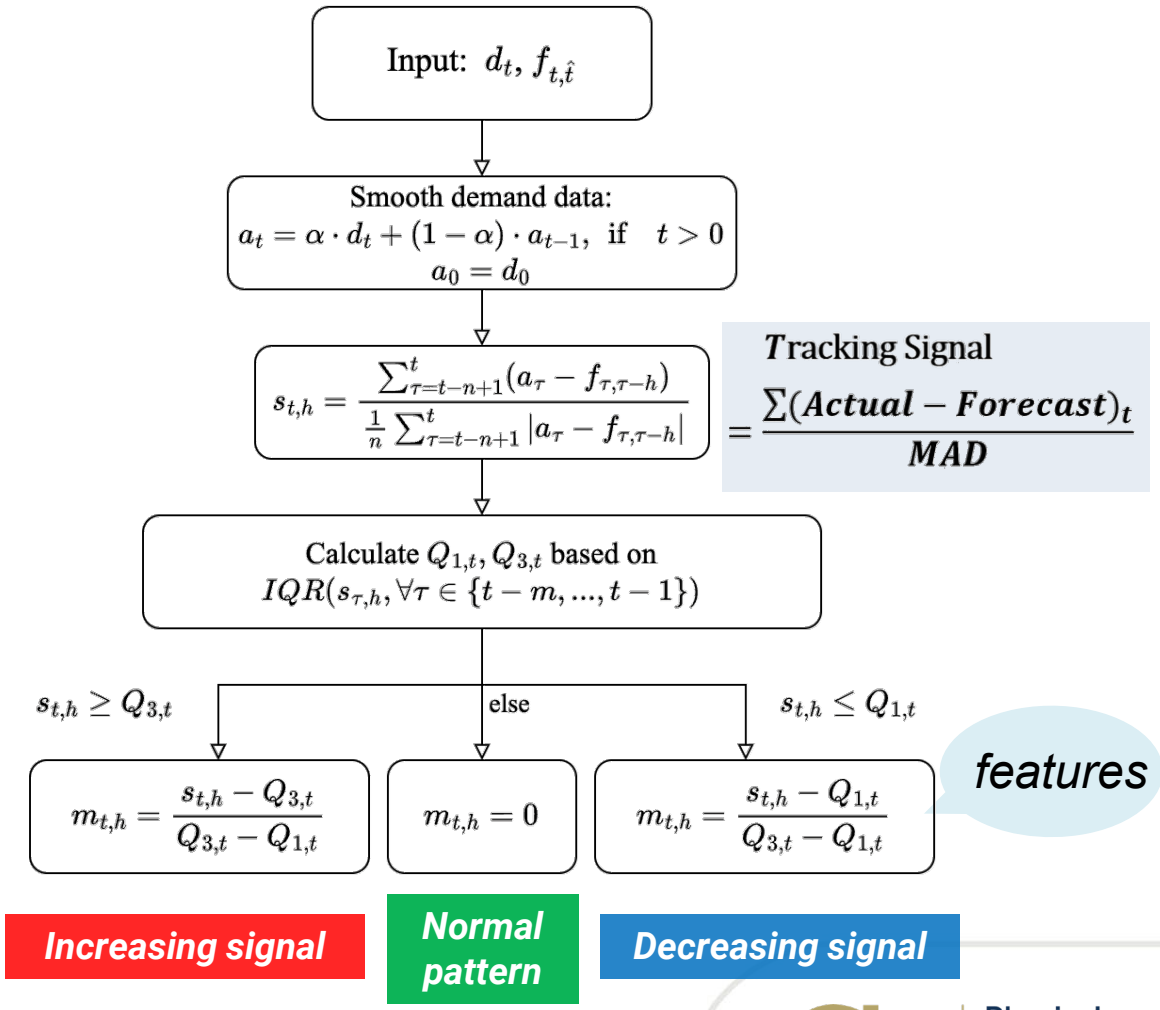


Modified Tracking Signals as Engineered Features

- **Increasing signal:** Demand >> forecast (positive bias), forecast needs to be increased
- **Decreasing signal:** Demand << forecast (negative bias), forecast needs to be decreased
- **Normal pattern:** Forecast could capture the change in demand pattern

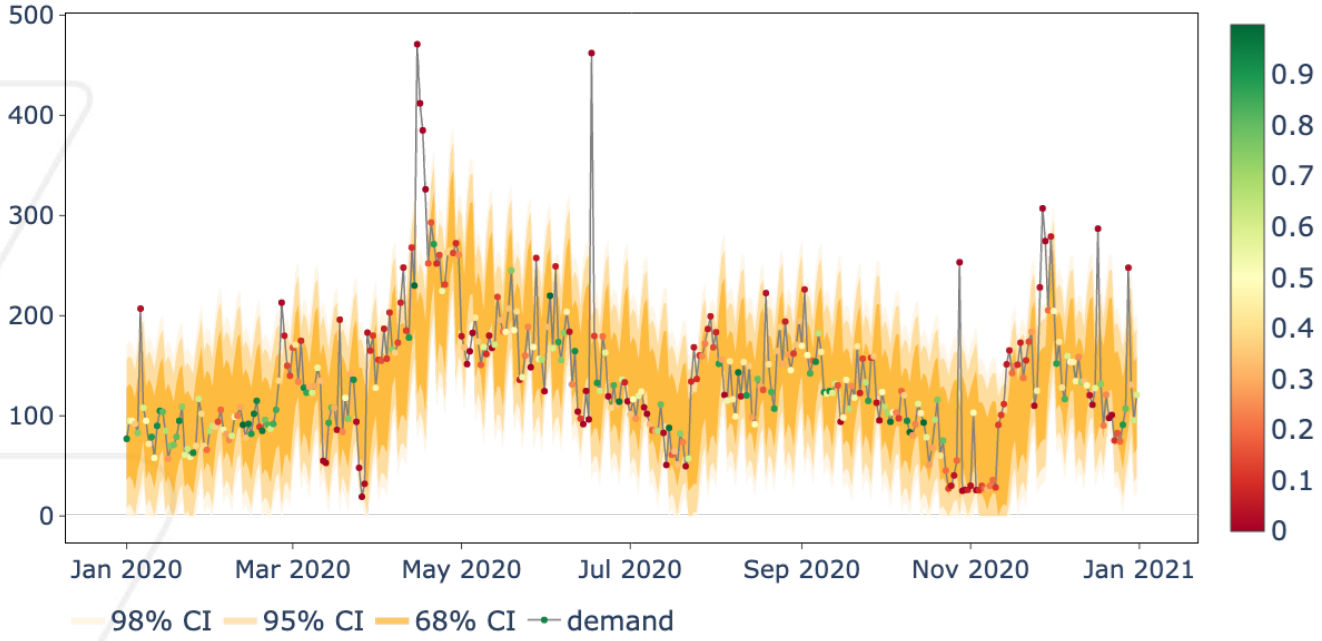
Notation	Definition
$\mathcal{T} = \{1, ..., T\}$	set of days considered
$\mathcal{H} = \{1, 2, 3, ...\}$	set of days-ahead forecast considered
d_t	observed demand on day t
a_t	exponentially smoothed demand on day t
$f_{t,\hat{t}}$	demand forecast generated on day $\hat{t}$ for day t
n	length of rolling horizon
$e_{t,h}$	rolling-horizon Mean Absolute Deviation of h-days-ahead forecast errors
$s_{t,h}$	tracking signal on day t, based on h-days-ahead forecast
$m_{t,h}$	modified tracking signal on day t, based on h-days-ahead forecast
b_t	forecast bias using forecast generated on day t

Flowchart of feature generation algorithm



Filtering Method: Use P-Values to Filter Data

- **Filtering method:**
  - Positive bias and negative bias
  - P-value < 0.3



Demand in 2020 with CI using 1-day ahead forecast

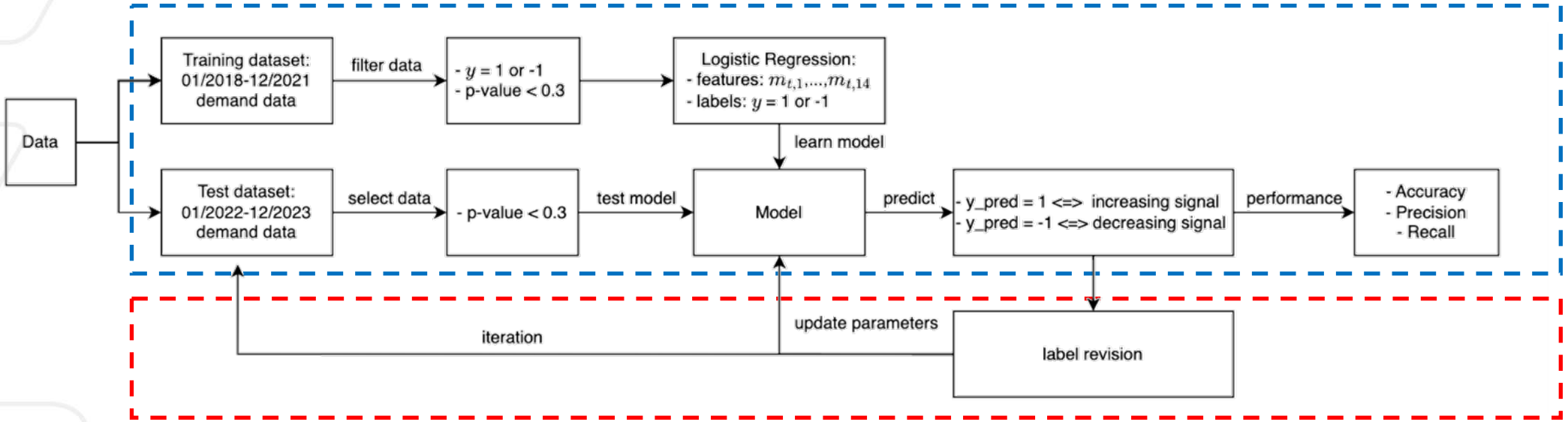
Calculation method of p-value:
Compute the percentile of the test residual in the empirical distribution of training residuals

Remark:
If the demand data is far from prediction, then the p-value will be very small

- Red: p-value is small (signal)
- Yellow: p-value is intermediate
- Green: p-value is large (normal pattern)

Dynamic Demand Disruption Signals Generation

- **Data:** four-year demand history for model training, and two-year for evaluation



how we create, train, and evaluate our model

how we dynamically update our model every day to sense and generate demand disruption signals

Example of an Increasing Demand Disruption Signal

for Master-Bedroom Bed product type

	Modified Tracking Signal (based on x-days-ahead forecast)																
Date	1	2	3	4	5	6	7	8	9	10	11	12	13	14	p-value	Signal	Confidence
2020-03-20	-0.29	-0.26	-0.17	-0.08	-0.03	-0.13	-0.19	-0.25	-0.09	0.00	0.00	0.00	0.00	0.00	0.51		
2020-03-21	-0.29	-0.19	-0.10	-0.05	-0.14	-0.20	-0.27	-0.13	0.00	0.00	0.00	0.00	0.00	0.13	0.76		
2020-03-22	-0.21	-0.10	-0.05	-0.15	-0.25	-0.32	-0.14	0.00	0.00	0.00	0.00	0.20	0.32	0.39	0.30		
2020-03-23	-0.11	-0.06	-0.20	-0.30	-0.44	-0.22	0.00	0.00	0.00	0.05	0.47	0.66	0.59	0.60	0.92		
2020-03-24	-0.08	-0.26	-0.37	-0.52	-0.28	0.00	0.00	0.00	0.24	0.78	1.03	1.01	0.82	0.81	0.02	Increasing	84%
2020-03-25	-0.29	-0.43	-0.61	-0.28	0.00	0.00	0.00	0.58	1.09	1.50	1.46	1.33	0.78	0.66	0.03	Increasing	92%
2020-03-26	-0.44	-0.65	-0.21	0.00	0.00	0.39	1.04	1.67	1.94	2.04	1.42	0.88	0.63	0.53	0.00	Increasing	98%
2020-03-27	-0.67	-0.16	0.00	0.14	1.14	1.33	2.14	2.57	2.51	1.44	0.86	0.67	0.51	0.52	0.02	Increasing	100%
2020-03-28	-0.13	0.00	0.39	1.29	1.93	2.25	2.95	2.51	1.37	0.76	0.61	0.50	0.50	0.49	0.03	Increasing	100%
2020-03-29	0.00	0.22	1.12	1.66	2.56	2.47	1.94	1.14	0.68	0.48	0.41	0.45	0.45	0.34	0.09	Increasing	100%
2020-03-30	0.04	0.84	1.36	2.10	1.71	1.28	0.84	0.56	0.43	0.32	0.35	0.38	0.31	0.21	0.12	Increasing	100%
2020-03-31	0.69	1.00	1.45	1.04	0.79	0.63	0.41	0.35	0.28	0.29	0.32	0.28	0.21	0.07	0.46		
2020-04-01	0.84	1.27	0.78	0.56	0.50	0.34	0.27	0.25	0.27	0.28	0.25	0.20	0.08	0.00	0.10	Increasing	98%
2020-04-02	1.53	0.90	0.58	0.47	0.39	0.32	0.24	0.31	0.32	0.22	0.19	0.08	0.04	0.00	0.15	Increasing	97%
2020-04-03	1.31	0.73	0.52	0.37	0.37	0.28	0.30	0.37	0.27	0.17	0.08	0.03	0.04	0.00	0.07	Increasing	96%
2020-04-04	1.08	0.65	0.42	0.36	0.33	0.38	0.41	0.34	0.23	0.07	0.03	0.03	0.04	0.00	0.12	Increasing	95%
2020-04-05	0.84	0.47	0.35	0.32	0.44	0.51	0.38	0.27	0.10	0.04	0.04	0.03	0.03	0.00	0.09	Increasing	94%

Modified Tracking signals

±0 | ±1 | ±2 | ±3

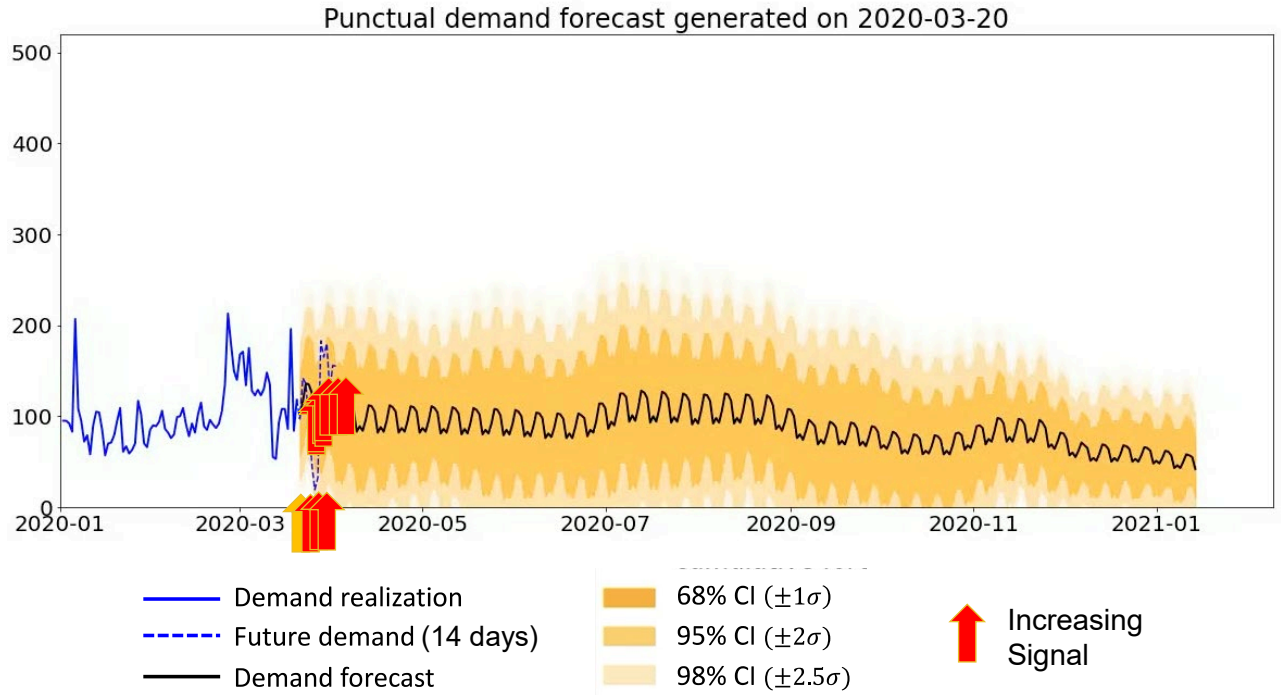
*A tracking statistic denoting **deviation** of today's realized demand from forecast generated x-days ago*

p-value

0.00 | 0.25 | 0.50 | 0.75 | 1.00

*A tracking statistic denoting **position** of today's realized demand with respect to forecast confidence interval*

0: demand is far outside confidence intervals
1: demand is well within confidence intervals



Warning - Demand is growing faster than predicted!
With **94%** confidence, we are under-forecasting demand for the upcoming 2 weeks

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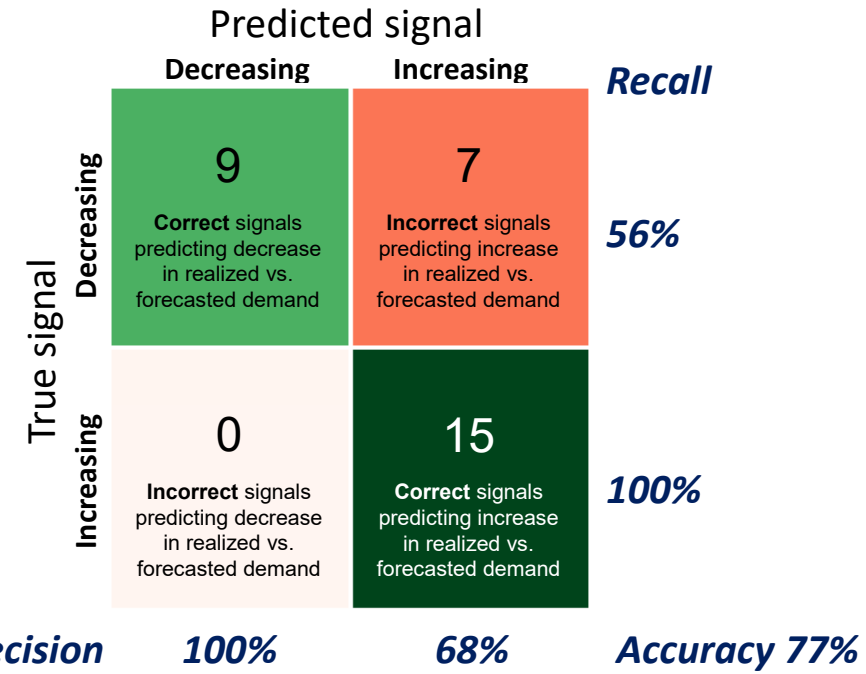
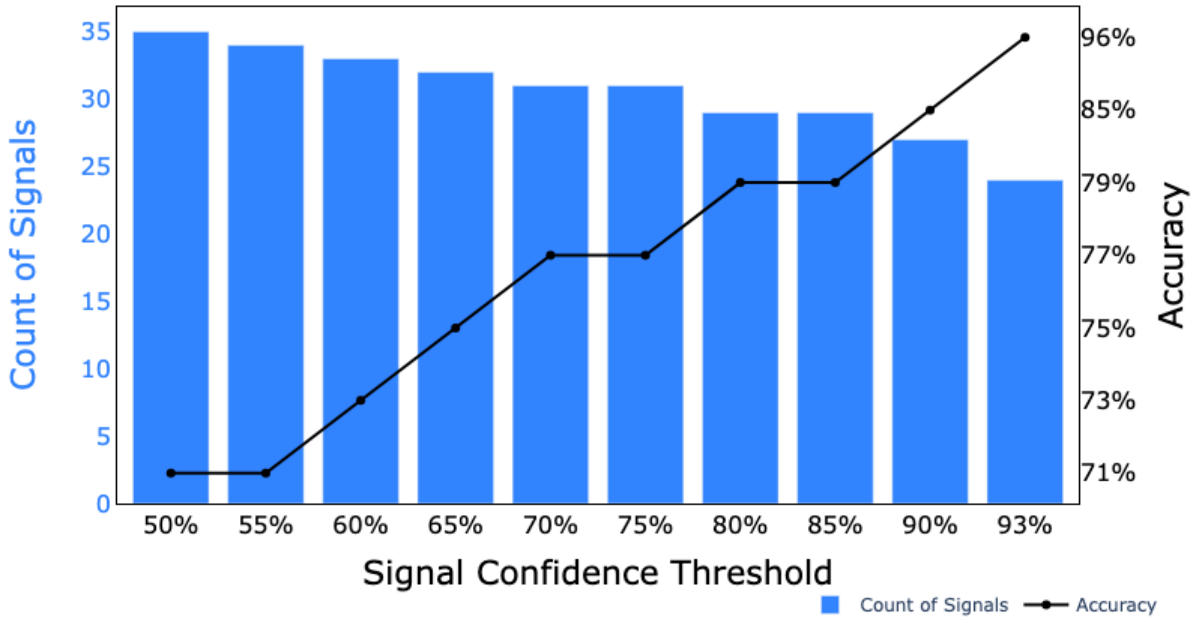
Results on Validity of Signal Quality

- **Precision -** proportion of predicted signals correctly captured by model, for each signal type
- **Recall -** proportion of true signals correctly captured by model, for each signal type
- **Accuracy -** proportion of all signals correctly captured by model



*** Signal Confidence Threshold: 75%**

(considering signals with confidence greater than 75%)



Signal accuracy increases with signal confidence threshold, implying signals with higher confidence have higher accuracy

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Comparison of Different Signal Generation Methods
for Global Master-Bedroom Bed Product Type

- **Precision -** proportion of predicted signals correctly captured by model
- **Recall -** proportion of true signals correctly captured by model
- **Accuracy -** proportion of all signals correctly captured by model

Method \ Metric	Precision	Recall	Accuracy	Signal Count	Missing Value
Adaptive Tracking Signal	**84%**	**78%**	**77%**	31	14
Tracking Signal	42%	45%	41%	34	11
Change-point	20%	50%	40%	30	15

- *Training duration: 01/2018 – 12/2021 (4y)*
- *Testing duration: 01/2022 – 12/2023 (2y)*
- *Signal Confidence Threshold: 75%*

(considering signals with confidence greater than 75%)

- Overall, we achieved 77% accurate demand disruption signals
- Our developed methodology will be utilized for generating early warning signals for various in-network and external demand, supply, and supply chain disruptions

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Conclusions and Future Research

Conclusions

- Our model could identify disruptions in early phases
- Our model performs better than baseline models with 77% accuracy
- Our model could update daily to be used in real-world industry

Future work

- Extend disruption signal generation to logistics, production, and supply
- Generate external signals to identify disruptions through external factors

References

- Clements, C. F., McCarthy, M. A., & Blanchard, J. L. (2019). Early warning signals of recovery in complex systems. Nature communications, 10(1), 1681.
- Ismail, Mohd Sabri, et al. "Early warning signals of financial crises using persistent homology." Physica A: Statistical Mechanics and Its Applications 586 (2022): 126459.
- Southall, Emma, et al. "Early warning signals of infectious disease transitions: a review." Journal of the Royal Society Interface 18.182 (2021): 20210555.
- Sirsha Pattanayak, Ramkumar M Arputham, Mohit Goswami, and Nripendra P Rana. Blockchain technology and its relationship with supply chain resilience: A dynamic capability perspective. IEEE Transactions on Engineering Management, 2023
- Mark Hillman and Stephen Hochman. Supply chain technology landscape has radically changed for everyone. Supply chain management review, v. 11, no. 1 (Jan. 2007), p. 6-16: ill, 2007.
- Aminikhanghahi, S., & Cook, D. J. (2017). A survey of methods for time series change point detection. Knowledge and information systems, 51(2), 339-367.
- Ralph D Snyder and Anne B Koehler. Incorporating a tracking signal into a state space model. International Journal of Forecasting, 25(3):526–530, 2009.
- Sumit Saroha, Marta Zurek-Mortka, Jerzy Ryszard Szymanski, Vineet Shekher, and Pardeep Singla. Forecasting of market clearing volume using wavelet packet-based neural networks with tracking signals. Energies, 14(19): 6065, 2021.
- Muhammad Rizki, Alex Wenda, Farhan Dio Pahlevi, Muhammad Isnaini Hadiyul Umam, Muhammad Luthfi Hamzah, and Sutoyo Sutoyo. Comparison of four time series forecasting methods for coal material supplies: Case study of a power plant in indonesia. In 2021 International Congress of Advanced Technology and Engineering (ICOTEN), pages 1–5. IEEE, 2021.

Thank You!

Questions, comments, and suggestions are most welcome!

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