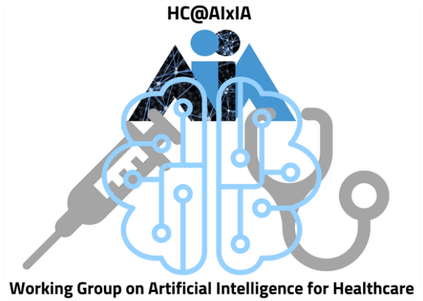



Relevance-Aware Thresholding in Online Conformal Prediction for Time Series

Théo DUPUY[1], Binbin XU[1], Stéphane PERREY[2], Jacky MONTMAIN[3], Abdelhak IMOUSSATEN[3]

[1]EuroMov Digital Health in Motion, Univ Montpellier, IMT Mines Alès, Alès, France
[2]EuroMov Digital Health in Motion, Univ Montpellier, IMT Mines Alès, Montpellier, France
[3]SyCoIA, IMT Mines Alès, Alès, France

EuroMov Digital Health in Motion



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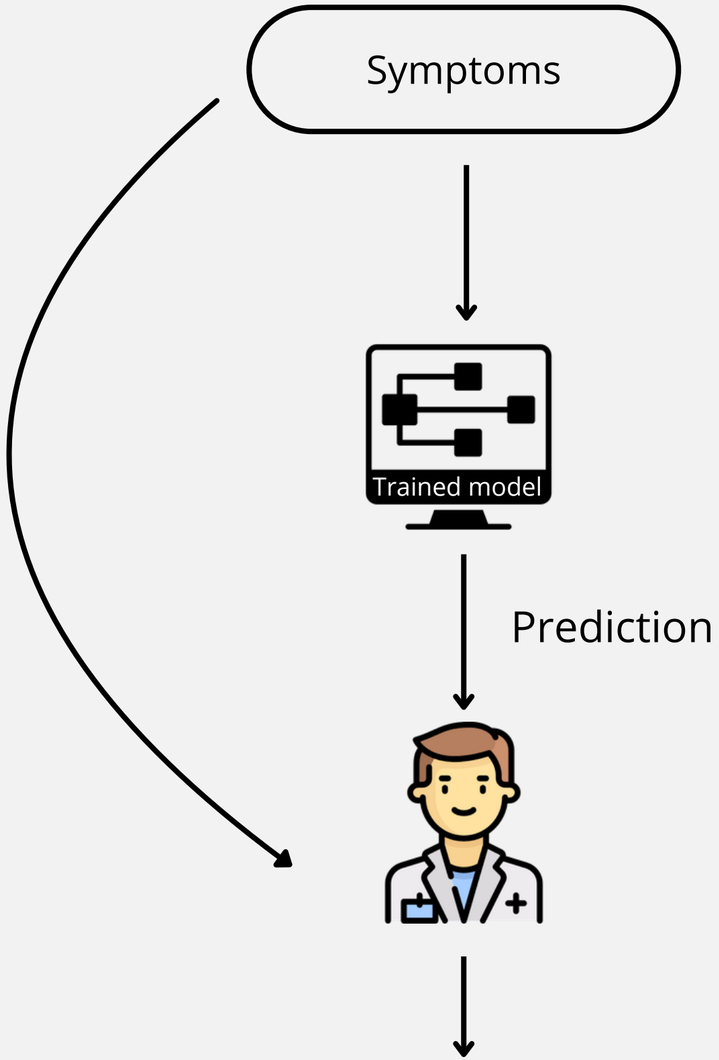
Decision support system

Symptoms



Decision support system



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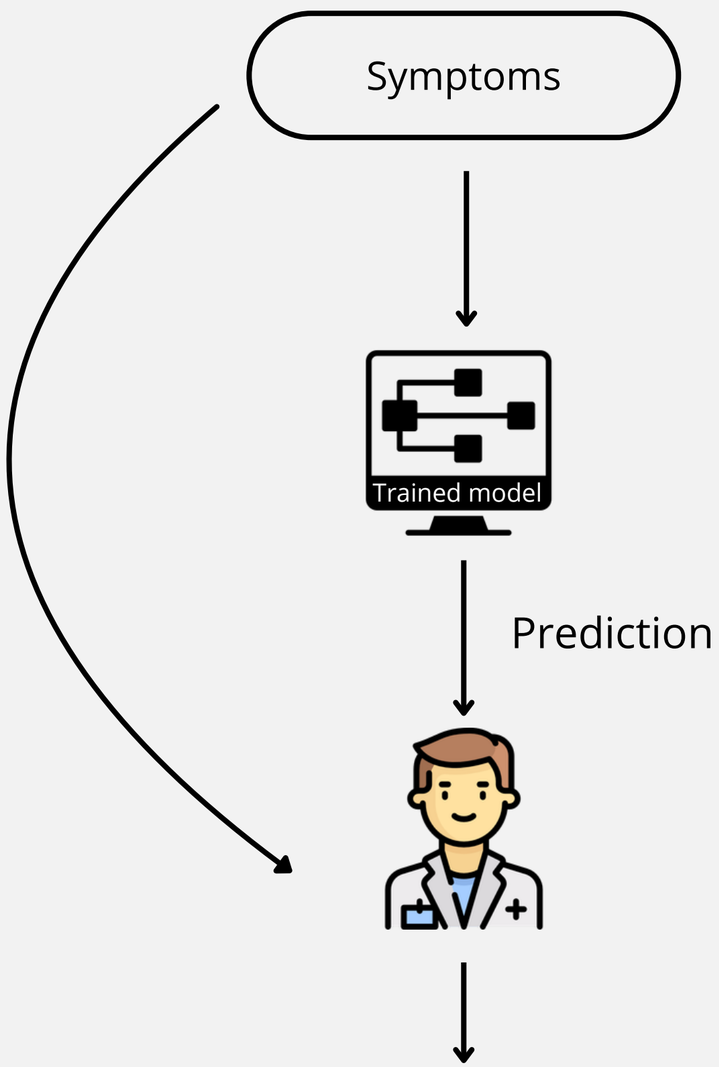

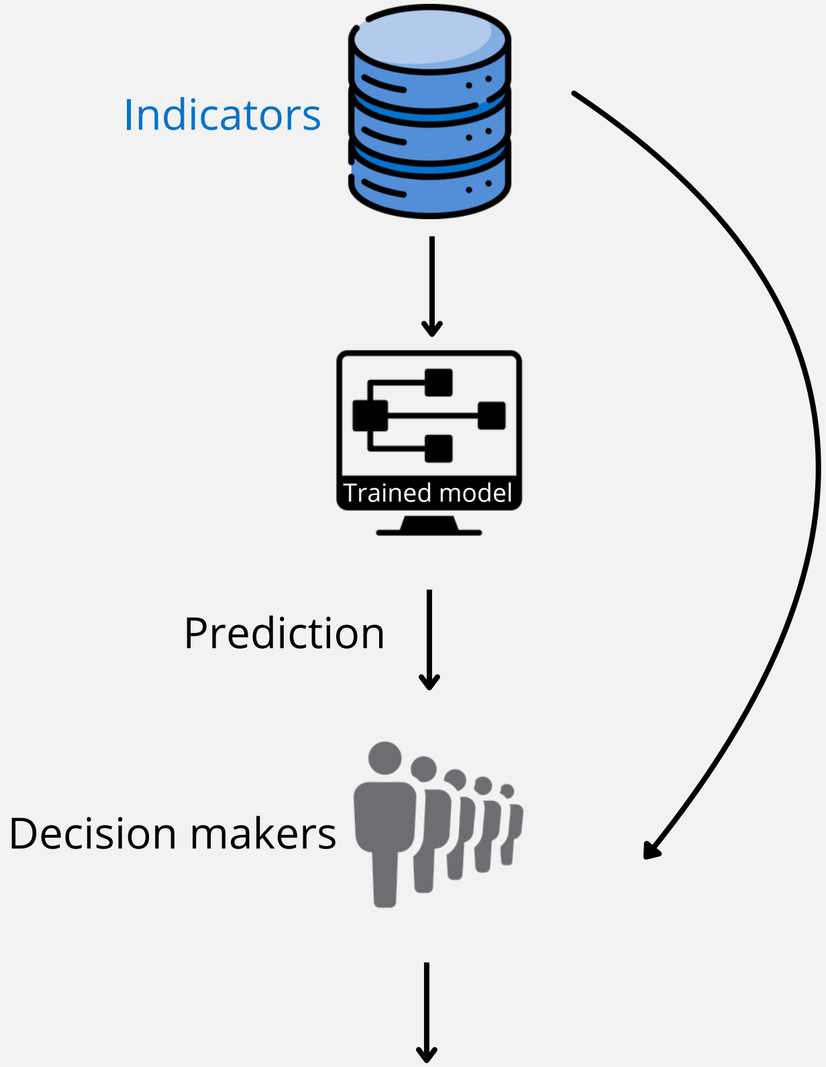

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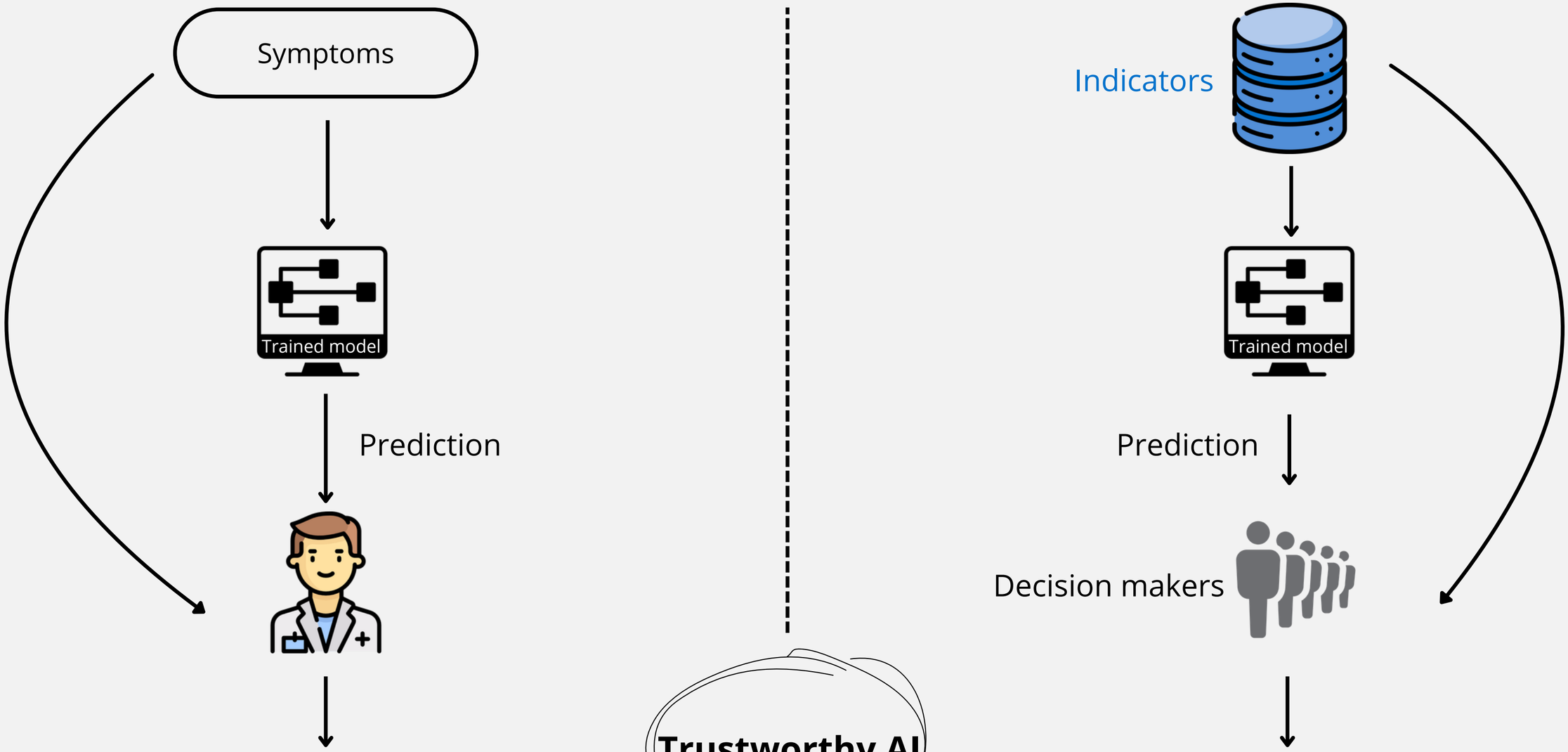

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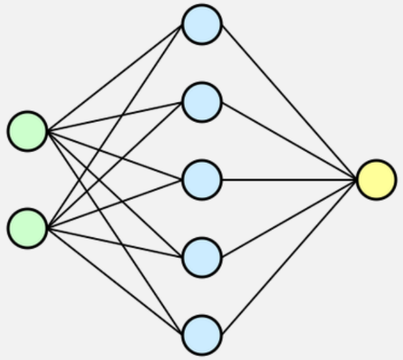

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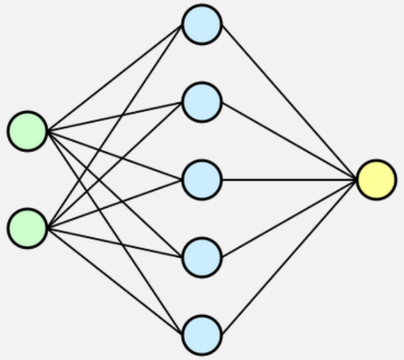

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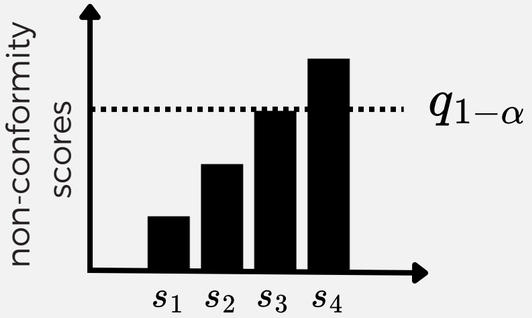

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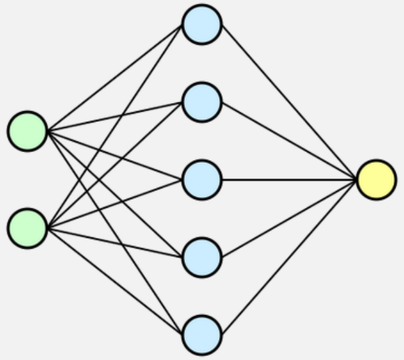

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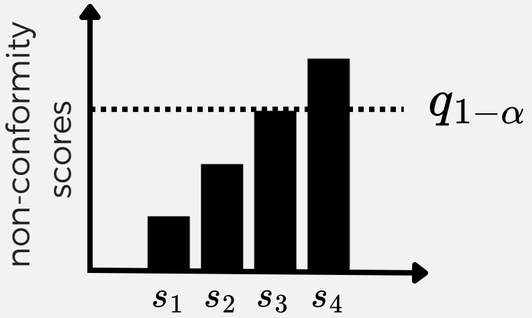

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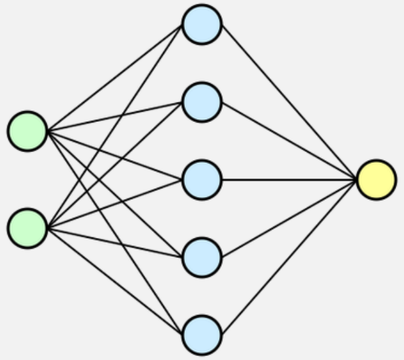

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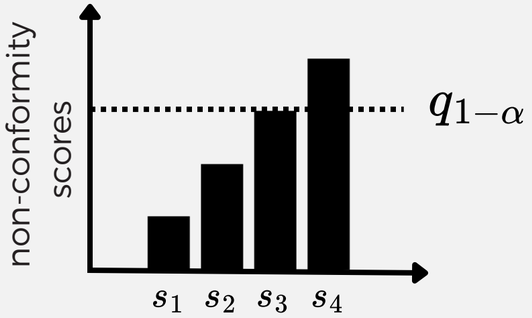

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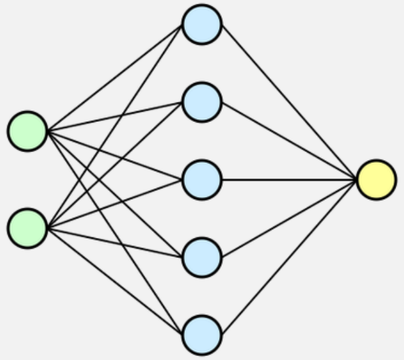

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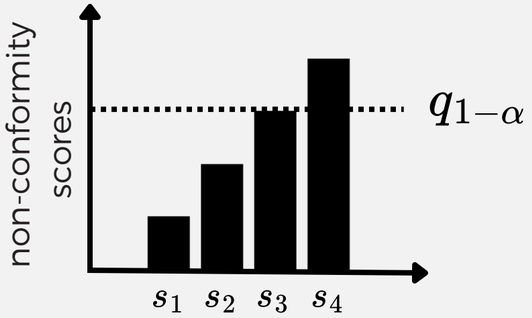

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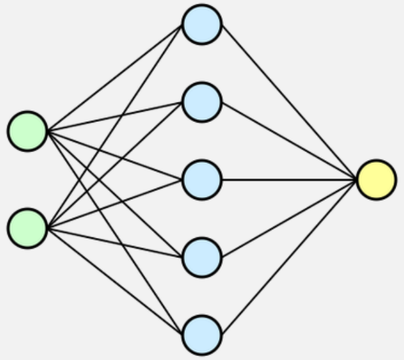

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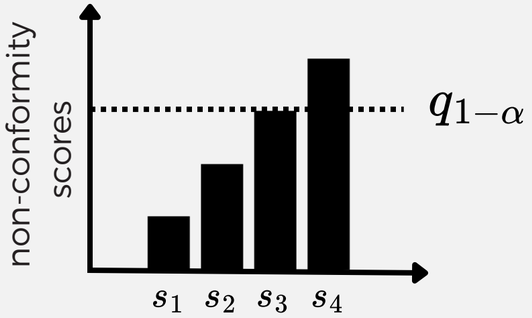

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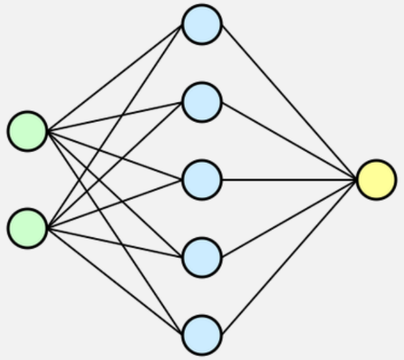

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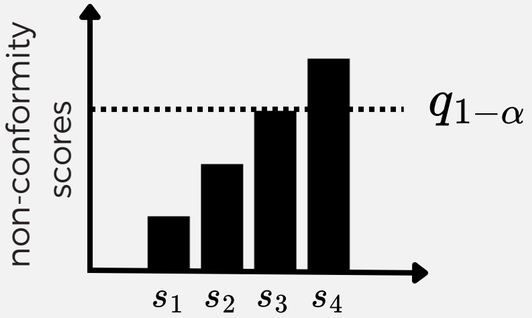

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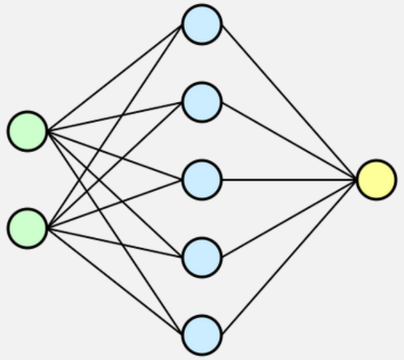

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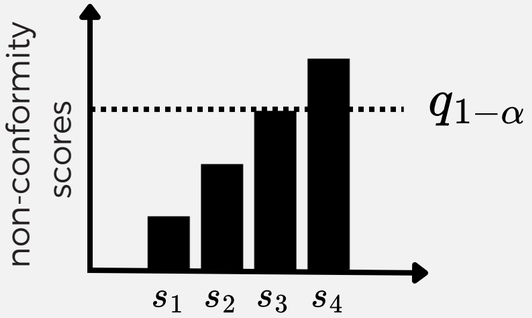

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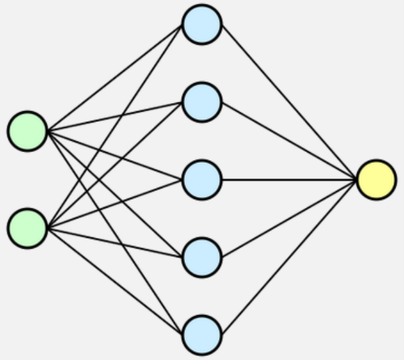

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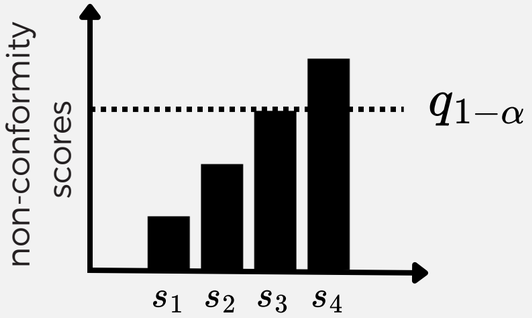

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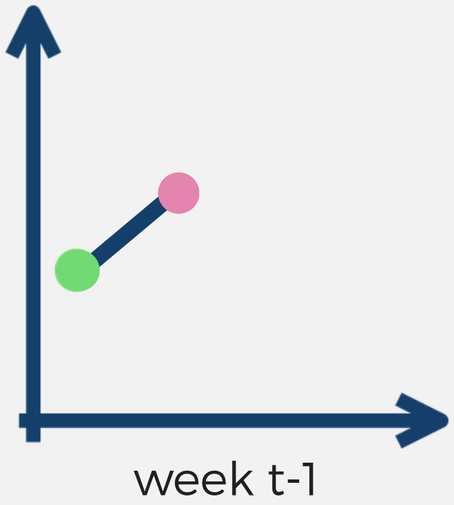

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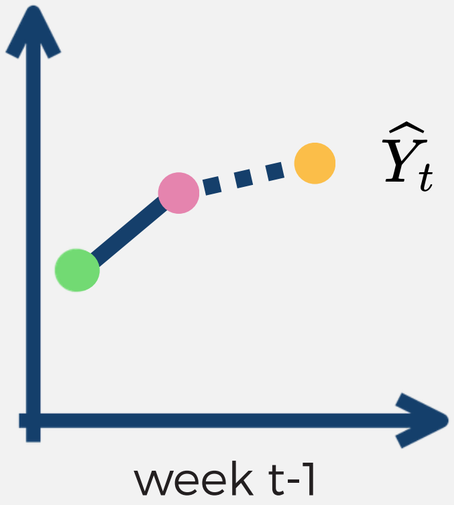

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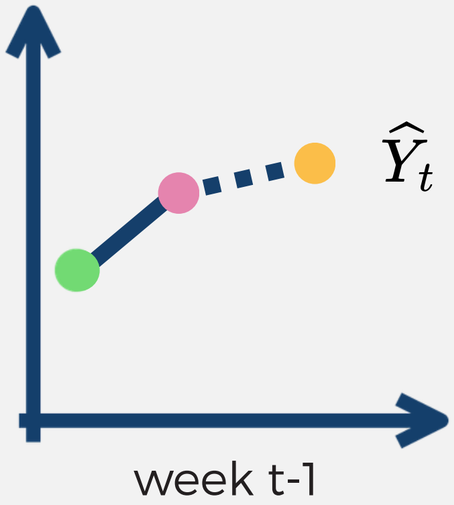

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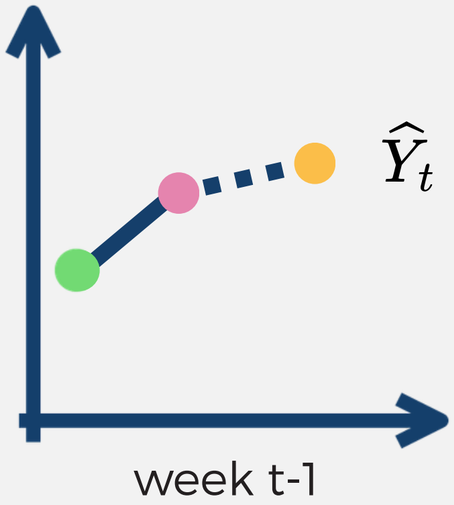

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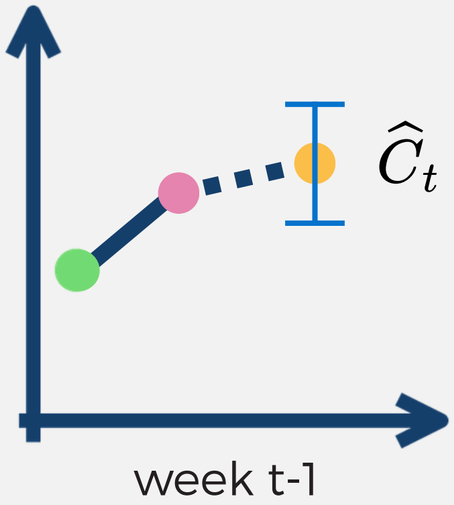

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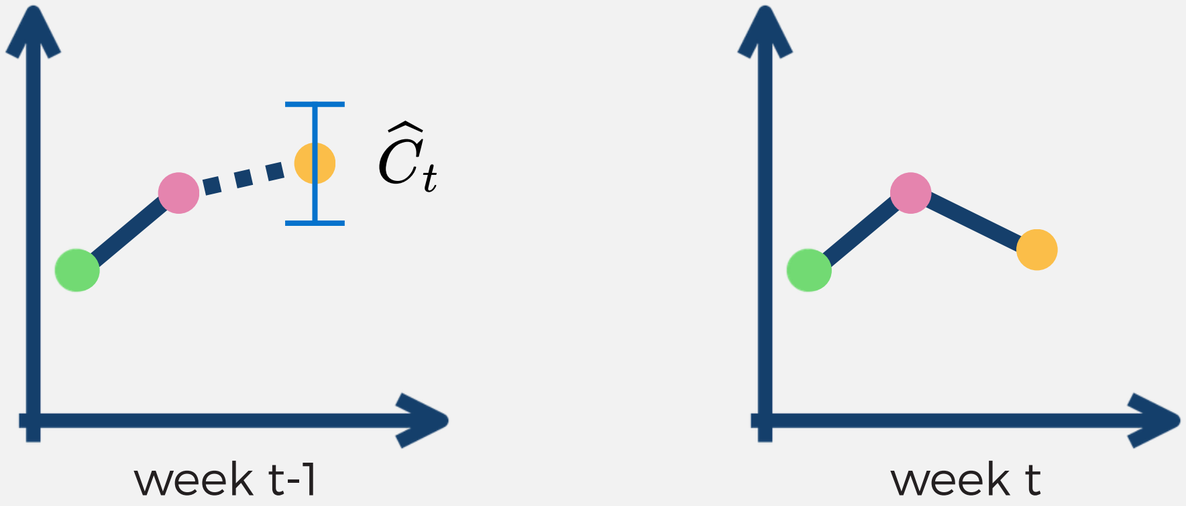

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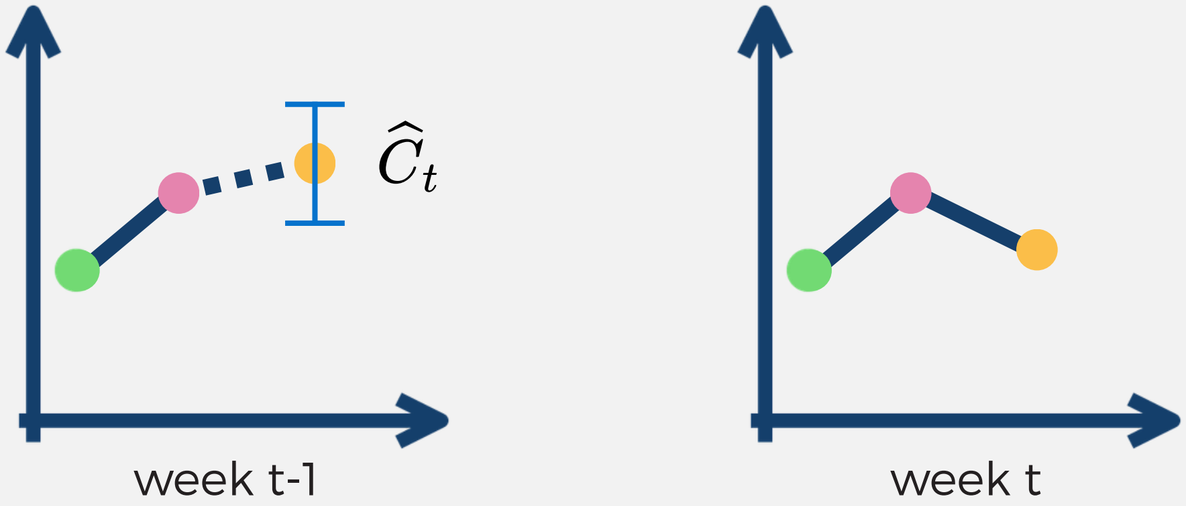

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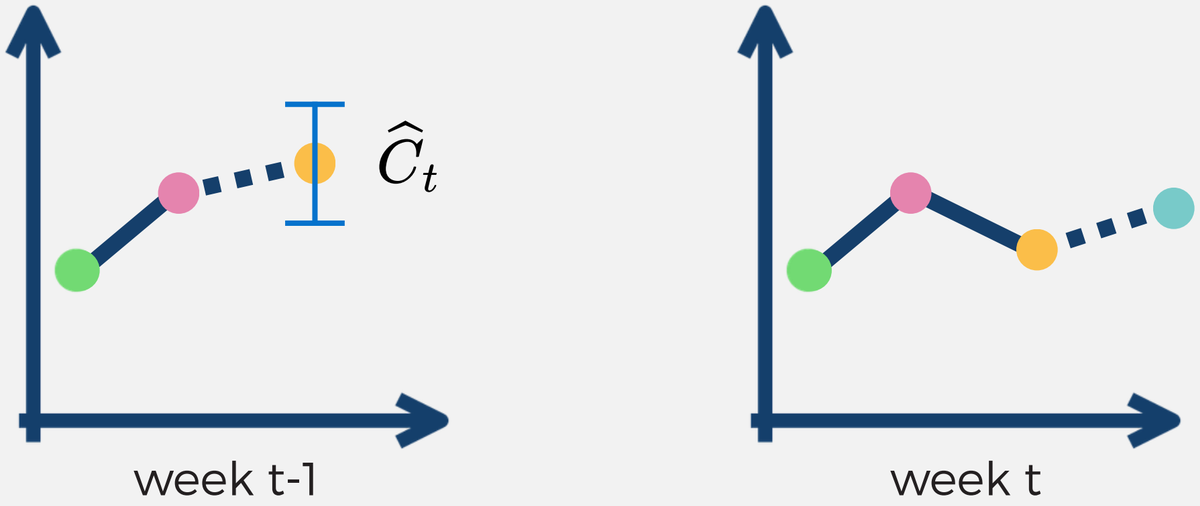

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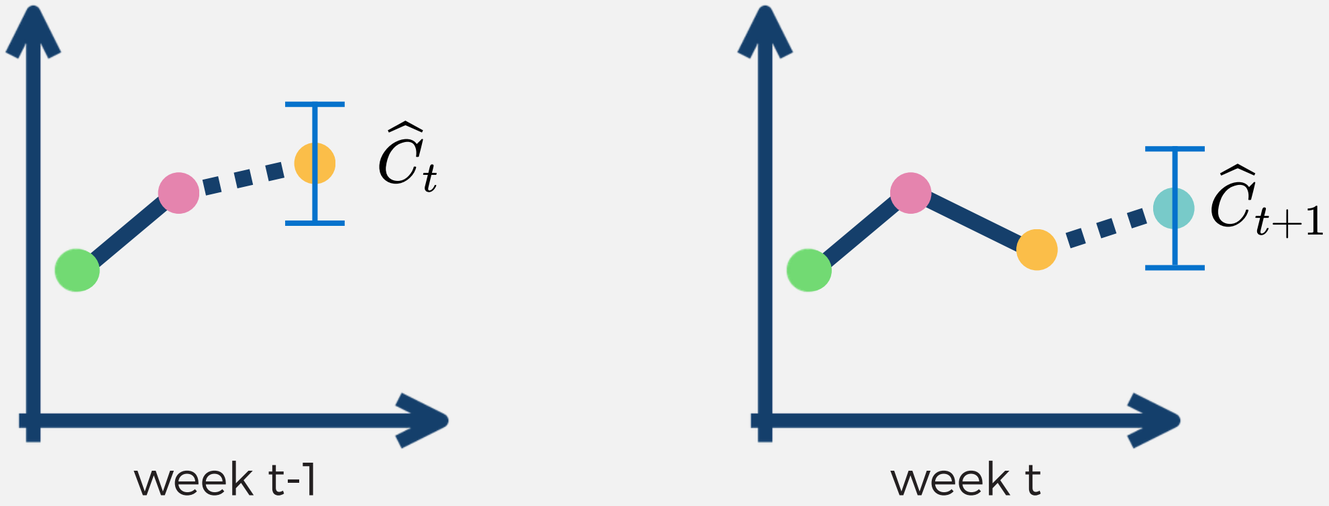

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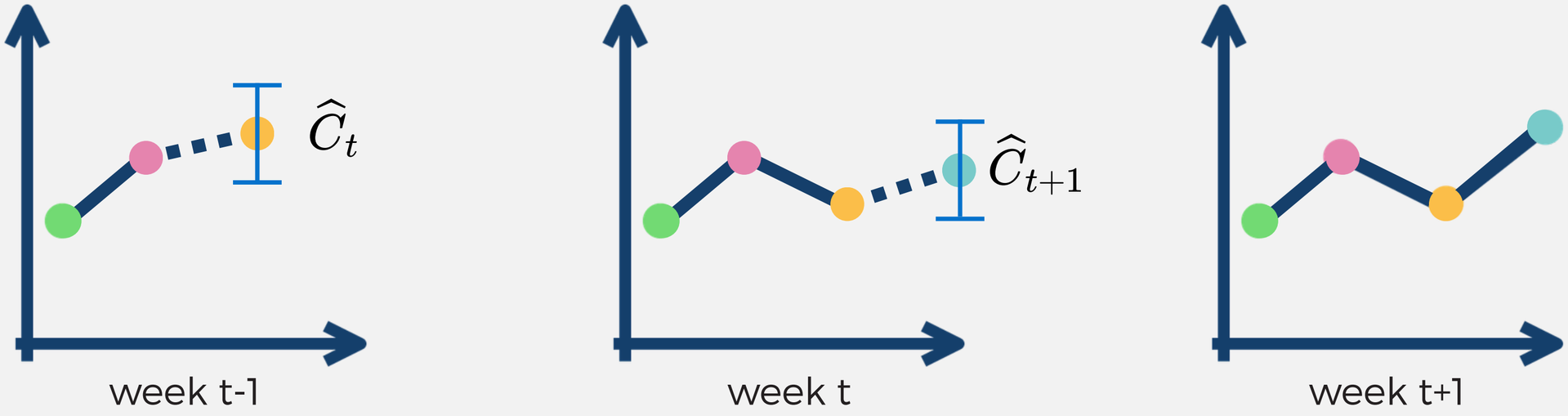

$$\forall t \in \mathbb{N},\ \widehat{C}_t = [\widehat{Y}_t \pm q_t] \text{ with } q_{t+1} = q_t + \eta(1\{Y_t \notin \widehat{C}_t\} - \alpha).$$

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How could we replace the indicator function ?

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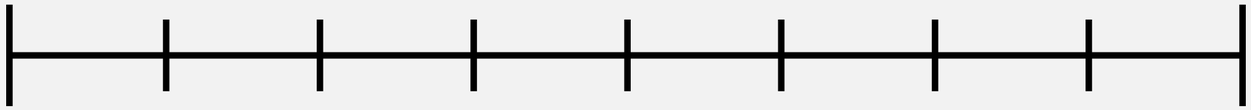
Why is the distance important ?



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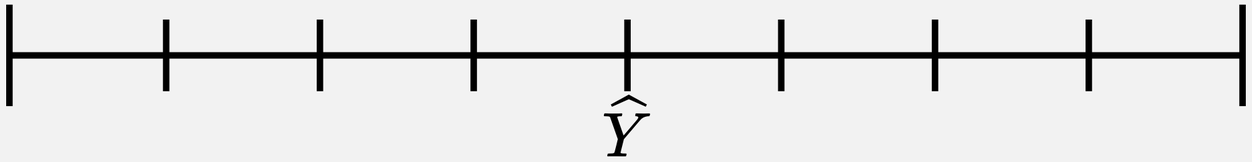

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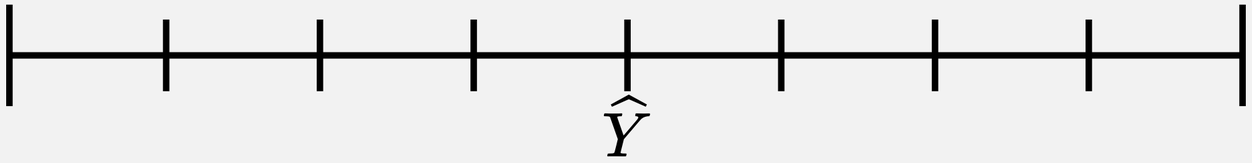

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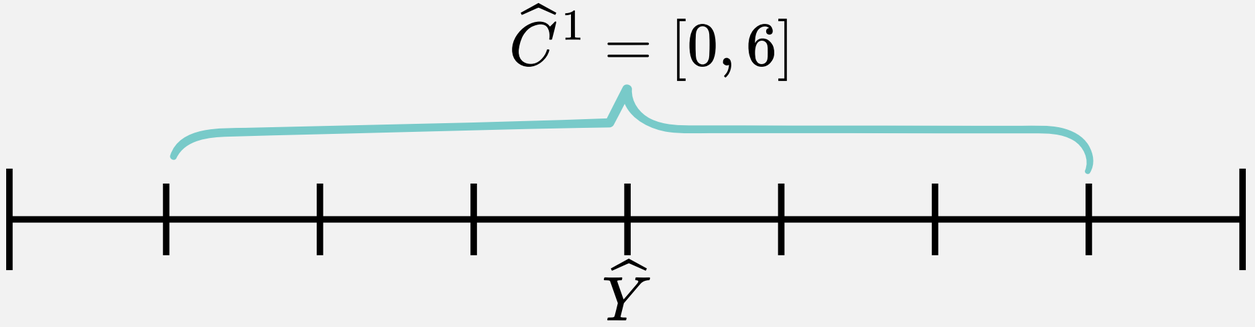

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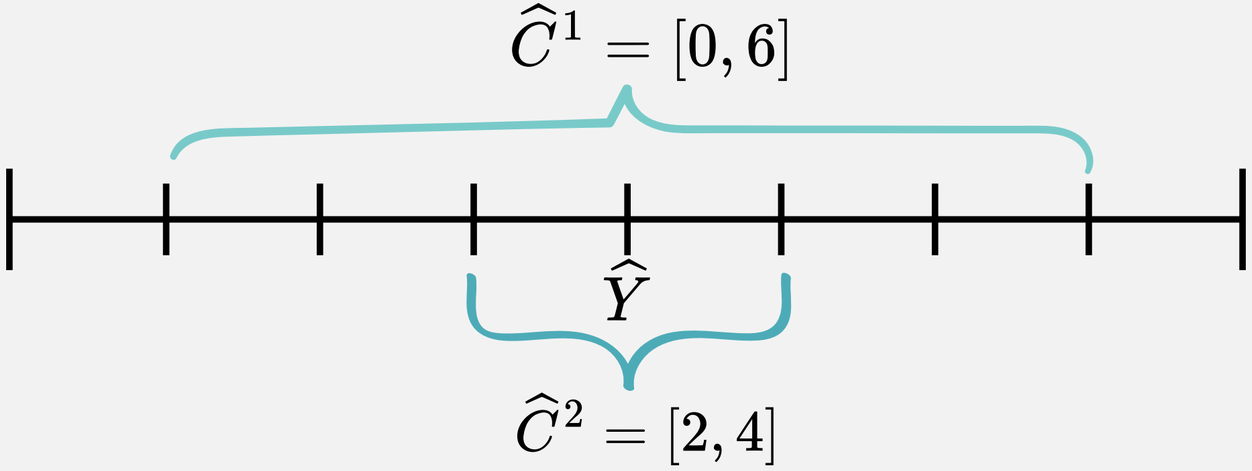

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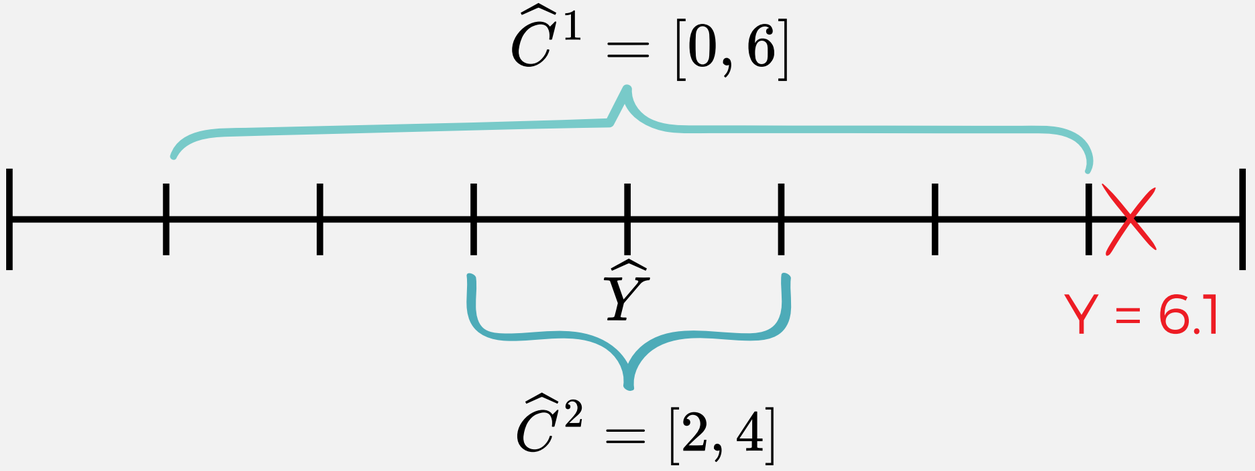

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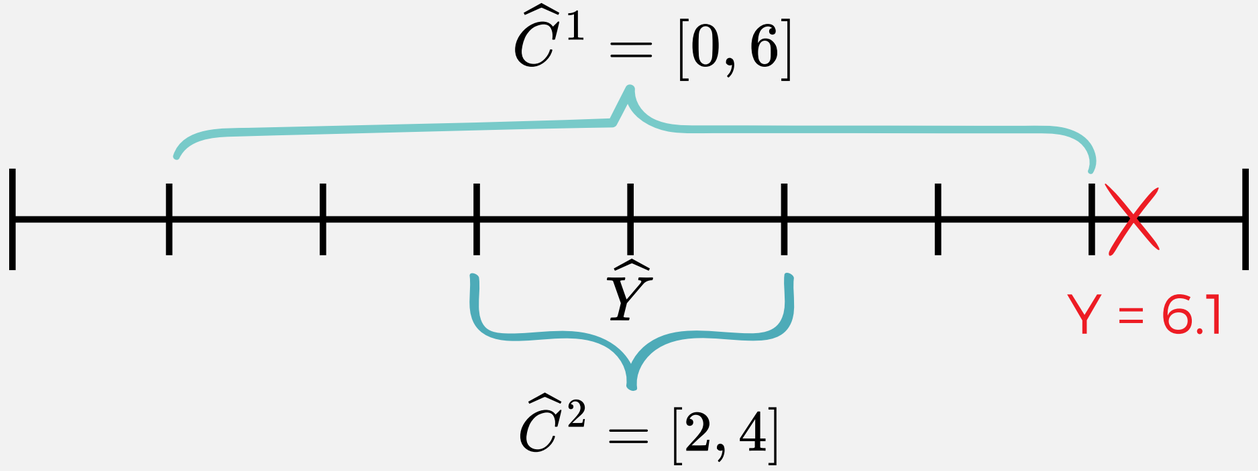

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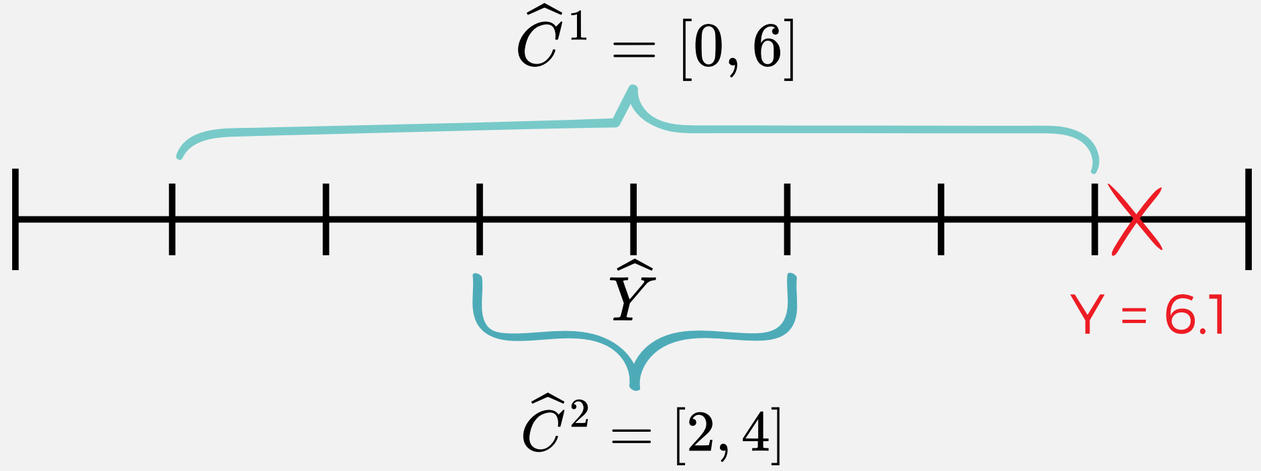

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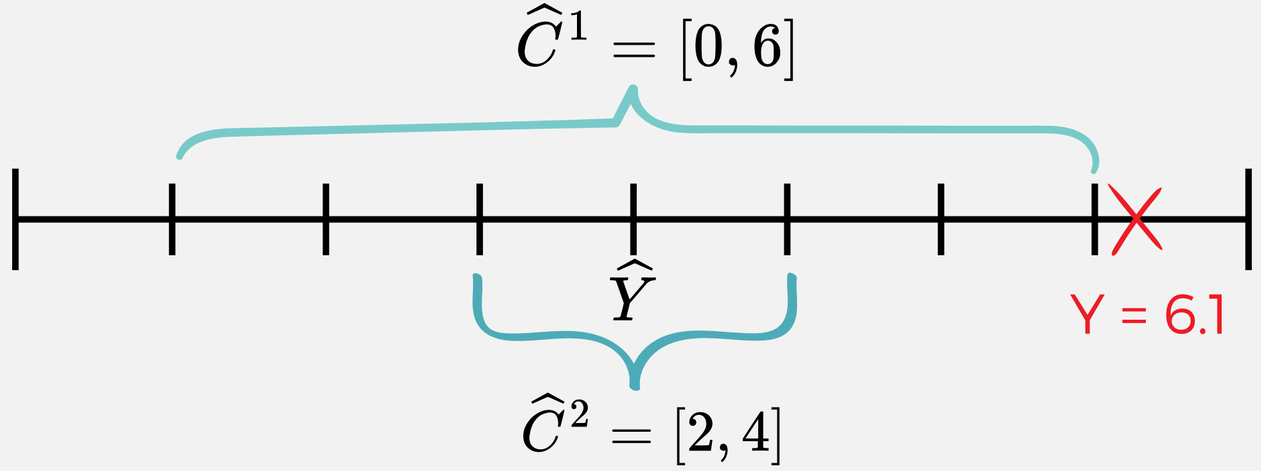

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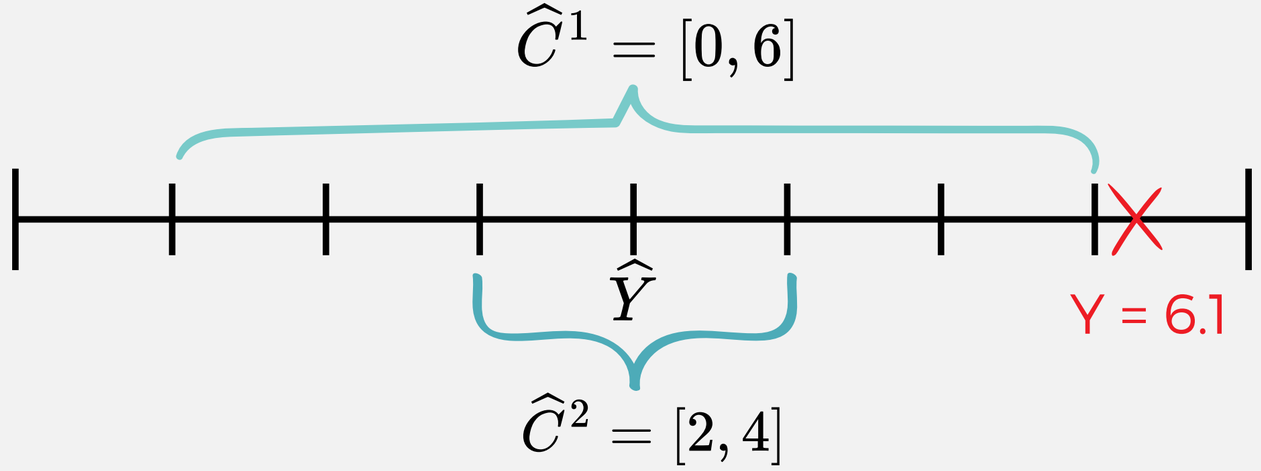

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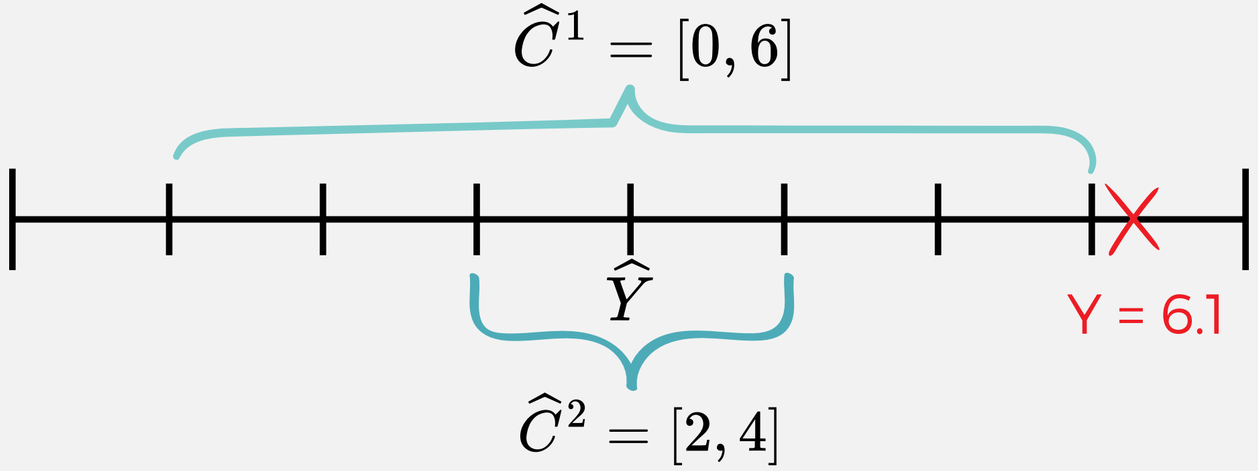

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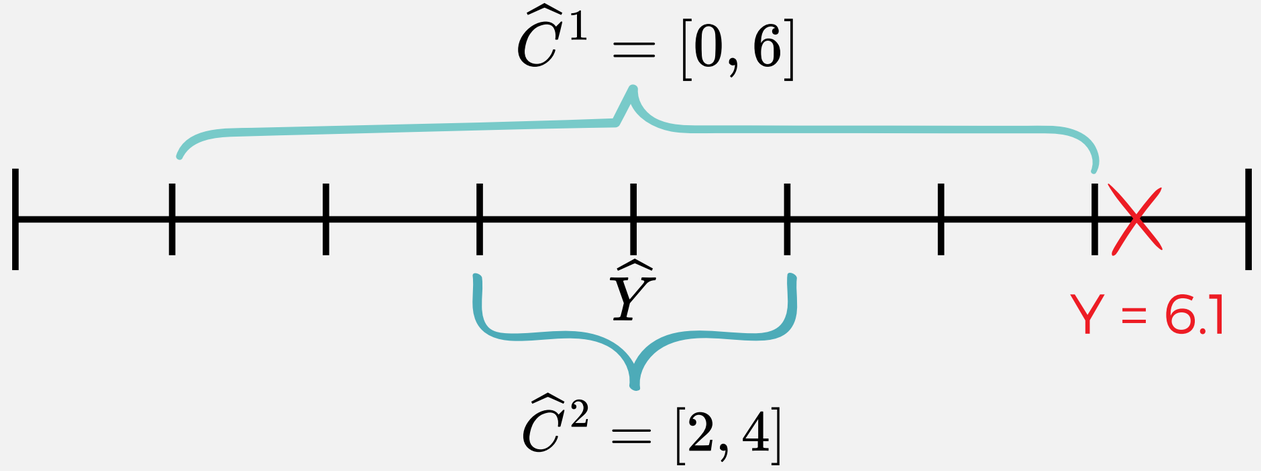

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How can the **distance** be used to estimate the **relevance** of a prediction subset ?

Our proposed functions

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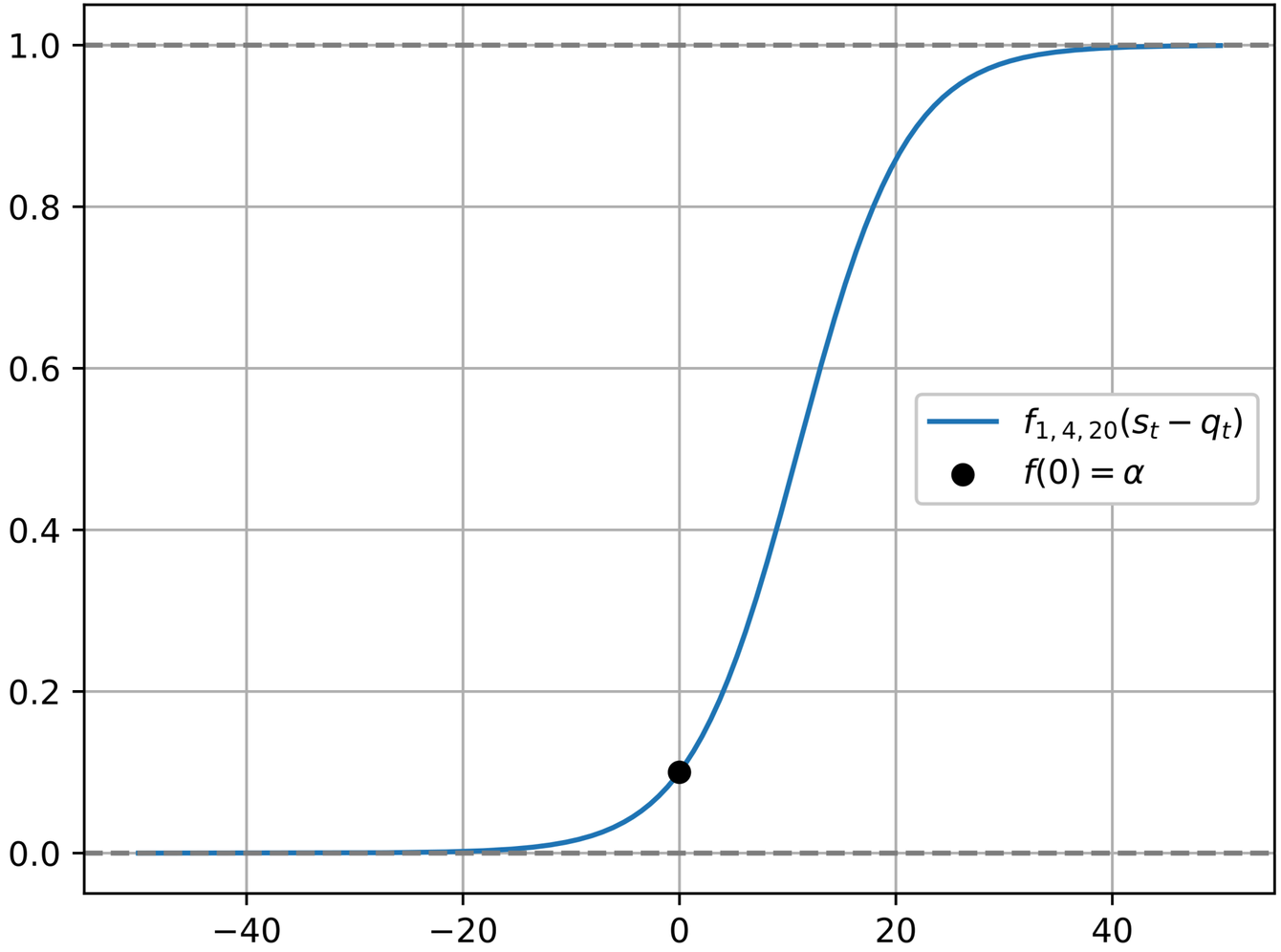

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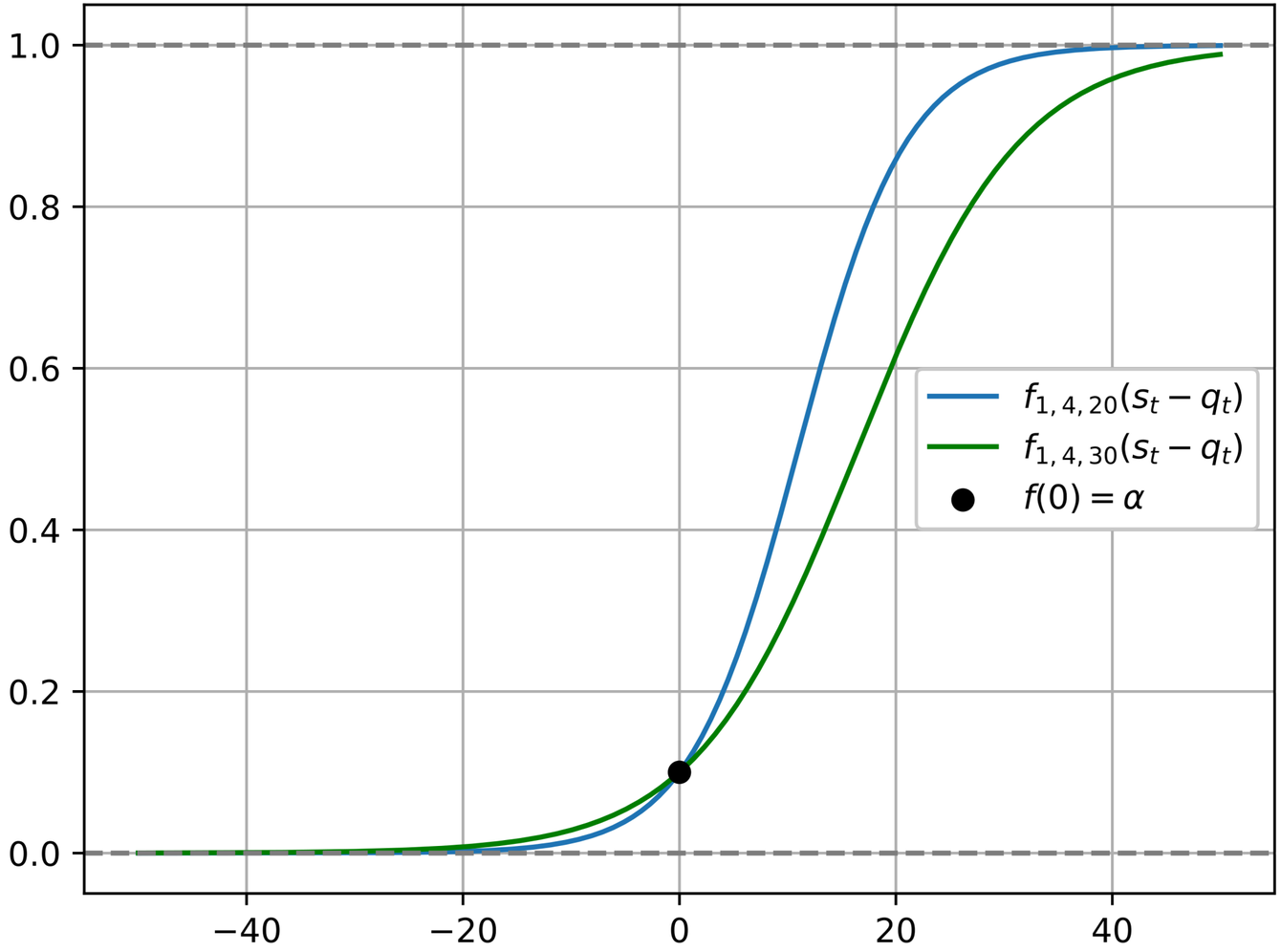

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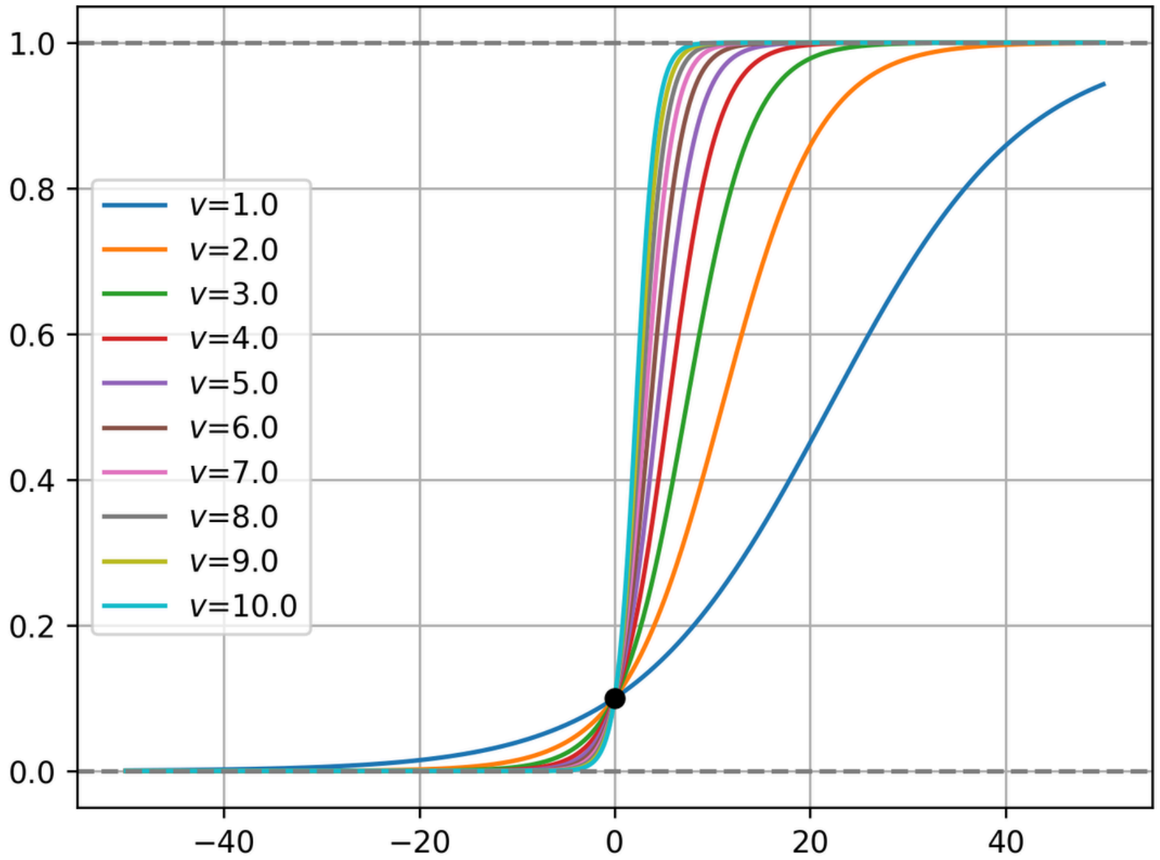

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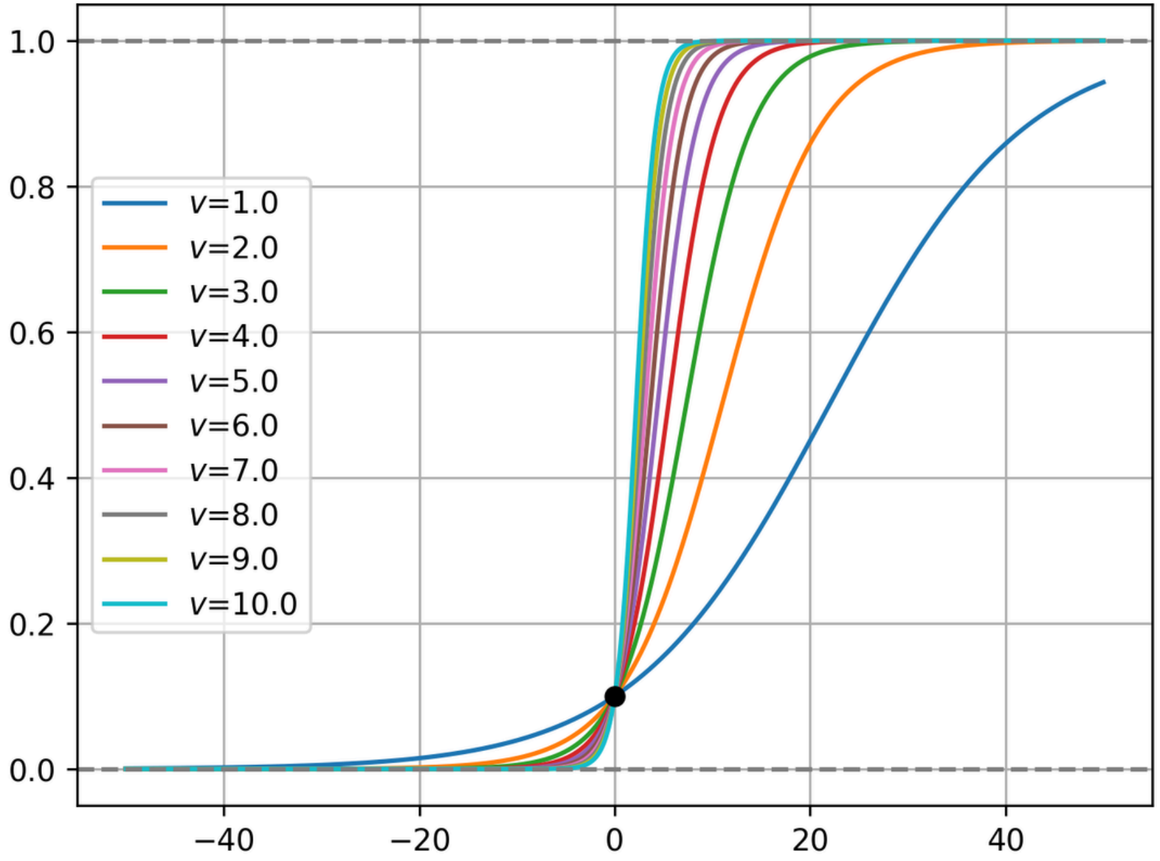

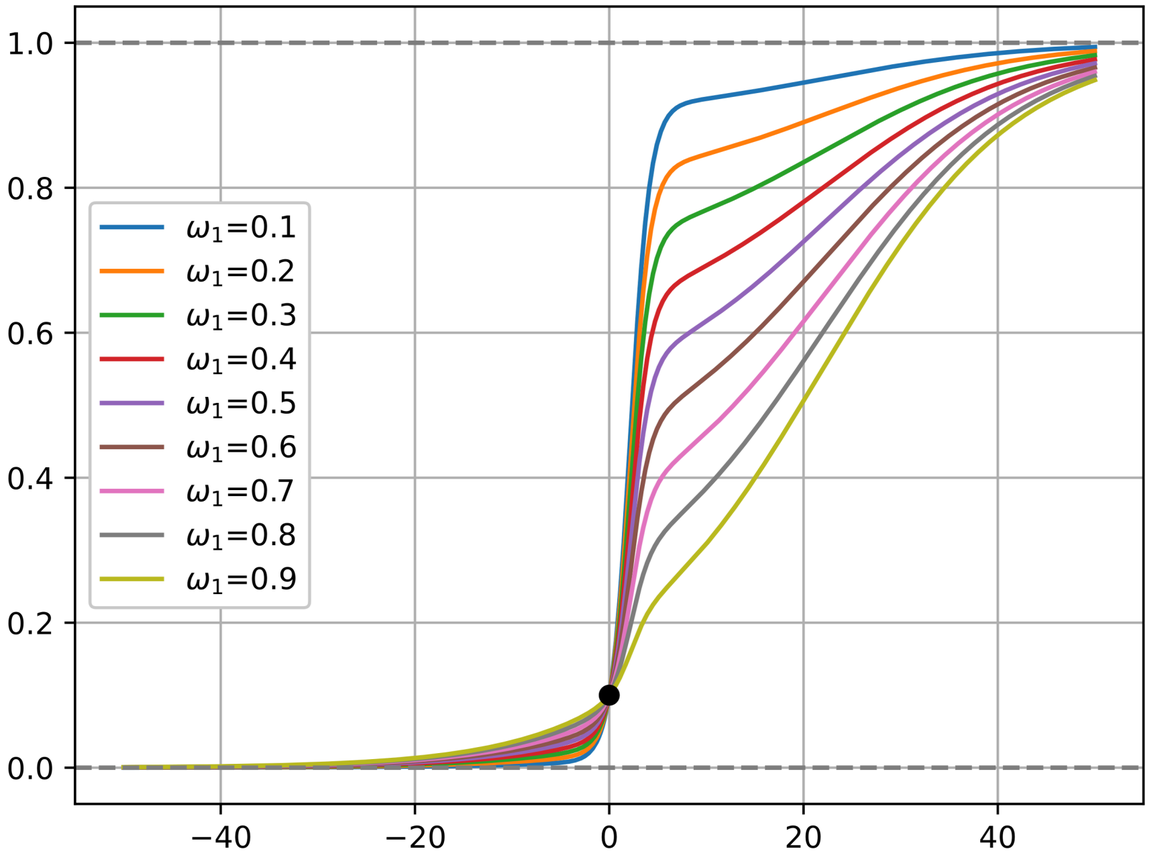

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Results



PID



ECI

Google stock price dataset

Regressor	AR		Theta	
Method	PID	modified PID	PID	modified PID
Coverage	**0.91**	0.90	0.91	0.91
Average interval width	43.75	**34.96**	38.61	**35.48**
Median interval width	39.44	**35.14**	31.97	**27.85**

Thanks for your attention !

Link to the paper

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Digital Health in Motion



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