

# EEP 596: Adv Intro ML || Lecture 12

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# Last Time

- a) Anomaly Detection Use-Cases

# Last Time

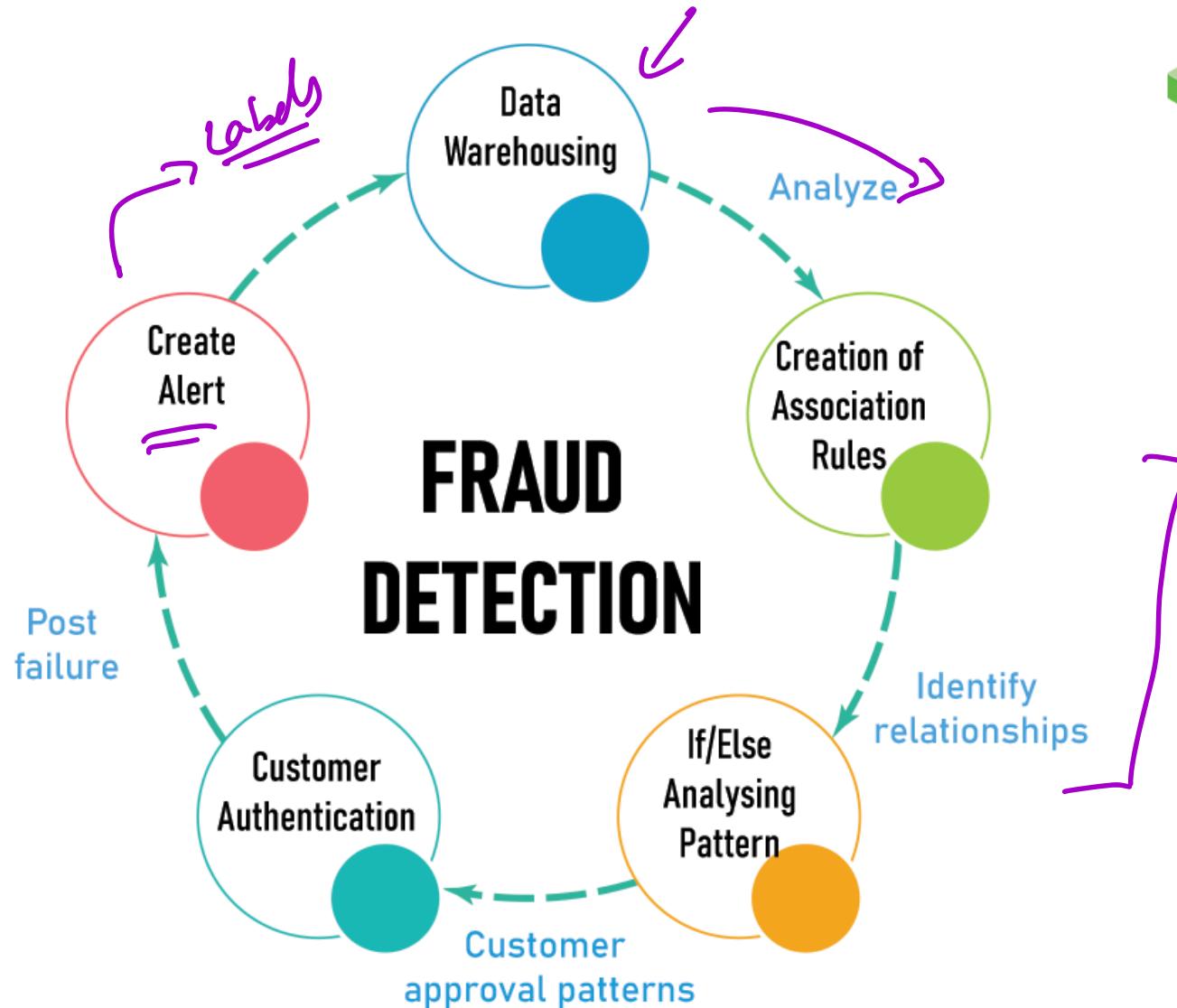
- (a) Anomaly Detection Use-Cases
- (b) Anomaly Detection Baselines

# Today

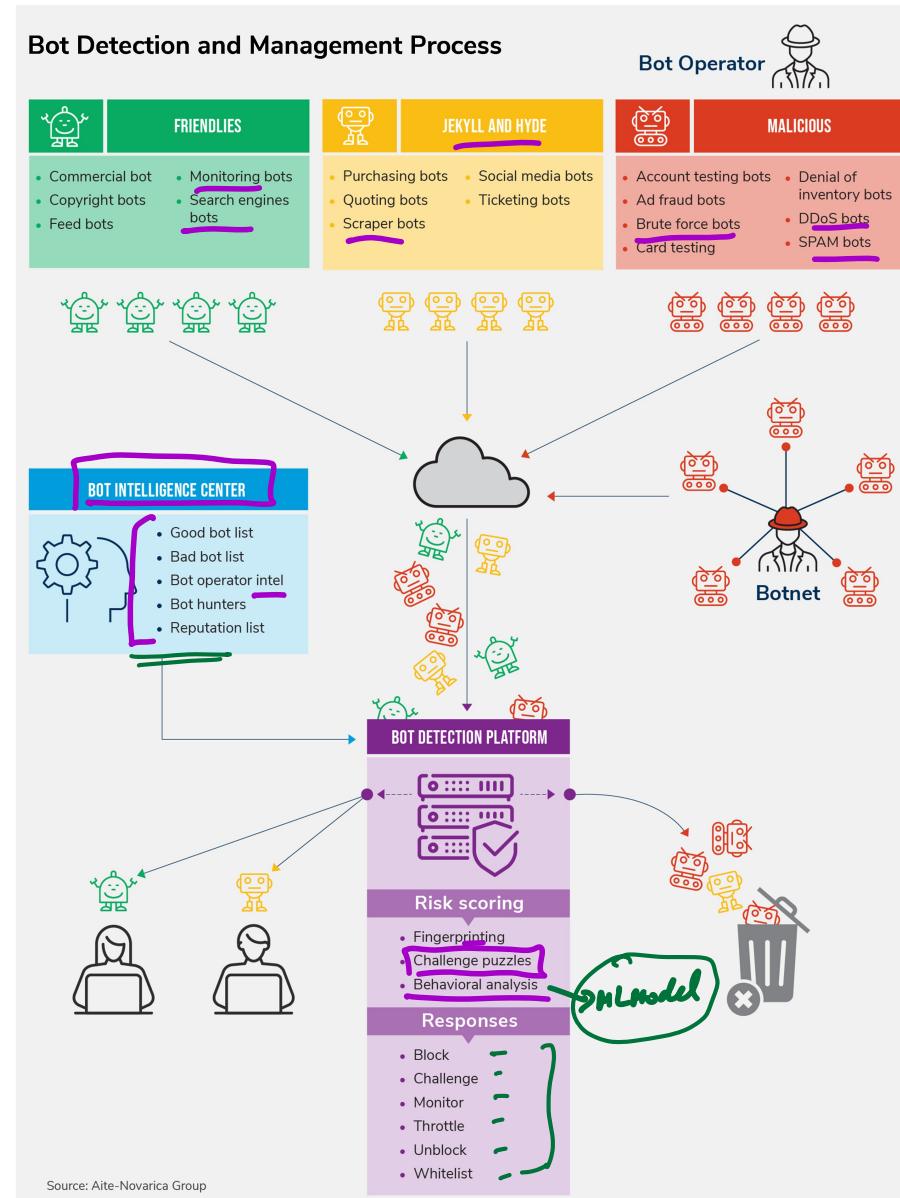
- More Baselines for anomaly detection
- GMMs
- Anomaly Detection for Time-series
- **STL model** for anomaly detection



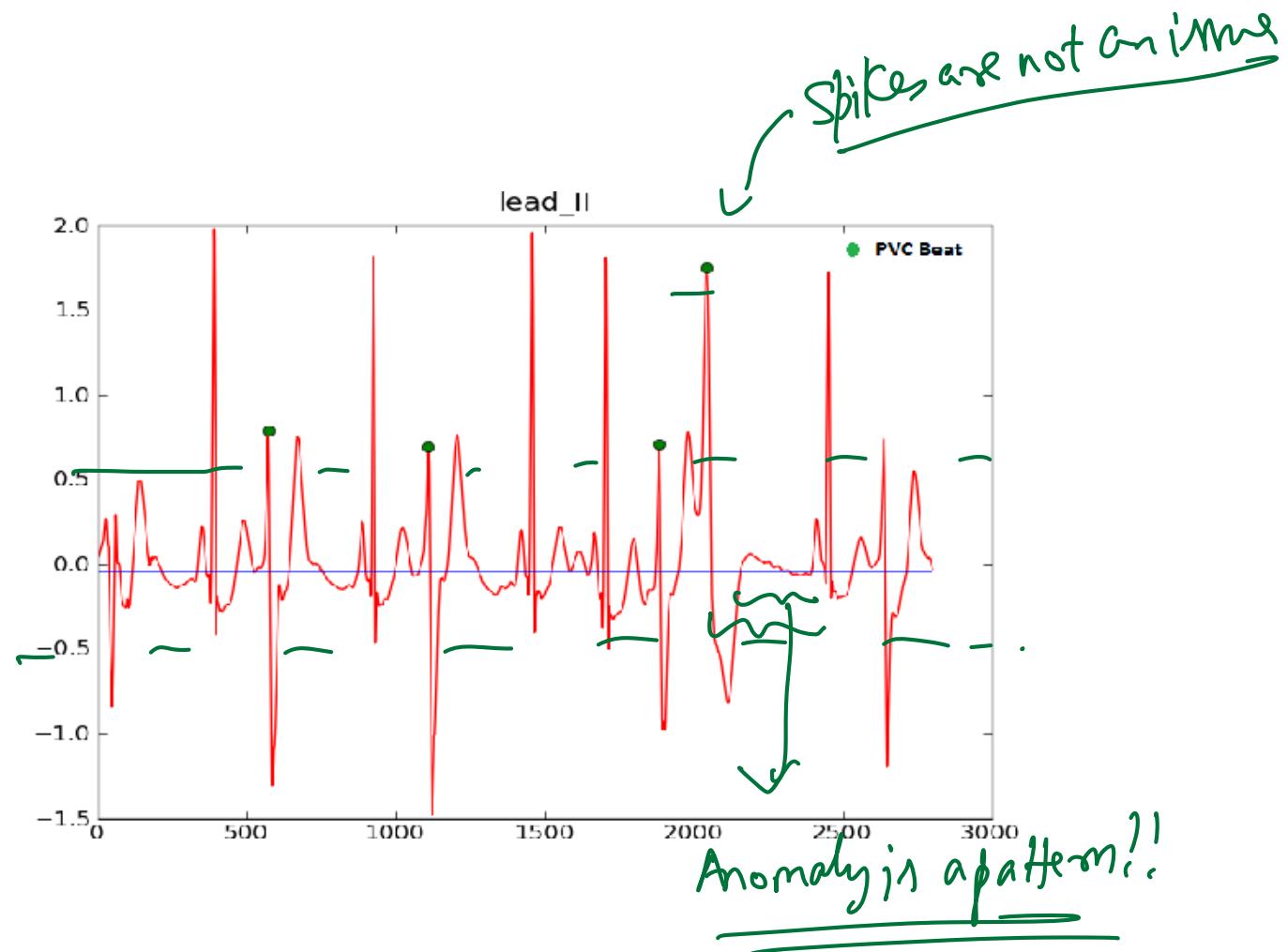
# Fraud Detection



# Got Bot?

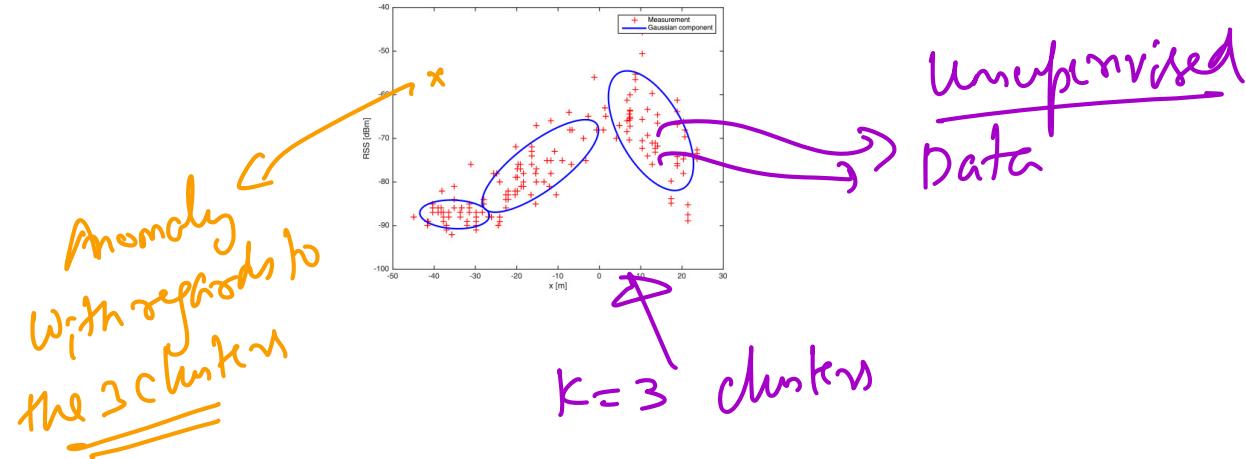


# Arrhythmia Detection



# Types of Anomalies

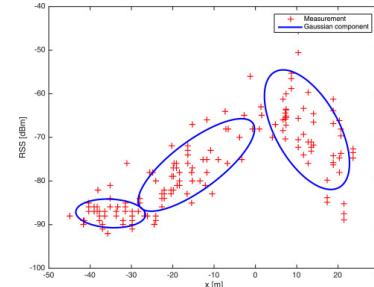
- ① **Point Anomaly:** Deviation from a set of data points.



# Types of Anomalies

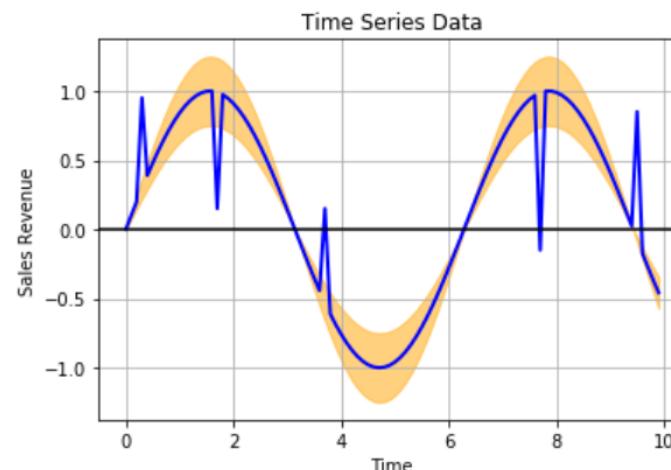
- ① **Point Anomaly:** Deviation from a set of data points.

→ Find in real-world settings



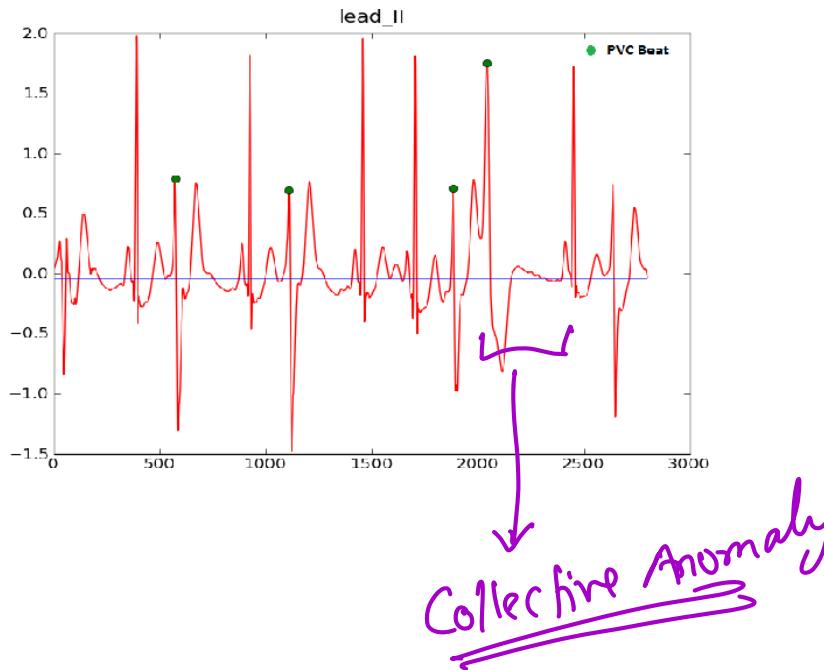
- ② **Contextual Anomaly:** Depending on the context, a data point could be an anomaly or not. For instance 35 degrees is not an anomalous temperature for Seattle winter but it is for Seattle summer. Same is true for anomalies in a time-series data e.g. Sales Revenue data.

Context  
Thanksgiving week → Regular days



# Types of Anomalies

- ③ **Collective Anomalies:** No one data point is anomalous but a collection of them become anomalous. E.g. the Arrhythmia time series.



# ICE #1

## Anomaly Type

You are tasked with detecting if a particular stock is trending downwards or upwards. So far its been trending downwards. You need to identify if at the end of next week, it is still trending downwards or upwards. This is an example of:

- (a) Point anomaly detection
- (b) Contextual anomaly detection
- (c) Collective anomaly detection
- (d) Not an anomaly detection problem

# ICE #2

## Anomaly Type

You are tasked with identify which clusters of servers are under-utilized based on cpu-utilization rates and re-purpose them as needed. This is an example of:

- (a) Point anomaly detection
- (b) Contextual anomaly detection
- (c) Collective anomaly detection
- (d) Not an anomaly detection problem

# Broadly Speaking

- ① **Un-Supervised Methods:** Clustering based, statistical methods  
(mean, standard deviation based alarming), etc
- ② **Supervised Methods:** Requires enough labels for positives and negatives

# Anomaly Detection Baselines

## Baseline Algorithm

Classify a data point as an anomaly if your data point is  $\alpha$  standard deviations ( $\sigma$ ) away from the mean. Here  $\alpha$  is typically greater than 3.

Cpu-utilization @ 4pm <  $\overline{\text{Mean}} - 3\sigma$   
 $\overline{\text{utilization}}$   
⇒ under-utilized

# Anomaly Detection Baselines

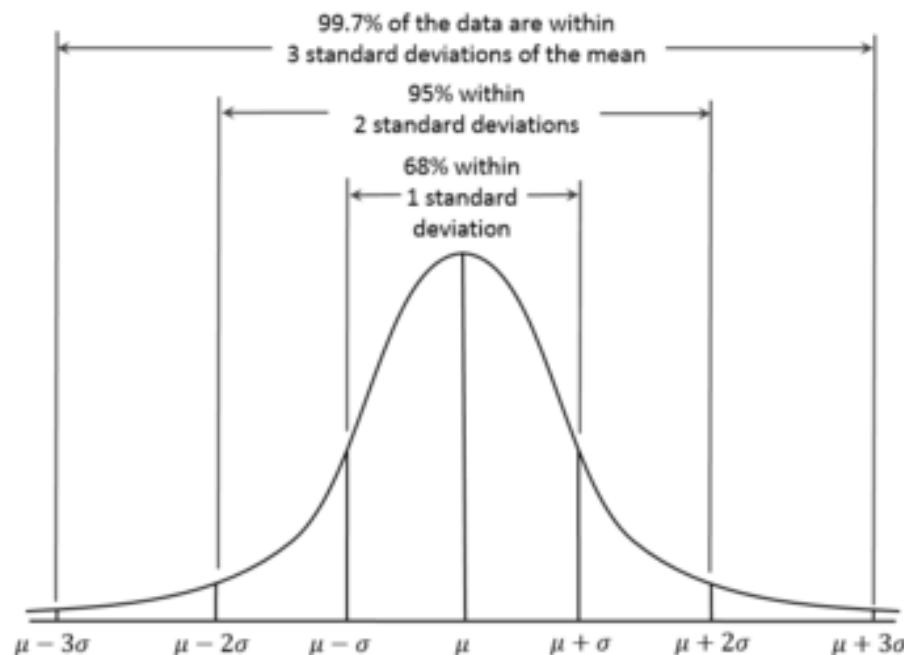
## Temperature Example

The mean human body temperature is 98.4 F. Assume now that the thermometer is accurate but normal body temperature fluctuations are expected to be within 0.5 degrees F, then there is cause for concern if temperature deviates beyond  $98.4 \pm 1.5$  for  $\alpha = 3$ .

# Anomaly Detection Baselines

## Temperature Example

The mean human body temperature is 98.4 F. Assume now that the thermometer is accurate but normal body temperature fluctuations are expected to be within 0.5 degrees F, then there is cause for concern if temperature deviates beyond  $98.4 \pm 1.5$  for  $\alpha = 3$ .



# Anomaly Detection Baselines

## Temperature Example

	$\alpha$	Outcome
1	<u>2</u>	Lots of false positives and un-necessary trips to urgent care
2	<u>6</u>	Almost no false positives. Might miss early signs of a flu
3	<u>4</u>	Fewer false positives. Get to urgent care at the right time!

[ ]

# Anomaly Detection Baselines

## Faulty thermometer

Assume you only have a faulty thermometer to measure your body temperature. Sometimes its accurate and sometimes it is not. You get to know that its reading can fluctuate up to 3 degrees over or below the true temperature. You measure your temperature and its 102 degrees F. Should you head to the urgent care?

# Anomaly Detection Baselines

## Faulty thermometer

Assume you only have a faulty thermometer to measure your body temperature. Sometimes its accurate and sometimes it is not. You get to know that its reading can fluctuate up to 3 degrees over or below the true temperature. You measure your temperature and its 102 degrees F. Should you head to the urgent care?

## False positives vs False Negatives

Anomaly Detection methods get caught between controlling false positives and not missing True positives (i.e. having false negatives). Would you rather flag a social media post as inappropriate and capture 90% of inappropriate posts but cause a stir with remaining 10% users or would you rather capture 80% of inappropriate posts and have zero false positives?

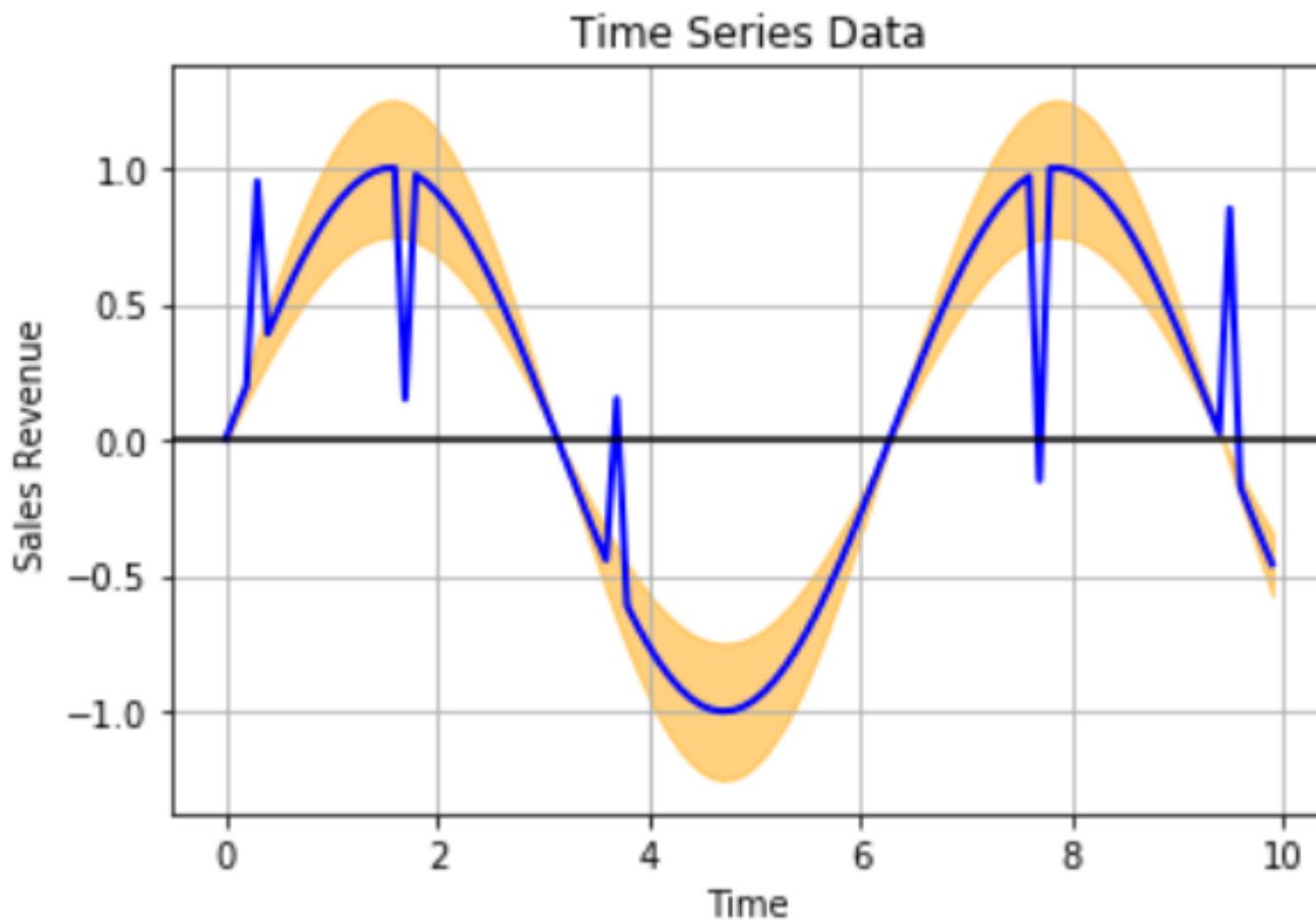
# Detecting bots/in-appropriate posts

## Biasing the metrics

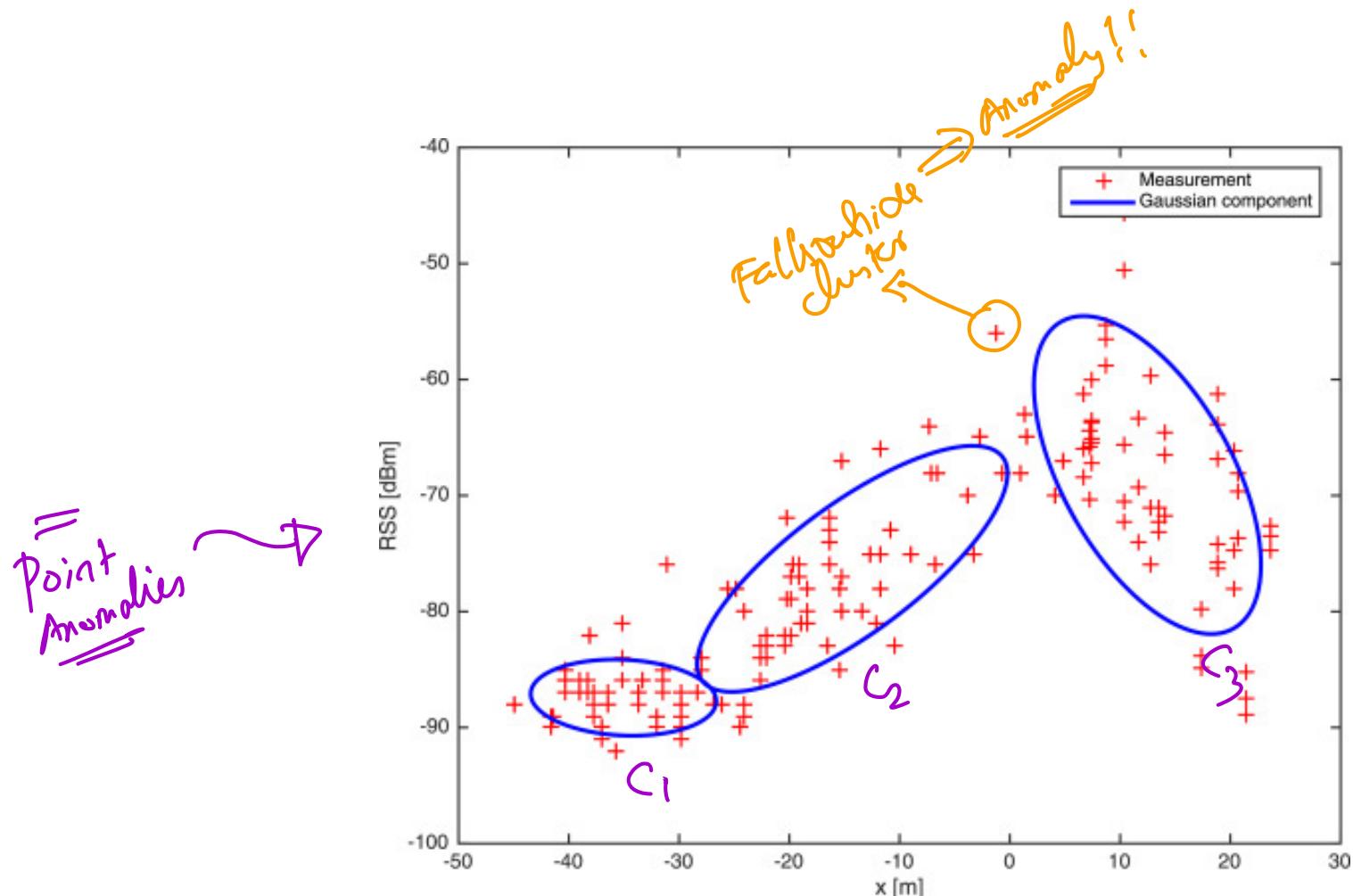
Do you bias more towards high precision or high recall? Is there a middle ground? Can we have higher recall (i.e. detect the bots/inappropriate posts) without pissing people off with incorrect flags?

- 1. Human Bias
  - 2. Privacy Concerns
- 

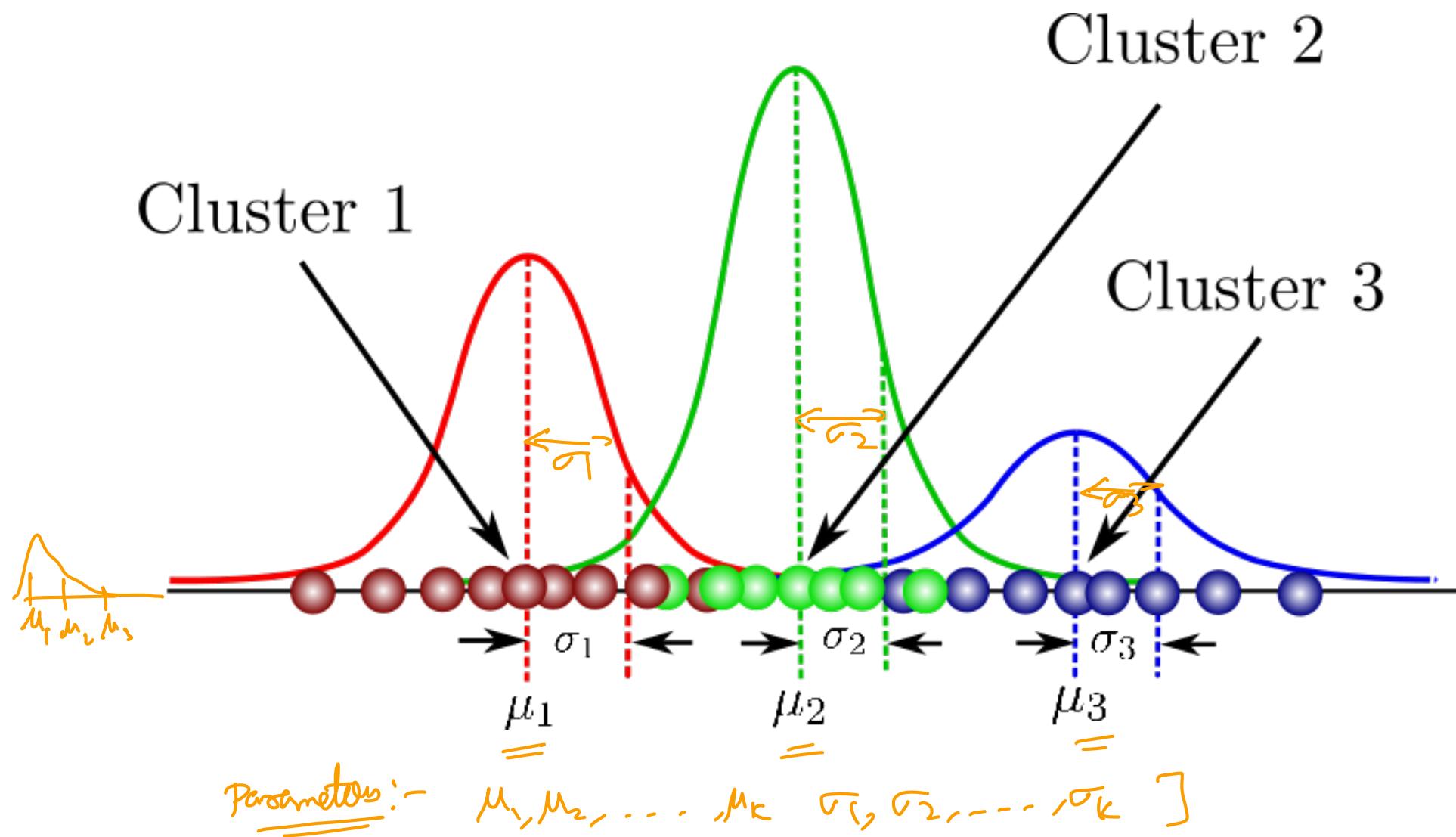
# Time series anomalies



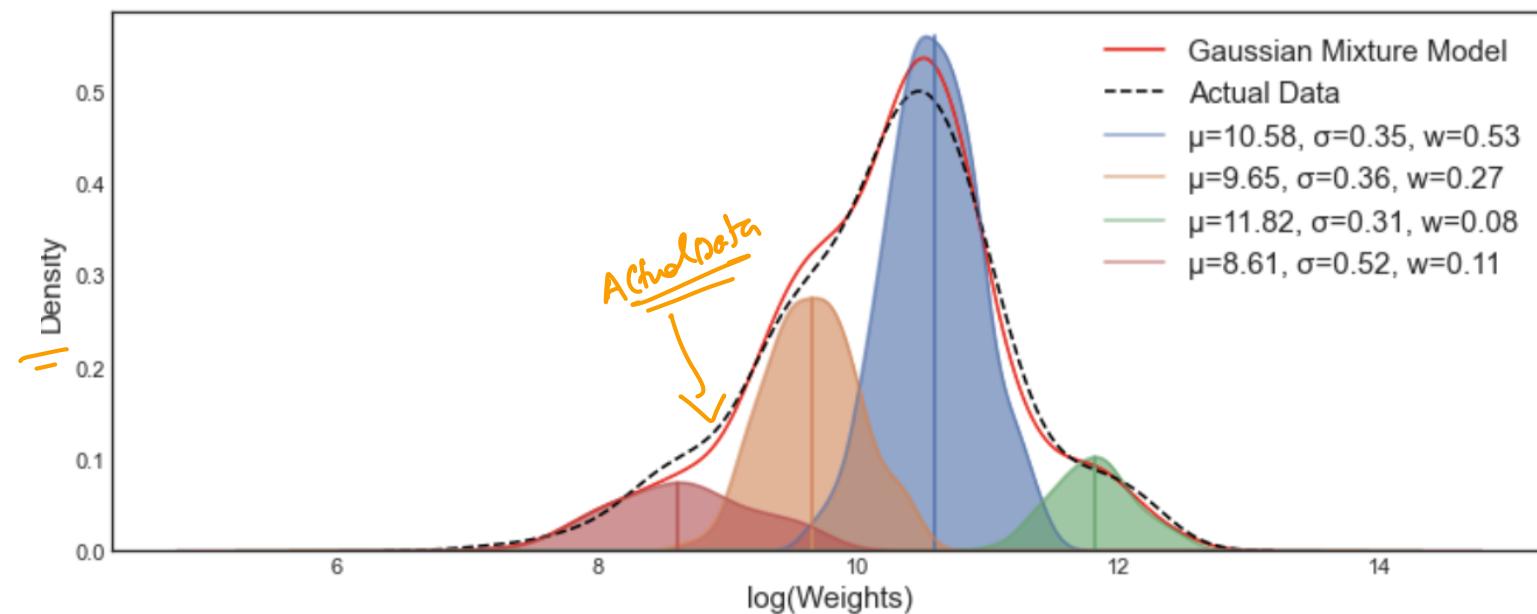
# GMM - Better than Baseline



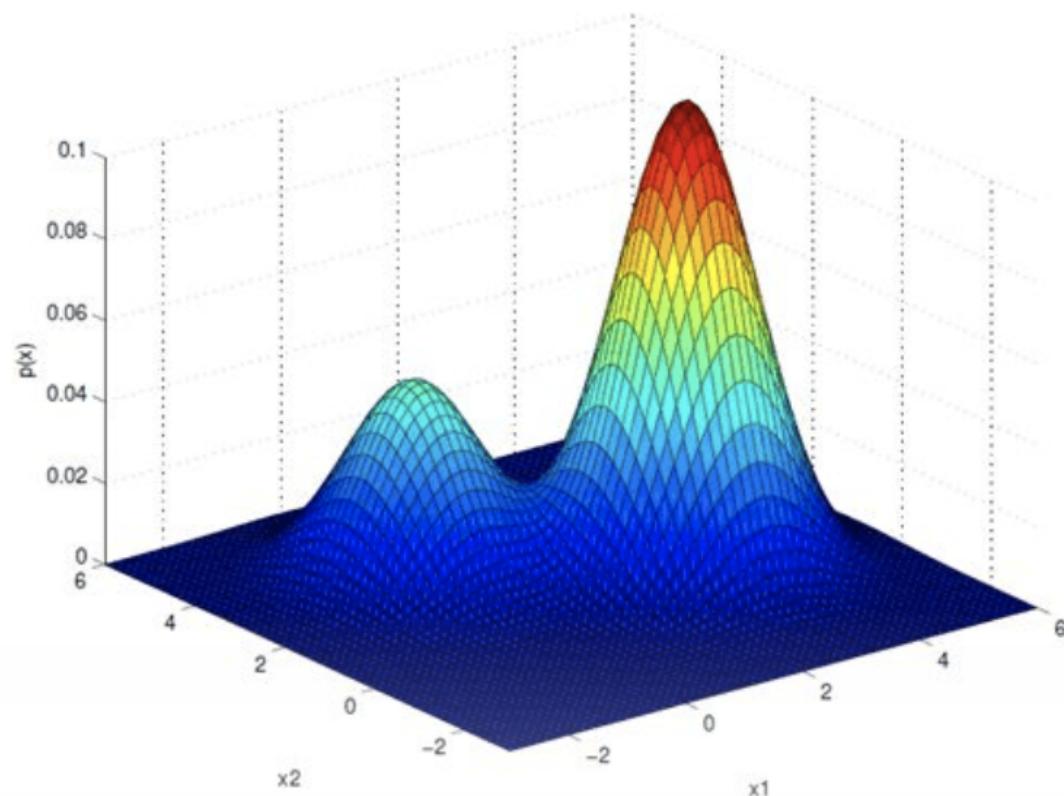
# GMM - Better than Baseline



# GMM - Better than Baseline



# GMM - Better than Baseline



# GMM - PDF

PDF

The **Probability Density Function (PDF)** for GMM at any given point  $x$ :

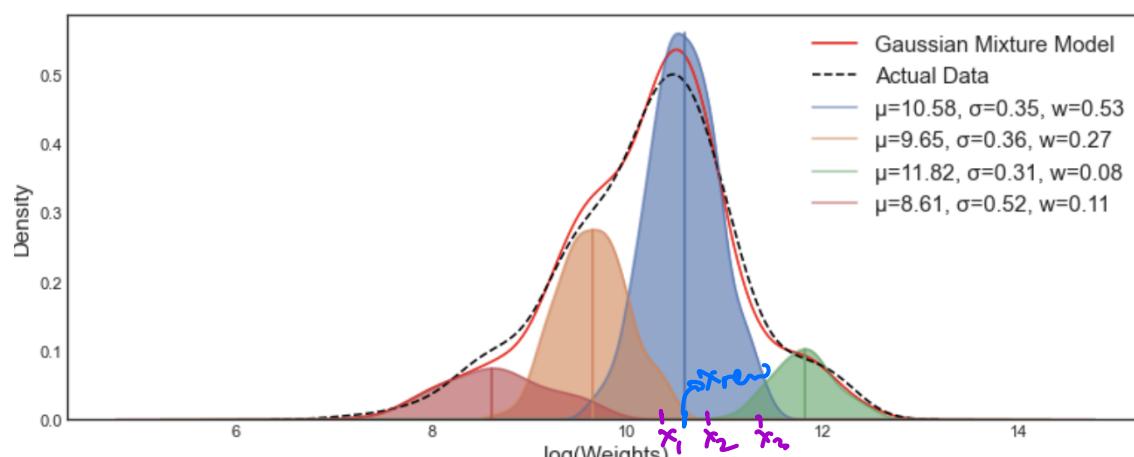
$$\sum_{k=1}^K \pi_k \mathcal{N}(x|\mu_k, \Sigma_k)$$

*Mixture weights*

*Gaussian k*

*GMM*

where  $\sum_{k=1}^K \pi_k = 1$ ,  $\mu_k$  are the means/centroids of the  $k$  clusters and  $\Sigma_k$  are the co-variances!  $\pi_k$  represents the contribution of cluster  $k$  to the overall density.



# GMM - Loss function

Loss function

$$\max_{\{\pi_k, \mu_k, \Sigma_k\}} \prod_{i=1}^N \left\{ \sum_{k=1}^K \pi_k \mathcal{N}(x | \mu_k, \Sigma_k) \right\}$$

maximizing      Likelihood of the data

parameters

For each datapoint

$$p(x|y) \rightarrow p(y|x) \quad i=1, \dots, N$$

Ans :- Generative Model :- You can generate data like in the training dataset!!

$p(y|x)$   $\leftarrow$  Discriminative Model (e.g. Logistic regression)

# GMM - Loss function

~~Loss function~~  
Max Likelihood

$$\max_{\{\pi_k, \mu_k, \Sigma_k\}} \prod_{i=1}^N \left\{ \sum_{k=1}^K \pi_k \mathcal{N}(x | \mu_k, \Sigma_k) \right\}$$

Product  $\xrightarrow{\text{log}}$  Summation

Negative Log-likelihood loss function for learning GMM

$$\min_{\{\pi_k, \mu_k, \Sigma_k\}} - \sum_{i=1}^N \log \left( \left\{ \sum_{k=1}^K \pi_k \mathcal{N}(x | \mu_k, \Sigma_k) \right\} \right)$$

# Identifying anomalies from GMMs

Algorithm for Point Anomaly Detection

## Algorithm for Anomaly Detection based on GMM

- a Fit a GMM model to the data with  $K$  clusters.  $K$  is a modeling choice! ( $k$ -means++ can be used!)
- b For a candidate data point  $x_j$ , identify the probability of  $\underline{x_j}$  belonging to each of the clusters - call it  $p_k$ .
- c If  $\max_k p_k < \alpha$  where  $\alpha$  is an anomaly probability threshold, then flag  $\underline{x_j}$  as an anomaly.

hyper-parameter

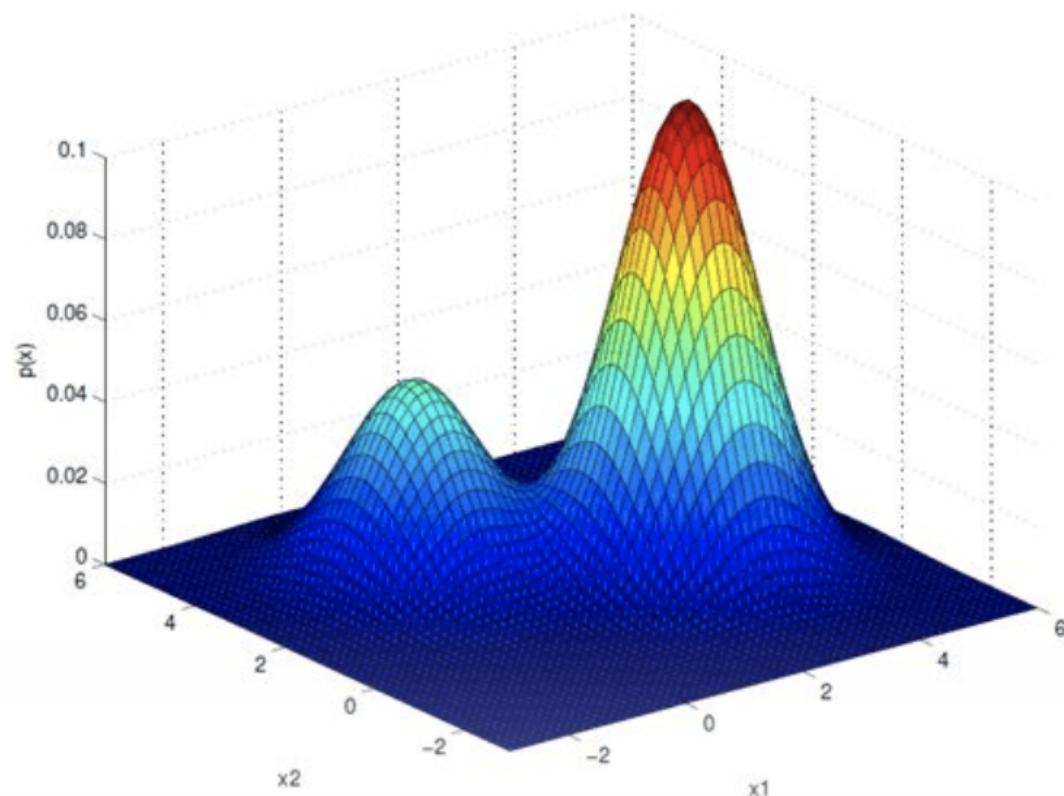
# Identifying anomalies from GMMs

## Algorithm for Anomaly Detection based on GMM

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- ② For a candidate data point  $x_j$ , identify the probability of  $x_j$  belonging to each of the clusters - call it  $p_k$ .
- ③ If  $\max_k p_k < \alpha$  where  $\alpha$  is an **anomaly probability threshold**, then flag  $x_j$  as an anomaly.

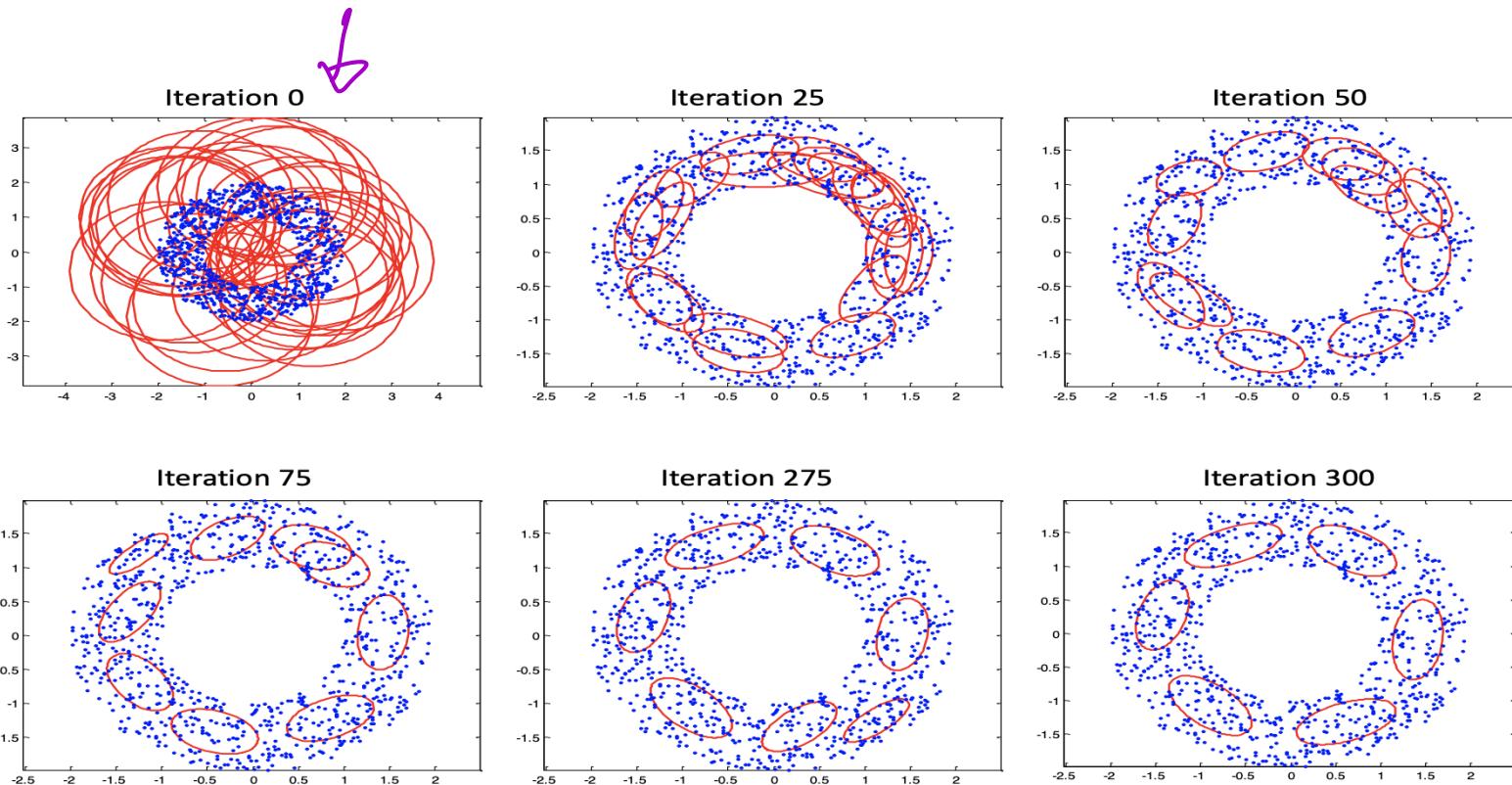
How to compute the probability  $p_k$ ?

# GMM Anomaly Detection Example

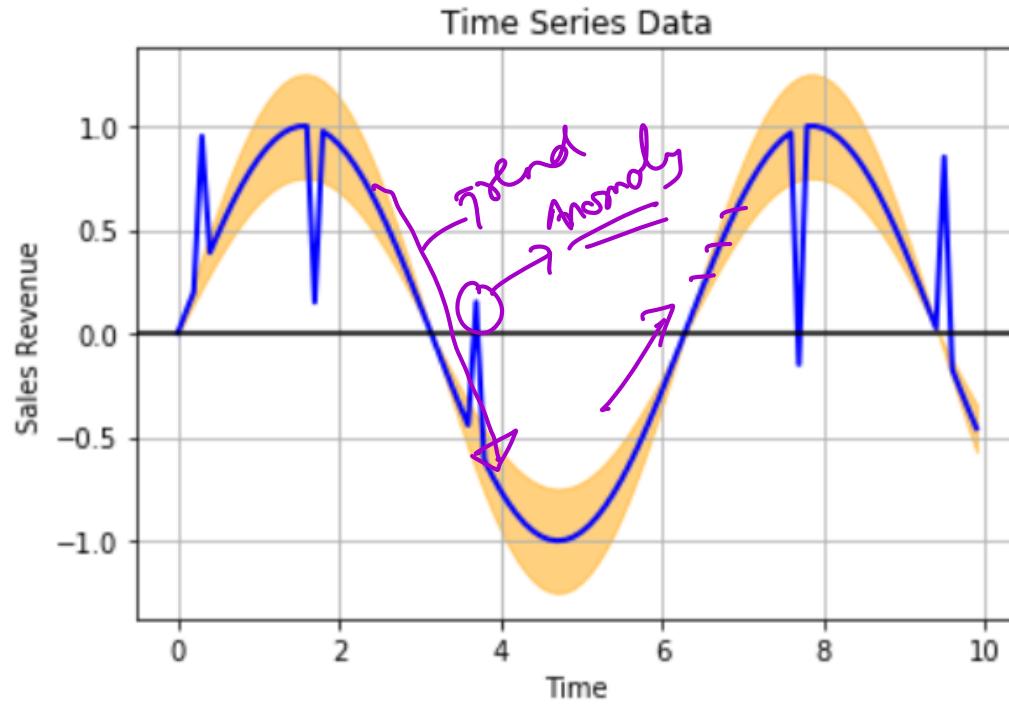


# GMM Learning through EM algorithm

Expectation Maximization



# Time-series Anomaly Detection



Local window anomalies ] Contextual Anomaly Detection → unsupervised Learning

Fit a linear model that captures local trends and compute a probability for a new data point being an anomaly w.r.t local model.

# Time-series Anomaly Detection

## Un-supervised Learning

If we don't have enough labels for anomalies (or positive class), we have no choice but to resort to **un-supervised learning**.

# Time-series Anomaly Detection

## Un-supervised Learning

If we don't have enough labels for anomalies (or positive class), we have no choice but to resort to **un-supervised learning**.

## Un-supervised Learning

However, un-supervised learning for anomaly detection is fraught with issues. What are they?

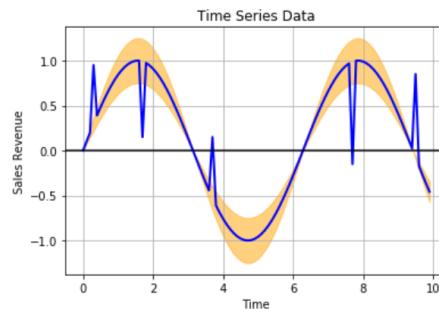
# Time-series Anomaly Detection



## Semi-supervised Learning

Learn good features from un-supervised learning and use a simple classifier - such as logistic regression model to fine tune the probability computations! **Example features:** Deviation from a local linear regression model fit on a local window. Deviation from median of a local window.

# Time-series Anomaly Detection

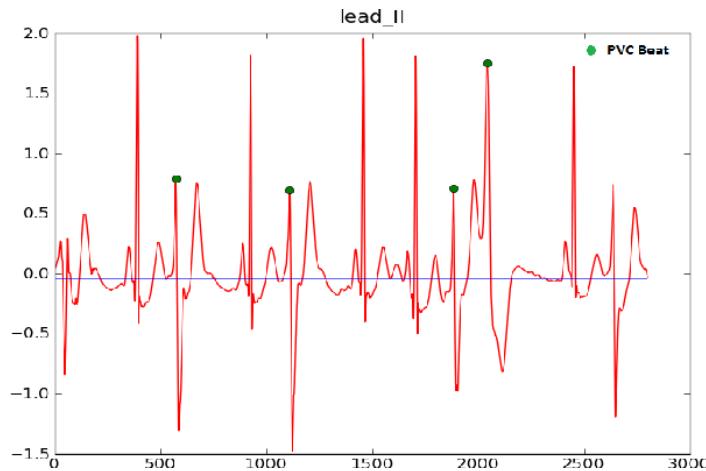


## ICE #3

What are the hyper-parameters for the semi-supervised logistic regression based anomaly detection approach we just described?

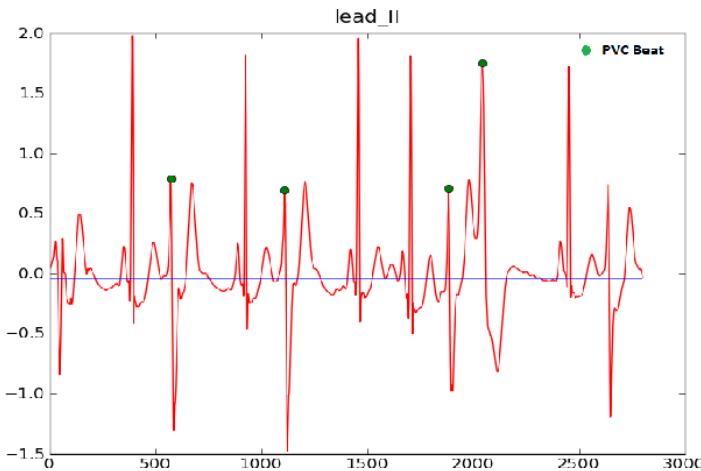
- (a) The weights for the different features learned from un-supervised learning that are then combined to get a probability prediction from logistic regression
- (b) The number of (unsupervised learning) features used in the logistic regression
- (c) The size of the local window used to compute these features
- (d) The probability of a data point being an anomaly

# Arrhythmia detection



# Arrhythmia detection

Next Assignment



## ICE #4 Automated Arrhythmia Detection

You want to build an automated algorithm for Arrhythmia detection from time-series data on heart beats. What would be a baseline un-supervised learning algorithm you can think of Arrhythmia detection? If you wanted to do supervised learning for arrhythmia detection, what features would you use? How would you cast it as a machine learning problem? How would you evaluate the performance of your automated algorithm? What would be the metrics you would use? Discuss in groups - We will implement this as part of the next programming assignment.

# Deep Learning for Anomaly Detection

## Deep Learning

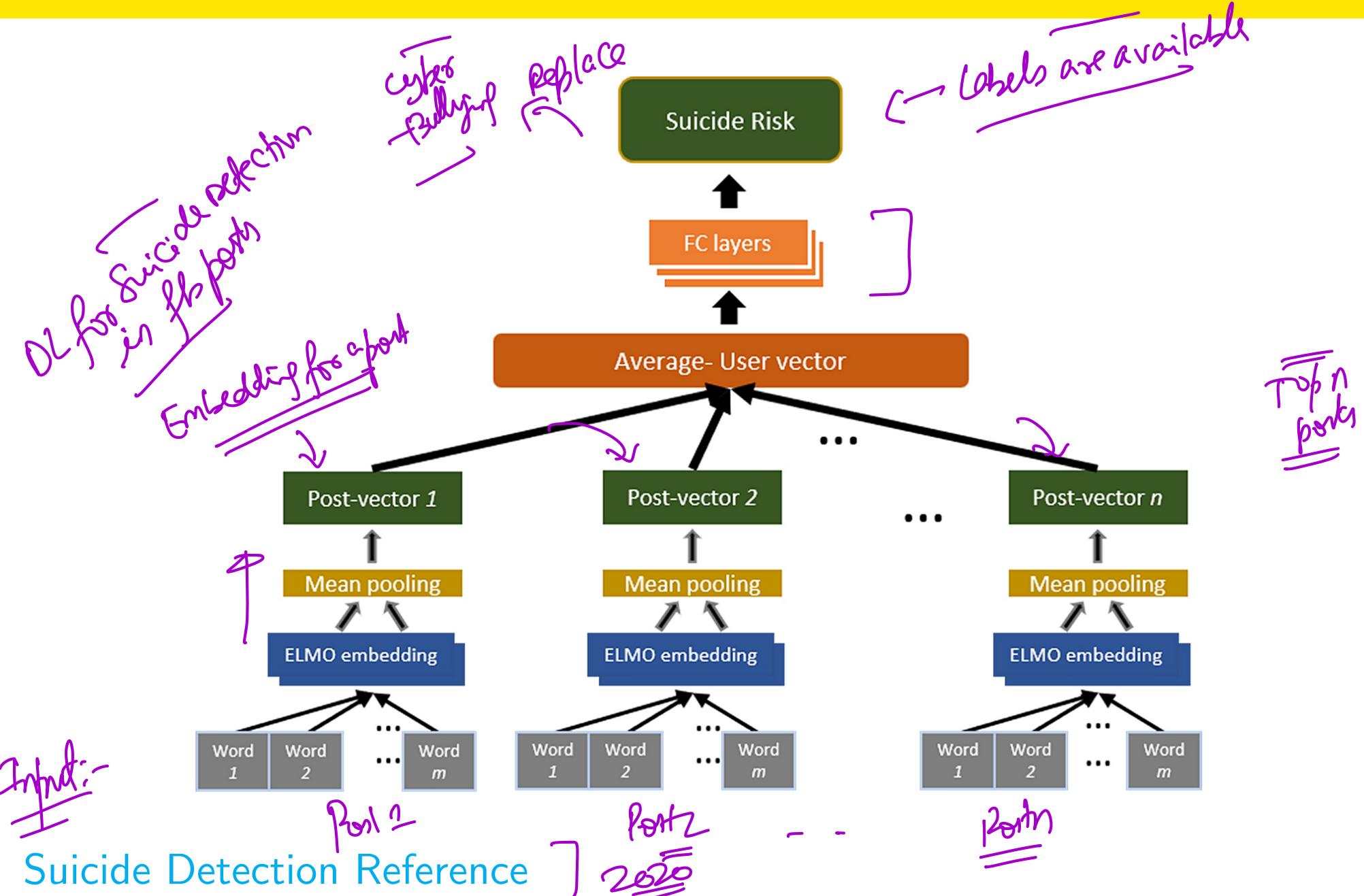
Deep Learning can provide powerful non-linear supervised models for anomaly detection provided there is enough data (both positive and negative examples) and we account for over-fitting. On the upcoming assignment, can also try out deep learning!

# Detecting bots/in-appropriate posts

## Biasing the metrics

Do you bias more towards high precision or high recall? Is there a middle ground? Can we have higher recall (i.e. detect the bots/inappropriate posts) without pissing people off with incorrect flags?

# Suicide detection from Social Media posts



# Anomaly Detection Methods so far

*unsupervised*

	Method	Pros	Cons
1	Mean/Std Deviation	Identifies some anomalies	False positives
2	Supervised Learning	Precise detection	As good as features

3. GMM *—unsupervised model*

# Anomaly Detection Methods - Coming up

	Method	Pros
1	Mean/Std Deviation	Identifies some anomalies
2	Supervised Learning	Precise detection
3	<b>Simple Moving Average (SMA)</b>	Improves on mean/std deviation
4	<b>Exponential Moving Average (EMA)</b>	More sensitive than SMA
5	<b>STL</b>	Accounts for seasonality

# Moving Averages - Simple Moving Average



# Simple Moving Average and Anomalies

## SMA

- ① There is a window size that helps you track the **moving** average.
- ② 50-SMA is a 50 day moving average
- ③  $50\text{-SMA}(i) = \frac{1}{50} \sum_{j=i-50}^{i-1} x_j$

# Simple Moving Average and Anomalies

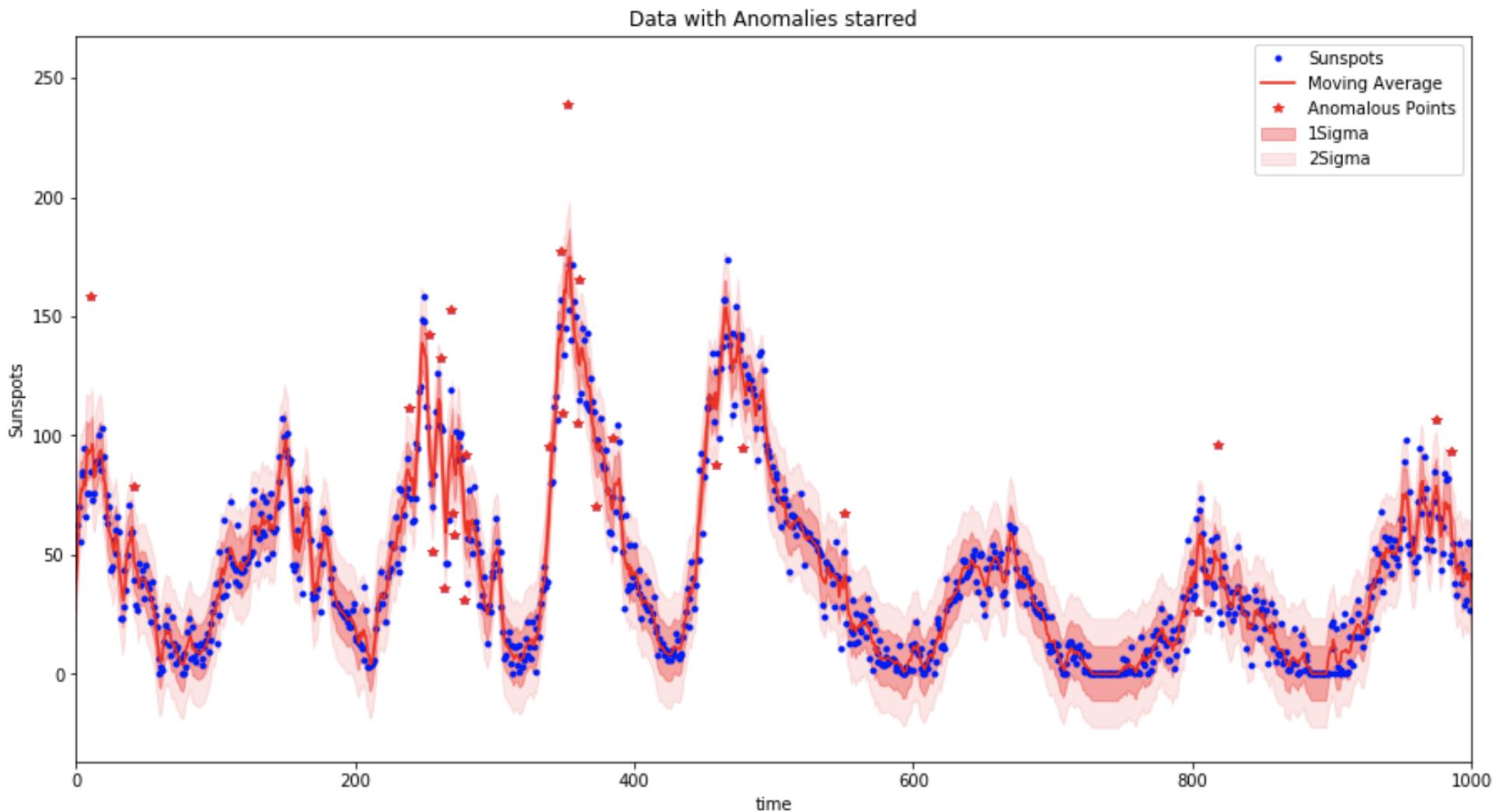
## SMA

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- ③  $50\text{-SMA}(i) = \frac{1}{50} \sum_{j=i-50}^{i-1} x_j$

## Anomaly detection

- ①  $x_i$  is an anomaly if  $\|SMA(i) - x_i\|$  deviates above a  $t \times SD(i)$  where  $SD(i)$  is the standard deviation and  $N$  is the size of the window,  $t$  is the threshold.

# SMA example



Github Library to try!

# ICE #5

## Moving mean computation

Let's say you wanted to implement SMA yourself. Let the window size be 100. You have  $SMA(i - 1)$ . How do you compute it from  $SMA(i - 1)$ ?

- (a)  $SMA(i) = SMA(i - 1) + (x_i - x_{i-1})/N$
- (b)  $SMA(i) = SMA(i - 1) + x_i/N$
- (c)  $SMA(i) = SMA(i - 1)$
- (d)  $SMA(i) = SMA(i - 1) - x_{i-1}/N$

# ICE #6

## Moving mean computation

Based on the previous question, what's the computational complexity and memory/storage complexity of SMA at point  $i$ , i.e.  $SMA(i)$ ?

- a  $O(N), O(N)$
- b  $O(1), O(N)$
- c  $O(N), O(1)$
- d  $O(1), O(1)$

# Moving Variance computation for SMA

## Moving Variance

Same principle as computing the moving mean for SMA.

# Exponential Moving Average and Anomalies

## EMA

- ① Similar to SMA - Except the moving window is **soft**
- ② Weight more of the recent terms than before and weight it exponentially.
- ③  $EMA(i) = (1 - \beta) * EMA(i - 1) + \beta * x_i$ ; where  $0 \leq \beta \leq 1$
- ④  $EMA(i) = \beta x_i + \beta(1 - \beta)x_{i-1} + \beta(1 - \beta)^2x_{i-2} + \dots$
- ⑤ EMA has a hyper-parameter  $\beta$  instead of window size  $N$  as in SMA.

# Exponential Moving Average and Anomalies

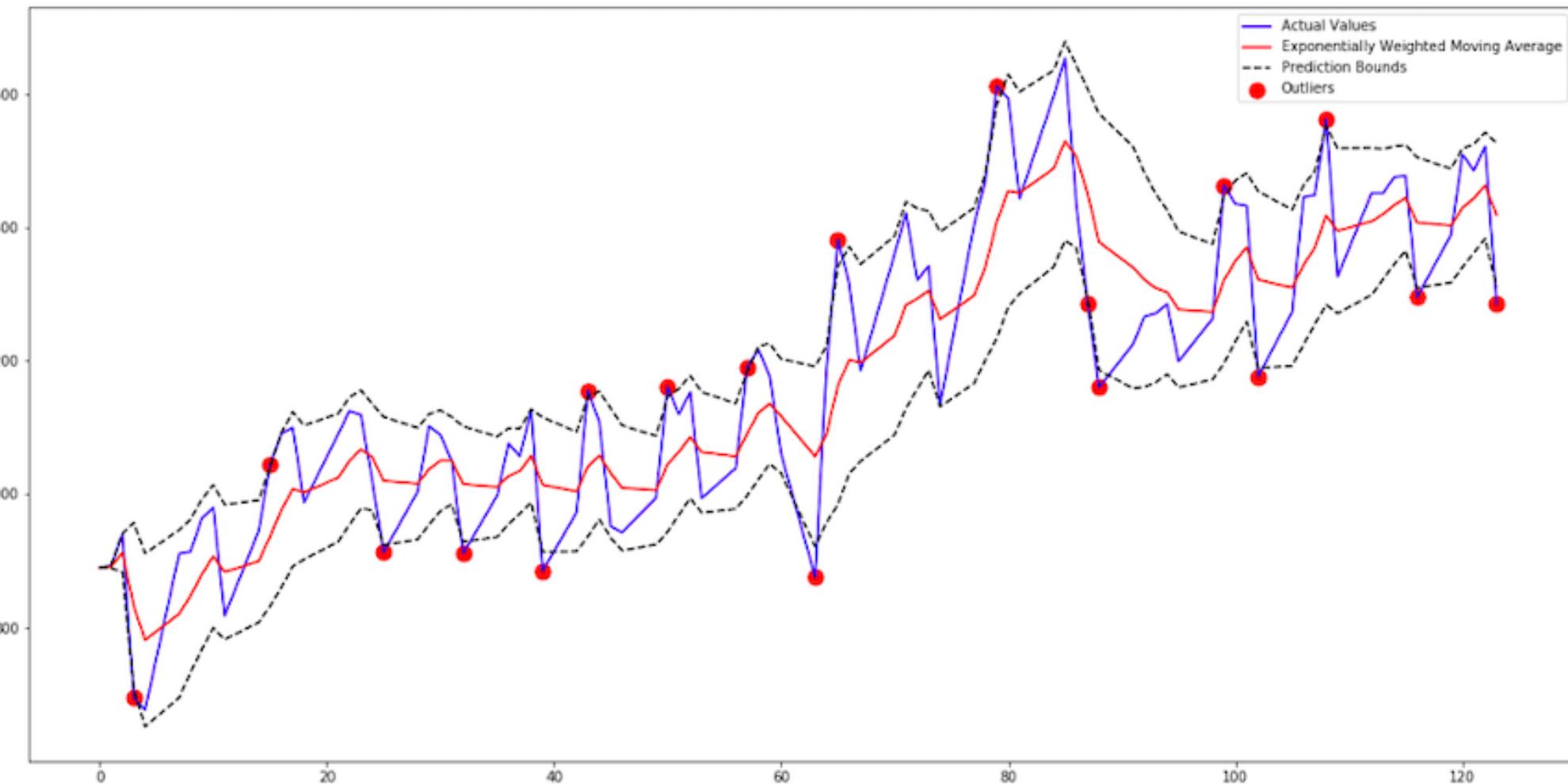
## EMA

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- ⑤ EMA has a hyper-parameter  $\beta$  instead of window size  $N$  as in SMA.

## Anomaly detection

- ①  $x_i$  is an anomaly if  $\|EMA(i) - x_i\|$  deviates above a  $t \times SD(i)$  where  $SD(i)$  is the standard deviation of the deviation.

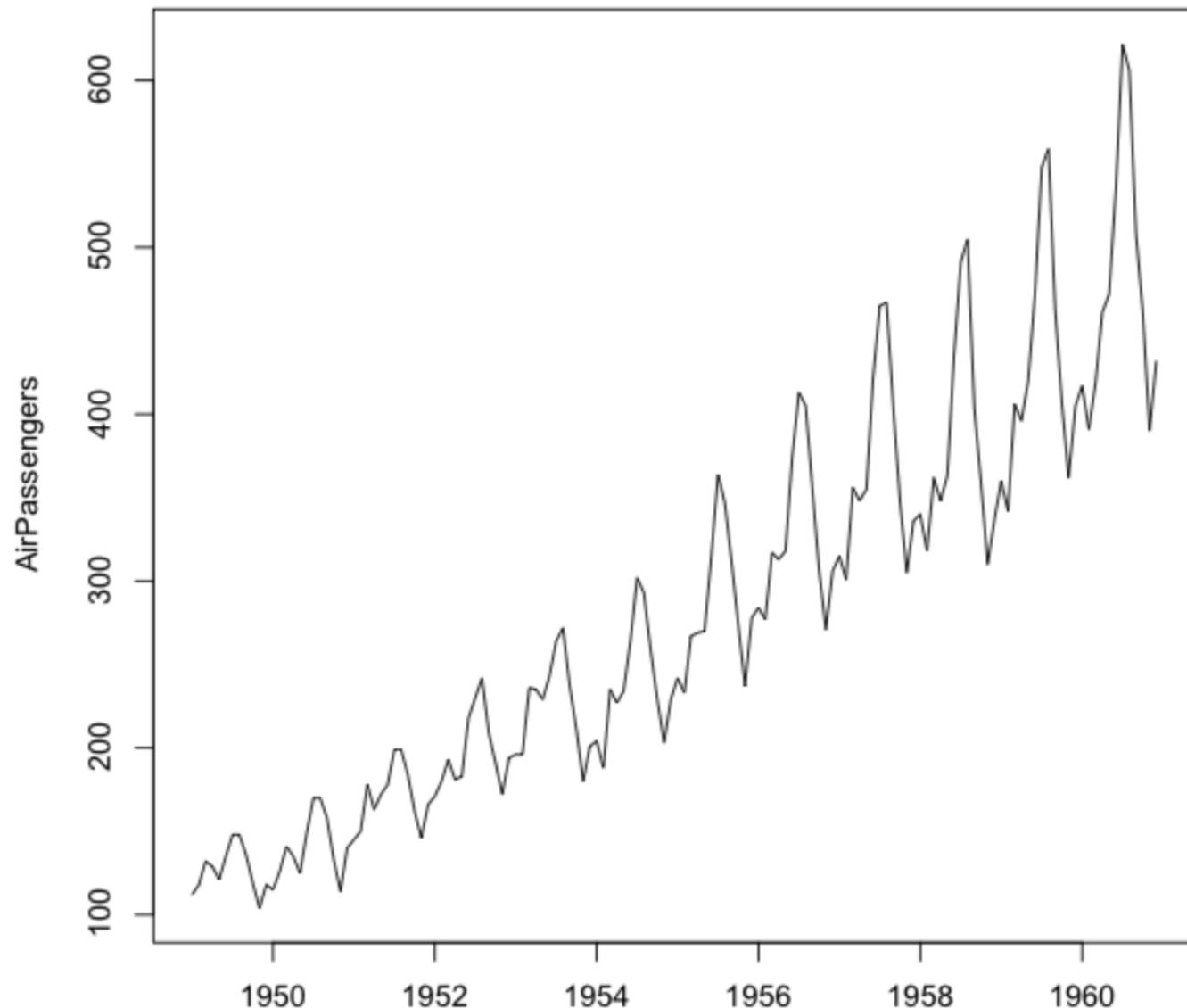
# Exponential Moving Average



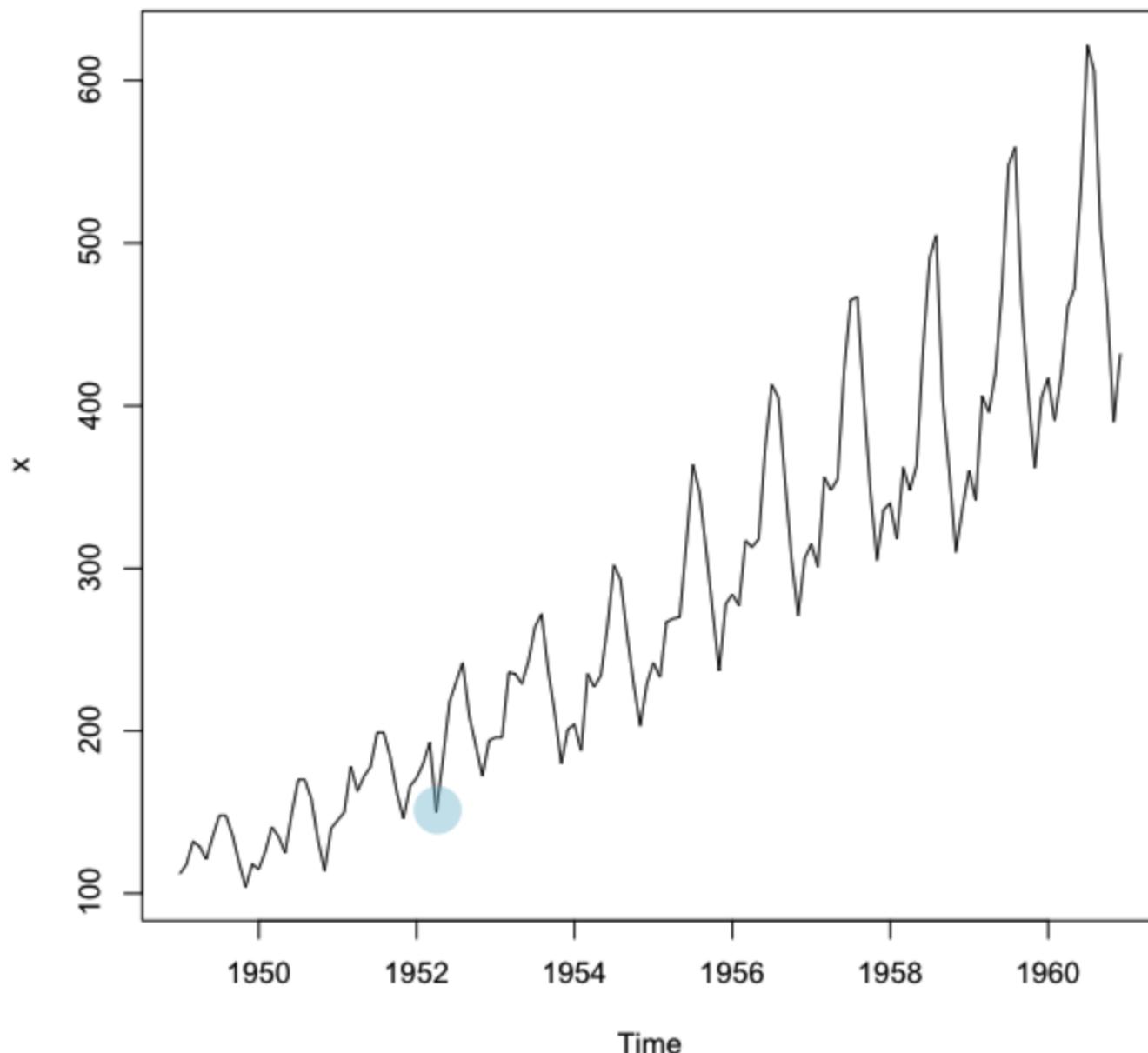
# SMA vs EMA



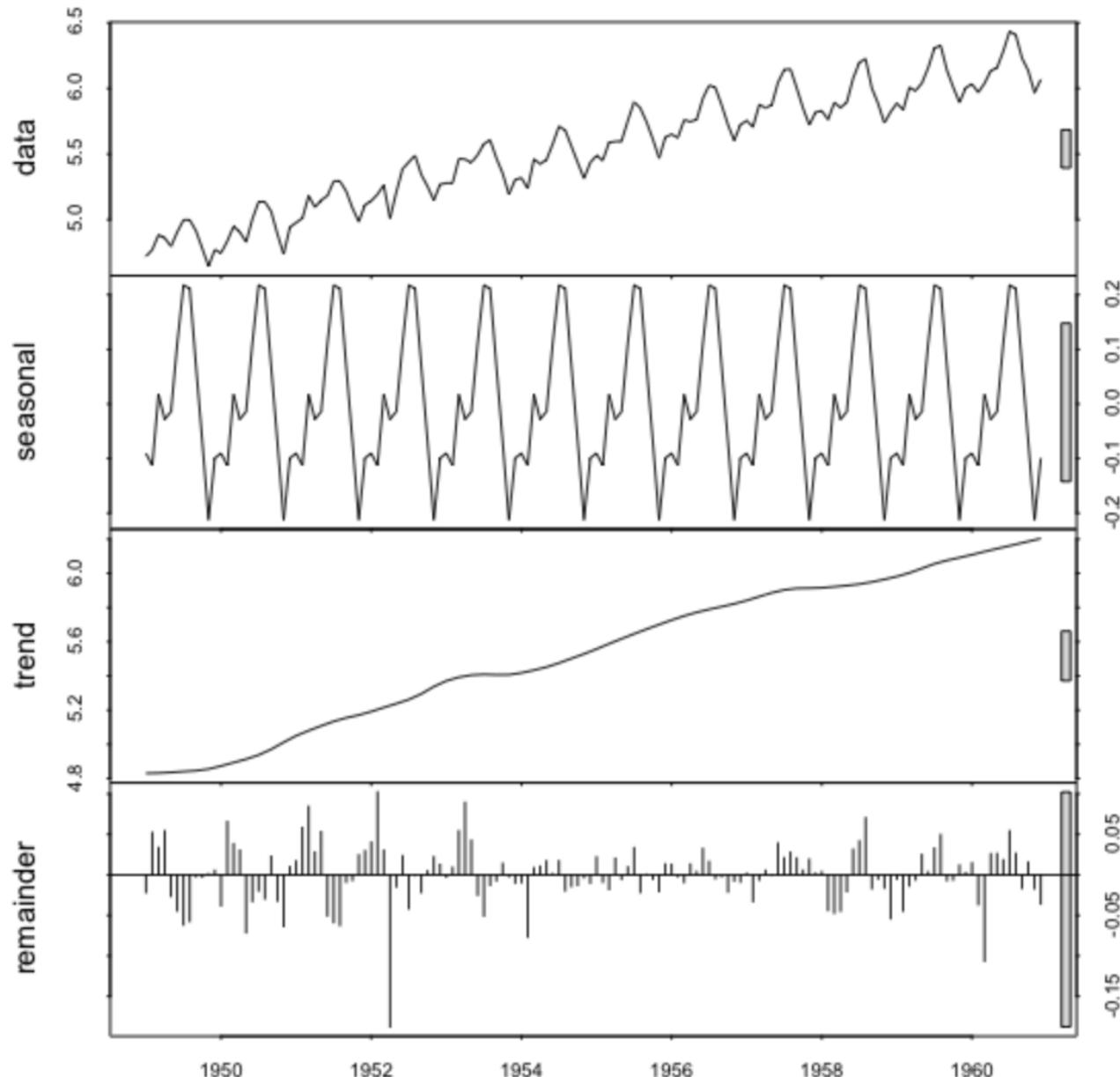
# Accounting for Seasonality



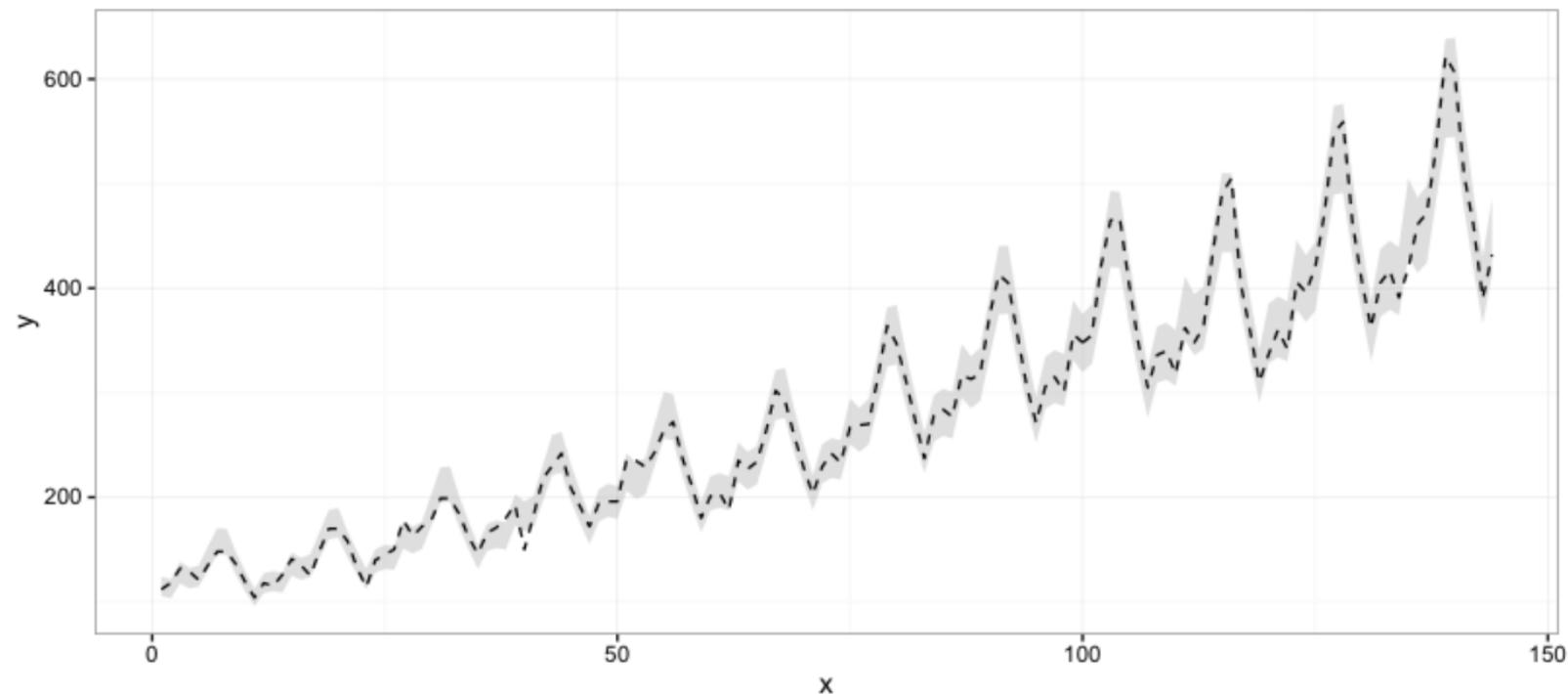
# Accounting for Seasonality



# STL: Accounting for Seasonality



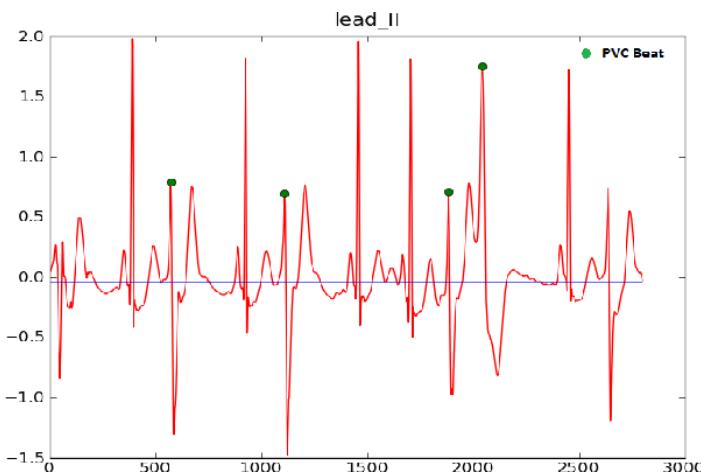
# STL: Accounting for Seasonality



# STL Library

## Prophet Anomaly Detection

# For the upcoming assignment on Arrhythmia Detection



- ① Try SMA/EMA (unsupervised baseline)
- ② Try a supervised method baseline like Logistic Regression
- ③ Try a deep learning model

# Questions?

# Extra Slides

# Anomaly Detection - Baselines

## ICE #1

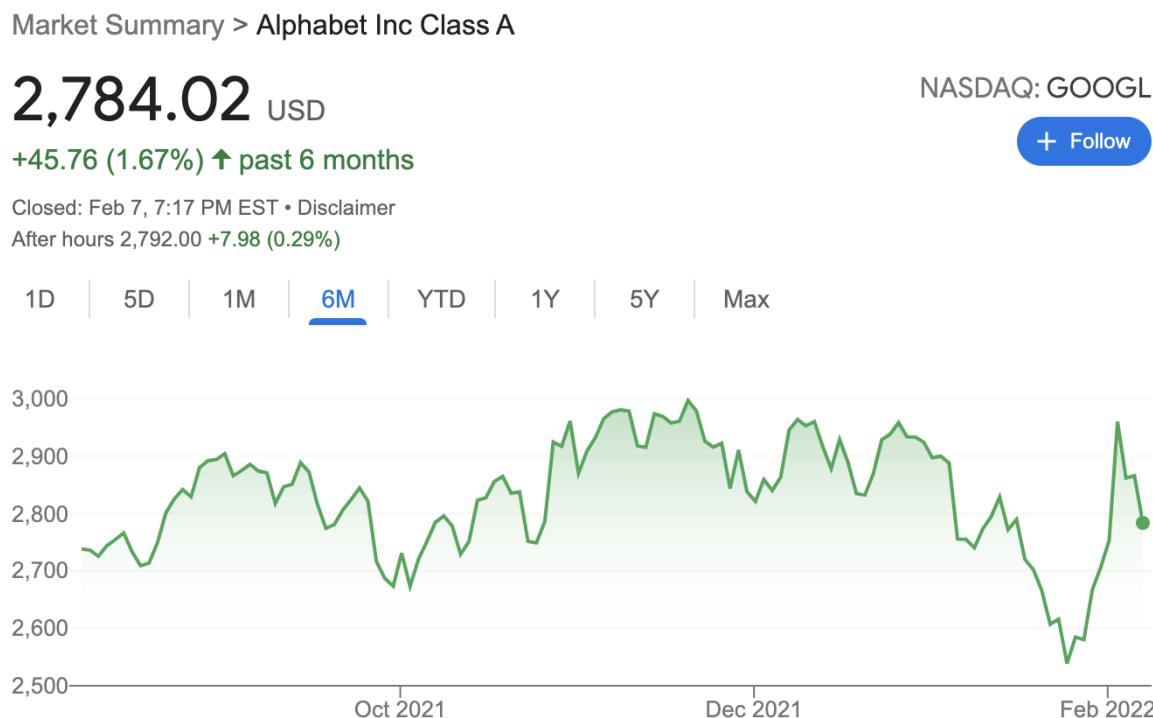
Suppose you have a data for product sales of all of groceries for a particular retail company by the hour for each day. Let the maximum product sales for any given hour is  $30k$  and minimum is  $5k$ . Suppose you notice today that for the hour starting at 6 pm, the sales was  $29k$  and for the hour starting at 10 am, the sales was  $6k$ . Which would be more suspect to be an anomaly sales data point?

- (a) Sales at 10 am
- (b) Sales at 6 pm
- (c) Could be both
- (d) Neither

# Stock Price Prediction

Can this be modeled as an anomaly detection problem?

Can you build a ML model that can predict when to buy a stock and when to sell a stock to maximize your profits. How exactly would you do it? And how could you cast it as an anomaly detection model?



# Stock Price Prediction

## Local Window

What would be the local window size you would choose for stock price prediction?

