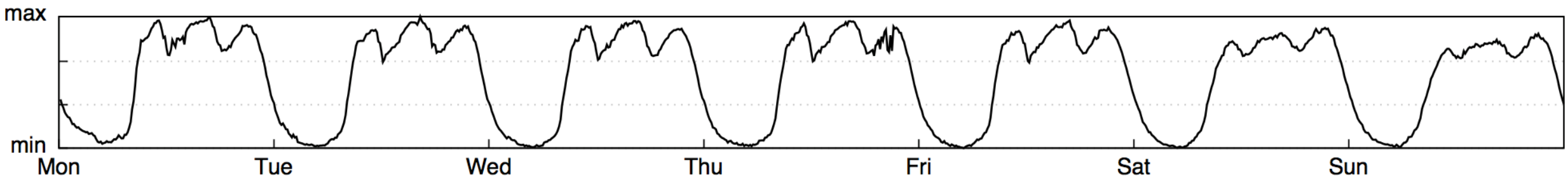
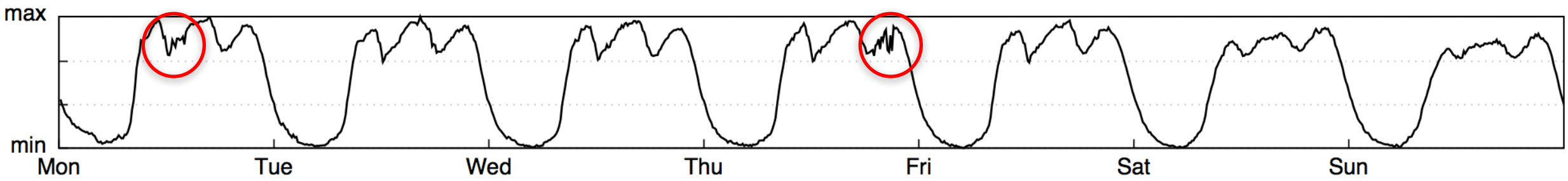
KPIs and Anomaly Detection



Page views (PV) of Baidu

KPIs (Key Performance Indicators): A set of performance measures that evaluate the service quality

KPIs and Anomaly Detection



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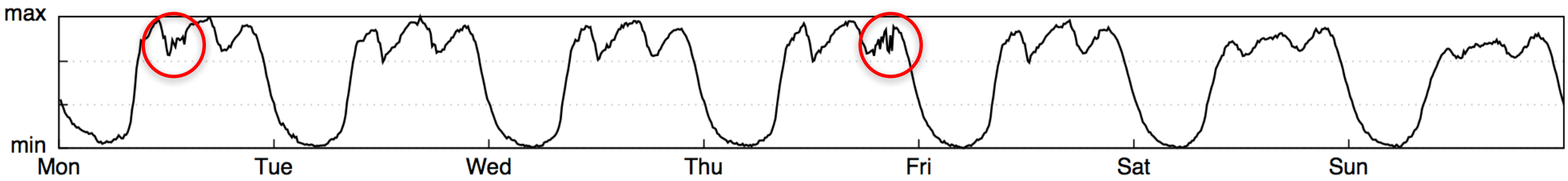
KPIs (Key Performance Indicators): A set of performance measures that evaluate the service quality

KPI anomalous (unexpected) behaviors → Potential failures, bugs, attacks...

KPIs and Anomaly Detection



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KPIs (Key Performance Indicators): A set of performance measures that evaluate the service quality

KPI anomalous (unexpected) behaviors → Potential failures, bugs, attacks...

Anomaly detection matters: Find anomalous behaviors of the KPI curve

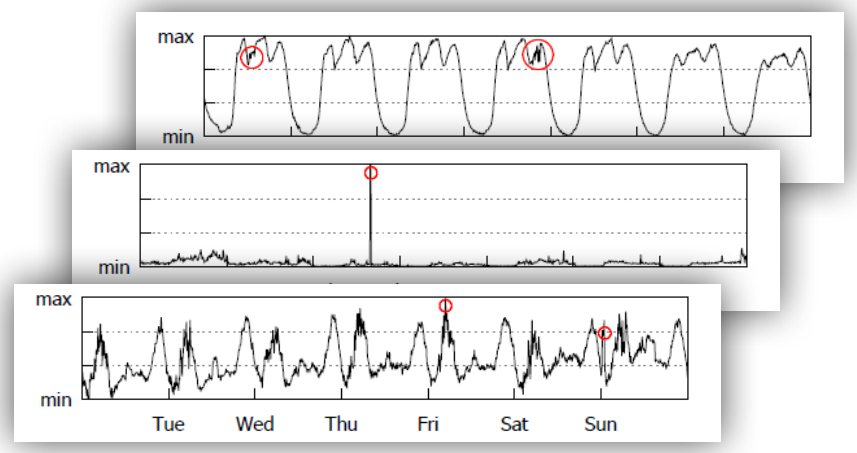
→ Diagnose and fix it

→ Avoid further influences and revenue losses

How to Build an Anomaly Detection System

Domain experts (Operators)

- Responsible for the KPIs
- Knowing the KPI behaviors well



Developers

- Building the detection system
- Knowing several anomaly detectors

Simple threshold

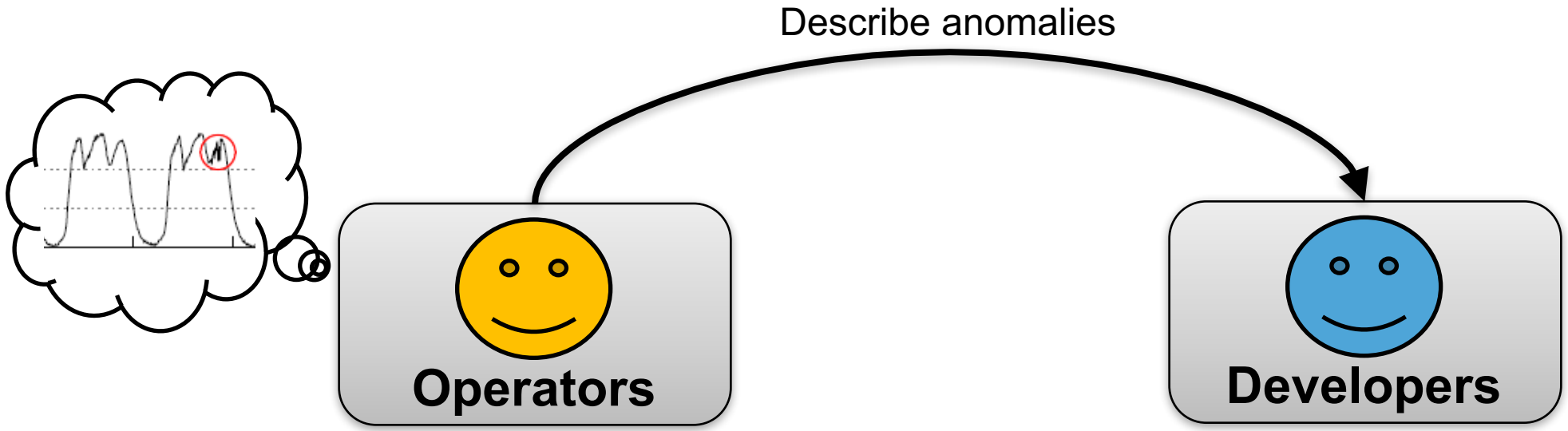
Historical Average

Wavelet

Holt-Winters

...

In practice, it is more complex



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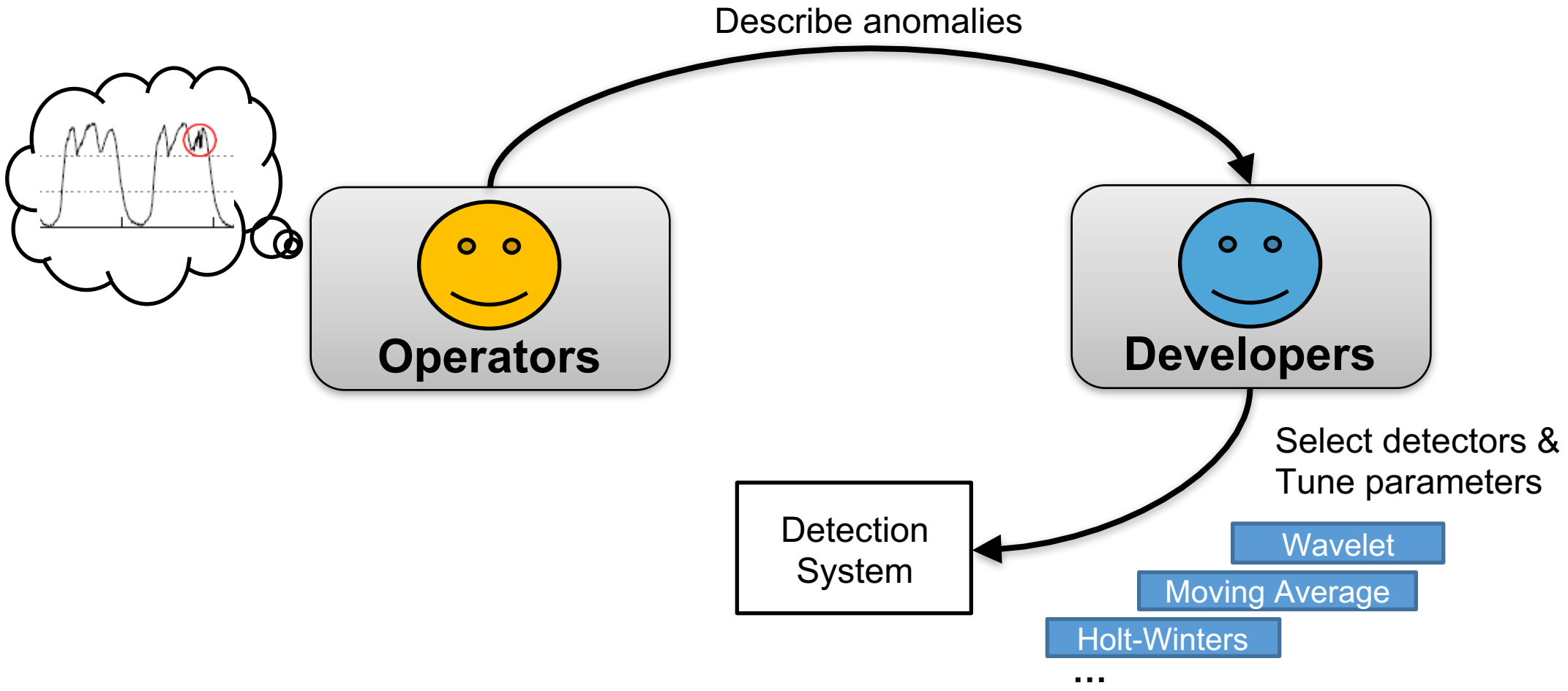

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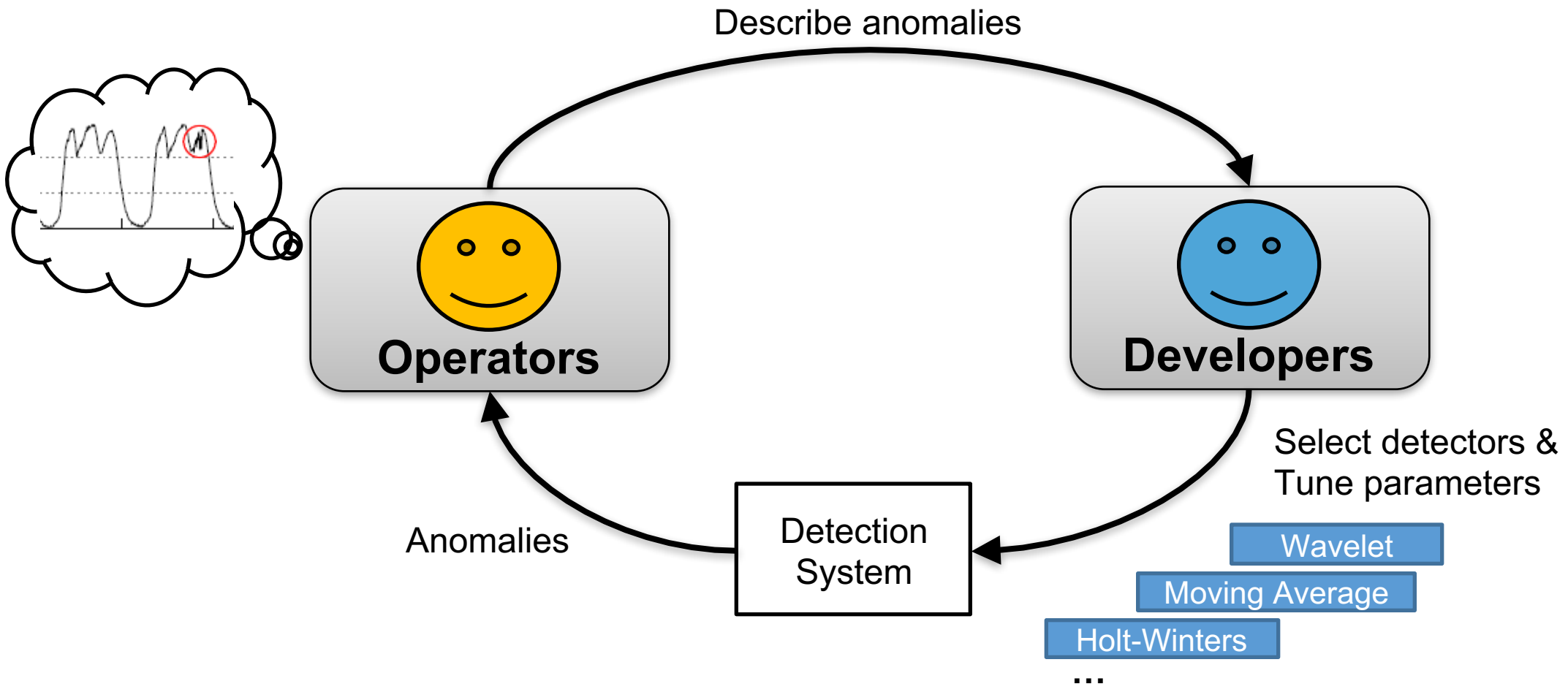

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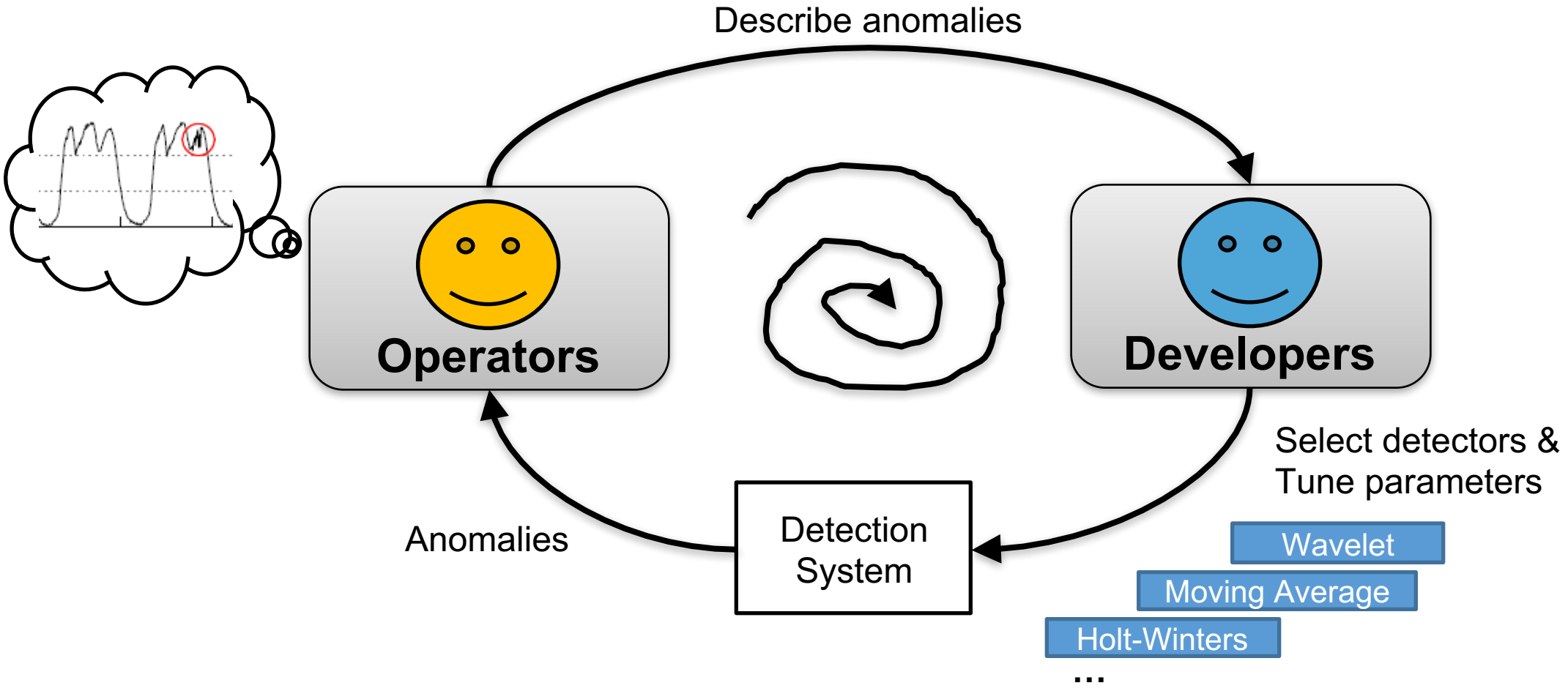
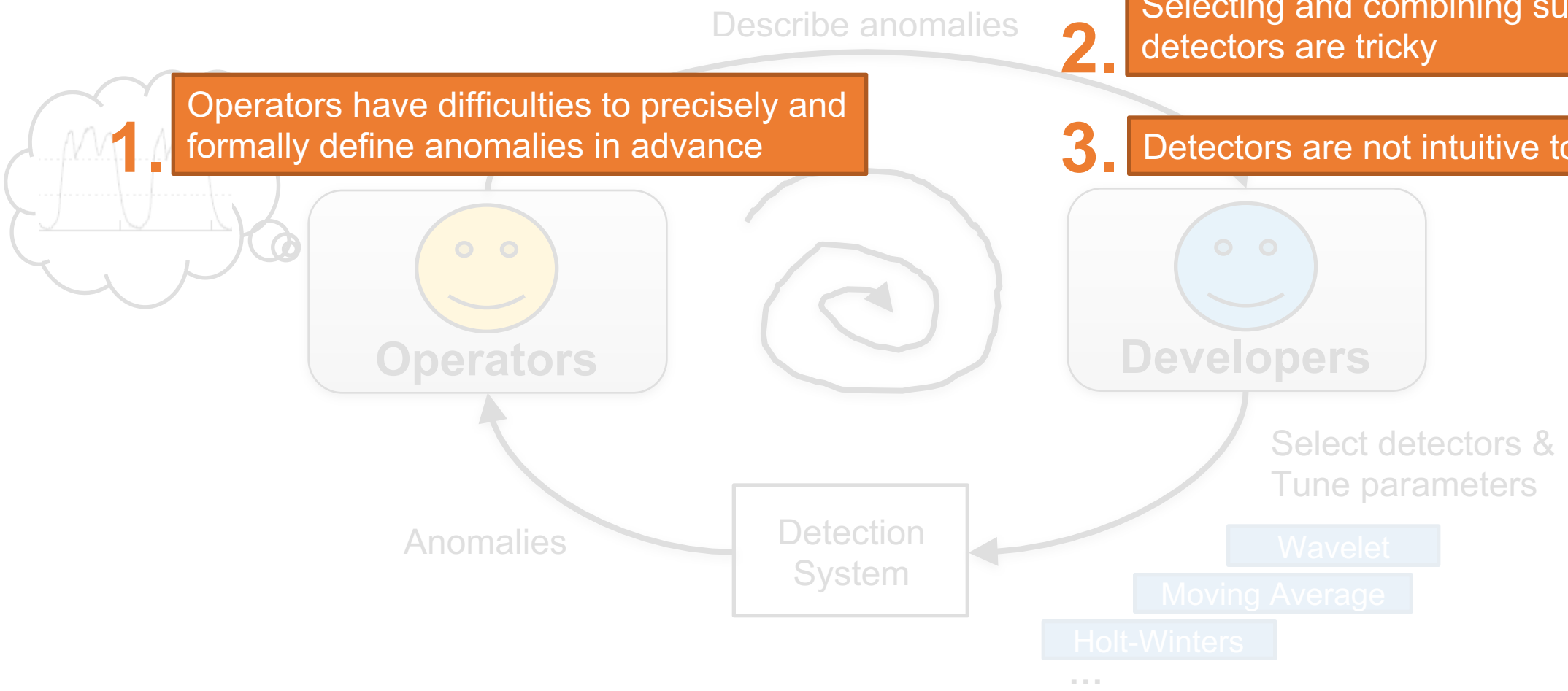


Challenges

1. Operators have difficulties to precisely and formally define anomalies in advance

2. Selecting and combining suitable detectors are tricky

3. Detectors are not intuitive to tune

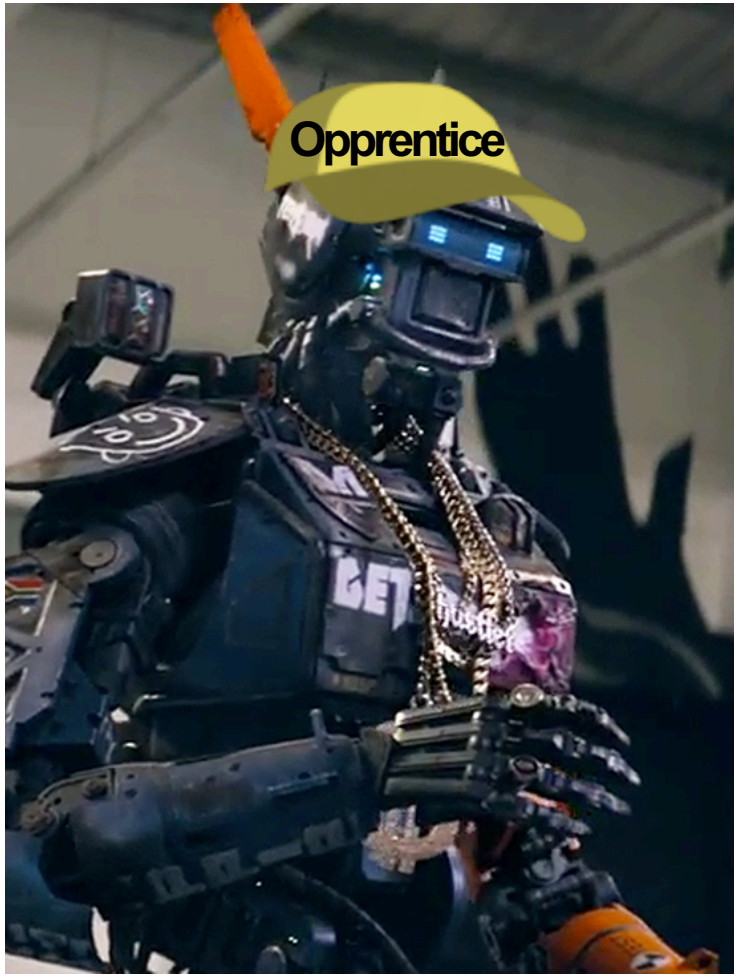


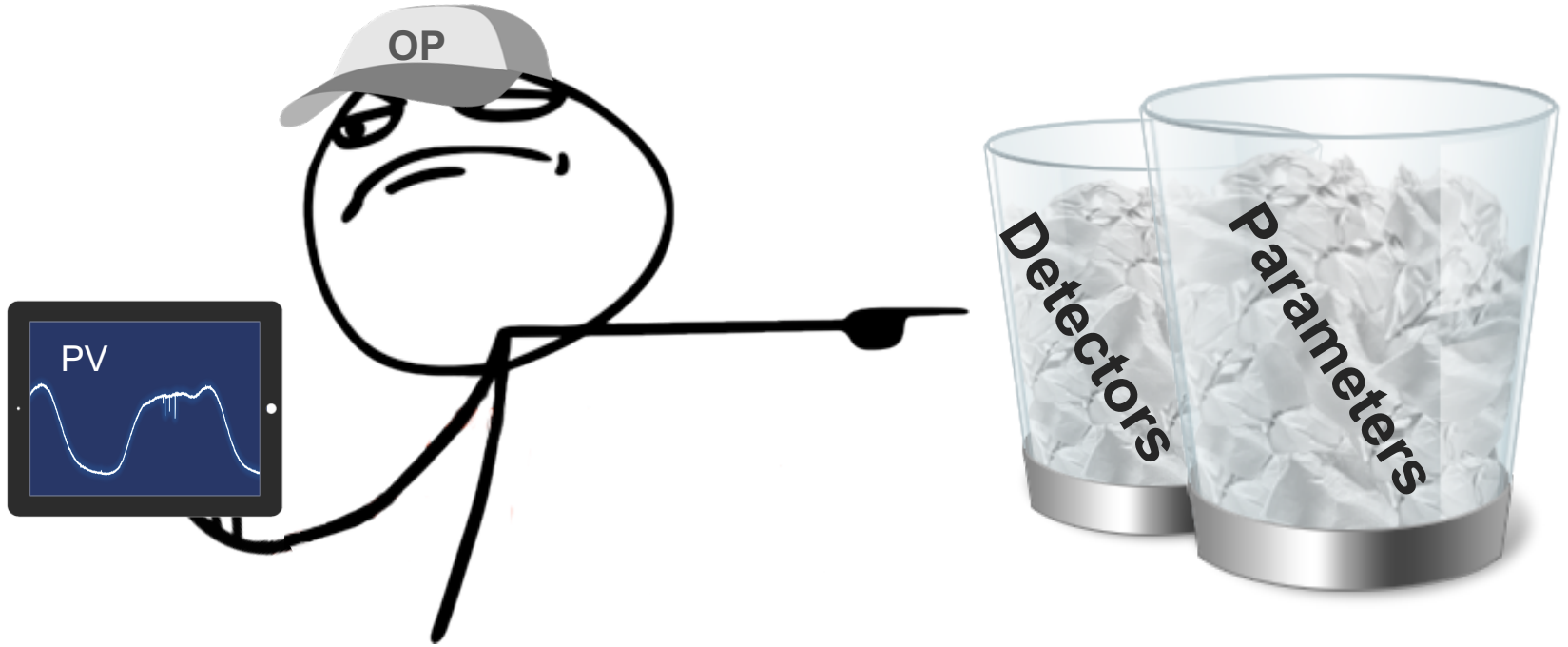

CHAPPiE
DADDY
CHAPPIE

Opprentice

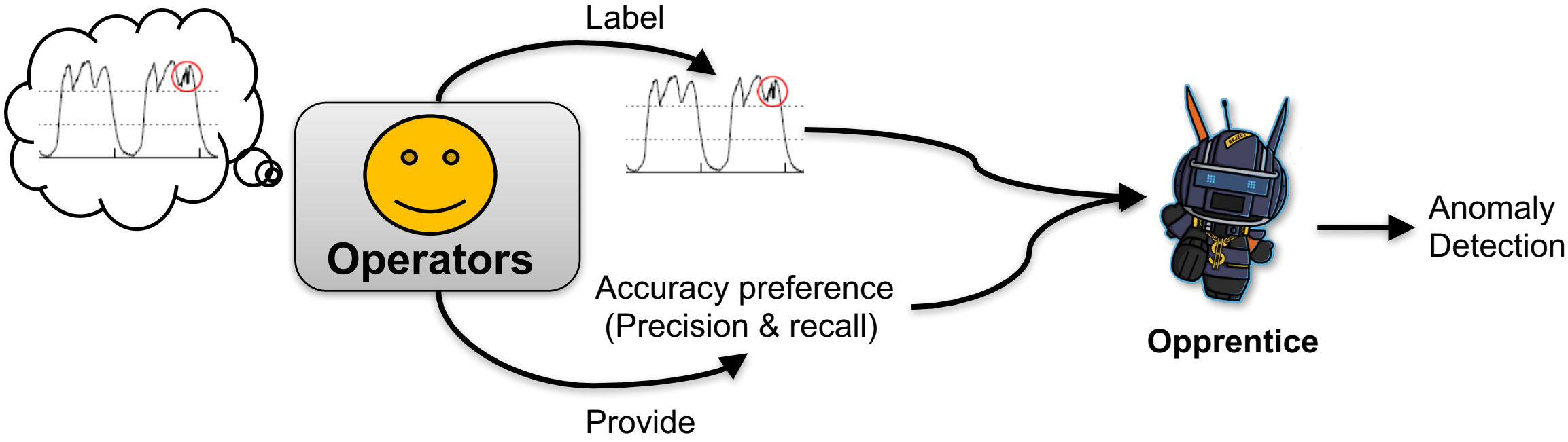
(Operators' apprentice)

A More Natural Way

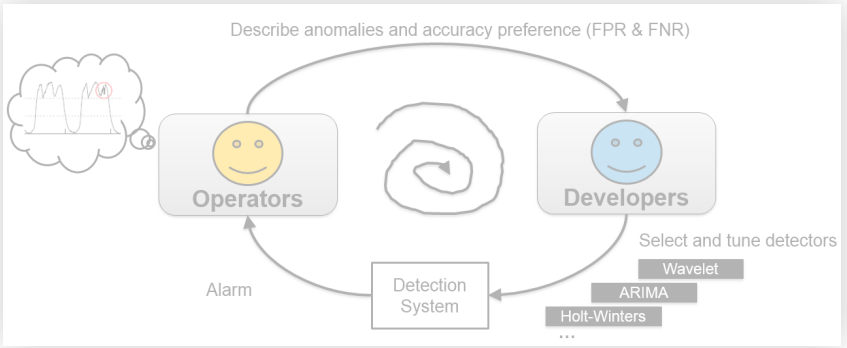




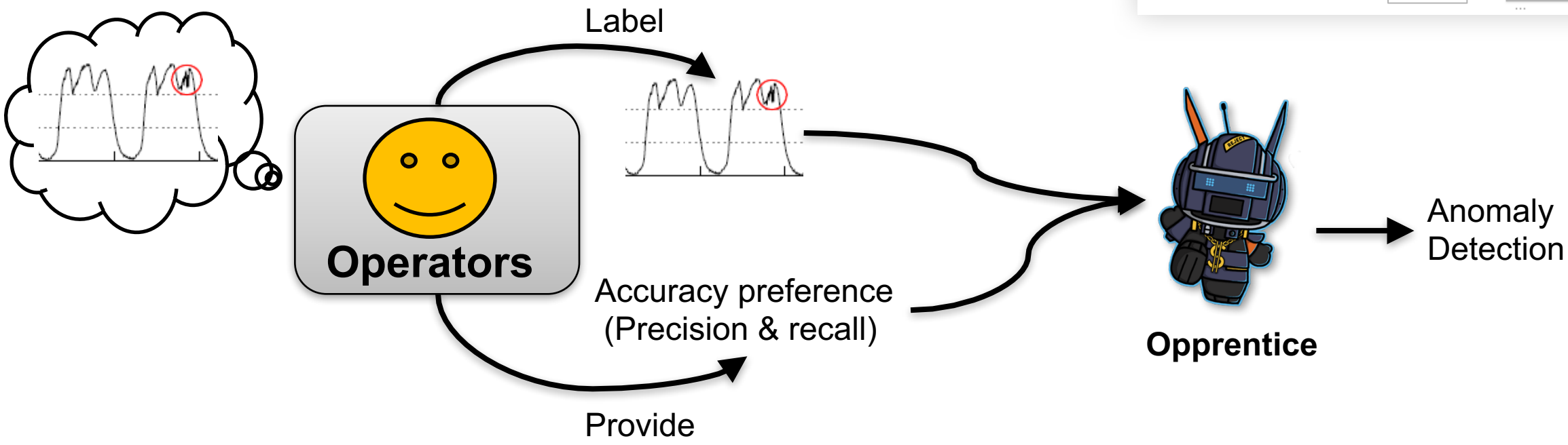
Design Goal


Label
Operators
Accuracy preference
(Precision & recall)
Provide
Opprentice
Anomaly
Detection

Design Goal



VS.



Outline

- Background and Motivation
- **Key Ideas**
- Results
- Conclusion

Key Ideas

Detector model:

$$\text{data point} \xrightarrow{\text{a detector with parameters } \{p\}} \text{severity} \xrightarrow{\text{sThld}} \{1, 0\}$$

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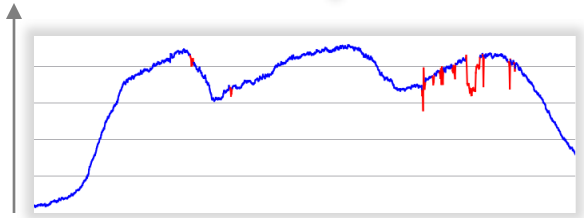
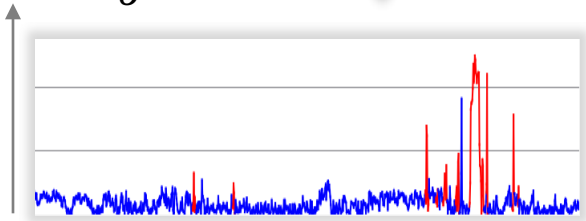
For example

$value$



Historical Average

$$\text{severity} = \frac{|value - \mu|}{\sigma}$$



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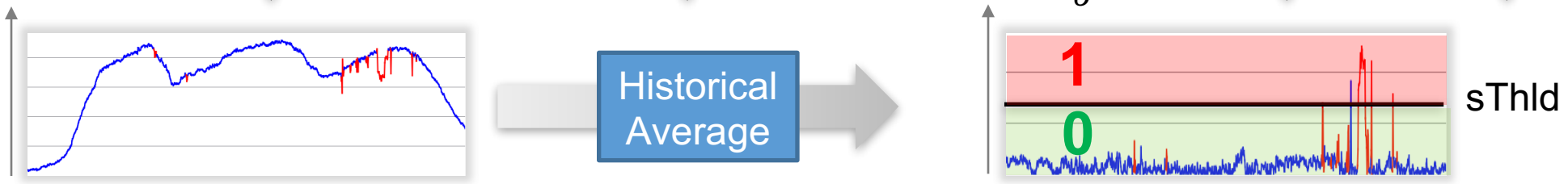

Key Ideas

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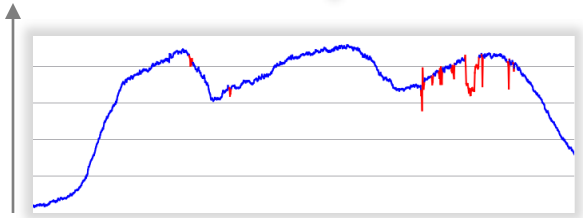

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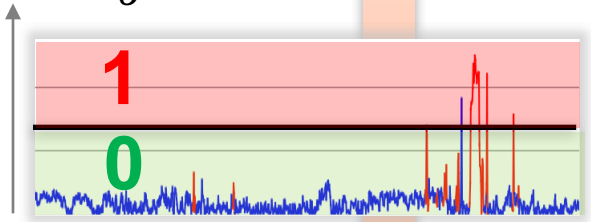
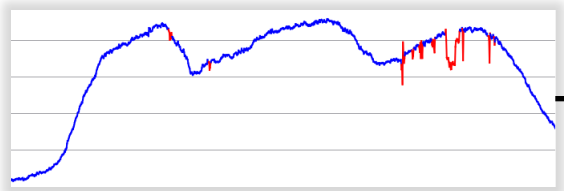


sThld

Anomaly feature

Key Ideas

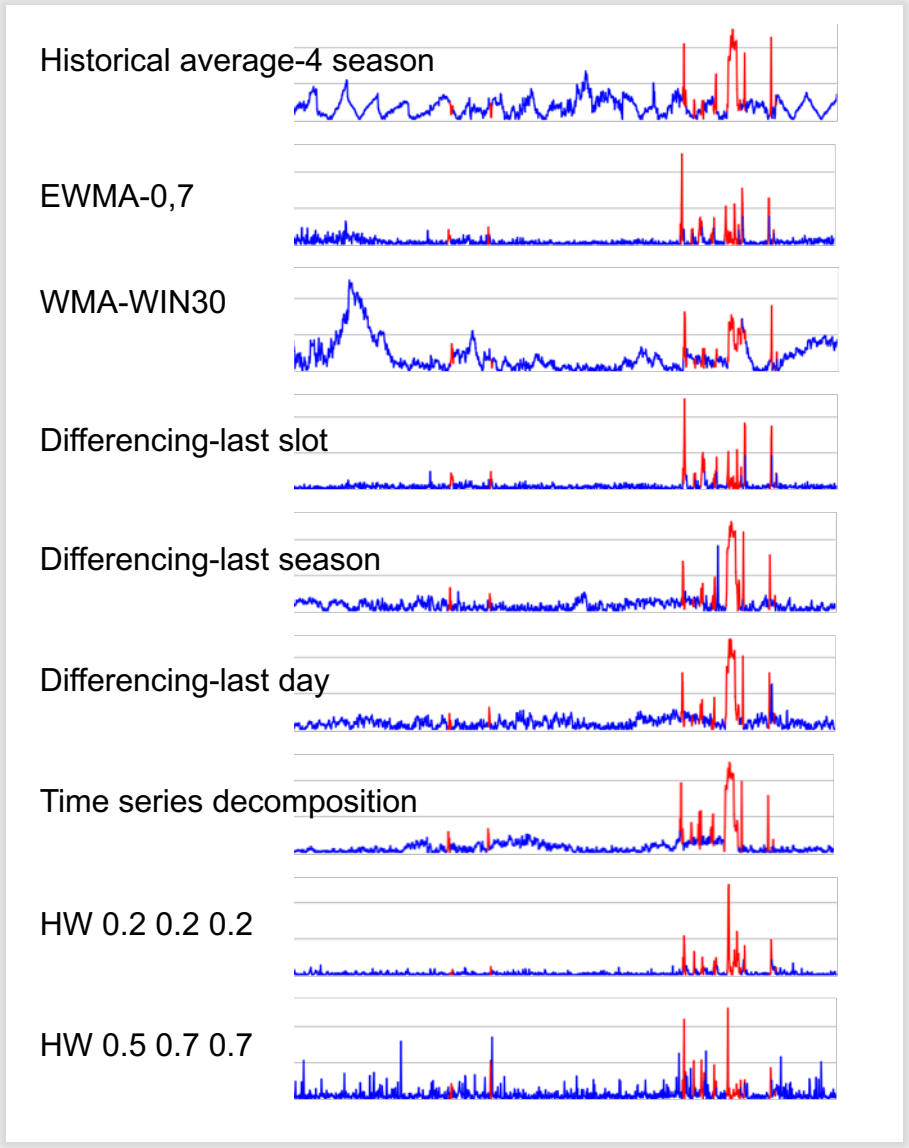


KPI data

Configurations

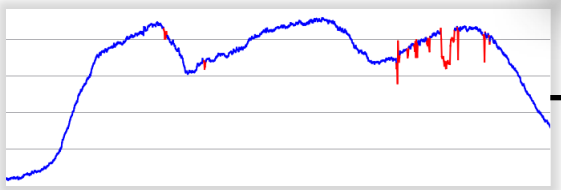
(Detectors with different parameters)

Extract features



Key Ideas

Detector / # of configurations	Sampled parameters
Simple threshold [24] / 1	none
Diff / 3	last-slot, last-day, last-week
Simple MA [4] / 5	win = 10, 20, 30, 40, 50 points
Weighted MA [11] / 5	
MA of diff / 5	
EWMA [11] / 5	$\alpha = 0.1, 0.3, 0.5, 0.7, 0.9$
TSD [1] / 5	win = 1, 2, 3, 4, 5 week(s)
TSD MAD / 5	
Historical average [5] / 5	
Historical MAD / 5	
Holt-Winters [6] / $4^3 = 64$	$\alpha, \beta, \gamma = 0.2, 0.4, 0.6, 0.8$
SVD [7] / $5 \times 3 = 15$	row =10, 20, 30, 40, 50 points, column =3, 5, 7
Wavelet [12] / $3 \times 3 = 9$	win = 3, 5 ,7 days, freq = low, mid, high
ARIMA [10] / 1	Estimation from data
In total: 14 basic detectors / 133 configurations	



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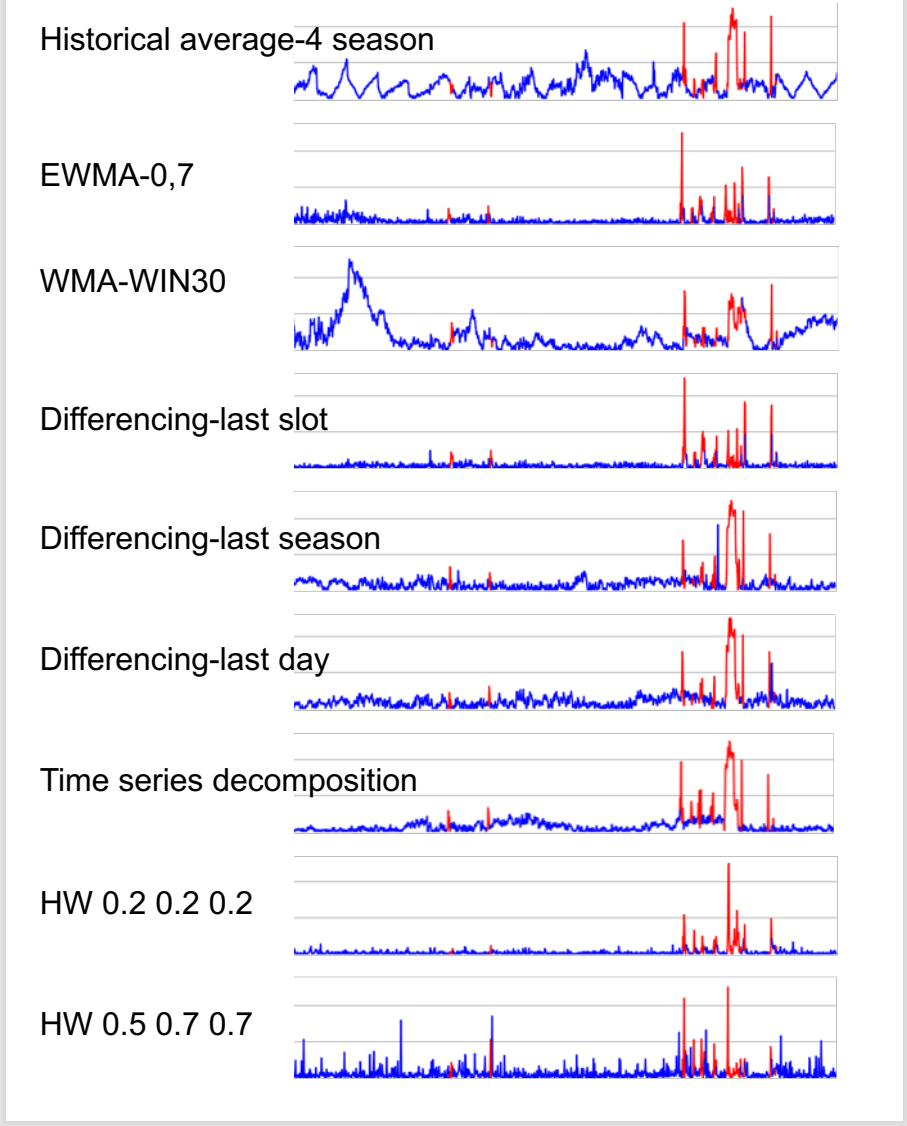

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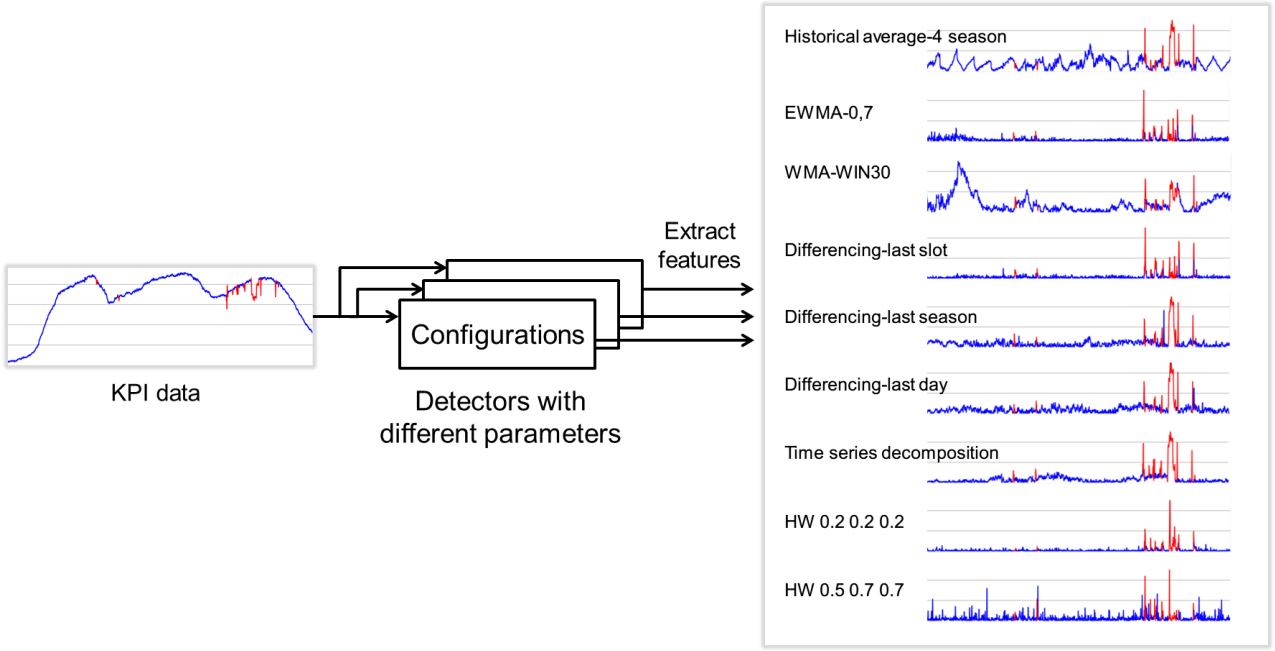
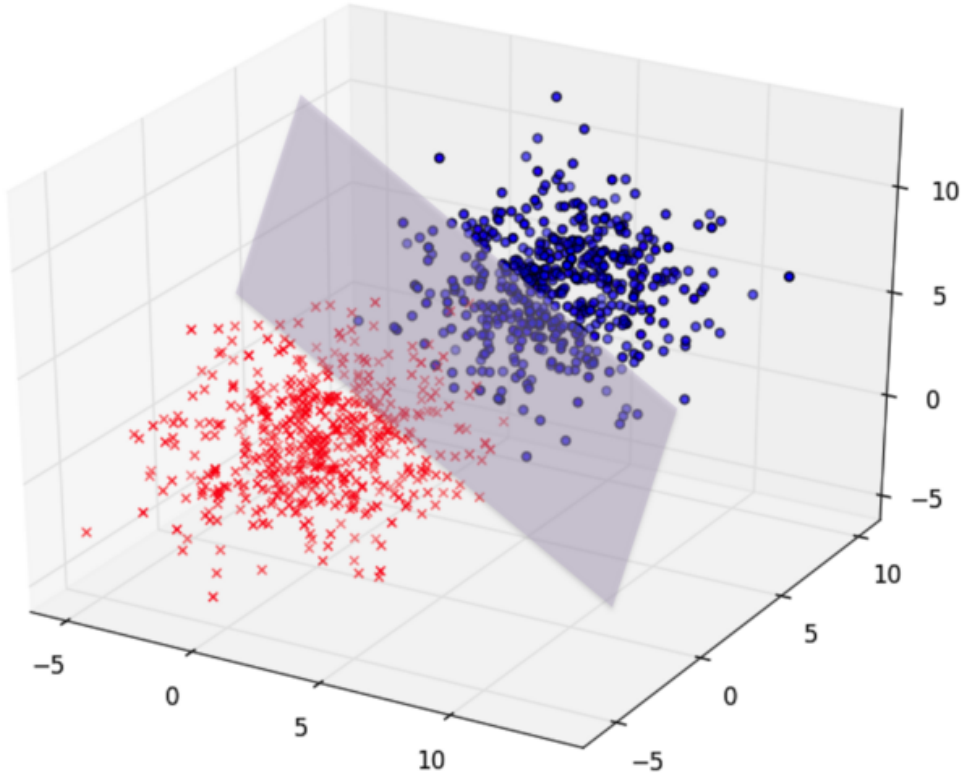


Classification in the feature space (Supervised machine learning)



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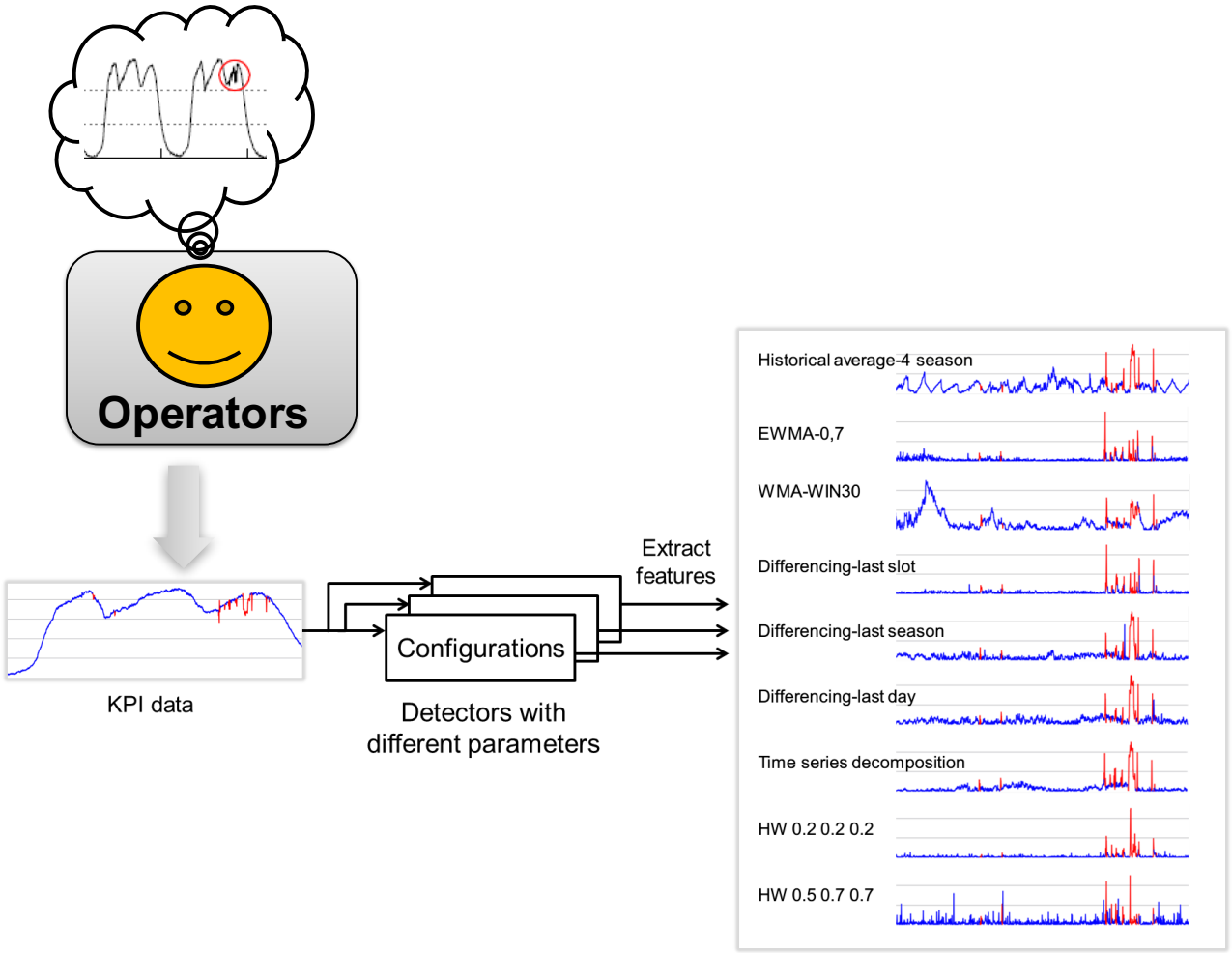

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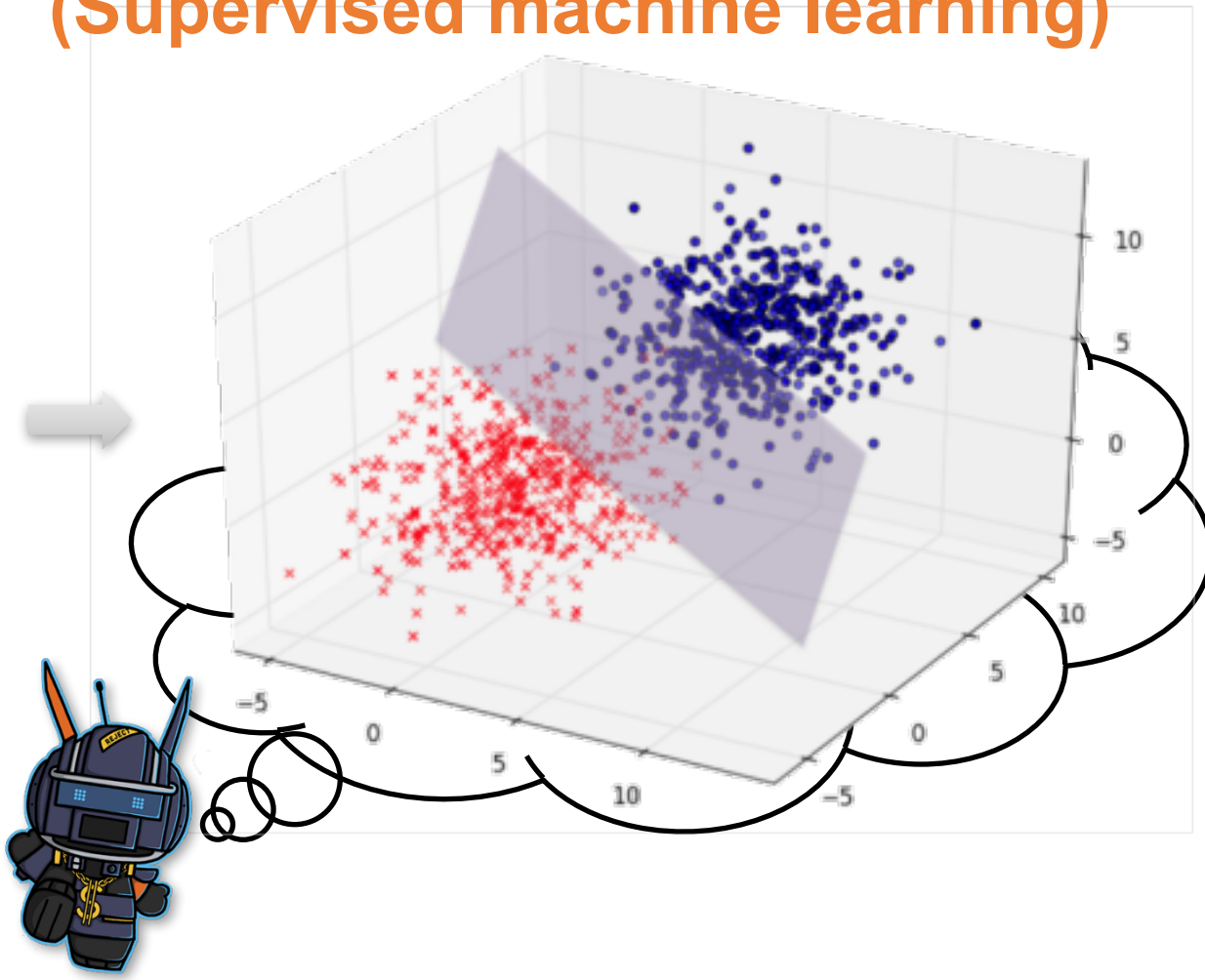
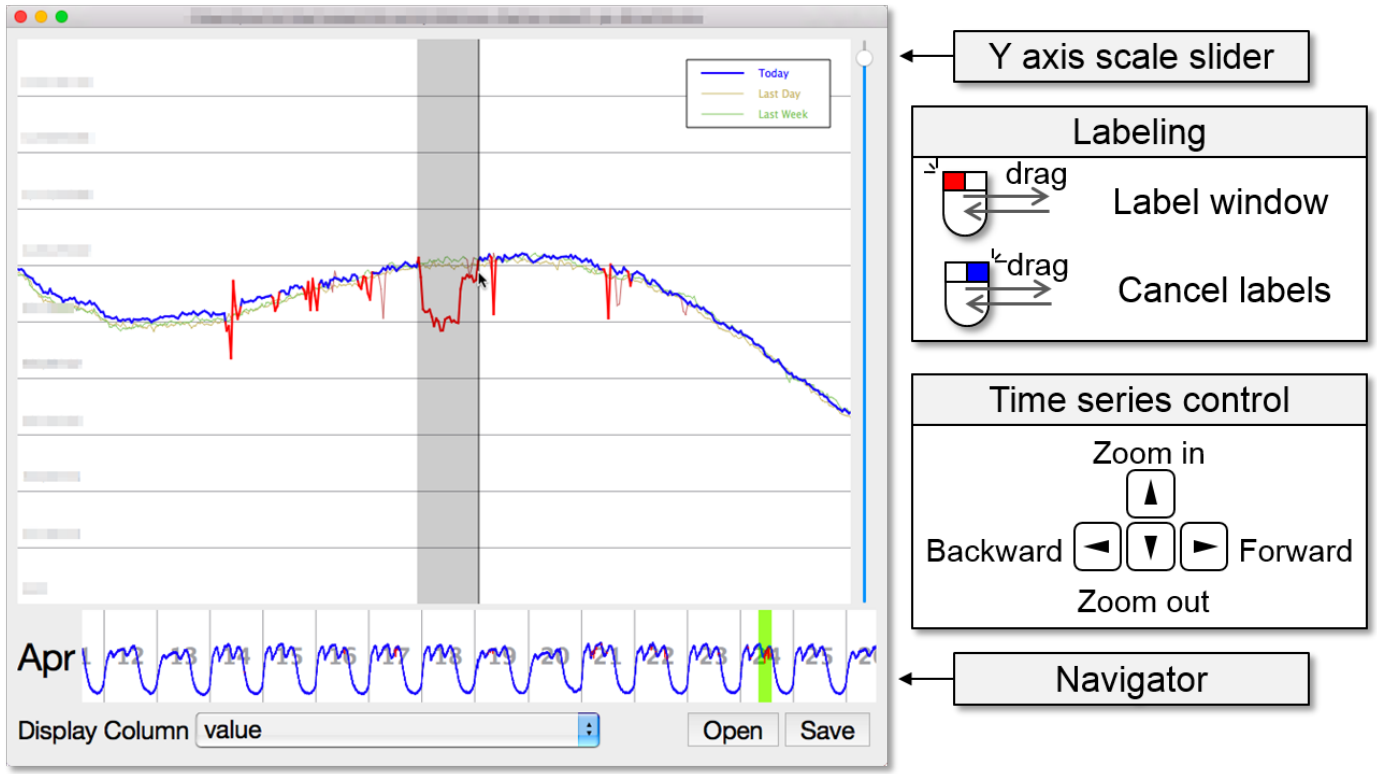
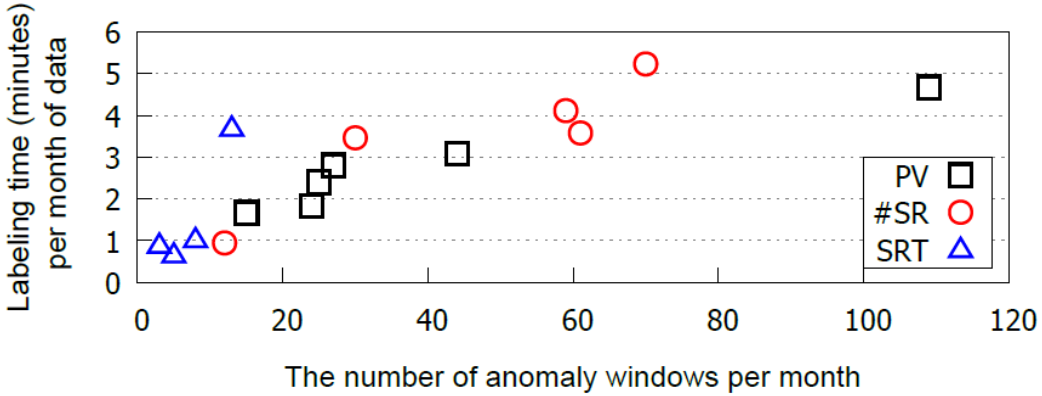


Address Challenges of Designing Opprentice

- Labeling overhead
  - Solution: an effective labeling tool





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- Class imbalance problem
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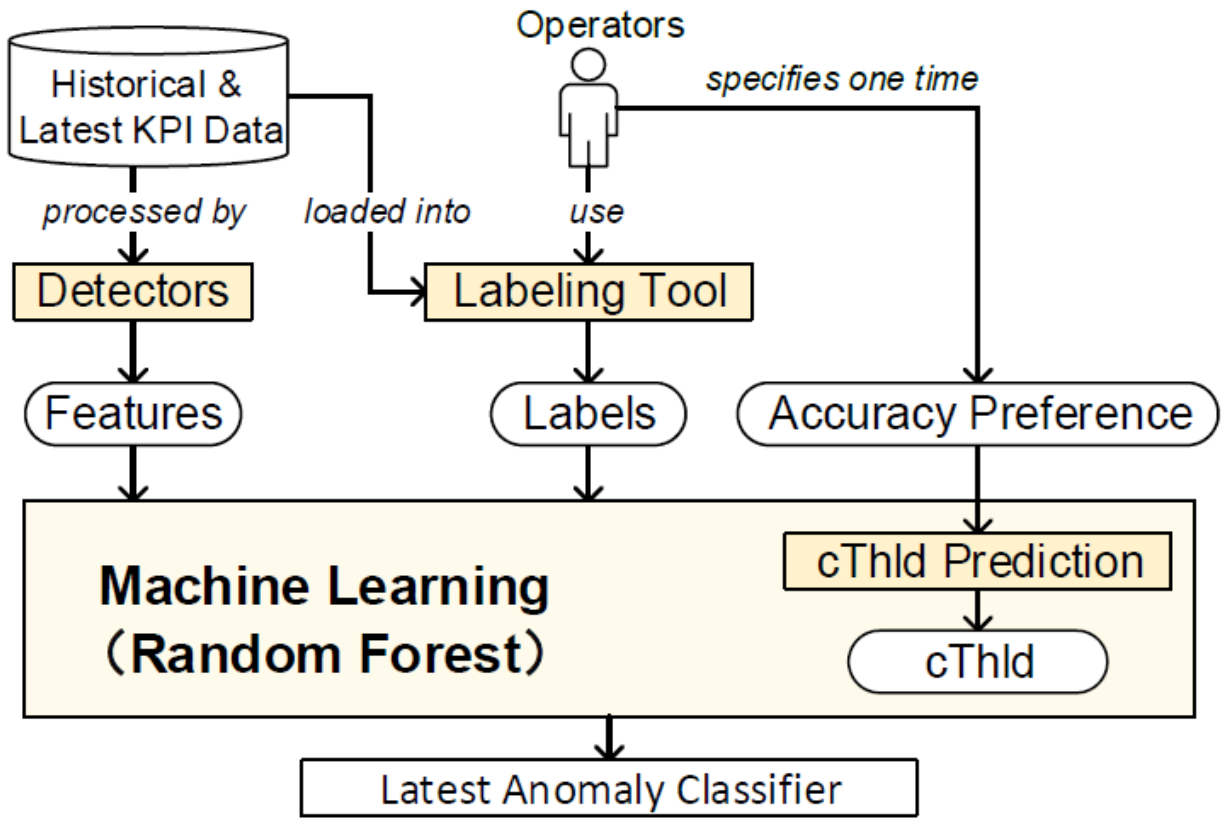
- Irrelevant and redundant features
  - Solution: random forests

Design Overview

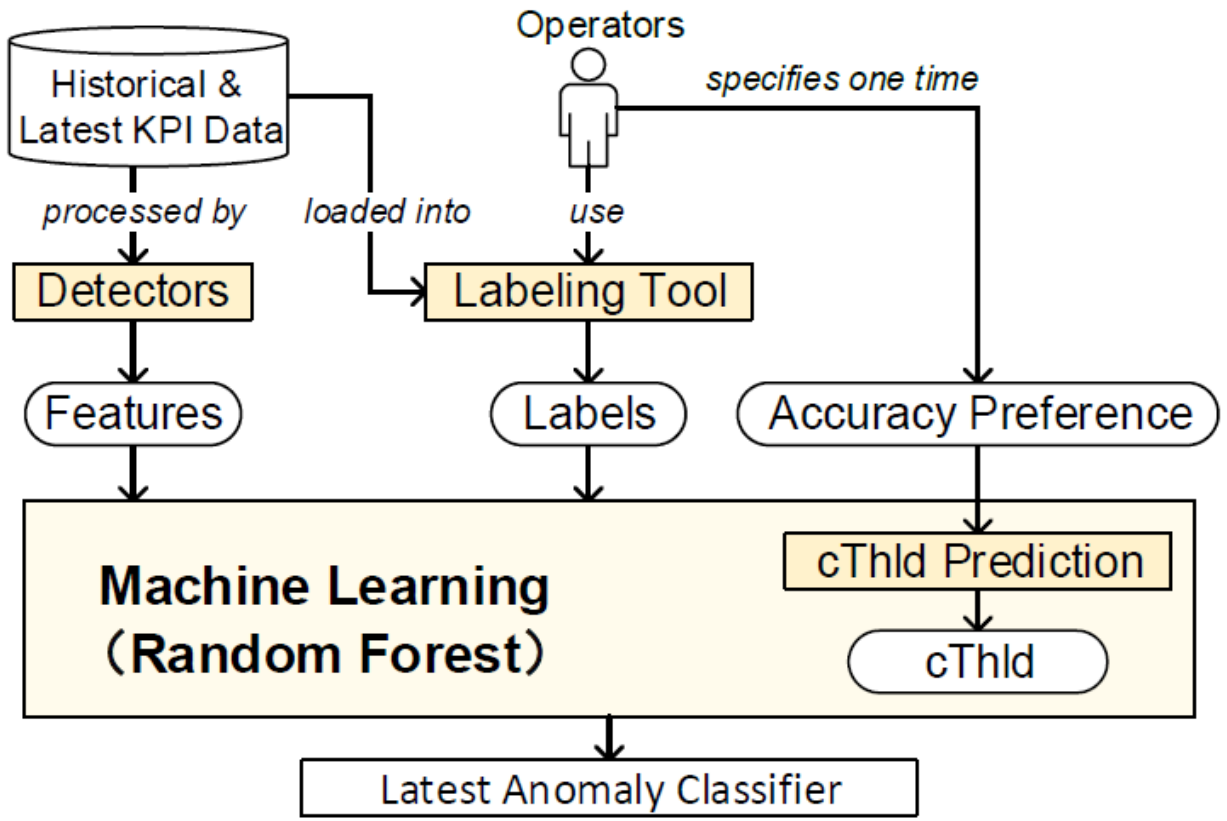
Training a classifier



See the paper for full details

Design Overview

Training a classifier



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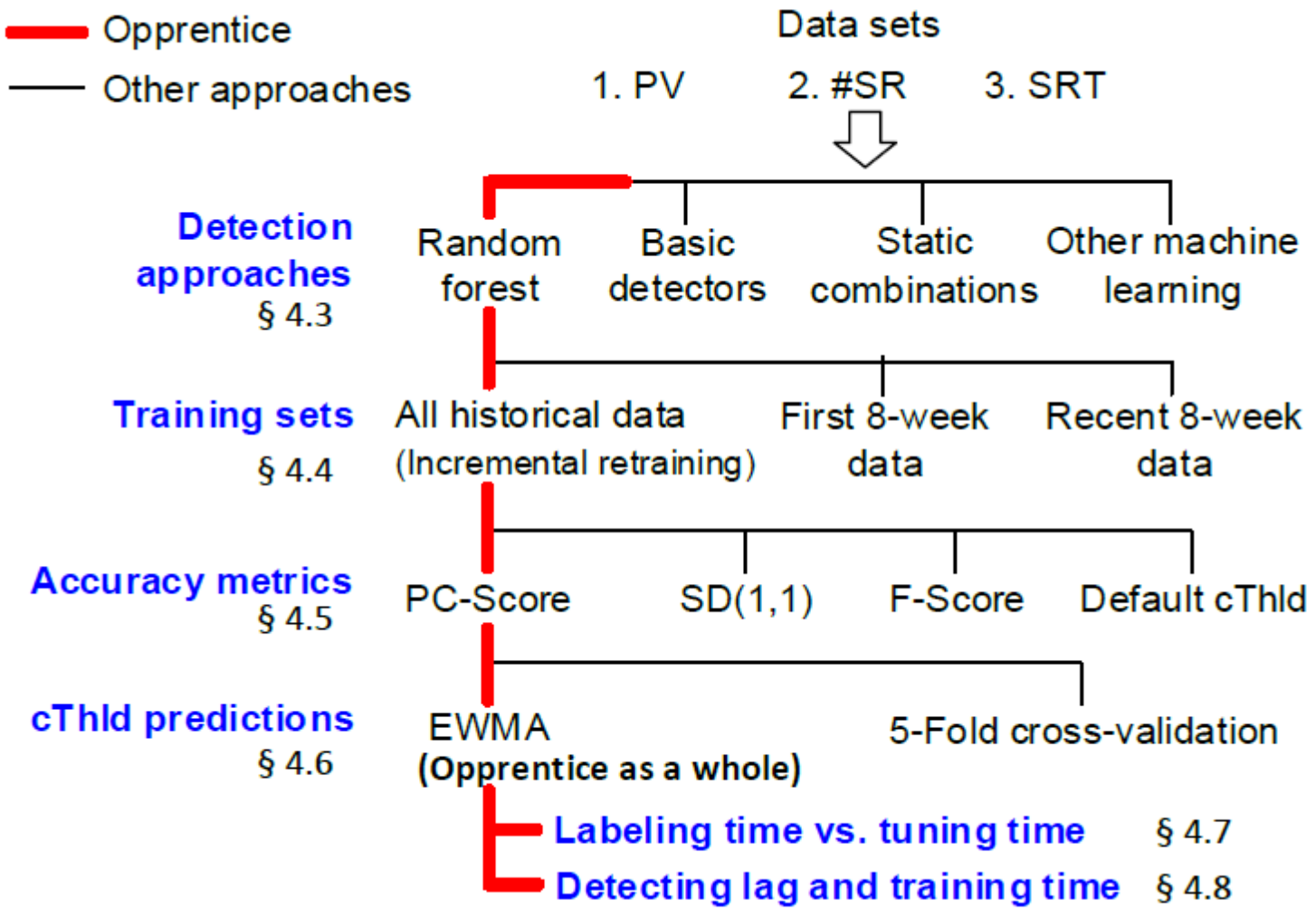
Detecting anomalies

Outline

- Background and Motivation
- Key Ideas
- **Results**
- Conclusion

Evaluation


Opprentice
Other approaches
Data sets
1. PV
2. #SR
3. SRT
Detection approaches § 4.3
Random forest
Basic detectors
Static combinations
Other machine learning
Training sets § 4.4
All historical data (Incremental retraining)
First 8-week data
Recent 8-week data
Accuracy metrics § 4.5
PC-Score
SD(1,1)
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Default cThld
cThld predictions § 4.6
EWMA (Opprentice as a whole)
5-Fold cross-validation
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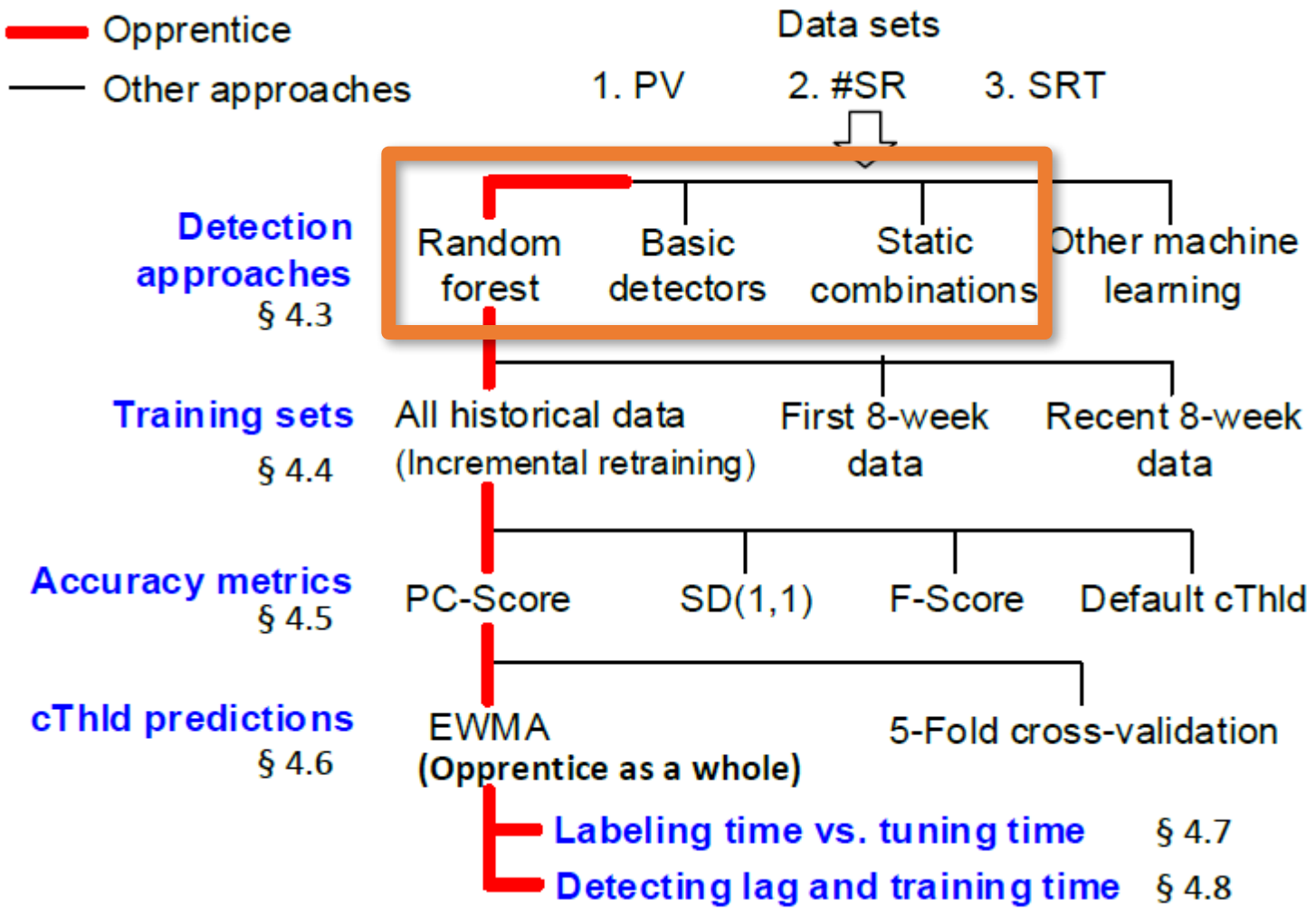
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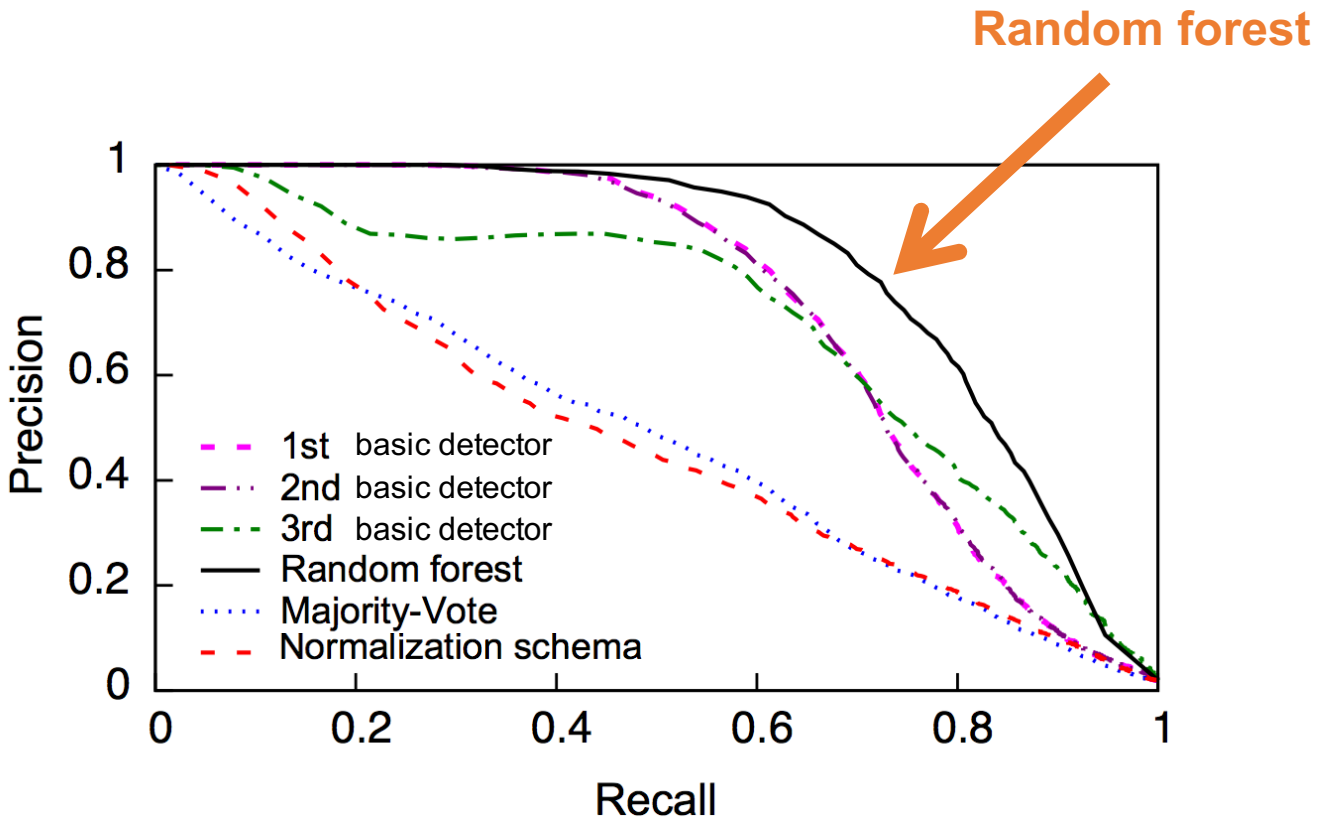
Random forests vs. Basic Detectors and Static Combinations



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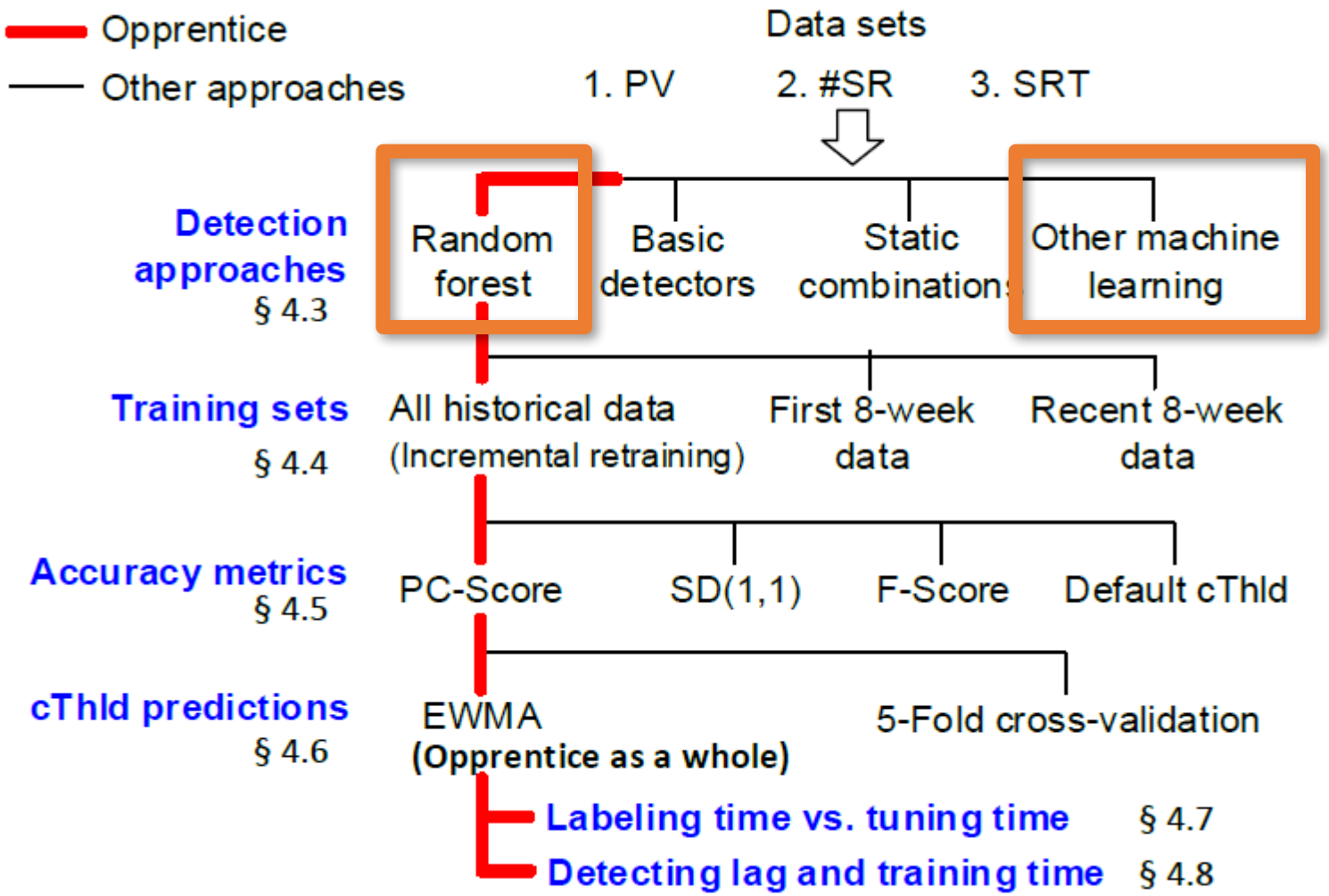
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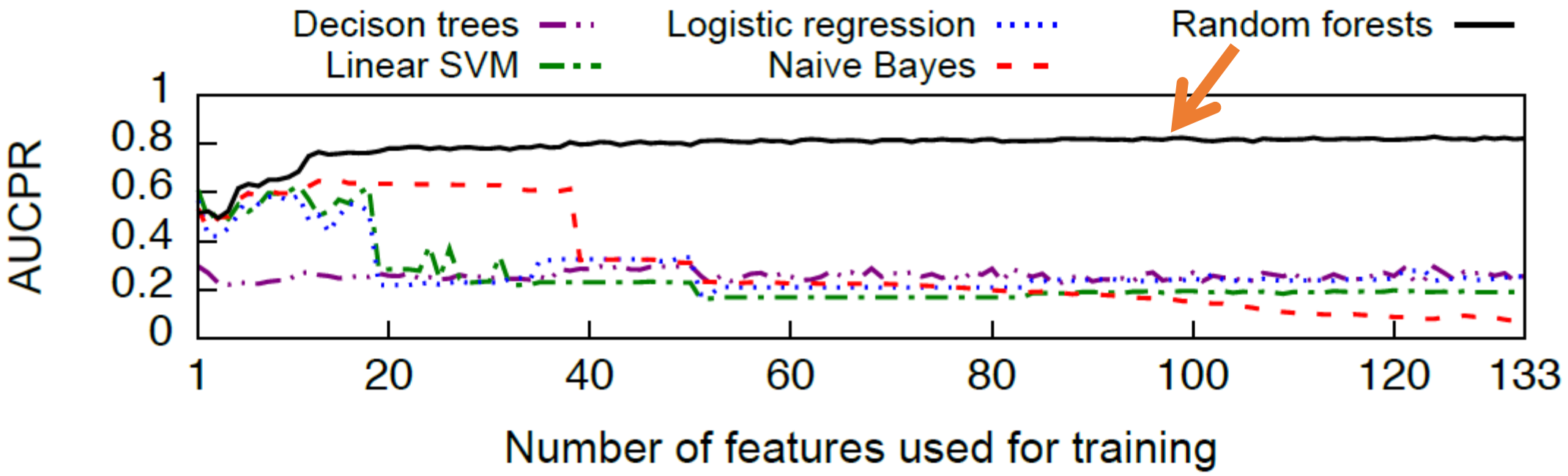
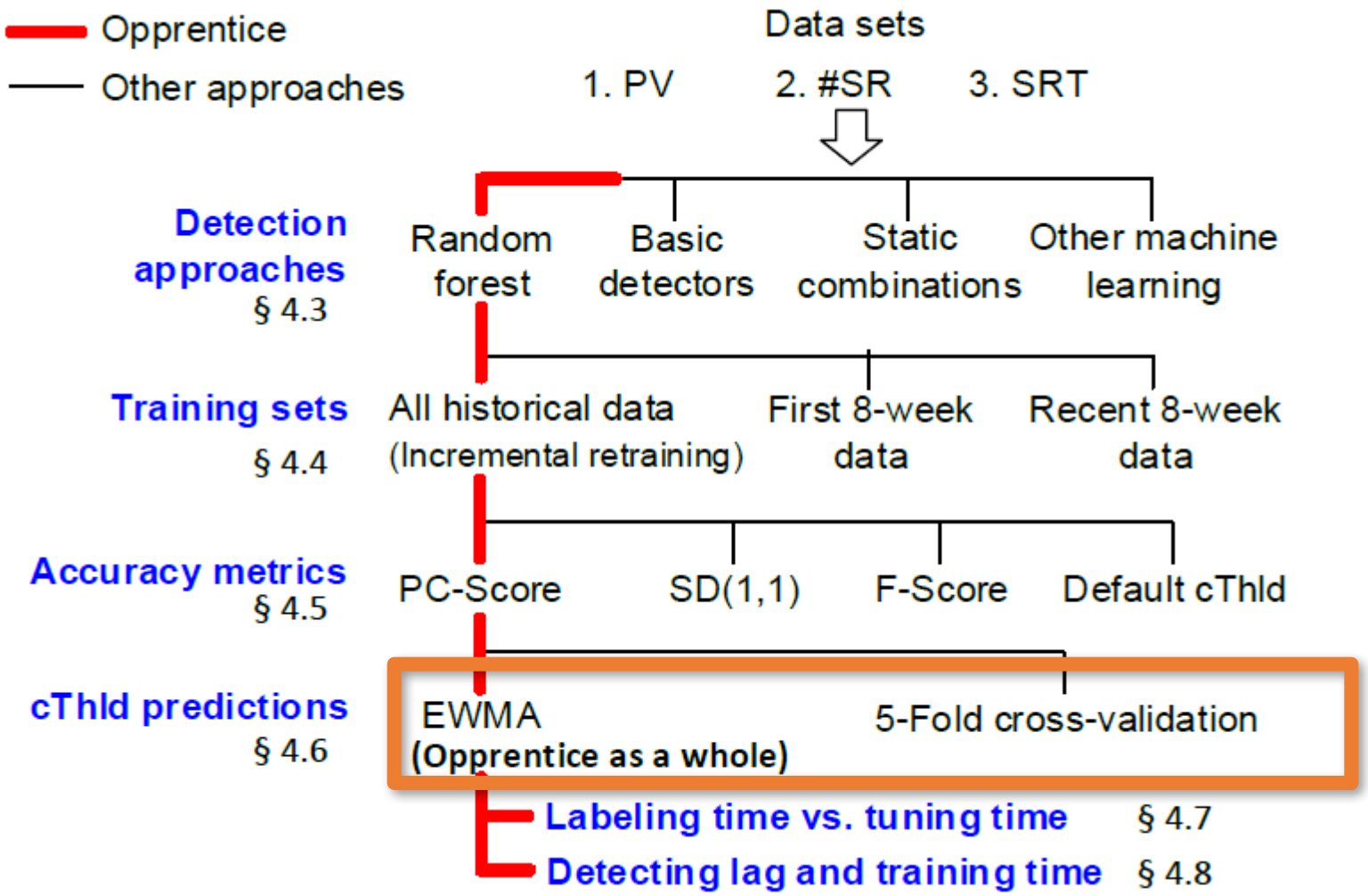
Random Forests vs. Other Learning Algorithms



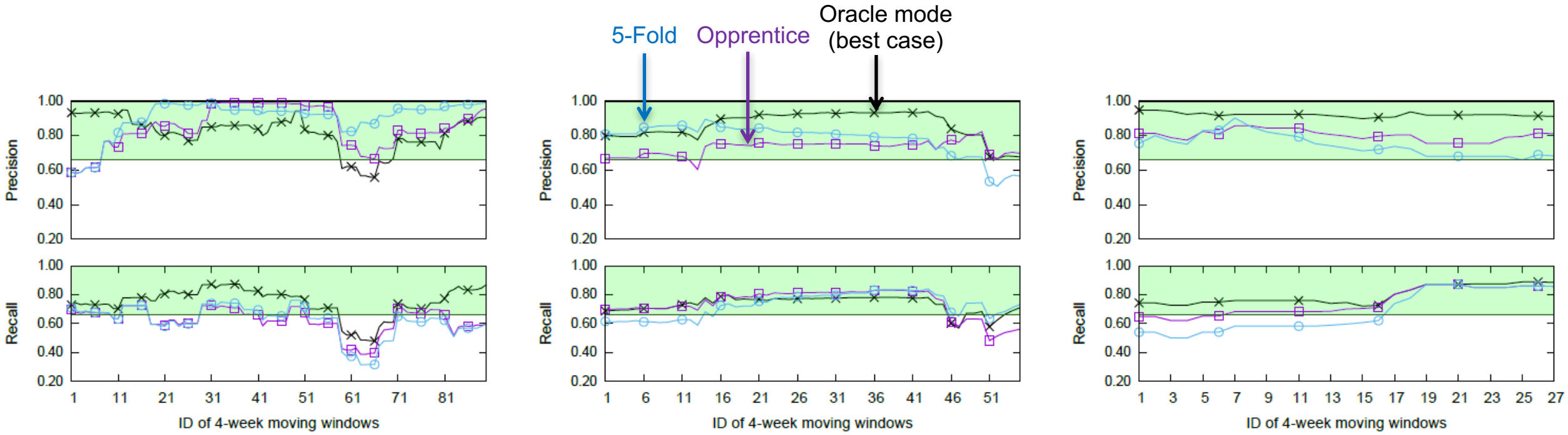
(The order of features is based on *mutual information*)

Evaluation



See the paper for full details

Opprentice as a whole



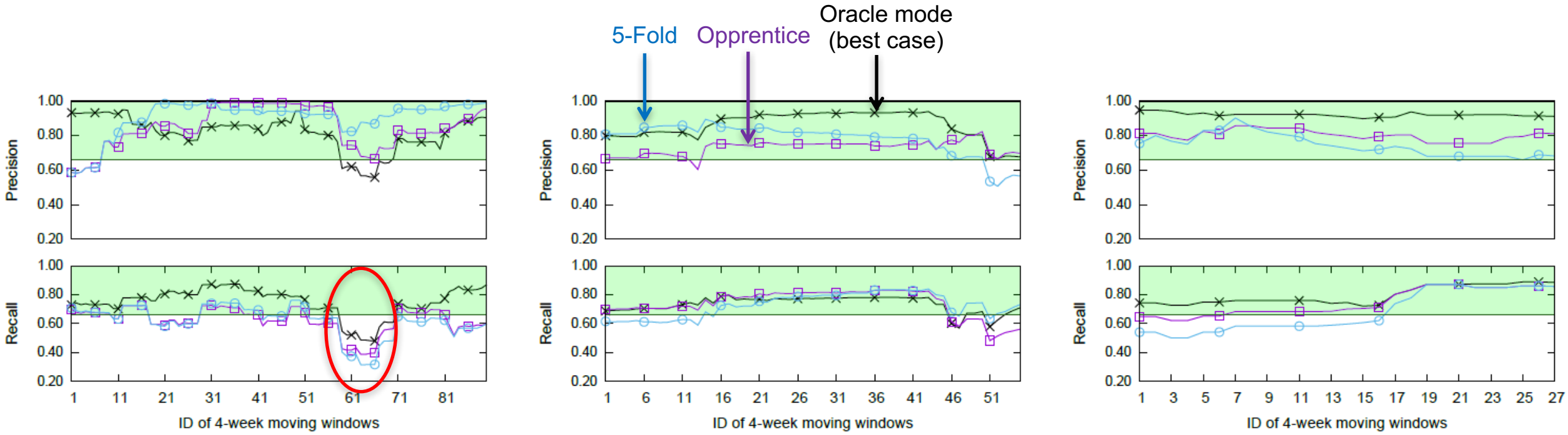
(a) KPI: PV (b) KPI: #SR (c) KPI: SRT

Opprentice achieves

40% **23%** **110%**

more points inside the preference regions than 5-Fold cross-validation

Opprentice as a whole



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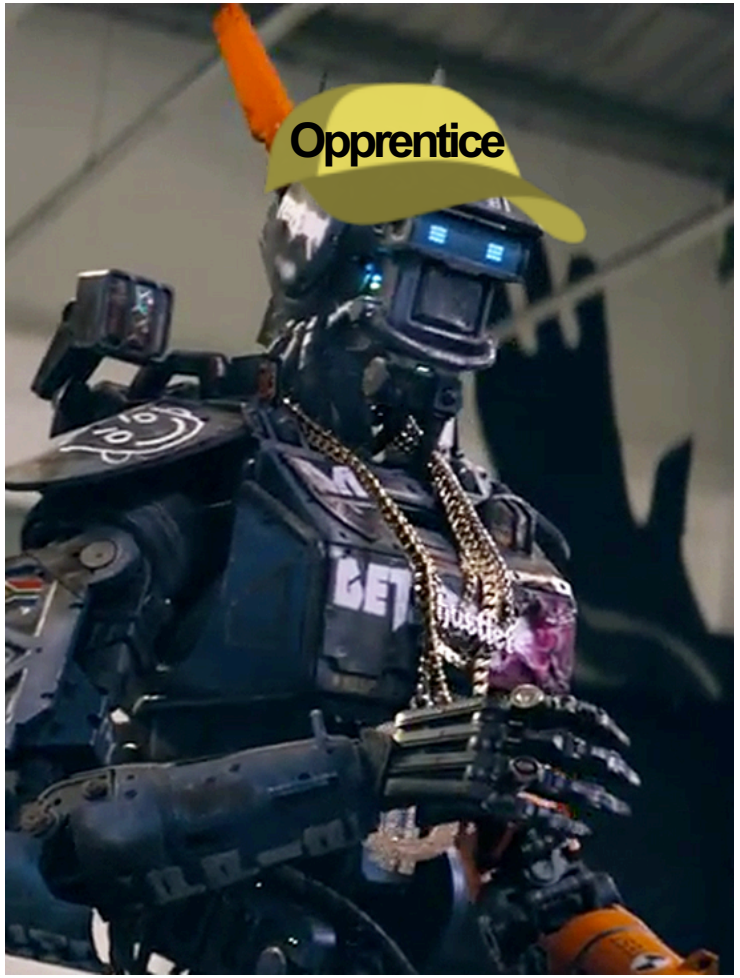

- Opprentice is an **automatic** and **accurate** machine learning framework for KPI anomaly detection

~~Defining anomalies~~ ~~Selecting detectors~~ ~~Tuning detectors~~

- Opprentice **bridges the gap** in applying complex detectors in practice

- The idea of Opprentice

  i.e., **using machine learning to model the domain knowledge**

could be a very promising way to automate other service managements

Thank you

liudp10@mails.tsinghua.edu.cn