Anomaly Detection and Failure Prediction

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Outline

What data are already being collected

Heat & power plant - 10^3 observations/ms

Rolled metal production - 10^4 observations/ms

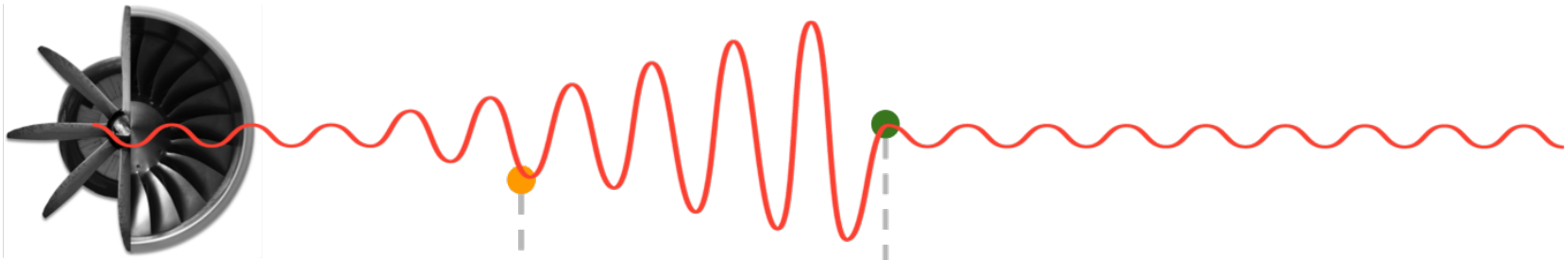
Modern aircraft – up to **0.5 Tb for one flight**

- Less than 1% of data is used, most of the data is not stored and used
- The next generation of Pratt & Whitney engines will produce up to **10 Gb/sec**

Self-driving Google car – up to **1 Gb/sec**

- Formula-1 car - **1.2 Gb/sec**

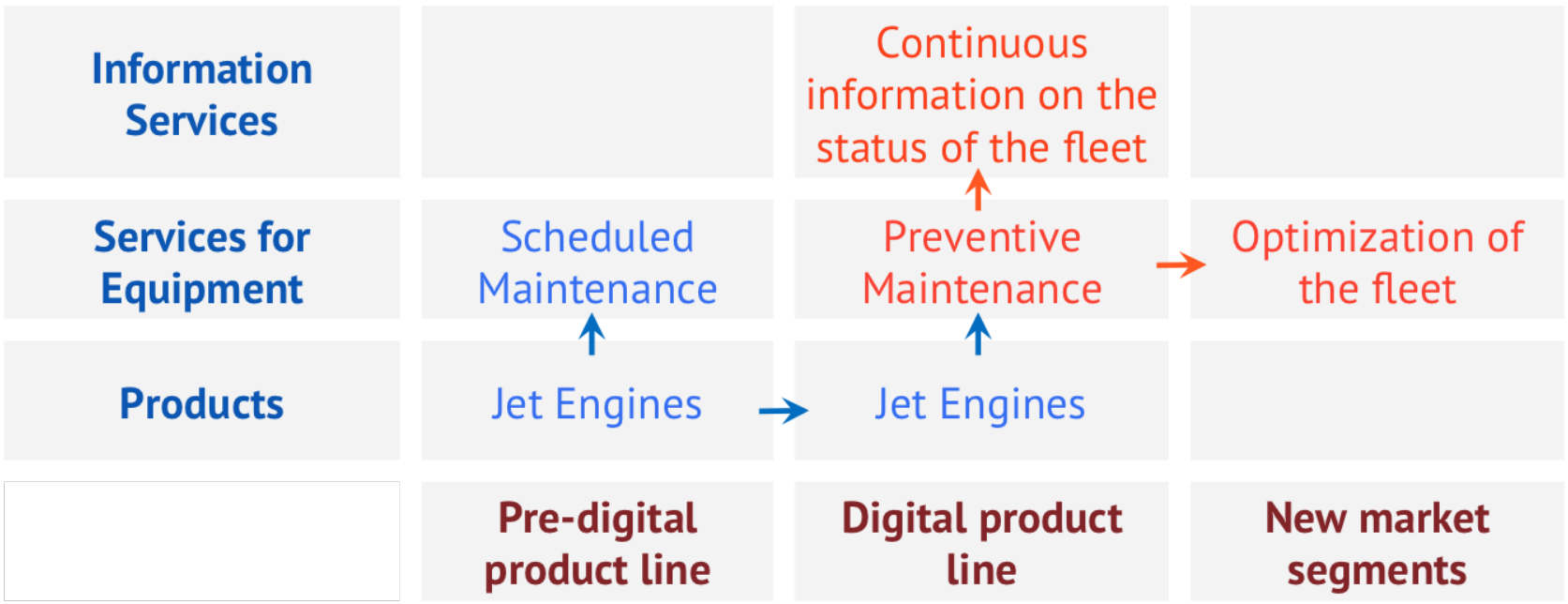
PHM concept



Exploitation	Time to Failure					Failure
Years/months	**Months**		**Weeks**	**Days**		
Optimal condition	Vibrations	Signs of wear	Decrease of main KPIs	Noise	Overheating	Failure (repair or a full replacement)
Intelligent Monitoring and Predictive Maintenance	First detection of a degradation		Corrective Maintenance			Failure is prevented
Other approaches to Maintenance	Scheduled Maintenance. Collected data is not used					Emergency Repair

New service models

Example from aviation industry on construction of brand new services based on predictive analytics of already available data



Selection of Maintenance Strategy

- Often when selecting a strategy it is necessary to optimize multiple targets
- Data Analytics can help to balance the "contradicting" targets

Example from Aviation

When performing technical maintenance it is necessary to

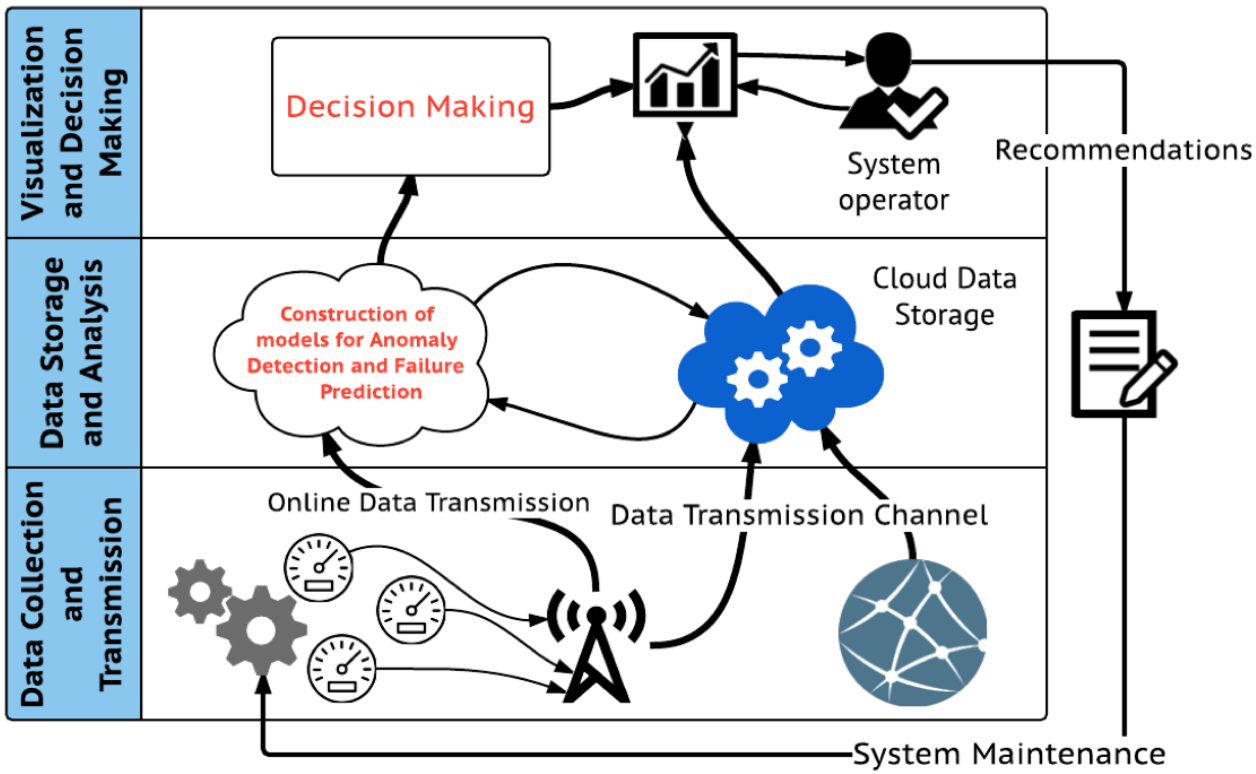
- Increase the availability of an aircraft
- Reduce maintenance costs
- Minimize a number of operational interruptions
- Increase safety

Intelligent Maintenance System

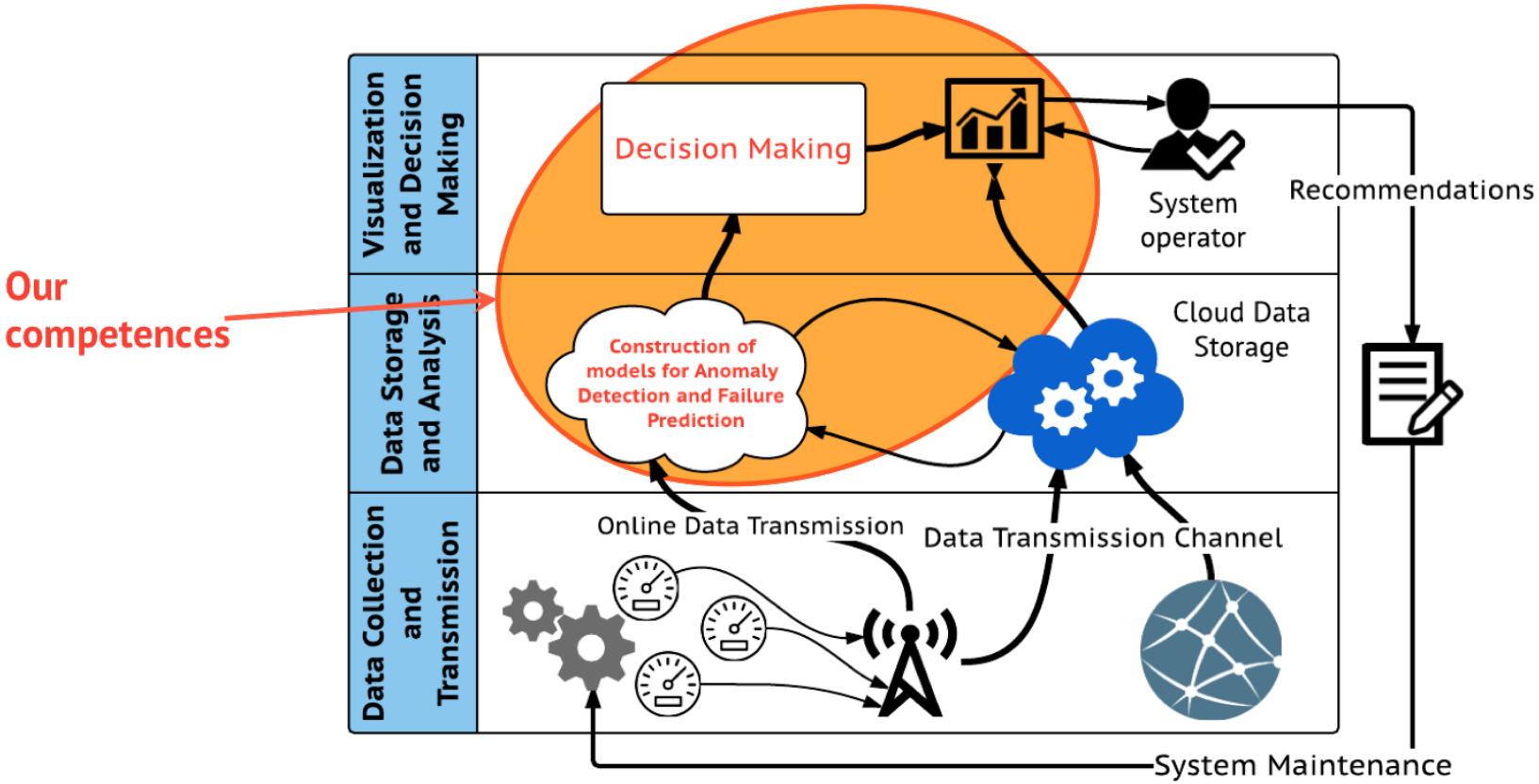
Specific for a lifecycle management system

Can be unified

Industry Specific

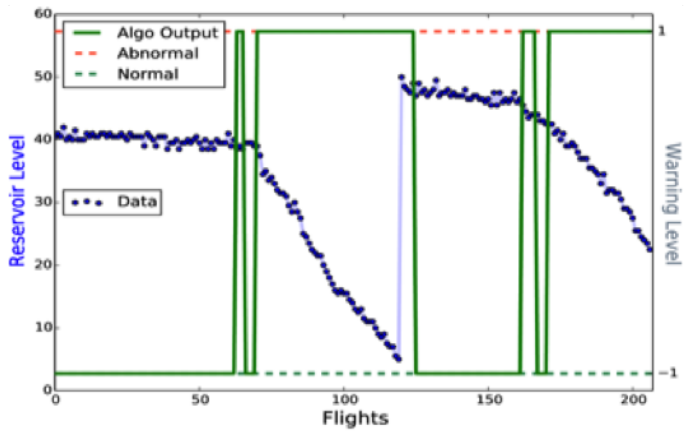


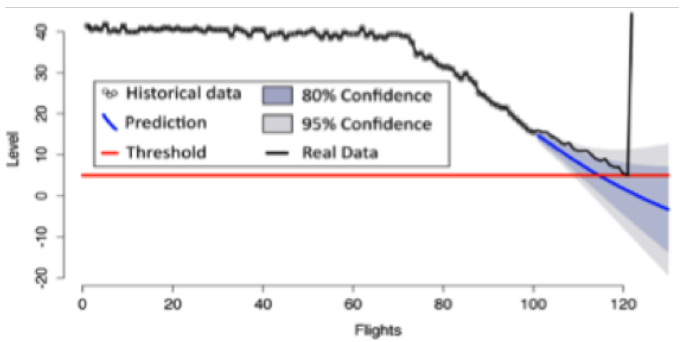
Intelligent Maintenance System



Aircraft Engine Cooling System

- **Objective:** optimize maintenance of the cooling system
- **Subtasks:**
  - Quick leakage detection
  - Determine whether a current refrigerant level is critical
  - Prediction of time until achieving a critical level



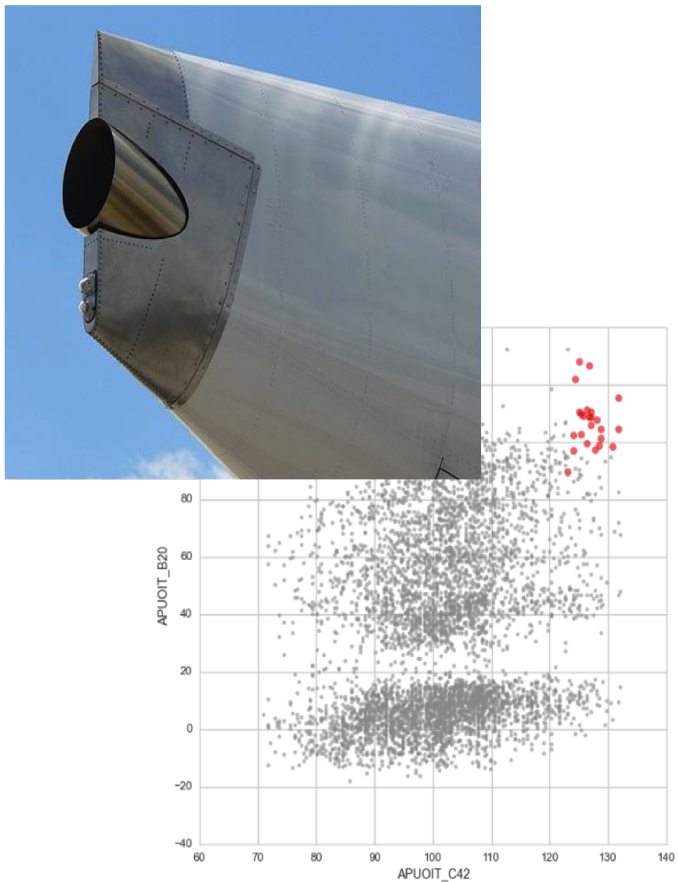


- **Data:**
  - Time-series of levels of refrigerant
  - 17 aircrafts, ~ 400 flights of each
- **Results:**
  - False positive rate is $< 1\%$
  - Rate of correct detection is $> 99\%$
  - Average error of prediction before 10 flights until achieving a critical level is < 1 flight

In collaboration with Datadvance llc.

Auxiliary Power Unit Failures Prediction

- **Objective:** to reduce costs associated with aircraft downtime due to unforeseen APU failures
- **Data:**
  - 30 aircrafts, $200+$ parameters for each aircraft
  - Learning: 3 years (400 flights per year)
  - Testing: $1/2$ year
- **Conclusion/Benefits:**
  - Early warnings about some types of failures
  - **Coverage** (detected failures) $\sim 34\%$
  - **Accuracy** of Failures Detection is $\sim 90\%$ (for 9 correctly predicted failures on average we get only 1 false alarm)



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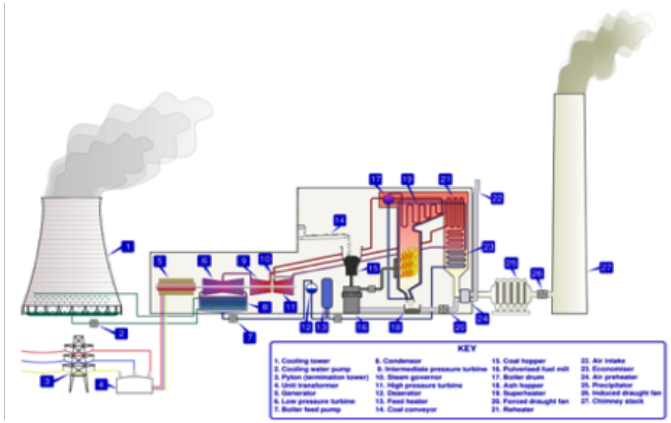
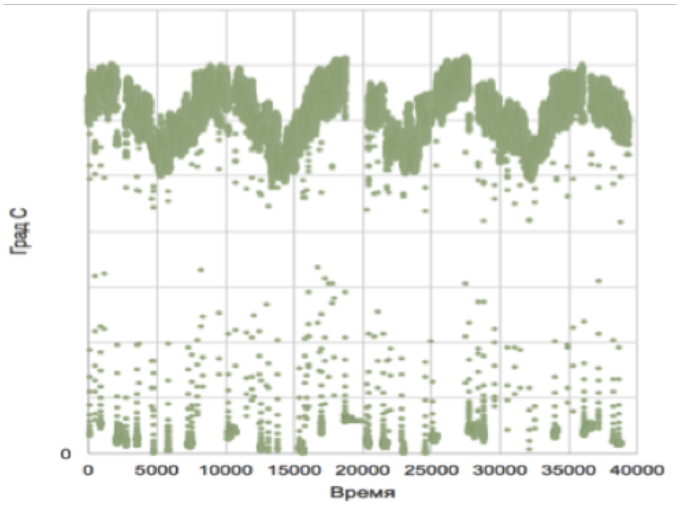
Power Losses in Thermal Power Plant

- **Objective**:
  1. Detect Power Losses in the system
  2. Localize origins of power losses
- **Subtasks**:
  - Construct a model of a system in normal regime
  - Model sensitivity analysis w.r.t. a change in a system behavior (potential failures)





- **Data:** $200+$ dimensional time-series, one-observation per 10 min.
- **Results**:
  - Detection of power losses in the system
  - Localization of the power losses origins
  - Results were confirmed by experts

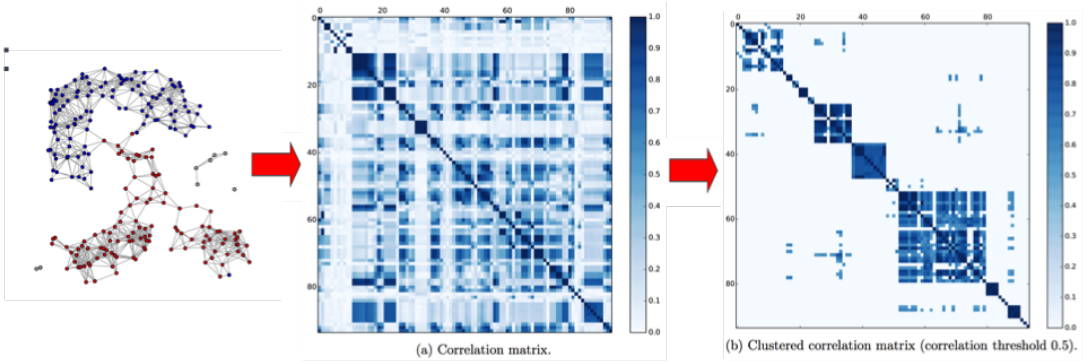
In collaboration with Datadvance llc.

Challenges

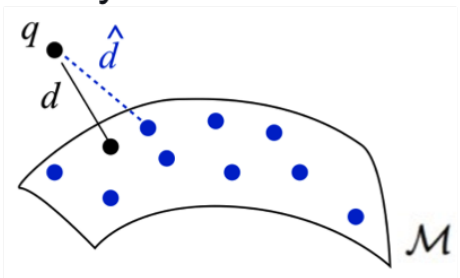
- Multistream/multichannel scenarios with unstructured hypotheses/patterns
- High-dimensionality and Large data volumes
- Composite hypotheses
- Stochastic models with non-stationary and dependent observations of a very general structure
- Prior uncertainty with respect to pre- and post-change distributions
- Parametric assumptions are inefficient
- Imbalanced learning samples

Methodology Principles (macro-steps)

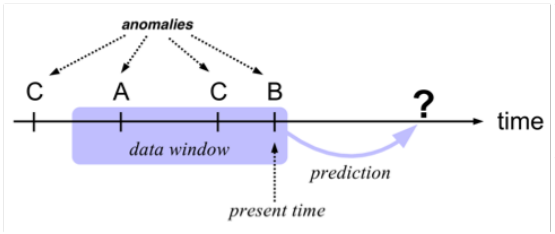
1. Subsystems Identification: Identification of groups of dependent parameters, corresponding to different subsystems



2. Anomalies Detection: Detection of Anomalies based e.g. on Manifold Learning for identified subsystems

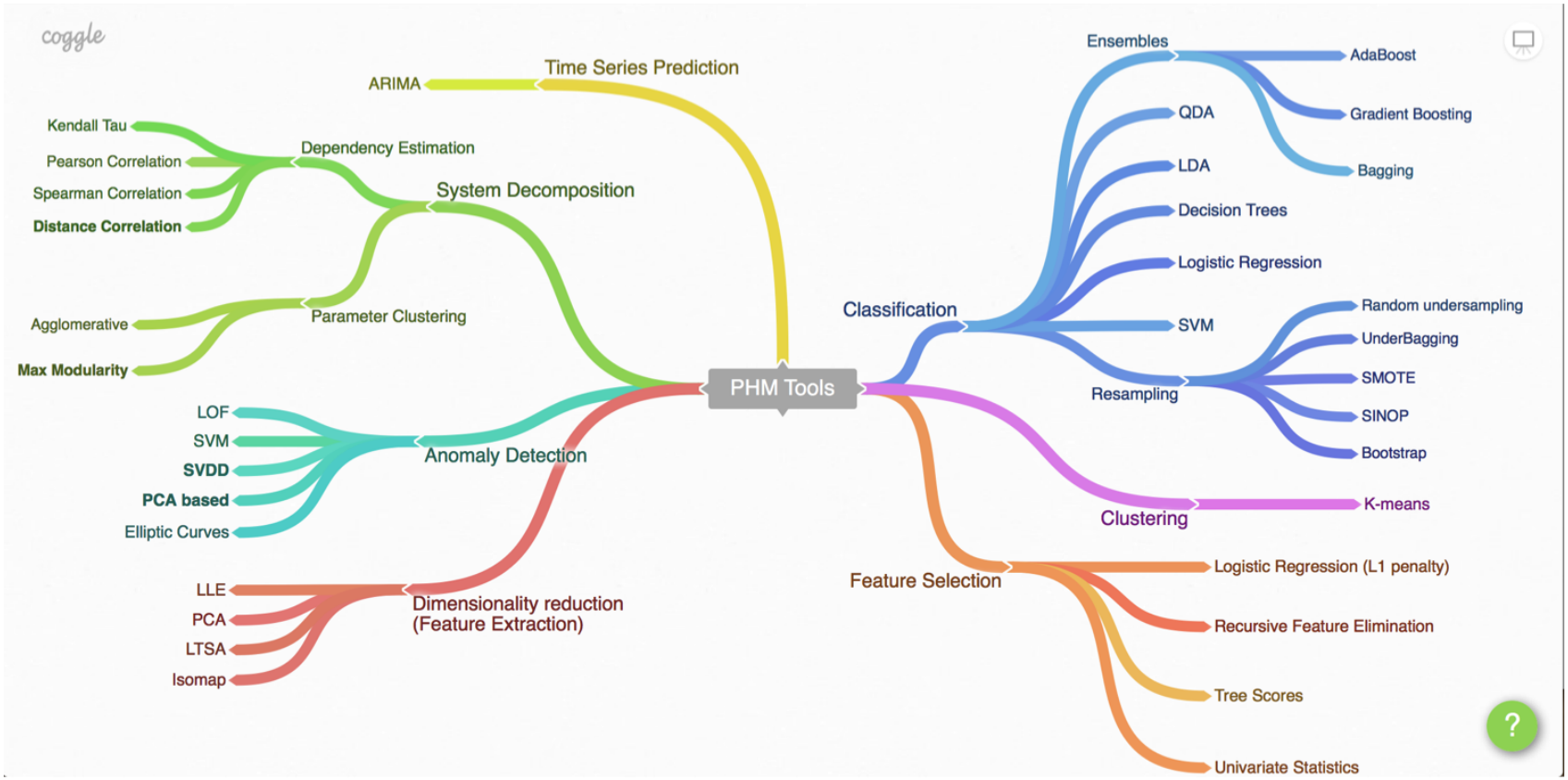


3. Events Matching: Statistical techniques used to identify best anomalies preceding warnings (and not happening anywhere else).



4. Validation: Apply anomalies detection logics in a new airplane (left apart) to calculate the prediction performances.

Methods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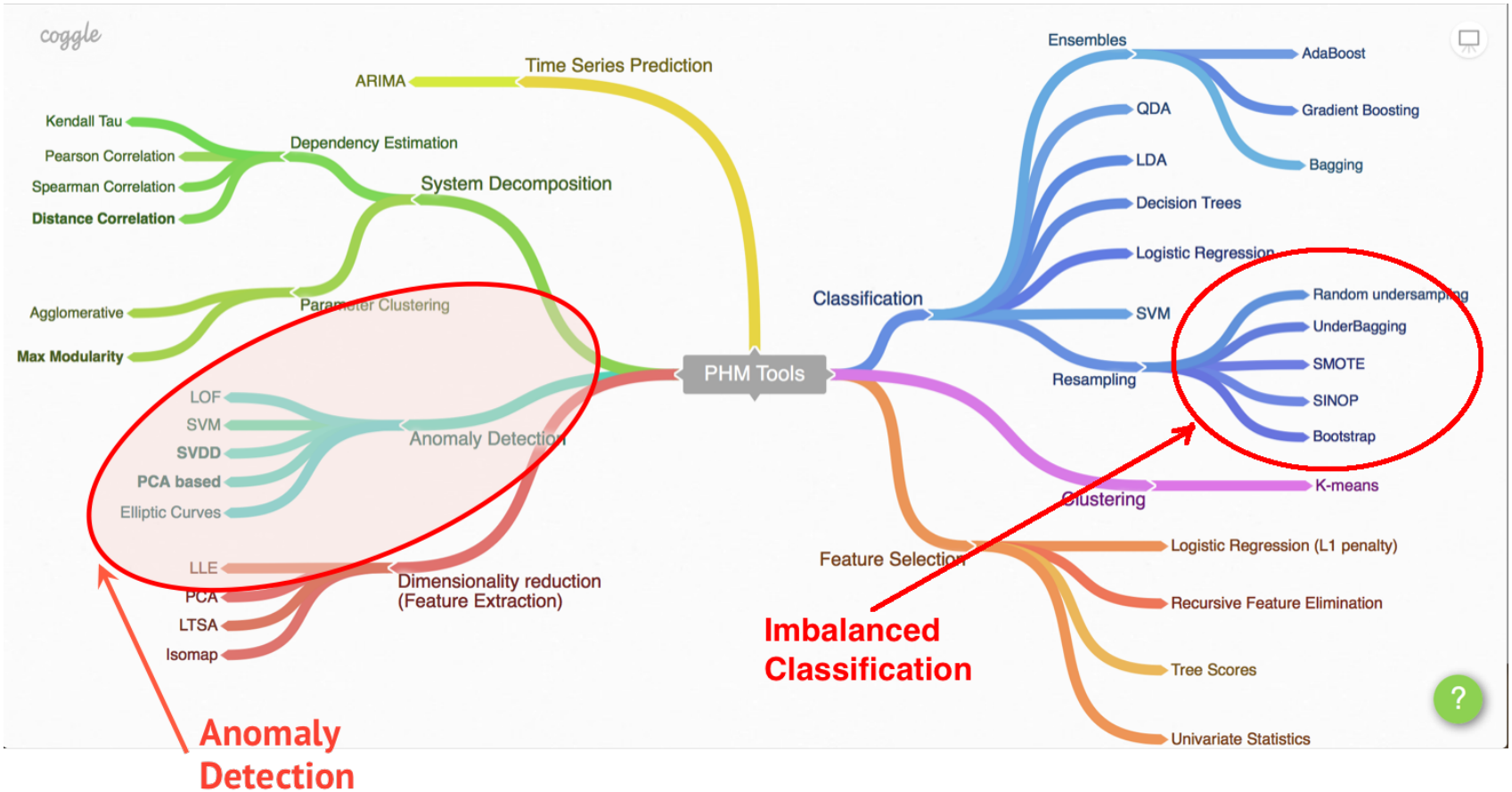
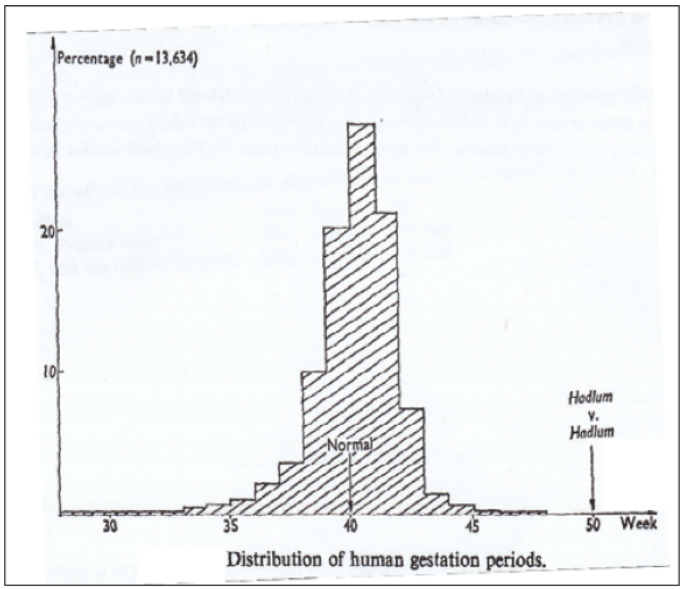
PHM Tools
Time Series Prediction
ARIMA
System Decomposition
Dependency Estimation
Kendall Tau
Pearson Correlation
Spearman Correlation
Distance Correlation
Parameter Clustering
Agglomerative
Max Modularity
Anomaly Detection
LOF
SVM
SVDD
PCA based
Elliptic Curves
Dimensionality reduction
(Feature Extraction)
LLE
PCA
LTSA
Isomap
Classification
Ensembles
AdaBoost
Gradient Boosting
Bagging
QDA
LDA
Decision Trees
Logistic Regression
SVM
Resampling
Random undersampling
UnderBagging
SMOTE
SINOP
Bootstrap
Clustering
K-means
Feature Selection
Logistic Regression (L1 penalty)
Recursive Feature Elimination
Tree Scores
Univariate Statistics

Anomaly Detection

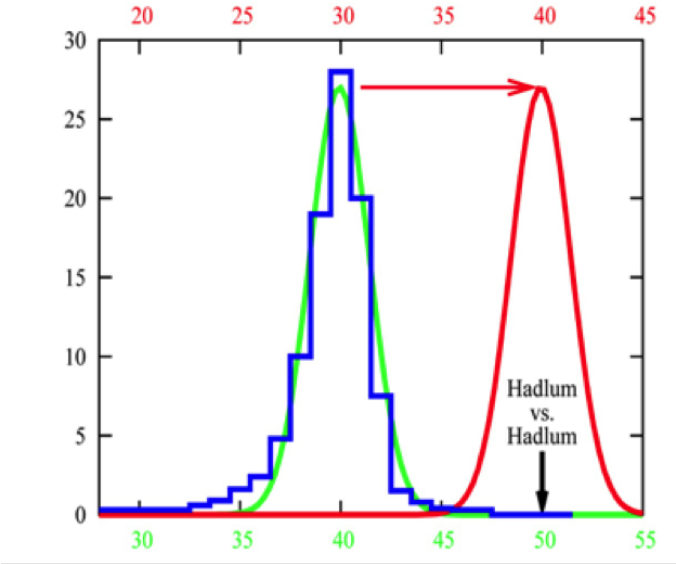


Hadlum vs. Hadlum (1949) [Barnett, 1978]



- The birth of a child to Mrs. Hadlum happened 349 days after Mr. Hadlum left for military service
- Average human pregnancy period is 280 days (40 weeks)
- Statistically, 349 days is an outlier

Hadlum vs. Hadlum (1949) [Barnett, 1978]



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- Average human pregnancy period is 280 days (40 weeks)
- Statistically, 349 days is an outlier

Definition of the anomaly [Howkins, 1980]

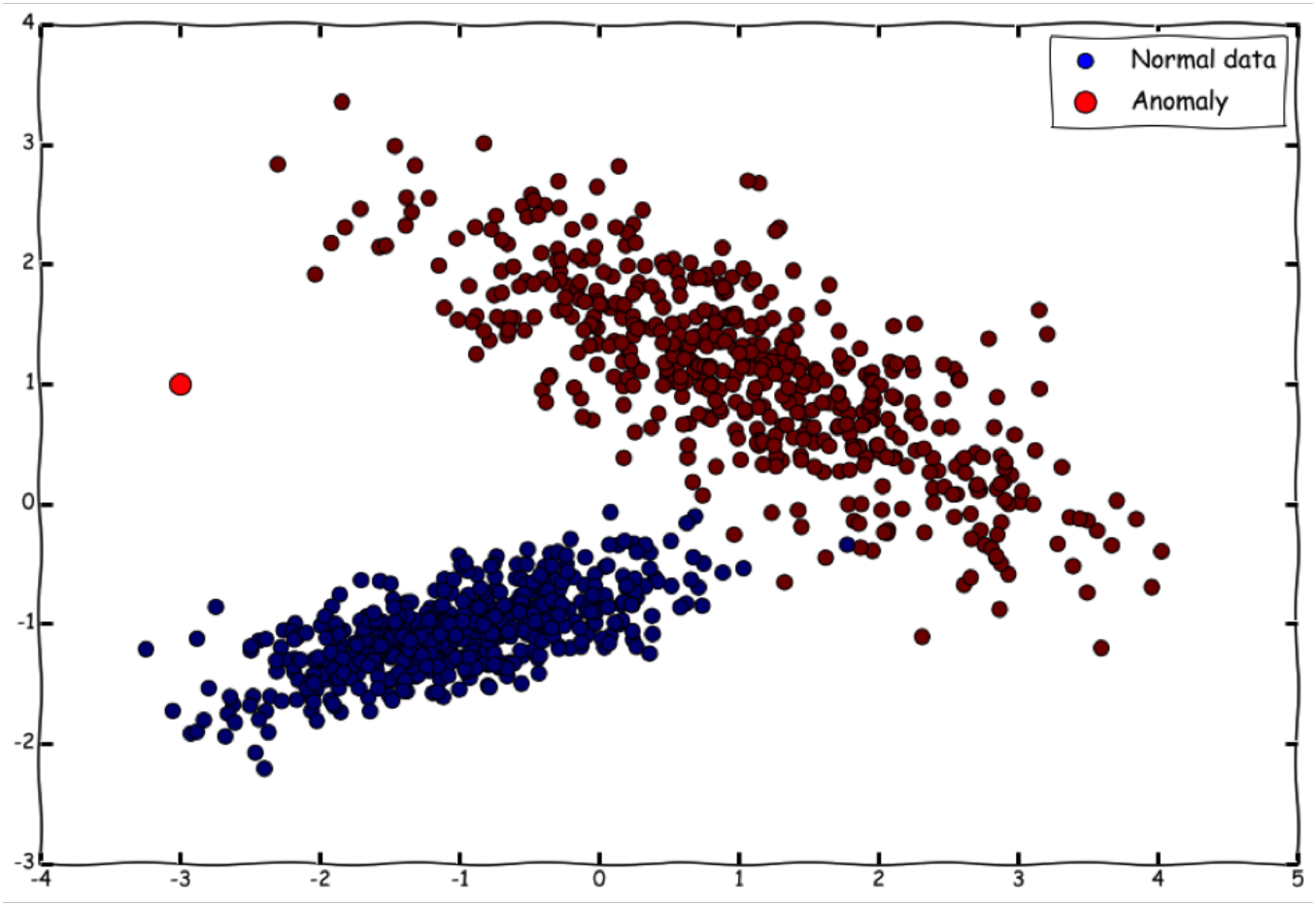
"An outlier is an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism"

Real world problems

- Data is multivariate
- There is usually more than one generating mechanism/statistical process underlying the "normal" data
- Anomalies may represent a different class (generating mechanism) of objects, so there may be a large class of similar objects that are the outliers
- Domain specific definition of what to count as anomaly
- Normal behavior keeps evolving
- Malicious adversaries
- Availability of labeled data for training/validation

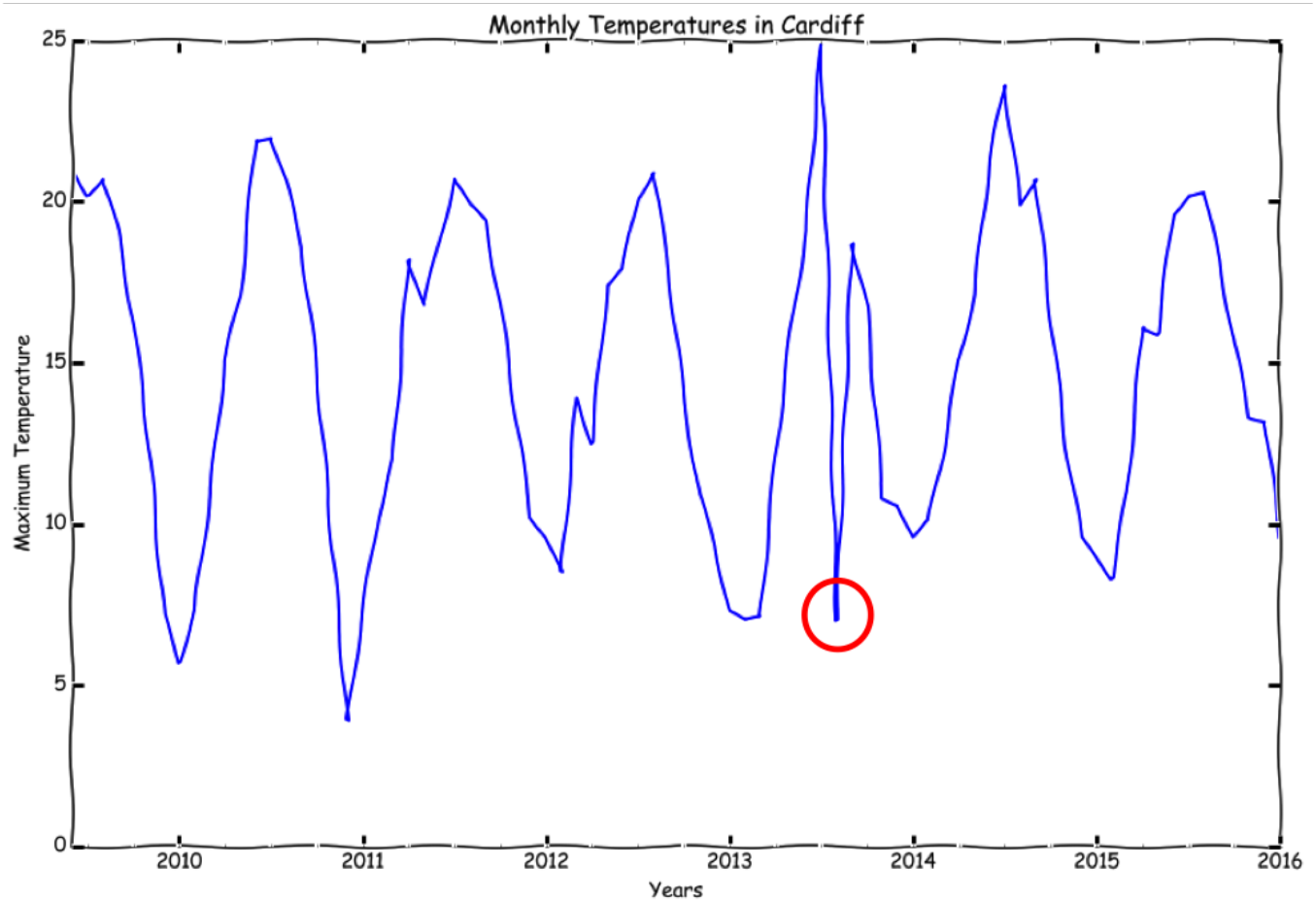
Anomaly taxonomy: Point Anomalies

- An individual data instance is anomalous w.r.t. the data



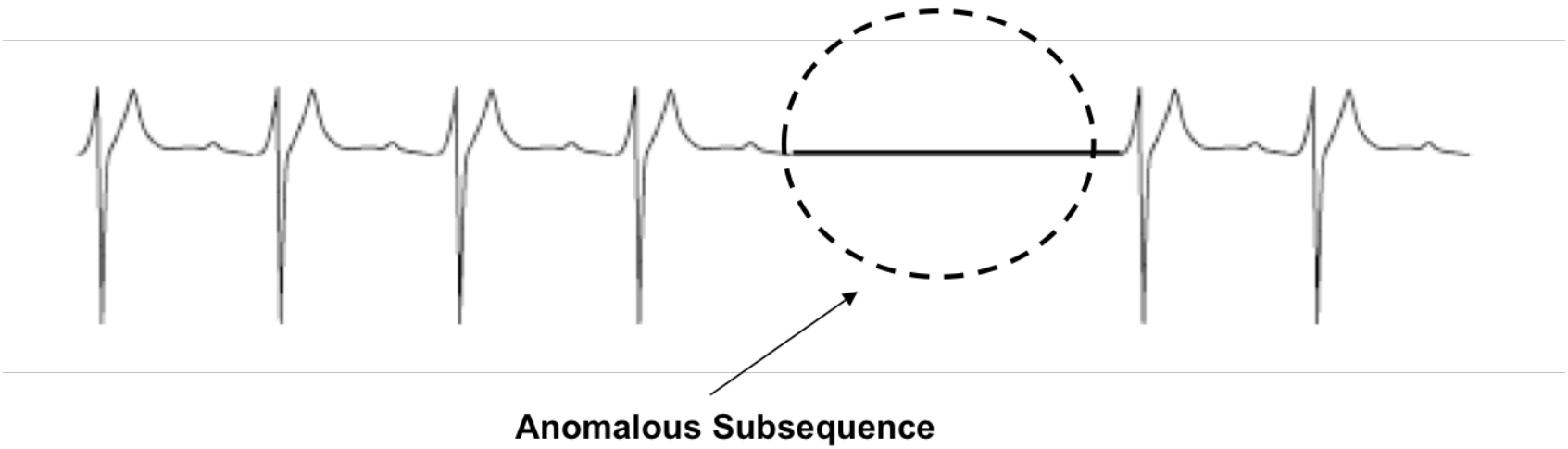
Anomaly taxonomy: Contextual Anomalies

- An individual data instance is anomalous within a context
- Requires a notion of context
- Also referred to as conditional anomalies

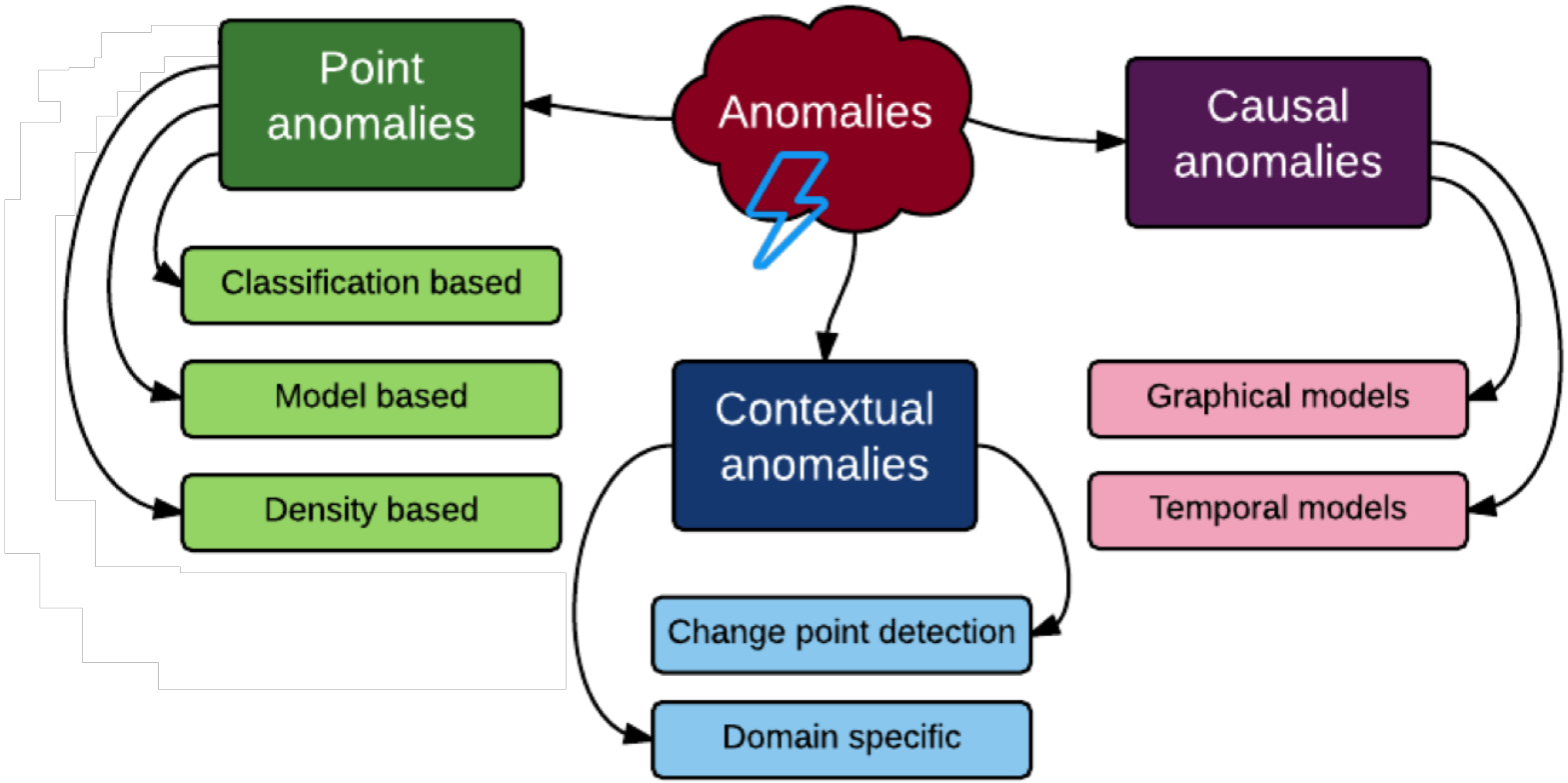


Anomaly taxonomy: Causal Anomalies

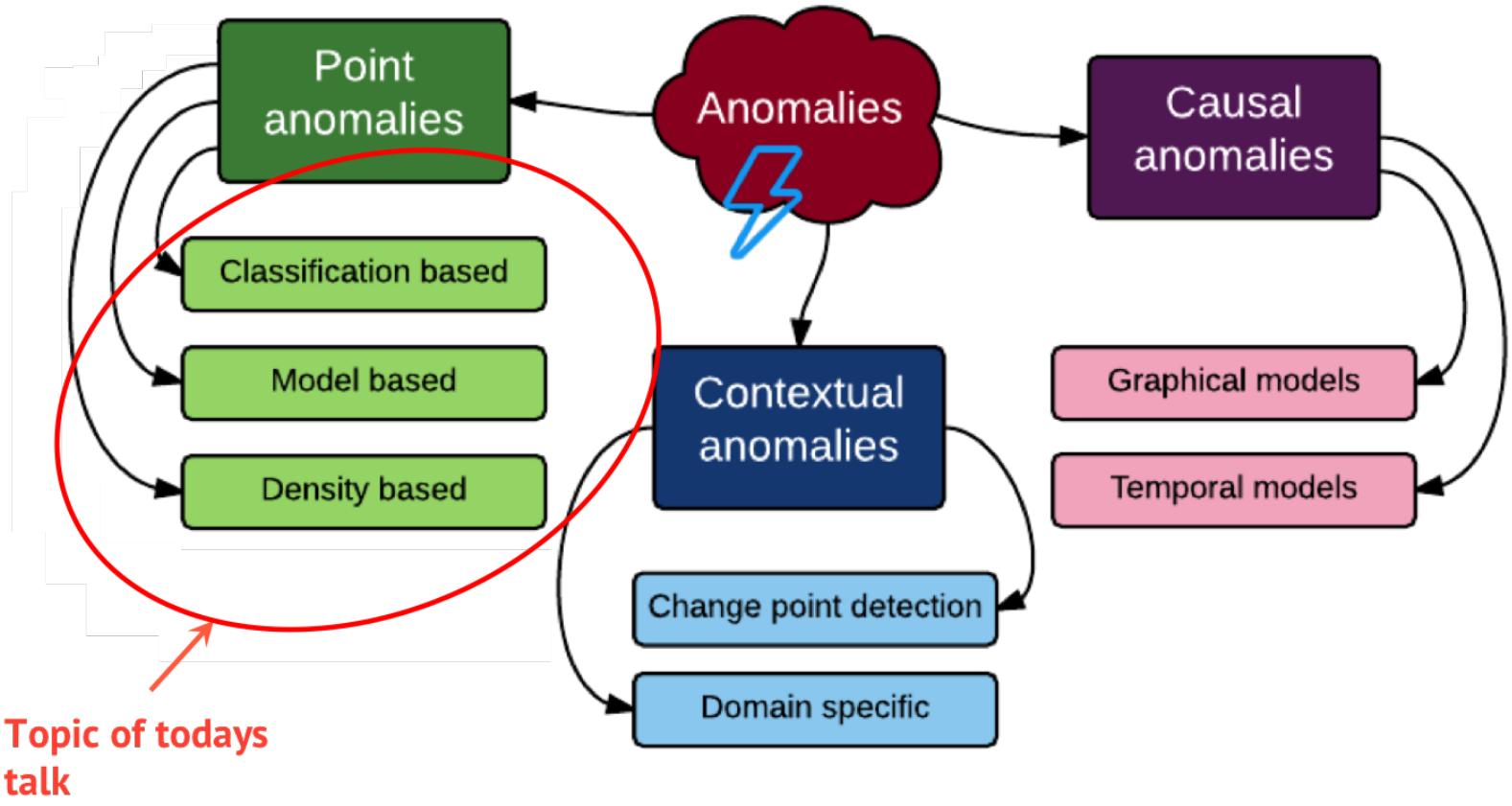
- A collection of related data instances is anomalous
- Requires a relationship among data instances
  - Sequential Data
  - Spatial Data
  - Graph Data
- The individual instances within a set of causal anomalies are not anomalous by themselves



Anomaly taxonomy



Anomaly taxonomy



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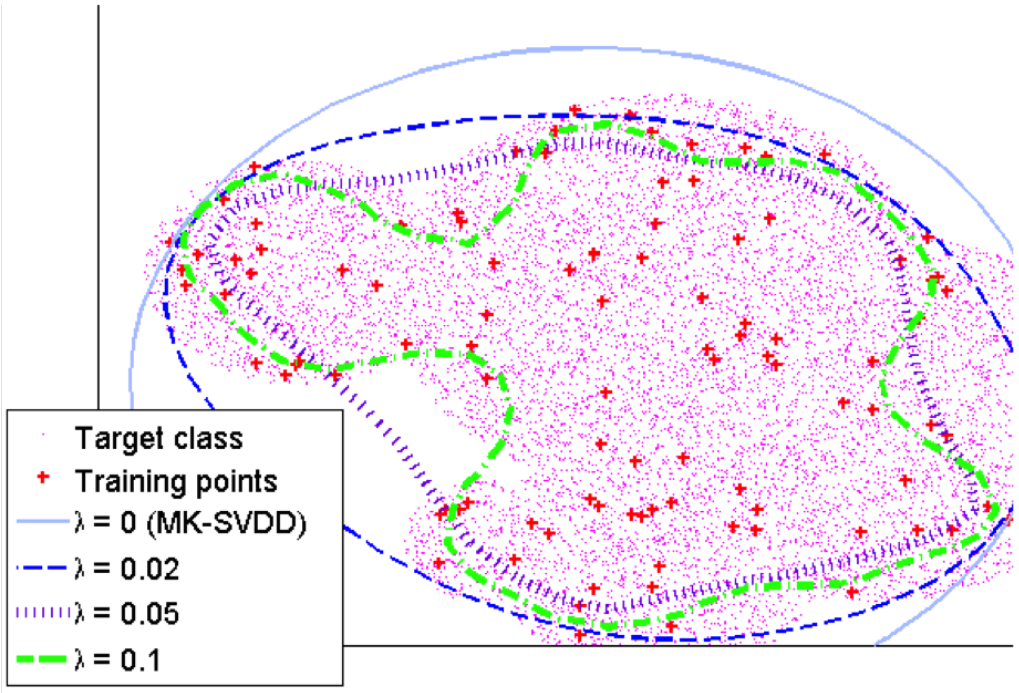
Imbalanced Classification

- Weights for classes
  - Proved not to be helpful in most cases
- Resampling methods
  - Oversampling (Bootstrap, SMOTE, etc.)
  - Undersampling
- How to choose which method to use?
- How to choose resampling parameter?

Statistics-based models

- Assumption on normal data generation procedure (e.g. Gaussian distribution, etc.)
- PCA is a method commonly used to extract most variant combinations in data
- PCA based anomaly detection is good for highly correlated environments

Density-based models



- SVM-based and nearest neighbours based
- How to choose best kernel parameter?

Objectives

1. Consider Anomaly Detection with Privileged Information
2. Modify accordingly One-Class Classification approach
3. Test Vapnik's methodology in some real-life application

Problem Formulation

- Let $S = \{\mathbf{x}_1, \ldots, \mathbf{x}_m\}, \mathbf{x}_i \in \mathbb{R}^p$ be an unlabeled sample (possibly containing some anomalies)
- We want to learn $f : \mathbf{x} \to \{-1, 1\}$ using the sample

$$\mathbf{x} = \begin{cases} \text{normal, if } \ f(\mathbf{x}) = +1, \\ \text{anomaly, if } \ f(\mathbf{x}) = -1, \end{cases}$$

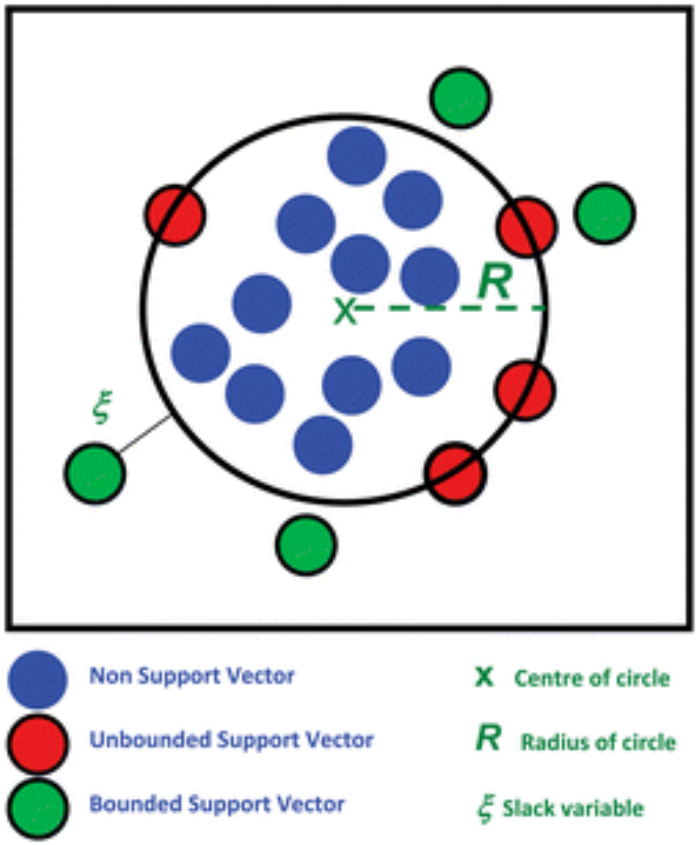
Support Vector Data Description

$$R + \frac{1}{m\nu}\sum_{i=1}^{m}\xi_i \to \min_{R,a,\xi}$$

$$s.t.\ \|\phi(\mathbf{x}_i) - a\|_2^2 \leq R + \xi_i$$

$$\xi_i \geq 0$$

$$R \geq 0$$



- ν is an upper bound on the fraction of anomalous patterns in the sample S
- $\phi(\mathbf{x}_i)$ is the mapping to a high dimensional space

We consider the dual problem

$$\sum_{i=1}^{m} \alpha_i \phi(\mathbf{x}_i) \cdot \phi(\mathbf{x}_i)^\top - \sum_{i,j=1}^{m} \alpha_i \alpha_j \phi(\mathbf{x}_i) \cdot \phi(\mathbf{x}_j)^\top \to \max_{\alpha}$$

$$s.t. \sum_{i=1}^{m} \alpha_i = 1$$

$$0 \leqslant \alpha_i \leqslant \frac{1}{m\nu}, \quad i = 1, \ldots, m$$

We don't need to use explicit expression for $\phi(\cdot)$, we need only a definition of a dot product. We can use a kernel trick

$$K(\mathbf{x}, \mathbf{x}') = \phi(\mathbf{x}) \cdot \phi(\mathbf{x}')^\top$$

E.g. $K(\mathbf{x}, \mathbf{x}') = \exp(-\|\mathbf{x} - \mathbf{x}'\|^2/\sigma^2)$

Solution of the primal problem

- We can write out the solution of the primal problem using the solution of the dual problem

$$a = \sum_{i=1}^{m} \alpha_i \phi(\mathbf{x}_i), \quad R = \|\phi(\mathbf{x}_j)\|_2^2 - 2(a \cdot \phi(\mathbf{x}_j)^\top) + \|a\|_2^2,$$

  where we can use any $\mathbf{x}_j$, such that $\alpha_j > 0$
- Here

$$\|\phi(\mathbf{x})\|_2^2 = K(\mathbf{x}, \mathbf{x}),$$

$$(a \cdot \phi(\mathbf{x})^\top) = \sum_{i=1}^{m} \alpha_i K(\mathbf{x}_i, \mathbf{x}),$$

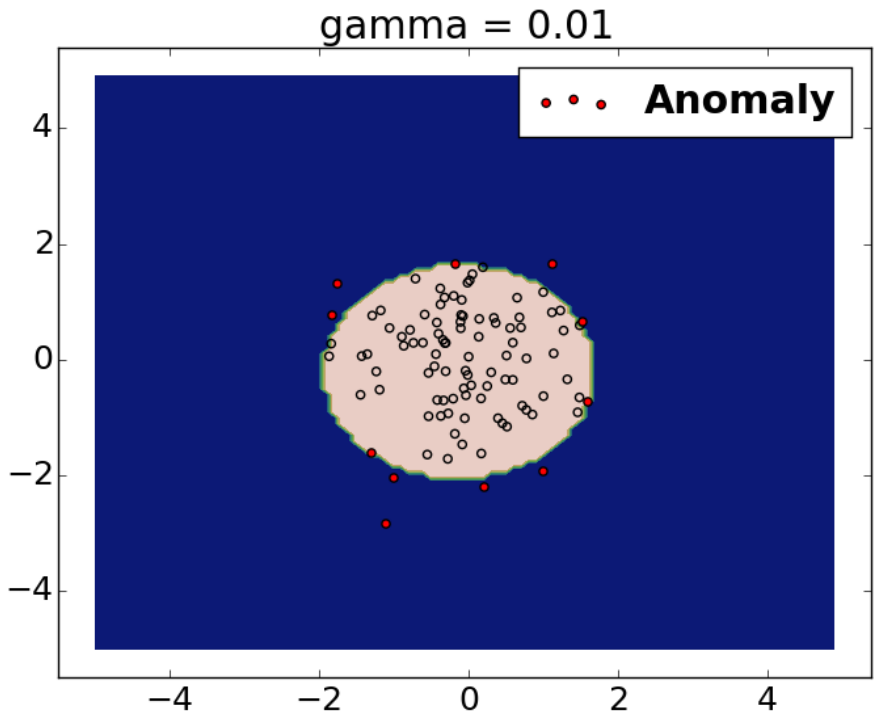
$$\|a\|_2^2 = \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_i \alpha_j K(\mathbf{x}_i, \mathbf{x}_j)$$

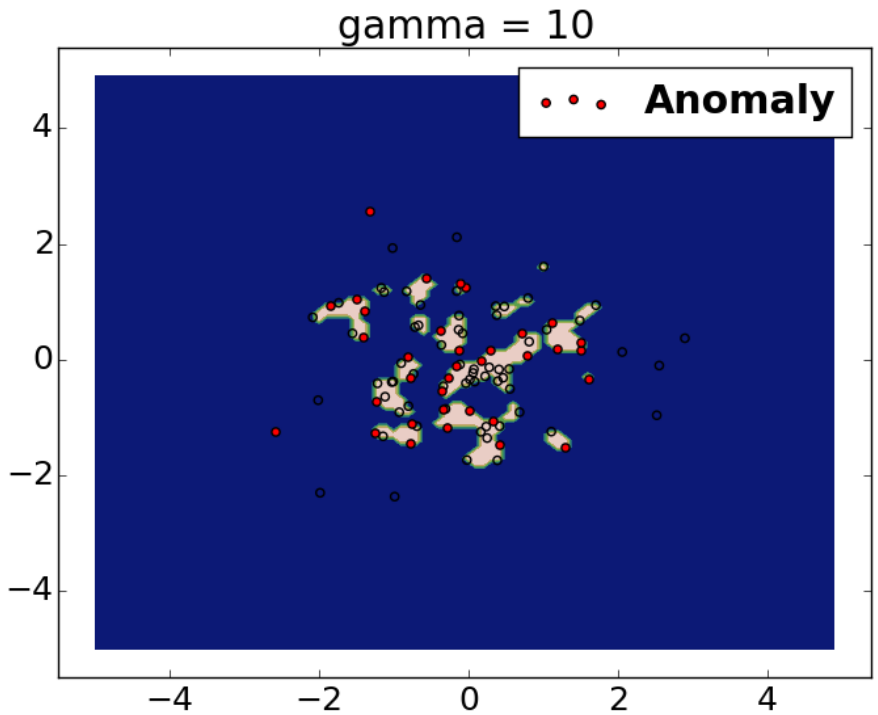
- The **decision function** has the form

$$f(\mathbf{x}) = \text{sign}\left\{ R - K(\mathbf{x}, \mathbf{x}) + 2 \sum_{i=1}^{m} \alpha_i K(\mathbf{x}, \mathbf{x}_i) - \|a\|_2^2 \right\}$$

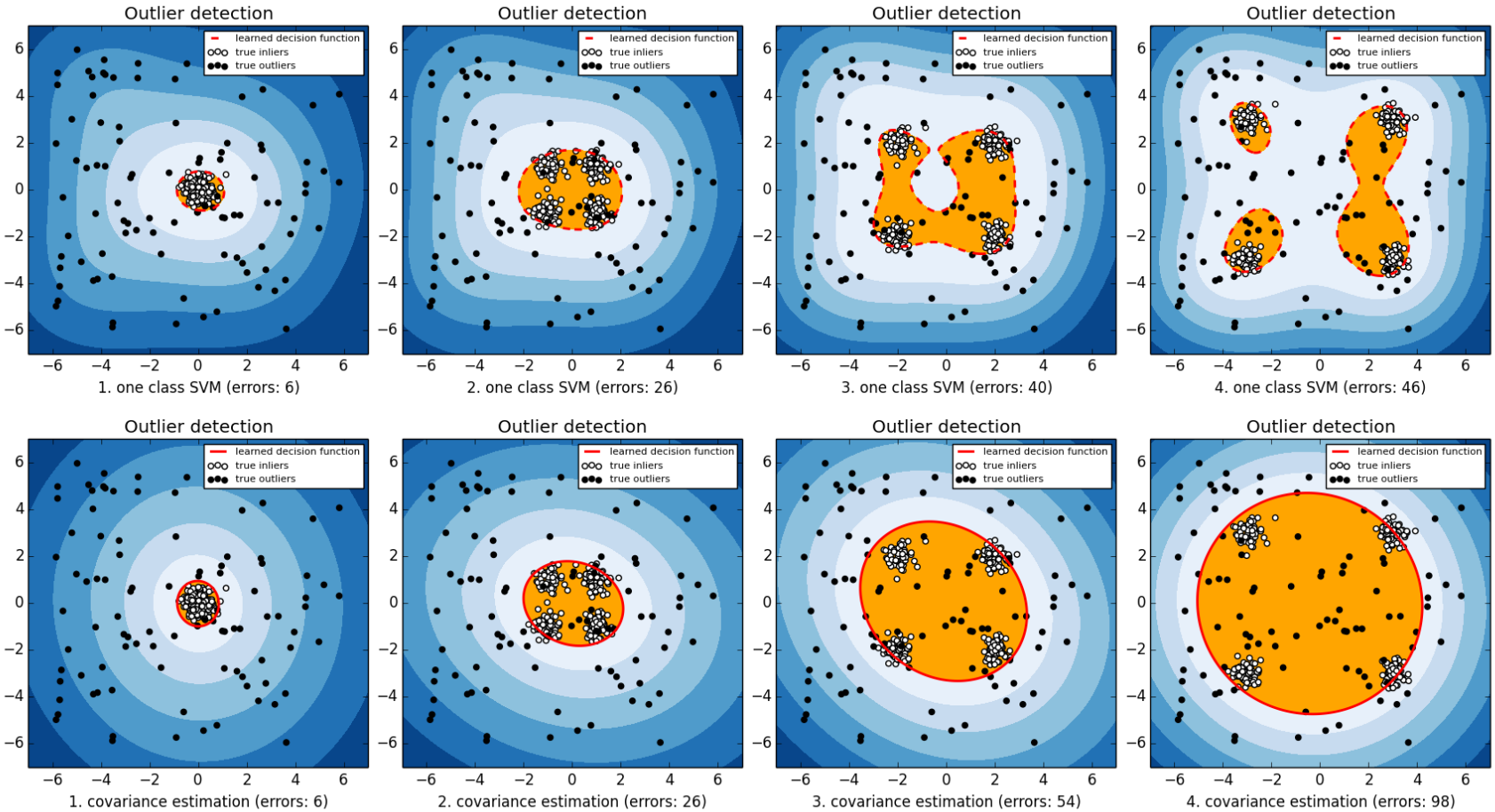
Kernel Selection

Results can significantly depended on a kernel hyperparameters





Example of the decision function



1. Supervised Learning
   - Sample $S = \{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_m, y_m)\}$
   - We want to learn $f : \mathbf{x} \to y$ using the sample S

2. Supervised Learning with Privileged Information (Vapnik, 2009)
   - Sample $S^* = \{(\mathbf{x}_1, \mathbf{x}_1^*, y_1), \ldots, (\mathbf{x}_m, \mathbf{x}_m^*, y_m)\}$
   - We want to learn $f : \mathbf{x} \to y$ using the sample S^*
   - Privileged Information:
     - in the form of additional patterns $\mathbf{x}^*$
     - is not available at the test time
   - Example:
     - image classification problem
     - as the privileged information we can use a textual image description
     - such information is not available during the test phase

One-Class Classification with Privileged Information

- Original patterns $(\mathbf{x}_1, \ldots, \mathbf{x}_m) \subset \mathbb{R}^p$
- Additional patterns $(\mathbf{x}_1^*, \ldots, \mathbf{x}_m^*) \subset \mathbb{R}^q$
- We train a decision rule on pairs of patterns $\{(\mathbf{x}_i, \mathbf{x}_i^*)\}_{i=1}^m \in \mathbb{R}^{p+q}$, but when making decisions we can use only test patterns $\mathbf{x} \in \mathbb{R}^p$

$$R + \frac{1}{m\nu}\sum_{i=1}^{m}\xi_i \to \min_{R,a,\xi}$$
$$s.t.\ \|\phi(\mathbf{x}_i) - a\|_2^2 \leqslant R + \xi_i$$
$$\xi_i \geqslant 0$$
$$R \geqslant 0$$

- The slack variables ξ_i characterizes the distance from the patterns $\mathbf{x}_i$ to the separating boundary $\|\phi(\mathbf{x}_i) - a\|_2$
- We assume that using the privileged patterns $(\mathbf{x}_1^*, \ldots, \mathbf{x}_m^*)$ we can refine the location of the separating boundary
- We model a slack variable ξ as

$$\xi = \xi(\mathbf{x}^*) = (\phi^*(\mathbf{x}^*) \cdot w^*) + b^*,$$

where $\phi^*(\cdot)$ is a feature map in the space of privileged patterns

We incorporate the privileged information

$$\nu m R + \frac{\gamma}{2}\|w^*\|_2^2$$

$$+\sum_{i=1}^{m}\left[(w^*\cdot\phi^*(\mathbf{x}_i^*)^\top)+b^*+\zeta_i\right]\to\min_{R,a,w^*,b,\zeta}$$

$$s.t.\ \|\phi(\mathbf{x}_i)-a\|_2^2\le R+[(w\cdot\phi^*(\mathbf{x}_i^*)^\top)+b^*],$$

$$(w^*\cdot\phi^*(\mathbf{x}_i^*)^\top)+b^*+\zeta_i\ge 0,\ \zeta_i\ge 0.$$

Let us formulate the dual problem:

$$\sum_{i=1}^{m} \alpha_i K(\mathbf{x}_i, \mathbf{x}_i) - \frac{1}{2\nu m} \sum_{i,j} \alpha_i \alpha_j K(\mathbf{x}_i, \mathbf{x}_j)$$

$$- \sum_{i,j} \frac{1}{2\gamma} (\alpha_i - \delta_i) K^*(\mathbf{x}_i^*, \mathbf{x}_j^*)(\alpha_j - \delta_j) \to \max_{\alpha,\delta}$$

$$s.t. \ \sum_{i=1}^{m} \alpha_i = \nu m, \ \sum_{i=1}^{m} \delta_i = \nu m, \ 0 \le \delta_i \le 1, \ \alpha_i \ge 0.$$

The **decision function** has again the same form

$$f(\mathbf{x}) = \text{sign} \left\{ R - K(\mathbf{x}, \mathbf{x}) + 2 \sum_{i=1}^{m} \alpha_i K(\mathbf{x}, \mathbf{x}_i) - \|a\|_2^2 \right\}$$

Data Description

- Synthetic data
- Real data from the Microsoft Malware Classification Challenge (BIG 2015)

Let us provide an example of synthetic data

- Let $c_1 = (2, 2)$ and $c_2 = (-2, -2)$
- $\mathbf{x} \in \mathbb{R}^2$ and is generated from:

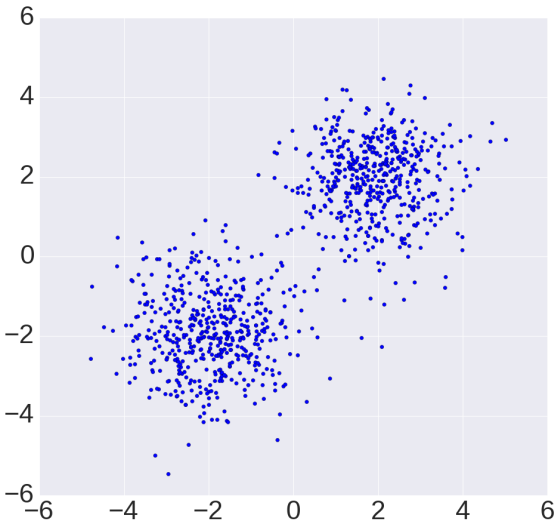
$$\mathbf{x} \sim \phi \cdot N(c_1, I) + (1 - \phi) \cdot N(c_2, I), \quad \phi \sim Ber(0.5)$$

- As a privileged information we use coordinates of a pattern after subtracting the nearest mean vector, i.e.

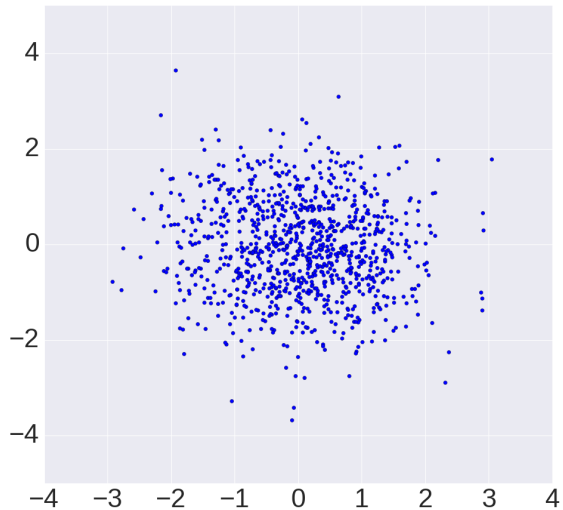
$$\mathbf{x}^* = \mathbf{x} - \arg\min_{c_1, c_2}(\|\mathbf{x} - c_1\|, \|\mathbf{x} - c_2\|)$$

- A uniformly distributed anomalies are generated and added to the sample

Synthetic Data



Mixture of Gaussians



Mixture of Gaussians, priviledged feature space

Accuracy:

- **SVDD**: 0.55
- **SVDD+**: 0.98

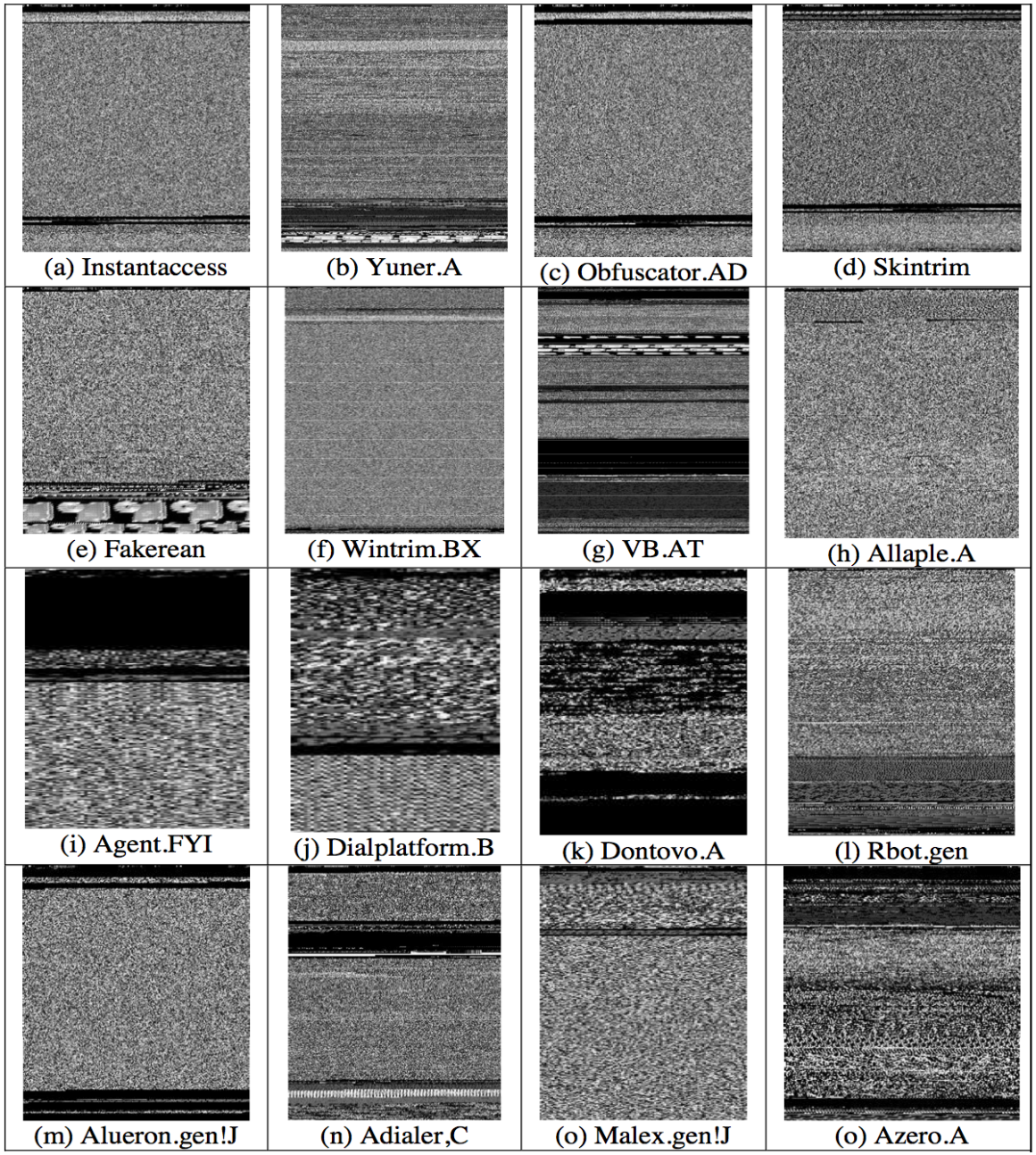
Real-World Data

- Microsoft Malware Classification Challenge (2015)
- Nine malware families
- Raw data contains:
  - the hexadecimal representation of the file's binary content
  - logs containing various metadata information extracted from the binary, such as function calls, strings, etc.
- As the original features we use information, obtained from the binary files
  - frequencies of bytes
  - number of different four-grams, etc.

Real-World Data

- As the privileged information we use features, obtained from the assembly code
  - frequencies of each command
  - a number of calls to external dll files
  - transformation of the assembly code to an image
  - we use a feature based on image texture which is commonly used in scene category classification such as coast, mountain, forest, street, etc.
  - Here, instead of scene categories, we have malware families

Malware Images of Various Families



Setup of Experiments

- We select one of the nine classes
- As a train set we use half of patterns from the selected class
- As a test set we use patterns from another half of the selected class, as well as patterns from other eight classes
- We consider patterns from the selected class to be “normal” and patterns from other classes as “abnormal”
- We use predictions on the test set to calculate the area under the precision/recall curve, representing the accuracy of anomaly detection

Results on Malware Classification Challenge

Algorithm/Malware Class	1	2	3	4	5
SVDD	0.67	0.93	0.97	0.69	0.57
SVDD+	**0.81**	**0.95**	**0.99**	**0.72**	**0.57**

Algorithm/Malware Class	6	7	8	9
SVDD	0.80	0.82	0.84	0.60
SVDD+	**0.81**	**0.87**	**0.88**	**0.62**

Table – Malware Detection problem