Network (Entities) Profiling

for classification and anomaly detection

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Data Inputs

- Raw data inputs are possible, however its increases the complexity of the machine learning algorithm.
  - Worse results, longer calculation/response times.
- Input data should be the result of raw data processing (complexity reduction).
  - Observation features.
  - Statistical metrics, statistical functions, PCA, scale analysis metrics/descriptors, …
- Inputs should be normalized.
  - Usually

Variable Reduction

- An event/entity is many times described by multiple descriptors/metrics.
  - e.g., mean, variance, maximum, skewness, percentile x%, etc...
  - a.k.a. features.

$$e_i = [y_1, y_2, \ldots, y_m]$$

- The reduction of variables is mandatory to simplify classification.
- **Principal Components Analysis (PCA)**
  - Uses a transformation to convert a set of possibly correlated features into a set of values of uncorrelated variables called principal components.
  - The principal components of an event will be a linear combination of the that event features.

$$t_i = e_i W, W = [w_{ij}]_{i,j=1,\ldots,m}$$

  - The number of principal components is less than or equal to the number of original features.
    - Defined in such a way that the first principal component has the largest possible variance, and the m^{th} (last) component has the smallest variation.
    - The first n components can be chosen to describe the event.
    - W is a (m x n) matrix.

Data Normalization/Scaling

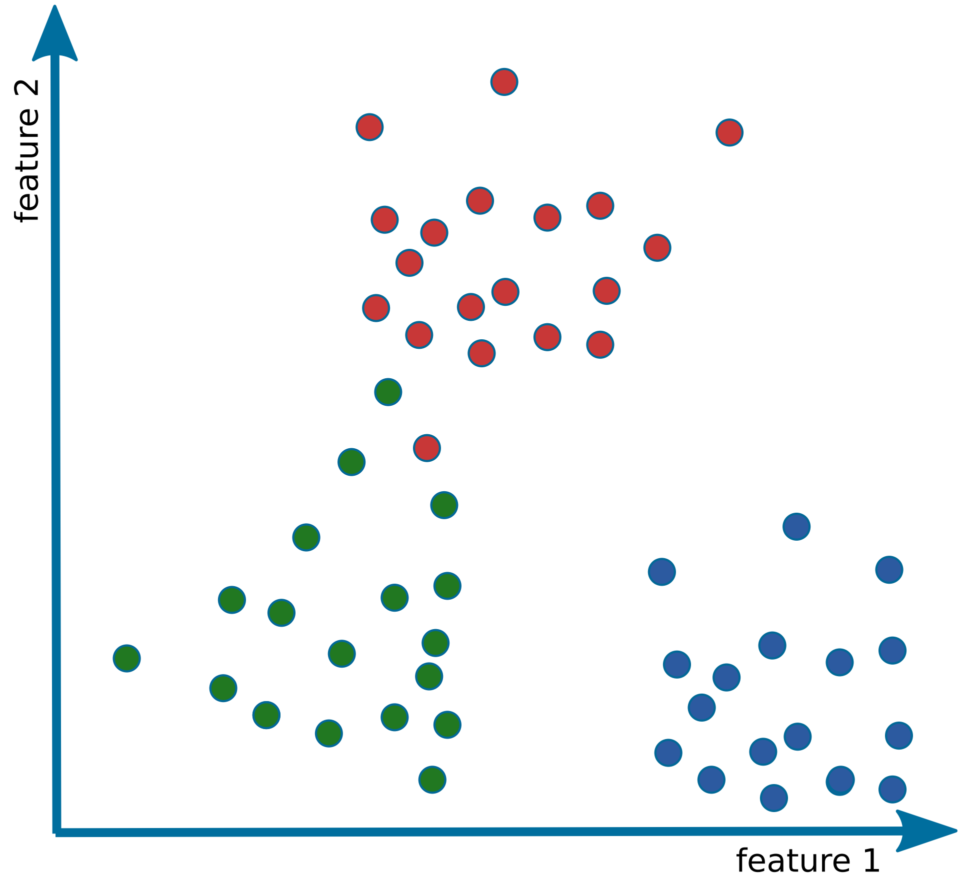
- Methods:
  - By maximum absolute value,
  - By min/max, scaling each feature to a given range,
  - Standard, removes the mean and scales to unit variance.
  - …
- Mandatory when variables/features have different orders of magnitude.
- Removes data bias from quantity, allow to focus on variable and time correlations on data.
  - e.g., YouTube traffic pattern correlation with video definition must be removed.

Classification vs. Anomaly Detection

- Classification
  - Requires knowledge (historic data) on all patterns/classes.
  - Does not cope with pattern evolution and appearance of new patterns/classes.
- Anomaly Detection
  - Requires only knowledge (historic data) known of normal patterns/classes.
  - Does not require knowledge (historic data) anomalous patterns/classes.
  - Identify all significantly different patterns as anomalous.
  - Allows to identify never seen anomalies (zero-day detection).
  - May identify as anomalous licit patters that are evolving

Profile as a N-Dimensional Euclidean Universe

- Each set of N features (reduced or not) in each observation can be seen as a point a N-dimensional Euclidean universe.
- Each point can be:
  - Pre-classified to identify know behaviors/activities.
  - Classified as an belong to a specific group
    - Short Euclidean distance from the known group points.
    - Short Euclidean distance from group points previously “grouped” (cluster).
  - Classified as an anomaly.
    - Large Euclidean distance from the other points.



Decision by Statistical Patterns

for differentiation, classification, and anomaly detection

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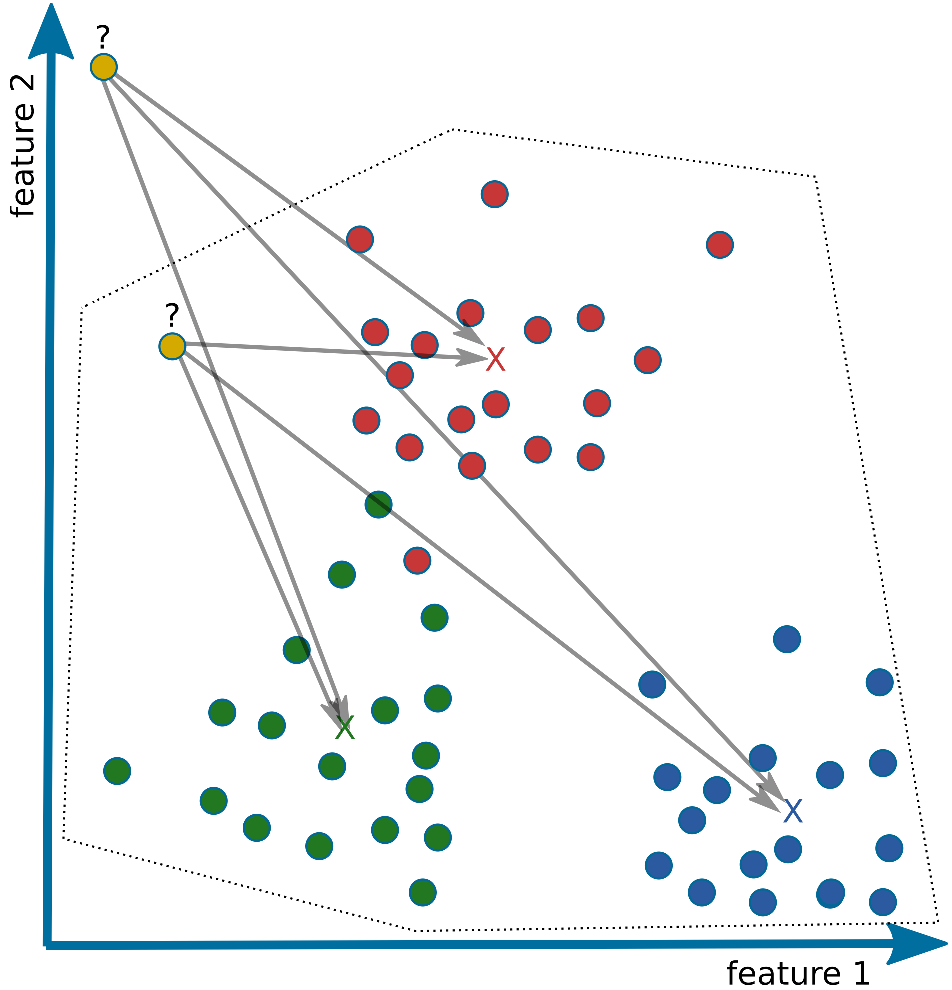
Distances to Central Point(s)

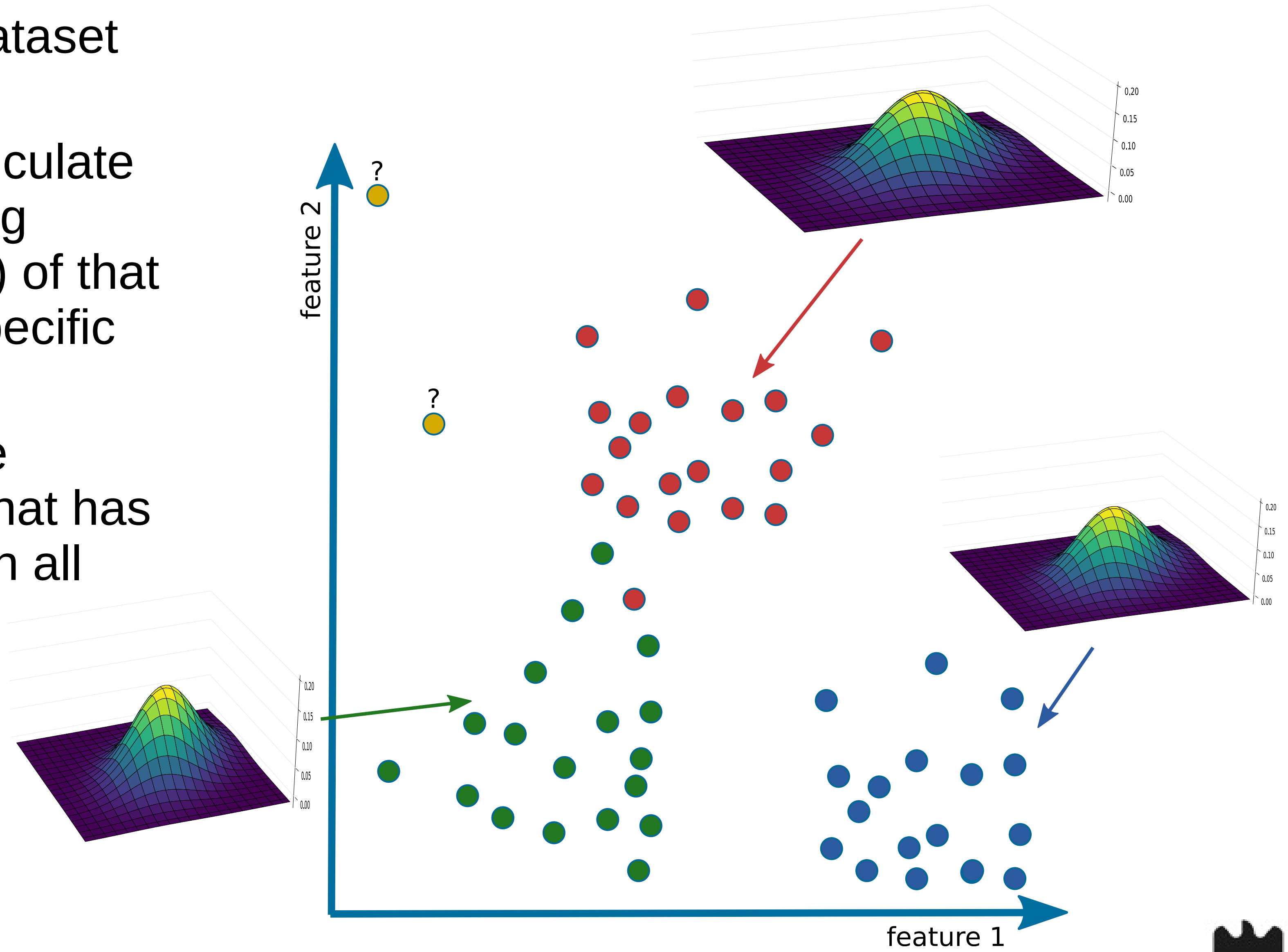
- Group dataset points
  - Use a single group (to detect anomalies),
  - By known classification,
  - By clustering algorithms.
- Find central point of each group.
- For each new dataset point:
  - Calculate Euclidean distances to each group central point,
  - Use distances to classify:
    - Shortest distance to group,
    - Probabilistic result based on the relative distances,
      - Ex: d1=10, d2=20, d3=30 → Group1 prob.=10/(10+20+30)=16.6%
    - Define as anomaly if distance(s) above predefined threshold.



X - Group Central Point
... - Anomaly Boundary

N-Dimensional Distributions

- Infer the multivariate PDF of each group of dataset points.
- For a new point, calculate the probability (using respective the PDF) of that point belong to a specific group.
- An anomaly may be defined as a point that has lower probabilities in all groups.



Decision by Machine Learning

for differentiation, classification, and anomaly detection

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Categories

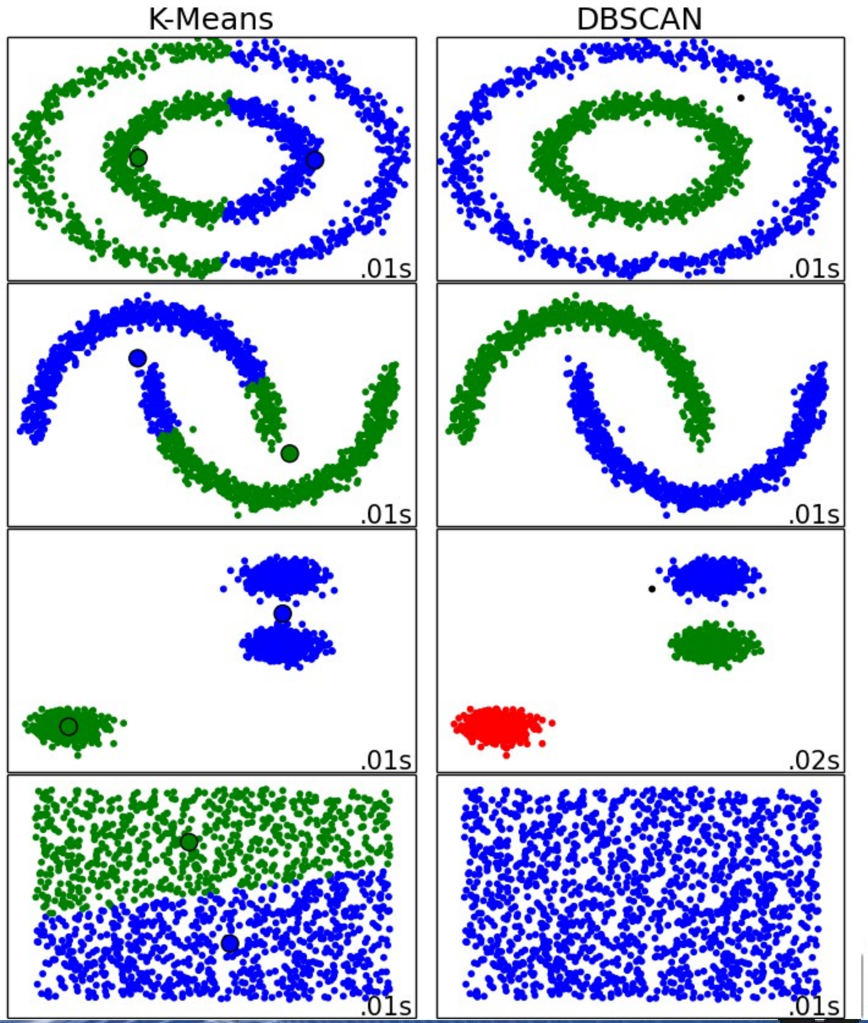
- Supervised learning
  - Inputs and outputs are given.
    - Outputs may be classification labels or system quantifiers.
  - Creates a general mapping rule between input and output.
- Unsupervised learning
  - Only inputs are given.
    - Algorithm must by structure in input data.
  - Post-classification based on known inputs and found data structure may be done to create a classifier.
- Reinforcement learning
  - Inputs are given, and “quality” of outputs is defined in terms of reward and penalization (cost functions) relative to the problem goal.

Approaches

- Clustering
- Support vector machines
- Artificial neural networks
  - Composed of one input and one output layer, and at most one hidden layer in between.
- Deep learning
  - ANN with more than three layers (including input and output).
    - More than one hidden layer.
- Other
  - Bayesian networks
  - Decision tree learning
  - Genetic algorithms
  - ...

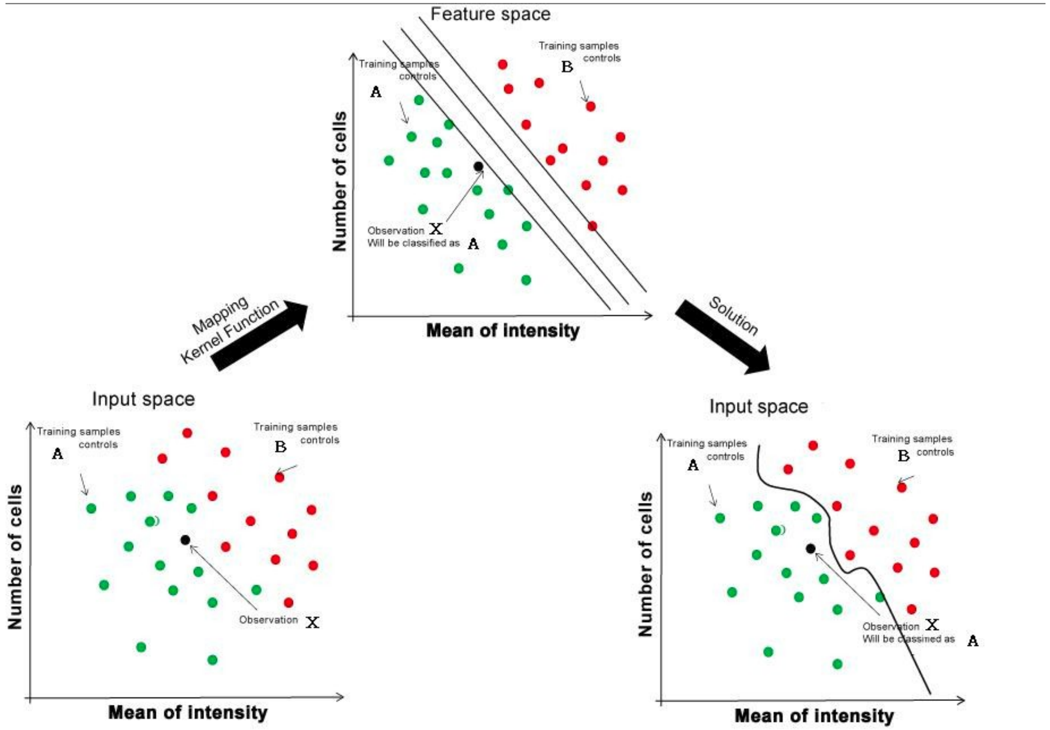
Classification / Clustering

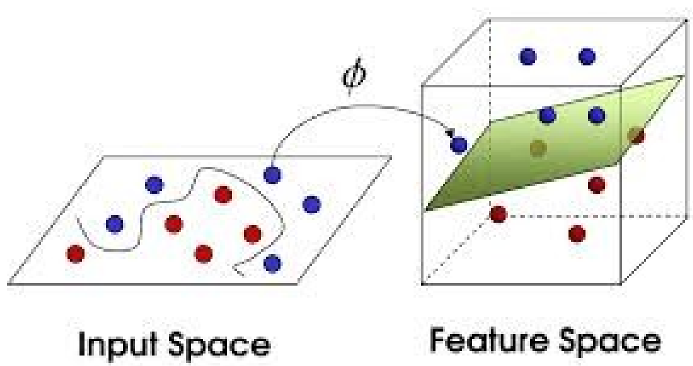
- Clustering is the process of grouping (classifying) a set of objects in such a way that objects in the same group (cluster) are more “similar” to each other than to those in other clusters.
- Algorithms:
  - K-Means
    - Requires the a priori knowledge of the number of clusters.
    - Uses the distances between points as metric.
  - DBSCAN
    - Requires the a priori definition of the neighborhood size.
    - Uses the distances between nearest points as metric.
  - Others…



Support Vector Machines (SVM)

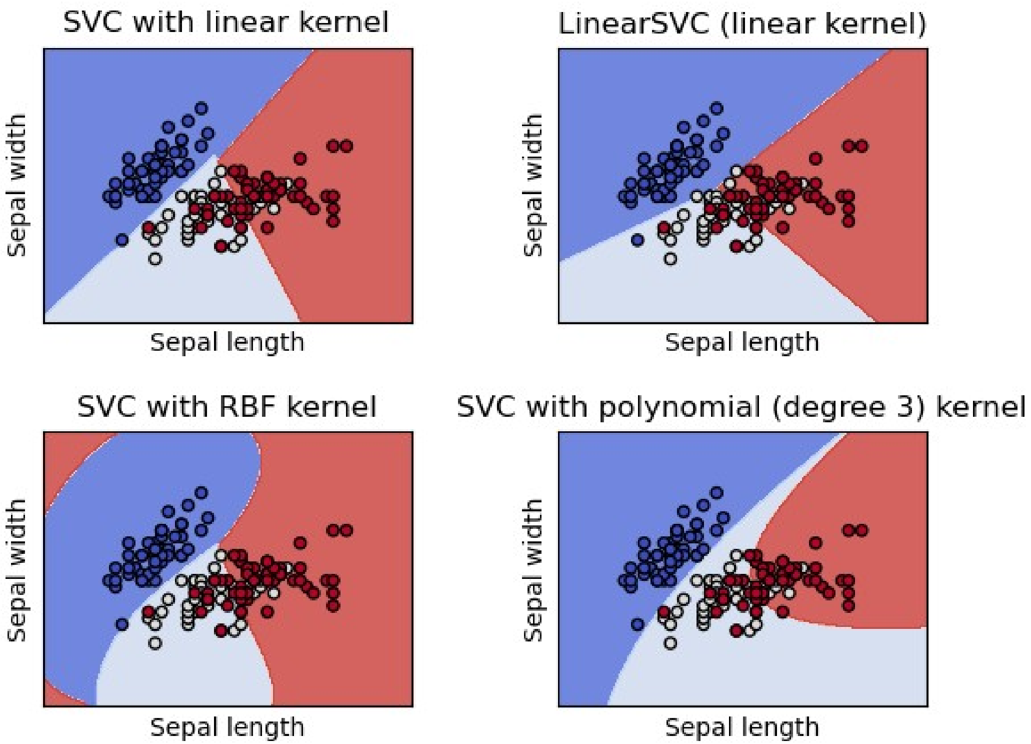
- Classification defined by a separating hyper-plane-
- Optimal hyper-plane for linearly separable patterns.
- Kernel functions allow the separation of patterns that are not linearly separable by transformations of original data.
- Solutions found using a minimization problem.



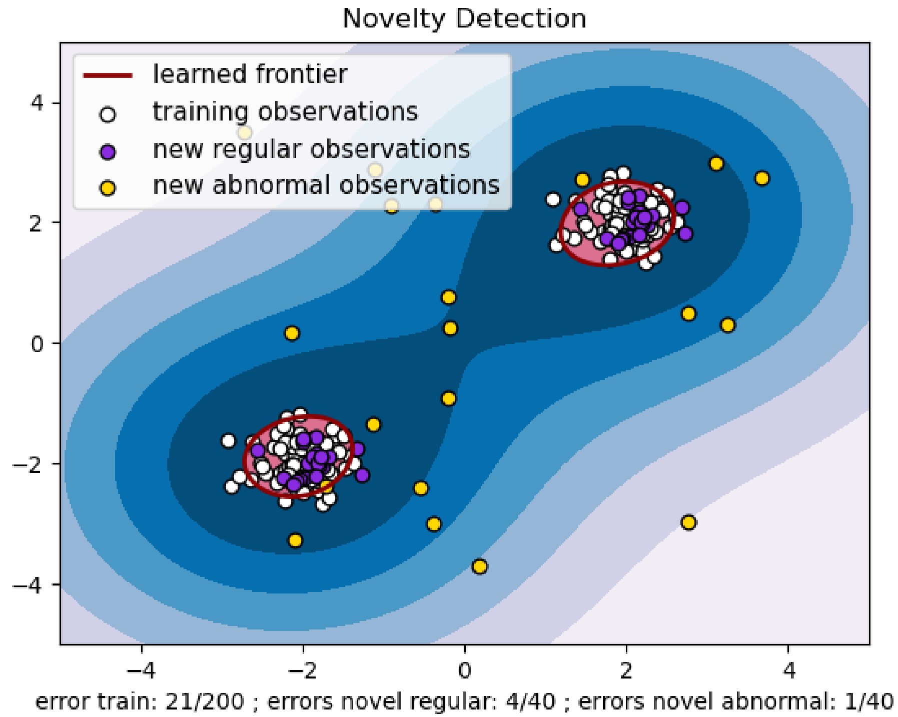


One-Class SVM vs. N-Class SVM

- N-Class SVM
  - Infers boundaries between each class.



- One-Class SVM
  - Infers “a boundary” that contains all known normal/licit traffic.

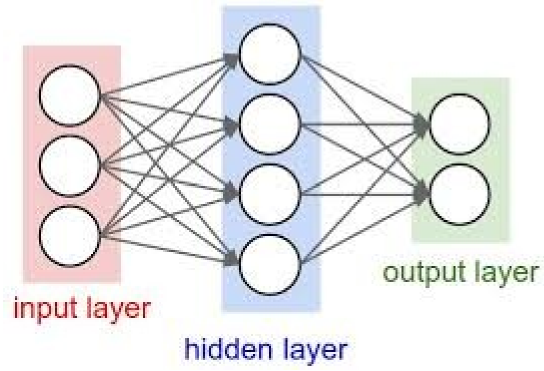


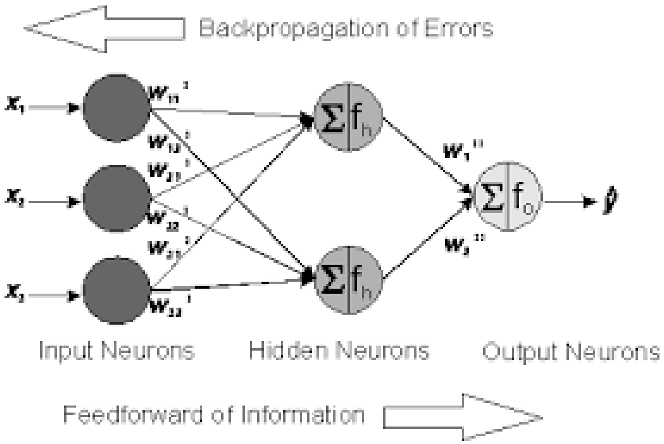
Decision Trees

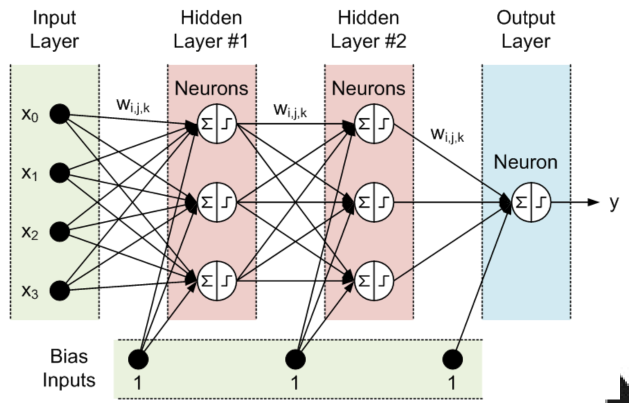
- Data partitions by branching decisions based on features values.
- Decision based on:
  - Location of an observation on the decision tree;
  - Location of an observation on multiple decision trees (forest);
  - Number of partitions/branches required to isolate an observation.
- Variants:
  - Tree Regressor
    - Classification based on data partitions (over branches).
  - Isolation Forests
    - Detects anomalies based on the low number of branches (data partitions) required to isolate an observation.
  - Random Forests
    - Uses multiple tree classifiers on various random sub-samples of the dataset.
    - Averages the results.

Artificial Neural Networks

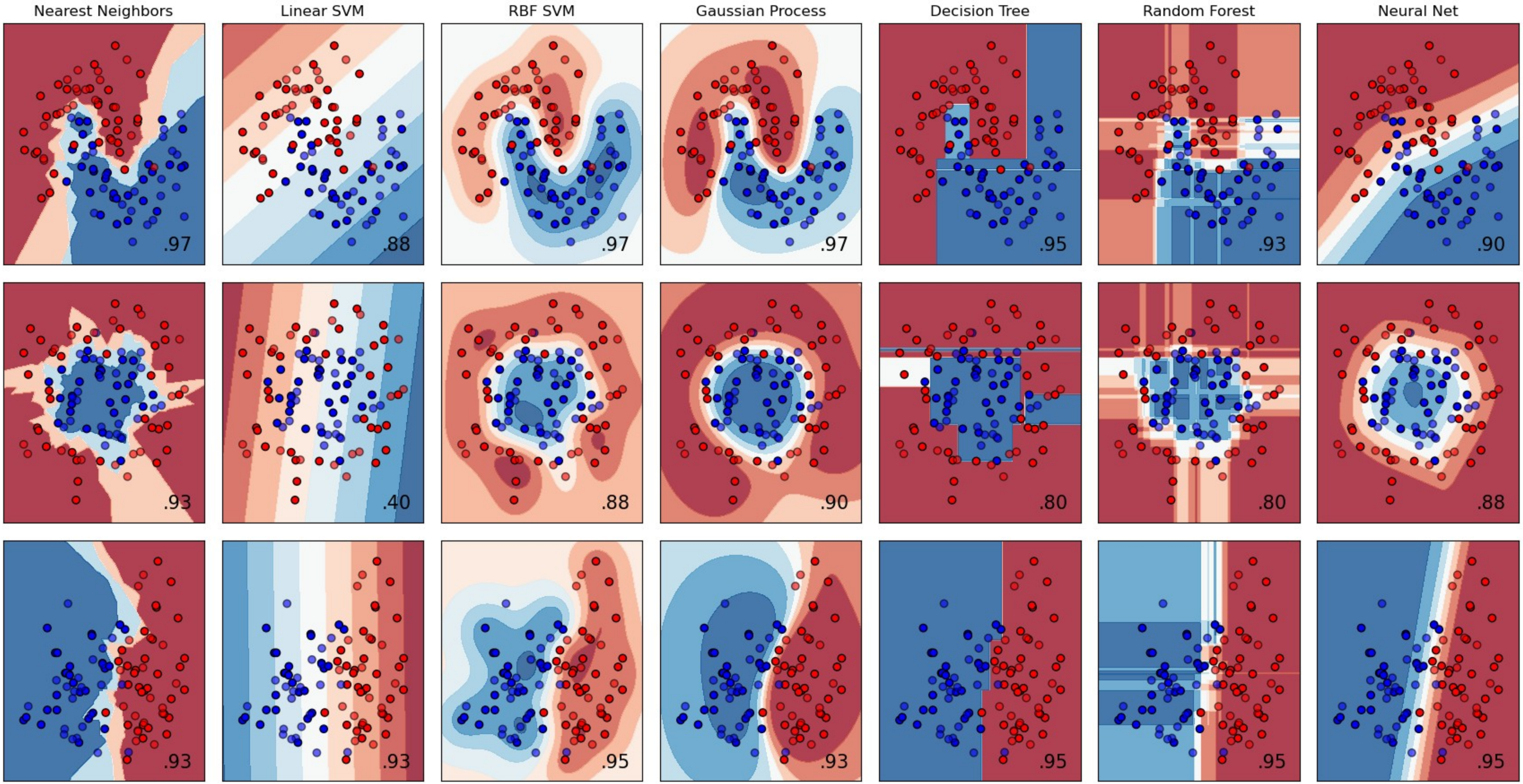
- Composed by input and output layers, and an optimal hidden layers
  - More than one hidden layer, becomes a deep learning NN.
- Hidden and output layers, perform a weighted sum of the values outputted by the nodes of the previous layer and applies an activation function.
  - Activation functions: linear, tanh, arctan, etc…
  - Weights define the NN, and must be inferred by a training algorithm.
    - Each node-node connection have a different weight.
- Training algorithms adjust connection weights to minimize the error between inputs and training outputs.
  - Back propagation of error.
  - Levenberg-Marquardt algorithm, Newton and quasi-Newton methods, Gradient descent, and Conjugate gradient.
- Some nodes/layers may have bias inputs to activate/deactivate and/or offset node outputs.







Overview


Nearest Neighbors
Linear SVM
RBF SVM
Gaussian Process
Decision Tree
Random Forest
Neural Net
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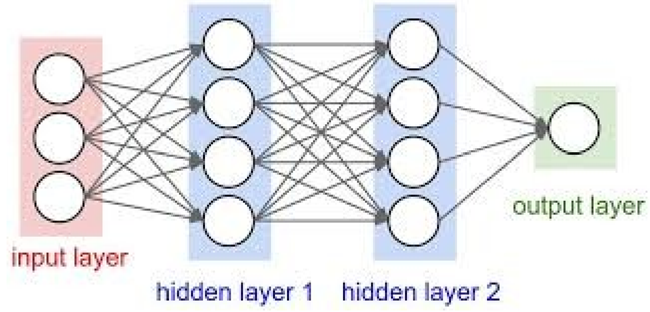
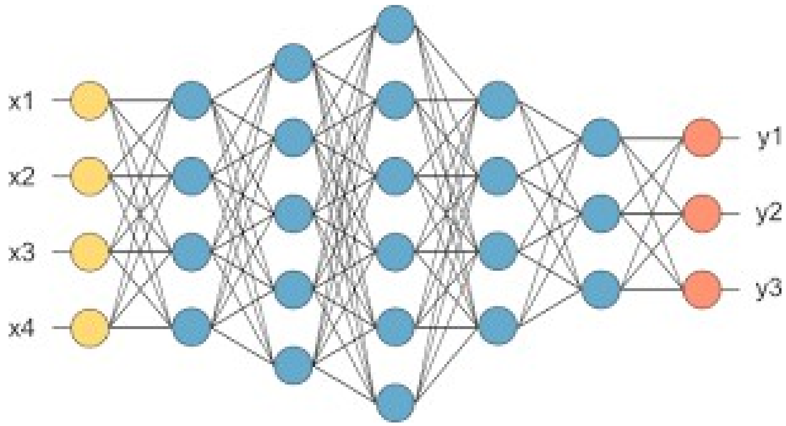
Deep Learning

- Supervised learning algorithms
  - Logistic Regression.
  - Multilayer perceptron.
  - Deep Convolutional Network.
- Unsupervised and semi-supervised learning algorithms
  - Auto Encoders
  - Denoising Autoencoders
  - Stacked Denoising Auto-Encoders
  - Restricted Boltzmann Machines
  - Deep Belief Networks



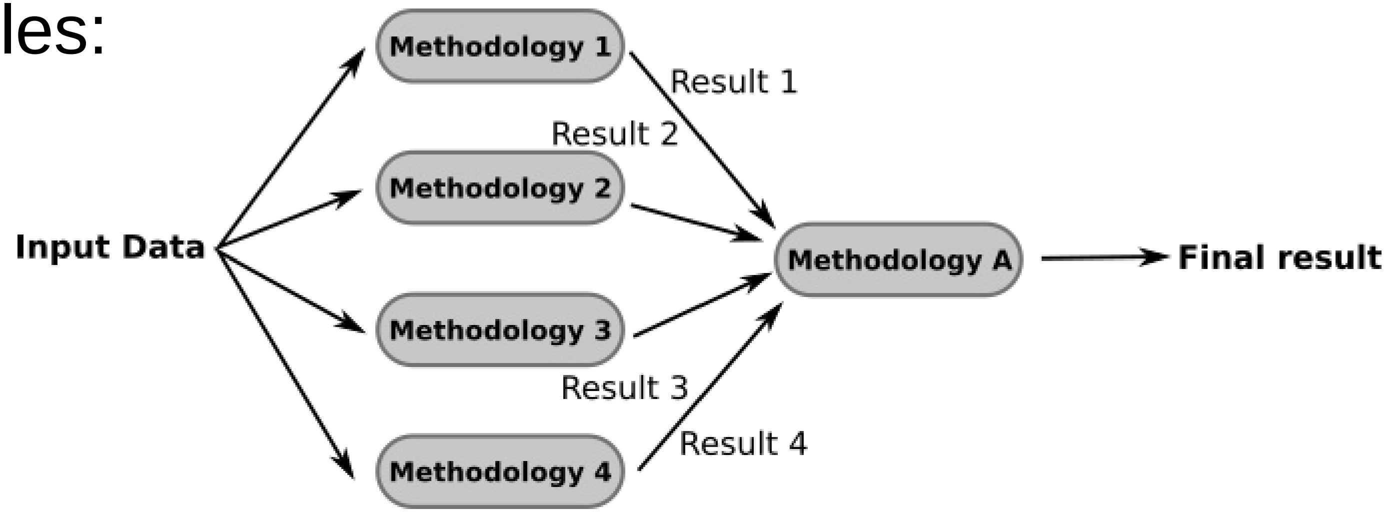


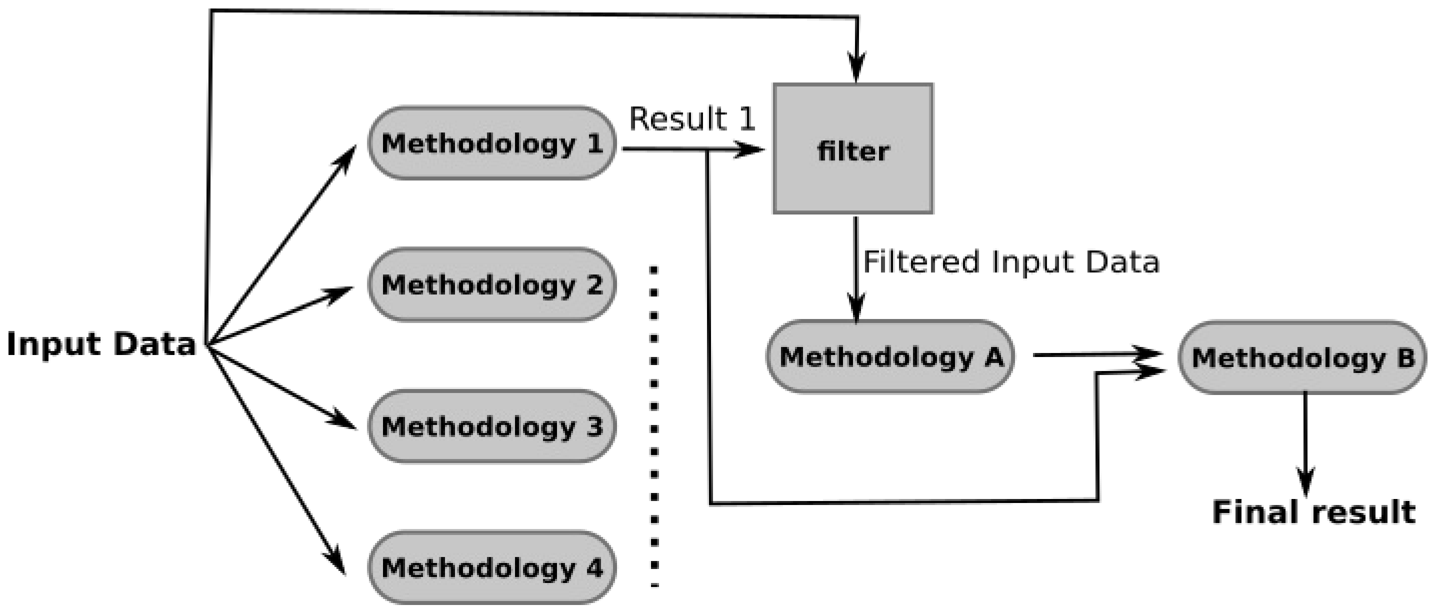
Ensemble (1)

- Ensemble methods use multiple learning methodologies to obtain better that the individual methods.
- Methods:
  - Bayes optimal classifier
    - Final decision based on the probabilities given by each methodology
  - Bagging
    - Final decision based on the results given by each methodology with equal weight.
    - Input data may differ between methodologies
      - Aims to decrease final result variance.
  - Boosting
    - Final decision based on different methodologies applied in sequence (to correct wrong classifications by the previous methodology).
    - Previous results may be used to filter input data given to next level classification methodologies.

Ensemble (2)

- Examples:





Performance Evaluation

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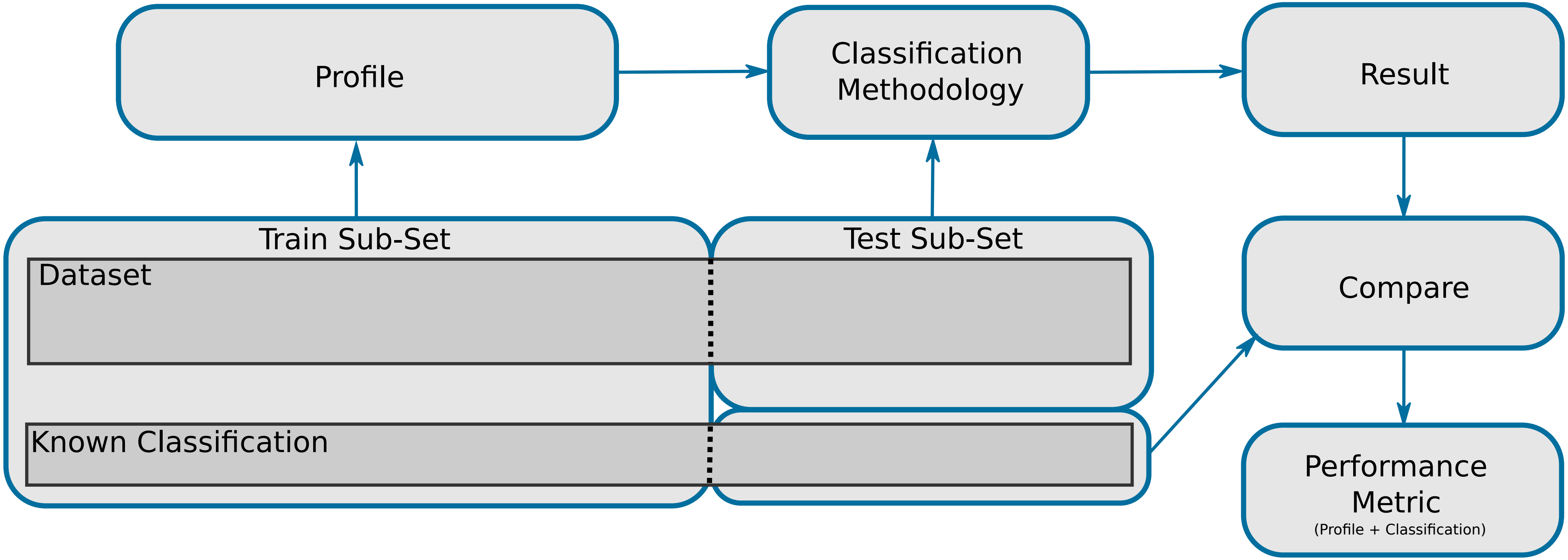
Evaluation Process



Metrics

- True Positive (TP) - Correctly predicted positive
  - True Negative (TN) - Correctly predicted negative
- False Positive (FP) - Wrongly predicted as positive
  - False Negative (FN) - Wrongly predicted as negative
- Metrics
  - Accuracy=(TP+TN)/(TP+TN+FP+FN)
  - Precision=TP/(TP+FP)
  - Recall=TP/(TP+FN)
  - F1-Score== 2*(Recall * Precision) / (Recall + Precision)

		Predicted class	
Actual Class		Class = Yes	Class = No
	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

Confusion Matrix