Understanding Network Traffic
An Introduction to Machine Learning in Networking

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Creating Communication Technologies

Outline

1. What is Machine Learning (ML) and why ML in Networking?
2. General overview on Machine Learning techniques:
   - Supervised Learning
   - Unsupervised Learning
   - Semi-Supervised Learning
   - Ensemble Learning
3. Features Extraction and Features Selection
   - Feature Extraction
   - Feature Selection
4. Final Remarks: Overfitting and Learning Evaluation
5. Machine Learning in Networking:
   - PSQA: Neural Networks for QoE Assessment
   - Sub-Space Clustering for Self Network Defense

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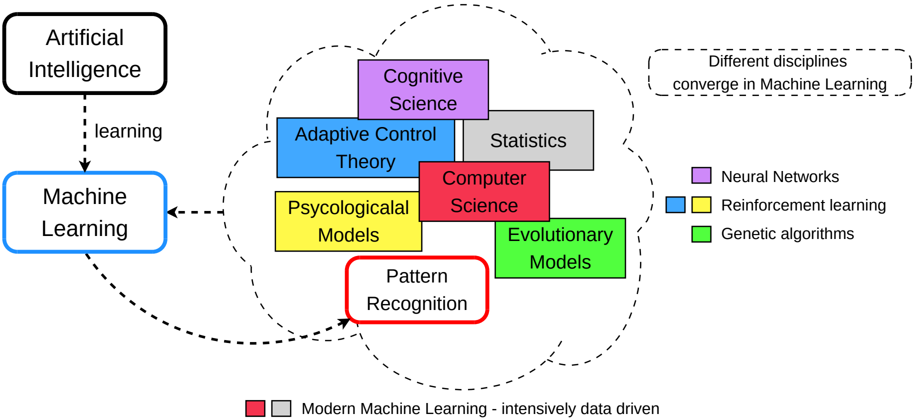
A little bit of history...



1956 John McCarthy (Stanford): "**Artificial Intelligence** is the science and engineering of making intelligent machines, which can perceive their environment and take actions to maximize their chances of success".

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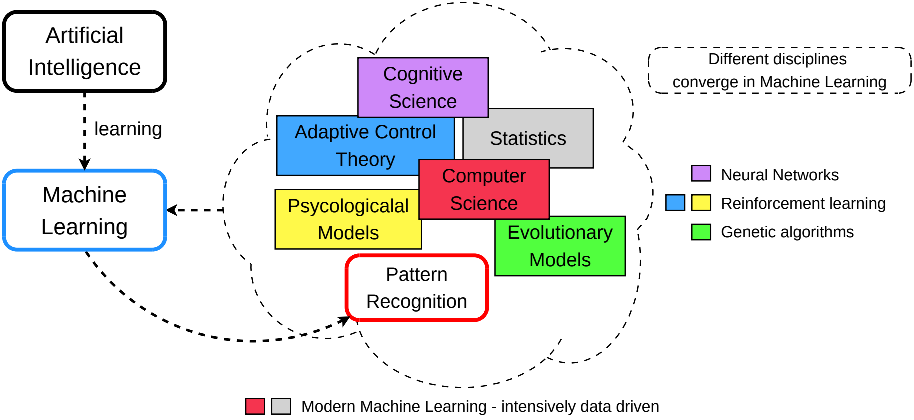

1956 Ray Solomonoff first mentioning the term "Learning Machines"...

1980 ...but the first International Workshop on Machine Learning, in Pittsburgh (currently ICML) appears almost 25 years later.

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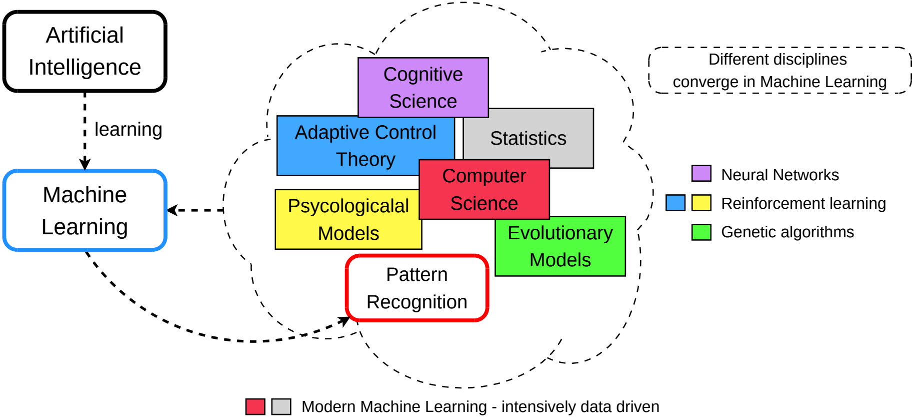

Machine Learning (ML) is about computational approaches to learning: ML aims to understand **computational mechanisms** by which **experience can lead to improved performance**, traducing these into computer algorithms.

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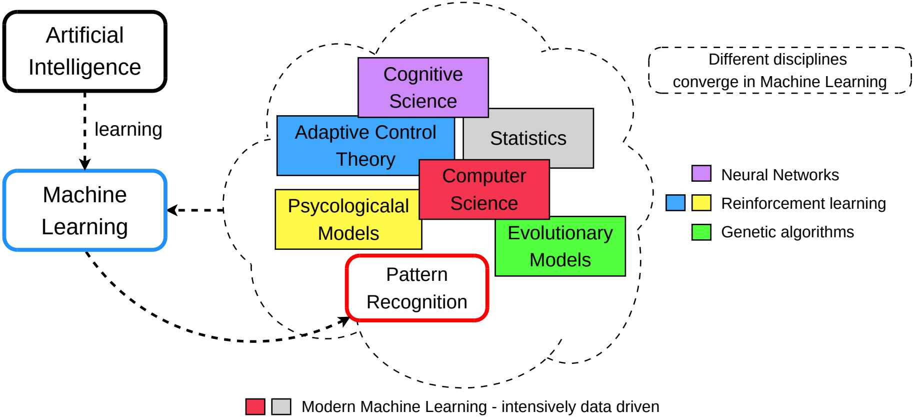

Tom Mitchell (Chair ML Dept. in Carnegie Mellon): "ML consists in computer algorithms that improve their performance $\mathbf{P}$ on some task $\mathbf{T}$ through the experience $\mathbf{E}$...a well-defined learning task is given by $<\mathbf{P},\mathbf{T},\mathbf{E}>$".

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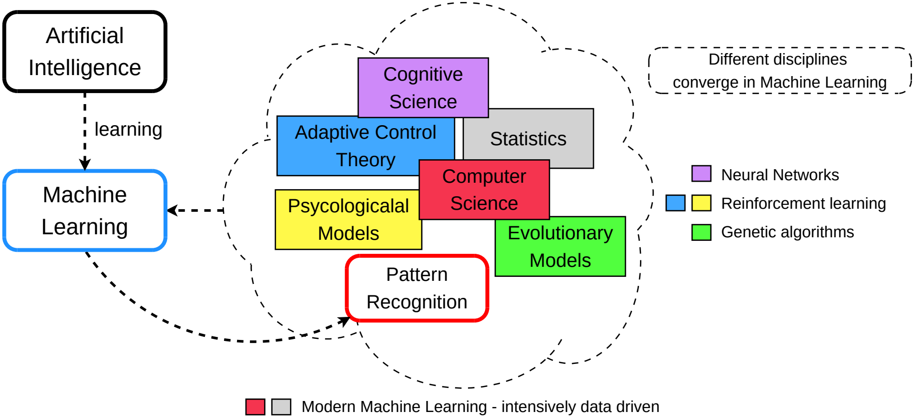

ML in Traffic Analysis is mainly about **Pattern Recognition (PR)***: learn to automatically recognize complex patterns in data.

∗ C. Bishop, "Pattern Recognition and Machine Learning", Springer, 2006.

Machine Learning and Pattern Recognition in TMA

The **ever increasing amount of networking data** is a good reason to believe that **smart data analysis** will become even more pervasive as a necessary ingredient for **technological progress**:

Some good reasons for ML and PR in TMA:

- Proliferation of network traffic (social networking, web 2.0, video).

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- Too many sources of knowledge to process by humans.
- Black-boxes: some tasks cannot be well defined except by input/output examples.
- Need for aggregated value solutions: *get the most out of data*.

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Some relevant examples in Traffic Monitoring and Analysis:

T $\longrightarrow$ Traffic-Flow Classification

P $\longrightarrow$ Percentage of flows correctly classified

E $\longrightarrow$ Set of labeled traffic flows: {flow descriptors, application}

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T $\longrightarrow$ 0-day Attacks Detection

P $\longrightarrow$ Detection and false alarm rates

E $\longrightarrow$ Set of traffic flows free of attacks: {flow descriptors for normal activity}

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Some relevant examples in Traffic Monitoring and Analysis:

T $\longrightarrow$ QoE Modeling and Prediction

P $\longrightarrow$ Percentage of correctly predicted QoE levels

E $\longrightarrow$ Set of subjective tests: {QoS/app. descriptors, QoE level}

ML: discipline vs tool to solve complex problems

ML in TMA IS NOT about trying different algorithms to obtain better results. To build a solid house on your own, you need to know about architecture, as well as about the intrinsic characteristics of the construction toolbox...

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Two commonly arising problems when coupling ML and Networking:

You have to understand the problem:

- Even a ML expert fails to achieve a good networking solution if he neither knows the good descriptors nor understands the problem (e.g., try to classify flows using only port numbers).
- Keep the scope narrow, to better understand the overall process (i.e., from selecting features to evaluation and conclusions).
- The solution must be meaningful in practical terms (e.g., predicting QoE from descriptors that can't be controlled is pretty useless for QoE management).

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Two commonly arising problems when coupling ML and Networking:

You have to understand the tool:

- The broader overview you have about the particularities of each ML approach, the better chances to apply the correct one (e.g., avoid killing mosquitos with a hammer).
- The research community does not benefit any further from yet another untried ML approach (e.g., IDS based on KDD'99 dataset).
- A good grasp of calculus, linear algebra, and probability is essential for a clear understanding of ML and PR in TMA and Networking.

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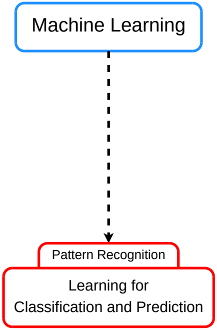

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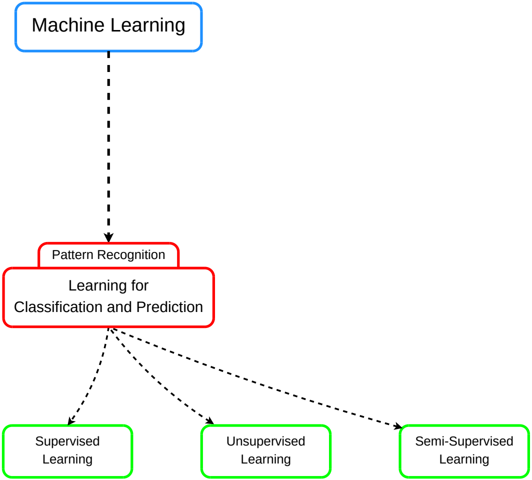

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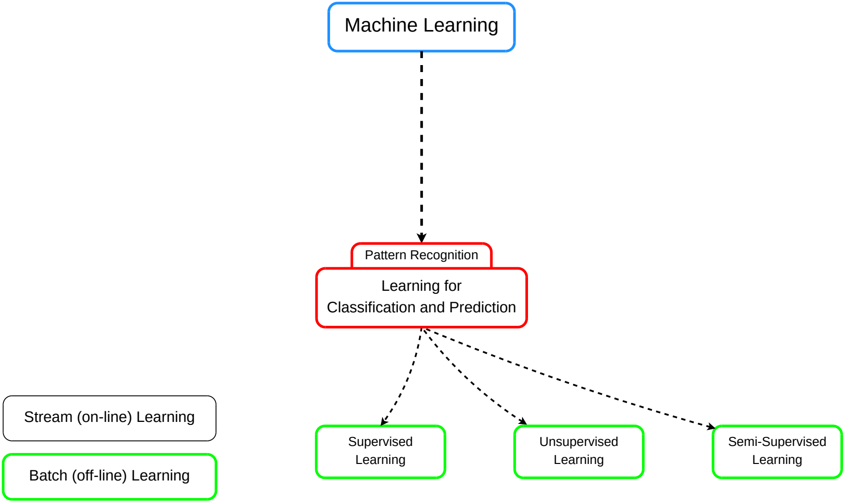

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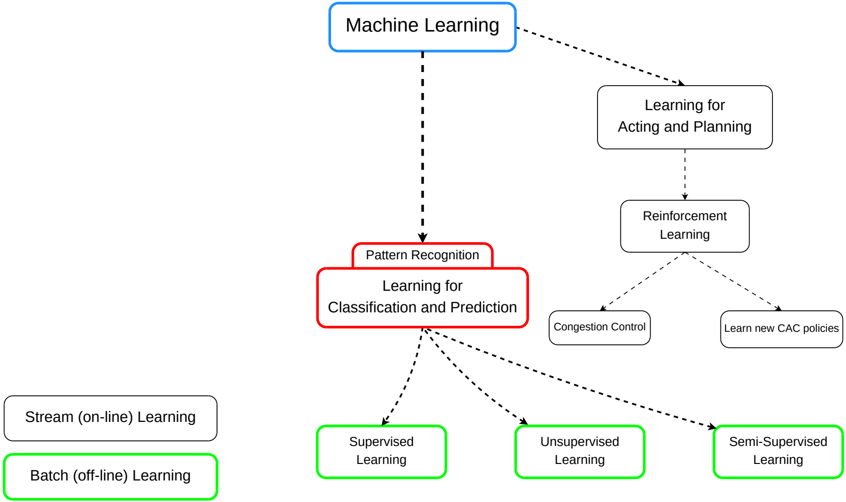

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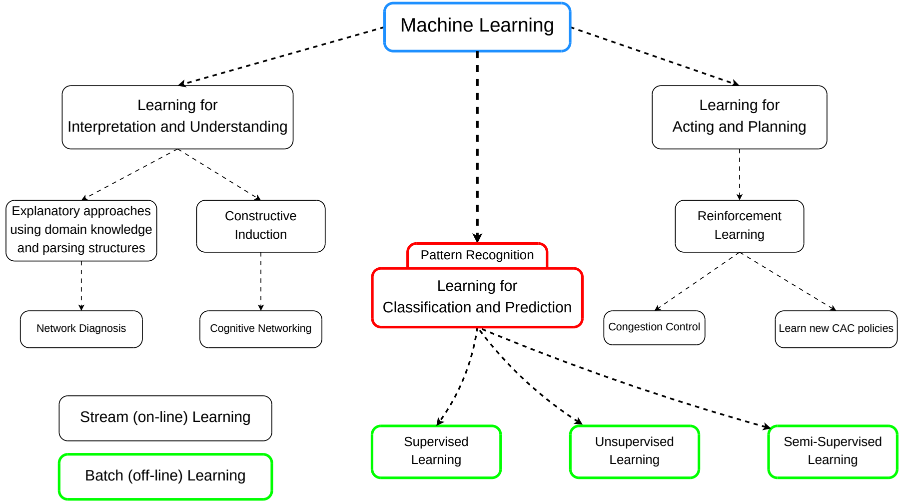

Patterns and Features

A **pattern** p represents the object under analysis, for which we want to draw some conclusion or **answer some particular question**:

In Traffic Classification, p could be a 5-tuple IP flow $\{IP_{src/dst}, port_{src/dst}, proto\}$

- Which of these applications generated flow p: Skype, YouTube, or µTorrent?

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In QoE, p could represent a Skype call performed in some known network conditions.

- Which is the MOS value that an end-user would assign to this call?

Patterns and Features

Each **pattern** p is represented by a set of d descriptors or **features**, thus it can be interpreted as a point in a d-dimensional **feature space**:

$$p \rightarrow \mathbf{x} = \{x_1, x_2, x_3, \ldots, x_d\}$$

- Features represent the most critical part of the overall analysis; their accurate definition requires extensive domain knowledge.
- Quantitative: discrete or continuous, and qualitative: ordinal or nominal.

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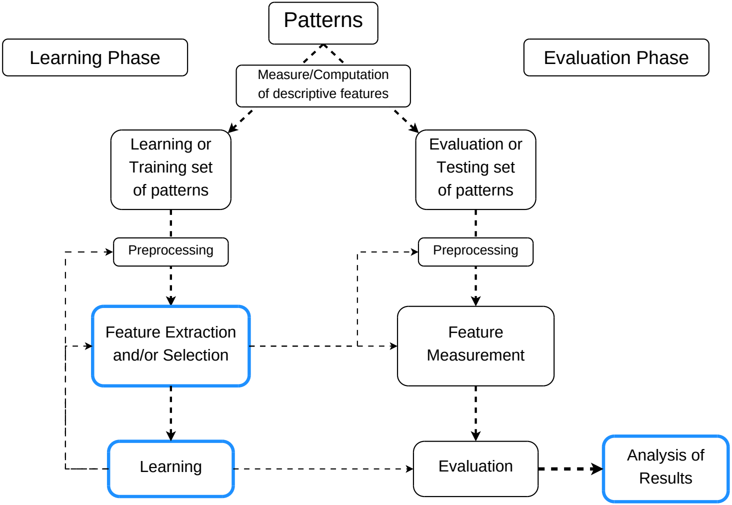
Some examples:

- Flow descriptors: # pkts, average pkt size, flow size and duration, average inter-pkts time, first 10 Fourier coefficients of pkt size, etc.
- Traffic descriptors: # IP flows, # IP srcs and dsts, # dsts ports, in time-slot t, etc.
- Video Streaming descriptors: codec, video bit-rate, video content nature, link bandwidth, loss rate, loss pattern, etc.

Design of a Learning Classification/Prediction System

Steps in the design of a **batch learning classifier/predictor**:



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Supervised Learning

In **supervised learning**, there is a **label** associated to each pattern, which is supposed to **answer a particular question** about it:

- If the label is discrete, we talk about **Classification**
- If the label is continue, we talk about **Regression**
- We shall refer to these labels as the **Ground Truth** for our problem.

Supervised Learning

In Classification, we consider c classes $w_1, w_2, \ldots, w_c$, and assume:

- Classes are complete: $\cup_{i=1}^{c} w_i$ defines the problem space.
- Classes are mutually exclusive: $w_i \cap w_j = \emptyset$.
- Then, each label l_i corresponds to one single class w_i.

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The Classification Problem:

Given a pattern p described by $\mathbf{x} = \{x_1, \ldots, x_d\}$, decide which of the c classes the pattern belongs to, i.e., decide which is its label l.

The Supervised Classification Problem:

Take a better decision by relying on a **training** ground truth set of patterns correctly classified:

$$S = \{p_i, l_i\}$$

Classification: a Probabilistic Approach

We assume that $\mathbf{x}$ belonging to class w_i is an observation drawn randomly from the class-conditional probability density function $p(x|w_i)$.

Imagine we know the *prior* probabilities of the classes $P(w_i)$ ($\sum_{i=1}^{c} P(w_i) = 1$).

Based only on $P(w_i)$, one would $\boxed{\text{decide label } l_i \text{ if } P(w_i) > P(w_j), \forall j \neq i.}$

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If we now consider the conditional densities $p(x|w_i)$, we can refine our decision, using a **Bayesian approach** to get the *posterior* class probability:

$$P(w_i|\mathbf{x}) = \frac{p(\mathbf{x}|w_i)\, P(w_i)}{p(\mathbf{x})}$$

$$p(\mathbf{x}) = \sum_{i=1}^{c} p(\mathbf{x}|w_i)\, P(w_i)$$

Classification: Optimal Bayes Decision Rule

A decision problem has a *loss function* associating a cost to the decision.

$L(w_i|w_j)$ is the loss incurred in deciding w_i when the correct class is w_j.

The *expected loss* of deciding w_i, known as the *risk* of deciding w_i, is:

$$R(w_i|\mathbf{x}) = \sum_{i=1}^{c} L(w_i|w_j)\, P(w_j|\mathbf{x})$$

The optimal Bayes decision rule is the one that minimizes the risk:

$$\boxed{\text{decide } w_i \text{ if } R(w_i|\mathbf{x}) < R(w_j|\mathbf{x}), \forall j \neq i}$$

In classification, we use a binary loss function (0 correct, 1 otherwise).

The optimal decision becomes then a Maximum A Posteriori (MAP) rule:

$$\boxed{\text{decide } w_i \text{ if } P(w_i|\mathbf{x}) > P(w_j|\mathbf{x}), \forall j \neq i}$$

The Naïve Bayes Classifier

Using Bayes decision rule we can build a simple classifier.

$$P(w_i|\mathbf{x}) \propto p(\mathbf{x}|w_i)\, P(w_i)$$

$P(w_i)$ can be estimated from the training data set S ($P(w_i) = \#w_i/\#S$).
Regarding $p(\mathbf{x}|w_i)$, we can take the *naïve* approach (independent features):

$$\boxed{P(w_i|\mathbf{x}) \propto P(w_i) \prod_{j=1}^{d} p(x_j|w_i)}$$

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The class-conditional probabilities $p(x_j|w_i)$ can be estimated in multiple ways:

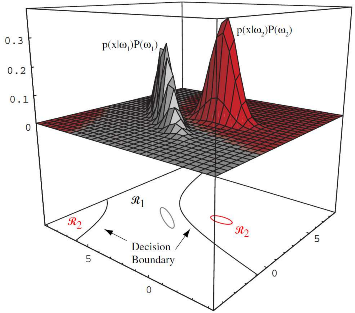
- Discretizing the values of x_j (e.g. histogram).
- Parametric estimation (maximum-likelihood estimation, using for example Gaussian distributions - Central Limit Theorem).
- Non-parametric estimation (e.g. kernel density estimation).

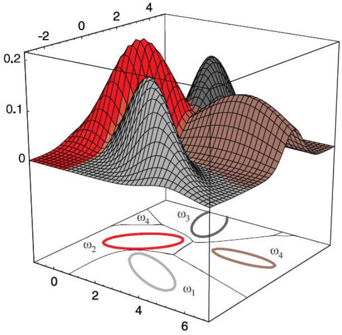
Discriminant Analysis

One common way to classify patterns is by defining a set of **discriminant functions** $g_i(\mathbf{x})$, $i = 1, \ldots, c$.

$$\boxed{l(\mathbf{x}) = \arg \max_{i=1,\ldots,c} g_i(\mathbf{x})}$$

The set of c discriminant functions divides the feature space into c *decision regions* $\mathcal{R}_i$, separated by *decision boundaries*:





Discriminant Analysis

A $0/1$-loss Bayes classifier (MAP classifier) is easily represented in this way, taking $g_i(\mathbf{x}) \propto P(w_i|\mathbf{x}) \propto p(\mathbf{x}|w_i)\,P(w_i)$.

For practical reasons, we usually take a logarithmic transformation of the discriminant functions:

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Let us assume that class-conditional probabilities are multivariate normal: $p(\mathbf{x}|w_i) \sim N(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$. In this case, we can write $g_i(\mathbf{x})$ as:

$$g_i(\mathbf{x}) = -\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^{\mathsf{T}}\, \boldsymbol{\Sigma}_i^{-1}\,(\mathbf{x}-\boldsymbol{\mu}_i) - \frac{1}{2}\ln|\boldsymbol{\Sigma}_i| + \ln P(w_i) + \text{cte}$$

$$g_i(\mathbf{x}) = \mathbf{x}^{\mathsf{T}}\, \mathbf{W}_i^{-1}\, \mathbf{x} + \mathbf{w}_i^{\mathsf{T}}\, \mathbf{x} + \lambda_i \longrightarrow \text{a } \textbf{hyperquadric}$$

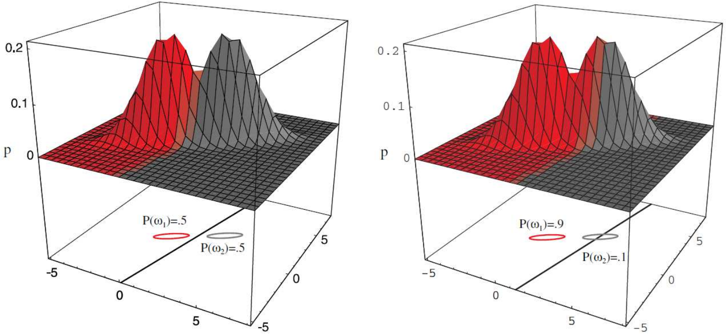
$$\mathbf{W}_i = -\frac{1}{2}\boldsymbol{\Sigma}_i^{-1}, \quad \mathbf{w}_i = \boldsymbol{\Sigma}_i^{-1}\,\boldsymbol{\mu}_i, \quad \lambda_i = -\frac{1}{2}\boldsymbol{\mu}_i^{\mathsf{T}}\, \boldsymbol{\Sigma}_i^{-1}\, \boldsymbol{\mu}_i - \frac{1}{2}\ln|\boldsymbol{\Sigma}_i| + \ln P(w_i)$$

Linear Discriminant Analysis

A particularly interesting case arises when the covariance matrices are identical, $\mathbf{\Sigma}_i = \mathbf{\Sigma}, \forall i = 1, \ldots, c$.

In this case, the hyperquadric becomes an **hyperplane** (i.e. the term $\mathbf{W}_i$ is the same $\forall g_i(\mathbf{x})$):

$$\boxed{g_i(\mathbf{x}) = \left(\mathbf{\Sigma}^{-1}\,\boldsymbol{\mu}_i\right)^{\mathsf{T}}\mathbf{x} - \left(\frac{1}{2}\boldsymbol{\mu}_i^{\mathsf{T}}\,\mathbf{\Sigma}^{-1}\,\boldsymbol{\mu}_i - \ln P(w_i)\right)}$$

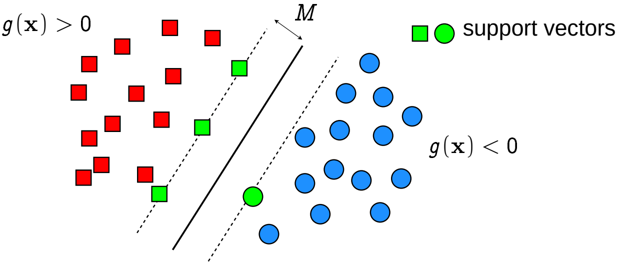


A Non-Probabilistic Approach: Support Vector Machines

Let us return to a two-class classification problem with labels $l_1 = 1$ and $l_2 = -1$, using a linear discriminant function:

$$\begin{aligned} g(\mathbf{x}) &= \mathbf{w}^{\mathsf{T}}\mathbf{x} + \lambda \\ \text{if } g(\mathbf{x}) > 0 &\rightarrow \text{decide } l = 1 \\ \text{if } g(\mathbf{x}) < 0 &\rightarrow \text{decide } l = -1 \end{aligned}$$

Let us assume that the training patterns are linearly separable in the feature space. We want to find the hyperplane $\{\mathbf{w}_0^{\mathsf{T}}, \lambda_0\}$ that maximizes the *margin* M:



Support Vector Machines

In this case, the n training patterns verify $l_i \, g(\mathbf{x}_i) > 0$, $i = 1, \ldots, n$. The margin M is the minimum distance from $g(\mathbf{x}_i)$ to a training pattern.

Using a proper change of variables, it can be shown that maximizing M is equal to the following quadratic optimization problem:

$$\boxed{\begin{array}{ll} & \min \ \frac{1}{2}\|\mathbf{w}\|^2 \\ \text{subject to} & l_i \, g(\mathbf{x}_i) > 1, \ \forall i = 1, \ldots, n \end{array}}$$

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Using Lagrange multipliers α_i, we compute the Lagrangian function:

$$L(\mathbf{w}, \lambda, \boldsymbol{\alpha}) = \frac{1}{2}||\mathbf{w}||^2 - \sum_{i=1}^{n} \alpha_i \left(l_i\, (\mathbf{w}^{\mathsf{T}}\, \mathbf{x}_i + \lambda) - 1 \right)$$

The solution to $\left(\min_{\mathbf{w},\lambda} \max_{\boldsymbol{\alpha}} L(\mathbf{w}, \lambda, \boldsymbol{\alpha}) \right)$ gives $\mathbf{w}_0 = \sum_{i=1}^{n} \alpha_i\, l_i\, \mathbf{x}_i$ and λ_0.

Support Vector Machines

In the sum $\mathbf{w}_0 = \sum_{i=1}^{n} \alpha_i \, l_i \, \mathbf{x}_i$, it can be shown that $\alpha_i > 0$ only for the Support Vectors (SV): the patterns at the max M hyperplanes, i.e., $l_i \, (\mathbf{w}_0^{\mathsf{T}} \mathbf{x}_i + \lambda_0) = 1$.

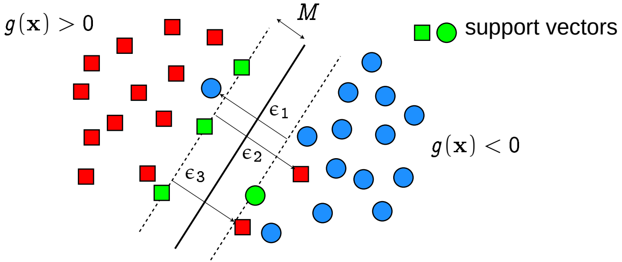
The only important patterns for the classification are the SV. The final classifier is given by $\boxed{g(\mathbf{x}) = (\sum_{i \in \mathrm{SV}} \alpha_i \, l_i \, \mathbf{x}_i)^T \mathbf{x} + \lambda_0.}$

Support Vector Machines

In the sum $\mathbf{w}_0 = \sum_{i=1}^{n} \alpha_i \, l_i \, \mathbf{x}_i$, it can be shown that $\alpha_i > 0$ only for the Support Vectors (SV): the patterns at the max M hyperplanes, i.e., $l_i \left(\mathbf{w}_0^{\mathsf{T}} \mathbf{x}_i + \lambda_0 \right) = 1$.

The only important patterns for the classification are the SV. The final classifier is given by $\boxed{g(\mathbf{x}) = \left(\sum_{i \in \text{SV}} \alpha_i \, l_i \, \mathbf{x}_i \right)^T \mathbf{x} + \lambda_0.}$

SVM can be slightly modified to consider misclassifications, adding some penalization ϵ_i for a misclassified pattern i:



Support Vector Machines

In this case, the optimization problem is the following:

$$\boxed{\begin{array}{rl} & \min C \sum_{i=1}^{n} \epsilon_i + \frac{1}{2}\|\mathbf{w}\|^2 \\ \text{subject to} & l_i\, g(\mathbf{x}_i) \geqslant 1 - \epsilon_i,\ \epsilon_i > 0,\ \forall i = 1, \ldots, n \end{array}}$$

where $C > 0$ is a controls the tradeoff between penalty and the margin.

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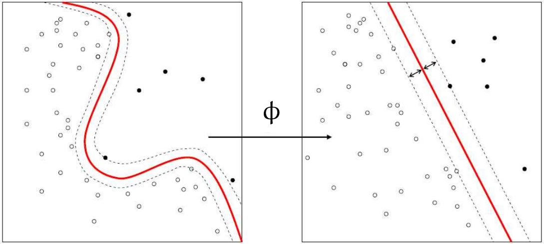
So far we have considered a linear SVM classifier, but what about this case:



Non-linear SVM and the Kernel Trick

In a general case, the linear classifier can be rewritten as:

$$g(\mathbf{x}) = \mathbf{w}^{\mathsf{T}} \, \phi(\mathbf{x}) + \lambda$$

where $\phi(\mathbf{x}) : \mathbb{R}^d \rightarrow \mathcal{F}$ is a feature space transformation. The corresponding SVM solution is exactly the same as before:

$$g(\mathbf{x}) = \left(\sum_{i \in \mathsf{SV}} \alpha_i \, l_i \, \phi(\mathbf{x}_i) \right)^{\mathsf{T}} \phi(\mathbf{x}_i) + \lambda_0$$

To apply the SVM solution in any general mapped feature space $\mathcal{F}$, it is only neccesary to know the inner product $\phi(\mathbf{x}_i)^{\mathsf{T}} \, \phi(\mathbf{x})$.

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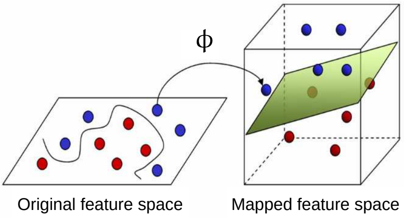
Patterns in higher dimensional spaces becomes separated, thus the linear SVM solution provides proper solution if the mapping is done to a much higher feature space $\mathcal{F} \in \mathbb{R}^m$, with $m >> d$:



Non-linear SVM and the Kernel Trick

But as we saw, we don't need to explicitly do the mapping, as we only need the inner product in $\mathcal{F}$.

The **kernel trick** permits to map the feature space into a high dimensional space with better structural properties, without actually doing the mapping.

We define the inner product in terms of a **kernel function** $k(\mathbf{x}, \mathbf{x}_i) = \phi(\mathbf{x}_i)^\mathsf{T} \phi(\mathbf{x})$:

$$\boxed{g(\mathbf{x}) = \sum_{i \in \text{SV}} \alpha_i \, l_i \, k(\mathbf{x}, \mathbf{x}_i) + \lambda_0}$$

Some standard kernel functions:

- Linear: $k(\mathbf{x}, \mathbf{x}_i) = \mathbf{x}_i^\mathsf{T} \mathbf{x}$
- Polynomial: $k(\mathbf{x}, \mathbf{x}_i) = (1 + \mathbf{x}_i^\mathsf{T} \mathbf{x})^p$
- Gaussian radial basis function: $k(\mathbf{x}, \mathbf{x}_i) = e^{-\gamma \, ||\mathbf{x} - \mathbf{x}_i||^2}$

Non-linear SVM and the Kernel Trick

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In a **Multiclass SVM** problem, we can take two simple procedures to generalize the above classifier:

- **one-vs-all**: c different SVMs, the classifier with the highest output assigns the class (classifiers must be scaled for comparison):

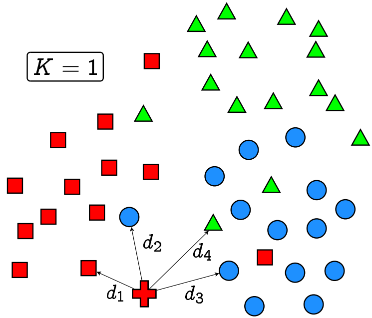
$$l(\mathbf{x}) = \arg \max_{i=1,\ldots,c} g_i(\mathbf{x})$$

- **one-vs-one**: $c(c-1)/2$ different 2-class SVMs, then every classifier assigns a class, and the class with more votes is chosen.

* **Note:** SVM can also be used for regression.

A Metric-based Classifier: K-Nearest Neighbors

The simplest and most intuitive classifier is based on the concept of **similarity**: similar patterns should be assigned to the same class:



In K-NN, we decide the class of a new pattern by a majority vote of its k neighbors, **given a similarity measure** (e.g. Euclidean distance).

K-NN assumes no knowledge on the underlying classes; it is based on the training patterns alone. Note that K-NN has no training phase.

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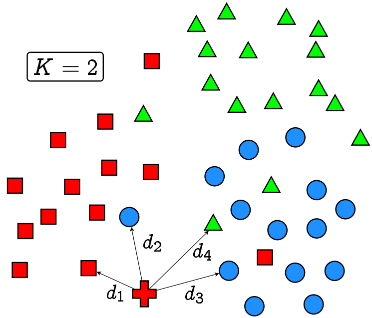

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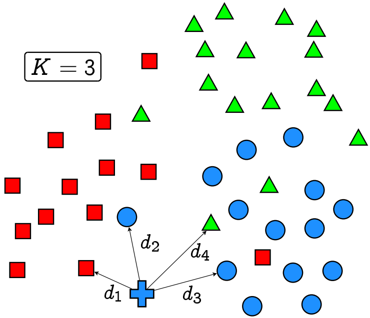

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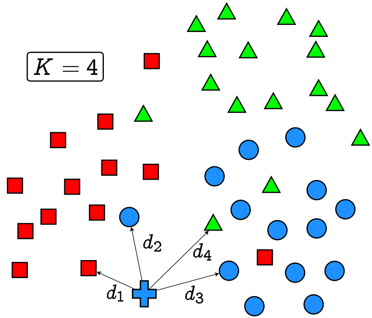

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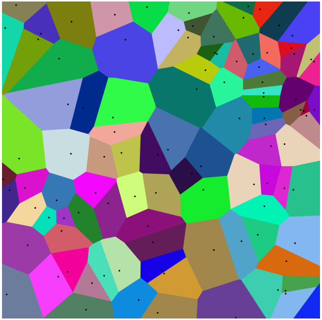
An interesting case is obtained for $K = 1$, where we get a decomposition of the feature space in n convex regions called **Voronoi cells**:



Note: if the number of training samples n is very large, then the error rate of 1-NN is never worse than twice the Bayes (minimum) error rate, awesome for such a simple algorithm!

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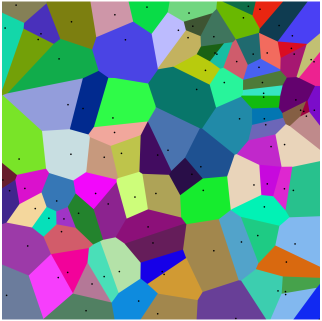


Some limitations of K-NN:

- Computationally expensive in both time and memory.
- Classes with more frequent examples tend to dominate the classification.

* **Note:** K-NN can also be used for regression.

A Non-Metric Classifier: Decision Trees

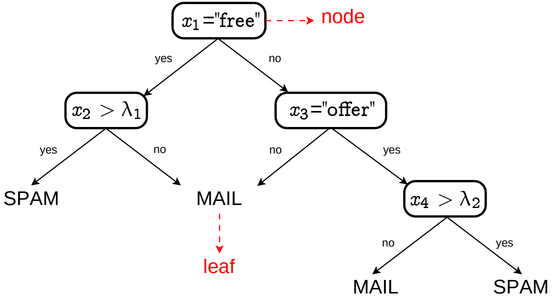
Consider a feature space with no similarity metric, e.g., nominal features (for continuous features, we do not consider any *distance* among them).

How to construct a classifier with no-metric features?

We can build a partition of the feature space by **asking multiple questions.**

The next question depends on the previous answer; questions do not repeat.

These questions build a **decision tree**; we use only binary questions.



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A Non-Metric Classifier: Decision Trees

How do we build such a tree?

- At each node N, we make the question that minimizes the *impurity* in the immediate descendant nodes.
- The most popular impurity measure is the **entropy impurity**:

$$\begin{aligned} i(N) &= -\sum_{j=1}^{c} P(w_j) \log_2 P(w_j), \quad i(N) \in [0, \log_2(c)] \\ P(w_j) &= \% \text{ patterns at } N \in w_j \end{aligned}$$

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  $\Delta i(N) = i(N) - P_L i(N_L) - P_R i(N_R),\; P_L$ % patterns $\in$ left node N_L

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- So at each step, we create a new node by taking the feature that maximizes $\Delta i(N)$.
- This recursive-growing approach is the one used in $\mathrm{ID3}$ and its successor $\mathrm{C4.5}$ trees.

A Non-Metric Classifier: Decision Trees

Stopping Criterion:

- Growing the tree to the minimum impurity may cause **overfitting**.
- In the practice, there is a post-pruning of the tree to reduce overfitting.
- Occam's razor principle: prefer compact trees with few nodes.

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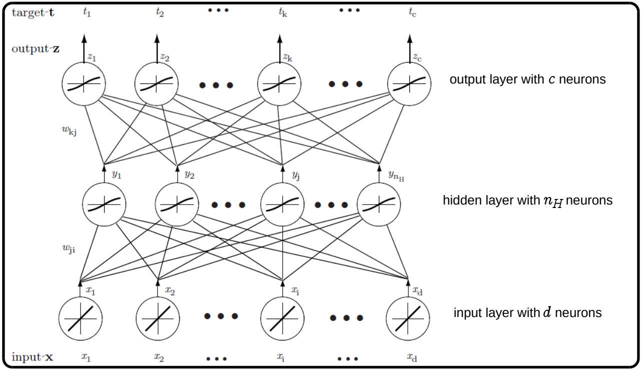
Properties of Decision Trees:

- Very easy to interpret, provide basic filtering rules.
- Very fast classification.
- It is simple to include domain knowledge from experts.
- Explicitly shows the importance of different features.

Multilayer Feed-forward Neural Networks

Neural networks provide a powerful model for classification and regression. We describe a particular model: **3-layers feed-forward neural network**:



c discriminant functions $g_k(\mathbf{x}) = f\left(\sum_{j=1}^{n_H} w_{kj}\, f\left(\sum_{i=1}^{d} w_{ji}\, x_i + w_{j0}\right) + w_{k0}\right)$

Multilayer Feed-forward Neural Networks

In this 3-layers model:

- Neurons in one layer connect to the next through **neural weights** w_{ji} .
- Each input neuron i just copies its input x_i at the output.
- The output of hidden neuron j is a non-linear function f applied to the weighted sum of input layer outputs.
- The output of output neuron k is a non-linear function f applied to the weighted sum of hidden layer outputs.

Multilayer Feed-forward Neural Networks

The neural network training (i.e., estimating the neural weights $\mathbf{w}$) is done from the set of training patterns, minimizing the squared estimation error:

$$J(\mathbf{w}) = \frac{1}{2}\sum_{k=1}^{c}\left(g_k(\mathbf{x}) - z_k(\mathbf{x})\right), \quad z_k(\mathbf{x}) \text{ is the ground truth output}$$

which is generally achieved by gradient descent. **Backpropagation** is the simplest method for doing this supervised learning of the weights $\mathbf{w}$.

NOTE: the number of input and output neurons is defined by the problem itself, but for n_H we are free to choose; n_H generally has an important influence on the performance of the network (i.e., overfitting, input/output mapping, etc).

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Universal approximation theorem:
Any continuous input/output function can be implemented in a 3-layer-ff-net, given sufficient number of hidden neurons, proper non-linearities, and weights.

Outline

1. What is Machine Learning (ML) and why ML in Networking?
2. General overview on Machine Learning techniques:
   - Supervised Learning
   - Unsupervised Learning
   - Semi-Supervised Learning
   - Ensemble Learning
3. Features Extraction and Features Selection
   - Feature Extraction
   - Feature Selection
4. Final Remarks: Overfitting and Learning Evaluation
5. Machine Learning in Networking:
   - PSQA: Neural Networks for QoE Assessment
   - Sub-Space Clustering for Self Network Defense

Unsupervised Learning

In **unsupervised learning**, the set of patterns for training has **no labels**.

This is the case in many (or most) real life applications, where labeling is a very expensive and difficult (sometimes even impossible) to achieve task.

Therefore, unsupervised learning is about **finding relevant structures in the data** (overlapping with data-mining).

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Standard approaches to unsupervised learning include:

- Parametric: mixture-resolving or identifying modals in data.
- Non-Parametric: find natural groupings or **clusters**.

So what is Clustering about?

The objective of clustering is to **divide a set of unlabeled patterns into homogeneous groups of similar characteristics**, based on some measure of similarity.

The Clustering Problem:

- Given a set of n d-dimensional **unlabeled patterns** $\mathbf{X} = \{\mathbf{x}_1, .., \mathbf{x}_n\}$
- and given some measure of **similarity** among these patterns,
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- Clustering is the first step when analyzing unknown data (i.e. unlabeled data).
- Clustering is a natural classification process: degree of similarity among forms.
- Clustering is about data exploration: discover underlying structure in the data, generate hypotheses, detect anomalies.
- **Cluster analysis is an exploratory tool**.

Clustering Algorithms

- Clustering analysis first appeared in the title of a paper analyzing anthropological data back in 1954.
- Today, we have hundreds of clustering algorithms to choose from.

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- **Hierarchical clustering**: produce multiple "nested" partitions in a hierarchical structure.

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A bit of history in Clustering developments:

1957 Hierarchical Clustering
1967 k-Means
1970 Mixture models
1971 Graph-theoretic methods
1973 Fuzzy Clustering (soft clustering)
1982 Self Organization Maps (based on ANN)
1992 Vector Quantization (density identification of High Dimensional data)
1996 Density-based Clustering (DBSCAN)
1998 Sub-Space Clustering (High Dimensional data)
2000 Spectral Clustering (dimensionality reduction)
2002 Ensemble Clustering (combine weak partitions)
2004 Semi-Supervised Clustering
... and the list goes on

The User's Dilemma

Clustering involves taking many decisions:

- What is a cluster?

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- **Which features to use?**
- How to define pair-wise similarity?
- **Which clustering algorithm?**
- How many clusters?
- Does the data has a clustering tendency/underlying structure?
- **Are the discovered clusters and partition valid?**

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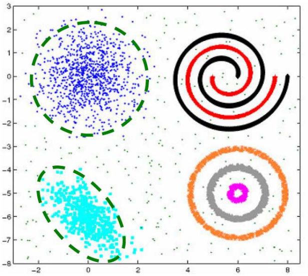

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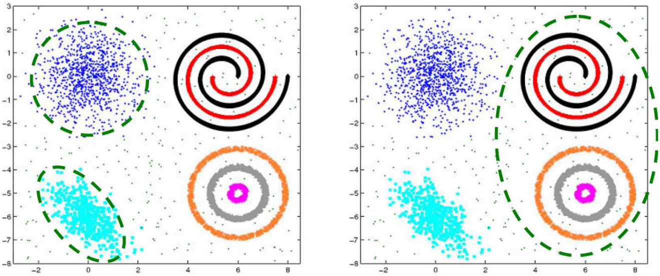

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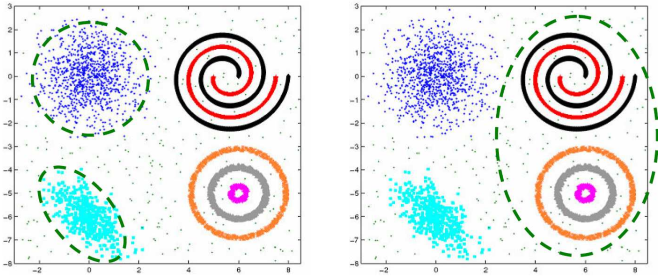

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- ...but cluster's definition depends on how we define similarity:
- **Compact clusters:** intra-cluster distance < inter-cluster distance
- **Connected clusters:** intra-cluster connectivity > inter-cluster connectivity
- Different algorithms use different notions of cluster $\longrightarrow$ they provide different identification results.
- Domain specific knowledge is useful in determining the most useful cluster shape.

Which Features to Use?

- A good representation leads to compact and isolated clusters.
- Using the **best** and **least** features is paramount in Clustering.
- **Feature Engineering if the key** in any machine learning algorithm.
- We talk about **Dimensionality Reduction**.

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And what for?

- Improving accuracy of the analysis.
- Reduce measurement costs.
- Create faster systems with less memory constraints.
- Simplify the interpretation of results.

Dimensionality Reduction

Naive approach: adding more features does not hurt, since at worst they provide no new information $\longrightarrow$ **WRONG!**

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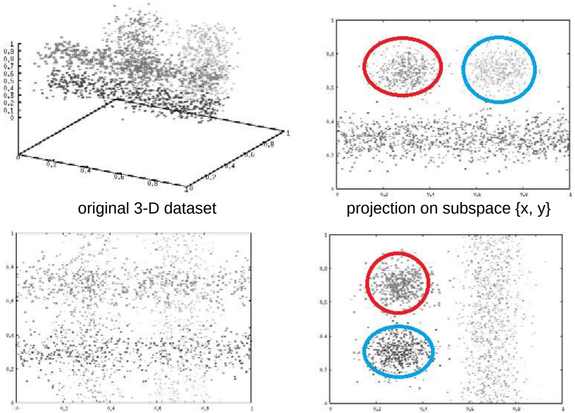

original 3-D dataset

projection on subspace {x, y}

projection on subspace {x, z}

projection on subspace {y, z}

- **Irrelevant features mask real clusters and complicates clustering.**

Feature Extraction and Feature Selection

- Patterns are generally located in low dimensional manifolds embeded in the input space. **How to find them?**

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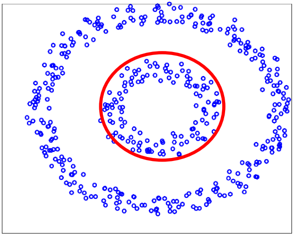
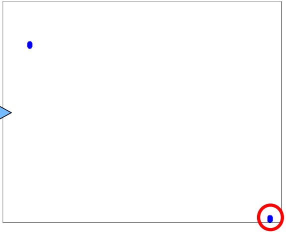
Feature extraction

- Transform the input space into a new space of smaller dimensions.
- Eliminating redundancy and extracting relevant information.
- New features may not have a clear physical meaning.



2D Space

$\mathcal{F}\{\cdot\}$



Representation based on eigenvectors of RBF kernel

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- Identify a sub-set of m out of the d original features.
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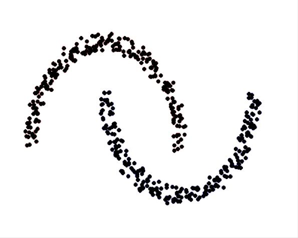
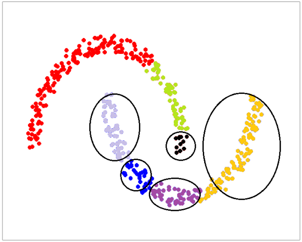
- Problem of feature extraction and selection in Clustering: **we do not have the ground truth**.
- The very nature of clustering means that in many cases, **we know little about the clusters to uncover**.

Which Algorithm?

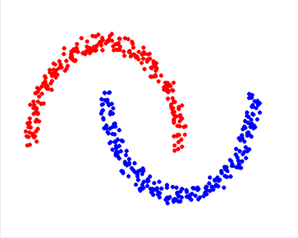
- Each algorithm imposes a structure on data.
- Good fit between model and data $\longrightarrow$ success.



2 Semi-Rings



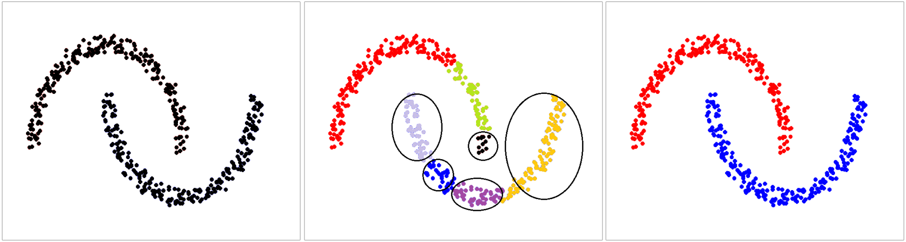
Spherical-based Clustering



Density-based Clustering

Which Algorithm?

- Each algorithm imposes a structure on data.
- Good fit between model and data $\longrightarrow$ success.

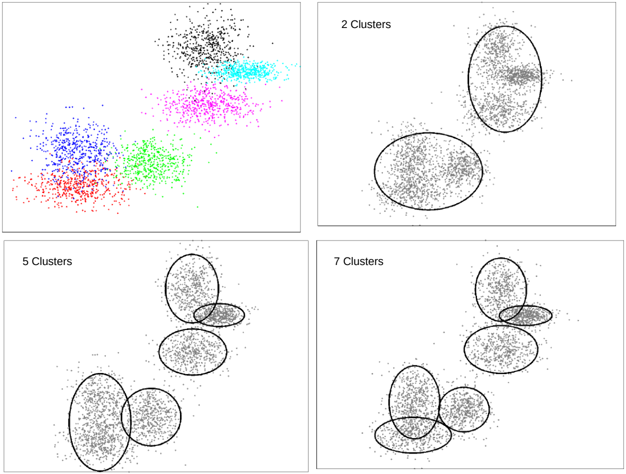


2 Semi-Rings | Spherical-based Clustering | Density-based Clustering

- There is no *silver bullet* in Clustering.

How Many Clusters?

- Some algorithms need the number of clusters as input.
- Difficult to know, requires knowledge on the structure of data.



The most well-known partitioning algorithm: k-means

The k-means algorithm separates the n patterns $p_j \in S$ in k clusters (predefined number), iteratively assigning p_j to the *closest cluster*.

The algorithm:

1. Select an initial random partition in k clusters.
2. Compute the centroids μ_i, $i = 1, \ldots, k$ of each cluster.
3. For each p_j, (re)assign it to the cluster which minimizes distance to μ_i.
4. Continue until no re-assignations are possible.

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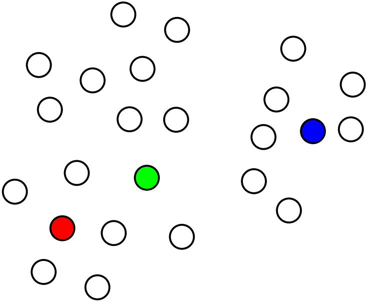

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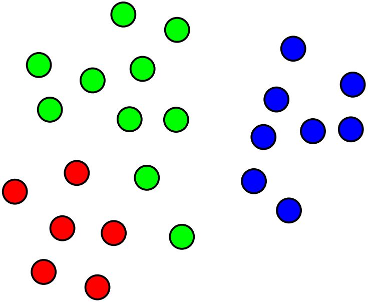

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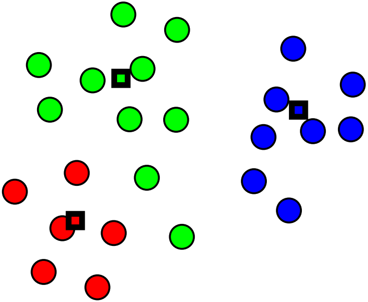

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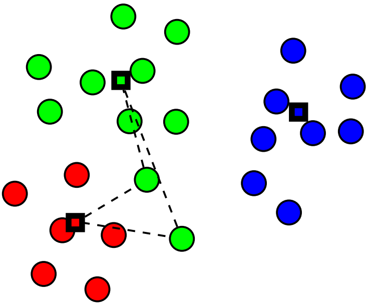

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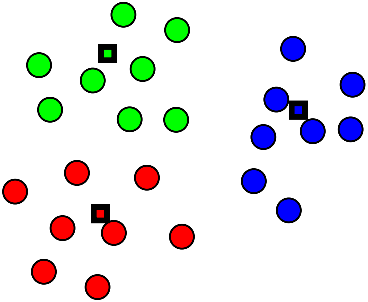


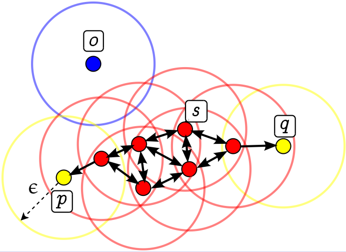
DBSCAN: a density-based notion of clusters

DBSCAN identifies clusters using a notion of density: clusters are high-density regions separated by low-density regions.

DBSCAN: a density-based notion of clusters

The notion of density in DBSCAN:

1. Two parameters: search distance ϵ and minimum cluster size m.
2. The ϵ-neighborhood of pattern p, $N_\epsilon(p)$ is the set of q_i closer than ϵ.
3. p is *directly density reachable* from q if $p \in N_\epsilon(q)$ and $\#N_\epsilon(q) > m$.
4. p is *density reachable* (dr) from q if there is a chain of inter-directly density reachable patterns between them.
5. p and q are *density connected* (dc) is there is s such that both p and q are (dr) from s.



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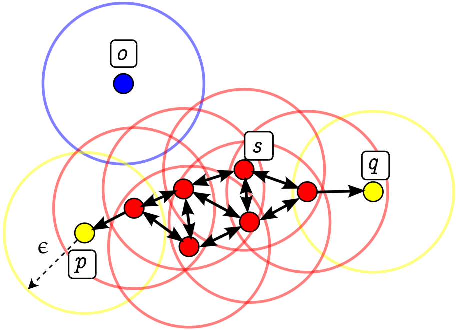

A DBSCAN cluster C_i is a sub-set of S satisfying the following conditions:

- $\forall\, p, q$: if $p \in C_i$ and q is dr from $p \rightarrow q \in C_i$.
- $\forall\, p, q \in C_i$, p and q are dc.
- Any pattern o_j not belonging to any cluster C_i is defined as *noise* (**outliers**).

k-means vs DBSCAN

Which is "better"?

- k-means is faster than DBSCAN (multiple implementations of both algorithms improve computational time).

k-means vs DBSCAN

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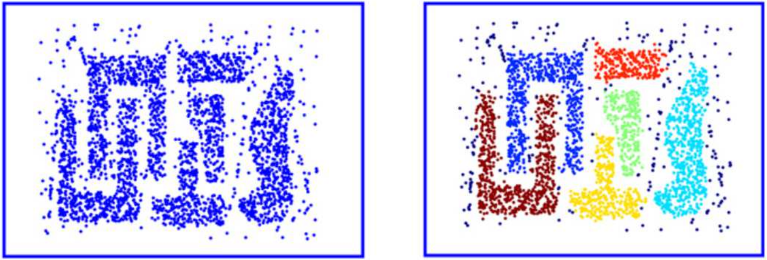
- k-means is faster than DBSCAN (multiple implementations of both algorithms improve computational time).
- k-means works well only for spherical-like clusters.
- DBSCAN finds clusters of arbitrary shapes and sizes.



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- DBSCAN is deterministic, k-means depends on the initial conditions.
- DBSCAN uses the notion of outliers (heuristics in k-means).

High Dimensional Data

- In multiple data analysis problems, we have to deal with **high dimensional** and **massive datasets**.

Clustering High Dimensional Data

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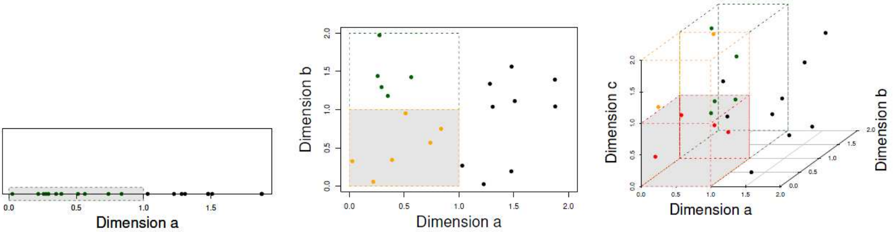
Clustering high dimensional data is challenging:

- Structure-masking by irrelevant features (i.e., noise).
- **The Curse of Dimensionality**

The Curse of Dimensionality

- The term was first coined by Bellman in 1961 to refer to multiple problems associated with high-dimensional data analysis.
- When **dimensionality increases**, the volume of the space increases so fast that the available **data becomes sparse**.



(a) 11 Objects in One Unit Bin (b) 6 Objects in One Unit Bin (c) 4 Objects in One Unit Bin

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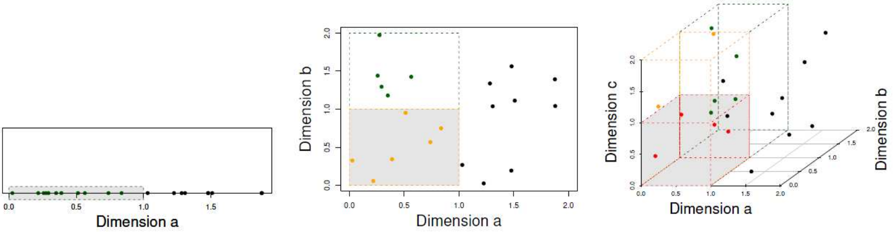

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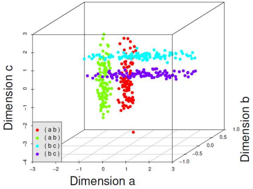
The notion of cluster in high-dimensional data vanishes:

- Inter-pattern **distance** becomes increasingly **meaningless**.
- Data becomes sparse and **patterns** tend to be **equidistant**.
- **Intuition fails in high dimensions**: the volume of an hyper-sphere is in the shell!

Subspace Clustering - A Graphical Example

The key to find clusters is to identify the correct subspaces:



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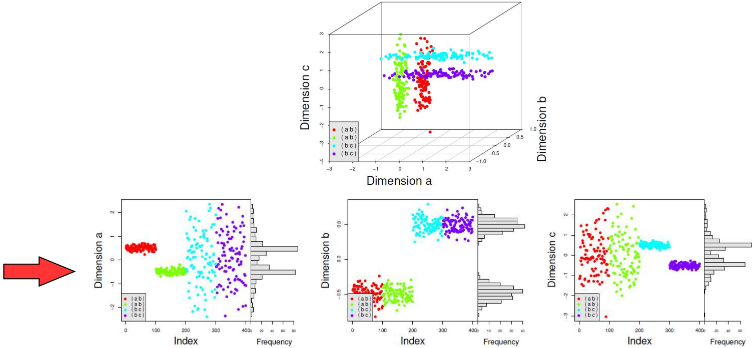

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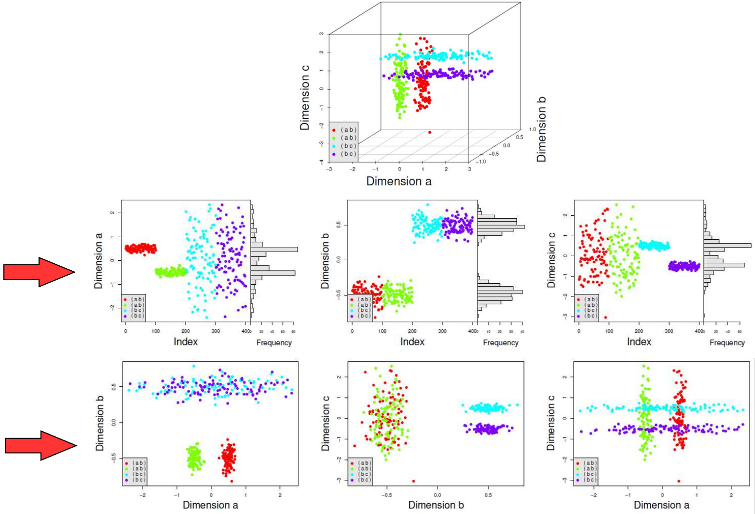

(a) Dims a & b (b) Dims b & c (c) Dims a & c

Subspace Clustering (SSC)

SSC: automatically find clusters in different subspaces

- SSC is an approach to do clustering in high-dimensional data.
- An **unsupervised** extension for **feature selection**.
- SSC algorithms **search for relevant dimensions**, finding clusters in multiple, possibly overlapping subspaces.
- SSC algorithms **find low-dimensional clusters in high-dimensional data**.
- SSC algorithms are distinguished by their **search strategy**.

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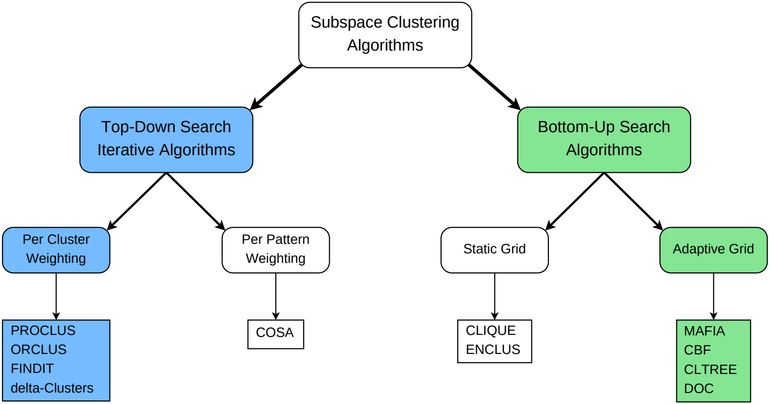
Two major branches of SSC algorithms:

- **Bottom-Up** search SSC algorithms
- Iterative **Top-Down** search SSC algorithms

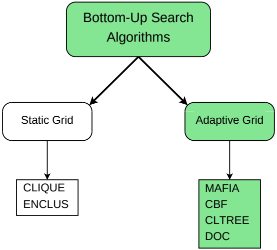
SSC Taxonomy

- **Search heuristics** are optimized for working in massive datasests.
- Different **measures of locality** to recognize clusters in subspaces.



Bottom-Up search SSC

Bottom-Up search



- **Downward closure property** to reduce the search space:

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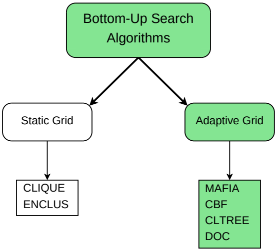

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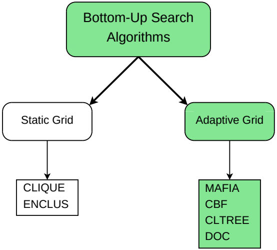

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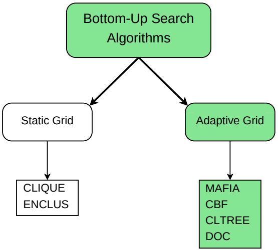

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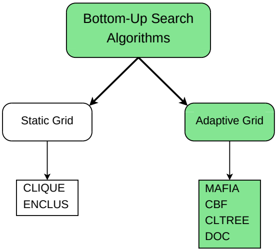

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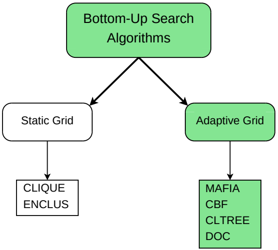

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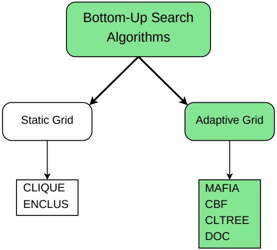

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- Different **heuristics to combine and prune dense regions** and form clusters.

Bottom-Up search SSC

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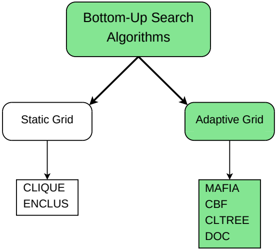
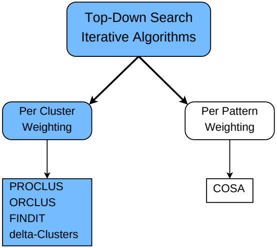


Some observations:

- Bottom-Up algorithms leads to **overlapping clusters**.
- **Grids** can be of **fixed** or **dinamic**, data-based **size**.
- Clusters can be of **arbitrary shape** and size.
- **No need** to specify the **number of clusters** to identify.

Iterative Top-Down search SSC

Iterative Top-Down search



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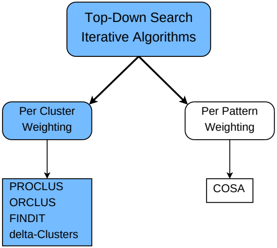

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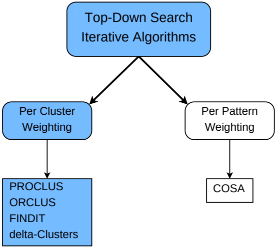

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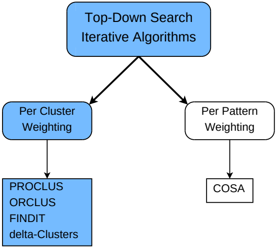

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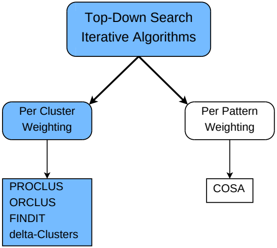

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- **Pruning:** clusters are refined by **selecting the top-weighted dimensions**.
- Different **stopping conditions**, but relative to the **stability of the obtained results** (i.e., no more changes between iterations)

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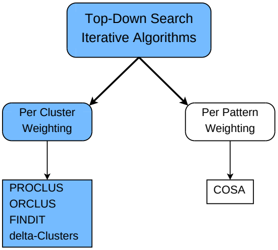
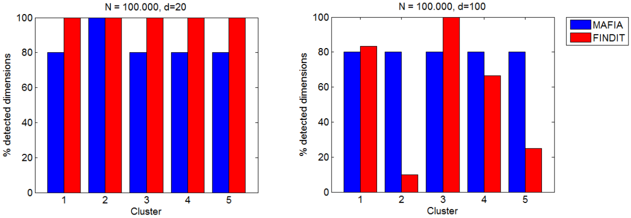


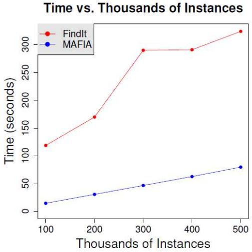
Some observations:

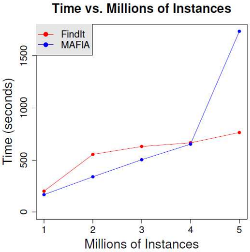
- Top-Down algorithms require to specify the **number of clusters**.
- Tend to **find spherical clusters** in the same or **similar** sized **subspaces**.
- **Sampling** is fundamental to **scale-up** in massive datasets.

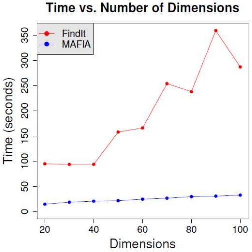
Which SSC Approach to Use?

- Low-dimensional clusters ($k = 2, ..., 7$) embeded in d-dimensional data.
- Evaluate the number of correctly detected dimensions when d increase.
- Evaluate computational time when N = n^{o} patterns and d increase.









Outline

1. What is Machine Learning (ML) and why ML in Networking?
2. General overview on Machine Learning techniques:
   - Supervised Learning
   - Unsupervised Learning
   - Semi-Supervised Learning
   - Ensemble Learning
3. Features Extraction and Features Selection
   - Feature Extraction
   - Feature Selection
4. Final Remarks: Overfitting and Learning Evaluation
5. Machine Learning in Networking:
   - PSQA: Neural Networks for QoE Assessment
   - Sub-Space Clustering for Self Network Defense

Semi-Supervised Learning: between Supervised and Unsupervised

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- Some applications may provide little information for training issues, but still we would like to use it to improve the analysis.

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In **semi-supervised learning**, we combine a small amount of labeled data with a large amount of unlabeled data for training.

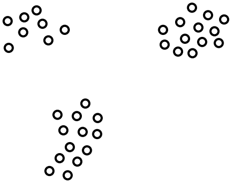
When used in conjunction with a small amount of labeled data, and **under certain assumptions**, unlabeled data can produce considerable improvement in the learning accuracy!

The semi-supervised literature is extensive and there is a whole spectrum of interesting ideas on how to learn from combining labeled and unlabeled data.

Semi-Supervised Learning: between Supervised and Unsupervised

A very intuitive and basic example: build a classifier using clustering and a maximum-likelihood labeling with a small set of labeled flows:

- We first cluster a set of unlabeled patterns.



A very intuitive and basic example: build a classifier using clustering and a maximum-likelihood labeling with a small set of labeled flows:

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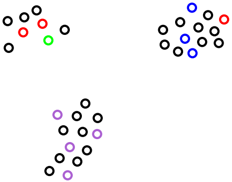

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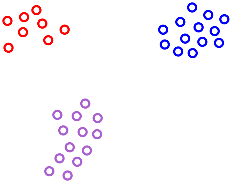

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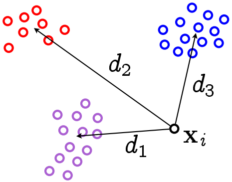

- Then we consider the labels of a small fraction λ of patterns.
- Maximum-Likelihood Labeling: label each cluster with the most present label among the λ patterns.
- Classify an unknown pattern $\mathbf{y}_i$ based on its distance to the centroid of each cluster $\mathbf{o}_k$:

$$l_i = \text{label}\left(\arg\min_k d(\mathbf{x}_i, \mathbf{o}_k)\right)$$

Outline

1. What is Machine Learning (ML) and why ML in Networking?
2. General overview on Machine Learning techniques:
   - Supervised Learning
   - Unsupervised Learning
   - Semi-Supervised Learning
   - Ensemble Learning
3. Features Extraction and Features Selection
   - Feature Extraction
   - Feature Selection
4. Final Remarks: Overfitting and Learning Evaluation
5. Machine Learning in Networking:
   - PSQA: Neural Networks for QoE Assessment
   - Sub-Space Clustering for Self Network Defense

Ensemble Learning: Combining Multiple Algorithms

Union and diversity provide strength - combining multiple (independent) learnings can be useful in many situations:

- Use different algorithms on the same data to improve performance through diversity.
- Different descriptions of the same problem with different kinds of data (i.e., identify botnets by analyzing flow descriptors, geographical data, dns-based features, etc.).
- Multiple training sets available, collected at different time and different environment (i.e., build a flow classifier with traffic from different ISPs).
- Use the same algorithm with different parametrizations and/or initial conditions (multiple attempts to learn).

Ensemble Learning: Combining Multiple Algorithms

Union and diversity provide strength - combining multiple (independent) learnings can be useful in many situations:

A typical combination scheme consists of an ensemble of individual algorithms and a combiner which merges the results of the individual approaches.

Architecture of combining schemes:

- Parallel combination - individual algorithms are used independently.
- Serial combination - from simple to more complex algorithms.
- Hierarchical combination - refined algorithms for particular data characteristics.

A very large number of ensemble approaches are proposed in the literature.

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Dimensionality Reduction

Using the best and the least features to describe a learning problem is extremely important in Machine Learning. In the feature space terminology, we talk about **Dimensionality Reduction**. And what for?

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Using the best and the least features to describe a learning problem is extremely important in Machine Learning. In the feature space terminology, we talk about **Dimensionality Reduction**. And what for?

- $\boxed{\text{Improving accuracy of the analysis.}}$
- Reduce measurement costs.
- Create faster systems with less memory constraints.
- Simplify the interpretation of results.

Dimensionality Reduction

Reducing the number of features may lead to a loss in discrimination power, so why performance would degrade when using more features?

- In clustering: working in higher dimensions makes feature spaces become sparser, blurring the notions of similarity.
- In supervised learning: tradeoff between number of features, size of the training set, and algorithm complexity (degrees of freedom).

The Curse of Dimensionality: as the number of features increases, the training set has to increase exponentially to avoid degradations. The more complex the algorithm, the worse it gets.

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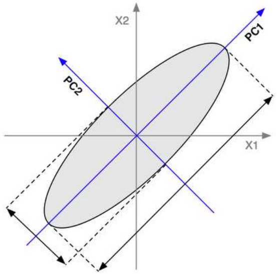
Feature Extraction

Feature extraction uses a (non)-linear transformation of the feature space into a new space of smaller dimensions, eliminating redundancy and extracting particular information. New features may not have a clear physical meaning.

- Principal Components Analysis (PCA) - standard linear mapping: simple rotation of axes to capture the most of the “energy” of the data.



Other approaches: ICA (linear, assumes independence of sources), kernel PCA (non-linear), SOM (non-linear, based on grids of neurons), etc.

Outline

Feature Selection

Feature selection identifies a sub-set of m out of the d original features, optimizing some performance criterion.

Feature selection consists in two tasks:

- Defining the evaluation criterion used to assess the quality of a sub-set.
- Defining the search strategy to look for the candidate sub-set (heuristic-based search, using graph exploration; optimal exhaustive search is prohibitive!).

Three different approaches for Feature Selection (FS):

- Filter FS: the evaluation criterion is independent of the ML algorithm.
- Wrapper FS: the evaluation criterion is the performance of a certain ML algorithm (i.e., depends o the ML algorithm to be used).
- Embedded FS: the feature selection is part of the ML algorithm itself (e.g., decision trees,).

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An example of heuristic-search and filter FS:

- Evaluation criterion - Correlation-based FS (CFS): selects sub-sets with small inter-pattern correlation but highly correlated with the classes.
- Search strategy - Best First search (BF): explores a tree-like graph of features, adding or removing features to improve the criterion; BF permits backtracking to avoid local minima.

Note: “FS can also be done” in clustering $\longrightarrow$ Sub-Space Clustering.

Outline

Some Practical Concepts in Machine Learning

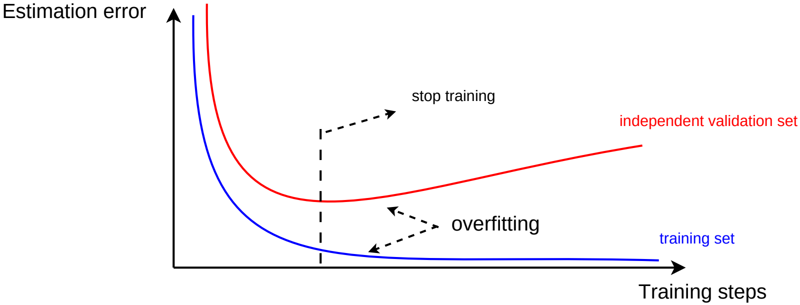
A usual problem in learning is **overfitting**: “learn to remember the training patterns but fail to predict for unseen ones”.

Why overfitting occurs?

- The training set is small w.r.t. the number of parameters to estimate (excessively complex models).
- The number of features is big w.r.t. the size of the training set (curse of dimensionality).
- The training procedure is not stopped at the right moment (“learn” the training set).

Avoiding overfitting

- **Early stopping**: stop the training when the algorithm stops learning the underlying model.
- Train in a sub-set of the training set S, evaluate the predictive expression with the rest of the patterns.



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- k**-fold cross validation**: split the training set in k separated sub-sets.
- Learn from $k-1$ sub-sets, evaluate in the remaining set.
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Rule of thumb: use at least 10 times as many training patterns per class n_i as the number of features d:

$$n_i/d > 10$$

The more complex the machine learning model, the larger this ratio should be.

Evaluation of a Machine Learning algorithm

The evaluation of a machine learning algorithm depends on the particular learning approach and on the specific application:

- **Classification**: true positives, false positives, global accuracy, recall, precision, ROC curves.
- **Regression**: estimation/prediction error.
- **Clustering**: cluster homogeneity, number of clusters, outliers analysis.

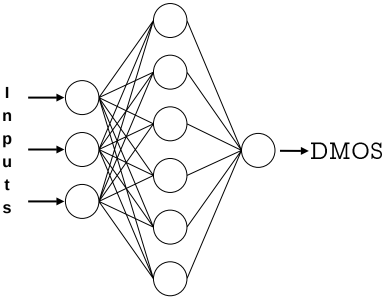
- Always **favor proper and focused evaluations** (less is more).
- **Don't forget sensitivity analysis**: it is easy to find particular cases, but if you want to get useful results, provide robust analysis.

Outline

Outline

PSQA: Neural Networks for QoE Assessment

The **Pseudo-Subjective Quality Assessment** approach (Gerardo Rubino, INRIA/IRISA, France) relies on Neural Networks (NN) to build an estimation model for QoE in multimedia services:

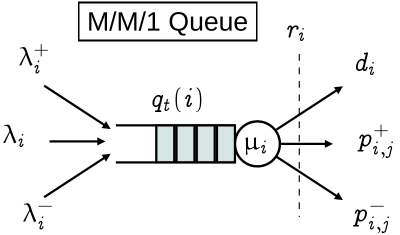


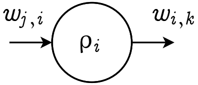
- PSQA uses a particular NN model: Random Neural Networks (RNN).
- Inputs: QoS network features $\{x_n\}$ and sequence characteristics $\{y_m\}$.
- Training step, using subjective tests and inputs $(\{x_i\}, \{y_i\}, \mathrm{DMOS})$.

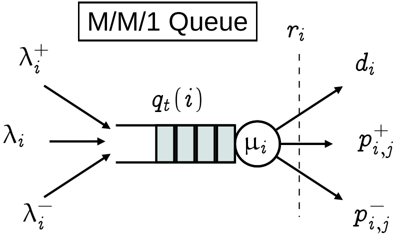
PSQA mapping function:

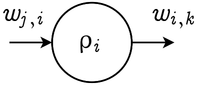
$$\boxed{\mathrm{DMOS} = \mathcal{F}\left(\{x_1, ., x_n\}, \{y_1, ., y_m\}\right)}$$

The Random Neuron Model









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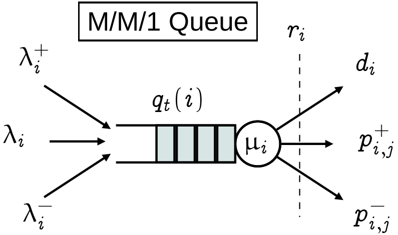

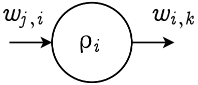

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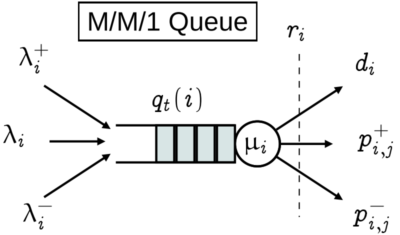

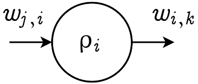

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$$\rho_i \quad = \quad \frac{\lambda_i}{\mu_i}$$

$$\lambda_i \quad = \quad \lambda_i^+ + \sum_{j=1}^{N} \rho_j \, r_j \, p_{j,i}^+$$

$$\mu_i \quad = \quad r_i + \lambda_i^- + \sum_{j=1}^{N} \rho_j \, r_j \, p_{j,i}^-$$

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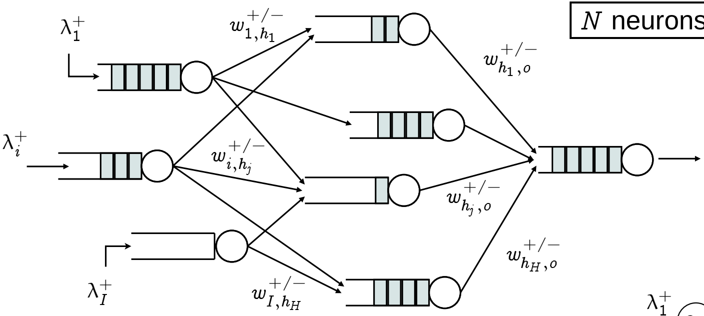
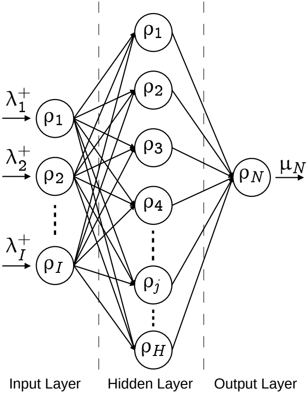


N neurons

$$
\begin{aligned}
\lambda_i^- &= 0,\ \forall i \\
w_{i,j}^+ &= r_i p_{i,j}^+ \\
w_{i,j}^- &= r_i p_{i,j}^-
\end{aligned}
$$

$2H(I+1)$ weights to calibrate
gradient descent



Using the RNN for QoE Estimation

3-layer Feed Forward RNN Model:

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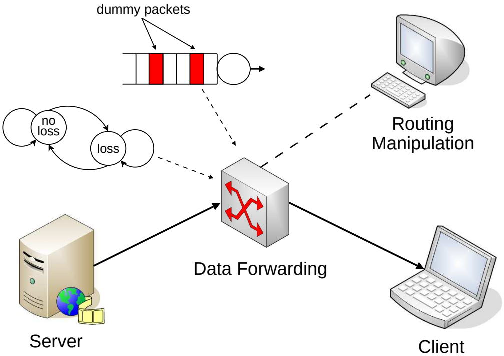
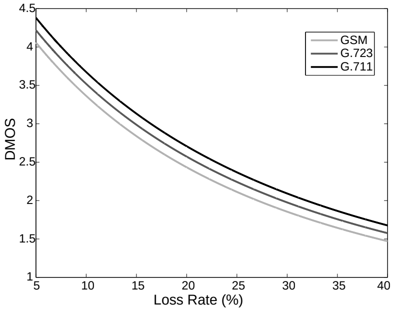
Evaluation Testbed



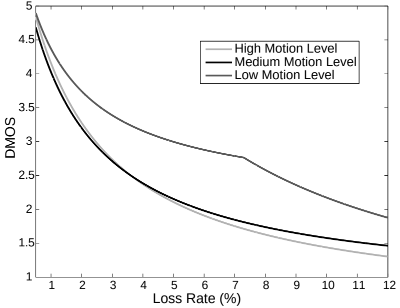
- Intermediate router generates losses and jitter (simple Bernoulli loss model, losses in bursts).
- Short video and audio sequences transmitted from the endpoints.
- Complete Dataset for audio and video, after subjective tests.

QoE analysis through PSQA

DMOS vs loss rate (Mean Loss Burst Length = 5 packets).



(a) Audio Codecs (G.711, G.723, GSM-LPC)

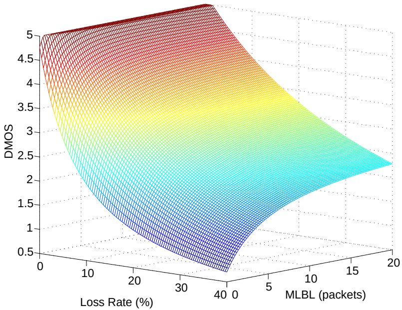


(b) Different video motion levels

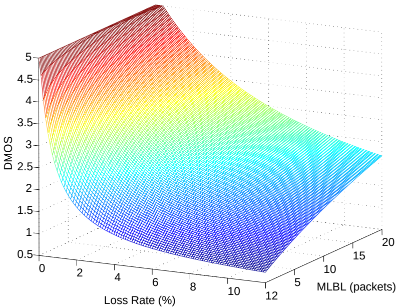
- Audio results are as expected, less impacted by losses than video.
- Video motion level may impact QoE.

QoE analysis through PSQA

$\mathtt{DMOS}$ vs loss rate and mean loss burst length.



(a) Audio Evaluation (G.711 coding)



(b) Video Evaluation (MPEG4 coding)

- QoE in audio is less sensitive to losses than in video (visual system is more developed than the auditory system).
- For the same loss rate, QoE increases with the Mean Loss Burst Length (we prefer concentrated to spread losses).

Outline

Unsupervised NIDS based on Clustering Analysis

We propose a NIDS based on clustering analysis and outliers detection.

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- $(+)$ highly effective to detect what it is programmed to alert on.
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Anomaly detection: detect what DIFFERS from WHAT I KNOW

- $(+)$ it can detect new attacks out-of a baseline profile.
- $(-)$ requires some kind of training for profiling.
- $(-)$ robust and adaptive models are difficult to conceive, specially in an evolving context.

Unsupervised Detection of Network Attacks

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- HYPOTHESIS: attacking flows are sparse and different from normal traffic....in some representation (traffic aggregation)!!

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Clustering for Unsupervised Detection is CHALLENGING

- lack of robustness: general clustering algorithms are sensitive to initialization, specification of number of clusters, etc.
- difficult to cluster high-dimensional data: structure-masking by irrelevant features, sparse spaces ("the curse of dimensionality").

UNADA: Unsupervised Detection of Network Attacks

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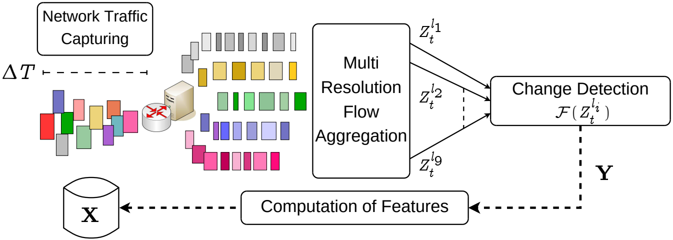

(1) Multi-resolution change-detection & features computation.

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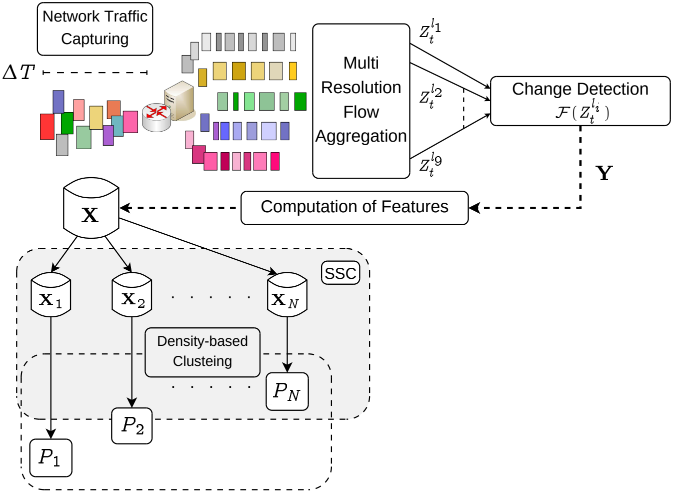

(2) Sub-Space Clustering.

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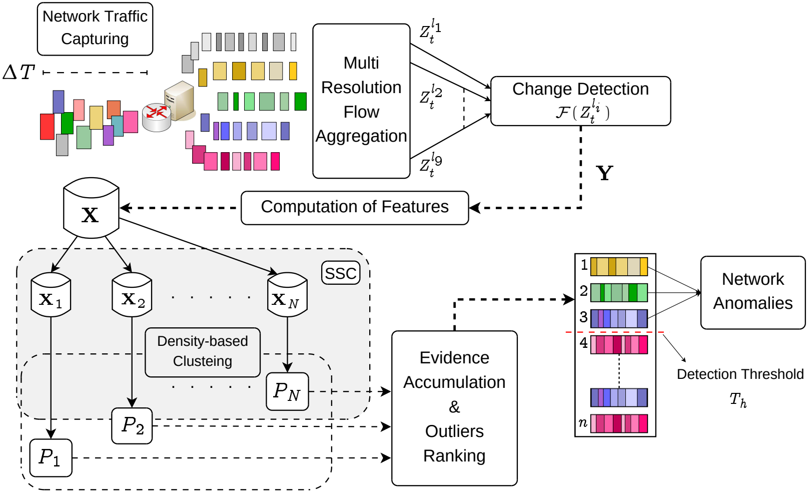

(3) Evidence Accumulation and Flow Ranking.

Change-detection in Multi-resolution Traffic Flows

Traffic Aggregation and Change-Detection

- Traffic is captured and aggregated in IP flows (5-tuples) every ΔT seconds, using a temporal sliding-window.

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- Scan in both directions (IPsrc and IPdst) permits to detect $1\text{-}\mathrm{to}\text{-}1$, $1\text{-}\mathrm{to}\text{-}N$, and $N\text{-}\mathrm{to}\text{-}1$ attacks of different intensities.

Clustering for Anomaly Detection

- Let $\mathbf{Y} = \{\mathbf{y}_1, \ldots, \mathbf{y}_n\}$ be the set of n macro-flows in the flagged time slot, aggregated at $\mathrm{IP}/32$.

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- Each macro-flow $\mathbf{y}_i \in \mathbf{Y}$ is described by a set of m traffic features: $\mathbf{x}_i = (x_i(1), .., x_i(m)) \in \mathbb{R}^m$.

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- Each macro-flow $\mathbf{y}_i \in \mathbf{Y}$ is described by a set of m traffic features: $\mathbf{x}_i = (x_i(1), .., x_i(m)) \in \mathbb{R}^m$.
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- $\mathbf{X} = \{\mathbf{x}_1, .., \mathbf{x}_n\}$ is the complete matrix of features, referred to as the *feature space*.

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$\mathbf{X}$ is a black box

How to detect an anomalous macro-flow in $\mathbf{X}$ via clustering?

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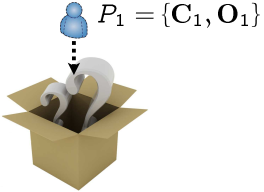

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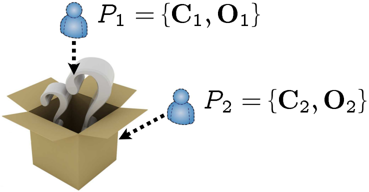

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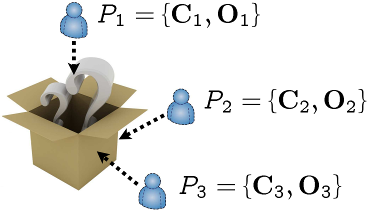

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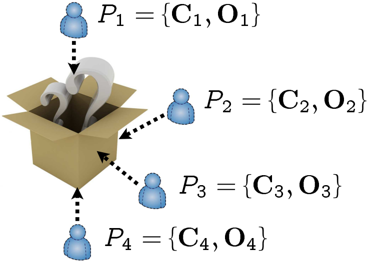

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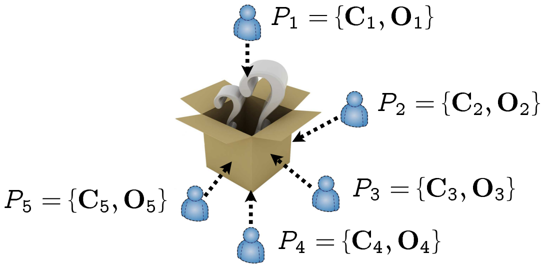

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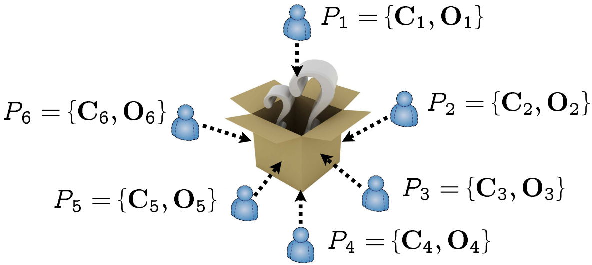

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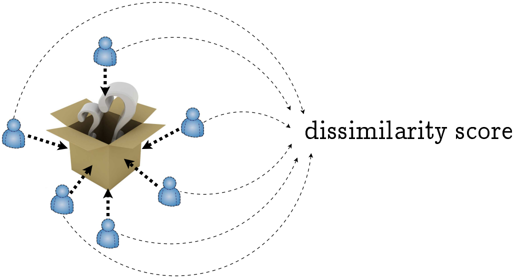

Evidence Accumulation for Outliers Ranking

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- Build a new dissimilarity measure $D = \{d_1, d_2, \ldots, d_n\}$: d_i measures how different is flow i from the majority of the traffic.

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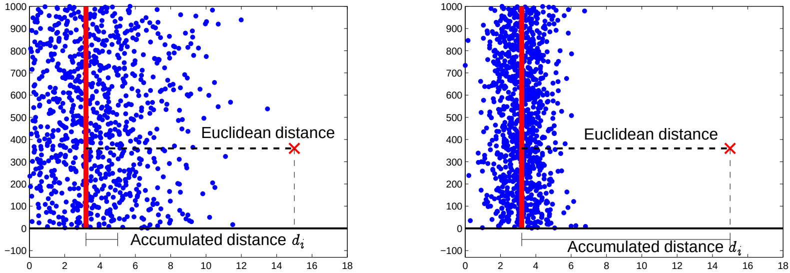

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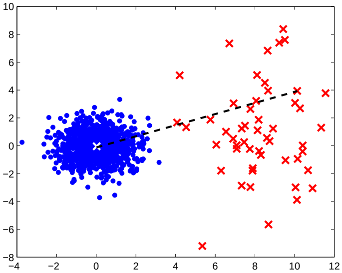

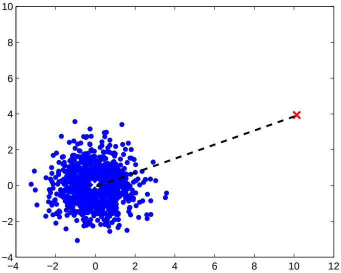

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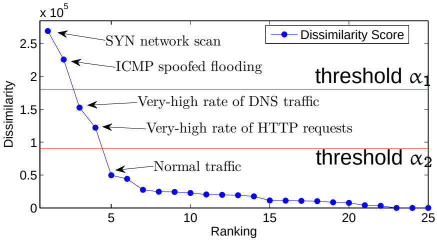

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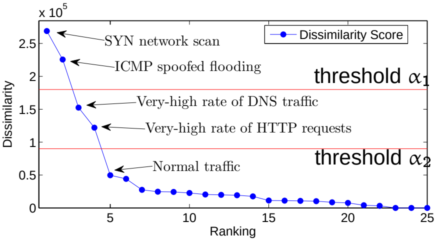

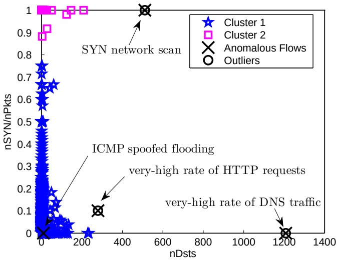

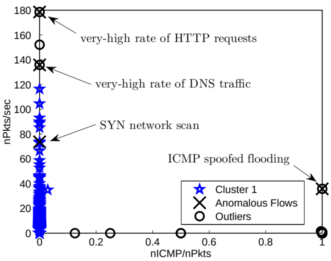

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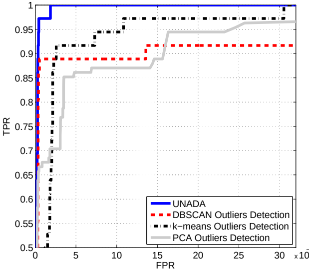
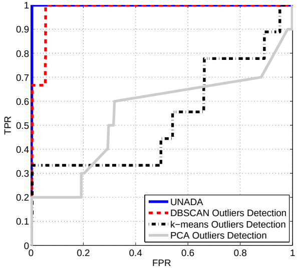


(a) MAWI, IPsrc key.



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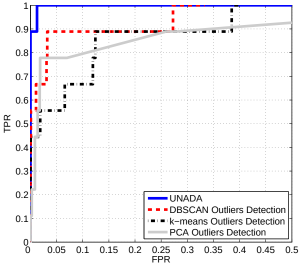

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Detectiong Attacks in KDD99

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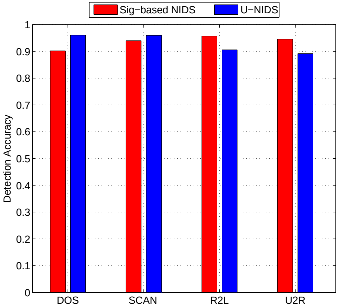

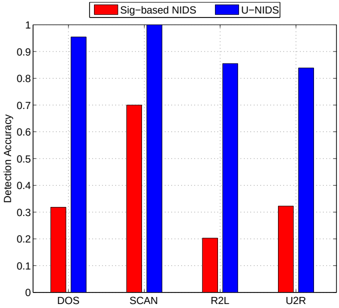

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Thank You for Your Attention!!

Remarks & Questions?