

# Machine Learning and Extremes for Anomaly Detection

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**'Finding patterns in the data that do not conform to expected behavior'**



Huge number of applications: Network intrusions, credit card fraud detection, insurance, finance, military surveillance,...

## Different kinds of Anomaly Detection

- ▶ **Supervised AD** (not dealt with)  
Labels available for both normal data and anomalies  
(similar to rare class mining)
- ▶ **Novelty Detection** (our theoretical framework)  
The algorithm learns on normal data only
- ▶ **Outlier Detection** (extended application framework)  
Training set (unlabeled) = normal + abnormal data  
(assumption: anomalies are very rare)

- ▶ **Statistical AD techniques**

[Hawkins 1980, Liu and Weng 1991, Eskin 2000, Agarwal 2006]

- ▶ **K-nearest neighbors**

[Breunig *et al.* 2000, Tang *et al.* 2002, Papadimitriou *et al.* 2002, Hautamaki *et al.* 2004]

- ▶ **Support estimation**

[Einmahl and Mason 92, Polonik 97, Schölkopf *et al.* 2000, Vert and Vert 2006, Scott and Nowak 2006]

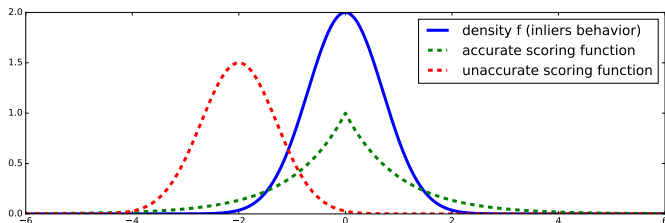
- ▶ **High-dimensional techniques**

[Aggarwal and Yu 2001, Shyu *et al.* 2003, Shi and Horvath 2012, Liu *et al.* 2008]

AD algorithm returns a **scoring function**  $s : \mathbb{R}^d \rightarrow \mathbb{R}$

- ▶  $s$  defines a **pre-order** on  $\mathbb{R}^d$  = 'degree of normality'.
- ▶  $s$  level sets are estimates of  $f$  level sets.
- ▶  $s$  can be interpreted as a **continuum of level sets estimates** (at different levels).

**Remark.** Ideal scoring functions:  $s = T \circ f$  any increasing transform of  $f$ .



Part I: Performance criterion for scoring functions

Part II: Learning accurate scoring functions on extreme regions

Part III: Heuristic contributions and perspectives

Part I: Performance criterion for scoring functions

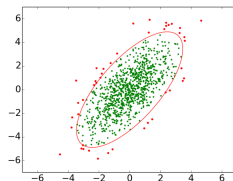
Part II: Learning accurate scoring functions on extreme regions

Part III: Heuristic contributions and perspectives

# Existing criterion: Mass-Volume curve

**Minimum volume set** [Einmahl and Mason 1992, Polonik 1997]

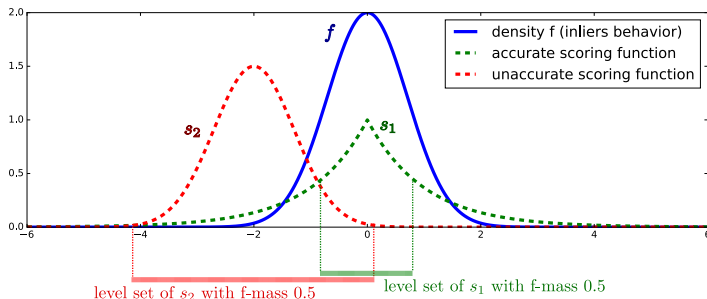
$$\Gamma_{\alpha}^* = \arg \min_{\Gamma \text{ borelian}} \text{Leb}(\Gamma) \quad \text{s.t.} \quad \mathbb{P}(\mathbf{X} \in \Gamma) \geq \alpha$$



**Mass Volume curve** of a scoring function  $s$  [Cl  men  on and Jakubowicz, 2013]:

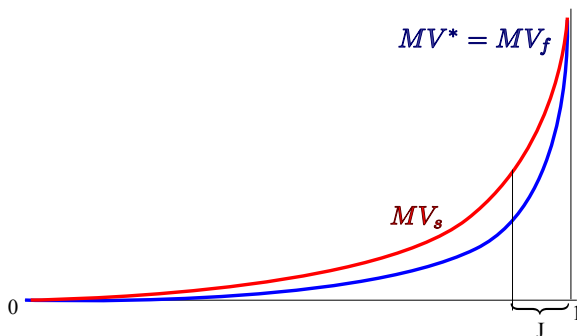
$$MV_s(\alpha) := \inf_{\Gamma \text{ level-set of } s} \{ \text{Leb}(\Gamma) \quad \text{s.t.} \quad \mathbb{P}(\mathbf{X} \in \Gamma) \geq \alpha \}$$

$$MV^*(\alpha) := \min_{\Gamma \text{ borelian}} \{ \text{Leb}(\Gamma) \quad \text{s.t.} \quad \mathbb{P}(\mathbf{X} \in \Gamma) \geq \alpha \} \stackrel{\text{prop}}{=} MV_f(\alpha)$$





## Existing criterion: Mass-Volume curve



Main drawbacks of MV:

- ▶ When optimized *w.r.t.* different levels  $\alpha$  over a finite class, produces **not necessarily nested** empirical level sets.
- ▶  $\rightarrow$  **low convergence rates** – of order  $O(n^{-1/4})$ .
- ▶ MV **diverges** in 1 in case of unbounded support.

# Our solution: Excess-Mass curve

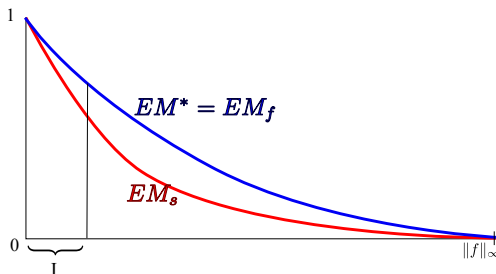
Excess-Mass curve [G., Sabourin, Cléménçon 2015]

$$EM_s(t) := \sup_{\Omega \text{ level-set of } s} \{ \mathbb{P}(\mathbf{X} \in \Omega) - t \text{Leb}(\Omega) \}$$

$$EM^*(t) := \max_{\Omega \text{ borelian}} \{ \mathbb{P}(\mathbf{X} \in \Omega) - t \text{Leb}(\Omega) \} \stackrel{\text{prop}}{=} EM_f(t)$$

Property: Previous drawbacks are fixed with EM.

- ▶ Produces **nested** empirical level sets.
- ▶  $\rightarrow$  **convergence rates** of order  $O(n^{-1/2})$ .
- ▶ EM curve **finite** even in case of unbounded support.



# Learning a scoring function with M-estimation

We are looking for nearly optimal scoring functions of the form

$$s(x) = \sum_{j=1}^N a_j \mathbb{1}_{x \in \Omega_j}, \text{ with } a_j \geq 0, \Omega_j \in \mathcal{G} \text{ a VC-class.}$$

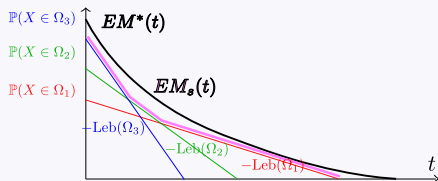
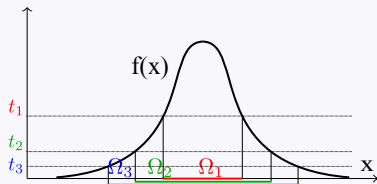
**Procedure:** Fix  $t_0 > 0$

For  $k = 1, \dots, N$ ,

$$t_{k+1} = \frac{t_k}{\left(1 + \frac{1}{\sqrt{n}}\right)}$$

$$\hat{\Omega}_{t_{k+1}} = \arg \max_{\Omega \in \mathcal{G}, \hat{\Omega}_{t_k} \subset \Omega} \mathbb{P}_n(X \in \Omega) - t_{k+1} \text{Leb}(\Omega)$$

$$s_N(x) := \sum_{j=1}^N (t_j - t_{j+1}) \mathbb{1}_{x \in \Omega_j}$$

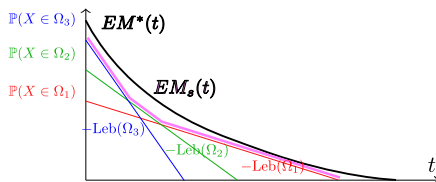
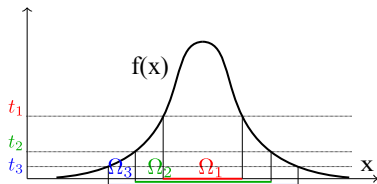


# Learning a scoring function with M-estimation

**Theorem** [G., Sabourin, Cl  men  on 2015]

Assume the density  $f$  bounded, with compact support and without flat parts and  $\mathcal{G}$  VC-class. Then if  $t_N = \mathcal{O}(n^{-1/2})$ , with probability at least  $1 - \delta$ ,

$$\sup_{t \in ]0, t_1]} |EM^*(t) - EM_{s_N}(t)| \leq \left[ A + \sqrt{2 \log(1/\delta)} \right] \frac{1}{\sqrt{n}} + \text{bias}(\mathcal{G}).$$



Part I: Performance criterion for scoring functions

Part II: Learning accurate scoring functions on extreme regions

Part III: Heuristic contributions and perspectives

## General ideas:

- ▶ Extreme observations play a special role when dealing with outlying data.
- ▶ But no anomaly detection algorithm has **specific treatment for such multivariate extreme observations**. Univariate EVT: [Roberts 99, Lee and Roberts 2008, Clifton *et al.* 2011]
- ▶ Our goal:
  - ▶ Define a notion of sparsity for extremes observations.
  - ▶ Provide a method which can improve performance of standard AD algorithms by combining them with a **multivariate extreme analysis** of the **dependence structure**, using this notion of sparsity.

$$\mathbf{X} = (X_1, \dots, X_d)$$

Goal: find the groups of features which can be large together

ex:  $\{X_1, X_2\}$ ,  $\{X_1, X_3, X_4\}$ ,  $\{X_5\}$

Namely: characterize the extreme dependence structure

→ Anomalies = points which violate this structure

- ▶ **Context**

- ▶ Random vector  $\mathbf{X} = (X_1, \dots, X_d)$
- ▶ Margins:  $X_j \sim F_j$  ( $F_j$  continuous)

- ▶ **Preliminary step: Standardization of each marginal**

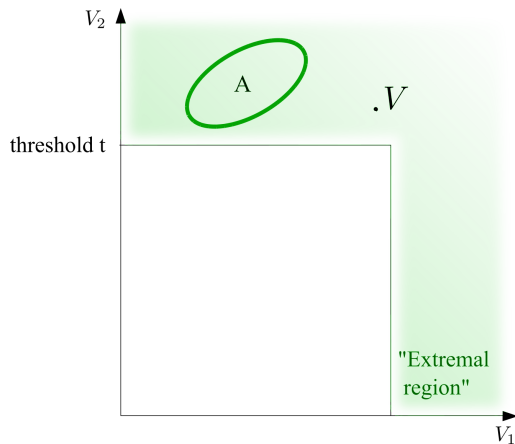
- ▶ Standard Pareto:  $V_j = \frac{1}{1-F_j(X_j)}$  ( $\mathbb{P}(V_j \geq x) = \frac{1}{x}, \quad x \geq 1$ )



# Problematic of Extreme Value Theory

Describe  $\mathbf{V}$ 's distribution, when  $\mathbf{V}$  exceeds some large threshold.

$$\mathbb{P}(\mathbf{V} \in A) = ? \quad (A \text{ 'far from the origin'}).$$



# Fundamental hypothesis and consequences

- ▶ Standard assumption: let  $A$  extreme region,

$$\mathbb{P}[\mathbf{V} \in tA] \simeq t^{-1} \mathbb{P}[\mathbf{V} \in A] \quad (\text{radial homogeneity})$$

- ▶ Formally:

**regular variation** (after standardization):

$$\text{If } 0 \notin \bar{A}, \quad t\mathbb{P}[\mathbf{V} \in tA] \xrightarrow[t \rightarrow \infty]{} \mu(A).$$

$\mu$ : exponent measure

Necessarily:  $\mu(tA) = t^{-1}\mu(A)$

- ▶  $\Rightarrow$  **angular measure** on sphere  $\mathbf{S}_{d-1}$ :  $\Phi(B) = \mu\{tB, t \geq 1\}$

$\mathbb{P}[\mathbf{V} \in A] \simeq \mu(A)$ , if  $A$  extreme region.

## Model for excesses

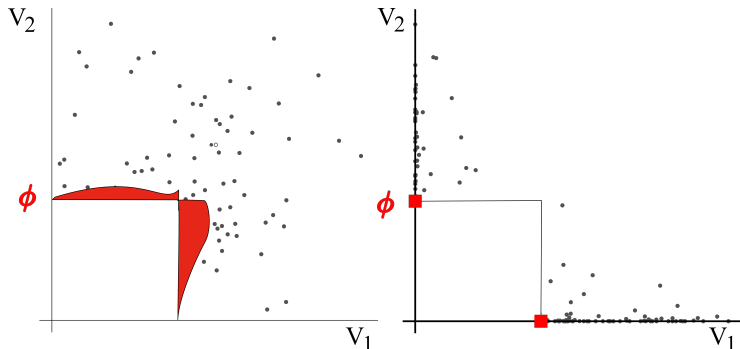
For a large  $r > 0$  and a region  $B$  on the unit sphere:

$$\mathbb{P} \left[ \|\mathbf{V}\| > r, \frac{\mathbf{V}}{\|\mathbf{V}\|} \in B \right] \underset{r \rightarrow \infty}{\sim} \frac{1}{r} \Phi(B) = \mu(\{tB, t \geq r\})$$

$\Rightarrow \Phi$  (or  $\mu$ ) **rules the joint distribution of extremes** (if margins are known).

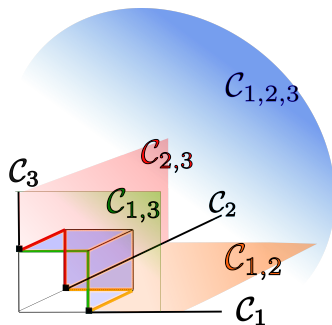
# Angular distribution

$\Phi$  rules the joint distribution of extremes:



Asymptotic dependence:  
( $V_1$ ,  $V_2$ ) may be large together.

Asymptotic independence:  
Only  $V_1$  or  $V_2$  may be large.



- ▶ Sub-cones:  $\mathcal{C}_\alpha = \{\|v\| \geq 1, v_j > 0 (j \in \alpha), v_j = 0 (j \notin \alpha)\}$
- ▶ Corresponding sub-spheres:  $\{\Omega_\alpha, \alpha \subset \{1, \dots, d\}\}$  ( $\Omega_\alpha = \mathcal{C}_\alpha \cap \mathbf{S}_{d-1}$ )

- ▶ Natural decomposition of the angular measure :

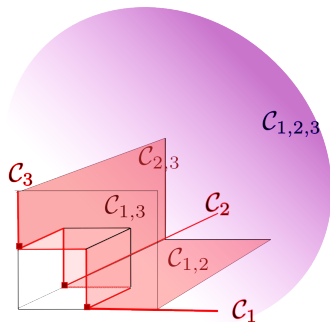
$$\Phi = \sum_{\alpha \subset \{1, \dots, d\}} \Phi_{\alpha} \quad \text{with } \Phi_{\alpha} = \Phi|_{\Omega_{\alpha}} \leftrightarrow \mu|_{\mathcal{C}_{\alpha}}$$

- ▶  $\Rightarrow$  yields a representation

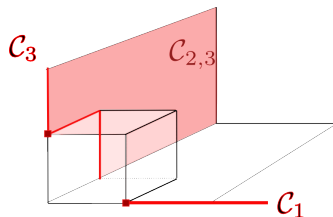
$$\begin{aligned} \mathcal{M} &= \left\{ \Phi(\Omega_{\alpha}) : \emptyset \neq \alpha \subset \{1, \dots, d\} \right\} \\ &= \left\{ \mu(\mathcal{C}_{\alpha}) : \emptyset \neq \alpha \subset \{1, \dots, d\} \right\} \end{aligned}$$

- ▶ Assumption:  $\frac{d\mu|_{\mathcal{C}_{\alpha}}}{d\nu_{\alpha}} = O(1)$ .

# Sparse Representation ?



Full pattern :  
anything may happen



Sparse pattern  
( $V_1$  not large if  $V_2$  or  $V_3$  large)

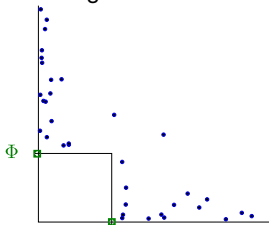
**Estimation Problem:**  $\mathcal{M}$  is an **asymptotic** representation

$$\mathcal{M} = \{ \Phi(\Omega_\alpha), \alpha \} = \{ \mu(\mathcal{C}_\alpha), \alpha \}$$

is the restriction of an asymptotic measure

$$\mu(A) = \lim_{t \rightarrow \infty} t\mathbb{P}[\mathbf{V} \in tA]$$

to a representative class of set  $\{\mathcal{C}_\alpha, \alpha\}$ , but only the central sub-cone has positive Lebesgue measure!

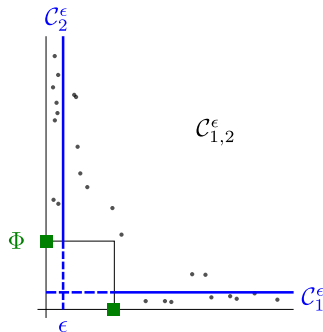


$\Rightarrow$  Cannot just do, for large  $t$ :

$$\Phi(\Omega_\alpha) = \mu(\mathcal{C}_\alpha) \simeq \widehat{t\mathbb{P}}(t\mathcal{C}_\alpha)$$



**Fix  $\epsilon > 0$ . Affect data  $\epsilon$ -close to an edge, to that edge.**



$$\mathcal{C}_\alpha \rightarrow \mathcal{C}_\alpha^\epsilon = \{\|v\| \geq 1, \quad v_j > \epsilon (j \in \alpha), \quad v_j \leq \epsilon (j \notin \alpha)\}.$$

New partition of  $\mathbf{S}_{d-1}$ .

# Resulting estimation procedure

$$\hat{V}_i^j = \frac{1}{1 - \hat{F}_j(X_i^j)} \text{ with } \hat{F}_j(X_i^j) = \frac{\text{rank}(X_i^j) - 1}{n}$$

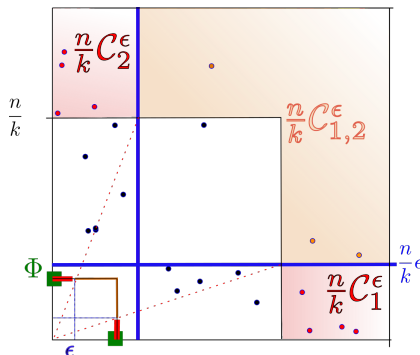
Recall that:

$$\mu(A) = \lim_{t \rightarrow \infty} t \mathbb{P}[\mathbf{V} \in t A]$$

$\Rightarrow$  get an natural estimate of  $\Phi(\Omega_\alpha)$

$$\hat{\Phi}(\Omega_\alpha) := \frac{n}{k} \mathbb{P}_n(\hat{V} \in \frac{n}{k} \mathcal{C}_\alpha^\epsilon)$$

( $\frac{n}{k}$  large,  $\epsilon$  small)



$\Rightarrow$  we obtain

$$\hat{\mathcal{M}} := \{ \hat{\Phi}(\Omega_\alpha), \alpha \}$$

## Theorem [G., Sabourin, Cl  men  on 2016]

There is an absolute constant  $C > 0$  such that for any  $n > 0$ ,  $k > 0$ ,  $0 < \epsilon < 1$ ,  $\delta > 0$  such that  $0 < \delta < e^{-k}$ , with probability at least  $1 - \delta$ ,

$$\|\widehat{\mathcal{M}} - \mathcal{M}\|_{\infty} \leq Cd \left( \sqrt{\frac{1}{\epsilon k} \log \frac{d}{\delta}} + Md\epsilon \right) + \text{bias}(\epsilon, k, n)$$

### Comments:

- ▶  $M = \sup(\text{density on sub-cones})$
- ▶ Existing litterature (for spectral measure) [Einmahl and Segers 09, Einmahl *et al.* 01]

$d = 2$ , asymptotic behaviour, rates in  $1/\sqrt{k}$ .

- ▶ Here:  $1/\sqrt{k} \rightarrow 1/\sqrt{\epsilon k} + \epsilon$ . Price to pay for biasing our estimator with  $\epsilon$ .

## Theorem's proof: key ingredient

Would like to use concentration inequality...

$$\text{In our case: } \sup_{A \in \mathcal{A}} \frac{n}{k} \left| (\mathcal{P} - \mathcal{P}_n) \left( \frac{k}{n} A \right) \right|$$

$$\text{But usually: } \sup_{A \in \mathcal{A}} |(\mathcal{P} - \mathcal{P}_n)(A)|$$

- ▶ scaling  $\frac{n}{k}$
- ▶ classical VC-inequality:  $\frac{k}{n}$  nice but not used !  
→ high proba bound in

$$\frac{n}{k} \times \sqrt{\frac{1}{n} \log \frac{1}{\delta}} \rightarrow \infty \quad !!$$

⇒ Needs to take into account that the proba of  $\frac{k}{n} A$  is small.

**Key:** VC-inequality adapted to rare regions  $\rightarrow$  bound in

$$\sqrt{\mathbf{p}} \frac{n}{k} \sqrt{\frac{d}{n} \log \frac{1}{\delta}}$$

with  $p$  the probability to be in the union class  $\cup_{A \in \mathcal{A}} A$ .

$$\mathbf{p} \leq d \frac{k}{n}$$

$\Rightarrow$  bound in

$$d \sqrt{\frac{1}{k} \log \frac{1}{\delta}}$$

$k \propto$  number of data considered as extreme (data used for estimation)

## DAMEX in $O(dn \log n)$

**Input:** parameters  $\epsilon > 0$ ,  $k = k(n)$

**for**  $i = 1, \dots, n$  **do**

  # Standardize via marginal rank-transformation:

$$\hat{V}_i := (1/(1 - \hat{F}_j(X_i^j)))_{j=1, \dots, d}.$$

**if**  $\hat{V}_i > \frac{n}{k}$  **then**

    # Assign to each  $\hat{V}_i$  the cone  $\frac{n}{k}C_\alpha^\epsilon$  it belongs to:

$$\alpha = \alpha(V_i)$$

$$C_\alpha ++$$

**end if**

**end for**

$$\Phi_n^{\alpha, \epsilon} := \frac{n}{k} C_\alpha$$

**Output:** (sparse) representation of the dependence structure:

$\Phi_n^{\alpha, \epsilon} = \hat{\Phi}(\Omega_\alpha) = \frac{n}{k} \mathbb{P}_n(\hat{V} \in \frac{n}{k} C_\alpha^\epsilon)$ , estimate of the  $\alpha$ -mass of  $\Phi$  for every  $\alpha$ .

$$\widehat{\mathcal{M}} := (\Phi_n^{\alpha, \epsilon})_{\alpha \in \{1, \dots, d\}, \Phi_n^{\alpha, \epsilon} > \Phi_{\min}}$$

# Application to Anomaly Detection

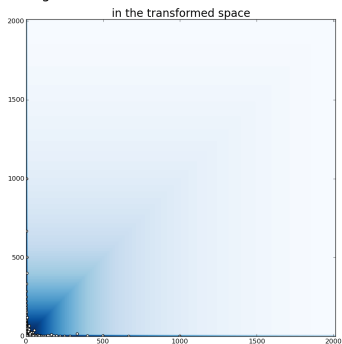
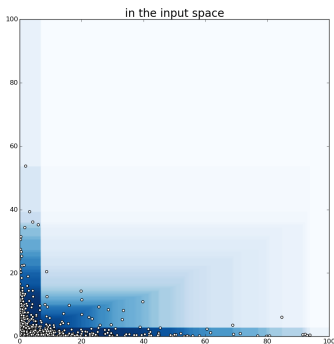
Recall that after standardization of marginals:  $\mathbb{P}[R > r, \mathbf{W} \in B] \simeq \frac{1}{r} \Phi(B)$

→ scoring function =  $\Phi_n^\epsilon \times 1/r$ :

$$s_n(\mathbf{x}) := (1/\|\hat{T}(\mathbf{x})\|_\infty) \sum_{\alpha} \Phi_n^{\alpha, \epsilon} \mathbb{1}_{\hat{T}(\mathbf{x}) \in \mathcal{C}_\alpha^\epsilon}.$$

where  $\hat{T} : \mathbf{X} \mapsto \mathbf{V}$  ( $\hat{V}_j = \frac{1}{1 - \hat{F}_j(X_j)}$ )

levels set of DAMEX scoring function



# Experiments

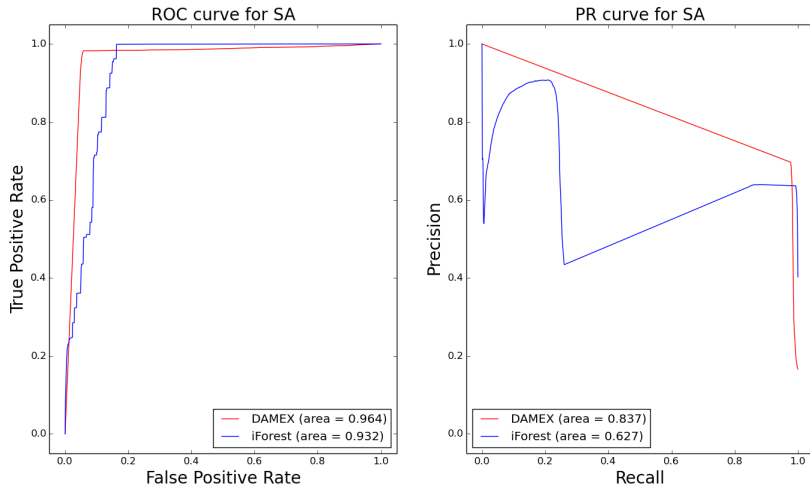


Figure: ROC and PR curve on SA dataset



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# EM and MV curves for model selection?

## Practical motivations:

Most of the time, data come without any label.

→ no ROC or PR curves!

## Implicit (natural) simplification of the problem:

How good is an anomaly detection algorithm?

→ How good is it estimating the level sets of the inliers distribution?

## Estimation:

$$\widehat{MV}_s(\alpha) = \inf_{u \geq 0} \text{Leb}(s \geq u) \quad \text{s.t.} \quad \mathbb{P}_n(s \geq u) \geq \alpha \quad \rightarrow \widehat{\mathcal{C}}^{EM}(s) = \|MV_s\|_{1,J}$$

$$\widehat{EM}_s(t) = \sup_{u \geq 0} \mathbb{P}_n(s \geq u) - t \text{Leb}(s \geq u) \quad \rightarrow \widehat{\mathcal{C}}^{MV}(s) = \|EM_s\|_{1,I}$$

[Thomas et al. 2015, 2016]

**Issue in large dimension:** The volume  $\text{Leb}(s \geq u)$  has to be estimated!

# EM and MV curves for model selection?

## Heuristic extension for large dimension:

### Random projection and averaging

**Inputs:** AD algorithm  $\mathcal{A}$ , data set  $X$  size  $n \times d$ , feature sub-sampling size  $d'$ , number of draws  $m$ .

**for**  $k = 1, \dots, m$  **do**

-randomly select a sub-group  $F_k$  of  $d'$  features

-compute the associated scoring function  $s_k = \mathcal{A}((x_i^j)_{1 \leq i \leq n, j \in F_k})$

-compute  $\widehat{C}_k^{EM} = \|\widehat{EM}_{s_k}\|_{L^1(I)}$  or  $\widehat{C}_k^{MV} = \|\widehat{MV}_{s_k}\|_{L^1(J)}$

**end for**

**Return** performance criteria:

$$\widehat{C}_{high.dim}^{EM}(\mathcal{A}) = \frac{1}{m} \sum_{k=1}^m \widehat{C}_k^{EM} \quad \text{or} \quad \widehat{C}_{high.dim}^{MV}(\mathcal{A}) = \frac{1}{m} \sum_{k=1}^m \widehat{C}_k^{MV}.$$

Seems to work in practice but no statistical guarantees.

# One Class Random Forests

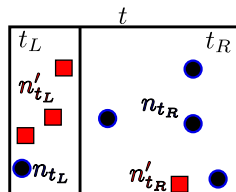
Existing litterature: [Désir et al., 2013, Liu et al., 2008, Shi and Horvath, 2012].

## Two-Class impurity decrease

$$I_G(t_L, t_R) = \frac{n_{t_L} n'_{t_L}}{n_{t_L} + n'_{t_L}} + \frac{n_{t_R} n'_{t_R}}{n_{t_R} + n'_{t_R}}.$$

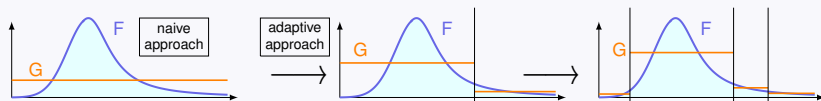
$n_t$  : nb of observations with label 0 in node  $t$ .

$n'_t$  : nb of observations with label 1 in node  $t$ .



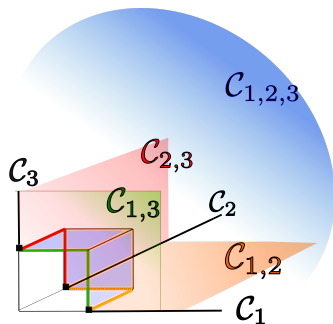
## One-Class splitting criterion

$$n'_{t_L} \rightarrow n_t \frac{\text{Leb}(t_L)}{\text{Leb}(t)} \quad \text{and} \quad n'_{t_R} \rightarrow n_t \frac{\text{Leb}(t_R)}{\text{Leb}(t)}$$



$F$  is the inliers distribution,  $G$  is the assumed outliers distribution.

Does theoretical guaranties apply ? [Biau et al. 2008, Biau and Scornet, 2016]



A more accurate sparse representation?

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	number of samples	number of features
shuttle	85849	9
forestcover	286048	54
SA	976158	41
SF	699691	4
http	619052	3

Table: Datasets characteristics



$$\epsilon = 0.01, k = n^{1/2}$$

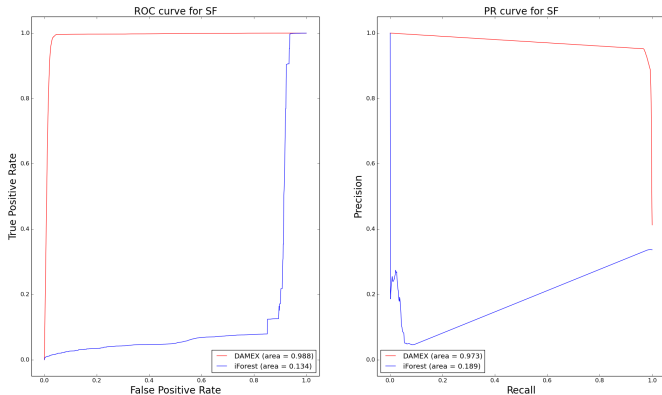


Figure: ROC and PR curve on SF dataset

$$\epsilon = 0.01, k = n^{1/2}$$

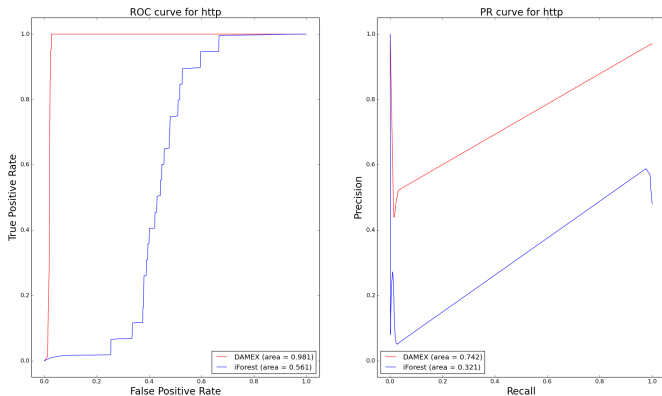


Figure: ROC and PR curve on http dataset

$$\epsilon = 0.01, k = n^{1/2}$$

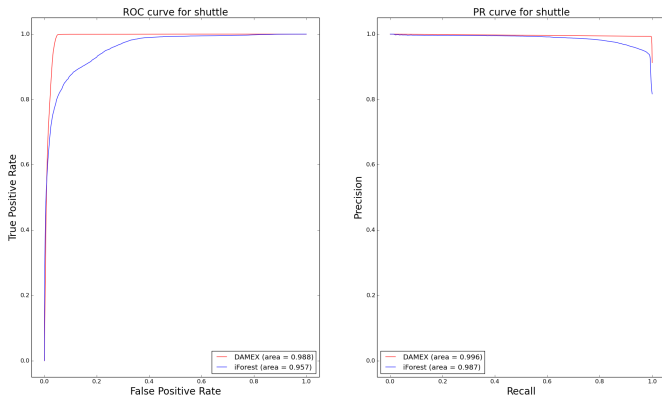


Figure: ROC and PR curve on shuttle dataset

$$\epsilon = 0.01, k = n^{1/2}$$

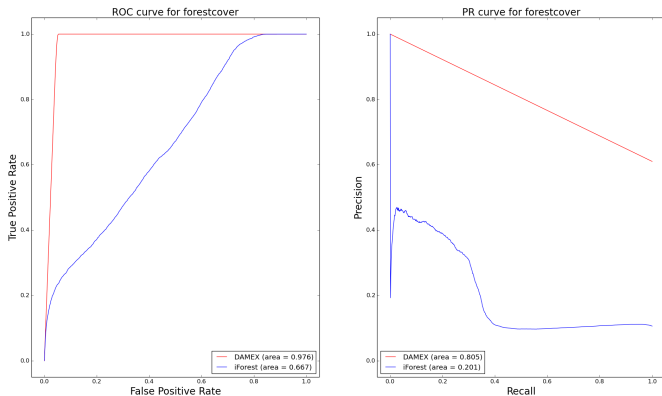


Figure: ROC and PR curve on forestcover dataset

Does performance in term of EM/MV correspond to performance in term of ROC/PR?

- **Experiments:** 12 datasets, 3 AD algorithms (LOF, OCSVM, iForest)  $\rightarrow$  36 possible pairwise comparisons:

$$\left\{ \left( A_1 \text{ on } \mathcal{D}, A_2 \text{ on } \mathcal{D} \right), A_1, A_2 \in \{\text{iForest, LOF, OCSVM}\}, \right. \\ \left. \mathcal{D} \in \{\text{adult, http, } \dots, \text{spambase}\} \right\}.$$

- **Results:** If we only consider the pairs *s.t.* ROC and PR agree on which algorithm is the best, we are able (with EM and MV scores) to recover it in 80% of the cases.

Table: Original Datasets characteristics

	nb of samples	nb of features	anomaly class	
adult	48842	6	class '> 50K'	(23.9%)
http	567498	3	attack	(0.39%)
pima	768	8	pos (class 1)	(34.9%)
smtpt	95156	3	attack	(0.03%)
wilt	4839	5	class 'w' (diseased trees)	(5.39%)
annthyroid	7200	6	classes $\neq 3$	(7.42%)
arrhythmia	452	164	classes $\neq 1$ (features 10-14 removed)	(45.8%)
forestcover	286048	10	class 4 (vs. class 2 )	(0.96%)
ionosphere	351	32	bad	(35.9%)
pendigits	10992	16	class 4	(10.4%)
shuttle	85849	9	classes $\neq 1$ (class 4 removed)	(7.17%)
spambase	4601	57	spam	(39.4%)

**Table:** Results for the novelty detection setting. One can see that ROC, PR, EM, MV often do agree on which algorithm is the best (in bold), which algorithm is the worse (underlined) on some fixed datasets. When they do not agree, it is often because ROC and PR themselves do not, meaning that the ranking is not clear.

Dataset	iForest				OCSVM				LOF			
	ROC	PR	EM	MV	ROC	PR	EM	MV	ROC	PR	EM	MV
adult	<b>0.661</b>	<b>0.277</b>	<b>1.0e-04</b>	<b>7.5e01</b>	0.642	0.206	2.9e-05	4.3e02	<u>0.618</u>	<u>0.187</u>	<u>1.7e-05</u>	<u>9.0e02</u>
http	0.994	0.192	1.3e-03	9.0	<b>0.999</b>	<b>0.970</b>	<b>6.0e-03</b>	<b>2.6</b>	<u>0.946</u>	<u>0.035</u>	<u>8.0e-05</u>	<u>3.9e02</u>
pima	0.727	0.182	5.0e-07	<b>1.2e04</b>	<b>0.760</b>	<b>0.229</b>	<b>5.2e-07</b>	<u>1.3e04</u>	<u>0.705</u>	<u>0.155</u>	<u>3.2e-07</u>	2.1e04
smtp	0.907	<u>0.005</u>	<u>1.8e-04</u>	<u>9.4e01</u>	<u>0.852</u>	<b>0.522</b>	<b>1.2e-03</b>	8.2	<b>0.922</b>	0.189	1.1e-03	<b>5.8</b>
wilt	0.491	0.045	<u>4.7e-05</u>	<u>2.1e03</u>	<u>0.325</u>	<u>0.037</u>	<b>5.9e-05</b>	<b>4.5e02</b>	<b>0.698</b>	<b>0.088</b>	<u>2.1e-05</u>	1.6e03
annthyroid	<b>0.913</b>	<b>0.456</b>	<b>2.0e-04</b>	2.6e02	<u>0.699</u>	<u>0.237</u>	<u>6.3e-05</u>	<b>2.2e02</b>	0.823	0.432	6.3e-05	<u>1.5e03</u>
arrhythmia	<b>0.763</b>	<b>0.487</b>	<b>1.6e-04</b>	<b>9.4e01</b>	0.736	0.449	1.1e-04	1.0e02	<u>0.730</u>	<u>0.413</u>	<u>8.3e-05</u>	<u>1.6e02</u>
forestcov.	<u>0.863</u>	<u>0.046</u>	<u>3.9e-05</u>	<u>2.0e02</u>	0.958	0.110	5.2e-05	1.2e02	<b>0.990</b>	<b>0.792</b>	<b>3.5e-04</b>	<b>3.9e01</b>
ionosphere	<u>0.902</u>	<u>0.529</u>	<u>9.6e-05</u>	<u>7.5e01</u>	<b>0.977</b>	<b>0.898</b>	<b>1.3e-04</b>	<b>5.4e01</b>	0.971	0.895	1.0e-04	7.0e01
pendigits	0.811	0.197	2.8e-04	2.6e01	0.606	0.112	2.7e-04	2.7e01	<b>0.983</b>	<b>0.829</b>	<b>4.6e-04</b>	<b>1.7e01</b>
shuttle	0.996	0.973	1.8e-05	5.7e03	<u>0.992</u>	<u>0.924</u>	<b>3.2e-05</b>	<b>2.0e01</b>	<b>0.999</b>	<b>0.994</b>	<u>7.9e-06</u>	<u>2.0e06</u>
spambase	<b>0.824</b>	<b>0.371</b>	<b>9.5e-04</b>	<b>4.5e01</b>	<u>0.729</u>	0.230	4.9e-04	1.1e03	0.754	<u>0.173</u>	<u>2.2e-04</u>	<u>4.1e04</u>