Advances in Knowledge-Based Technologies

Proceedings of the
Master and PhD Seminar
Summer term 2018, part 1

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Program

Session 1. Chair: Thomas Vetterlein

9:00 F. Sobieczky:
Unimodularity of graphs for unbiased parameter estimation

9:30 G. Badia:
Maximality of First-order Logics Based on Finite MTL-chain

Session 2. Chair: Bernhard Moser

10:15 U. Anlauf:
The Steiner Tree Problem Considering Obstacles

10:35 A-M. Meder:
Optimization of Electrical Drives Using Deep Learning Techniques

Statistical Depth

Florian Sobieczky – scch

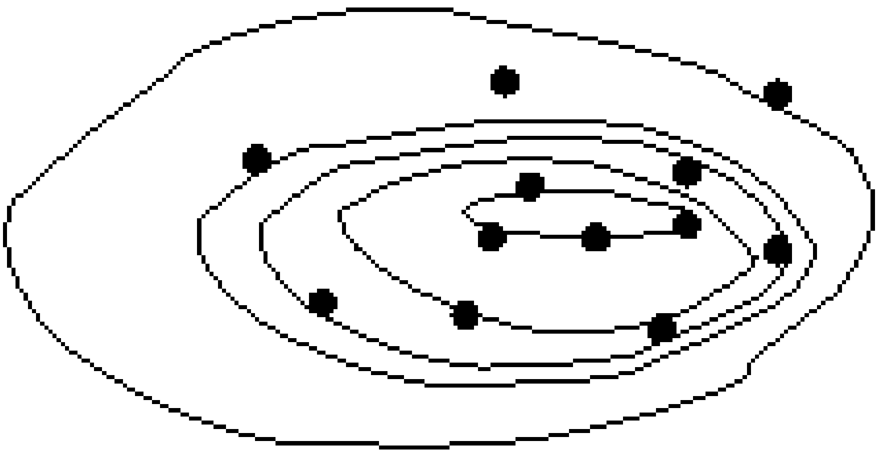
2017-11-13

Overview

1. Definition of Statistical Depth
   - Location Depth, Regression Depth
   - Convex Peeling, Mahalanobis Depth
   - Oja Depth, Simplicial Depth
2. Robustness
   - High Breakpoint
3. Implementation
   - $O(n^2 \log n)$
   - R-Package
4. Literature

Idea of Statistical Depth

For a given statistical model $\langle S, \mathcal{F}, \mathcal{P} \rangle$ to give an estimate of the probability density of the distribution from which a sample $X \in \mathbb{R}^{N \times d}$ is drawn.



- Tukey, 1975 [1]

1. Definition of Halfspace Depth

Statistical Depth of a point in a sample space of a statistical model is relative to a given sample $X \in \mathbb{R}^{n \times d}$:

- supposed to give an approximation of the density function of the distribution from which the sample has been drawn.

1. Location Depth (Halfspace-Depth, [2]):

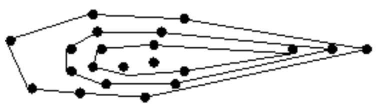
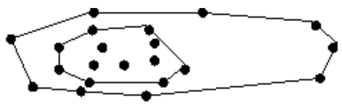
$$\mathrm{dep}_n(x, X) = \min |\{v \in \mathbb{R}, y \mathrm{row}(X) \mid \|v\| = 1, \ \langle (x \ - \ y), v\rangle \geq 0\}|$$

- Restriction on $\mathcal{P}$: Unimodal Distributions with convex contourplanes
- High Robustness: Breakpoint is fraction of removable data points without estimator turning 'bad'

1. Other Depth Notions

Convex Peeling:

- Remove consecutive convex hulls
- Not robust: Outer Contours depend heavily on configuration of data points

Mahalanobis Depth:

- Remove consecutive *furthest* outliers with resp. to Mahalanobis distance
- Not Robust: 'Mean' instead of Median is used

Oja Depth (1983): Volume of simplices data point x falls into

Simplicial Depth (Liu, 1990): Number of simplices x falls into

2. Robustness (Now classical results)

- Halfspace depth has *high breakpoint* (Donoho and Gasko[2]):

1.)

$$\liminf_{n\to\infty} \max\left(\mathrm{dep}_n(x)/n\right) \;\geq\; \frac{1}{d+1}$$

2.) For centrosymmetric underlying distributions:

$$\liminf_{n\to\infty} \max\left(\mathrm{dep}_n(x)/n\right) \;\geq\; \frac{1}{2}$$

More precisely: $\max\left(\mathrm{dep}_n(x)/n\right) \;>\; \frac{1}{2} \;-\; O\left(\frac{1}{\sqrt{n}}\right)$

3.) For distributions ϵ-close to centrosymmetry:

$$\max\left(\mathrm{dep}_n(x)/n\right) \;>\; \frac{1}{2}(1 \;-\; \epsilon)$$

3. Implementation

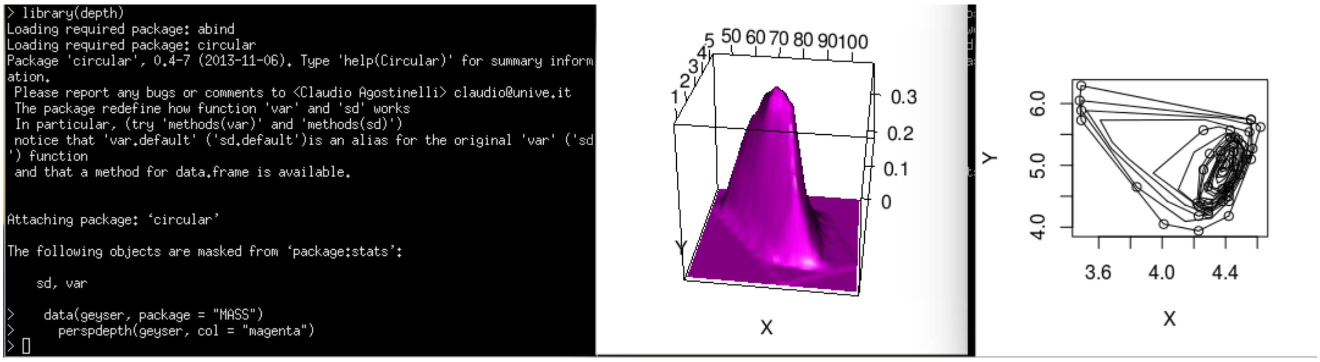
Rousseew and Struyf have found fast algithms for computing $\mathrm{dep}(x, X)$ in

- $O(N \log N)$ steps for $d = 2$,
- $O(N^2 \log N)$ steps for $d = 3$.

Moreover, they define the *regression depth* as the number of sign flips of residuals in a linear regression to be performed when shifting approximating hyperplane to lie 'outside' of data cloud. This can be computed in

- $O(N^2 \log N)$ steps for arbitrary dimenion.
- Generalizing concept of depth which encompasses location depth and regression depth: [4].

3. R-Package ‘depth’




```r
library(depth)
A<-matrix(rnorm(100), ncol=2)
depth::depth(c(0,0), A)
```

```
## [1] 0.34
```

Literature

[1] J. Tukey: ‘Mathematicss and the picturing of data’, 1975, Proc. Int. Congr. Mathem., 2, Vancouver, pp. 523-531

[2] D.L. Donoho, M. Gasko: ‘Breaking Properties of Location Estimates Based on Halfspace Depth’, 1992, Ann. Stat, 20, 4, 1803

[3] P. J. Rousseeuw, A. Struyf: ‘Computing location depth and regression depth in higher dimensions’, 1998, Statist. Comput., 8, pp 193-203

[4] M. Hubert, P. J. Rousseeuw, Van Alst: ‘Similarities between location depth and regression depth’, 2001, in: Statistics in Genetics and in the Environmental Sciences, Birkhauser, pp. 159-172

[5] P. J. Rousseeuw, M. Hubert: ‘Statistical depth meets computational geometry: a short survey’, arxiv 1508.03828

Maximality of First-order Logics Based on Finite MTL-chains

Guillermo Badia

April 3, 2018

A pair formed by a formal language and a semantics (i.e., a function that evaluates the formulas in our residuated lattice) is called a *model-theoretic logic*. I will begin by considering a first order language (with the finitary propositional connectives of the so called monoidal t-norm logic (MTL) and the usual quantifiers $\forall, \exists$) over systems of relations evaluated on a finite MTL-chain (a linearly ordered commutative integral residuated lattice denoted by $\boldsymbol{A}$). MTL-chains are the basis of a very large number of fuzzy logics. I will denote my starting model-theoretic logic by $\mathscr{L}^{\boldsymbol{A}}_{\omega\omega}$.

An expressive extension of $\mathscr{L}^{\boldsymbol{A}}_{\omega\omega}$ could be obtained by, say, allowing infinitary propositional connectives, second order quantifiers or a quantifier to capture cardinality relations such as "most". The relation "being as expressive as" between model-theoretic logics is a partial ordering $\leq$. A Lindström theorem is a characterization of a given model-theoretic logic in the aforementioned partial order in terms of some combination of semantic properties.

In this talk, I will present the following two Lindström theorems for $\mathscr{L}^{\boldsymbol{A}}_{\omega\omega}$.

Theorem 1. (First Lindström Theorem) *Let $\mathscr{L}^{\boldsymbol{A}}$ be a model-theoretic logic such that $\mathscr{L}^{\boldsymbol{A}}_{\omega\omega} \leq \mathscr{L}^{\boldsymbol{A}}$. If $\mathscr{L}^{\boldsymbol{A}}$ has the Löwenheim-Skolem property for countable sets of formulas and the Compactness property, then $\mathscr{L}^{\boldsymbol{A}} \leq \mathscr{L}^{\boldsymbol{A}}_{\omega\omega}$.*

Theorem 2. (Second Lindström Theorem) *Let $\mathscr{L}^{\boldsymbol{A}}$ be an effective model-theoretic logic (i.e., the collection of its formulas is recursive) such that $\mathscr{L}^{\boldsymbol{A}}_{\omega\omega} \leq \mathscr{L}^{\boldsymbol{A}}$. If $\mathscr{L}^{\boldsymbol{A}}$ has the Löwenheim-Skolem property for countable sets of formulas and the abstract Weak Completeness property (the collection of its validities is recursively enumerable), then $\mathscr{L}^{\boldsymbol{A}} \leq \mathscr{L}^{\boldsymbol{A}}_{\omega\omega}$.*

These results shed light on the methamatematics of predicate fuzzy logic, providing an answer to the question: what is special about a first order language in the context of monoidal t-norm logics?

The Steiner Tree Problem Considering Obstacles

Ulrike Anlauf

Knowledge-Based Mathematical Systems (KBMS) - Johannes Kepler University Linz

Abstract – A first glance at the Euclidean Steiner Tree Problem and its obstacle-avoiding variant by means of evolutionary computation techniques.

Optimization of Electrical Drives Using Deep Learning Techniques

Adela-Maria Meder

Knowledge-Based Mathematical Systems (KBMS) - Johannes Kepler University Linz

Abstract – In order to be effective in electrical drive-design use cases, multi-objective optimization algorithms must rely heavily on model-based surrogate evaluators (i.e., regression models) that replace the finite element simulations. Surrogates based on various machine learning paradigms (like shallow multi-layer perceptrons, support vector machines, radial basis functions) have been previously tested with mixed success. As recent types of deep structured neural networks have shown very promising results in several application fields, the goal is to test the potential of these advanced machine learning techniques in the context of existing electrical drive design frameworks.