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15-826: Multimedia Databases and Data Mining

Outlier detection
C. Faloutsos

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Citation:

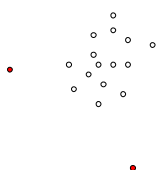
LOCI: Fast Outlier Detection Using The Local Correlation Integral,
Spiros Papadimitriou,
Hiroyuki Kitagawa,
Phillip B. Gibbons,
Christos Faloutsos
ICDE 2003, Bangalore, India



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What is an outlier?

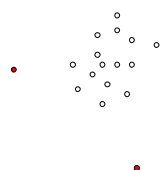


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What is an outlier?

“An outlier is an observation that *deviates* so much from other observations as to arouse suspicions that it was generated by a different *mechanism*” [Hawkins 80]



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Why outlier detection?

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Why outlier detection?

- Rare events, exceptions, alerts
- Surveillance / auditing
- Health monitoring
- Stock market analysis
- cyber-security
- ...

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Requirements

- Fast
 - Large datasets
 - Single pass over the data
- Multi-dimensional
 - Arbitrary (numeric) tuples
- Limited/simple user intervention
 - No “magic cut-offs”
 - Intuitive criteria for flagging outliers

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Assumptions

- Metric space
 - Distance provided (by “expert”)

OR

- Vector space (d dimensions) with some L_p norm

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Overview

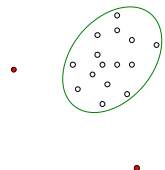
- Related work
- Definitions
- Approximate estimation
- Experimental results

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Distribution Based

- Assume data are drawn from a certain distribution (model)
 - E.g., multivariate Gaussian
- Estimate the model
- Identify points that do not fit well



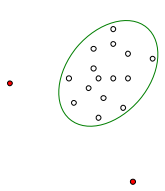
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Distribution Based

- Assume data are drawn from a certain distribution (model)
 - E.g., multivariate Gaussian
- Estimate the model
- Identify points that do not fit well

- Prior knowledge of distribution, *or*
- Expensive statistical tests to determine suitable model
- Typically few degrees of freedom
 - E.g., $O(dim^2)$ (covariance matrix)

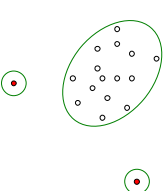


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Clustering by-products

- Outlier is a “cluster”
 - One point
 - Very few points (“micro-cluster”)

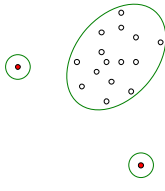


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Clustering by-products

- Outlier is a “cluster”
 - One point
 - Very few points (“micro-cluster”)
- Potentially much unnecessary work
- Implicit outlier-ness criteria



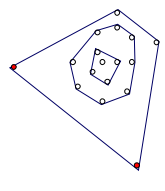
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Depth based

[Johnson, Kwok, Ng 98]

- Computational geometry
- Compute several layers of convex hull — *depth contours* [Tukey 75]
- Points in outer layers are more likely to be outliers



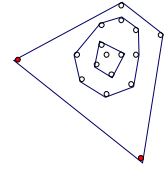
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Depth based

[Johnson, Kwok, Ng 98]

- Computational geometry
- Compute several layers of convex hull — *depth contours* [Tukey 75]
- Points in outer layers are more likely to be outliers
- Exponential growth with dimensionality
 - Unsuitable for high dimensions

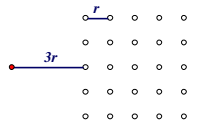


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Distance based

Overview [Knorr, Ng 98]



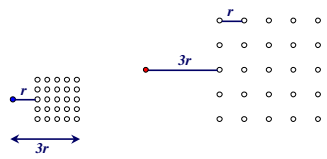
- Point x is an outlier iff
 $\#(\text{points at distance} > R) > a \% \# \text{points}$
 where R, a : are global parameters

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Distance based

Assumptions [Knorr, Ng 98]



- One global criterion
- Local density variations

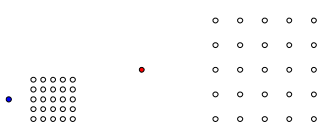
Global may not be enough...

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Density based (LOF)

Overview [Breuning, Kriegel, Ng et al 00]



- Compute (smoothed) average neighbor distance (over m neighbors)
- Compare against average of averages

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Density based (LOF)

Overview [Breuning, Kriegel, Ng et al 00]



E.g., $m = 3$

- Local Outlier Factor (LOF)

$$\text{LOF}(p, m) = \frac{\text{avg. distance of } m \text{ nearest neighbours of } p}{\text{avg. of avg. distance of } m \text{ nearest neighbours over the } m \text{ nearest neighbours of } p}$$

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Density based

Assumptions



- Multiple granularity
- Here, $m > 9$ (micro-cluster size)
- If $m < 9$, then none are outliers (LOF = 1)

Local may not be enough either...

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Contributions

- Multi-scale
 - Complete distance distribution...
 - ...around each point
- Fast estimation
 - Practically linear in #points and dimensions
 - First use of approximate estimation in outlier detection
- “Natural” cut-off
 - Probabilistically intuitive, data-dictated

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Overview

- Related work
- Definitions
- Approximate estimation
- Experimental results

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Main questions/ideas:

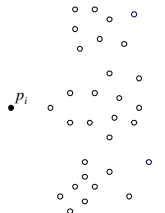
- Q1: What is a neighbor?
- Q2: how to measure difference from neighbors?
- Q3: how much difference is ‘too much’?

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Comparing distances

Q1: who is a neighbor?



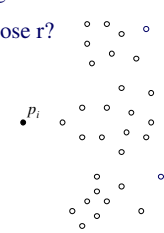
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Comparing distances

Q1: who is a neighbor? A: all within distance r

Q1': how to choose r ?



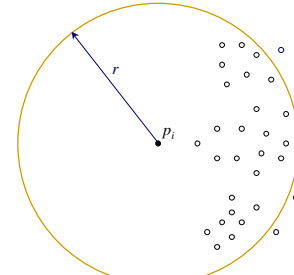
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Comparing distances



sampling neighbourhood

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Main questions/ideas:

- ✓ Q1: What is a neighbor?
- ➡ Q2: how to measure difference from neighbors?
- Q3: how much difference is 'too much'?

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Main questions/ideas:

- ✓ Q1: What is a neighbor?
- ➡ Q2: how to measure difference from neighbors?
- A: count the number of neighbors!

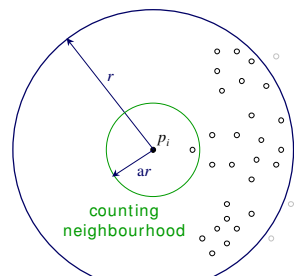
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Comparing distances



$n(p_i, r) = 2$

counting neighbourhood

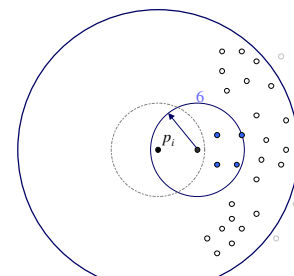
$a = 1/3$
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Comparing distances



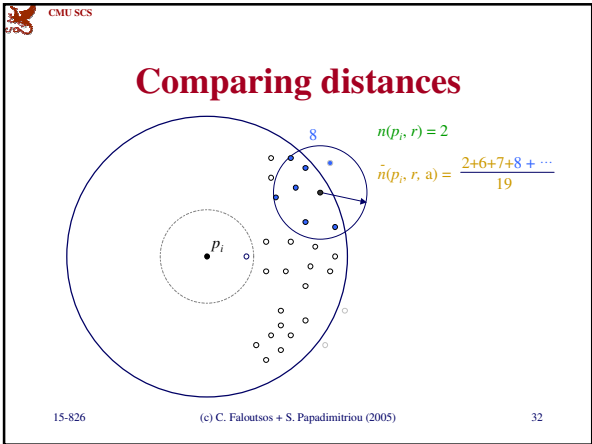
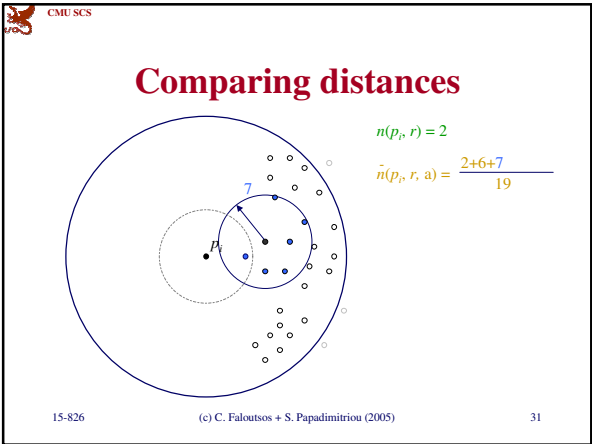
$n(p_i, r) = 2$

$\tilde{n}(p_i, r, a) = \frac{2+6}{19}$

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Main questions/ideas:

- ✓ Q1: What is a neighbor?
- ✓ Q2: how to measure difference from neighbors?
- ➡ Q3: how much difference is 'too much'?

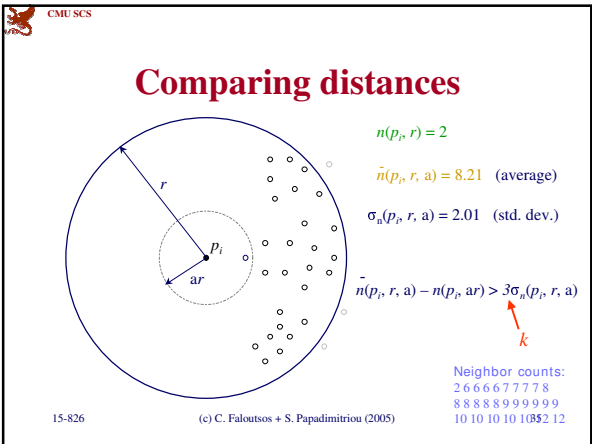
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Main questions/ideas:

- ✓ Q1: What is a neighbor?
- ✓ Q2: how to measure difference from neighbors?
- ➡ Q3: how much difference is 'too much'?
- A: 3 std away (or k std)

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Main questions/ideas:

- ✓ Q1: What is a neighbor?
- A: everybody within distance r
- ➡ Q1': how to choose r ?
- A:
- ✓ Q2: how to measure difference from neighbors?
- ✓ Q3: how much difference is 'too much'?

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Main questions/ideas:

- ✓ Q1: What is a neighbor?
 - A: everybody within distance r
- ➡ – Q1': how to choose r ?
 - A: don't choose it – MANY r 's!
- ✓ Q2: how to measure difference from neighbors?
- ✓ Q3: how much difference is 'too much'?

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End result:

- LOCI plot for each point p
- (LOCI = Local Correlation Integral)

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LOCI plot Definition

- Plot of $\left\langle \text{count } n \right\rangle \pm k_\sigma \times \left\langle \text{std dev } \hat{\sigma}_n \right\rangle$ vs. radius

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LOCI plot Definition

count of neighbors for point p at distance r

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LOCI plot Definition

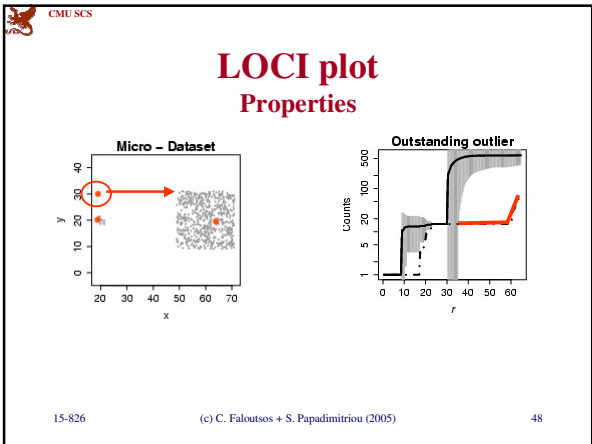
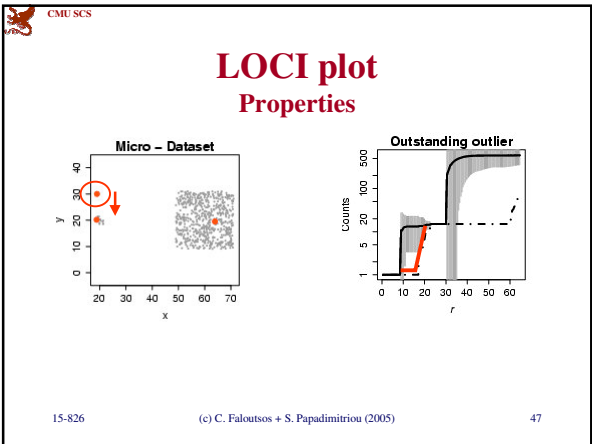
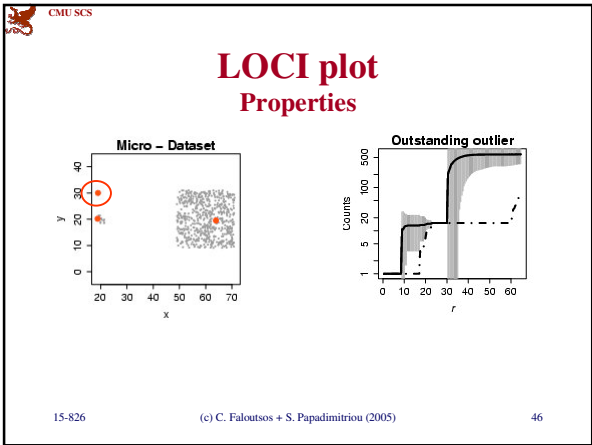
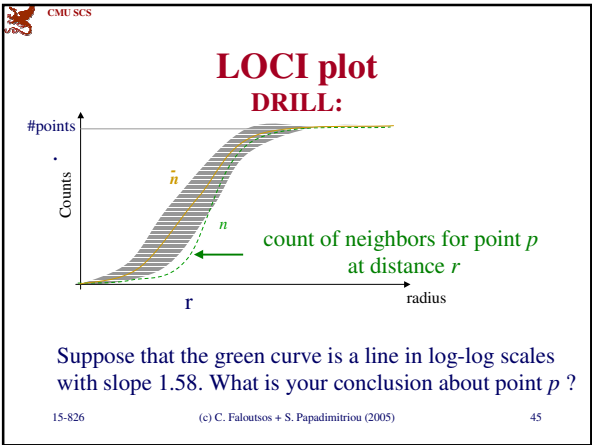
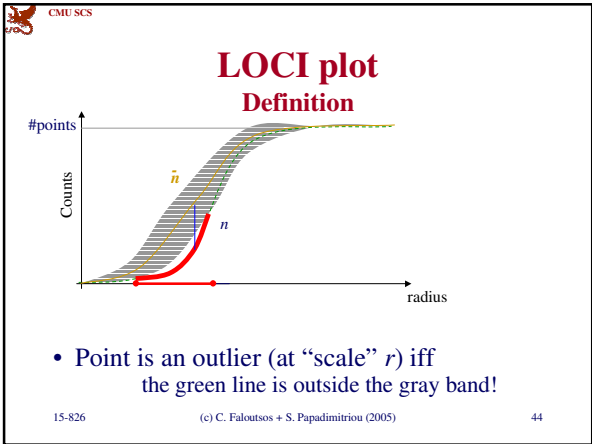
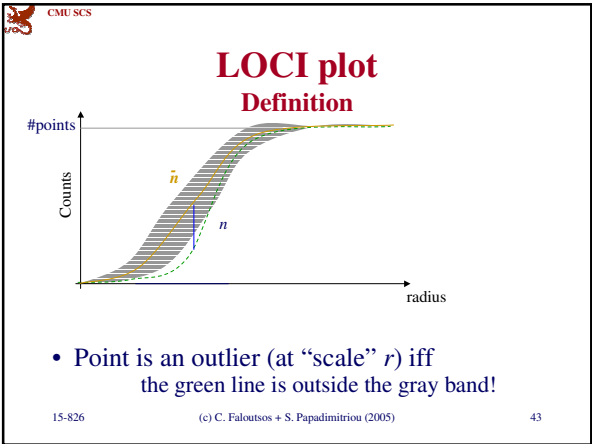
avg # of neighbors (of neighbors)

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LOCI plot Definition

std of neighbors of neighbors
avg # of neighbors (of neighbors)

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Overview

- Related work
- Definitions
- **Approximate estimation**
- Experimental results

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Speed?

- seems quadratic or worse:
 - for every radius, count the neighbors,
 - the neighbors of the neighbors
 - and the std of them
- How to ‘cut corners’?

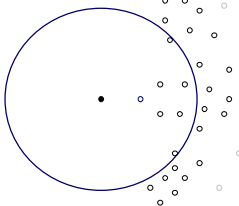
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Box counting

Introduction by example

Exact

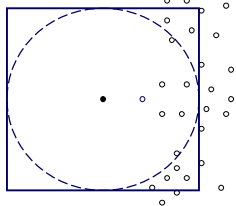


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Box counting

Introduction by example



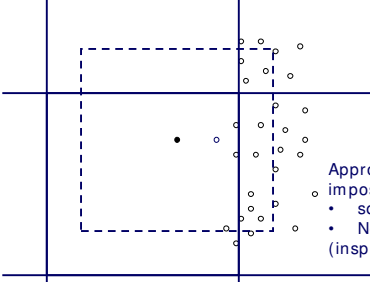
Approximate:
impose a grid of side r
• squares (L-infinity)

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Box counting

Introduction by example



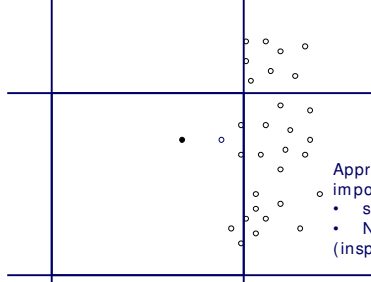
Approximate:
impose a grid of side r
• squares (L-infinity)
• Not necessarily centered
(inspired by box-counting)

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Box counting

Introduction by example



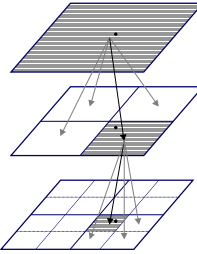
Approximate:
impose a grid of side r
• squares (L-infinity)
• Not necessarily centered
(inspired by box-counting)

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Quad-trees

SKIP



- Cell side (radius) can be arbitrary, however...
- Quad-trees:
 - Split each cell into 2^d sub-cells
 - Small depth, easy updates

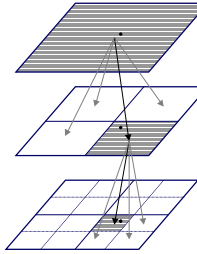
Radii = powers of 2

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Quad-trees

SKIP



- Store only counters

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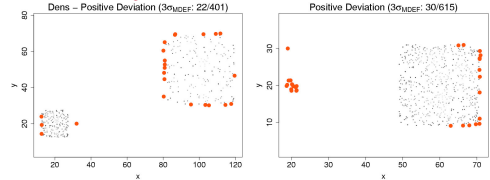
Overview

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Synthetic — LOCI



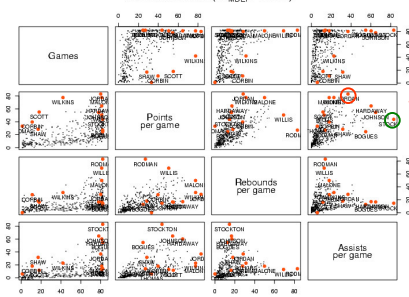
- Captures outstanding outlier
- Captures outstanding outlier...
- ...and entire micro-cluster

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NBA — LOCI

Positive Deviation (30μDEF: 13/459)



Jordan

Stockton

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Conclusion

- Multi-scale
 - Complete distance distribution...
 - ...around each point
- Fast estimation
 - Box-counting, practically linear
 - First use of approximate estimation in outlier detection
- “Natural” cut-off
 - Probabilistically intuitive, data-dictated

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References

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[Hawkins 80]
Identification of Outliers, Chapman and Hall, London, 1980

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