Explanation of rare events

Need for explanation of outliers

- A user need to understand why an instance is detected as an outlier
- For many applications, **explanation** (interpretation, description, outlying property detection, characterization) of outliers is as important as identification
- Outlier factor (degree) and ranking is only quantitative information
- Not only for high-dimensional data we need qualitative information

Based also on *ODD v5.0: Outlier Detection De-constructed ACM SIGKDD 2018 Workshop* keynote speeches, namely Making sense of unusual suspects - Finding and Characterizing Outliers (Ira Assent) and Outlier Description and Interpretation (Jian Pei)

How to generate explanation?

- Compare with inlying data as well as confirmed outlying data
- Find outlier explanatory component / outlying property / outlier context / outlier characteristic
- Help domain expert in verifying outliers and understanding how the outlier method works

What is meaningfull explanation

A method for finding of explanation must be

- **helpful** for a user, namely easy to understand. E.g. the smallest subset of attributes
- **efficient**, scalable

Most frequent approaches

- visual
- look for **a subset of attributes** where each outlier has its own explanatory subspace

Finding the most important attributes

For an object q, find the subspaces where q is most unusual compared to the rest of the data

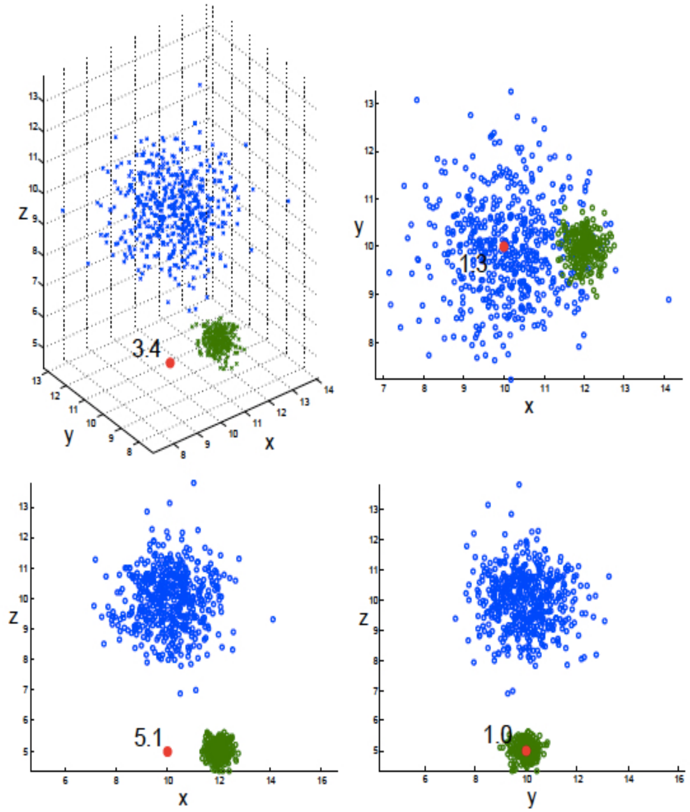


Figure 4.1: A 3D space $\{x, y, z\}$ and all its 2D projections. $\{x, z\}$ is an explanatory subspace.

A 3D space $\{x, y, z\}$ and all its 2D projections. $\{x, z\}$ is an explanatory subspace (Micenkova 2015)

Strongest, weak and trivial outliers

Knorr and Ng 1998

Non-trivial outliers

P is a *non-trivial outlier* in space A if P is not an outlier in any subspace of A.

Strongest outlier

The space A containing one or more outliers is called a *strongest outlying space* if no outlier exist in any subspace of A.

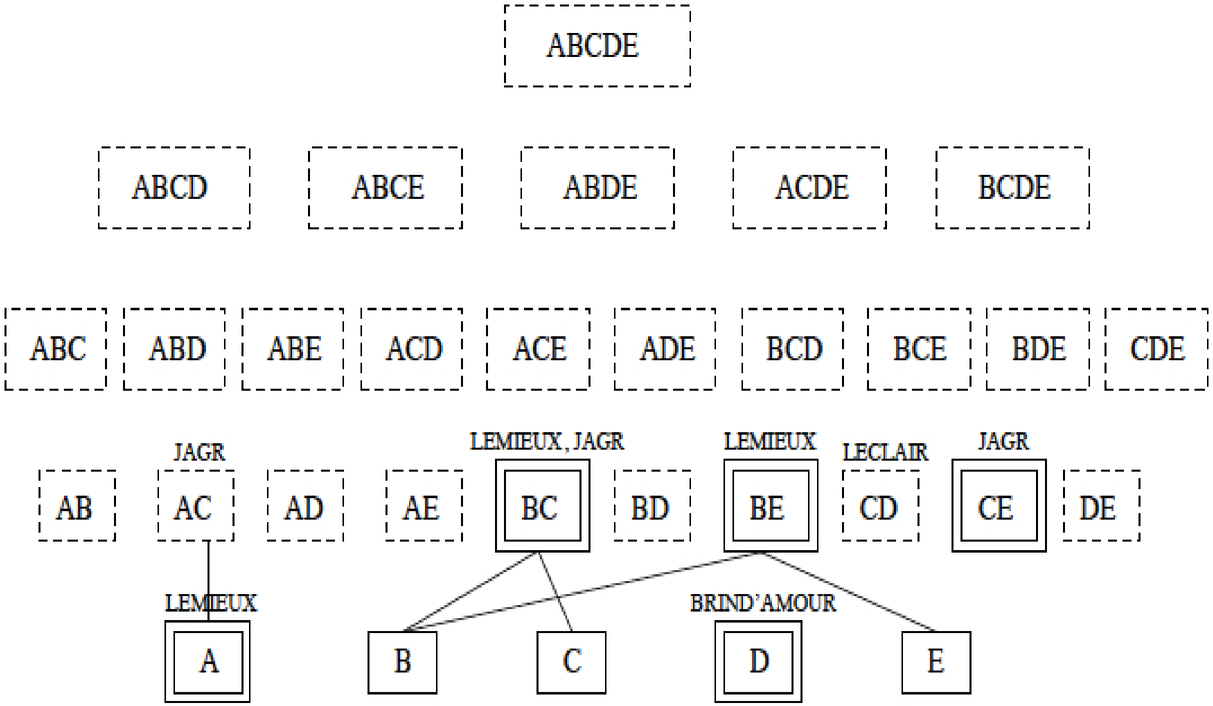
Any P that is an outlier in A is called a *strongest* outlier.

Any non-trivial outlier that is not strongest is called *weak* outlier.

Example: NHL ice hockey players

Knorr and Ng 1999

5-D space $\{A, B, C, D, E\}$ of power-play goals, short-handed goals, game-winning goals, game-tying goals, and game played



Lattice representation

Explaining outliers by subspace separability
(Micenkova and Ng 2013)

- Cannot derive explanatory subspace just by analyzing vicinity of the point in full space $\Rightarrow$ need to consider different subspace projections
- no monotonicity property for outliers wrt. subspaces
- need for heurstics because of exponential complexity,

look for a subspace A where the outlier factor is high and the dimension of A is low

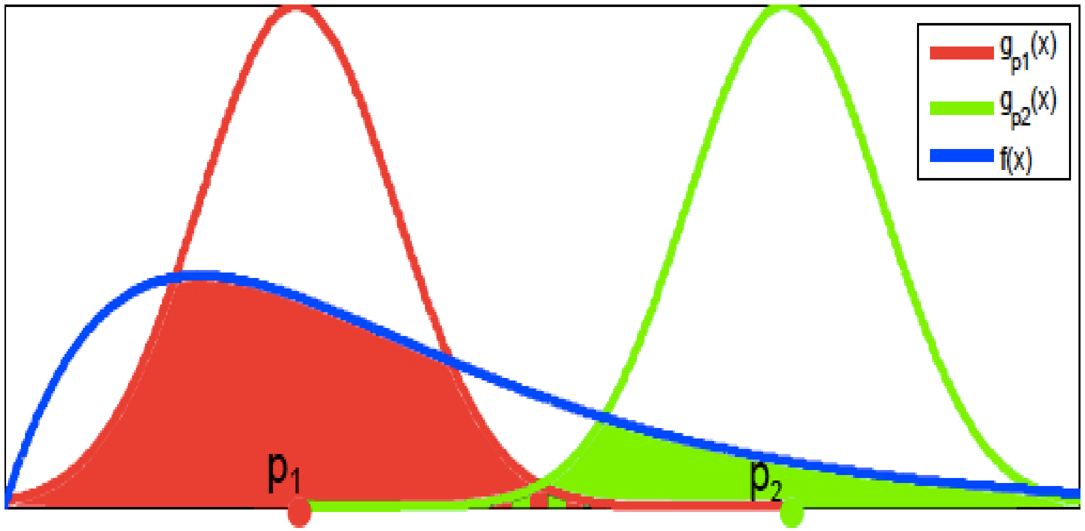
- separability - instance outlierness is related to its separability from the rest of the data

B. Micenková, R. T. Ng, X. H. Dang, and I. Assent. Explaining outliers by subspace separability. In IEEE ICDM 2013

Outlierness as accuracy of classification

(Micenkova and Ng 2013)

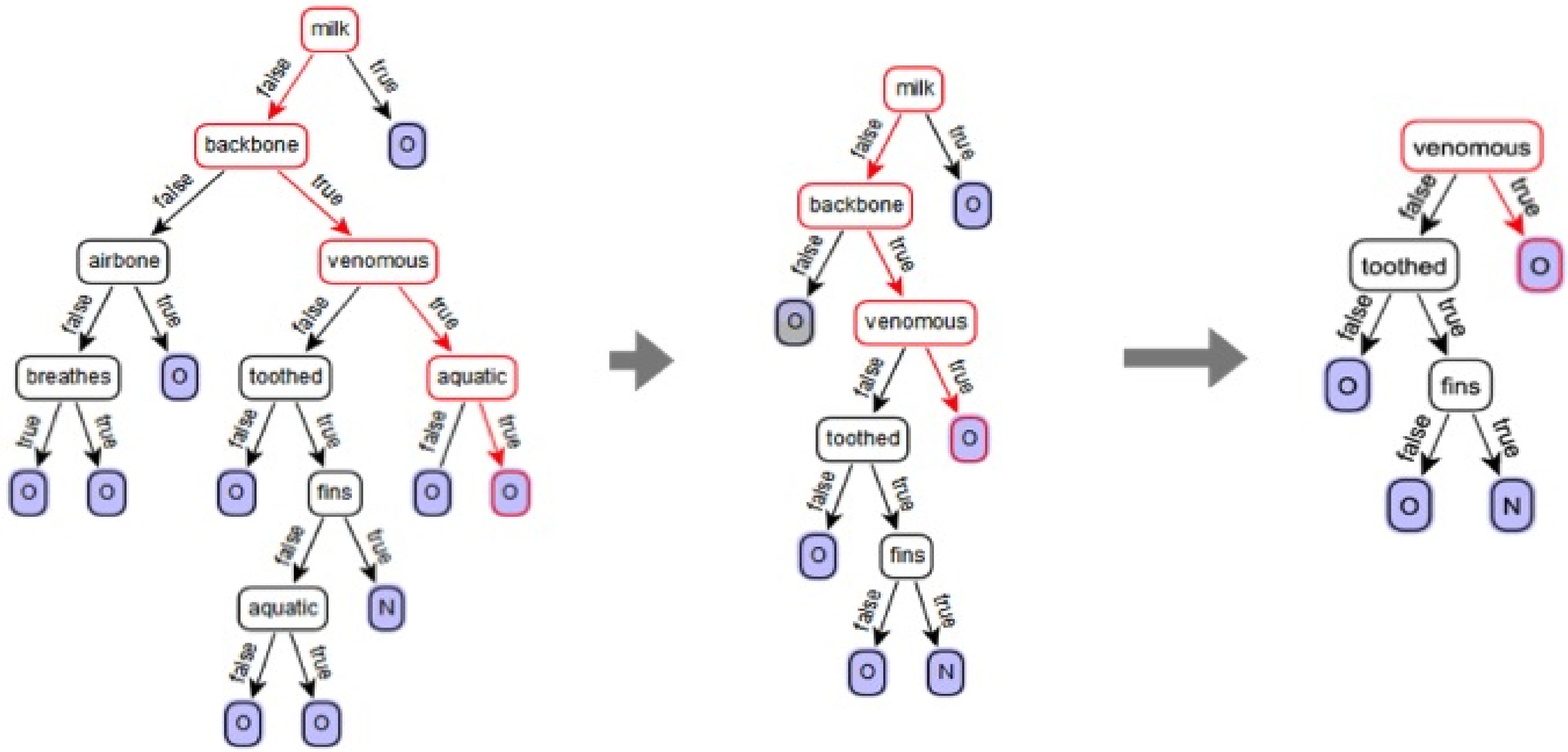
- separablity as error at classification. Assume that the data follows a distribution f
- original data = inlierclass; outlier + artificial points = outlierclass
- use standard feature selection methods to find explanatory subspaces



Measuring outlierness by separability. $p1, p2$ are points from the distribution $f(x)$ and the normal distributions $g_{p1}(x)$ and $g_{p2}(x)$ were artificially generated.

RF-OEX: Analysis of Random Forest

two methods: 1. search for frequent branches and **2. reduction of trees**



NEZVALOVÁ, Leona et al. Class-Based Outlier Detection: Staying Zombies or Awaiting for Resurrection? In Proceedings of IDA 2015.

RF-OEX

Examples of explanation

Form: (Condition, certainty factor)

Zoo dataset

Instance number: 64, Class: mammal

eggs=true, 0.51

toothed=false, 0.49

Iris dataset

Instance number: 19, Class: Iris-setosa

sepallength $>=$ 5.5 && sepalwidth $<$ 4, 0.53

sepallength $>=$ 5.5, 0.47

Recent work

Beyond Outlier Detection: LookOut for Pictorial Explanation, ECML PKDD. (Gupta et al. 2018)

Explaining anomalies in groups with characterizing subspace rules.Data Mining and Knowledge Discovery (2018) 32 (Macha and Akoglu 2018)

Oui! Outlier Interpretation on Multi-dimensional Data viaVisual Analytics Eurographics Conference on Visualization (EuroVis) (Xun Zhao et al. 2019)

Sequential Feature Explanation for Anomaly Detection. ACM Transactions on Knowledge Discovery from Data, Vol. 13, No. 1, (Siddiqui et al. 2019)

Towards explaining anomalies. A deep Taylor decomposition of one-class models. Pattern Recognition 101 (2020) 1071098 (Kauffmann et al. 2020)