Machine Learning

Anomalies, Music, Time Series

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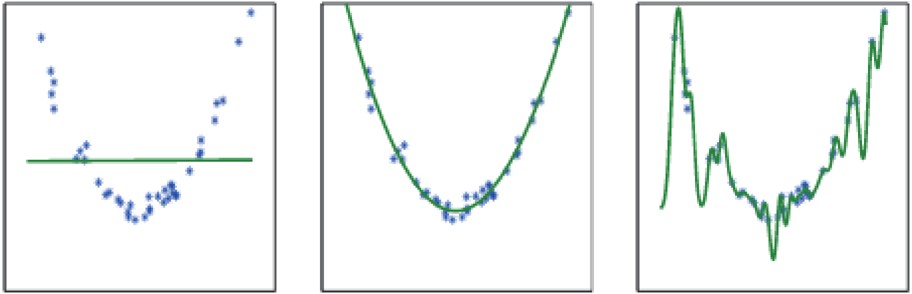
octobre 2020

Review

Underfitting, overfitting



Linear Regression

Logistic Regression

SVM

CART

Random Forests

PCA

Handwriting Recognition

Clustering

Anomaly Detection (not time)

Introduction to Anomaly Detection

- Supervised
- Unsupervised

Introduction to Anomaly Detection

Supervised anomaly detection:

- Training data: normal, abnormal
- Train a classifier

So reduced to existing problem of supervised classification.

Introduction to Anomaly Detection

Unsupervised anomaly detection:

- Mostly, this is clustering
- Increasingly, this is neural networks in advanced applications

Introduction to Anomaly Detection

Applications:

- Intrusion detection (physical or electronic)
- Fraud detection
- Health monitoring (people, animals, machines)

Introduction to Anomaly Detection

Techniques:

- Density: kNN, local outlier factor
- SVM
- Clustering: *k*-Means

kNN techniques and variations

- Voronoi diagrams
- aNN

k-Means

Local Outlier Factor (LOF)

- Measure average density using kNN
- Points with low local density are suspect outliers
- There is no good thresholding technique

Local Outlier Factor (LOF)

Let a be an object (point) in the set of samples.

Let $N_k(a)$ be the set of k nearest neighbours to a.

Define the k-distance from a:

$$d_k(a) = \max_{p \in N_k(A)} d(a, p)$$

Local Outlier Factor (LOF)

Define now the reachability distance:

$$r_k(a, b) = \max(d_k(a), d(a, b))$$

In otherwords, r_k is the distance between two points, but is no less than the k-distance.

So all the points in $N_k(a)$ are considered equally r_k distant from a.

Math note: r_k is not a true distance function.

Local Outlier Factor (LOF)

Define the *local reachability density* of object *a* by

$$\operatorname{lrd}(a) = \frac{1}{\left(\frac{\sum_{b \in N_k(a)} r_k(a,b)}{|N_k(A)|}\right)} = \left(\frac{|N_k(A)|}{\sum_{b \in N_k(a)} r_k(a,b)}\right)$$

This is the (inverse of the) average reachability distance of the *k* nearest neighbours.

Local Outlier Factor (LOF)

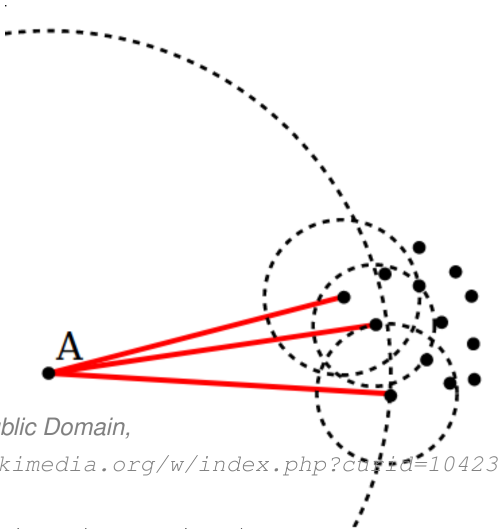
The

$$\mathrm{LOF}_k(a) = \left(\frac{\sum_{b \in N_k(a)} \frac{\mathrm{lrd}(b)}{\mathrm{lrd}(a)}}{|N_k(a)|} \right) = \left(\frac{\sum_{b \in N_k(a)} \mathrm{lrd}(b)}{|N_k(a)| \quad \mathrm{lrd}(a)} \right)$$

Interpretation:

- 1 indicates a point is comparable to its neighbours
- < 1 indicates more densely packed than its neighbours
- > 1 indicates more sparsely packed than its neighbours

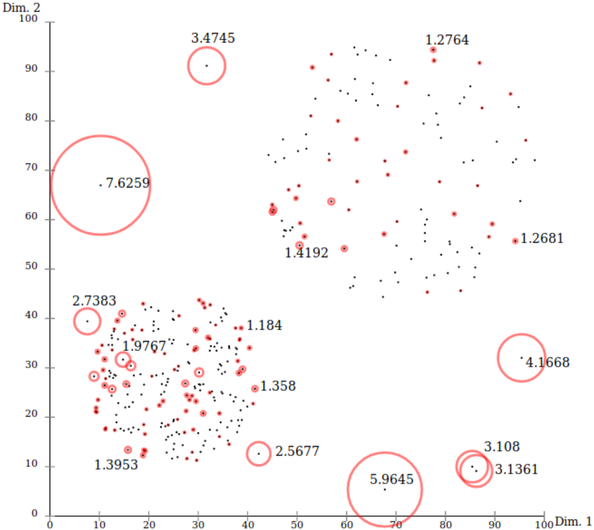
Local Outlier Factor (LOF)



By Chire - Own work, Public Domain,

https://commons.wikimedia.org/w/index.php?curid=10423954

Local Outlier Factor (LOF)



By Chire - Own work, Public Domain

Local Outlier Factor (LOF)

Advantages: intuitive, often works well (e.g., intrusion detection)

Disadvantages: fails at higher dimension (curse of dimensionality), hard to interpret

Examples

ping times

httpd response times

Examples

single/multiple host access abuse (DOS/DDOS)

Examples

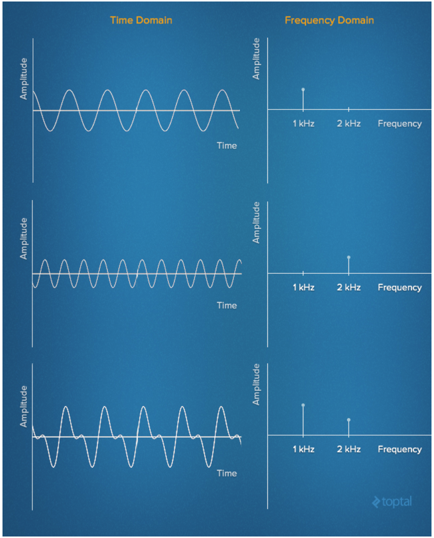
bank card fraud

Examples

spam

questions?

Music



http://www.toptal.com/algorithms/
shazam-it-music-processing-fingerprinting-and-recognition

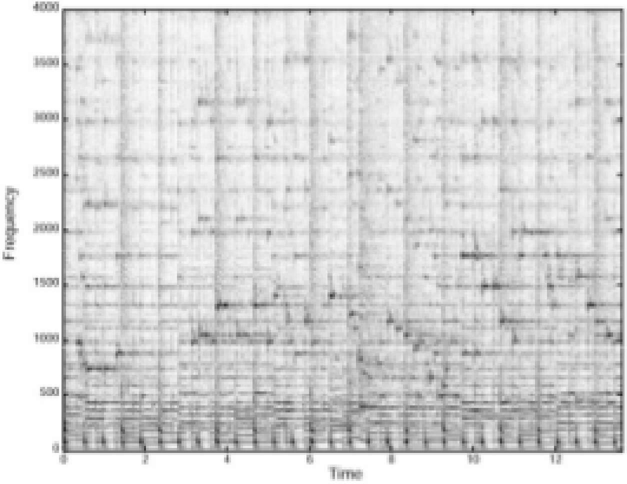


Fig. 1A - Spectrogram

https://www.ee.columbia.edu/~dpwe/papers/Wang03-shazam.pdf

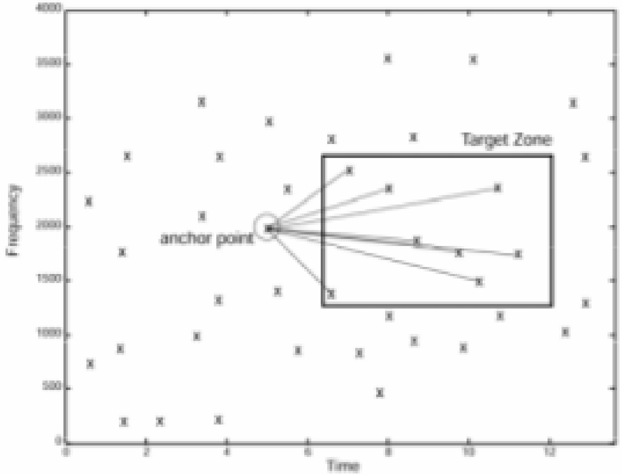


Fig. 1C - Combinatorial Hash Generation

https://www.ee.columbia.edu/~dpwe/papers/Wang03-shazam.pdf

questions?

Time Series

Introduction to time series

This is hard, but it depends on your goals. And on context.

Introduction to time series

Definition (discrete time series):

$$\{s_t \mid t \in \mathbb{R}^+ \land s \in \mathbb{R}\}$$

(though s in any vector space is fine)

Introduction to time series

Examples domains:

- Weather
- Economics
- Industry (e.g., factories)
- Medicine
- Web
- Biological processes

Introduction to time series

Why?

- Predict
- Control
- Understand
- Describe

Introduction to time series

Some strategies:

- Differencing:

$$y'_t = y_t - y_{t-1}$$

- Second-order differencing:

$$y''_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) = y_t - 2y_{t-1} + y_{t-2}$$

Introduction to time series

Some strategies:

- Clustering
- Hidden Markov Models (HMM)
- Recurrent neural networks (RNN)
- Autoregressive integrated moving average (ARIMA)
  - Generalisation of autoregressive moving average (ARMA) model
  - Regress on series' own lag

One model:

$$s_t = g(t) + \phi_t$$

where

$g(t)$ is deterministic: signal (or trend)

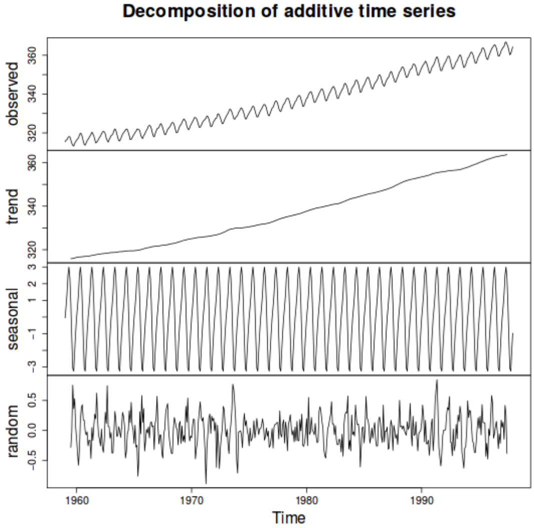
ϕ_t is stochastic noise

Introduction to time series

Variation types:

- Trend (g)
- Seasonal effect (g)
- Irregular fluctuation (residuals: ϕ)

Introduction to time series



http://www.ulb.ac.be/di/map/gbonte/ftp/time_ser.pdf

Some easy things to try

- Introduce features to break out seasonality
- Introduce lags as features
- Some domain-specific transformation

HMM

“simplest dynamic Bayesian network”

Markov Chains

A **Discrete time Markov chain (DTMC)** is a random process that undergoes state transitions**.**

Markov Chains

$$\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & xnn \end{bmatrix} \begin{bmatrix} v_1^{(i)} \\ v_2^{(i)} \\ \vdots \\ v_n^{(i)} \end{bmatrix} = \begin{bmatrix} v_1^{(i+1)} \\ v_2^{(i+1)} \\ \vdots \\ v_n^{(i+1)} \end{bmatrix}$$

Markov Chains

$$Xv_i = v_{i+1}$$

Markov Chains

Examples:

- Random walks
- Weather (first approximation in many places)
- Thermodynamics
- Queuing theory (so also telecommunications)
- Spam

Markov Chains

Properties:

- Stochastic process
- Memoryless (“Markov property”)

HMM's

- State is not visible
- Output of state is visible

Examples: noisy sensor, medical diagnosis

HMM's

What we have:

- State space $S = \{s_1, \ldots, s_n\}$
- Observation space $O = \{o_1, \ldots, o_k\}$
- Transition matrix A of size $n \times n$
- Emission matrix B of size $n \times k$
- Initial state probabilities $\pi = \{\pi_1, \ldots, \pi_n\}$
- A sequence of observations $X = \{x_1, \ldots x_T\}$

Here

- $y_t = i \iff$ observation at time t is o_i
- $\Pr(x_1 = s_i) = \pi_i$

We want the sequence of states $X = \{x_1, \ldots, x_T\}$.

HMM's

Some pointers to learn more about HMM:

- Forward-Backward Algorith
- Viterbi Decoding
- Baum-Welch Algorithm


questions?