Knowledge Discovery in Databases II

Lecture 3 – Data Streams

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Credits:

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Kapitel 1: Intorduction i

A Disclaimer (kind of ...)

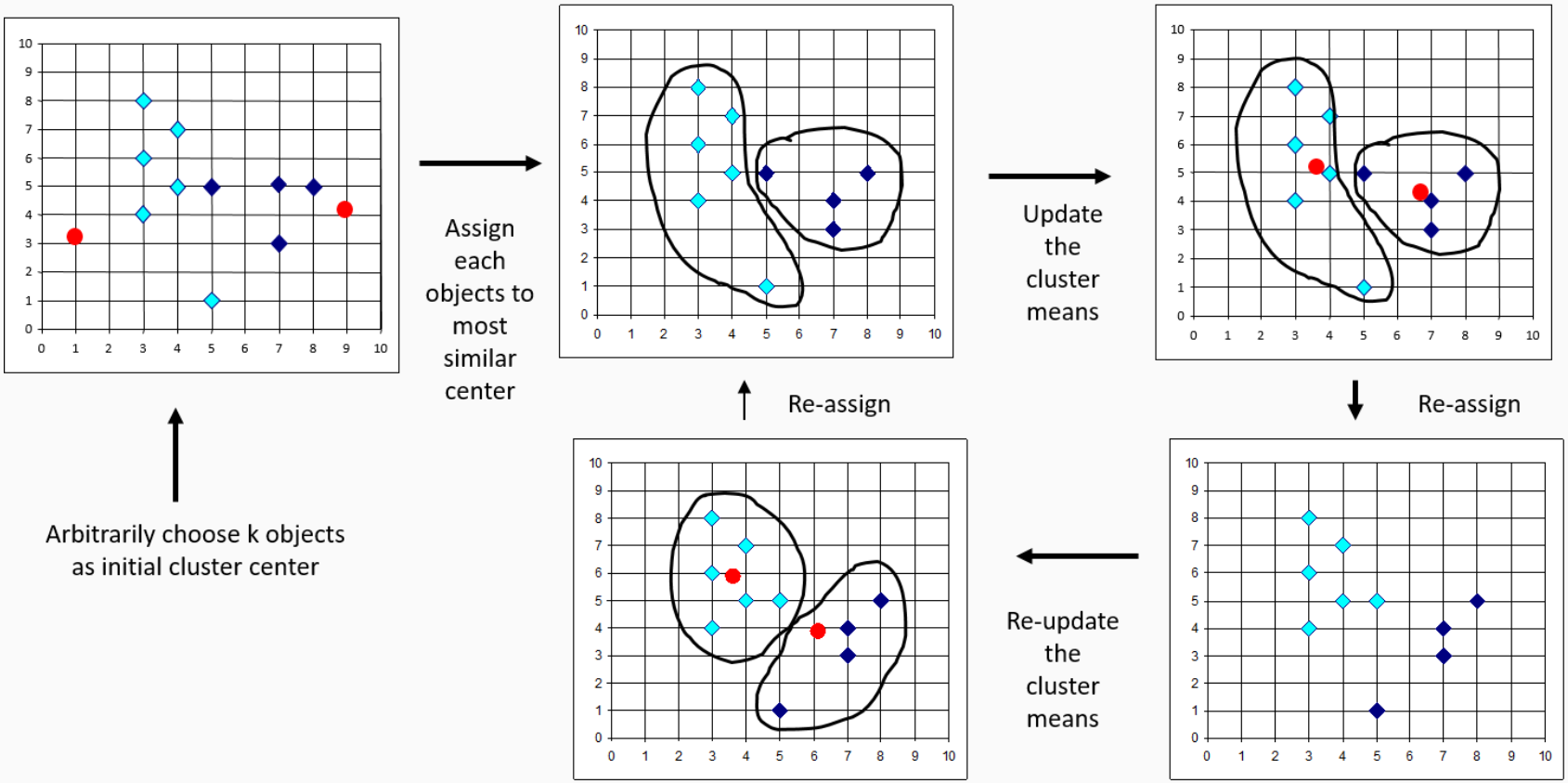
- Data streams usually are a very challenging source of data
- Analysis of data streams require to address several aspects such as
  - The hardware
  - The processing environment (like the operating system, the programming language and the programming schema, . . .)
  - The algorithmic design
  - . . .
- In this lecture, we focus on the algorithmic aspects that are necessary for processing data streams
- The lecture Big Data Management focuses on other aspects

Batch Learning

- Most of the DM algorithms focus on batch learning
  - The complete training/data set is available to the learning algorithm
  - Data instances can be accessed multiple times
  - e.g., for clustering: k-Means, DBSCAN
  - e.g., for classification: decision trees, Naïve Bayes
- Implict assumption: instances are generated by some stationary probability distribution; data is not volatile and so are patterns

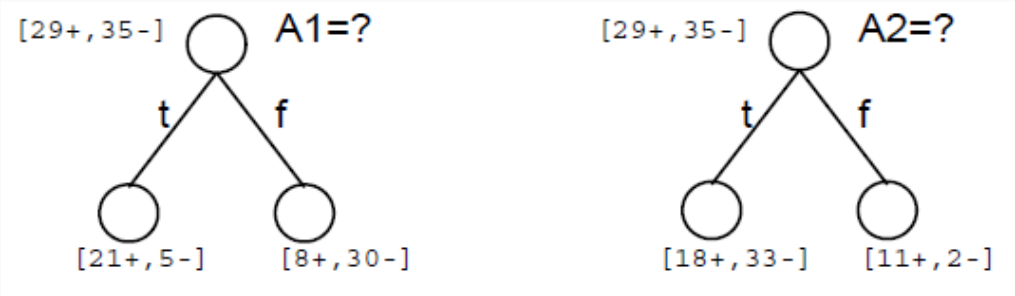
Example: Batch Clustering

- k-means (here $k = 2$) needs full access to the data in each iteration



Example: Batch Classification

- Decision Trees are constructed in a top-down recursive divide-and-conquer manner requiring full access to the data for each split
  - At start, all the training examples are at the root node
  - Select the best attribute for the root
  - For each possible value of the test attribute, a descendant of the root node is created and the instances are mapped to the appropriate descendant node
  - Repeat the splitting attribute decision for each descendant node, so instances are partitioned recursively

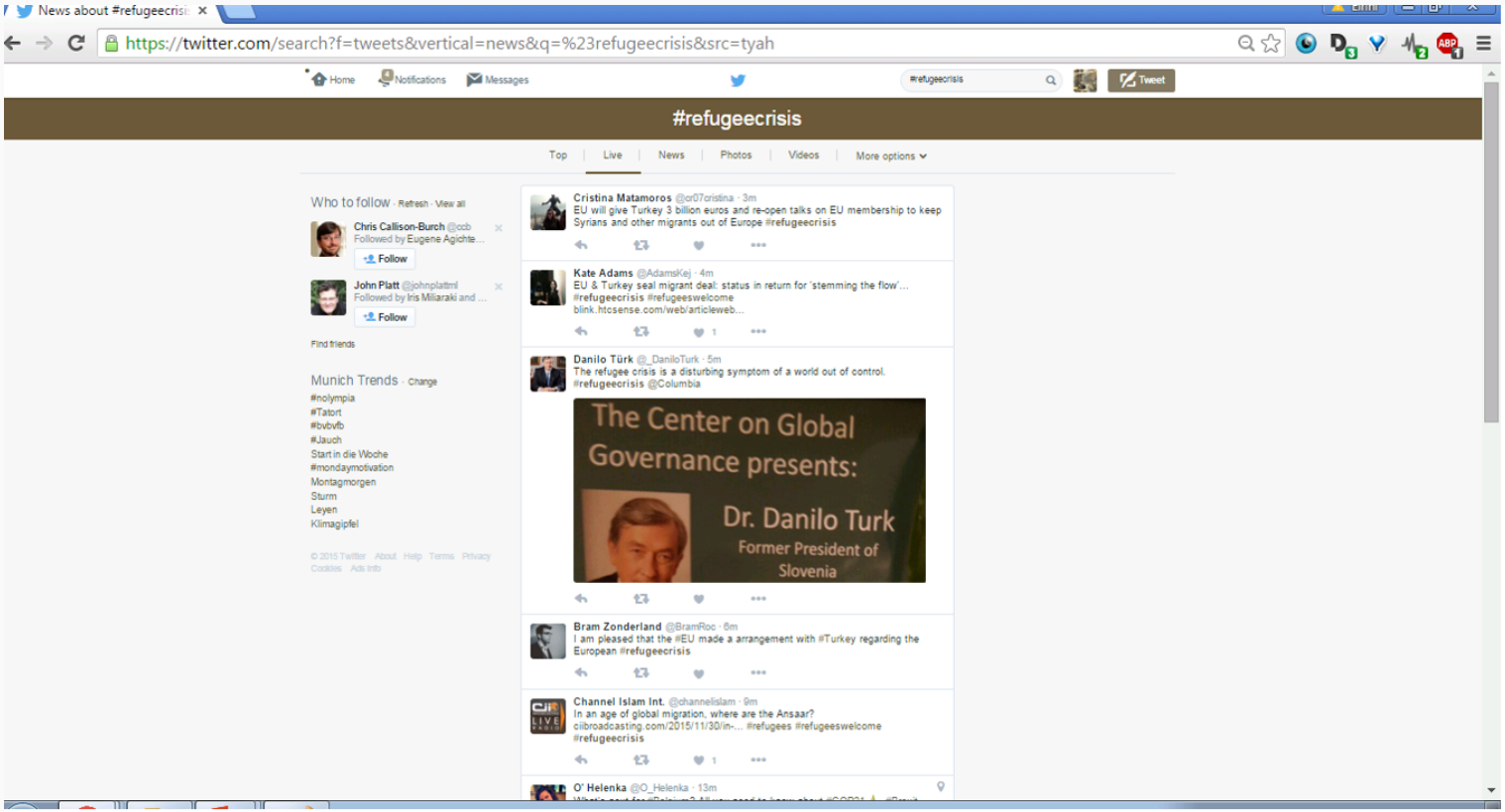


From Batch to Streams

- Many interesting applications nowadays come from dynamic environments where data are generated over time, e.g., customer transactions, call records, customer click data, social media interactions
- Batch learning is not sufficient anymore as
  - Data is never ending. What is the training set?
  - Multiple access to the data is not possible or desirable
- And also, the data generation process is subject to changes over time
  - The patterns extracted upon such sort of data are also evolving
  - Algorithms should respond to change (incorporate new data instances, forget obsolete data instances)

Examples

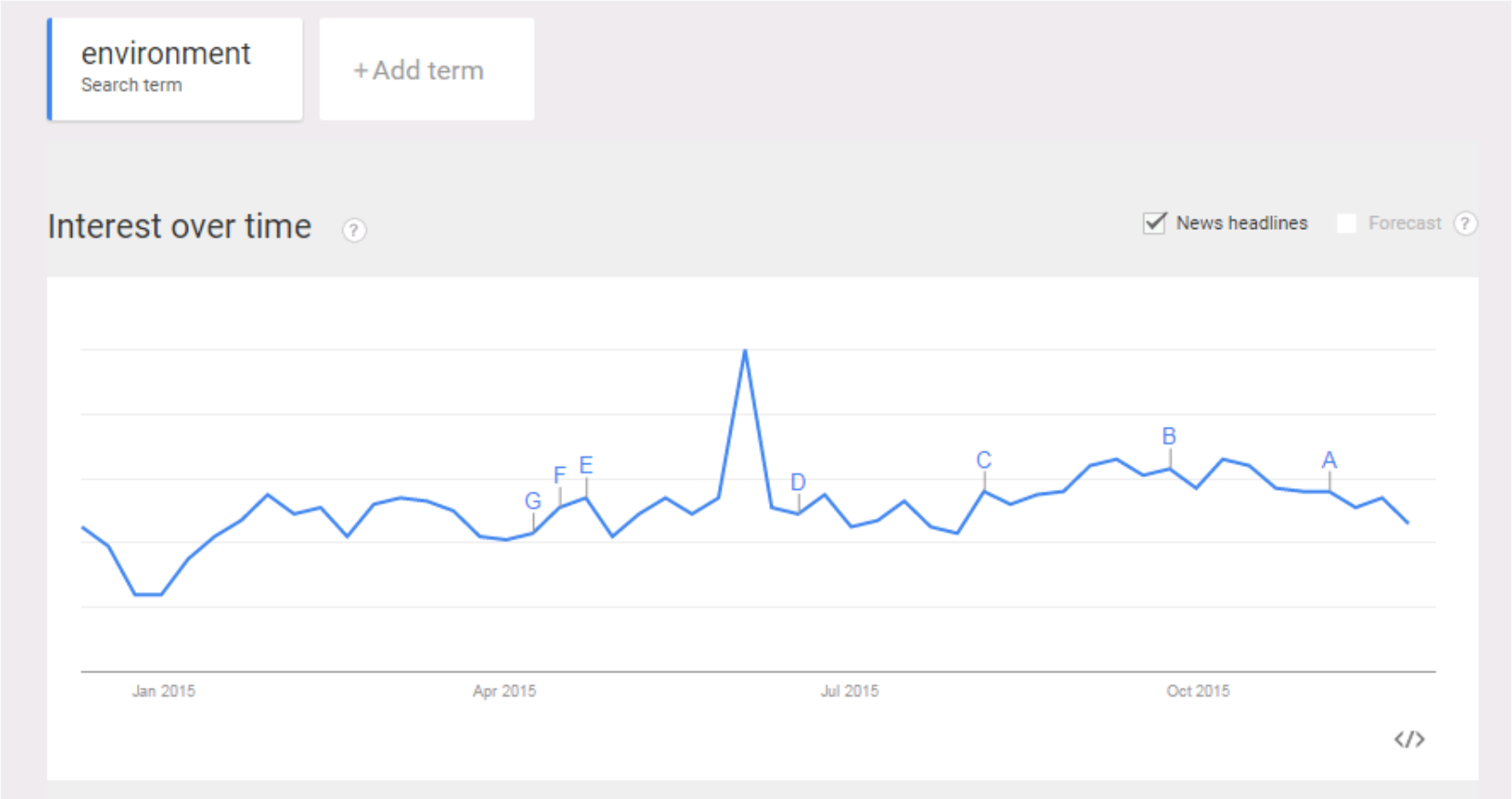
- Twitter stream for hastag “#refugeecrisis”



Source: `https://www.twitter.com/`

Examples

- Trend of the search for “environment”



Source: https://www.google.com/trends/

Examples

- Experiments at CERN are generating an entire petabyte (1PB=106 GB) of data every second as particles fired around the Large Hadron Collider (LHC) at velocities approaching the speed of light are smashed together
- “We do not store all the data as that would be impractical. Instead, from the collisions we run, we only keep the few pieces that are of interest, the rare events that occur, which our filters spot and send on over the network”
- This still means CERN is storing 25PB of data every year — the same as 1,000 years’ worth of DVD quality video — which can then be analyzed and interrogated by scientists looking for clues to the structure and make-up of the universe

Source: `http://public.web.cern.ch/public/en/LHC/Computing-en.html`

Source: `http://www.v3.co.uk/v3-uk/news/2081263/cern-experiments-generating-petabyte`

Examples

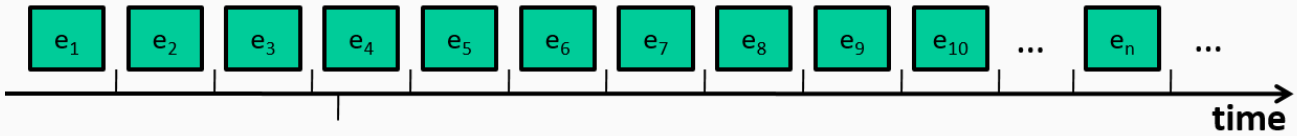
- Network monitoring records e.g. TCP connection records of LAN network traffic
- A connection is a sequence of TCP packets starting and ending at some well defined times, between which data flows to and from a source IP address to a target IP address under some well defined protocol
- Connections are described in terms of 42 features like duration, protocol type, service, flag, src bytes, dst bytes etc.
- Each connection is labeled as either normal, or as an attack, with exactly one specific attack type
- Most of the connections are usually normal, but occasionally there could be a burst of attacks at certain times

Source (with link to a real data set): `http://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html`

What is a Data Stream?

Everything flows, nothing stands still

Heraclitus (535-475 BC)



- Data evolve over time as new data arrive (and old data become obsolete/irrelevant)
- We can distinguish between:
  - Dynamic data arriving at a low rate (as e.g. in DWs): incremental methods might work for such cases
  - Data streams: possible infinite sequence of elements arriving at a rapid rate: new methods are required to deal with the amount and complexity of these data

Incremental Methods

- Focus is on how to update the current pattern based on the newly arrived data, without re-computing the pattern from scratch
- Requires (limited) access to raw data (i.e., only the data that is affected by the changes)
- Example: incremental DBSCAN (insertion of a new point *p*)

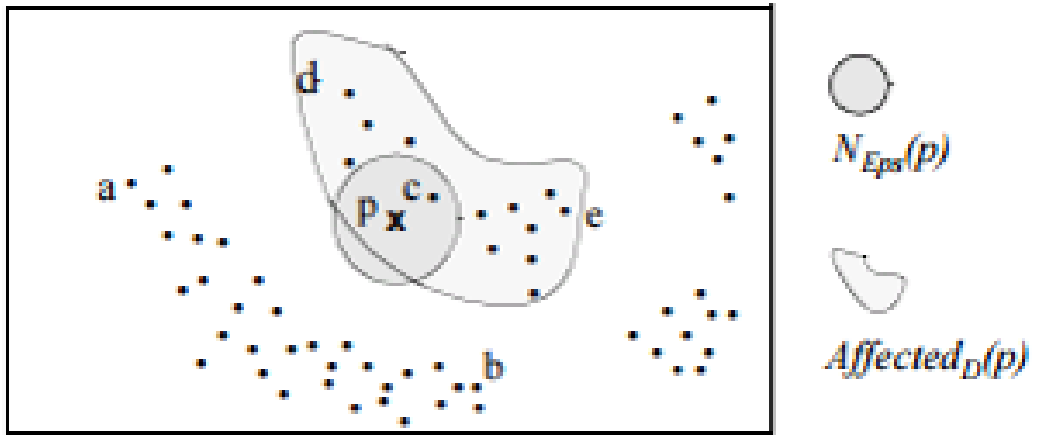


Figure 3: : Affected objects in a sample database

Challenges for Streams

- Data Mining over stream data is more challenging than batch learning
  - Huge amounts of data, thus, only a small amount can be stored in memory
  - Arrival at a rapid rate, thus, no much time for processing
  - The generative distribution of the stream might change over time rather than being stationary, thus, adapt and report on changes
- Requirements for stream mining algorithms
  - Use limited computational resources (bounded memory, small amount of available processing time)
  - No random access to the data but rather only one look at the data (upon their arrival)

From Data Changes to Pattern Changes

Example: cluster evolution over time

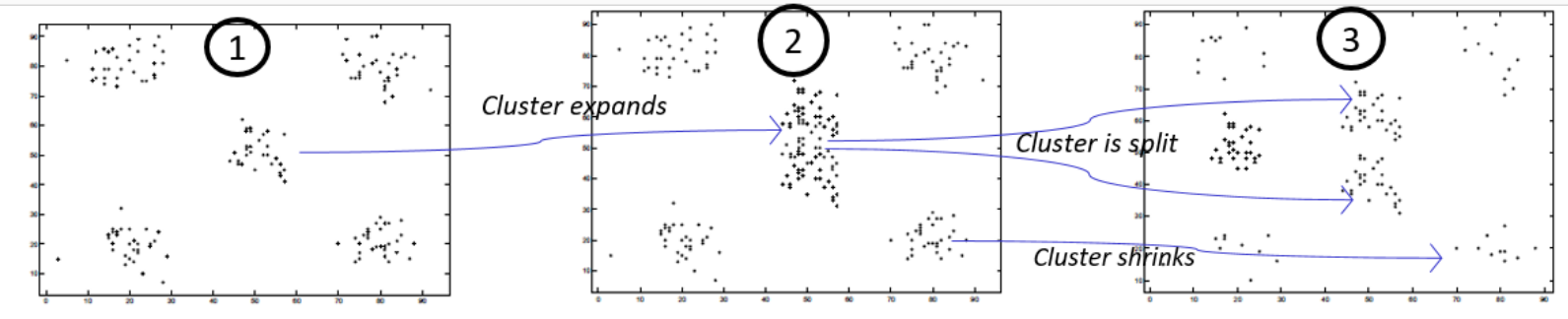


Figure: Data records at three consecutive time stamps, the clustering gradually changes
(from: *MONIC - Modeling and Monitoring Cluster Transitions*, Spiliopoulou et al, KDD 2006)

Example: decision boundary drift over time

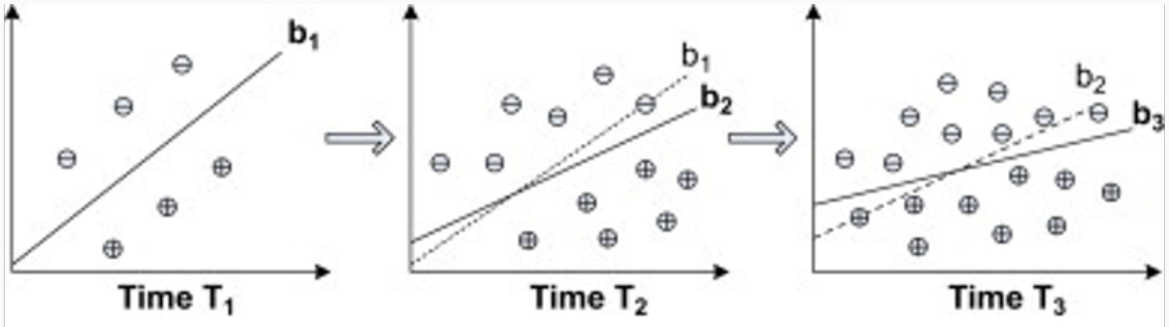


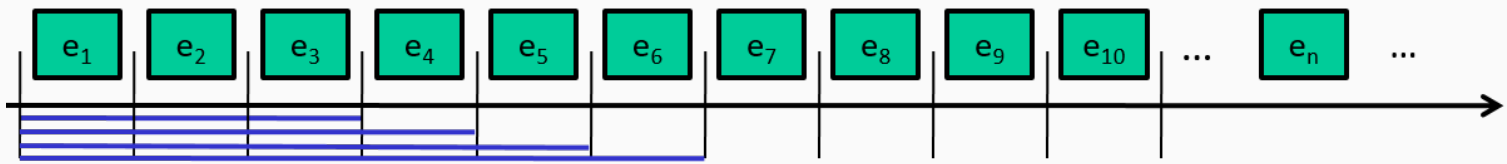
Fig. 1. An illustration of concept drifting in data streams. In the three consecutive time stamps T_1, T_2 and T_3, the classification boundary gradually drifts from b_1 to b_2 and finally to b_3.
(from: *A framework for application-driven classification of data streams*, Zhang et al, Journal Neurocomputing 2012)

Data Ageing

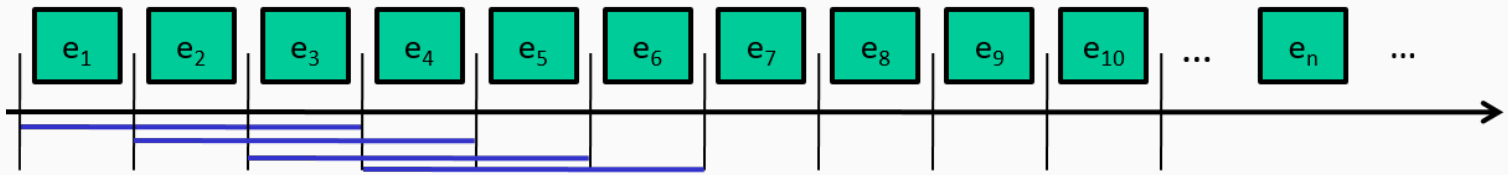
- Usually we are not interested in the whole history of the stream but only in the recent history
- There are different ageing/weighting mechanisms or window models that reflect which part of the stream history is important for learning
  - Landmark window model
  - Sliding window model
  - Damped window model

Data Ageing Models

- Landmark (window) model
  - Include all objects from a given landmark
  - All points have an equal weight (usually $w = 1$)

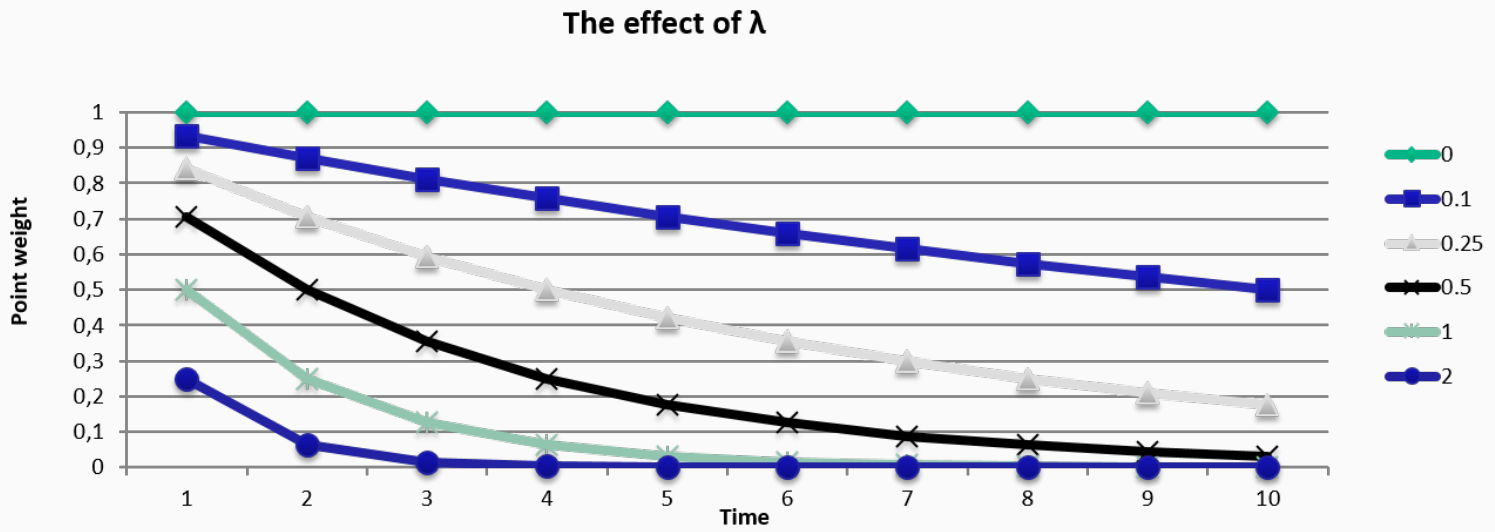


- Sliding window model
  - Remember only the n most recent entries, where n is the window size
  - All points within the window have a weight $w = 1$, for the rest: $w = 0$



Data Ageing Models

- Damped window model
  - Data are subject to ageing according to a fading function $f(t)$, i.e., each point is assigned a weight that decreases with time t via $f(t)$
  - A widely used fading function in temporal applications is the exponential fading function: $f(t) = 2^{-\lambda t}$, where $\lambda > 0$ is the decae rate that determines the importance of historical data (the higher the value of λ, the lower the importance of old data)



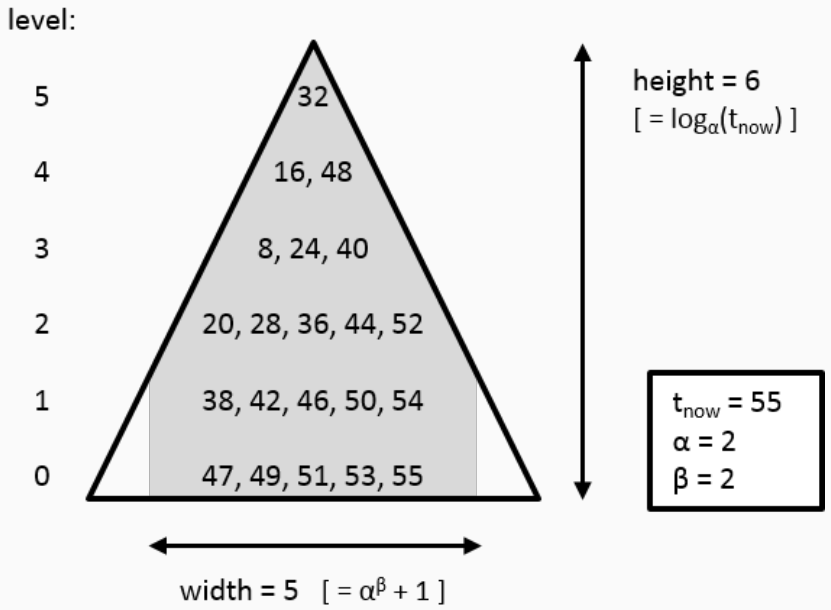
Time Frames

- Task: maintain the history of the stream
  - Store snapshots at (regular) time intervals
  - Use finer granularity for recent data for a detailed representation
  - Use coarser granularity for older data to save space

- Tilted time frame (tilt time frame)
  - Example: align time axis with natural calendar time, e.g.:
    1 snapshot per minute for the 15 most recent minutes
    1 snapshot per quarter for the 4 most recent quarters
    1 snapshot per hour for the 24 most recent hours
    1 snapshot per day for the 30 most recent day
    1 snapshot per month for the 12 most recent months
    Total number of snapshots for one year: 85
    (compare to 60*24*30*12 = 518400 snapshots)

Pyramidal Time Frame Model

- Stores snapshots in levels of decreasing cardinality (pyramid)
- Size (number of snapshots) is controlled by two parameters $\alpha, \beta \in \mathbb{N}$



- For a new snapshot *A* provided at time t_{now}
  - Store *A* on the highest level *i* with $t_{now} mod \alpha^i = 0$
  - If a level contains more than $\alpha^\beta + 1$ snapshots, remove the oldest
- Maximal height $\lceil \log_\alpha(t_{now}) \rceil$
- Number of snapshots is smaller than $(\alpha^\beta + 1) \cdot \lceil \log_\alpha(t_{now}) \rceil$
- Example: 1 snapshot per second for 100 years using $\alpha = 2$ and $\beta = 1$ results in 96 snapshots

Overview

- The (batch) clustering problem
  - Given a set of measurements, observations, etc., the goal is to group the data into groups of similar data objects (clusters)
- The data stream clustering problem
  - Continuously maintain a consistently good clustering of the sequence observed so far, using a small amount of memory and time
- This implies
  - Use incremental computations and techniques
  - Maintaining cluster structures that evolve over time
  - Working with summaries (of such cluster structures) instead of raw data

Challenges

- Traditional clustering methods require access upon the whole data set
- Rather, we need online maintenance of patterns that captures pattern drifts
- The underlying population distribution might change: drifts/ shifts of concepts
- One clustering model might not be adequate to capture the evolution
- The role of outliers and clusters are often exchanged in a stream
- A clear and fast identification of outliers is often crucial for the success

Overview

Cluster Model	Batch/static clustering	Dynamic/stream clustering
Partitioning methods	k-means, k-medoid	– Leader – STREAM k-Means – CluStream
Density-based methods	DBSCAN, OPTICS	– DenStream – incDBSCAN – incOPTICS
Grid-based methods	STRING	– Dstream

Overview

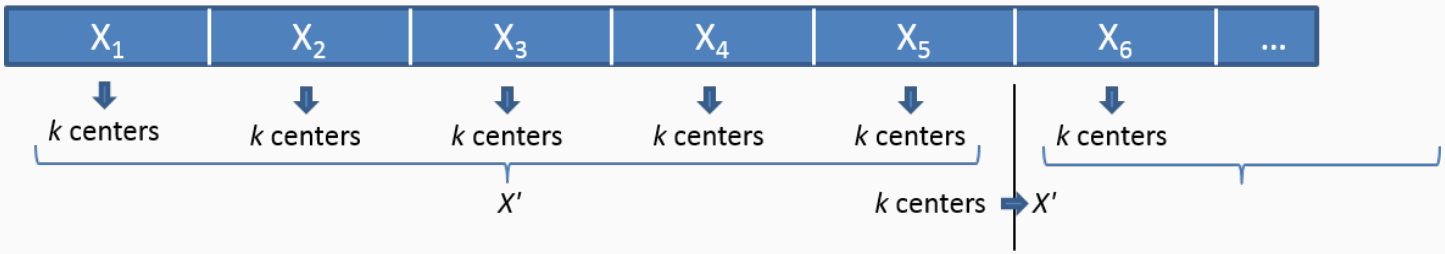
- Goal: Construct a partition of a set of objects into k clusters
- Two types of methods
  - Adaptive methods such as Leader (Spath 1980), Simple single pass k-Means (Farnstrom et al., 2000), STREAM k-Means (OCaEtAl02)
  - Online summarization - offline clustering methods such as CluStream (AggEtAl03), DenStream (CaoEtAl06)
  - Continous grid-based such as DStream (CheTu07)

Leader

- The simplest single-pass partitioning algorithm
- Whenever a new instance p arrives from the stream
  - Find its closest cluster (leader), c_{clos}
  - Assign p to c_{clos} if their distance is below the threshold d_{thresh}
  - Otherwise, create a new cluster (leader) with p
- Properties
  - 1-pass and fast algorithm
  - No prior information on the number of clusters required
  - Result depends on the order of the examples
  - Sensitive to a correct guess of d_{thresh} (which is fixed)

STEAM k-Means

- Simple extension of batch k-Means to streams:
  - Use a buffer (chunk) that fits in memory and apply k-Means locally in the buffer
- STEAM k-Means:
  - Apply k-Means on chunk X_i
  - X' denotes the set of $i \cdot k$ cluster centers from all chunks $X_1, \ldots X_i$ each weighted by the number of points assigned to it
  - Output the k centers obtained by clustering X'



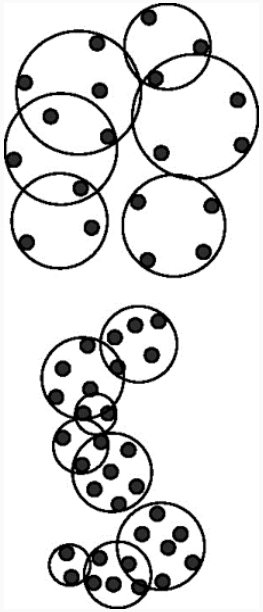
STEAM k-Means

Properties:

- Pros:
  - Single scan
- Cons:
  - Expensive (according to authors)
  - No aging
  - Cluster model inherent limitations (no noise handling, ...)
  - Fixed k in all chunks

Basic Idea

- Online component
  - Maintain a larger number of small clusters (micro-cluster)
  - Reduce data, keep sufficient details
  - Separate clusters for noise (improved robustness)
  - Provide accurate and fine grained input for further steps
- Offline component
  - Generate actual clustering on user request using micro-cluster information
  - Exchangeable clustering method
  - Individual and changing parameterization possible
  - Only approximate clustering



Micro Clusters: Cluster Features

- Clustering Features[1] for a set of points X: $CF_X = (N_X, LS_X, SS_X)$ with
  - N_X is the number of points, i.e., $|X|$
  - LS_X is the linear sum of all points in X, i.e., $\sum_{x_i \in X} x_i$
  - SS_X is the squared sum of all points in X, i.e., $\sum_{x_i \in X} x_i^2$
- From CF_X we can easily compute basic statistics of X such as
  - Mean (centroid) of X
  - Compactness measures such as radius, diameter, variance and std. deviation
- CFs are additive, i.e., given two (disjunctive) sets X and Y with their corresponding CF_X and CF_Y, we can compute $CF_{X \cup Y}$ as follows:

$$CF_{X \cup Y} = CF_X + CF_Y = (N_X + N_Y, LS_X + LS_Y, SS_X + SS_Y)$$

[1] Zhang, Ramakrishnan, Linvy: BIRCH: An Efficient Data Clustering Method for Very Large Databases. Proc. ACM SIGMOD 1996

Micro Clusters: Data Bubbles

- While CFs are good for partitioning based clustering, they do not capture density estimations necessary for e.g. OPTICS
- Data Bubbles[2] for a set of points X: $B_X = (N_X, M_X, r_X)$ with
  - N_X is the number of points, i.e., $|X|$
  - M_X is the centroid of X
  - r_X is the radius of the ball centered at M capturing all points in X
- Data Bubbles can be computed from CFs
- Data Bubbles allow a good approximation of core/reachability distances for hierarchical clustering

[2] Breunig, Kriegel, Kröger, Sander: Data Bubbles: Quality Preserving Performance Boosting for Hierarchical Clustering. Proc. ACM SIGMOD 2001

CluStream — Basics

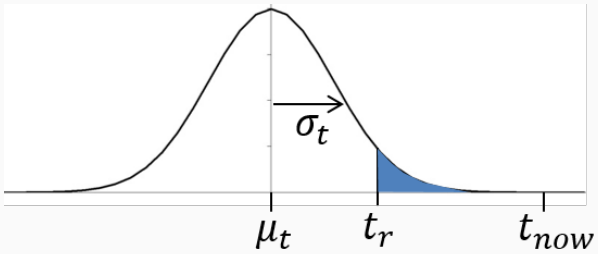
- One of the first algorithms for streams proposing an online/offline framework
- Uses cluster features to propose a k-Means like stream clustering method
- Cluster Features (see above) are extended by the information of the time slots T when points in X have arrived, i.e. x_i has arrived at time t_i:
  $CFT_X = (N_X, LS_X, SS_X, LST_X, SST_X)$, where
  - N, LS_X, and SS_X are defined as above (note that LS_X and SS_X are vectors)
  - LST_X is the linear sum of time slots of X, i.e., $\sum_{t_i \in T} t_i$
  - SST_X is the linear sum of time slots of X, i.e., $\sum_{t_i \in T} t_i^2$
- Again, important for the stream situation:
  - CFTs can be maintained incrementally, i.e. $CFT_{X \cup p} = CFT_X + p$

CluStream — Method at a Glance

- General idea: a fixed number of q micro-clusters (represented as CFTs) is maintained over time
- Initialize: apply q-Means over a buffer of *initP* observations and build a summary for each cluster
- Both q and *initP* are input parameters
- Upon request, k-Means can be applied to a snapshot of the q CFTs

CluStream — Online Phase

- Maintain q micro-clusters while adding a new observation x_i from the stream
  - Find closest micro-cluster MC_j according to distance $dist(x_i, \mu_j)$
  - If $dist(x_i, \mu_j) < \alpha \cdot \sigma_j$ then add x_i to MC_j
  - Else create a new micro-cluster containing only x_i and delete a micro cluster by using one of the following actions:
    - Delete the least recent MC if its relevance stamp $t_r < t_{now} - \tau$
    - Merge the two closest micro clusters
- $\alpha \cdot \sigma_j$ is called the maximal boundary of MC_j
- The relevance stamp t_r of MC_j approximates the average time stamp of the last m objects
- It is computed as the time of arrival of the $m/(2 \cdot N)$-th percentile (i.e., $1 - m/2 \cdot N$ of the time stamps in MC_j



CluStream — Offline Phase

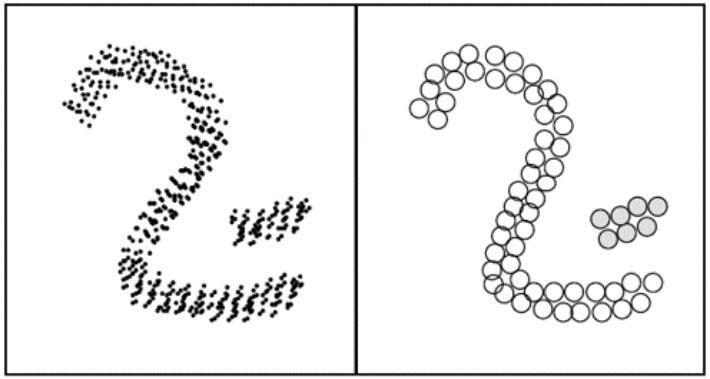
- Snapshots of micro-clusters are stored in pyramidal time frame
- Given k and a time horizon h
- Locate all valid micro-clusters within h
- Final clusters are gained using a modified k-Means
  - Micro-clusters over a certain time horizon are treated as pseudo-points
  - In the initialization: seeds are not picked randomly, but sampled with a probability proportional to N
  - Distances are calculated between centroids of the micro-clusters
  - New seeds are weighted by N
  - The k clusters obtained from applying k-Means on the micro-clusters are called macro-clusters

CluStream — Properties

- Single scan, stream compression using micro-clusters
- Views the stream as a changing process over time, rather than clustering the whole stream at a time
- Can characterize clusters over different time horizons in changing environment
- Aging only for entire clusters
- Noise handling offline
- Not adaptive q is fixed, requires $k < q$
- Many parameters
- Sensitive to outliers and noise (also model inherent)

DenStream — Motivation

- Density-base cluster model: clusters as regions of high density surrounded by regions of low density (noise)
- Very appealing for streams
  - No assumption on the number of clusters
  - Discovering clusters of arbitrary shapes
  - Ability to handle outliers and noise
- But, they miss a clustering model (or it is too complicated): clusters are represented by all their points
- So we can again only hope to approximate an arbitrary shaped cluster by many small (circular) micro-clusters



DenStream — Basics

- The DenStream algorithm uses time-weighted cluster features at time slot t given a time weighting function f for observations x_i arriving at time $t_i < t$:

$$CF_X^t = (N_X^t, LS_X^t, SS_X^t)$$

where

  - $N_X^t = \sum_{x_i \in X} f(t - t_i)$
  - $LS_X^t = \sum_{x_i \in X} f(t - t_i) x_i$
  - $SS_X^t = \sum_{x_i \in X} f(t - t_i) x_i^2$

- Usually, $f(t) = 2^{-\lambda t}$ models the damped window model (but other functions are possible)

- If a new observation x_i is added, a micro-cluster summary CF_X^t can be maintained incrementally (analogously as above)
- If no point is added to CF_X^t for time interval Δt, then $CF_X^t = (2^{-\lambda \Delta t} \cdot N, 2^{-\lambda \Delta t} \cdot LS_X^t, 2^{-\lambda \Delta t} \cdot SS_X^t)$
- The radius r_X of a micro-cluster X can be derived from the cluster feature CF_X^t as follows

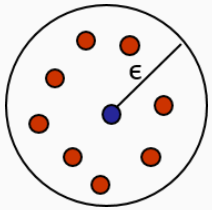
$$r_X = \sqrt{SS_X^t / N_X^t - (LS_X^t / N_X^t)^2}$$

- Analogously, the center c_X of a micro-cluster can be computed from its CF_X^t

DenStream — Basics

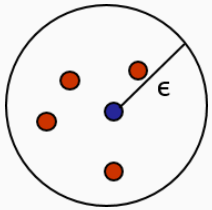
Given the density threshold μ (#points) and ε (volume) and a weighting factor β ($0 < \beta \leq 1$), DenStream maintains three different types of micro-clusters:

- Core (or dense) micro-clusters (CMC) X if $N_X^t \geq \mu$ and $r_X \leq \varepsilon$

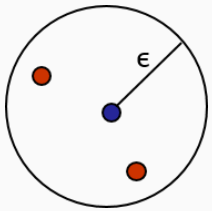


- Potential core micro-clusters (PCMC) X if $N_X^t \geq \beta \cdot \mu$ and $r_X \leq \varepsilon$

  (provides the opportunity for transitions between new clusters and outliers)



- Outlier micro-clusters (OMC) X if $r_X \leq \varepsilon$ and $N_X^t < \beta \cdot \mu$



Note: all MC types always have a radius $\leq \varepsilon$

DenStream — Initialization

- Collect a set I of *initP* of initial points
- For any $p \in I$:
  - Compute ε-neighborhood $N_\varepsilon(p)$ of p
  - If $|N_\varepsilon(p)| \geq \mu$ (p is core), create a new CMC $X = N_\varepsilon(p)$ and remove X from I
- For all remaining $p \in I$: create a new OMCs $X = N_\varepsilon(p)$ and remove X from I

DenStream — Online Phase

Online micro-cluster maintenance (when a new observation x_i arrives)

- Core micro-clusters are not considered
- Find closest potential core micro-cluster X_p
- If $dist(x_i, c_{X_p}) \leq \varepsilon$
  - Add x_i to X_p
  - Check if X_p becomes a CMC
- Else
  - Find closest outlier micro-cluster X_o
  - If $dist(x_i, c_{X_o}) \leq \varepsilon$, add x_i to X_o and check if X_o becomes a PCMC
  - Else: create a new OMC $X_{x_i} = \{x_i\}$
- After a given number of T time steps, check:
  - Delete all CMC X with $N_X^t < \mu$
  - Delete all OMC that did not become CMC within the last T time steps

DenStream — Offline Phase

- Upon user request, run DBSCAN on current CMCs and PCMCs
- Use centers and weights of the micro-clusters

DenStream — Discussion

- Single scan, stream compression using micro-clusters
- Noise/ outlier handling (model inherent)
- Flexible data aging model (for individual objects)
- Constant parameters over time, what about clusters with changing density?

Online/Offline-Approaches: Summary

	CluStream	DenStream
Online	convex micro cluster	
Offline	k-Means	DBSCAN
Aging	entire MCs	individual objects

- Cluster algorithm in offline phase exchangeable in principle
- Still “high” online costs (check all MCs)
- Many variants exist

Basic Idea

- A grid structure is used to capture the density of the data set
- A cluster is a set of connected dense cells (see e.g. STING)
- Appealing features
  - No assumption on the number of clusters
  - Discovering clusters of arbitrary shapes
  - Ability to handle outliers
- In case of streams
  - The grid cells are considered as micro-clusters, i.e., summary information on cells are maintained
  - Update these summaries on the grid structure as the stream proceeds
  - Sample method: DStream (CheTu07)

DStream — Basics

- DStream divides each dimension into l partitions resulting in l^d cells (d: data dimensionality)
- Populated grid cells are maintained in a hash list
- For a grid cell C, the following summary is stored:

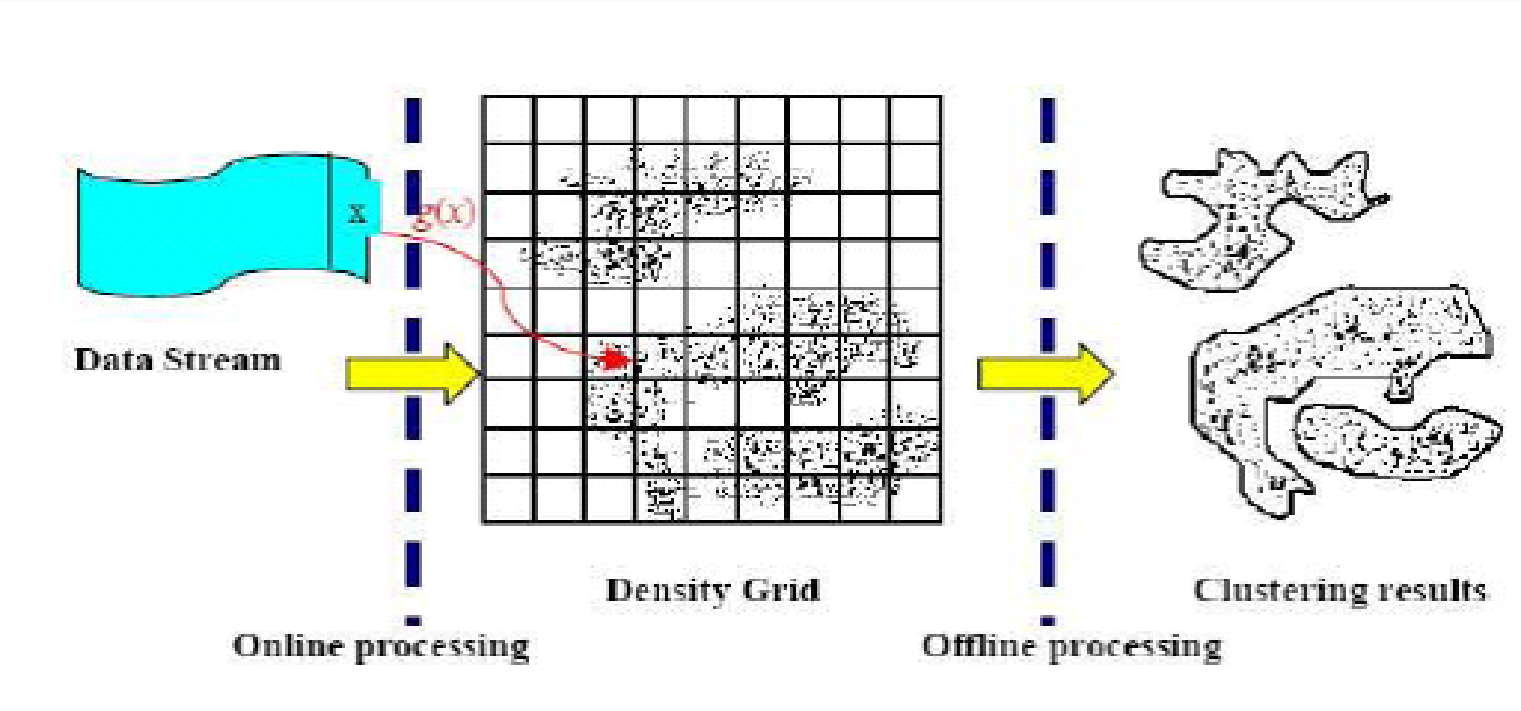
$$CF_C = (t_{update}, t_{spor}, N_C, label_C, status_C)$$

where

- t_{update} is the last update time
- t_{spor} last time, C has been removed
- $N_C = \sum_{x_i \in C} \lambda^{t-t_i} \cdot x_i$ (count using damped window aging)
- $label$ is the cluster label
- $status \in \{sporadic, normal\}$

DStream — Overview

- DStream follows the online/offline paradigm
- Online mapping of the new data into the grid
- Offline computation of grid density and clustering of dense cells



DStream — Summaries

- Three cell types are defined by parameters τ_{dense} and $\tau sparse$:
  - Cell C is dense if $N_C > \tau_{dense}$
  - Cell C is sparse if $N_C < \tau_{sparse}$
  - Cell C is transitional if $\tau_{sparse} < N_C < \tau_{dense}$
- Connected regions of dense or transitional cells form a cluster
- Changes of the *status* occur in the online component
  - Set status to *normal*, if C changed from *sparse* to another type
  - Set status to *sporadic*, if for C the number of insertions into C is less than expected since the last update

DStream — Online Phase

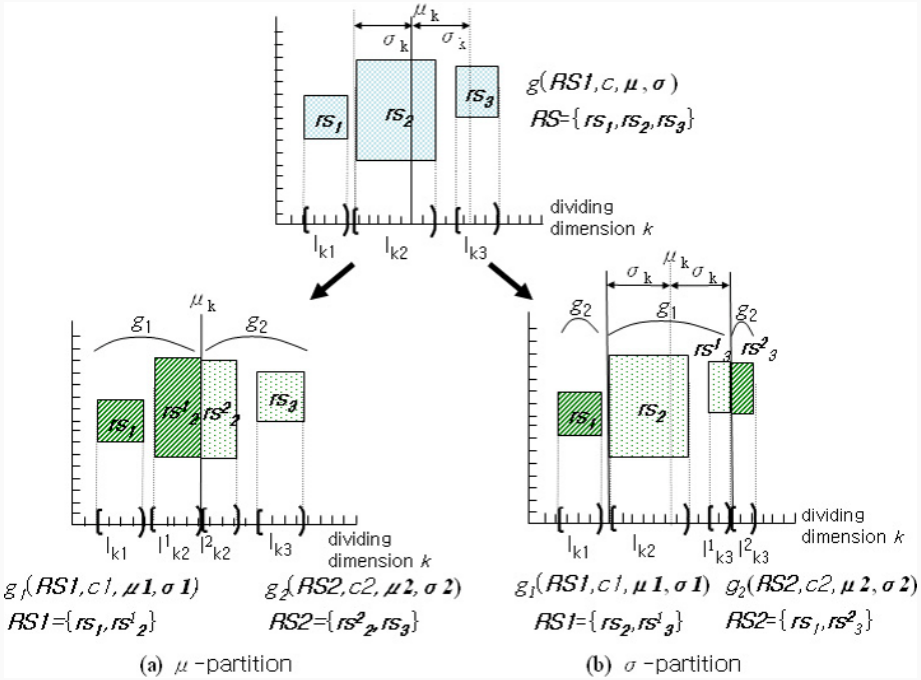
- Online grid cell maintenance (for new observation o_i):
  - Determine the grid cell C that x_i falls into
  - Add C to the hash list if it is not already contained
  - Update CF_C w.r.t. x_i and set status to normal if type changed from sparse
  - Periodically after T time steps
    - Delete all grid cells from the hash list that have been marked as *sporadic* and did not receive new points within the last T time steps
    - Mark sparse grid cells as *sporadic* if requirements (see previous slide) are met
    - Adjust the clustering

DenStream — Discussion

- Single scan, stream compression using micro-clusters
- Noise/ outlier handling (model inherent)
- Aging model for entire cells
- Constant parameters over time, what about clusters with changing density?
- Curse of dimensionality (number of grid cells is I^d)

Grid-based Variant: Dynamic Splitting

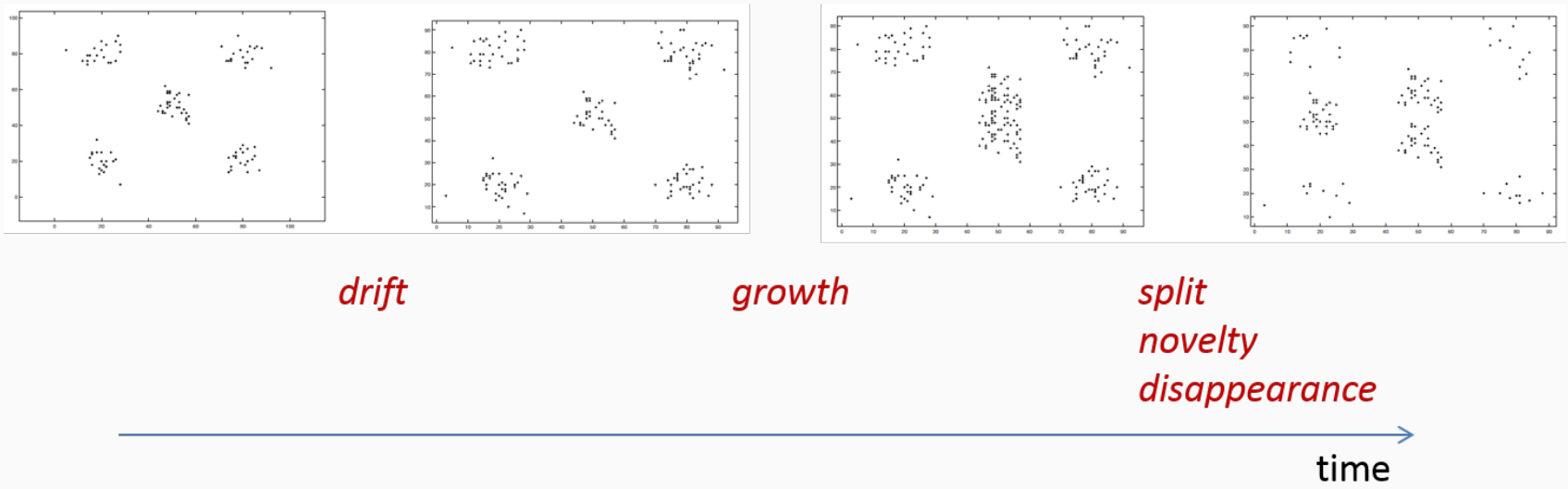
- Initially generate coarse grid
- Online split cells with interval $> \lambda$:
  - Mean split in the dimension with maximal variance
  - Around mean segment in the dimension with minimal variance



- Delete outdated cells based on user defined threshold (initial grid cells are never deleted)
- No particular offline component

Basic Idea

- Detect and differentiate different types of changes
  - Disappearance of concepts
  - Migration/changes/drift of concepts
  - Merging of existing concepts
  - Splitting of groups vs. newly emerging clusters



MONIC: Modeling and Monitoring Cluster Transitions

- MONIC[3] does not assume a particular cluster model
- Cluster matching for different points in time
  - Let X be a cluster at t_X and Y a cluster from the set of clusters ζ_Y at a later slot $t_Y > t_X$ and let the overlap between X and Y be

$$overlap(X, Y) = \frac{\sum_{o \in X \cap Y} age(t_Y, o)}{\sum_{x \in X} age(t_Y, x)}$$

  - Y is a match for X, $match_\tau(X, \zeta_Y) = Y$ subject to a threshold $\tau \in [0.5, 1]$ if Y is the cluster with the maximum overlap of at least τ where the overlap between two clusters X and Y is
  - If there is no cluster in the clustering ζ_Y at t_Y with an overlap of at least τ, then $match_\tau(X, \zeta_Y) = \emptyset$
  - The matching is not unique: several old clusters can be matched with the same new cluster

[3] Spiliopoulou et al.: MONIC - Modeling and Monitoring Cluster Transitions. Proc. KDD'06

MONIC: Cluster Transitions

Transition	*Notation*	*Indicator*
the cluster survives	$X \rightarrow Y$	$Y = match_\tau(X, \zeta_j)$ AND $\nexists Z \in \zeta_i \setminus \{X\} : Y = match_\tau(Z, \zeta_j)$
the cluster is split into multiple clusters	$X \overset{\subseteq}{\rightarrow} \{Y_1, \ldots, Y_p\}$	$(\forall u = 1 \ldots p : overlap(X, Y_u) \geq \tau_{split}) \wedge overlap(X, \cup_{u=1}^{p} Y_u) \geq \tau \wedge (\nexists Y \in \zeta_j \setminus \{Y_1 \ldots, Y_p\} : overlap(X, Y) \geq \tau_{split})$
the cluster is absorbed	$X \overset{\subseteq}{\rightarrow} Y$	$Y = match_\tau(X, \zeta_j)$ AND $\exists Z \in \zeta_i \setminus \{X\} : Y = match_\tau(Z, \zeta_j)$
the cluster disappears	$X \rightarrow \odot$	none of the above cases holds for X
a new cluster has emerged	$\odot \rightarrow Y$	

Table 1: External transitions of a cluster

Transition type	*Subtype*	*Notation*	*Indicators*
1. Size transition	1a. the cluster shrinks	$X \searrow Y$	$\sum_{x \in X} age(x, t_i) > \sum_{y \in Y} age(y, t_j) + \varepsilon$
	1b. the cluster expands	$X \nearrow Y$	$\sum_{y \in Y} age(y, t_j) > \sum_{x \in X} age(x, t_i) + \varepsilon$
2. Compactness transition	2a. the cluster becomes compacter	$X \overset{\bullet}{\rightarrow} Y$	$\sigma(Y) < \sigma(X) - \delta$
	2b. the cluster becomes diffuser	$X \overset{\star}{\rightarrow} Y$	$\sigma(Y) > \sigma(X) + \delta$
3. Location transition	Shift of center (I1) or distribution (I2)	$X \cdots \rightarrow Y$	I1. $\lvert\mu(X) - \mu(Y)\rvert > \tau_1$ `//mean` I2. $\lvert\gamma(X) - \gamma(Y)\rvert > \tau_2$ `//skewness`
No change		$X \leftrightarrow Y$	

Table 2: Internal transitions of a cluster

Source: Spiliopoulou et al.: MONIC - Modeling and Monitoring Cluster Transitions. Proc. KDD'06

Summary: Stream Clustering

- A very important task given the availability of streams nowadays
- Stream clustering algorithm maintain a valid clustering of the evolving stream population over time
- Two generic approaches
  - Online maintenance of a final clustering model
  - Online summarization of the stream and offline clustering
- Different window models
- Evaluation is not straightforward (existing measures mostly for static case)
- Specialized approaches for text streams, high-dimensional streams.

Selected Readings on Stream Clustering

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Vorlesungsteam