Online Mining of Data Streams: Problems, Applications and Progress

Haixun Wang[1] Jian Pei[2] Philip S. Yu[1]

[1]IBM T.J. Watson Research Center, USA

[2]Simon Fraser University, Canada

News

- The latest version of the slides can be found at:
  - http://wis.cs.ucla.edu/~hxwang
  - http://www.cs.sfu.ca/~jpei

Outline

- Introduction
  - Applications and Challenges
- Mining data streams
  - Problems and techniques
- Summary
  - Inherent challenges and open problems

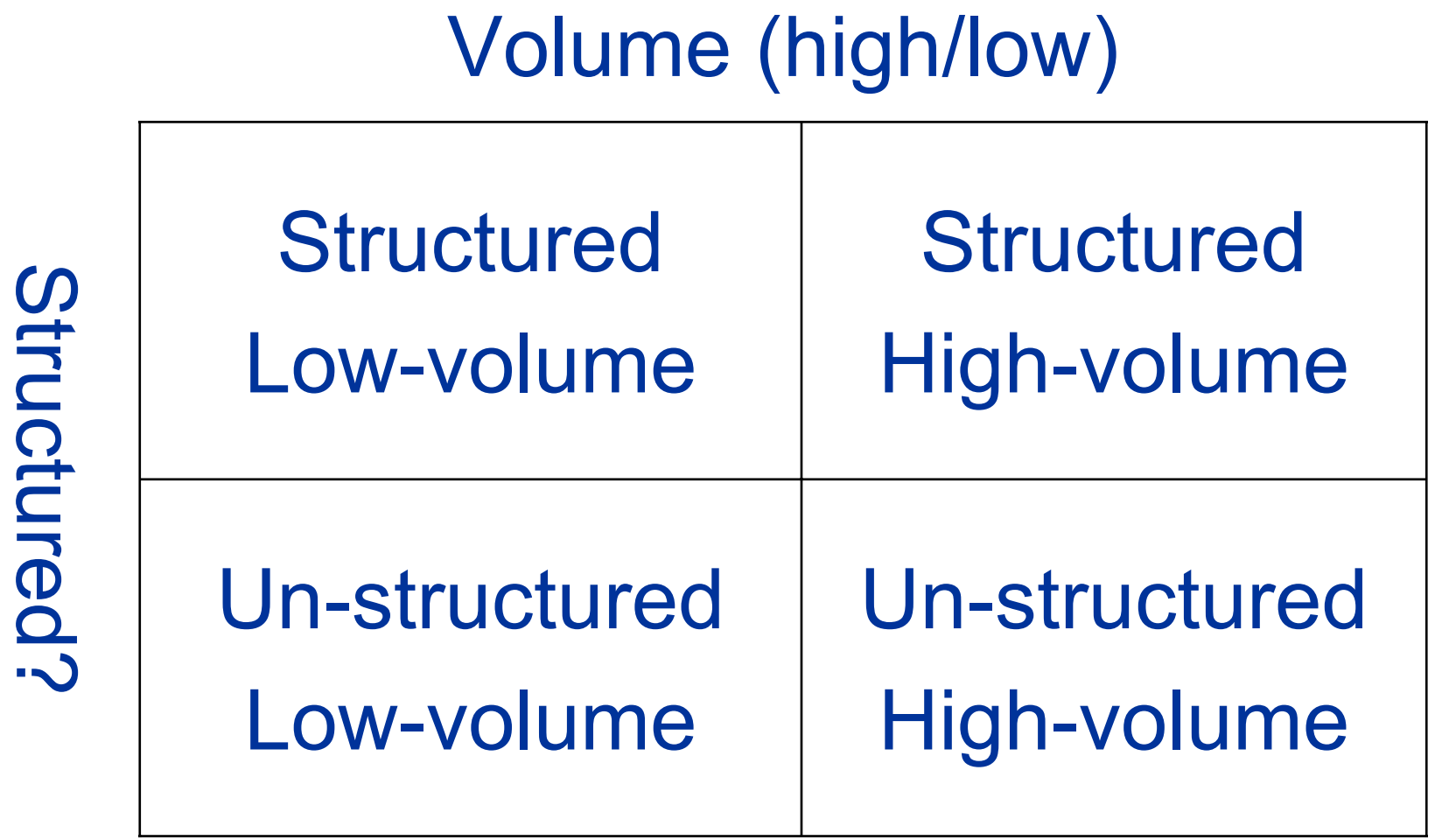
Motivations

- A large number of applications generate data streams
  - Telecommunication (call records)
  - System management (network events)
  - Surveillance (sensor network, audio/video)
  - Financial market (stock exchange)
  - Day to day business (credit card, ATM transactions, etc)
- Tasks: Real time query answering, statistics maintenance, and pattern discovery on data streams

Data Streams: Characteristics

- High volume (possibly infinite) of continuous data
- Data arrive at a rapid rate
- Data distribution changes on the fly

Classification on Data Sources



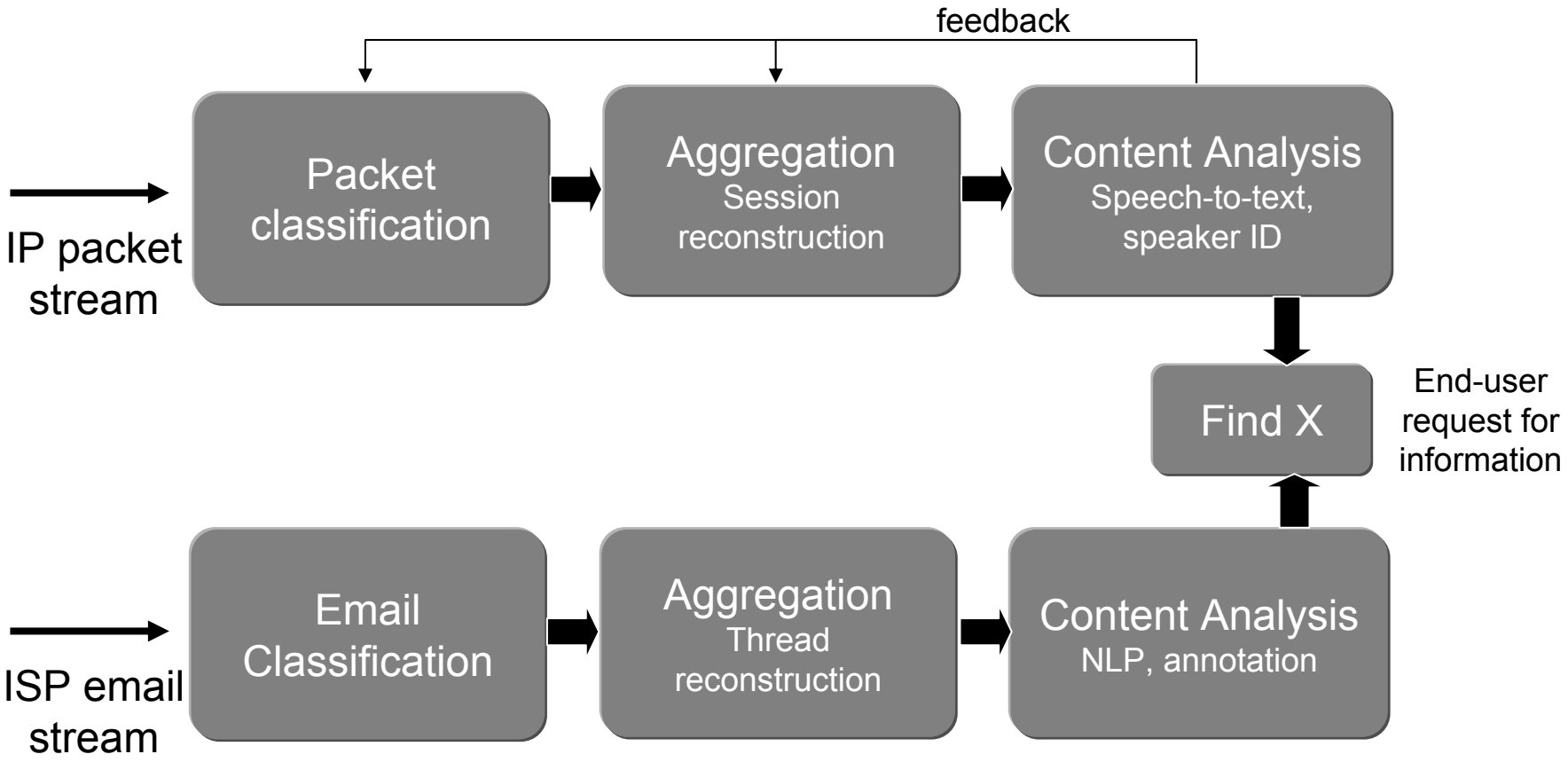
Data Sources: Structured

- Structured low-volume
  - Wire services , Phone call connection reports, Phone and organization directory, Badge access tracking, Customer Lists, Account History, Personal address book, Personal records, Payroll data bases, Expense reports, Logs of tunnel activities, Purchasing logs, Supplier relationships, Work logs/project history, Temperature in machine room for IS reliability, Active monitoring remote copy to disaster site, Disaster site monitoring, Credit reports, Biometric access control
- Structured high-volume
  - Stock Exchange Transactions, Web pages for news/weather, Access, audit records, CRM Data bases, Web access logs and network logs, Company Web site, Mutual fund valuation and transactions, "Financial product" sales, Credit/Debit card transactions, RFID Tracking Logs, Analog Signatures

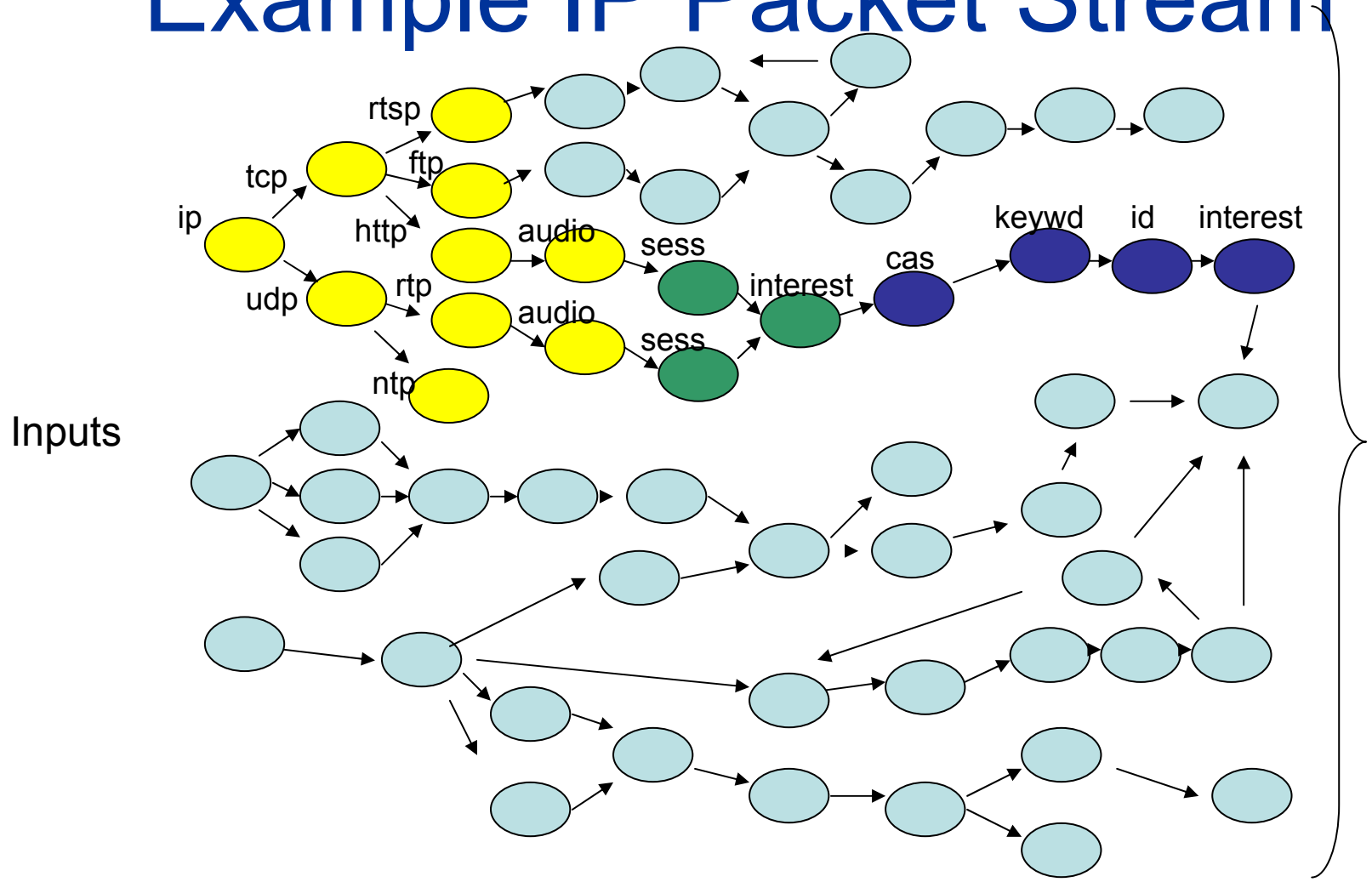
Data Sources: Un-Structured

- Unstructured low-volume
  - Email, Trading floor sound, Chat, Instant Messages, Reports – Internal, Printed reports, Hand phone logs, Courier records, Call Center Data & Logs, Pager, External proprietary reports and data, Customer enquiries, Customer complaints, Public records, Patents, FAX, Scanned checks, RF Monitoring (look for rogue hubs), Print stream monitoring, Calendars
- Unstructured high-volume
  - Phone calls (e.g. voip) content, Broadcast media (TV& Radio), Web Radio, Web cams, Web crawl, Surveillance cameras (internal), Video conferences, Phone conferences, Voice Mail, Satellite photos, Laptop Desktop contents, Cypher detection, Pervasive device communication (second path outside infrastructure), Baby monitor

A Stream Application Example



Example IP Packet Stream



Ingested data discarded	90%	90%	~ 1% of ingested data

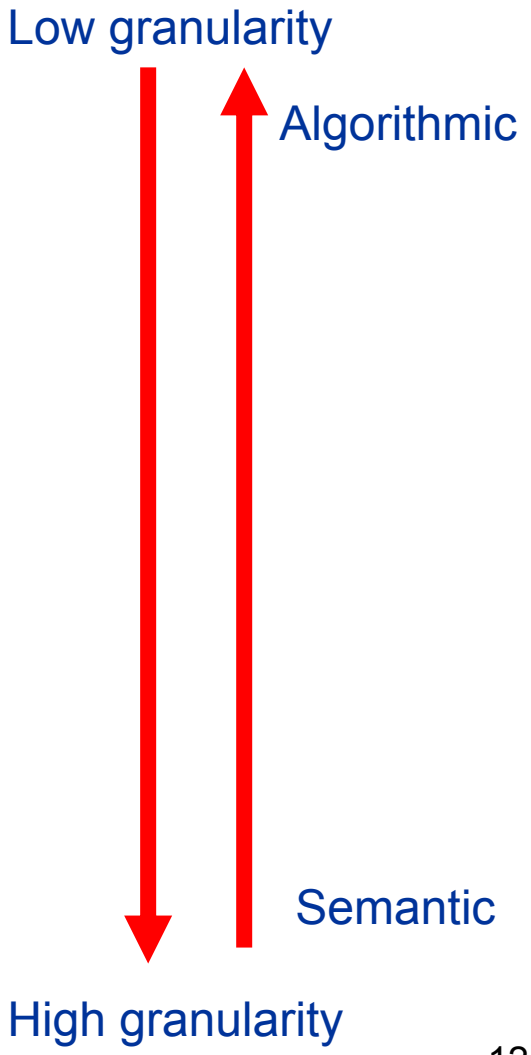
Data Driven Computing

Technology breakthroughs are needed to

- manage and analyze continuous streams for knowledge extraction
- adapt system management rapidly based on changes of the data and the environment
- make numerous real-time decisions about priorities of what inputs to examine, what analyses to execute, etc
- operate over physically distributed sites
- be highly secure and to support protection of private information
- be scalable in many dimensions

Computation at different granularity

- Low granularity
  - e.g. monitor network links
  - Sampling, sketch maintenance
  - Memory space constraints
- In-between
  - e.g. query processing, data mining, knowledge discovery
  - Classification, clustering, and load shedding
  - Evolving concepts
- High granularity
  - e.g. stream management system
  - Planning, scheduling, service composition
  - Ontology, description logics



Online Mining Data Streams

- Synopsis/sketch maintenance
- Classification, regression and learning
- Stream data mining languages
- Frequent pattern mining
- Clustering
- Change and novelty detection

Compute Synopses on Streams

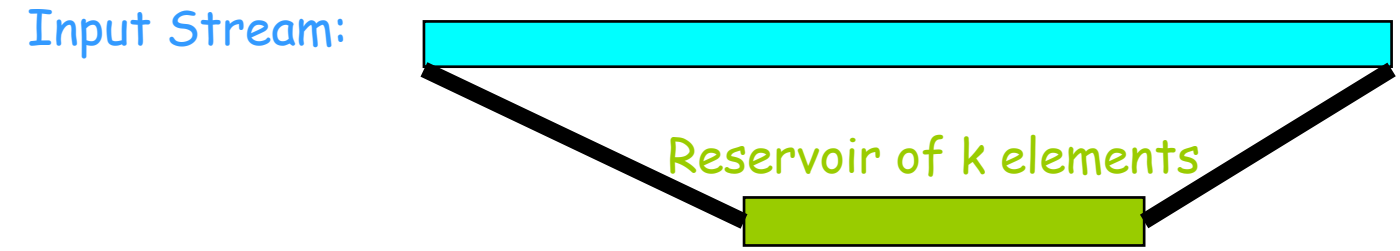
- Sampling
  - Find uniform random samples of an infinite data stream
- Approximate order statistics
  - Medians and quantiles
- Sketch/synopsis maintenance

Sampling

- Input:
  - Stream of data that arrive online
  - Sample size k
  - Sample range
    - entire stream
    - most recent window (count-based or time-based)
- Output:
  - k elements chosen uniformly at random within the sample range

Reservoir Sampling

- Classical algorithm by Vitter (1985):
  - Size of data stream is not known in advance
  - Goal: maintains a *fixed-size uniform random sample*



  - Put the first k elements from the stream into the repository
  - When the i-th element arrives
    - Add it to reservoir S with probability p= k/i
    - If added, randomly remove an element from S
    - Instead of flipping a coin for each element, determine the number of elements to skip before the next to be added to S

Duplicates in Stream

- Observation:
  - Stream contains duplicate elements
  - e.g. Zipf distribution
  - Any value occurring frequently in the sample is a wasteful use of the available space

Concise Sampling

- By Gibbons and Matias, 1998
  - Represent an element in the sample by (value, count)
  - τ = 1
  - Add new element with probability 1 / τ (increase count if element already in S)
  - If S is full
    - increase τ to τ'
    - evict each element (or decrease count) from S with probability τ / τ'

Sampling from a Moving Window

- Timeliness: old data are not useful
- Restrict samples to a window of recent data
  - As new data arrives, old data “expires”
- Reservoir sampling cannot handle data expiration
  - Replace an “expired” element in the reservoir with a random element in the current window
  - But we cannot access the window!

A Naïve Algorithm

- Place a moving window of size N on the stream
  - an old element *y* expires when a new element *x* arrives
- If *y* is in not in the reservoir, we do nothing, otherwise we replace *y* with *x*
- Problem: periodicity
  - If j-th element is in the sample, then any element with index j+cN is in the sample

Chain Sampling

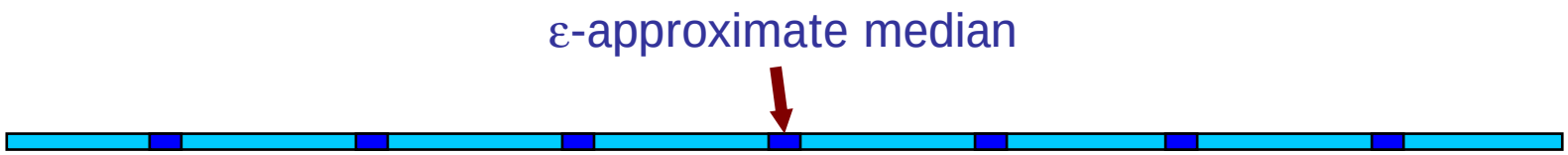
- Babcock, Datar, Motwani, 2002
- Motivation:
  - When an element x is added to the sample, decide immediately which future element y will replace x when x expires
  - Store y when y arrives (x has not expired yet)
  - Of course, we must decide which future element will replace y, …
  - Thus, we don't have to look back!

Chain Sampling

- Create a chain (for sample of size 1)
- Include each new element in the sample with probability 1/min(i,N)
- When the i-th element is added to the sample …
  - we randomly choose a future element whose index is in [i+1, i+N] to replace it when it expires
- Once the element with that index arrives, store it and choose the index that will replace it in turn, building a “chain” of potential replacements

Order Statistics

- Median
- φ-Quantile: element with rank $\lceil \varphi N \rceil$ $0 < \varphi < 1$
- Finding exact quantile requires linear space
- ε-Approximate φ-quantile: any element with rank $\lceil (\varphi \pm \varepsilon) N \rceil$ $0 < \varepsilon < 1$



Approximate Quantile

- **Task:** given ε, δ and φ, devise an online algorithm to compute, with probability at least 1-δ, an ε-approximate φ-quantile of a stream.
- Typical $\varepsilon = 0.01$
- Typical $\delta = 0.0001$

φ-Quantile and Sample Size

- Reservoir sampling generates a sample of size k without a priori knowledge of stream size
- Known fact: if sample size is $O(\varepsilon^{-2}\log\delta^{-1})$ then the φ-quantile of the sample is an ε-approximate quantile of the input with probability at least 1- δ
- However, ε^{-2} is too large!

Sampling with Unknown N

Given

b buffers of *k* elements each.

Repeatedly

If there is an empty buffer

Fill buffer with elements in the stream

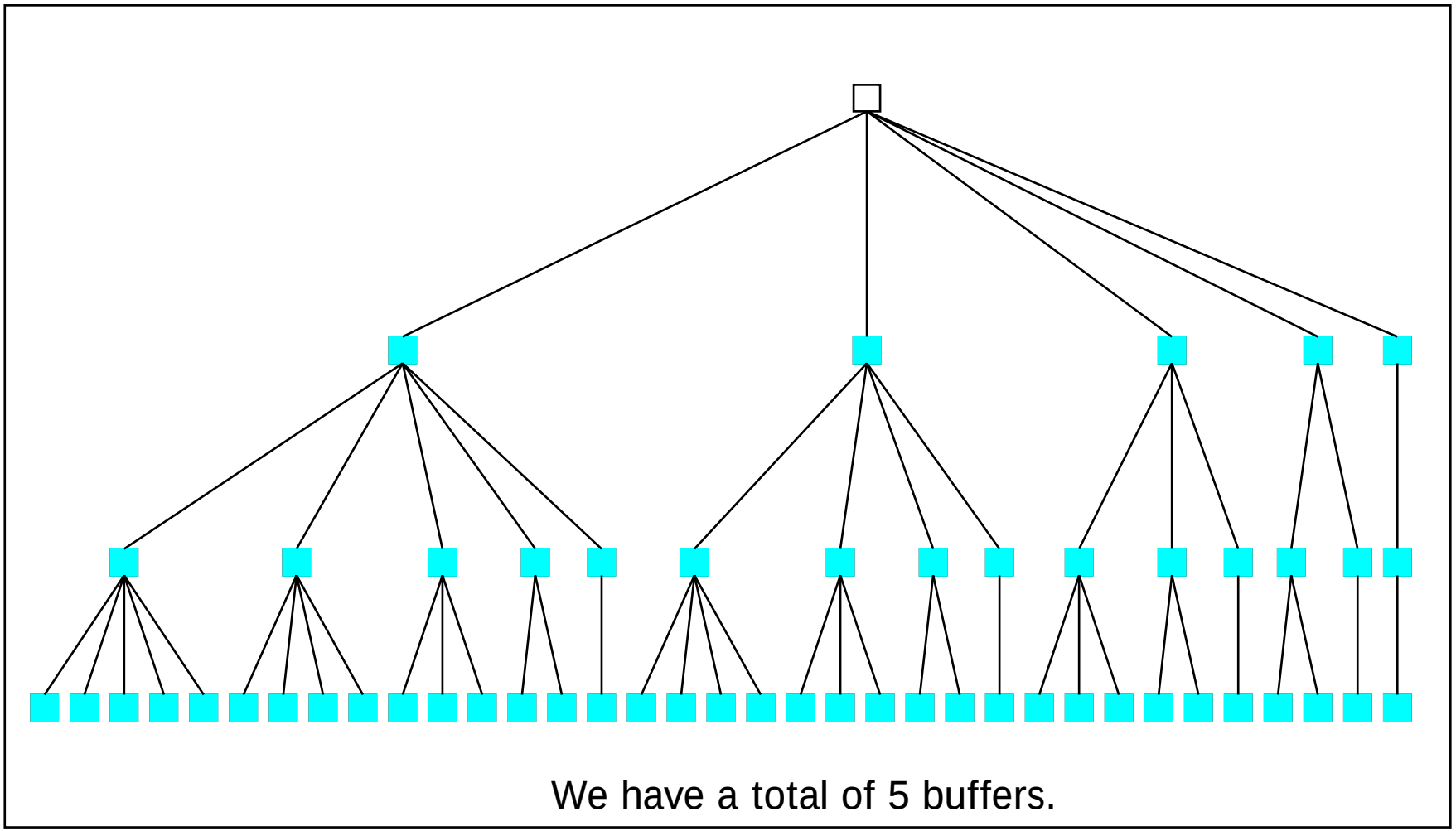
Assign buffer with weight 1

Reclaim space with COLLAPSE.

Finally

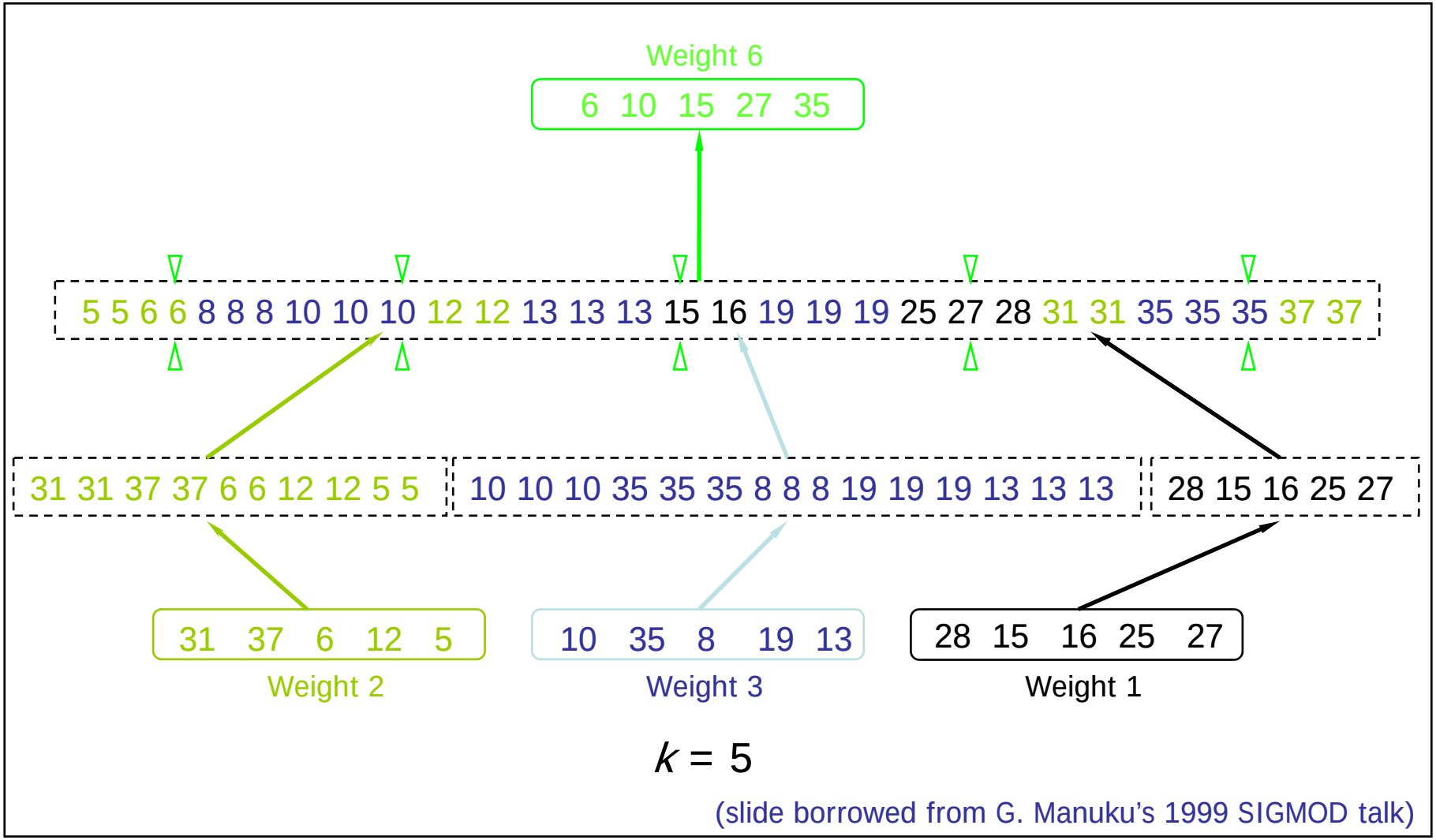
Output the φ-quantiles of last buffer.

When to COLLAPSE?



(slide borrowed from G. Manuku's 1999 SIGMOD talk)

How to COLLAPSE?



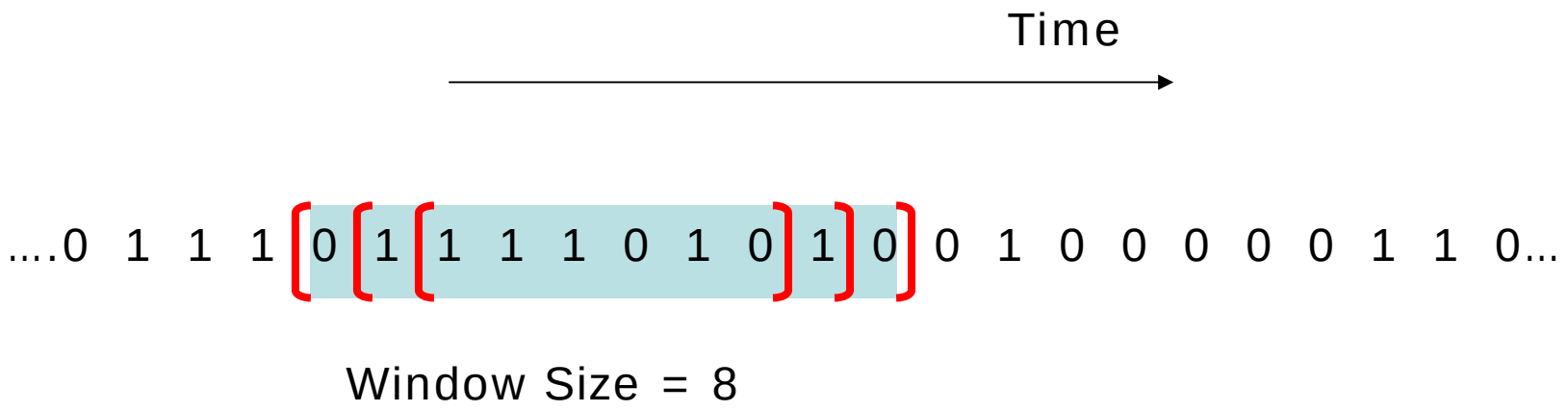
Memory Requirement

- Memory size = $b \cdot k$
  - b: # of buffers
  - k: buffer size
- Output is an ε-approximate quantile of the input with probability at least 1-δ if b and k satisfy certain constraints
- For $\varepsilon = 0.01$ and $\delta = 0.0001$, $b \cdot k$ can be an order of magnitude smaller than $O(\varepsilon^{-2}\log\delta^{-1})$

Statistics from a Moving Window

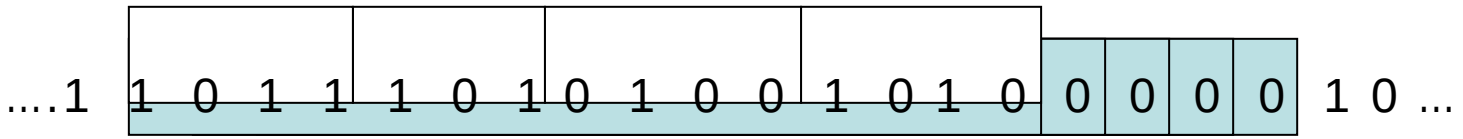
- Maintaining statistics
  - Count/Sum of non-zero elements
  - Variance
  - K-Mean
  - …
- Moving window
  - add/delete operation on synopsis data structure
  - but the exact expiring element is not known!

Moving Window



Moving Window

- **Challenge**: how to update synopsis data structure when we don't have the exact value of the expired element?
- **Example**: sum of elements in a window on a bit stream



Bucket Sums = {4,2,1,2}

Bucket Sums = {3,2,1,2}

Error Analysis

- Error comes from the last bucket
- Exponential Histogram, by Datar et al

  Solution: Ensure the contribution of last bucket is not too big

Exponential Histograms

- Divide window into multiple buckets
- Create buckets whose sizes are non-decreasing powers of 2
- For every bucket (except for the last bucket), there are at least k/2 and at most k/2+1 buckets of the same size

Online Mining Data Streams

- Synopsis maintenance
- Classification, regression and learning
- Stream data mining languages
- Frequent pattern mining
- Clustering
- Change and novelty detection

Classification of Data Streams

- Challenges
- The Decision Tree Classifier
- Hoeffding Trees
- VFDT and CVFDT
- Ensemble of Classifiers
- Load Shedding in Classification

What are the Challenges?

- Data Volume
  - impossible to mine the entire data at one time
  - can only afford **constant memory** per data sample
- Concept Drifts
  - previously learned models are invalid
- Cost of Learning
  - model updates can be costly
  - can only afford **constant time** per data sample

The Decision Tree Classifier

- Learning (Training) :
  - Input: a data set of (a, b), where a is a vector, b a class label
  - Output: a model (decision tree)
- Testing:
  - Input: a test sample (x, ?)
  - Output: a class label prediction for x

The Decision Tree Classifier

- A divide-and-conquer approach
  - Simple algorithm, intuitive model
- Compute information gain for data in each node
  - Super-linear complexity
- Typically a decision tree grows one level for each scan of data
  - Multiple scans are required
- The data structure is not ‘stable’
  - Subtle changes of data can cause global changes in the data structure

Challenge #1

- Task:
  - Given enough samples, can we build a tree in constant time that is ***nearly identical*** to the tree a batch learner (C4.5, Sprint, etc.) would build?
- Intuition:
  - With increasing # of samples, the # of possible decision trees becomes smaller
- Forget about concept drifts for now.

Hoeffding Bound

- Also known as additive Chernoff Bound
- Given
  - r : real valued random variable
  - n : # independent observations of r
  - R : range of r
- Mean of r is at least r_{avg}-ε, with probability 1-δ, or:
- $P(\mu_r \geq r_{avg} - \varepsilon) = 1-\delta$ and $\varepsilon = \sqrt{\frac{R^2 \ln(1/\delta)}{2n}}$

Hoeffding Bound

$$\varepsilon = \sqrt{\frac{R^2 \ln(1/\delta)}{2n}}$$

- Properties:
  - Hoeffding bound is independent of data distribution
  - Error ε decreases when n (# of samples) increases
- At each node, we shall accumulate enough samples (n) before we make a split

Nearly Identical?

- Categorical attributes
  - with high probability, the attribute we choose for split is the same attribute as would be chosen by a batch learner
  - identical decision tree
- Continuous attributes
  - discretize them into categorical ones

Hoeffding Tree: Pros and Cons

- Scales better than traditional DT algorithms
  - Incremental
  - Sub-linear with sampling
  - Small memory requirement
- Cons:
  - Only consider top 2 attributes
  - Tie breaking takes time
  - Grow a deep tree takes time
  - Discrete attribute only

Concept Drifts

- Time-changing data streams
- Incorporate new samples and eliminate effect of old samples
- Naïve approach
  - Place a sliding window on the stream
  - Reapply C4.5 or VFDT whenever window moves
  - Time consuming!

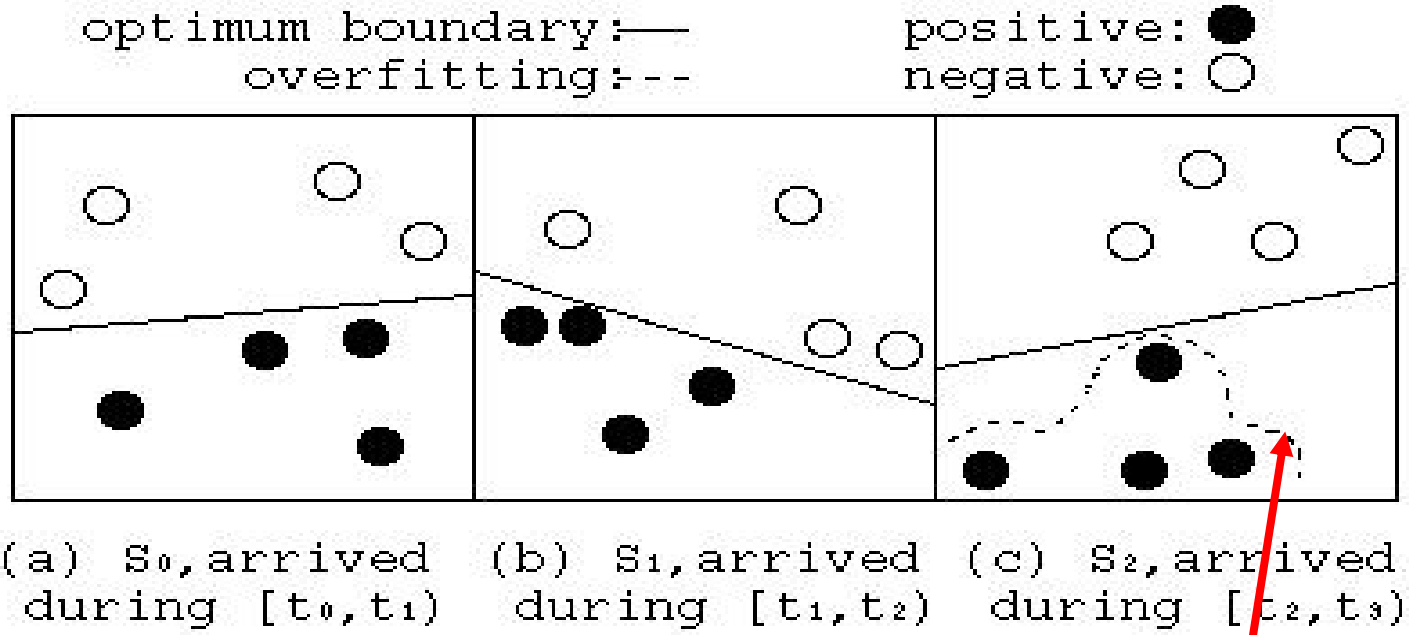
CVFDT

- Concept-adapting VFDT
  - Hulten, Spencer, Domingos, 2001
- Goal
  - Classifying concept-drifting data streams
- Approach
  - Make use of Hoeffding bound
  - Incorporate “windowing”
  - Monitor changes of information gain for attributes.
  - If change reaches threshold, generate alternate subtree with new “best” attribute, but keep on background.
  - Replace if new subtree becomes more accurate.

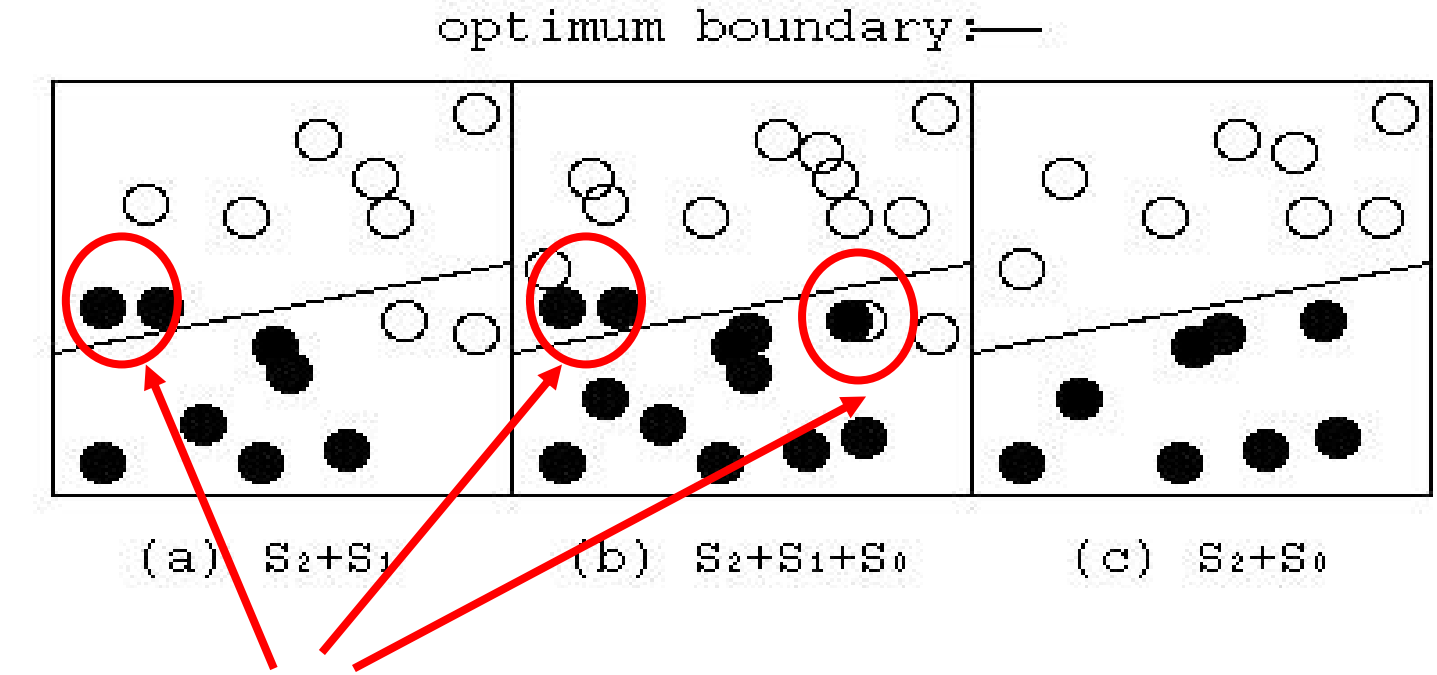
Data Expiration Problem

- Incremental algorithm
  - window-based
  - incorporate new samples and eliminate effects of old samples
- We eliminate effects of samples arrived **T** time units ago
- For the sake of prediction accuracy, how to decide **T**?

Data Distribution and Optimal Decision Boundaries



Data Distribution and Optimal Decision Boundaries

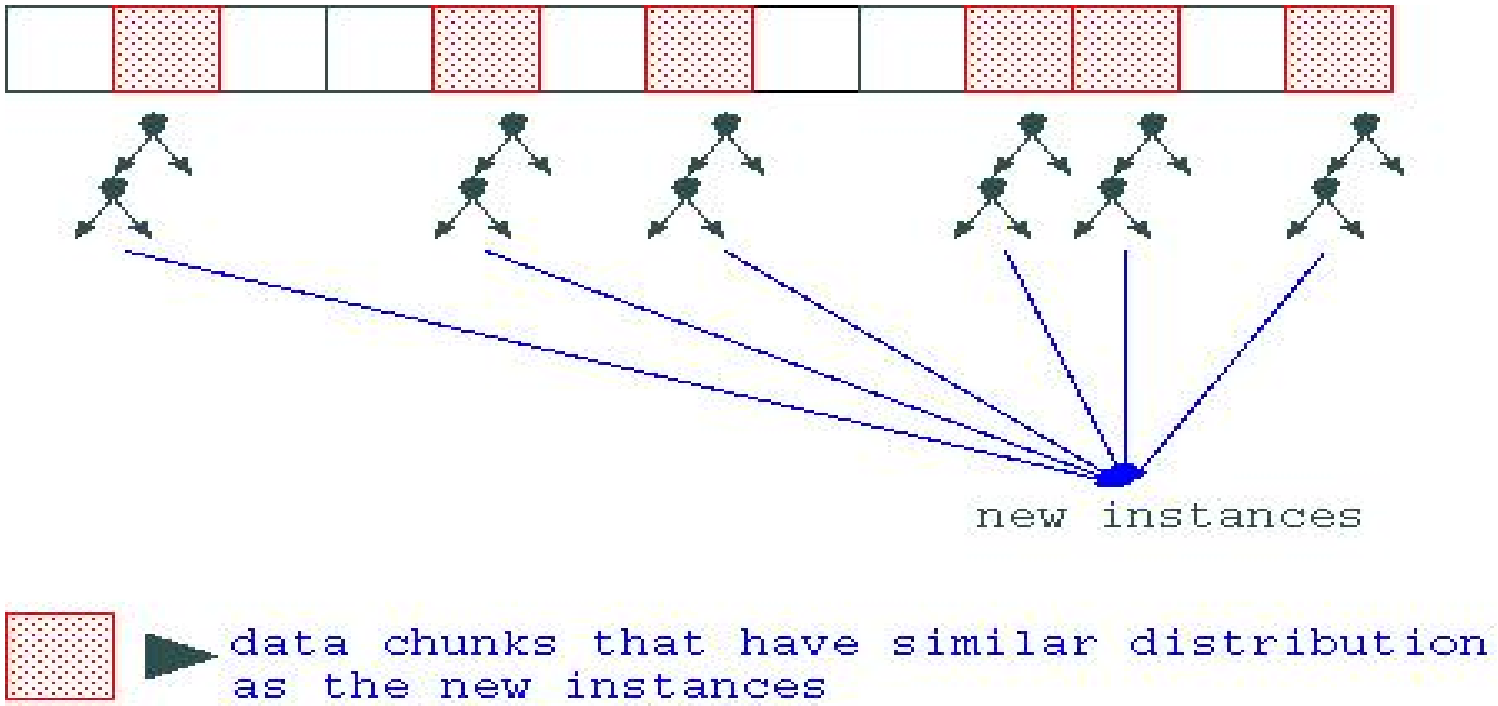


Conflicting Concepts!

Challenges

- How to ‘forget’ old samples?
  - Discard instances after a fixed time period **T**
  - **T** is too large: conflicting concepts
  - **T** is too small: overfitting
- Other issues of a single model approach
  - Runtime performance
  - Ease of use
  - Parallelizability
  - …

Classifier Ensemble Method



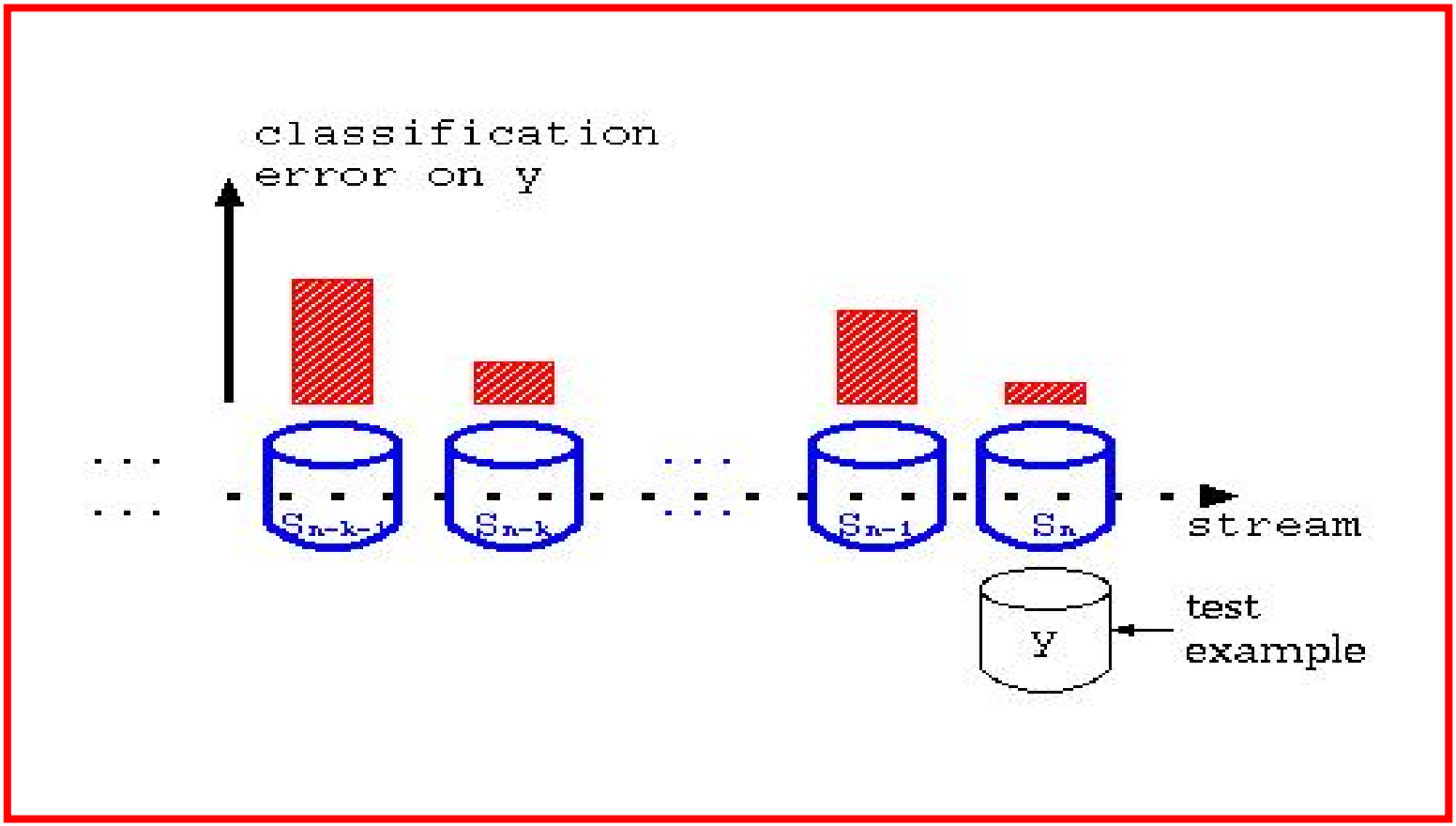
Basic Idea

- Stream data is partitioned into sequential chunks
- Train a classifier from each chunk
- The weight of a classifier is assigned based on its **expected prediction accuracy** on the current test examples
- By bias-variance decomposition, we can show it improves prediction accuracy
- Only top K classifiers are kept

But in Reality …

- We do not know
  - Error or variance or the function being learned
- Solution:
  - Use estimation!
  - Apply the i-th classifier on the current training data to estimate the error of the classifier

Weight Estimation



Online Mining Data Streams

- Synopsis maintenance
- Classification, regression and learning
- Stream data mining languages
- Frequent pattern mining
- Clustering
- Change and novelty detection

Hancock

- Hancock: a language for data mining on streams [Cortes et al, KDD 2002]
- Maintain *signatures* of stream
  - signature = aggregate = synopsis data structure
- Goal: to replace hard-to-maintain, hand-written C code with Hancock code, so that users can shift focus from *how* to manage the data to *what* to compute.

ATLAS: Minimalist's Extension of SQL

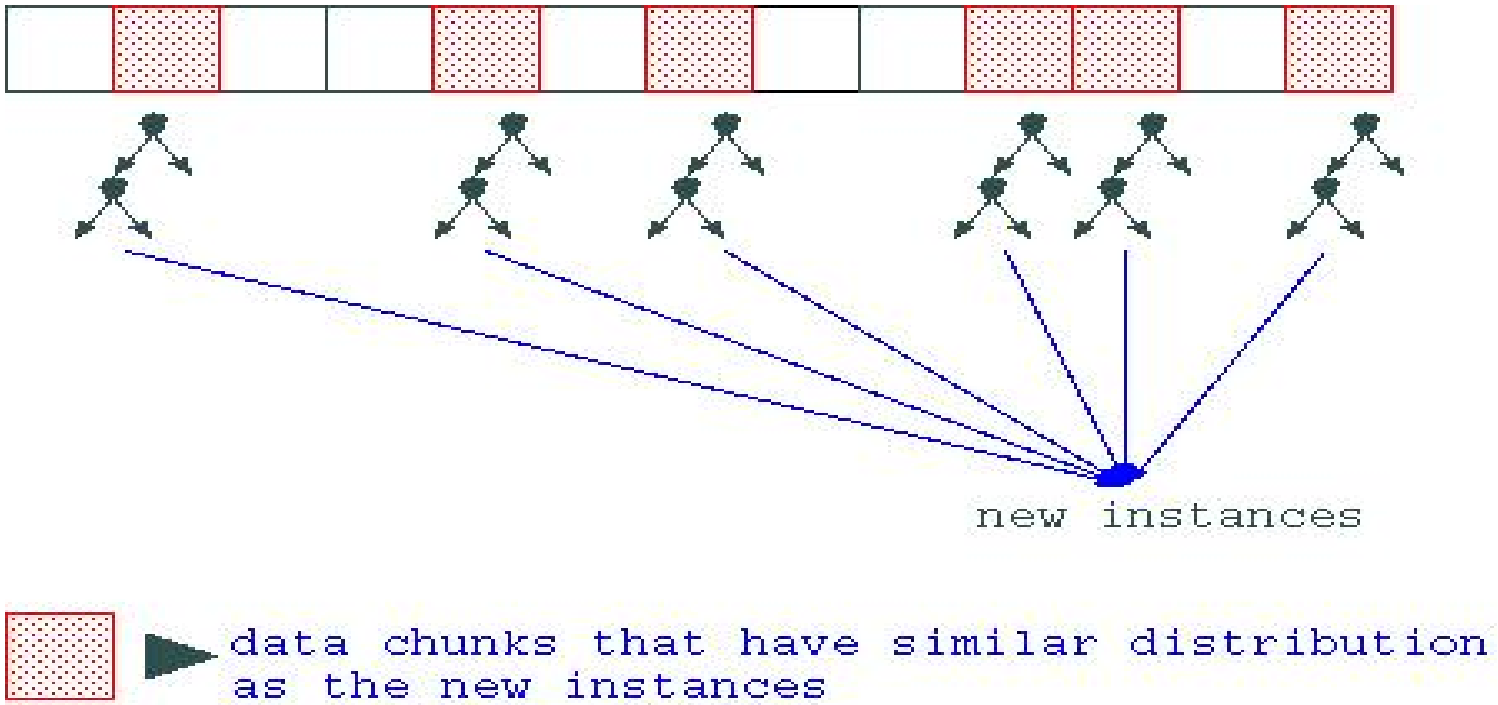
- Wang, Zaniolo et al, VLDB00, SIAM DM 02, VLDB04
- Computation model:

```
AGGREGATE avg (next INT)
{       TABLE memo(sum INT, cnt INT);
        INITIALIZE: {
                INSERT INTO memo VALUES (next, 1);
        }
        ITERATE: {
                UPDATE memo SET sum=sum+next, cnt = cnt + 1;
                INSERT INTO return SELECT sum/cnt FROM memo;
        }
        EXPIRE:{
                UPDATE memo SET sum=sum-next, cnt = cnt -1;
       }
}
```

Why SQL Matters to Data Streams and Data Mining

- Why SQL Matters to Data Streams and Data Mining?
  - The code is very short, which saves programming efforts
  - It is implemented in a declarative language, which means optimization opportunity
- It is a tightly-coupled approach, where you don't
  - move the data outside a DBMS
  - write ad-hoc programs to mine the data
  - lose the support of DBMS, or worry about data generated on the fly
- Extended SQL for stream processing has strong expressive power
  - Law, Wang, Zaniolo VLDB 2004

Mining Streams with Concept Drifts



Mining Data Streams in SQL

```
AGGREGATE classifystream(col1, ..., coln, label Int) : Int
{   TABLE state(cnt Int) AS VALUES (0);
    INITIALIZE : ITERATE : {}
    REVISE : {
        SELECT learn(W.*) FROM WINDOW AS W
                WHERE ((SELECT cnt FROM state) = 0
                OR ((SELECT cnt FROM state) % 1000 = 0 AND
                (SELECT sum(|classify(W.*)-W.label|) FROM WINDOW AS W
                WHERE W.label=NULL)⩾ threshold))
                AND W.label <> NULL;
        UPDATE state SET cnt=cnt+1;
        INSERT INTO RETURN
        SELECT classify(V.*) FROM VALUES(col1,...,coln) AS V
        WHERE label = NULL;
    }
}
```

The Beauty of SQL

```
SELECT classifystream(S.*)
OVER (ROWS 10000 PRECEDING)
FROM stream AS S;
```

- The implementation has taken into consideration:
  - Code optimization;
  - Parallelization;
  - Distributed databases;
  - Ease of use;
  - ...

Online Mining Data Streams

- Synopsis maintenance
- Classification, regression and learning
- Stream data mining languages
- Frequent pattern mining
- Clustering
- Change and novelty detection

Frequent Pattern Mining

- Frequent patterns: patterns (set of items, sequence, etc.) that occur frequently in a database [AIS93]
- Frequent pattern mining: finding regularities in data
  - What products were often purchased together?
  - What are the subsequent purchases after buying a PC?
  - What kinds of DNA are sensitive to this new drug?
  - Can we classify web documents based on key-word combinations?

Why Is Frequent Pattern Mining Essential?

- Foundation for many data mining tasks
  - Association rules, correlation, causality, sequential patterns, spatial and multimedia patterns, associative classification, cluster analysis, iceberg cube, …
- Broad applications
  - Basket data analysis, cross-marketing, catalog design, sale campaign analysis, web log (click stream) analysis, …

Basics

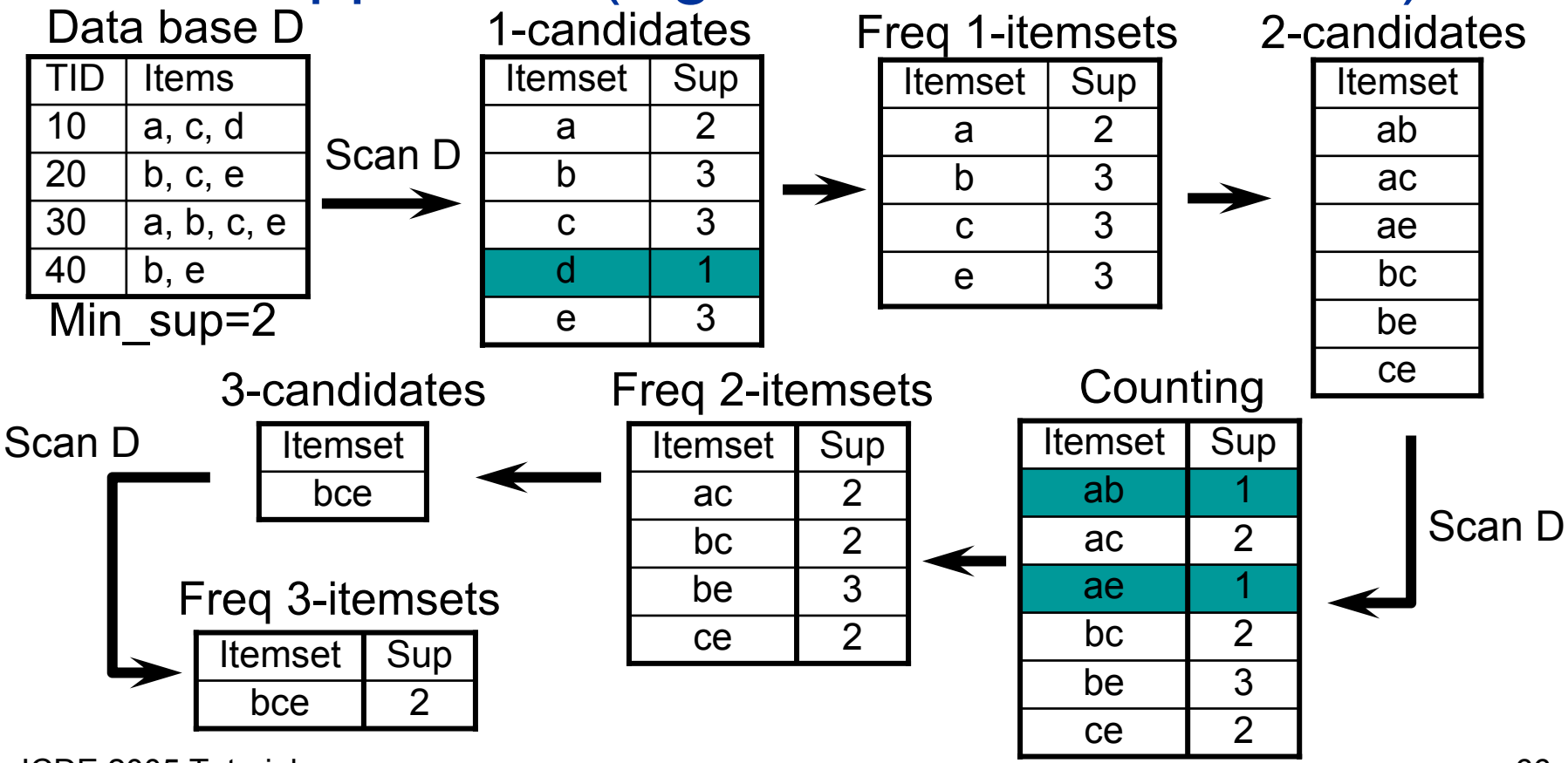
- Itemset: a set of items
  - E.g., acm={a, c, m}
- Support of itemsets
  - Sup(acm)=3
- Given min_sup = 3, acm is a frequent pattern
- Frequent pattern mining: find all frequent patterns in a database

Transaction database TDB

TID	Items bought
100	f, a, c, d, g, l, m, p
200	a, b, c, f, l, m, o
300	b, f, h, j, o
400	b, c, k, s, p
500	a, f, c, e, l, p, m, n

Apriori Algorithm

- A level-wise, candidate-generation-and-test approach (Agrawal & Srikant 1994)



The Apriori Algorithm

- C_k: Candidate itemset of size k
- L_k : frequent itemset of size k

- L_1 = {frequent items};
- for (k = 1; L_k !=∅; k++) do
  - C_{k+1} = candidates generated from L_k;
  - for each transaction t in database do increment the count of all candidates in C_{k+1} that are contained in t
  - L_{k+1} = candidates in C_{k+1} with min_support
- return $\cup_k L_k$;

Mining Data Streams – Challenges

- Maintaining exact counts for all (frequent) itemsets needs multiple scans of the stream
  - Maintain approximation of counts
- Finding the exact set of frequent itemsets from data streams cannot be online
  - Have to scan data streams multiple times
  - Space overhead
  - Finding approximation of set of frequent itemsets

Mining Data Streams – A Roadmap

- Basic extensions
  - Finding frequent items/itemsets from a stream
- Advanced extensions – mining time-sensitive frequent patterns
  - Finding frequent patterns in sliding window
  - Mining recently frequent patterns
  - Mining temporal frequent patterns
- Applications
  - Hierarchical heavy hitters and semi-structured patterns

Finding Frequent Items in Streams

- $S=x_1x_2\ldots x_n$ is a stream of items, where $x_i \in I$, and I is the set of items
  - An item x can appear multiple times in the stream
  - Assumption: $n \gg |I| \gg 1/\theta$
- For a support threshold θ ($0 \leqslant \theta \leqslant 1$), find the set of items that appears more than θn times in S?
  - Small average processing time of each item in S
  - Worst-case time: the maximal time among all items in S
  - Number of passes: one scan for online algorithms
  - Space overheads: should be bounded

Space Requirement

- Any online algorithm for computing frequent items needs in the worse case $\Omega(|I| log(n/|I|))$ bits
  - $|I|$: the number of distinct items
  - n: the length of the stream
  - [Karp et al. 03] and [Demaine et al. 02]
- Intuition: in the middle of a stream S, if no item so far has a count over θn, then the count of each item has to be remembered
  - Keep the count combinations i.e., the set of all sequences of $|I|$ integers between 0 and $\theta n-1$ adding to $\lfloor n/2 \rfloor$

Idea

- Given a stream of two symbols: *x* and *y*, find the dominating symbol by using only one counter
- Set count=0
- If we see x, count=count+1
- If we see y, count=count-1
- After all
  - If count>0, then x is the dominant symbol
  - If count=0, then tie
  - If count <0, then y is the dominant symbol

Generalization for Multiple Items

- Observation: # of frequent items <= $1/\theta$
- Compute top-$\lfloor 1/\theta \rfloor$ most frequent items using $O(1/\theta)$ memory cells

let K be a set of $\lfloor 1/\theta \rfloor$ counters, each counter can have a label
initially, the counters are set to 0;
for i=1 to n do
    if x_i is in K then increase its count
    else // i.e., x_i is not in K
        if |K| < $\lfloor 1/\theta \rfloor$ then insert x_i into K and set its count to 1
        else // i.e., K is full at the current moment
            decrease each counter by 1;
            delete all items from K whose count is 0;
Output K // the counts in K are not the real counts

Completing the Job

- K tells the frequent items, but not the counts
- Another scan over the bag tells the counts
  - Another scan over the stream may not be feasible in practice
  - One scan algorithms obtaining both frequent items and the estimated counts will be discussed soon

Approximating Frequency Counts

- [Manku & Motwani, 02]
- Input
  - Support threshold s, 0 < s < 1
  - Error parameter e, 0 < e < 1, e « s
  - The length of the stream s is n
- Features
  - No false negatives: all frequent item(set)s are output
  - No item(set)s whose true frequency is less than *(s-e)n* is output
  - Estimated frequencies are less than the true frequencies by at most *en*

Sticky Sampling – Ideas

- Central idea: frequent items and their supports can be estimated by a good sample
- One sample rate cannot handle a potentially infinite stream – the sample is also a stream
  - Adjust (decrease) sample rate progressively to handle more and more new data
  - The first t items, take them; the next 2t items, sample using rate 0.5; the next 4t items, sample using rate 0.25, and so on
- How to keep counts from samples of different rates consistent?
  - Adjust counts according to the sampling rate

Sticky Sampling – Algorithm

- Maintain a set S of entries (x, f), where x is an item and f is the estimated count
- Initially, S is empty, sampling rate r=1
  - An element has a probability of 1/r to be sampled/counted
  - If an item is in S, increment the frequency
  - Otherwise, add an entry (x, 1) into S

Sticky Sampling – Algorithm

- Adjust sampling rate to handle more data
  - $t = e^{-1}\log(s^{-1}\delta^{-1})$, δ is the probability of failure
  - First 2t elements, r=1; next 2t elements, r=2, next 4t elements, r=4, …
- Update estimated counts for adjusted sampling rates
  - Diminishing f by a random variable in geometric distribution,
  - After adjustment, f is as if counted with the adjusted sampling rate
- Frequent items: entries in S where $f \geq (s-e)n$

Sticky Sampling – Properties

- Compute frequent items with error bound e
  - With probability at least 1- δ using at most $2/e\log(s^{-1}\delta^{-1})$ expected number of entries
- Space complexity is independent of n
- May still have chance to fail – violate one of the following three requirements
  - No false negatives: all frequent item(set)s are output
  - No item(set)s whose true frequency is less than $(s-e)n$ is output
  - Estimated frequencies are less than the true frequencies by at most en

Lossy Counting – Ideas

- Divide the stream into buckets, maintain a global count of buckets seen so far
- For any item, if its count is less than the global count of buckets, then its count does not need to be maintained
  - How to divide buckets so that the possible errors are bounded?
  - How to guarantee the number of entries needed to be recorded is also bounded?

Lossy Counting – Algorithms

- Divide a stream into buckets of width $w=\lceil 1/e \rceil$
  - The current bucket id $b=\lceil n/w \rceil$
- Maintain a set D of entries (x, f, Δ), where Δ is the maximum possible error in f
- Whenever a new x arrives, lookup D
  - If x is in D, update f
  - Otherwise, add (e, 1, b-1) into D
- After a bucket, remove entries where $f+\Delta \leq b$
- At most $e^{-1}\log(en)$ entries in S
  - Practically better than Sticky Sampling

From Frequent Items to Itemsets

- Maintain a set D of entries (X, f, Δ), where X is an itemset
- Divide the incoming transaction stream into buckets, each has w= $\lceil 1/e \rceil$ transactions
  - The current bucket id is b

Finding Frequent Itemsets

- Fill available main memory with as many transactions as possible
  - B: # buckets in main memory in the current batch, must be a large number
  - For each entry (X, f, Δ) in D, update f; if f+Δ≤b, delete the entry
  - If an itemset X not in D has frequency f≥B in the current batch, create a new entry (X, f, b-B)
- Efficient implementation techniques in [Manku & Motwani, 02]

More Interesting Patterns from Streams

- People sometimes are more interested in recently frequent patterns or frequent patterns in some specific periods, instead of patterns in the stream having seen so far
- Challenges
  - How to answer queries about patterns in different periods?
    - Space and time overheads
  - How to summarize data and forget details?

Summary – Frequent Patterns

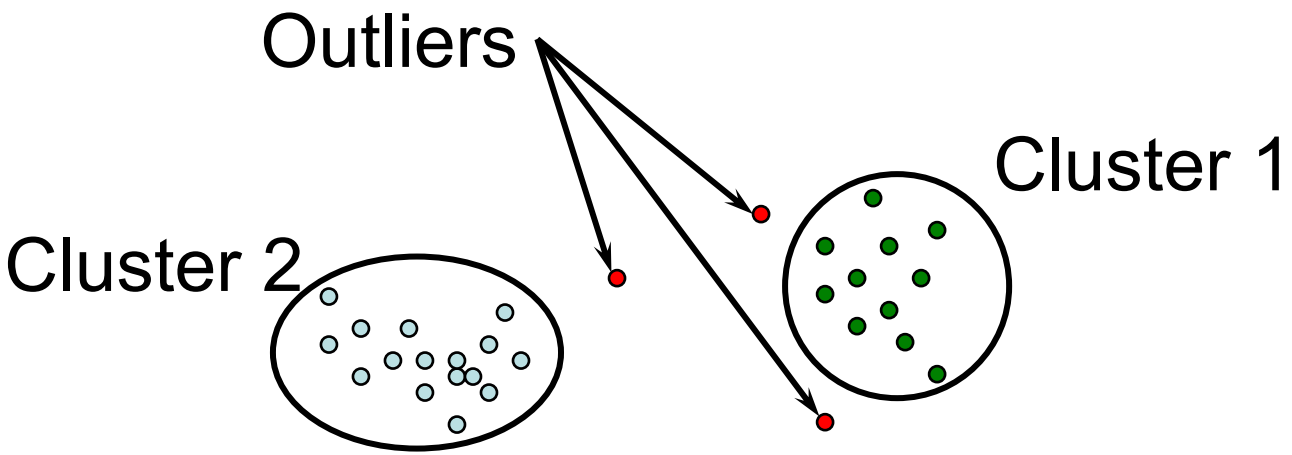
- Mining frequent patterns from data streams is challenging
  - A data stream can be scanned only once
  - Limited space for storing support counts
  - Quality warrant expected
- Solutions
  - Carefully designed sketches to capture the critical counting information
- Applications
  - With various constraints, different types of data

Online Mining Data Streams

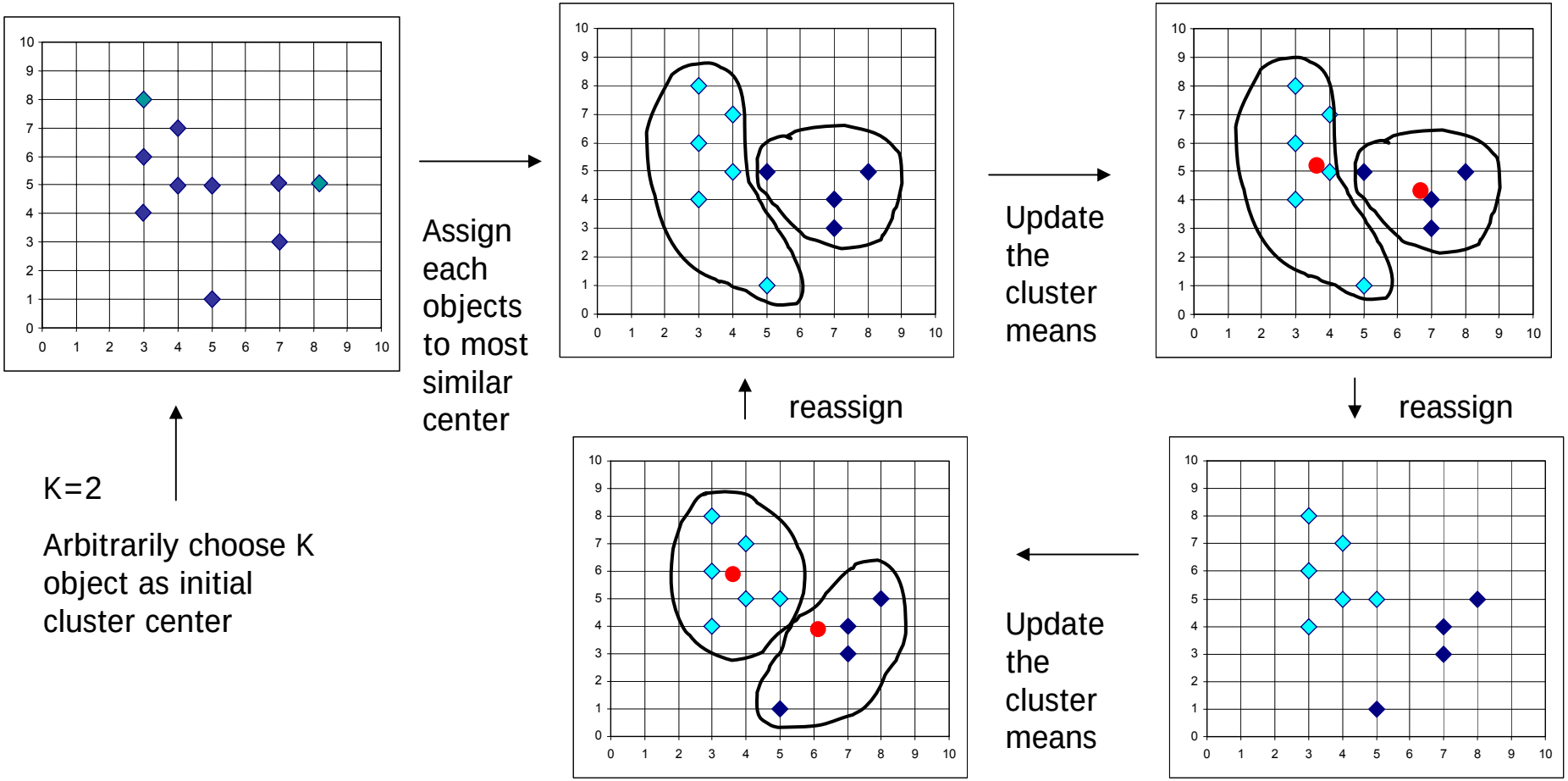
- Synopsis maintenance
- Classification, regression and learning
- Stream data mining languages
- Frequent pattern mining
- Clustering
- Change and novelty detection

What Is Clustering?

- Group data into clusters
  - Similar to one another within the same cluster
  - Dissimilar to the objects in other clusters
  - Unsupervised learning: no predefined classes



K-Means: Example



K-means Clustering on Streams

- A data stream arrives in chunks X_1, …, X_n, each chunk fits in main memory
- Assumptions
  - Each chunk can be loaded into main memory only once
  - Limited main memory
- Challenges
  - Can we find a simple, fast, constant-factor-approximation k-median algorithm on one chunk?
  - How to derive global clusters?
- [O'Callaghan et al., 02]

Finding Good Initial Clustering

- Applied on the first chunk, 8-approximation to optimum
- Parameter: z – facility cost
- Steps
  - Reorder data points randomly
  - Create a cluster center at the first point
  - For every point after the first
    - Let *d* be the distance from the current data point to the nearest existing cluster center
    - With probability *d/z* create a new cluster center at the current data point; otherwise, add the current point to the best current cluster

LOCALSEARCH

- Starting from the initial clustering
- If the number of clusters in the initial clustering is far from k, adjust z
- Otherwise, adjust centers and assignments of points to clusters
- Details in [O'Callaghan et al., 02]

Deriving Global Clusters

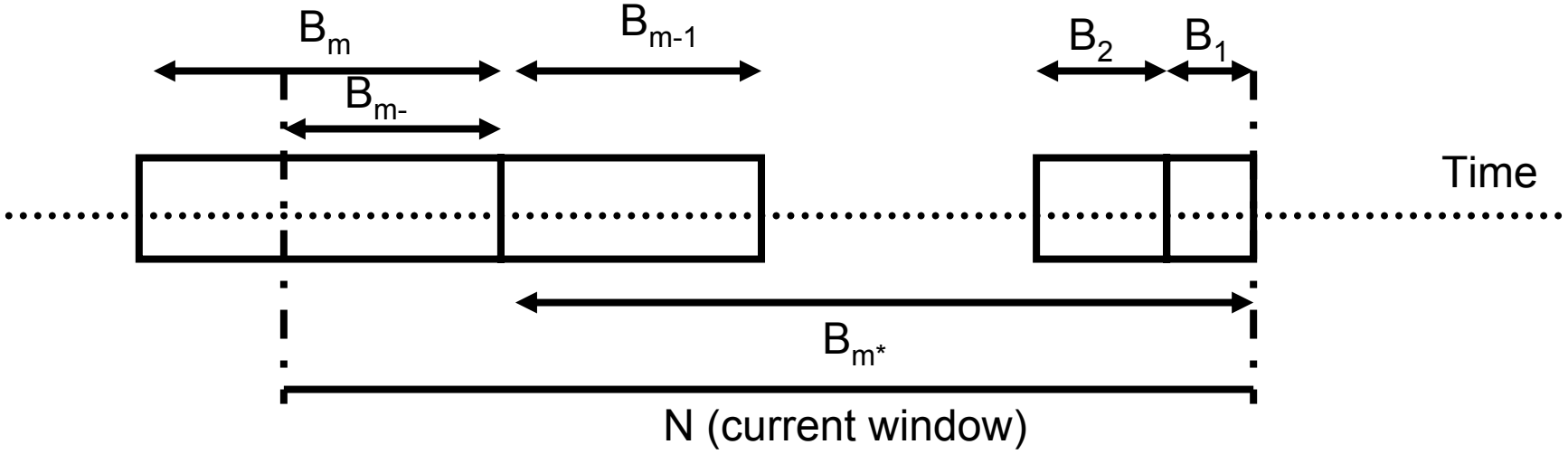
- For each chunk
  - Determine whether the chunk consists of mostly of a set of fewer than k points repeated over and over. If so, re-represent the chunk as a weighted data set such that each distinct point appears only once with a weight
  - Cluster the chunk using LOACLSEARCH, each cluster center has the weight of number of points it has
- Apply LOCALSEARCH to the weighted centers we have retained from the chunks so far

Clustering a Whole Stream Or a Sliding Window?

- In many applications, very old data is considered less useful and relevant
  - In some applications, it is required to cluster a sliding window instead of the whole stream
  - Network management, telecommunication, financial services, …
- How to “forget” stale data?
  - Aging – data items are associated with weights decaying over time
  - Sliding window – only consider the last n items

General Idea

- Divide the stream into buckets
  - Maintain statistics (e.g., # elements, mean, and variance) or local clustering in the buckets
- Derive global variance and clustering from locals
- Details in [Babcock et al., 03]



Other Than One Pass?

- One pass clustering algorithms are scalable, but may not be capable on streams evolving considerably
- How to explore clusters over different portions of the stream?
- Instead of one pass, clustering can be done in two phases
  - Online component: periodically summarize statistics
  - Offline component: in depth analysis based on the statistics
- [Aggarwal et al., 03]

Summarizing Using Micro-Clusters

- Micro-clusters using temporal extension of cluster feature vector
- For n d-dimensional points, a micro-cluster is defined as a (2d+3) tuple ($CF2^x$, $CF1^x$, $CF2^t$, $CF1^t$, n)
  - $CF2^x$ and $CF1^x$ are vectors of d entries, recording the sum of the squares and sum of the data values in each dimension, respectively
  - $CF2^t$ and $CF1^t$ record the sum of the squares and the sum of the time stamps, respectively

Additivity of Micro-Clusters

- The cluster feature vector of a larger micro-cluster can be derived from the cluster feature vectors of the sub-micro-clusters
- A natural choice for data stream processing

Pyramidal Time Frame

- The micro-clusters are stored at snapshots in time following a pyramidal pattern
  - Different levels of granularity depending on the recency
  - Snapshots are classified into different orders from 1 to log(T), where T is the clock time elapsed since the beginning of the stream
- For any user-specified time window of h, at least one stored snapshot can be found within 2h units of the current time
  - An effective trade-off between the storage requirements and the ability to recall summary statistics from different time horizons

An Example

- For any user-specified time window, let t_c be the current time and t_s be the time of the last stored snapshot of any order just before the time t_c-h. Then $(t_c - t_s) \leq 2h$

Order of snapshots	Clock time (last 5 snapshots)
0	55 54 53 52 51
1	54 52 50 48 46
2	52 48 44 40 36
3	48 40 32 24 16
4	48 32 16
5	32

Summary – Clustering

- Clustering data stream with one scan and limited main memory
  - Clustering the whole stream
  - Clustering in a sliding window
- How to handle evolving data?
  - Online summarization and offline analysis
- Applications and extensions
  - Outlier detection, nearest neighbor search, reverse nearest neighbor queries, …

Online Mining Data Streams

- Synopsis maintenance
- Classification, regression and learning
- Stream data mining languages
- Frequent pattern mining
- Clustering
- Change and novelty detection

Difference Between Static and Streaming Data

- "If the data distribution is stable, mining a data stream is largely the same as mining a large data set, since statistically we can draw and mine a sufficient sample"
- What are the expectations of mining data streams?
  - Assumption: the data is evolving
  - Finding and understanding changes!
  - Maintaining an updated model

Challenges in Change Detection

- How to measure the changes?
- How to describe and visualize the changes?
- How to characterize different types of changes?
- How to conduct reasoning on changes?
  - Why do we see the change?
  - What will follow?
  - …
- A new problem inherent to data streams

Diagnosing Changes in Streams

- The distribution of data can be measured by kernel density estimation
- Velocity density estimation: the rate of change in data density at each spatial location
- Visualization by temporal/spatial velocity profiles
- [Aggarwal, 03]

Burst Detection

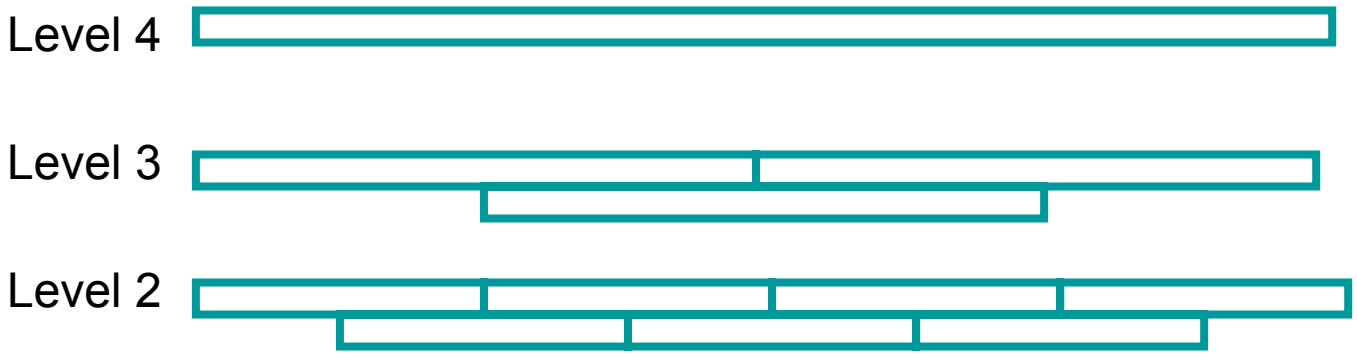
- Finding abnormal aggregates in data streams
- Monitor many sliding window sizes simultaneously and report those windows with aggregates significantly different from other periods
- Applications
  - Astronomy: Gamma ray burst
  - Network management: number of packages lost within a short period exceeds some threshold
  - Finance: stocks with unusually high trading volumes or with usually high price fluctuations within a short period

Three Types of Windows

- Landmark windows: the average stock price of IBM from Jan 1st, 2002 to today
- Sliding windows: the average stock price of IBM in the last 5 days
- Damped window: the weights of data decrease exponentially into the past
- Elastic window model – a generalization
  - Parameters: the range of the sliding window sizes [Zhu & Shasha, 03]

Shifted Wavelet Tree

- The adjacent windows of the same level are half overlapping



Building a Shifted Wavelet Tree

- Input: x[1..n], $n=2^a$ ($a=\log_2 n$)
- Output: shifted wavelet tree SWT[1..a][1..]
- Method:
  - b ← x;
  - for i=1 to a
  - // merge consecutive windows and form level i of SWT
  - for j=1 to size(b)-1 step 2
  - SWT[i][j]=b[j]+b[j+1];
  - for j=1 to size(SWT[i])/2
  - b[j]=SWT[i][2*j-1];

Detecting Burst

- If the sum at a high level window fails the threshold for the lowest level, no low level window will have a burst
- Can be extended to k-d shifted wavelet tree

Burst Detection in Text Streams

- Applications
  - Emails, published literature, …
- Modeling the stream using an infinite-state automaton
  - Busts: state transitions
  - Details in [Kleinberg, 02]

Novelty Detection

- Novelty: the newly arrive value x_t is substantially away from the prediction using $x_1, \ldots, x_{t-1}$, or part of the sequence
- Use support vector regression to generate a model to predict x_t
  - Details in [Ma & Perkins, 03]
- Generalization
  - Online prediction and model maintenance
  - Novelty detection: outliers that the model fails

Summary – Change Detection

- An inherent problem for data streams
- Challenges
  - How to define meaningful changes?
    - Changes, burst, novelty, …
  - How to mine changes efficiently?
  - How to summarize/visualize changes?
- Good news: not much work yet!

Summary

- Mining data streams
  - Challenging problems
  - Exciting progress
- What is the next?
  - What have been done?
  - What have been started?
  - What should be done in the future?

What Have Been Done?

- Stream data management
  - Join, SQL query answering, …
- Synopsis monitoring
  - Basic aggregates, with or without sliding windows
- Critical tools: statistics + database techniques
- Achievements: accuracy + scalability

Challenges

- Standard for stream data management and processing
  - Schema?
  - Query language?
  - Benchmark?
- Real large applications of stream data management and processing systems
  - Killer applications?

What Have Been Just Started?

- Mining data streams
- Extensions of data mining tasks
  - Frequent pattern mining, classification, clustering, …
  - Extensions of conventional methods
- Stream-oriented mining
  - Change detection

Challenges

- Standard
  - Mining query language?
  - Benchmark?
- Large applications
- Stream mining systems – putting pieces together
  - Conducting multiple mining tasks on one stream?

What Should Be Done?

- Applications
  - If we have a system fast enough, do we still need stream processing/mining systems?
  - Killer applications are deadly wanted!
- Stream-oriented data mining
  - New types of patterns/knowledge from streams
- Interactive stream mining
  - Support interactive exploration

References – Synopsis and Classification (1)

- Arvind Arasu, Gurmeet Singh Manku. Approximate Counts and Quantiles over Sliding Windows. In the ACM Symposium on Principles of Database Systems (PODS) 2004.
- Brian Babcock, Chris Olston. Distributed Top-k Monitoring. In the ACM International Conference on Management of Data (SIGMOD) 2003.
- Brian Babcock, Mayur Datar, Rajeev Motwani, LiadanO O'Callaghan. Maintaining Variance and k-Medians over Data Stream Windows. In the ACM Symposium on Principles of Database Systems (PODS) 2003.
- Yunyue Zhu, Dennis Shasha. StatStream: Statistical Monitoring of Thousands of Data Streams in Real Time. In the International Conference on Very Large Data Bases (VLDB) 2002.
- Diane Lambert, Jose C. Pinheiro. Mining A Stream of Transactions for Customer Patterns. In the ACM International Conference on Knowledge Discovery and Data Mining (SIGKDD) 2001.

References – Synopsis and Classification (2)

- Gurmeet Singh Manku, Sridhar Rajagopalan, Bruce G. Lindsay. Approximate Medians and other Quantiles in One Pass and with Limited Memory. In the ACM International Conference on Management of Data (SIGMOD) 1998.
- Gurmeet Singh Manku, Sridhar Rajagopalan, Bruce G. Lindsay. Random Sampling Techniques for Space Efficient Online Computation of Order Statistics of Large Datasets. In the ACM International Conference on Management of Data (SIGMOD) 1999.
- Yan-Nei Law, Haixun Wang, Carlo Zaniolo. Query Languages and Data Models for Database Sequences and Data Streams. In the International Conference on Very Large Data Bases (VLDB) 2004.
- Haixun Wang, Carlo Zaniolo. ATLaS: A Native Extension of SQL for Data Mining. In the SIAM International Conference on Data Mining (SIAM DM) 2003.
- Wei Fan, Yi-an Huang, Haixun Wang, Philip S Yu. Active Mining of Data Streams. In the SIAM International Conference on Data Mining (SIAM DM) 2004.

References – Synopsis and Classification (3)

- Wei-Guang Teng, Ming-Syan Chen, Philip S. Yu. A Regression-Based Temporal Pattern Mining Scheme for Data Streams. In the International Conference on Very Large Data Bases (VLDB) 2003.
- Haixun Wang, Wei Fan, Philip S. Yu, Jiawei Han. Mining Concept Drifting Data Streams using Ensemble Classifiers. In the ACM International Conference on Knowledge Discovery and Data Mining (SIGKDD) 2003.
- Pedro Domingos, Geoff Hulten. Mining High Speed Data Streams. In the ACM International Conference on Knowledge Discovery and Data Mining (SIGKDD) 2000.
- Geoff Hulten, Laurie Spencer, Pedro Domingos. Mining Time-Changing Data Streams. In the ACM International Conference on Knowledge Discovery and Data Mining (SIGKDD) 2001.

References – Frequent Patterns (1)

- R. Agrawal, T. Imielinski, and A. Swami. Mining association rules between sets of items in large databases. SIGMOD'93, 207-216, Washington, D.C.
- R. Agrawal and R. Srikant. Fast algorithms for mining association rules. VLDB'94 487-499, Santiago, Chile.
- A. Arasu and G.S. Manku. Approximate counts and quantiles over sliding windows. PODS'04.
- T. Asai, H. Arimura, K. Abe, S. Kawasoe, and S. Arikawa. Online algorithms for mining semi-structured data stream. ICDM'02.
- J.H. Chang and W.S. Lee. Finding recent frequent itemsets adaptively over online data streams. In KDD'03.

References – Frequent Patterns (2)

- G. Cormode, F. Korn, S. Muthukrishnan, and D. Srivastava. Finding hierarchical heavy hitters in data streams. VLDB'03.
- G. Cormode and S. Muthukrishnan. What's hot and what's not: Tracking most frequent items dynamically. PODS'03.
- C. Giannella, J. Han, J. Pei, X. Yan, and P.S. Yu. Mining frequent patterns in data streams at multiple time granularities. in H. Kargupta, A. Joshi, K. Sivakumar, and Y. Yesha (eds.), *Next Generation Data Mining*, AAAI/MIT, 2003.
- J. Han, J. Pei, and Y. Yin: "Mining frequent patterns without candidate generation". In Proc. ACM-SIGMOD'2000, pp. 1-12, Dallas, TX, May 2000.

References – Frequent Patterns (3)

- R. Jin and G. Agrawal. An algorithm for in-core frequent itemset mining on streaming data. Submitted for publication
- C. Jin, W. Qian, C. Sha, J.X. Yu, A. Zhou. Dynamically maintaining frequent items over a data stream. CIKM'03.
- R.M. Karp and S. Shenker. A simple algorithm for finding frequent elements in streams and bags. In ACM TODS, Vol. 28, No. 1, Marge 2003, pages 51-55.
- G.S. Manku and R. Motwani. Approximate frequency counts over data streams. VLDB'02.
- W-G. Teng, M-S. Chen, and P.S. Yu. A regression-based temporal pattern mining scheme for data streams. VLDB'03

References – Clustering (1)

- R. Agrawal, J. Gehrke, D. Gunopulos, and P. Raghavan. Automatic subspace clustering of high dimensional data for data mining applications. SIGMOD'98
- M. R. Anderberg. Cluster Analysis for Applications. Academic Press, 1973.
- M. Ankerst, M. Breunig, H.-P. Kriegel, and J. Sander. Optics: Ordering points to identify the clustering structure, SIGMOD'99.
- P. Arabie, L. J. Hubert, and G. De Soete. Clustering and Classification. World Scietific, 1996
- M. Ester, H.-P. Kriegel, J. Sander, and X. Xu. A density-based algorithm for discovering clusters in large spatial databases. KDD'96.
- M. Ester, H.-P. Kriegel, and X. Xu. Knowledge discovery in large spatial databases: Focusing techniques for efficient class identification. SSD'95.
- D. Fisher. Knowledge acquisition via incremental conceptual clustering. Machine Learning, 2:139-172, 1987.

References – Clustering (2)

- D. Gibson, J. Kleinberg, and P. Raghavan. Clustering categorical data: An approach based on dynamic systems. In Proc. VLDB’98.
- S. Guha, R. Rastogi, and K. Shim. Cure: An efficient clustering algorithm for large databases. SIGMOD'98.
- A. K. Jain and R. C. Dubes. Algorithms for Clustering Data. Printice Hall, 1988.
- D. Jiang, J. Pei and A. Zhang. Interactive Exploration of Coherent Patterns in Time-Series Gene Expression Data. In KDD'03.
- L. Kaufman and P. J. Rousseeuw. Finding Groups in Data: an Introduction to Cluster Analysis. John Wiley & Sons, 1990.
- E. Knorr and R. Ng. Algorithms for mining distance-based outliers in large datasets. VLDB’98.
- G. J. McLachlan and K.E. Bkasford. Mixture Models: Inference and Applications to Clustering. John Wiley and Sons, 1988.
- P. Michaud. Clustering techniques. Future Generation Computer systems, 13, 1997.

Reference – Clustering (3)

- R. Ng and J. Han. Efficient and effective clustering method for spatial data mining. VLDB'94.
- J. Pei, X. Zhang, M. Cho, H. Wang and P.S. Yu. MaPle: A Fast Algorithm for Maximal Pattern-based Clustering. In ICDM'03.
- E. Schikuta. Grid clustering: An efficient hierarchical clustering method for very large data sets. Proc. 1996 Int. Conf. on Pattern Recognition, 101-105.
- G. Sheikholeslami, S. Chatterjee, and A. Zhang. WaveCluster: A multi-resolution clustering approach for very large spatial databases. VLDB'98.
- C. Tang, A. Zhang, and J. Pei. Mining Phenotypes and Informative Genes from Gene Expression Data. In KDD'03.
- W. Wang, Yang, R. Muntz, STING: A Statistical Information grid Approach to Spatial Data Mining, VLDB'97.
- T. Zhang, R. Ramakrishnan, and M. Livny. BIRCH : an efficient data clustering method for very large databases. SIGMOD'96.

References – Clustering Streams

- C.C. Aggarwal, J. Han, J. Wang, and P.S. Yu. A framework for clustering evolving data streams. In VLDB'03.
- B. Babcock, M. Datar, R. motwani, and L. O'Callaghan. Maintaining variance and k-medians over data stream windows. In PODS'03.
- F. Korn, S. Muthukrishnan, and D. Srivastava. Reverse nearest neighbor aggregates over data streams. In VLDB'02.
- L. O'Callaghan, N. Mishra, A. Meyerson, S. Guha, and R. Motwani. Streaming-data algorithms for high-quality clustering. In ICDE'02.

References – Change Detection

- C.C. Aggarwal. A framework for diagnosing changes in evolving data streams. SIGMOD'03.
- J. Kleinberg. Bursty and hierarchical structure in streams. KDD'02.
- J. Ma and S. Perkins. Online novelty detection on temporal sequences. KDD'03.
- Y. Zhu and D. Shasha. Efficient elastic burst detection in data streams. KDD'03.