CSE 564 VISUALIZATION & VISUAL ANALYTICS

TIME SERIES & STREAMING DATA

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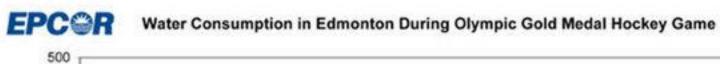
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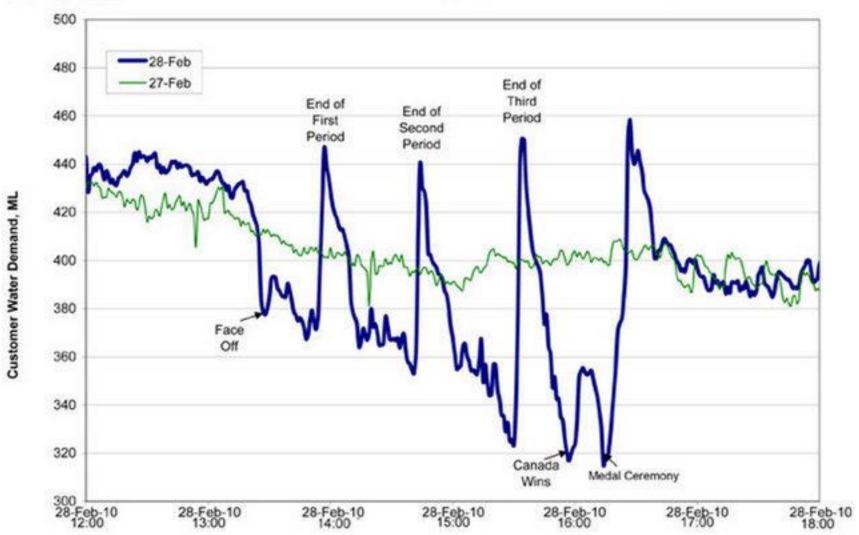
Traditional Time Series Visualizations

NVIDIA stock vs. NASDAQ (from yahoo! finance)



Fun one... (found in J. Stasko lecture)



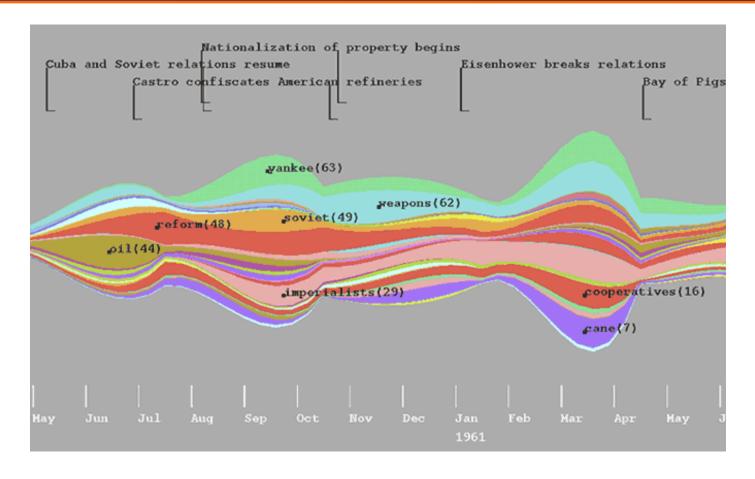


Next...

A few good visualization metaphors for time

• there are quite a few of them...

ThemeRiver (Havre et al., 2002)



River widens or narrows to depict changes in the collective strength of selected themes in the underlying documents. Individual themes are represented as colored "currents" flowing within the river.

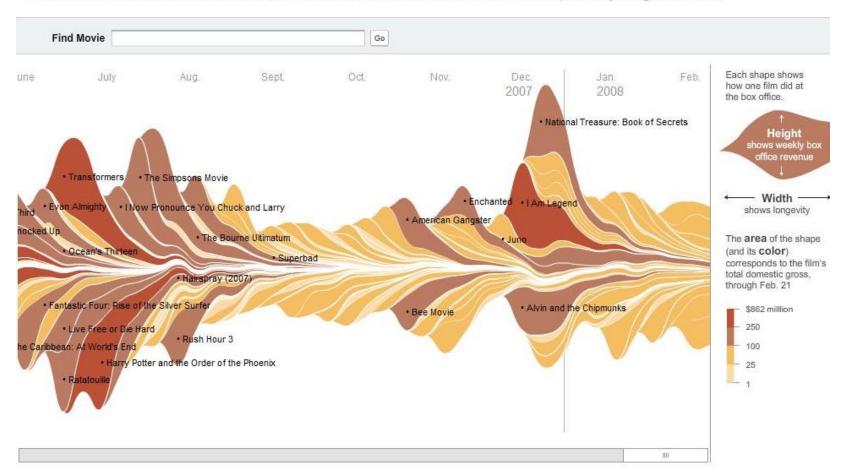
Example shown here: newspaper themes around the Cuban Missile crisis

Stream Graphs

February 23, 2008
☐ SIGN IN TO E-MAIL OR SAVE THIS FEEDBACK

The Ebb and Flow of Movies: Box Office Receipts 1986 — 2008

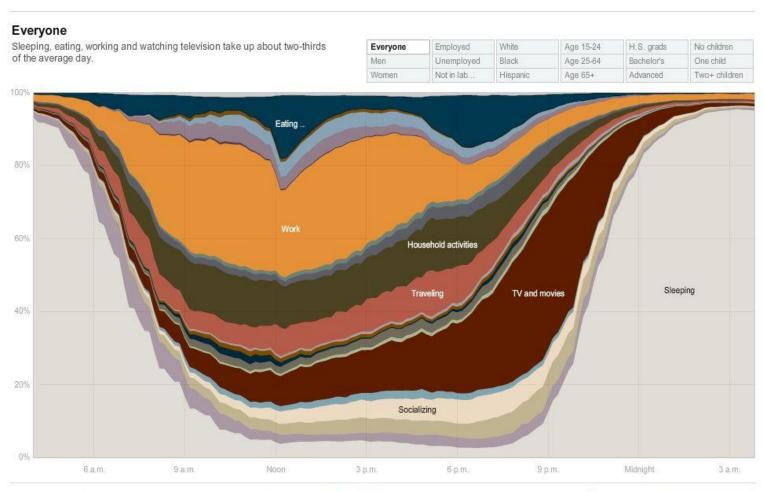
Summer blockbusters and holiday hits make up the bulk of box office revenue each year, while contenders for the Oscars tend to attract smaller audiences that build over time. Here's a look at how movies have fared at the box office, after adjusting for inflation.

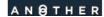


Stacked Area Charts

How Different Groups Spend Their Day

The American Time Use Survey asks thousands of American residents to recall every minute of a day. Here is how people over age 15 spent their time in 2008. Related article





Name Voyager (http://www.babynamewizard.com)



Question

Can you tell me who is who?

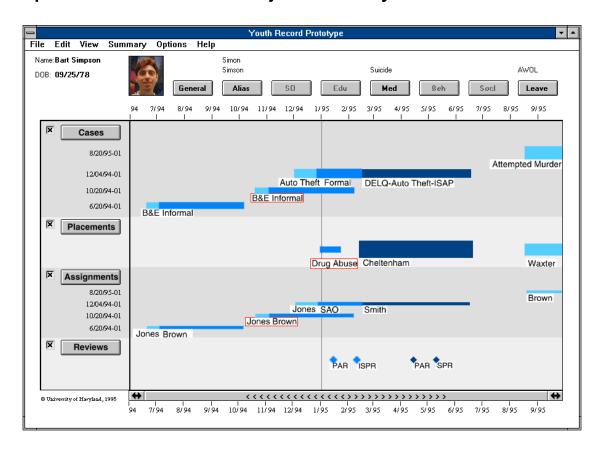
- I tell you all the names there are and the age of each person
- can you assign them? (hint: use the Name Voyager)



Chronological Flow Charts

Criminal record for Bart Simpson

- B&E = breaking and entering
- length mapped to duration
- width mapped to severity
- intensity mapped to penetration into the juridical system



Medical Data

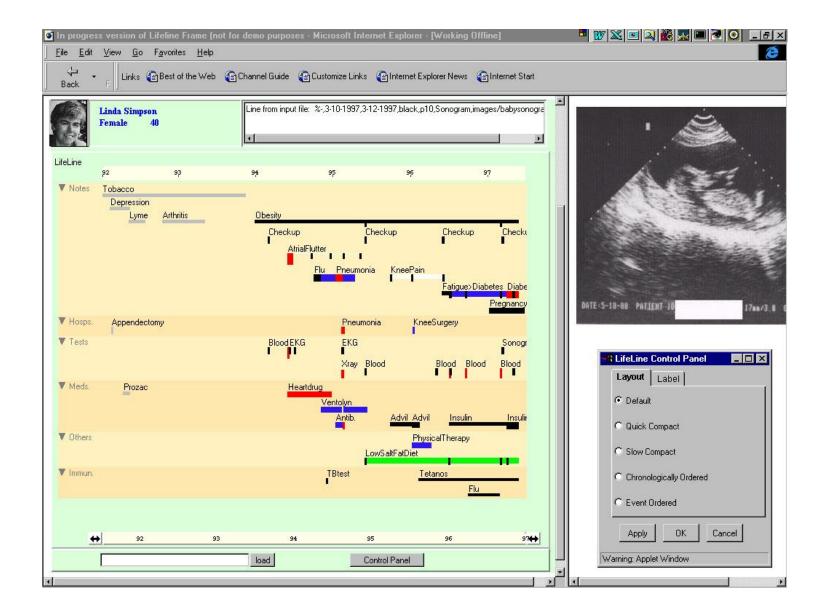
Medical data are often displayed along time

- natural to humans
- progression of disease
- appearance of symptoms
- time course of treatment and outcome
- but also time signals (ECG, blood pressure, etc.)

A popular example is Lifelines and Lifelines2

- Shneiderman and Plaisant et al.
- http://www.cs.umd.edu/hcil/lifelines/

LifeLines: Patient-Centric



LifeLines2: Pattern-Centric

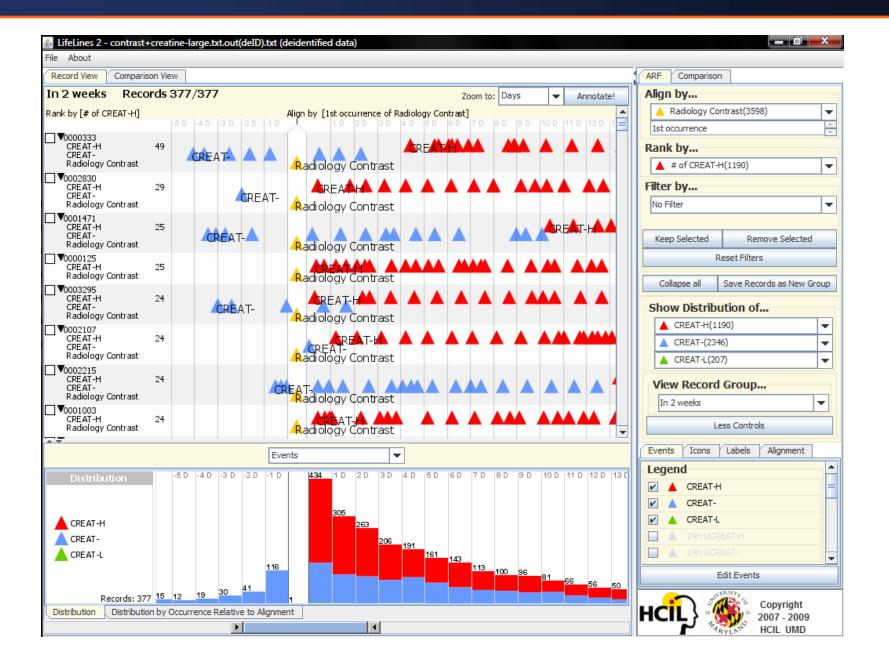
Goals:

- bring out temporal categorical patterns across multiple records
- categorical event data such as complaints, diagnoses, treatments
- play important roles in health providers decision making

Features

- allows users to manipulate multiple records simultaneously
- understand relative temporal relationships across records
- 3 operators: align, rank, filter
- temporal summaries allow multiple groups of records to be compared

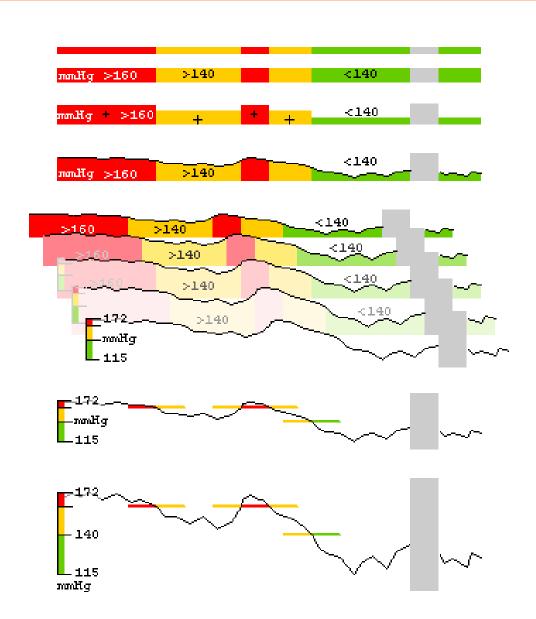
LifeLines2: Screenshot



Multi-Scale and Abstractions (Aigner at al., IEEE TVCG, 2008)

Deal with different levels of detail

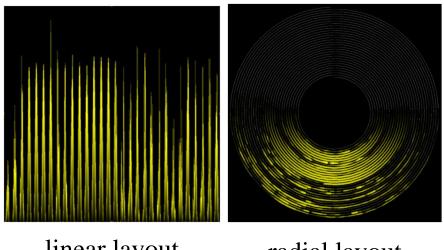
- illustrative abstraction
- overview + detail
- used here for medical data



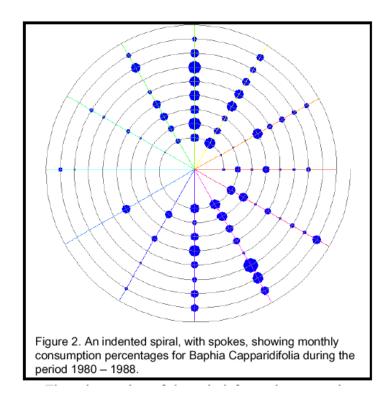
Cyclic Patterns

Time data are often cyclic

- spiral displays are good to bring out cyclic patterns
- one period per loop (for example, a year)

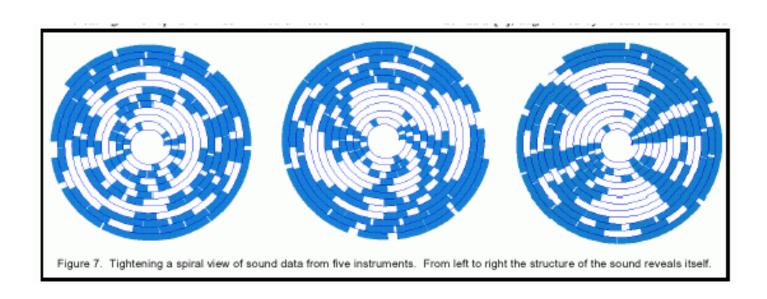


linear layout radial layout sunshine pattern



Cyclic Patterns

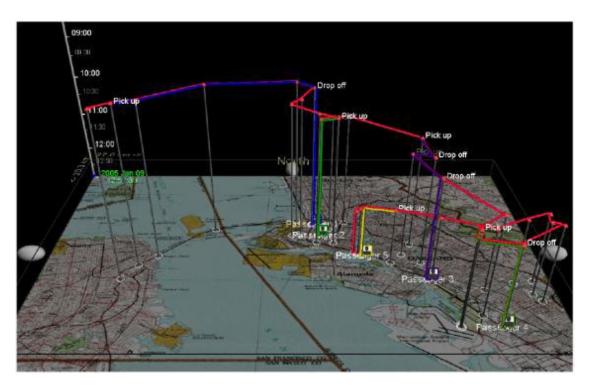
May have to play around to discover the cycles



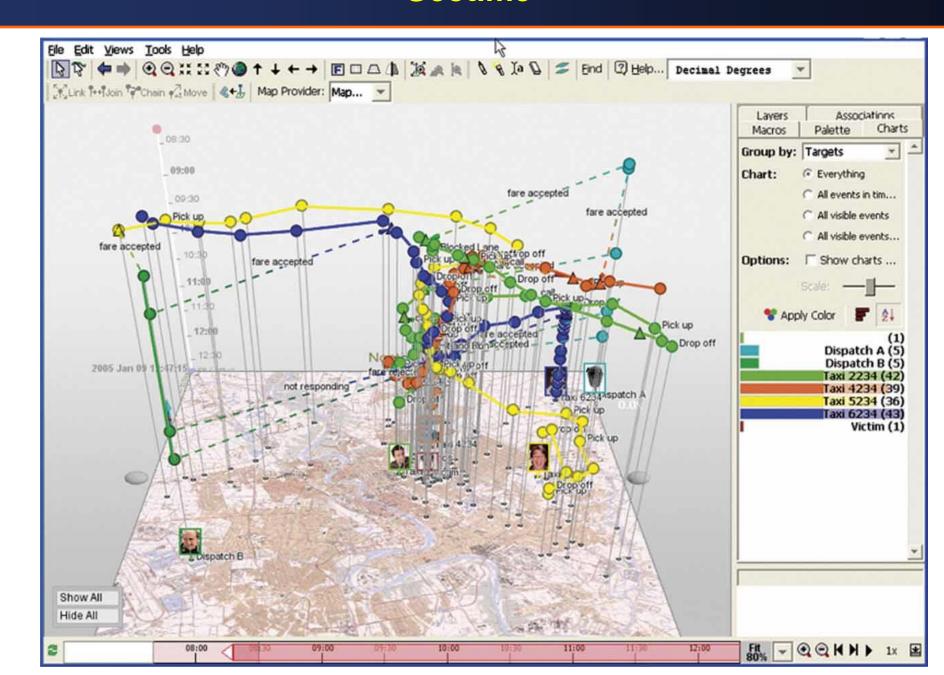
Combine Space and Time

OculusInfo Geotime application (video)

- events are represented in an X,Y,T coordinate space
- the X,Y plane shows geography
- the vertical T axis represents time
- events animate in time vertically through the 3-D space as the time slider bar is moved.



Geotime



Interaction

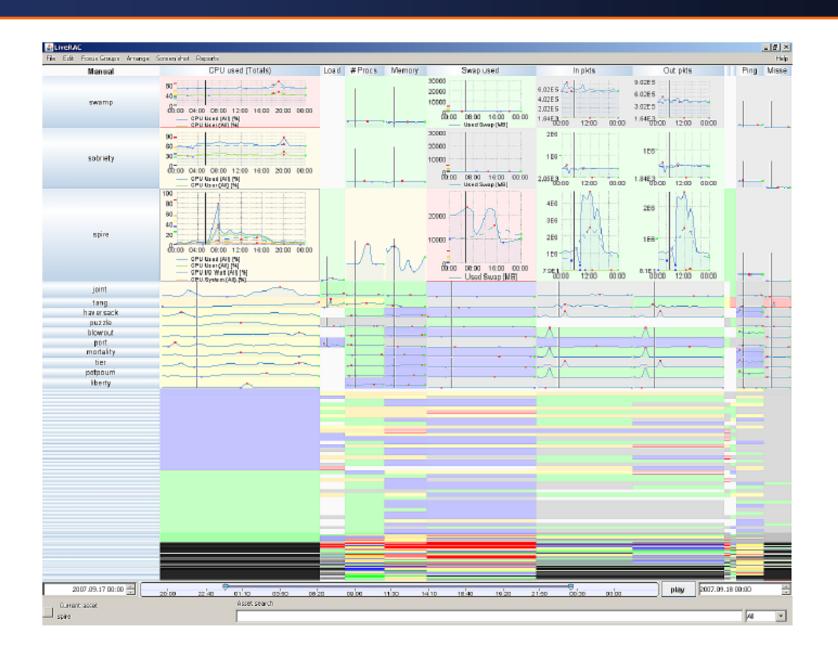
As complexity increases, interaction capabilities are key

- show more context of what else was going on at that time
- likely have to abstract some of the information
- allow several different levels of detail at once
- allow drill-down for details
- use dashboard design with many linked information displays

Example: Computer system management

- LiveRAC system (McLachlan et al.)
- next two slides

LiveRAC



LiveRAC



Figure 3. LiveRAC shows a full day of system management time-series data using a reorderable matrix of area-aware charts. Over 4000 devices are shown in rows, with 11 columns representing groups of monitored parameters. (a): The user has sorted by the maximum value in the CPU column. The first several dozen rows have been stretched to show sparklines for the devices, with the top 13 enlarged enough to display text labels. The time period of business hours has been selected, showing the increase in the $In\ pkts$ parameter for many devices. (b): The top three rows have been further enlarged to show fully detailed charts in the CPU column and partially detailed ones in Swap and two other columns. The time marker (vertical black line on each chart) indicates the start of anomalous activity in several of spire's parameters. Below the labeled rows, we see many blocks at the lowest semantic zoom level, and further below we see a compressed region of highly saturated blocks that aggregate information from many charts.

LiveRAC Video

<u>video</u>

Next – Streaming Data

Time series data with no end...

Types of Streaming data

Transaction streams

- credit card, point-of-sale transaction
- at a supermarket, or online purchase of an item

Web click-streams

Social streams

- online social networks such as Twitter
- speed and volume of the stream typically scale super-linearly with the number of actors

Network streams

- communication networks contain large volumes of traffic streams
- often mined for intrusions, outliers, or other unusual activity

Challenges (1)

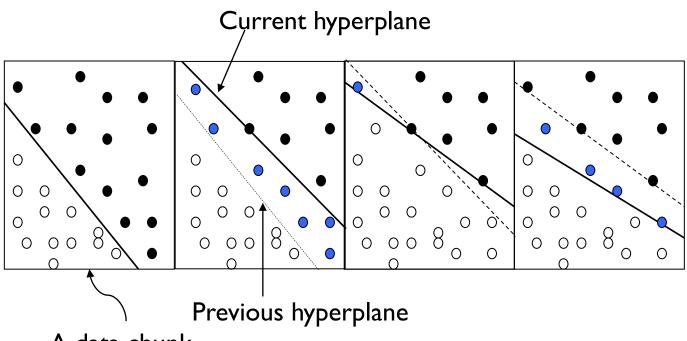
One-pass constraint

- data is generated continuously and rapidly
- it is assumed that the data can be processed only once
- archival for future processing is not possible
- prevents use of iterative mining or model building algorithms that require multiple passes over the data

Concept drift, concept evolution, feature evolution

- data may evolve over time
- various statistical properties, such as correlations between attributes, correlations between attributes and class labels, and cluster distributions may change over time

Concept Drift



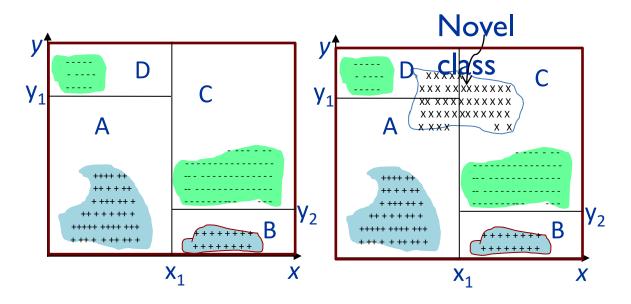
A data chunk

Negative instance •

Positive instance o

Instances victim of concept-drift

Concept Evolution



Classification rules:

R1. if $(x > x_1)$ and $y < y_2$ or $(x < x_1)$ and $y < y_1$ then class = +

R2. if $(x > x_1 \text{ and } y > y2)$ or $(x < x_1 \text{ and } y > y_1)$ then class = -

Existing classification models misclassify novel class instances

CluStream Clustering

The concept drift in an evolving data stream changes the clusters significantly over time

- need a clustering algorithm that can deal with this
- CluStream is such an algorithm

CluStream's online microclustering clustering stage

 processes the stream in real time to continuously maintain summarized but detailed (micro-)cluster statistics of the stream

CluStream's offline macroclustering stage

- further summarizes these detailed clusters
- provides the user with a more concise understanding of the clusters over different time horizons and levels of temporal granularity.

Microclustering Algorithm

There are k microclusters

 a new data point either needs to be absorbed by a microcluster, or it needs to be put in a cluster of its own

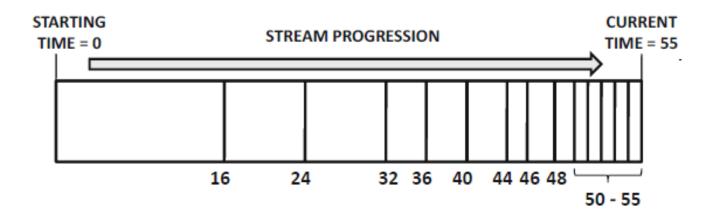
Algorithm

- determine distance of the new data point to all current microcluster centroids
- assign the point to the closest cluster and update the statistics
- if the point does not fall within the maximum boundary of any microcluster create a new microcluster
- to create this new microcluster, the number of other microclusters must be reduced by 1 to free memory availability
- achieve this by either deleting an old microcluster or merging two of the older clusters
- decide by examining the staleness (using the time stamp statistics) of the different clusters, and the number of points in them
- determine whether one of them is "sufficiently" stale to merit removal
- if no microcluster is stale, then a merging of the two microclusters is initiated

Pyramidal Time Frame

Store microclusters statistics periodically to enable time horizon-specific analysis of the clusters

 the microcluster snapshots are stored at varying levels of granularity depending on the recency of the snapshot



Other Stream Mining Issues

Streaming outlier (anomaly) detection

- use time windows and k-nearest neighbor scores
- new concepts or trends can manifest themselves as outliers in the onset

Streaming classifiers

 the Hoeffding tree is constructed incrementally by growing the tree simultaneously with stream arrival.

