Monitoring

6.872/HST950

Peter Szolovits

Outline

- Problem of information overload
- How to reason with/about time
- Interpreting temporal data

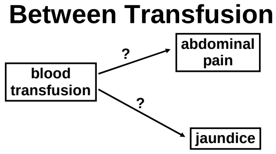
Problem

- ICU alarms sound roughly every 30 seconds, in a typical (full) ICU
- Nurse takes ~minutes to resolve alarm
- How to resolve?
  – Ignore (turn off) alarms
  – Prioritize
  – Automate
  – Make alarming algorithms more intelligent

Time is Critical

- Some systems have no explicit representation of time
  – E.g., Internist
    - <ABDOMEN TRAUMA RECENT>
    - <ABDOMEN TRAUMA REMOTE HX>
    - <CHEST PAIN SUBSTERNAL LASTING GTR THAN 20 MINUTE <S>>
    - <CHEST PAIN SUBSTERNAL LASTING LESS THAN 20 MINUTE <S>>
- No representation of these pairs being "the same," but at different times.
- Note: Same problem with space; need orthogonality!

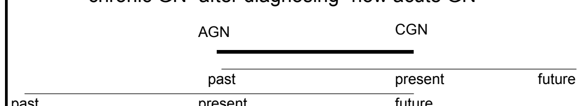
Motivating Example: Distinguishing Four Possible Relationships Between Transfusion and Jaundice



- Post-transfusion antigen incompatibility hemolytic anemia
- Post-Transfusion Hepatitis B: Acute Hepatitis
- G-6-PD hemolytic anemia treated by transfusion
- Post-Transfusion Hepatitis B: Chronic Active

Even Simple Models Help

- PIP's temporal model:
  – PAST, RECENT, NOW, SOON, FUTURE
- Example:
  – in "chronic glomerulonephritis" model, "past acute GN"
  – (to my surprise), program hypothesized "future chronic GN" after diagnosing "now acute GN"



What is Time?

- (Macroscopically) unidirectional
- Related to causality
- May be modeled in various ways
  - Continuous quantity, as in differential equations
  - Discrete time points, as in discrete event simulations
  - Intervals, as in ordinary descriptions of durations, processes, etc.

  … or combinations

Continuous View

$$\frac{d^2x}{dt^2} = -g$$

$$\frac{dx}{dt} = -gt + v_0$$

$$x = -gt^2 + v_0 t + x_0$$

- Differential equation view of world
- States (state variables) evolve according to their laws

Discrete Event View

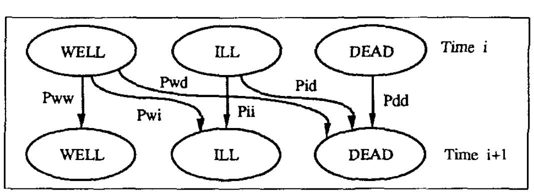
- Designated (countable) time points
- Nothing “interesting” between events
- Events may be defined by
  - Clock “ticks”
  - Interactions among objects in universe
  - Distinguished points in representation of state variables (e.g., highest point of cannon shell)

What Can Be a Time Point?

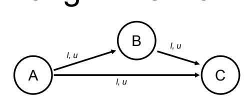
- Calendrical point—a specific date/time
- Recognizable event—e.g., “when I had my tonsils out,” or “start of high school,” or “my ninth birthday”
- Now—special, because it moves

Discrete Events are Associated with State Transitions

E.g., Beck & Pauker’s model to help compute quality-adjusted years of survival:

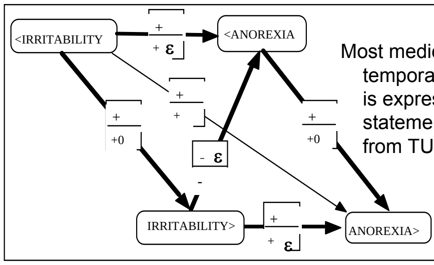


Constraint Propagation among Time Points



- Clearly, T(A,B)+T(B,C) = T(A,C)
- But we only know lower/upper bounds on T
- L(A,C) = L(A,B)+L(B,C)
- U(A,C) = U(A,B)+U(B,C)
- and thus, we can infer relationships

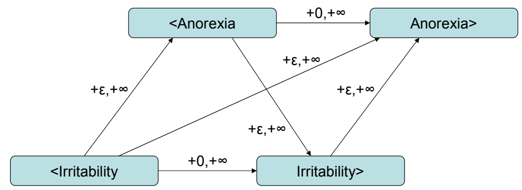
Interval "Overlaps" in TUPese



Most medical history temporal terminology is expressible in statements composed from TUP assertions.

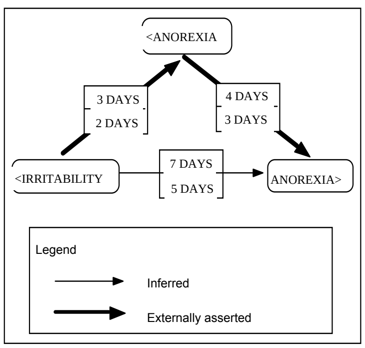
Intervals and Points are Alternate Representations

- "Overlaps" defined in terms of its endpoints:

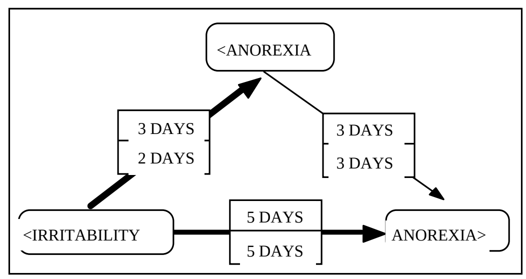


Initial Assertions

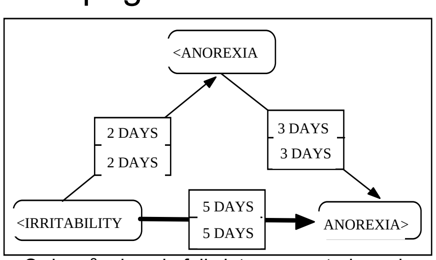
- Completing all the relations not explicitly asserted



Constraint



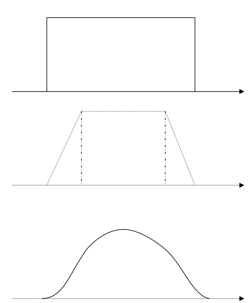
Propagated Constraint



- Order n^2 edges in fully interconnected graph
- Order n^3 computation
- Work to localize propagation to semantically related events

Forms of Temporal Uncertainty

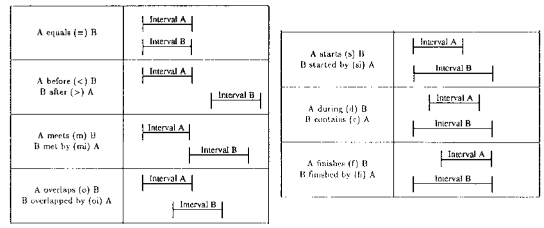
- Lower/upper bounds on temporal distances
- Central range + fringe
- Continuous distributions



Interval View

- Activities, processes take place over extended intervals of time
- Observations are true over periods of time
- Systems remain in steady (from some viewpoints) states over intervals

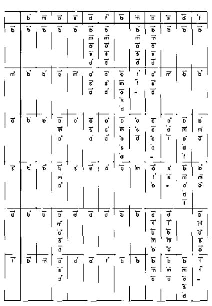
Allen's Temporal Intervals



Inference among Intervals by Composition

Y-Z

X-Y



e.g., if A starts B and B overlaps C,

what are the possible relationships between A and C?

1. A before C
2. A meets C
3. A overlaps C

Temporal Control Structure. - T. Russ

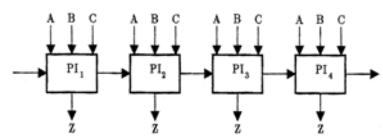


Figure 2-8: A Chain of Reasoning Processes.

- Processes maintaining truth of abstractions over specified interval
- Update of past beliefs from corrections or new data.
- Actions are permanent.

Back to Monitoring

- Detecting Trends
- Language for Trend Description
- Matching algorithms
- Top-down vs. bottom-up vs. both
- Learning trend detectors

"Two-Point" Trend Detectors

- Restricted to hospitals with the most complete information systems
- Rind & Safran, 1992
- Two point event detector
  - rise in creatinine > 0.5 mg/dl
- Therapeutic context
  - Renally cleared or nephrotoxic medication
  - Possible care providers
- Implementation
  - M procedures linked to E-mail

BIH Experience (cont'd)

- Time series trial
- 607 in 348 admissions during control periods
- 497 events in intervention period
- 369 alerts, sent to 584 different physicians, 9.25 recipients per alert
- Improved response time
- Improved outcomes

Figure 1: Example of an alert

FROM CLINICAL COMPUTING THU MAR 21,1991 10:41 AM PAGE 1 OF 1

SMITH,JOHN K (#112233)
had a rise in creatinine from 1.2 on 03/20/91 to 2 on 03/21/91
while on the following potentially nephrotoxic medications:
GENTAMICIN
CAPTOPRIL
and while on the following renally excreted medications:
DIGOXIN
RANITIDINE

If this patient is under your care, you can, if you wish, mark this message 'TAKEN CARE OF' for other message recipients by typing 'T'.

END OF MESSAGE (RETURN)
REPLY/FORWARD/EDIT/CALENDAR/PRINT/HOLD/DELETE/TAKEN CARE (R/F/E/C/P/H/D/T):

◆Representation

Easily implemented as an Arden Syntax MLM

Are these two-point trend detectors sufficient?

- If not, why not?
- Noisy data.
- Multi-phased processes.
- Uncertainty over time.
- Uncertainty over values.

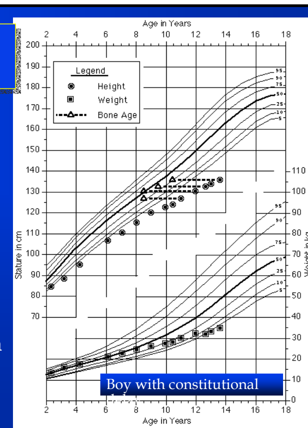
Issues in Trend Detection

- Defining significant trends
  - Multiple variables
  - Multiple phases
  - Temporal and value uncertainty
- Detecting trends from data
- Generating alarms
- Displaying, explaining results
- Changing clinical context

Pediatric Growth Monitoring

- Data:
  - heights, weights
  - family history
  - bone ages
  - pubertal data, stages
  - hormone values
- Disorders show characteristic patterns on growth chart.

--Haimowitz



Curve Fitting Approach

$$\text{Height}(t) = \frac{a_1}{1 + e^{-b_1 (t - c_1)}} + \frac{a}{1 + e^{-b_2^2 (t - c_2)}} + \frac{a}{1 + e^{-b_3^3 (t - c_3)}}$$

Triple-logistic curve [Thissen and Bock 1990]

a_k = component k's contribution to mature stature

b_k = a parameter proportional to the maximum growth velocity of the component (maximum rate of growth is (a * b) /4 centimeters per year)

c_k = the age in years at which the maximum growth velocity occurs

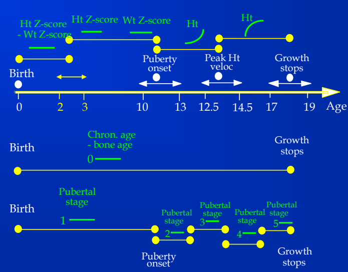
Describing Average Normal Growth

- **Def. Z-score** ≡ Number of standard deviations a patient's parameter is from the mean for that age.
- From birth until age 2 - 3 years, height and weight vary together and establish baseline Z-scores.
- From then until onset of puberty, height and weight maintain approximately the same Z-scores.
- Throughout this time, bone age is approximately equal to chronological age.

Trend Template for Male Average Normal Growth

Landmark points
- Time constraints

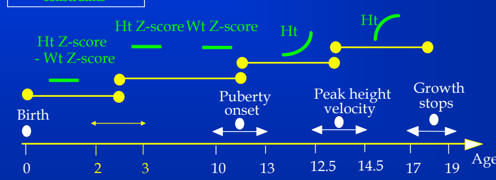
Intervals
- Time constraints
- Value constraints



Trend Template, continued

Landmark points
- Time constraints

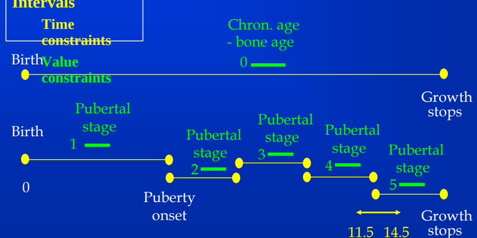
Intervals
- Time constraints
- Value constraints



Trend Template, continued

Landmark points
- Time constraints

Intervals
- Time constraints
- Value constraints



Value Constraints Have Regression Models

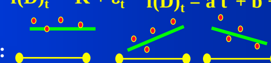
- Low-order polynomials
- Parameter estimates: quantitative or qualitative

Constant

$f(D)_t = K + \varepsilon_t$

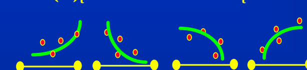
Linear

$f(D)_t = a\,t + b + \varepsilon_t$



Quadratic

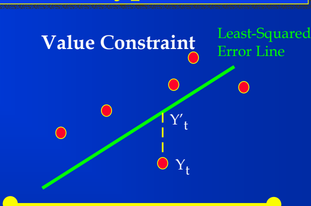
$f(D)_t = a\,t^2 + b\,t + c + \varepsilon_t$



Goodness of Fit of a Hypotheses

Mean Absolute % Error

$$= \frac{\sum_t \left| \frac{Y_t - Y'_t}{Y_t} \right|}{N - \text{(no. estim. pars.)}}$$

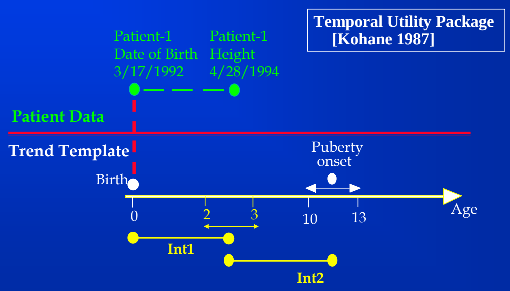


- Hypothesis score is weighted average of value constraint scores.

TrenDx

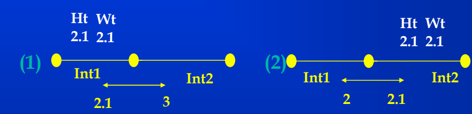
- Matches process data to trend templates.
- Optimizes over alternate trend chronologies.
- Compares best matches of competing trends within same clinical context.

Linking Patient Data to Trend Template



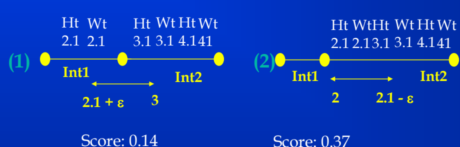
Processing height and weight, 2.1 years

- Branch to two hypotheses of average normal growth:

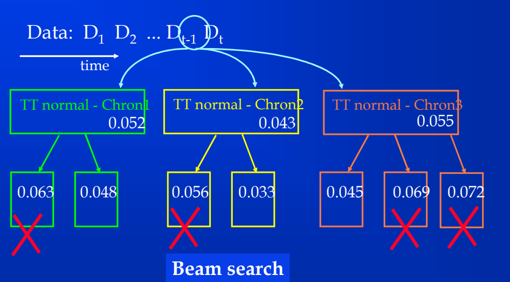


Processing data through age 4.1

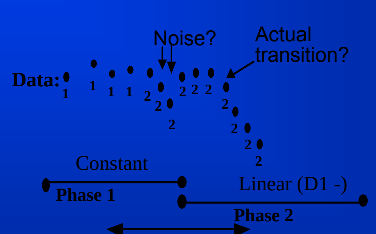
- First hypothesis has lower error.
- Refining patient history from population pattern and data.



Maximizing Chronologies for a Trend



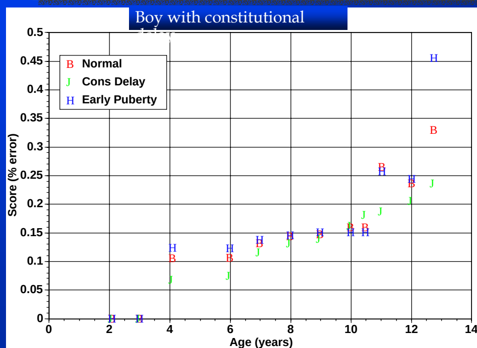
Beam search - soundness vs. efficiency



Diagnostic Monitoring Framework

- Clinical context
  - Partition of trend templates
  - One normal; others faulty
  - TrenDx concurrently matches to same process data
- Compare best matching hypothesis of each trend template
- Significant faulty trend match triggers actions
  - Alarms
  - Displays
  - Other clinical contexts

TrenDx Results on Growth Patient

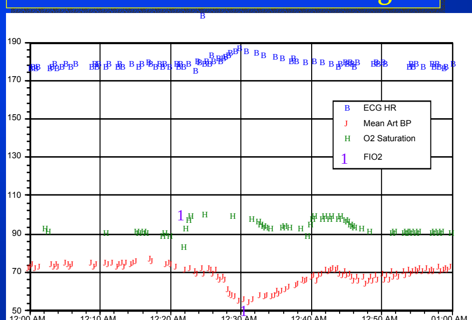


Exploratory Clinical Trial

- 30 growth records from Children's Hospital Endocrinology Clinic
  - 26 have disorders; 4 normals.
- 20 growth records from general pediatrician
  - All 20 declared normal
- Alarm based on (TT_F - TT_N)
  - Single wide gap
  - Persistent narrower gap

	Constitutional delay	Early puberty
Sensitivity	.52	.67
Specificity	.96	.75

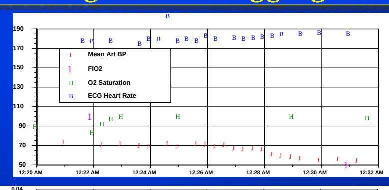
Intensive Care Unit Monitoring

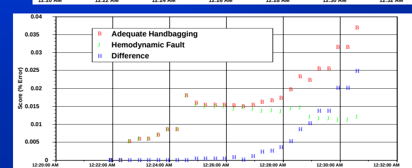


Hemodynamic fault during oxygen handbagging

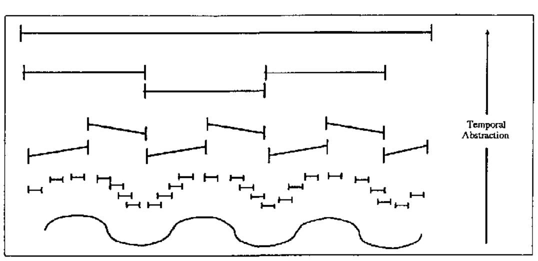
TrenDx Matching to Handbagging Case

Hemodynamic fault becomes significant trend.





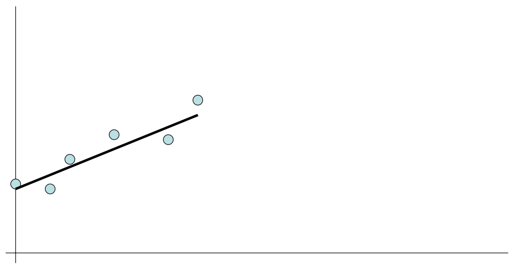
Top-Down vs. Bottom-Up



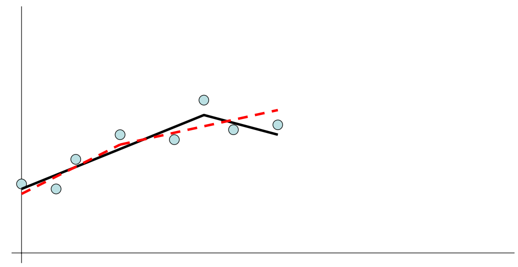
Long's Signal Segmentation Algorithm

- Goals:
  - Segment multiple data streams into a sequence of time intervals (cover time line)
  - Within each interval, characterize each signal by a (linear) regression line
  - Optimize for least total residual (greedy)
  - Parameter controls maximum tolerable error
    - Trades fitting error vs. number of segments

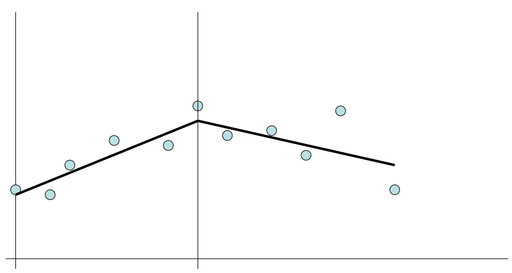
Segmentation



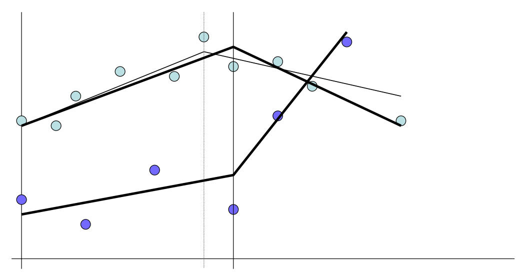
Segmentation



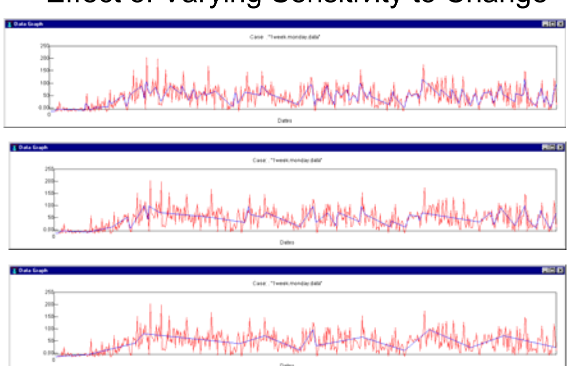
Segmentation



Multiple Data Streams



Effect of Varying Sensitivity to Change



Event Discovery in Medical Time-Series Data

Christine L. Tsien, Ph.D.

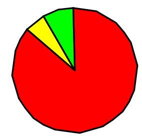
Harvard Medical School, Boston MA
Massachusetts Institute of Technology, Cambridge MA

Overview

- Background: Intensive Care Unit (ICU)
- TrendFinder approach to event discovery
  - components
  - performance metrics
- Applications: ICU signal artifacts, events
- Summary

Observational Study of ICU Alarms

- Prospective 10-wk study at Children's Hospital
- 2942 alarms; 298 hours



Alarm Types

- Problems
  - Wider limits
  - Silenced alarms
  - Stress

TrendFinder Approach to Event Discovery

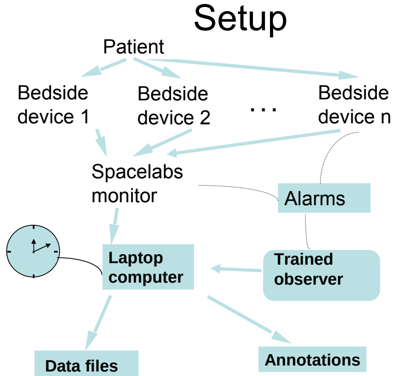
Event Identification → Annotated Data Collection → Annotated Data Preprocessing → Model Derivation → Performance Evaluation

TrendFinder Application: Detecting Events in the MICU

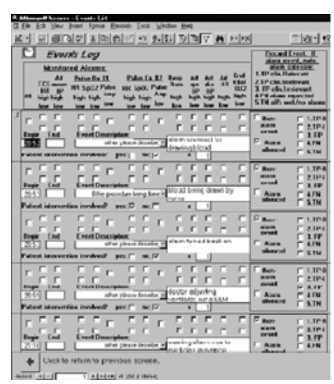
- Event: clinically-relevant systolic BP alarms
- Data collection (Children's Hospital)
  - 12 weeks
  - 585 hours of 5-sec data
- Prospective alarm annotations

Event Identification → Annotated Data Collection → Annotated Data Preprocessing → Model Derivation → Performance Evaluation

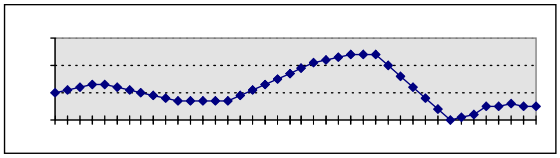
Annotated Data Collection Setup



Annotated Data Collection Program



Feature Attribute Derivation



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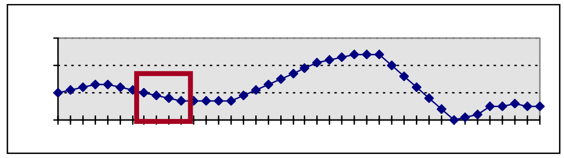
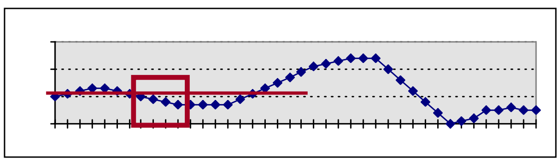
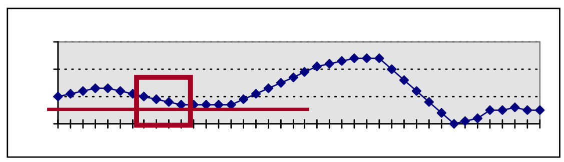


Feature Attribute Derivation



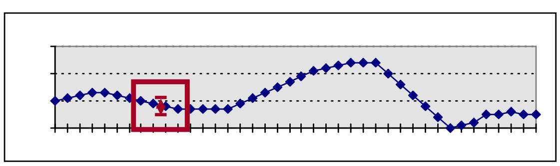
maximum = 10

Feature Attribute Derivation



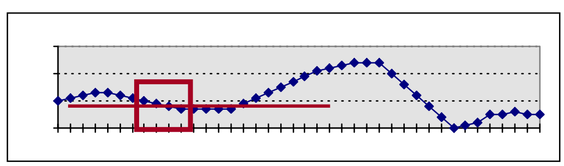
minimum = 7

Feature Attribute Derivation



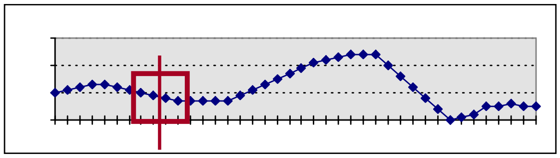
range = 3

Feature Attribute Derivation



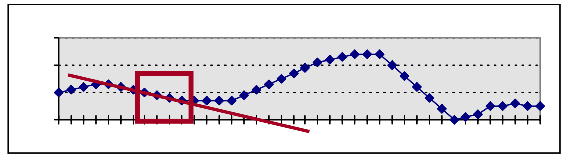
mean = 8.5

Feature Attribute Derivation



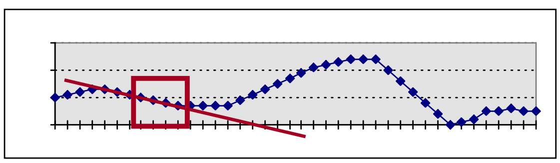
median = 8.5

Feature Attribute Derivation



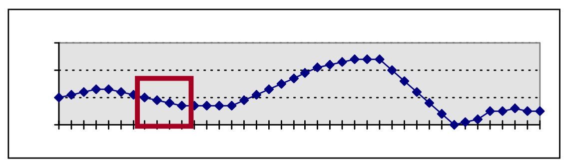
slope = -1

Feature Attribute Derivation



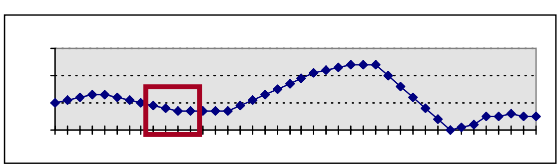
absolute value of slope = +1

Feature Attribute Derivation

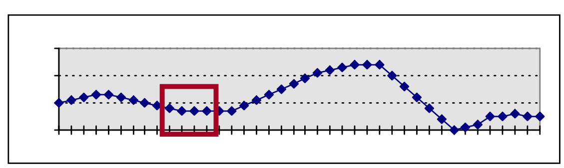


standard deviation = 1.29

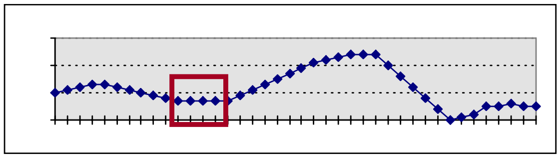
Feature Attribute Derivation



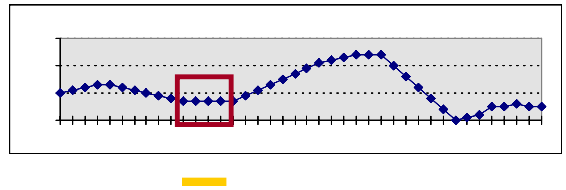
Feature Attribute Derivation



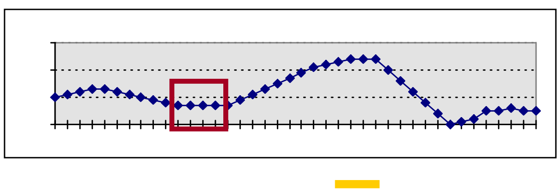
Feature Attribute Derivation



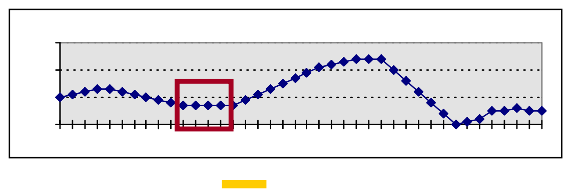
Feature Attribute Derivation



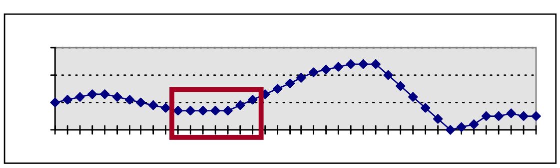
Feature Attribute Derivation



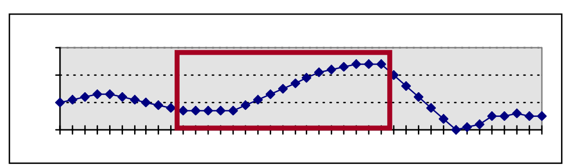
Feature Attribute Derivation



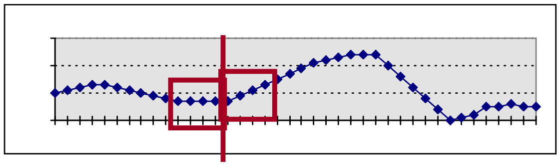
Feature Attribute Derivation



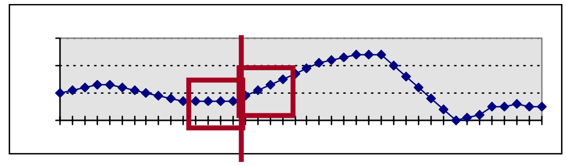
Feature Attribute Derivation



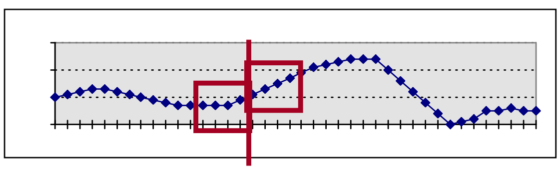
Feature Attribute Derivation



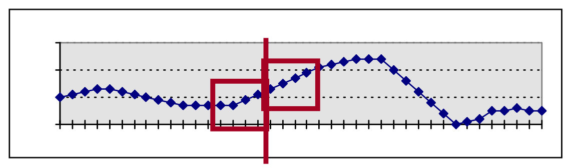
Feature Attribute Derivation



Feature Attribute Derivation



Feature Attribute Derivation



Model Derivation

- Data
  - labeled feature vectors of derived values
  - training, evaluation, test sets
- Supervised machine learning methods
  - Decision trees (c4.5)
  - Neural networks (LNKnet)
  - Logistic regression (JMP)
- Models: labels previously unseen feature vectors as event or non-event

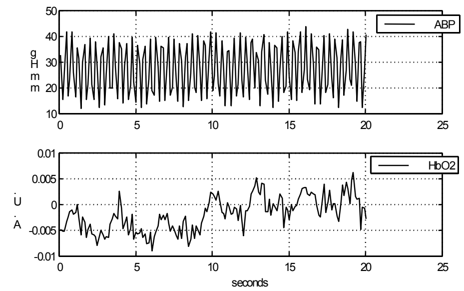
Example Decision Tree Model for BP Artifact Detection

bp_med3 <= 4: artifact (114.0/3.0)
bp_med3 > 4:
bp_range3 <= 7: non-artifact (10959.0/72.5)
bp_range3 > 7:
bp_med10 > 46: non-artifact (126.0/23.7)
bp_med10 <= 46:
bp_std_dev3 <= 5.51: non-artifact (78.0/28.5)
bp_std_dev3 > 5.51:
co2_low10 <= 5.3: artifact (46.0/10.1)
co2_low10 > 5.3:
hr_high5 <= 157: non-artifact (27.0/12.8)
hr_high5 > 157: artifact (21.0/8.2)

If temporal representation provides leverage in reasoning over time...

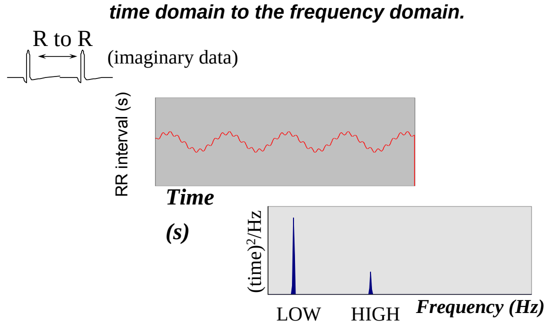
- What temporal representation have we overlooked?

Time series: Arterial BP and HbO_2

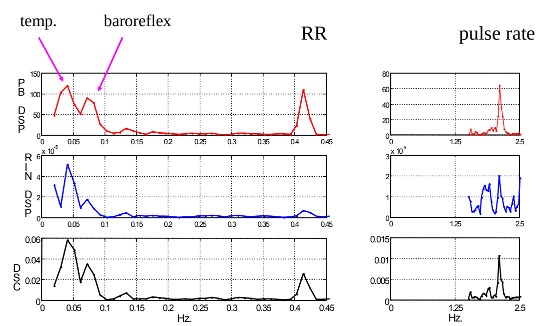


Methods

Fourier transformation: translation from the time domain to the frequency domain.



Frequency Domain



Opportunities of the frequency domain

- For new kinds of alarms
- Machine learning on different part of the feature space
- Informative displays
- Toolkit to focus on events with time-constants of interest

Summary

- Careful selection of temporal representations are necessary to capture the aspect of interest of a biological/clinical system.
- Temporal reasoning programs have been developed but are not widely used.
- Trend detection with on-line data can be useful (low-hanging fruit)
- Much can be accomplished with simple 1 and 2 point trend detectors
- Noisy data and medically complex trends require more sophisticated representation and reasoning mechanisms
  - E.g. conversion into the frequency domain