Data Processing

Técnicas de Perceção de Redes

Mestrado Integrado em
Engenharia de Computadores e Telemática
DETI-UA

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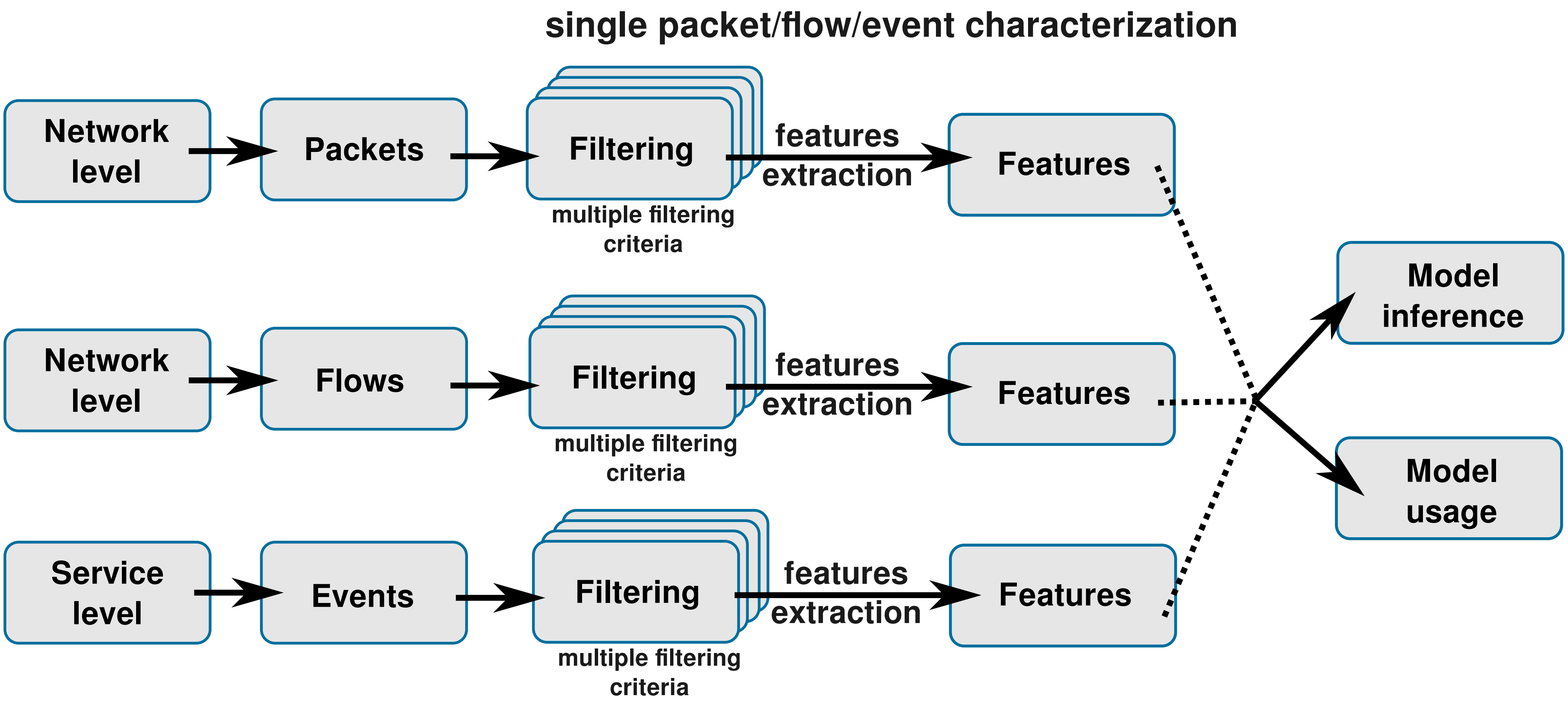
Qualitative Data

- Most monitored data is qualitative.
  - An event (with description) at a specific time (with a time-stamp).
    - 00:01:23.4566 – IP Packet [from A to B with 64 bytes]
    - 21:04:23.4566 – Error [id 404]
    - ...
- Must be converted to quantitative data.
- Some is pre-processed and it is already presented as quantitative.
  - Packets sent: 5467.
  - Bytes seen in the last 10 minutes: 18471947.
  - May require some additional processing.
    - Packets sent at 1s: 300pkts, Packets sent at 2s: 350pkts → Packets sent between 1s-2s: 350-300=50pkts.

Modeling Single Actions vs. Behaviors

- Models require numerical/quantitative data.
  - Inputs for any descriptive model are usually called features.
  - Features should describe the modeling object.
  - Excluding NLM models.
- Models may describe single events:
  - One packet sent/received, one conversation (flow), one service request…
  - For network awareness the information of a single event is not enough to describe and detect advanced anomalies. Specially stealth anomalies.
    - Allow the detection of port scans, unusual service requests, etc…
- Any complex interaction generates multiple events.
- Behavior models describe the characteristics of a set of complex interactions over time.
  - Requires the aggregation of single events data over time.
  - Models are constructed based on historic data.
    - Using a set of multiple observations (time windows).
  - This models should allow to test new data and make decisions periodically.

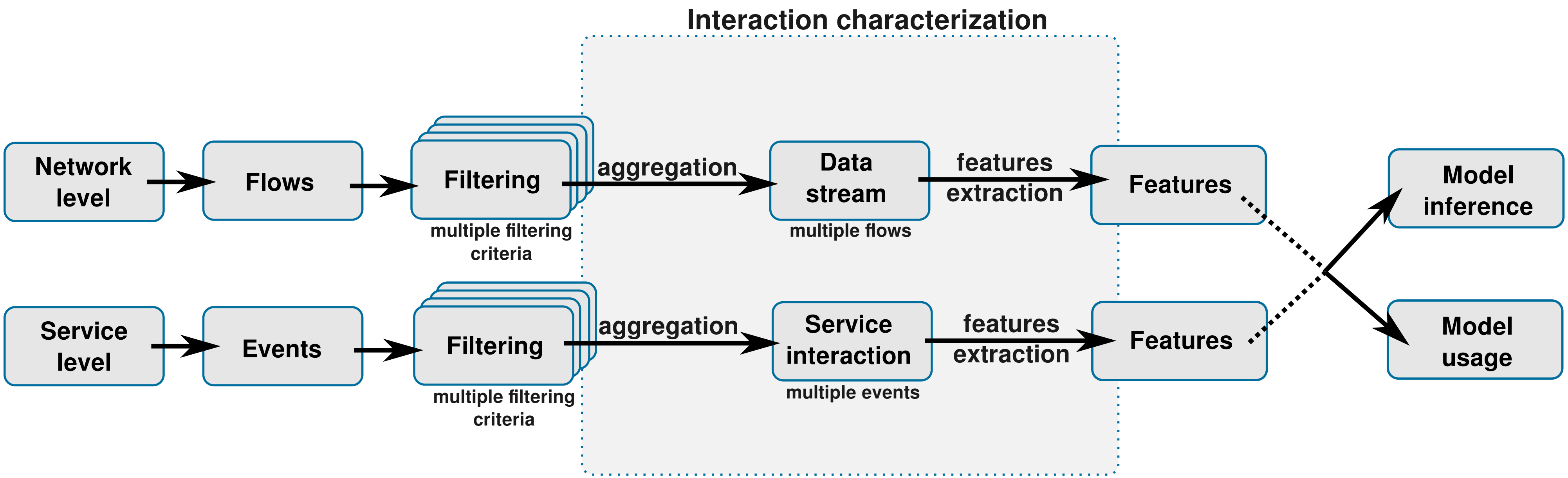
Single Event Model Features



Data Filtering and Aggregation (1)

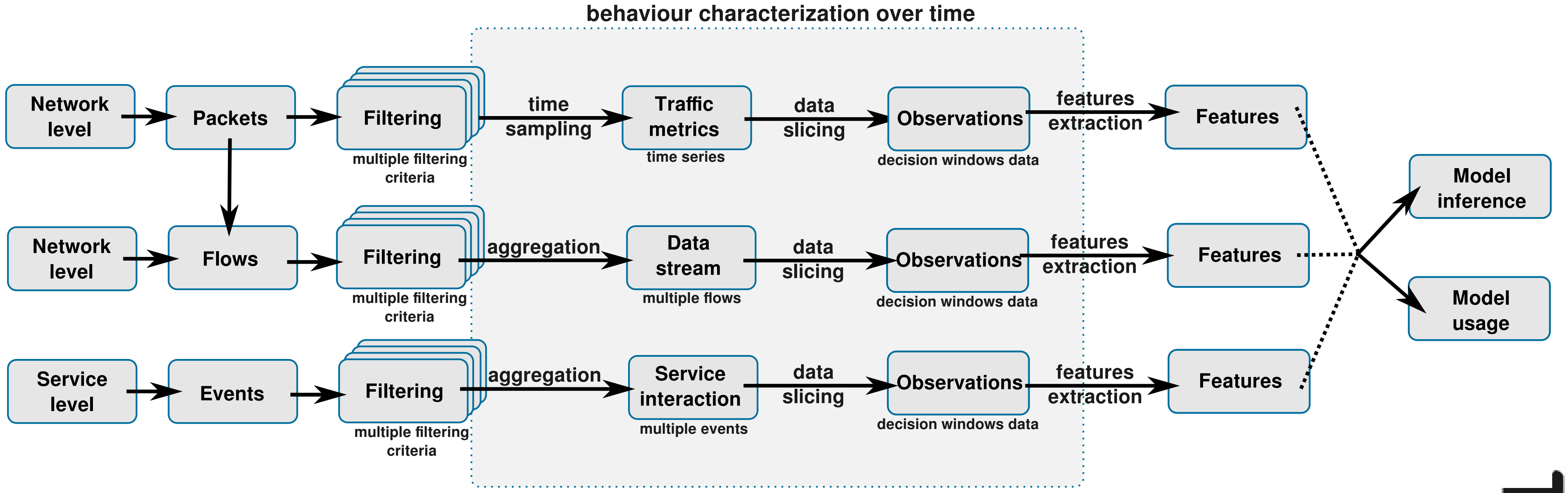
- Filtering is the method by the raw data is selected according to multiple criteria.
  - Some data may be discarded.
  - Data may be divided to created differentiated and relevant features.
    - E.g., download/upload, to TCP port 443, 80 or 22, with destination/source in different IP networks, etc...
- Aggregation is the fist step to create a behavior model.
  - Any network entity (human or non-human) interaction results in multiple observable events.
    - Multiple packets, multiple flows, multiple service requests, etc...
  - A set of aggregated network flows is usually called datastream.
    - A flow is described by a 5-tupple (transport protocol and source IP addresses and ports) .
    - A datastream is any aggregation of flow using a tuple smaller than 5.
      - Ex1 - all traffic from a specific terminal (1-tuple: source address);
      - Ex2 - all traffic from a specific terminal to port TCP 443 (3-tuple: TCP transport, source address, destination port);
      - Ex2 - all traffic from a specific terminal using port TCP 443 to a specific service (4-tuple: TCP transport, source address, destination port, destination server addresses);
  - A set of service events is called a service interaction.

Data Filtering and Aggregation (2)



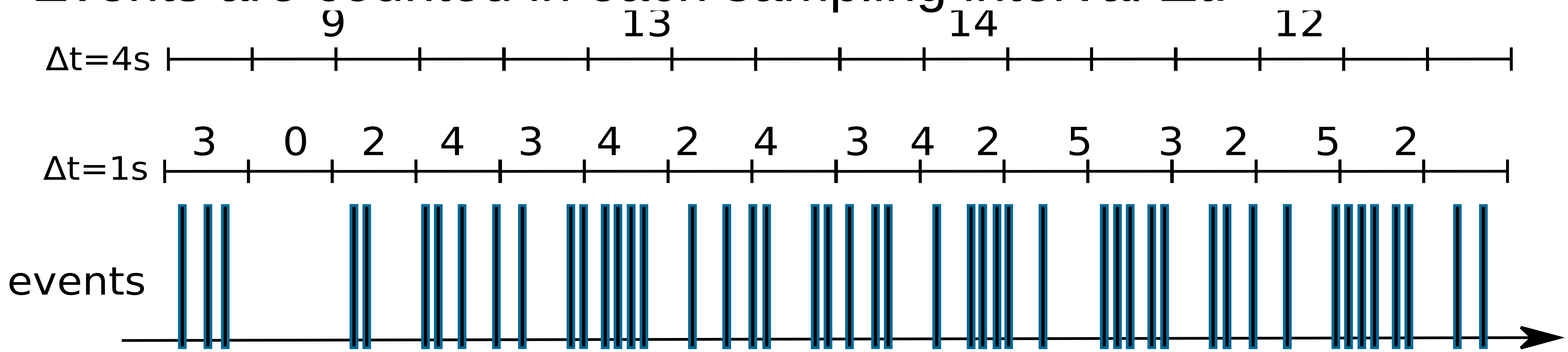
Behavior Models

- Any behavior should be **described over time**.
  - Data must be sliced over time, to create sub-sets of data that will allow to describe complex interactions within a time window, over time.
  - Behavior may change from observation window to observation window.
  - Model should be created from a set of historic observation windows.
  - Model is applied to any new data (new observation window data).
- Raw packet data is qualitative and must be sampled (a simplified aggregation process).



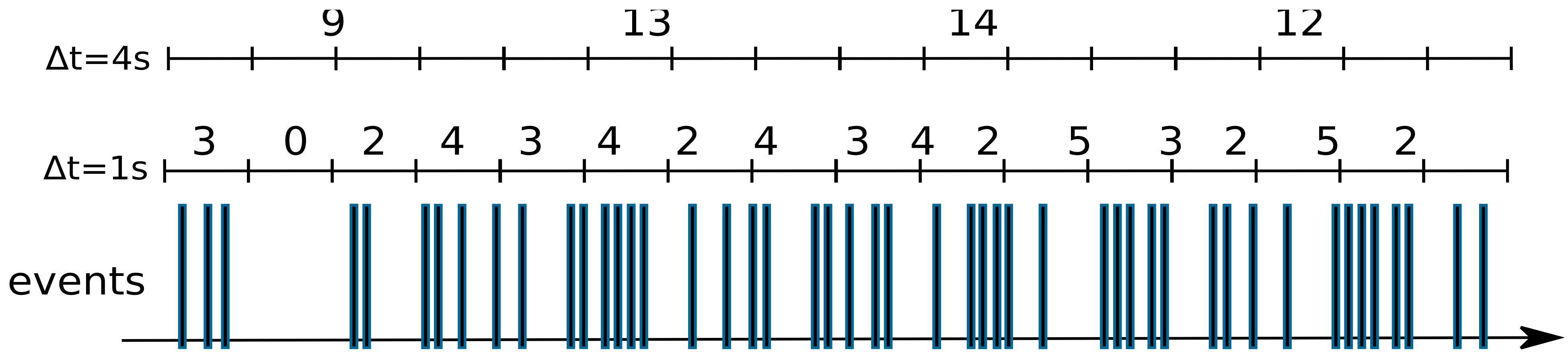
Data Sampling (1)

- Sampling transforms Qualitative into Quantitative data.
- Events must be defined, identified and grouped:
  - All packets from IP 10.0.0.1,
  - All 400 errors accessing site X, etc...
- Sampling/Counting Interval
  - Time window in each the number of a specific event is counted, associated with a time index, and stored.
  - Minimum timescale.
- Events are counted in each sampling interval Δt.



Data Sampling (2)

- Results in discrete time sequences for event:
  - For $\Delta t=1$: $X_k=\{3,0,2,4,3,4,2,4,3,4,2,5,3,2,5,2\}$
    - $X_0=3$, $X_1=0$, …, $X_{12}=2$
  - For $\Delta t=4$: $Y_k=\{9,13,14,12\}$
- Time sequences may be multi-dimensional:
  - Time sequences of n-tuples.
  - e.g., Number of packets, upload e download.
  - $Z_k=\{(3,9),(0,45),...(67,90)\}$

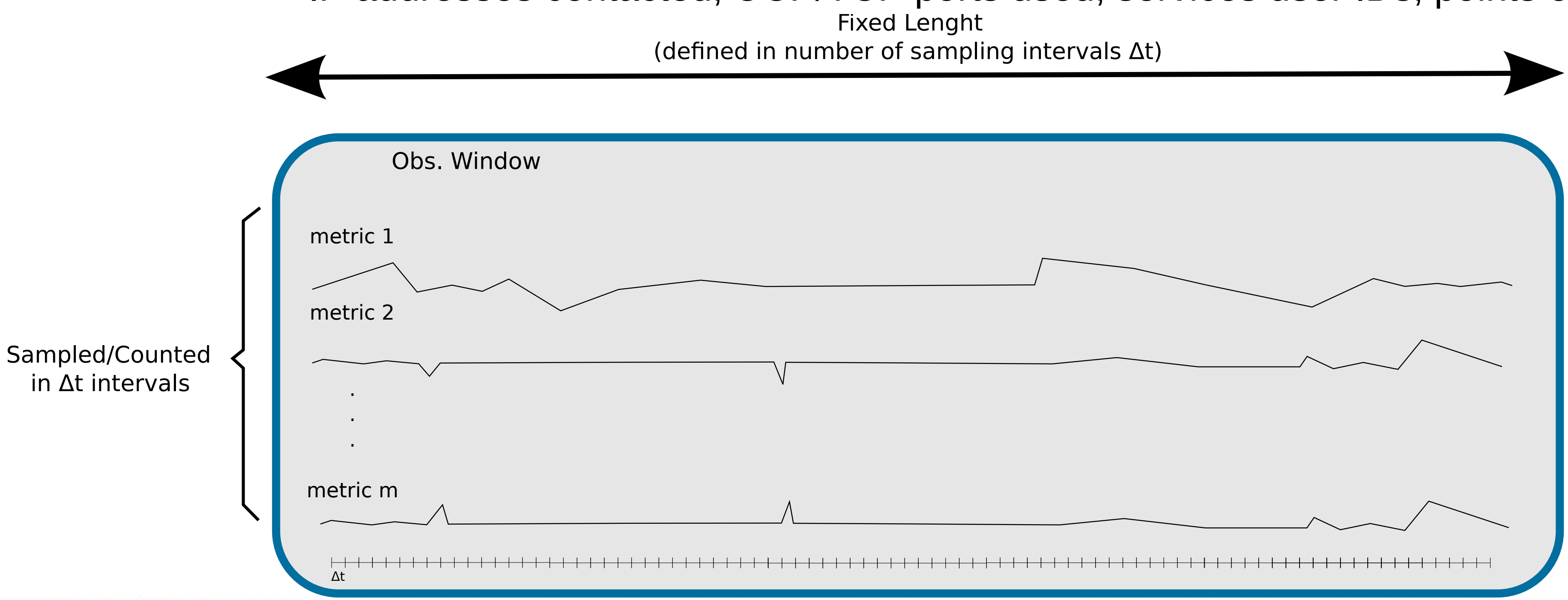


Time Windows and Entity Behavior Profile

- Sampling/Counting Window.
  - Provides time series of multiple metrics.
  - e.g., number of packets received by a terminal each second.
- Observation Window.
  - Features/Characteristics extraction Window.
  - Uses multiple Sampling/Counting Windows,
    - Statistics of respective time series.
  - Provides a n-tuple characterizing an entity behavior at a specif time.
  - e.g., 2-tuple with mean and variance of the number of packets received by a terminal in 30 seconds (30 counting 1s windows).
- Entity Behavior Profile
  - Pattern from multiple Observation Windows.
  - Provides a model to classify entities and detect anomalies.
  - May include time dynamics over time.

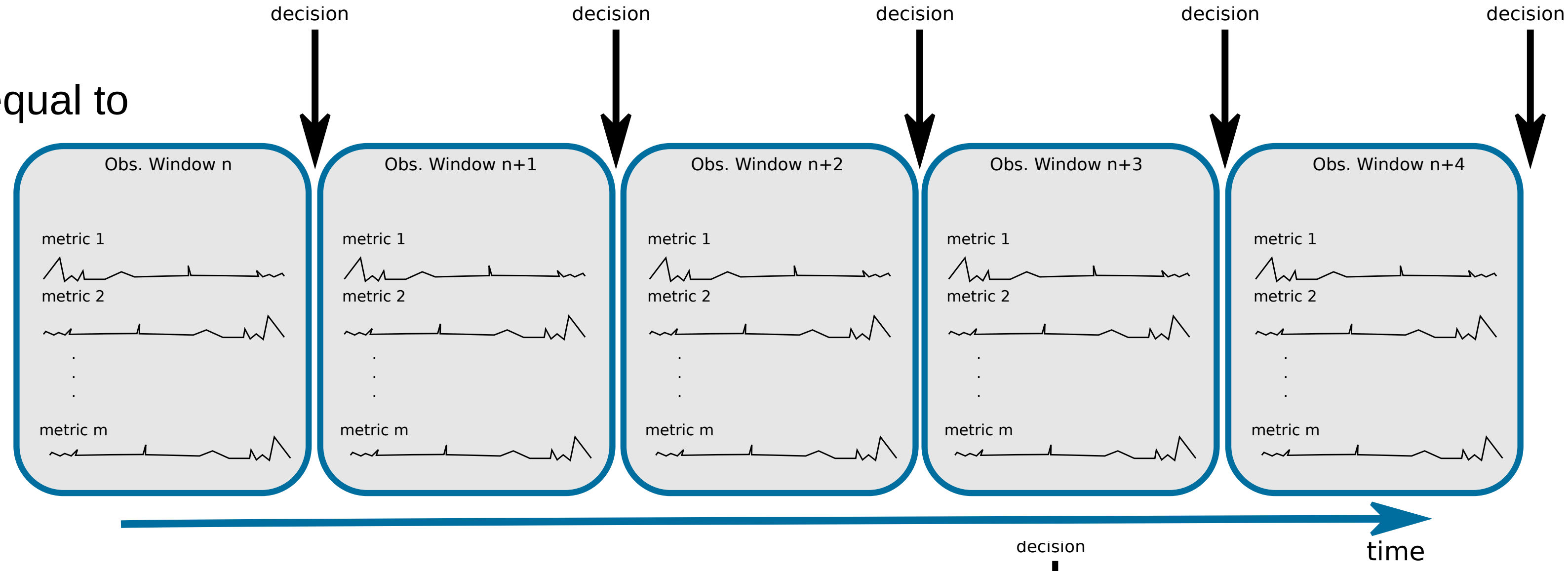
Observation Window (1)

- An observation is constructed based on multiple sampling/counting metrics.
- Sampling/counting metrics should quantify activity events:
  - Start/End of activity.
    - Traffic Flows, Calls, Service usage, etc…
  - Amount of activity.
    - Traffic per sampling interval, activity duration, actions per sampling interval, etc…
  - Activity targets
    - IP addresses contacted, UCP/TCP ports used, services user IDs, points of access, etc…

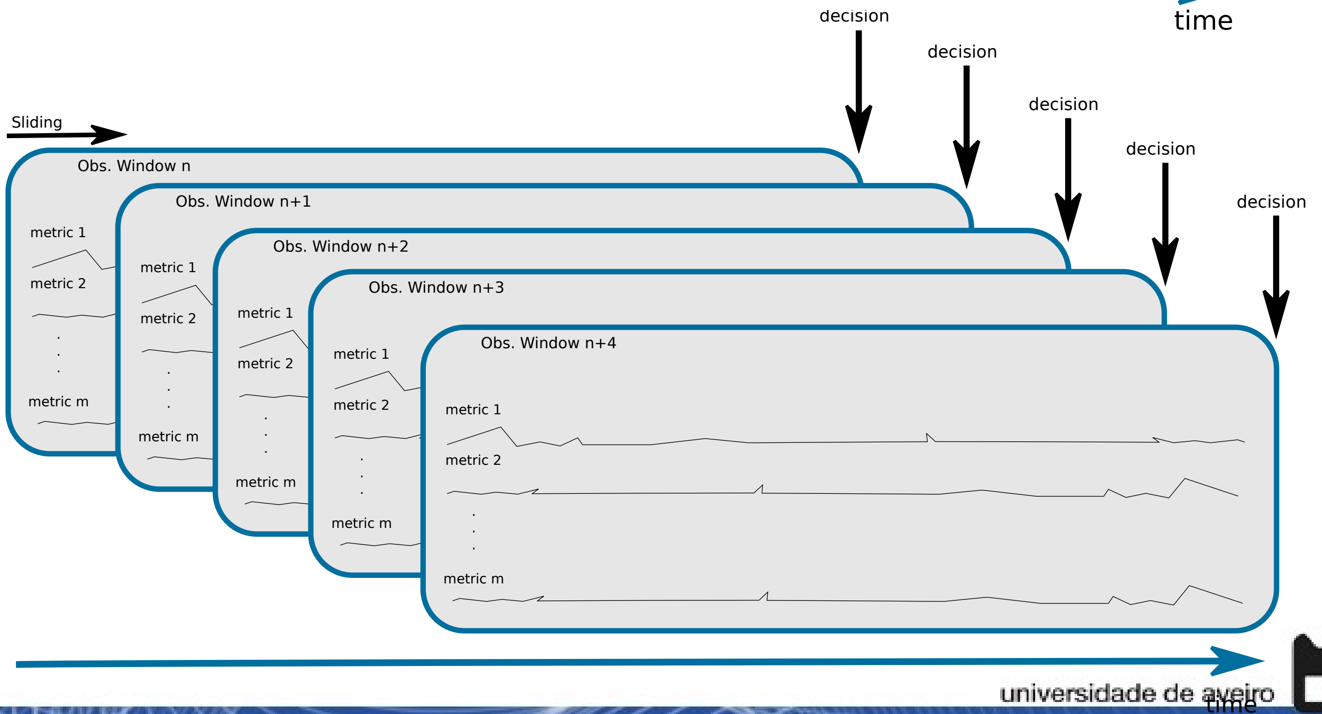


Observation Window (2)

- Sequential
  - Decision interval is equal to window size.

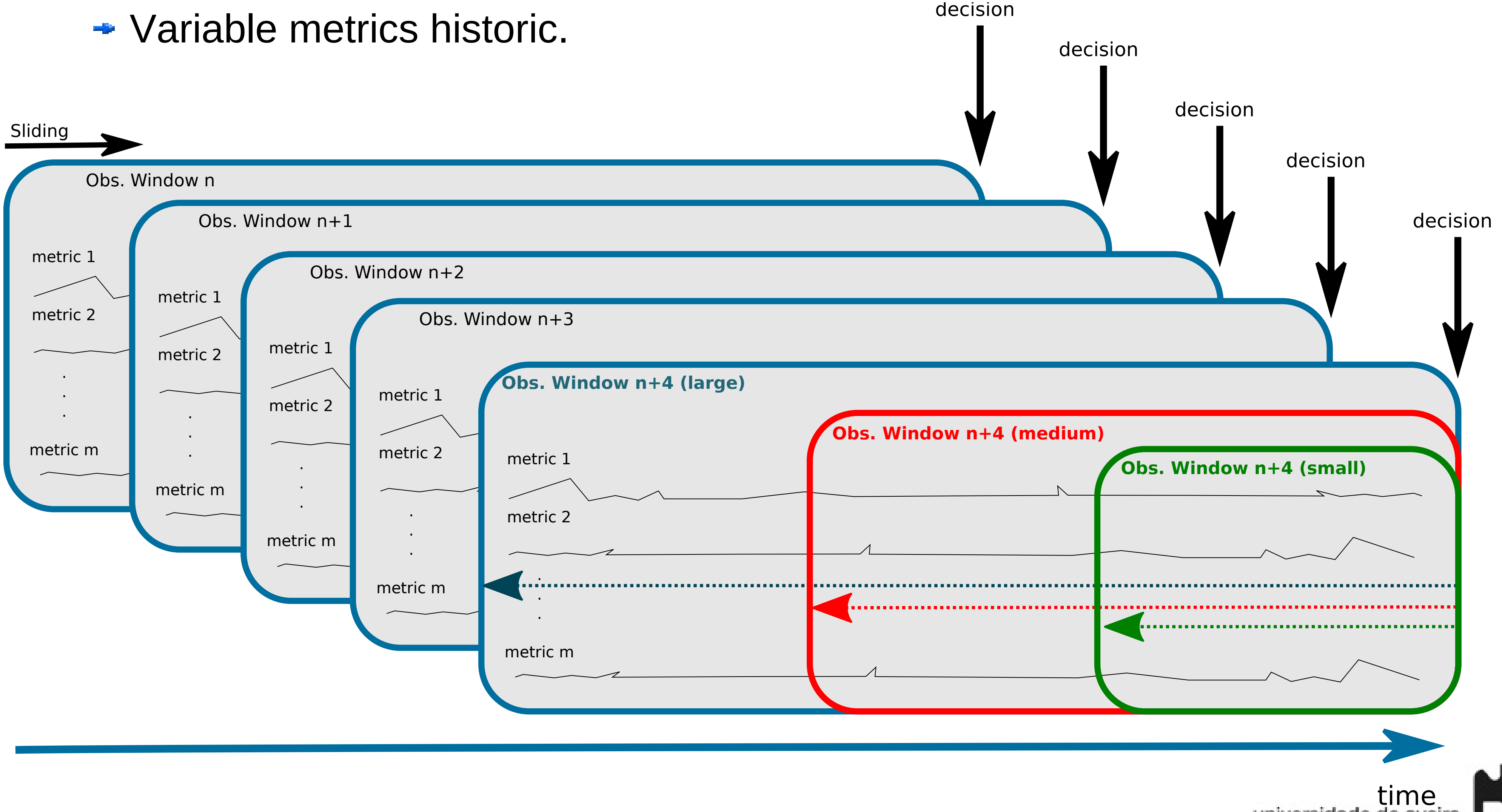


- Sliding
  - Allows for longer periods of observation, while maintaining a short period of decision.



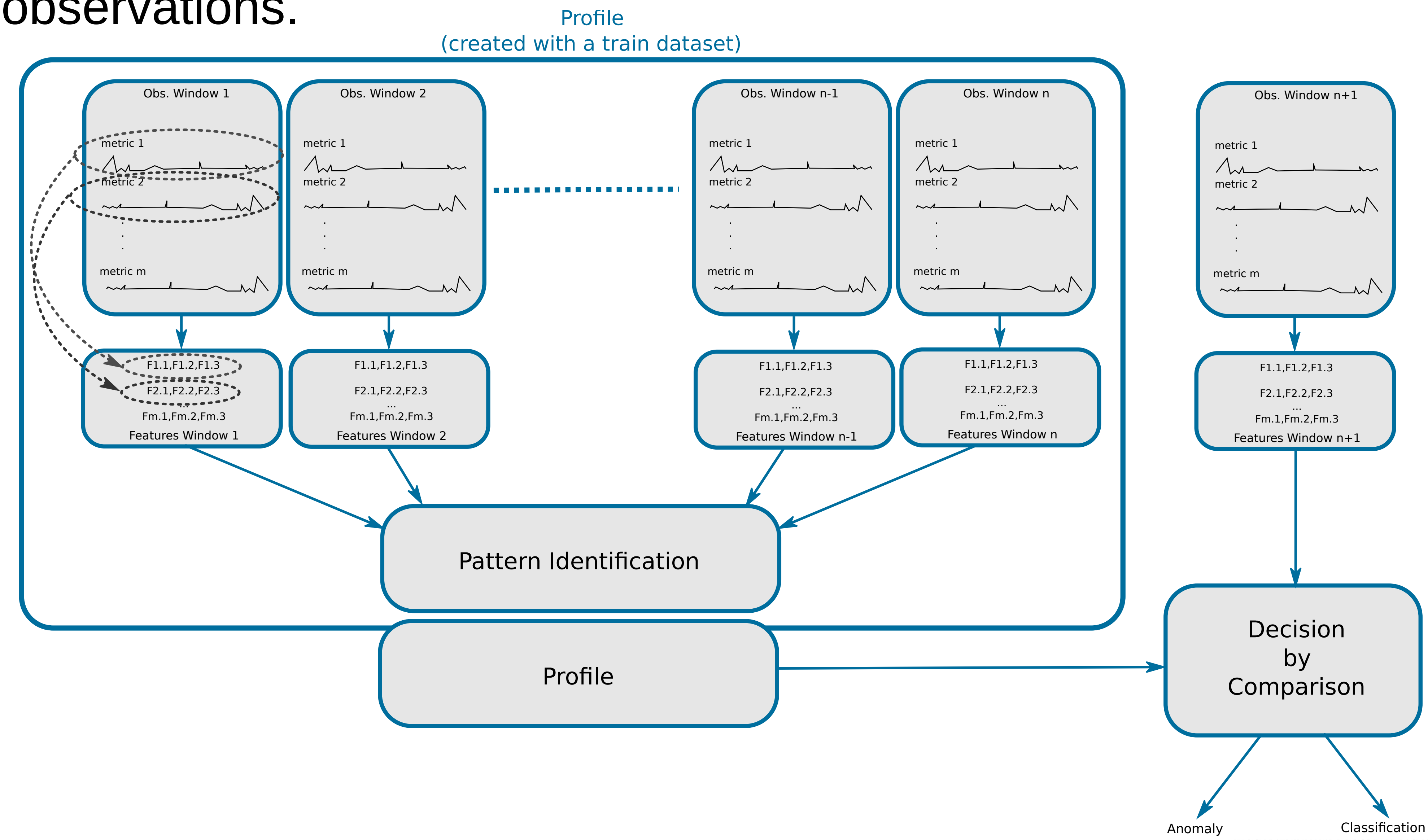
Multiple Observation Windows

- At each decision time point.
  - Construct observation widows with different lengths.
    - Variable metrics historic.



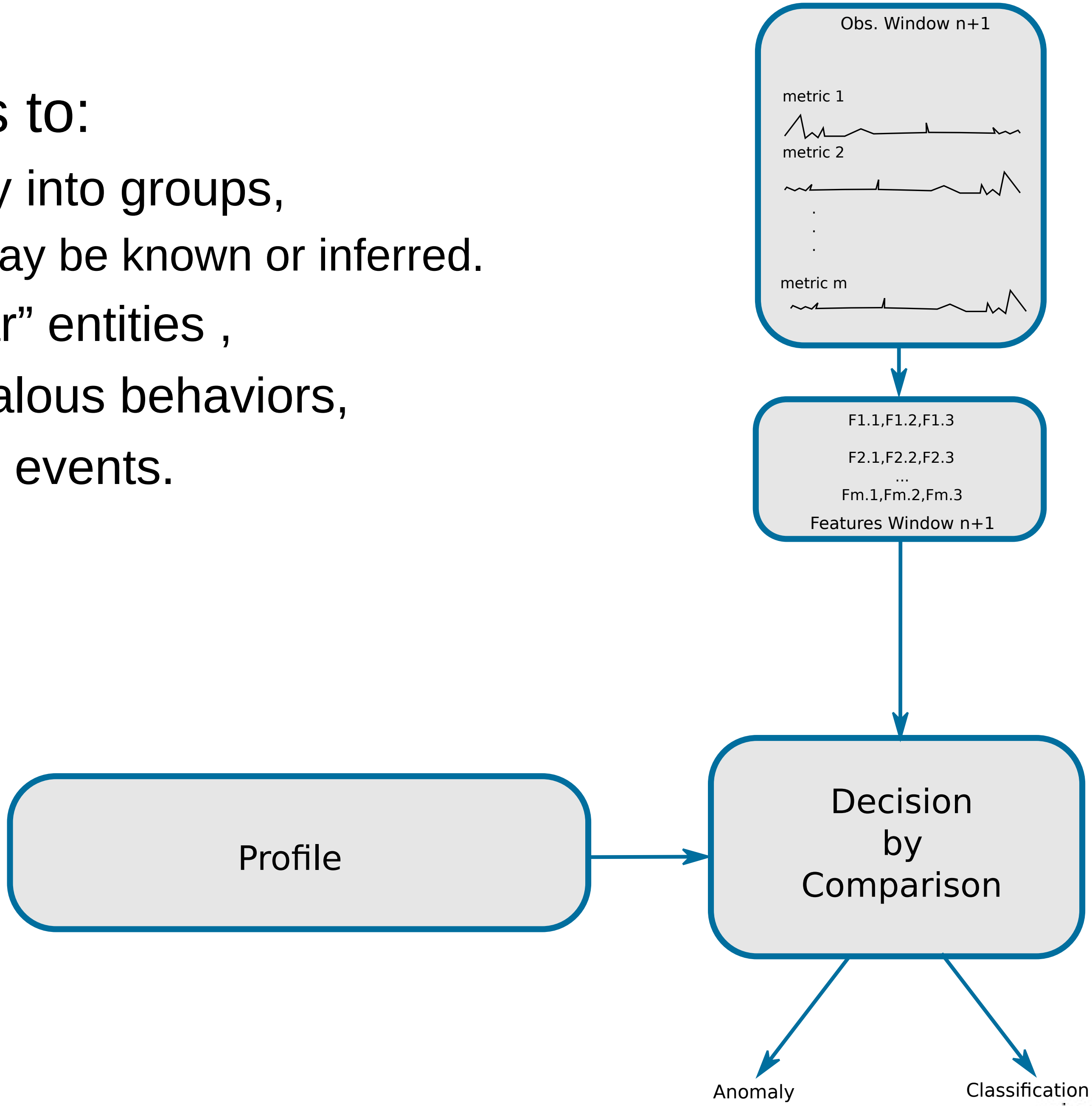
Entity Profiling

- Characterization of the observation windows after multiple observations.



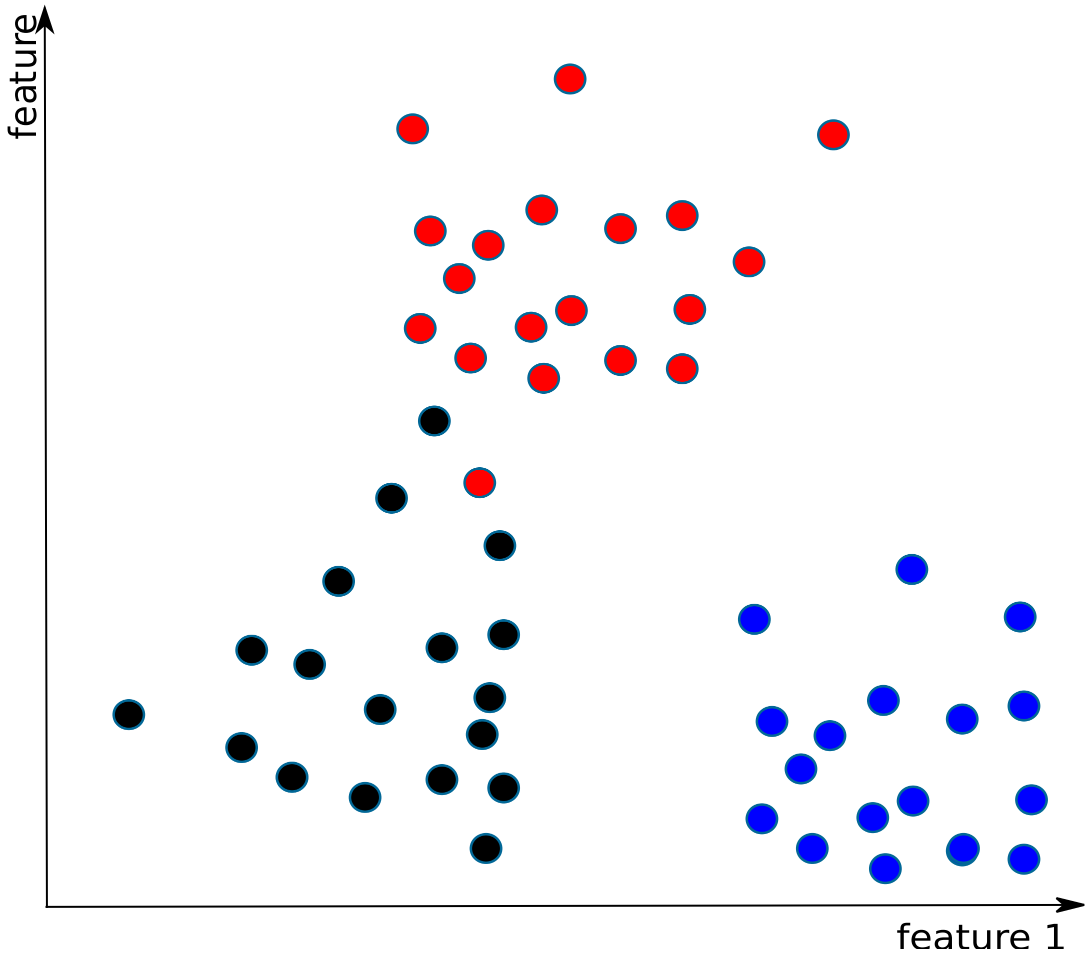
Profile Comparison

- A profile allows to:
  - Classify entity into groups,
    - Groups may be known or inferred.
  - Group “similar” entities ,
  - Detect anomalous behaviors,
  - Predict future events.



N-Dimensional Features Space

- A features' n-tuple defines a point in a N-Dimensional space that describes an entity behavior at a specific time.
- Allows to detect and define repetitive events and evolution over time.
- Allows to classify and discriminate behaviors.
- Allows to detect anomalies.



Data Formats

- The ideal data format is a n-tuple per time interval.
  - n metrics measured over time (n per observation).

    $(x1,x2,x3,x4,..,xn)_k$
  - Bi-dimensional data structure (time x metrics).
  - Optimal storing digital format:
    - Binary storage (array/matrix).
    - Sparse matrices could be advantageous.
    - Usage of fixed formats with integer indexes.
      - Avoid complex data structures with complex indexing of data, e.g.: python dictionaries.
    - Text formats are acceptable only in test scenarios.
    - Non-relational databases could also be an option.

Observation Features

- Time-independent descriptive statistics.
  - Mean, variance, standard deviation, quantiles, etc...
- Time-dependent descriptive statistics.
  - Time-relations between metrics over time
    - E.g., mean/std of length of silences [number of sampling slots with metric equal to zero], mean/std of length of activity [number of sampling slots with metric greater than zero], etc…
  - (Pseudo-)Periodicity components.
    - Time dependent.
      - Time multi-fractality (repetition of “similar events” in multiple time-scale).
    - Auto-correlation, FFT, CWT, DWT, and other spectral/frequency analysis.
- (Parameters of) Probabilistic functions/models.
  - Base function/model may be time independent or time dependent.

Descriptive Statistics (1)

- For a (equally) sampled-continuous time process:

$$X = \{x'_t = x_k, T_0 + k\Delta t \leq t < T_0 + (k+1)\Delta t, k = 1, 2, \ldots, N\}$$

- **Mean**: $\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$
- **Median**: $m_d = F^{-1}(0.5)$
- **Variance**: $Var(X) = \sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2$
- **Standard deviation**: *SQRT(Var(X))*
- **Quantiles/Percentiles** $Y = \{y_j\}_{1\leq j\leq N} = \text{sorted}(\{x_k\}_{1\leq k\leq N})$
  - 64th percentile (64%)=0.64 quantile
  - Quartiles: 25%, 50%, and 75%

$$\pi_p = \min(y_{j\geq pN})$$

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Descriptive Statistics (3)

- Covariance
  - Metric that quantifies how much two random variables have simultaneous variations:

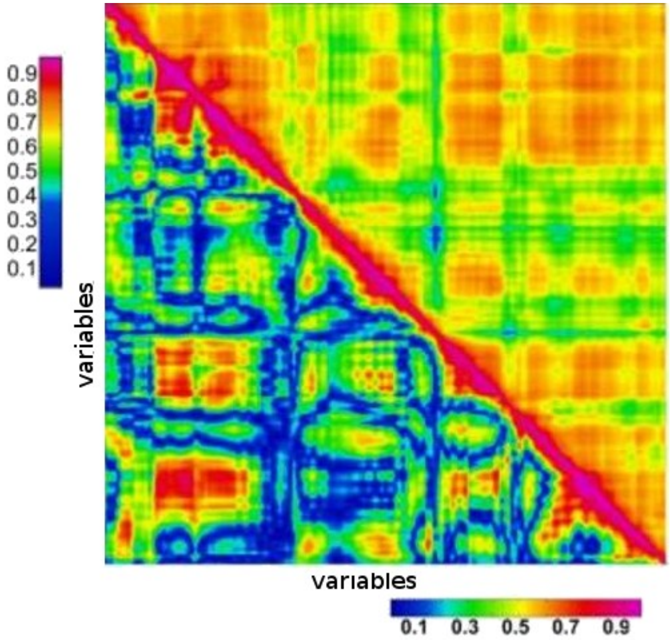
$$\mathrm{Cov}_{X,Y} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu_X)(y_i - \mu_Y)$$

- Correlation coefficient
  - Normalized covariance, varies between -1 and 1:

$$\rho_{X,Y} = \frac{\mathrm{Cov}_{X,Y}}{\sigma_X \sigma_Y} \qquad \sigma_X = \sqrt{\mathrm{Var}(X)}$$

- Correlation matrix
  - Defined by a (MxM) matrix, to quantify the correlation between M variables X_i:

$$C = \{c_{i,j}\}, i, j = 1, \ldots, M$$
$$c_{i,j} = \rho_{X_i, X_j}$$



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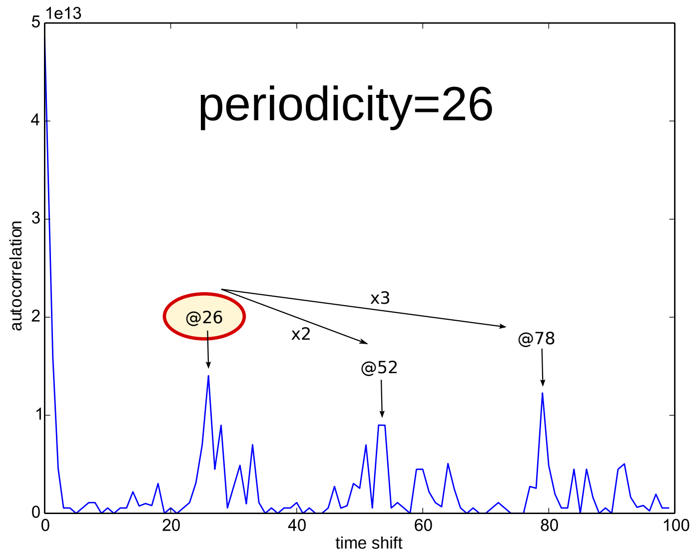
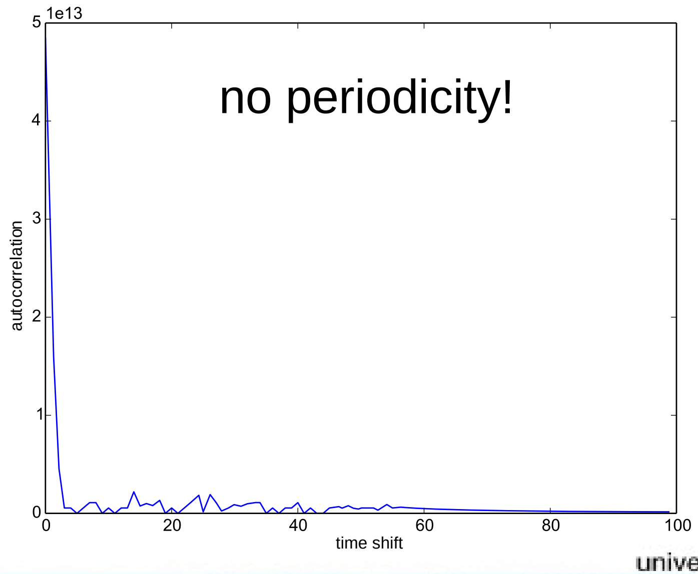
Periodicity Analysis (1)
Autocorrelation

- Autocorrelation
  - Correlation between the process and a shifted version (in time, by k samples) of the same process:

$$r_k = \frac{\sum_{i=1}^{N-k}(x_i - \mu_X)(x_{i+k} - \mu_X)}{\sum_{i=1}^{N}(x_i - \mu_X)^2}$$

- Autocorrelation local maximums (peaks), reveal periodicity.
  - Differences between positions (k) of local maximums give periodicity.



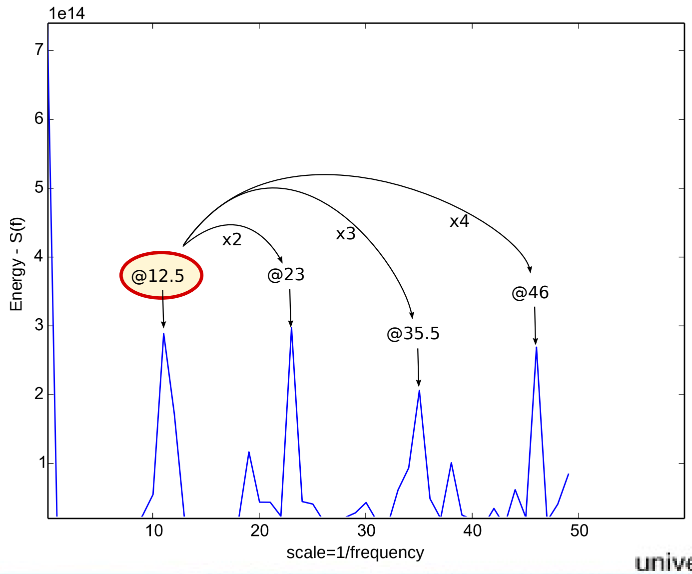


Periodicity Analysis (2)
Periodograms

- Periodogram
  - Frequency analysis → Spectral density estimation: Energy per frequency.
  - Given by the modulus squared of the discrete Fourier transform.
    - For a signal x_i sampled every Δt:

$$S(f) = \frac{\Delta t}{N} \left| \sum_{n=1}^{N} x_n e^{-j2\pi n f} \right|^2, -\frac{1}{2\Delta t} < t \leq \frac{1}{2\Delta t}$$

  - The inverse of the frequencies with higher energy give the different periods (of periodicity).



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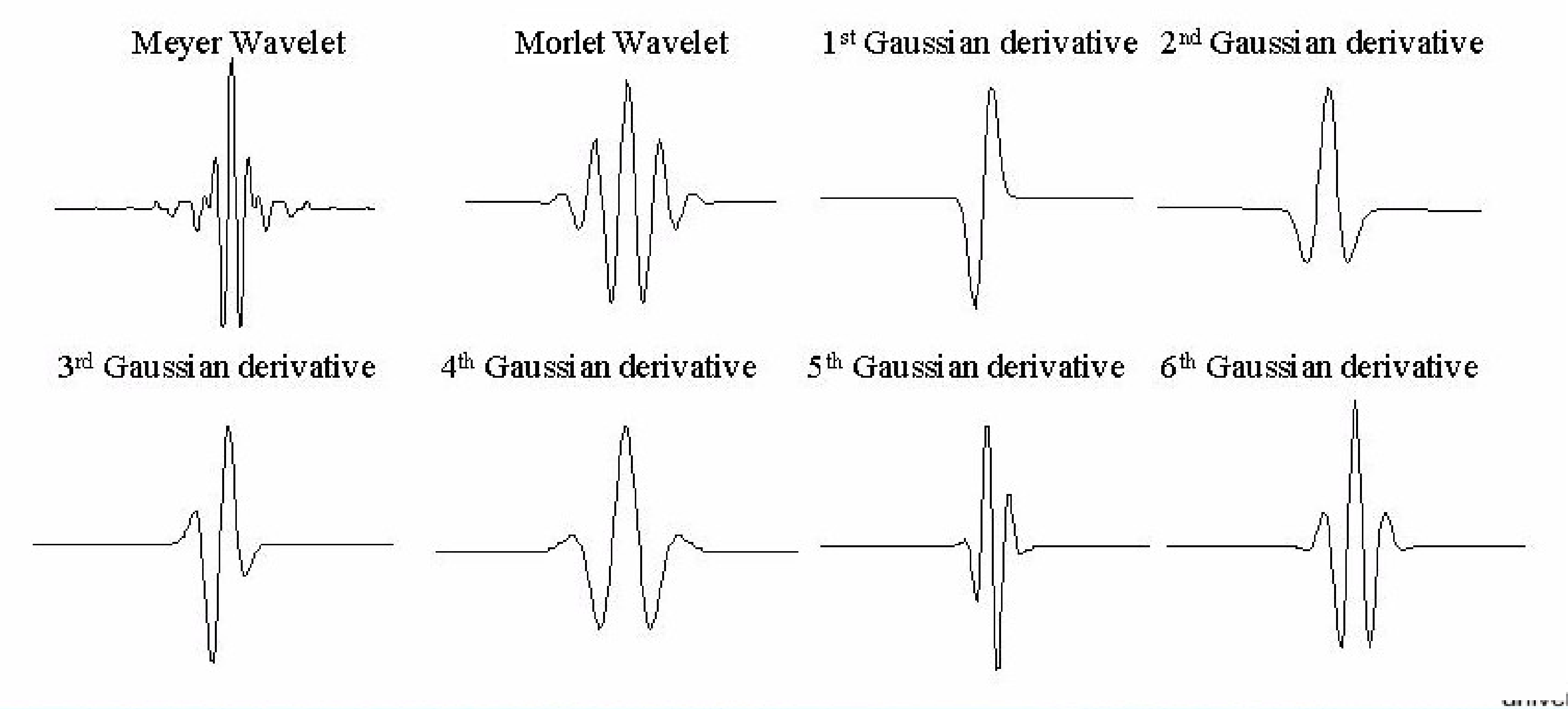
Periodicity Analysis (3)
Scalograms

- Scalogram
  - Joint Frequency/Time analysis → Wavelet Analysis
    - Energy per frequency/time.

$$\Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{+\infty}^{-\infty} x(t)\psi^*(\frac{t-\tau}{s})dt$$

Wavelet functions

$\psi^*(t)$



Periodicity Analysis (4)
Scalograms

- Given by the normalized modulus squared of the Wavelet transform.

$$\hat{E}_x(\tau,s)=\frac{\left|\Psi_x^{\psi}(\tau,s)\right|^2}{\sum_{\tau'\in\mathbf{T}}\sum_{s'\in\mathbf{S}}\left|\Psi_x^{\psi}(\tau',s')\right|^2}$$

  - Averaged over time.

$$\bar{e}_x(s)=\frac{1}{|\mathbf{T}|}\sum_{\tau\in\mathbf{T}}\hat{E}_x(\tau,s),\forall s\in\mathbf{S}$$