Parallel Data Series Indexing and Similarity Search on Modern Hardware

Panagiota Fatourou, Professor

University of Crete and FORTH Laboratoire d'Informatique Paris Descartes, Université de Paris Cité

Joint work with:

Botao Peng, Chinese Academy of Sciences and **Themis Palpanas**, Université de Paris Cité

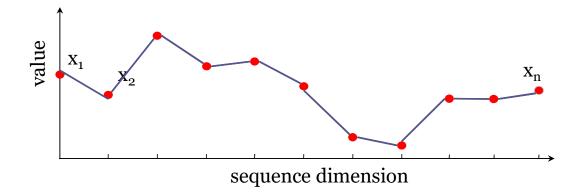






Data series

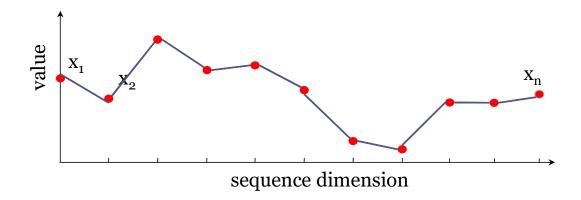
• Sequence of points ordered along some dimension





Data series

• Sequence of points ordered along some dimension



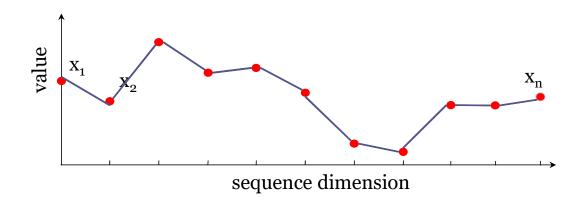


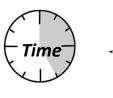


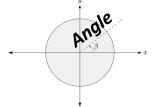


Data series

• Sequence of points ordered along some dimension

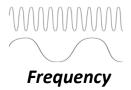










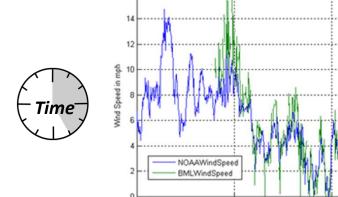






Scientific Monitoring

meteorology, oceanography, volcanology, seismology, astronomy, finance, sociology, etc.



Wind speed

From ocean observing node project, http://bml.ucdavis.edu/boon/wind.html

UTC Time in Minutes

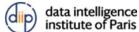
Wind Speed Comparison



Volcanic Activity Indicators

From British Geological Survey https://www.bgs.ac.uk/geology-projects/volcanoes/





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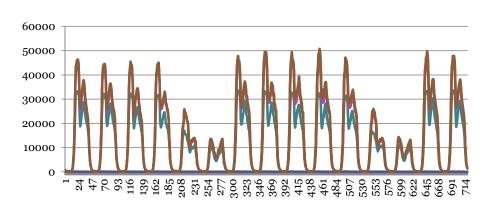
1500





Telecommunications

• analysis of call activity patterns, Telecom Italia



average number of calls





clustermap of incoming calls time series





Neuroscience

- functional Resonance Magnetic Imaging (fMRI) data
 - primary experimental tool of neuroscientists
 - reveal how different parts of brain respond to stimuli







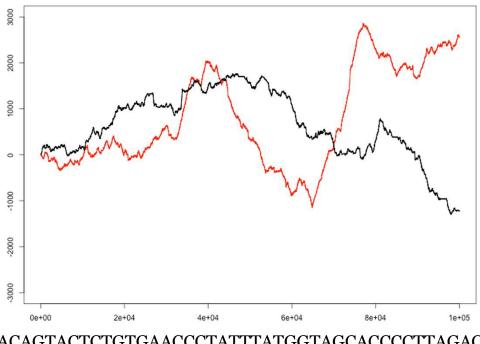




Biology

GTCAATGGCCAGGATATTAGAACAGTACTCTGTGAACCCTATTTATGGTGGCACCCCTTAG





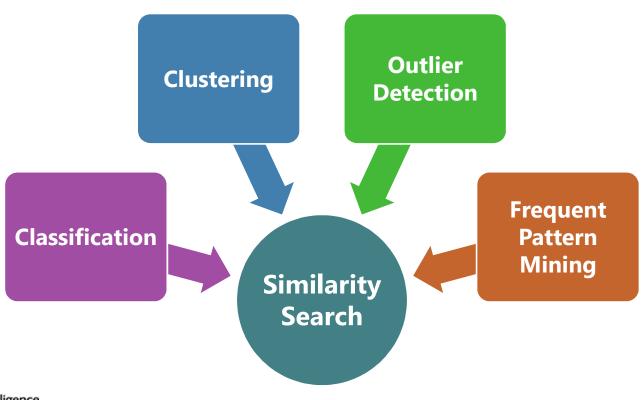
GGGAAGCCTCC AGGGAAAGCCA AAGATATTACA **TGAATAATCCC** ACCGGTTGAA **AACTGGCAACT** CTCCCAAGGAT AGGGCTTTGG **AGCCAGTGACA ITTATGTCTTA GGCCAAGCAT GTGGTTATTTA AGAGCAGAATC GCAAGATGAG CAAGAGCCCA** AATGGCCAGG

ATATTAGAACAGTACTCTGTGAACCCTATTTATGGTAGCACCCCTTAGACTAAGATAACACA GGGAGCAAGAGGTT





What do we want to do with data series?

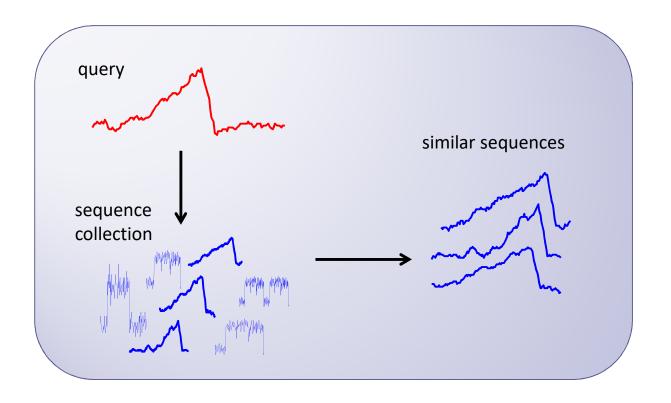


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What do we want to do with data series?



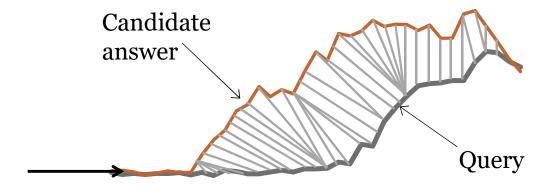




What do we want to do with data series? Complex analytics







Dynamic Time Warping



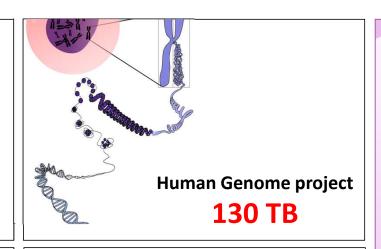


Challenge - Massive data Series collections



1.5 TB per day

Large Synoptic Survey
Telescope
~30 TB per night



passenger aircrafts

20 TB per hour

data center and services monitoring
2B data series
4M points/sec



HARD,
because of
very high
dimension
ality:
each data
series has
several
hundreds
to several
thousands
of points!





Contributions

- ParIS+, a disk-based concurrent data series index for modern hardware
 - Multi-threaded design, SIMD instructions
 - Similarity search up to 15x faster (10sec on 100GB dataset)

 IEEE Trans. on Knowledge & Data Engineering 2021, IEEE Big Data 2018
- MESSI, an in-memory data series index for modern hardware
 - Lower synchronization index design
 - Novel algorithms for query processing
 - Similarity search at interactive speeds (50msec on 100GB dataset)
 VLDB Journal 2021, IEEE International Conference on Data Engineering (ICDE) 2020
- SING, a data series similarity search accelerated by GPUs
 - CPU-GPU collaborative framework
 - Expands scalability of exact similarity search (~30msec on 100GB dataset)

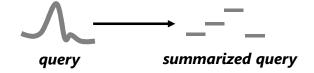
 IEEE International Conference on Data Engineering (ICDE) 2020

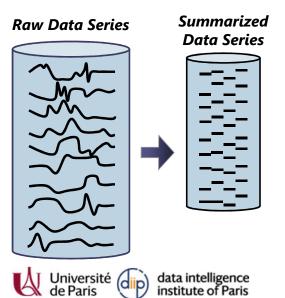




State-of-the-Art: ADS, the Adaptive Data Series Index

[Zoumpatianos et al., VLDBJ'16]







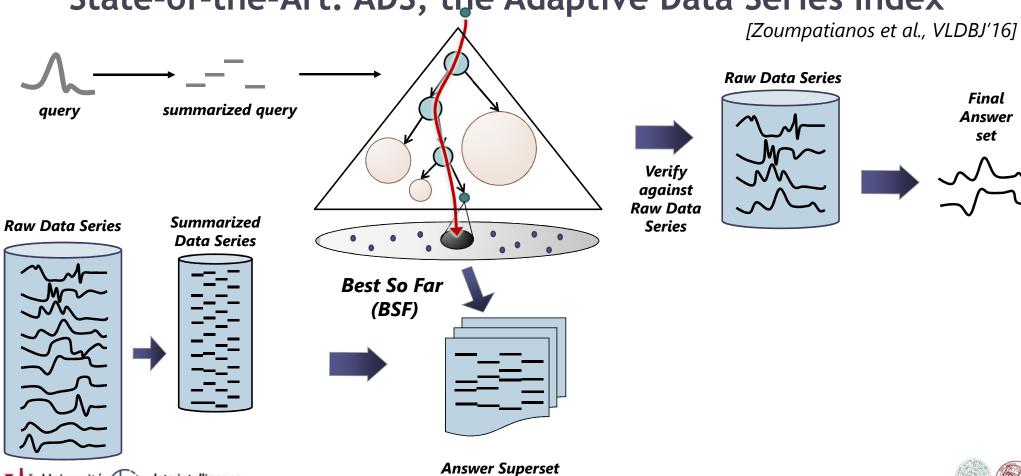
State-of-the-Art: ADS, the Adaptive Data Series Index

summarized query query **Summarized Raw Data Series Data Series Best So Far** (BSF) **Answer Superset** data intelligence institute of Paris Université dip Panagiota Fatourou

[Zoumpatianos et al., VLDBJ'16]



State-of-the-Art: ADS, the Adaptive Data Series Index



Panagiota Fatourou

data intelligence institute of Paris

Université dip



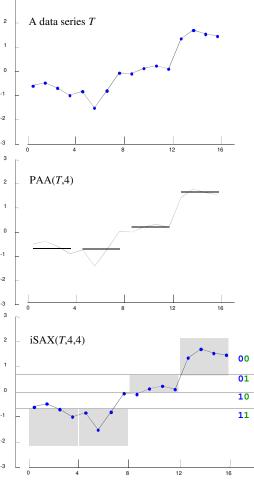
Symbolic Aggregate approXimation (SAX).

- (1) Represent data series *T* of length *n* with *w* segments using Piecewise Aggregate Approximation (PAA)
 - *T* typically normalized to $\mu = 0$, $\sigma = 1$

• PAA
$$(T,w) = \overline{T} = \overline{t}_1, \dots, \overline{t}_w$$
where $\overline{t}_i = \frac{w}{n} \sum_{j=\frac{n}{w}(i-1)+1}^{\frac{n}{w}i} T_j$

- (2) Discretize into a vector of symbols
 - Breakpoints map to small alphabet *a* of symbols







iSAX Representation

• iSAX offers a bit-aware, quantized, multi-resolution representation with variable granularity

Lower Bound distance Calculation: Calculate distance between the iSAX summary of a data series and the query PAA

Real Distance Calculation: Calculate real Euclidean distance between the query and a data series **Lower-Bound Property of iSAX summaries**: If the lower bound distance between a query Q and the data series DS is higher than a value v, then the real distance between Q and DS is also higher than v.



