Mahsa Ashouri

PhD student - Institute of Service Science - National Tsing Hua University – Taiwan.

Department Of Mathematics, Isfahan University of Technology, Sep. 2008 – Jun. 2011 (Statistic)
Department Of Mathematics, Isfahan University of Technology, Sep. 2002 – Jun. 2007 (Statistic)

I. Publications and conference papers

1. M. Ashouri, K. Cai, F. Lin, G. Shmueli, **"Assessing the Value of an Information System for Developing Predictive Analytics: The Case of Forecasting School-Level Demand in Taiwan" (2018)** , Journal of Service Science, informs (accepted paper) and presented in "TSWIM, June 26-28, 2016, Chiayi, Taiwan.
2. M. Ashouri, G. Shmueli, **"A New Tree-Based Method for Clustering Time Series"**, **working paper,** presented in SCECR, June 26-28, 2017, Ho Chi Minh City, Vietnam and will be presented in Informs international meeting, June 17-20, 2018, Taipei, Taiwan.
3. M. Ashouri, "**Using Centered and Non-centered Algorithms for Simulating S&P Share Index Data**", CIAS, January, 2012, Indian Statistical Institute, Kolkata, India.
4. M. Ashouri, M. Alimirzaei, "**Non-centered Algorithm for Simulating Non-Gaussian Ornstein-Uhlenbeck Stochastic Volatility Processes**", Proceedings of the International Seminar on Probability and Stochastic Processes, September, 2011, University of Rasht, Iran.

II. Research interests

- Data mining (decision trees and random forests), Time series analysis and time series clustering, Big data analysis.

III. Open questions

1. How to use decision trees for time series forecasting?
2. How to visualize many time series?
3. How to evaluate time series clustering?

George Athanasopoulos

Associate Professor and Deputy HoD: Econometrics and Business Statistics.

- Forecasting hierarchical and grouped time series
  - Student numbers for Monash University.
  - Prison population across Australia.
  - Nowcasting with temporal hierarchies.
  - Working on a panel setting.
- Forecasting restaurant bookings. The case of Taiwan.
- Macroeconomic forecasting
  - for Australia using a large number of predictors ausmacrodata.org.
  - R package for EC-VARMA models
- Supervision of Thiyanga Thalagala

MONASH BUSINESS SCHOOL | MONASH University

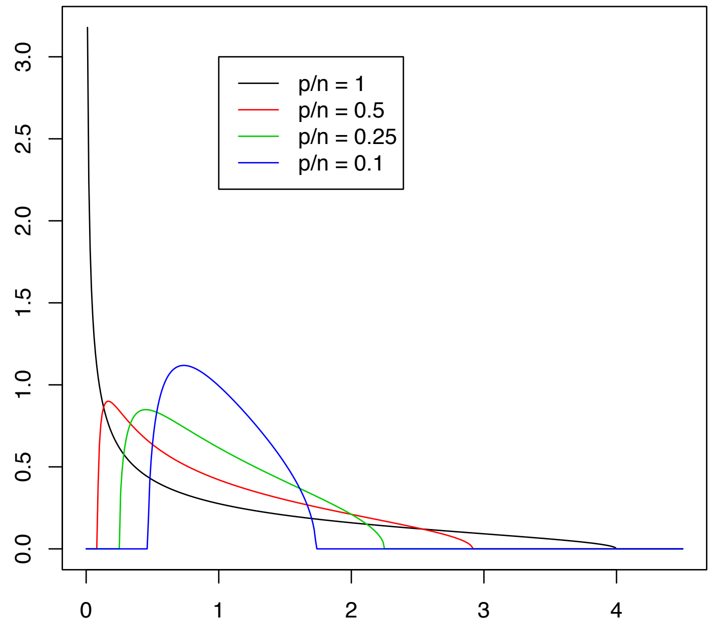
Alexander Aue

Department of Statistics

Graduate Group of Applied Mathematics

University of California, Davis

aaue@ucdavis.edu



Very Short Bio

2000 Diplom in Mathematics, Marburg

2004 PhD in Applied Mathematics, Köln

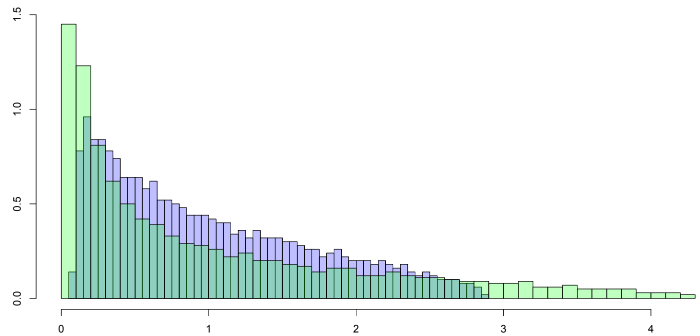
Since 2007 at UC Davis

Research Interests

Functional time series (more in survey talk)

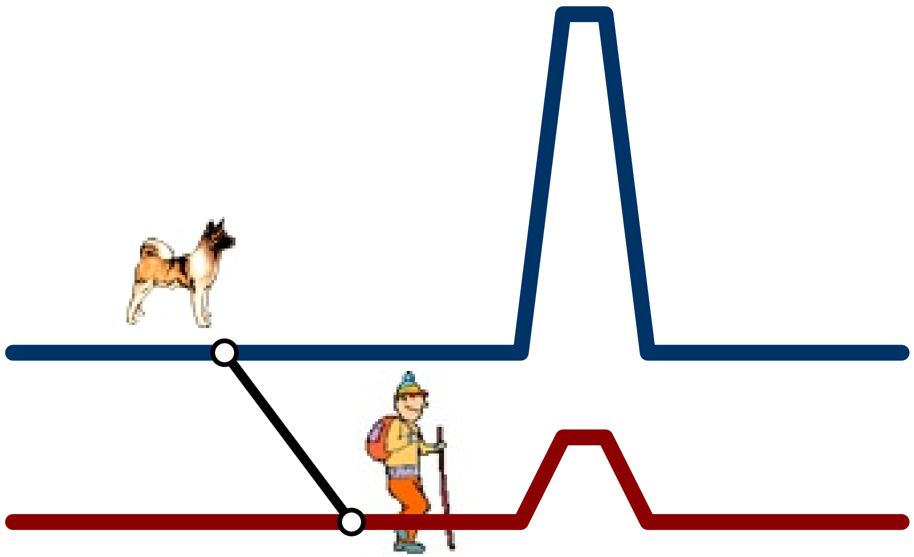
Random matrix theory in statistics

High-dimensional time series

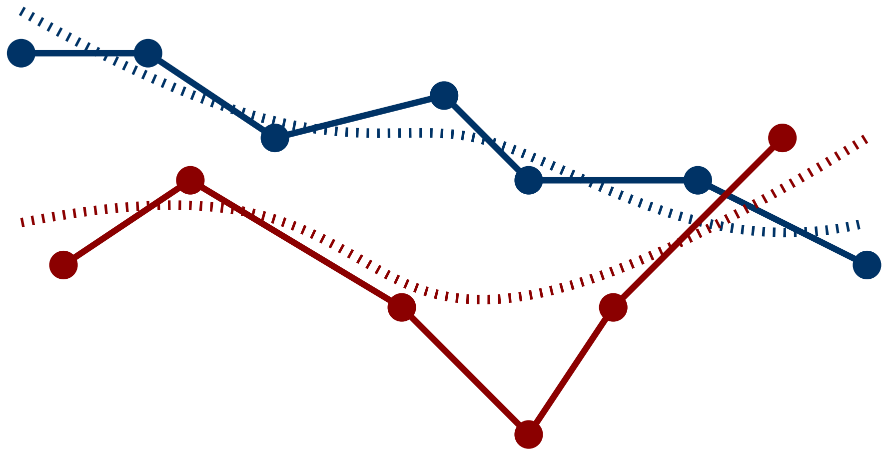


Maike Buchin

Technical University Dortmund



Computational Geometry:
Curves and Surfaces

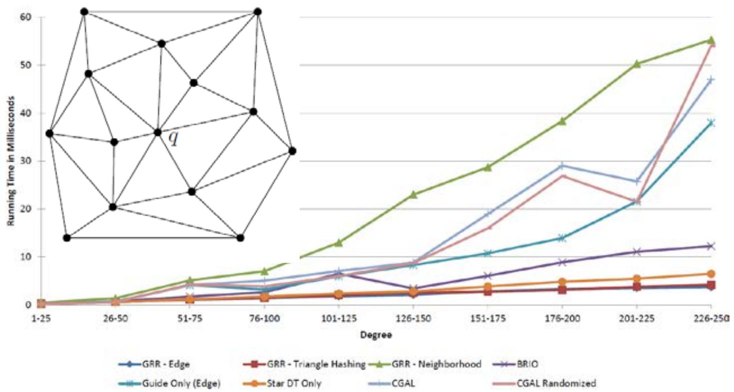


Computational
Movement Analysis

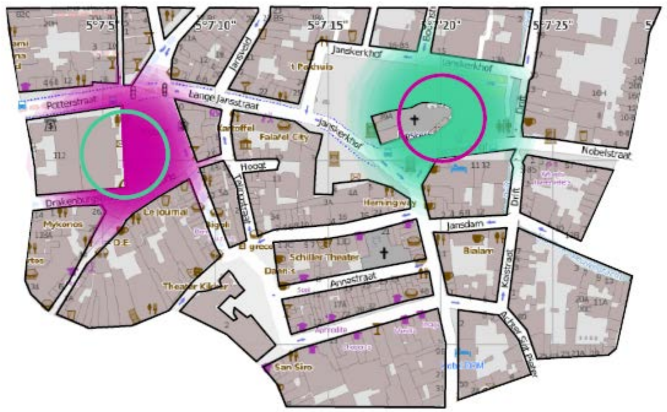
Kevin Buchin, TU Eindhoven – Geometric Algorithms

Movement Data

Motion Planning



Algorithm Engineering



Uncertain Geometric Data

Anne Driemel

Assistant professor
TU Eindhoven, the Netherlands

Research topics:

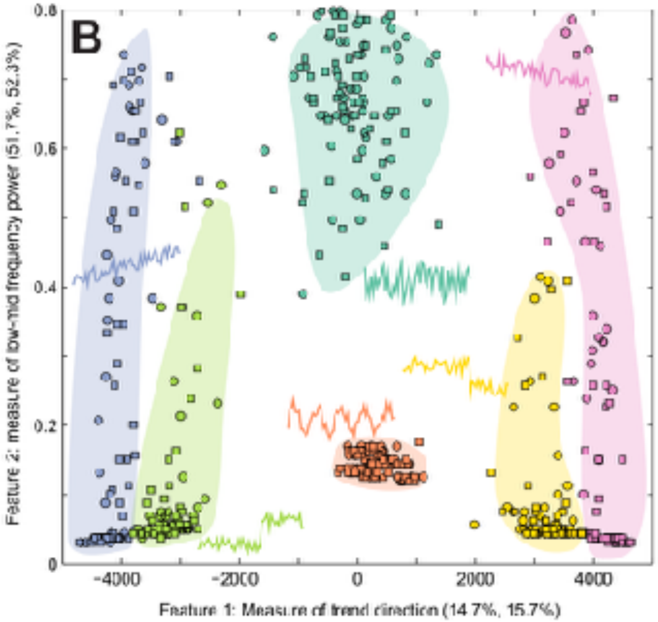
- Computational Geometry
- Algorithms and Complexity
- High-dimensional data structuring

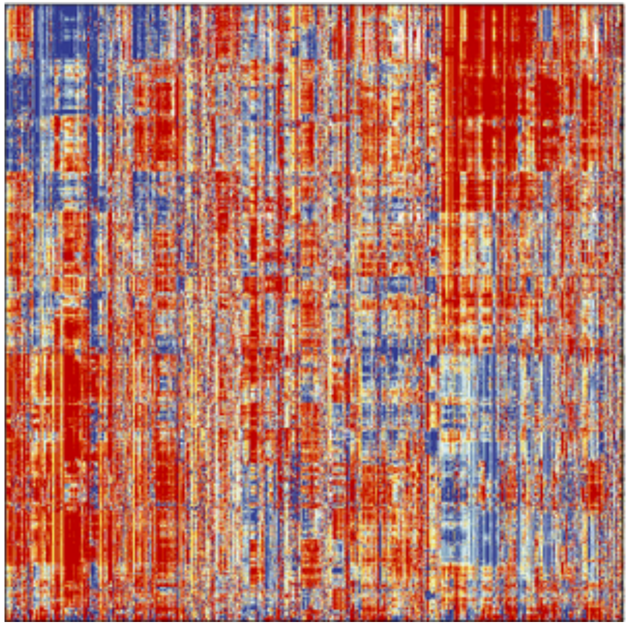
$$\left.\begin{array}{l}\text{Clustering}\\ \text{Classification}\\ \text{Density estimation}\\ \text{Outlier detection}\end{array}\right\}\ \text{for}\ \left\{\begin{array}{l}\text{Time Series / Trajectories}\\ \text{Non-Euclidean distance measures}\\ \text{Fréchet distance}\\ \text{Statistical divergence}\end{array}\right.$$

Ben Fulcher

Physics Department, The University of Sydney

- Background in physics & brain modeling (Sydney)
- PhD in feature-based time-series analysis, involved assembling large and diverse libraries of time-series data (>30K) and algorithms for time-series feature extraction (>7K) (Oxford)
- Biological/medical applications — postdoc working with brain-imaging and other neuroscience data (Monash)
- Recent appointment to complex systems group in physics allows more theoretical work on feature-based time-series analysis.





Jie Gao, Stony Brook University

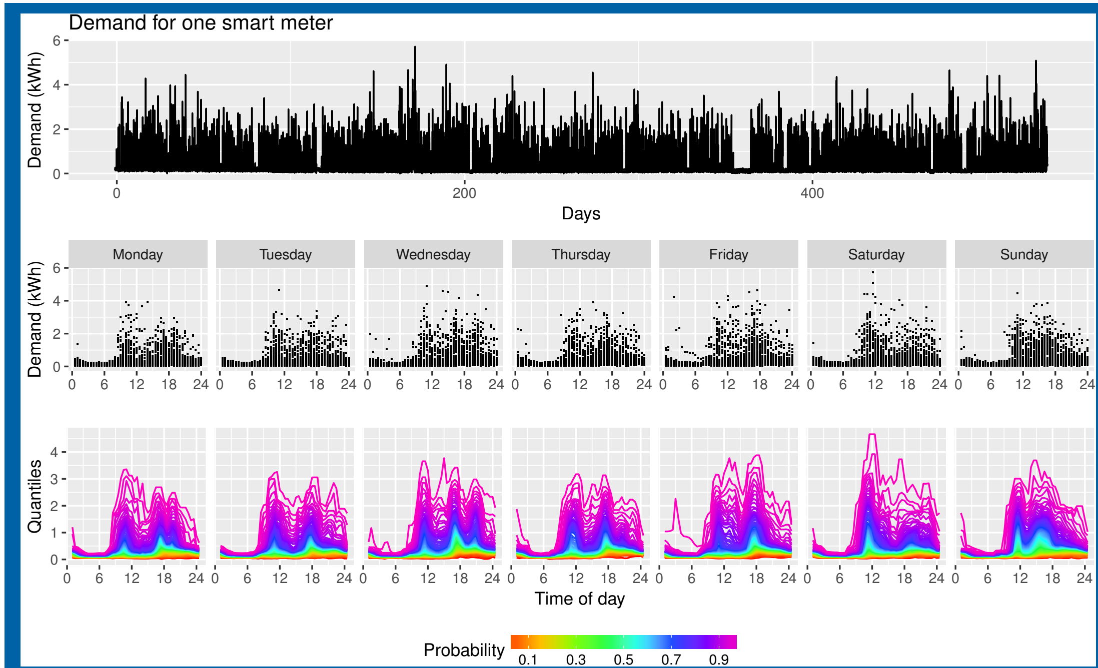
- Bio: Faculty at Stony Brook, CS department.
- Research Interests: Sensing + Motion + Algorithms
- Problems to work on
    - Trajectory clustering
    - Distributed sensing and anonymization of trajectories
    - Privacy in sensing and learning

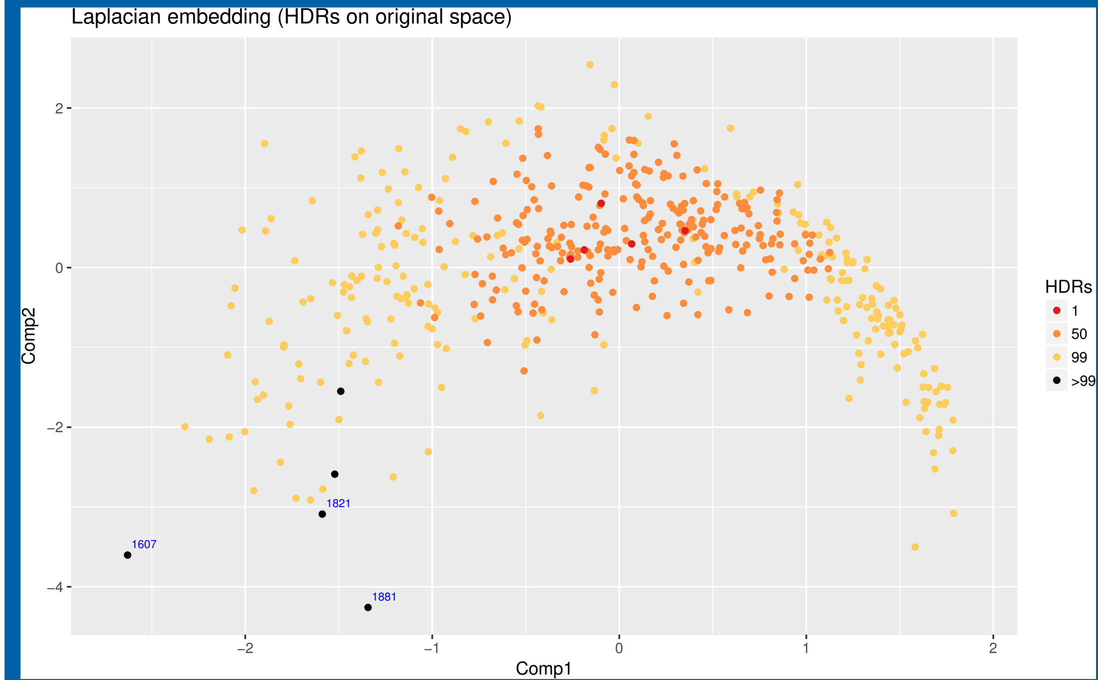
Michael Horton – The University of Sydney

- Short Bio
  - Postdoctoral Researcher at School of Information Technologies
- Research Interests
  - Computational Geometry
  - Machine Learning
  - Particular focus on spatio-temporal data
  - Sports analysis

Rob J Hyndman

Monash University, Australia
robjhyndman.com





Maarten Löffler

computer scientist

Theorem 1 *Given a set $\mathscr{D}$ of n connected regions in $\mathscr{R}^d$, and a trajectory T,*

- *there is a randomized strategy for the online tracking problem that achieves a competitive ratio of $O(\log\Delta)$; and*
- *there are deterministic strategies for the online tracking problem that achieve a competitive ratio of $O(\log\Delta)$ when $d=1$ or $O(\Delta)$ when $d>1$.*

Each of these strategies may be implemented in polynomial time.

Theorem 2 *Let $\mathscr{D}$ be a set of n disjoint unit disks in $\mathscr{R}^2$. We can build a data structure that stores $\mathscr{D}$, of size $O(n)$, in $O(n\log n)$ expected time, such that given a sample P of $\mathscr{D}$, we can compute $\mathit{onion}(P)$ in $O(n\log k)$ time, where k is the number of layers in $\mathit{onion}(P)$.* □

Theorem 3 *Let P be a planar point set and T be a compressed quadtree or a c-cluster quadtree for P. Then $\mathrm{DT}(P)$ can be computed in time $O(|P|)$.*

Theorem 4 *Let $\mathscr{R}$ be a set of unit disks in $\mathscr{R}^2$, and let p and q be two points. We can compute in $O(2^{f(\Delta,\varepsilon,\beta)}n^7)$ time a path π between p and q, whose resilience is at most $\le(1+\varepsilon)r(p,q)$, for some polynomial function $f(\Delta,\varepsilon,\beta)$ of constant degree.*

Theorem 5 *The homotopic median of m trajectories with n edges can be computed in $O(nm\log^2(nm)+(nm+k)\alpha(nm)\log(nm))$ expected time, where k is the size of the output, if the sampling assumption is satisfied.*

Theorem 6 *Algorithm minimisePly with n entities that have been last queried, on average, at time $t^0-\ell$ and have intrinsic ply Δ at time $t^*=t^0+\tau$ yields uncertainty regions at time t^* with ply $O(1)\Delta$, if $\tau\ge 2n$, $O(\min\{n/\Delta,\lambda,\alpha^{d+1}\}^{d/(d}$ … Δ, if $\tau=n+n/\alpha$ and $1<\alpha\le$ … $O(\min\{n/\Delta$ … $/(d+1)}$ …*

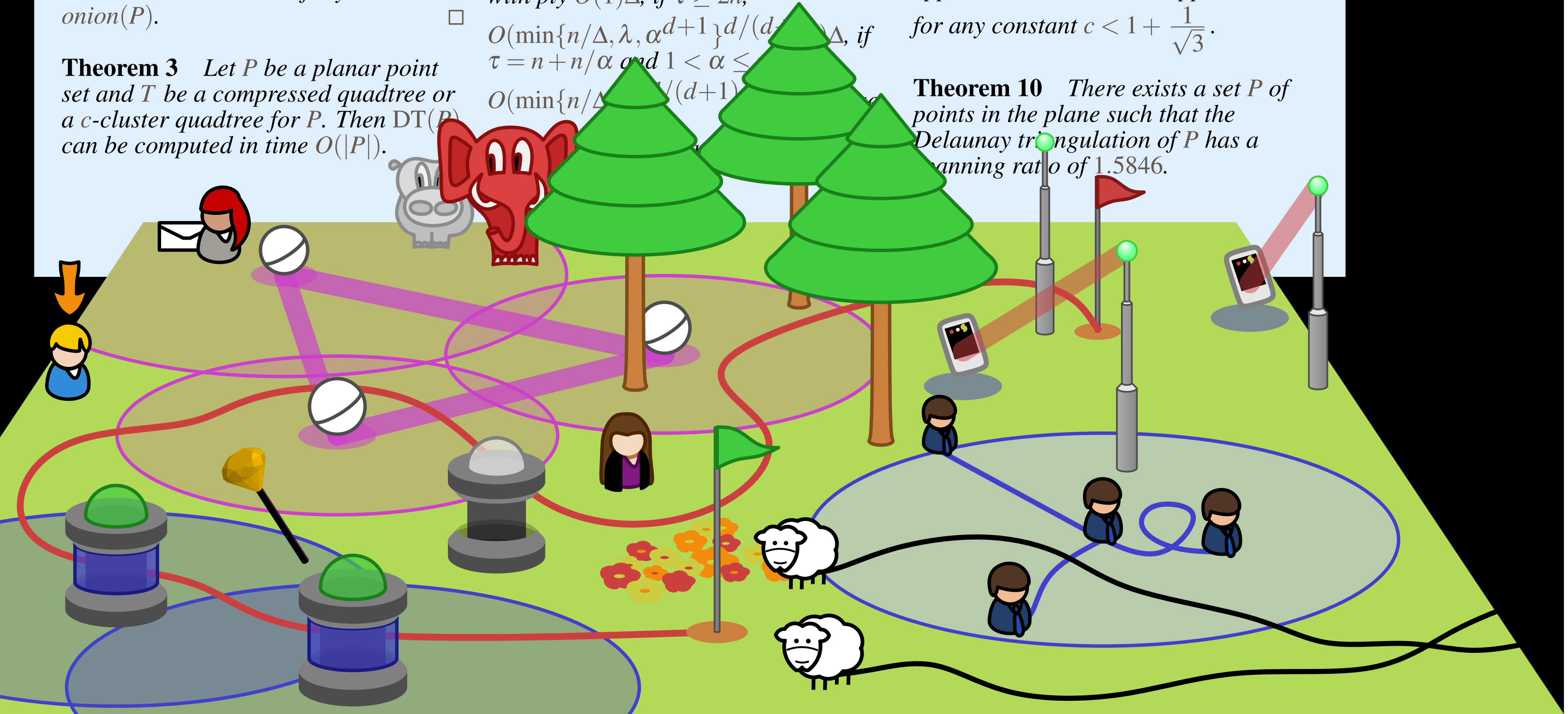
Theorem 7 *A set of n disjoint polygonal δ-wide objects of constant combinatorial complexity in $\mathscr{R}^2$ can be maintained in a $O(\delta n)$ size data structure that supports insertion, deletion and point location queries in $O(\delta\log n)$ time, and ρ-similar updates in $O(\delta\log\log n+\log(\delta\rho))$ time. All time bounds are worst-case, and the data structure can be implemented on a real-valued pointer machine.*

Theorem 8 *If G is connected, there exists $\mathscr{S}$ s.t. routing works and $md(\mathscr{S})=O((diam(G)+\log(n))^2)$.*

Theorem 9 *Approximation algorithm A is a $(\frac{1}{2}\rho+1)$-approximation of the minimum RBP spanning graph, where ρ is the Steiner ratio. The approximation is not a c-approximation for any constant $c<1+\frac{1}{\sqrt{3}}$.*

Theorem 10 *There exists a set P of points in the plane such that the Delaunay triangulation of P has a spanning ratio of 1.5846.*

Universiteit Utrecht



Julie Novak

Bio

- Currently, streaming experimentation at Netflix- focus on developing statistical methodology for A/B tests on Quality of Experience metrics
- Research staff member at IBM Research- focus on forecasting IBM revenue at all levels of its organizational hierarchy
- PhD in Statistics- focus on Bayesian hierarchical modeling with applications to missing data in marketing

Research Interests

- Hierarchical forecasting, forecast reconciliation
    - Missing data
    - Covariance matrices
    - Bayesian priors
    - Application areas
- Bayesian nonparametric methodology applied to A/B experimentation

Visualising the economy

Australian Macro Database

Categories

National Accounts, Flow of Funds & International Trade

national accounts: national» | national accounts: state» | flow of funds» | balance of payments and international finance |

Labour Statistics

labour force» | weekly earnings | vacancies

Industry (excluding series found in national accounts)

industry capital expenditure | building and construction | housing finance | business indicators | retail trade | vehicle sales

Money, Credit, Interest rates and Exchange Rates

monetary aggregates | lending and credit aggregates | bank lending | debt securities | int

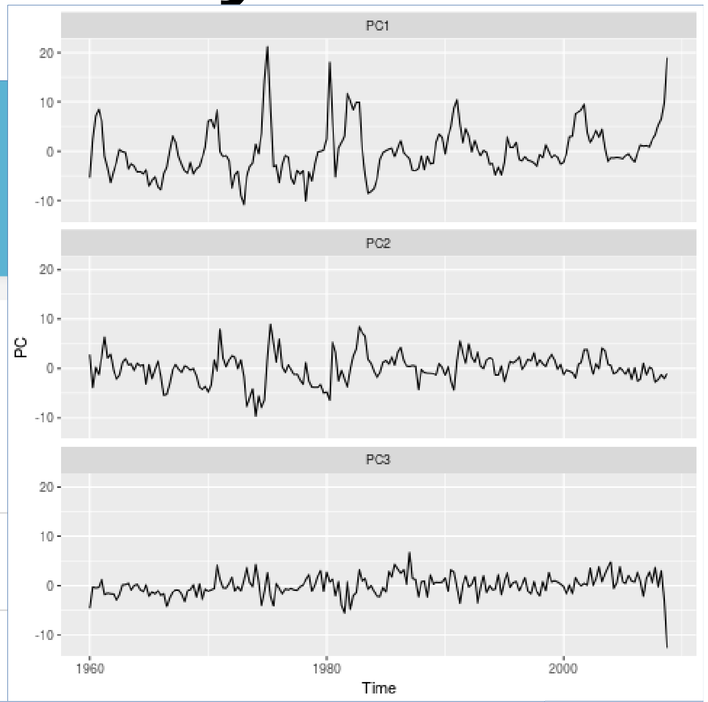
monetary statistics (imf framework) | exchange rates

Prices & Inflation

cpi | inflation expectations | house prices | ppi | trade price indices | wage price index

Other

demography | rba's monthly indicators (includes consumer and business sentiment)



Real gross national income

add to list

narrow category: key aggregates and analytical series, annual

broad category: australian national accounts: national income, expenditure and product

Initial Date: Jun-1960
Freq: Annual
Series Type: Original
ID: rgnickaasaoa

Latest Date: Jun-2017
Unit: $ Millions
Prices: Real

Real net national disposable income

add to list

narrow category: key national accounts aggregates

broad category: australian national accounts: national income, expenditure and product

Initial Date: Sep-1959
Freq: Quarter
Series Type: Trend
ID: rnndicknaatq

Latest Date: Sep-2017
Unit: $ Millions
Prices: Real

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MONASH University

Nalini Ravishanker, Dept. of Statistics, UConn, USA

Interests: Time series analysis; Times-to-events analysis; Bayesian dynamic modeling; Signal processing; Predictive inference.

Interdisciplinary Research Areas: biology, biomedicine, climate, finance, marketing, and transportation engineering.

Current Research Focus - Interest.

- Clustering and Classification of Time Series. Frequency domain methods - Explore use of TDA.
- High-frequency, High-dimensional Time series. Estimating Function (EF) approach - Explore use with streaming data.
- Bayesian Hierarchical Dynamic Modeling of Time Series. MCMC and INLA - Explore divide and combine schemes.

Introduction, Open problems

1. Hanlin Shang is an Associate Professor of Statistics at the Australian National University
2. Obtained a First Class Honours degree in Statistics from LaTrobe University in 2006
3. Obtained a Ph.D. with Mollie Holman medal from Monash University in 2010

1. His main research interest is functional time series inference, modeling and forecasting
2. From the seminar, I hope to learn some latest work in the field of functional time series analysis
3. The open problems I would like to work on are: non-linear time series modeling and forecasting; various dimension reduction methods for functional time series

Galit Shmueli (徐茉莉)

www.galitshmueli.com

Research in Time Series

Disease/Bio-surveillance

- Burkom et al (*Stat in Med* 2007), Automated time series forecasting for biosurveillance
- Goldenberg et al (*PNAS* 2002), Early statistical detection of Anthrax outbreaks by tracking over-the-counter medication sales

Functional Data Analysis in Online Auctions

- Wang et al (JBES 2008), Explaining and forecasting online auction prices and their dynamics using FDA
- Jank & Shmueli (Stat Sci 2006), Functional data analysis in electronic commerce research

Visualization

- Shmueli et al. (DSS 2006), Exploring auction databases through interactive visualization
- Shmueli & Jank (JCGS 2005), Visualizing online auctions

2 2000-2002
Carnegie Mellon Univ.
Dept. of Statistics

1 1994-2000
Israel Institute of Technology
MSc + PhD, Statistics

2014-... **NTHU (Taiwan)**
Institute of Service Science
College of Tech Management

3 2002-2012
Univ. of Maryland
Smith School of Business

4 2011-2014
Indian School of Business
Business Analytics & Info Systems

2008-2014
Rigsum Institute (Bhutan)

Research

'Entrepreneurial' statistical & data mining modeling

- **Interdisciplinary**
- **Info Systems, healthcare**
- **Behavioral big data**

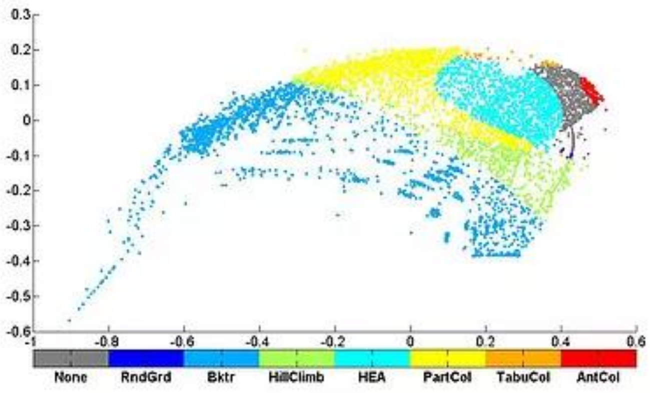
Statistical Strategy

- To Explain or To Predict?
- Information Quality
- Data Mining for Causality
- Predicting with Causal models

Time Series Teaching

Forecasting Analytics

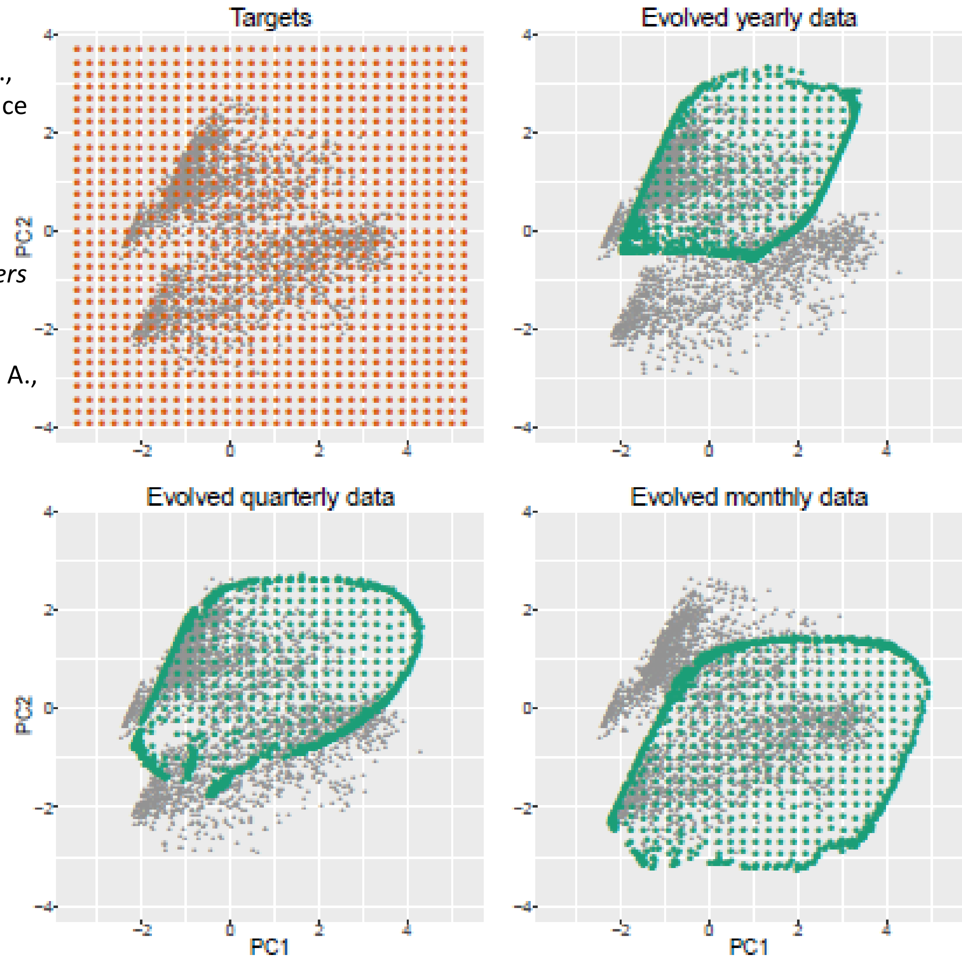
- Kate Smith-Miles, The University of Melbourne http://katesmithmiles.wixsite.com/home
- ARC Australian Laureate Fellowship (2014-2019) "Stress-testing algorithms: generating new test instances to elicit insights"



Smith-Miles, K. A., Baatar, D., Wreford, B. and Lewis, R., "Towards Objective Measures of Algorithm Performance across Instance Space", *Computers & Operations Research*, vol. 45, pp. 12-24, 2014.

Smith-Miles, K. A. and Bowly, S., "Generating New Test Instances by Evolving in Instance Space", *Computers & Operations Research*, vol. 63, pp. 102-113, 2015.

Muñoz, M. A., Villanova, L., Baatar, D. , Smith-Miles, K. A., "Instance Spaces for Machine Learning Classification", *Machine Learning*, vol. 107, no. 1, pp. 109-147, 2018.



Kang, Y., Hyndman, R. and Smith-Miles, K., "Visualising Forecasting Algorithm Performance using Time Series Instance Spaces", *International Journal of Forecasting*, vol. 33, no. 2, pp. 345-358, 2017.

Wang, X., Smith, K. A., and Hyndman, R., "Rule induction for forecasting method selection: meta-learning the characteristics of univariate time series", *Neurocomputing*, vol. 72, no. 10-12, pp. 2581-2594, 2009.

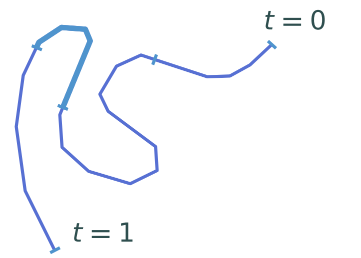
Wang, X., Smith, K. A., Hyndman, R., "Characteristic-based Clustering for Time Series Data", *Data Mining & Knowledge Discovery*, vol. 13, no. 3, pp. 335-364, 2006.

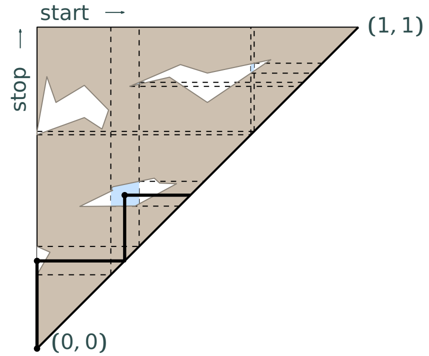
Also interested in anomaly detection in noisy time series … (weather, security, pollution, etc.)
Kang, Y., Belusic, D. and Smith-Miles, K., "Detecting and Classifying Events in Noisy Time Series", *Journal of the Atmospheric Sciences*, vol. 71, pp. 1090-1104, 2014.

Frank Staals

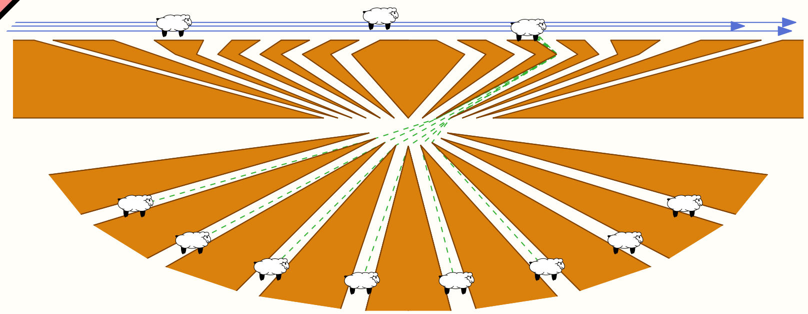
PostDoc/Lecturer at Utrecht University

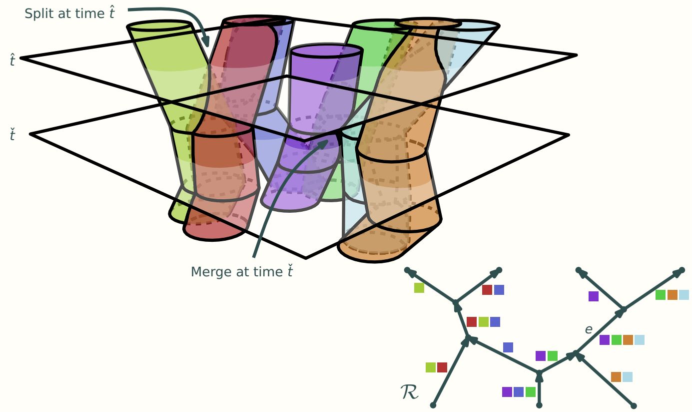
Trajectory Segmentation



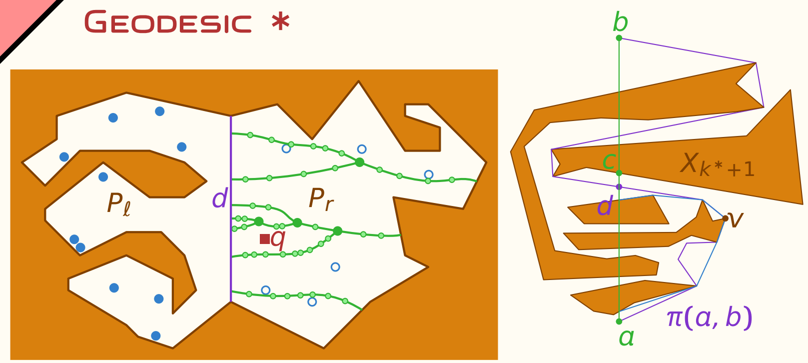


Trajectory Grouping Structure

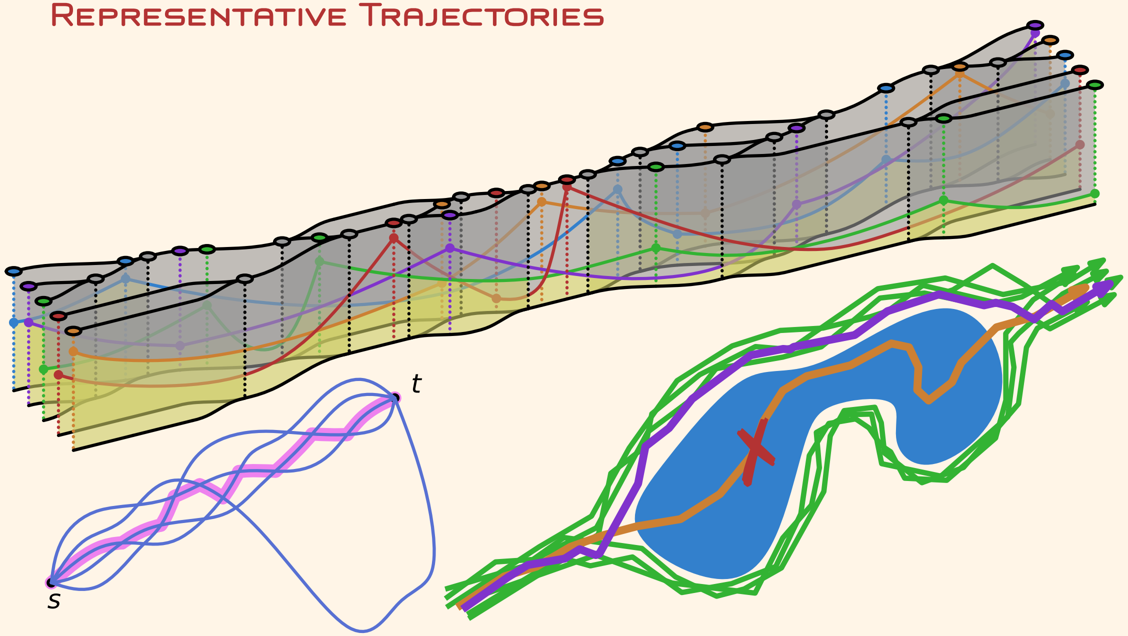




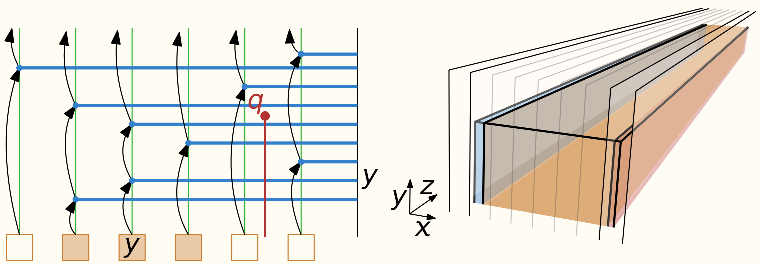
Geodesic *



Representative Trajectories



Geometric Data Structures



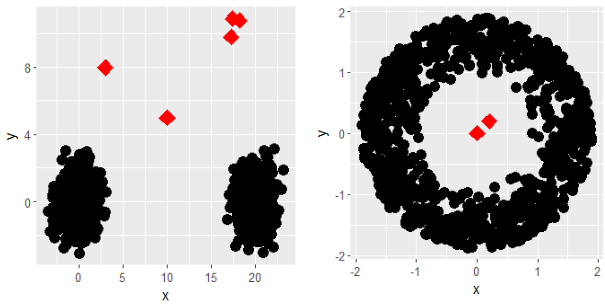
Dilini Talagala

PhD Candidate, Monash University, Australia

pridital

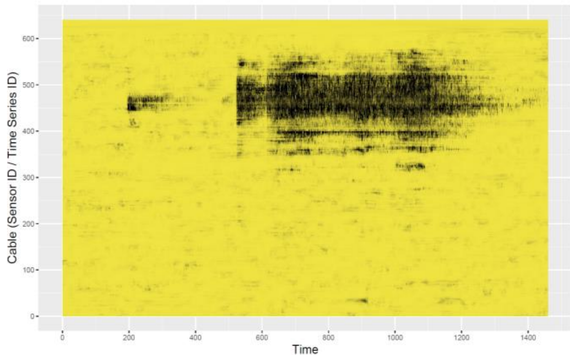
stray

- **High Dimensional Data**
- Deal with masking problem
- Multimodal typical classes
- Streaming temporal data

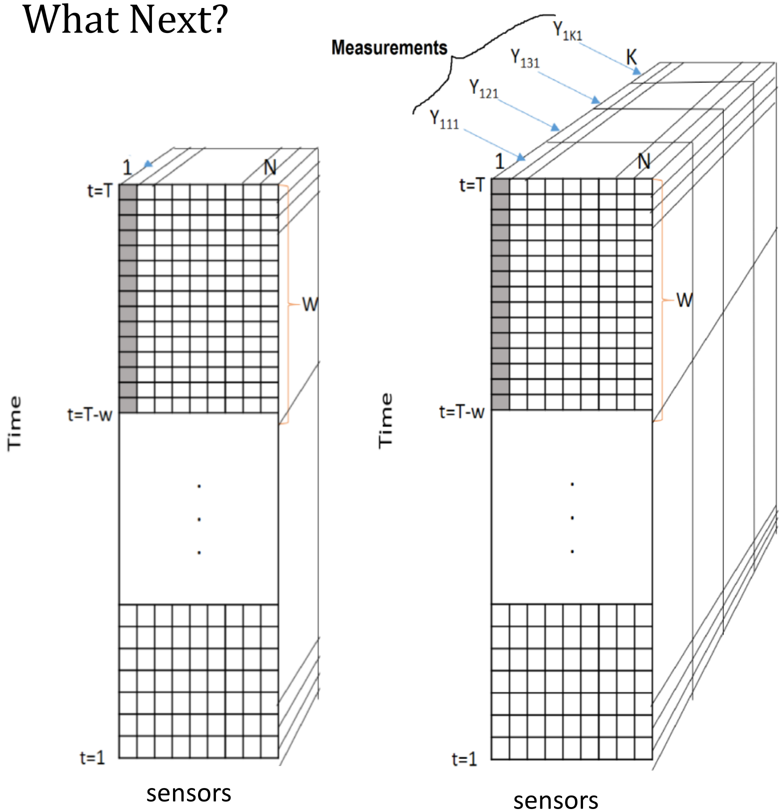


oddstream

- **Streaming data**
- **Concept drift**/ nonstationary temporal data



What Next?



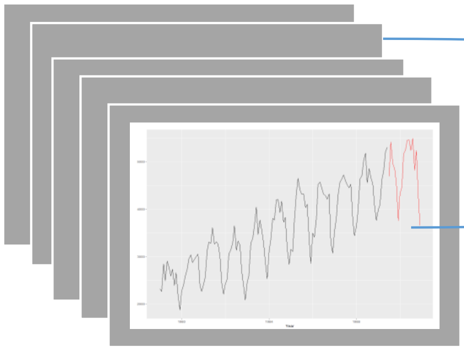
- Tensor decomposition
- Nonstationary streaming temporal data
- Time series features

Thiyanga Talagala
PhD Candidate – Monash University, Australia

github: thiyangt
twitter: @thiyangt

Key words:
- Meta-learning
- Ensemble learning
- Algorithm selection problem
- Classification
- Time series generation

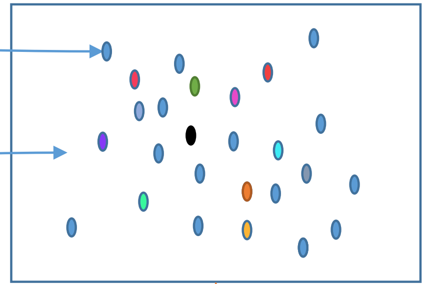
Large collection of time series



1

- Time series features
- Class imbalance
- Augmenting training set with simulated series

Forecasting Methods



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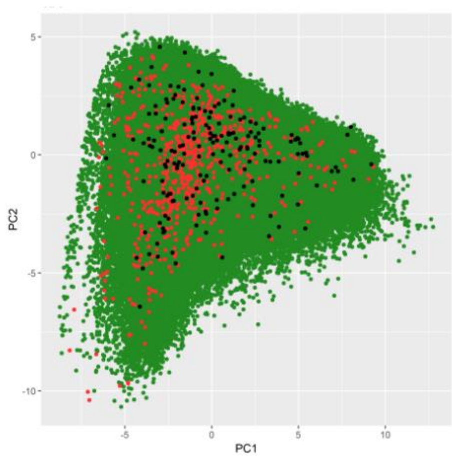


2

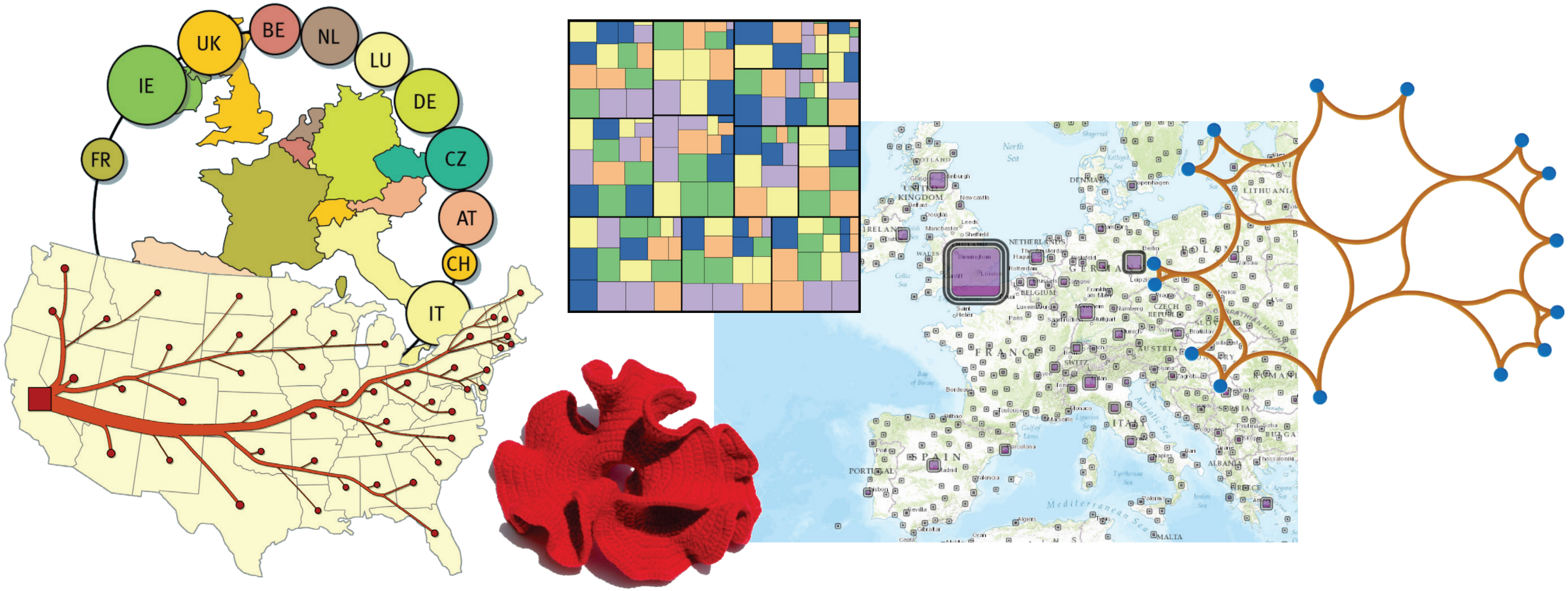
- Classification
- Class labels
- Combined forecast

Introduction

Name: Kevin Verbeek

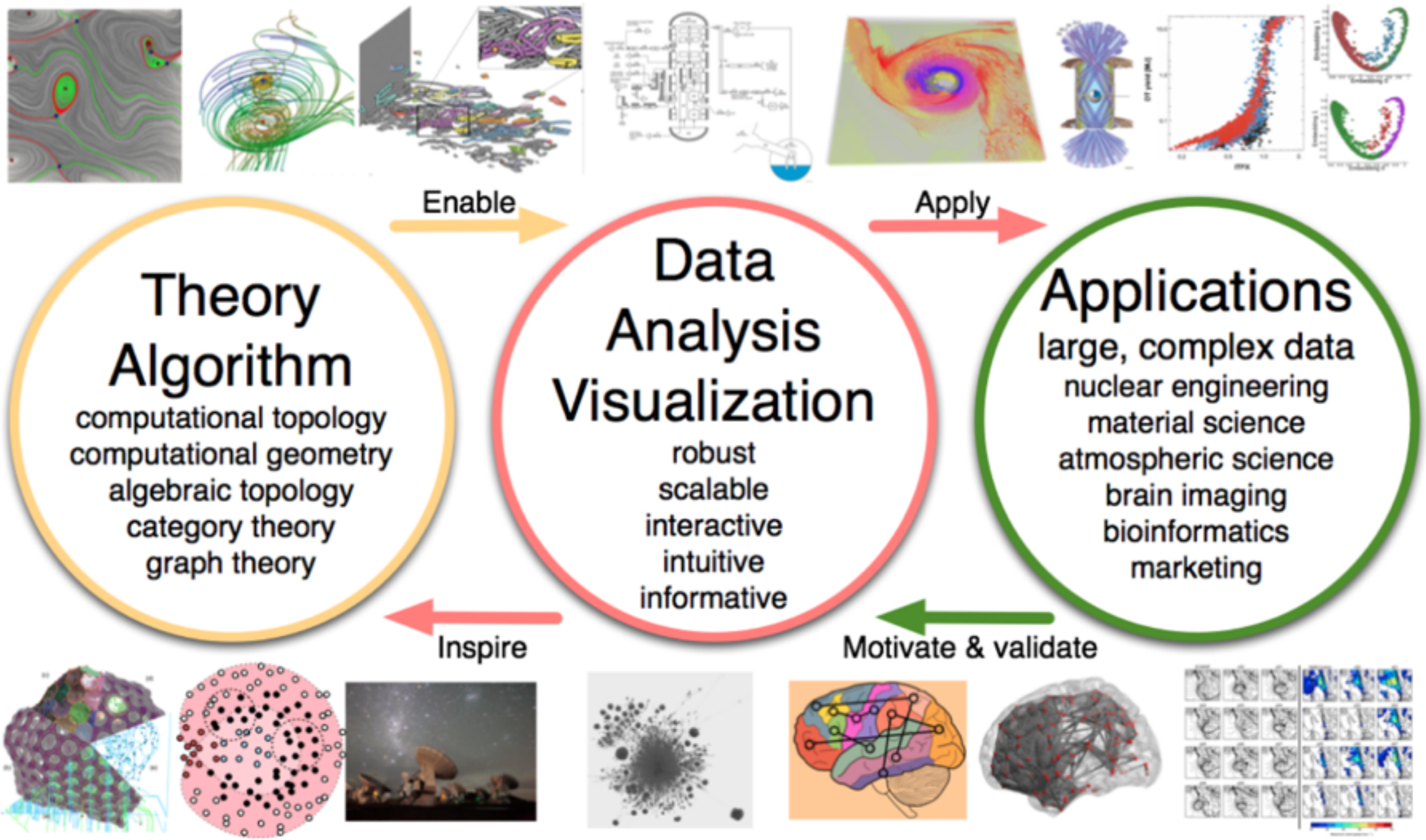
2008 – 2012	PhD Student	TU Eindhoven
2012 – 2014	PostDoc	UC Santa Barbara
Since 2014	Assistant professor	TU Eindhoven

Research Interests: Computational geometry, automated cartography, graph drawing, social network analysis, information visualization



Topological Data Analysis and Visualization

Combine topological, geometric, data analysis and visualization techniques to **study** large and complex data that require rich structural descriptions



Bei Wang, University of Utah, http://www.sci.utah.edu/~beiwang/

Qiwei Yao, Department of Statistics, London School of Economics

- Factor modelling: $\mathbf{y}_t = \mathbf{A}\mathbf{x}_t + \varepsilon_t$, $\mathbf{A}$ is $p \times d$, $d << p$, ε_t is WN.
  - ◇ high-D volatility processes
  - ◇ high-D high-frequency modelling
  - ◇ high-D spatio-temporal modelling
  - ◇ functional TS
- TS-PCA: $\mathbf{y}_t = \mathbf{A}\mathbf{x}_t$, $\mathbf{A}$ is invertible, Corr$(x_{ti}, x_{sj}) = 0 \, \forall \, i \neq j$.

  Also applicable to high-D volatility processes
- Tests for high-D white noise
  - ◇ normal approximation
  - ◇ random matrix theory

Current/Future research

- ▲ Complex TS: network, space, tensor
- ▲ Beyond linear dependence/correlation