

# 37<sup>th</sup> Finnish Summer School on Probability and Statistics

	Monday 30.5	Tuesday 31.5	Wednesday 1.6	Thursday 2.6	Friday 3.6
08:00 - 09:00		08:00 - 09:00 breakfast	08:00 - 09:00 breakfast	08:00 - 09:00 breakfast	08:00 - 09:00 breakfast
09:00 - 10:00		09:15 - 10:00 Litvak	09:15 - 10:00 Van Zanten	09:15 - 10:00 Van Zanten	09:15 - 10:00 Litvak
10:00 - 11:00		10:15 - 11:00 Litvak	10:15 - 11:00 Van Zanten	10:15 - 11:00 Van Zanten	10:15 - 11:00 Rüschendorf
11:00 - 12:00		11:15 - 12:00 Lember	11:15 - 12:00 Rüschendorf	11:15 - 12:00 Scricciolo	11:15 - 12:00 Rüschendorf
12:00 - 13:00	12:00 - 12:50 lunch	12:00 - 13:00 lunch	12:00 - 13:00 lunch	12:00 - 13:00 lunch	12:05 - 13:00 lunch
13:00 - 14:00	12:50 - 13:00 Sottinen				
14:00 - 15:00	13:00 - 13:45 Litvak	13:45 - 14:30 Van Zanten	13:45 - 14:30 Rüschendorf	13:45 - 14:30 Litvak	
15:00 - 16:00	14:45 - 15:15 coffee	14:30 - 15:00 coffee	14:30 - 15:00 coffee	14:30 - 15:00 coffee	
16:00 - 17:00	15:15 - 16:00 Litvak	15:00 - 15:45 Van Zanten	15:00 - 17:00 Guided Excursion	15:00 - 15:45 Rüschendorf	
	16:10 - 16:30 Shokrollahi	16:00 - 16:30 Sova		16:00 - 16:45 Rüschendorf	
	16:40 - 17:00 Ylinen	16:30 - 17:00 Westerlund			
	17:00 - 18:00 dinner	17:00 - 18:00 dinner	17:00 - 20:00 sauna	17:00 - 18:00 dinner	
	19:00 - 22:00 sauna	19:00 - 22:00 sauna	(ladies first) 20:00 - 22:00 conference dinner	19:00 - 22:00 sauna	
	(ladies first)	(ladies first)		(ladies first)	

## 1. ABSTRACTS

**On Bayesian segmentation with hidden Markov models**

JÜRI LEMBER

University of Tartu

**Abstract** We consider the segmentation or decoding problem with hidden Markov models in a fully Bayesian setup. The main focus is MAP or Viterbi segmentation where the goal is to find the path with maximum posterior probability. In the Bayesian setup the Viterbi path cannot be found by a dynamic programming (Viterbi) algorithm any more. We compare several iterative methods for finding the MAP path including simulated annealing, the frequentist's parameter estimation, variational Bayes approach, the segmentation EM approach and many more.

**Random graphs and ranking**

NELLY LITVAK

University of Twente

**Abstract** Network science is an exciting multidisciplinary research area that studies the network phenomenon and its applications ranging from web search and transportation networks to understanding the structure of social connections, and processes on networks such as infection and information spreading. The networks are often chaotic and highly dynamic. Mathematics helps us to understand their structure and predict their development. We start this course with Introduction, in which we cover most essential surprising properties shared by complex networks on entirely different nature. This includes the famous small-world phenomenon, scale-free phenomenon and friendship paradox. Next, we will cover Configuration Model (CM) – one of most natural and essential random graph models for networks. We will discuss under which conditions CM results in a simple graph, which is important because all real world graphs are simple. Finally, we will discuss the PageRank algorithm, which was one of most important factors in success of Google, and have a quick look at recent mathematical results and challenges in its analysis. The course consists of 6 lectures, each 45 minutes. The overview of the course is as follows.

- Lectures 1-2: Complex networks and their properties. Exercises: 1-8 (Exercises 1 and 2 are easy and can be skipped).
- Lectures 3-5: Complex networks and their properties. Exercises: 9-11.
- Lecture 6: PageRank. Exercises: 12.

**Study material.** In the lectures 1-5 we use the book ‘Random Graphs and Complex Networks’ by Remco van der Hofstad, chapter 1 and 7. <http://www.win.tue.nl/~rhofstad/NotesRGCN.pdf>

**Asymptotics for empirical Bayes posteriors**

CATIA SCRICCILOLO, BASED ON JOINT WORKS WITH S. DONNET, S. PETRONE, V. RIVOIRARD AND J. ROUSSEAU

University of Verona

Empirical Bayes methods are widely used, especially when a data-driven choice of the prior hyperparameter value is adopted as a convenient way to by-pass difficulties arising from a hierarchical specification of the prior. A plug-in estimate solution is expected to lead to inferential answers that are similar, for large sample sizes, to those of a hierarchical prior elicitation. Understanding of this commonly believed asymptotic agreement between Bayes and empirical Bayes and, more generally, of the theoretical performance of empirical Bayes methods in non-parametric problems is difficult at this stage, having been so far studied only in a limited number of special cases. In this talk, admitting that Bayes and empirical Bayes procedures are evaluated under the assumption that the data are generated from a given “true” parameter, we first present results on the asymptotic agreement, in terms of merging, between empirical Bayes and Bayes posterior distributions, which is equivalent to concentration of the empirical Bayes posterior measure around the “truth”, the main argument used to deal with data-dependent priors being based on the idea of shifting the effect of data in the prior to the likelihood by a suitable parameter transformation. We then refine the analysis providing tools for the study of empirically selected priors in non-parametric problems, with a focus on optimal and adaptive posterior concentration rates, stating sufficient conditions that are exemplified in two statistical settings: density estimation with Dirichlet

process mixtures, along with the related inverse problem of density deconvolution, and estimation of intensity functions in Aalen models. On the whole, when the hyper-parameter does not affect posterior contraction rates, there is a lot of flexibility in the choice of the estimator: different choices are indistinguishable in terms of the posterior behaviour they induce and empirical Bayes posterior concentration rates are the same as those of any prior associated with a fixed hyper-parameter value. In those cases where, instead, the hyper-parameter influences posterior contraction rates, the choice of the plug-in estimator may be crucial and require special care.

## Pricing European currency options in a mixed fractional Brownian motion with jump environment

FOAD SHOKROLLAHI

University of Vaasa

**Abstract** This study deals with the problem of pricing European currency options in the mixed fractional Brownian motion with jumps environment. Both, the pricing formula and the jumps mixed fractional partial differential equation for European call currency options are obtained. Some Greeks and the impact of the Hurst parameter  $H$  are discussed. Finally the numerical simulations illustrate that our model is flexible and easy to implement.

## The existence of infinite Viterbi path for PMC models

JÜRI LEMBER AND JOONAS SOVA

University of Tartu

**Keywords:** pairwise Markov chain, hidden Markov chain, Viterbi path, Viterbi alignment, Viterbi algorithm, Viterbi training, maximum a posteriori path.

We consider a two dimensional homogeneous Markov chain  $((X_1, Y_1), (X_2, Y_2), \dots)$  where r.v.-s  $X_i$  (observations) are taking values from  $d$ -dimensional real space  $\mathbb{R}^d$  and r.v.-s  $Y_i$  (un-observed or “hidden” states) are taking values from a finite state space  $\mathcal{Y} = \{1, \dots, |\mathcal{Y}|\}$ . Following Pieznicky [1] we call this model a pairwise Markov chain (PMC). The name reflects the fact that conditionally, given the marginal process  $X = (X_1, X_2, \dots)$ , process  $Y = (Y_1, Y_2, \dots)$  is a Markov chain, and conditionally, given  $Y$ ,  $X$  is a Markov chain. In general though, neither  $X$  nor  $Y$  are necessarily Markov chains. PMC is a natural generalization of hidden Markov model (HMM). In particular, just like in case of HMM, given a realization  $x_{1:n}$  of  $X_{1:n}$ , the Viterbi algorithm can be employed to find the maximum a posteriori (MAP) estimate  $(v_1(x_{1:n}), \dots, v_n(x_{1:n}))$  of  $Y_{1:n}$ . This estimate is also called the Viterbi path or Viterbi alignment. We study the problem of extending the Viterbi path to infinity.

## REFERENCES

- [1] Pieczynski, W. (2003). Pairwise Markov chains. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **25**, 634–634.

## Stochastic Analysis of Gaussian (Fredholm) Processes

TOMMI SOTTINEN

University of Vaasa

## Variational estimates for BSDEs

JUHA YLINEN

University of Jyväskylä

We fix a finite time horizon  $T > 0$ , and consider Backward Stochastic Differential Equations (BSDEs) of type

$$Y_t = \xi + \int_t^T f(r, Y_r, Z_r) dr - \int_t^T Z_r dW_r, \quad t \in [0, T]. \quad (1)$$

The “data” of the BSDE is  $(\xi, f)$ , and the solution consists of the processes  $(Y, Z)$ , where  $Y$  is a continuous adapted process and  $Z$  can be thought of as the derivative of  $Y$ . Here  $W$  is a  $d$ -dimensional Brownian motion,  $(\mathcal{F}_t)_{t \in [0, T]}$  its augmented natural filtration,  $\xi \in L_2(\mathcal{F}_T)$ , and the main assumption on the generator  $f$  is:

- $(t, \omega) \mapsto f(t, \omega, y, z)$  is predictable for all  $(y, z) \in \mathbb{R} \times \mathbb{R}^d$ , and
- there exist  $L_y, L_z \geq 0$  and  $\theta \in [0, 1]$  such that

$$|f(t, \omega, y_1, z_1) - f(t, \omega, y_2, z_2)| \leq L_y |y_1 - y_2| + L_z (1 + |z_1| + |z_2|)^\theta |z_1 - z_2|$$

for all  $(t, \omega, y_1, y_2, z_1, z_2) \in [0, T] \times \Omega \times \mathbb{R} \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^d$ .

With  $\theta = 0$  the equation (1) is referred to as a Lipschitz BSDE, with  $\theta = 1$  to a quadratic BSDE, and if  $\theta \in (0, 1)$  we call the BSDE subquadratic.

When  $\theta = 0$  or  $\theta = 1$ , there has been extensive study of the conditions that should be imposed on  $(\xi, f)$  to guarantee the existence of a solution to (1), and conditions to guarantee the uniqueness of this solution in some class.

In this talk we focus on a different question: how regular is a solution of BSDE (1)? To be more precise, under some additional assumptions we derive upper bounds of

$$\left\| \sup_{r \in [s, t]} |Y_r - Y_s| \right\|_{L_p(\Omega)} + \left\| \left( \int_s^t |Z_r|^2 dr \right)^{\frac{1}{2}} \right\|_{L_p(\Omega)} \quad (2)$$

for any  $[s, t] \subseteq [0, T]$  and an appropriate range of  $p \in [2, \infty)$ . This question can be motivated by considering simulation schemes of BSDEs, as then one expects (see for example [1] in the Lipschitz case with backward Euler scheme) that the  $(L_p)$ -simulation error is upper bounded by the  $L_p$ -variation of the solution itself.

The upper bounds we receive are given in terms of certain  $L_p$ -quantities that describe the regularity of the pair  $(\xi, f)$  on the interval  $[s, t]$ . The main idea of deriving this consists in the following observation:

$$\begin{aligned} \|Y_t - Y_s\|_p &\leq \|Y_t - \mathbb{E}[Y_t | \mathcal{F}_s]\|_p + \|\mathbb{E}[Y_t | \mathcal{F}_s] - Y_s\|_p \\ &\leq \|Y_t - Y_t^{(s, t]}\|_p + \|\mathbb{E}[Y_t | \mathcal{F}_s] - Y_s\|_p, \end{aligned}$$

where  $Y_t^{(s, t]}$  is obtained from  $Y_t$  by changing the underlying Brownian motion  $W$  to an independent Brownian motion  $W'$  on the interval  $(s, t]$ . Once we note that  $(Y - Y^{(s, t]}, [Z1_{(0, s] \cup (t, T]}, Z^{(s, t]}1_{(s, t]})$  is a solution of a BSDE of type (1) with the  $2d$ -dimensional Brownian motion  $(W, W')$ , terminal value  $\xi - \xi^{(s, t]}$ , and generator that corresponds to  $f - f^{(s, t]}$ , we use an apriori estimate for this BSDE to deduce our result.

The talk is based on [2], which is a joint work with Stefan Geiss.

#### REFERENCES

- [1] B. Bouchard, R. Elie, and N. Touzi: Discrete-time approximation of BSDEs and probabilistic schemes for fully nonlinear PDEs. Radon Series Comp. Appl. Math, 8, 1-34, 2009.
- [2] S. Geiss and J. Ylinen: Decoupling on the Wiener space and applications to BSDEs. arXiv:1409.5322v2
- [3] J. Ylinen: Decoupling on the Wiener space and variational estimates for BSDEs. PhD Thesis. Report 148 of the Department of Mathematics and Statistics, University of Jyväskylä, 2015.
- [4] J. Ylinen: Tales and tails of BSDEs. arXiv:1501.01183.

## Prediction of time for preventive maintenance

PER WESTERLUND

KTH Stockholm

**Keywords:** linear regression, martingale theory, health index, maintenance planning

In maintenance planning a crucial question is when some asset should be maintained. As preventive maintenance often needs outages it is necessary to predict the condition of an asset until the next possible outage. The degradation of the condition can be modelled by a linear function. One method of estimating the condition is linear regression, which requires a number of measured values for different times and gives an interval within which the asset will reach a condition when it should be maintained [1]. A more sophisticated calculation of the uncertainty of the regression is presented based on [2, section 9.1].

Another method is martingale theory [3, chapter 24], which serves to deduce a formula for the time such that there is a probability of less than a given  $\alpha$  that the condition has reached 0 before that time. The formula contains an integral, which is evaluated numerically for different values of the measurement variance and the variance of the Brownian motion, which must be estimated by knowing the maximum and the minimum degradation per time interval. Then just one measured value is needed together with an estimate of the variance.

The two methods are compared, especially with regard to the size of the confidence interval of the time when the condition reaches a predefined level. The application for the methods is the development of so called health indices for the assets in an engineering system, which should tell which asset need maintenance first. We present some requirements for a health index and check how the different predictions fulfil these requirements.

#### REFERENCES

- [1] S.E. Rudd, V.M. Catterson, S.D.J. McArthur, and C. Johnstone. Circuit breaker prognostics using SF6 data. In IEEE Power and Energy Society General Meeting, Detroit, MI, United States, 2011.
- [2] Bernard W. Lindgren. Statistical theory. Macmillan, New York, 2nd edition, 1968.
- [3] Jean Jacod and Philip Protter. Probability essentials. Springer-Verlag, Berlin, 2000

## Nonparametric Bayesian Statistics

HARRY VAN ZANTEN

University of Amsterdam

**Abstract:** In statistics and machine learning, nonparametric Bayesian methods have become more and more common in recent years. The use of such methods raises all kinds of interesting questions. For instance, how does one construct reasonable prior distributions on infinite-dimensional spaces (for example function spaces)? How can the posterior, which involves integrals over these spaces, be computed or approximated? What is the theoretical performance of these procedures, for instance in terms of consistency or convergence rates? We will address these issues in the lectures, focussing on the development of asymptotic theory.

## 2. PARTECIPANTS

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### 3. PARTICIPATION AND ACCOMODATION FEES

The participation fee (20 €) is to be paid on location in cash.

The accomodation fee depends on the number of nights the participant is staying and the type of room. The participants who have been awarded a travel grant from the summer school do not need to pay the accomodation fee.

The participants who are visiting the summer school for the day and don't need accomodation, can pay on place their lunch or dinner directly to the biological station cantine.

The accomodation fee for each night is

- 67 € in single room with WC and shower
- 59,25 € in single room
- 51,50 € in double room with WC and shower
- 46,35 € in double room

which includes also breakfast,lunch,coffee and dinner.

The accomodation fee (depending on the number of nights and the type of room) can be paid by the participants or their supporting institutions by bank transfer to the University of Helsinki, with the following information:

Recipient: Helsingin Yliopisto

Bank account: Nordea 166030-77720

Iban: FI23 1660 3000 0777 20

Swift: NDEAFIHH

Payment: First Name Family Name Summer School on Probability and Statistics Lammi

Reference Number: wbs 7516824/ H516

Amount: ? €× number of nights



## 4. USEFUL INFORMATION

Venue:

Lammi Biological Station

Pääjärventie 320

16900 Lammi, Finland

phone +358-(0)9 191 40733

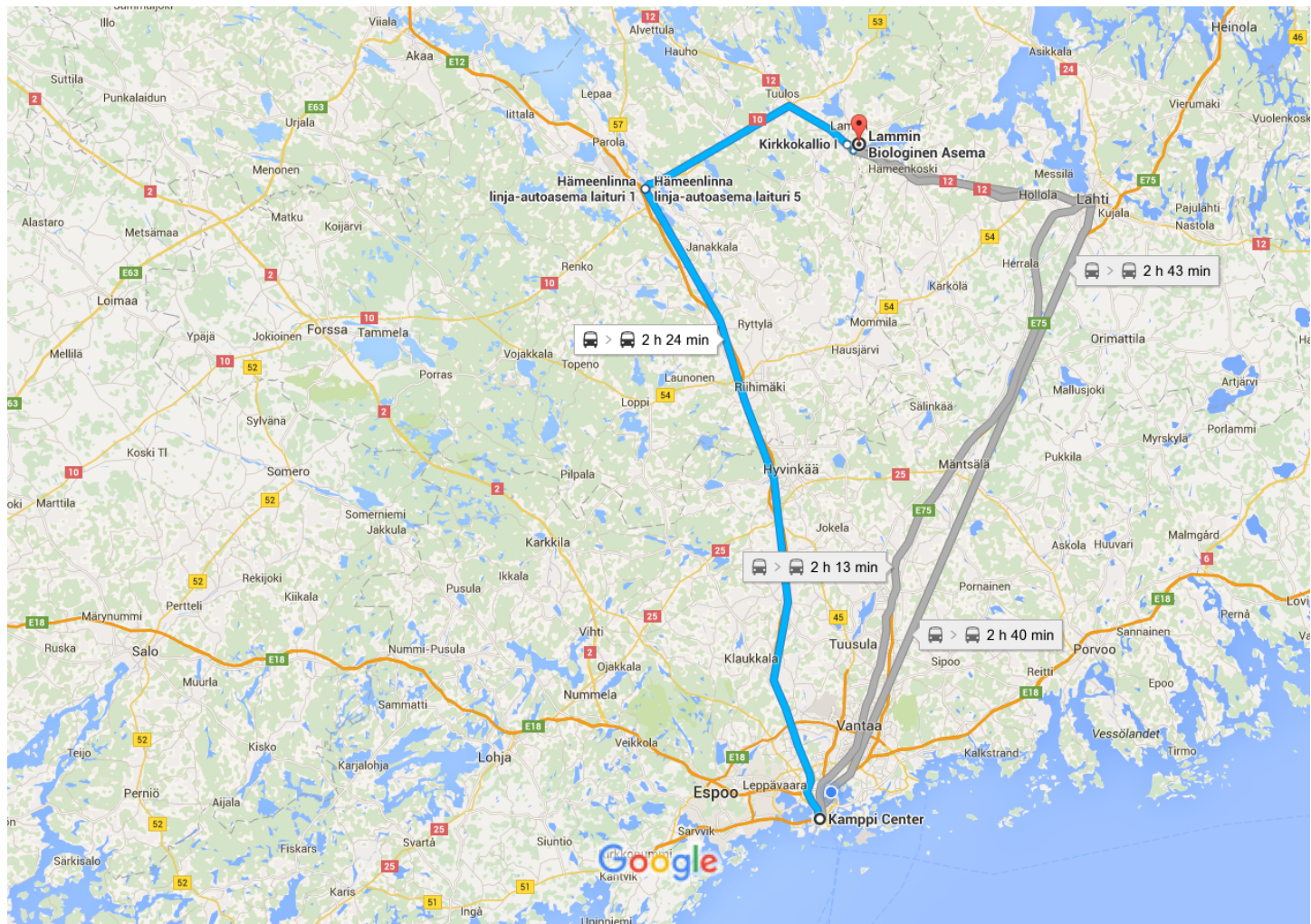
fax +358-(0)9 191 40746

Organizer's phone numbers: +358503754069 , +358294151407 (Dario Gasbarra)



Kamppi Center to Lammin Biologinen Asema

9:13 AM - 11:37 AM (2 h 24 min)



Map data ©2016 Google 10 km

**9:13 AM** ○ **Kamppi Center**  
Urho Kekkosen katu 1, 00100 Helsinki

🚶 **Walk**  
About 2 min , 110 m  
Use caution - may involve errors or sections not suited for walking

↑ Head northeast on Urho Kekkosen gata/Urho Kekkosen katu toward Annankatu/Annegatan  
25 m

↩ Turn left at Annankatu/Annegatan  
Destination will be on the left  
80 m

**9:15 AM** ○ Helsinki linja-autoasema, Kamppi laituri 20

🚌 **Helsinki - Valkeakoski - Tampere** Tampere linja-autoasema T  
1 h 15 min (15 stops)  
Service run by Matkahuolto / Väinö Paunu Oy

**10:30 AM** ○ Hämeenlinna linja-autoasema laituri 5

**10:35 AM** ○ Hämeenlinna linja-autoasema laituri 1

🚌 **Turku - Hämeenlinna - Lahti** Lahti Matkakeskus T  
30 min (7 stops)  
Service run by Matkahuolto / Koiviston Auto Oy

**11:05 AM** ○ Kirkkokallio I

🚶 **Walk**  
About 32 min , 2.7 km  
Use caution - may involve errors or sections not suited for walking

↑ Head southeast on Valtatie 12/Route 12 toward Mommilantie/Route 2951  
1.3 km

↩ Turn left onto Pääjärventie  
Destination will be on the right  
1.4 km

**11:37 AM** ○ **Lammin Biologinen Asema**  
Pääjärventie 320, 16900 Lammi

#### Tickets and information

Matkahuolto / Koiviston Auto Oy - 0200 4000

Matkahuolto / Väinö Paunu Oy - 0200 4000

These directions are for planning purposes only. You may find that construction projects, traffic, weather, or other events may cause conditions to differ from the map results, and you should plan your route accordingly. You must obey all signs or notices regarding your route.