Brain Imaging and Beyond

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St Mary's College, Durham, UK, 14.00

Outline

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- In 2007 281 billion *gigabytes* of data was generated. In terms of digital bits this corresponds to a number exceeding the number of stars in the universe or Avogadro's number.

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- John Tukey once said “The best thing about being a statistician is that you get to play in everyone’s backyard.”

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- The hypotheses are sometimes difficult to formalize, and the temporal sampling very sparse.

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- A scanner can then measure the energy released by the molecules.

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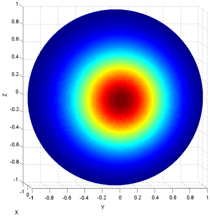
- In neurodegenerative diseases the directionality of the density usually becomes less clear.

Diffusions in Space



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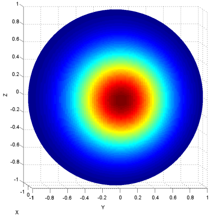

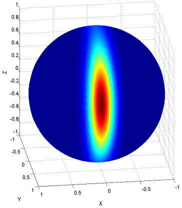

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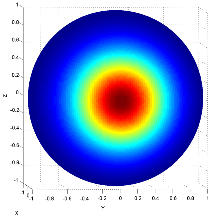

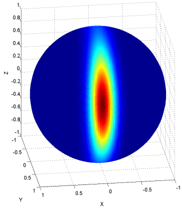

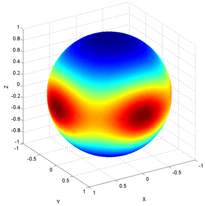

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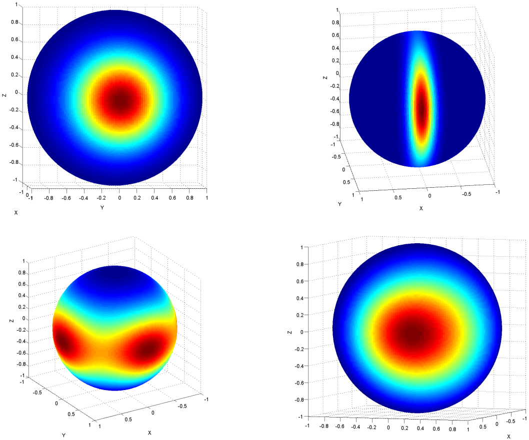

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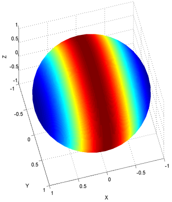

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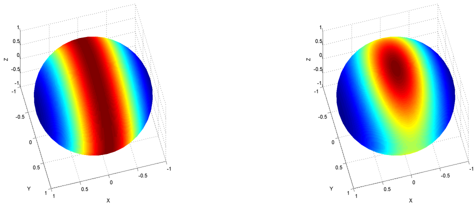

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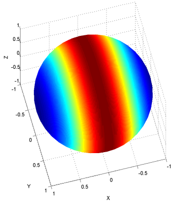

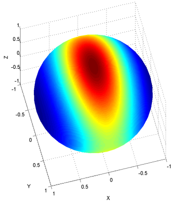

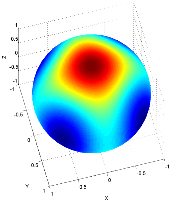

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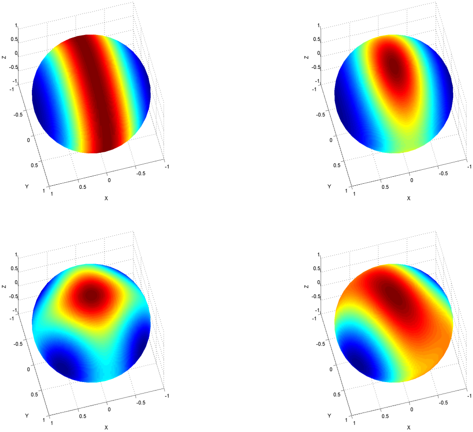

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- This is known not to fit well (excess kurtosis), even in the simplest case of no orientational heterogeneity [5, 2].
- From all individually fitted PDFs, a connectivity map is obtained from “connect the dots”, or “tracking”.

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- “Far better an approximate answer to the right question, than the exact answer to the wrong question, which can always be made precise.”

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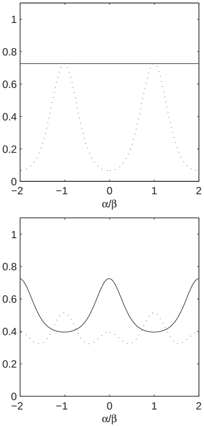

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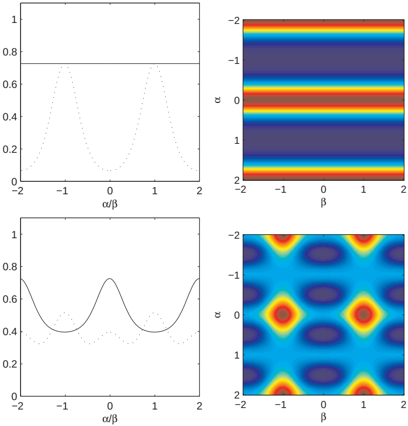

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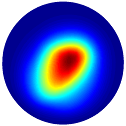

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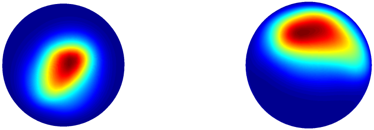

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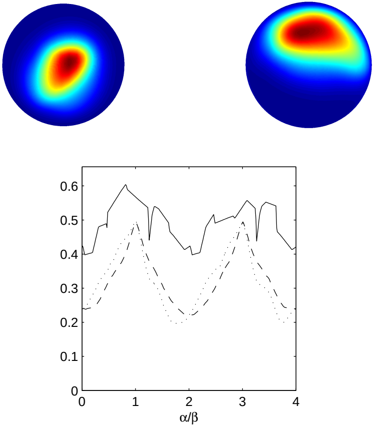

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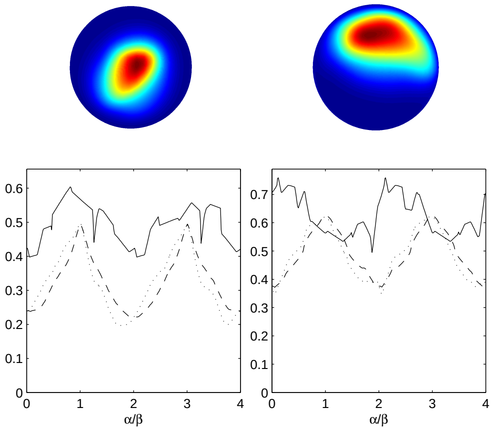

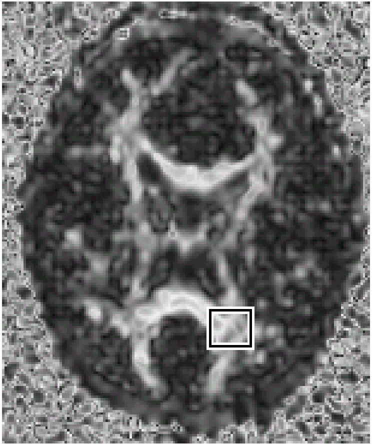

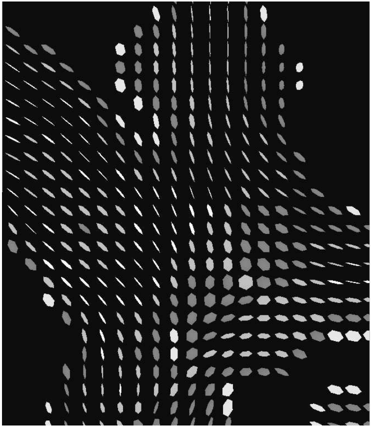

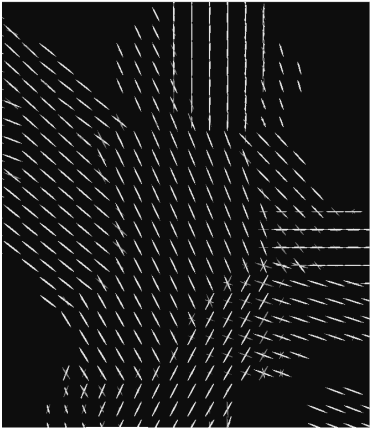

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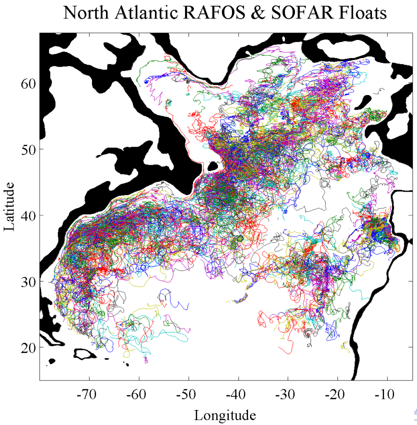

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- To improve the training of PhD students there are a number of graduate training centres, notably Academy for PhD Training in Statistics, the London Taught Course Centre and the Scottish Mathematical Sciences Training Centre.

Important Developments:

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- Problems motivated by imaging (i.e. fMRI).

UK

- Areas include: *Biostatistics* (Wilkinson (Newcastle), Green (Bristol), Richardson (ICL), Balding (ICL)), *Causality*, (Dawid (Cambridge), Lauritzen (Oxford), Smith (Warwick)), *MCMC* (Andrieu (Bristol), Green (Bristol), Richardson (ICL), Roberts (Warwick)...), *time series and statistical signal processing* (Holmes (Oxford), Nason (Bristol), Olhede (ICL & UCL), Walden (ICL)), Machine learning (Cristianini (Bristol), Shawe-Taylor (UCL), Titterington (Glasgow)), *Shape Analysis*, (Bowman (Glasgow), Kent, Mardia (Leeds)), *large p small n*, (Meinshausen (Oxford), Cheng (UCL), Yao (LSE), Samworth (Cambridge)), *functional data analysis*, (Farraway (Bath), Guillas (UCL)), *Algebraic Statistics* (Wynn (LSE)), *Model Choice*, (Jon Foster (Southampton), Brown (Kent)), *Bayesian Theory* Walker (Kent), *Ecological Statistics* (Morgan (Kent)) *etc*.

UCL

- **Computational Statistics** Trevor Sweeting, Jing-Hao Xue, Serge Guillas, Ricardo Silva, Alex Beskos.
- **Medical Statistics** Rumana Omar, Julie Barber and Gareth Ambler.
- **Multivariate and High Dimensional Data** Tom Fearn, Christian Hennig, Jing-Hao Xue, Ming-Yen Cheng, Ricardo Silva, Sofia Olhede.
- **Non-Parametric Methods** Ming-Yen Cheng , Christian Hennig, Sofia Olhede, Serge Guillas.
- **Stochastic Modelling** Valerie Isham, Paul Nothrup, Richard Chandler, Hilde Herdeboot.
- **Time Series** Richard Chandler, Sofia Olhede, Serge Guillas.

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- UCL also has an interdisciplinary PhD training centre CoMPLEX of which Statistical Science is a member.

References I

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