Computational Modelling for Biomedical Imaging

Daniel Alexander
D.Alexander@ucl.ac.uk

Course aims

- Practical introduction to the computational tools underlying modeling and indirect estimation.
- Framed within the application of biomedical imaging.
- Learn about some interesting imaging and image analysis techniques.

Learning outcomes

- Practical modelling and estimation techniques:
  - Experience with fitting algorithms and common models
  - How to handle real-world data
- Common aims in imaging science
- Some specific imaging techniques
- Some matlab programming

Related courses

- Inverse problems in imaging GV08
  - Simon Arridge
- Machine vision GI14
  - Gabriel Brostow
- Medical imaging MPHYGB10 and MPHYGB11
  - Various
- Information processing in medical imaging MPHYGB06
  - Sebastien Ourselin

Prerequisites

- Engineering mathematics
  - Probability
  - Linear algebra
  - Statistics
  - Calculus
- Mathematical programming
  - Matlab

Course components

- Danny Alexander: fundamentals of parameter estimation.
- Gary Zhang: advanced models – statistical inference and ill-posed problems.
- Ivana Drobnjak: practical modelling and estimation.

Week starting	Monday 15-18	Friday 14-16	Milestones
12/1/15	Danny		CW1 set
19/1/15	Danny		
26/1/15	Danny		
2/2/15	Gary		CW2 set
9/2/15	Gary		CW1 deadline (Monday noon)
16/2/15	Reading week: no lectures or lab classes		
23/2/15	Danny 1h/ Gary 2h		
2/3/15	Gary		
9/3/15	Ivana		CW2 deadline (Monday noon)
16/3/15	Ivana (Gary 1h)		
23/3/15	Ivana	Project	Project deadline after

Assessment

- Three courseworks:
- CW1: Fundamentals of modelling and estimation
  - Danny 35%
- CW2: Multi-scale and non-parametric models
  - Gary 15%
- Group and individual projects
  - Ivana 50%
- Collaboration vs plagiarism.

Lecture support

- Lab classes
  - Fridays 14-16
  - Lab demonstrators: Andrada Ianus and Alexandra Young.
  - CS Accounts required
- Project leaders
  - Enrico Kaden, Andrew Melbourne, Jamie McClelland
- Moodle site
  - Lecture slides, supporting material, coursework information.
- Pen and paper!

Part 1

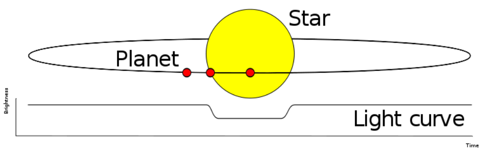
- Parameter estimation
- Uncertainty
- Model selection
- Experiment design

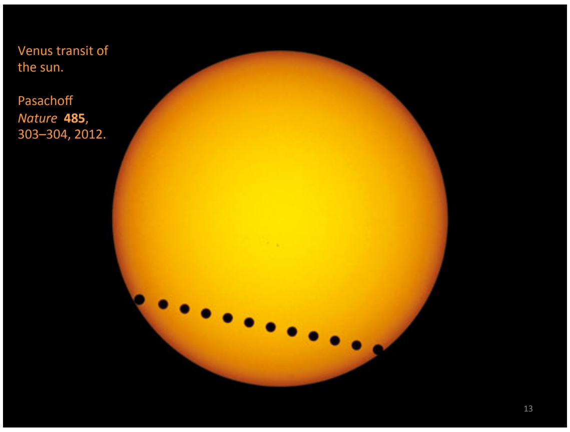
Recommended reading:
www.causascientia.org/**math**_stat/Tutorial.pdf

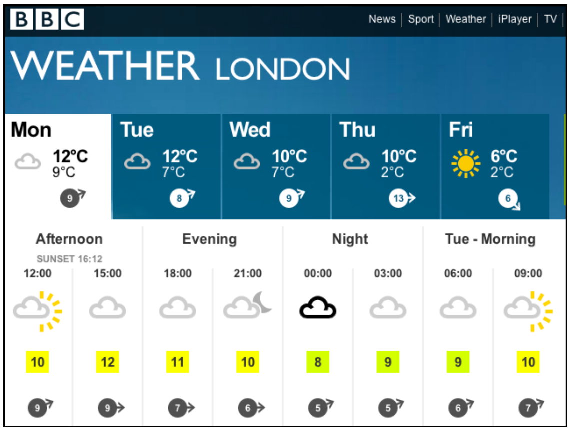
Indirect measurement

- Evaluate a quantity we cannot measure directly.
- We can measure something else sensitive to that quantity.
- We need a model to relate the quantity we want to what we can measure.

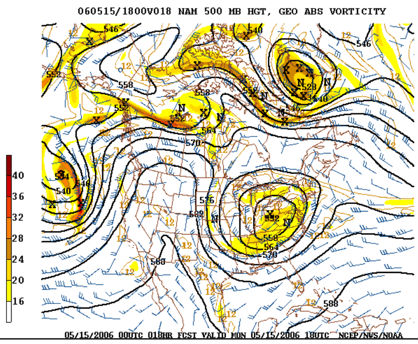
Example: exoplanets







Weather forecast



15

What is a model?

- Set of equations (mathematical model) or algorithms (computational model) that relate properties of a system to an observable signal.

Physical system → Signal → Sensor → Noise statistics → Measurement

Some unknown parameters $\mathbf{x} = (x_1, \ldots, x_N)^T$

Mostly known settings $\mathbf{y} = (y_1, \ldots, y_M)^T$

Known or unknown parameters $\mathbf{z} = (z_1, \ldots, z_L)^T$

For a more general discussion of this question, see: http://www.emily-griffiths.postgrad.shef.ac.uk/models.pdf

CMBI: Daniel Alexander 16

What is a parameter?

- Parameters are, often unknown, properties of the system that become variables of the model.

Physical system → Signal → Sensor → Noise statistics → Measurement

Some unknown parameters $\mathbf{x} = (x_1, \ldots, x_N)^T$

Mostly known settings $\mathbf{y} = (y_1, \ldots, y_M)^T$

Known or unknown parameters $\mathbf{z} = (z_1, \ldots, z_L)^T$

CMBI: Daniel Alexander 17

What is data?

- Data are measurements from a device/sensor that have sensitivity to the parameters of the system.

Physical system → Signal → Sensor → Noise statistics → Measurement

Some unknown parameters $\mathbf{x} = (x_1, \ldots, x_N)^T$

Mostly known settings $\mathbf{y} = (y_1, \ldots, y_M)^T$

Known or unknown parameters $\mathbf{z} = (z_1, \ldots, z_L)^T$

CMBI: Daniel Alexander 18

What is noise?

- Noise is any influence on the data not explained by the model.

Physical system → Signal → Sensor → Noise statistics → Measurement

Some unknown parameters $\mathbf{x} = (x_1, \ldots, x_N)^T$

Deterministic or statistical

Mostly known settings $\mathbf{y} = (y_1, \ldots, y_M)^T$

Usually deterministic

Known or unknown parameters $\mathbf{z} = (z_1, \ldots, z_L)^T$

Usually statistical

Usually statistical

Types of noise

- Measurement error
- Quantization or truncation error
- Modelling error
- Catastrophic failure

- E.g. for additive noise $A(\mathbf{y}) = S(\mathbf{x};\mathbf{y}) + \eta(\mathbf{z})$

What can we do with a model?

- Learn about the world
  - By studying its behaviour
- Estimate parameters
  - By fitting the model to data
- Make predictions
  - By propagating its behaviour into the future

Where do they come from?

- Models themselves come from deep understanding of a system.
- The course focuses on tools for exploiting models once we have them.
- That knowledge is helpful in designing models themselves, but only a small component!