



Computational Uncertainty Quantification for Inverse problems

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Inverse Problems

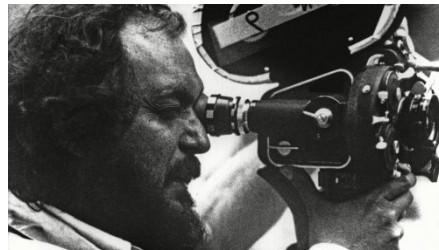
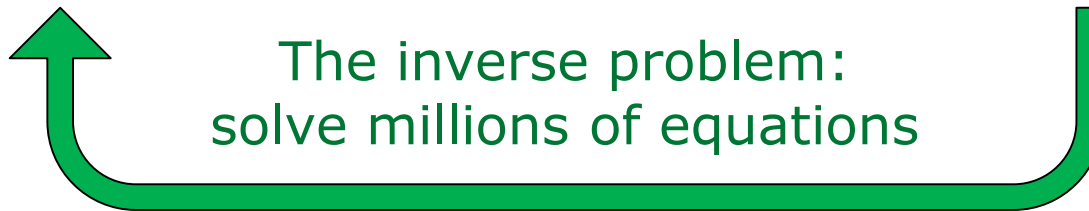
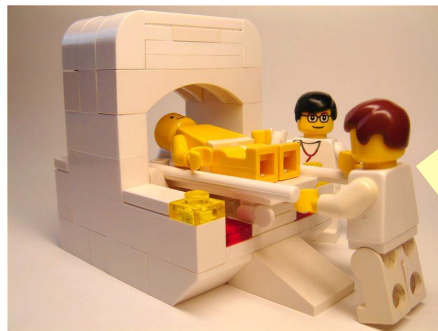


Image
deblurring

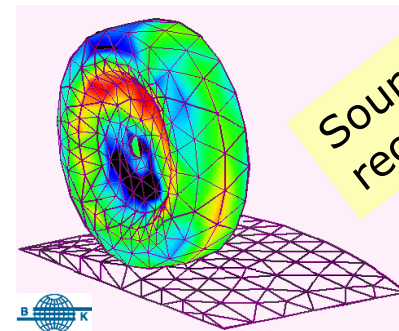


The inverse problem:
solve millions of equations

Light influx
thru windows



Computed
tomography

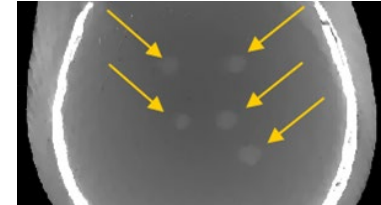


Sound source
reconstruction

Uncertainty Quantification (UQ)

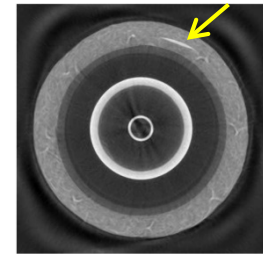
X-ray medical imaging (CT)

- How reliable are the computed spots?



Tomographic industrial inspection

- How reliable are the computed defects?



All kinds of errors have influence on, e.g., a least squares solution:

$$\mathbf{x} = \text{arg min} \|\mathbf{A} \mathbf{x} - \mathbf{b}\|_2$$

Diagram illustrating the components of the least squares solution equation:

- \mathbf{x} is associated with **algorithm-error**.
- \mathbf{A} is associated with **model-error**.
- \mathbf{b} is associated with **data-error**.



UQ: the mathematical study of the impact of all forms of error and uncertainty.

OK – I Know How to Do That ...

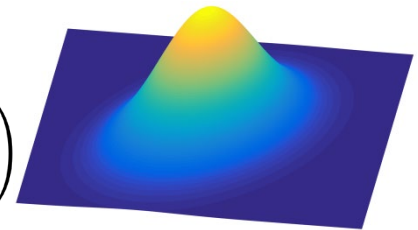
Statistics 101

Linear model with Gaussian noise and a Gaussian prior for \mathbf{x} :

$$\mathbf{b} = \mathbf{A} \mathbf{x} + \mathbf{n} , \quad \mathbf{n} \sim \mathcal{N}(\mathbf{0}, \lambda^{-1} \mathbf{I}) , \quad \mathbf{x} \sim \mathcal{N}(\mathbf{0}, \delta^{-1} \mathbf{I}) .$$

The *posterior* for the solution \mathbf{x} is

$$p(\mathbf{x}|\mathbf{b}, \lambda, \delta) \propto \exp \left(-\frac{\lambda}{2} \|\mathbf{A} \mathbf{x} - \mathbf{b}\|_2^2 \right) \cdot \exp \left(-\frac{\delta}{2} \|\mathbf{x}\|_2^2 \right)$$



and it gives a complete statistical quantification of the uncertainty in \mathbf{x} .

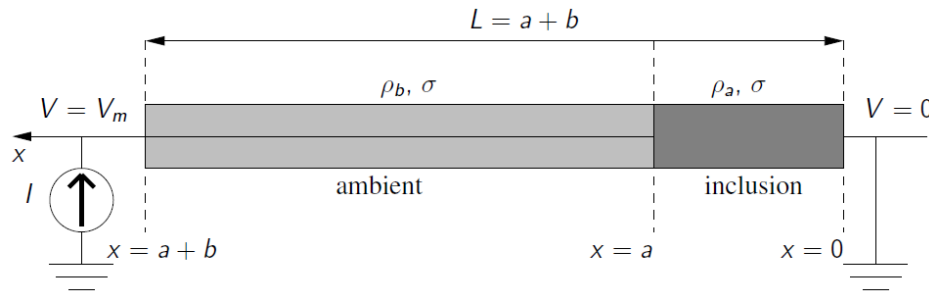
But this basic result can **only** be used:

- for least squares problems
- with Gaussian noise, uncertainties, and priors
- and without constraints (e.g. non-negativity).

- CUQI**
1. Define a common **framework** for general UQ problems.
 2. Develop new sampling **methods** and yet unknown **algorithms**.

Case: UQ for Electric Conductivity

Mirza Karamehmedovic
DTU Compute



Unknown: the length a .

Cannot use Ohm's law.

Use a stochastic differential equation to model the current.

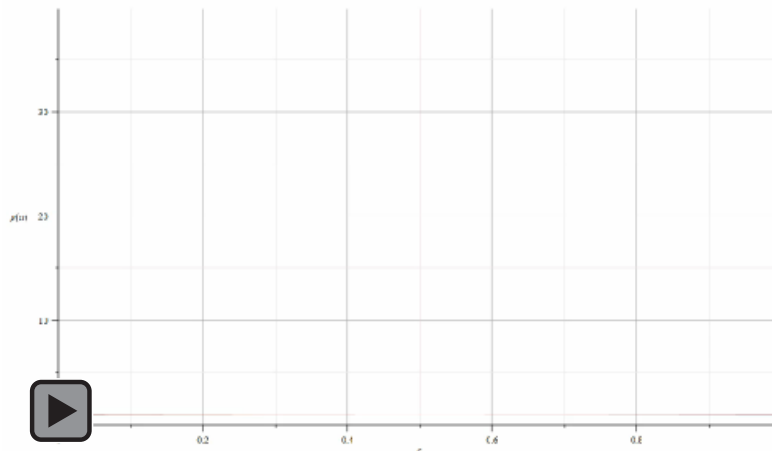
Bayes theorem:

$$p(a|V_m) \propto p(V_m|a) \cdot p(a) .$$

solution's posterior

data likelihood
Gaussian

prior for solution
truncated Gaussian



The evolution of the
solution's posterior $p(a|V_m)$
as we increase the number of
observations.

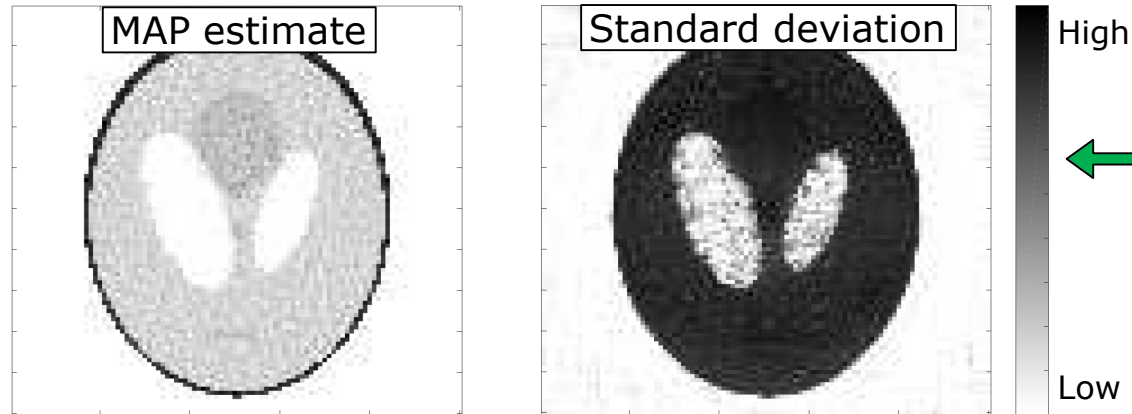
Case: UQ for Non-Negative Prior

Johnathan M. Bardsley
Univ. of Montana

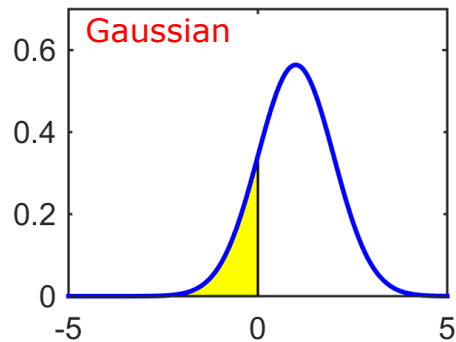
PCH, DTU Compute

Positron emission tomography

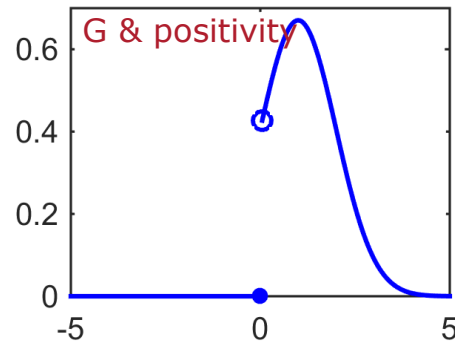
- How reliable is the image?



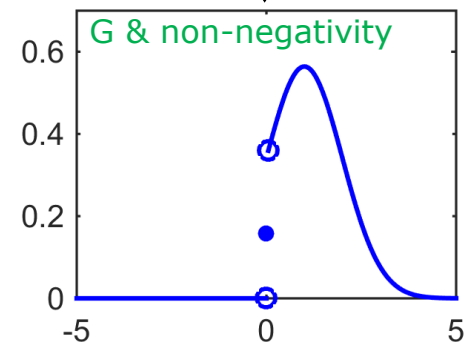
$$\min_x \|Ax - b\|_2 \quad \text{s.t.} \quad x \geq 0, \quad x \sim \mathcal{N}(0, \delta^{-1}I)$$



Analytical solution



Variable transform
 $x = \exp(z)$

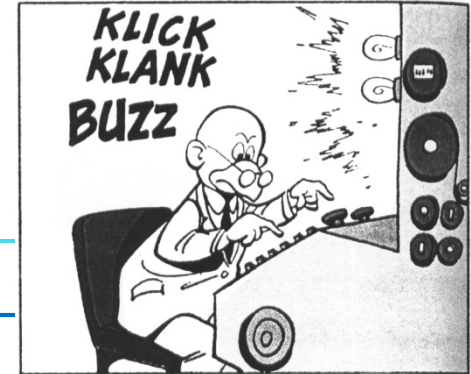


New MCMC method
*Nonnegative Hierarchical
Gibbs Sampler.*

Case: UQ for compressed sensing

$$\min_x \|A x - b\|_2 \quad \text{s.t.} \quad \|x\|_1 \leq \delta$$

➤ Today: 500 lines of code



Future: 5 lines of model description

```
variable x(n,1) % Define unknown vector.
parameter delta:Gauss(mean=0.1,std=0.02) % Parameter with Gauss distrib.
UQ_data_model(b,Poisson,mean=A*x_exact) % Data with Poisson noise
UQ_minimize misfit(A*x,b) % Solution that fits data
subject_to UQ_prior(x,sparse,delta) % ... with a sparsity prior.
```

CUQI

1. **Mathematical models** for non-Gaussian cases.
2. **Algorithms** for sampling large-scale UQ problems.
3. **Modeling platforms** with software to aid non-experts.

More Examples and Stuff

Please visit CUQI's homepage: compute.dtu.dk/cuqi

