GEOS F493 / F693
Geodetic Methods and Modeling

– Lecture 08b: Parameter Estimation –

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“Guess the Process”

This more of a “different angles on the same process:”

`http://topex.ucsd.edu/Ecuador/`

Parameter Estimation

- We have measurements and an idea about the process - how do we get **best estimate** for parameters? E.g.,

$$d = a + b * x$$

  where

  - d are the measurements (column vector)
  - x are the “coordinates” of the measurements (column vector)
  - a, b describe the process (scalars)
- What is a **best estimate**?
- Yes, inference of parameters from measurements is an **estimation**! WHY?

Matrix Notation (annotate here...)

Parameter Estimation

Let's look at an example (`least_squares.py`) ...

Least Squares Solution

- least squares is general approach to solve **linear** systems of equations
- linear systems obey superposition and scaling
- assume m_i are model parameters, which of these are linear?

$$
\begin{aligned}
d &= m_1 + m_2 x - (1/2) m_3 x^2 \\
d &= (m_1 - m_2 x)^{1/2} - m_3^2 x
\end{aligned}
$$

- General form: $\mathbf{d} = \mathbf{G}\mathbf{m} + \epsilon$

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  - **d** is data vector
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  - **m** model parameters that “tweak” **G**
  - ϵ residuals / measurement errors

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  - ϵ residuals / measurement errors
- Solve for **m**!

Least Squares Solution

- General form: $\mathbf{d} = \mathbf{Gm} + \epsilon$
- Least squares solution: $\mathbf{m_{est}} = (\mathbf{G^T G})^{-1} \mathbf{G^T d}$

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Most problems result in same least squares solution

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- Probabilistic approach:
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- Geometric approach:
  - solution is a projection from data space into model space, what is projection of vector b in direction of vector a

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Variational Approach

- choose solution where residual vector **r** has minimum length
- most common is standard geometric / Euclidean length / L_2 - norm:

$$L_2 = (r_1^2 + r_2^2 + r_3^2 + r_4^2 \dots)^{-1/2} = \sqrt{\sum_{i=1}^{N} r_i^2}$$

- L_1 - norm less sensitive to bias from single bad points:

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- L_1 solution: $\mathbf{G^T R G m_{est}} = \mathbf{G^T R d}$
  - R: diagonal weighting matrix : $R_{i,i} = 1/|r_i|$
  - nonlinear, need iterative alorithm (IRLS) to solve
  - IRLS starts with $m_{est}^0 = m_{est,L_2}$ solution, construct R^0 using residuals
  - iterate until some threshold reached

Variational Approach

- $\mathbf{d} = \mathbf{Gm} + \epsilon$
- calculate $\mathbf{m_{est}} = (\mathbf{G^T G})^{-1}\mathbf{G^T d}$
- get residuals $\mathbf{r_{est}} = \mathbf{d} - \mathbf{Gm_{est}}$
- define $j(\mathbf{m}) = \mathbf{r^T r} = (\mathbf{d} - \mathbf{Gm})^{\mathbf{T}}(\mathbf{d} - \mathbf{Gm})$
- find minimum j: $\delta j(\mathbf{m_{est}}) = 0$

Confidence Intervals

- if independent and normally distributed data errors:
- $COV(m_{L_2}) = \sigma^2(G^TG)^{-1}$
- get 95% confidence intervals:
  - each model parameter m_i has normal distribution
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  - 1.96 comes from:

$$\frac{1}{\sigma\sqrt{2\pi}} \int_{-1.96\sigma}^{1.96\sigma} e^{-\frac{x^2}{2\sigma^2}} dx \approx 0.95$$

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- model uniqueness

- instability

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- instability
  - small change in measurement results in enormous change in parameter estimates
  - possibly stabilize such problems regularization (smoothing)