Gradient and other methods

Session 5
State of the art

• Machine learning to breed next trial solution
• Polynomial Chaos/maximum likelihood
• L1/Entropy norm based minimization (sparse minimization)
• Variational and matrix minimization (non parametric)
Identify and prioritize gaps

- Met data with errors you can trust.
- More obs (any kinds, better the parameters you are interested in).
- Novel cost function to improve convergence
Suggest path forward

• Better use of knowledge gained during the estimation procedure (stochastic optimization)
• Representative meteorology ensemble
• Estimation of model error
• Source parameters uncertainty characterization

More observations
• The problem (rapid response/reconstruction and observations quality) defines the method.
• Meteorology cannot be 100% trusted
• 2 approaches:
  – Precalculations
  – Inversion
• Some precalculations can be done to allow computationally expensive solution be used in rapid response (eg: Finland, France agencies)
  – This works if you know a priori where release is likely to come from, eg: power plants, etc.
• Parametric / non parametric methods
  – Parametric better suited to local problems.
  – Non parametric is akin to meteorological data assimilation better suited to synoptic and regional problems.
- Rain washing can play key role and can hardly be reconstructed even with the best model.
- Forward models are not good enough if we start to look at different scales, and particularly above the boundary layer for long range transport.
• Group expertise covers gradient and evolutionary algorithm, machine learning.
• Function evaluations
• Number of sources is big issues, because it’s an integer.
• Identify source number (L1 norm) first then refine with a gradient descent for the strength.
• Machine learning (trees and rules)
• Each algorithm needs to be courageous at the beginning and chicken at the end
• The cost function needs to be smoothed to reduce iterations.
Uncertainty

• Uncertainty propagation:
  – Use of ensemble, EnVar
  – Polynomial Chaos