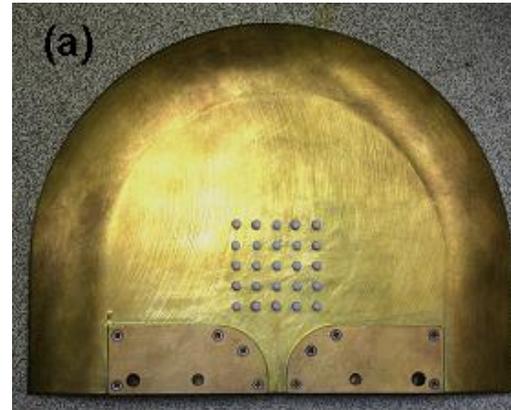
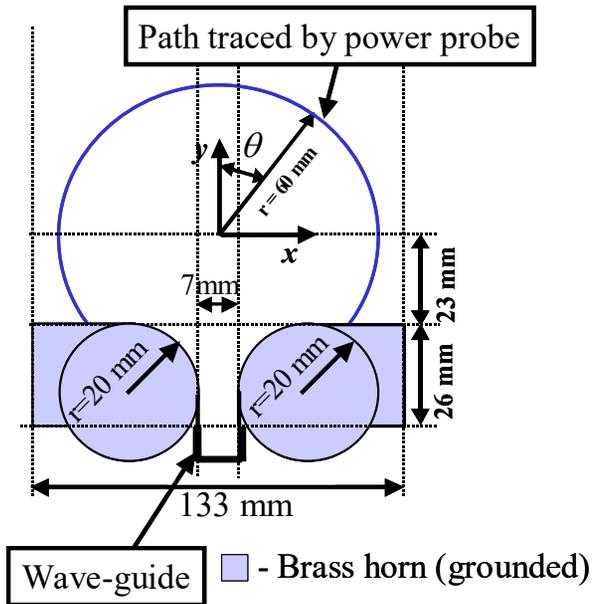


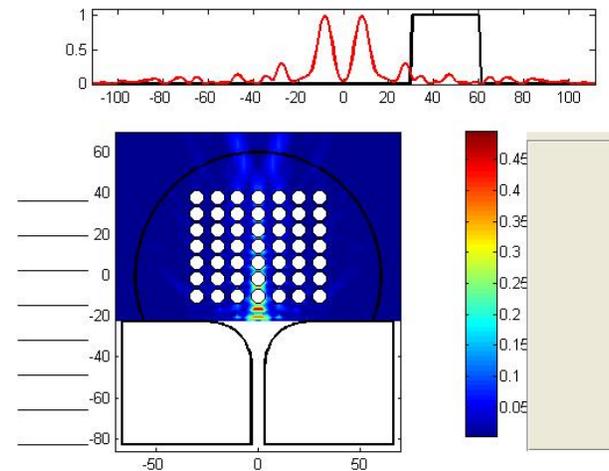
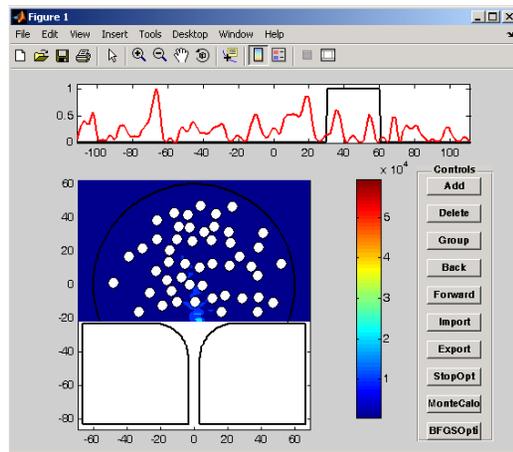
# A practical introduction to adjoint methods

**Leslie Greengard**  
CCM

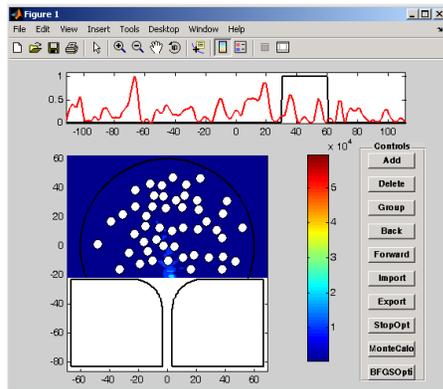
# Model Problem: Electromagnetic Design



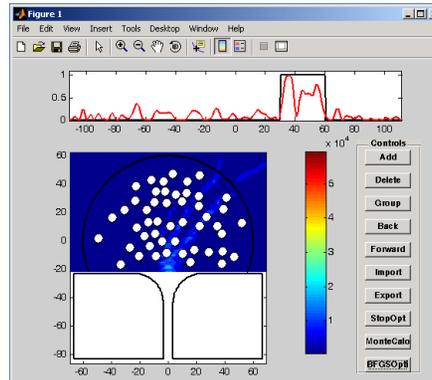
Gheorma, Haas, Levi (2004)  
 Zhao, Cheng, Gimbutas, G- (2007)



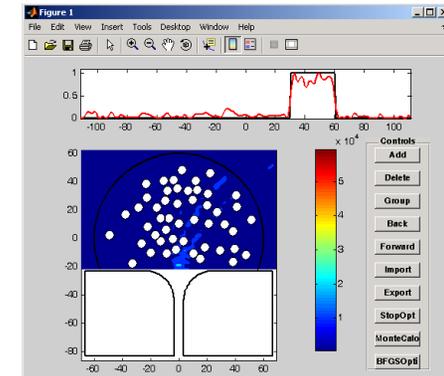
# Model Problem: Electromagnetic Design



Snapshot of the GUI for the initial configuration (randomly place rods).



Snapshot of the GUI after 14 BFGS iterations.

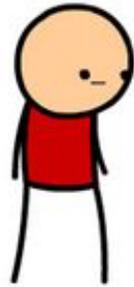


Snapshot of the GUI after 60 BFGS iterations.

Adjoint methods allow for the calculation of the gradient of the objective function with respect to all cylinder center coordinates using only 4 solutions of the adjoint of the scattering problem. (Finite difference approximation of the gradient would require  $2N$  scattering calculations, where  $N$  is the number of rods.)

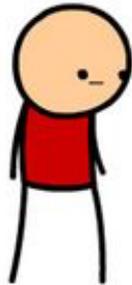
# Scenario 1

I have to solve a large linear system with many right-hand sides. What's the fastest method I can use?



# Scenario 1

Well, if you factor A  
using  $N^3$  operations, solving for  
each right hand side takes only  $N^2$   
work



I have to solve a large  
linear system with many right-  
hand sides. What's the fastest  
method I can use?



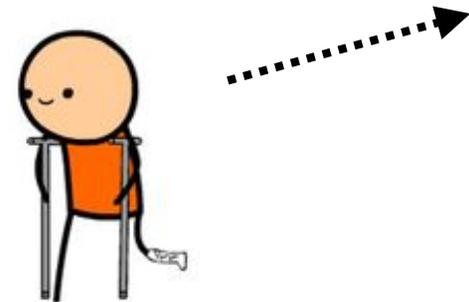
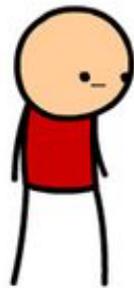
$$A = LU \quad \Rightarrow \quad A^{-1} = U^{-1}L^{-1}$$

$$A \in \mathbb{R}^{N \times N}$$

# Algorithm 1

- 1) **Compute**  $A = LU$   $\leftarrow O(N^3)$  work
- 2) For  $i = 1, \dots, M$   
 $x_i = U^{-1}L^{-1}b_i$   $\leftarrow O(MN^2)$  work

Thanks - bye.



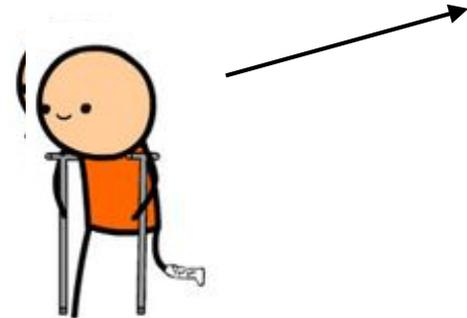
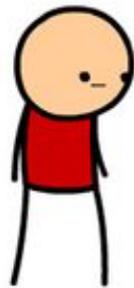
# Algorithm 1

1) **Compute**  $A = LU$

2) For  $i = 1, \dots, M$

$$x_i = U^{-1}L^{-1}b_i$$

Hey, wait a minute. What are you going to do with the answers?



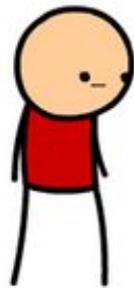
# Algorithm 1

1) Compute  $A = LU$

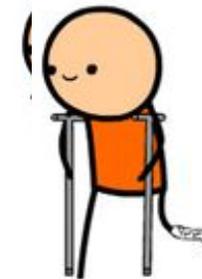
2) For  $i = 1, \dots, M$

$$x_i = U^{-1}L^{-1}b_i$$

Hey, wait a minute. What are you going to do with the answers?



Compute their average  
 $a_i = \langle c, x_i \rangle = c^T x_i$

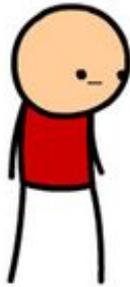


$$c = \frac{1}{N}(1, 1, \dots, 1)$$

# Algorithm 2 (Adjoint State Method)

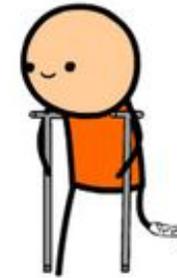
But then I have a *much better idea*

$$a_i = c^T x_i = c^T A^{-1} b_i = b_i^T A^{-T} c$$



Compute their average

$$a_i = \langle c, x_i \rangle = c^T x_i$$



1) **Compute**  $A = LU$   $\leftarrow O(N^3)$  work

3)  $q \equiv A^{-T} c = L^{-T} U^{-T} c$   $\leftarrow O(N^2)$  work

4) For  $i = 1, \dots, M$

$a_i = b_i^T q$   $\leftarrow O(MN)$  work!

# Gradient Evaluation

- Suppose  $\mathbf{x}$  is the solution of a linear system (linear PDE, etc.) that involves  $\mathbf{p} = (p_1, p_2, \dots, p_M)$  design parameters or control variables
- We would like to compute the gradient of some objective function  $g(\mathbf{p}, \mathbf{x})$  with respect to parameters  $p_1, p_2, \dots, p_M$ :

$$\frac{dg}{dp_j} = \frac{\partial g}{\partial p_j} + \sum_{i=1}^N \frac{\partial g}{\partial x_i} \frac{\partial x_i}{\partial p_j}$$

$$\frac{dg}{d\mathbf{p}} = \mathbf{g}_p + \mathbf{g}_x \mathbf{X}_p$$

The diagram illustrates the dimensions of the terms in the equation  $\frac{dg}{d\mathbf{p}} = \mathbf{g}_p + \mathbf{g}_x \mathbf{X}_p$ . The dimension  $1 \times M$  is associated with the gradient vector  $\frac{dg}{d\mathbf{p}}$ . The dimension  $1 \times N$  is associated with the row vector  $\mathbf{g}_x$ . The dimension  $N \times M$  is associated with the matrix  $\mathbf{X}_p$ . Arrows indicate that  $\mathbf{g}_p$  and the product  $\mathbf{g}_x \mathbf{X}_p$  both result in a  $1 \times M$  dimension.

# Gradient Evaluation

$$\frac{dg}{dp_j} = \frac{\partial g}{\partial p_j} + \sum_{i=1}^N \frac{\partial g}{\partial x_i} \frac{\partial x_i}{\partial p_j}$$

$$\frac{dg}{d\mathbf{p}} = g_{\mathbf{p}} + g_{\mathbf{x}} \mathbf{X}_{\mathbf{p}}$$

- Reasonable to assume  $g$  is known analytically so that  $\frac{\partial g}{\partial p_j}, \frac{\partial g}{\partial x_i}$  are easily computed.

- $\mathbf{x}$  on the other hand is the solution to  $A\mathbf{x} = \mathbf{b}$  so that

$$A_{p_j} \mathbf{x} + A \mathbf{x}_{p_j} = b_{p_j} \Rightarrow \mathbf{x}_{p_j} = A^{-1} [b_{p_j} - A_{p_j} \mathbf{x}]$$



**M applications of  $A^{-1}$**

# Gradient Evaluation

$$\frac{dg}{dp_j} = \frac{\partial g}{\partial p_j} + \sum_{i=1}^N \frac{\partial g}{\partial x_i} \frac{\partial x_i}{\partial p_j} \qquad \frac{dg}{d\mathbf{p}} = g_{\mathbf{p}} + g_{\mathbf{x}}\mathbf{X}_{\mathbf{p}}$$

The most expensive term (from previous slide) can be written:

$$g_{\mathbf{x}}\mathbf{X}_{\mathbf{p}} = g_{\mathbf{x}}A^{-1}[b_{\mathbf{p}} - A_{\mathbf{p}}\mathbf{x}]$$

We have  $g_{\mathbf{x}}\mathbf{X}_{\mathbf{p}} = [g_{\mathbf{x}}A^{-1}][b_{\mathbf{p}} - A_{\mathbf{p}}\mathbf{x}] = \mathbf{q}[b_{\mathbf{p}} - A_{\mathbf{p}}\mathbf{x}]$

$1 \times N \qquad N \times M$

where.  $\mathbf{q}^T = A^{-T}g_{\mathbf{x}}^T$

# Nonlinear Problems

$$\frac{dg}{dp_j} = \frac{\partial g}{\partial p_j} + \sum_{i=1}^N \frac{\partial g}{\partial x_i} \frac{\partial x_i}{\partial p_j} \quad \frac{dg}{d\mathbf{p}} = \mathbf{g}_p + \mathbf{g}_x \mathbf{X}_p \quad (\text{still})$$

Suppose

$$\mathbf{f}(\mathbf{x}, \mathbf{p}) = 0 \Rightarrow \mathbf{f}_x \mathbf{x}_p + \mathbf{f}_p = 0 \Rightarrow \mathbf{x}_p = -\mathbf{f}_x^{-1} \mathbf{f}_p = -\mathbf{J}^{-1} \mathbf{f}_p$$

Then.  $\mathbf{g}_x \mathbf{x}_p = [\mathbf{g}_x \mathbf{J}^{-1}] \mathbf{f}_p = \mathbf{q} \mathbf{f}_p$

where  $\mathbf{q}^T = \mathbf{J}^{-T} \mathbf{g}_x^T$

$N \times N$  **Jacobian**

(Recall this is just a linearization about current guess)

# Initial Value Problems

$$\frac{d\mathbf{x}}{dt} = \mathbf{B} \mathbf{x}, \quad \mathbf{x}(0) = \mathbf{b} \quad \Rightarrow \quad \mathbf{x}(t) = e^{\mathbf{B}t} \mathbf{b}$$

Looks like  $A\mathbf{x} = \mathbf{b}$  with  $A = e^{-\mathbf{B}t}$ . Suppose now that we want to optimize some function  $g(\mathbf{p}, \mathbf{x}(t))$  based on the solution  $\mathbf{x}$  at time  $t$ .

$$\text{Then } g_{\mathbf{x}}\mathbf{x}_{\mathbf{p}} = g_{\mathbf{x}}A^{-1}[b_{\mathbf{p}} - A_{\mathbf{p}}\mathbf{x}] = \mathbf{q}[b_{\mathbf{p}} - A_{\mathbf{p}}\mathbf{x}]$$

$$\text{where } \mathbf{q}^T = A^{-T}g_{\mathbf{x}}^T = e^{\mathbf{B}^T t}g_{\mathbf{x}}^T$$

$$\text{That is, } \frac{d\mathbf{q}^T}{dt} = \mathbf{B}^T \mathbf{q}^T, \quad \mathbf{q}^T(0) = g_{\mathbf{x}}^T$$

$$\frac{dg}{d\mathbf{p}} = g_{\mathbf{p}} + g_{\mathbf{x}}\mathbf{x}_{\mathbf{p}} = g_{\mathbf{p}} + \mathbf{q}b_{\mathbf{p}} + \int_0^t \mathbf{q}(t-t')B_{\mathbf{p}}\mathbf{x}(t')dt'$$

# Summary

- **Start with the big picture**
- **Always consider adjoint ideas when computing gradients of functionals (objective functions)**

# References

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**<https://math.mit.edu/~stevenj/notes.html>**
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