



# ME 597/AAE 590 : Introduction to Uncertainty Quantification

Lecture 2: Sensitivity Analysis  
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# Why Sensitivity and Adjoint?

What inputs yield desired outputs ?

Can gain a lot more information than conventional single-point simulations!

**Tangent Problem:**  
How does a specific input affect all outputs?

**Adjoint Problem:**  
How is a specific output affected by all inputs?

Determine effect of uncertainties and tolerances

Plan experiments better

Improve single-point simulations

- Mesh sensitivity
- Sensitivity to iteration parameters

# Approaches

Jacobian

$$\mathbf{J} = \begin{bmatrix} \frac{\partial y_m}{\partial x_n} \end{bmatrix}_{m \times n}$$

m outputs

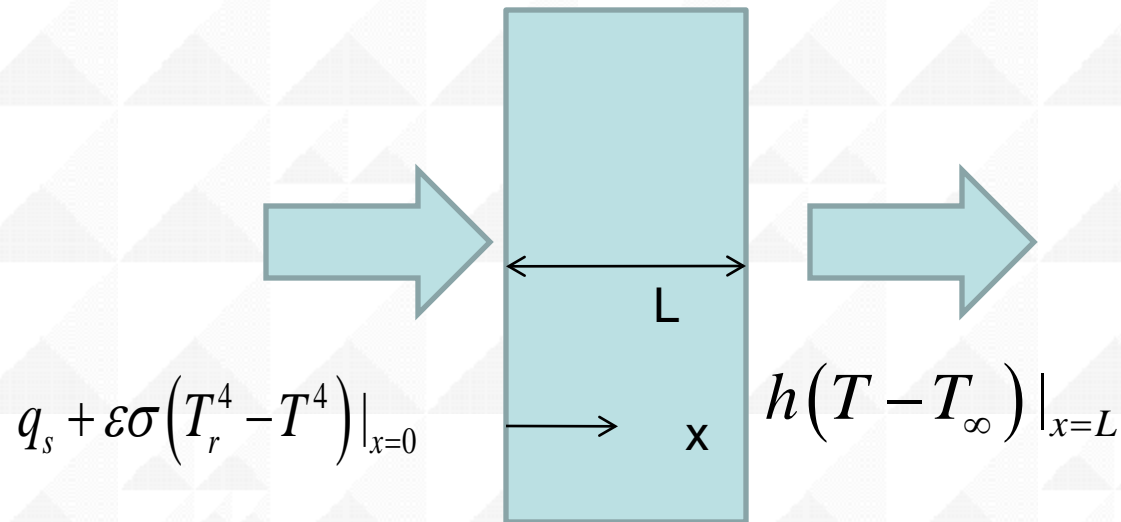
n inputs

- Continuous approach
  - Derive sensitivity/adjoint versions of pde
  - Discretize and solve
  - Need to repeat for each physical model
  - Generally more complex
- Discrete approach
  - Start with discrete pde and add sensitivity/adjoints
  - Easier to automate
  - Adjoints more difficult

# Continuous Approach: Sensitivity Equation

- Governing equations are differentiated with respect to each parameter of interest
- New PDEs are derived for the sensitivity coefficients, as well as appropriate boundary conditions
- These are solved using numerical methods similar (but not identical) to the original PDE
- CPU times scale sub-linearly with the number of parameters

# Example: Transient Heat Conduction in a 1D Slab



$$C \frac{\partial T}{\partial t} + \frac{\partial q}{\partial x} = 0 \quad q = -k \frac{\partial T}{\partial x}$$

$$q|_{x=0} = -k \frac{\partial T}{\partial x} \Big|_{x=0} = q_s + \epsilon\sigma(T_r^4 - T^4) \Big|_{x=0}$$

$$q|_{x=L} = -k \frac{\partial T}{\partial x} \Big|_{x=L} = h(T - T_\infty) \Big|_{x=L}$$

$$T(x, 0) = T_i$$

$$\text{Parameters: } C, k, q_s, \epsilon, T_r, h, T_\infty, T_i$$

# Sensitivity Equation for Heat Capacity

Differentiate energy equation wrt C:

$$\frac{\partial}{\partial C} \left[ C \frac{\partial T}{\partial t} + \frac{\partial q}{\partial x} \right] = C \frac{\partial}{\partial t} \left[ \frac{\partial T}{\partial C} \right] + \frac{\partial T}{\partial t} + \frac{\partial}{\partial x} \left[ \frac{\partial q}{\partial C} \right] = 0$$

Multiply by nominal value of C:

$$C \frac{\partial}{\partial t} \left[ C \frac{\partial T}{\partial C} \right] + C \frac{\partial T}{\partial t} + \frac{\partial}{\partial x} \left[ C \frac{\partial q}{\partial C} \right] = 0$$

Scaled sensitivity of q wrt C:

$$q_c = C \frac{\partial q}{\partial C} = -k \frac{\partial}{\partial x} \left( C \frac{\partial T}{\partial C} \right) = -k \frac{\partial}{\partial x} (T_c)$$

PDE for new variable  $T_c$  :

$$C \frac{\partial T_c}{\partial t} - \frac{\partial}{\partial x} \left[ k \frac{\partial T_c}{\partial C} \right] = -C \frac{\partial T}{\partial t}$$

# Boundary and Initial Conditions

At  $x=0$

$$q_C |_{x=0} = C \frac{\partial q}{\partial C} |_{x=0} = -k \frac{\partial T_C}{\partial x} |_{x=0} = -4\varepsilon\sigma T^3 T_C |_{x=0}$$

$$\text{i.e., } -k \frac{\partial T_C}{\partial x} |_{x=0} = -4\varepsilon\sigma T^3 T_C |_{x=0} \quad (\text{Linear in } T_C)$$

At  $x=L$

$$q_C |_{x=L} = C \frac{\partial q}{\partial C} |_{x=L} = -k \frac{\partial T_C}{\partial x} |_{x=L} = -h T_C |_{x=L} \quad (\text{Linear in } T_C)$$

Initial condition:

$$T_C(x, 0) = 0 \quad (\text{Homogeneous})$$

# Solution Procedure

- Need  $T$  to solve for  $T_C$  but not vice versa
- LHS of  $T_C$  equation identical to  $T$  equation (but not always true for all parameters)
  - Same coefficient matrix may be used
- Solution procedure would march  $T$  one time step, and then march  $T_C$  the same time step using just-computed  $T$
- Even for a non-linear problem, the sensitivity equation is linear
  - Solution cost lower than for original PDE
- But we have to create a new sensitivity PDE for each new parameter of interest!
- Very intrusive – have to code this in, debug, parallelize etc!



# Discrete Sensitivity Approaches

Jacobian

$$\mathbf{J} = \begin{bmatrix} \frac{\partial y_m}{\partial x_n} \end{bmatrix}_{m \times n}$$

m outputs

n inputs

- Objective is to determine the derivative of all outputs to a single input
- Useful if number of output parameters is large ( $m \gg n$ )
- Three main methods
  - Finite difference
  - Complex variables
  - Code differentiation

# Finite Difference Method

$$\frac{\partial f_j}{\partial x_k} = \frac{f_j(x_k + \Delta x_k) - f_j(x_k)}{\Delta x_k} + O(\Delta x_k)$$

- No code modification – unintrusive!
- Run code N+1 times to find derivatives wrt N parameters
- Each solve is a non-linear solve if original PDE is non-linear
- Need to choose  $\Delta$  carefully
  - too small -> roundoff errors
  - too large -> truncation errors
- Can yield very poor results for noisy functions
  - Most iterative solutions with finite termination criteria are noisy

# Complex Variables

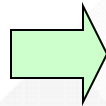
$$f_j(x_k + i\Delta x_k) = f_j(x_k) + i \frac{\partial f_j}{\partial x_k} \Delta x_k + O(i\Delta x_k)^2$$

- Replace all floating point variables with complex variables
- Set imaginary component to  $\Delta x_k$  for the variable we want derivatives with respect to
- No roundoff problems
- Still has truncation error
- Need to deal with relational operators etc.

# Code Differentiation

Consider code as a composition of unary and binary operations

We know how to propagate inputs to outputs for elementary operations



$$z = f(u) \quad z' = \frac{\partial f}{\partial u} u'$$

$$z = f(u, v) \quad z' = \frac{\partial f}{\partial u} u' + \frac{\partial f}{\partial v} v'$$

Apply chain rule

This process can be automated !

# Simple Example

Original Functions:

$$p = 3 * x^2 + \sin(y) \quad q = p / y$$

x,y: inputs    p,q: outputs

## Elemental Decomposition

$$t_1 = x * x$$

$$t_2 = 3 * t_1$$

$$t_3 = \sin(y)$$

$$p = t_2 + t_3$$

$$q = p / y$$

## Elemental Derivatives

$$t'_1 = x * x' + x' * x$$

$$t'_2 = 3 * t'_1$$

$$t'_3 = \cos(y) * y'$$

$$p' = t'_2 + t'_3$$

$$q' = (p' * y - y' * p) / y^2$$

# Simple Example (Cont'd)

Inputs:

$$x=10, y=\pi/3, x' = 1, y' = 0$$

Outputs:

$$p' = 60.0 = \left. \frac{\partial p}{\partial x} \right|_{x=10, y=\pi/3}$$

$$q' = 2958 = \left. \frac{\partial q}{\partial x} \right|_{x=10, y=\pi/3}$$

Derivatives are exact!

Inputs:

$$x=10, y=\pi/3, x' = 0, y' = 1$$

$$p' = -273.8795 = \left. \frac{\partial p}{\partial y} \right|_{x=10, y=\pi/3}$$

$$q' = -273.8795 = \left. \frac{\partial q}{\partial y} \right|_{x=10, y=\pi/3}$$

# What Did We Get?

- **Exact** value of derivative wrt variable whose prime was set to unity
  - Not subject to truncation as in finite difference
- Each variable and its prime must be stored
- Obtains numerical value of derivative, not symbolic
- Process works through loops, conditionals and iterations
- To evaluate derivative wrt another input, need to run code again
  - However, can exploit linearity of sensitivity calculation by turning on sensitivity only after basic single-point computation has converged
- Sensitivity is obtained at the nominal condition at which the single-point computation is done

# Conventional C Implementation

## Original C code

```
void myfunc (double x, double y, double *p, double *q){  
  
*p=3*x*x+sin(y);  
  
*q=*p/y; }  

```

## Differentiated code

```
void myfunc (double x, double y, double *p, double *q,  
double xp, double yp, double *pp, double *qp){  
double t1, tp1,t2, t2p, t3, t3p;  
t1 = x*x;          t1p = x*xp + xp*x;  
t2 = 3*t1;         t2p = 3*t1p;  
t3 = sin(y);       t3p = cos(y) * yp;  
*p = t2+t3;        *pp = t2p + t3p;  
*q = *p/y;         *qp = ((*pp)*y - yp*(*p))/(y*y);  
}  

```



# Conventional Code Differentiation

- For every variable we introduce a companion primed variable
- This process can be automated by tools like ADIFOR and ADIC
  - Parse FORTRAN/C code and produce new code with additional lines
- Need to deal with two versions of the code!
- Need to generate differentiated code every time original changes
- Often requires modifications of original code for special situations
- Generated code is not human readable
  - Harder to debug

# Alternative: Let the Compiler Do It!

- Use C++ language features
  - User-defined data types (classes)
  - Operator overloading
  - Templates and template meta-programming
  - Static initialization
  - Shared libraries

We define a template for the whole code which can be instantiated for any well defined algebra

# C++ Implementation

## Original C++ code

```
void myfunc (const double& x, const double& y,  
double& p, double& q){  
  
p=3*x*x+sin(y);  
q=p/y;}
```

## Templated C++ code

```
Template <class T>  
  
void myfunc (const T& x, const T& y,  
T& p, T& q){  
  
p=3*x*x+sin(y);  
q=p/y;}
```

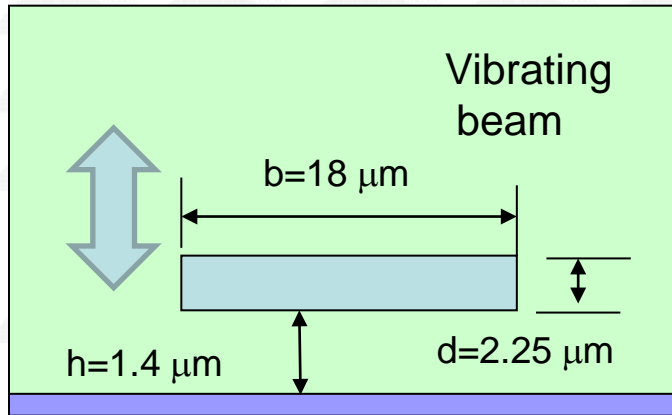
Tangent class T  
contains  
value and derivative

Operators are overloaded  
to operate on both

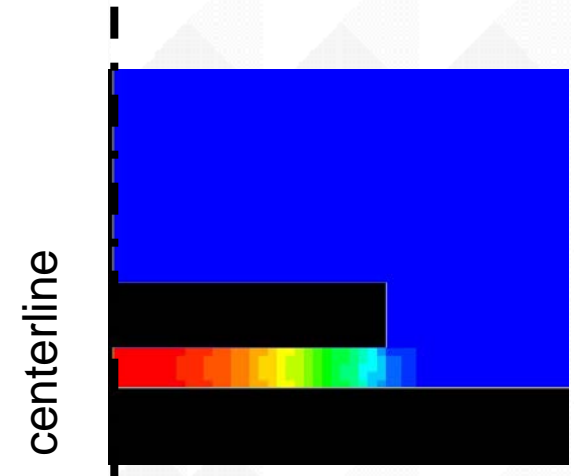
# Advantages of C++ Approach

- Does not rely on external parser like ADIFOR
- One source code to maintain and debug
  - Instantiate sensitivity version when required
- No penalty for normal usage
- Can switch from double to Tangent mode as desired
  - Very useful for non-linear problems

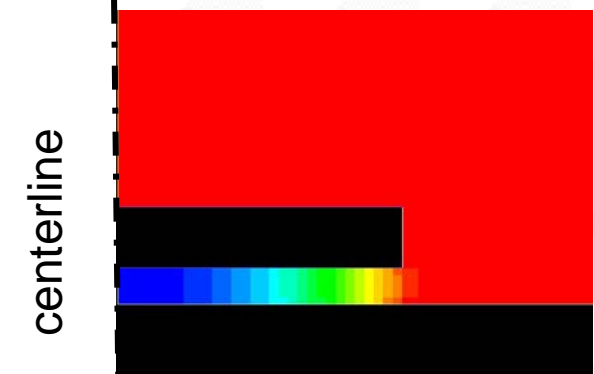
# Sensitivity Analysis of Squeeze Film Damping



- $\Delta p = (p - \bar{p}_{top\ wall})$  greatest at center and decreases outwards
- $d(\Delta p)/dh$  most negative at center and increases to zero outward
- As  $h$  decreases,  $\Delta p$  increases;
  - Vertical force  $F$  on cantilever increases
  - $dF/dh = -4460 \text{ N/m}$  at  $h = 1.4 \text{ microns}$ .

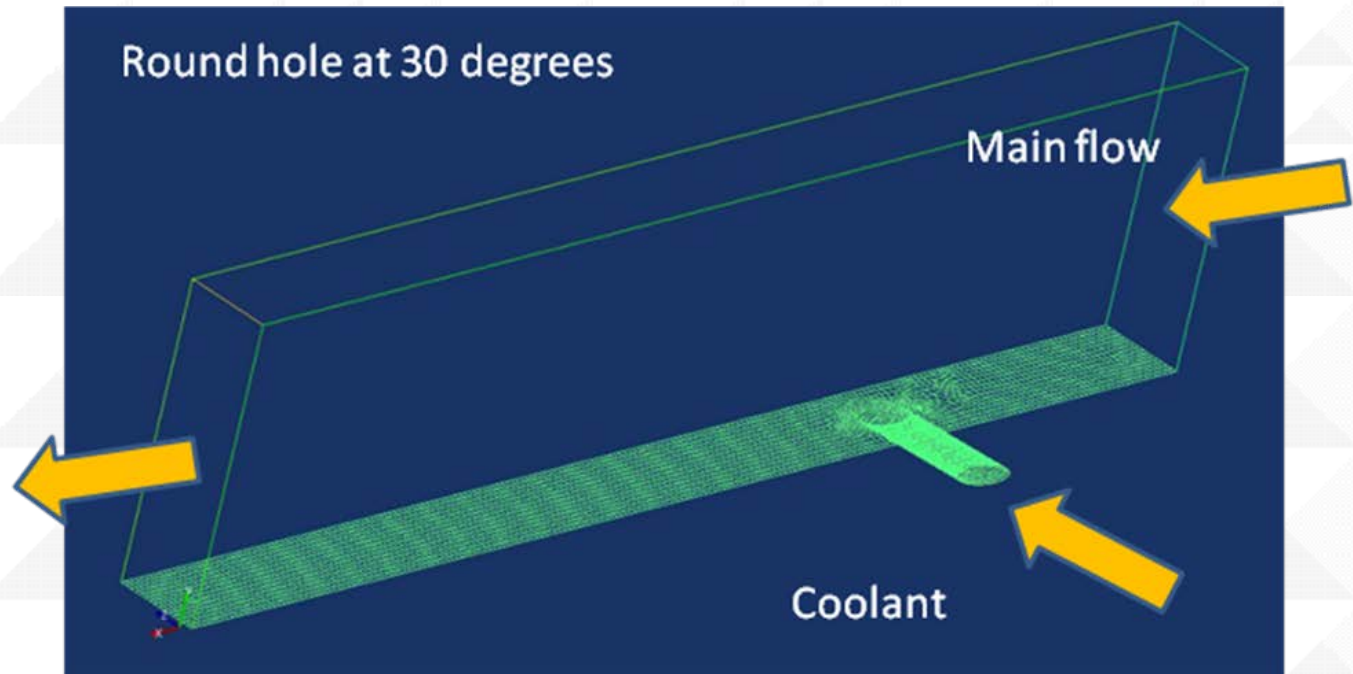


$$(p - \bar{p}_{top\ wall})$$



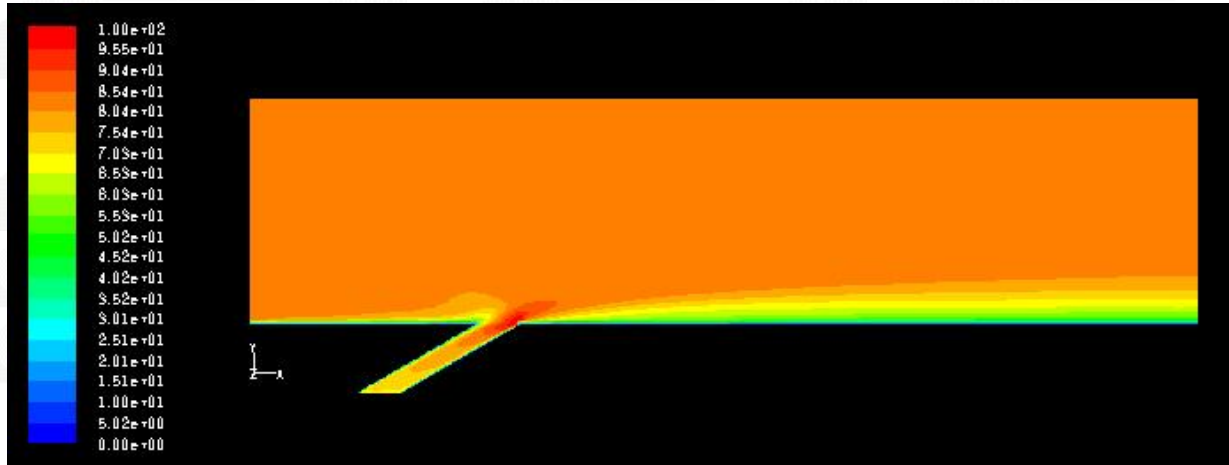
$$\frac{d}{dh}(p - \bar{p}_{top\ wall})$$

# Sensitivity Analysis of Film Cooling



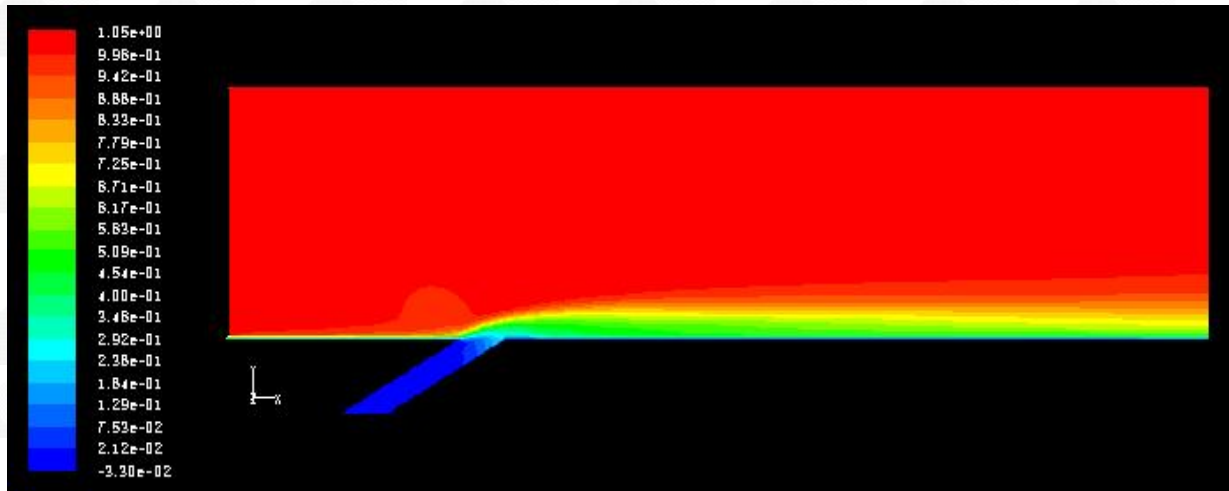
Compute sensitivity of flow and temperature field and area-averaged effectiveness to hot gas inlet velocity and temperature

# Sensitivity of U-Velocity to Hot Gas Inlet Velocity



M=1.0  
T ratio=1.05

$u$



$$\frac{\partial u}{\partial U_{main}}$$

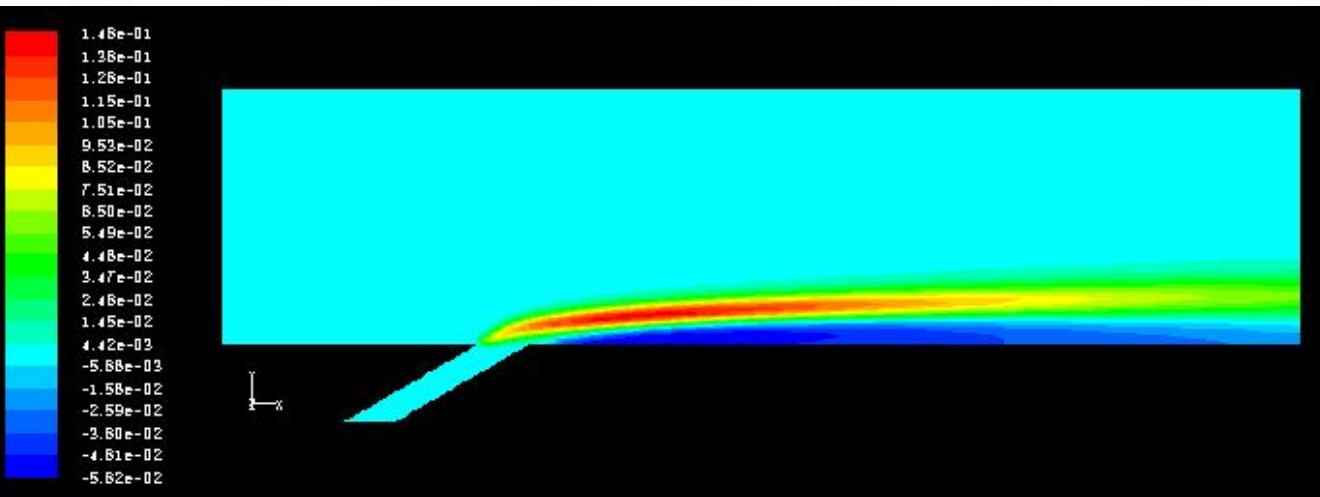
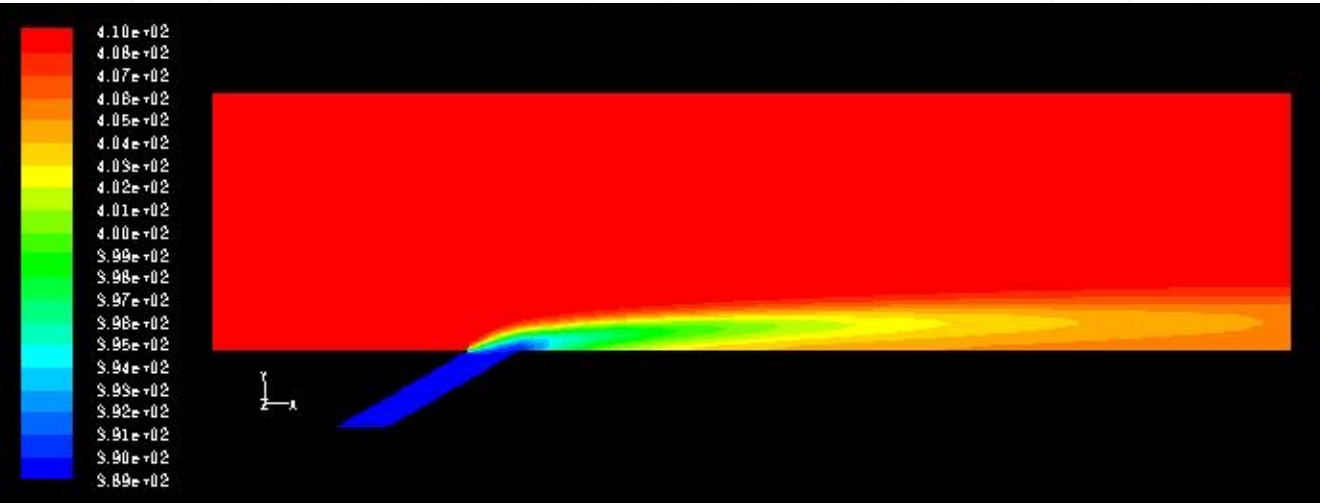
# Sensitivity of Temperature to Hot Gas Inlet Velocity

M=1.0

T ratio=1.05

$T$

$$\frac{\partial T}{\partial U_{main}}$$





# Summary

- Our objective is to find the local Jacobian (sensitivity) of outputs to inputs
- We described two ways of doing this
  - Continuous - sensitivity equation
  - Discrete – automatic code differentiation
- Sensitivities are useful in their own right, but have many other uses
  - Optimization, variance propagation
- In the next lecture, we will describe how these derivatives can be used to propagate variances from inputs to outputs