

Numerical Optimization Using PETSc/TAO

Presented to
ATPESC 2022 Participants

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ATPESC Numerical Software Track



What is optimization?

$$\underset{p}{\text{minimize}} \quad f(p)$$

- Optimization variables $p \in \mathbb{R}^n$
 - e.g.: boundary conditions, parameters, geometry
- Objective function $f: \mathbb{R}^n \rightarrow \mathbb{R}$
 - e.g.: lift, drag, max stress, total energy, error norms, etc.

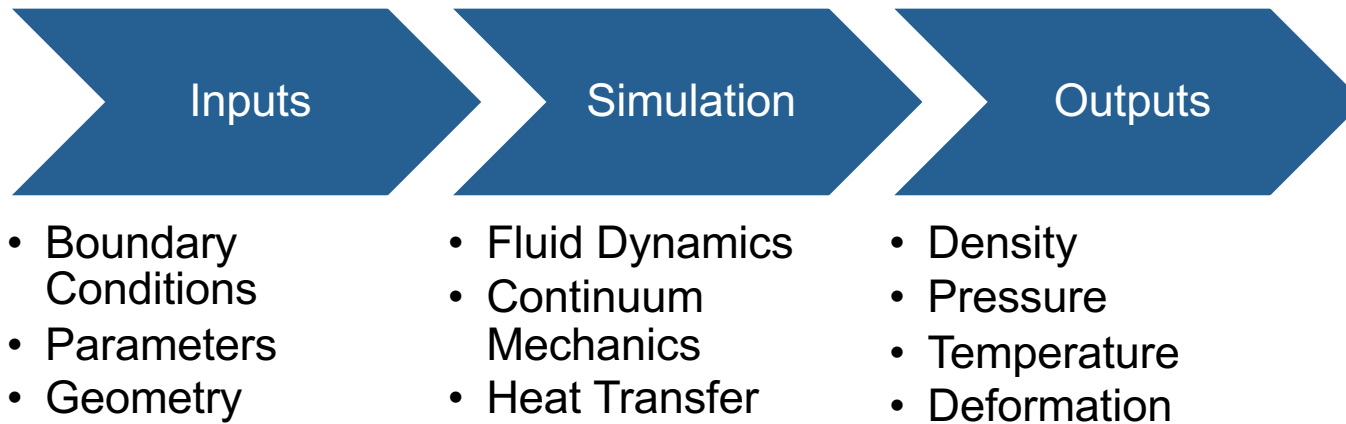
What is optimization?

$$\underset{p}{\text{minimize}} \quad f(p)$$

- Simplification: $f(p)$ is minimized where $\nabla_p f(p) = 0$
- **Gradient-free:** Heuristic search through p space
 - Easy to use, no sensitivity analysis required
- **Gradient-based:** Find search directions based on $\nabla_p f$
 - Converges to local minima with significantly fewer function evaluations than gradient-free methods

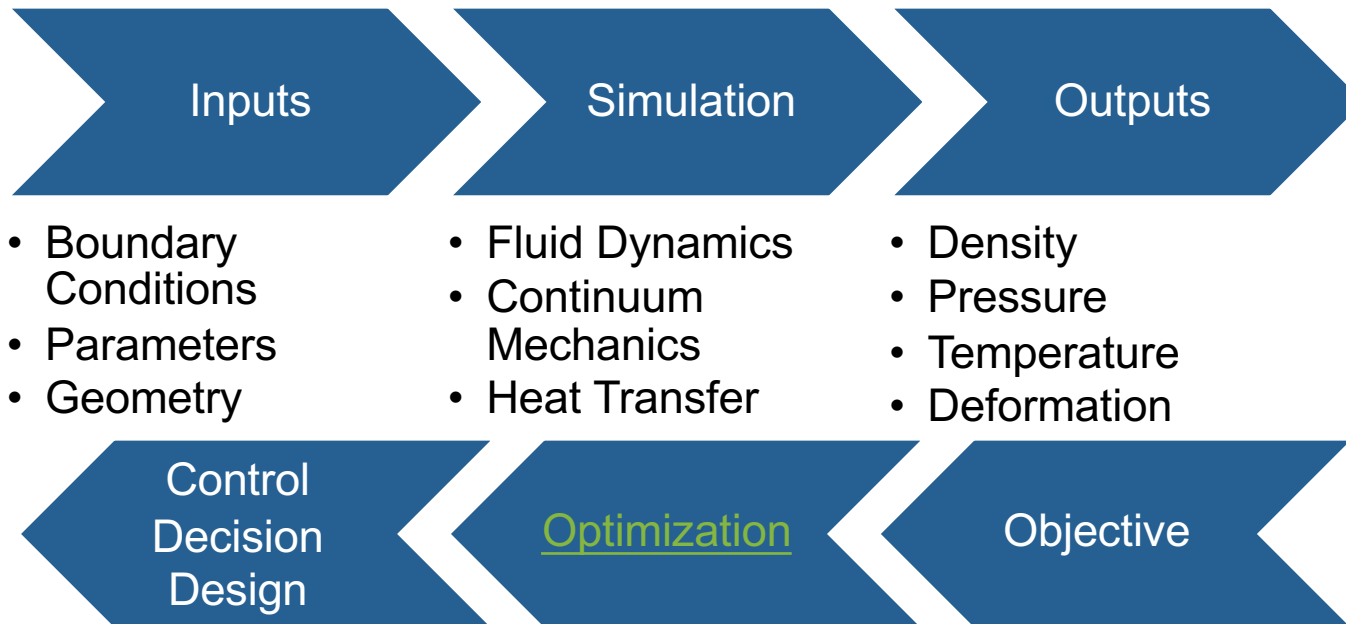
Why do we care?

We know a lot about how to solve the forward problem...



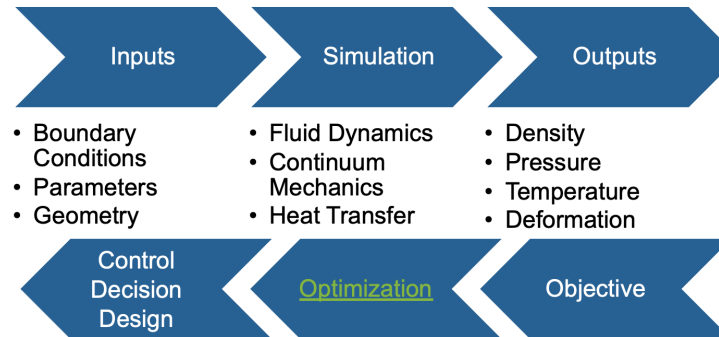
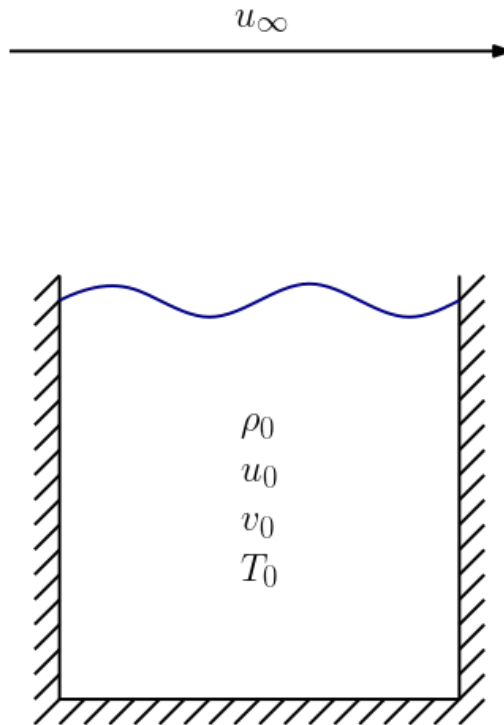
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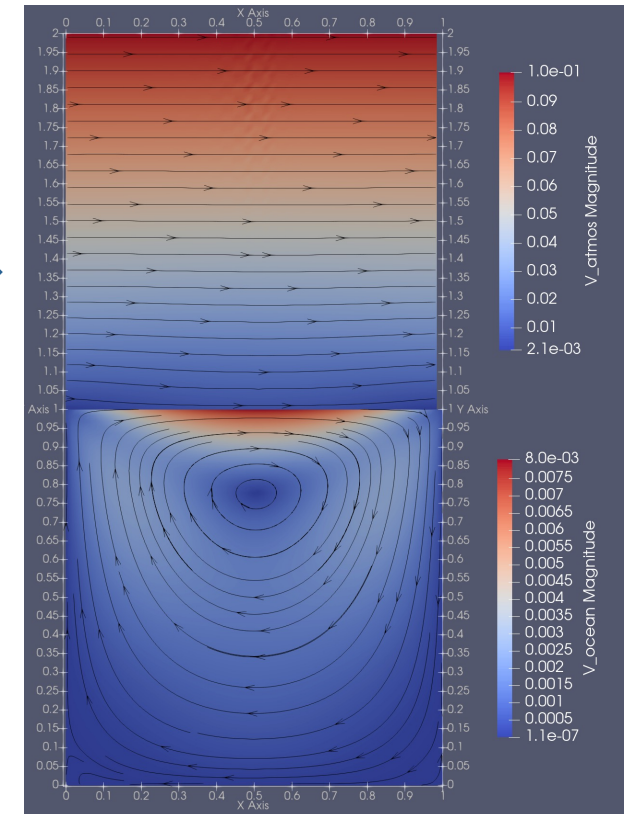


...many scientific questions present as inverse problems!

Why do we care?



...many scientific questions present as inverse problems!



Outline

- Introduction to Gradient-Based Optimization
 - Sequential Quadratic Programming
 - Sensitivity Analysis
- Introduction to TAO
 - Sample main program
 - User/problem callback function
- Hands-on Examples: Rosenbrock Equation
 - 2-dimensional unconstrained
 - Multidimensional unconstrained
 - 2-dimensional with general constraints

Intro to Numerical Optimization

$$\underset{p}{\text{minimize}} \quad f(p)$$

- Optimization variables $p \in \mathbb{R}^n$
- Objective function $f: \mathbb{R}^n \rightarrow \mathbb{R}$
- Local minima where gradient is zero (optimality condition)
- Optimality condition is **necessary** but not sufficient
 - Other stationary points (e.g., maximums) also satisfy $\nabla_p f(p) = 0$

Sequential Quadratic Programming

for $k=0,1,2,\dots$ **do**

$$\min_d f_k + d^T g_k + 0.5d^T H_k d$$

$$\min_{\alpha} \Phi(\alpha) = f(p_k + \alpha d)$$

$$p_{k+1} \leftarrow p_k + \alpha d$$

end for

- Solution at k^{th} iteration p_k
- Gradient $g_k = \nabla_p f(p_k)$
- Hessian $H_k = \nabla_{pp}^2 f(p_k)$
- Search direction $d \in \mathbb{R}^n$
- Step length α

- Replace original problem with a sequence of quadratic subproblems
 - Solution given by $d = -H_k^{-1} g_k$
- Line search maintains consistency between local quadratic model and global nonlinear function (globalization)
 - Avoids undesirable stationary points

Sequential Quadratic Programming

```
for k=0,1,2,... do
  mind  $f_k + d^T g_k + 0.5d^T H_k d$ 
  min $\alpha$   $\Phi(\alpha) = f(p_k + \alpha d)$ 
   $p_{k+1} \leftarrow p_k + \alpha d$ 
end for
```

- Solution at k^{th} iteration p_k
- Gradient $g_k = \nabla_p f(p_k)$
- Hessian $H_k = \nabla_{pp}^2 f(p_k)$
- Search direction $d \in \mathbb{R}^n$
- Step length α

- Different approximations to search direction yield different algorithms
 - **Newton's method:** $d = -H_k^{-1} g_k$, no approximation
 - **Quasi-Newton:** $d = -B_k g_k$ with $B_k \approx H_k^{-1}$ based on the secant condition
 - **Conjugate Gradient:** $d_k = -g_k + \beta_k d_{k-1}$ with β defining different CG updates
 - **Gradient Descent:** $d = -g_k$, replace Hessian with identity

PDE-Constrained Optimization

$$\begin{array}{ll} \underset{p,u}{\text{minimize}} & f(p, u) \\ \text{subject to} & R(p, u) = 0 \end{array}$$



$$\underset{p}{\text{minimize}} \quad f(p, u(p))$$

Full-Space Formulation

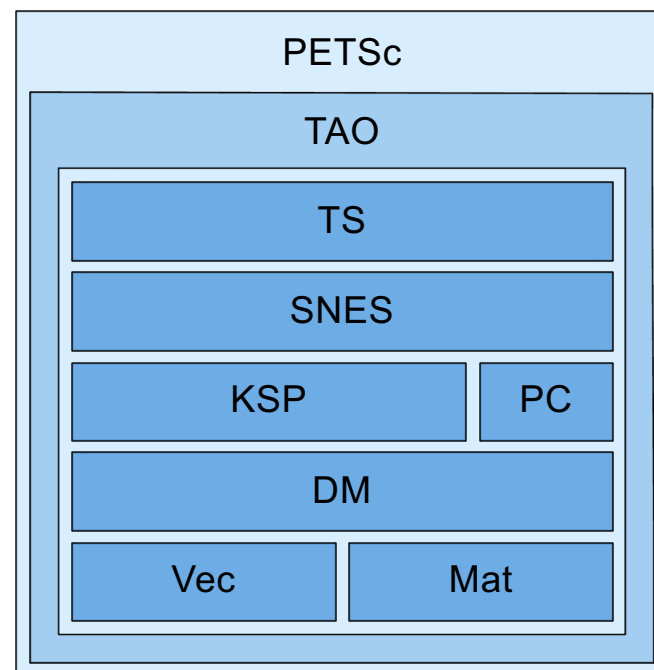
- State variables $u \in \mathbb{R}^m$
- State equations $R: \mathbb{R}^{n+m} \rightarrow \mathbb{R}^m$

Reduced-Space Formulation

- State variables are implicit functions of parameters
- Reduced-space formulation enables use of conventional unconstrained optimization algorithms to solve PDE-constrained problems
- Each reduced-space function evaluation requires a full PDE solution
- See ATPESC 2019 lesson for more details

PETSc TAO Toolkit for Advanced Optimization

- General-purpose continuous optimization toolbox for large-scale problems
 - Parallel (via PETSc data structures)
 - Gradient-based
 - Bound-constrained
 - Nonlinear/general constraint support under development
 - PDE-constrained problems w/ reduced-space formulation
- Distributed with PETSc (<https://petsc.org>)
- Similar packages:
 - Rapid Optimization Library (<https://trilinos.github.io/rol.html>)
 - HiOP (<https://github.com/LLNL/hiop>)



TAO: The Basics

- Sample main program

```
AppCtx user;
Tao tao;
Vec P;

PetscInitialize( &argc, &argv, (char *)0, help );
VecCreateMPI(PETSC_COMM_WORLD, user.n, user.N, &P);
VecSet(P, 0.0);

TaoCreate(PETSC_COMM_WORLD, &tao);
TaoSetType(tao, TAOBQNLS);          /* bound-constrained quasi-Newton */
TaoSetInitialVector(tao, P);
TaoSetObjectiveRoutine(tao, FormFunction, &user);
TaoSetGradientRoutine(tao, FormGradient, &user);
TaoSetFromOptions(tao);
TaoSolve(tao);

VecDestroy(&P);
TaoDestroy(&tao);
PetscFinalize();
```

TAO: The Basics

- User provides function for problem implementation

```
AppCtx user;
Tao tao;
Vec P;

PetscInitialize( &argc, &argv, (char *)0, help );
VecCreateMPI(PETSC_COMM_WORLD, user.n, user.N, &P);
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TaoSetFromOptions(tao);
TaoSolve(tao);

VecDestroy(&P);
TaoDestroy(&tao);
PetscFinalize();
```

TAO: User Function

- User functions compute objective and gradient

```
typedef struct {  
    /* user-created context for storing application data */  
} AppCtx;
```

```
PetscErrorCode FormFunction (Tao tao, Vec P, PetscReal *fcn, void *ptr)  
{  
    AppCtx *user = (AppCtx*) ptr;  
    const PetscScalar *pp;  
  
    VecGetArrayRead(P, &pp);  
  
    /* USER TASK: Compute objective function and store in fcn */  
  
    VecRestoreArrayRead(P, &pp);  
  
    return 0;  
}
```

```
PetscErrorCode FormGradient(Tao tao, Vec P, Vec G, void *ptr)  
{  
    AppCtx *user = (AppCtx*) ptr;  
    const PetscScalar *pp;  
    PetscScalar *gg;  
  
    VecGetArrayRead(P, &pp);  
    VecGetArray(G, &gg);  
  
    /* USER TASK: Compute compute gradient and store in gg */  
  
    VecRestoreArrayRead(P, &pp);  
    VecRestoreArray(G, &gg);  
  
    return 0;  
}
```

TAO: User Function

- **Objective evaluation:**
 - Compute $f(p)$ at given p
- **Sensitivity analysis:**
 - Compute $G = \nabla_p f$ at given p
- **(ADVANCED) Second-order Methods:**
 - Compute $H = \nabla_p^2 f$ at given p
 - Use `TaoSetHessian()` interface
- **(ADVANCED) Constraints:**
 - Set bound constraints $p_l \leq p \leq p_u$
 - Define nonlinear constraints $c_e(p) = 0, c_i(p) \geq 0$

TAO: User Function

- **Objective evaluation:**

- Compute $f(p)$ at given p

- **Sensitivity analysis:**

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- **(ADVANCED) Second-order Methods:**

- Compute $H = \nabla_p^2 f$ at given p
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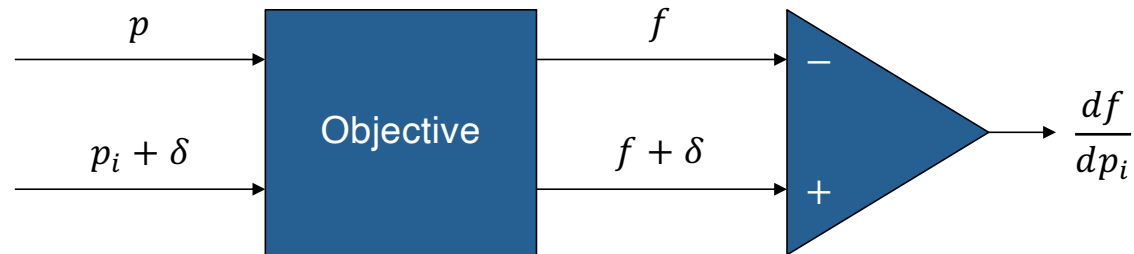
- **(ADVANCED) Constraints:**

- Set bound constraints $p_l \leq p \leq p_u$
- Define nonlinear constraints $c_e(p) = 0, c_i(p) \geq 0$

- Necessary for gradient-based optimization algorithms

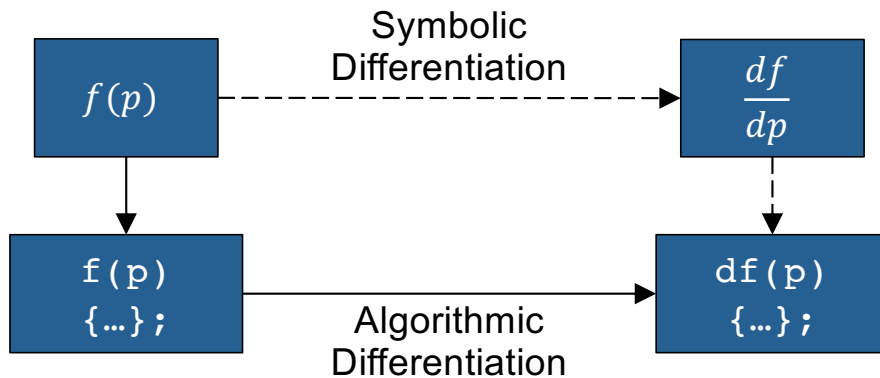
- Types:
 - Numerical
 - Analytical

Sensitivity Analysis: Numerical Differentiation



- Finite-difference method is easy to implement
 - Only requires function evaluations
- Inefficient for large numbers of optimization variables
- Step-size dilemma – truncation error vs. subtractive cancellation
- TAO provides automatic FD gradient and Hessian evaluations

Sensitivity Analysis: Analytical Differentiation



- **Symbolic** – hand-derived gradient with direct code implementation
- **Algorithmic** – source code transformation or operator overloading via AD tool/library (i.e., chain rule!)

- Computational cost is (mostly) independent of the number of optimization variables
- Some popular AD tools:
 - ADIC (ANSI C)
 - ADIFOR (Fortran77/Fortran95)
 - OpenAD (Fortran77/Fortran95/C/C++)
 - Sacado (C/C++)
 - ForwardDiff.jl (Julia)
 - JAX (Python)

TAO: Bound Constraints

- What if we wanted to restrict the solution variables?

$$\begin{array}{ll}\text{minimize} & f(x) \\ \text{subject to} & x_l \leq x \leq x_u\end{array}$$

```
VecDuplicate(X, &XL);  
VecSet(XL, PETSC_NINFINITY);  
VecDuplicate(X, &XU);  
VecSet(XU, 0.0);  
TaoSetVariableBounds(tao, XL, XU);
```

- Must use bound-constrained TAO algorithms
 - TAOBNLS: Bounded Newton Line-Search
 - TAOBNTR: Bounded Newton Trust Region
 - TAOBQNLS: Bounded quasi-Newton Line-Search
 - TAOBNCG: Bounded Nonlinear Conjugate Gradient

TAO: General Nonlinear Constraints

- Incorporate all constraint types

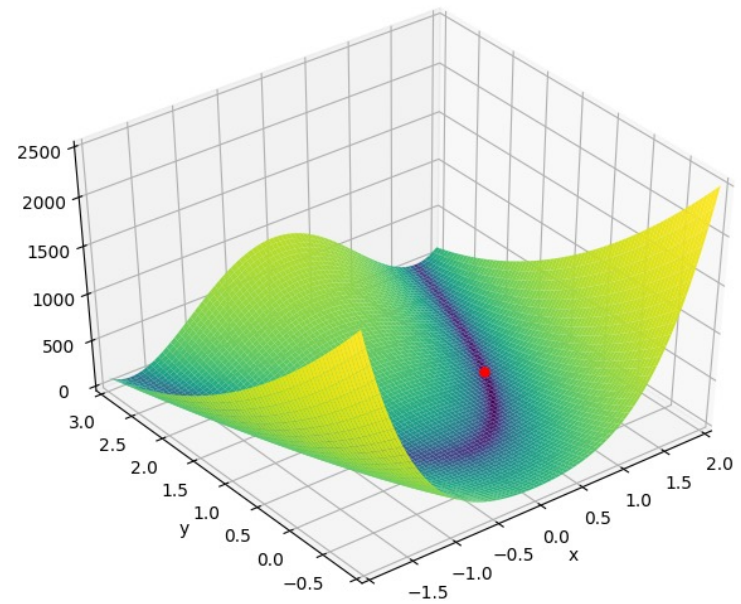
$$\begin{aligned} & \underset{x}{\text{minimize}} && f(x) \\ & \text{subject to} && c_e(x) = 0 \\ & && c_i(x) \geq 0 \\ & && x_l \leq x \leq x_u \end{aligned}$$

- Must use TAOALMM solver
 - Augmented Lagrangian method w/ interior-point formulation for inequality constraints
- Define constraints with user call-backs
 - `FormEqualityConstraints(Tao,Vec,Vec,void*) → TaoSetEqualityConstraintsRoutine()`
 - `FormEqualityJacobian(Tao,Vec,Mat,Mat,void*) → TaoSetJacobianEqualityRoutine()`
 - `FormInequalityConstraints(Tao,Vec,Vec,void*) → TaoSetInequalityConstraintsRoutine()`
 - `FormInequalityJacobian(Tao,Vec,Mat,Mat,void*) → TaoSetJacobianInequalityRoutine()`

Hands-on Example: 2-dimensional Rosenbrock

$$\underset{p}{\text{minimize}} \quad f(p) = (1 - p_1)^2 + 100(p_2 - p_1^2)^2$$

- Global minimum at $p = (1, 1)$
- Also called the “banana function”
- Canonical test problem for optimization algorithms
- Easy to find the valley, difficult to traverse it towards the solution



Hands-on Example: Multidimensional Rosenbrock

$$\underset{p}{\text{minimize}} \quad f(p) = \sum_{i=1}^{N-1} (1 - p_i)^2 + 100(p_{i+1} - p_i^2)^2$$

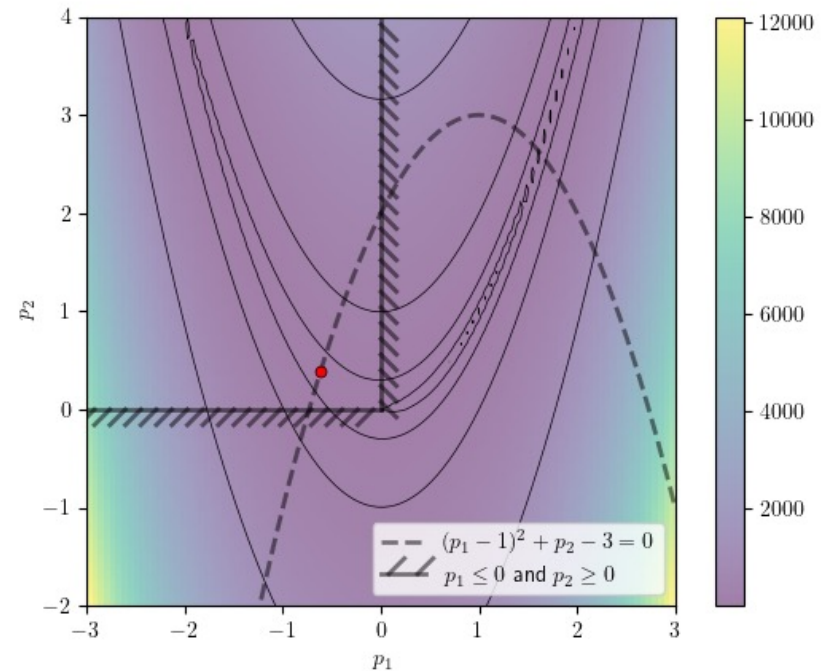
- Global minimum at $p_i = 1, \forall i = 1, 2, \dots, N$
- Implementation supports parallel runs and provides analytical gradient and sparse Hessian
 - Simulation-based / HPC apps. would use algorithmic differentiation
- TAO can compute sensitivities via finite-differencing when analytical derivatives are not available
 - Convenient for prototyping or debugging
 - Computationally expensive for large optimization problems or expensive objectives
- Hands-on Activities:

https://xsdk-project.github.io/MathPackagesTraining2022/lessons/numerical_optimization_tao/

Hands-on Example: 2D Rosenbrock w/ Constraints

$$\begin{aligned} & \underset{p}{\text{minimize}} && f(p) = (1 - p_1)^2 + 100(p_2 - p_1^2)^2 \\ & \text{subject to} && (p_1 - 1)^2 + p_2 - 3 = 0 \\ & && p_1 \leq 0 \\ & && p_2 \geq 0 \end{aligned}$$

- Bound-constrained global minimum at $f(0,0) = 1$
- Equality-constraints have two local minima
 - $f(-0.62, 0.38) = 2.62$
 - $f(1.62, 2.62) = 0.38$
- Combined constraints yield global minimum at $f(-0.62, 0.38) = 2.62$
- Constraints are not valid for the multidimensional Rosenbrock problem



Take Away Messages

- PETSc/TAO offers parallel optimization algorithms for large-scale problems.
- Efficient gradients are needed for best results (e.g., algorithmic differentiation), and second-order methods don't always achieve faster/better solutions.
- PETSc/TAO can automatically compute gradients via finite differencing.
- PETSc/TAO can incorporate bound, equality and inequality constraints into the solution.
- Most scientific problems are nonlinear and nonconvex... starting point matters!

Acknowledgements

PETSc/TAO Documentation: <https://petsc.org>

GitLab Repo: <https://gitlab.com/petsc/petsc>

Offline questions: tmunson@anl.gov

Need help with your PETSc/TAO application? petsc-users@mcs.anl.gov

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