

# Deflation techniques for distinct solutions of nonlinear PDEs

P. E. Farrell<sup>1,2</sup>    Á. Birkisson<sup>1</sup>    S. W. Funke<sup>2</sup>

<sup>1</sup>University of Oxford

<sup>2</sup>Simula Research Laboratory, Oslo

June 16, 2015

# Section 1

## Motivation

A central question in scientific computing

How can we compute multiple solutions of PDEs?

## A central question for my talk

Why should we compute multiple solutions of PDEs?

A central question for my talk

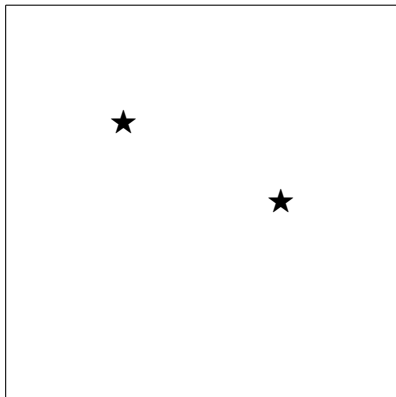
Why should we compute multiple solutions of PDEs?

Answer #1

Prediction.

## A central question for my talk

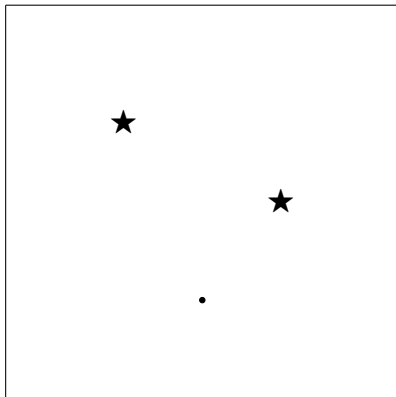
Why should we compute multiple solutions of PDEs?



A PDE with two unknown solutions.

## A central question for my talk

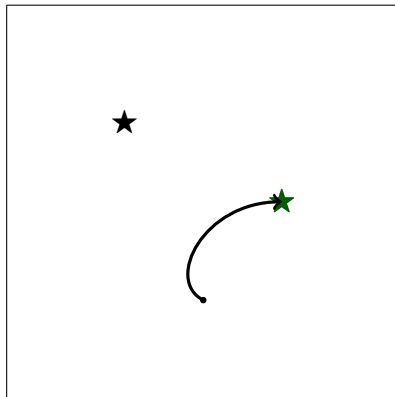
Why should we compute multiple solutions of PDEs?



Start from some initial guess.

## A central question for my talk

Why should we compute multiple solutions of PDEs?

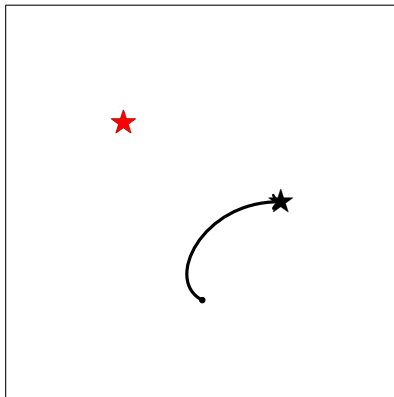


We converge to one solution, our prediction.



## A central question for my talk

Why should we compute multiple solutions of PDEs?



But nature has chosen another (unknown) solution!

## A central question for my talk

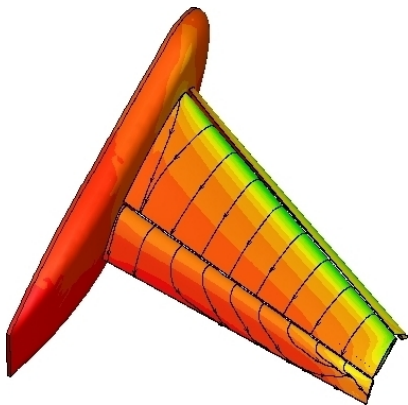
Why should we compute multiple solutions of PDEs?



The AIAA/NASA high lift prediction test case (Kamenetskiy et al., 2013).

## A central question for my talk

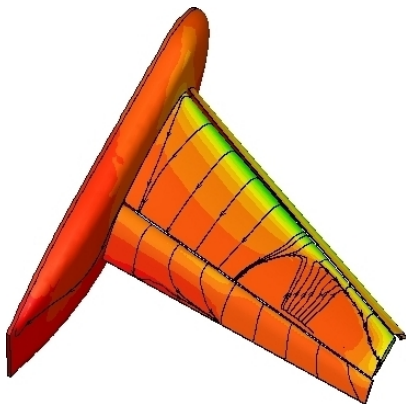
Why should we compute multiple solutions of PDEs?



The AIAA/NASA high lift prediction test case (Kamenetskiy et al., 2013).

## A central question for my talk

Why should we compute multiple solutions of PDEs?



The AIAA/NASA high lift prediction test case (Kamenetskiy et al., 2013).

## A central question for my talk

Why should we compute multiple solutions of PDEs?

*We have encountered unexpected multiple solutions in both simple and complex configurations in computational fluid dynamics (CFD); this phenomenon is both extremely important and not well understood. It has serious implications for the use of CFD as a predictive tool.*

— Venkat Venkatakrishnan  
Computational Aerodynamic Optimization  
Boeing Research & Technology

A central question for my talk

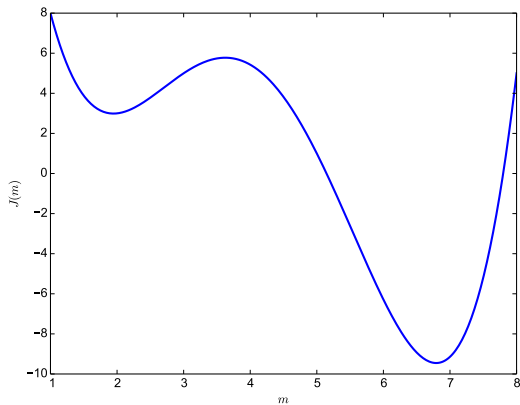
Why should we compute multiple solutions of PDEs?

Answer #2

Optimisation.

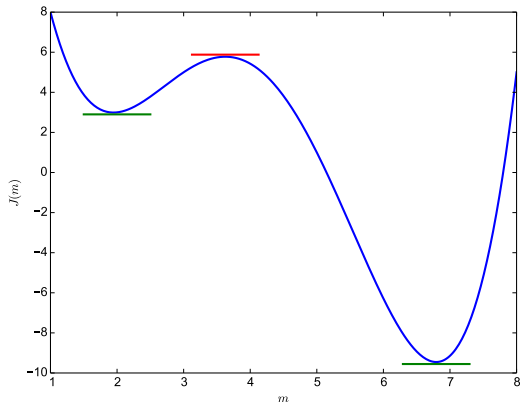
## A central question for my talk

Why should we compute multiple solutions of PDEs?



## A central question for my talk

Why should we compute multiple solutions of PDEs?



By solving  $\nabla J = 0$ , we can find a superset of the minima.



A central question for my talk

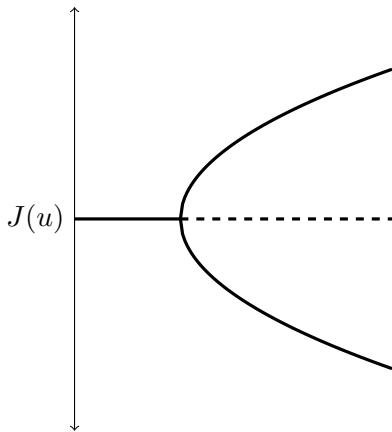
Why should we compute multiple solutions of PDEs?

Answer #3

Applications.

## A central question for my talk

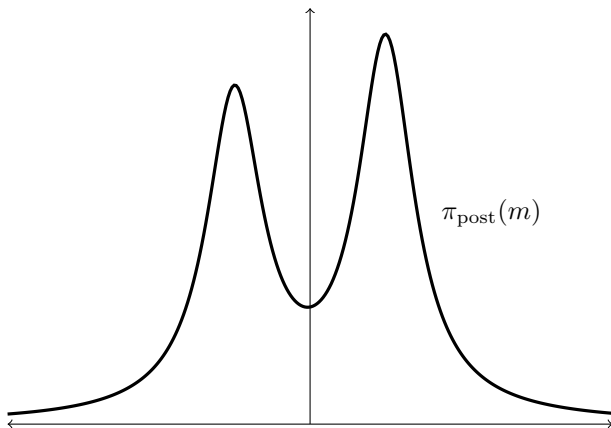
Why should we compute multiple solutions of PDEs?



Scalable tracing of bifurcation diagrams.

## A central question for my talk

Why should we compute multiple solutions of PDEs?



Multimodal Bayesian inference.

## Section 2

## Deflation

# The core idea

## Deflation

Given

- ▶ a Fréchet differentiable residual  $\mathcal{F} : V \rightarrow W$
- ▶ a solution  $r \in V$ ,  $\mathcal{F}(r) = 0$ ,  $\mathcal{F}'(r)$  nonsingular
- ▶  $\tilde{r} \in V$ ,  $\tilde{r} \neq r$

# The core idea

## Deflation

Given

- ▶ a Fréchet differentiable residual  $\mathcal{F} : V \rightarrow W$
- ▶ a solution  $r \in V$ ,  $\mathcal{F}(r) = 0$ ,  $\mathcal{F}'(r)$  nonsingular
- ▶  $\tilde{r} \in V$ ,  $\tilde{r} \neq r$

construct a **new nonlinear problem**  $\mathcal{G} : V \rightarrow Z$  such that:

# The core idea

## Deflation

Given

- ▶ a Fréchet differentiable residual  $\mathcal{F} : V \rightarrow W$
- ▶ a solution  $r \in V$ ,  $\mathcal{F}(r) = 0$ ,  $\mathcal{F}'(r)$  nonsingular
- ▶  $\tilde{r} \in V$ ,  $\tilde{r} \neq r$

construct a **new nonlinear problem**  $\mathcal{G} : V \rightarrow Z$  such that:

- ▶ (Preservation of solutions.)  $\mathcal{F}(\tilde{r}) = 0 \iff \mathcal{G}(\tilde{r}) = 0$ .

# The core idea

## Deflation

Given

- ▶ a Fréchet differentiable residual  $\mathcal{F} : V \rightarrow W$
- ▶ a solution  $r \in V$ ,  $\mathcal{F}(r) = 0$ ,  $\mathcal{F}'(r)$  nonsingular
- ▶  $\tilde{r} \in V$ ,  $\tilde{r} \neq r$

construct a **new nonlinear problem**  $\mathcal{G} : V \rightarrow Z$  such that:

- ▶ (Preservation of solutions.)  $\mathcal{F}(\tilde{r}) = 0 \iff \mathcal{G}(\tilde{r}) = 0$ .
- ▶ (Deflation property.) Newton's method applied to  $\mathcal{G}$  will never converge to  $r$  again, starting from any initial guess.



# The core idea

## Deflation

Given

- ▶ a Fréchet differentiable residual  $\mathcal{F} : V \rightarrow W$
- ▶ a solution  $r \in V$ ,  $\mathcal{F}(r) = 0$ ,  $\mathcal{F}'(r)$  nonsingular
- ▶  $\tilde{r} \in V$ ,  $\tilde{r} \neq r$

construct a **new nonlinear problem**  $\mathcal{G} : V \rightarrow Z$  such that:

- ▶ (Preservation of solutions.)  $\mathcal{F}(\tilde{r}) = 0 \iff \mathcal{G}(\tilde{r}) = 0$ .
- ▶ (Deflation property.) Newton's method applied to  $\mathcal{G}$  will never converge to  $r$  again, starting from any initial guess.

Find more solutions, starting from the same initial guess.

# The core idea

## Deflation

Given

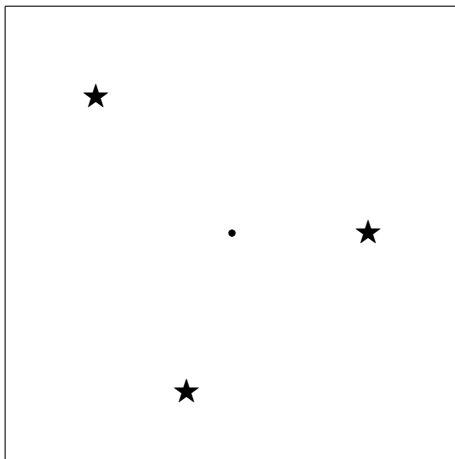
- ▶ a Fréchet differentiable residual  $\mathcal{F} : V \rightarrow W$
- ▶ a solution  $r \in V$ ,  $\mathcal{F}(r) = 0$ ,  $\mathcal{F}'(r)$  nonsingular
- ▶  $\tilde{r} \in V$ ,  $\tilde{r} \neq r$

construct a **new nonlinear problem**  $\mathcal{G} : V \rightarrow Z$  such that:

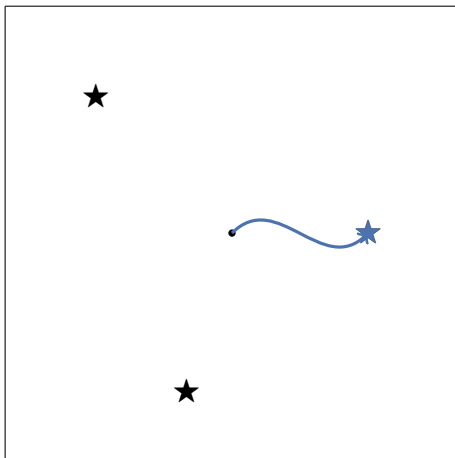
- ▶ (Preservation of solutions.)  $\mathcal{F}(\tilde{r}) = 0 \iff \mathcal{G}(\tilde{r}) = 0$ .
- ▶ (Deflation property.) Along any sequence converging to  $r$ ,  $\|\mathcal{G}\|_Z$  is bounded away from 0.

Find more solutions, starting from the same initial guess.

# Finding many solutions from the same guess

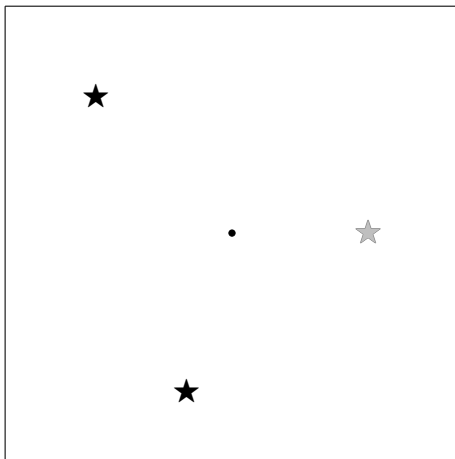


# Finding many solutions from the same guess



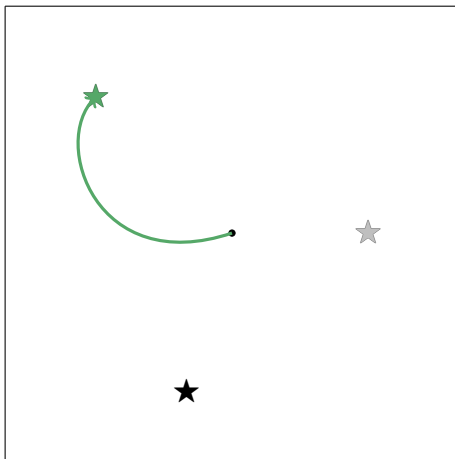
Step I: Newton from initial guess

## Finding many solutions from the same guess



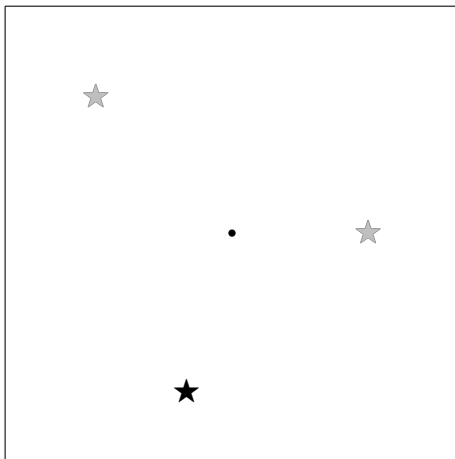
Step II: deflate solution found

## Finding many solutions from the same guess



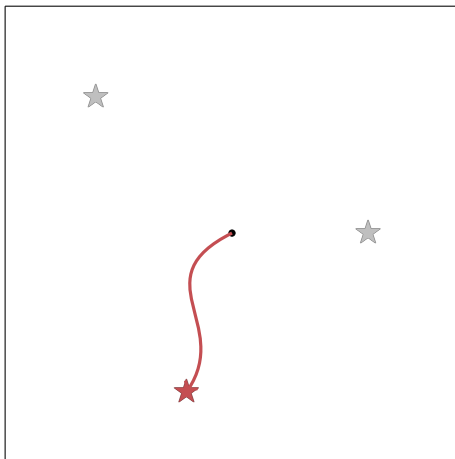
Step I: Newton from initial guess

## Finding many solutions from the same guess



Step II: deflate solution found

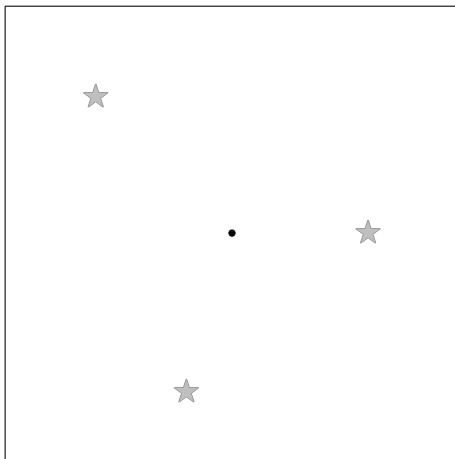
## Finding many solutions from the same guess



Step I: Newton from initial guess

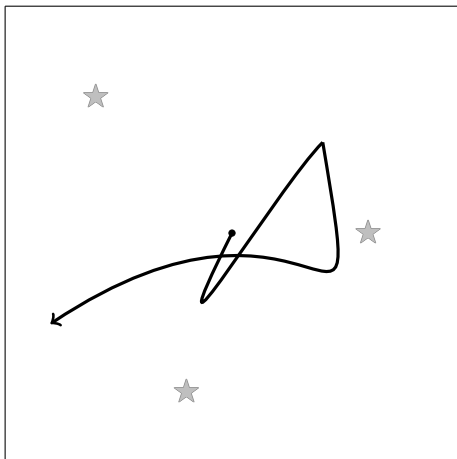


## Finding many solutions from the same guess



Step II: deflate solution found

## Finding many solutions from the same guess



Step III: termination on nonconvergence

## Finding many solutions from the same guess



Step III: termination on nonconvergence

# Construction of deflated problems

A nonlinear transformation

$$\mathcal{G}(u) = \mathcal{M}(u; r)\mathcal{F}(u)$$

# Construction of deflated problems

## A nonlinear transformation

$$\mathcal{G}(u) = \mathcal{M}(u; r)\mathcal{F}(u)$$

## A deflation operator

For  $r \in V, u \in V \setminus \{r\}$ , let  $\mathcal{M}(u; r)$  be an invertible linear operator.

$\mathcal{M}(u; r) : W \rightarrow Z$  is a **deflation operator** if for any sequence  $u_i \xrightarrow{U} r$

$$\liminf_{i \rightarrow \infty} \|\mathcal{M}(u_i; r)\mathcal{F}(u_i)\|_Z > 0.$$

# Construction of deflated problems

## A nonlinear transformation

$$\mathcal{G}(u) = \mathcal{M}(u; r)\mathcal{F}(u)$$

## A deflation operator

For  $r \in V, u \in V \setminus \{r\}$ , let  $\mathcal{M}(u; r)$  be an invertible linear operator.

$\mathcal{M}(u; r) : W \rightarrow Z$  is a **deflation operator** if for any sequence  $u_i \xrightarrow{U} r$

$$\liminf_{i \rightarrow \infty} \|\mathcal{M}(u_i; r)\mathcal{F}(u_i)\|_Z > 0.$$

## Theorem (F., Birkiison, Funke 2014)

The following are deflation operators.

$$\mathcal{M}(u; r) = \frac{\mathcal{I}}{\|u - r\|}$$

# Construction of deflated problems

## A nonlinear transformation

$$\mathcal{G}(u) = \mathcal{M}(u; r)\mathcal{F}(u)$$

## A deflation operator

For  $r \in V, u \in V \setminus \{r\}$ , let  $\mathcal{M}(u; r)$  be an invertible linear operator.

$\mathcal{M}(u; r) : W \rightarrow Z$  is a **deflation operator** if for any sequence  $u_i \xrightarrow{U} r$

$$\liminf_{i \rightarrow \infty} \|\mathcal{M}(u_i; r)\mathcal{F}(u_i)\|_Z > 0.$$

## Theorem (F., Birkiison, Funke 2014)

The following are deflation operators.

$$\mathcal{M}(u; r) = \frac{\mathcal{I}}{\|u - r\|^p}$$

# Construction of deflated problems

## A nonlinear transformation

$$\mathcal{G}(u) = \mathcal{M}(u; r)\mathcal{F}(u)$$

## A deflation operator

For  $r \in V, u \in V \setminus \{r\}$ , let  $\mathcal{M}(u; r)$  be an invertible linear operator.

$\mathcal{M}(u; r) : W \rightarrow Z$  is a **deflation operator** if for any sequence  $u_i \xrightarrow{U} r$

$$\liminf_{i \rightarrow \infty} \|\mathcal{M}(u_i; r)\mathcal{F}(u_i)\|_Z > 0.$$

## Theorem (F., Birkiison, Funke 2014)

The following are deflation operators.

$$\mathcal{M}(u; r) = \frac{\mathcal{I}}{\|u - r\|^p} + \alpha\mathcal{I}.$$



# Prior work

Wilkinson (1963)

Deflation for polynomials, rounding error analysis

# Prior work

Wilkinson (1963)

Deflation for polynomials, rounding error analysis

Brown and Gearhart (1971)

Generalisation to  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$

# Prior work

Wilkinson (1963)

Deflation for polynomials, rounding error analysis

Brown and Gearhart (1971)

Generalisation to  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$

Levy and Gomez (1985)

Used deflation in the “tunnelling” method for global optimisation

## Prior work

### Wilkinson (1963)

Deflation for polynomials, rounding error analysis

### Brown and Gearhart (1971)

Generalisation to  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$

### Levy and Gomez (1985)

Used deflation in the “tunnelling” method for global optimisation

### This work

Generalisation to Banach spaces, shifting, applications, **preconditioning**

## Section 3

# Analysis

# Newton–Krylov

## A Newton step

$$P_F^{-1} J_F(u_i) \delta u_i = -P_F^{-1} F(u_i)$$

# Newton–Krylov

## A Newton step

$$P_F^{-1} J_F(u_i) \delta u_i = -P_F^{-1} F(u_i)$$

## A deflated Newton step

$$P_G^{-1} J_G(u_i) \delta u_i = -P_G^{-1} G(u_i)$$

# Newton–Krylov

A Newton step

$$P_F^{-1} J_F(u_i) \delta u_i = -P_F^{-1} F(u_i)$$

A deflated Newton step

$$P_G^{-1} J_G(u_i) \delta u_i = -P_G^{-1} G(u_i)$$

A problem

$J_G$  is dense.



# Preconditioning

Theorem (F., Birkišon, Funke, 2014).

Construct a  $P_G$  such that

$$\|P_G^{-1}J_G - I\| \leq s(\dots)\|P_F^{-1}J_F - I\|$$

with  $s(\dots)$  well-behaved away from previous solutions.

# Preconditioning

Theorem (F., Birkisson, Funke, 2014).

Construct a  $P_G$  such that

$$\|P_G^{-1}J_G - I\| \leq s(\dots)\|P_F^{-1}J_F - I\|$$

with  $s(\dots)$  well-behaved away from previous solutions.

But ..

Good preconditioners don't need to control  $\|P_F^{-1}J_F - I\|$ .

# Block-triangular factorisations

For example, if

$$J_F = \begin{bmatrix} A & B^T \\ C & 0 \end{bmatrix}$$

then

$$P_F^{-1} J_F = \begin{bmatrix} A^{-1} & 0 \\ 0 & (CA^{-1}B^T)^{-1} \end{bmatrix} \begin{bmatrix} A & B^T \\ C & 0 \end{bmatrix}$$

has three distinct eigenvalues (Murphy, Golub, Wathen, 2000).

# A new bound

## New theorem (F., 2015)

Suppose  $P_F^{-1}J_F$  is diagonalisable. Then  $P_G^{-1}J_G$  can be solved in **no more than twice as many Krylov iterations** as  $P_F^{-1}J_F$ .

# A new bound

## New theorem (F., 2015)

Suppose  $P_F^{-1}J_F$  is diagonalisable. Then  $P_G^{-1}J_G$  can be solved in **no more than twice as many Krylov iterations** as  $P_F^{-1}J_F$ .

## Theorem (F., 2015)

Let  $A$  be diagonalisable and  $B$  be rank-one. Then  $A + B$  has at most twice as many distinct eigenvalues as  $A$ .

# A new bound

## New theorem (F., 2015)

Suppose  $P_F^{-1}J_F$  is diagonalisable. Then  $P_G^{-1}J_G$  can be solved in **no more than twice as many Krylov iterations** as  $P_F^{-1}J_F$ .

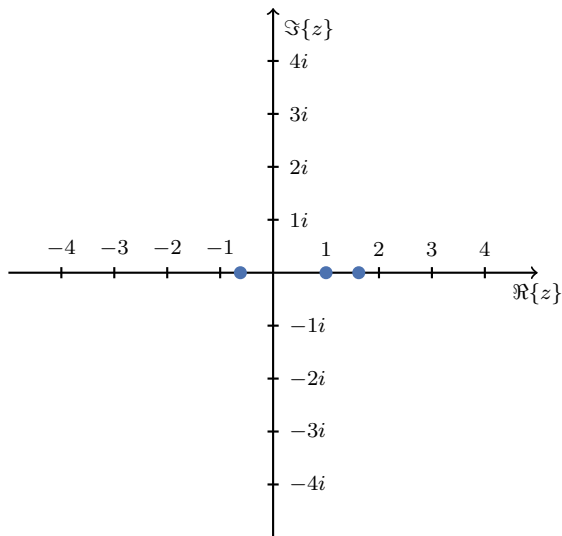
## Theorem (F., 2015)

Let  $A$  be diagonalisable and  $B$  be rank-one. Then  $A + B$  has at most twice as many distinct eigenvalues as  $A$ .

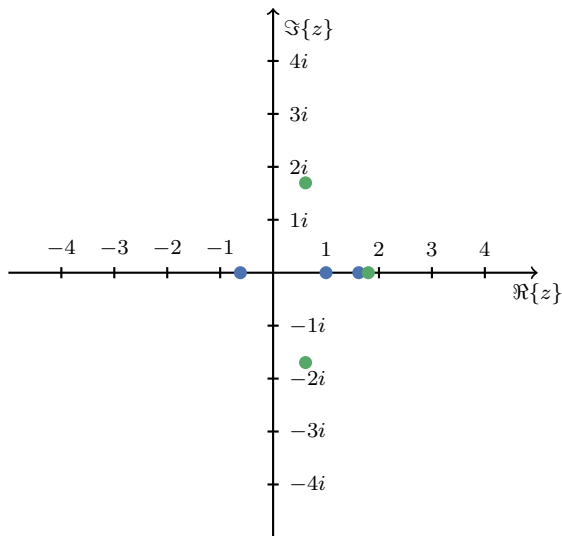
## Theorem (F., 2015)

Let  $A$  be symmetric and  $B$  be nondefective rank-one. Then all but one of the eigenvalues of  $A + B$  are interlaced with those of  $A$ .

# Eigenvalues after deflation

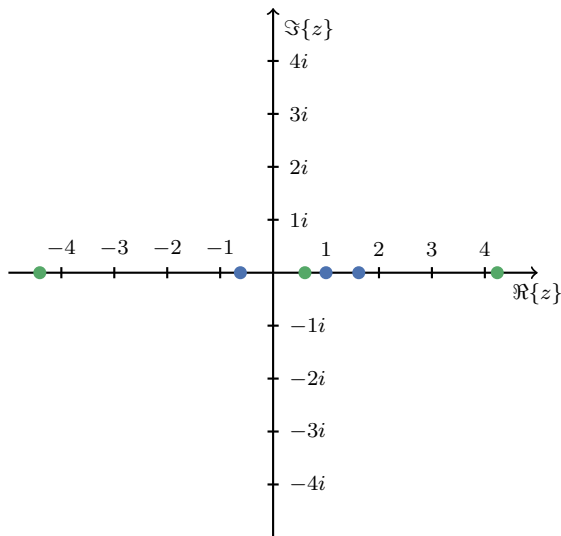


## Eigenvalues after deflation

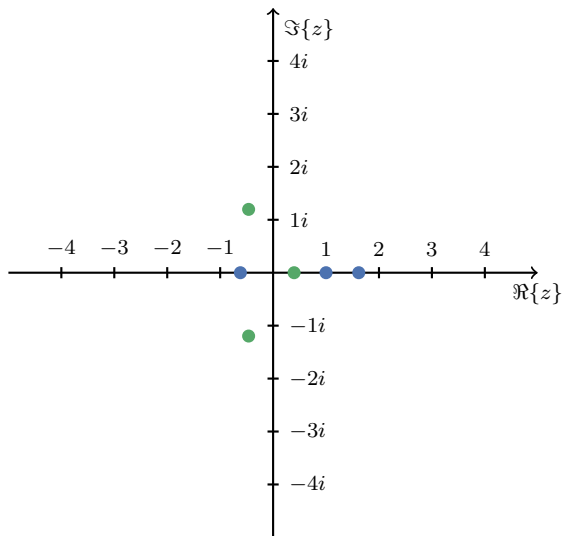




# Eigenvalues after deflation



# Eigenvalues after deflation



## Section 4

# Applications

# The Yamabe problem

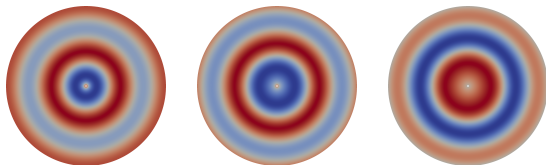
Application: differential geometry (Erway & Holst, 2011).

## The Yamabe equation

$$\begin{aligned} -8\nabla^2 u - \frac{1}{10}u + \frac{1}{r^3}u^5 &= 0 && \text{in } \Omega, \\ u &= 1 && \text{on } \partial\Omega. \end{aligned}$$

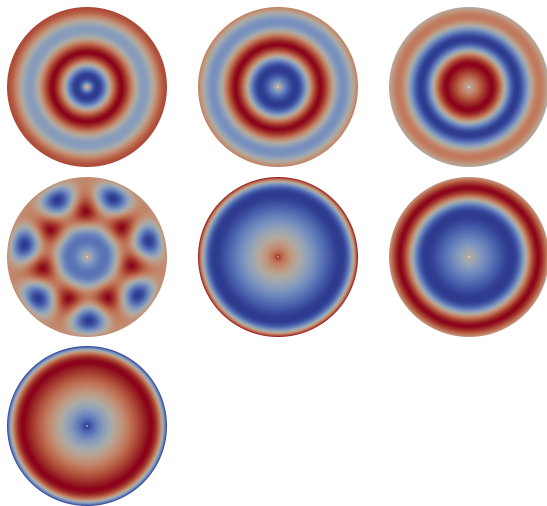
Discretisation:  $\mathbb{P}_1$  finite elements.

# Yamabe: solutions



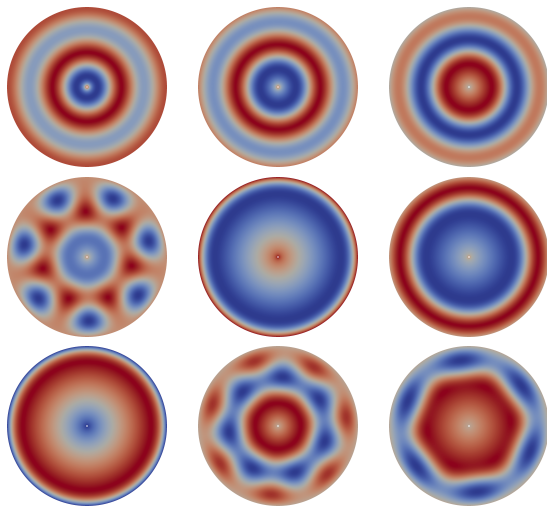
Solutions found using deflation from  $u = 1$

## Yamabe: solutions



Solutions found using deflation from  $u = 1$

## Yamabe: solutions



Solutions found using deflation from  $u = 1$  and negation.

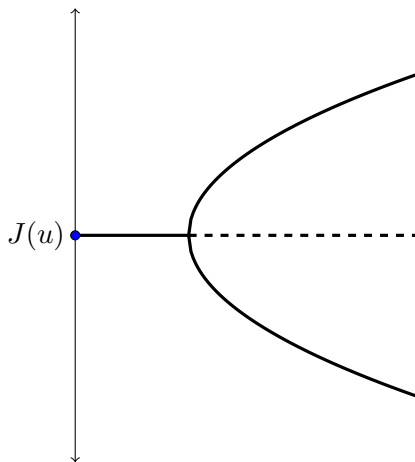
# Yamabe: preconditioner performance

# of deflations	average Krylov iterations per solve
0	15.2
1	17.1
2	15.1
3	16.9
4	11.2
5	12.4
6	10.9
7	15.5
8	13.9

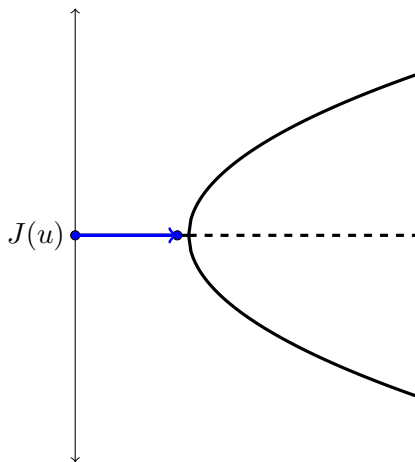
Good preconditioner performance up to  $\sim 2$  billion dofs.



# Tracing bifurcation diagrams (classical)

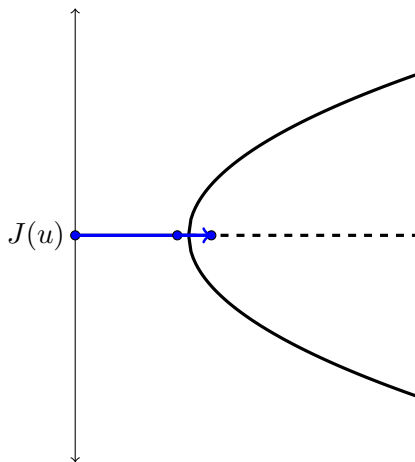


# Tracing bifurcation diagrams (classical)



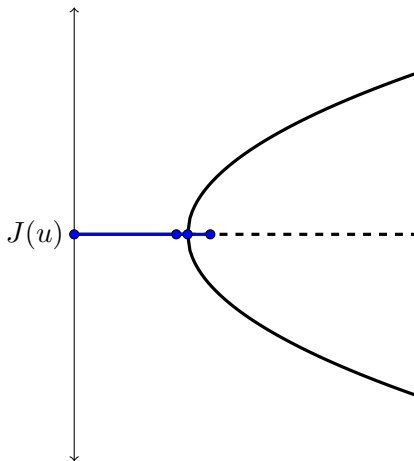
Step I: continuation

# Tracing bifurcation diagrams (classical)



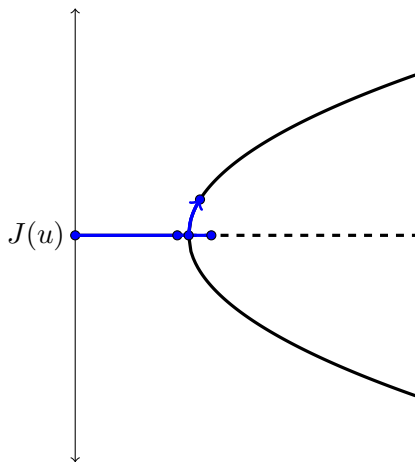
Step II: continuation

# Tracing bifurcation diagrams (classical)



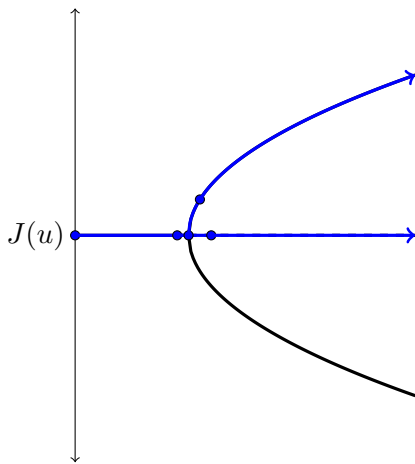
Step III: identify bifurcation point (**tricky**)

# Tracing bifurcation diagrams (classical)



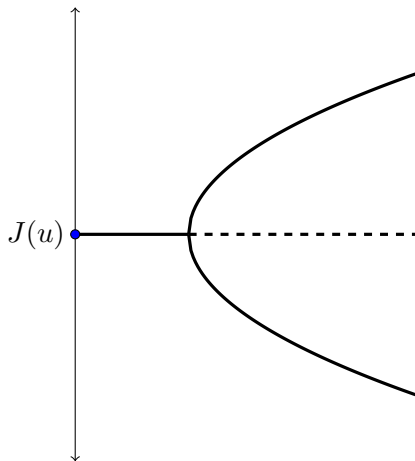
Step IV: compute eigenvectors (**expensive**) and switch (**tricky**)

# Tracing bifurcation diagrams (classical)

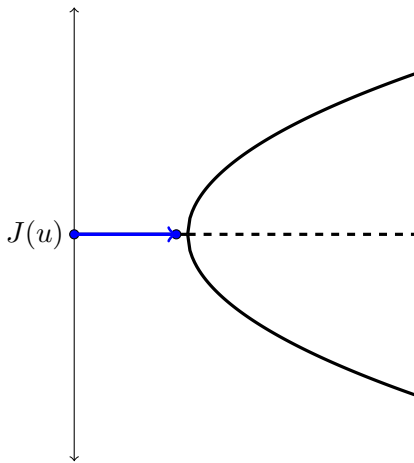


Step V: continuation on branches

# Tracing bifurcation diagrams (deflation)



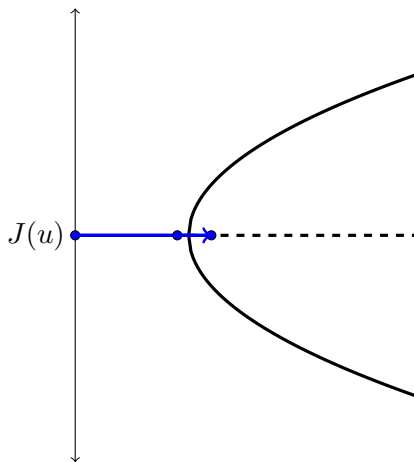
# Tracing bifurcation diagrams (deflation)



Step I: continuation

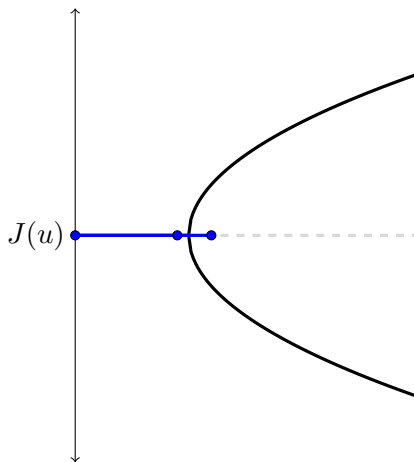


# Tracing bifurcation diagrams (deflation)



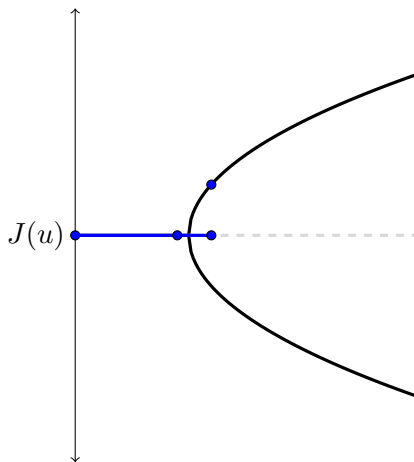
Step II: continuation

# Tracing bifurcation diagrams (deflation)



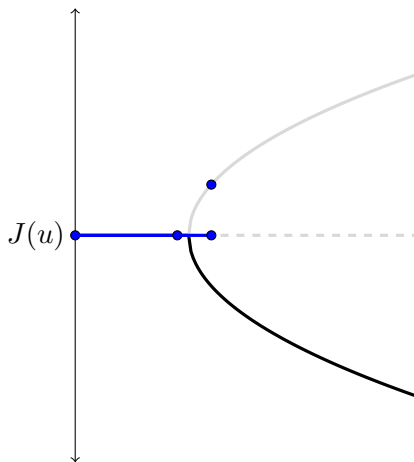
Step III: deflate

# Tracing bifurcation diagrams (deflation)



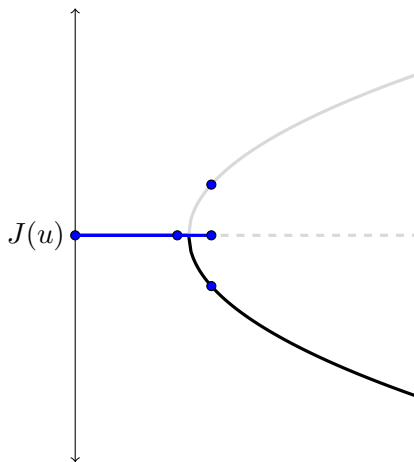
Step III<sub>+</sub>: solve deflated problem

# Tracing bifurcation diagrams (deflation)



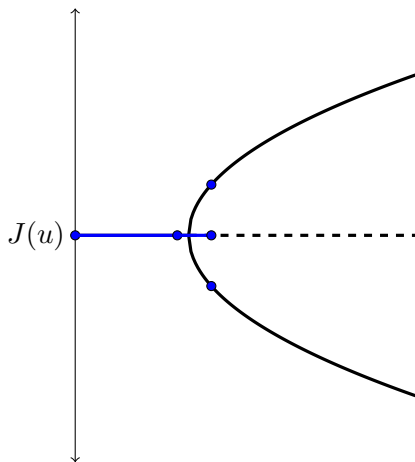
Step III: deflate

# Tracing bifurcation diagrams (deflation)



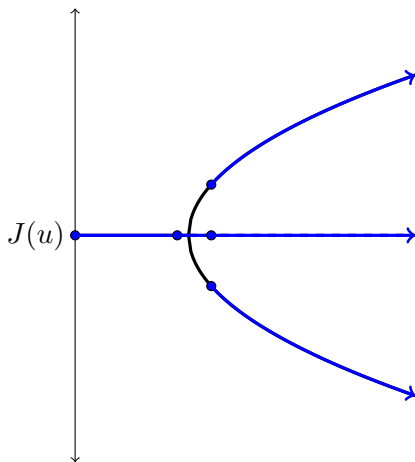
Step III<sub>+</sub>: solve deflated problem

# Tracing bifurcation diagrams (deflation)



Step IV: continuation on branches

# Tracing bifurcation diagrams (deflation)



Step IV: continuation on branches

# Hyperelastic buckling

Application: buckling of a column under loading.

## Compressible neo-Hookean hyperelasticity

Define the potential energy

$$\Pi = \int_{\Omega} \psi(u) \, dx - \int_{\Omega} B \cdot u \, dx - \int_{\partial\Omega} T \cdot u \, ds.$$

Then

$$\begin{aligned} \Pi'(u; v) &= 0 & \forall v \in V, \\ u_0 &= 0 & \text{on } x = 0, \\ u_0 &= -\text{load} & \text{on } x = L, \\ u_1 &= 0 & \text{on } x = L. \end{aligned}$$

Discretisation:  $[\mathbb{P}_1]^2$  finite elements.

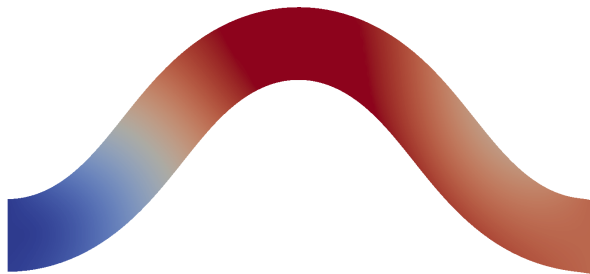


# Hyperelastic buckling: some solutions



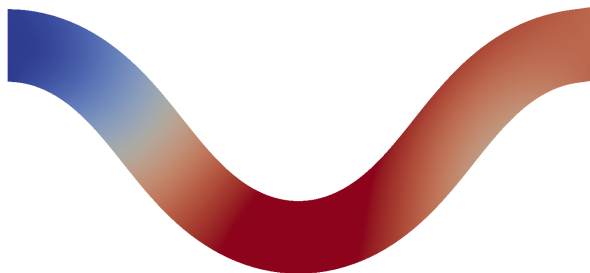
7/13 solutions of the problem for load = 0.3.

# Hyperelastic buckling: some solutions



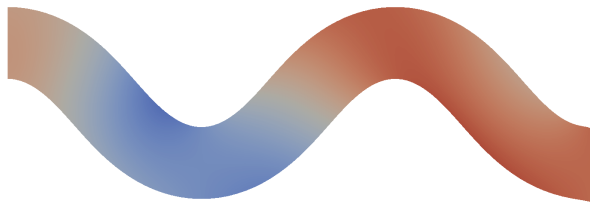
7/13 solutions of the problem for load = 0.3.

# Hyperelastic buckling: some solutions



7/13 solutions of the problem for load = 0.3.

# Hyperelastic buckling: some solutions



7/13 solutions of the problem for load = 0.3.

# Hyperelastic buckling: some solutions



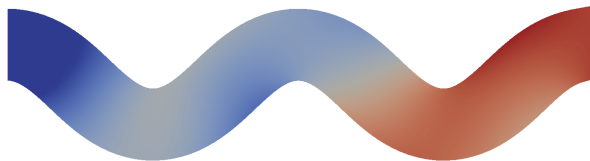
7/13 solutions of the problem for load = 0.3.

# Hyperelastic buckling: some solutions



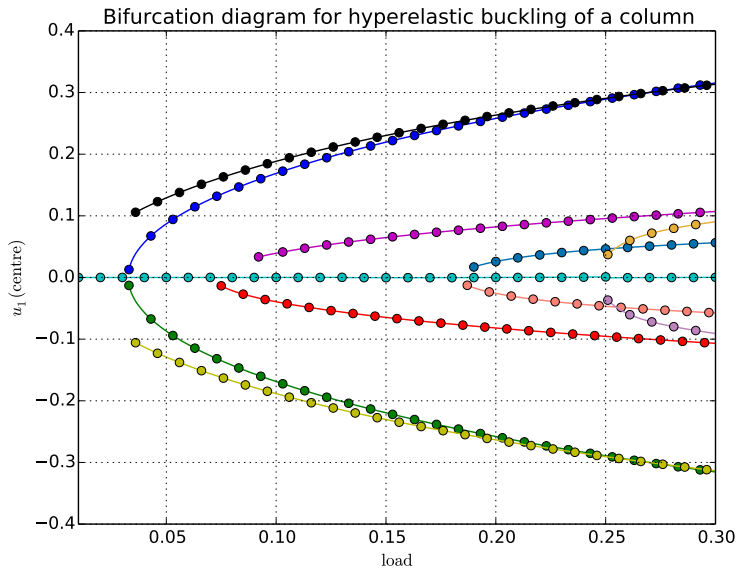
7/13 solutions of the problem for load = 0.3.

# Hyperelastic buckling: some solutions



7/13 solutions of the problem for load = 0.3.

# Hyperelastic buckling: bifurcation diagram





# Deflation vs. global optimisation

## Global optimisation techniques

Computes **global minima** for problems of **small dimension** ( $\sim 10$ ).

# Deflation vs. global optimisation

## Global optimisation techniques

Computes **global minima** for problems of **small dimension** ( $\sim 10$ ).

## Deflation + local optimisation

Computes **some minima** for problems of **arbitrary dimension**.

# Equality-constrained optimisation problems

Multiple solutions of optimality conditions  $\leftrightarrow$  multiple candidate optima

## PDE-constrained optimisation problem

$$\begin{array}{ll} \underset{y \in H_0^1, u \in L^2}{\text{minimise}} & \frac{1}{2} \int_{\Omega} (y - y_A)^2 & + \frac{\beta}{2} \int_{\Omega} u^2 \\ \text{subject to} & -\nabla^2 y = u & \text{in } \Omega. \end{array}$$

# Equality-constrained optimisation problems

Multiple solutions of optimality conditions  $\leftrightarrow$  multiple candidate optima

## PDE-constrained optimisation problem

$$\begin{aligned} & \underset{y \in H_0^1, u \in L^2}{\text{minimise}} && \frac{1}{2} \int_{\Omega} (y - y_A)^2 (y - y_B)^2 + \frac{\beta}{2} \int_{\Omega} u^2 \\ & \text{subject to} && -\nabla^2 y = u \quad \text{in } \Omega. \end{aligned}$$

# Equality-constrained optimisation problems

Multiple solutions of optimality conditions  $\leftrightarrow$  multiple candidate optima

## PDE-constrained optimisation problem

$$\begin{aligned} & \underset{y \in H_0^1, u \in L^2}{\text{minimise}} && \frac{1}{2} \int_{\Omega} (y - y_A)^2 (y - y_B)^2 + \frac{\beta}{2} \int_{\Omega} u^2 \\ & \text{subject to} && -\nabla^2 y = u \quad \text{in } \Omega. \end{aligned}$$

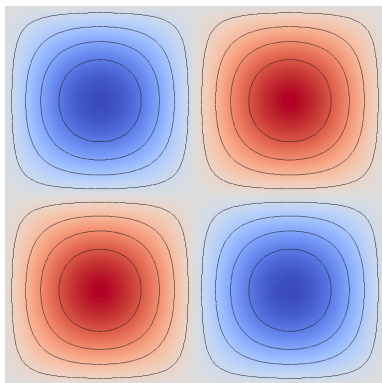
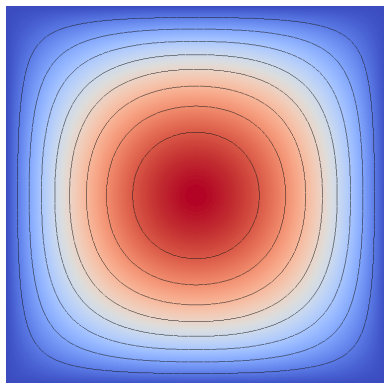
## Karush–Kuhn–Tucker optimality conditions

$$\nabla \mathcal{L} = 0.$$

Discretisation:  $[\mathbb{P}_1]^3$  finite elements.

# Equality-constrained optimisation problems

Multiple solutions of optimality conditions  $\leftrightarrow$  multiple candidate optima



2 minima of 7 stationary points, found from  $(y, u, \lambda) = (0, 0, 0)$ .

# Complementarity problems

Complementarity problems arise with inequality constraints.

## Canonical complementarity problem in $\mathbb{R}^n$

Given a residual  $F : \mathbb{R}^n \rightarrow \mathbb{R}^n$ , a lower bound  $l \in \mathbb{R}_\infty^n$  and an upper bound  $u \in \mathbb{R}_\infty^n$ , find  $x \in \mathbb{R}^n$  such that exactly one of the conditions

$$l_i < x_i < u_i \text{ and } F_i(x) = 0;$$

$$l_i = x_i \quad \text{and } F_i(x) > 0;$$

$$x_i = u_i \text{ and } F_i(x) < 0;$$

holds for each  $i$ .

# Complementarity problems

Complementarity problems arise with inequality constraints.

## Canonical complementarity problem in $\mathbb{R}^n$

Given a residual  $F : \mathbb{R}^n \rightarrow \mathbb{R}^n$ , a lower bound  $l \in \mathbb{R}_\infty^n$  and an upper bound  $u \in \mathbb{R}_\infty^n$ , find  $x \in \mathbb{R}^n$  such that exactly one of the conditions

$$l_i < x_i < u_i \text{ and } F_i(x) = 0;$$

$$l_i = x_i \quad \text{and } F_i(x) > 0;$$

$$x_i = u_i \text{ and } F_i(x) < 0;$$

holds for each  $i$ .

## Theorem (F., Croci, 2015)

Deflation also applies to complementarity problems.



# Topology optimisation constrained by the Stokes equations

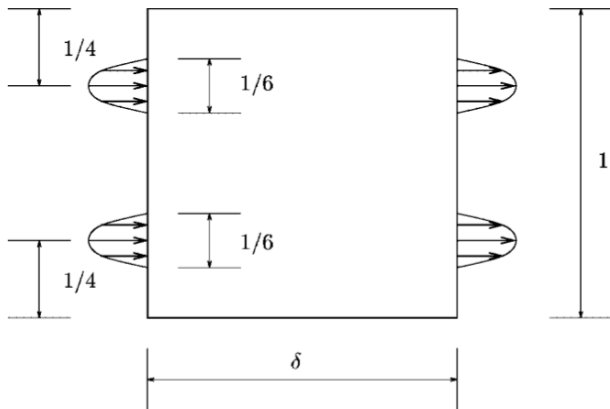


Figure 10. Design domain for the double pipe example.

What is the best pipe that connects inflow to outflow?

# Stokes: governing PDE

We wish to minimise the dissipated power in the fluid

$$J = \frac{1}{2} \int_{\Omega} \alpha(\rho) u \cdot u + \frac{1}{2} \mu \int_{\Omega} \nabla u : \nabla u$$

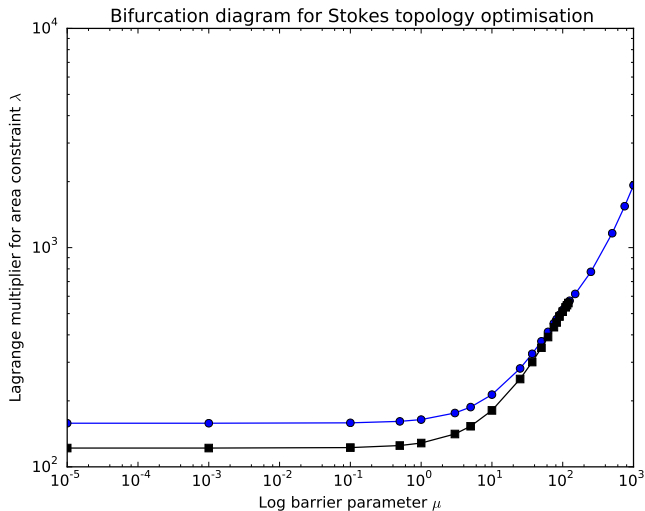
subject to the Stokes equations with a permeability term:

$$\begin{aligned} \alpha(\rho)u - \mu \nabla^2 u + \nabla p &= 0 && \text{in } \Omega, \\ \nabla \cdot u &= 0 && \text{in } \Omega, \\ u &= b && \text{on } \delta\Omega, \\ \rho(x) &\in [0, 1] && \text{a.e. in } \Omega, \\ \int_{\Omega} \rho &\leq V. \end{aligned}$$

Configuration and nonuniqueness: Borrvall and Petersson (2003).

Discretisation:  $[\mathbb{P}_2]^2 - \mathbb{P}_1$ .

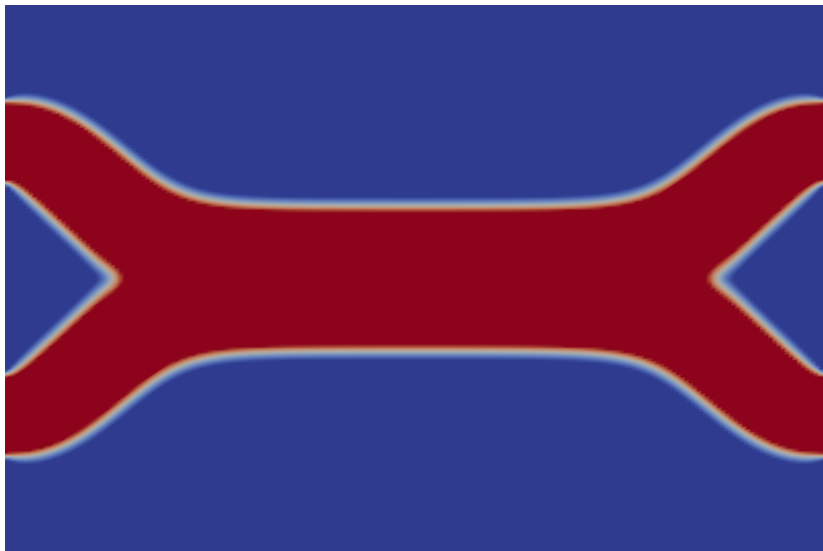
# Stokes: bifurcation diagram



# Stokes: two solutions



# Stokes:



# Conclusions

- ▶ Multiple solutions of PDEs are **ubiquitous and important**.

# Conclusions

- ▶ Multiple solutions of PDEs are ubiquitous and important.
- ▶ Deflation is a **useful technique for computing** them.

# Conclusions

- ▶ Multiple solutions of PDEs are ubiquitous and important.
- ▶ Deflation is a useful technique for computing them.
- ▶ **Deflation and continuation** are natural complements.



# Conclusions

- ▶ Multiple solutions of PDEs are ubiquitous and important.
- ▶ Deflation is a useful technique for computing them.
- ▶ Deflation and continuation are natural complements.
- ▶ There are **interesting applications** in:
  - ▶ nonlinear PDEs,
  - ▶ tracing bifurcation diagrams,
  - ▶ multimodal Bayesian inference,
  - ▶ and large-scale optimisation with constraints.