

# Using `oomph-lib` to study bifurcation phenomena in fluid flows

Andrew Hazel, Phil Haines, Matthias Heil & Rich Hewitt

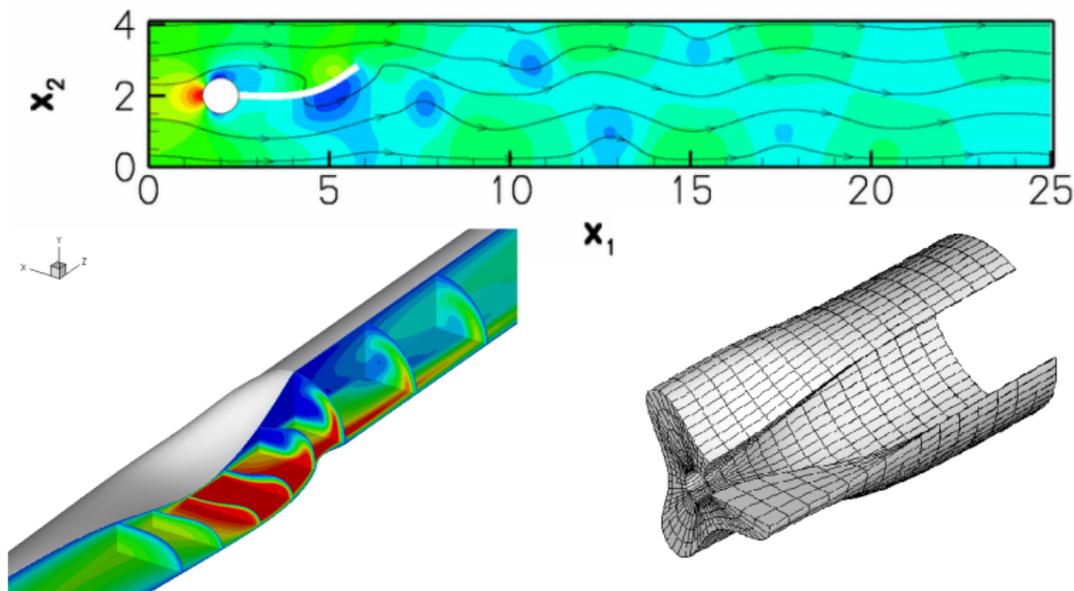
School of Mathematics  
The University of Manchester

# The framework

oomph-lib

the object-oriented multi-physics finite-element library

- ▶ A C++ library designed for the solution of multi-physics problems (e. g. fluid-structure interaction).



- ▶ OOMPH-LIB “responsible” for problem formulation  
Linear algebra performed by third-party libraries (LAPACK, Trilinos, etc)

# The framework

oomph-lib

the object-oriented multi-physics finite-element library

- ▶ Design aims:
  - ▶ Robust (without being inefficient),
  - ▶ Flexible (non-standard boundary conditions),
  - ▶ “Easy-to-use” high-level interfaces,
  - ▶ Access to parallel methods (MPI), continuation, timestepping, bifurcation detection **without** change in problem formulation,
  - ▶ Lots of documentation and demonstration codes/problems,
  - ▶ Freely available at <http://www.oomph-lib.org>
  - ▶ Link to directory

# Overall Design

- ▶ Problems (once discretised) treated as a set of algebraic equations for the unknowns  $\mathbf{u}$  with parameters  $\boldsymbol{\lambda}$

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$$\mathbf{u}_{\text{new}} = \mathbf{u}_{\text{old}} + \boldsymbol{\delta}\mathbf{u}, \quad \text{for} \quad \mathcal{J}\boldsymbol{\delta}\mathbf{u} = -\mathbf{R},$$

where  $\mathcal{J}$  is the Jacobian matrix  $\mathcal{J}_{ij} \equiv \frac{\partial R_i}{\partial u_j}$ .

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- ▶ For linear **stability analysis**, assume  $\mathbf{u}(\mathbf{x}, t) = e^{\lambda t} \mathbf{v}(\mathbf{x})$  and form generalised eigenproblem

$$\mathcal{J}\mathbf{v} = \lambda\mathcal{M}\mathbf{v},$$

where  $\mathcal{M}$  is the mass matrix.

Real part of  $\lambda$  positive  $\Rightarrow$  solution is linearly unstable.



# The general data structure

Node



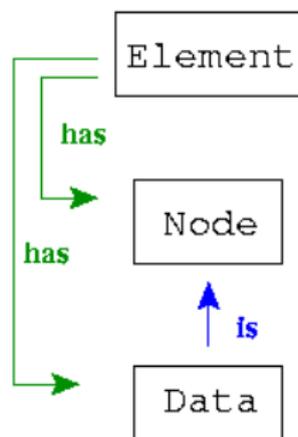
Data

Stores the Eulerian position

[Note: the Eulerian position may be an unknown and is then represented by Data]

Stores "values", their global equation numbers, and associated "history values"

# The general data structure

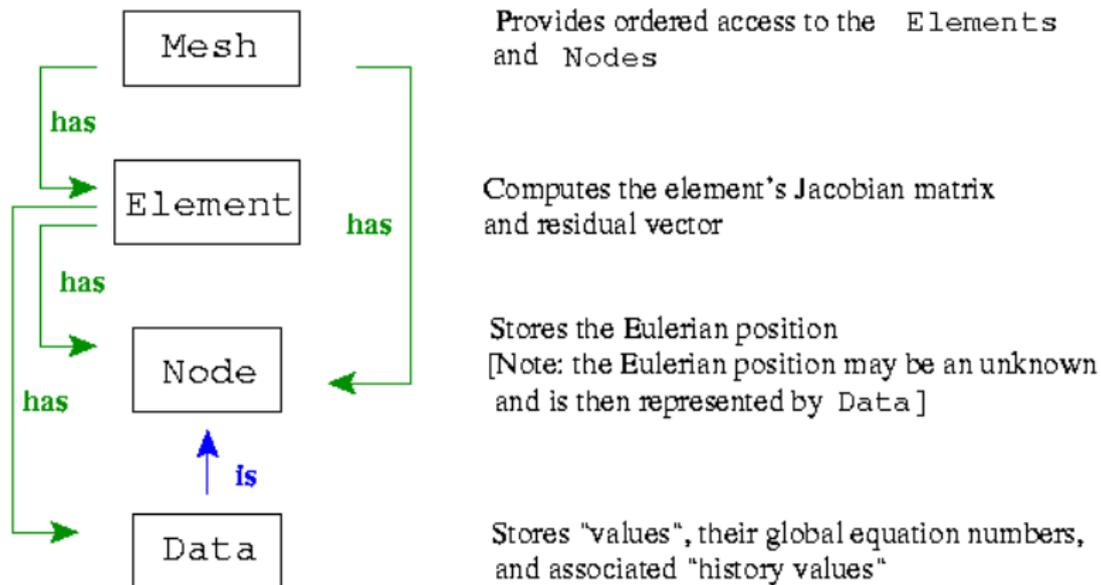


Computes the element's Jacobian matrix and residual vector

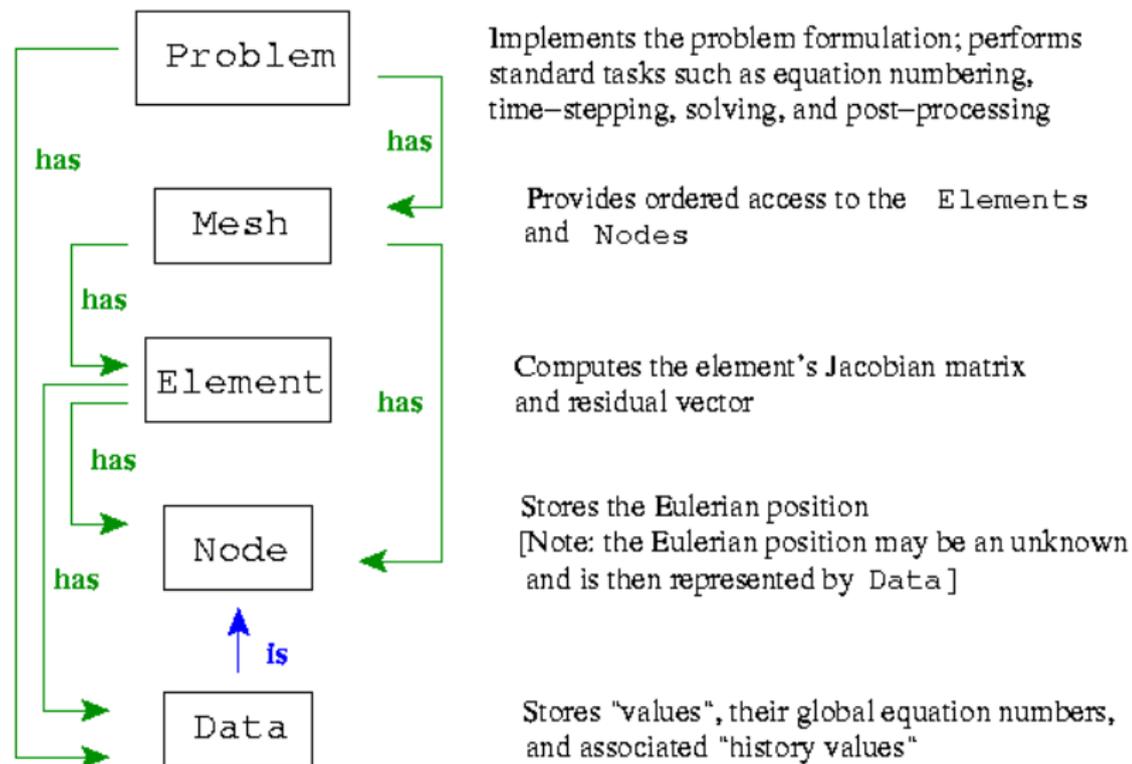
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  - ▶ Specify domain, equations, boundary conditions, etc.
  - ▶ Choose linear solver, eigensolver, timestepping scheme  
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- ▶ Must write your own specific Problem object.
  - ▶ Specify domain, equations, boundary conditions, etc.
  - ▶ Choose linear solver, eigensolver, timestepping scheme  
Sensible defaults are provided
- ▶ Then use generic high-level functions, e. g.

```
//Find steady solutions for different Reynolds numbers
for(int i=0;i<700;i++)
  { Re += 0.01; problem.steady_newton_solve(); }
double dt = 0.1;
//Assume system at current solution for all t-
problem.assign_initial_values_impulsive(dt);
//Unsteady simulation at current Reynolds number
for(int t=0;t<2000;t++)
  { problem.unsteady_newton_solve(dt); }
```

# Bifurcation Detection

```
//Solve steady problem
problem.steady_newton_solve();
//Find the four eigenvalues with real part near zero
problem.solve_eigenproblem(4,eigenvalues,eigenvectors);
//Assemble the augmented system associated with a
//Pitchfork bifurcation
problem.activate_pitchfork_tracking(&Re,eigenvectors[0]);
//Solve the augmented system
problem.steady_newton_solve();
//Continue the bifurcation in a second parameter
problem.arc_length_step_solve(&Gamma,ds);
```

# Bifurcation Detection

- ▶ Finding the bifurcation point “exactly”:
  - ▶ Solve for the unknowns and critical eigenfunction simultaneously

$$\begin{pmatrix} \mathbf{R} \\ \mathcal{J}\mathbf{v} \\ \mathbf{v} \cdot \mathbf{V} - 1 \end{pmatrix} = 0,$$

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- ▶ (Optionally) block-decompose to reduce problem to a few linear solves with original Jacobian matrix (Fold & Pitchfork).
- ▶ For Hopf bifurcation assemble the augmented matrix

$$\begin{pmatrix} \mathcal{J} & \omega\mathcal{M} \\ -\omega\mathcal{M} & \mathcal{J} \end{pmatrix},$$

where  $\omega$  is the imaginary part (frequency) of the eigenvalue.

# Handling large problems: computational approach

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  - ▶ Use error estimators\* and spatial adaptivity to refine only where needed — RefinableMesh objects.

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- ▶ Distribute the problem:
  - ▶ Memory is always an ultimate limit. If the problem does not fit on the computer, cannot solve it.
  - ▶ Element-by-element assembly leads to natural decompositions — hold a subset of the elements on each processor.

# Spatial adaptivity

Strategy:

- ▶ Start with coarse mesh and refine it automatically.

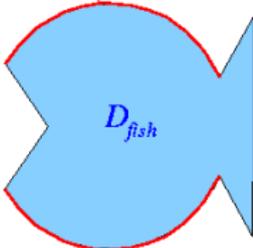
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**Example:** Poisson equation in a fish-shaped domain

circular arc; centre at  $(X_c, Y_c)$



$D_{fish}$

$$\nabla^2 u = 1 \quad \text{in } D_{fish}$$

subject to

$$u = 0 \quad \text{on } \partial D_{fish}$$

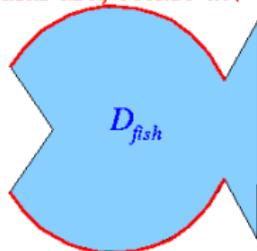
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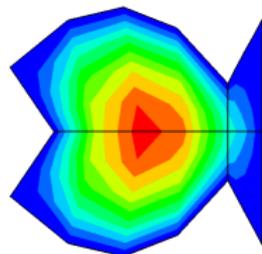
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Solve

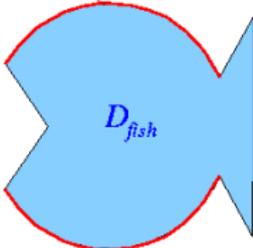
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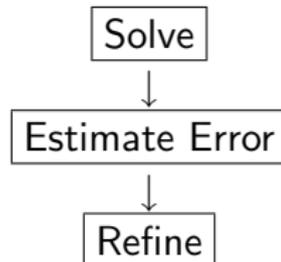
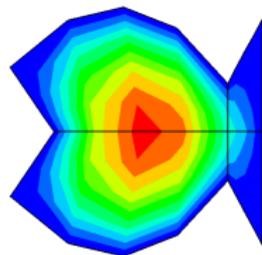
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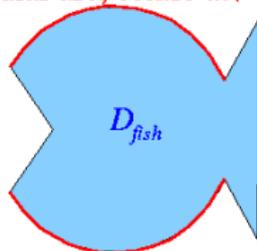
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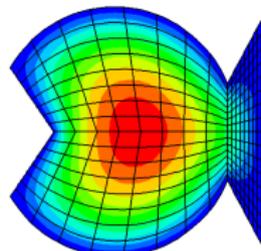
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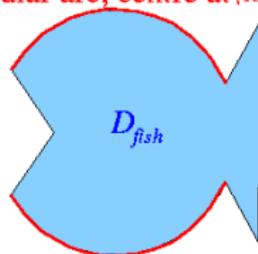
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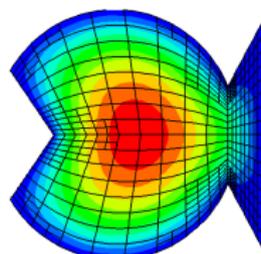
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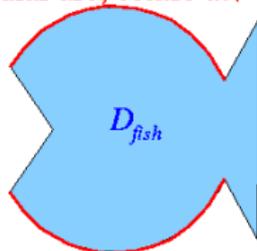
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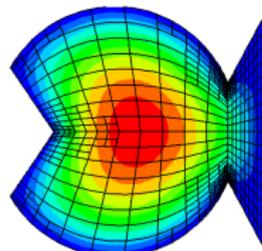
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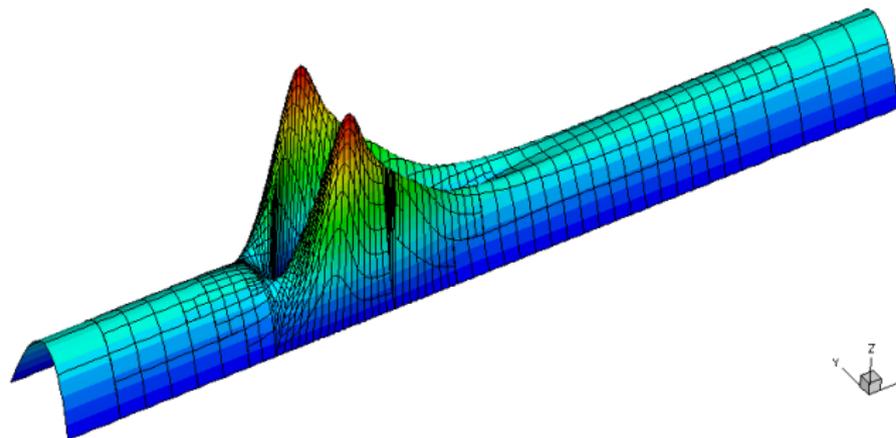
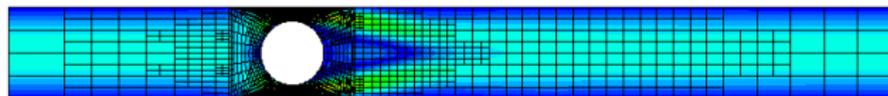


Note the resolution of curvilinear boundaries

```
problem.newton_solve(3);
```

# Adaptivity and bifurcation detection

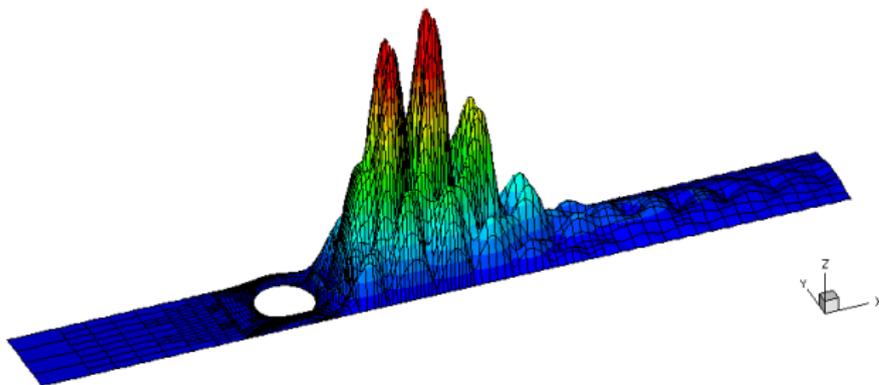
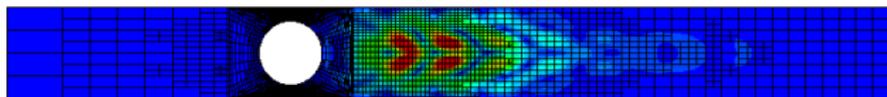
- ▶ Must accurately resolve base flow and eigenfunction.



- ▶ Flow past cylinder in channel at  $Re = 90$   
 $L =$  diameter of cylinder,  $U =$  inlet flow integrated over cylinder,  
*c. f.* Cliffe & Tavener (2004)

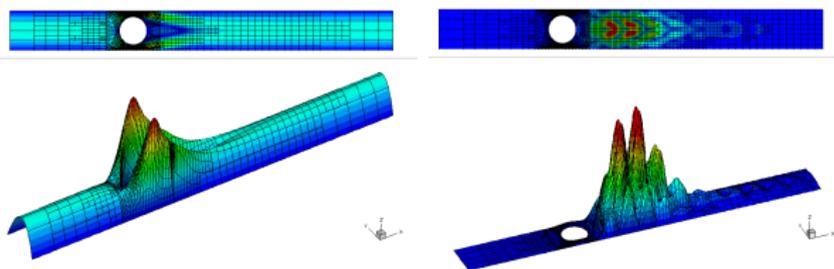
# Adaptivity and bifurcation detection

- ▶ Must accurately resolve base flow and eigenfunction.



- ▶ Critical eigenfunction associated with Hopf bifurcation at  $Re \approx 92$  has very different spatial structure.

# Adaptivity and bifurcation detection



- ▶ Current strategy is to refine mesh based on a weighted sum of the estimated error for base flow and critical eigenfunction.

No. of elements	$Re_c$	$\omega$	Comments
1458	92.3798	0.568019	Z2 error $\approx$ 0.001 (base flow)
2826	91.9916	0.569385	
3348	91.9927	0.569382	
3366	91.9927	0.569382	combined Z2 error $<$ 0.001
14400	91.9944	0.5694	Cliffe & Tavener (2004), uniform?

## Linear solvers & Problem distribution

- ▶ Problem distribution complete.
- ▶ Bifurcation detection algorithms partially parallelised.
- ▶ Block-decomposition of augmented system allows re-use of optimal solvers in detection and tracking of Fold and Pitchfork bifurcations.
  - ▶ Implementation of Elman, Silvester & Wathen's LSC preconditioner for the Navier–Stokes equations works well.
  - ▶ Resolves are not as cheap for iterative solvers vs direct solvers.
- ▶ Need good preconditioners for the augmented matrix required when tracking Hopf bifurcations

$$\begin{pmatrix} \mathcal{J} & \omega\mathcal{M} \\ -\omega\mathcal{M} & \mathcal{J} \end{pmatrix},$$

# Application to similarity solutions

## Similarity solutions

- ▶ In certain cases, Navier–Stokes equations can be simplified by using similarity reductions
  - assume a particular functional form, e. g.  $u = xF(y)$ .
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- ▶ ... and we are making the **tacit** assumptions that:
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# Similarity solutions

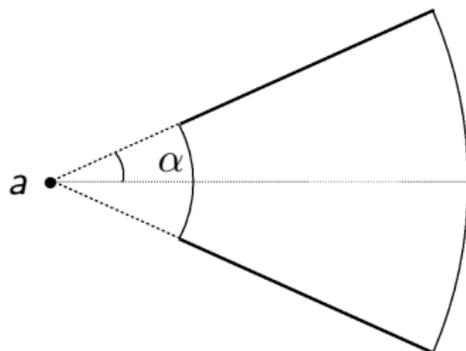
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## Questions:

- ▶ Are similarity solutions a good approximation for sufficiently long physical domains?
- ▶ Do the (neglected) boundary conditions that must be applied in finite domains influence the system's dynamics?

## Jeffrey–Hamel flow

- ▶ 2D flow of fluid between two non-parallel plane walls — model for flow in a channel expansion.

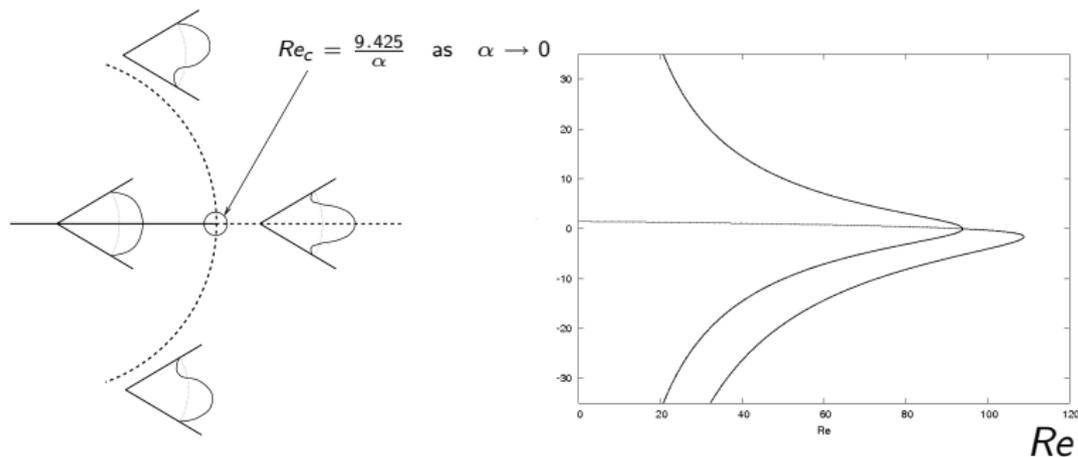


- ▶ The idealised problem of flow in an infinite wedge of semi-angle  $\alpha$  with a source at the apex  $a$  admits a similarity solution of the form

$$\hat{\mathbf{u}} = \frac{\hat{f}(\theta)}{r} \mathbf{e}_r \quad (\text{Jeffrey–Hamel flow}).$$

# Similarity solution behaviour

- ▶ Rich dynamics in similarity solution behaviour.
- ▶ In particular, the symmetric “pure outflow” solution loses stability via a **subcritical** pitchfork bifurcation.



Adapted from Kerswell, Tutty & Drazin (2003)

$$\alpha = 0.1$$

- ▶ N.B.  $Re \equiv \frac{Q}{\nu}$ , where  $Q$  is the radial mass flux,  $\nu = \mu/\rho$  is the kinematic viscosity of the fluid.

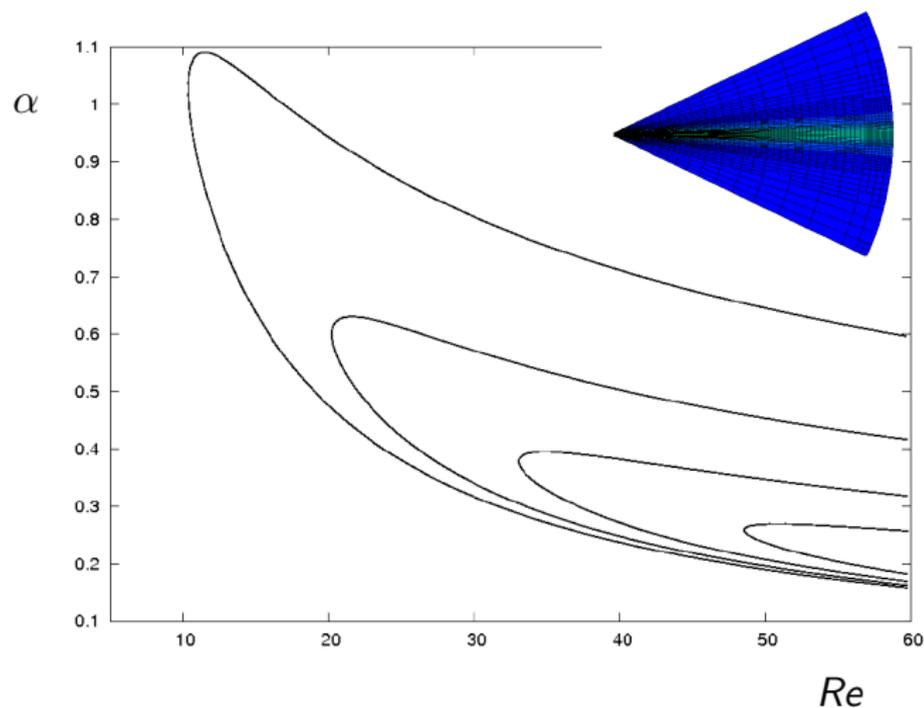
## Finite-domain effects

- ▶ Can actually be realised experimentally!
- ▶ Bifurcation is **supercritical** when flows are realised in finite domains either experimentally or numerically.  
(also true in sudden-expansion geometry)
- ▶ Yet, critical Reynolds number in good agreement with Jeffrey–Hamel solution.

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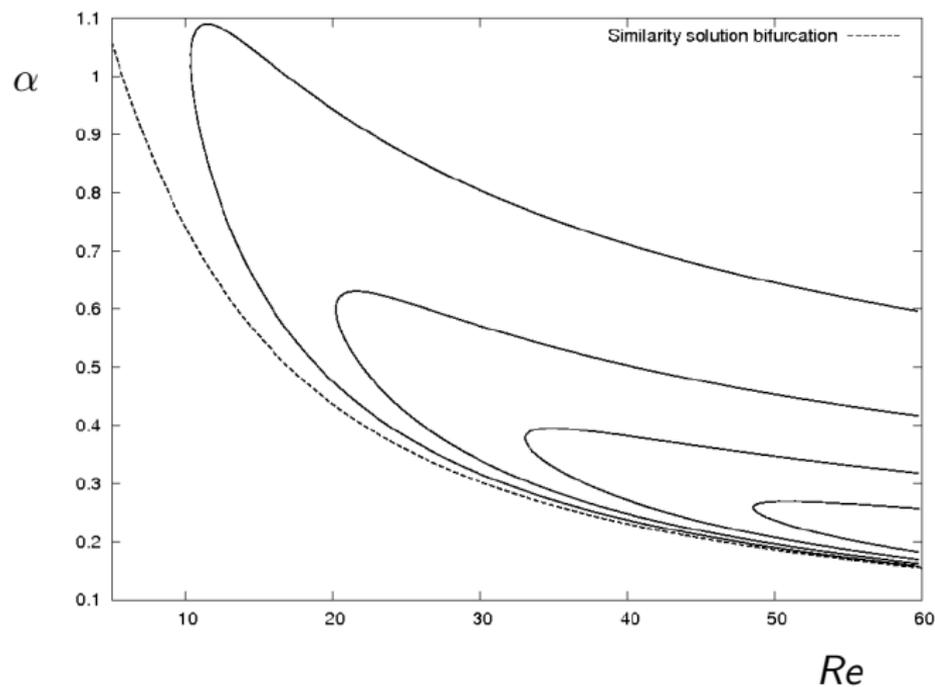
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- 
- ▶ Radius ratio fixed at 100.
  - ▶ Two boundary conditions at inlet and outlet.
  - ▶ Prescribe parabolic inflow with volume flux 1  
$$u = \frac{3}{4\alpha r} (1 - (\theta/\alpha)^2).$$
  - ▶ Leave outlet pseudo-traction free.

## Locus of bifurcations in the $(Re, \alpha)$ plane



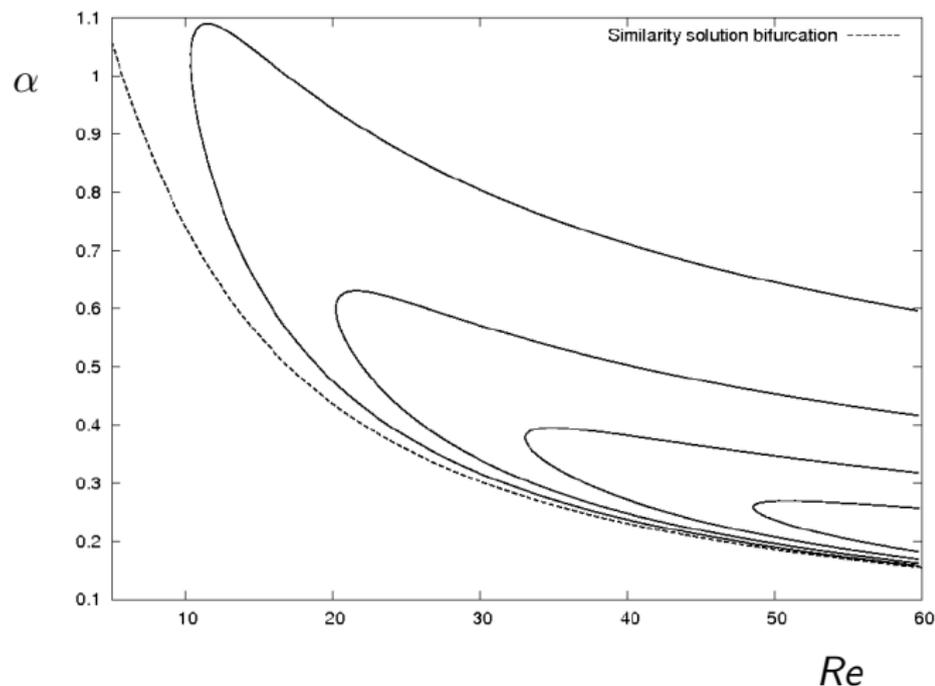
- ▶ All bifurcations are supercritical pitchforks in the Reynolds number.

## Locus of bifurcations in the $(Re, \alpha)$ plane



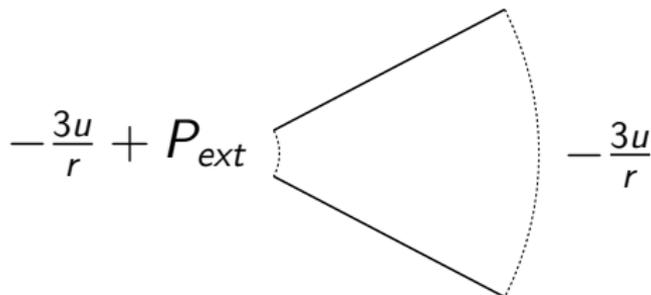
- ▶ Supercritical finite-domain pitchforks approach the subcritical similarity-solution pitchfork for small  $\alpha$ .

## Locus of bifurcations in the $(Re, \alpha)$ plane



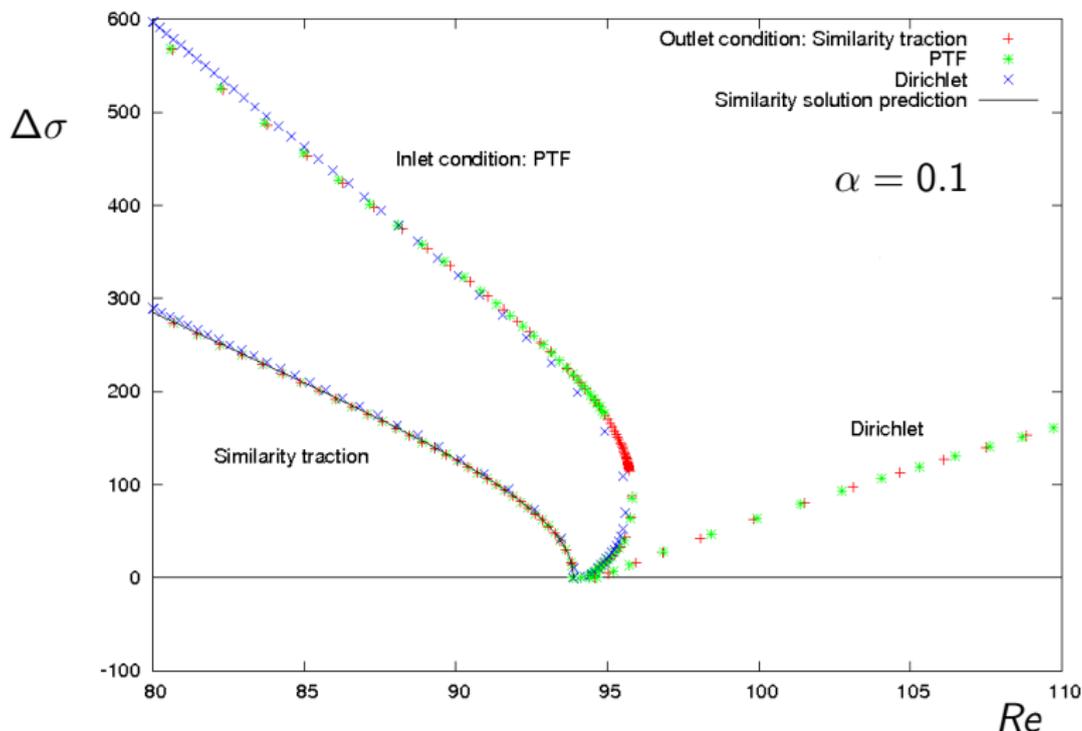
- ▶ For small  $\alpha$ , eigenfunction over most of finite domain is indistinguishable from a similarity solution (spatial) eigenfunction, but **not** the critical one.

## Forcing the similarity solution



- ▶ Replicate similarity solution behaviour (subcriticality) by applying consistent traction conditions at inlet and outlet.
- ▶ Specify the desired value of  $-\rho + \frac{\partial u}{\partial r}$  along boundary.
- ▶ For the similarity solution,  $-\rho + \frac{\partial u}{\partial r} = -\frac{3u}{r} + C$
- ▶ External pressure ( $P_{ext}$ ) used to drive volume flux of one.
- ▶ Recover similarity solution behaviour. Subcritical pitchfork.

# Changing boundary conditions — Inlet dominance



- ▶ Outlet condition has little effect on solution branches.

# Jeffrey–Hamel Conclusions

- ▶ Critical Reynolds number in good agreement between similarity solution and finite domains for small angles (irrespective of boundary conditions).
- ▶ Critical eigenfunction close to a spatial eigenfunction of the similarity solution.
- ▶ Yet, criticality of bifurcation is determined by inflow boundary condition and is, generically, supercritical in finite domains, but subcritical in the similarity solution.
- ▶ Structure independent of radius ratio of finite domain.

## Similarity Solutions — the verdict

- ▶ The base flow is usually well-approximated by the similarity solution over the majority of a finite domain, irrespective of the boundary conditions.
- ▶ For special choices of boundary conditions, similarity solutions and their bifurcation structures can be realised in finite domains.
- ▶ For more general boundary conditions, modification/suppression of the similarity solution eigenfunctions renders the similarity-solution bifurcation diagrams meaningless.
- ▶ The bifurcations in finite domains can be connected to the similarity solution bifurcations via non-trivial paths in a space spanned by the  $Re$  the length (aspect ratio) of the domain and a homotopy parameter.

# Open questions

- ▶ Can we determine *a priori* when a similarity solution can give useful information about the general nonlinear dynamics?
- ▶ Temporal dynamics of the systems?
  - ▶ Rotating disk and porous channel similarity solutions undergo Hopf bifurcations. Are these realised in finite domains?
  - ▶ What about period doubling, chaos?
- ▶ Can we make theoretical progress by assuming nonlinear wave-like structures in the eigenfunctions? (*c.f.* Kerswell, Tutty & Drazin)
- ▶ Why is the symmetry-breaking bifurcation in Jeffrey–Hamel flow so insensitive to boundary conditions? (fluke?)

# Acknowledgements

- ▶ Tom Wright (early studies of porous-channel flow)
- ▶ Dr. Andy Gait (problem distribution)
- ▶ Richard Muddle (block preconditioning & parallel solvers)
- ▶ Dr. Jonathan Boyle (interfaces to third-party iterative solvers)
- ▶ Cedric Ody (Young–Laplace elements)
- ▶ Renaud Schleck (octree-based refinement for 3D problems)
- ▶ ... and many others who have worked on or with OOMPH-LIB