

# Fast Iterative Solvers for Reaction-Diffusion Control Models of Chemical and Biological Processes

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## PDE-Constrained Optimization

- A general PDE-constrained optimization problem may be written as

$$\begin{aligned} \min_{y,f} \quad & \frac{1}{2} \|y - \hat{y}\|_{L_2(\Omega)}^2 + \frac{\beta}{2} \|f\|_{L_2(\Omega)}^2 \\ \text{s.t.} \quad & \mathcal{L}y = f, \quad \text{in } \Omega, \\ & y = g, \quad \text{on } \partial\Omega. \end{aligned}$$

- Applications in far-reaching areas such as [flow control](#), [semiconductor design](#), [electromagnetic inverse problems](#), [weather forecasting](#), [medical imaging](#) and [finance](#).

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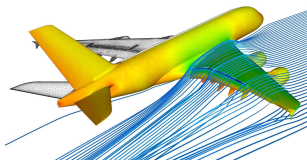
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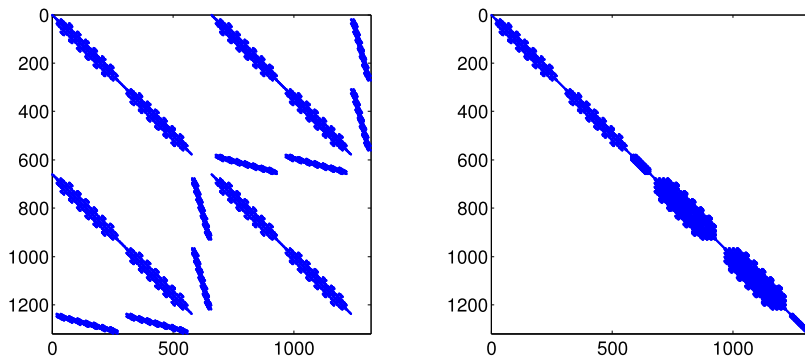
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	Flow control	Image processing	Chemical reactions
State	Velocity and pressure of fluid	Image post-processing	Concentrations of reactants
Control	Energy put into system	Data-driven terms in processing	Rate at which reactants inserted



## PDE-Constrained Optimization

- Problems clearly defined, but in general **extremely difficult to solve**.
- Using a finite element method  $\rightarrow$  matrix system of very high dimension.
- Very effective approach for solving these systems is to **construct iterative methods which are accelerated by powerful preconditioners**.
- When solving matrix system  $\mathcal{A}\mathbf{x} = \mathbf{b}$ , a good preconditioner  $\mathcal{P}$  will be cheap to apply & such that  $\mathcal{P}^{-1}\mathcal{A}$  has desirable properties.
- Many advantages: can exploit sparsity and structure of matrices, don't have to store the entire system, can solve **large problems rapidly & in parallel**.



Matrix  $\mathcal{A}$  & Preconditioner  $\mathcal{P}$

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## Saddle Point Systems

- For the problems we consider, the matrices are of *saddle point* structure:

$$\mathcal{A} = \begin{bmatrix} A & B^\top \\ B & -C \end{bmatrix}.$$

- Two preconditioners are [Kuznetsov, 1995], [Murphy, Golub & Wathen, 2000]:

$$\mathcal{P}_D = \begin{bmatrix} A & 0 \\ 0 & S \end{bmatrix}, \quad \mathcal{P}_T = \begin{bmatrix} A & 0 \\ B & -S \end{bmatrix}.$$

- Here,  $S = C + BA^{-1}B^\top$  is the (negative) *Schur complement*.
- **Excellent spectral properties:** if  $\mathcal{P}_D^{-1}\mathcal{A}$  and  $\mathcal{P}_T^{-1}\mathcal{A}$  are nonsingular [Murphy, Golub & Wathen, 2000], [Ipsen, 2001]:

$$\lambda(\mathcal{P}_D^{-1}\mathcal{A}) \in \left\{ 1, \frac{1}{2}(1 \pm \sqrt{5}) \right\}, \quad \text{if } C = 0,$$

$$\lambda(\mathcal{P}_T^{-1}\mathcal{A}) \in \{1\}, \quad \text{generally.}$$

- In general  $A$ ,  $S$  are not practical preconditioners, so **devise approximations**  $\hat{A}$ ,  $\hat{S}$ .



$$\begin{aligned} \min_{y,f} \quad & \frac{1}{2} \|y - \hat{y}\|_{L_2(\Omega)}^2 + \frac{\beta}{2} \|f\|_{L_2(\Omega)}^2 \\ \text{s.t.} \quad & -\nabla^2 y = f, \quad \text{in } \Omega, \\ & y = g, \quad \text{on } \partial\Omega. \end{aligned}$$

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## Distributed Poisson Control

- Differentiating (with respect to  $\mathbf{y}$ ,  $\mathbf{f}$ ,  $\mathbf{p}$ ) the cost functional:

$$\mathcal{L}(\mathbf{y}, \mathbf{f}, \mathbf{p}) = \frac{1}{2} (\mathbf{y} - \hat{\mathbf{y}})^\top M (\mathbf{y} - \hat{\mathbf{y}}) + \frac{\beta}{2} \mathbf{f}^\top M \mathbf{f} + \mathbf{p}^\top (K \mathbf{y} - M \mathbf{f} - \mathbf{g}),$$

where  $M$  is a finite element *mass matrix*, and  $K$  a *stiffness matrix*, gives

$$\left[ \begin{array}{cc|c} M & 0 & K \\ 0 & \beta M & -M \\ \hline K & -M & 0 \end{array} \right] \begin{bmatrix} \mathbf{y} \\ \mathbf{f} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} M \hat{\mathbf{y}} \\ \mathbf{0} \\ \mathbf{g} \end{bmatrix}.$$

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- This is a saddle point system with

$$A = \begin{bmatrix} M & 0 \\ 0 & \beta M \end{bmatrix}, \quad S = KM^{-1}K + \frac{1}{\beta}M.$$

- We may precondition  $A$  using Chebyshev semi-iteration to approximate  $M^{-1}$ .

## Approximating the Schur Complement – Matching Strategy

- We aim to capture both terms of the Schur complement by writing

$$S = KM^{-1}K + \frac{1}{\beta}M, \quad \hat{S} = \left( K + \frac{1}{\sqrt{\beta}}M \right) M^{-1} \left( K + \frac{1}{\sqrt{\beta}}M \right).$$

- This ensures that [Pearson & Wathen, 2012]:

$$\lambda(\hat{S}^{-1}S) \in \left[ \frac{1}{2}, 1 \right]$$

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- Our preconditioner requires four ingredients:

- ① Saddle point approximation,
- ② Approximation of mass matrix by Chebyshev semi-iteration,
- ③ Matching strategy for Schur complement,
- ④ Effective multigrid method for  $K + \frac{1}{\sqrt{\beta}}M$  to apply  $\hat{S}$ .

- Only  $\sim 15$  iterations required for 6 digits of accuracy using MINRES.

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J. W. Pearson and A. J. Wathen, *A New Approximation of the Schur Complement in Preconditioners for PDE-Constrained Optimization*, Numerical Linear Algebra with Applications, 2012.

## Extension to Time-Dependent Problems

- When solving an analogous time-dependent (heat equation control) problem:

$$\min_{y,f} \frac{1}{2} \int_0^T \int_{\Omega} (y(\mathbf{x}, t) - \hat{y}(\mathbf{x}, t))^2 \, d\Omega dt + \frac{\beta}{2} \int_0^T \int_{\Omega} (f(\mathbf{x}, t))^2 \, d\Omega dt,$$

$$\text{s.t.} \quad \begin{aligned} y_t - \nabla^2 y &= f, & \text{for } (\mathbf{x}, t) \in \Omega \times [0, T], \\ y &= g, & \text{on } \partial\Omega \times [0, T], \\ y &= y_0, & \text{at } t = 0, \end{aligned}$$

one is faced with a system of the form:

$$\left[ \begin{array}{cc|c} \tau \mathcal{M}_{1/2} & 0 & \mathcal{K}^\top \\ 0 & \beta \tau \mathcal{M}_{1/2} & -\tau \mathcal{M} \\ \hline \mathcal{K} & -\tau \mathcal{M} & 0 \end{array} \right] \begin{bmatrix} \mathbf{y} \\ \mathbf{f} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} \tau \mathcal{M}_{1/2} \hat{\mathbf{y}} \\ \mathbf{0} \\ \mathbf{g} \end{bmatrix},$$

where

$$\mathcal{K} = \begin{bmatrix} M + \tau K & & & & \\ & -M & M + \tau K & & \\ & & \ddots & \ddots & \\ & & & & -M & M + \tau K \end{bmatrix},$$

$$\mathcal{M}_{1/2} = \text{blkdiag} \left( \frac{1}{2} M, M, \dots, M, \frac{1}{2} M \right), \quad \mathcal{M} = \text{blkdiag} (M, \dots, M).$$

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- We construct our preconditioner as follows [Pearson, Stoll & Wathen, 2012]:

$$S = \frac{1}{\tau} \mathcal{K} \mathcal{M}_{1/2}^{-1} \mathcal{K}^\top + \frac{\tau}{\beta} \mathcal{M} \mathcal{M}_{1/2}^{-1} \mathcal{M}, \quad \hat{S} = \frac{1}{\tau} \left( \mathcal{K} + \frac{\tau}{\sqrt{\beta}} \mathcal{M} \right) \mathcal{M}_{1/2}^{-1} \left( \mathcal{K} + \frac{\tau}{\sqrt{\beta}} \mathcal{M} \right)^\top$$

$$\hookrightarrow \mathcal{P} = \begin{bmatrix} \tau \mathcal{M}_{1/2} & 0 & 0 \\ 0 & \beta \tau \mathcal{M}_{1/2} & 0 \\ 0 & 0 & \frac{1}{\tau} \left( \mathcal{K} + \frac{\tau}{\sqrt{\beta}} \mathcal{M} \right) \mathcal{M}_{1/2}^{-1} \left( \mathcal{K} + \frac{\tau}{\sqrt{\beta}} \mathcal{M} \right)^\top \end{bmatrix}.$$

$$S_G = XX^\top + YY^\top$$
$$\hat{S}_G = (X + Y)(X + Y)^\top$$

$X, Y$  real  
 $S_G, \hat{S}_G$  invertible

→

$$\lambda(\hat{S}_G^{-1}S_G) \geq \frac{1}{2}$$



$$\begin{array}{ll}
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## Uses of Matching Strategy

- Complex valued linear algebraic systems [Axelsson et al., 2014], [Bai et al., 2013].
- Cahn-Hilliard models in imaging [Bosch, Stoll & Benner, 2014], [Boyanova, Do-Quang & Neytcheva, 2012].
- Phase Field Crystal equation in soft matter physics [Praetorius & Voigt, 2015].

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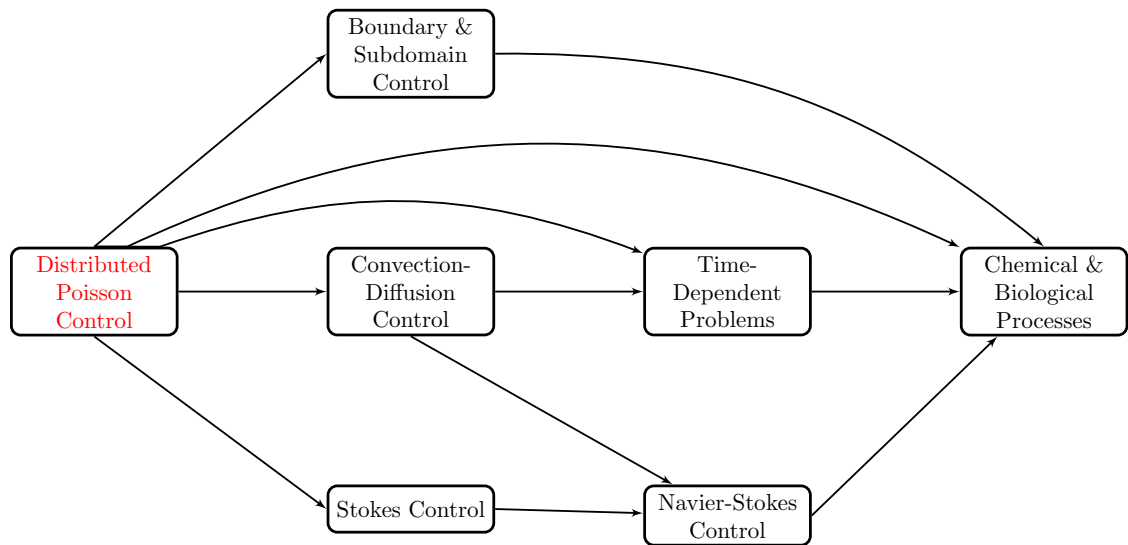
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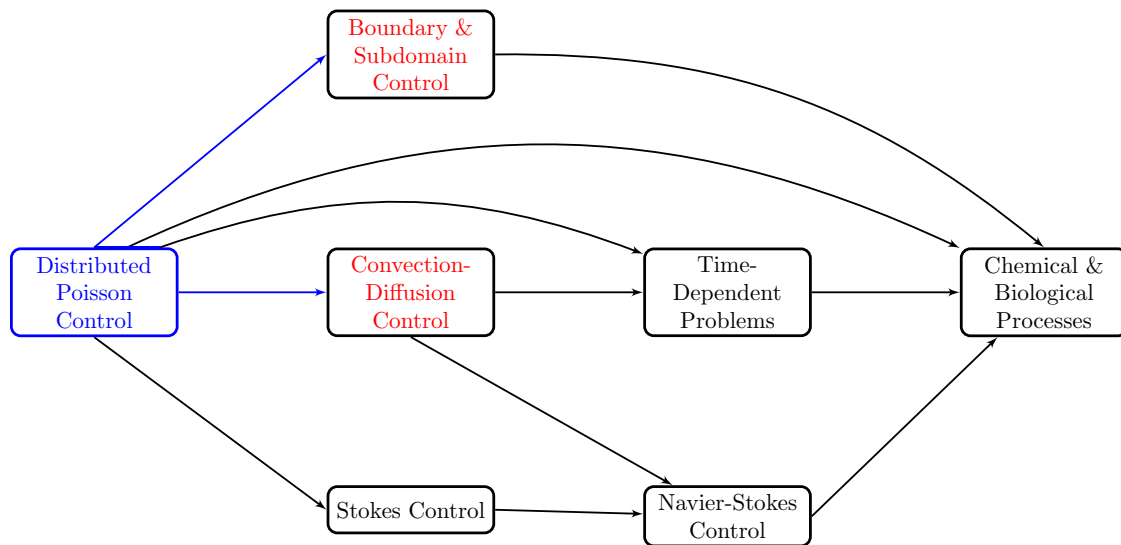
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- Phase Field Crystal equation in soft matter physics [Praetorius & Voigt, 2015].
- Interior point methods for linear (and quadratic) programming:

$$A = \begin{array}{|c|c|c|} \hline A_1 & 0 & B_1^\top \\ \hline 0 & A_2 & B_2^\top \\ \hline B_1 & B_2 & 0 \\ \hline \end{array}, \quad A_1 \prec A_2.$$

The Schur complement may be approximated as follows:

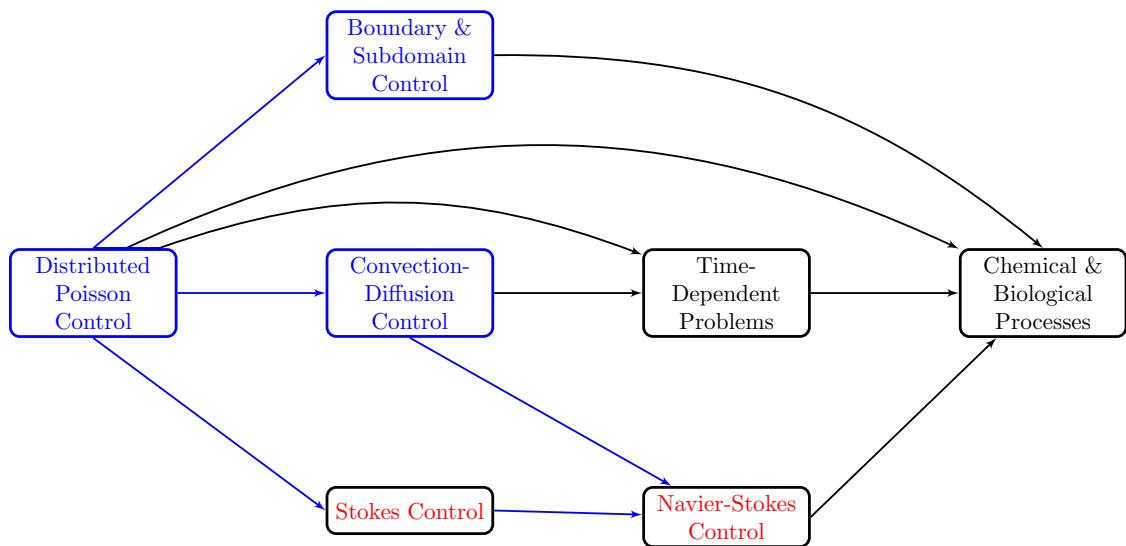
$$\begin{aligned}
 S = B_1 A_1^{-1} B_1^\top + B_2 A_2^{-1} B_2^\top &\rightarrow \hat{S} = (B_1 + \hat{D}) A_1^{-1} (B_1 + \hat{D})^\top, \\
 &\hat{D} A_1^{-1} \hat{D} \approx \text{diag} (B_2 A_2^{-1} B_2^\top).
 \end{aligned}$$





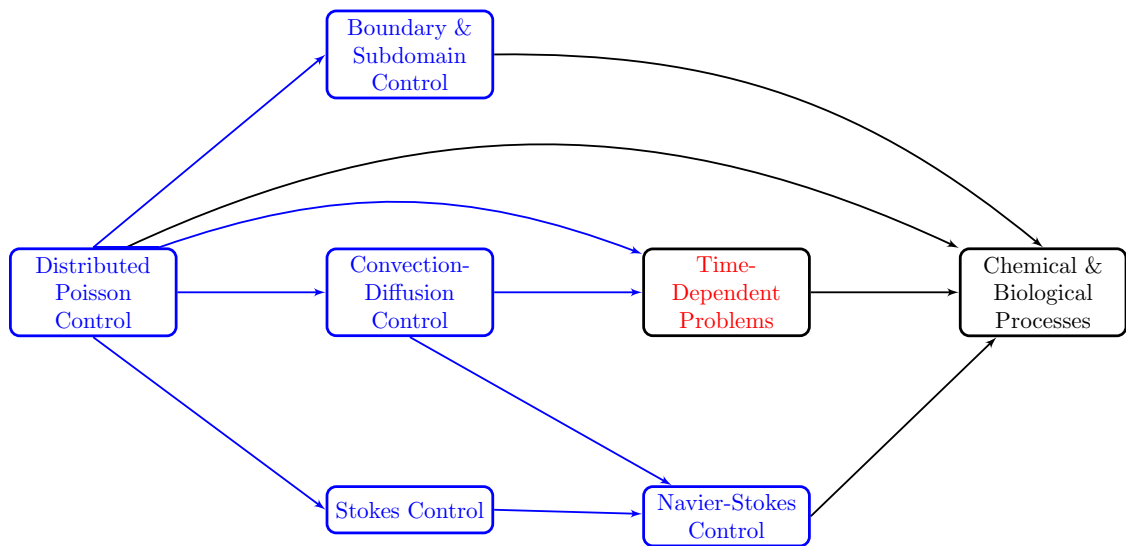

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JWP and A. J. Wathen, *Fast Iterative Solvers for Convection-Diffusion Control Problems*, Electronic Transactions on Numerical Analysis, 2013.



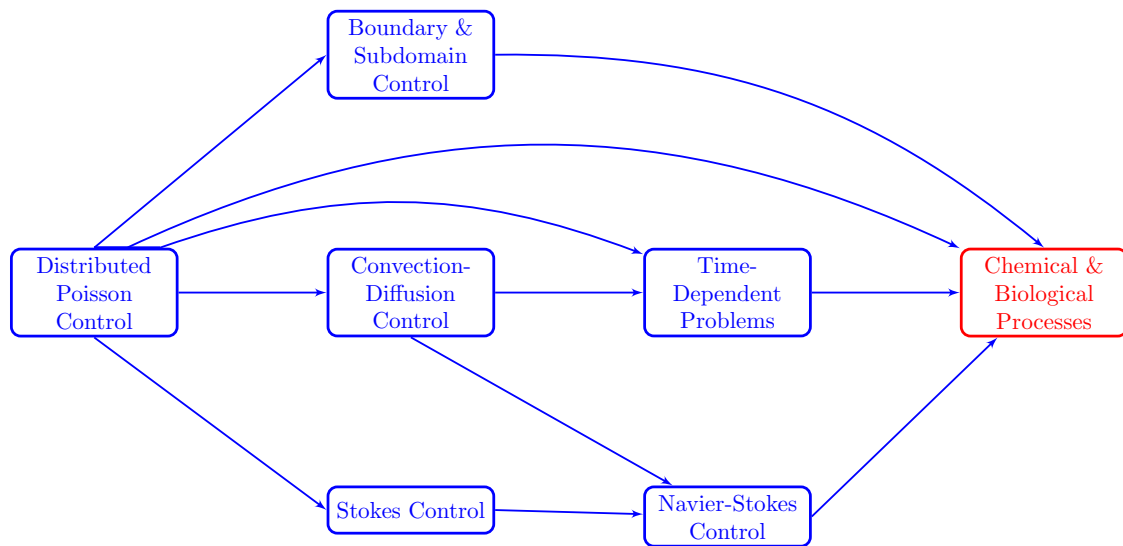
JWP, *On the Development of Parameter-Robust Preconditioners and Commutator Arguments for Solving Stokes Control Problems*, Electronic Transactions on Numerical Analysis, 2015.

JWP, *Preconditioned Iterative Methods for Navier-Stokes Control Problems*, Journal of Computational Physics, 2015.



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JWP, M. Stoll and A. J. Wathen, *Regularization-Robust Preconditioners for PDE-Constrained Optimization Problems*, SIAM Journal on Matrix Analysis and Applications, 2012.



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## Reaction-Diffusion Control from Chemical Processes

- A problem which we are now keen to consider is the following optimal control problem involving reaction-diffusion equations. We wish to minimize

$$\mathcal{J}(u, v, c) = \frac{\alpha_u}{2} \|u - \hat{u}\|_{L_2(Q)}^2 + \frac{\alpha_v}{2} \|v - \hat{v}\|_{L_2(Q)}^2 + \frac{\alpha_c}{2} \|c\|_{L_2(\Sigma)}^2,$$

subject to the following PDE constraints:

$$\begin{aligned} u_t - D_1 \nabla^2 u + k_1 u &= -\gamma_1 uv, & \text{in } Q := \Omega \times [0, T], \\ v_t - D_2 \nabla^2 v + k_2 v &= -\gamma_2 uv, & \text{in } Q, \\ D_1 \frac{\partial u}{\partial n} &= c, & \text{on } \Sigma := \partial\Omega \times [0, T], \\ D_2 \frac{\partial v}{\partial n} + \epsilon v &= 0, & \text{on } \Sigma, \\ u(\mathbf{x}, 0) &= u_0(\mathbf{x}), & \text{in } \Omega, \\ v(\mathbf{x}, 0) &= v_0(\mathbf{x}), & \text{in } \Omega. \end{aligned}$$

- We may also incorporate the control constraints:

$$c \in C_{ad} := \{c \in L_\infty(\Sigma) : c_a \leq c \leq c_b \text{ a.e. on } \Sigma\}.$$

- Examined in e.g. [Barthel, John & Tröltzsch, 2010], [Griesse & Volkwein, 2006].

## Optimality Conditions

- On the continuous level, we consider the Lagrangian

$$\begin{aligned}
 \mathcal{L}(u, v, c, p, q) = & \frac{\alpha_u}{2} \|u - \hat{u}\|_{L_2(Q)}^2 + \frac{\alpha_v}{2} \|v - \hat{v}\|_{L_2(Q)}^2 + \frac{\alpha_c}{2} \|c\|_{L_2(\partial Q)}^2 \\
 & + \int_Q p_\Omega (u_t - D_1 \nabla^2 u + k_1 u + \gamma_1 uv) \\
 & + \int_Q q_\Omega (v_t - D_2 \nabla^2 v + k_2 v + \gamma_2 uv) \\
 & + \int_{\partial Q} p_{\partial \Omega} \left( D_1 \frac{\partial u}{\partial n} - c \right) + \int_{\partial Q} q_{\partial \Omega} \left( D_2 \frac{\partial v}{\partial n} + \epsilon v \right).
 \end{aligned}$$

## Optimality Conditions

- On the continuous level, we consider the Lagrangian

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- Differentiating with respect to  $p$ ,  $q$  gives the *state equations*:

$$u_t - D_1 \nabla^2 u + k_1 u = -\gamma_1 uv, \quad v_t - D_2 \nabla^2 v + k_2 v = -\gamma_2 uv.$$

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- Differentiating with respect to  $p, q$  gives the *state equations*:

$$u_t - D_1 \nabla^2 u + k_1 u = -\gamma_1 uv, \quad v_t - D_2 \nabla^2 v + k_2 v = -\gamma_2 uv.$$

- Differentiating with respect to  $u, v$  gives the *adjoint equations*:

$$\begin{aligned} -p_t - D_1 \nabla^2 p + k_1 p + \gamma_1 p v + \gamma_2 q v + \alpha_u u &= \alpha_u \hat{u}, \\ -q_t - D_2 \nabla^2 q + k_2 q + \gamma_2 q u + \gamma_1 p u + \alpha_v v &= \alpha_v \hat{v}. \end{aligned}$$

## Optimality Conditions

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- Differentiating with respect to  $c$  gives the *gradient equation*:

$$\alpha_c c - p = 0, \quad \text{on } \partial Q.$$

## Newton Iteration – Matrix System

- In matrix form, the Newton system is written as

$$\begin{bmatrix} \alpha_u \text{Id} & \gamma_1 \bar{p} + \gamma_2 \bar{q} & 0 & \mathcal{D}'_u & \gamma_2 \bar{v} \\ \gamma_1 \bar{p} + \gamma_2 \bar{q} & \alpha_v \text{Id} & 0 & \gamma_1 \bar{u} & \mathcal{D}'_v \\ 0 & 0 & \alpha_c D_1^{-1} \text{Id} & -D_1^{-1} \text{Id} & 0 \\ \mathcal{D}_u & \gamma_1 \bar{u} & -D_1^{-1} \text{Id} & 0 & 0 \\ \gamma_2 \bar{v} & \mathcal{D}_v & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} s_u \\ s_v \\ s_c \\ s_p \\ s_q \end{bmatrix} = b,$$

where

$$\begin{aligned} \mathcal{D}_u &= \frac{\partial}{\partial t} - D_1 \nabla^2 + k_1 \text{Id} + \gamma_1 \bar{v}, & \mathcal{D}'_u &= -\frac{\partial}{\partial t} - D_1 \nabla^2 + k_1 \text{Id} + \gamma_1 \bar{v}, \\ \mathcal{D}_v &= \frac{\partial}{\partial t} - D_2 \nabla^2 + k_2 \text{Id} + \gamma_2 \bar{u}, & \mathcal{D}'_v &= -\frac{\partial}{\partial t} - D_2 \nabla^2 + k_2 \text{Id} + \gamma_2 \bar{u}. \end{aligned}$$

- The vector  $b$  represents the terms from the previous iteration:

$$\begin{bmatrix} \alpha_u \hat{u} - (-\bar{p}_t - D_1 \nabla^2 \bar{p} + k_1 \bar{p} + \gamma_1 \bar{p} \bar{v} + \gamma_2 \bar{q} \bar{v} + \alpha_u \bar{u}) \\ \alpha_v \hat{v} - (-\bar{q}_t - D_2 \nabla^2 \bar{q} + k_2 \bar{q} + \gamma_2 \bar{q} \bar{u} + \gamma_1 \bar{p} \bar{u} + \alpha_v \bar{v}) \\ -(\alpha_c \bar{c} - \bar{p}) \\ -(\bar{u}_t - D_1 \nabla^2 \bar{u} + k_1 \bar{u} + \gamma_1 \bar{u} \bar{v}) \\ -(\bar{v}_t - D_2 \nabla^2 \bar{v} + k_2 \bar{v} + \gamma_2 \bar{u} \bar{v}) \end{bmatrix}.$$

## Newton Iteration – Matrix System

- Applying a finite element method at the Newton step, we obtain the matrix:

$$\begin{bmatrix} \tau\alpha_u\mathbf{M} & \tau(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q) & 0 & \mathbf{L}_{u,C}^\top & \tau\gamma_2\mathbf{M}_v \\ \tau(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q) & \tau\alpha_v\mathbf{M} & 0 & \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \\ 0 & 0 & \tau\alpha_c D_1^{-1}\mathbf{M}_\Gamma & -\tau D_1^{-1}\mathbf{N}^\top & 0 \\ \mathbf{L}_{u,C} & \tau\gamma_1\mathbf{M}_u & -\tau D_1^{-1}\mathbf{N} & 0 & 0 \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} & 0 & 0 & 0 \end{bmatrix},$$

where

$$\mathbf{L}_{u,C} = \mathbf{M}_E + \tau D_1 \mathbf{K} + \tau k_1 \mathbf{M} + \tau \gamma_1 \mathbf{M}_v,$$

$$\mathbf{L}_{v,C} = \mathbf{M}_E + \tau D_2 \mathbf{K} + \tau k_2 \mathbf{M} + \tau \gamma_2 \mathbf{M}_u.$$

- Here  $\mathbf{M}$  and  $\mathbf{K}$  are block diagonal matrices with mass and stiffness matrices for each time-step,  $\mathbf{M}_\Gamma$  is associated boundary mass matrix,  $\mathbf{N}$  the trace operator mapping onto the boundary, and  $\mathbf{M}_E$  mass matrices from time-stepping.
- All other  $\mathbf{M}_\psi = \text{blkdiag}(M_\psi, \dots, M_\psi)$  are obtained from evaluating integrals of the form  $[M_\psi]_{ij} = \int \psi \phi_i \phi_j$  for each matrix entry.

## Newton Iteration – Matrix System

$$\begin{bmatrix} \tau\alpha_u\mathbf{M} & \tau(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q) & 0 & \mathbf{L}_{u,C}^\top & \tau\gamma_2\mathbf{M}_v \\ \tau(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q) & \tau\alpha_v\mathbf{M} & 0 & \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \\ 0 & 0 & \tau\alpha_c D_1^{-1}\mathbf{M}_\Gamma & -\tau D_1^{-1}\mathbf{N}^\top & 0 \\ \mathbf{L}_{u,C} & \tau\gamma_1\mathbf{M}_u & -\tau D_1^{-1}\mathbf{N} & 0 & 0 \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{s}_u \\ \mathbf{s}_v \\ \mathbf{s}_c \\ \mathbf{s}_p \\ \mathbf{s}_q \end{bmatrix} = \mathbf{b}$$

- The vector  $\mathbf{b}$  represents the discretization of

$$\begin{bmatrix} \int \alpha_u \hat{u} - \int (-\bar{p}_t - D_1 \nabla^2 \bar{p} + k_1 \bar{p} + \gamma_1 \bar{p} \bar{v} + \gamma_2 \bar{q} \bar{v} + \alpha_u \bar{u}) \\ \int \alpha_v \hat{v} - \int (-\bar{q}_t - D_2 \nabla^2 \bar{q} + k_2 \bar{q} + \gamma_2 \bar{q} \bar{u} + \gamma_1 \bar{p} \bar{u} + \alpha_v \bar{v}) \\ \quad - \int (\alpha_c \bar{c} - \bar{p}) \\ - \int (\bar{u}_t - D_1 \nabla^2 \bar{u} + k_1 \bar{u} + \gamma_1 \bar{u} \bar{v}) \\ - \int (\bar{v}_t - D_2 \nabla^2 \bar{v} + k_2 \bar{v} + \gamma_2 \bar{u} \bar{v}) \end{bmatrix},$$

at each time-step.



$$\left[ \begin{array}{ccc|cc} \tau\alpha_u\mathbf{M} & \tau(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q) & 0 & \mathbf{L}_{u,C}^\top & \tau\gamma_2\mathbf{M}_v \\ \tau(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q) & \tau\alpha_v\mathbf{M} & 0 & \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \\ 0 & 0 & \tau\alpha_c D_1^{-1}\mathbf{M}_\Gamma & -\tau D_1^{-1}\mathbf{N}^\top & 0 \\ \hline \mathbf{L}_{u,C} & \tau\gamma_1\mathbf{M}_u & -\tau D_1^{-1}\mathbf{N} & 0 & 0 \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} & 0 & 0 & 0 \end{array} \right]$$

### Preconditioning the Matrix System – (1, 1)-block

- Let us apply saddle point theory when approximating the (1, 1)-block, and take

$$\hat{A} = \tau \left[ \begin{array}{ccc|cc} \alpha_u\mathbf{M} - \alpha_v^{-1}(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q)\mathbf{M}^{-1}(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q) & 0 & 0 & & \\ & \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q & & \alpha_v\mathbf{M} & 0 \\ & 0 & & 0 & \alpha_c D_1^{-1}\mathbf{M}_\Gamma \end{array} \right].$$

- We replace  $\mathbf{M}^{-1}$  with  $[\text{diag}(\mathbf{M})]^{-1}$ , and apply Chebyshev semi-iteration to approximate  $\mathbf{M}_\Gamma^{-1}$ .
- Preconditioner will be non-symmetric  $\rightarrow$  apply BICG, GMRES, or other non-symmetric solver.

JWP and M. Stoll, *Fast Iterative Solution of Reaction-Diffusion Control Problems Arising from Chemical Reactions*, SIAM Journal on Scientific Computing, 2013.

$$\left[ \begin{array}{ccc|cc} \tau\alpha_u\mathbf{M} & \tau(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q) & 0 & \mathbf{L}_{u,C}^\top & \tau\gamma_2\mathbf{M}_v \\ \tau(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q) & \tau\alpha_v\mathbf{M} & 0 & \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \\ 0 & 0 & \tau\alpha_c D_1^{-1}\mathbf{M}_\Gamma & -\tau D_1^{-1}\mathbf{N}^\top & 0 \\ \hline \mathbf{L}_{u,C} & \tau\gamma_1\mathbf{M}_u & -\tau D_1^{-1}\mathbf{N} & 0 & 0 \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} & 0 & 0 & 0 \end{array} \right]$$

### Preconditioning the Matrix System – Schur complement

- We now approximate

$$S = \frac{1}{\tau} \begin{bmatrix} \mathbf{L}_{u,C} & \tau\gamma_1\mathbf{M}_u \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \mathbf{L}_{u,C}^\top & \tau\gamma_2\mathbf{M}_v \\ \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \end{bmatrix} + \frac{\tau}{\alpha_c D_1} \begin{bmatrix} \mathbf{N}\mathbf{M}_\Gamma^{-1}\mathbf{N}^\top & 0 \\ 0 & 0 \end{bmatrix},$$

where

$$\mathbf{A}_{(1,2)} = \begin{bmatrix} \alpha_u\mathbf{M} & \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q \\ \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q & \alpha_v\mathbf{M} \end{bmatrix}.$$

- We make use of our matching strategy derived earlier to write:

$$\hat{S} = \frac{1}{\tau} \begin{bmatrix} \mathbf{L}_{u,C} + \widehat{\mathbf{M}} & \tau\gamma_1\mathbf{M}_u \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \mathbf{L}_{u,C}^\top + \widehat{\mathbf{M}} & \tau\gamma_2\mathbf{M}_v \\ \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \end{bmatrix}.$$

$$S = \frac{1}{\tau} \begin{bmatrix} \mathbf{L}_{u,C} & \tau\gamma_1\mathbf{M}_u \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \mathbf{L}_{u,C}^\top & \tau\gamma_2\mathbf{M}_v \\ \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \end{bmatrix} + \frac{\tau}{\alpha_c D_1} \begin{bmatrix} \mathbf{N}\mathbf{M}_\Gamma^{-1}\mathbf{N}^\top & 0 \\ 0 & 0 \end{bmatrix}$$

$$\hat{S} = \frac{1}{\tau} \begin{bmatrix} \mathbf{L}_{u,C} + \widehat{\mathbf{M}} & \tau\gamma_1\mathbf{M}_u \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \mathbf{L}_{u,C}^\top + \widehat{\mathbf{M}} & \tau\gamma_2\mathbf{M}_v \\ \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \end{bmatrix}$$

## Preconditioning the Matrix System – Schur complement

- We select  $\widehat{\mathbf{M}}$  such that

$$\frac{1}{\tau} \begin{bmatrix} \widehat{\mathbf{M}} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \alpha_u\mathbf{M} & \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q \\ \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q & \alpha_v\mathbf{M} \end{bmatrix}^{-1} \begin{bmatrix} \widehat{\mathbf{M}} & 0 \\ 0 & 0 \end{bmatrix} \approx \frac{\tau}{\alpha_c D_1} \begin{bmatrix} \mathbf{N}\mathbf{M}_\Gamma^{-1}\mathbf{N}^\top & 0 \\ 0 & 0 \end{bmatrix}.$$

$$S = \frac{1}{\tau} \begin{bmatrix} \mathbf{L}_{u,C} & \tau\gamma_1\mathbf{M}_u \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \mathbf{L}_{u,C}^\top & \tau\gamma_2\mathbf{M}_v \\ \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \end{bmatrix} + \frac{\tau}{\alpha_c D_1} \begin{bmatrix} \mathbf{N}\mathbf{M}_\Gamma^{-1}\mathbf{N}^\top & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}$$

$$\hat{S} = \frac{1}{\tau} \begin{bmatrix} \mathbf{L}_{u,C} + \widehat{\mathbf{M}} & \tau\gamma_1\mathbf{M}_u \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \mathbf{L}_{u,C}^\top + \widehat{\mathbf{M}} & \tau\gamma_2\mathbf{M}_v \\ \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \end{bmatrix}$$

### Preconditioning the Matrix System – Schur complement

- We select  $\widehat{\mathbf{M}}$  such that

$$\frac{1}{\tau} \begin{bmatrix} \widehat{\mathbf{M}} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \alpha_u\mathbf{M} & \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q \\ \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q & \alpha_v\mathbf{M} \end{bmatrix}^{-1} \begin{bmatrix} \widehat{\mathbf{M}} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \approx \frac{\tau}{\alpha_c D_1} \begin{bmatrix} \mathbf{N}\mathbf{M}_\Gamma^{-1}\mathbf{N}^\top & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}.$$

- This implies that

$$\frac{1}{\tau} \widehat{\mathbf{M}} \left( \alpha_u\mathbf{M} - \alpha_v^{-1}\mathbf{M}_{p,q}^{(1,2)} \right)^{-1} \widehat{\mathbf{M}} \approx \frac{\tau}{\alpha_c D_1} \mathbf{N}\mathbf{M}_\Gamma^{-1}\mathbf{N}^\top,$$

where  $\mathbf{M}_{p,q}^{(1,2)} := (\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q)\mathbf{M}^{-1}(\gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q)$ .

- An efficient and accurate approximation is a diagonal matrix with

$$[\widehat{\mathbf{M}}]_{jj} = \frac{\tau}{\sqrt{\alpha_c D_1}} \left| \left[ (\alpha_u\mathbf{M} - \alpha_v^{-1}\mathbf{M}_{p,q}^{(1,2)}) \right]_{jj} \right|^{1/2} \cdot [\mathbf{N}\mathbf{M}_\Gamma^{-1}\mathbf{N}^\top]_{jj}^{1/2}.$$

$$\left[ \begin{array}{ccc|cc} \tau\alpha_u\mathbf{M} & \mathbf{0} & \mathbf{0} & \mathbf{L}_{u,C}^\top & \tau\gamma_2\mathbf{M}_v \\ \mathbf{0} & \tau\alpha_v\mathbf{M} & \mathbf{0} & \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \\ \mathbf{0} & \mathbf{0} & \tau\alpha_c D_1^{-1}\mathbf{M}_\Gamma & -\tau D_1^{-1}\mathbf{N}^\top & \mathbf{0} \\ \hline \mathbf{L}_{u,C} & \tau\gamma_1\mathbf{M}_u & -\tau D_1^{-1}\mathbf{N} & \mathbf{0} & \mathbf{0} \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{array} \right]$$

### Deriving $\hat{S}$ – Gauss-Newton iteration

- Within the matching strategy, we select  $\hat{\mathbf{M}}$  such that

$$\frac{1}{\tau} \begin{bmatrix} \hat{\mathbf{M}} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \alpha_u\mathbf{M} & \mathbf{0} \\ \mathbf{0} & \alpha_v\mathbf{M} \end{bmatrix}^{-1} \begin{bmatrix} \hat{\mathbf{M}} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \approx \frac{\tau}{\alpha_c D_1} \begin{bmatrix} \mathbf{N}\mathbf{M}_\Gamma^{-1}\mathbf{N}^\top & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}.$$

- The resulting approximation  $\hat{\mathbf{M}}$  has diagonal entries given by

$$[\hat{\mathbf{M}}]_{jj} = \tau \sqrt{\frac{\alpha_u}{\alpha_c D_1}} [\mathbf{M}]_{jj}^{1/2} \cdot [\mathbf{N}\mathbf{M}_\Gamma^{-1}\mathbf{N}^\top]_{jj}^{1/2}.$$

$$\left[ \begin{array}{ccc|cc} \tau\alpha_u\mathbf{M} & \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q & 0 & \mathbf{L}_{u,C}^\top & \tau\gamma_2\mathbf{M}_v \\ \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q & \tau\alpha_v\mathbf{M} & 0 & \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \\ 0 & 0 & \tau D_1^{-1}(\alpha_c\mathbf{M}_\Gamma + \varepsilon^{-1}\mathbf{G}_\Delta) & -\tau D_1^{-1}\mathbf{N}^\top & 0 \\ \hline \mathbf{L}_{u,C} & \tau\gamma_1\mathbf{M}_u & -\tau D_1^{-1}\mathbf{N} & 0 & 0 \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} & 0 & 0 & 0 \end{array} \right]$$

### Deriving $\hat{\mathcal{S}}$ – Control constraints

- Within the matching strategy, we select  $\hat{\mathbf{M}}$  such that

$$\begin{aligned} \frac{1}{\tau} \begin{bmatrix} \hat{\mathbf{M}} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \alpha_u\mathbf{M} & \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q \\ \gamma_1\mathbf{M}_p + \gamma_2\mathbf{M}_q & \alpha_v\mathbf{M} \end{bmatrix}^{-1} \begin{bmatrix} \hat{\mathbf{M}} & 0 \\ 0 & 0 \end{bmatrix} \\ \approx \frac{\tau}{D_1} \begin{bmatrix} \mathbf{N}(\alpha_c\mathbf{M}_\Gamma + \varepsilon^{-1}\mathbf{G}_\Delta)^{-1}\mathbf{N}^\top & 0 \\ 0 & 0 \end{bmatrix}. \end{aligned}$$

- The resulting approximation  $\hat{\mathbf{M}}$  has diagonal entries given by

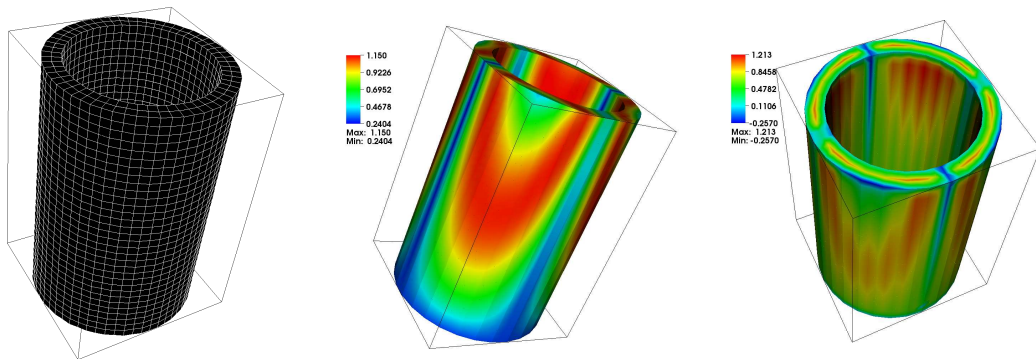
$$[\hat{\mathbf{M}}]_{jj} = \frac{\tau}{\sqrt{\alpha_c D_1}} \left| \left[ (\alpha_u\mathbf{M} - \alpha_v^{-1}\mathbf{M}_{p,q}^{(1,2)}) \right]_{jj} \right|^{1/2} \cdot [\mathbf{N}(\alpha_c\mathbf{M}_\Gamma + \varepsilon^{-1}\mathbf{G}_\Delta)^{-1}\mathbf{N}^\top]_{jj}^{1/2}.$$

$$\hat{S} = \frac{1}{\tau} \begin{bmatrix} \mathbf{L}_{u,C} + \widehat{\mathbf{M}} & \tau\gamma_1\mathbf{M}_u \\ \tau\gamma_2\mathbf{M}_v & \mathbf{L}_{v,C} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \mathbf{L}_{u,C}^\top + \widehat{\mathbf{M}} & \tau\gamma_2\mathbf{M}_v \\ \tau\gamma_1\mathbf{M}_u & \mathbf{L}_{v,C}^\top \end{bmatrix}$$

### Some Observations

- To apply  $\hat{S}^{-1}$  in practice, use fixed number of iterations of an Uzawa scheme, coupled with algebraic multigrid routine to approximate the diagonal blocks.
- Good lower bound of  $\lambda(\hat{S}^{-1}S)$ .
- Greater variation in upper bound due to range of parameters: mesh size  $h$ ,  $\tau$ ,  $\alpha_u$ ,  $\alpha_v$ ,  $\alpha_c$ ,  $D_1$ ,  $D_2$ ,  $k_1$ ,  $k_2$ ,  $\gamma_1$ ,  $\gamma_2$ ,  $\epsilon$ ,  $c_a$ ,  $c_b$ ,  $\epsilon$ .
- Best case scenario: when one term in  $S$  strongly dominates.
- Worst case scenario: when first term of  $S$  is (close to) indefinite.

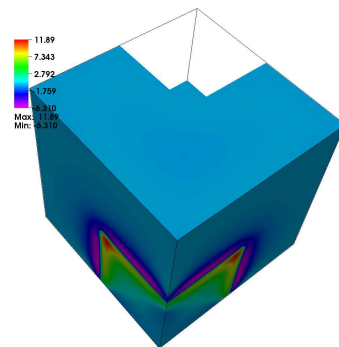
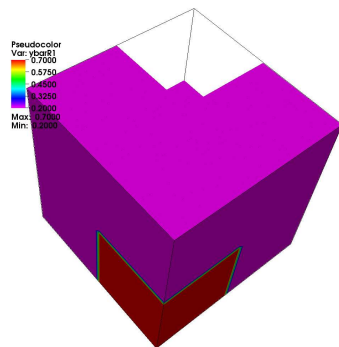
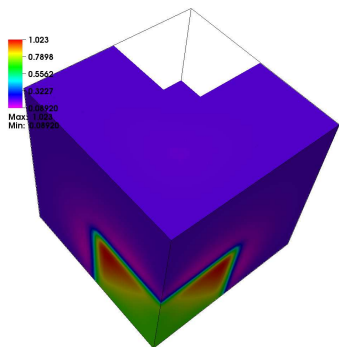
$$\hat{u} = t |\sin(2x_1 x_2 x_3)| + 0.3, \quad \hat{v} = 0, \quad k_1 = k_2 = D_1 = D_2 = 1, \quad \gamma_1 = \gamma_2 = 0.15$$



DoF	$\alpha_c = 10^{-3}$			$\alpha_c = 10^{-5}$		
	Time	Newton	Iterations	Time	Newton	Iterations
538, 240	1, 995	step 1	17	1, 726	step 1	16
		step 2	20		step 2	16
		step 3	20		step 3	16
3, 331, 520	14, 757	step 1	28	14, 904	step 1	28
		step 2	31		step 2	27
		step 3	29		step 3	34

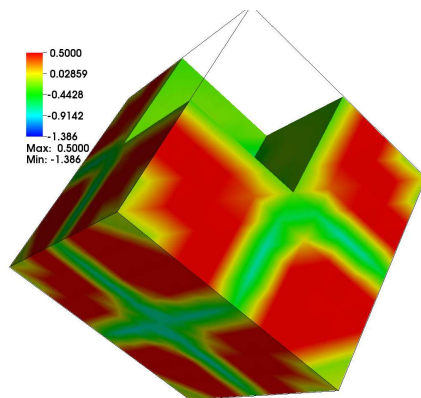
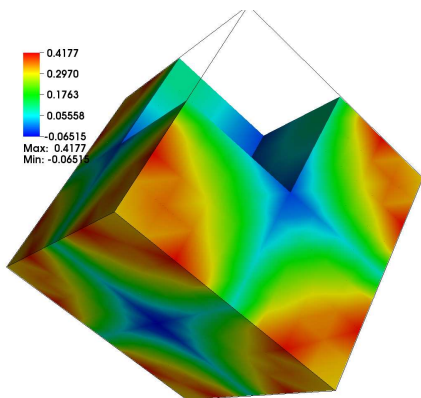


$$\hat{u} = \begin{cases} 0.7 & \text{if } \mathbf{x} \in [0, \frac{1}{2}]^3 \\ 0.2 & \text{otherwise} \end{cases}, \quad \hat{v} = 0, \quad k_1 = k_2 = D_1 = D_2 = 1, \quad \gamma_1 = \gamma_2 = 0.15$$



DoF	$\alpha_c = 10^{-3}$			$\alpha_c = 10^{-5}$		
	Time	Newton	Iterations	Time	Newton	Iterations
382, 840	2, 624	step 1	24	2, 819	step 1	29
		step 2	30		step 2	35
		step 3	33		step 3	33
2, 670, 200	19, 128	step 1	36	22, 976	step 1	46
		step 2	44		step 2	52
		step 3	44		step 3	53

$$\hat{u} = t |\sin(2x_1 x_2 x_3)|, \quad \hat{v} = 0, \quad k_1 = k_2 = D_1 = D_2 = 1, \quad \gamma_1 = \gamma_2 = 0.15, \quad c \leq 0.5$$



DoF	$\alpha_c = 10^{-3}$			$\alpha_c = 10^{-5}$		
	Time	Newton	Iterations	Time	Newton	Iterations
60,920	1,066	step 1	18	859	step 1	22
		step 2	21		step 2	26
		step 3	21			
382,840	5,498	step 1	26	13,358	step 1	29
		step 2	36		step 2	33
		step 3	35		step 3	33

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- 1 Background
- 2 Reaction-Diffusion Control Problems for Chemical Reactions
- 3 Optimal Control of Pattern Formation Processes

## Parameter Identification in Pattern Formation Processes

- Another important reaction-diffusion control problem concerns pattern formation processes. Here we wish to minimize

$$\mathcal{J}(u, v, a, b) = \frac{\beta_1}{2} \|u - \hat{u}\|_{L_2(Q)}^2 + \frac{\beta_2}{2} \|v - \hat{v}\|_{L_2(Q)}^2 + \frac{\nu_1}{2} \|a\|_{L_2(Q)}^2 + \frac{\nu_2}{2} \|b\|_{L_2(Q)}^2,$$

subject to PDE constraints given by the Gierer-Meinhardt equations

$$\begin{aligned} u_t - D_u \nabla^2 u - \frac{ru^2}{v} + au &= r, & \text{in } Q, \\ v_t - D_v \nabla^2 v - ru^2 + bv &= 0, & \text{in } Q, \\ u(\mathbf{x}, 0) &= u_0(\mathbf{x}), \quad v(\mathbf{x}, 0) = v_0(\mathbf{x}), \\ \frac{\partial u}{\partial n} &= \frac{\partial v}{\partial n} = 0, & \text{on } \partial Q \end{aligned}$$

## Parameter Identification in Pattern Formation Processes

- Another important reaction-diffusion control problem concerns pattern formation processes. Here we wish to minimize

$$\mathcal{J}(u, v, a, b) = \frac{\beta_1}{2} \|u - \hat{u}\|_{L_2(Q)}^2 + \frac{\beta_2}{2} \|v - \hat{v}\|_{L_2(Q)}^2 + \frac{\nu_1}{2} \|a\|_{L_2(Q)}^2 + \frac{\nu_2}{2} \|b\|_{L_2(Q)}^2,$$

subject to PDE constraints given by the Gierer-Meinhardt equations

$$\begin{aligned} u_t - D_u \nabla^2 u - \frac{ru^2}{v} + au &= r, & \text{in } Q, \\ v_t - D_v \nabla^2 v - ru^2 + bv &= 0, & \text{in } Q, \\ u(\mathbf{x}, 0) = u_0(\mathbf{x}), \quad v(\mathbf{x}, 0) &= v_0(\mathbf{x}), \\ \frac{\partial u}{\partial n} = \frac{\partial v}{\partial n} &= 0, & \text{on } \partial Q, \end{aligned}$$

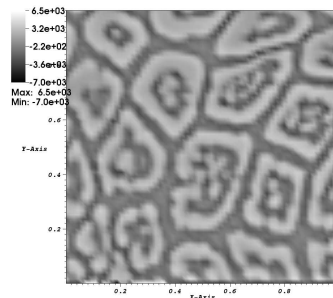
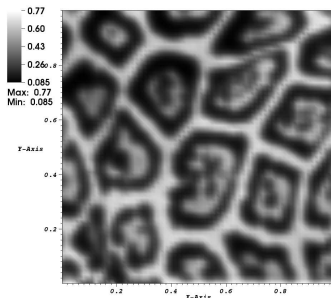
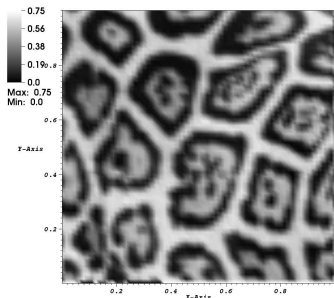
or the Schnakenberg equations

$$\begin{aligned} u_t - D_u \nabla^2 u + \gamma(u - u^2v) - \gamma a &= 0, & \text{in } Q, \\ v_t - D_v \nabla^2 v + \gamma u^2v - \gamma b &= 0, & \text{in } Q, \\ u(\mathbf{x}, 0) = u_0(\mathbf{x}), \quad v(\mathbf{x}, 0) &= v_0(\mathbf{x}), \\ \frac{\partial u}{\partial n} = \frac{\partial v}{\partial n} &= 0, & \text{on } \partial Q. \end{aligned}$$

## Parameter Identification in Pattern Formation

$$\min_{u,v,a,b} \frac{\beta_1}{2} \|u - \hat{u}\|_{L_2(Q)}^2 + \frac{\beta_2}{2} \|v - \hat{v}\|_{L_2(Q)}^2 + \frac{\nu_1}{2} \|a(\mathbf{x}, t)\|_{L_2(Q)}^2 + \frac{\nu_2}{2} \|b(\mathbf{x}, t)\|_{L_2(Q)}^2$$

$$\text{s.t.} \quad \begin{aligned} u_t - D_u \nabla^2 u - \frac{ru^2}{v} + au &= r, & \text{in } Q, \\ v_t - D_v \nabla^2 v - ru^2 + bv &= 0, & \text{in } Q, \\ u(\mathbf{x}, 0) = u_0(\mathbf{x}), \quad v(\mathbf{x}, 0) &= v_0(\mathbf{x}), \\ \frac{\partial u}{\partial n} = \frac{\partial v}{\partial n} &= 0, & \text{on } \partial Q. \end{aligned}$$



## Newton System – Schnakenberg Model

- The matrix system obtained from a finite element discretization at each Newton step is given by

$$\begin{bmatrix} \mathbf{A}_{u,S} & -2\tau\gamma\mathbf{M}_{u(q-p)} & 0 & 0 & -\mathbf{L}_{u,S}^\top & -2\tau\gamma\mathbf{M}_{uv} \\ -2\tau\gamma\mathbf{M}_{u(q-p)} & \mathbf{A}_{v,S} & 0 & 0 & \tau\gamma\mathbf{M}_{u^2} & -\mathbf{L}_{v,S}^\top \\ 0 & 0 & \tau\nu_1\mathbf{M} & 0 & \tau\gamma\mathbf{M} & 0 \\ 0 & 0 & 0 & \tau\nu_2\mathbf{M} & 0 & \tau\gamma\mathbf{M} \\ -\mathbf{L}_{u,S} & \tau\gamma\mathbf{M}_{u^2} & \tau\gamma\mathbf{M} & 0 & 0 & 0 \\ -2\tau\gamma\mathbf{M}_{uv} & -\mathbf{L}_{v,S} & 0 & \tau\gamma\mathbf{M} & 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{s}_u \\ \mathbf{s}_v \\ \mathbf{s}_a \\ \mathbf{s}_b \\ \mathbf{s}_p \\ \mathbf{s}_q \end{bmatrix} = \mathbf{b},$$

where

$$\mathbf{A}_{u,S} = \tau\beta_1\mathbf{M} + 2\tau\gamma\mathbf{M}_{v(q-p)},$$

$$\mathbf{A}_{v,S} = \tau\beta_2\mathbf{M},$$

$$\mathbf{L}_{u,S} = \mathbf{M}_E + \tau D_u \mathbf{K} + \tau\gamma\mathbf{M} - 2\gamma\mathbf{M}_{uv},$$

$$\mathbf{L}_{v,S} = \mathbf{M}_E + \tau D_v \mathbf{K} + \tau\gamma\mathbf{M}_{u^2},$$

- Here  $\mathbf{M}_E$  denotes the mass matrices appearing from time-stepping method.
- All other  $\mathbf{M}_\psi = \text{blkdiag}(M_\psi, \dots, M_\psi)$  are again obtained from evaluating integrals of the form  $[M_\psi]_{ij} = \int \psi \phi_i \phi_j$  for each matrix entry.

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- The matrix system obtained from a finite element discretization at each Newton step is given by

$$\begin{bmatrix} \mathbf{A}_{u,S} & -2\tau\gamma\mathbf{M}_{u(q-p)} & 0 & 0 & -\mathbf{L}_{u,S}^\top & -2\tau\gamma\mathbf{M}_{uv} \\ -2\tau\gamma\mathbf{M}_{u(q-p)} & \mathbf{A}_{v,S} & 0 & 0 & \tau\gamma\mathbf{M}_{u^2} & -\mathbf{L}_{v,S}^\top \\ 0 & 0 & \tau\nu_1\mathbf{M} & 0 & \tau\gamma\mathbf{M} & 0 \\ 0 & 0 & 0 & \tau\nu_2\mathbf{M} & 0 & \tau\gamma\mathbf{M} \\ -\mathbf{L}_{u,S} & \tau\gamma\mathbf{M}_{u^2} & \tau\gamma\mathbf{M} & 0 & 0 & 0 \\ -2\tau\gamma\mathbf{M}_{uv} & -\mathbf{L}_{v,S} & 0 & \tau\gamma\mathbf{M} & 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{s}_u \\ \mathbf{s}_v \\ \mathbf{s}_a \\ \mathbf{s}_b \\ \mathbf{s}_p \\ \mathbf{s}_q \end{bmatrix} = \mathbf{b}.$$

- The vector  $\mathbf{b}$  denotes the discrete representation of

$$\begin{bmatrix} \beta_1 \int (\hat{u} - \bar{u}) + \int (-\bar{p}_t - D_u \nabla^2 \bar{p} + 2\gamma \bar{u} \bar{v} (\bar{q} - \bar{p}) + \gamma \bar{p}) \\ \beta_2 \int (\hat{v} - \bar{v}) + \int (-\bar{q}_t - D_v \nabla^2 \bar{q} + \gamma \bar{u}^2 (\bar{q} - \bar{p})) \\ - \int (\nu_1 \bar{a} + \gamma \bar{p}) \\ - \int (\nu_2 \bar{b} + \gamma \bar{q}) \\ \int (\bar{u}_t - D_u \nabla^2 \bar{u} + \gamma (\bar{u} - \bar{u}^2 \bar{v}) - \gamma \bar{a}) \\ \int (\bar{v}_t - D_v \nabla^2 \bar{v} + \gamma \bar{u}^2 \bar{v} - \gamma \bar{b}) \end{bmatrix}.$$



$$\left[ \begin{array}{cccc|cc} \mathbf{A}_{u,S} & -2\tau\gamma\mathbf{M}_{u(q-p)} & 0 & 0 & -\mathbf{L}_{u,S}^\top & -2\tau\gamma\mathbf{M}_{uv} \\ -2\tau\gamma\mathbf{M}_{u(q-p)} & \mathbf{A}_{v,S} & 0 & 0 & \tau\gamma\mathbf{M}_{u^2} & -\mathbf{L}_{v,S}^\top \\ 0 & 0 & \tau\nu_1\mathbf{M} & 0 & \tau\gamma\mathbf{M} & 0 \\ 0 & 0 & 0 & \tau\nu_2\mathbf{M} & 0 & \tau\gamma\mathbf{M} \\ \hline -\mathbf{L}_{u,S} & \tau\gamma\mathbf{M}_{u^2} & \tau\gamma\mathbf{M} & 0 & 0 & 0 \\ -2\tau\gamma\mathbf{M}_{uv} & -\mathbf{L}_{v,S} & 0 & \tau\gamma\mathbf{M} & 0 & 0 \end{array} \right] \begin{bmatrix} \mathbf{s}_u \\ \mathbf{s}_v \\ \mathbf{s}_a \\ \mathbf{s}_b \\ \mathbf{s}_p \\ \mathbf{s}_q \end{bmatrix} = \mathbf{b}$$

### Preconditioning the Matrix System – (1, 1)-block

- We approximate the (1, 1)-block by:

$$\hat{\mathbf{A}} = \begin{bmatrix} \hat{\mathbf{A}}_1 & 0 & 0 & 0 \\ -2\tau\gamma\mathbf{M}_{u(q-p)} & \mathbf{A}_{v,S} & 0 & 0 \\ 0 & 0 & \tau\nu_1\mathbf{M} & 0 \\ 0 & 0 & 0 & \tau\nu_2\mathbf{M} \end{bmatrix},$$

where  $\hat{\mathbf{A}}_1$  is a Schur complement approximation defined by

$$\hat{\mathbf{A}}_1 = \mathbf{A}_{u,S} - (2\tau\gamma)^2\mathbf{M}_{u(q-p)}\mathbf{A}_{v,S}^{-1}\mathbf{M}_{u(q-p)}.$$

$$S = \begin{bmatrix} -\mathbf{L}_{u,S} & \tau\gamma\mathbf{M}_{u^2} \\ -2\tau\gamma\mathbf{M}_{uv} & -\mathbf{L}_{v,S} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} -\mathbf{L}_{u,S}^\top & -2\tau\gamma\mathbf{M}_{uv} \\ \tau\gamma\mathbf{M}_{u^2} & -\mathbf{L}_{v,S}^\top \end{bmatrix} + \tau\gamma^2 \begin{bmatrix} \nu_1^{-1}\mathbf{M} & 0 \\ 0 & \nu_2^{-1}\mathbf{M} \end{bmatrix}$$

$$\hat{S} = \begin{bmatrix} -\mathbf{L}_{u,S} + \widehat{\mathbf{M}}_1^{(1)} & \tau\gamma\mathbf{M}_{u^2} \\ -2\tau\gamma\mathbf{M}_{uv} & -\mathbf{L}_{v,S} + \widehat{\mathbf{M}}_2^{(1)} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} -\mathbf{L}_{u,S}^\top + \widehat{\mathbf{M}}_1^{(2)} & -2\tau\gamma\mathbf{M}_{uv} \\ \tau\gamma\mathbf{M}_{u^2} & -\mathbf{L}_{v,S}^\top + \widehat{\mathbf{M}}_2^{(2)} \end{bmatrix}$$

### Preconditioning the Matrix System – Schur complement

- We choose  $\widehat{\mathbf{M}}_1^{(1)}$ ,  $\widehat{\mathbf{M}}_1^{(2)}$ ,  $\widehat{\mathbf{M}}_2^{(1)}$ ,  $\widehat{\mathbf{M}}_2^{(2)}$  such that [Stoll, Pearson & Maini, 2014]:

$$\begin{bmatrix} \widehat{\mathbf{M}}_1^{(1)} & 0 \\ 0 & \widehat{\mathbf{M}}_2^{(1)} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \widehat{\mathbf{M}}_1^{(2)} & 0 \\ 0 & \widehat{\mathbf{M}}_2^{(2)} \end{bmatrix} \approx \tau\gamma^2 \begin{bmatrix} \nu_1^{-1}\mathbf{M} & 0 \\ 0 & \nu_2^{-1}\mathbf{M} \end{bmatrix}.$$

$$S = \begin{bmatrix} -\mathbf{L}_{u,S} & \tau\gamma\mathbf{M}_{u^2} \\ -2\tau\gamma\mathbf{M}_{uv} & -\mathbf{L}_{v,S} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} -\mathbf{L}_{u,S}^\top & -2\tau\gamma\mathbf{M}_{uv} \\ \tau\gamma\mathbf{M}_{u^2} & -\mathbf{L}_{v,S}^\top \end{bmatrix} + \tau\gamma^2 \begin{bmatrix} \nu_1^{-1}\mathbf{M} & 0 \\ 0 & \nu_2^{-1}\mathbf{M} \end{bmatrix}$$

$$\hat{S} = \begin{bmatrix} -\mathbf{L}_{u,S} + \widehat{\mathbf{M}}_1^{(1)} & \tau\gamma\mathbf{M}_{u^2} \\ -2\tau\gamma\mathbf{M}_{uv} & -\mathbf{L}_{v,S} + \widehat{\mathbf{M}}_2^{(1)} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} -\mathbf{L}_{u,S}^\top + \widehat{\mathbf{M}}_1^{(2)} & -2\tau\gamma\mathbf{M}_{uv} \\ \tau\gamma\mathbf{M}_{u^2} & -\mathbf{L}_{v,S}^\top + \widehat{\mathbf{M}}_2^{(2)} \end{bmatrix}$$

### Preconditioning the Matrix System – Schur complement

- We choose  $\widehat{\mathbf{M}}_1^{(1)}$ ,  $\widehat{\mathbf{M}}_1^{(2)}$ ,  $\widehat{\mathbf{M}}_2^{(1)}$ ,  $\widehat{\mathbf{M}}_2^{(2)}$  such that [Stoll, Pearson & Maini, 2014]:

$$\begin{bmatrix} \widehat{\mathbf{M}}_1^{(1)} & 0 \\ 0 & \widehat{\mathbf{M}}_2^{(1)} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \widehat{\mathbf{M}}_1^{(2)} & 0 \\ 0 & \widehat{\mathbf{M}}_2^{(2)} \end{bmatrix} \approx \tau\gamma^2 \begin{bmatrix} \nu_1^{-1}\mathbf{M} & 0 \\ 0 & \nu_2^{-1}\mathbf{M} \end{bmatrix}.$$

- Examining the diagonal blocks leads to approximations such that

$$\mathbf{M}_1^{(1)} \widehat{\mathbf{A}}_1^{-1} \mathbf{M}_1^{(2)} \approx \frac{\tau\gamma^2}{\nu_1} \mathbf{M}, \quad \widehat{\mathbf{A}}_1 = \mathbf{A}_{u,S} - (2\tau\gamma)^2 \mathbf{M}_{u(q-p)} \mathbf{A}_{v,S}^{-1} \mathbf{M}_{u(q-p)},$$

$$\mathbf{M}_2^{(1)} \widehat{\mathbf{A}}_2^{-1} \mathbf{M}_2^{(2)} \approx \frac{\tau\gamma^2}{\nu_2} \mathbf{M}, \quad \widehat{\mathbf{A}}_2 = \mathbf{A}_{v,S} - (2\tau\gamma)^2 \mathbf{M}_{u(q-p)} \mathbf{A}_{u,S}^{-1} \mathbf{M}_{u(q-p)}.$$

$$S = \begin{bmatrix} -\mathbf{L}_{u,S} & \tau\gamma\mathbf{M}_{u^2} \\ -2\tau\gamma\mathbf{M}_{uv} & -\mathbf{L}_{v,S} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} -\mathbf{L}_{u,S}^\top & -2\tau\gamma\mathbf{M}_{uv} \\ \tau\gamma\mathbf{M}_{u^2} & -\mathbf{L}_{v,S}^\top \end{bmatrix} + \tau\gamma^2 \begin{bmatrix} \nu_1^{-1}\mathbf{M} & 0 \\ 0 & \nu_2^{-1}\mathbf{M} \end{bmatrix}$$

$$\hat{S} = \begin{bmatrix} -\mathbf{L}_{u,S} + \widehat{\mathbf{M}}_1^{(1)} & \tau\gamma\mathbf{M}_{u^2} \\ -2\tau\gamma\mathbf{M}_{uv} & -\mathbf{L}_{v,S} + \widehat{\mathbf{M}}_2^{(1)} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} -\mathbf{L}_{u,S}^\top + \widehat{\mathbf{M}}_1^{(2)} & -2\tau\gamma\mathbf{M}_{uv} \\ \tau\gamma\mathbf{M}_{u^2} & -\mathbf{L}_{v,S}^\top + \widehat{\mathbf{M}}_2^{(2)} \end{bmatrix}$$

### Preconditioning the Matrix System – Schur complement

- We choose  $\widehat{\mathbf{M}}_1^{(1)}$ ,  $\widehat{\mathbf{M}}_1^{(2)}$ ,  $\widehat{\mathbf{M}}_2^{(1)}$ ,  $\widehat{\mathbf{M}}_2^{(2)}$  such that [Stoll, Pearson & Maini, 2014]:

$$\begin{bmatrix} \widehat{\mathbf{M}}_1^{(1)} & 0 \\ 0 & \widehat{\mathbf{M}}_2^{(1)} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \widehat{\mathbf{M}}_1^{(2)} & 0 \\ 0 & \widehat{\mathbf{M}}_2^{(2)} \end{bmatrix} \approx \tau\gamma^2 \begin{bmatrix} \nu_1^{-1}\mathbf{M} & 0 \\ 0 & \nu_2^{-1}\mathbf{M} \end{bmatrix}.$$

- This motivates selecting diagonal matrices with

$$\begin{aligned} [\widehat{\mathbf{M}}_1^{(1)}]_{jj} &= \sqrt{\frac{\tau}{\nu_1}} \gamma \cdot [\mathbf{M}]_{jj}^{1/2} \cdot |[\widehat{\mathbf{A}}_1]_{jj}|, & [\widehat{\mathbf{M}}_1^{(2)}]_{jj} &= \sqrt{\frac{\tau}{\nu_1}} \gamma \cdot [\mathbf{M}]_{jj}^{1/2}, \\ [\widehat{\mathbf{M}}_2^{(1)}]_{jj} &= \sqrt{\frac{\tau}{\nu_2}} \gamma \cdot [\mathbf{M}]_{jj}^{1/2} \cdot |[\widehat{\mathbf{A}}_2]_{jj}|, & [\widehat{\mathbf{M}}_2^{(2)}]_{jj} &= \sqrt{\frac{\tau}{\nu_2}} \gamma \cdot [\mathbf{M}]_{jj}^{1/2}. \end{aligned}$$

## Newton System – Gierer-Meinhardt Model

- The matrix system obtained from a finite element discretization at each Newton step is given by

$$\begin{bmatrix} \mathbf{A}_{u,GM} & -2\tau r \mathbf{M}_{up/v^2} & -\tau \mathbf{M}_p & 0 & -\mathbf{L}_{u,GM}^\top & 2\tau r \mathbf{M}_u \\ -2\tau r \mathbf{M}_{up/v^2} & \mathbf{A}_{v,GM} & 0 & -\tau \mathbf{M}_q & -\tau r \mathbf{M}_{u^2/v^2} & -\mathbf{L}_{v,GM}^\top \\ -\tau \mathbf{M}_p & 0 & \tau \nu_1 \mathbf{M} & 0 & -\tau \mathbf{M}_u & 0 \\ 0 & -\tau \mathbf{M}_q & 0 & \tau \nu_2 \mathbf{M} & 0 & -\tau \mathbf{M}_v \\ -\mathbf{L}_{u,GM} & -\tau r \mathbf{M}_{u^2/v^2} & -\tau \mathbf{M}_u & 0 & 0 & 0 \\ 2\tau r \mathbf{M}_u & -\mathbf{L}_{v,GM} & 0 & -\tau \mathbf{M}_v & 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{s}_u \\ \mathbf{s}_v \\ \mathbf{s}_a \\ \mathbf{s}_b \\ \mathbf{s}_p \\ \mathbf{s}_q \end{bmatrix} = \mathbf{b},$$

where

$$\begin{aligned} \mathbf{A}_{u,GM} &= \tau \beta_1 \mathbf{M} + 2\tau r \mathbf{M}_{p/v} + 2\tau r \mathbf{M}_q, \\ \mathbf{A}_{v,GM} &= \tau \beta_2 \mathbf{M} + 2\tau r \mathbf{M}_{u^2p/v^3}, \\ \mathbf{L}_{u,GM} &= \mathbf{M}_E + \tau D_u \mathbf{K} - 2\tau r \mathbf{M}_{u/v} + \tau \mathbf{M}_a, \\ \mathbf{L}_{v,GM} &= \mathbf{M}_E + \tau D_v \mathbf{K} + \tau \mathbf{M}_b. \end{aligned}$$

## Newton System – Gierer-Meinhardt Model

- The matrix system obtained from a finite element discretization at each Newton step is given by

$$\begin{bmatrix} \mathbf{A}_{u,GM} & -2\tau r \mathbf{M}_{up/v^2} & -\tau \mathbf{M}_p & 0 & -\mathbf{L}_{u,GM}^\top & 2\tau r r \mathbf{M}_u \\ -2\tau r r \mathbf{M}_{up/v^2} & \mathbf{A}_{v,GM} & 0 & -\tau \mathbf{M}_q & -\tau r r \mathbf{M}_{u^2/v^2} & -\mathbf{L}_{v,GM}^\top \\ -\tau \mathbf{M}_p & 0 & \tau \nu_1 \mathbf{M} & 0 & -\tau \mathbf{M}_u & 0 \\ 0 & -\tau \mathbf{M}_q & 0 & \tau \nu_2 \mathbf{M} & 0 & -\tau \mathbf{M}_v \\ -\mathbf{L}_{u,GM} & -\tau r r \mathbf{M}_{u^2/v^2} & -\tau \mathbf{M}_u & 0 & 0 & 0 \\ 2\tau r r \mathbf{M}_u & -\mathbf{L}_{v,GM} & 0 & -\tau \mathbf{M}_v & 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{s}_u \\ \mathbf{s}_v \\ \mathbf{s}_a \\ \mathbf{s}_b \\ \mathbf{s}_p \\ \mathbf{s}_q \end{bmatrix} = \mathbf{b}.$$

- The vector  $\mathbf{b}$  here denotes the discrete representation of

$$\begin{bmatrix} \beta_1 \int (\hat{u} - \bar{u}) + \int (-\bar{p}_t - D_u \nabla^2 \bar{p} - 2r \frac{\bar{u}}{\bar{v}} \bar{p} + \bar{a} \bar{p} - 2r \bar{u} \bar{q}) \\ \beta_2 \int (\hat{v} - \bar{v}) + \int (-\bar{q}_t - D_v \nabla^2 \bar{q} + r \frac{\bar{u}^2}{\bar{v}^2} \bar{p} + \bar{b} \bar{q}) \\ \int (\bar{u} \bar{p} - \nu_1 \bar{a}) \\ \int (\bar{v} \bar{q} - \nu_2 \bar{b}) \\ \int (\bar{u}_t - D_u \nabla^2 \bar{u} - \frac{r \bar{u}^2}{\bar{v}} + \bar{a} \bar{u} - r) \\ \int (\bar{v}_t - D_v \nabla^2 \bar{v} - r \bar{u}^2 + \bar{b} \bar{v}) \end{bmatrix}.$$

$$\left[ \begin{array}{cccc|cc}
 \mathbf{A}_{u,GM} & -2\tau r \mathbf{M}_{up/v^2} & -\tau \mathbf{M}_p & 0 & -\mathbf{L}_{u,GM}^\top & 2\tau r \mathbf{M}_u \\
 -2\tau r \mathbf{M}_{up/v^2} & \mathbf{A}_{v,GM} & 0 & -\tau \mathbf{M}_q & -\tau r \mathbf{M}_{u^2/v^2} & -\mathbf{L}_{v,GM}^\top \\
 -\tau \mathbf{M}_p & 0 & \tau \nu_1 \mathbf{M} & 0 & -\tau \mathbf{M}_u & 0 \\
 0 & -\tau \mathbf{M}_q & 0 & \tau \nu_2 \mathbf{M} & 0 & -\tau \mathbf{M}_v \\
 \hline
 -\mathbf{L}_{u,GM} & -\tau r \mathbf{M}_{u^2/v^2} & -\tau \mathbf{M}_u & 0 & 0 & 0 \\
 2\tau r \mathbf{M}_u & -\mathbf{L}_{v,GM} & 0 & -\tau \mathbf{M}_v & 0 & 0
 \end{array} \right] \begin{bmatrix} \mathbf{s}_u \\ \mathbf{s}_v \\ \mathbf{s}_a \\ \mathbf{s}_b \\ \mathbf{s}_p \\ \mathbf{s}_q \end{bmatrix} = \mathbf{b}$$

### Preconditioning the Matrix System – (1,1)-block

- We use saddle point theory to approximate the (1,1)-block by:

$$\hat{A} = \begin{bmatrix} \hat{\mathbf{A}}_1 & 0 & 0 & 0 \\ 0 & \hat{\mathbf{A}}_2 & 0 & 0 \\ -\tau \mathbf{M}_p & 0 & \tau \nu_1 \mathbf{M} & 0 \\ 0 & -\tau \mathbf{M}_q & 0 & \tau \nu_2 \mathbf{M} \end{bmatrix}.$$

$$\left[ \begin{array}{cccc|cc} \mathbf{A}_{u,GM} & -2\tau r \mathbf{M}_{up/v^2} & -\tau \mathbf{M}_p & 0 & -\mathbf{L}_{u,GM}^\top & 2\tau r \mathbf{M}_u \\ -2\tau r \mathbf{M}_{up/v^2} & \mathbf{A}_{v,GM} & 0 & -\tau \mathbf{M}_q & -\tau r \mathbf{M}_{u^2/v^2} & -\mathbf{L}_{v,GM}^\top \\ -\tau \mathbf{M}_p & 0 & \tau \nu_1 \mathbf{M} & 0 & -\tau \mathbf{M}_u & 0 \\ 0 & -\tau \mathbf{M}_q & 0 & \tau \nu_2 \mathbf{M} & 0 & -\tau \mathbf{M}_v \\ \hline -\mathbf{L}_{u,GM} & -\tau r \mathbf{M}_{u^2/v^2} & -\tau \mathbf{M}_u & 0 & 0 & 0 \\ 2\tau r \mathbf{M}_u & -\mathbf{L}_{v,GM} & 0 & -\tau \mathbf{M}_v & 0 & 0 \end{array} \right] \begin{bmatrix} \mathbf{s}_u \\ \mathbf{s}_v \\ \mathbf{s}_a \\ \mathbf{s}_b \\ \mathbf{s}_p \\ \mathbf{s}_q \end{bmatrix} = \mathbf{b}$$

### Preconditioning the Matrix System – (1,1)-block

- We use saddle point theory to approximate the (1,1)-block by:

$$\hat{\mathbf{A}} = \begin{bmatrix} \hat{\mathbf{A}}_1 & 0 & 0 & 0 \\ 0 & \hat{\mathbf{A}}_2 & 0 & 0 \\ -\tau \mathbf{M}_p & 0 & \tau \nu_1 \mathbf{M} & 0 \\ 0 & -\tau \mathbf{M}_q & 0 & \tau \nu_2 \mathbf{M} \end{bmatrix}.$$

- We seek  $\hat{\mathbf{A}}_1$  and  $\hat{\mathbf{A}}_2$  that satisfy:

$$\begin{bmatrix} \hat{\mathbf{A}}_1 & 0 \\ 0 & \hat{\mathbf{A}}_2 \end{bmatrix} \approx \mathbf{A}_{(1,2)} - \begin{bmatrix} \tau \nu_1^{-1} \mathbf{M}_p \mathbf{M}^{-1} \mathbf{M}_p & 0 \\ 0 & \tau \nu_2^{-1} \mathbf{M}_q \mathbf{M}^{-1} \mathbf{M}_q \end{bmatrix}.$$



$$\left[ \begin{array}{cccc|cc} \mathbf{A}_{u,GM} & -2\tau r \mathbf{M}_{up/v^2} & -\tau \mathbf{M}_p & 0 & -\mathbf{L}_{u,GM}^\top & 2\tau r \mathbf{M}_u \\ -2\tau r \mathbf{M}_{up/v^2} & \mathbf{A}_{v,GM} & 0 & -\tau \mathbf{M}_q & -\tau r \mathbf{M}_{u^2/v^2} & -\mathbf{L}_{v,GM}^\top \\ -\tau \mathbf{M}_p & 0 & \tau \nu_1 \mathbf{M} & 0 & -\tau \mathbf{M}_u & 0 \\ 0 & -\tau \mathbf{M}_q & 0 & \tau \nu_2 \mathbf{M} & 0 & -\tau \mathbf{M}_v \\ \hline -\mathbf{L}_{u,GM} & -\tau r \mathbf{M}_{u^2/v^2} & -\tau \mathbf{M}_u & 0 & 0 & 0 \\ 2\tau r \mathbf{M}_u & -\mathbf{L}_{v,GM} & 0 & -\tau \mathbf{M}_v & 0 & 0 \end{array} \right] \begin{bmatrix} \mathbf{s}_u \\ \mathbf{s}_v \\ \mathbf{s}_a \\ \mathbf{s}_b \\ \mathbf{s}_p \\ \mathbf{s}_q \end{bmatrix} = \mathbf{b}$$

### Preconditioning the Matrix System – (1, 1)-block

- We use saddle point theory to approximate the (1, 1)-block by:

$$\hat{\mathbf{A}} = \begin{bmatrix} \hat{\mathbf{A}}_1 & 0 & 0 & 0 \\ 0 & \hat{\mathbf{A}}_2 & 0 & 0 \\ -\tau \mathbf{M}_p & 0 & \tau \nu_1 \mathbf{M} & 0 \\ 0 & -\tau \mathbf{M}_q & 0 & \tau \nu_2 \mathbf{M} \end{bmatrix}.$$

- We then replace  $\mathbf{A}_{(1,2)}$  by its own saddle point approximation to write:

$$\begin{aligned} \hat{\mathbf{A}}_1 &= \mathbf{A}_{u,GM} - (2\tau r)^2 \mathbf{M}_{up/v^2} \mathbf{A}_{v,GM}^{-1} \mathbf{M}_{up/v^2} - \tau \nu_1^{-1} \mathbf{M}_p \mathbf{M}^{-1} \mathbf{M}_p, \\ \hat{\mathbf{A}}_2 &= \mathbf{A}_{v,GM} - \tau \nu_2^{-1} \mathbf{M}_q \mathbf{M}^{-1} \mathbf{M}_q. \end{aligned}$$

$$S = \begin{bmatrix} -\mathbf{L}_{u,GM} & -\tau r \mathbf{M}_{u^2/v^2} \\ 2\tau r \mathbf{M}_u & -\mathbf{L}_{v,GM} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} -\mathbf{L}_{u,GM}^\top & 2\tau r \mathbf{M}_u \\ -\tau r \mathbf{M}_{u^2/v^2} & -\mathbf{L}_{v,GM}^\top \end{bmatrix} \\ + \tau \begin{bmatrix} \nu_1^{-1} \mathbf{M}_u \mathbf{M}^{-1} \mathbf{M}_u & 0 \\ 0 & \nu_2^{-1} \mathbf{M}_v \mathbf{M}^{-1} \mathbf{M}_v \end{bmatrix} \\ \hat{S} = \begin{bmatrix} -\mathbf{L}_{u,GM} + \widehat{\mathbf{M}}_1^{(1)} & \tau r \mathbf{M}_{u^2/v^2} \\ -2\tau r \mathbf{M}_u & -\mathbf{L}_{v,GM} + \widehat{\mathbf{M}}_2^{(1)} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} -\mathbf{L}_{u,GM}^\top + \widehat{\mathbf{M}}_1^{(2)} & -2\tau r \mathbf{M}_u \\ \tau r \mathbf{M}_{u^2/v^2} & -\mathbf{L}_{v,GM}^\top + \widehat{\mathbf{M}}_2^{(2)} \end{bmatrix}$$

### Preconditioning the Matrix System – Schur complement

- We choose  $\widehat{\mathbf{M}}_1^{(1)}$ ,  $\widehat{\mathbf{M}}_1^{(2)}$ ,  $\widehat{\mathbf{M}}_2^{(1)}$ ,  $\widehat{\mathbf{M}}_2^{(2)}$  such that [Stoll, Pearson & Maini, 2014]:

$$\begin{bmatrix} \widehat{\mathbf{M}}_1^{(1)} & 0 \\ 0 & \widehat{\mathbf{M}}_2^{(1)} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \widehat{\mathbf{M}}_1^{(2)} & 0 \\ 0 & \widehat{\mathbf{M}}_2^{(2)} \end{bmatrix} \approx \tau \begin{bmatrix} \nu_1^{-1} \mathbf{M}_u \mathbf{M}^{-1} \mathbf{M}_u & 0 \\ 0 & \nu_2^{-1} \mathbf{M}_v \mathbf{M}^{-1} \mathbf{M}_v \end{bmatrix}.$$

$$S = \begin{bmatrix} -\mathbf{L}_{u,GM} & -\tau r \mathbf{M}_{u^2/v^2} \\ 2\tau r \mathbf{M}_u & -\mathbf{L}_{v,GM} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} -\mathbf{L}_{u,GM}^\top & 2\tau r \mathbf{M}_u \\ -\tau r \mathbf{M}_{u^2/v^2} & -\mathbf{L}_{v,GM}^\top \end{bmatrix} \\ + \tau \begin{bmatrix} \nu_1^{-1} \mathbf{M}_u \mathbf{M}^{-1} \mathbf{M}_u & 0 \\ 0 & \nu_2^{-1} \mathbf{M}_v \mathbf{M}^{-1} \mathbf{M}_v \end{bmatrix} \\ \hat{S} = \begin{bmatrix} -\mathbf{L}_{u,GM} + \widehat{\mathbf{M}}_1^{(1)} & \tau r \mathbf{M}_{u^2/v^2} \\ -2\tau r \mathbf{M}_u & -\mathbf{L}_{v,GM} + \widehat{\mathbf{M}}_2^{(1)} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} -\mathbf{L}_{u,GM}^\top + \widehat{\mathbf{M}}_1^{(2)} & -2\tau r \mathbf{M}_u \\ \tau r \mathbf{M}_{u^2/v^2} & -\mathbf{L}_{v,GM}^\top + \widehat{\mathbf{M}}_2^{(2)} \end{bmatrix}$$

### Preconditioning the Matrix System – Schur complement

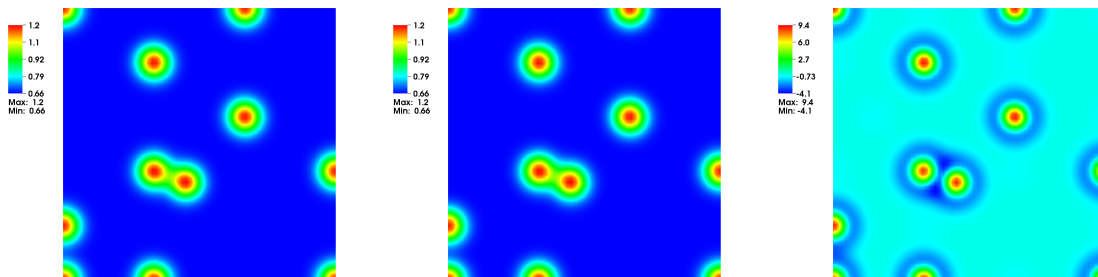
- We choose  $\widehat{\mathbf{M}}_1^{(1)}$ ,  $\widehat{\mathbf{M}}_1^{(2)}$ ,  $\widehat{\mathbf{M}}_2^{(1)}$ ,  $\widehat{\mathbf{M}}_2^{(2)}$  such that [Stoll, Pearson & Maini, 2014]:

$$\begin{bmatrix} \widehat{\mathbf{M}}_1^{(1)} & 0 \\ 0 & \widehat{\mathbf{M}}_2^{(1)} \end{bmatrix} \mathbf{A}_{(1,2)}^{-1} \begin{bmatrix} \widehat{\mathbf{M}}_1^{(2)} & 0 \\ 0 & \widehat{\mathbf{M}}_2^{(2)} \end{bmatrix} \approx \tau \begin{bmatrix} \nu_1^{-1} \mathbf{M}_u \mathbf{M}^{-1} \mathbf{M}_u & 0 \\ 0 & \nu_2^{-1} \mathbf{M}_v \mathbf{M}^{-1} \mathbf{M}_v \end{bmatrix}.$$

- We again examine the diagonal blocks, and select approximations such that

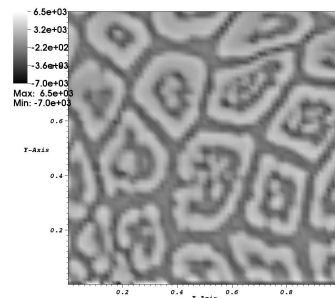
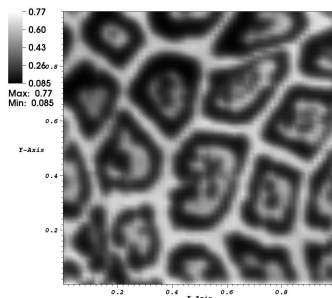
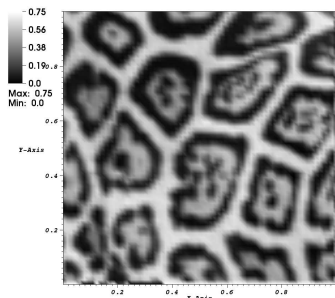
$$\mathbf{M}_1^{(1)} \widehat{\mathbf{A}}_1^{-1} \mathbf{M}_1^{(2)} \approx \frac{\tau}{\nu_1} \mathbf{M}_u \mathbf{M}^{-1} \mathbf{M}_u, \quad \widehat{\mathbf{A}}_1 = \mathbf{A}_{u,GM} - (2\tau r)^2 \mathbf{M}_{up/v^2} \mathbf{A}_{v,GM}^{-1} \mathbf{M}_{up/v^2}, \\ \mathbf{M}_2^{(1)} \widehat{\mathbf{A}}_2^{-1} \mathbf{M}_2^{(2)} \approx \frac{\tau}{\nu_2} \mathbf{M}_v \mathbf{M}^{-1} \mathbf{M}_v, \quad \widehat{\mathbf{A}}_2 = \mathbf{A}_{v,GM} - (2\tau r)^2 \mathbf{M}_{up/v^2} \mathbf{A}_{u,GM}^{-1} \mathbf{M}_{up/v^2}.$$

$$\beta_1 = 1, \quad \beta_2 = 10, \quad D_u = 1, \quad D_v = 10, \quad \gamma = 50$$



DoF	$\nu_1 = \nu_2 = 10^{-2}$		$\nu_1 = \nu_2 = 10^{-4}$		$\nu_1 = \nu_2 = 10^{-6}$	
	Newton	Iterations	Newton	Iterations	Newton	Iterations
43,740	step 1	11	step 1	13	step 1	9
	step 2	11	step 2	12	step 2	9
	step 3	11	step 3	12	step 3	9
	step 4	11	step 4	12		
	step 5	11	step 5	12		
294,780	step 1	11	step 1	13	step 1	11
	step 2	11	step 2	12	step 2	11
	step 3	11	step 3	12	step 3	11
	step 4	11	step 4	12	step 4	11
	step 5	11	step 5	12		
2,156,220	step 1	11	step 1	13	step 1	11
	step 2	11	step 2	12	step 2	11
	step 3	11	step 3	12	step 3	11
	step 4	11	step 4	12	step 4	11
	step 5	11	step 5	12		

$$\beta_1 = 10^2, \quad \beta_2 = 10^2, \quad D_u = 1, \quad D_v = 10, \quad r = 10^{-5}$$



DoF	$\nu_1 = \nu_2 = 10^{-2}$		$\nu_1 = \nu_2 = 10^{-4}$		$\nu_1 = \nu_2 = 10^{-6}$	
	Newton	Iterations	Newton	Iterations	Newton	Iterations
507,000	step 1	18	step 1	16	step 1	16
	step 2	20	step 2	15	step 2	15
	step 3	20	step 3	15	step 3	15
	step 4	20	step 4	15	step 4	15
	step 5	20	step 5	15		
1,996,920	step 1	23	step 1	17	step 1	17
	step 2	23	step 2	18	step 2	16
	step 3	24	step 3	18	step 3	16
	step 4	23	step 4	18	step 4	16
	step 5	23	step 5	18		

## Conclusions

- PDE-constrained optimization is a diverse and important field.
- Have built framework for examining problems motivated by applications.
- Matrix systems have **highly complex structure** → carefully chosen preconditioners.
- Key is powerful approximations of  $(1, 1)$ -block and Schur complement.
- **Image-driven**: can “read in” data from nature.
- Fast and efficient solvers, **often parallelizable**.

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## In the Future ...

- Efficient storage schemes for time-dependent nonlinear problems: **data stored for each time-step**.
- Pattern formation on more challenging/growing surfaces.
- Improved models using different norms.
- Tensor-train methodology & **low-rank methods**.

Thank you for your attention



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