



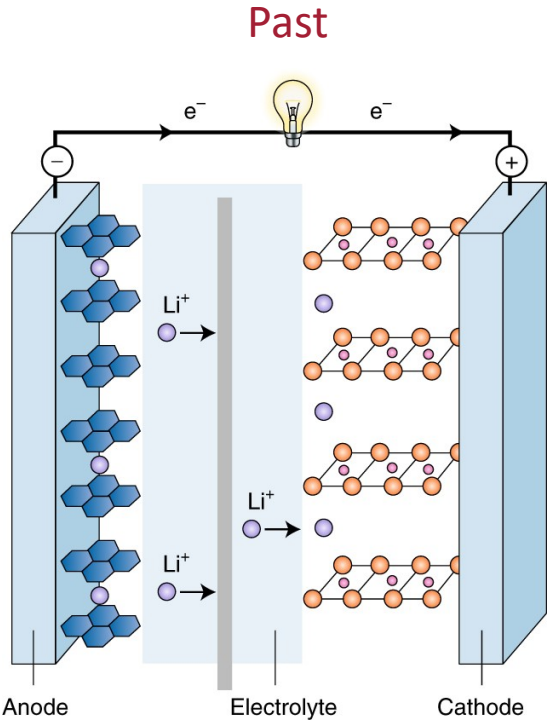
CahnHilliardSBM.jl

**A Case Study of Solving a Stiff, Nonlinear PDE in Custom Geometries
using the Smoothed Boundary Method (SBM)**

Samuel Degnan-Morgenstern (05/08/2023)

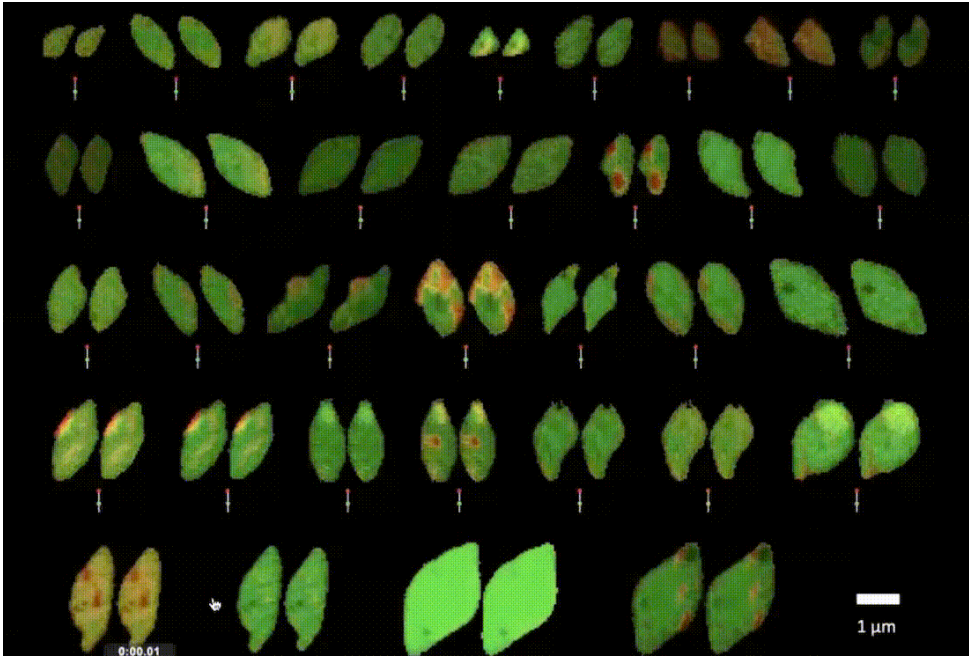
Motivation

Common lithium ion battery electrode materials exhibit complex, heterogeneous physics characterized by phase separation



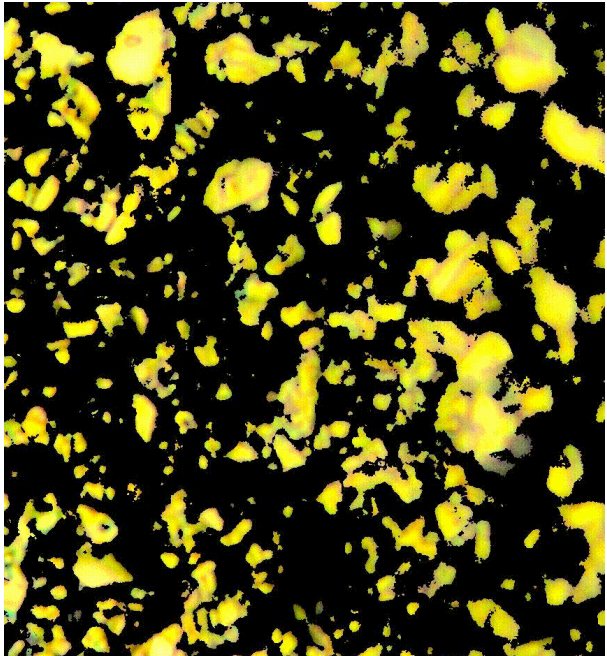
Goodenough, *Nat. Electron.*, 2018

Present



Zhao et al., *Preprint*, 2022

Future



A Crash Course in Non-Equilibrium Thermo

Mass Conservation & Linear Irreversible Thermodynamics

$$\frac{\partial c}{\partial t} = -\nabla \cdot F + \cancel{R_v}$$

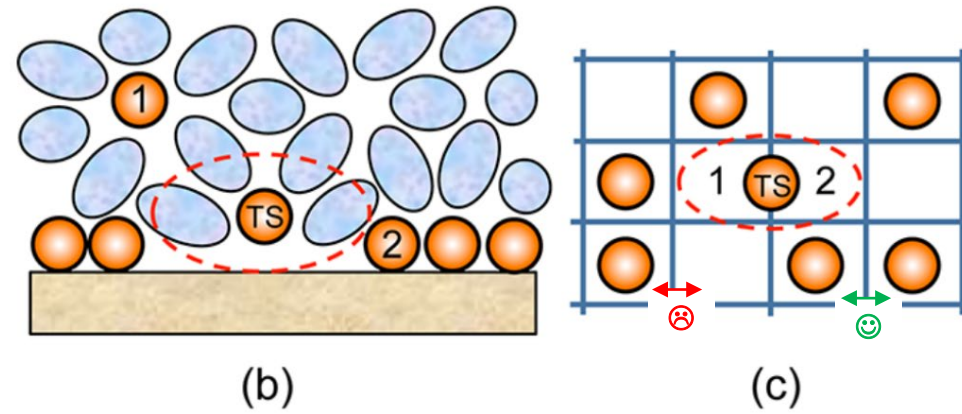
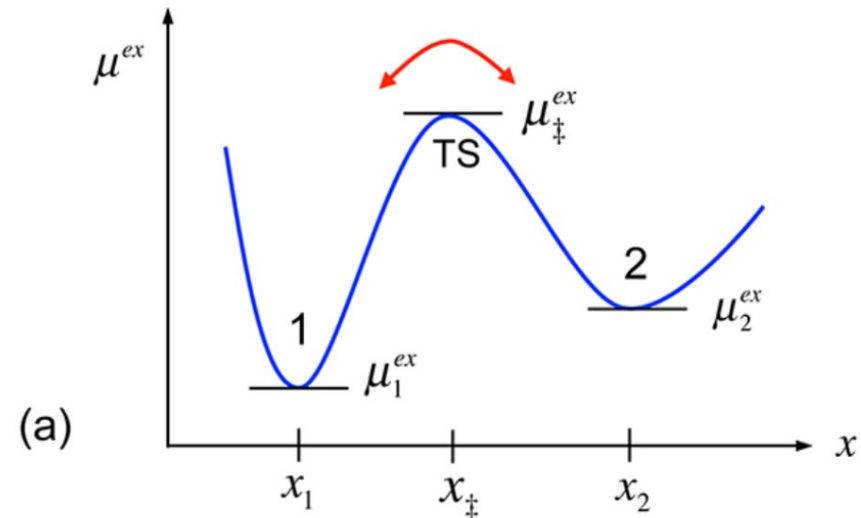
$$F = -D(c) \cdot \nabla \left(\frac{\delta G}{\delta c} \right)$$

$$\frac{\delta G}{\delta c} = \mu = \mu_h - \kappa \nabla^2 c$$

Cahn–Hilliard Partial Differential Equation

$$\frac{\partial c}{\partial t} = \nabla \cdot (D(c) \cdot \nabla \mu)$$

$$\mu = \underbrace{\log \left(\frac{c}{1-c} \right) + \Omega (1-2c)}_{\text{Regular Solution}} - \kappa \nabla^2 c$$



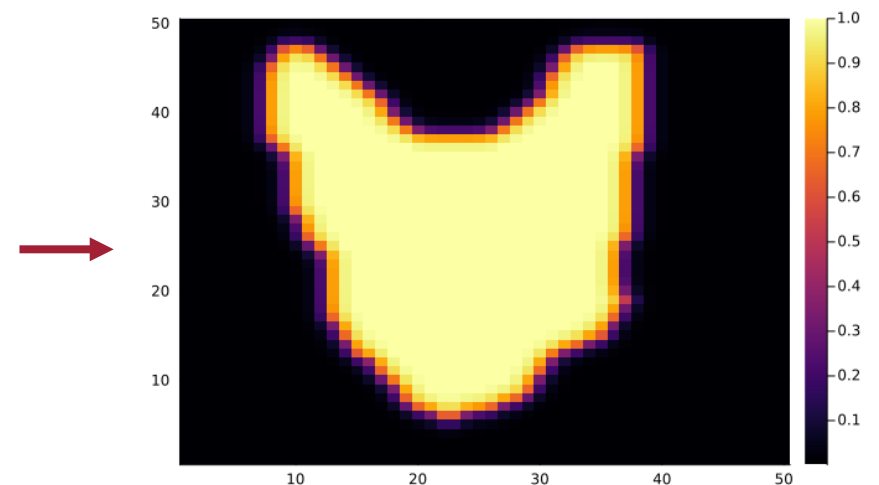
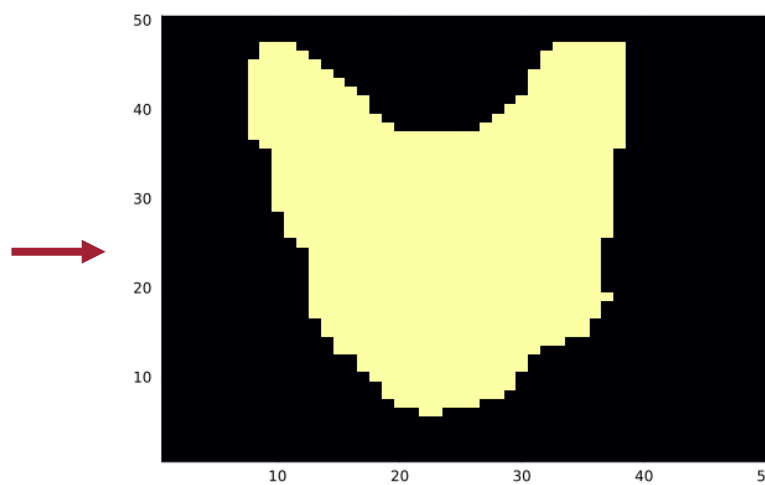
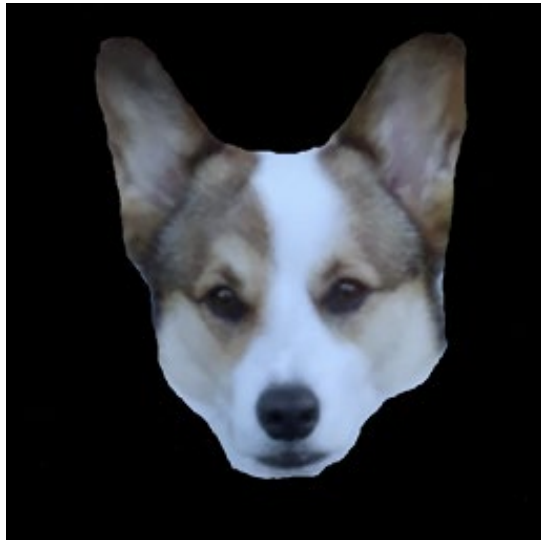
Smoothed Boundary Method

$$\psi(x, y) \frac{\partial c}{\partial t} = -\psi(x, y) \nabla \cdot (D(c) \cdot \nabla \mu)$$

$$\psi(x, y) = \begin{cases} 1 & \text{if } (x, y) \in \mathbf{S} \\ \approx 0.5 & \text{if } (x, y) \in \partial \mathbf{S} \\ 0 & \text{otherwise} \end{cases}$$

$$\frac{\partial c}{\partial t} = \frac{D(c)}{\psi} \nabla \psi \cdot \nabla \mu + \frac{\partial D}{\partial c} \nabla c \cdot \nabla \mu + D(c) \nabla^2 \mu$$

$$\mu = \log \left(\frac{c}{1-c} \right) + \Omega (1 - 2c) - \kappa \left(\frac{\nabla \psi \cdot \nabla c}{\psi} + \nabla^2 c \right)$$



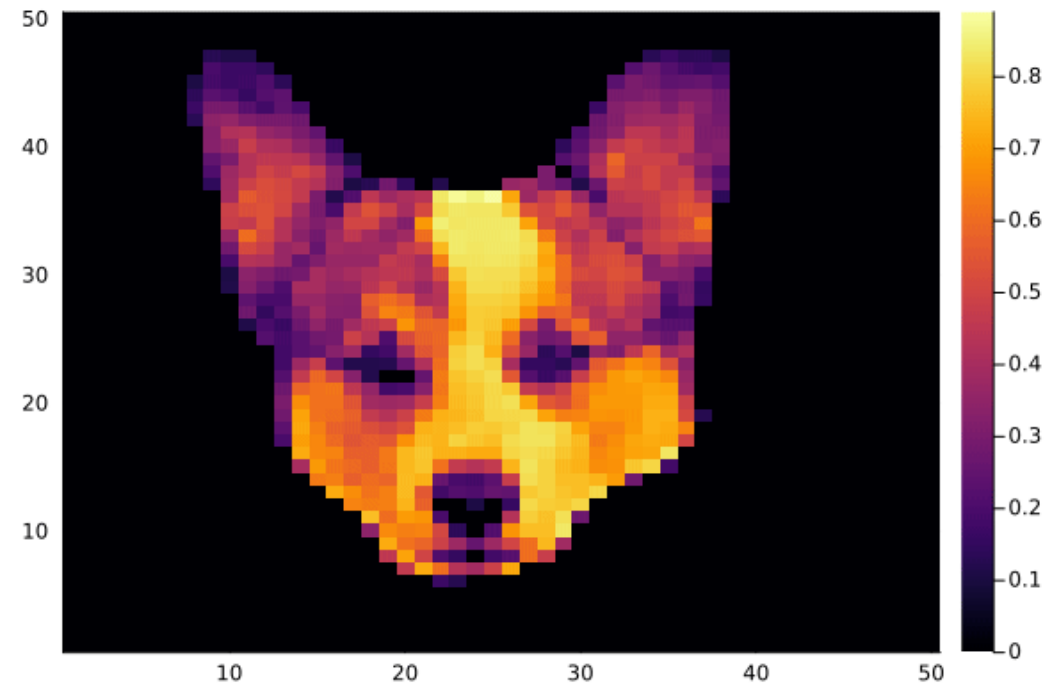
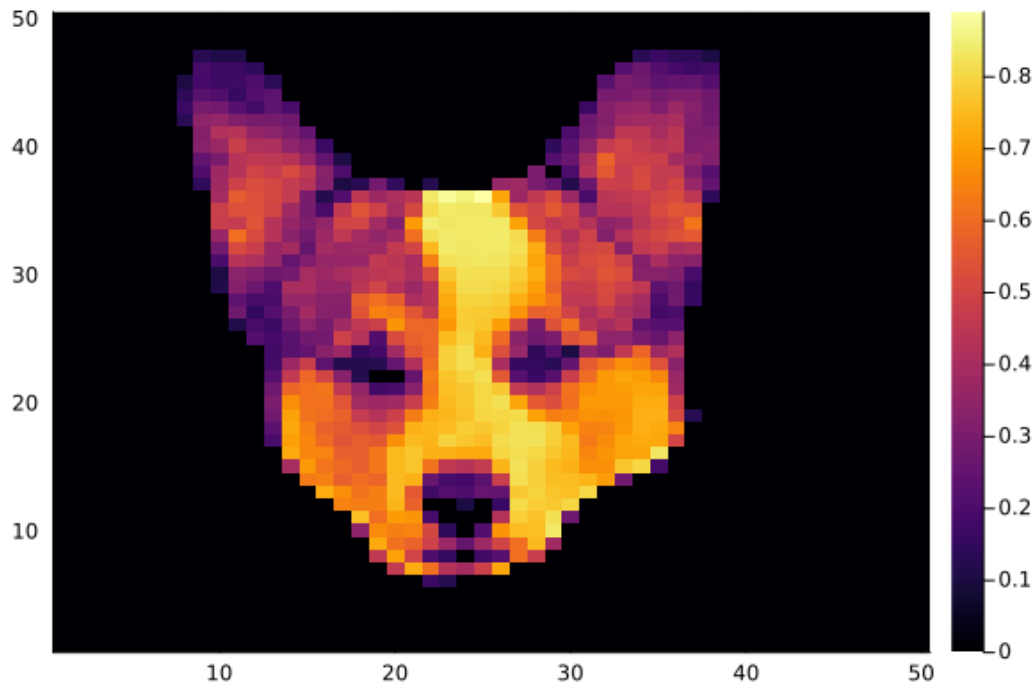
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$$\frac{\partial c}{\partial t} = \frac{D(c)}{\psi} \nabla \psi \cdot \nabla \mu + \frac{\partial D}{\partial c} \nabla c \cdot \nabla \mu + D(c) \nabla^2 \mu$$

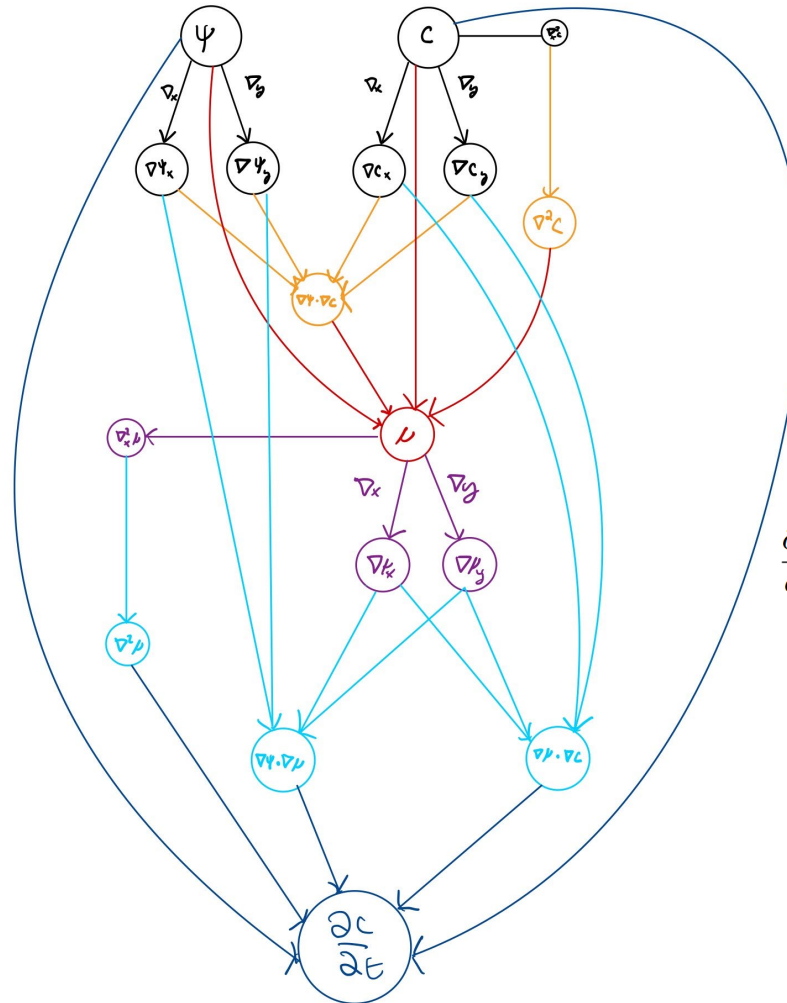
$$\mu = \log \left(\frac{c}{1-c} \right) + \Omega (1 - 2c) - \kappa \left(\frac{\nabla \psi \cdot \nabla c}{\psi} + \nabla^2 c \right)$$



*** No corgis harmed in the making of this project

A Naive Implementation

```
function GCH_2D_mask(dc,c,p,t)
    D, κ, 0, dx, dy, Nx, Ny, v = p
    ψ = @view Ψ[1,:]
    @inline function V2c(ix, iy)
        left = ix > 1 ? c[ix-1, iy] : c[ix+1, iy]
        right = ix < Nx ? c[ix+1, iy] : c[ix-1, iy]
        bottom = iy > 1 ? c[ix, iy-1] : c[ix, iy+1]
        top = iy < Ny ? c[ix, iy+1] : c[ix, iy-1]
        return ((right + left - 2.0*c[ix, iy])/dx^2 + (top + bottom - 2.0*c[ix, iy])/dy^2)
    end
    @inline function Vψc(ix, iy)
        ψleft = ix > 1 ? ψ[ix-1, iy] : ψ[ix+1, iy]
        ψright = ix < Nx ? ψ[ix+1, iy] : ψ[ix-1, iy]
        ψbottom = iy > 1 ? ψ[ix, iy-1] : ψ[ix, iy+1]
        ψtop = iy < Ny ? ψ[ix, iy+1] : ψ[ix, iy-1]
        cleft = ix > 1 ? c[ix-1, iy] : c[ix+1, iy]
        cright = ix < Nx ? c[ix+1, iy] : c[ix-1, iy]
        cbottom = iy > 1 ? c[ix, iy-1] : c[ix, iy+1]
        ctop = iy < Ny ? c[ix, iy+1] : c[ix, iy-1]
        return ((ψleft-ψright)/(2*dx))*((cleft-cright)/(2*dx)) + ((ψtop-ψbottom)/(2*dy))*((ctop-cbottom)/(2*dy))
    end
    @inline function μs(ix, iy)
        return log(max(1e-10, c[ix, iy]/(1-c[ix, iy]))) + 0*(1.0-2.0*c[ix, iy])
    end
    @inline function μ(ix, iy)
        return μs(ix, iy) - κ*(Vψc(ix, iy)/ψ[ix, iy] + V2c(ix, iy))
    end
    @inline function Vψμ(ix, iy)
        ψleft = ix > 1 ? ψ[ix-1, iy] : ψ[ix+1, iy]
        ψright = ix < Nx ? ψ[ix+1, iy] : ψ[ix-1, iy]
        ψbottom = iy > 1 ? ψ[ix, iy-1] : ψ[ix, iy+1]
        ψtop = iy < Ny ? ψ[ix, iy+1] : ψ[ix, iy-1]
        μleft = ix > 1 ? μ[ix-1, iy] : μ[ix+1, iy]
        μright = ix < Nx ? μ[ix+1, iy] : μ[ix-1, iy]
        μbottom = iy > 1 ? μ[ix, iy-1] : μ[ix, iy+1]
        μtop = iy < Ny ? μ[ix, iy+1] : μ[ix, iy-1]
        return ((ψleft-ψright)/(2*dx))*((μleft-μright)/(2*dx)) + ((ψtop-ψbottom)/(2*dy))*((μtop-μbottom)/(2*dy))
    end
    @inline function Vcψ(ix, iy)
        cleft = ix > 1 ? c[ix-1, iy] : c[ix+1, iy]
        cright = ix < Nx ? c[ix+1, iy] : c[ix-1, iy]
        cbottom = iy > 1 ? c[ix, iy-1] : c[ix, iy+1]
        ctop = iy < Ny ? c[ix, iy+1] : c[ix, iy-1]
        ψleft = ix > 1 ? ψ[ix-1, iy] : ψ[ix+1, iy]
        ψright = ix < Nx ? ψ[ix+1, iy] : ψ[ix-1, iy]
        ψbottom = iy > 1 ? ψ[ix, iy-1] : ψ[ix, iy+1]
        ψtop = iy < Ny ? ψ[ix, iy+1] : ψ[ix, iy-1]
        return ((cleft-cright)/(2*dx))*((ψleft-ψright)/(2*dx)) + ((ctop-cbottom)/(2*dy))*((ψtop-ψbottom)/(2*dy))
    end
    @inline function V2μ(ix, iy)
        left = ix > 1 ? μ[ix-1, iy] : μ[ix+1, iy]
        right = ix < Nx ? μ[ix+1, iy] : μ[ix-1, iy]
        bottom = iy > 1 ? μ[ix, iy-1] : μ[ix, iy+1]
        top = iy < Ny ? μ[ix, iy+1] : μ[ix, iy-1]
        return ((right + left - 2.0*μ[ix, iy])/dx^2 + (top + bottom - 2.0*μ[ix, iy])/dy^2)
    end
    @inline function getD(ix::Int, iy::Int)
        return D*(1.0-c[ix, iy])*c[ix, iy]
    end
    @inline function ∂∂c(ix, iy)
        return D*(1.0-2*c[ix, iy])
    end
    @inline function normμ(ix, iy)
        if ((ix > 1) && (ix < Nx) && (iy > 1) && (iy < Ny))
            return sqrt(((c[ix+1, iy]-c[ix-1, iy])/(2*dx))^2 + ((c[ix, iy+1]-c[ix, iy-1])/(2*dy))^2)
        else
            return 0.0
        end
    end
    @inbounds @views for I in CartesianIndices{2}(Nx, Ny)
        ix, iy = Tuple(I)
        dc[ix, iy] = (getD(ix, iy)/ψ[ix, iy])*Vψμ(ix, iy) + ∂∂c(ix, iy)*Vcψ(ix, iy) + getD(ix, iy)*V2μ(ix, iy)
    end
    return nothing
end
```



$$\frac{\partial c}{\partial t} = \frac{D(c)}{\psi} \nabla \psi \cdot \nabla \mu + \frac{\partial D}{\partial c} \nabla c \cdot \nabla \mu + D(c) \nabla^2 \mu$$

$$\mu = \log\left(\frac{c}{1-c}\right) + \Omega(1-2c) - \kappa\left(\frac{\nabla \psi \cdot \nabla c}{\psi} + \nabla^2 c\right)$$

A Naïve Implementation

40 x 40 system, $t \in (0,5)$

```
@benchmark sol_l=solve($prob,CVODE_BDF(linear_solver=:GMRES),save_everystep=false)
✓ 14.8s
BenchmarkTools.Trial: 9 samples with 1 evaluation.
Range (min ... max): 594.319 ms ... 610.479 ms   GC (min ... max): 0.00% ... 0.00%
Time (median):       602.146 ms                 GC (median):    0.00%
Time (mean ± σ):     601.627 ms ± 5.963 ms      GC (mean ± σ):  0.00% ± 0.00%

Histogram: frequency by time
594 ms                                     610 ms <
Memory estimate: 768.41 KiB, allocs estimate: 15489.
```

We can do better!



Several Iterations of Code Optimization...

```
function GCH_2D_mul_full2(du, u, p, t, ψ, ∇x, ∇y, ∇2x, ∇2y, ∇ψ_x, ∇ψ_y, ∇c_x, ∇c_y, ∇2c, μ, ∇2μ, ∇μ_x, ∇μ_y)
    D, κ, Ω = p
    c = @view u[:, :]
    dc = @view du[:, :]

    #Set up caches from DiffCache
    ∇c_x_t = get_tmp(∇c_x, u)
    ∇c_y_t = get_tmp(∇c_y, u)
    ∇2c_t = get_tmp(∇2c, u)
    μ_t = get_tmp(μ, u)
    ∇2μ_t = get_tmp(∇2μ, u)
    ∇μ_x_t = get_tmp(∇μ_x, u)
    ∇μ_y_t = get_tmp(∇μ_y, u)

    #Compute ∇c
    mul!(∇c_x_t, ∇x, c) # Compute (∇c)_x = ∇x*c
    mul!(∇c_y_t, ∇y, c) # Compute (∇c)_y = c*∇y

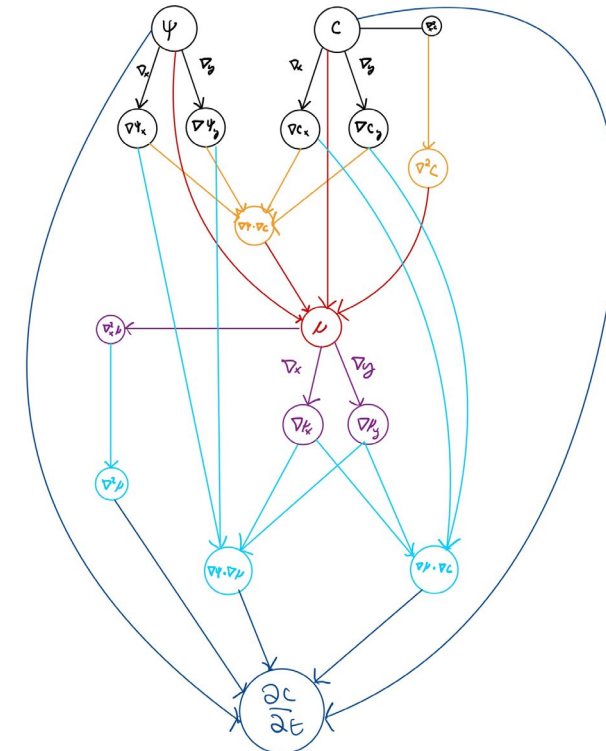
    #Compute ∇2c
    mul!(∇2c_t, ∇2x, c) # Compute (∇2c)_x = c*∇2x
    mul!(∇2c_t, c, ∇2y, 1.0, 1.0) #∇2c = 1*(∇2c)_x + 1*(∇2y)*c

    @. μ_t = log(max(1e-10, c./(1.0 - c))) + Ω*(1.0 - 2.0*c) .- κ*((∇c_x_t*∇ψ_x + ∇c_y_t*∇ψ_y)./ψ + ∇2c_t);

    #Compute ∇2μ
    mul!(∇2μ_t, ∇2x, μ_t) # Compute (∇2μ)_x = μ*∇2x
    mul!(∇2μ_t, μ_t, ∇2y, 1.0, 1.0) #∇2μ = 1*(∇2μ)_x + 1*(∇2y)*μ
    #Compute ∇μ
    mul!(∇μ_x_t, ∇x, μ_t) # Compute (∇μ)_x = ∇x*μ
    mul!(∇μ_y_t, ∇y, μ_t) # Compute (∇μ)_y = μ*∇y
    @. dc = D*(c*(1.0-c))*((∇ψ_x*∇μ_x_t + ∇ψ_y*∇μ_y_t)./ψ + ∇2μ_t) + (1.0-2.0*c)*(∇c_x_t*∇μ_x_t + ∇c_y_t*∇μ_y_t)
    return nothing
end
```

Key Differences:

- Finite differencing redone with matrix stencil operators
- ForwardDiff.jl compatible mul! caches
- Efficient use of broadcasting



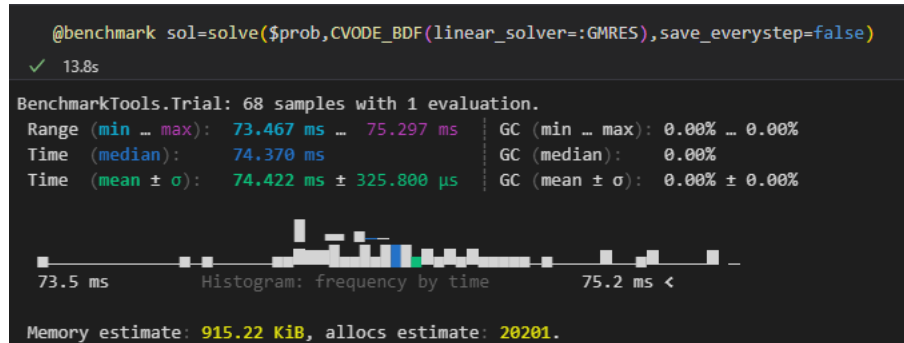
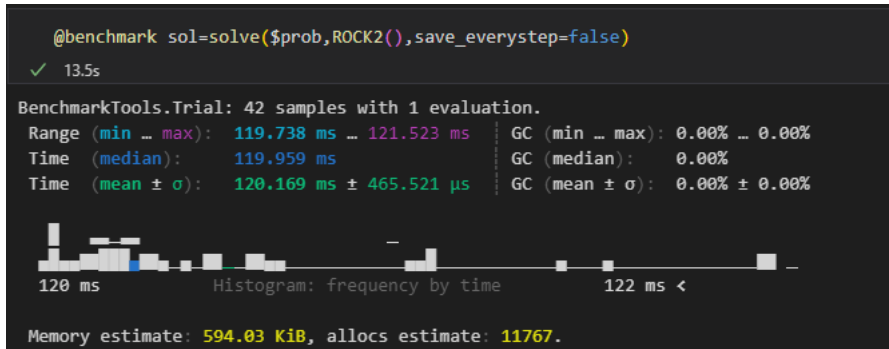
$$\frac{\partial c}{\partial t} = \frac{D(c)}{\psi} \nabla \psi \cdot \nabla \mu + \frac{\partial D}{\partial c} \nabla c \cdot \nabla \mu + D(c) \nabla^2 \mu$$

$$\mu = \log\left(\frac{c}{1-c}\right) + \Omega(1-2c) - \kappa\left(\frac{\nabla \psi \cdot \nabla c}{\psi} + \nabla^2 c\right)$$

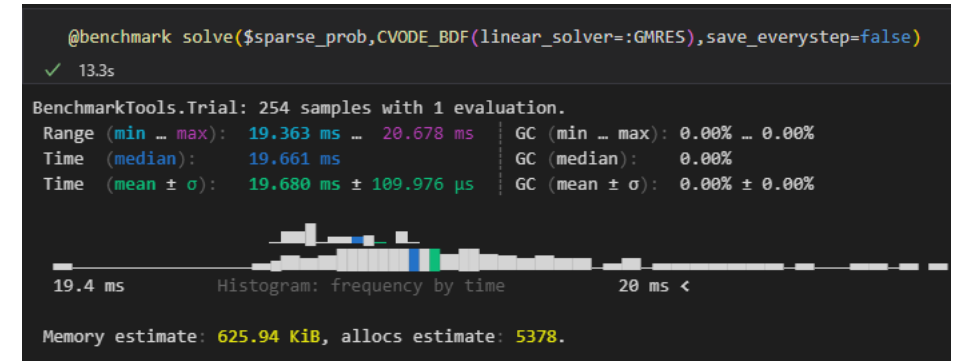
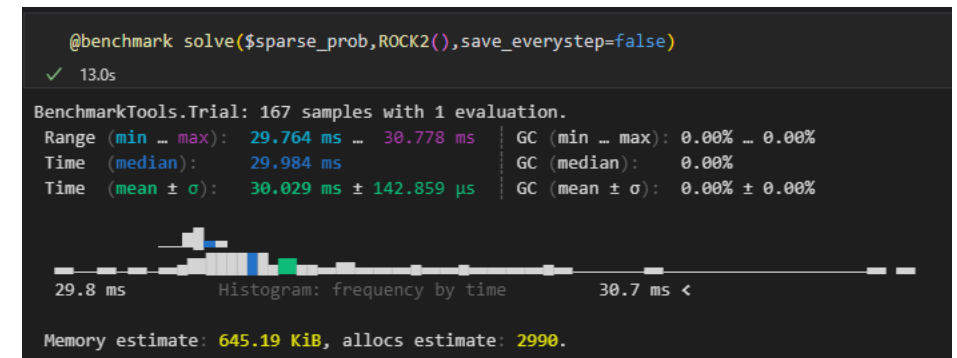


Several Iterations of Code Optimization...

Dense Jacobian:



Sparse Jacobian:



30x Speedup!!

Parameter Estimation via ForwardDiff

```
function proto_loss(theta, prob, tsteps, ode_data, psi_binary)
    tmp_prob = remake(prob, p = theta)
    tmp_sol = solve(tmp_prob, TRBDF2(), saveat = tsteps, sensealg = ForwardDiffSensitivity())
    #if tmp_sol.retcode == ReturnCode.Success
    if size(tmp_sol) == size(ode_data)
        return sum(abs2, (psi_binary.*(Array(tmp_sol) - ode_data)))
    else
        return Inf
    end
end

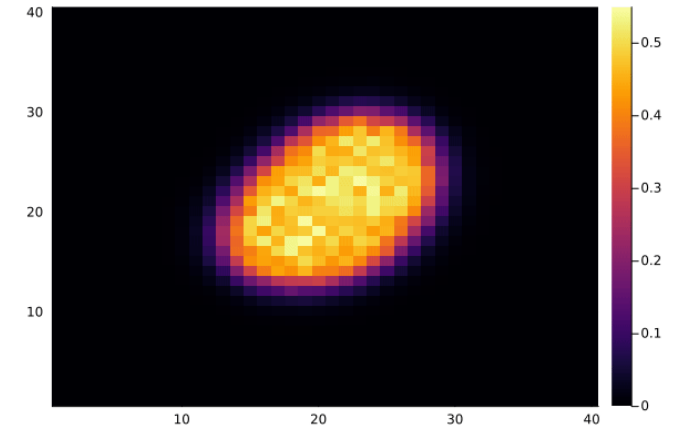
function set_pe(psi, c0_messy, ptruth, tspan, Nsteps; tcleaning=1e-4)
    tsteps = collect(range(tspan[1], tspan[2], length = Nsteps))
    x, y, rhsfunc = setup_CH(psi; gpuflag = false, levels=3)
    prob = makesparseprob(rhsfunc, c0, (theta, tcleaning), ptruth)
    tmpsol = solve(prob, TRBDF2(), save_everystep=false);
    newc0 = tmpsol.u[end];
    prob = remake(prob, tspan=tspan, c0=newc0);
    ode_data = Array(solve(prob, TRBDF2(), saveat = tsteps));
    return tsteps, ode_data, prob
end

function callback(p, l)
    global iter
    iter += 1
    display("Iteration $(iter), loss = $(l)")
    return false
end

function solve_pe(pinit, loss; iter_max=200)
    optfun = OptimizationFunction((u,_) -> loss(u), Optimization.AutoForwardDiff())
    optprob = OptimizationProblem(optfun, pinit)
    @time optsol = solve(optprob, Optim.NewtonTrustRegion(), callback=callback; maxiters=iter_max)
    return optsol
end

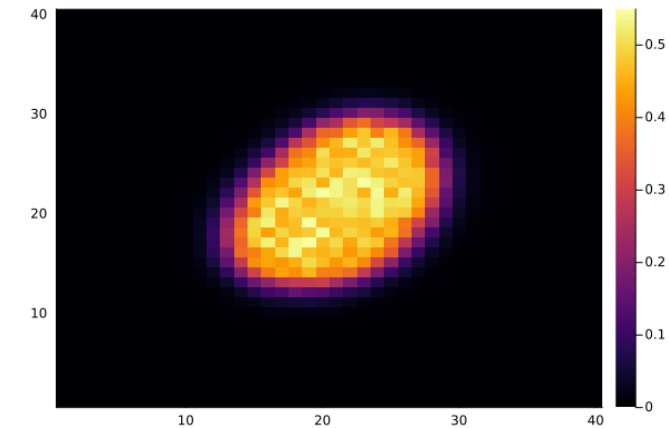
function run_pe(psi, psi_binary, c0_messy, ptruth; tspan=(0.0, 1.0), Nsteps=100, itmax=200)
    tsteps, ode_data, prob = set_pe(psi, c0_messy, ptruth, tspan, Nsteps)
    loss(theta) = proto_loss(theta, prob, tsteps, ode_data, psi_binary)
    optsol = solve_pe(pinit, loss; iter_max=itmax)
    return optsol
end
```

Initial Guess

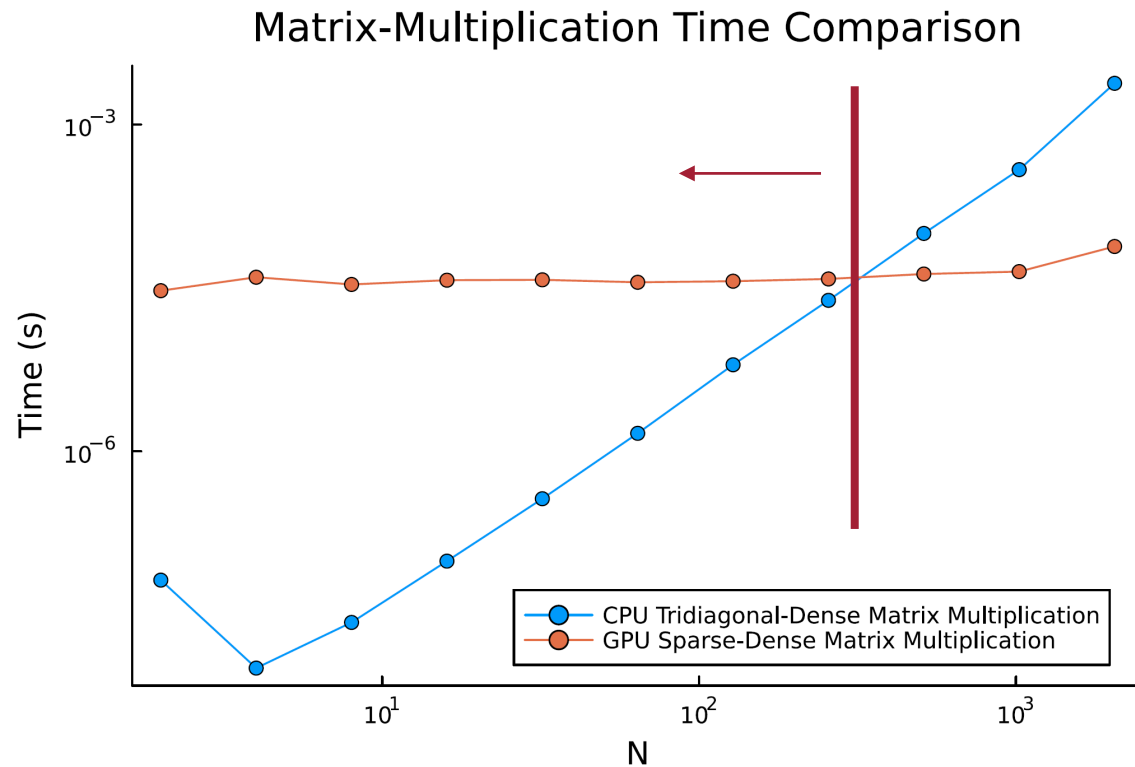


NewtonTrustRegion() 37 iterations

Recovers true solution



Within Method GPU Parallelization



To successfully implement GPU parallelization:

- Ease numerical instability
 - Larger systems lead to exploding Laplacian terms
- Move the needle to the left by writing custom GPU kernel

Questions? Collaboration?

- Opportunity to demonstrate capability of Julia SciML Ecosystem on a very complex physical problem
- Looking to improve performance & stability of within method GPU parallelization
- Hoping to set up further support for inversion using reverse mode AD