

Making point sets first class in UFL and Firedrake

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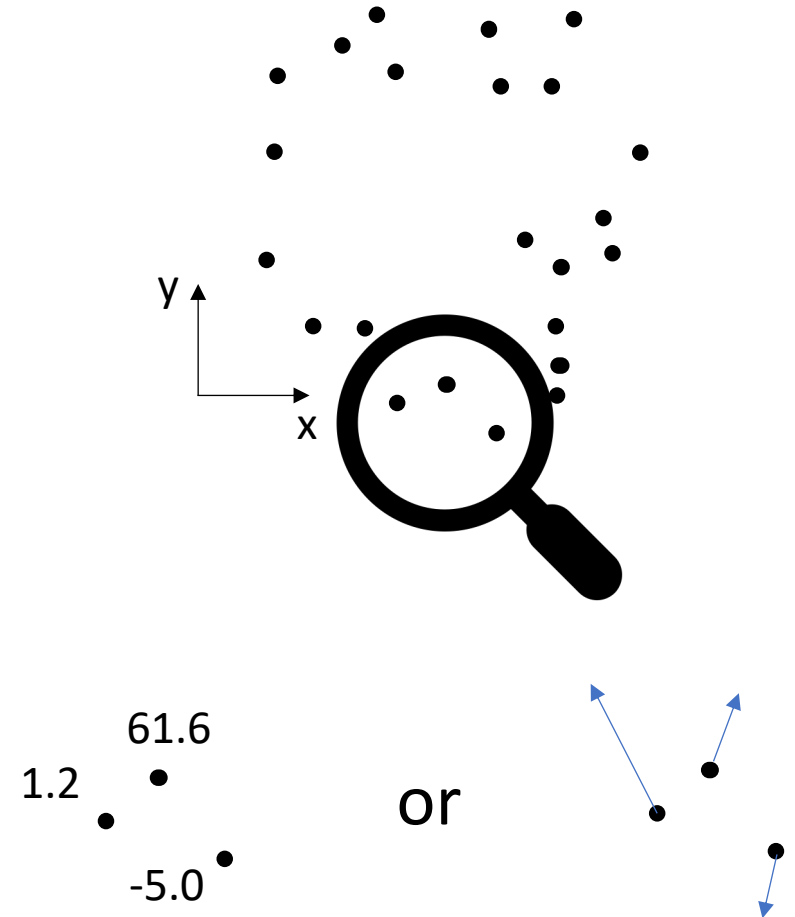


Why care about point data?

- Geoscience Examples
 - Ice Sheets: elevation from **satellite altimetry** and **ice cores**
 - Ocean: salinity and temperature from **drifting buoys**
 - Atmosphere Climate: conditions at **weather stations**
 - **And more!**
- Typical uses
 - **Point evaluation** of PDE solutions
 - PDE Constrained Optimisation
 - Variational **data assimilation**
 - Goal based error estimation
 - **And more!**

Definition: Point Data

1. A “point cloud” $\{X_i\}$ – a set of spatial coordinates and
2. Values y_i (scalar, vector or tensor valued) at those coordinates.



How we deal with point data at the moment


```
# UFL  
# evaluate coefficient f at two  
# 2-dimensional points  
vals[0] = f([0.2, 0.4])  
vals[1] = f([1.2, 0.5])
```

```
# Firedrake (dolfin similar)  
# evaluate Function f at two  
# 2-dimensional points  
from firedrake import *  
...  
vals = f.at([0.2, 0.4], [1.2, 0.5])
```

- UFL expressions of coefficients can be evaluated at given point coordinates
- Can get values from point clouds

How we deal with point data at the moment

```
# UFL
# evaluate coefficient f at two
# 2-dimensional points
vals[0] = f([0.2, 0.4])
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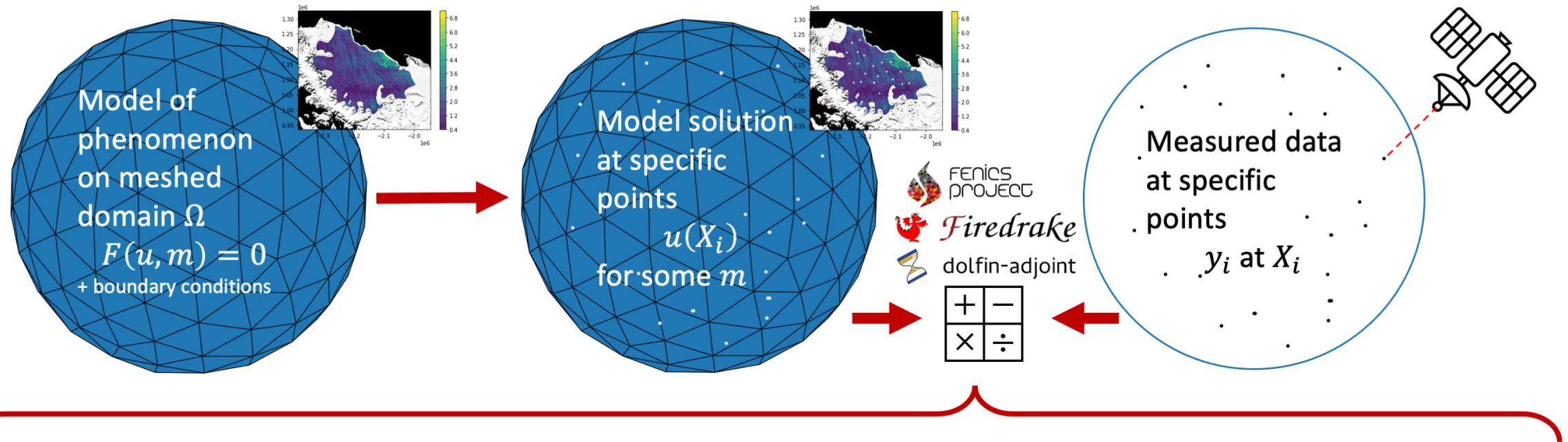
- **outside of the UFL type system of fields in function spaces on meshes**
- Value driven: no symbolic point evaluation.
- ~~ dolfin adjoint~~

```
# Firedrake
# evaluate Function f at two
# 2-dimensional points
from firedrake import *
...
vals = f.at([0.2, 0.4], [1.2, 0.5])
```

- end up special-casing point evaluation code pathways
- Often slow!

Example Use Case

Point Data Assimilation: A PDE Constrained Optimisation Problem



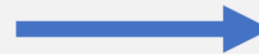
Minimization Problem:

$$\min_{u, m} J[u, m] \quad \text{where } J = \underbrace{\|u(X_i) - y_i\|^2}_{\text{misfit (Fit of model to data)}} + \underbrace{c\|m\|^2}_{\text{regularization (e.g. to ensure smooth fit)}}$$

subject to

$$F(u, m) = 0$$

+ boundary conditions



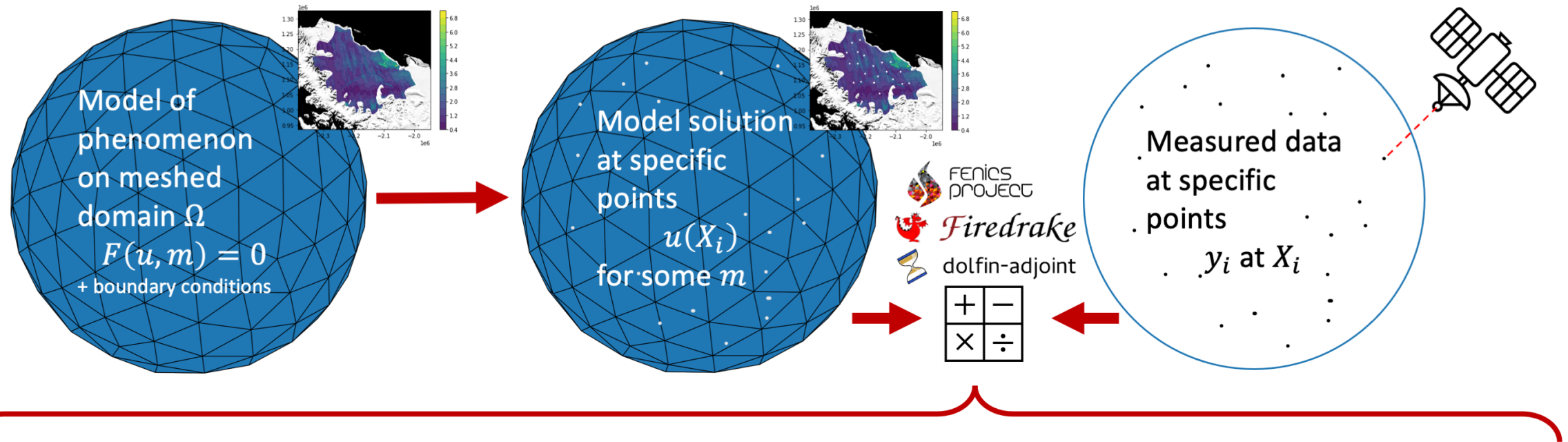
Gradient Based Optimisation Needs

$$\frac{\partial J}{\partial u} \frac{du}{dm}$$

Find via solution to the adjoint problem using  dolfin-adjoint

Example Use Case

Point Data Assimilation: A PDE Constrained Optimisation Problem



Minimization Problem:

$$\min_{u, m} J[u, m] \text{ where } J = \underbrace{\|u(X_i) - y_i\|^2}_{\text{data fit}} + \underbrace{c \|m\|^2}_{\text{regularization}}$$

Need to express this in UFL and annotate it with dolfin-adjoint/pyadjoint

Gradient Based Optimisation Needs

$$\frac{\partial J}{\partial u} \frac{du}{dm}$$

Find via solution to the adjoint problem using  dolfin-adjoint

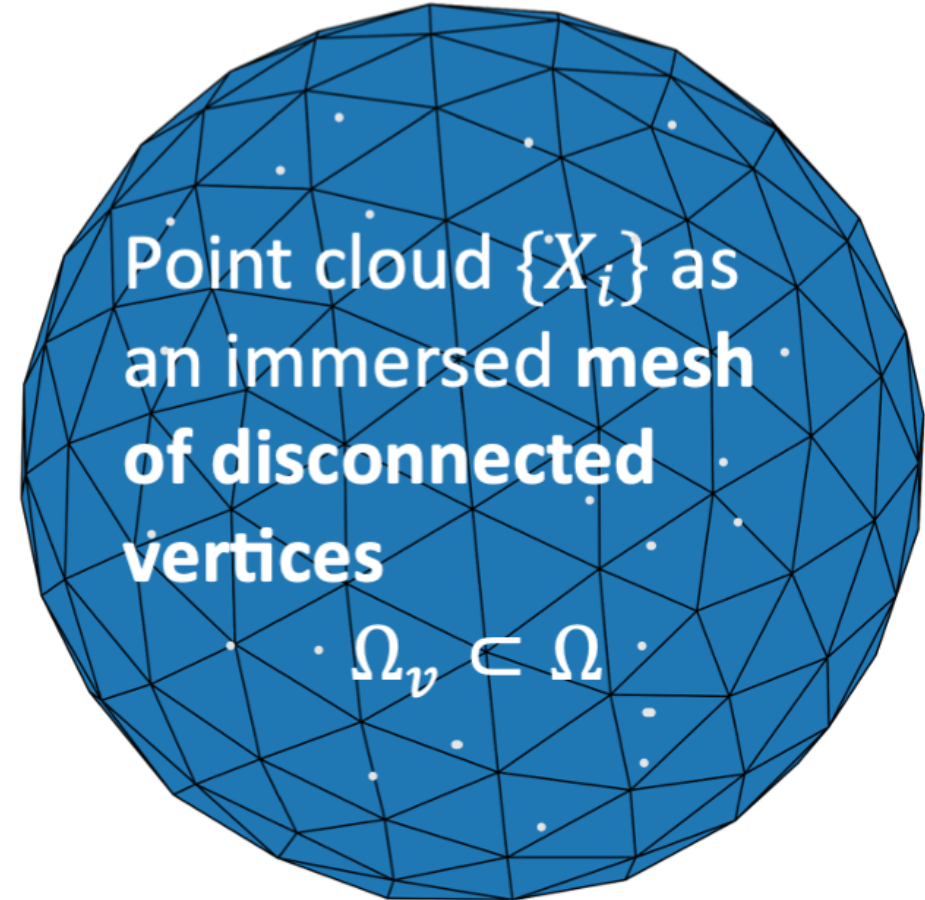
Solution Part 1: A point cloud is a mesh Ω_v

UFL

- Vertex Cells
- Topological dimension = 0
- Geometric dimension = $\dim(X_i)$ (point cloud coordinate dimension)

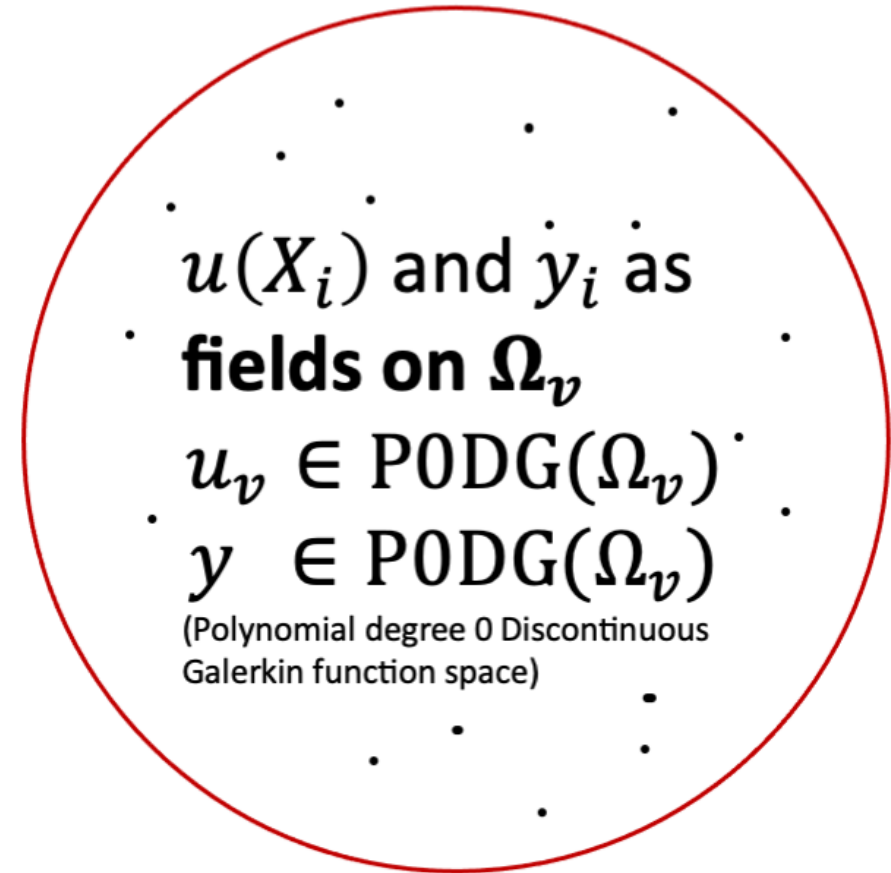
Firedrake

- Vertices at point cloud coordinates $\{X_i\}$
- Immersed (for now)
 - makes implementation simpler
 - care about the point data with respect to field on “parent” mesh Ω (e.g. a PDE solution)



Solution Part 2: Point data are functions in a PODG function space on Ω_v

- Scalar, vector or tensor valued
- Each function in this function space represents a **complete set of point data**
 - Vertex coordinates $\{X_i\}$ are fixed*
 - Can **declare UFL arguments to solve for values** at points $\{X_i\}$
- Changes: UFL ✓ FIAT ✓ Firedrake ✓



*unless we represent moving points – something for the future!

How do we use this?

Interpolate into the point data space

Point evaluation is now
interpolation into $W = P0DG(\Omega_v)$
 $u_v = I(u, W)$



Rewrite $J = \|u(X_i) - y_i\|^2 + c\|m\|^2$

$$J = \int_{\Omega_v} (I(u, W) - y)^2 dx + c\|m\|^2$$

$$\frac{\partial J}{\partial u} = \int_{\Omega_v} (I(u, W) - y) \underbrace{\frac{\partial I(u, W)}{\partial u}}_{\text{Newly added to}} dx$$

Newly added to

 *Firedrake* and  dolfin-adjoint

```
# UFL+Firedrake Pseudocode
```

```
# blue is proposed new UFL
```

```
# u is a solution from a function space on parent_mesh
```

```
# m is source term from some function space
```

```
vm = VertexOnlyMesh(parent_mesh, point_cloud_coords)
```

```
W = FunctionSpace(vm, "DG", 0)
```

```
# interpolate
```

```
v = TestFunction(W).dual()
```

```
u_v = interp(u, v) # or u_v = v(u)
```

```
... # create y in W from observation data
```

```
# Functional for minimisation
```

```
J = assemble( (u_v - y)**2 * dx + c*inner(m, m) * dx )
```

```
# Reduce using control from parameter space
```

```
hat_m = firedrake_adjoint.Control(m)
```

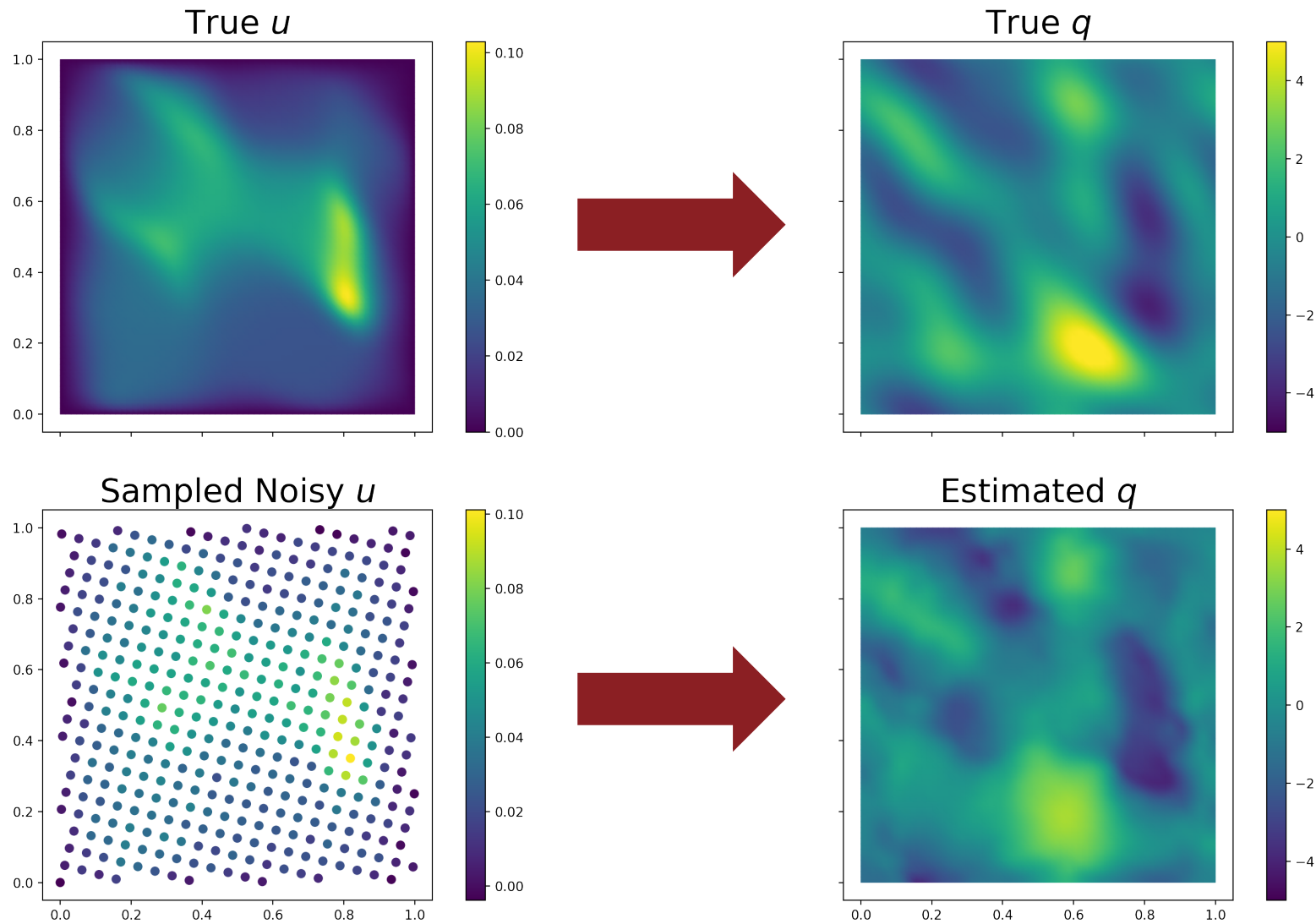
```
hat_J = firedrake_adjoint.ReducedFunctional(J, hat_m)
```

```
# Find optimal control
```

```
m_min = firedrake_adjoint.minimize(hat_J, method='Newton-CG')
```

It really works!

Estimating Log-Conductivity q
where $k = k_0 e^q$ and $-\nabla \cdot k \nabla u = f$ for known f



Future: UFL for Automated Diagnostics

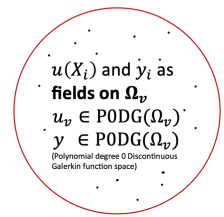
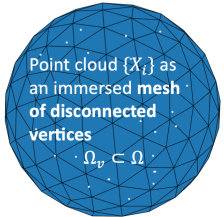
- Aim to develop UFL into a Domain Specific Language (DSL) for specifying model diagnostics
 - A user will specify, as some high level integration (e.g. over points or planes), the diagnostic then code will be generated to calculate it
 - Example: Ocean current from multiple climate models e.g. Atlantic Meridional Overturning Circulation in Medhaug and Furevik 2011 [4]
- Form compiler can then generate code for calculating the diagnostic
- **Scalable** and able to run on **big datasets** (e.g. climate) on the **HPCs closest to the data.**

¹ Medhaug, I., & Furevik, T. (2011). North Atlantic 20th century multidecadal variability in coupled climate models: Sea surface temperature and ocean overturning circulation. *Ocean Science*, 7(3), 389-404.

Conclusion

- Point data are everywhere and can be treated more rigorously
- We can represent point data as a function in a PODG function space on a point cloud mesh
- Point evaluations are interpolations into this function space
- `interp` proposed as new UFL operator for interpolation
- Can use point data in PDE constrained optimisation problems by annotating interpolation with `pyadjoint/dolfin-adjoint`
- First step towards turning UFL into a DSL for automated diagnostics

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Possible work-around existing limitations

Minimization Problem:

$$\min_{u,m} J[u,m] \quad \text{where } J = \|u(X_i) - y_i\|^2 + c\|m\|^2$$

subject to

$$F(u,m) = 0$$

+ boundary conditions

- Interpolate the point data into some function space on my mesh then calculate

$$J = \|u - y_{approx}\|^2 + c'\|m\|^2$$

- Have to make difficult-to-test decisions about appropriate interpolation hyperparameters to get y_{approx} ,
- Particularly a problem if the point data is sparse

Solution Part 2: Point data are functions in a PODG function space on Ω_v

Some Properties:

- Integrating sums values at points

$$\int_{\Omega_v} u_v dx = \sum_i u_v(X_i)$$

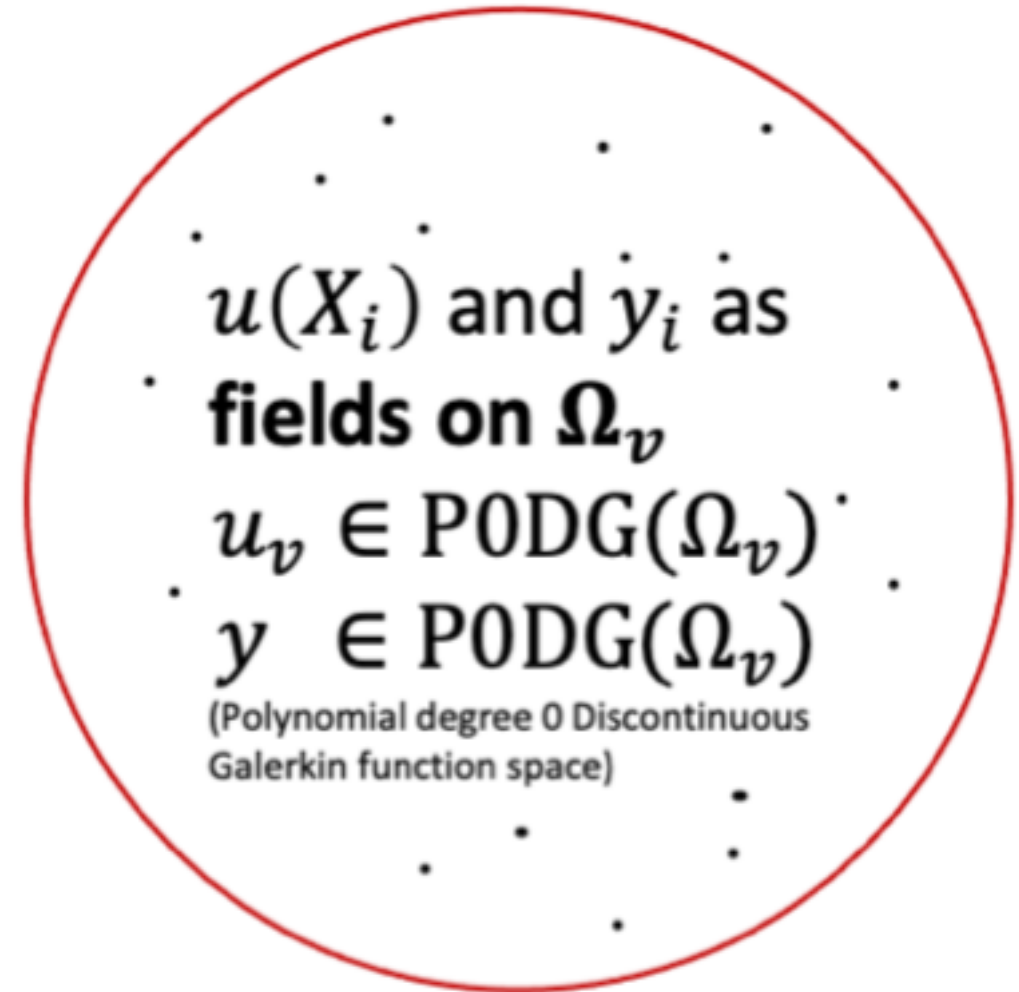
- L^2 inner product equivalent to l_2 inner product of each component (if vector or tensor valued)

$$\langle u_v, y \rangle_{L^2} = \int_{\Omega_v} u_v y dx = \dots = \sum_i u_v(X_i) y(X_i) = \langle u_v, y \rangle_{l_2}$$

- Mass matrix is identity matrix
- Non-differentiable
- Reisz map is L^2 inner product

$$\langle u_v, \cdot \rangle_{L^2} = u'_v(\cdot)$$

- Nodal interpolation is L^2 Galerkin projection



Why is this helpful in this example?

- No extra approximations necessary
- Can **be rigorous about the statistical interpretation** of data assimilation results via misfit functional (check if errors are normally distributed for example) and directly investigate different regularisations.
- **Feed back from modeller to experimenter**: can quickly model say, the impact of more measurements vs better SNR with simulated data.
- Dan and I working on a paper right now to make this point!

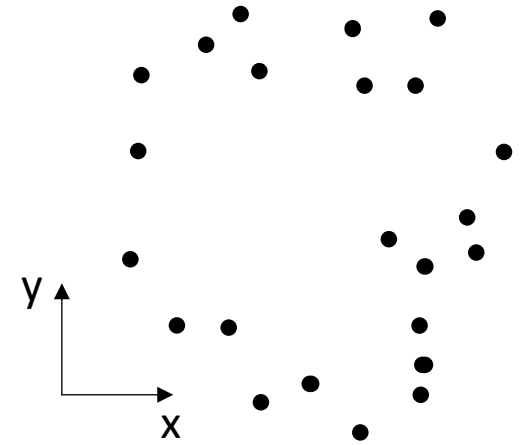
Future: UFL for Automated Diagnostics

- Possible approach:
 1. Read-in gridded field data as equivalent finite element field
 2. Create mesh to represent region to integrate:
 - Points - “Vertex Only Mesh”
 - lines “mesh of disconnected lines”
 - Planes “mesh of disconnected planes” etc.
 3. Calculate the diagnostic by interpolating onto the region and performing desired integration
 - Point evaluations
 - Fluxes etc.
- **Note:** Requires UFL to be extended to include interpolation operations in the language e.g. via the `interp` form.

Next Steps

Point Data

- Demonstration on real models showing advantages
- Moving points (optional)



Automated Diagnostics

- Higher dimension disconnected mesh abstractions (lines, planes and polyhedra) for interpolation onto
- Define the interpolation operations e.g. via supermeshing
- Improve dataset parsing tools
- Integration with existing tool-chains e.g. Pangeo

