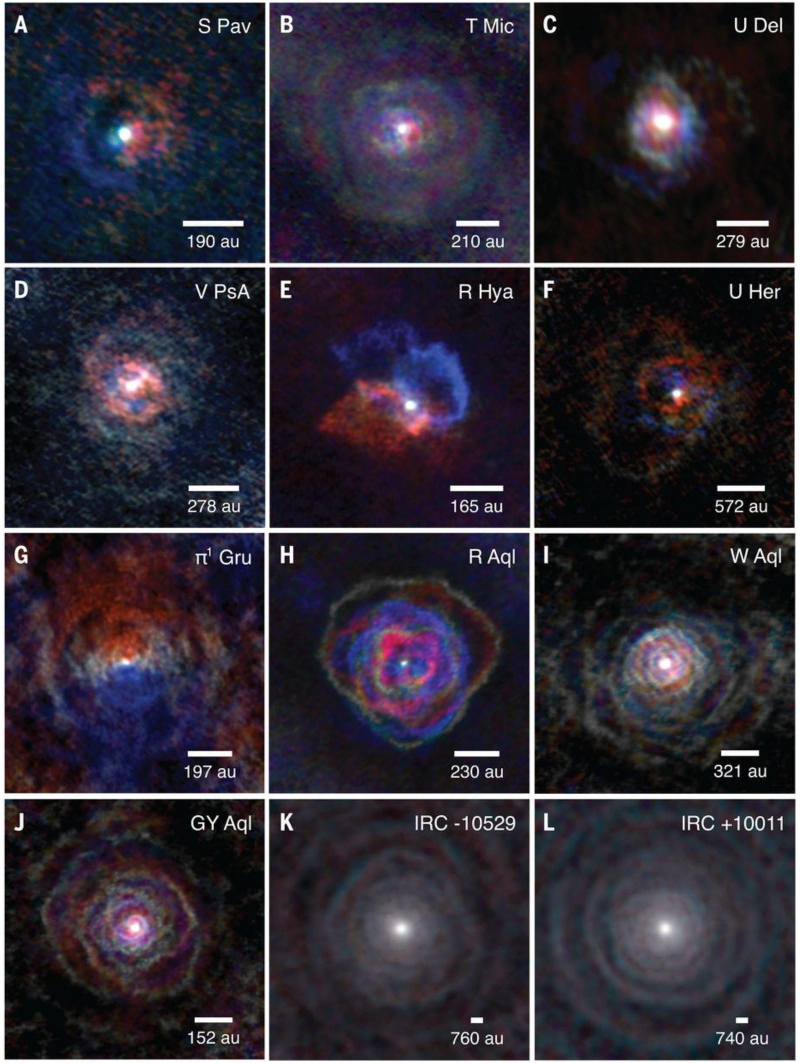
Probabilistic **3D reconstruction** of the **circumstellar environments** of evolved stars

Frederik De Ceuster (KU Leuven, FWO Fellow)

in collaboration with

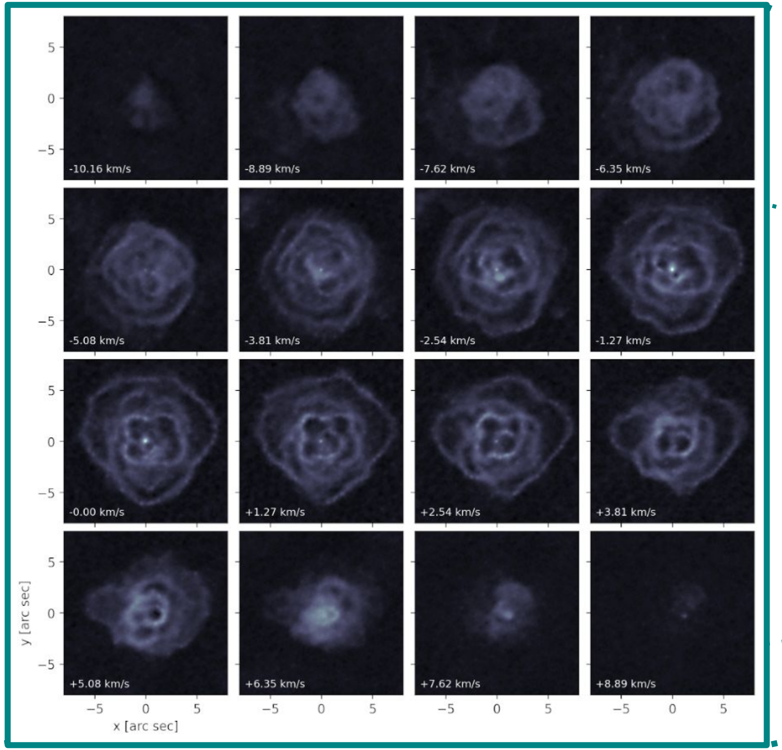
A. Coenegrachts, J. Malfait, T. Ceulemans, M. Esseldeurs, S. Maes,
T. Konings, T. Danilovich, J. Cockayne, L. Decin, J. Yates, (**You?**)

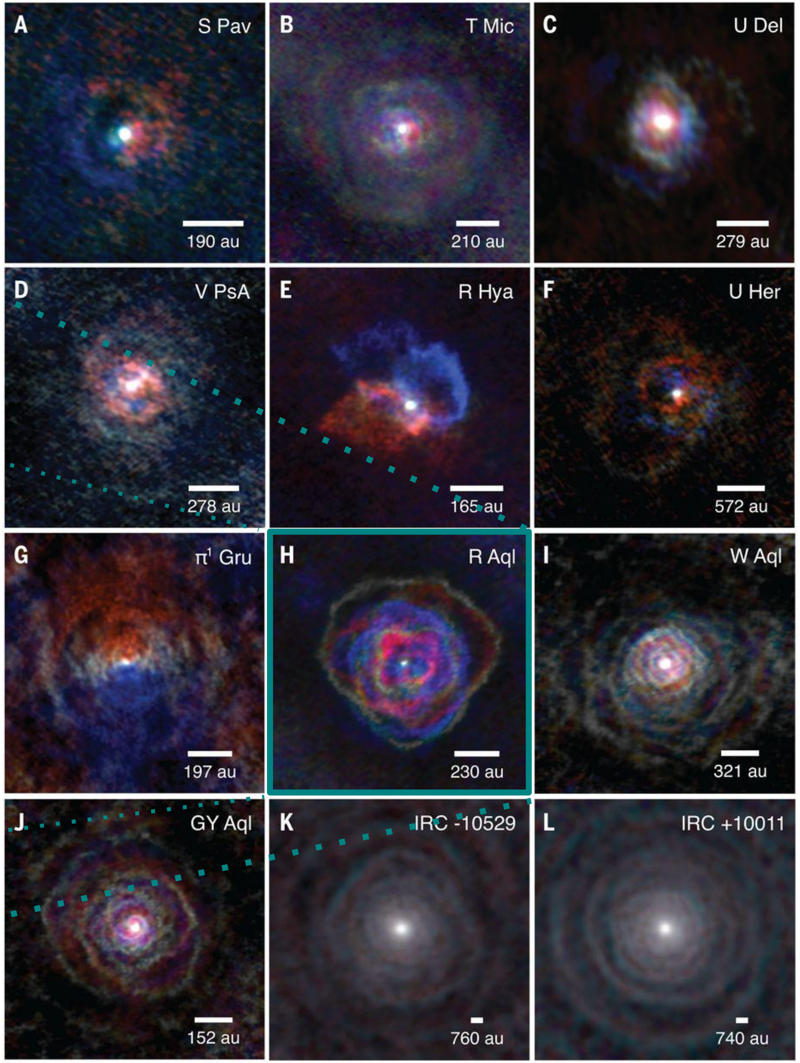
High-resolution observations revealed **complex morphologies**



ATOMIUM: ALMA Large Program, Decin et al. (2020)

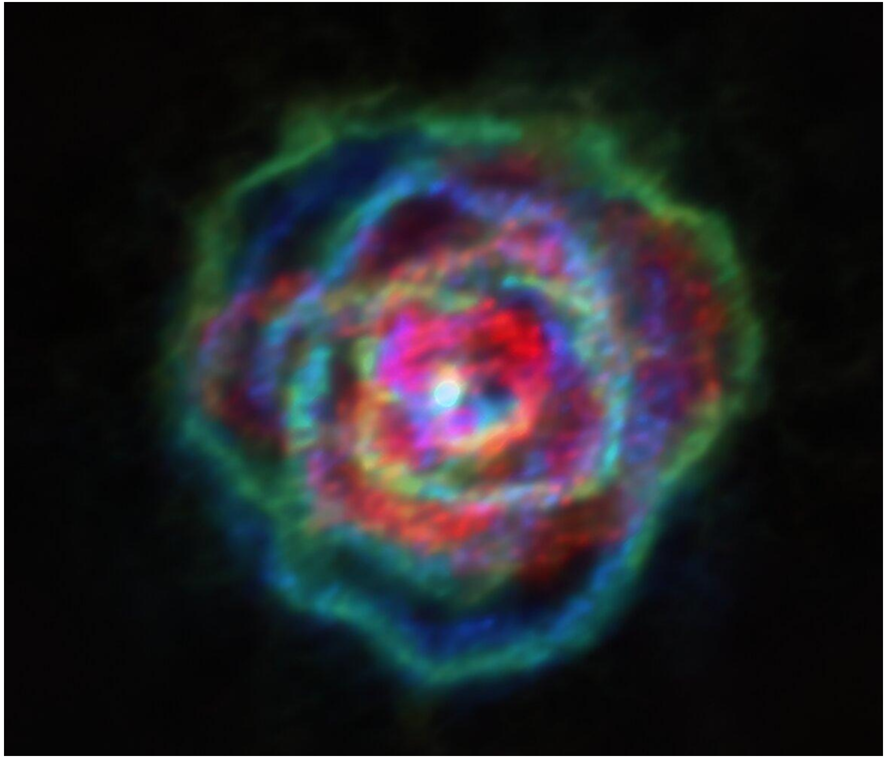
High-resolution observations revealed **complex morphologies**



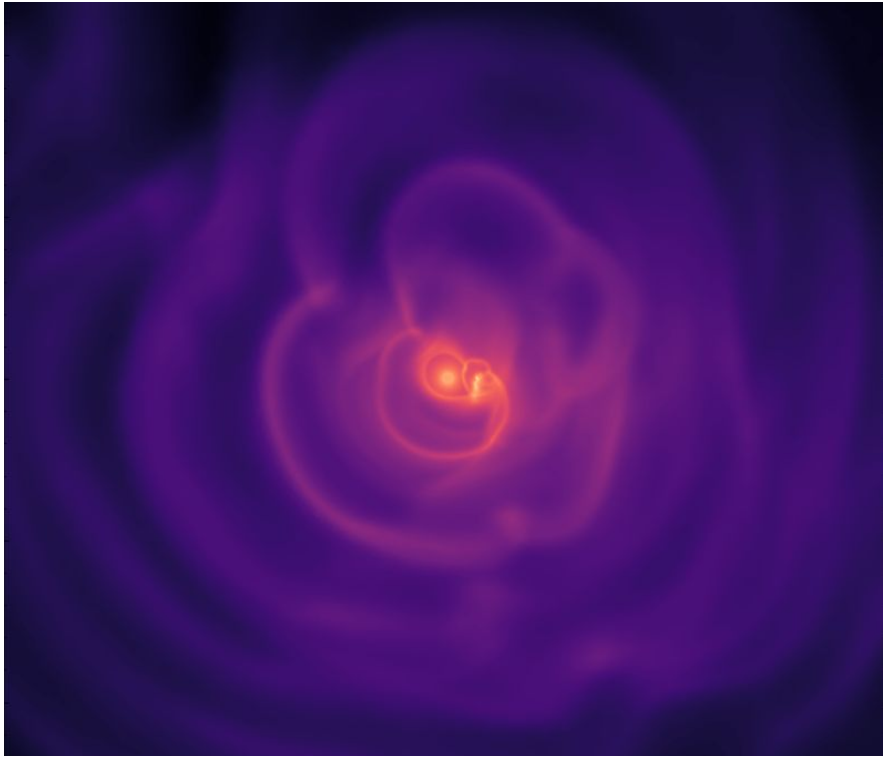


ATOMIUM: ALMA Large Program, Decin et al. (2020)

But, (forward) modelling these observations is **challenging**…



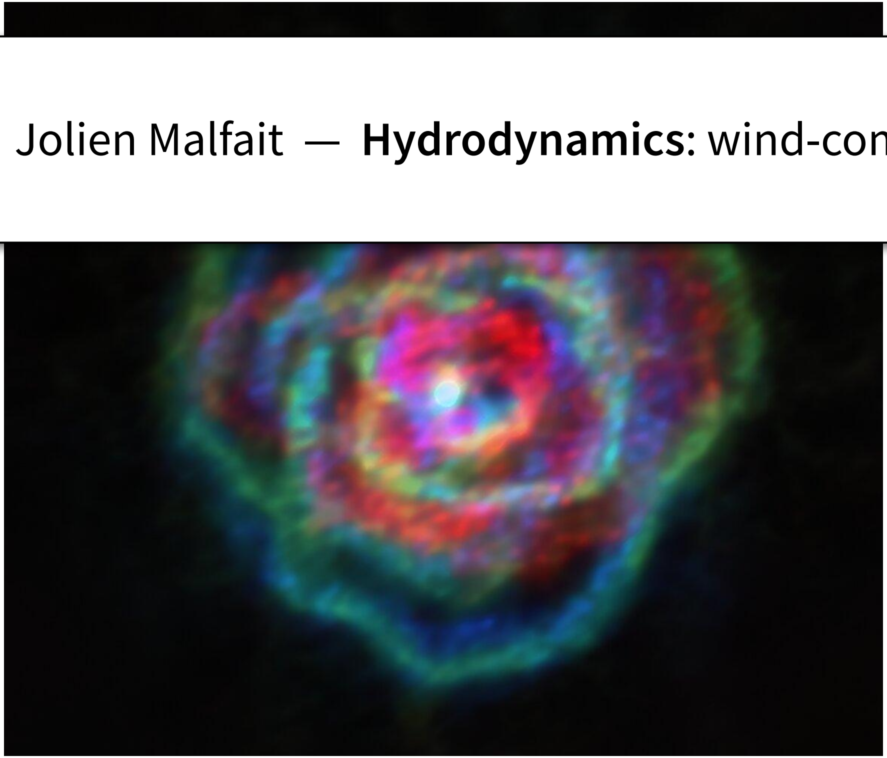
ATOMIUM: ALMA Large Program, Decin et al. (2020)



Malfait et al. (2021), Maes et al. (2021), Siess et al. (2022), Esseldeurs et al. (2023), …

But, (forward) modelling these observations is **challenging**...

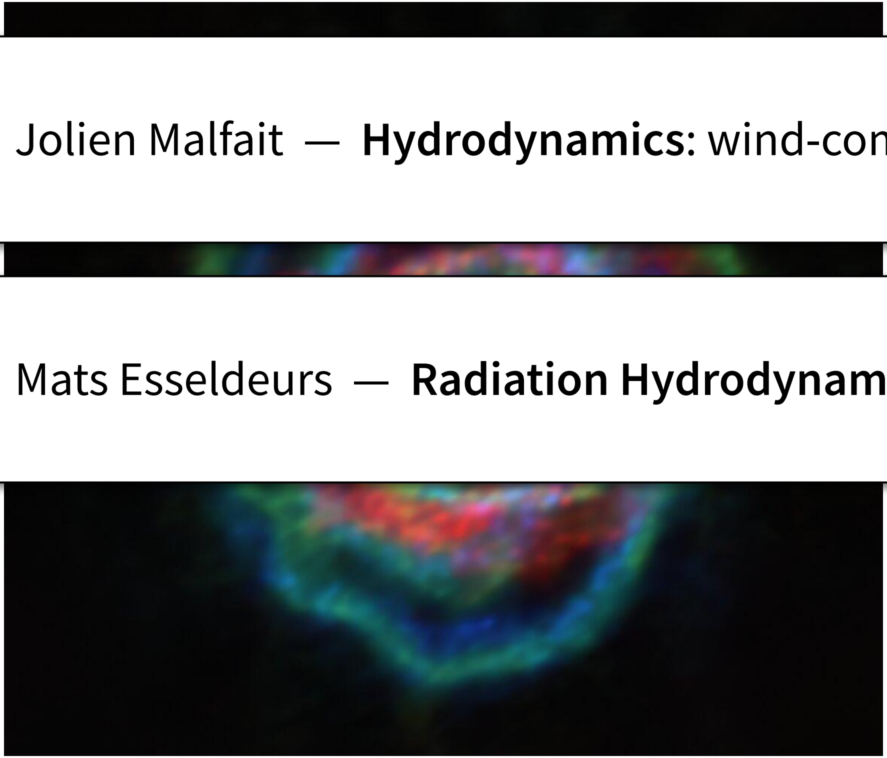
Jolien Malfait — **Hydrodynamics**: wind-companion interactions

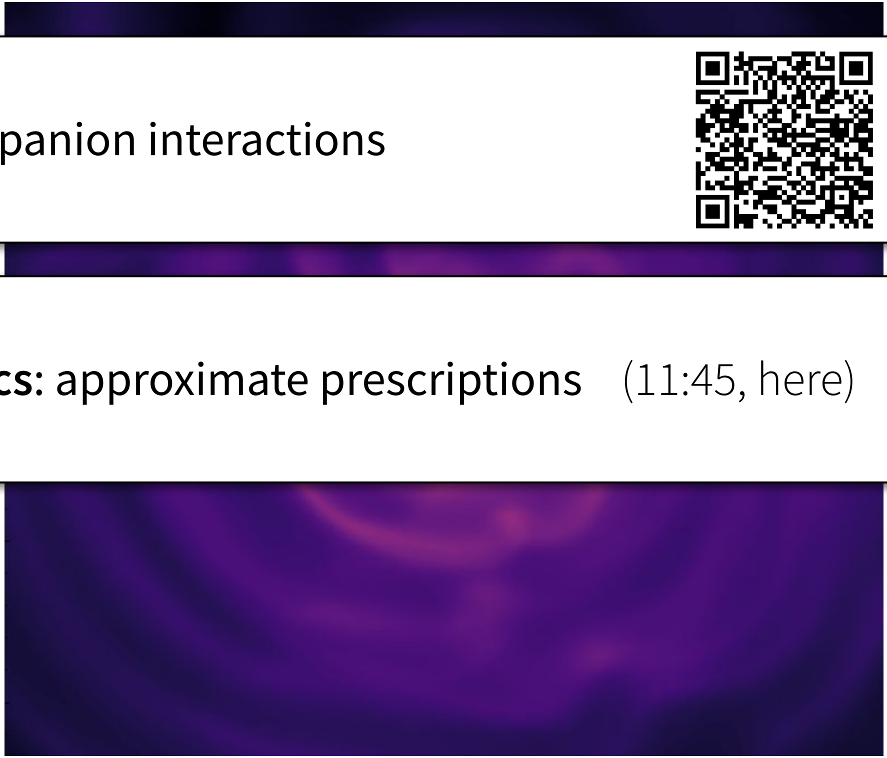


ATOMIUM: ALMA Large Program, Decin et al. (2020)

Malfait et al. (2021), Maes et al. (2021),
Siess et al. (2022), Esseldeurs et al. (2023), ...

But, (forward) modelling these observations is **challenging**...





Jolien Malfait — **Hydrodynamics**: wind-companion interactions

Mats Esseldeurs — **Radiation Hydrodynamics**: approximate prescriptions (11:45, here)

ATOMIUM: ALMA Large Program, Decin et al. (2020)

Malfait et al. (2021), Maes et al. (2021), Siess et al. (2022), Esseldeurs et al. (2023), ...

But, (forward) modelling these observations is **challenging**…

Jolien Malfait — **Hydrodynamics:** wind-companion interactions

Mats Esseldeurs — **Radiation Hydrodynamics:** approximate prescriptions (11:45, here)

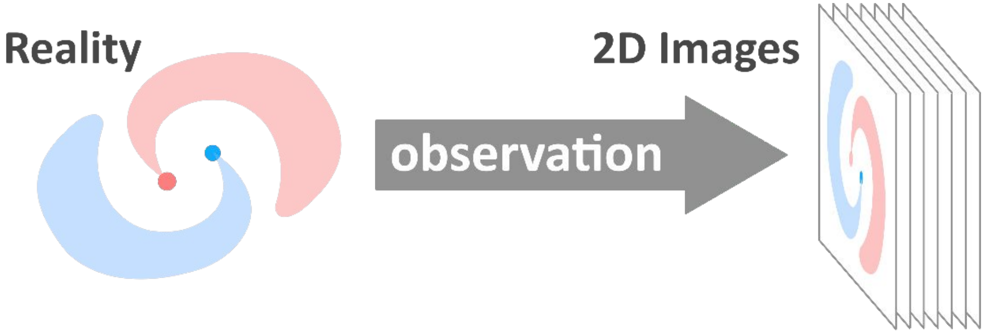
Thomas Ceulemans — **Radiative Transfer:** Magritte

ATOMIUM: ALMA Large Program, Decin et al. (2020)

Malfait et al. (2021), Maes et al. (2021), Siess et al. (2022), Esseldeurs et al. (2023), …

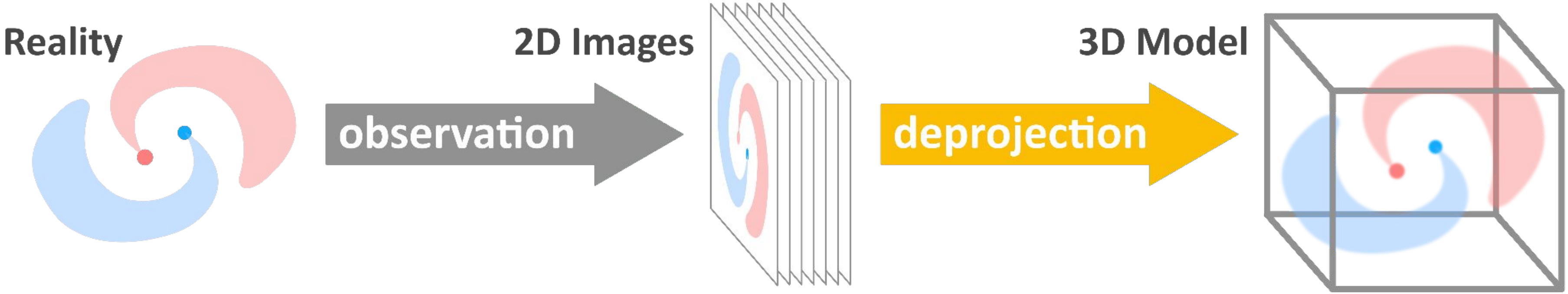
A promising approach: start from the observations, i.e.

inverse modelling / 3D reconstruction / deprojection



A promising approach: start from the observations, i.e.

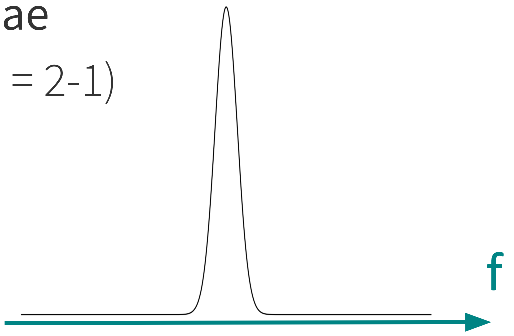
inverse modelling / 3D reconstruction / deprojection

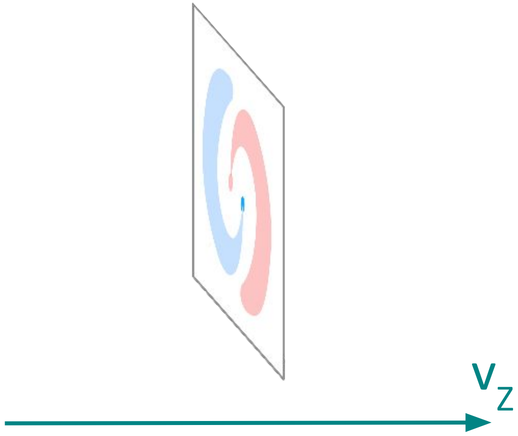


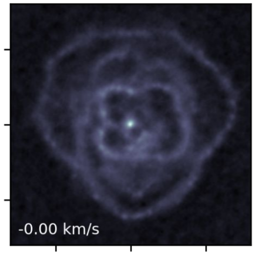
Spectral line **observations**

R Aquilae

CO (J = 2-1)



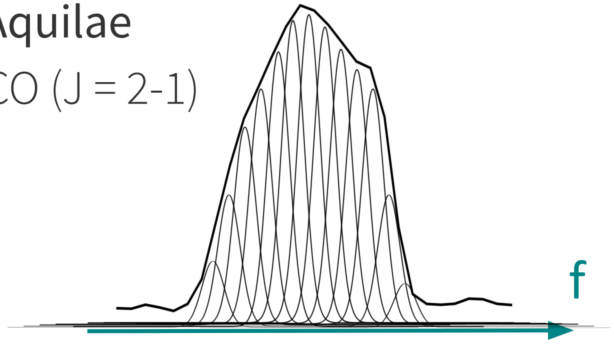


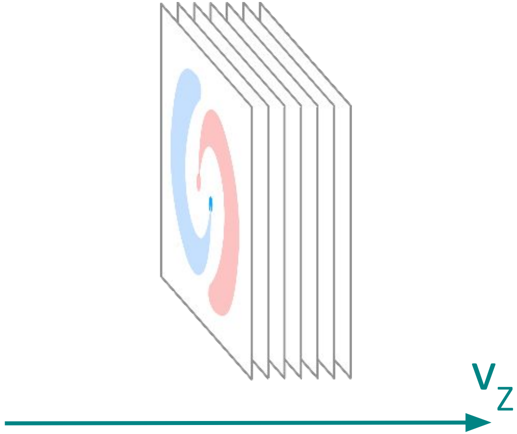


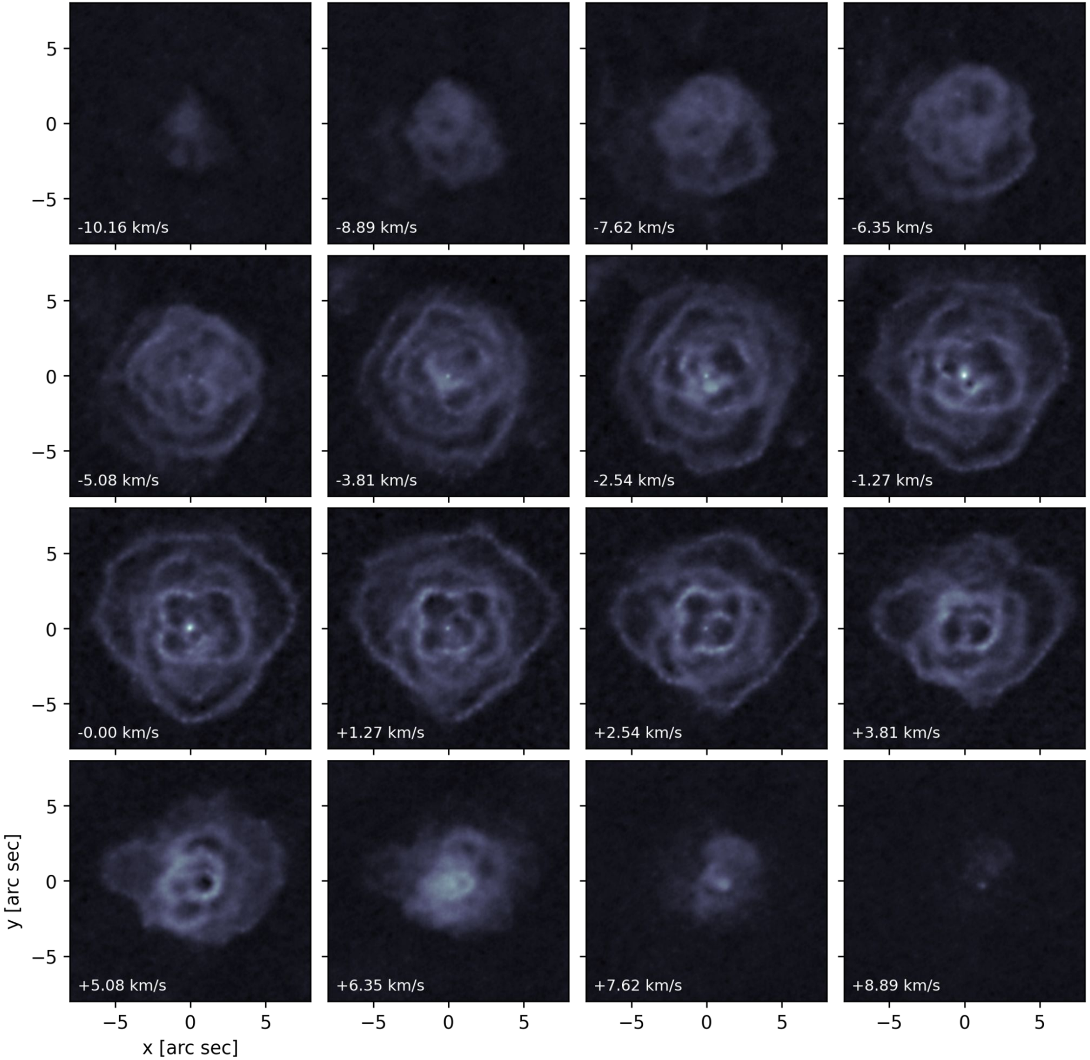
Spectral line **observations**

R Aquilae

CO (J = 2-1)





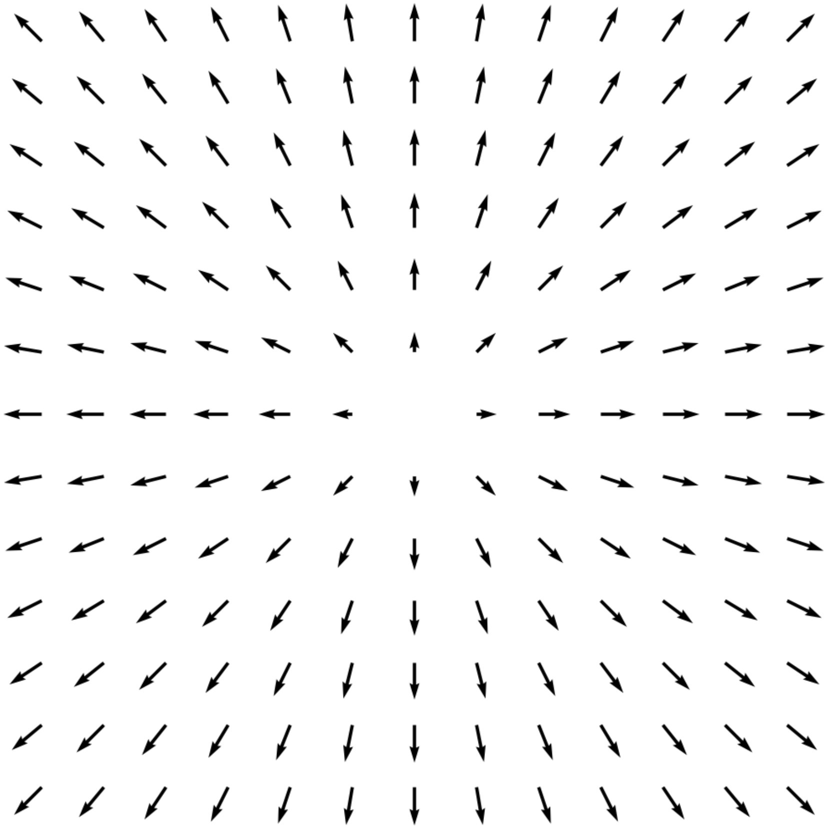


Deprojection as **we** know it

Guélin et al. (2018)
Montargès et al. (2019)
Coenegrachts et al. (2023)

Deprojection as **we** know it

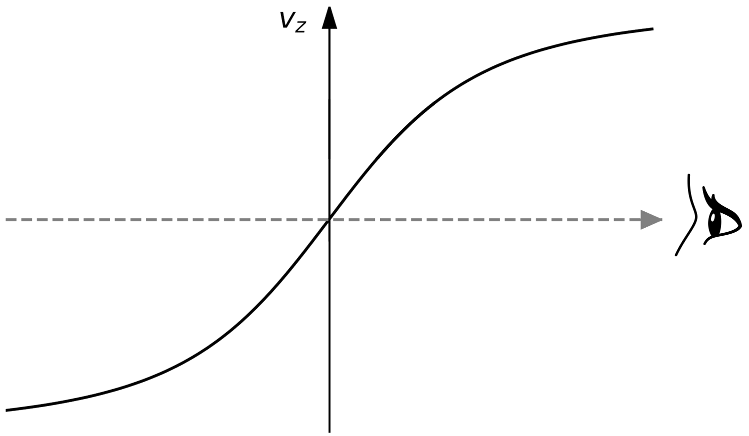
Assume a **velocity** field



Guélin et al. (2018)
Montargès et al. (2019)
Coenegrachts et al. (2023)

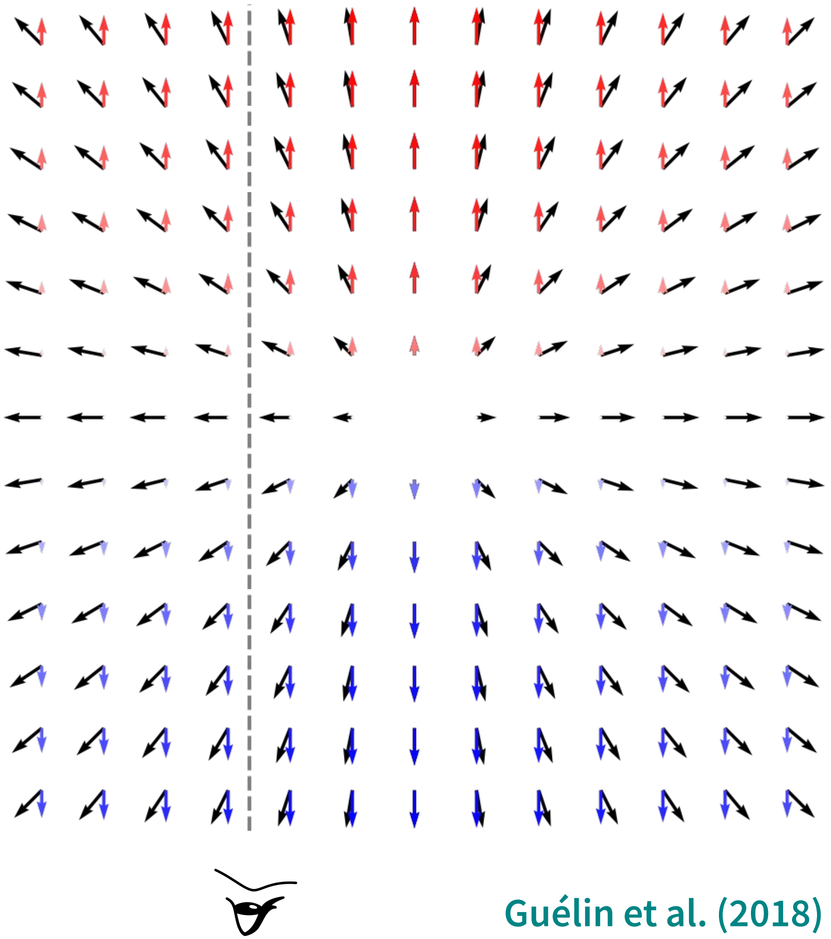
Deprojection as **we** know it

Assume a **velocity** field



➔ **Monotonic** projection along the line-of-sight

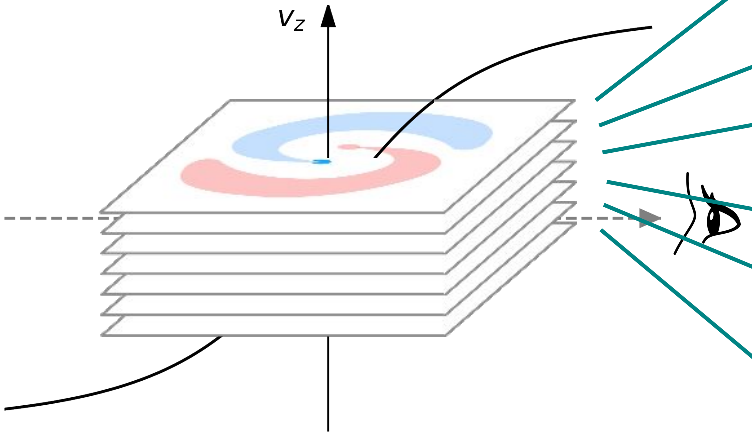
➔ Each velocity (frequency) corresponds to a **unique** position

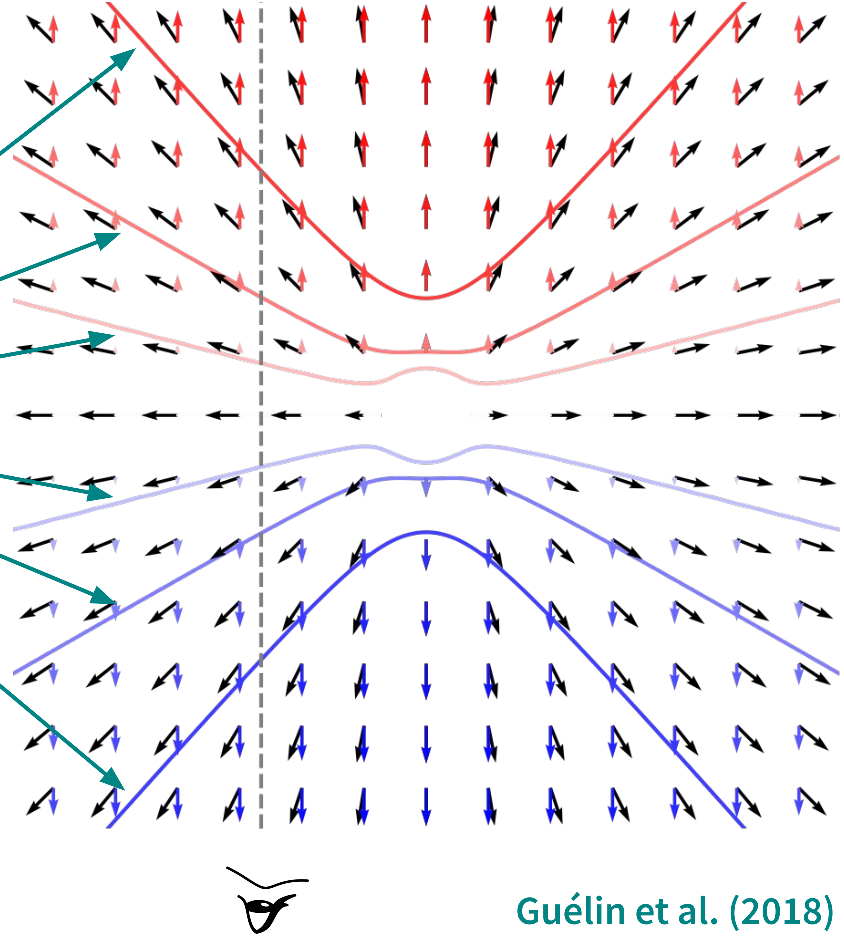


Guélin et al. (2018)
Montargès et al. (2019)
Coenegrachts et al. (2023)

Deprojection as **we** know it

Assume a **velocity** field





➔ **Monotonic** projection along the line-of-sight

➔ Each velocity (frequency) corresponds to a **unique** position

➔ Each channel map can be associated with a **unique** contour of constant velocity

Guélin et al. (2018)
Montargès et al. (2019)
Coenegrachts et al. (2023)

Deprojection as **we know it**

NaCl around **IK Tauri**

Coenegrachts et al. (2023)
arXiv: 2302.06221

Deprojection as **we** know it

Issues:

Deprojection as **we** know it

Issues:

- Strong (probably false) **assumption on the velocity structure**

Deprojection as **we** know it

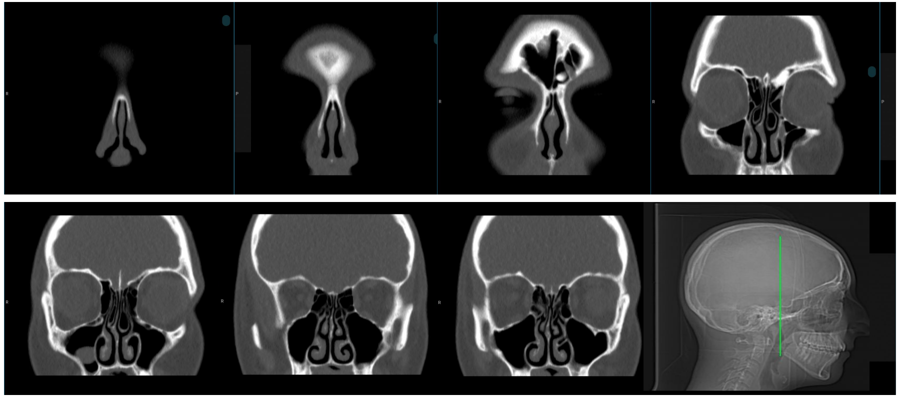
Issues:

- Strong (probably false) **assumption on the velocity structure**
- Difficult to **incorporate more physics** or **chemistry**
- Difficult to **combine** different observations
- Difficult to deal with **uncertainties**

Deprojection as **others** know it

Deprojection as **others** know it

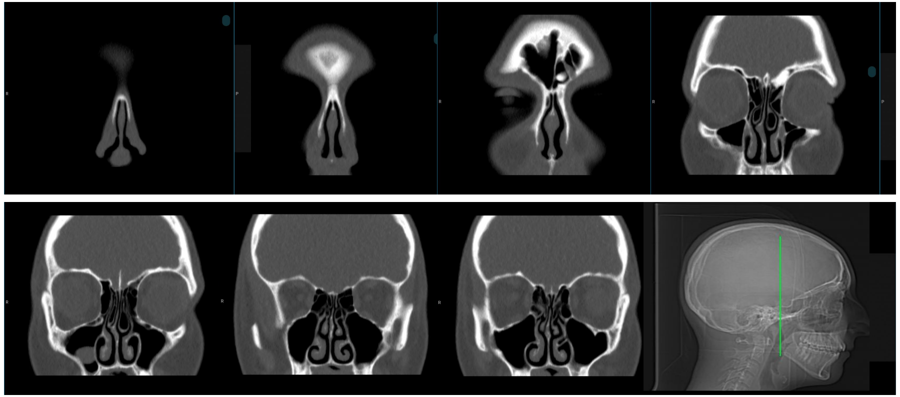
Inspiration from medical imaging



(see e.g. Herman 2009)

Deprojection as **others** know it

Inspiration from medical imaging, machine learning

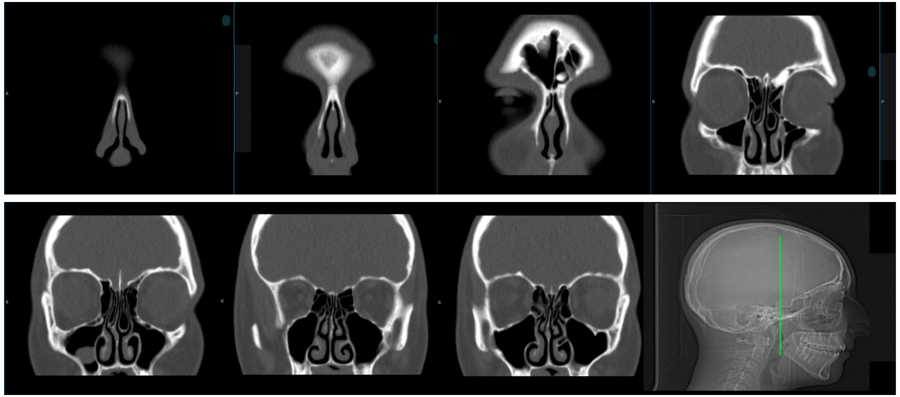


(see e.g. Herman 2009)

Visual deprojection — Balakrishnan et al. (2019)

Deprojection as **others** know it

Inspiration from medical imaging, machine learning, and solar/plasma physics



(see e.g. Herman 2009)

Visual deprojection — Balakrishnan et al. (2019)

Bayesian inversion, compressed sensing, …

Asensio Ramos et al. (2007)

Asensio Ramos & de la Cruz Rodríguez (2015)

…

Reviews

del Toro Iniesta & Ruiz Cobo (2016)

de la Cruz Rodríguez & van Noort (2017)

Recent developments

Asensio Ramos et al. (2022)

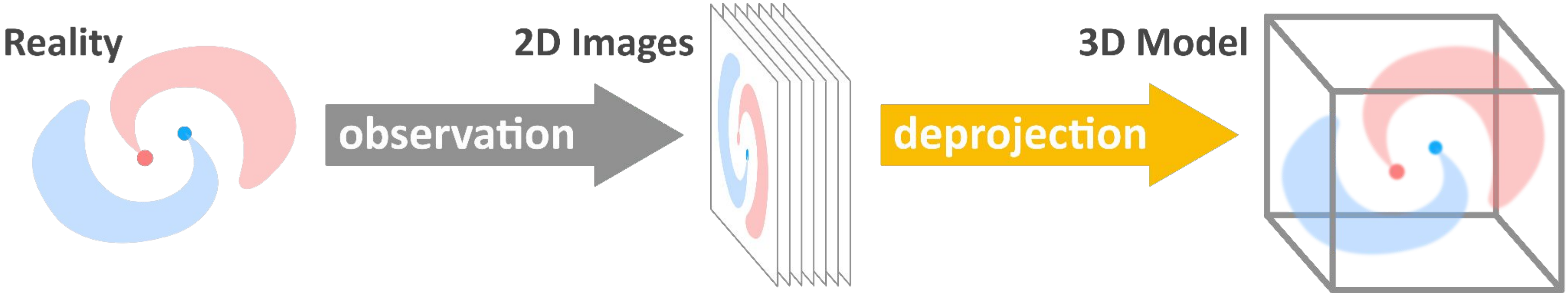
Díaz Baso et al. (2022)

Štepán et al. (2022)

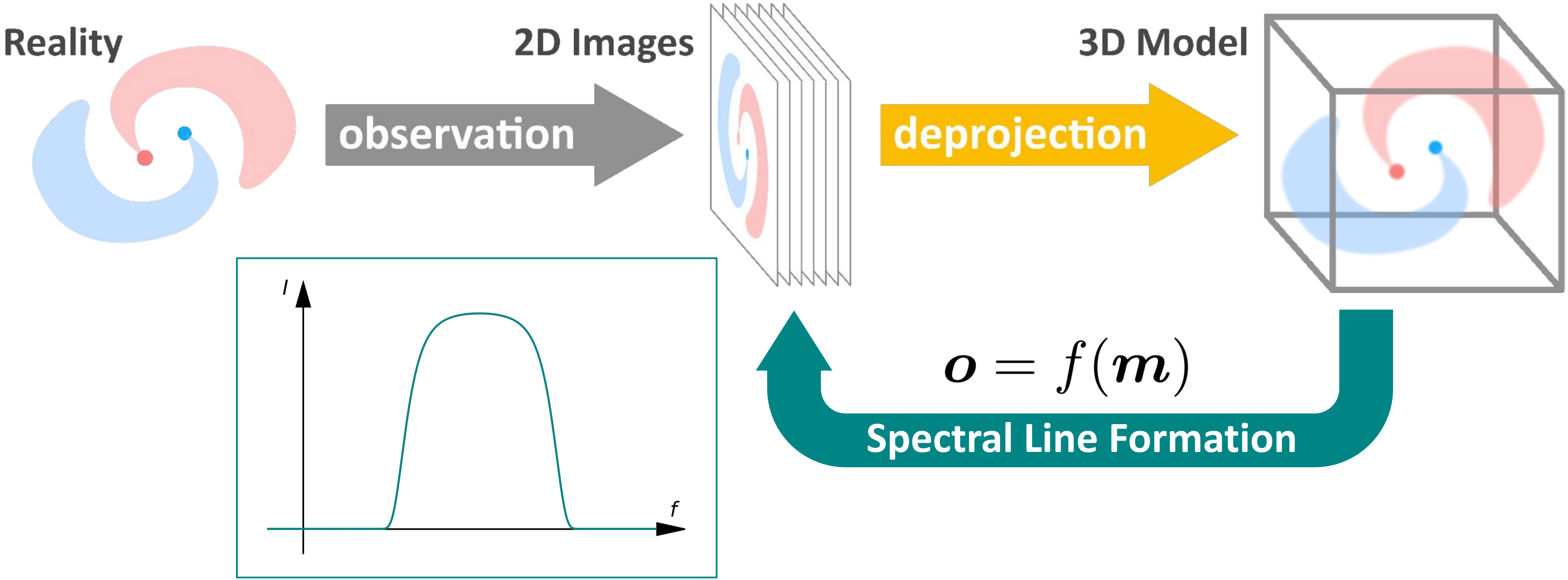
Vicente Arévalo et al. (2022)

Probabilistic 3D reconstruction

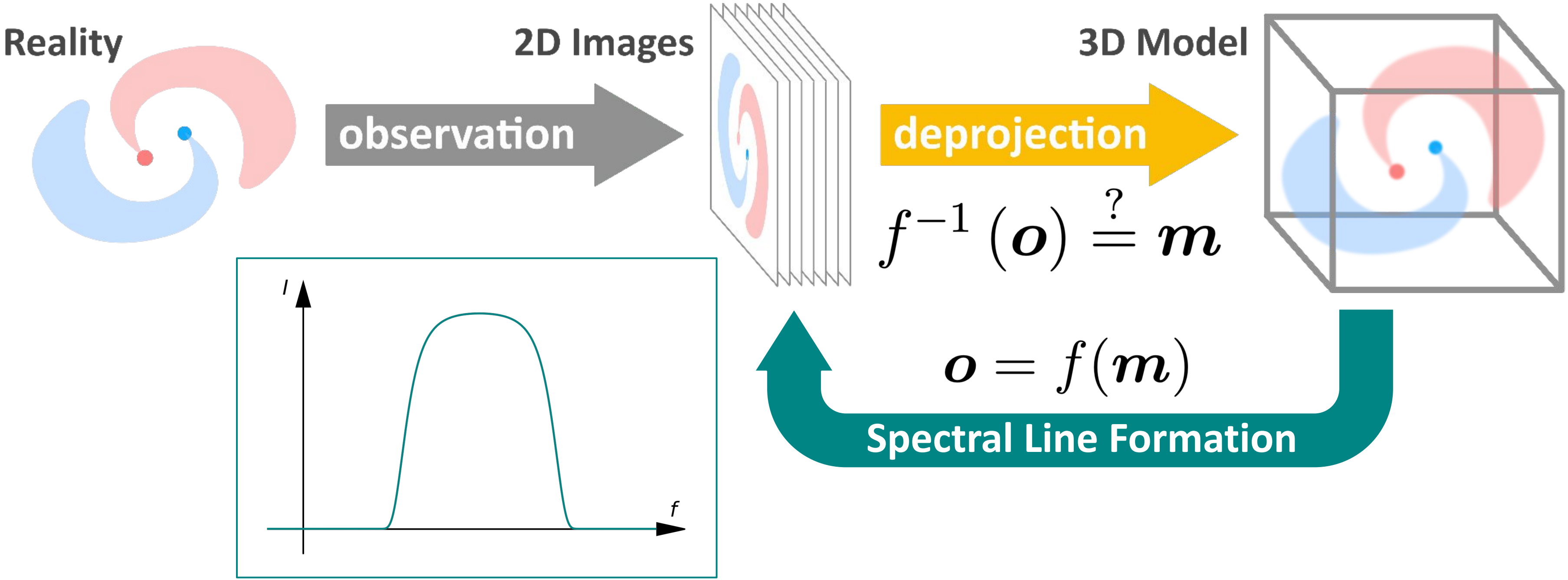
Probabilistic 3D reconstruction



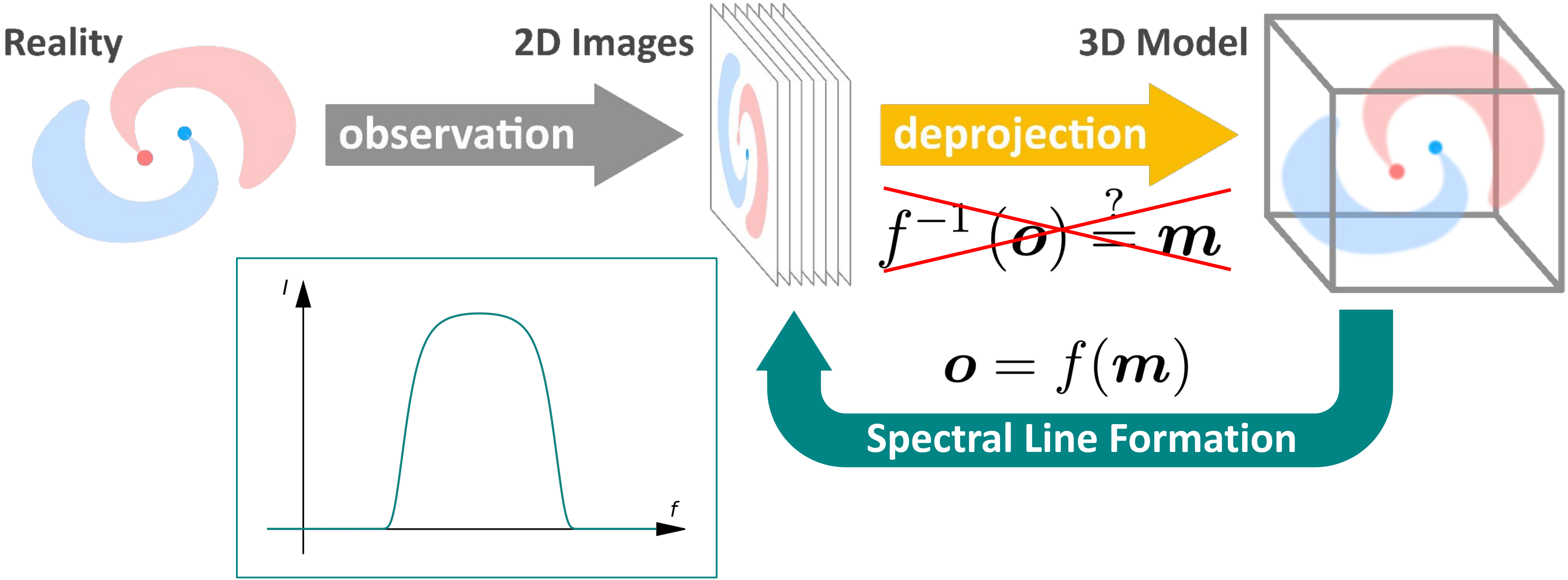
Probabilistic 3D reconstruction



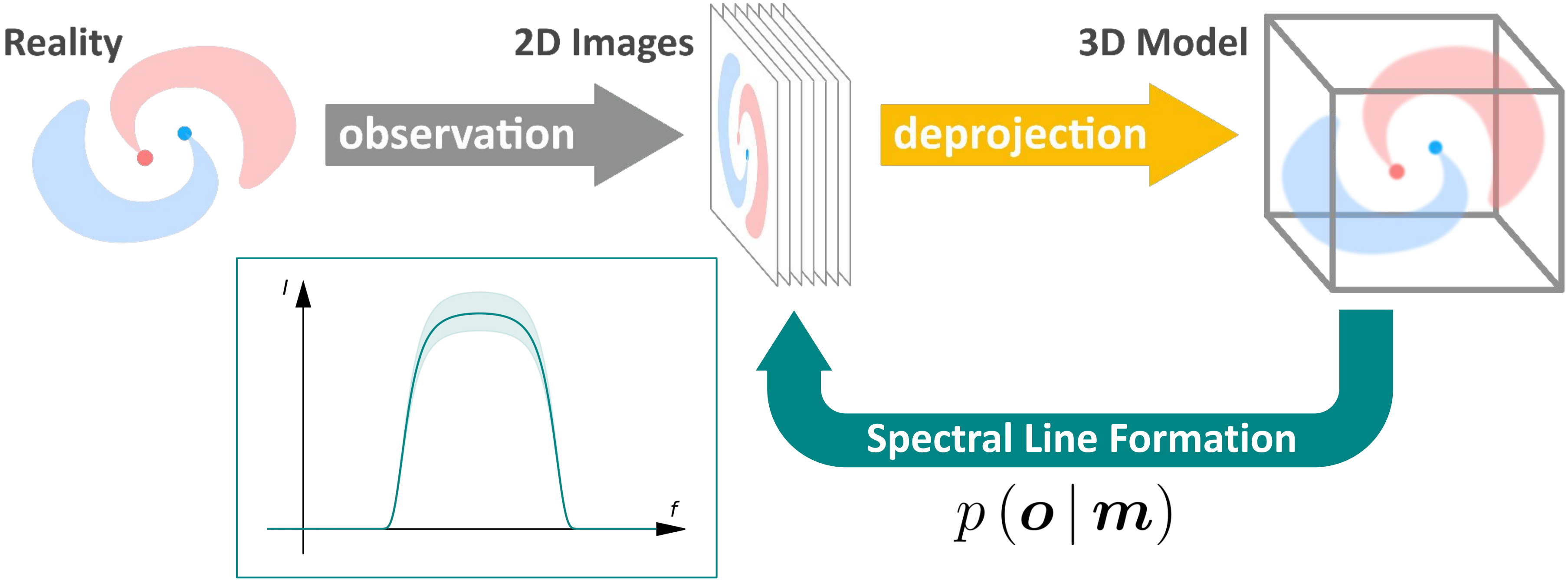
Probabilistic 3D reconstruction



Probabilistic 3D reconstruction

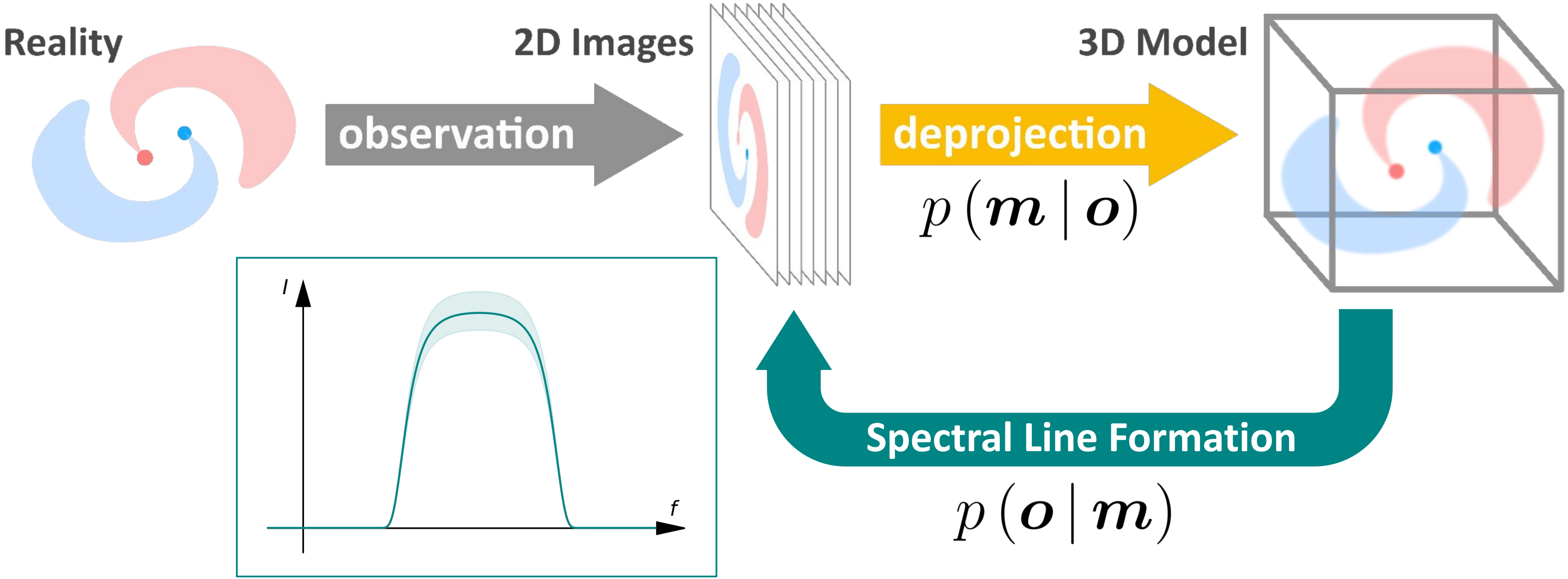


Probabilistic 3D reconstruction



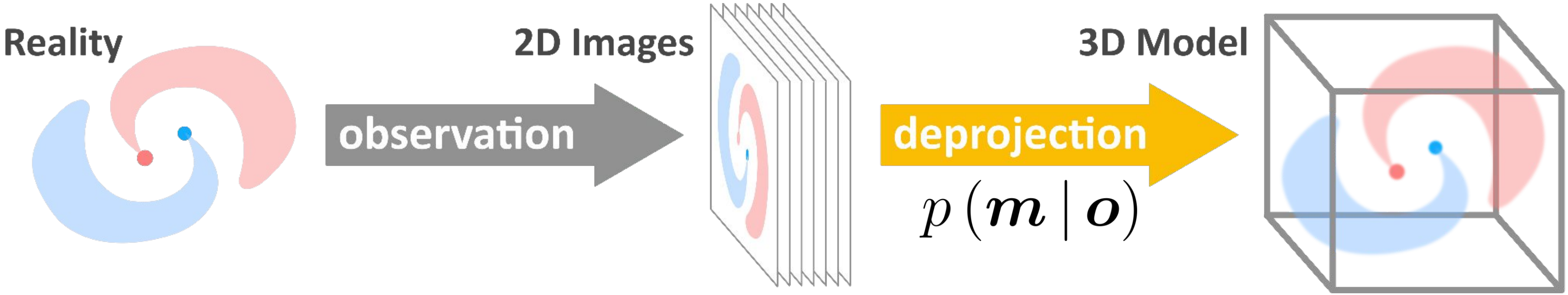
FDC, T. Ceulemans, J. Cockayne, L. Decin, and J. Yates (2023)

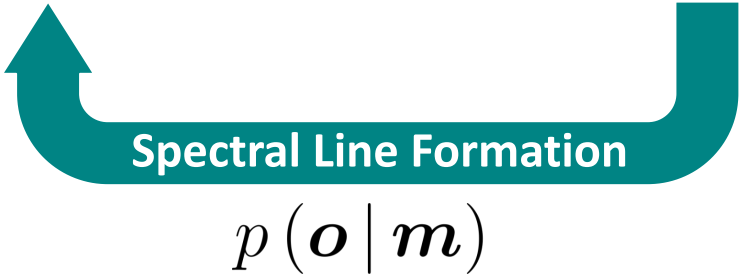
Probabilistic 3D reconstruction



FDC, T. Ceulemans, J. Cockayne, L. Decin, and J. Yates (2023)

Probabilistic 3D reconstruction





Bayes' rule

$$p\left(\boldsymbol{m} \mid \boldsymbol{o}\right) = \frac{p\left(\boldsymbol{o} \mid \boldsymbol{m}\right) p\left(\boldsymbol{m}\right)}{p\left(\boldsymbol{o}\right)}$$

Lucy (1974); Asensio Ramos et al. (2007); Stuart (2010)

Probabilistic 3D reconstruction

Bayes' rule

$$p\left(\boldsymbol{m} \,|\, \boldsymbol{o}\right) = \frac{p\left(\boldsymbol{o} \,|\, \boldsymbol{m}\right) p\left(\boldsymbol{m}\right)}{p\left(\boldsymbol{o}\right)}$$

Probabilistic 3D reconstruction

Bayes' rule

$$p\left(\boldsymbol{m}\,|\,\boldsymbol{o}\right) = \frac{p\left(\boldsymbol{o}\,|\,\boldsymbol{m}\right)p\left(\boldsymbol{m}\right)}{p\left(\boldsymbol{o}\right)}$$

Reconstruct $\boldsymbol{m}$ by maximising the posterior

$$\boldsymbol{m} = \left\{\rho(\boldsymbol{x}),\ \boldsymbol{v}(\boldsymbol{x}),\ T(\boldsymbol{x})\right\}$$

Probabilistic 3D reconstruction

Bayes' rule

$$p\left(\boldsymbol{m} \mid \boldsymbol{o}\right) = \frac{p\left(\boldsymbol{o} \mid \boldsymbol{m}\right) p\left(\boldsymbol{m}\right)}{p\left(\boldsymbol{o}\right)}$$

Reconstruct $\boldsymbol{m}$ by maximising the posterior, or, equivalently, by minimising the negative log posterior

$$-\log p\left(\boldsymbol{m} \mid \boldsymbol{o}\right) \;=\; -\log p\left(\boldsymbol{o} \mid \boldsymbol{m}\right) \;-\; \log p\left(\boldsymbol{m}\right)$$

Probabilistic 3D reconstruction

Bayes' rule

$$p(\boldsymbol{m} \mid \boldsymbol{o}) = \frac{p(\boldsymbol{o} \mid \boldsymbol{m})\, p(\boldsymbol{m})}{p(\boldsymbol{o})}$$

Reconstruct $\boldsymbol{m}$ by maximising the posterior, or, equivalently, by minimising the negative log posterior, or loss functions

$$-\log p(\boldsymbol{m} \mid \boldsymbol{o}) = -\log p(\boldsymbol{o} \mid \boldsymbol{m}) - \log p(\boldsymbol{m})$$

$$\downarrow \qquad\qquad\qquad \downarrow \qquad\qquad\qquad \downarrow$$

$$\mathcal{L}_{\text{tot}}(\boldsymbol{m}, \boldsymbol{o}) = \mathcal{L}_{\text{rep}}(f(\boldsymbol{m}), \boldsymbol{o}) + \mathcal{L}_{\text{reg}}(\boldsymbol{m})$$

Probabilistic 3D reconstruction

Bayes' rule

$$p(\boldsymbol{m} \mid \boldsymbol{o}) = \frac{p(\boldsymbol{o} \mid \boldsymbol{m})\, p(\boldsymbol{m})}{p(\boldsymbol{o})}$$

Reconstruct $\boldsymbol{m}$ by maximising the posterior, or, equivalently, by minimising the negative log posterior, or loss functions

$$\begin{array}{ccccc} -\log p(\boldsymbol{m} \mid \boldsymbol{o}) & = & -\log p(\boldsymbol{o} \mid \boldsymbol{m}) & - & \log p(\boldsymbol{m}) \\ \downarrow & & \downarrow & & \downarrow \\ \mathcal{L}_{\text{tot}}(\boldsymbol{m}, \boldsymbol{o}) & = & \mathcal{L}_{\text{rep}}(f(\boldsymbol{m}), \boldsymbol{o}) & + & \mathcal{L}_{\text{reg}}(\boldsymbol{m}) \end{array}$$

Mean square **reproduction loss** implies a Gaussian **likelihood**

$$\mathcal{L}_{\text{rep}}(f(\boldsymbol{m}), \boldsymbol{o}) = \|f(\boldsymbol{m}) - \boldsymbol{o}\|^2 \implies p(\boldsymbol{o} \mid \boldsymbol{m}) = \mathcal{N}(\mathbf{o}, \boldsymbol{\Sigma})$$

Probabilistic 3D reconstruction

Bayes' rule

$$p(\boldsymbol{m}\,|\,\boldsymbol{o}) = \frac{p(\boldsymbol{o}\,|\,\boldsymbol{m})\,p(\boldsymbol{m})}{p(\boldsymbol{o})}$$

Reconstruct $\boldsymbol{m}$ by maximising the posterior, or, equivalently, by minimising the negative log posterior, or loss functions

$$-\log p(\boldsymbol{m}\,|\,\boldsymbol{o}) = -\log p(\boldsymbol{o}\,|\,\boldsymbol{m}) - \log p(\boldsymbol{m})$$

$$\downarrow \qquad\qquad \downarrow \qquad\qquad \downarrow$$

$$\mathcal{L}_{\mathrm{tot}}(\boldsymbol{m},\boldsymbol{o}) = \mathcal{L}_{\mathrm{rep}}(f(\boldsymbol{m}),\boldsymbol{o}) + \mathcal{L}_{\mathrm{reg}}(\boldsymbol{m})$$

The **regularisation loss** / **prior** represents our prior assumptions about the model

e.g. **hydrodynamic steady state** $\partial_t\rho = \partial_t\boldsymbol{v} = \partial_t T = 0$

FDC, et al. (*in prep.*)

Summary

Ever more sophisticated radiation/hydro/chemical forward models are **not enough** to interpret our most complex observations…

→ **Probabilistic 3D reconstruction** promises a solution

More info:

freddeceuster.github.io/p3droslo

Get in touch!

frederik.deceuster@kuleuven.be