Appearance Changes in Image Registration

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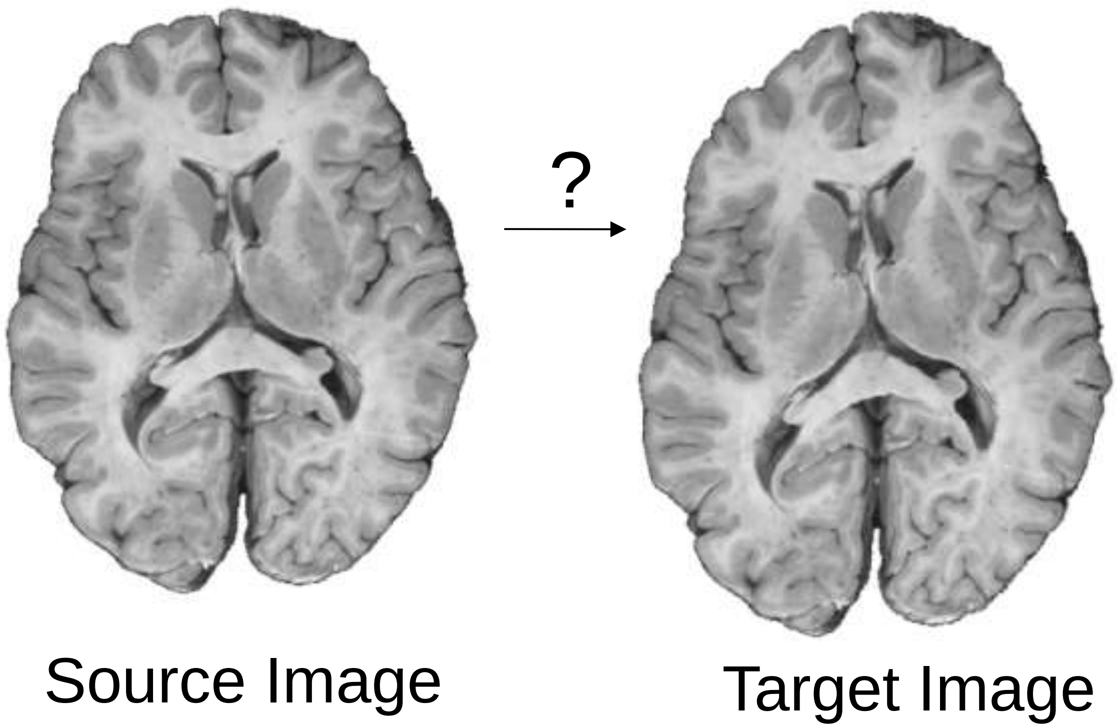
Warning

This talk is about approaches I have personally been involved with. Other people have been working in this area also and I will not do proper justice in terms of referencing.

Image Registration

Goal: Spatial alignment of two images



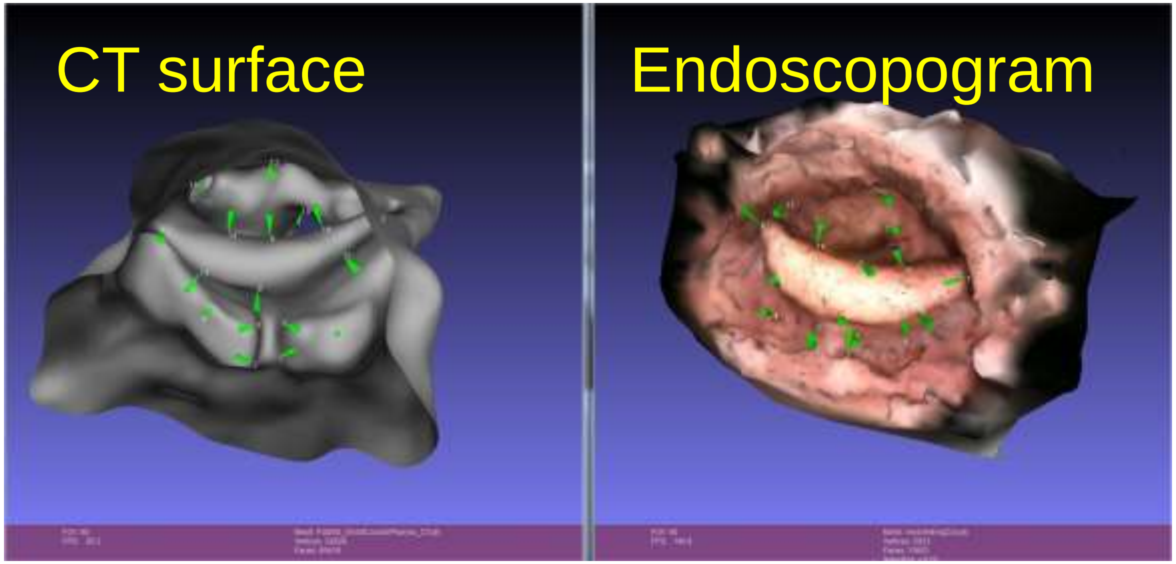
minimize Irregularity of transformation + image mismatch

Sounds simple enough …

The MD's perspective

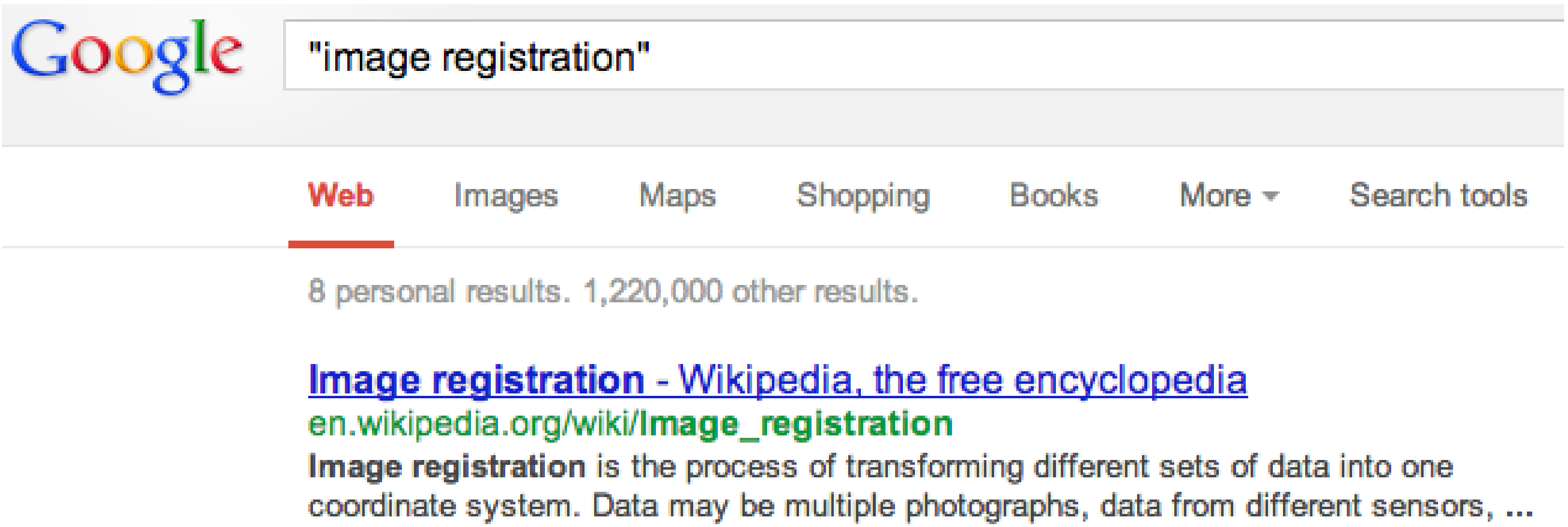
Example Goal: Combine endoscopy and CT images *for improved cancer treatment planning*.

Julian Rosenman, MD



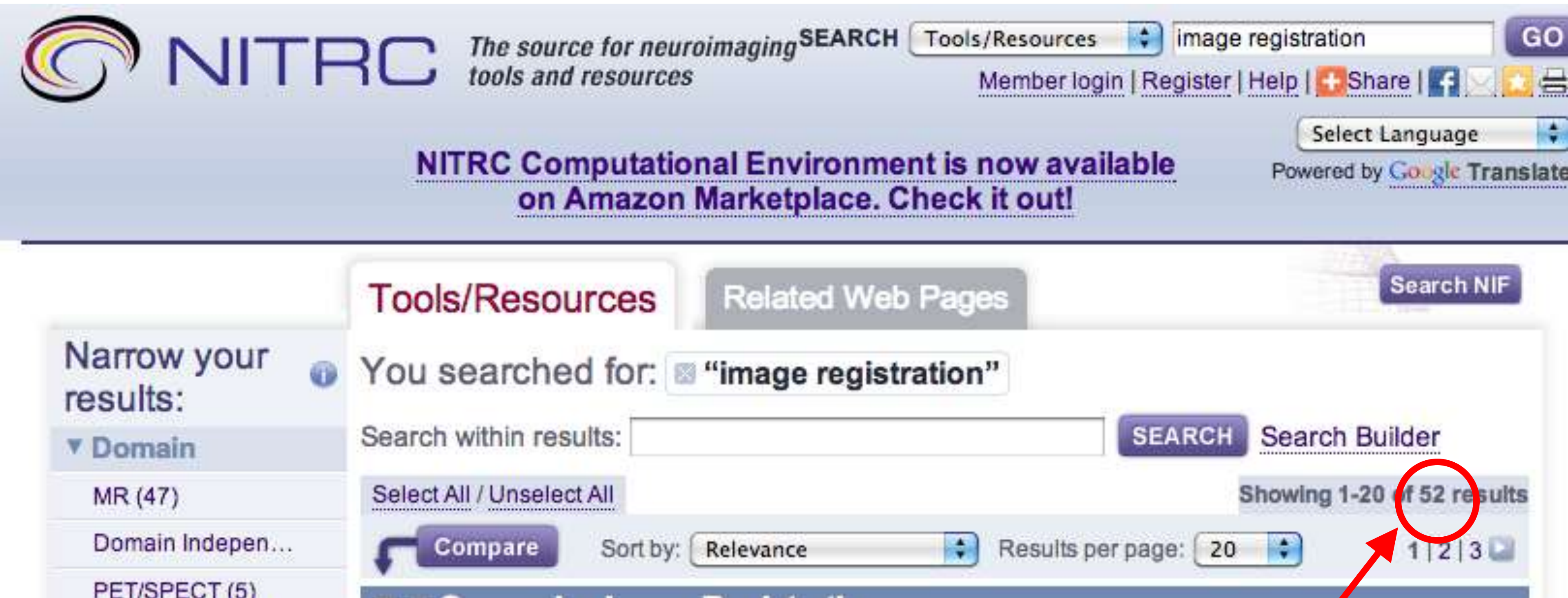
Approach: Registration (=spatial alignment)

The MD's perspective



A millions hits. "This is probably a solved problem."

The MD's perspective

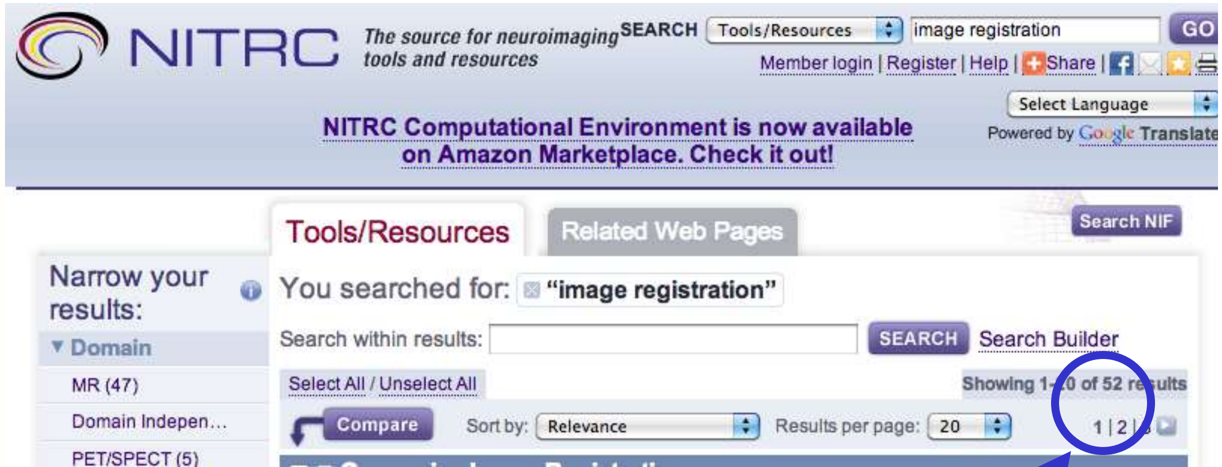


now we are down to 52 results

"Certainly 52 solutions to my problem are enough."

The MD’s perspective

Image: www.shapingyouth.org



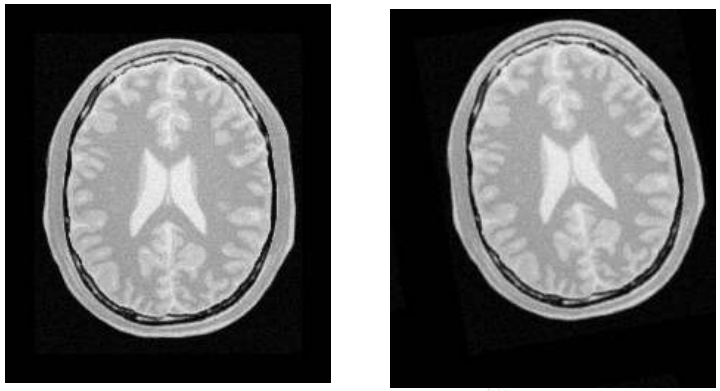
now we are down to 52 results

A closer look reveals:
None of these programs solve this problem.

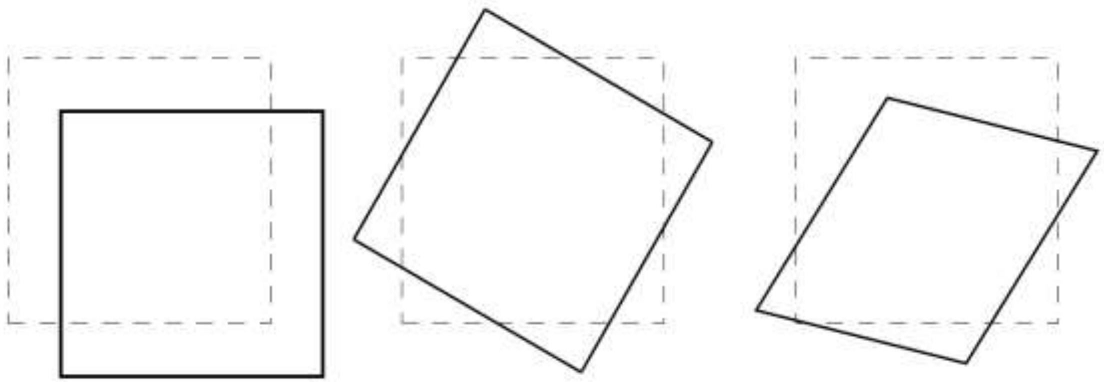
The sad reality: with a bit of hyperbole

Registration works really well when there is not much to register!

Similar images



Simple transforms



Translation
$f : \boldsymbol{x} \mapsto \boldsymbol{x} + \boldsymbol{t}$

Similarity Transform
$f : \boldsymbol{x} \mapsto sR\boldsymbol{x}$

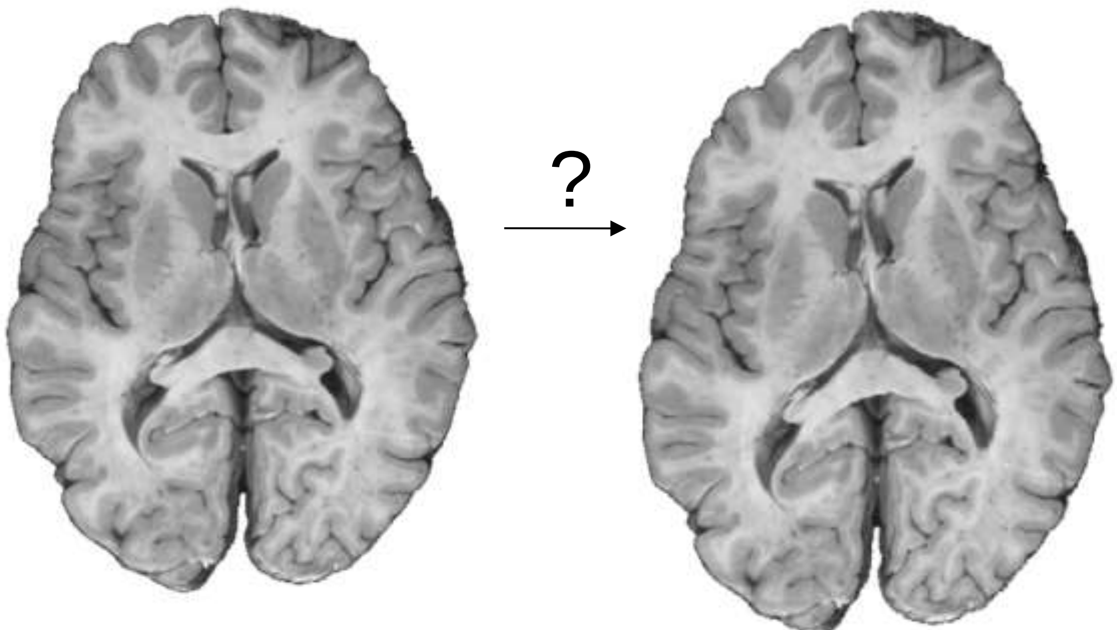
Affine Transform
$f : \boldsymbol{x} \mapsto A\boldsymbol{x} + \boldsymbol{t}$

However, in reality deformations are often more complex.
➔ Need for general deformable registration methods.

Deformable Image Registration

Goal: Spatial alignment of two images (beyond affine)

… for example to capture changes over time as in STIA …



Source Image Target Image

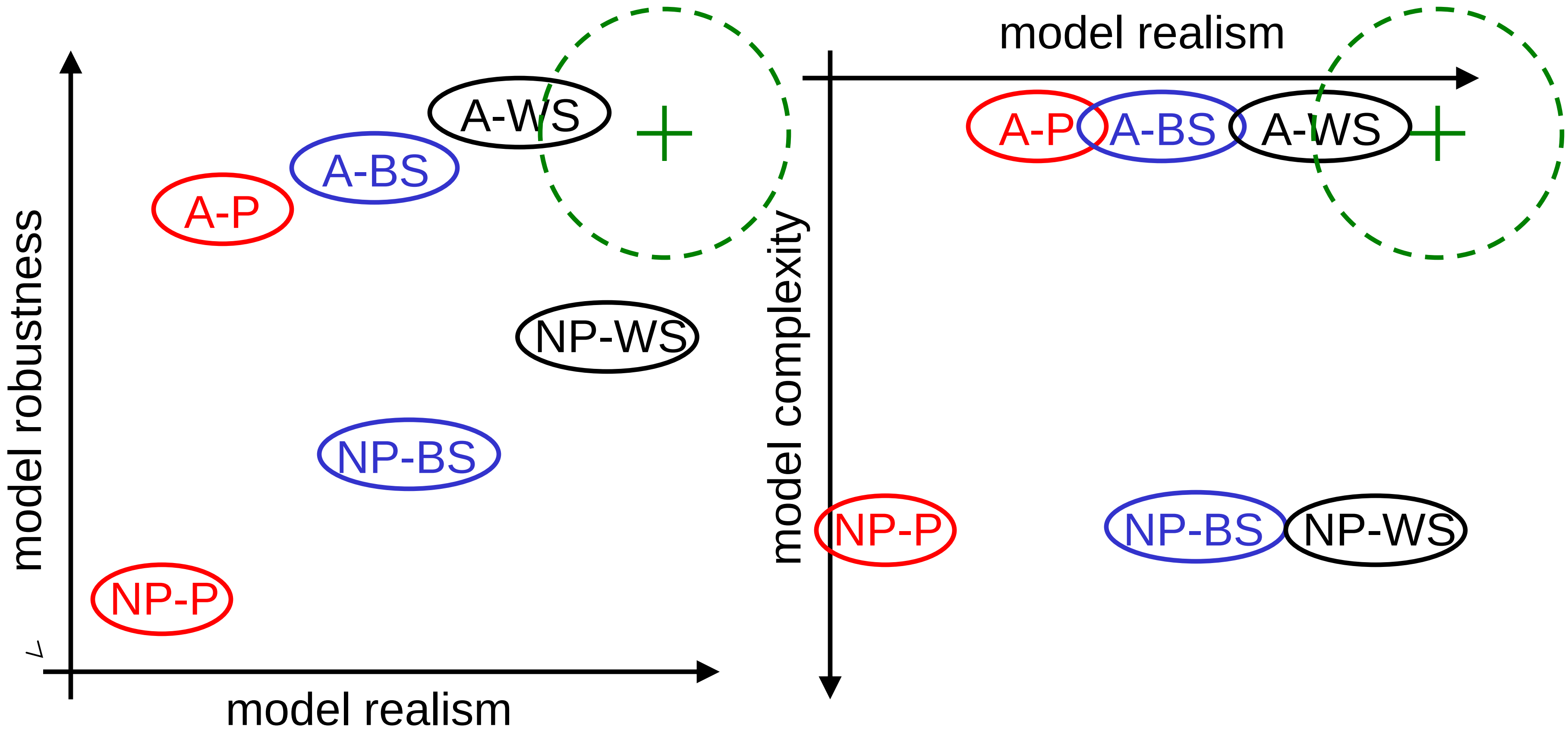
minimize Irregularity of transformation + image mismatch

Why is this hard?

Why is Deformable Image Registration Hard?

A: affine, **NP**: non-parametric (elastic, fluid, …)

Within subject **(WS)**; between subject **(BS)**; with pathology **(P)**



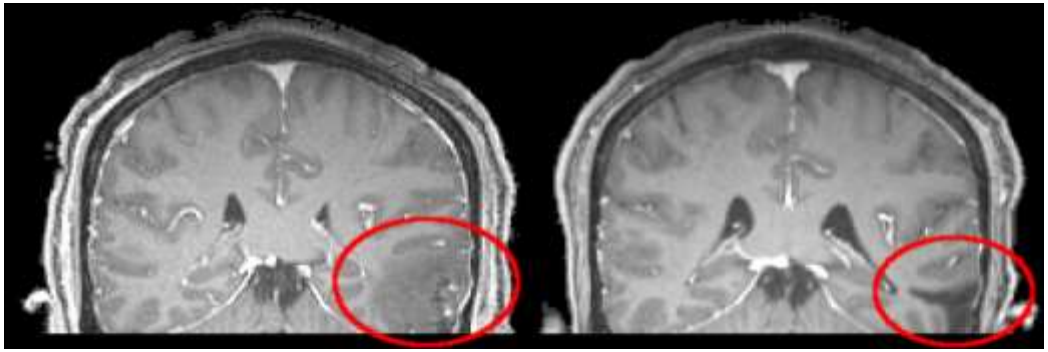
Why is Deformable Image Registration Hard?

Problem 1: Unsuitable deformation models

Does your brain, leg, heart, …
behave like a fluid?

Should it between two subjects?

Problem 2: Unsuitable similarity measures

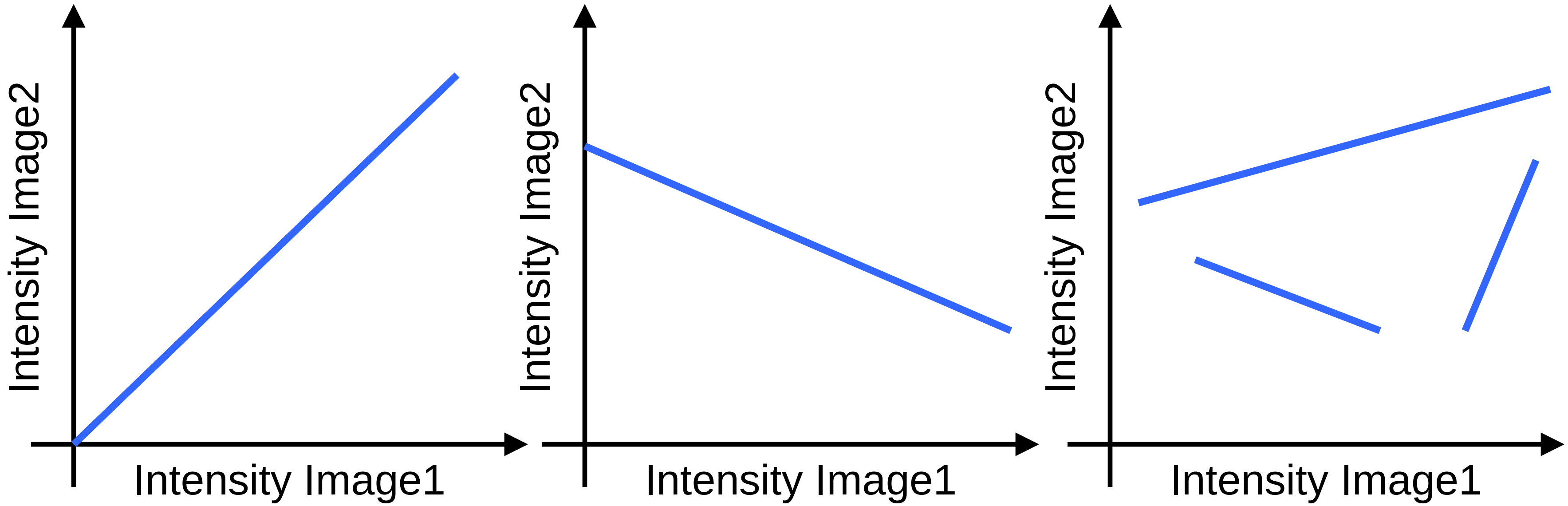


What if images have different appearances?

Problem 3: Unsuitable numerical solutions

Basis of Similarity Measures

What is considered similar?



SSD

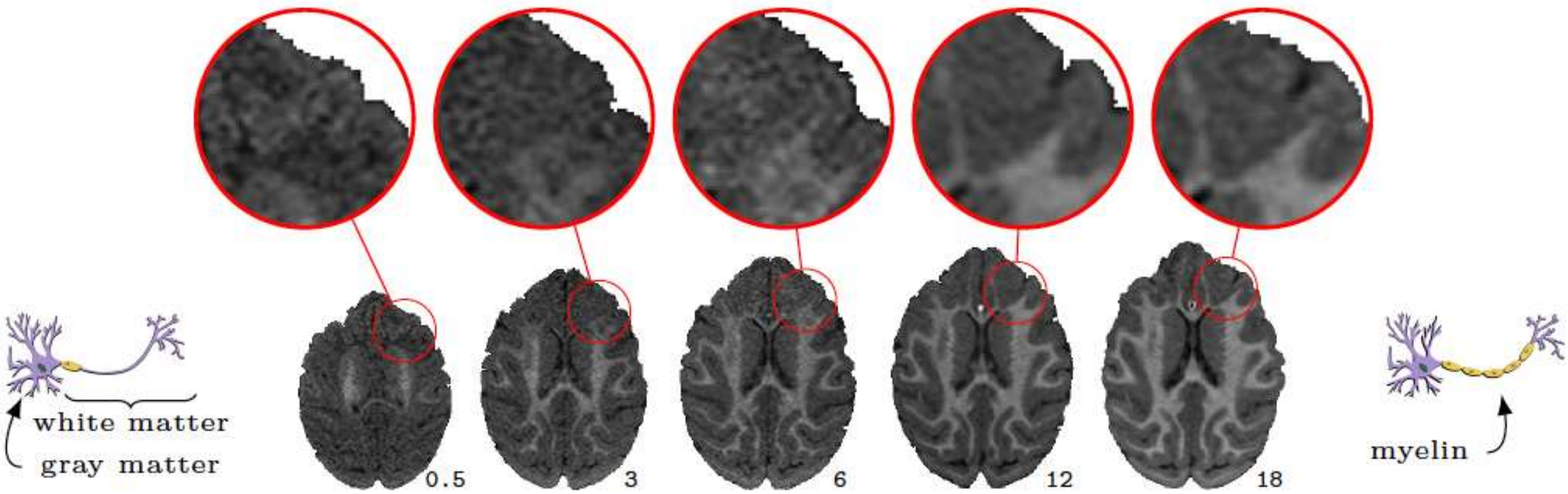
Normalized cross correlation

Mutual Information

But sometimes correspondences are not quite so easy …

Motivating issue 1: Intensity changes over time

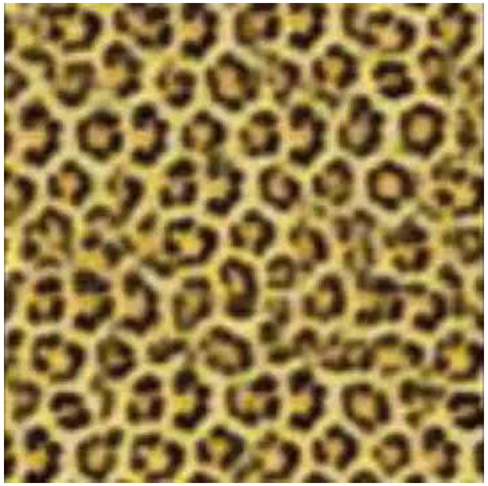
Normal brain development (macaque)

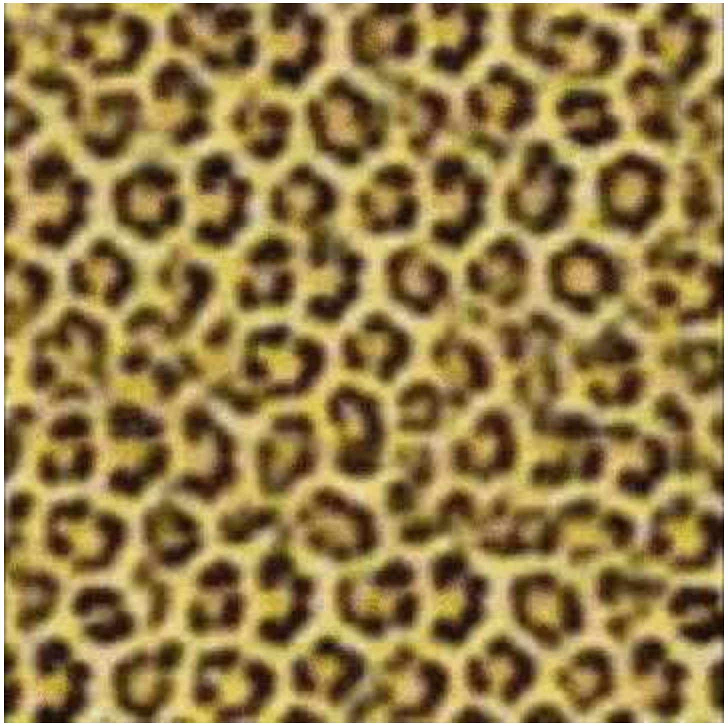


Locally changing image intensities cause problems for image similarity measures (SSD, mutual information, …)

Motivating issue 2: Texture-blending

Texture blending for computer graphics.

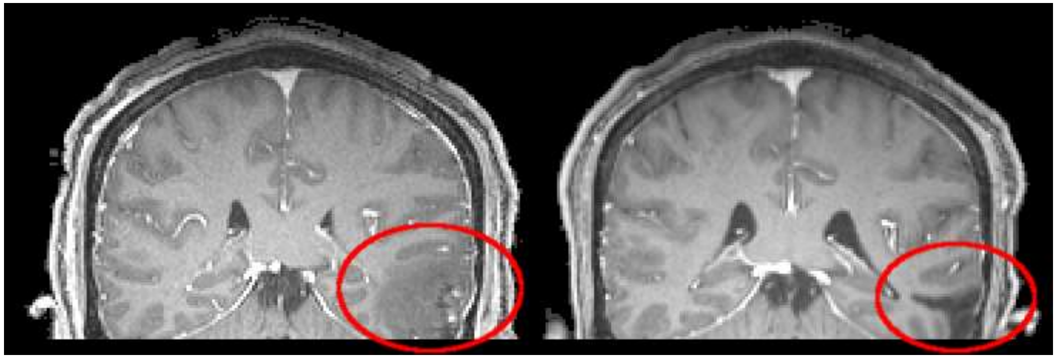




Extreme case: images are vastly different.

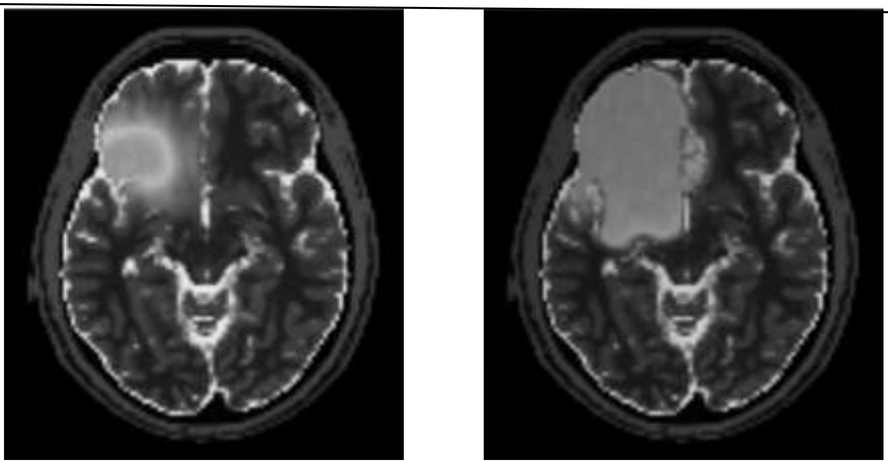
Motivating issue 3: Intensity/Structural changes

Traumatic brain injury
(real data)



Brain tumor

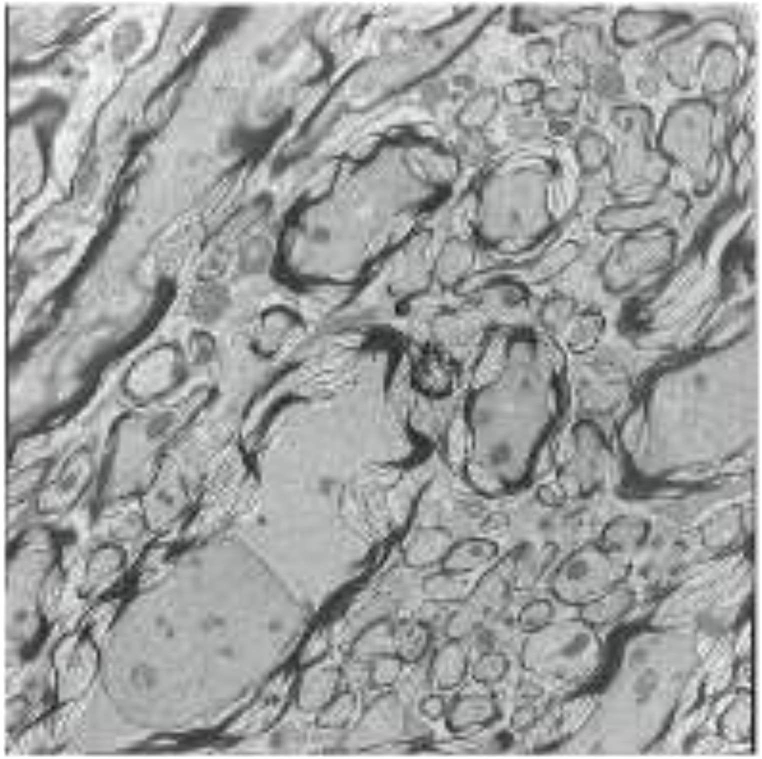
(simulated data)



"Similar looking regions" do not correspond.
Structures only exist in one of the two images.

Motivating issue 4: Multimodal Registration

Electron microscopy



Light microscopy

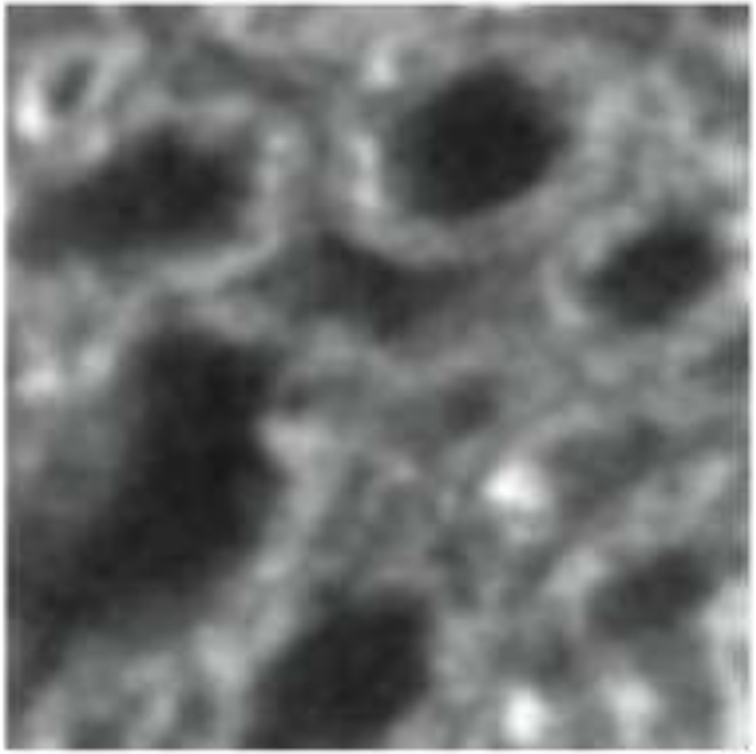


Image intensities differ, but additional complexities such as blurring are present and need to be accounted for.

What to do?

Is all hope lost here?

Possible Solutions

(Non)parametric modeling

vs

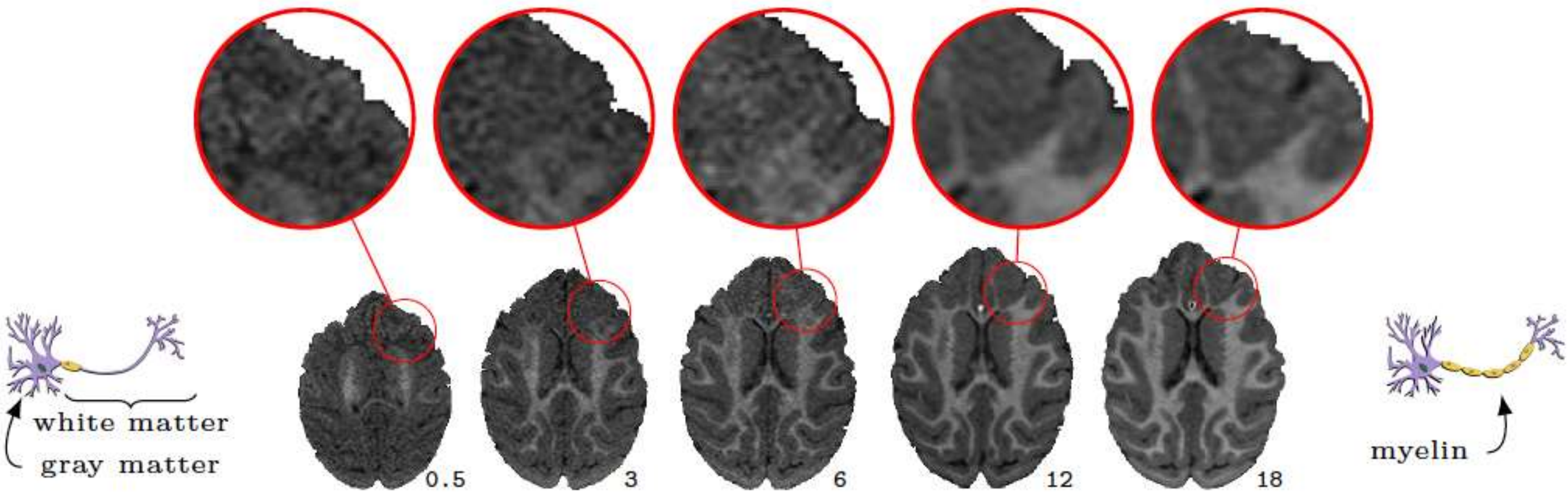
Data-driven approaches

Possible Solutions

Parametric Modeling

Motivating issue 1: Intensity changes over time

Normal brain development (macaque)

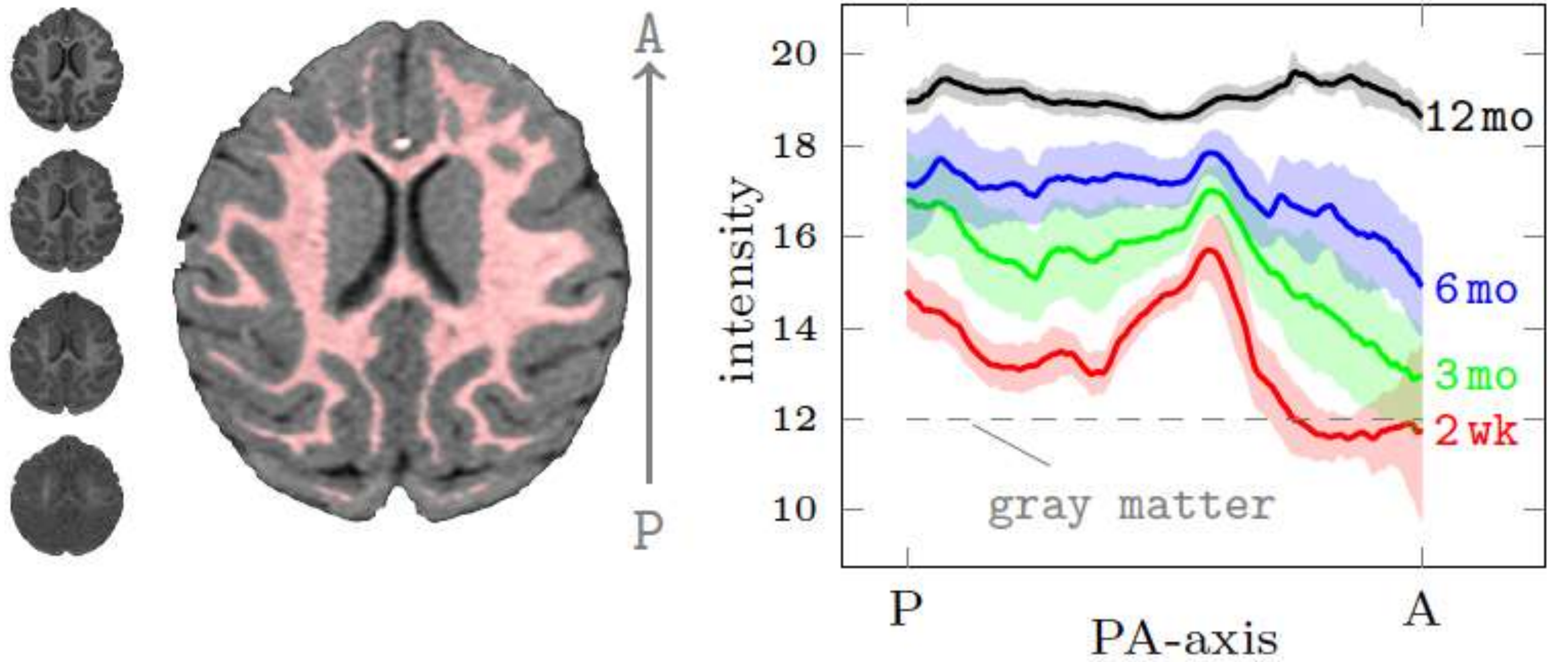


Possible solution:

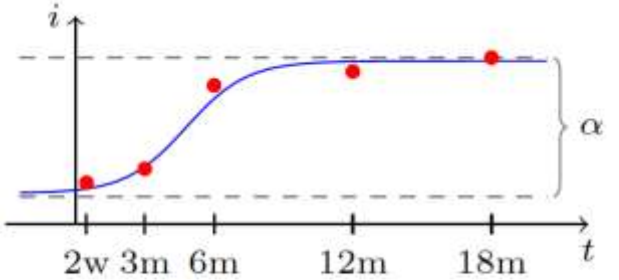
Impose a model over time to change your similarity measure

Modeling of Appearance Changes

Normal temporal change (for a macaque monkey)

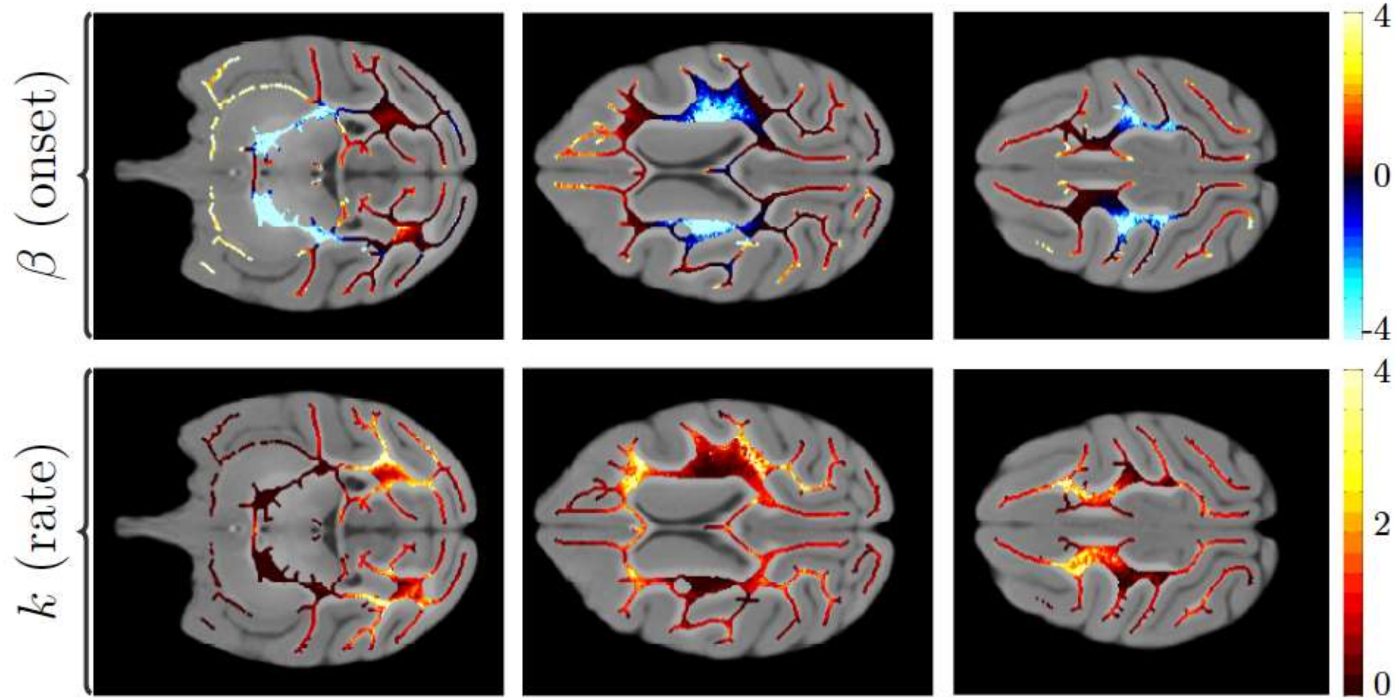


Concretely: Impose logistic model *[your favorite model]* to account for expected changes over time



Appearance Change: Brain Development

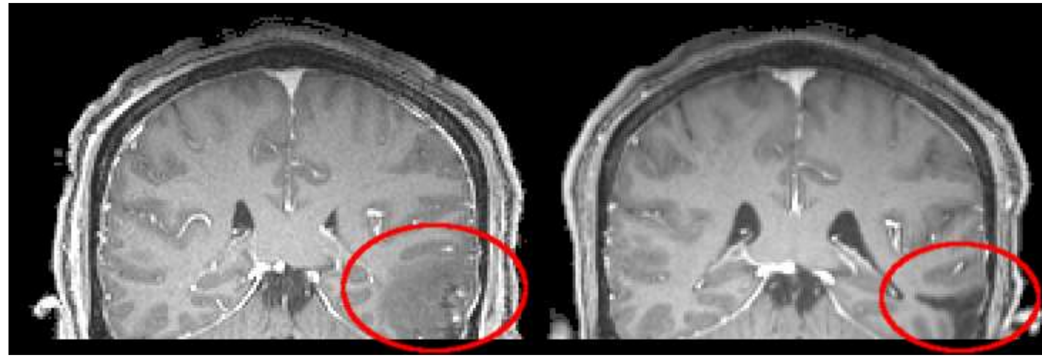
Inferior (bottom) → superior (top)



This strategy not only allows for improved registration results, but also provides interesting information about the general brain maturation process …

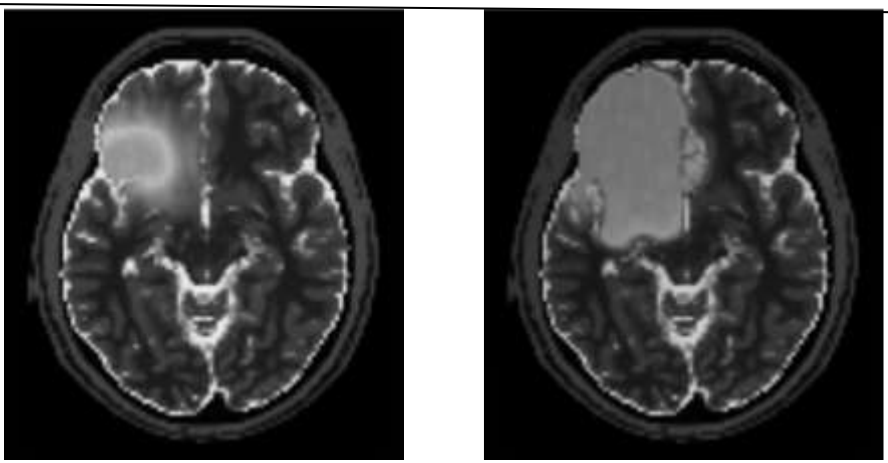
What do we do with non-corresponding regions?

Traumatic brain injury
(real data)



Brain tumor

(simulated data) –
TumorSim [Prastawa et al.]

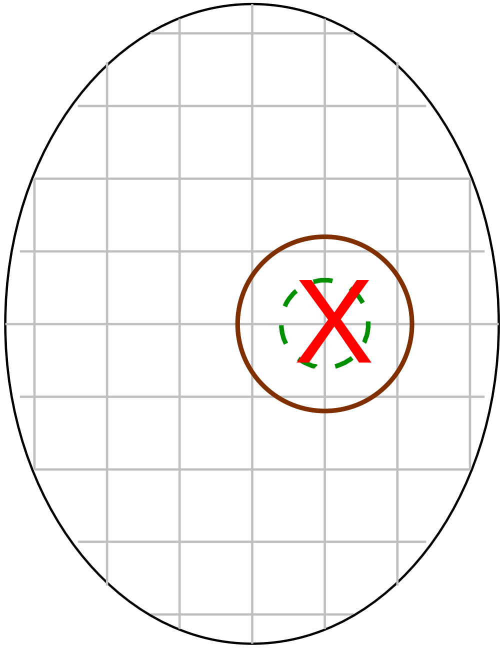


As we cannot match them we somehow need to **model or ignore** the changes.

Solution 1: Cost-function masking

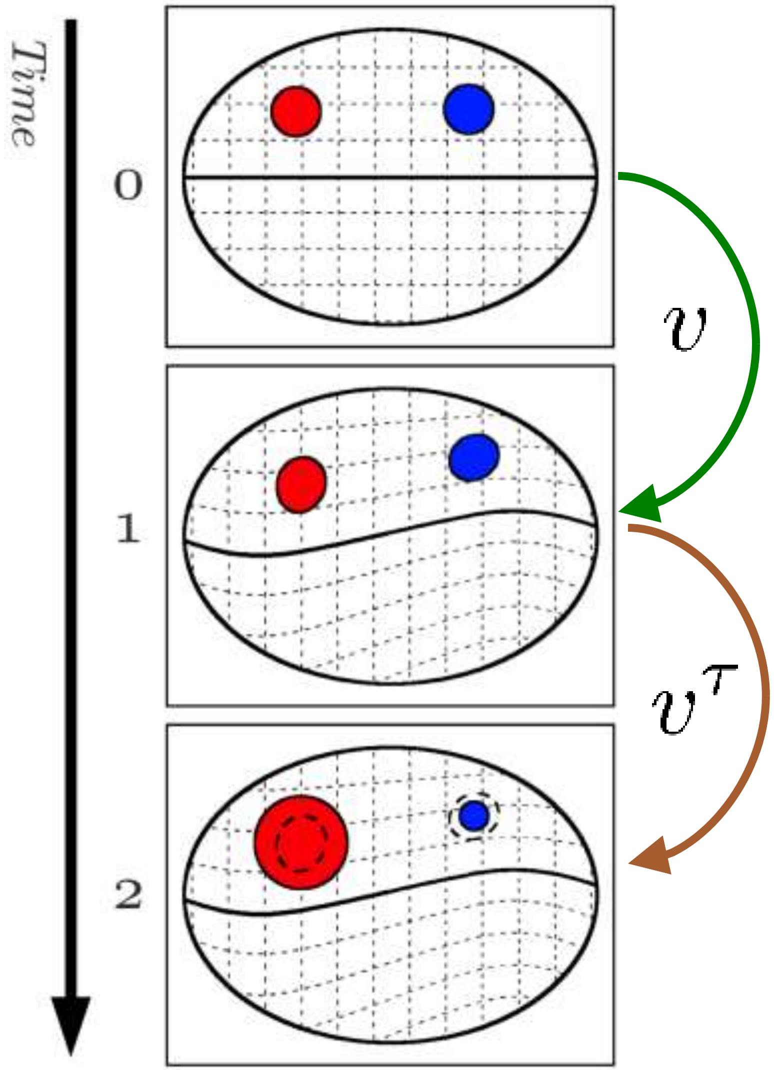
One solution: Cost function masking [Brett2001]

= ignoring matching cost in region of source image



… let's just not look at it!

Solution 2: Geometric Metamorphosis



Model lesion/tumor/… and its temporal change

- **Composition of two deformations**
  - e.g., tissue displacement & infiltration
  - jointly estimated

- **Image composition model**
  - = "glorified cost-function masking"

Model is probably more interesting from a *deformation modeling* perspective..

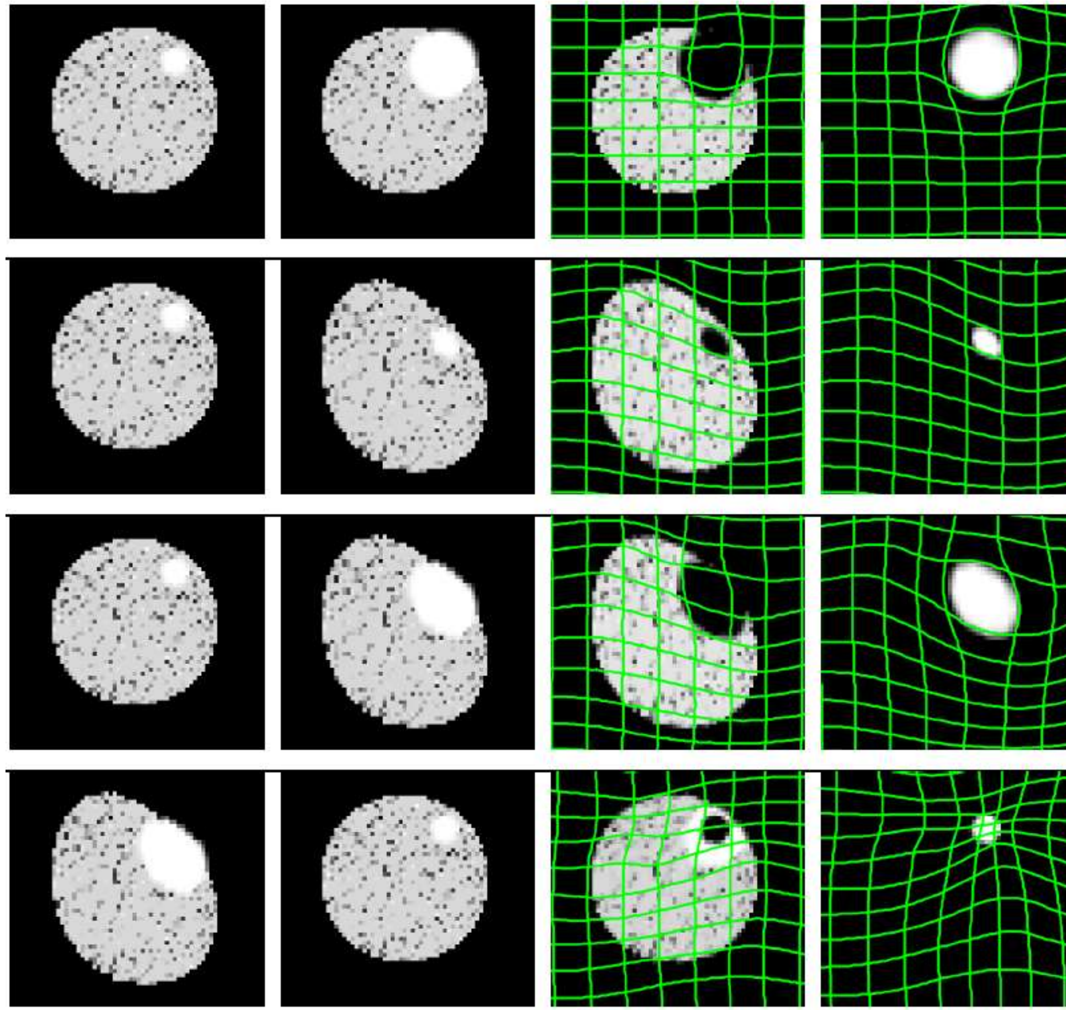
Geometric Metamorphosis: Synthetic Results

Only infiltration

Only deformation

Deformation + infiltration

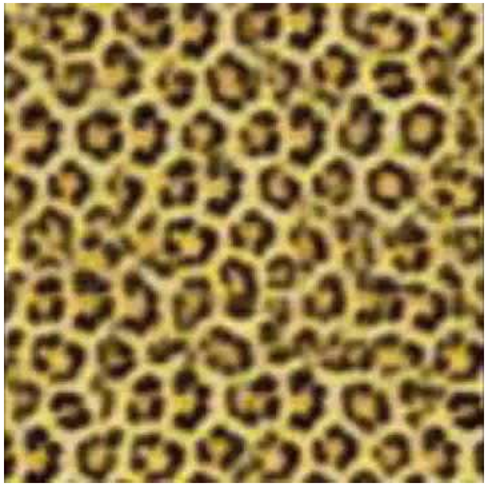
Deformation + recession



Possible Solutions

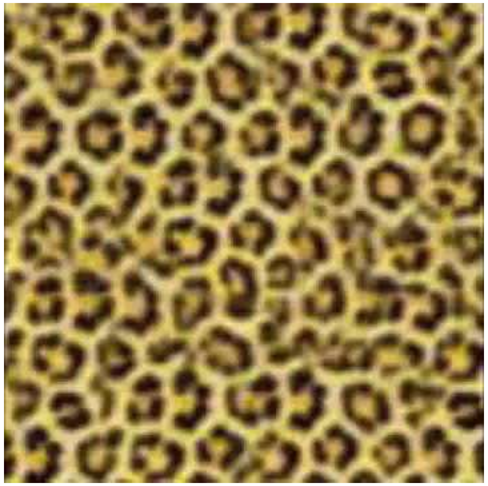
Non-parametric Modeling w/o learning

to deal with very complex changes

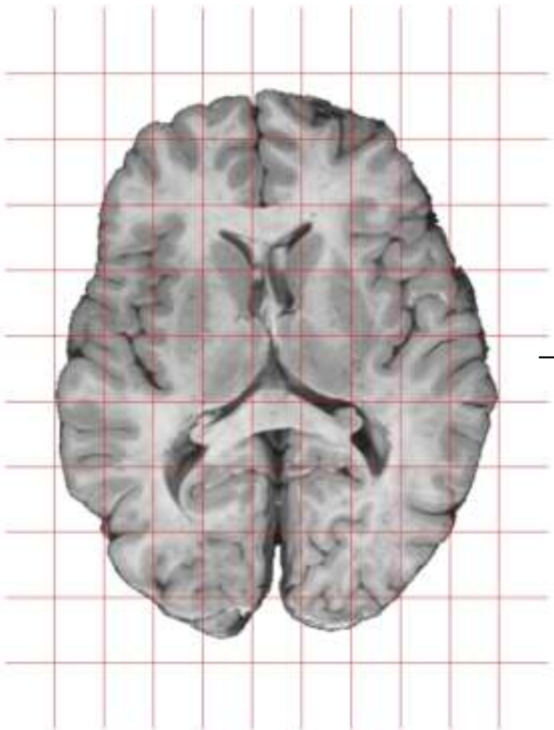


Possible Solutions

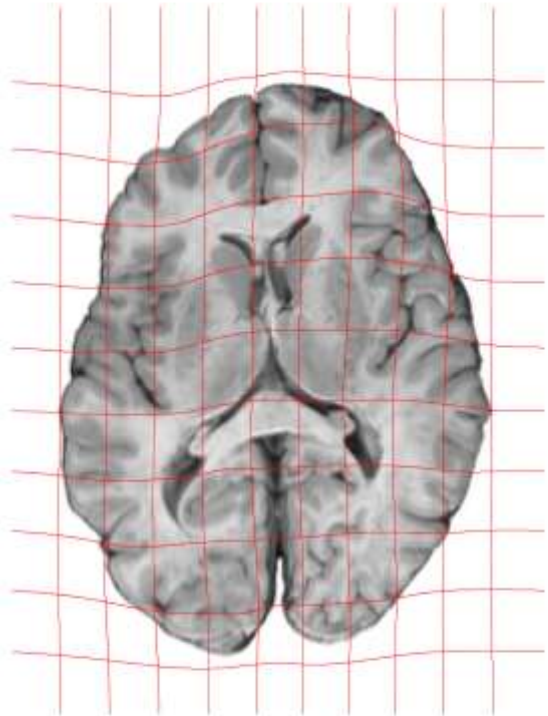
One solution is **metamorphosis**,
which requires a little LDDMM detour
[Miller, Trouve, Younes, …]



LDDMM detour



?



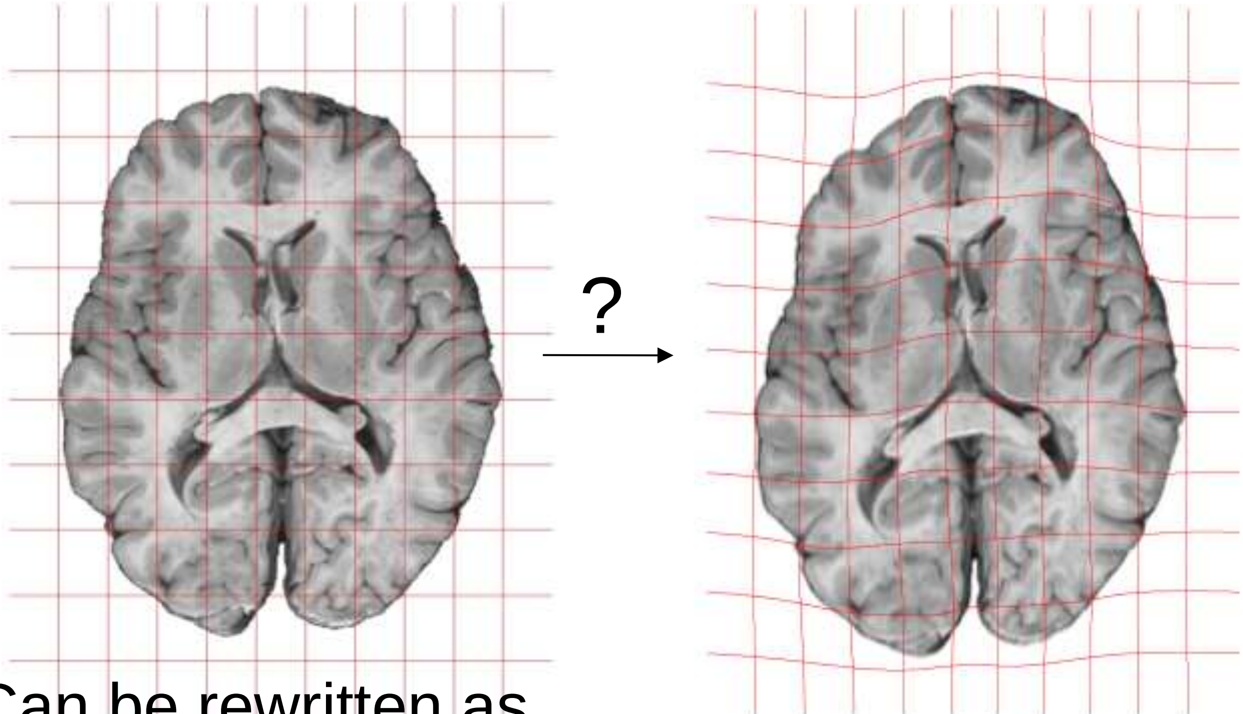
What is the best velocity field, v, to deform one image into the other?

Fluid flow setup [Miller, Younes, Trouve, …]:

$$E(v,\Phi) = \int_0^1 \|v\|_V^2 \; dt + \frac{1}{\sigma^2}\|I_0 \circ \Phi_{1,0} - I_1\|_{L_2}^2 \text{ s.t. } \dot{\Phi} = v \circ \Phi$$

Optimal control problem, which can can be rewritten as …

Constrained Optimization for LDDMM



Can be rewritten as

$$E(v, I) = \int_0^1 \|v\|_V^2 \; dt + \frac{1}{\sigma^2} \|I(1) - I_1\|_{L_2}^2$$

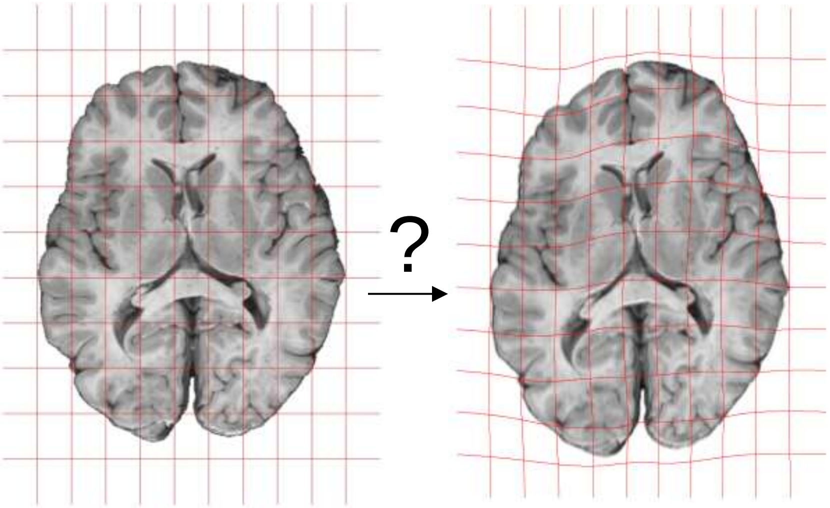
s.t. $I_t + \nabla I^T v = 0, \; I(0) = I_0$

This just requires infinite-dimensional constrained optimization.

… and I am telling you this because …

Image Registration + Image Metamorphosis

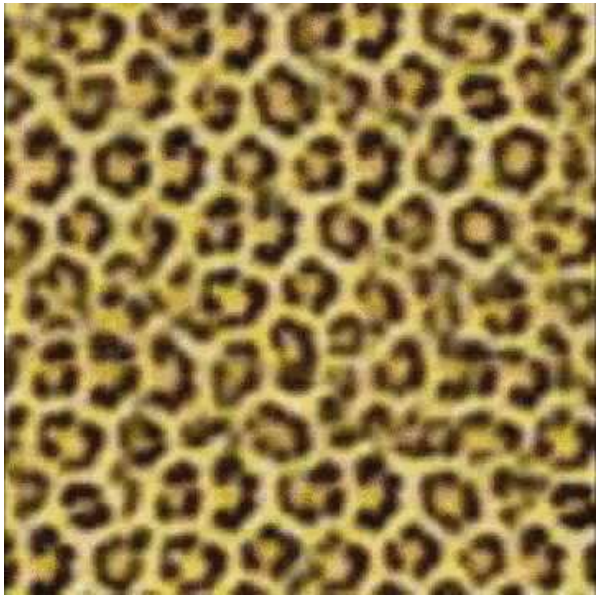
Standard Image Registration



$$I_t + \nabla I^T v = 0$$

Assumes **1-1 correspondence**

Image Metamorphosis



$$I_t + \nabla I^T v = q$$

Registration **and blending**

add $\int_0^1 \|q\|_Q^2 \, dt$ to energy

Image Metamorphosis

Metamorphosis is an elegant model,
but work remains to be done

- to improve the numerical solution methods
- to extend it to longitudinal data
- to possibly couple it with some parametric models for greater control over the appearance change

Possible Solutions

Let’s switch gears a bit …

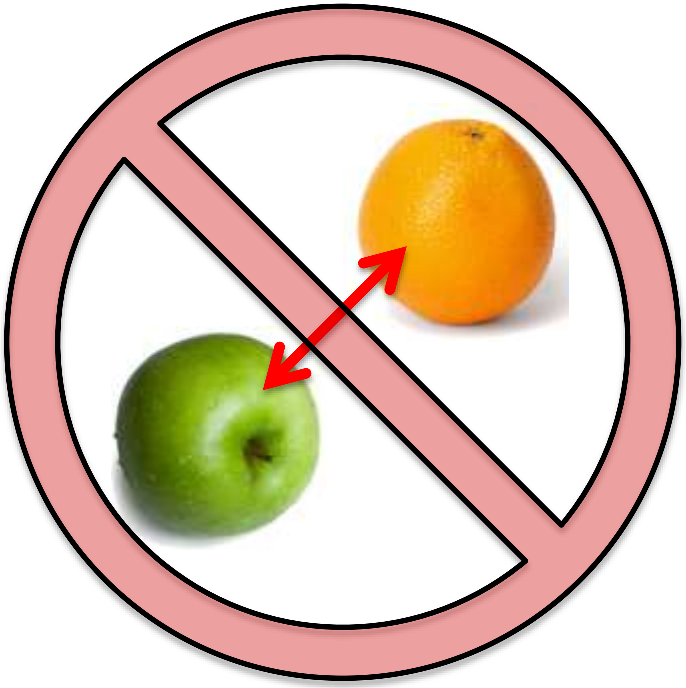
Data-Driven (Learning) Approaches

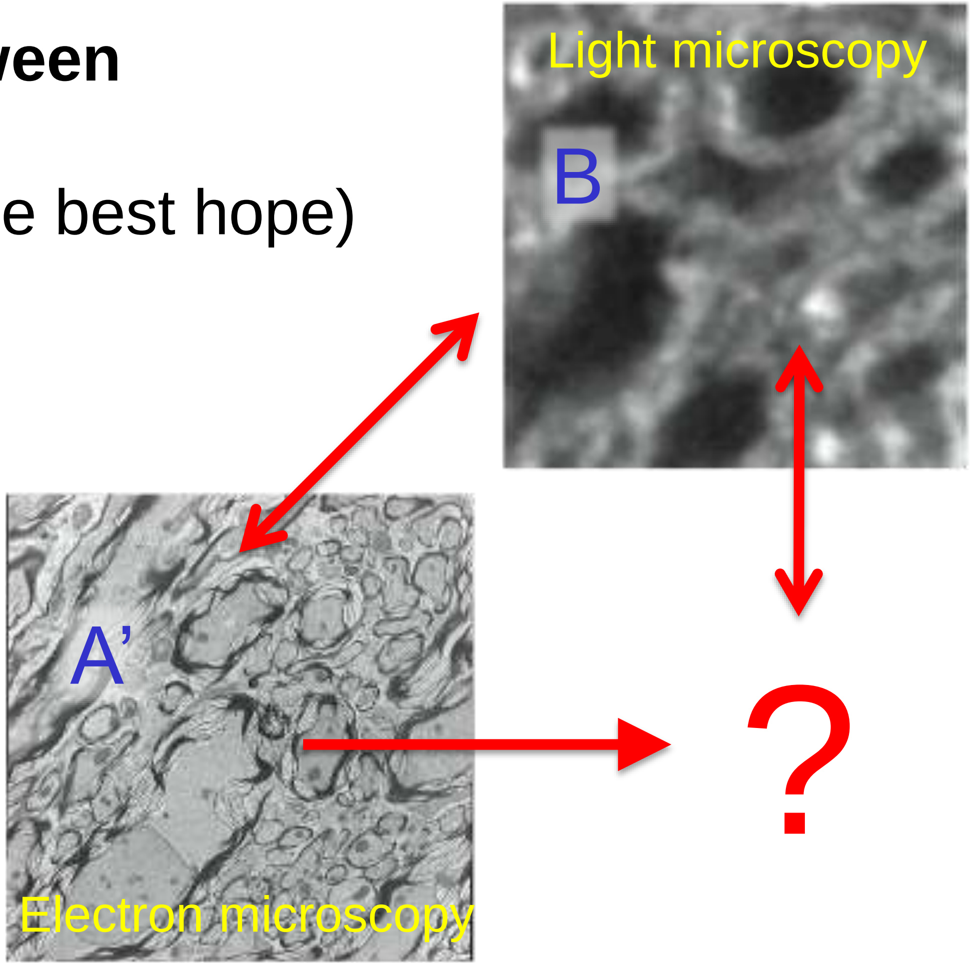
… will tell you about two different approaches:

1. Image analogies (for microscopy)
2. Recap of “Low-rank to the rescue”

Registration for Microscopy

Registration is difficult between different image modalities
(mutual information may be the best hope)





Other possible solution: Image Analogies (from graphics)

Registration for Microscopy: Image Analogies

Solution approach:

Image Analogies:

learned

A relates to B

A’ relates to B’

unknown

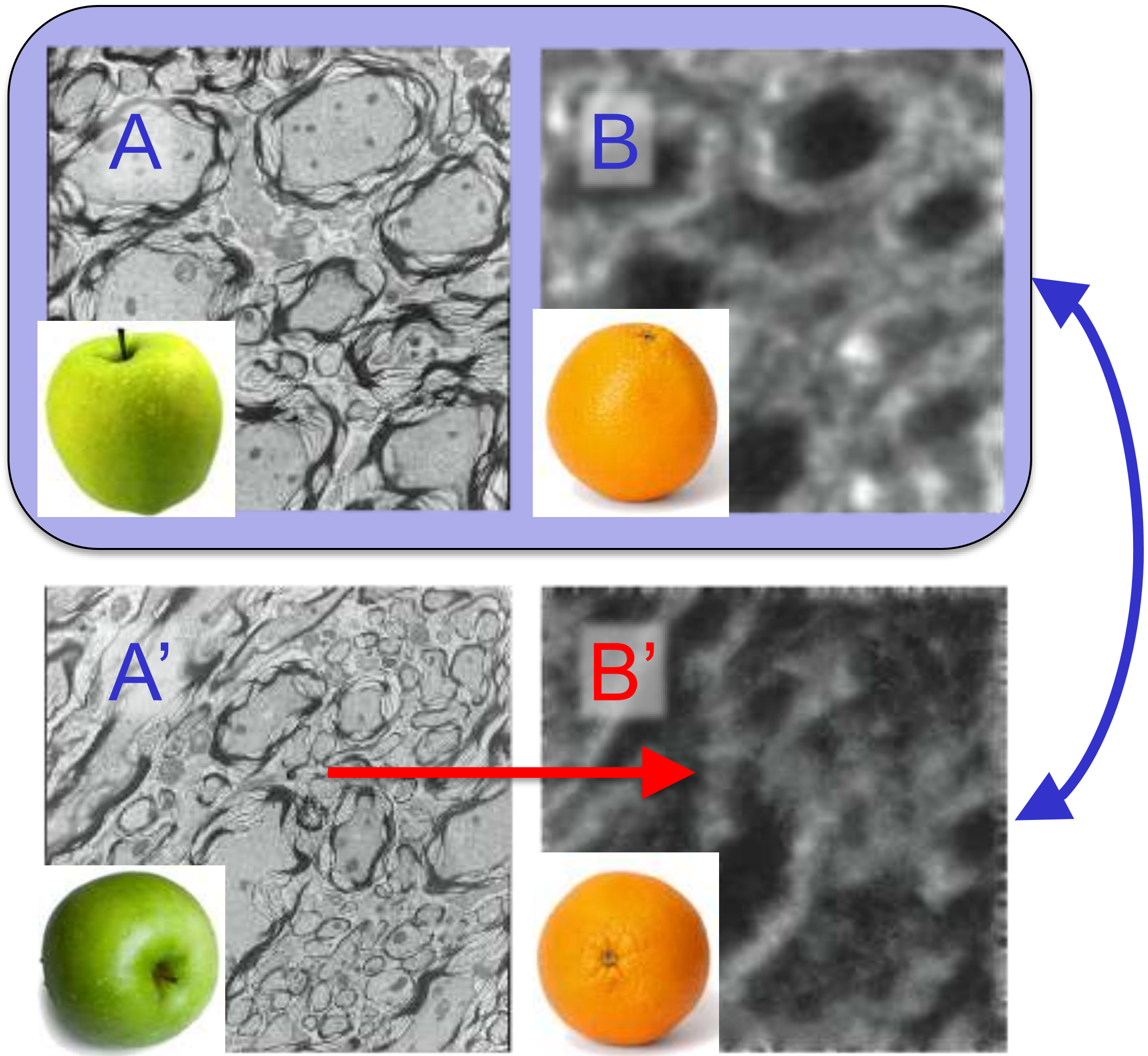


Image-Analogies by Lookup

Generate corresponding Image patches

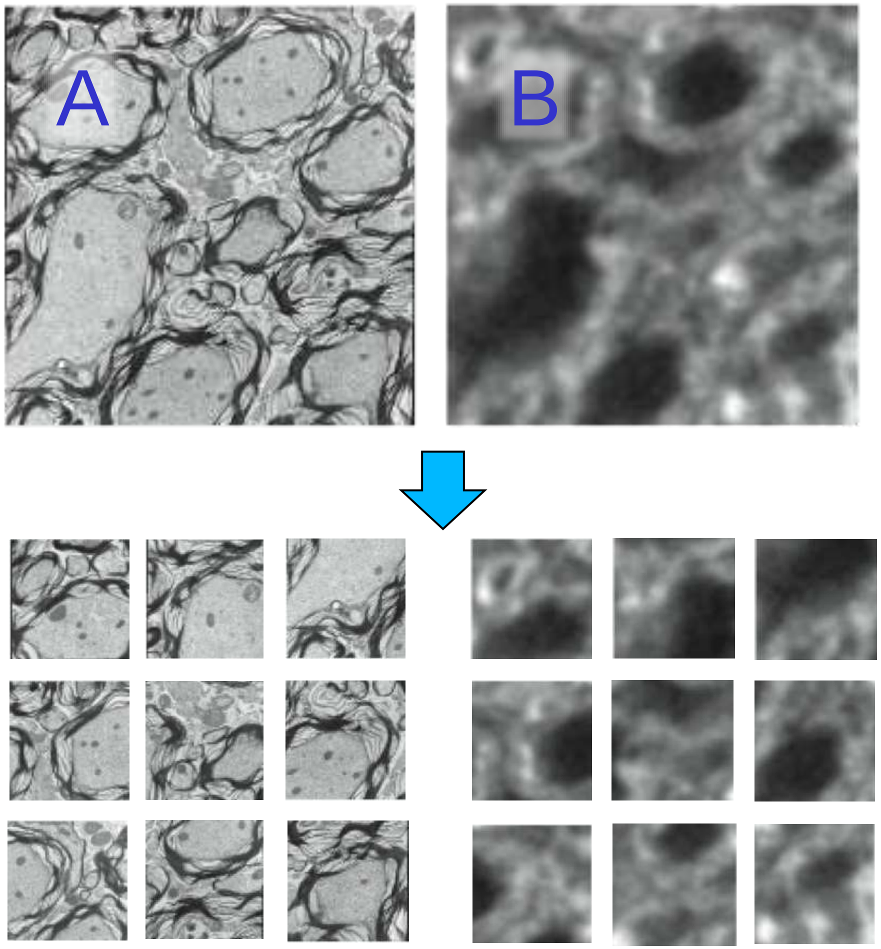
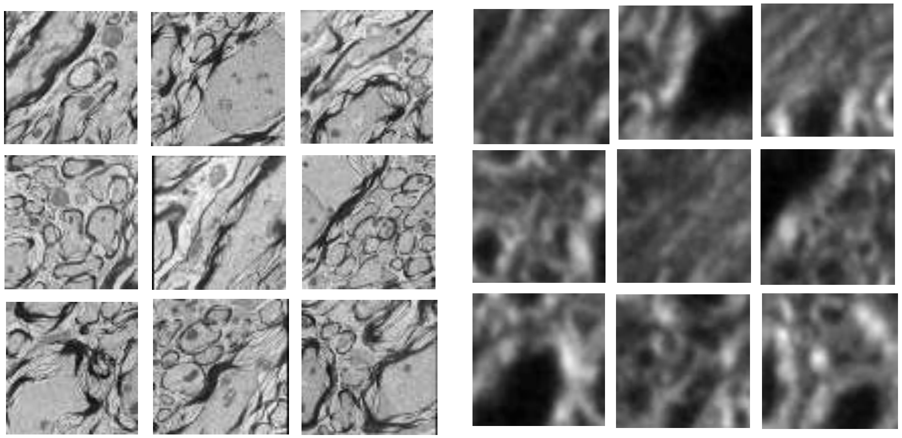


Image-Analogies by Lookup

Synthesize a new image by lookup



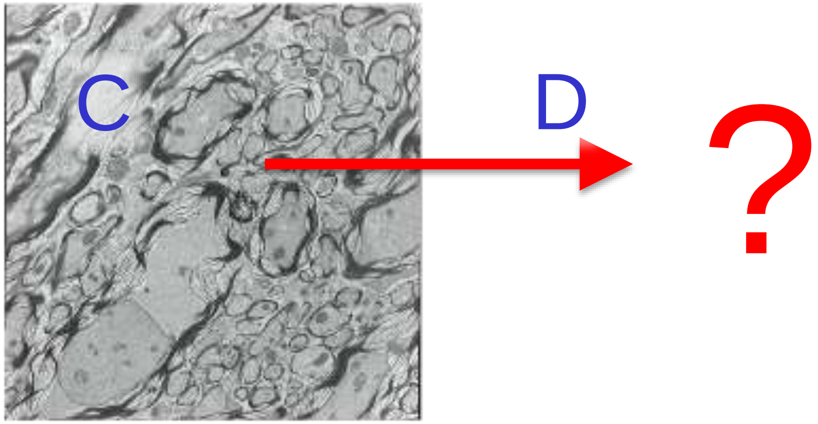


Image-Analogies by Lookup

Synthesize a new image by lookup

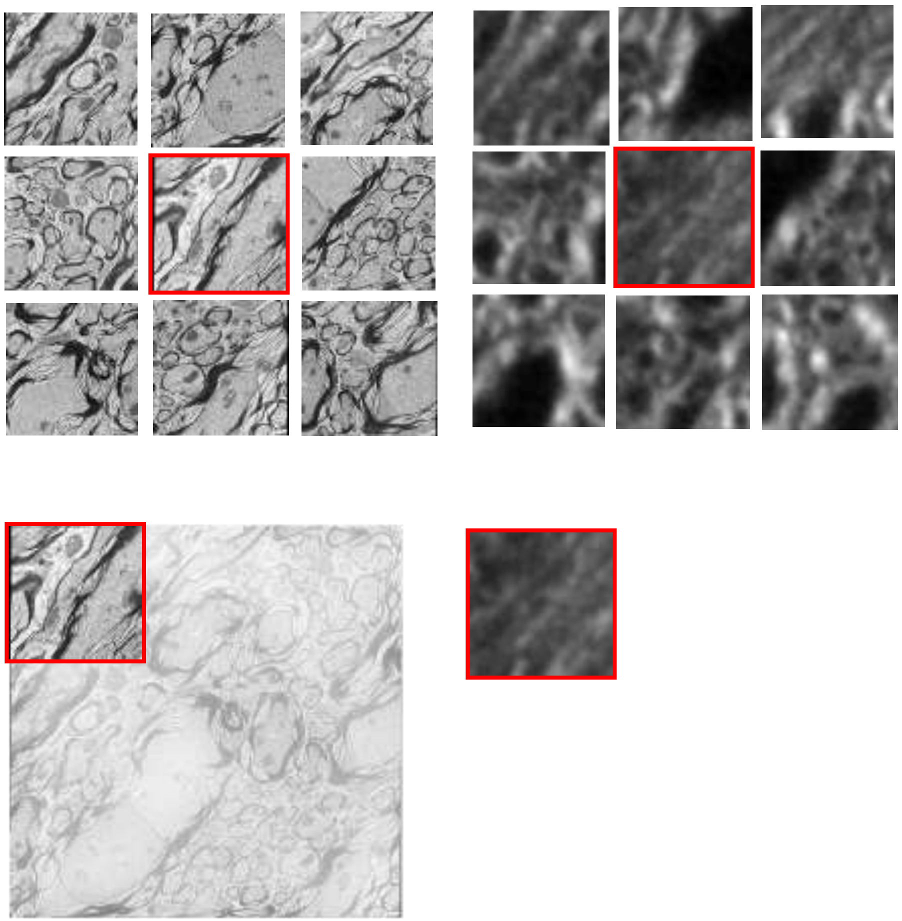


Image-Analogies by Lookup

Synthesize a new image by lookup

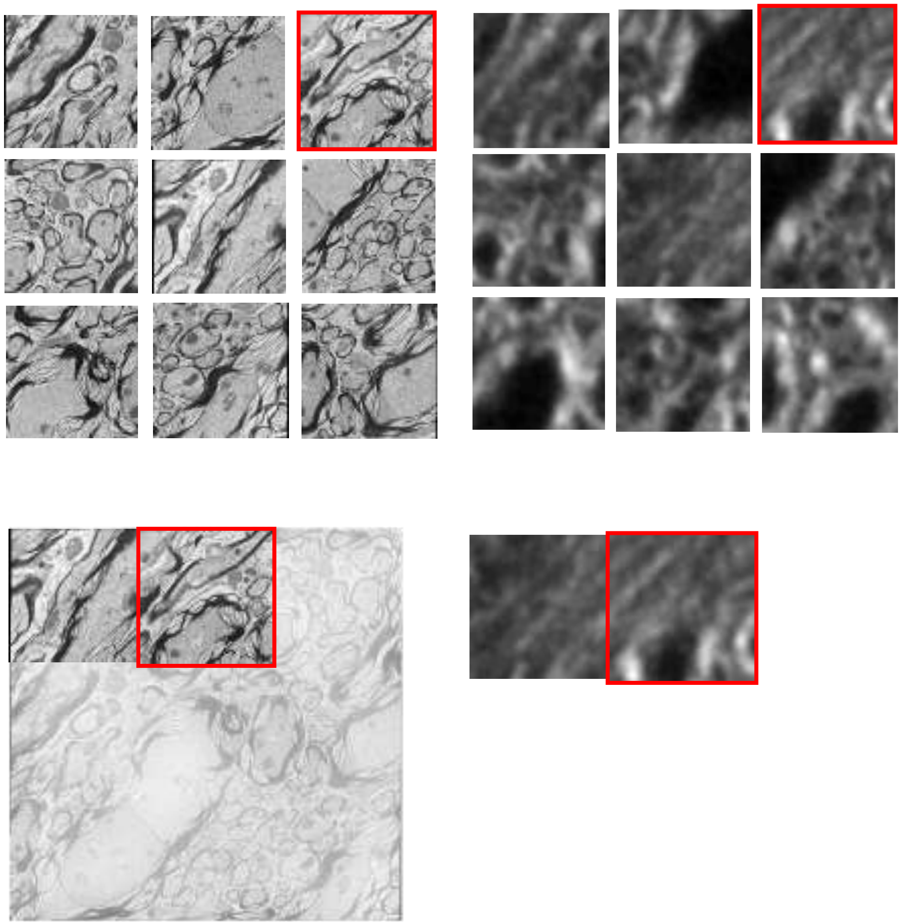
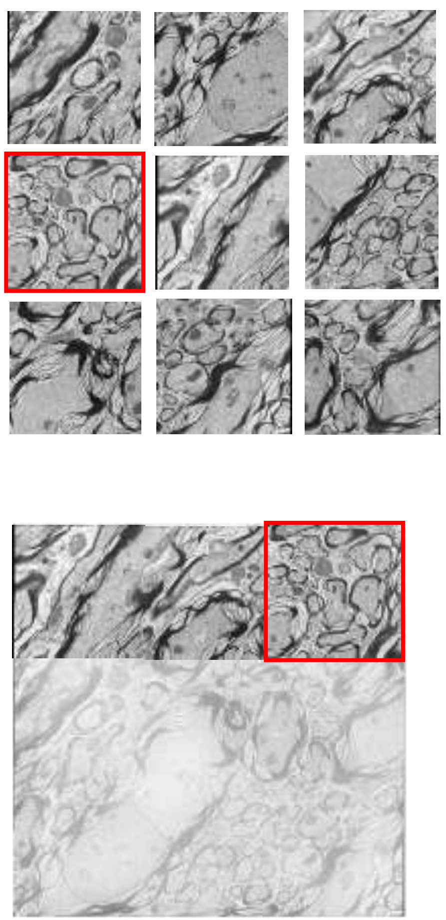


Image-Analogies by Lookup

Synthesize a new image by lookup



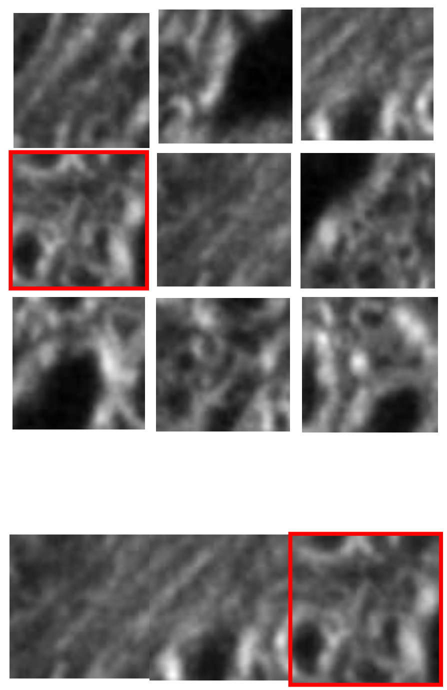


Image-Analogies by Lookup

Synthesize a new image by lookup

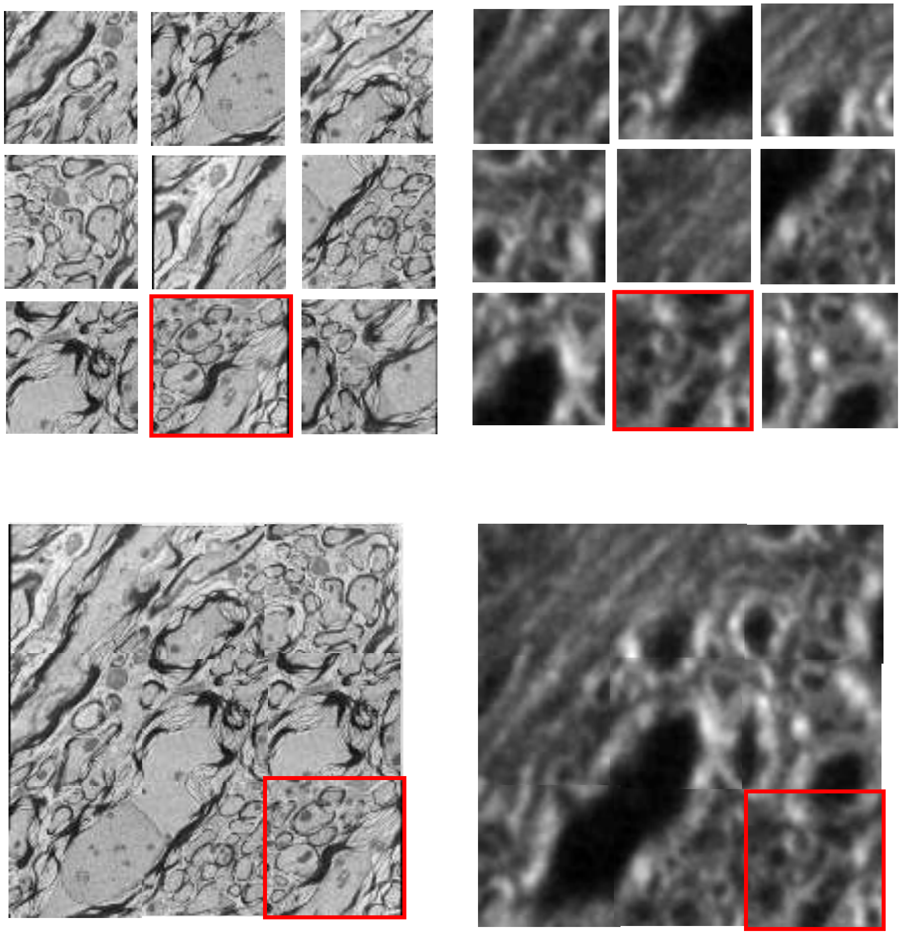
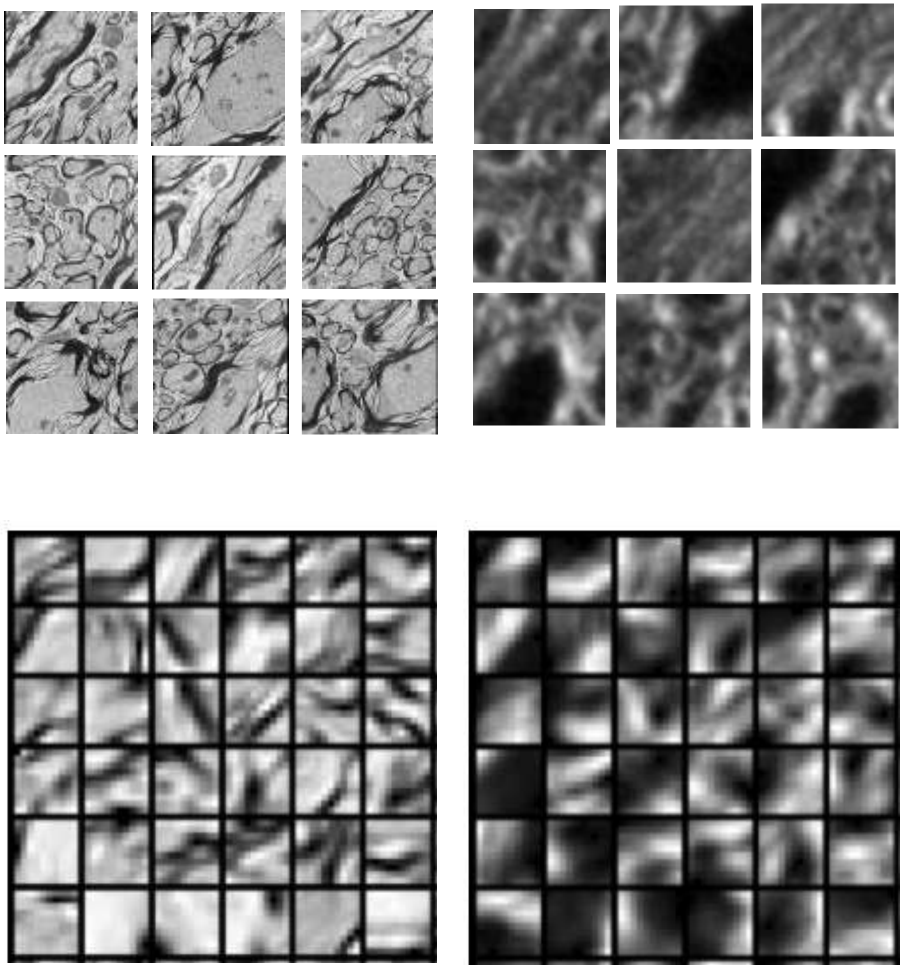


Image-Analogies by Dictionary Learning

Use **LASSO** for dictionary learning to learn a basis for patches which can be used to predict one modality from the other.



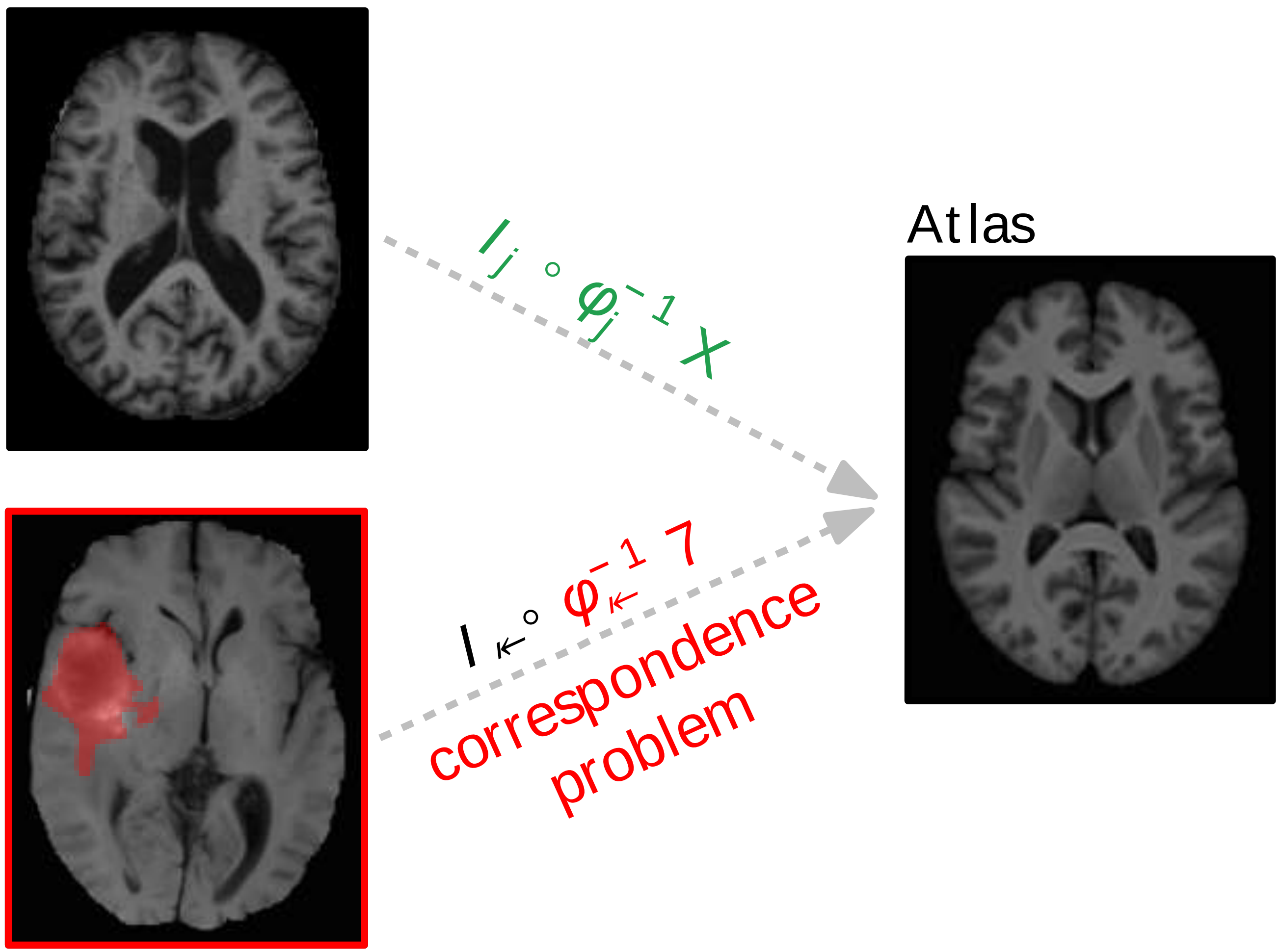
Possible Solutions

Learning from Populations

Super-brief summary of Roland Kwitt's talk from yesterday:

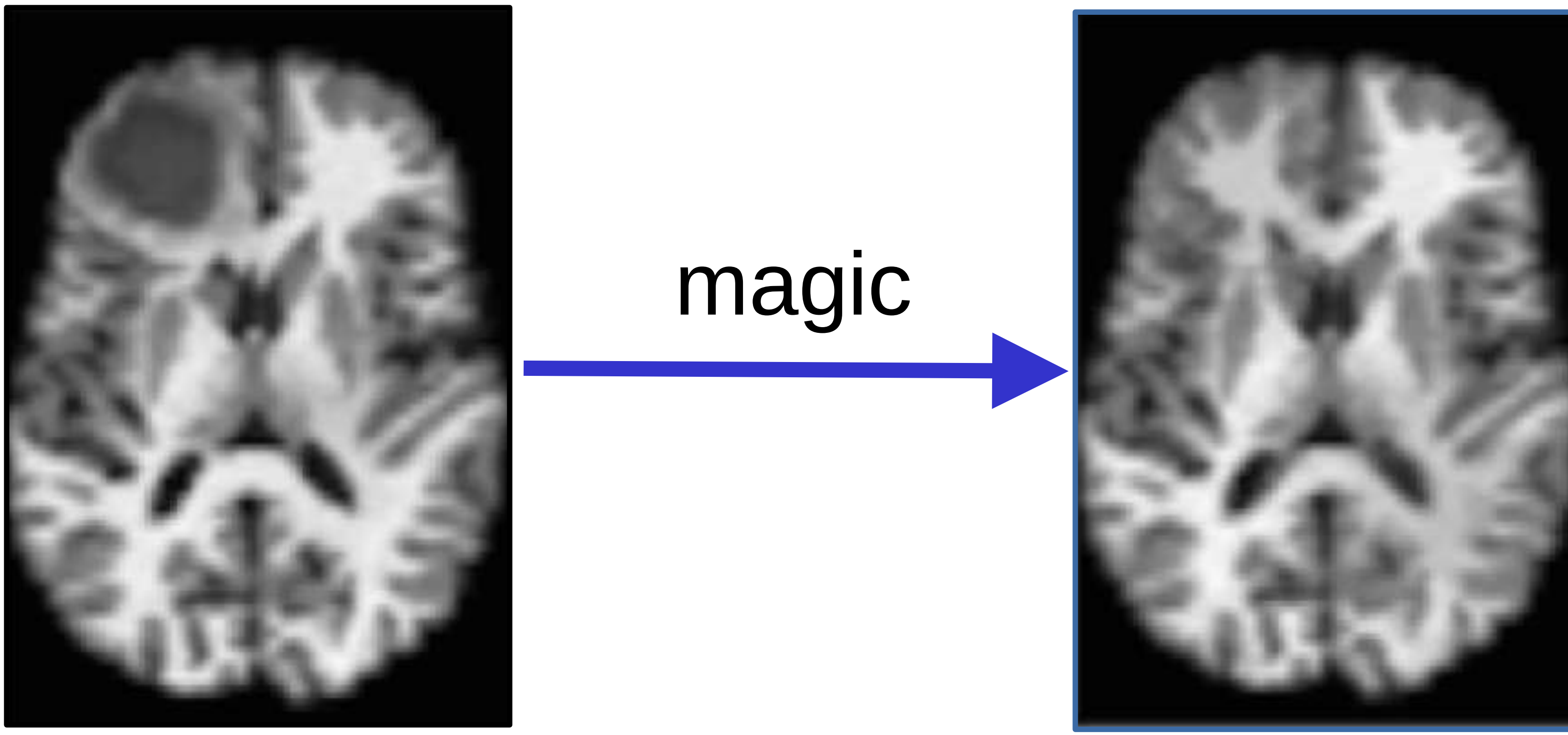
Low-rank to the rescue:
Atlas-Based Analyses in the Presence of Pathologies

Motivating Problem: Registration w/ Pathologies



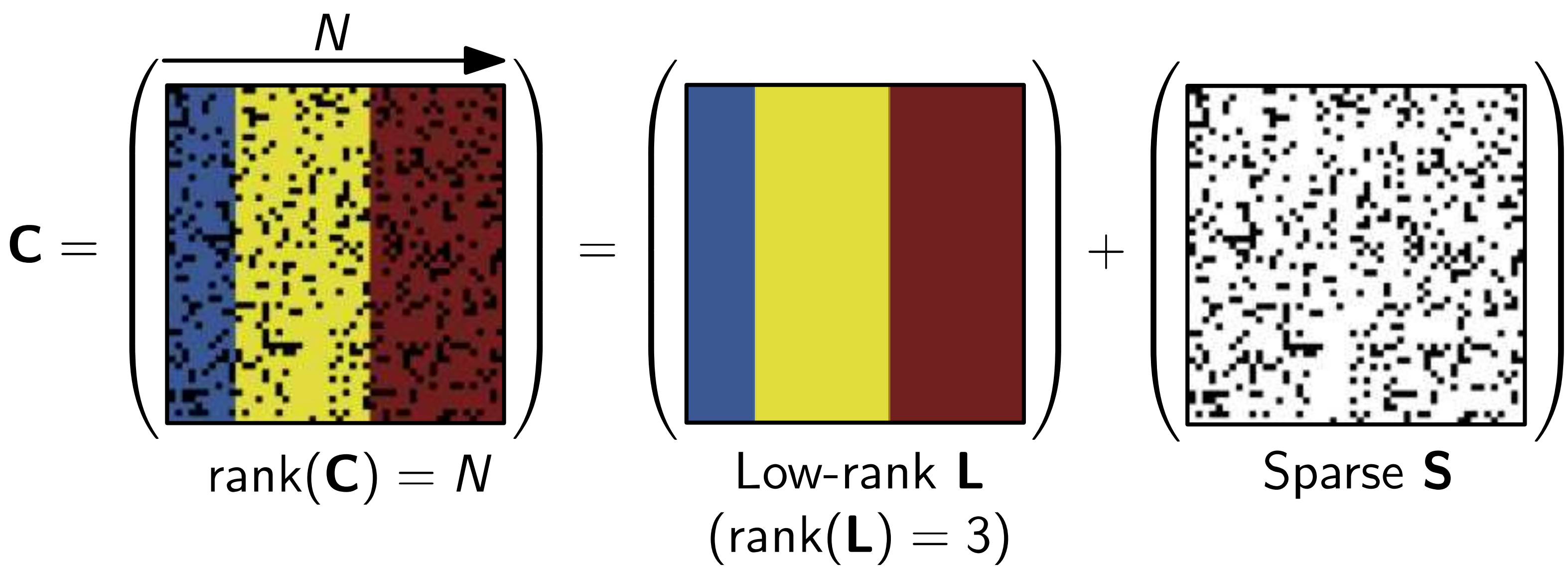
What if?

What if there were a method to transform an image with pathology into a healthy-looking image?



This is exactly what “Low-rank to the Rescue” does!

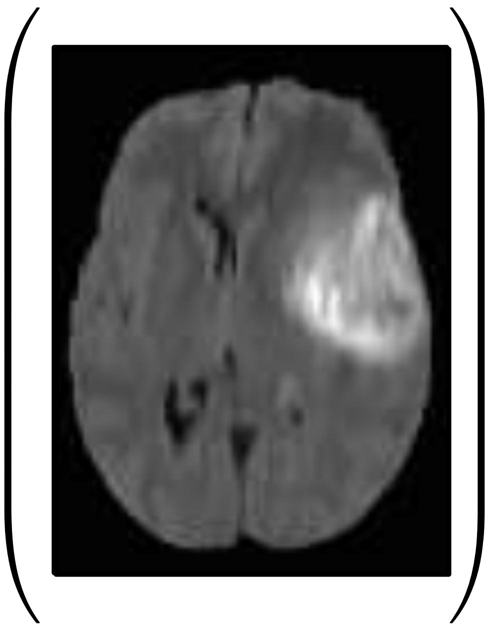
Low-rank + sparse decomposition



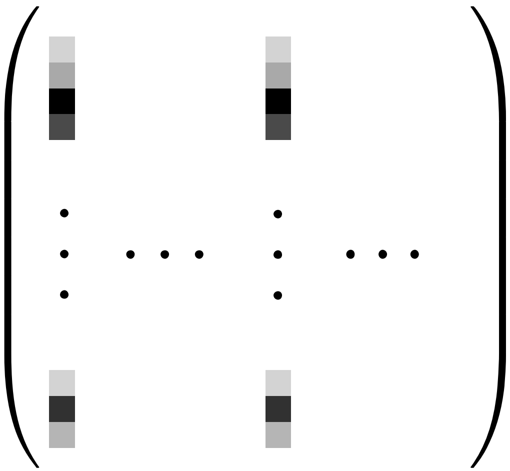
$$\{\mathbf{L}^*, \mathbf{S}^*\} = \underset{\mathbf{L},\mathbf{S}}{\operatorname{argmin}} \underbrace{\|\mathbf{L}\|_*}_{\text{low-rank}} + \lambda \underbrace{\|\mathbf{S}\|_1}_{\text{sparsity}}, \text{ s.t. } \mathbf{C} = \mathbf{L} + \mathbf{S}$$

Low-rank + sparse decomposition for images

Images are represented by column-vectors.

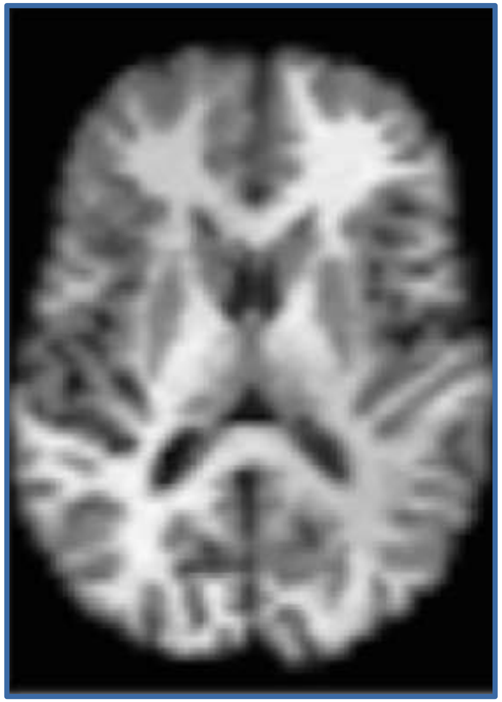


$\mathbf{C} =$



$= \mathbf{L} + \mathbf{S}$

Low-rank + sparse decomposition example

Input	Low-Rank	Sparse
		

Now we can work with "almost-normal" images!

Summary

Multiple possibilities to deal with image differences:

The classics: mutual information, normalized cross correlation

Explicit modeling:

- parametric (e.g., logistic curve)
- non-parametric (metamorphosis)
- cost-function masking

Data-driven modeling:

- image analogies through dictionary learning
- creating “normal images” using low-rank + sparse

Which method to use will of course be application-dependent.

Questions?

Questions?