Visual Data Science: Vis tools for decision making

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Overview

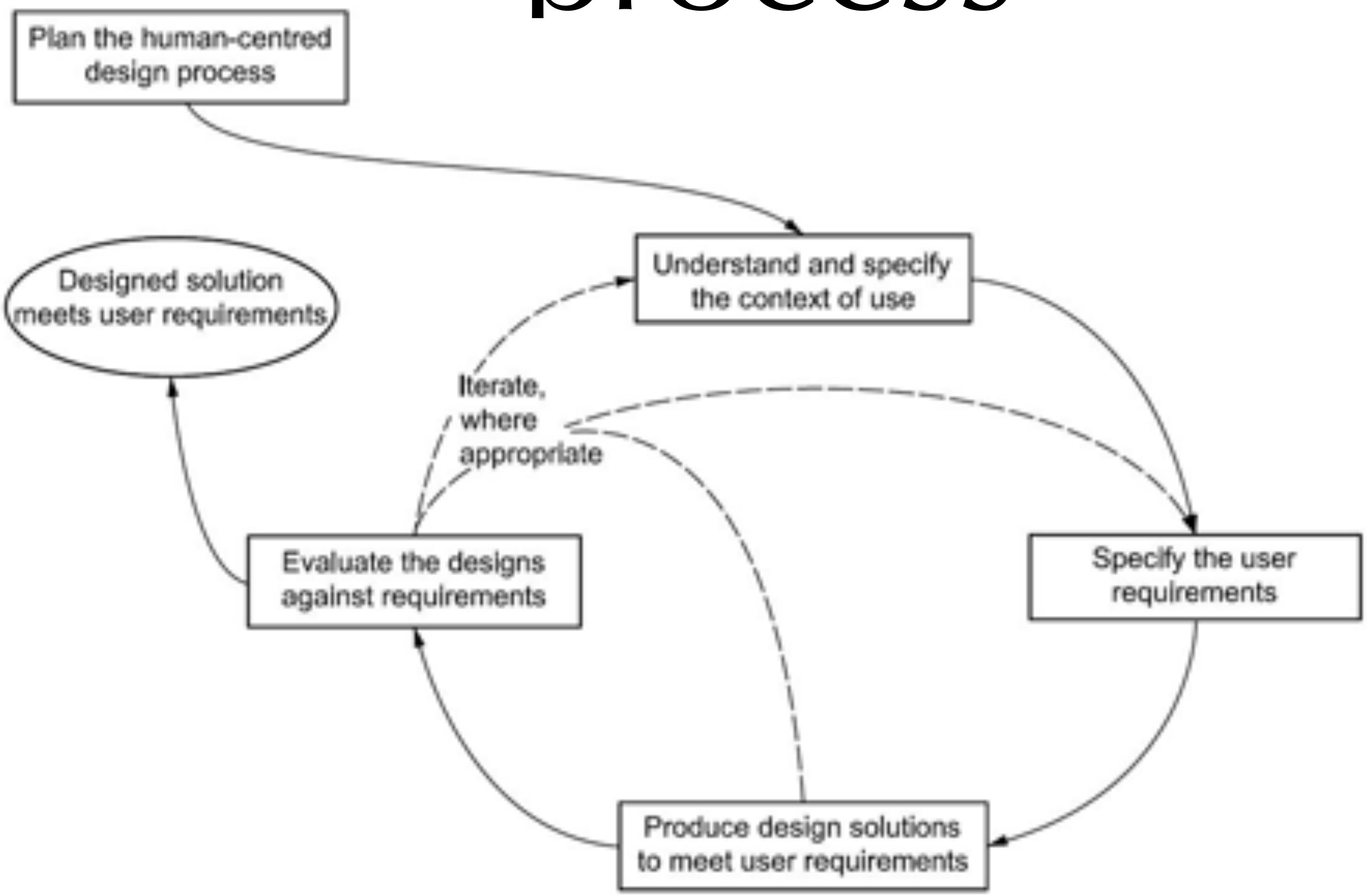
- Yesterday: 4 case studies
    - Tuner — Image segmentation
    - FluidExplorer — Fluid animation
    - Vismon — Fisheries science
    - FeatureExplorer — Classification
- Today: Abstraction / Theory
    - Design Studies
    - Principles of visual parameter space exploration
    - Visual Data Science — visual tools for modeling

General remarks on methodology

Development

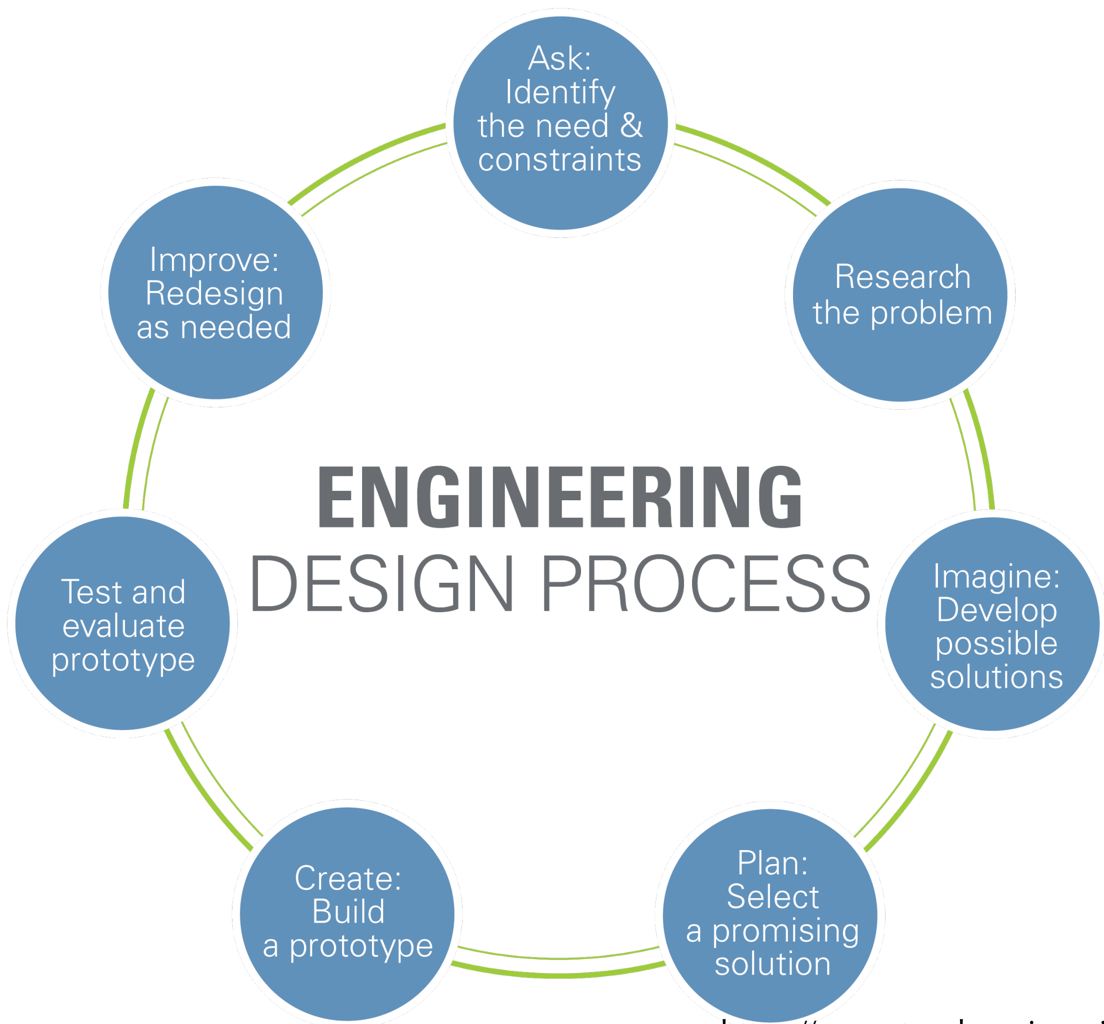
- Vismon: 4 years
- FluidExplorer: 1 year
- Tuner: 1 year
- FeatureFinder: 8 month

Human-centered design process



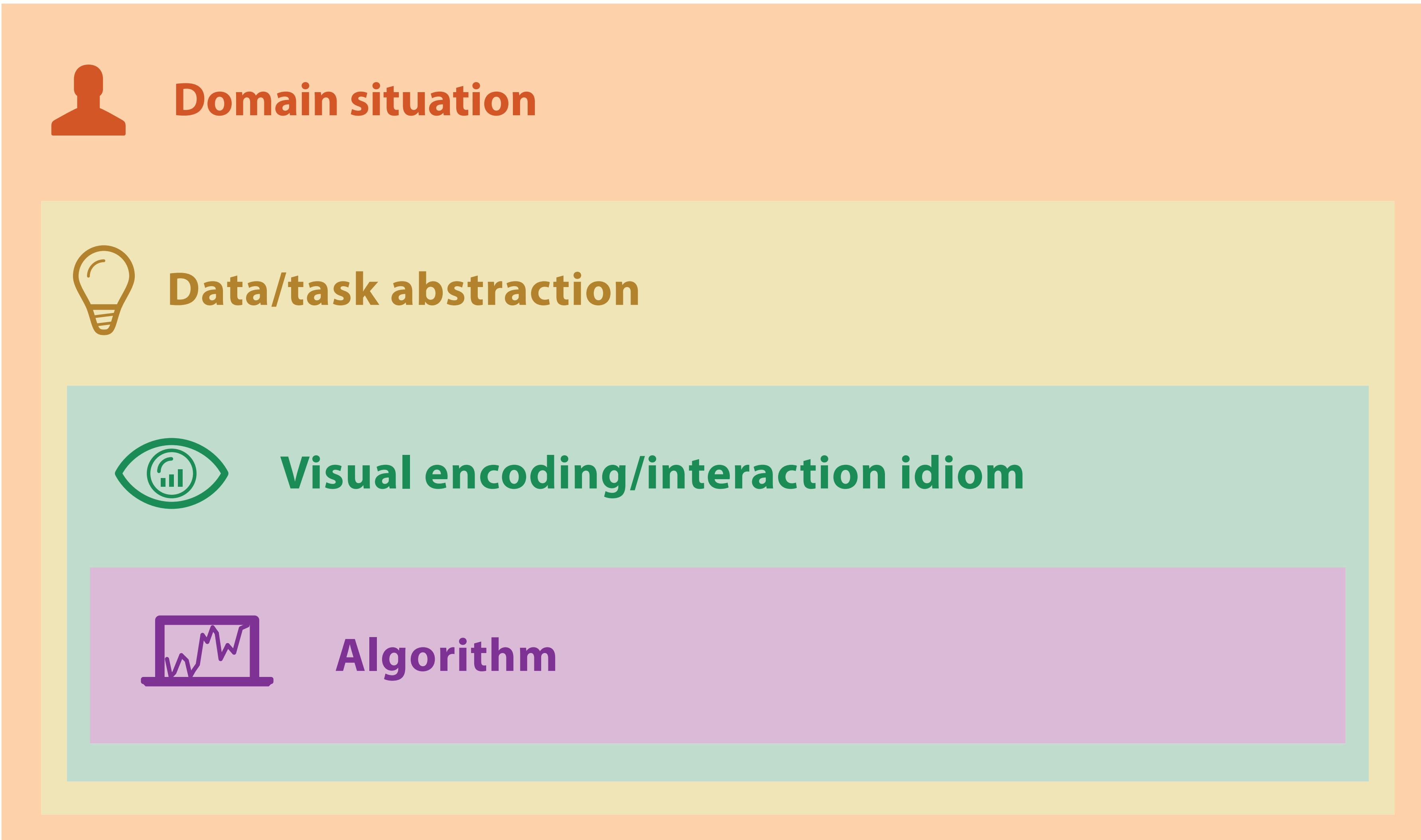
http://2011.hci.international/index.php?module=webpage&id=35

general Design process



https://www.teachengineering.org/engrdesignprocess.php

Munzner's Nested model



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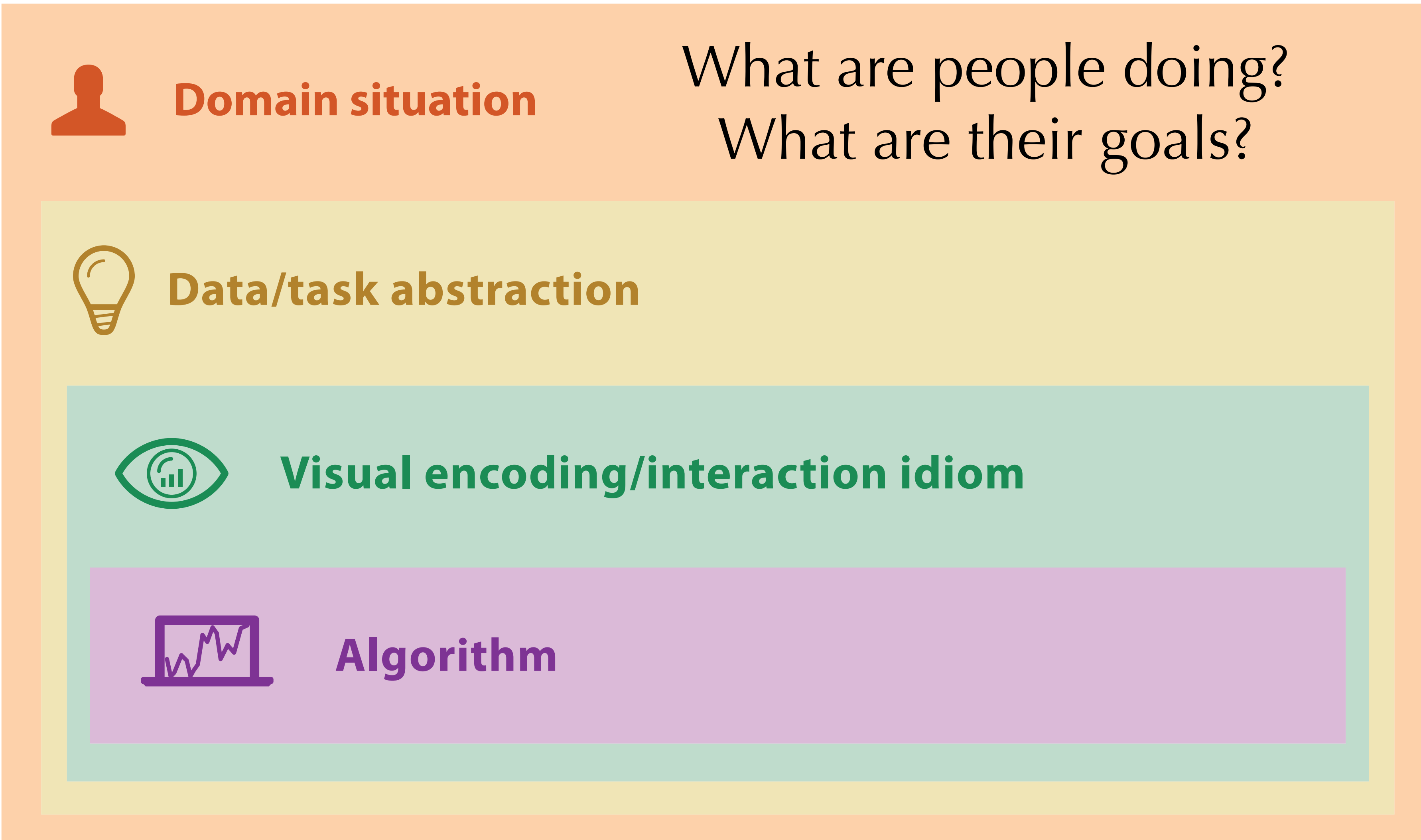

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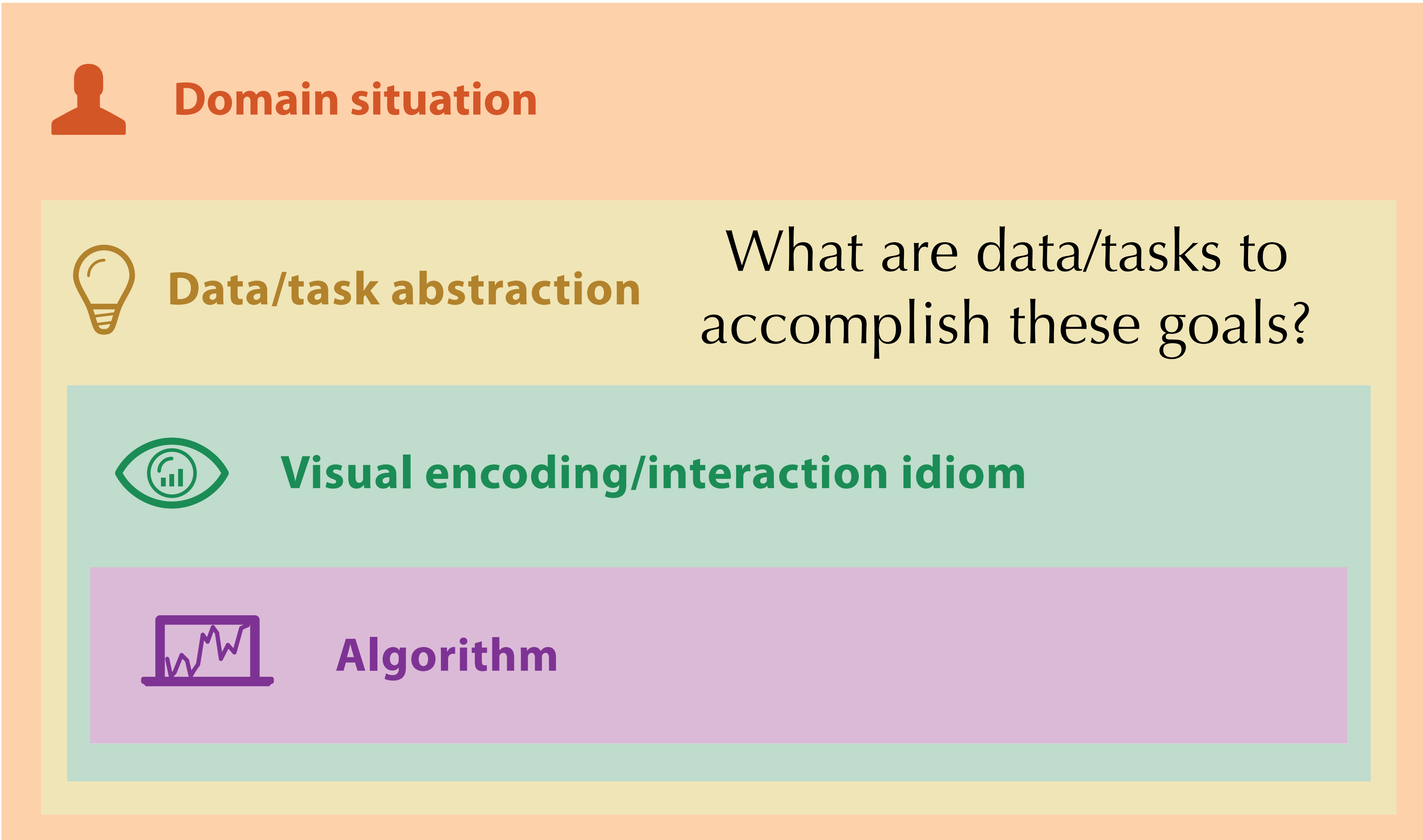

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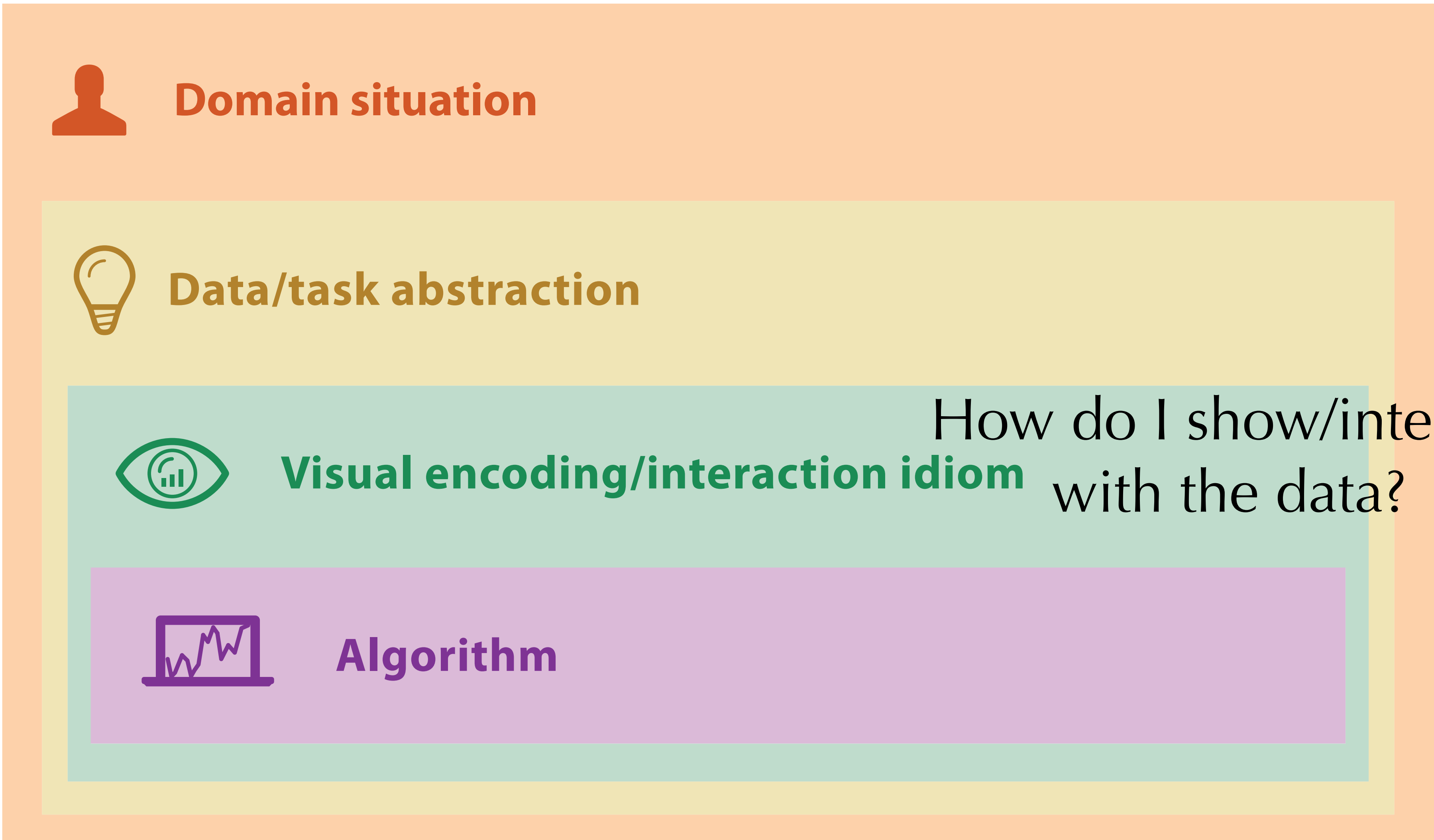
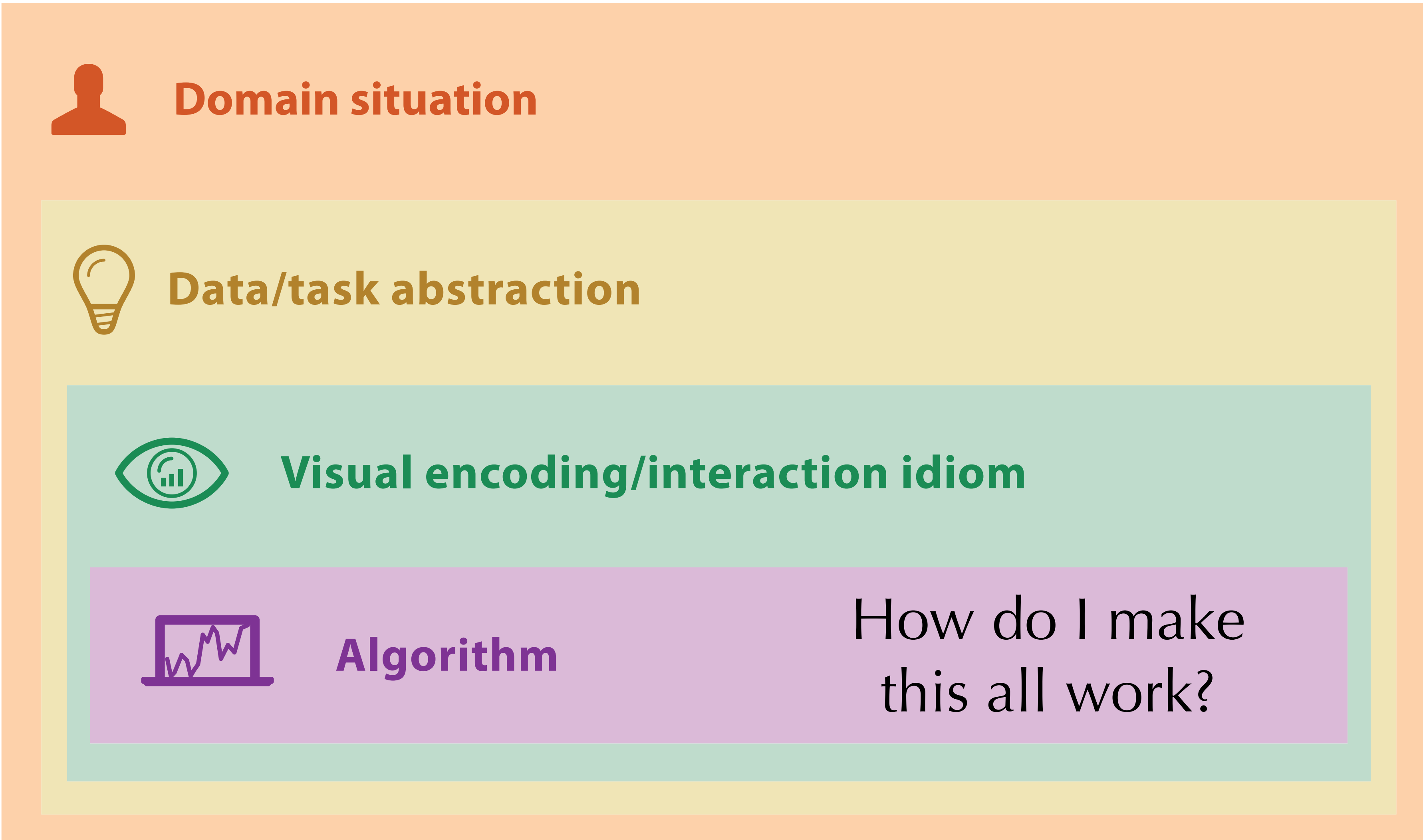


How do I show/interact with the data?

Munzner's Nested model



Munzner's Nested model

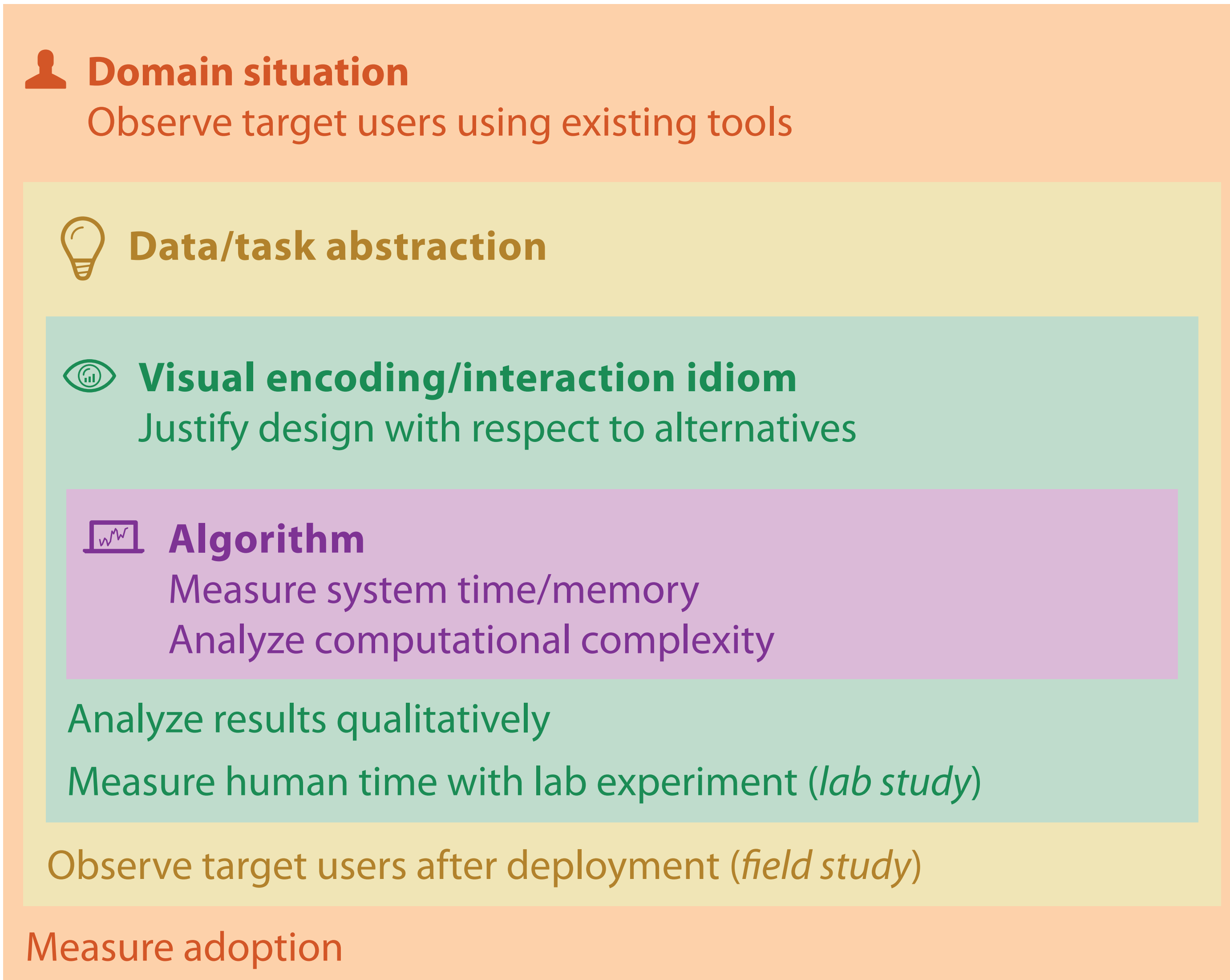
Domain situation
You misunderstood their needs

Data/task abstraction
You're showing them the wrong thing

Visual encoding/interaction idiom
The way you show it doesn't work

Algorithm
Your code is too slow

Munzner's Nested model



Workflow for designing a tool

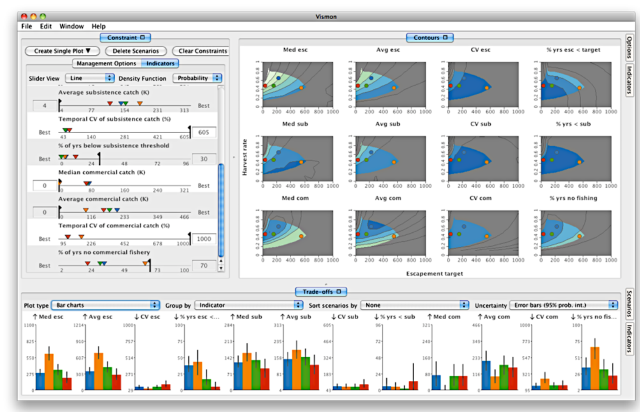
Making the right tool

Questions

Data

Tasks

Vis researcher



http://halalfocus.net/wp-content/uploads/2014/05/question-mark-nothing.jpg

Making the right tool

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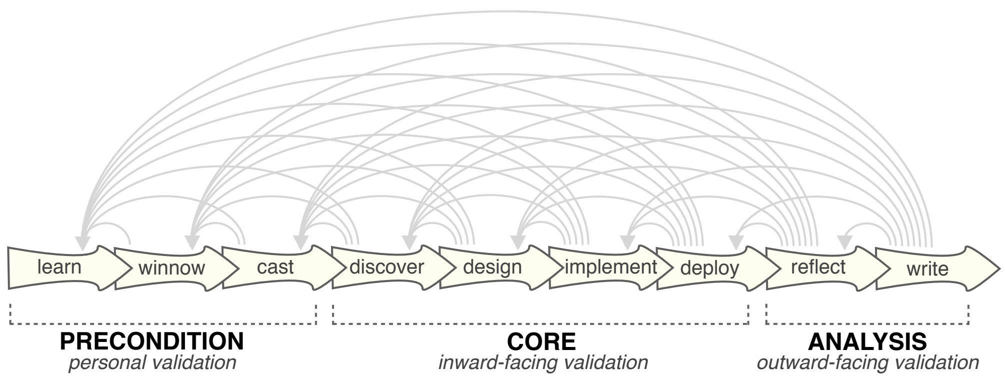
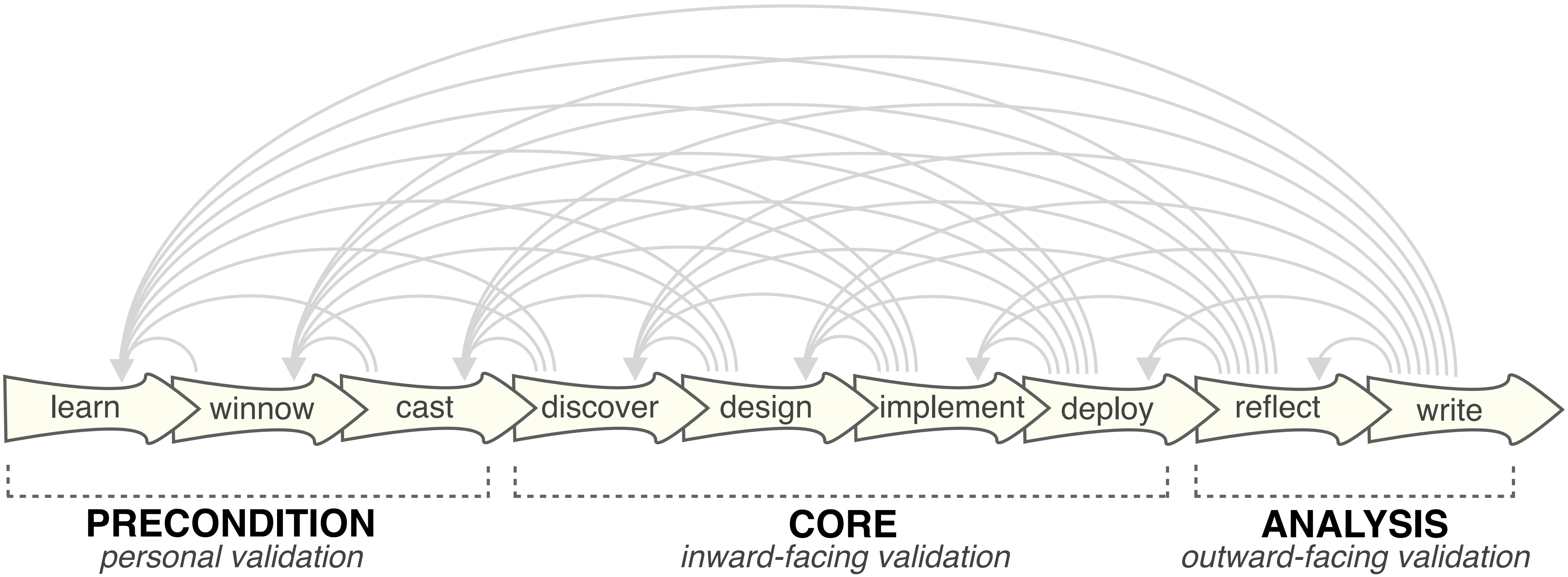


Design study methodology

Design study methodology



Sedlmair:2012

Design study definition

Design study papers explore the choices made when applying infovis techniques in an application area, for example relating the visual encodings and interaction techniques to the requirements of the target task. Although a limited amount of application domain background information can be useful to provide a framing context in which to discuss the specifics of the target task, the primary focus of the case study must be the infovis content. Describing new techniques and algorithms developed to solve the target problem will strengthen a design study paper, but the requirements for novelty are less stringent than in a Technique paper.

[InfoVis03 CFP, infovis.org/infovis2003/CFP]

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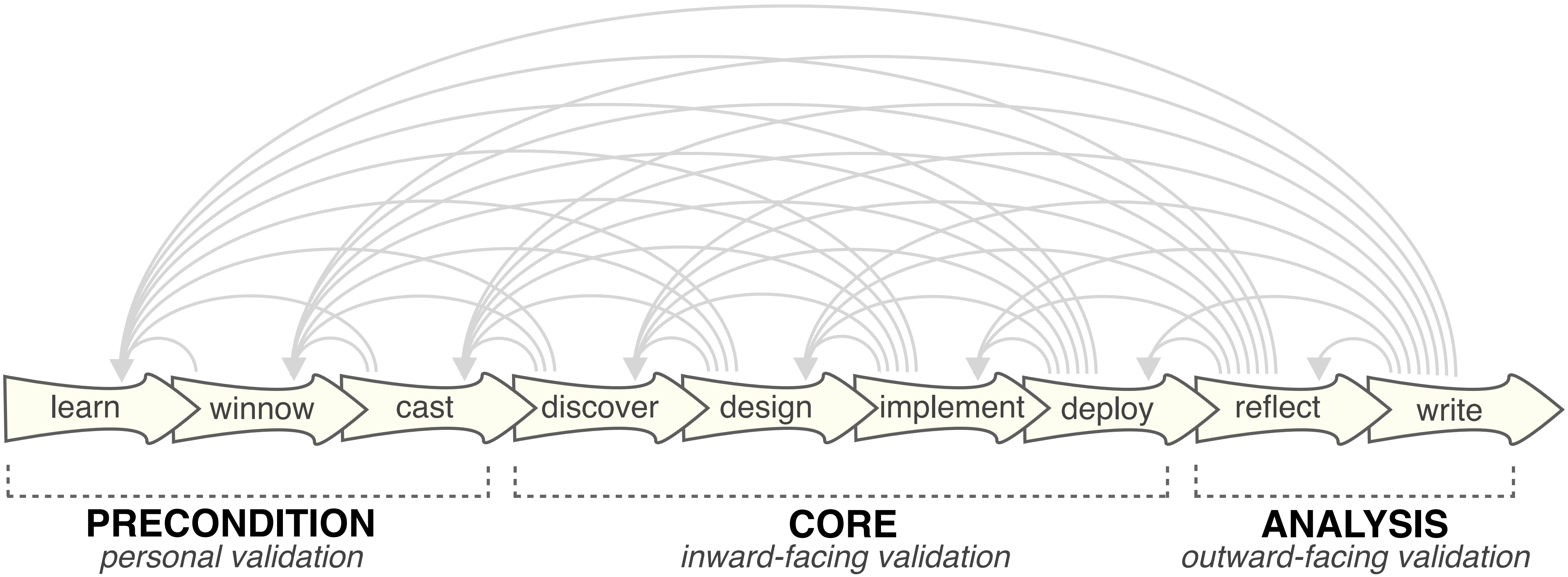

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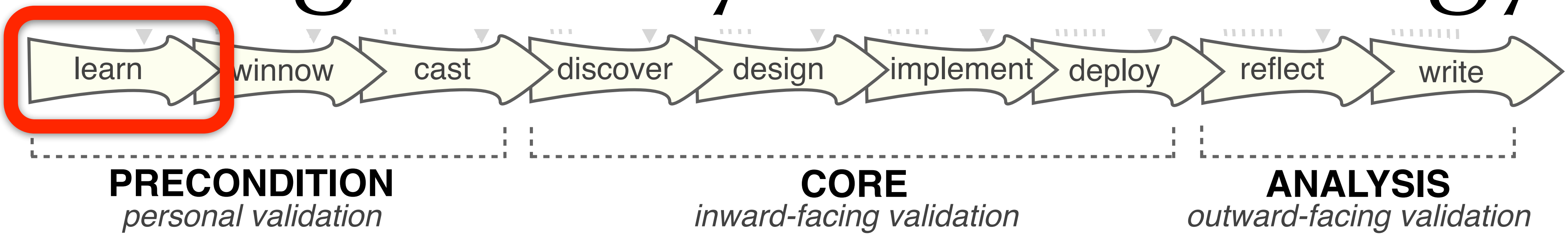
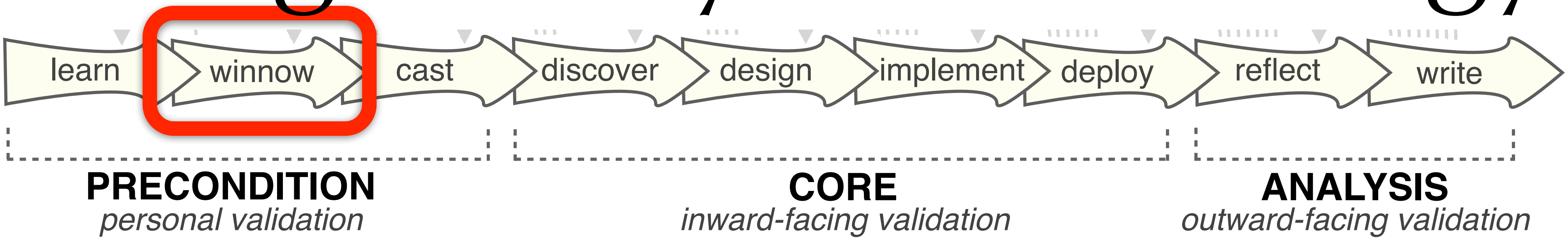


What tools/techniques are available?

- Read vis papers
- Read vis books
- Talk to vis practitioners

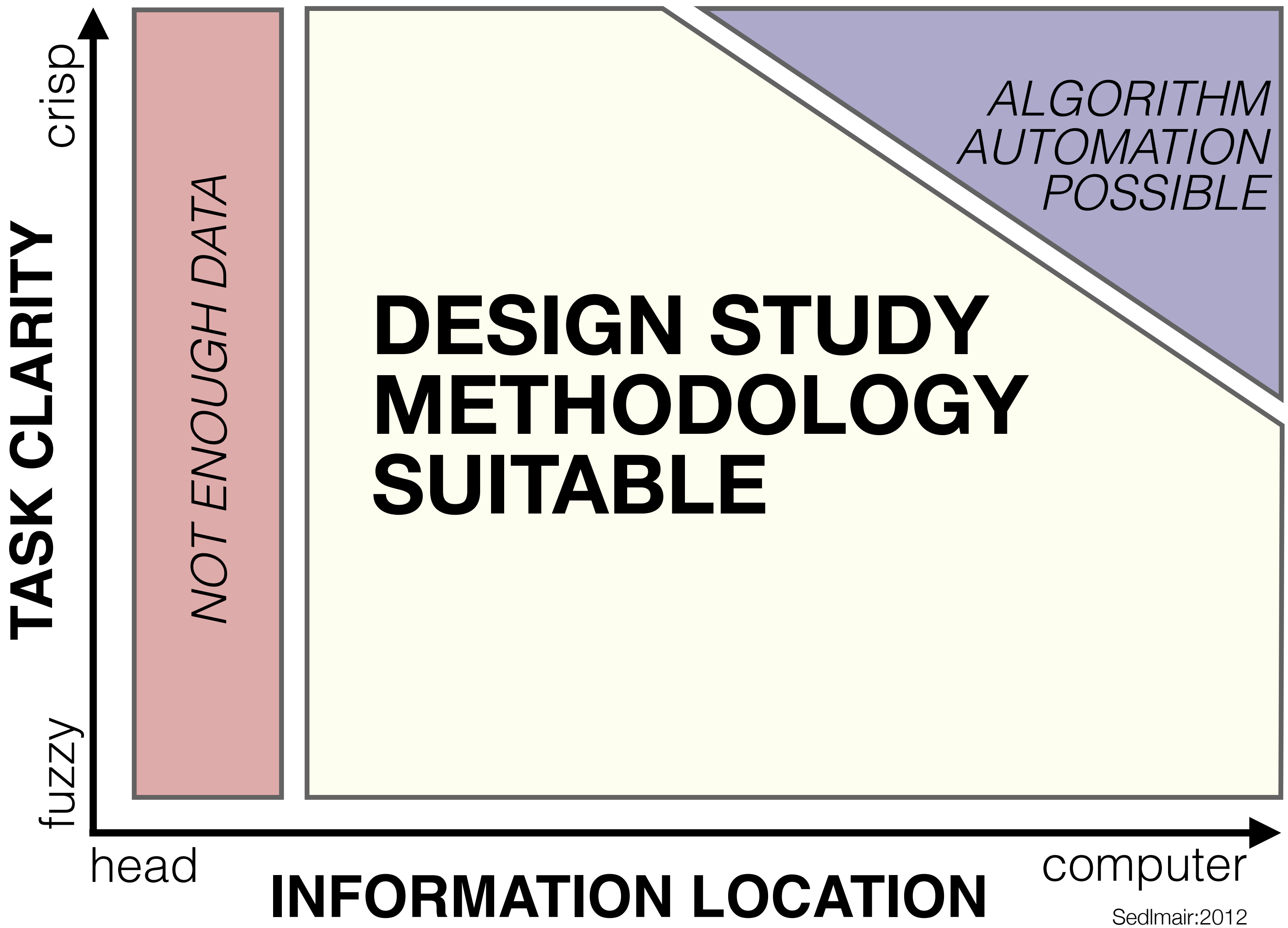
Design study methodology



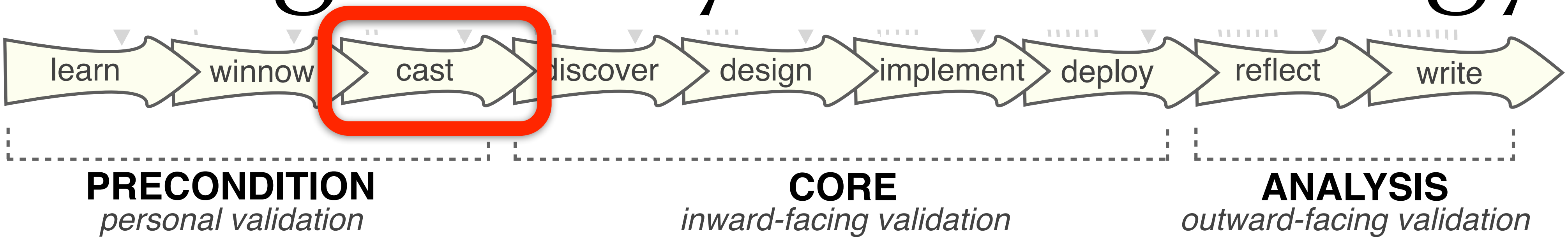
Are these good collaborators?

- Do they have interesting problems?
- Do they need novel solutions?
- Is there data?
- Can I work with these people?

When can you do a design study?



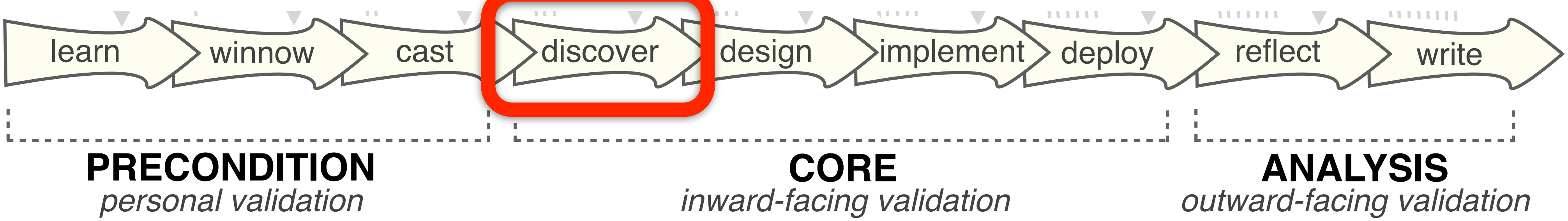
Design study methodology



Who's who?

- Do people have time for a new project?
- "Front-line analyst" is the domain expert
- Are there false "front-line analysts"?
- Do you need a "translator"?

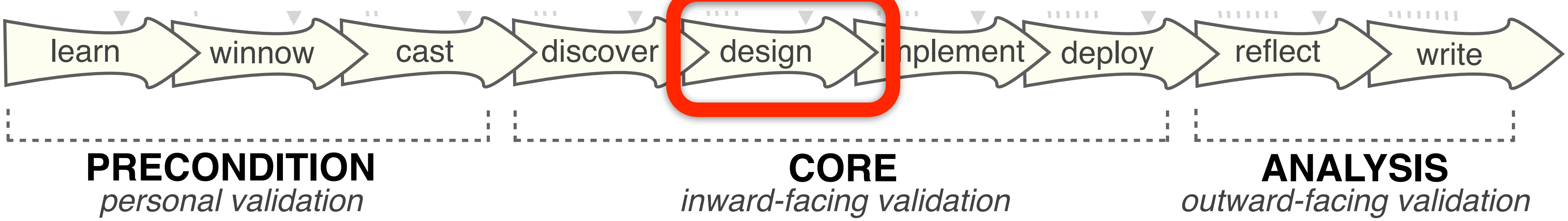
Design study methodology



Problem characterization and abstraction

- Requirements analysis
- Critical reflection on requirements!
- Abstraction is important for transferability
- Need some domain-expert knowledge

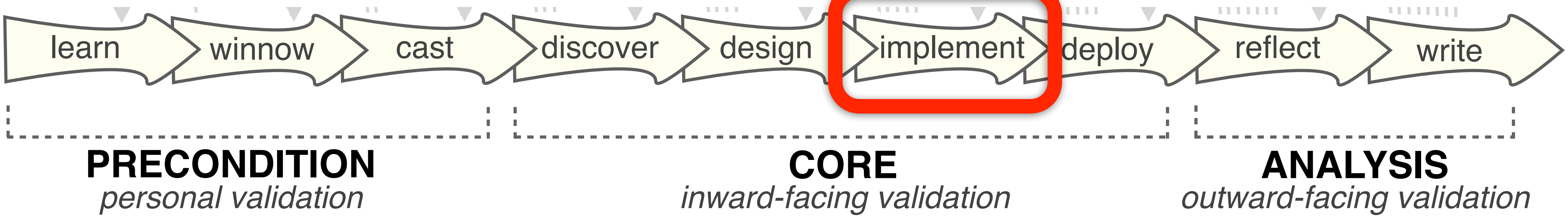
Design study methodology



Data abstraction, visual encoding, interaction

- What data transformations are needed?
- What visual designs to use?
- How to tie this together with interaction?
- Don't code!

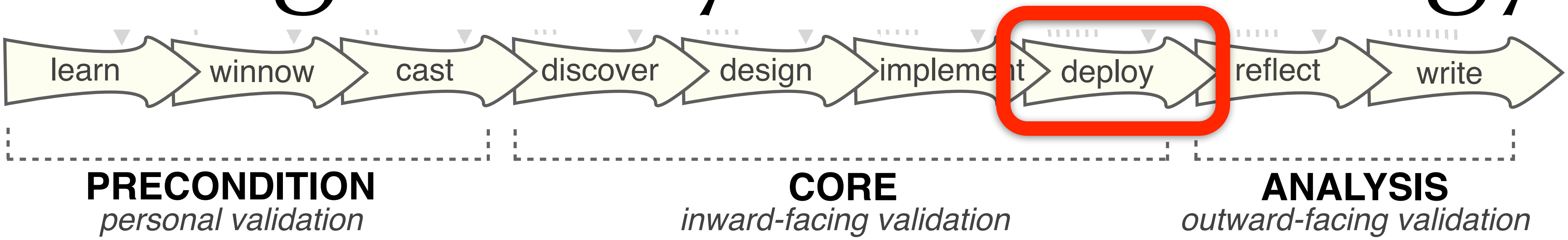
Design study methodology



Yay coding!

- Need to test design hypotheses
- Rapid prototyping (will probably throw away alot of code)
- Breaking bugs vs annoying bugs
- Fast usability testing

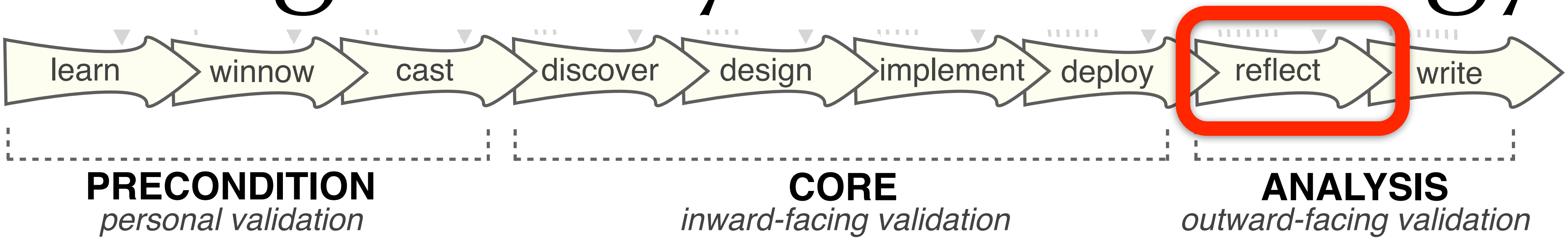
Design study methodology



Hand-off to the users

- Domain experts need to play with software
- What works, what doesn't?
- How to evaluate?
- May need to redesign/reimplement a lot

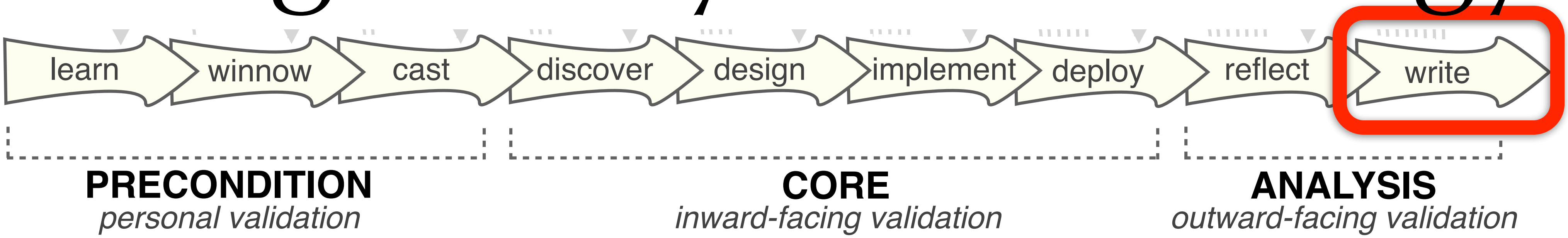
Design study methodology



Refine, reject, propose guidelines

- Compare to existing design guidelines
- Confirm which ones worked
- Reject which ones didn't work
- Come up with new guidelines

Design study methodology



Yay words!

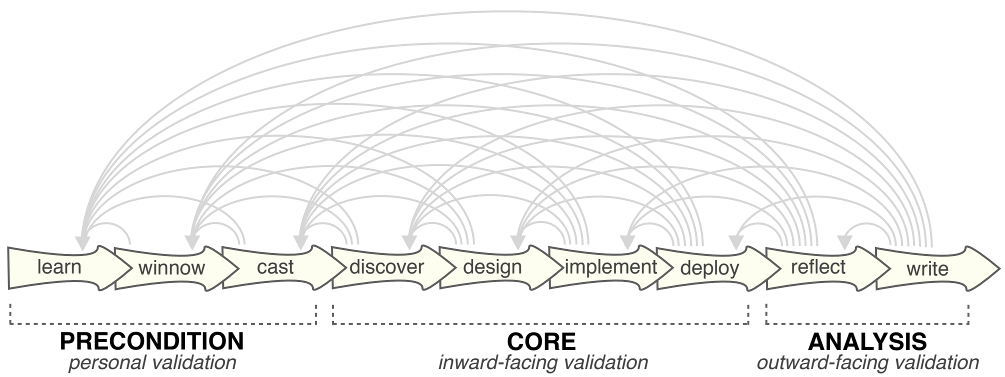
- Forces clear articulation of problem, tasks, solution
- Who else does my study help? - transferability!
- Think carefully about what readers will care about
- This takes time to do well!

Making the right tool

Questions

Data

Tasks



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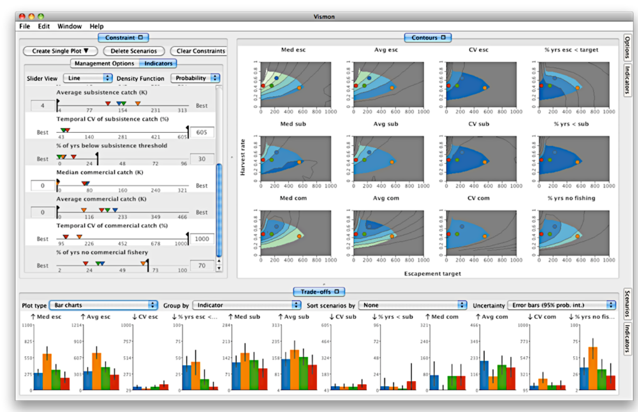

Where are design studies?

Domain situation
Observe target users using existing tools

Data/task abstraction

Visual encoding/interaction idiom
Justify design with respect to alternatives

Algorithm
Measure system time/memory
Analyze computational complexity

Analyze results qualitatively

Measure human time with lab experiment (*lab study*)

Observe target users after deployment (*field study*)

Measure adoption

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Pitfalls

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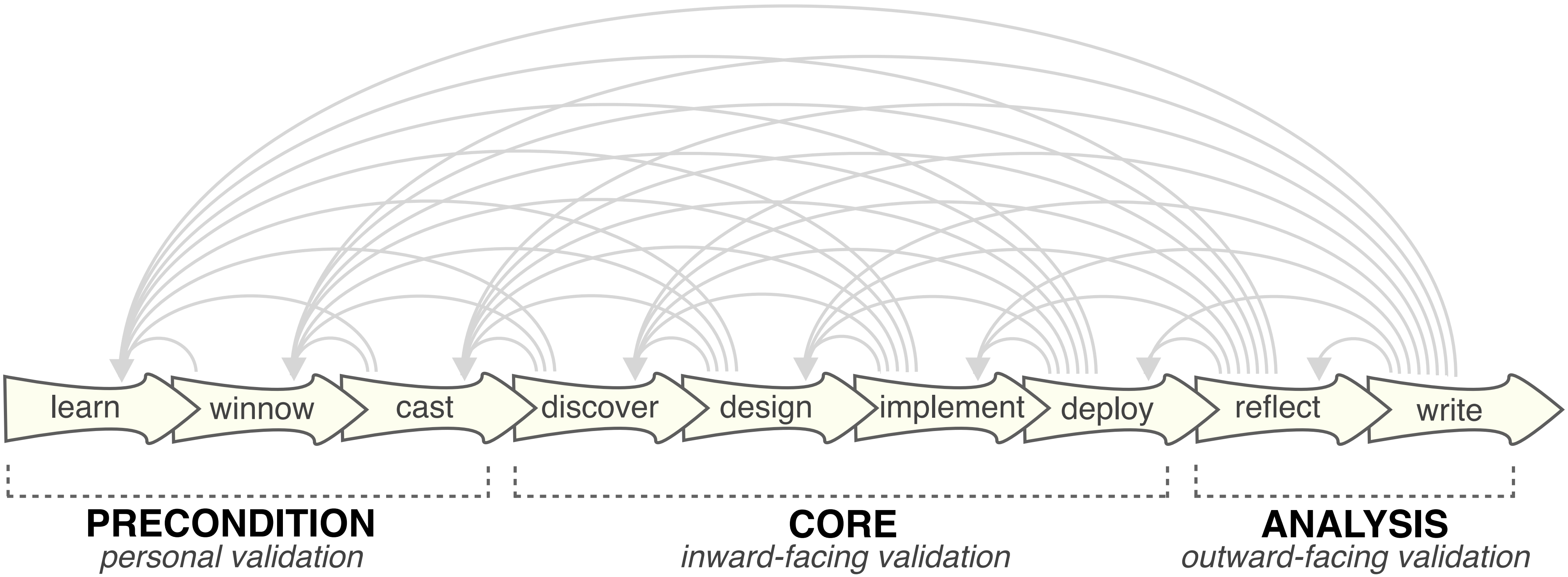
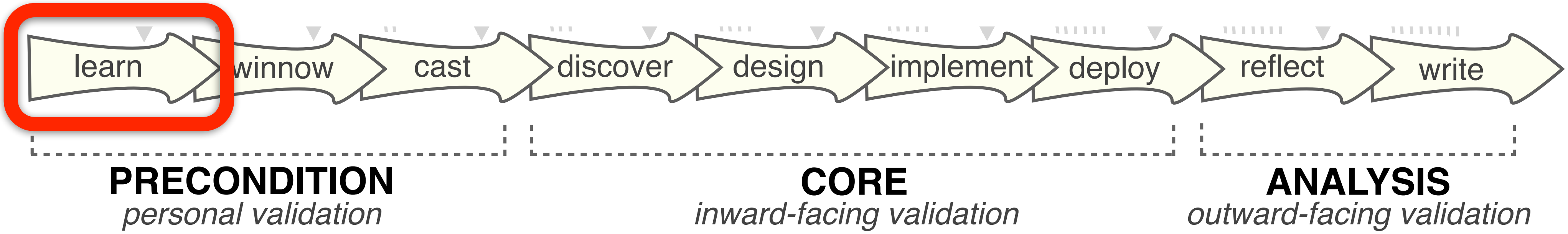


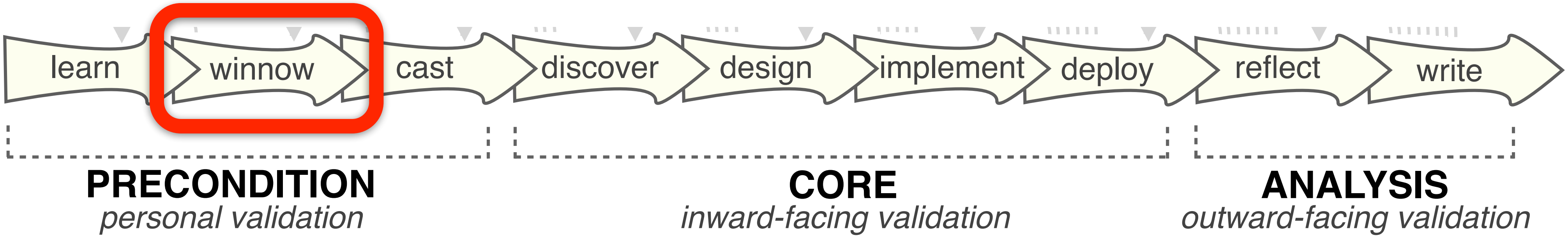
#1: Don’t skip steps!

Pitfalls



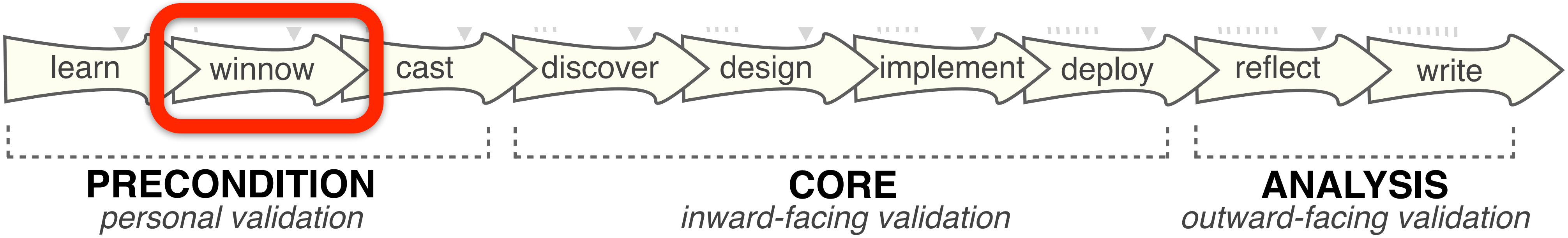
- insufficient knowledge of literature

Pitfalls



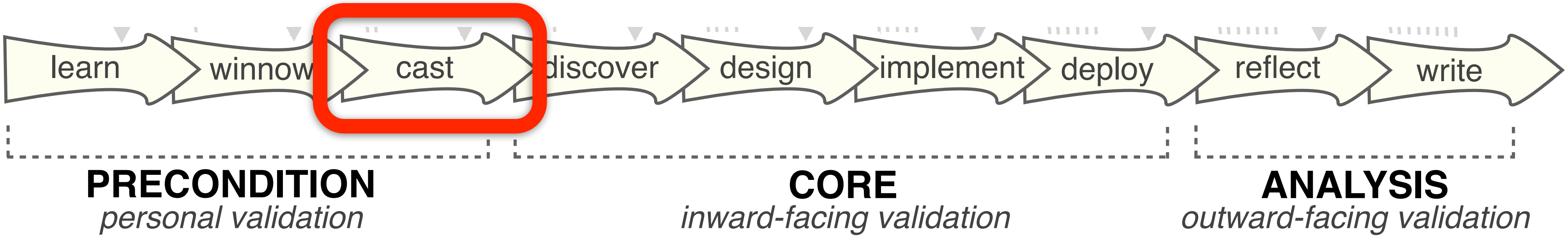
- collaboration with the wrong people
- **no real data available**
- insufficient time available from collaborators
- **no need for visualization: automate**
- no need for research: engineering project

Pitfalls



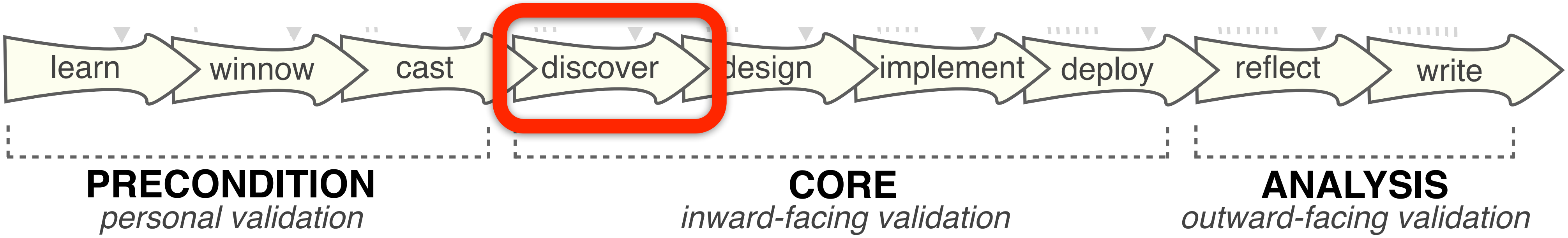
- **is this interesting to me?**
- existing tools are good enough
- **not an important/recurring task**
- no rapport with collaborators

Pitfalls



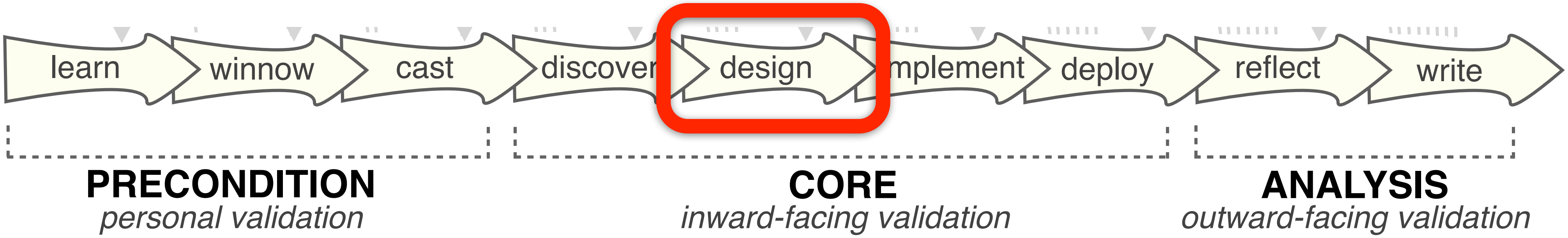
- **not identifying front-line analyst and gatekeeper**
- assuming same role distribution across projects
- mistaking tool-builders for real end users

Pitfalls



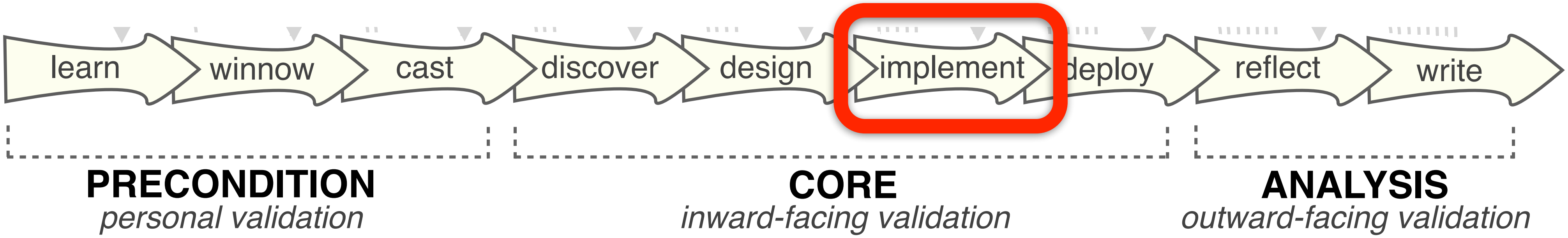
- **ignoring practices that currently work well**
- **expecting *just talking* or *fly on the wall* to work**
- **domain experts design the visualizations**
- too much/too little domain knowledge

Pitfalls



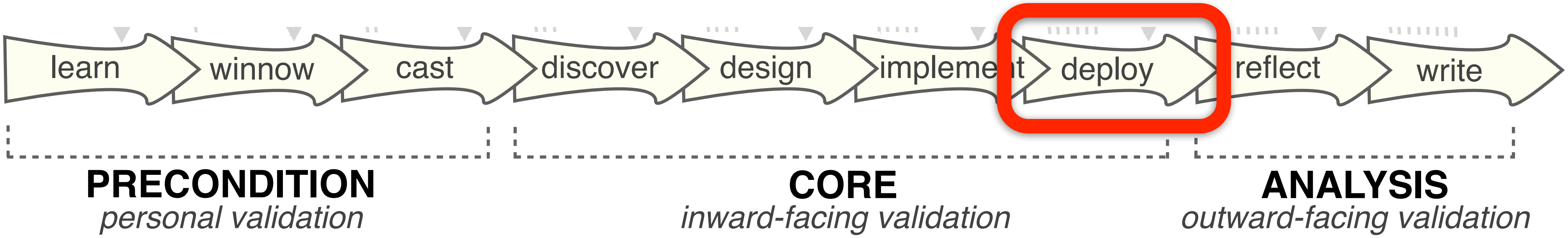
- too little abstraction
- **design consideration space too small**
- mistaking technique-driven and problem-driven work

Pitfalls



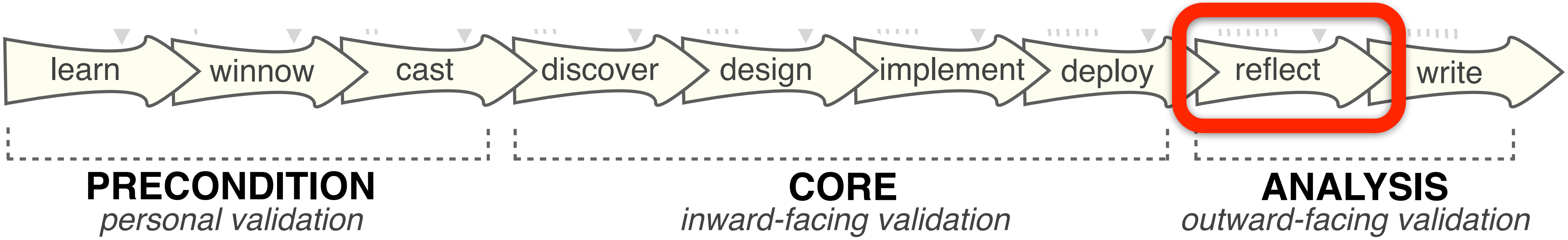
- **non-rapid prototyping**
- **usability: too little/too much**

Pitfalls



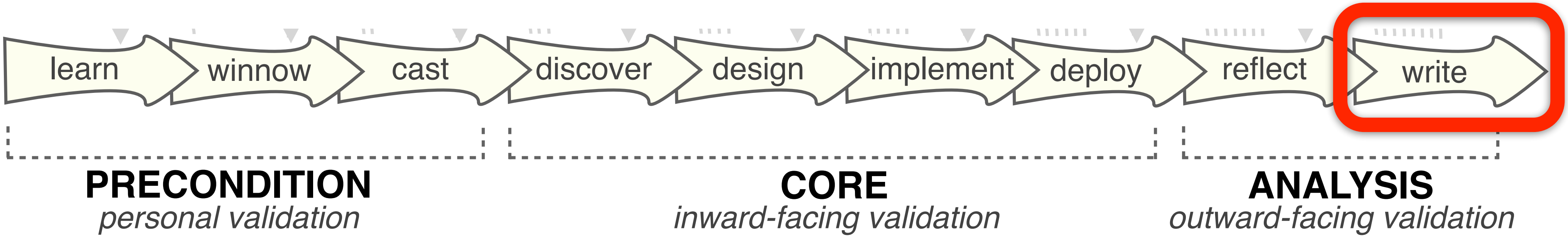
- **insufficient deploy time**
- non-real task/data/user
- *liking* a tool is not validation!

Pitfalls



- failing to improve guidelines

Pitfalls



- **not enough writing time**
- **no technique contribution ≠ write a design study**
- too much domain background
- chronological story vs concentrating on results
- **premature end to the project**

Vismon

1: Diverging	2: Converging	3: Deployment
early 2009	mid 2010	April 2012

- three stage process

Vismon

1: Diverging | 2: Converging | 3: Deployment

early 2009 | mid 2010 | April 2012

- Phase 1 - diverging phase
  - many data sketches (Lloyd+Dykes, 2011)
  - iterative formative testing (18 months)
  - close involvement of one scientist

Vismon

1: Diverging 2: Converging 3: Deployment

early 2009 mid 2010 April 2012

- Phase 2 - converging design
  - cognitive walkthrough
  - redesigned interface for usability
  - confirmed usability + utility with five scientists

Vismon

1: Diverging 2: Converging 3: Deployment

early 2009 mid 2010 April 2012

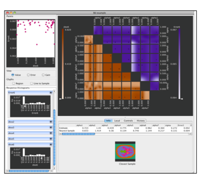
- Phase 3 - deployment
  - fall 2011: demo to 40 research biologists and high-level fisheries managers in Alaska
  - may 2012: training workshop for 14 managers in Alaska

Abstraction: (visual) Parameter space exploration (vPSA)

Other tools

Much recent attention in vPSA

- Image segmentation [Torsney Weir et al. 2011]
- Weather forecast [Potter et al. 2009]
- Disaster simulation [Waser et al. 2010]
- many more …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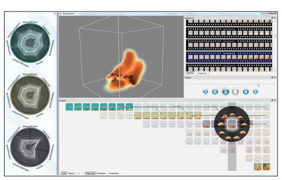
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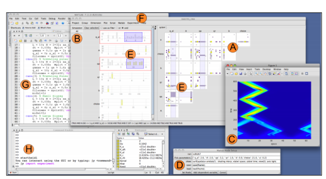
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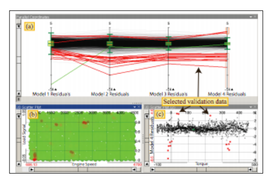
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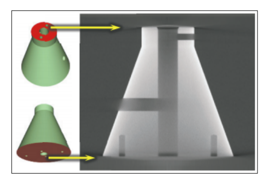
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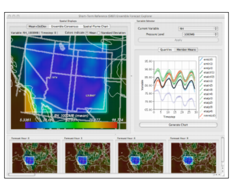
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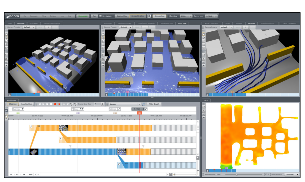
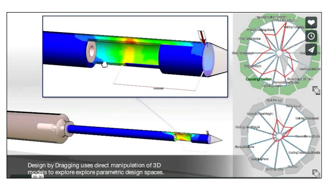
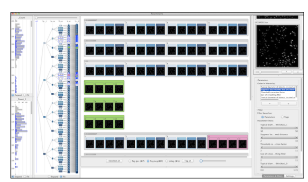

[Waser et al. 2010]


[Coffey et al. 2013]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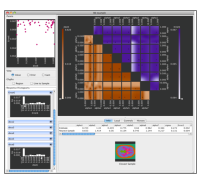
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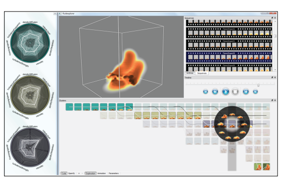
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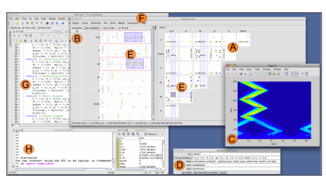
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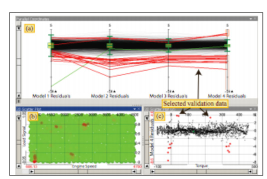
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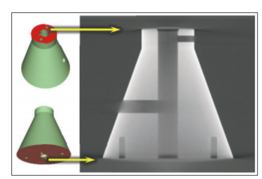
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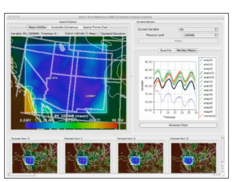
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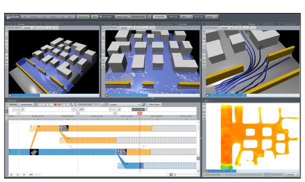
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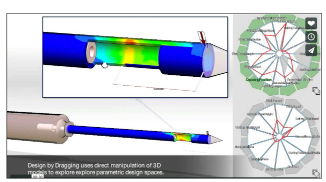
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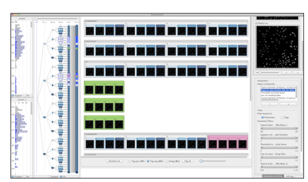
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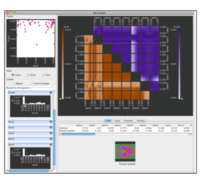
…etc.

Much recent attention in vPSA

- Image segmentation [Torsney Weir et al. 2011]
- **Weather forecast [Potter et al. 2009]**
- Disaster simulation [Waser et al. 2010]
- many more …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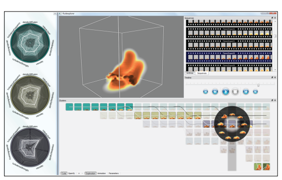
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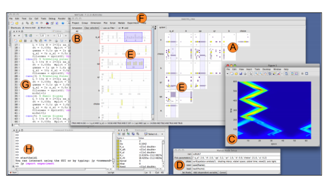
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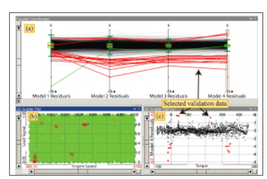
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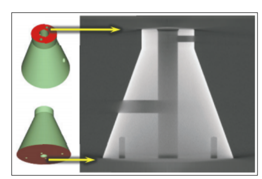
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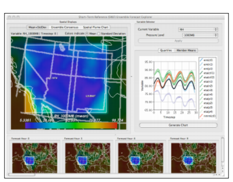
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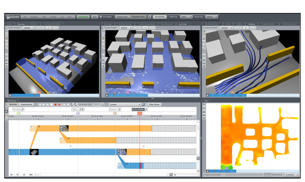
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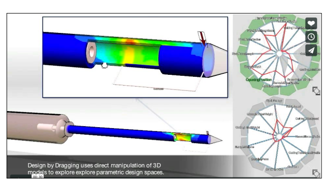
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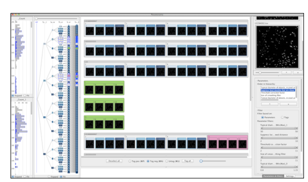
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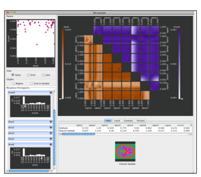
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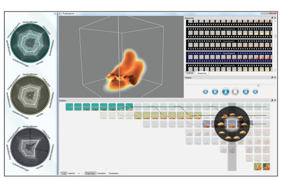
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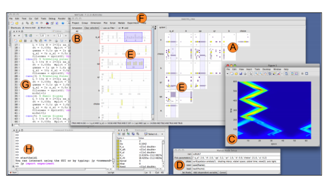
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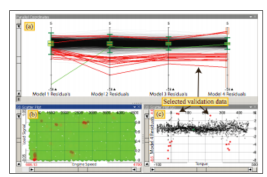
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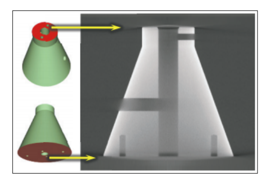
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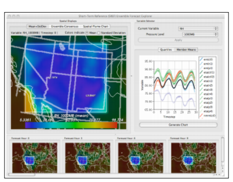
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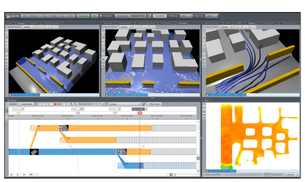
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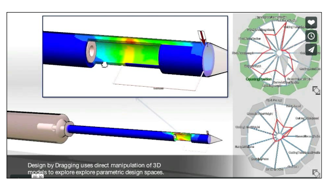
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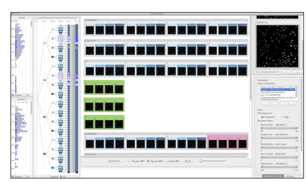
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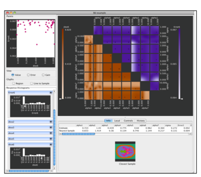
...etc.

Much recent attention in vPSA

- comprehensive study of 21 different tools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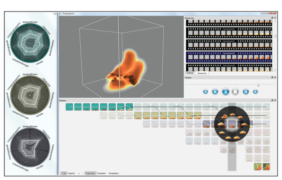
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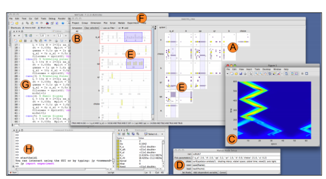
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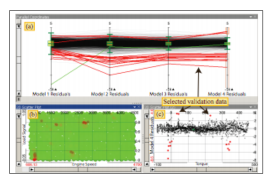
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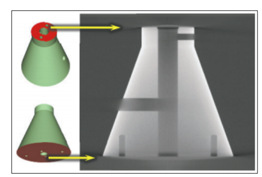
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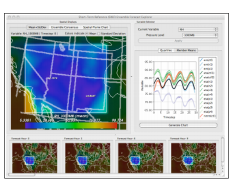
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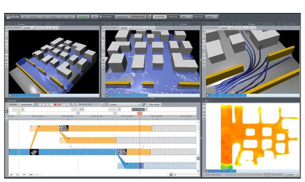
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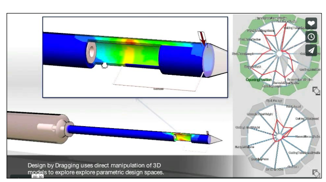
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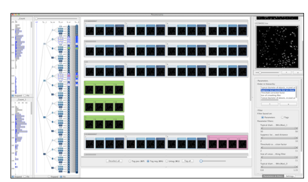
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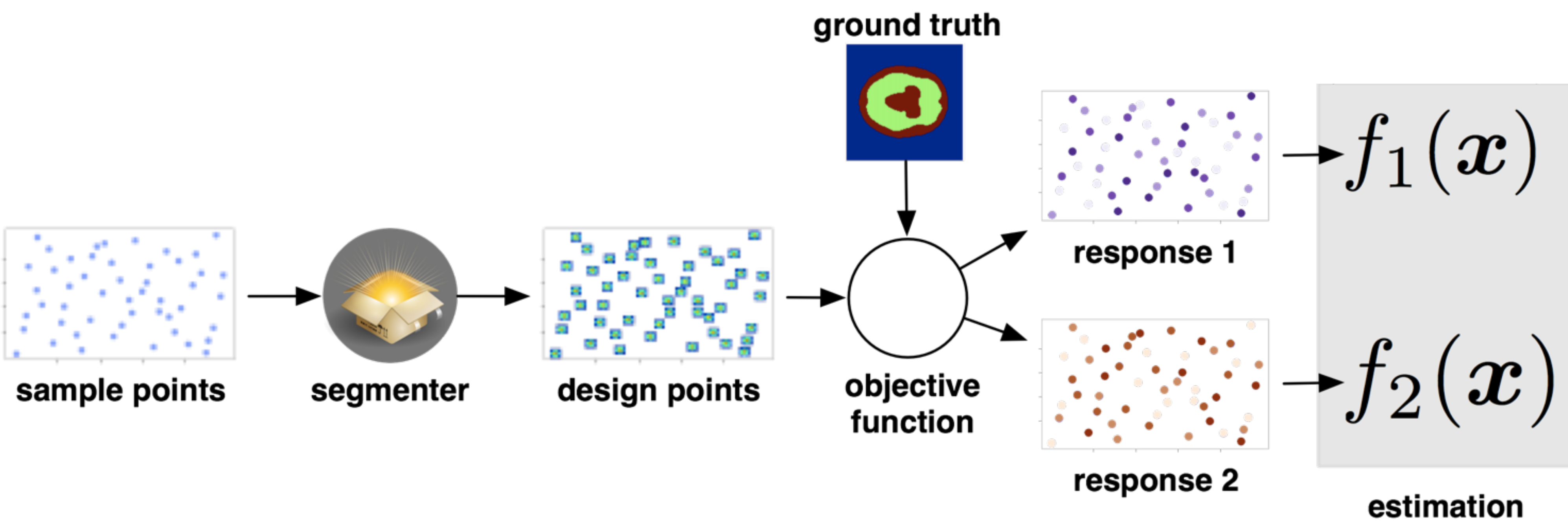
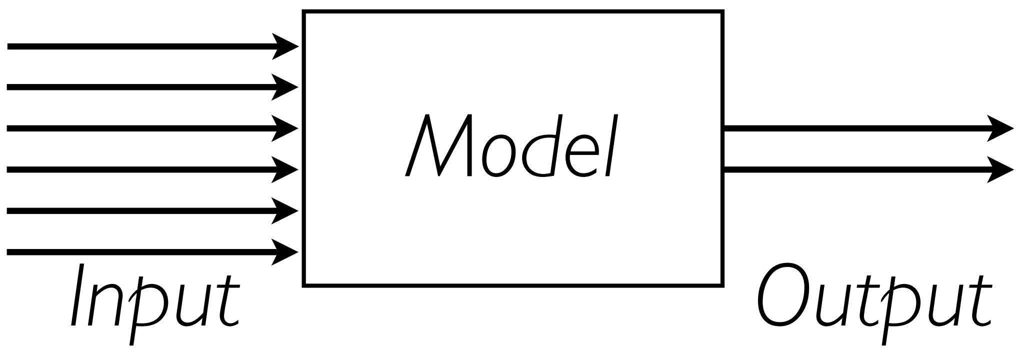
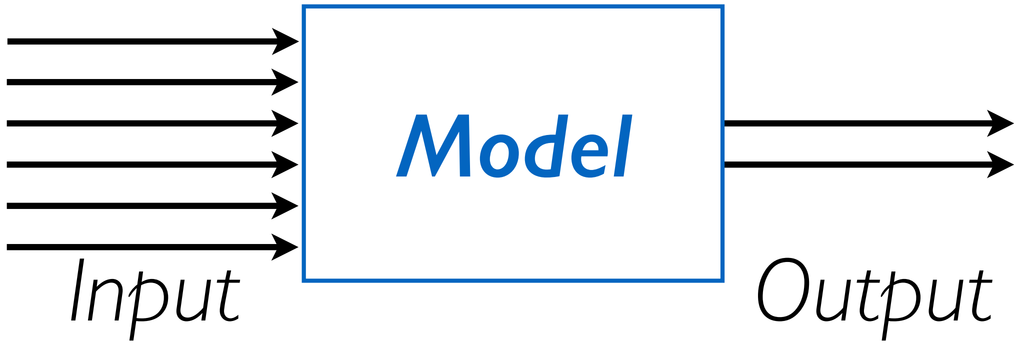
…etc.

Data Flow Model

Build an estimator

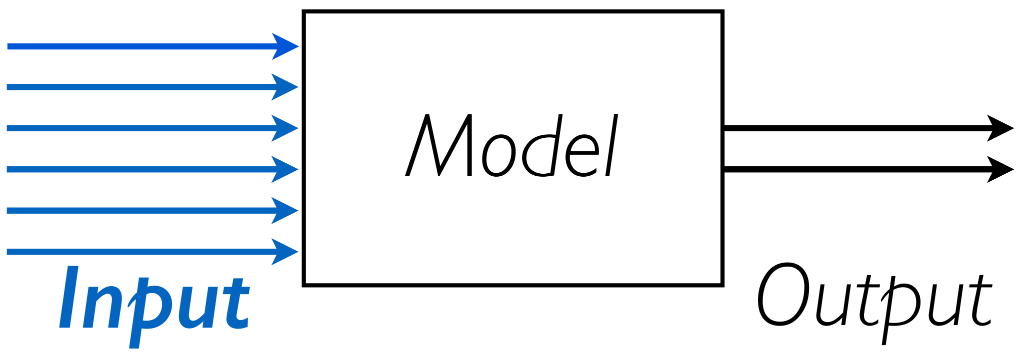



Model
Input
Output



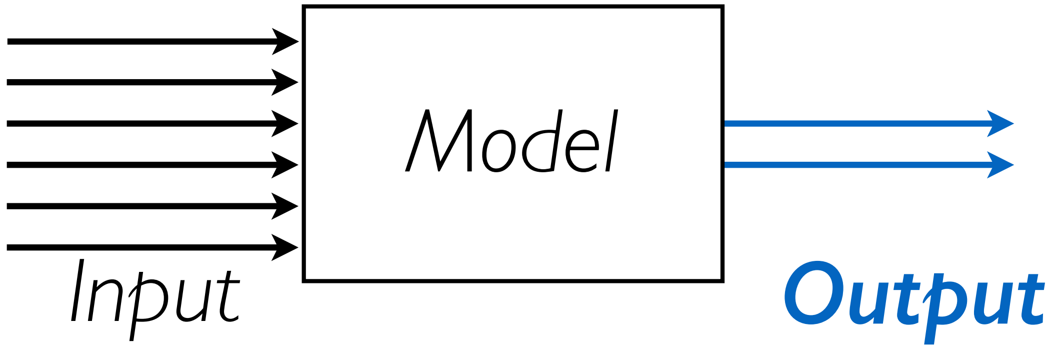
Model

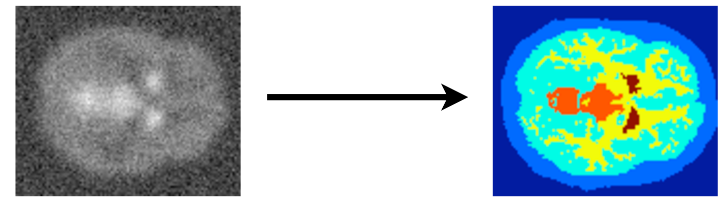
- simulation model, prediction model, …
- … but also algorithm
- stochastic, deterministic
- usually black box (to us as Vis researchers)



Inputs

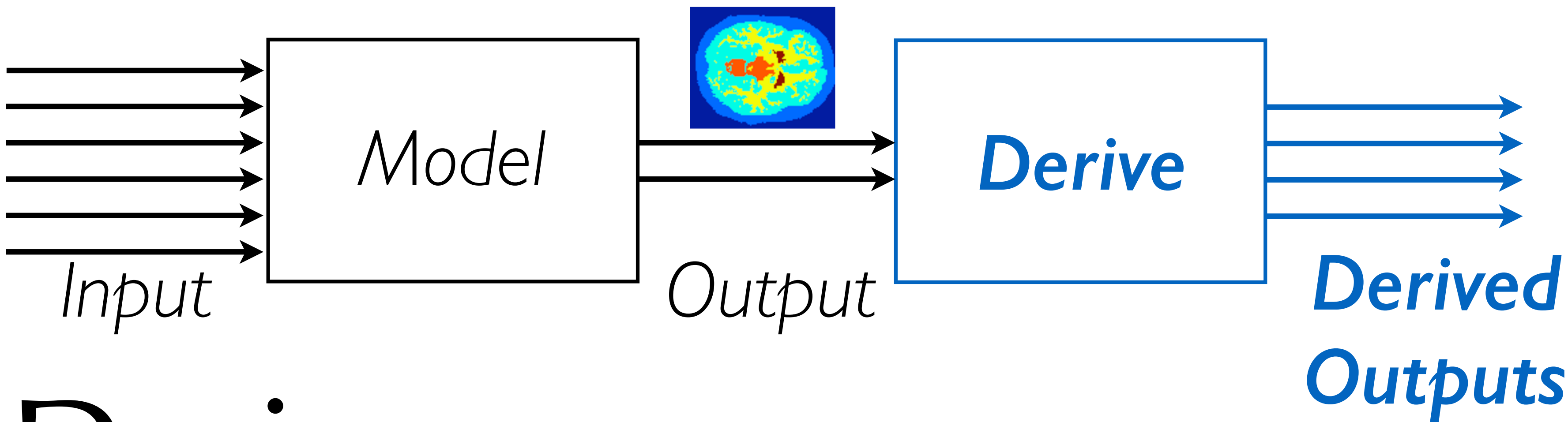
- well chosen by the scientist, i.e. people care about their inputs
- normally continuous (quantitative data)
  - need to sample the space
- categorical data common too (e.g. use of a different algorithm)





Outputs

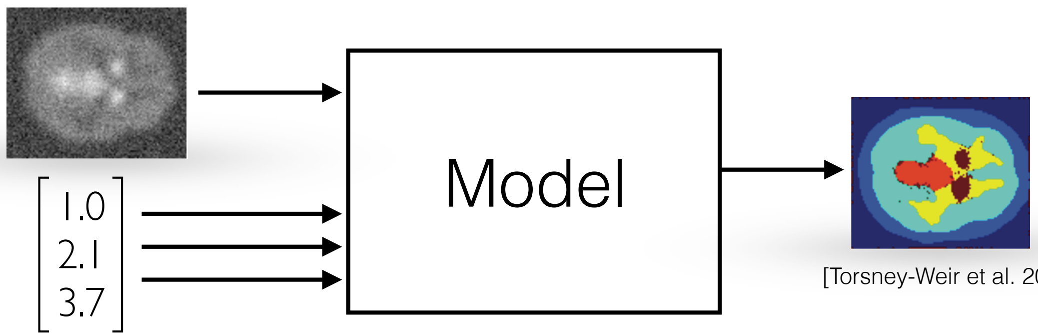
- typically complex objects, e.g.
  - 2D, 3D images (Tuner)
  - animations (FluidExplorer)
  - performance graphs (fuel cells)
- hard to evaluate / compare many complex outputs



Derive

- one-dimensional ("goodness") rating: $d(O_1)$
- two-dimensional comparison: $d(O_1, O_2)$
- objective measures can be
  - exact (reliable)
  - approximate - about right, but not 100% precise
  - unknown (active learning)

Complex objects (in 18/21 papers)



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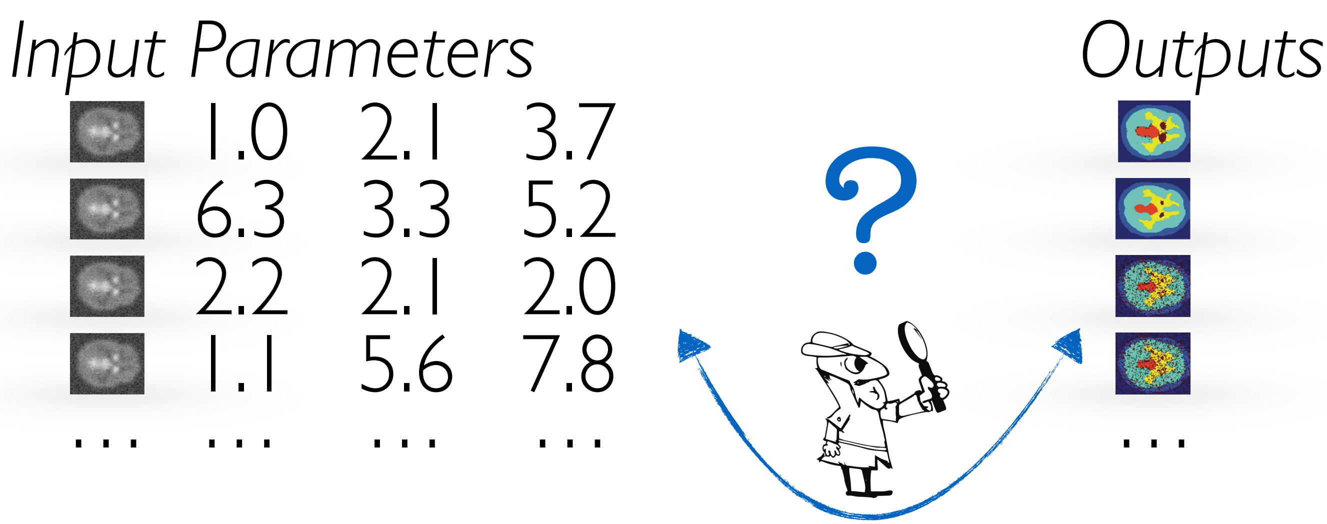
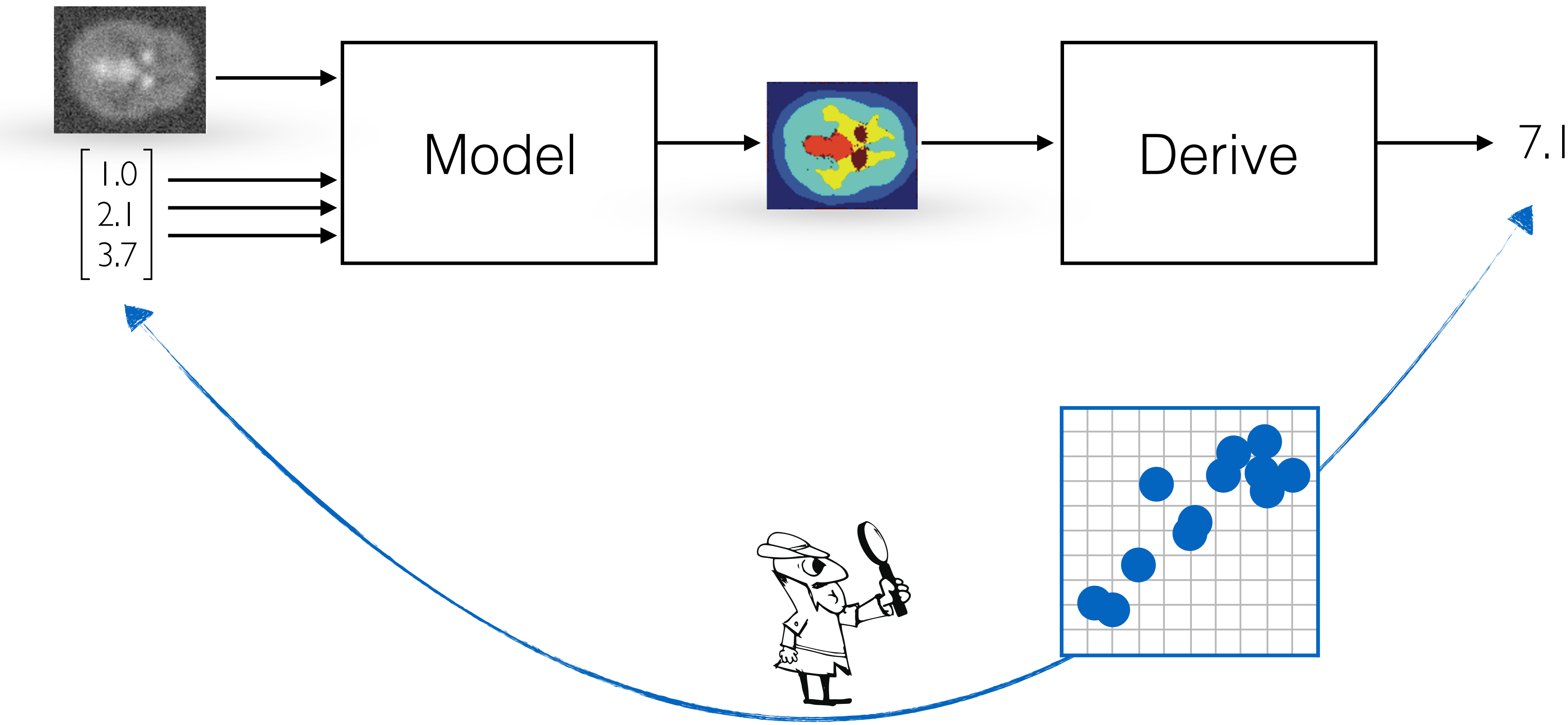
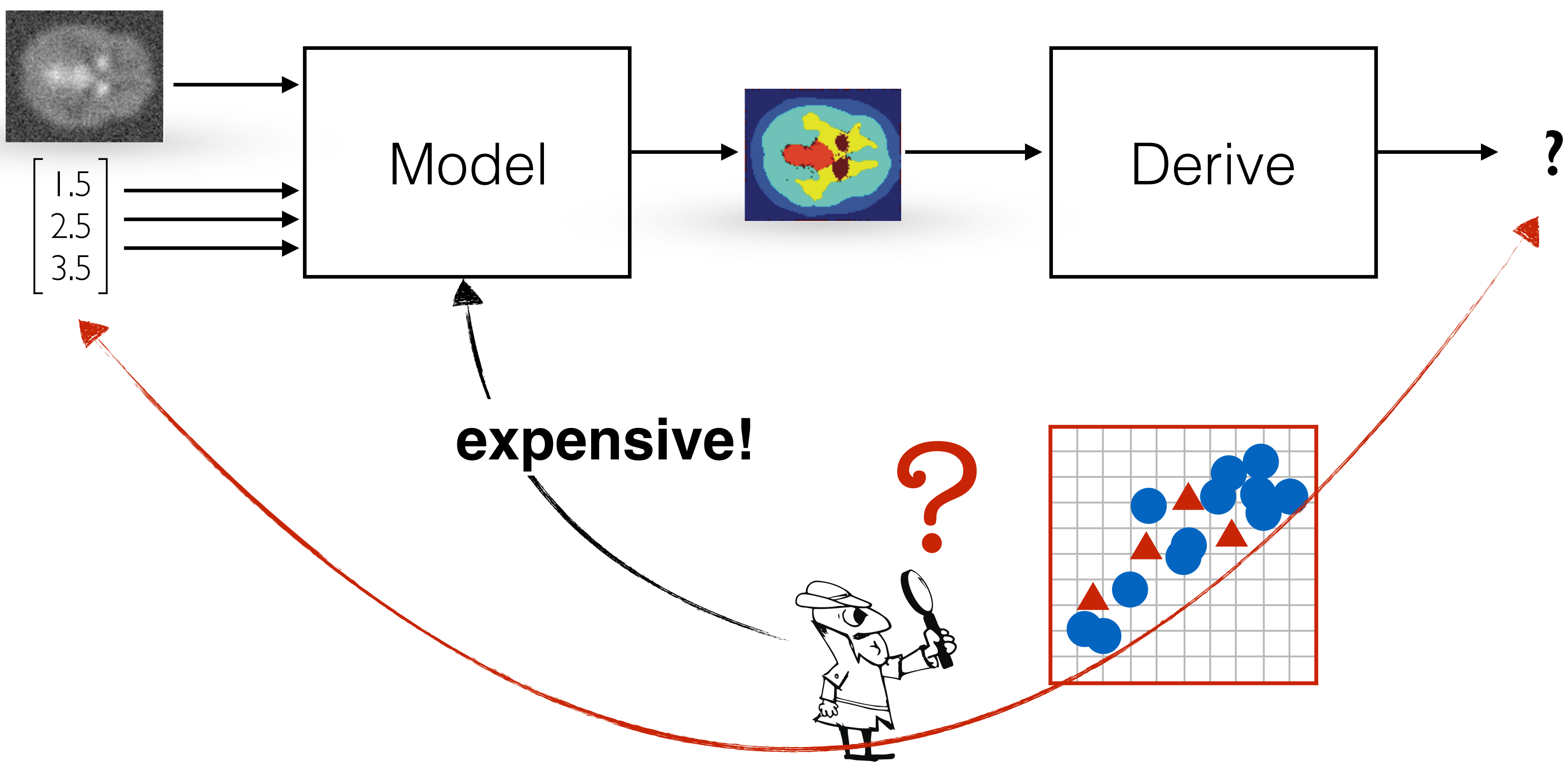


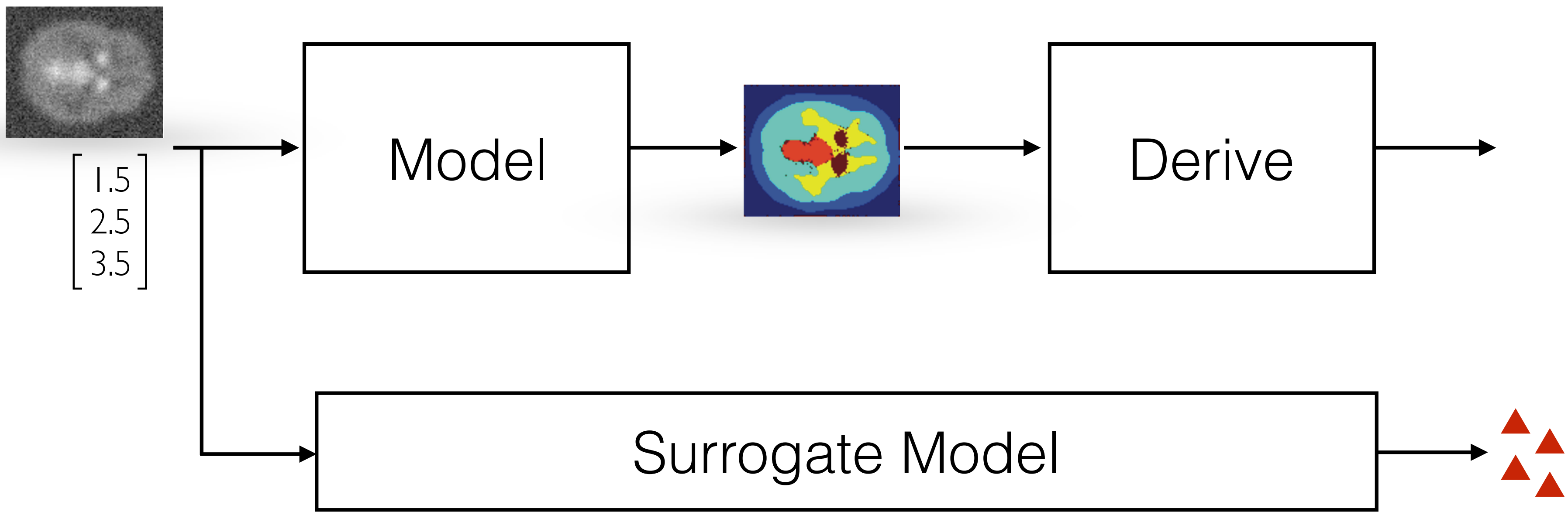
Derive objective measures



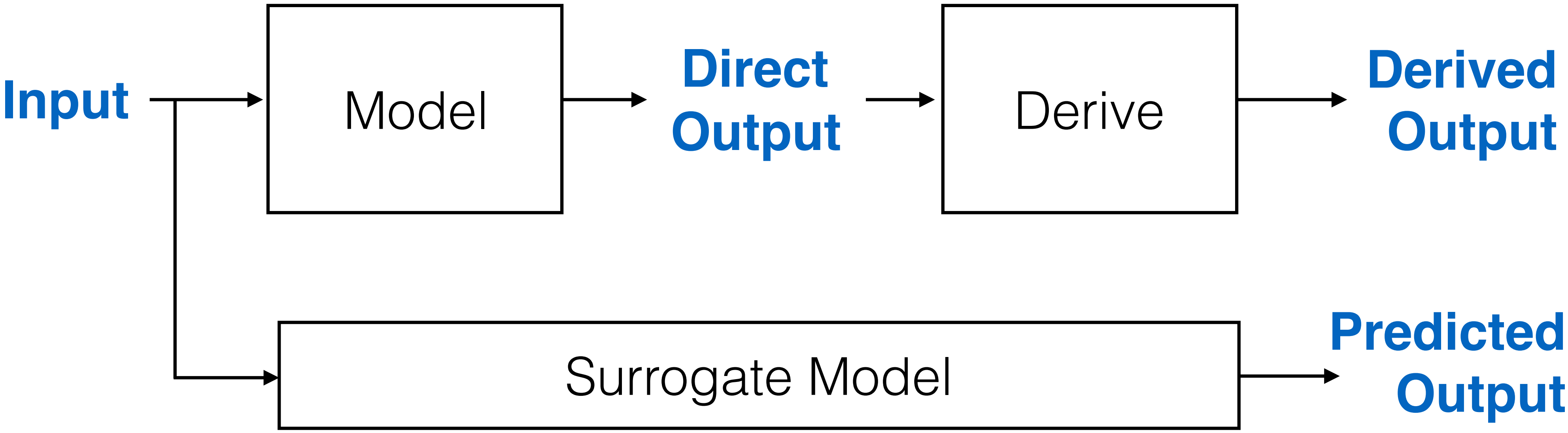
Surrogate models



Surrogate models



Data flow model



Navigation Strategies

Navigation strategies

- Trial and error (traditional approach)

Navigation strategies

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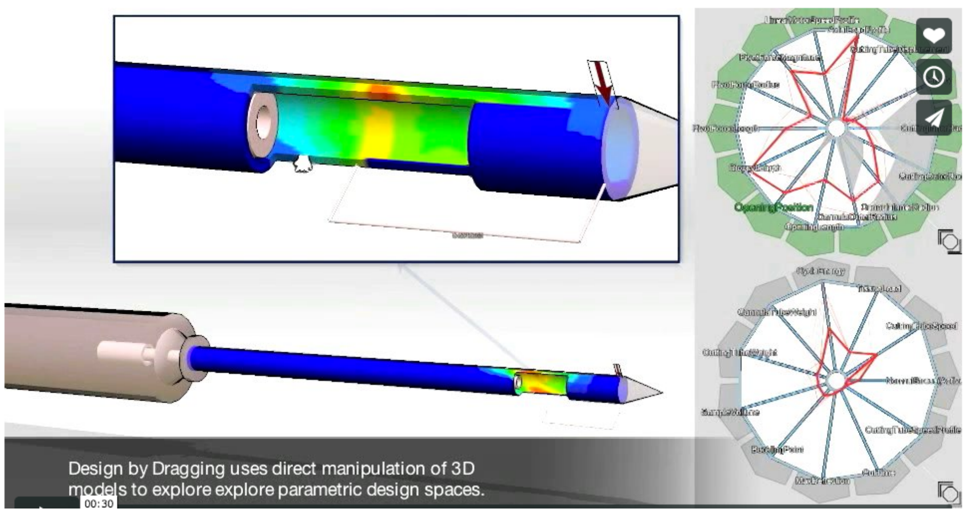
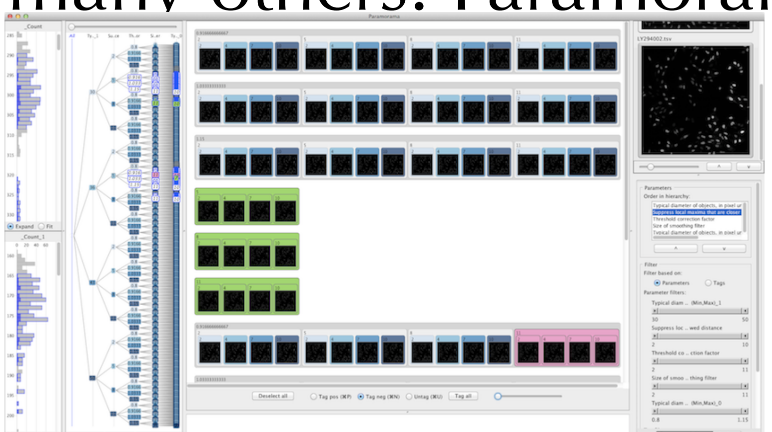
- Local —> global tweaking



Design by Dragging
[Coffey et al., SciVis 2013]

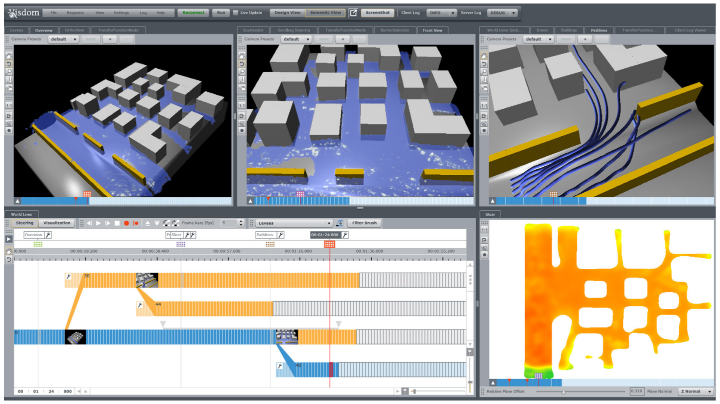
Navigation strategies

- Trial and error (traditional approach)
- Local —> global tweaking
- Global —> local exploration
  - FluidExplorer, Vismon, Tuner
  - many others: Paramorama [Pretorius et al., InfoVis 2011]



Navigation strategies

- Trial and error (traditional approach)
- Local —> global tweaking
- Global —> local exploration
- Steering
  - simulation steering: e.g. real-time simulators
  - computational steering: e.g. change the grid size, stop if no insight



World Lines
[Waser et al., Vis 2010]

Analysis Tasks

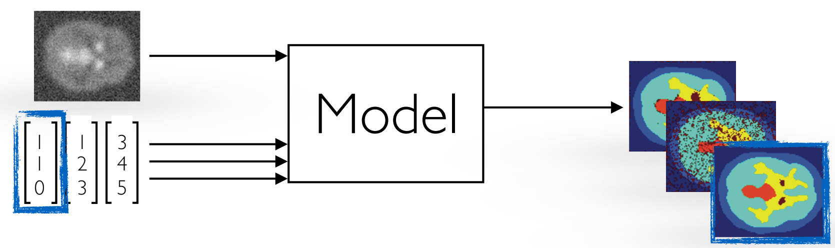
Analysis tasks

- Optimization
- Partitioning
- Fitting
- Outliers
- Uncertainty
- Sensitivity

Analysis tasks

- **Optimization**
- Partitioning
- Fitting
- Outliers
- Uncertainty
- Sensitivity

Find the best parameter combination given some objectives.

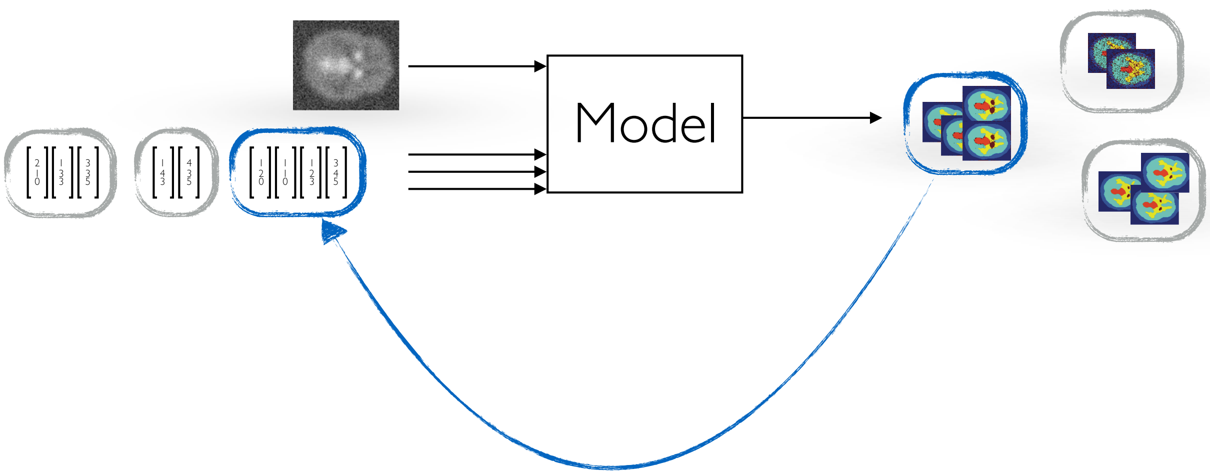


in 19/21 papers

Analysis tasks

- Optimization
- **Partitioning** **aka clustering**
- Fitting
- Outliers
- Uncertainty
- Sensitivity

How many different types of model behaviors are possible?

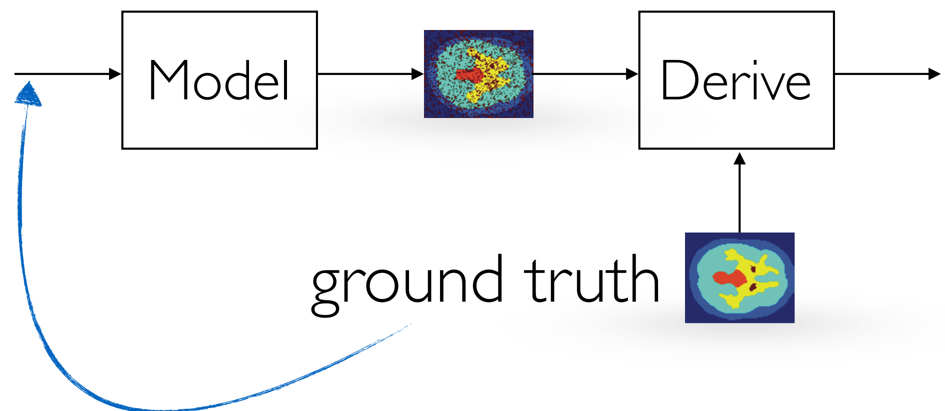


in 6/21 papers

Analysis tasks

- Optimization
- Partitioning
- **Fitting** **aka regression analysis**
- Outliers
- Uncertainty
- Sensitivity

Where in the input parameter space would actual measured data occur?

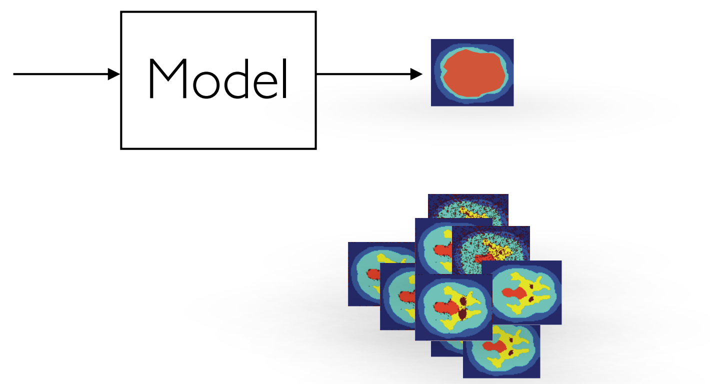


in 9/21 papers

Analysis tasks

- Optimization
- Partitioning
- Fitting
- **Outliers**
- Uncertainty
- Sensitivity

What outputs are special?

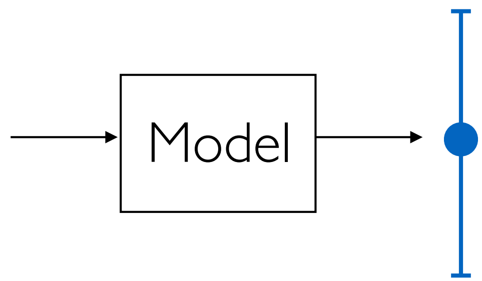


in 9/21 papers

Analysis tasks

- Optimization
- Partitioning
- Fitting
- Outliers
- **Uncertainty**
- Sensitivity

How reliable is the output?



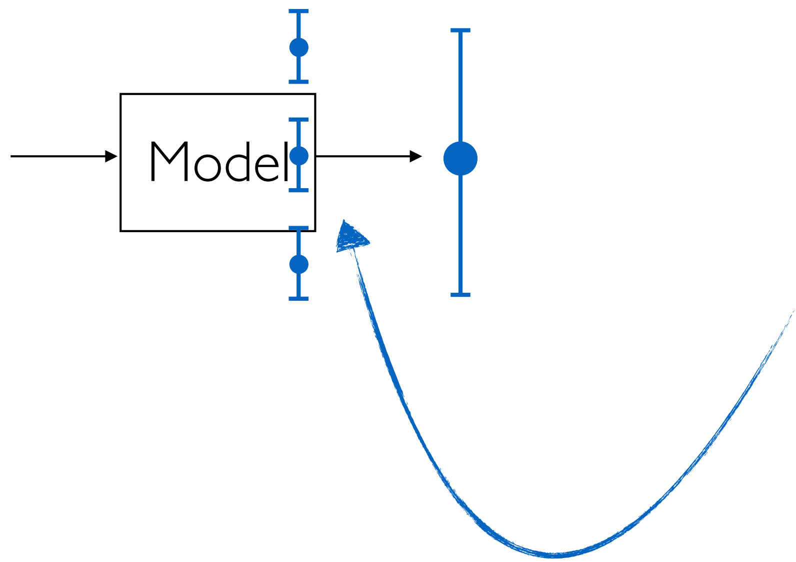
- model vs. reality
- non-deterministic model
- model vs. surrogate

in 7/21 papers

Analysis tasks

- Optimization
- Partitioning
- Fitting
- Outliers
- Uncertainty
- **Sensitivity**

What ranges/variations of outputs to expect with changes of input?



in 14/21 papers

Visual Data Science

Overview

- Data Science is all about modelling
- The three types of modelling
    - Computational modelling
    - Statistical modelling
    - Empirical modelling
- Challenges of Visual Data Science
- Conclusions

What is data science?

- Dhar 2013: “Data Science is the study of the generalizable extraction of knowledge from data.”

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http://simplystatistics.org/2013/12/12/the-key-word-in-data-science-is-not-data-it-is-science/

Data Science

- Jeff Leek: “The key word in ‘Data Science’ is not Data, it is Science”

> “The issue is that the hype around big data/ data science will flame out (it already is) if data science is only about "data" and not about "science". The long term impact of data science will be measured by the scientific questions we can answer with the data.”

Overview

- Data Science is all about modelling
- The three types of modelling
  - Computational modelling
  - Statistical modelling
  - Empirical modelling
- Challenges of Visual Data Science
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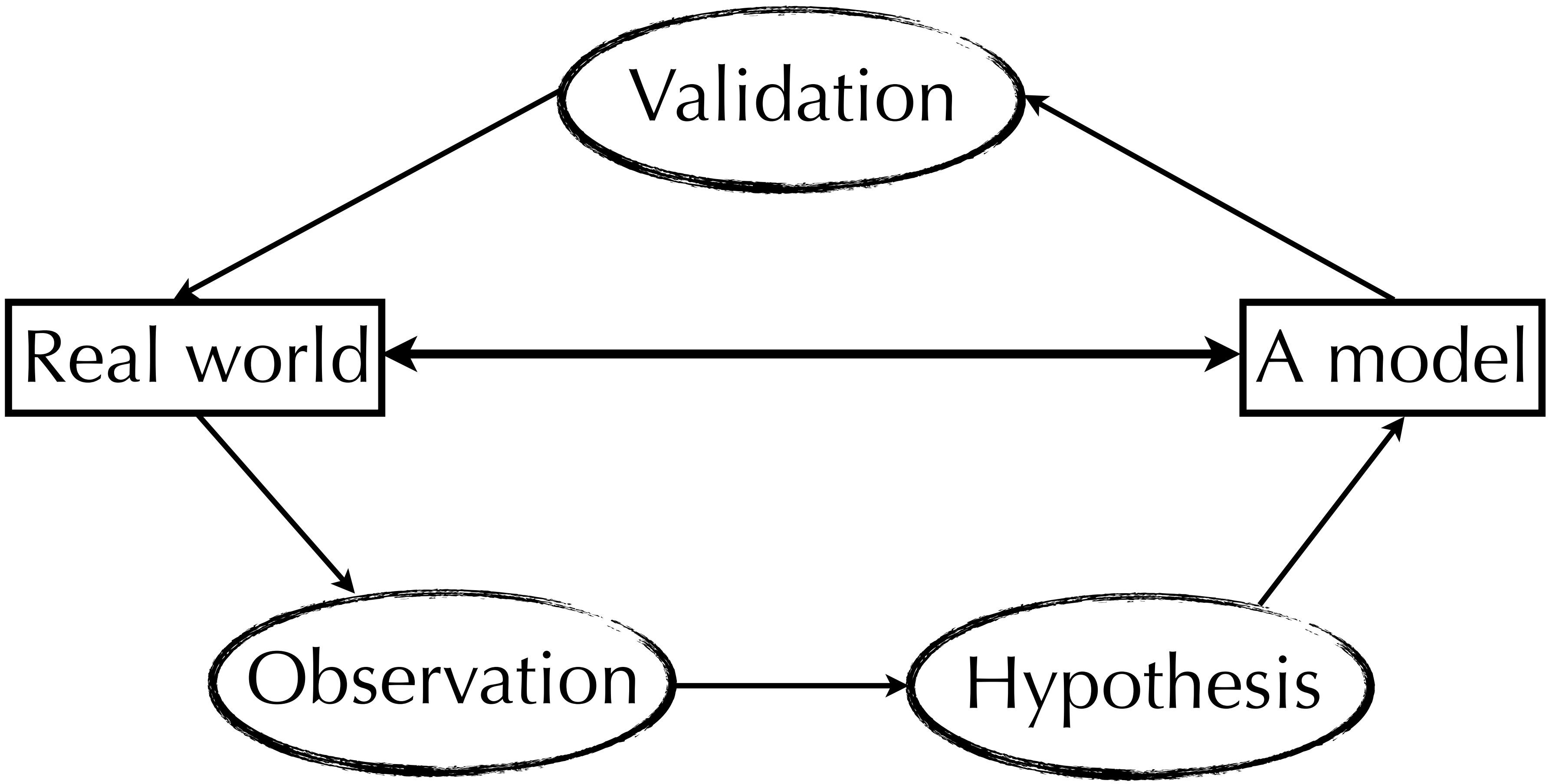
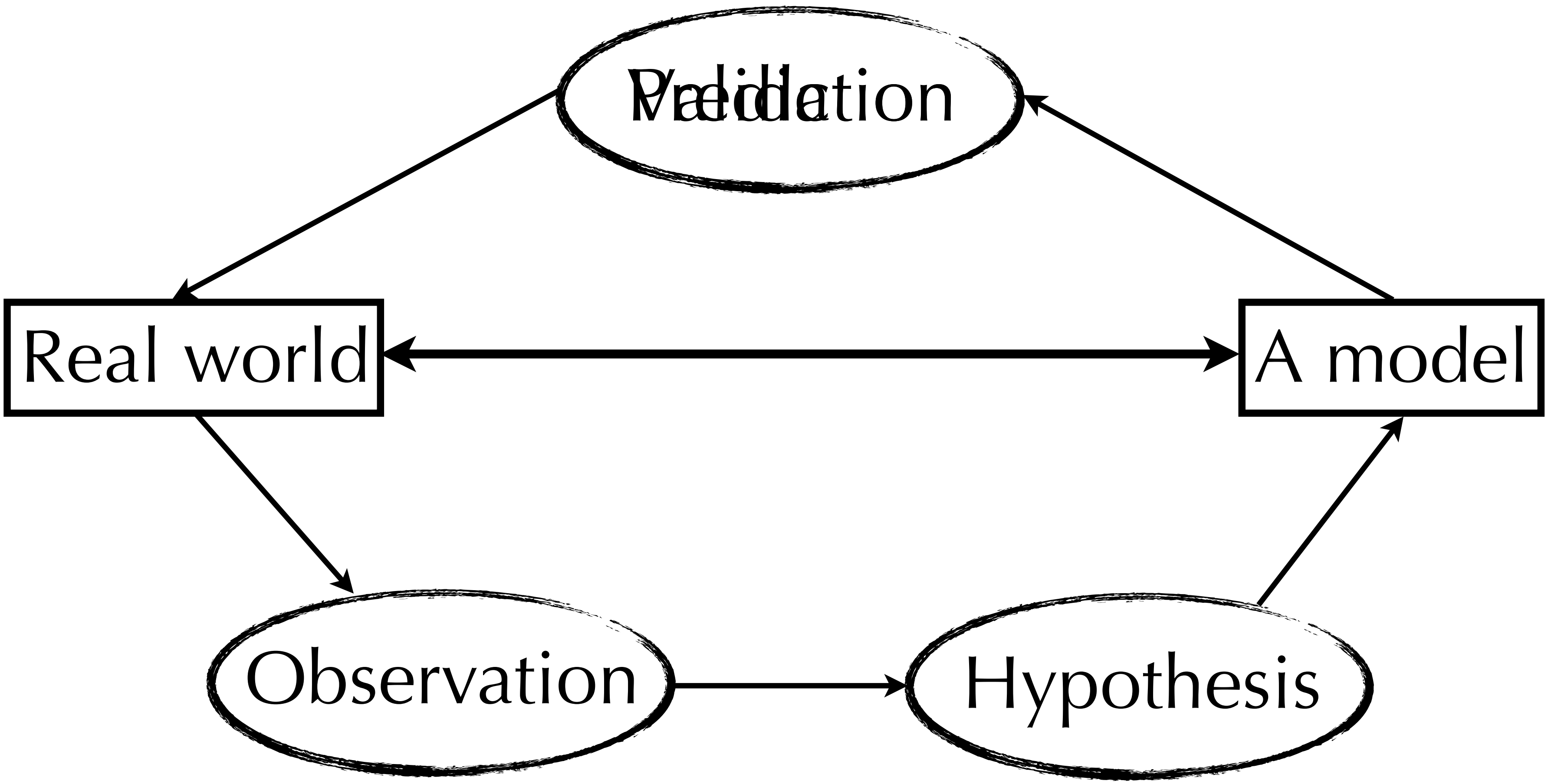
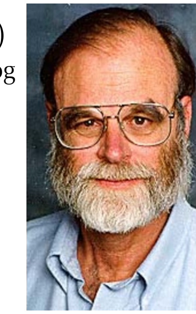
Scientific Method



Validation ➙ Prediction



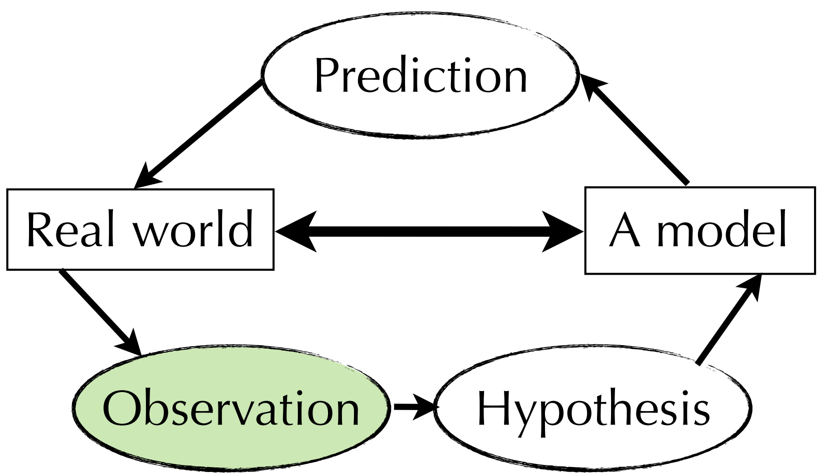
Jim Gray, “eScience -- A Transformed Scientific Method”, (2007)
https://en.wikipedia.org/wiki/File:Jim_Gray_portrait,_1999.jpg



1944-2007

4 Paradigms of Science

- empirical: observe, then derive



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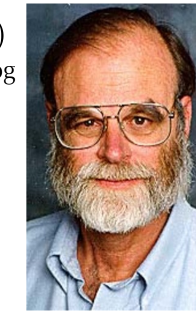
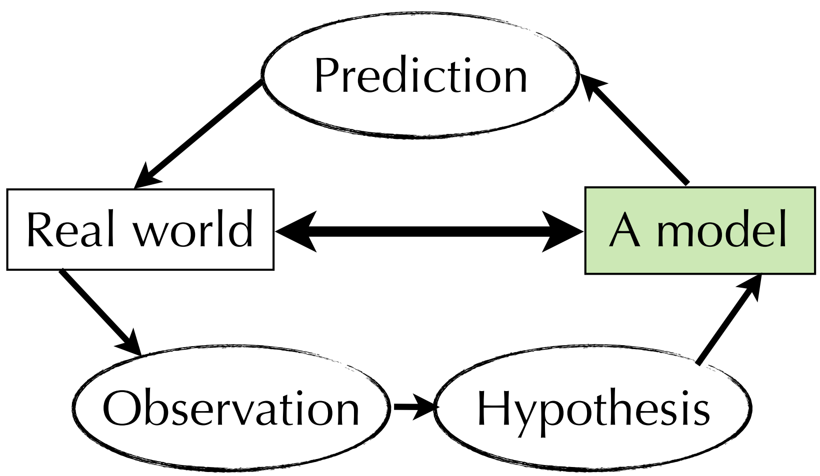

1944-2007

4 Paradigms of Science

- empirical: observe, then derive
- predictive: derive, then observe



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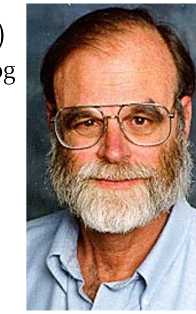
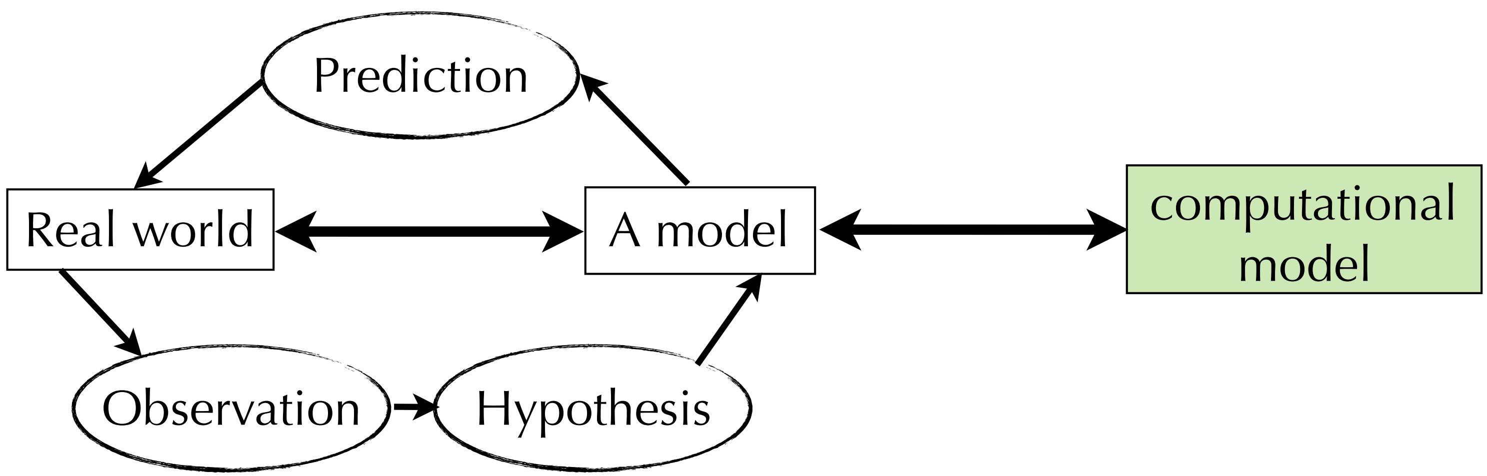


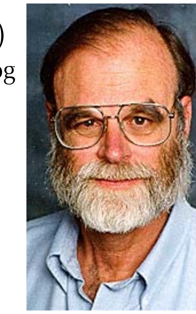
1944-2007

4 Paradigms of Science

- empirical: observe, then derive
- predictive: derive, then observe
- computational: simulate

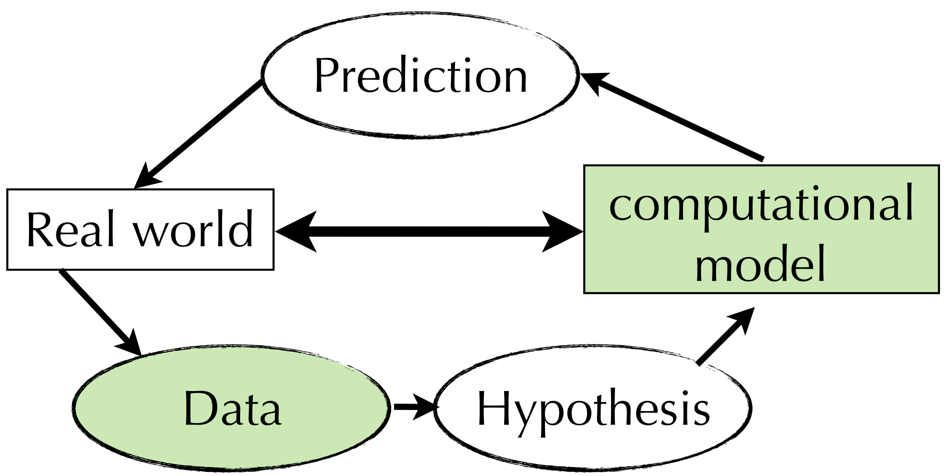


Jim Gray, "eScience -- A Transformed Scientific Method", (2007)
https://en.wikipedia.org/wiki/File:Jim_Gray_portrait,_1999.jpg


1944-2007

4 Paradigms of Science

- empirical: observe, then derive
- predictive: derive, then observe
- computational: simulate
- data-driven: measure



Three types of modelling

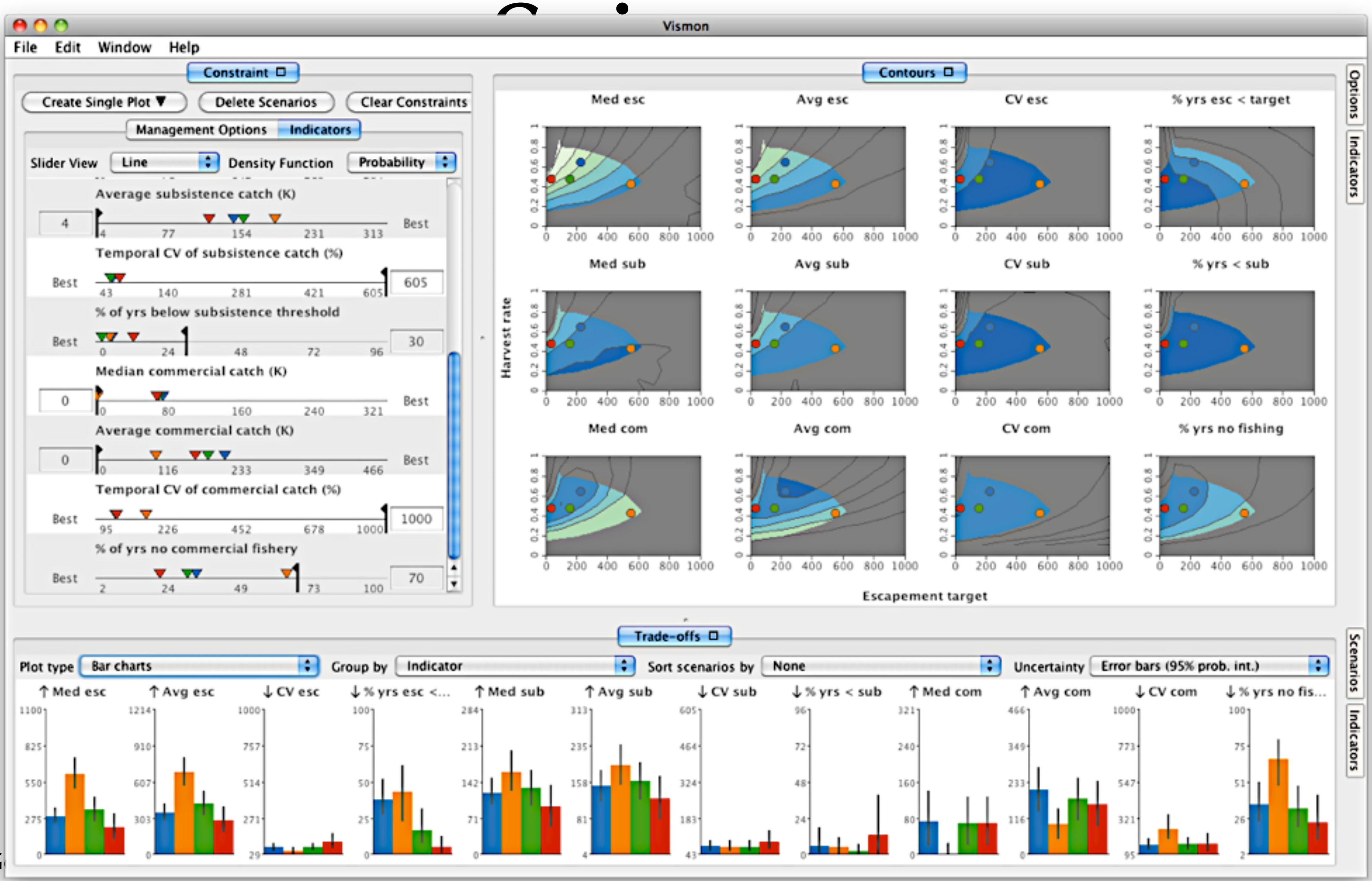
- computational: the simulation of discretized mathematical models (computational science)
- statistical: data-driven — extracting statistical models from data
- empirical: simple, often linear models

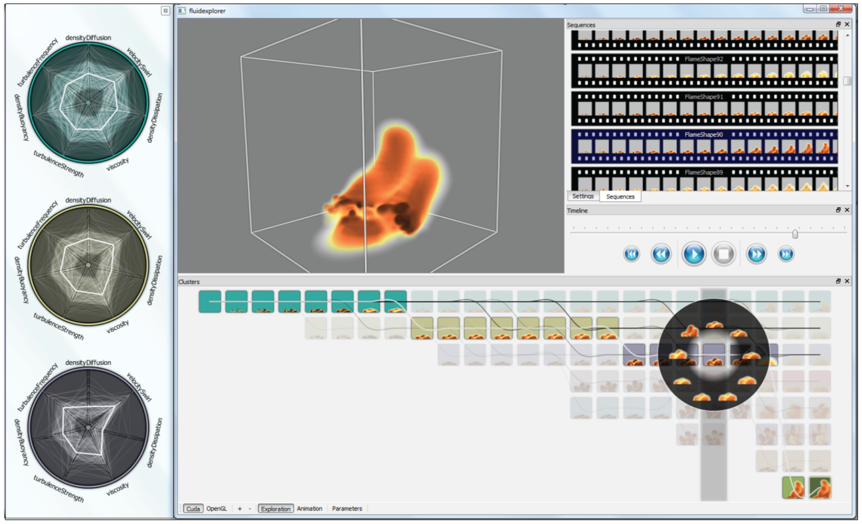
Computational Modelling

- (almost) every discipline has these models
- Examples:
  - Navier-Stokes, Maxwell, etc.
  - Population Dynamics
- computational science: experimentation through simulation of discretized models

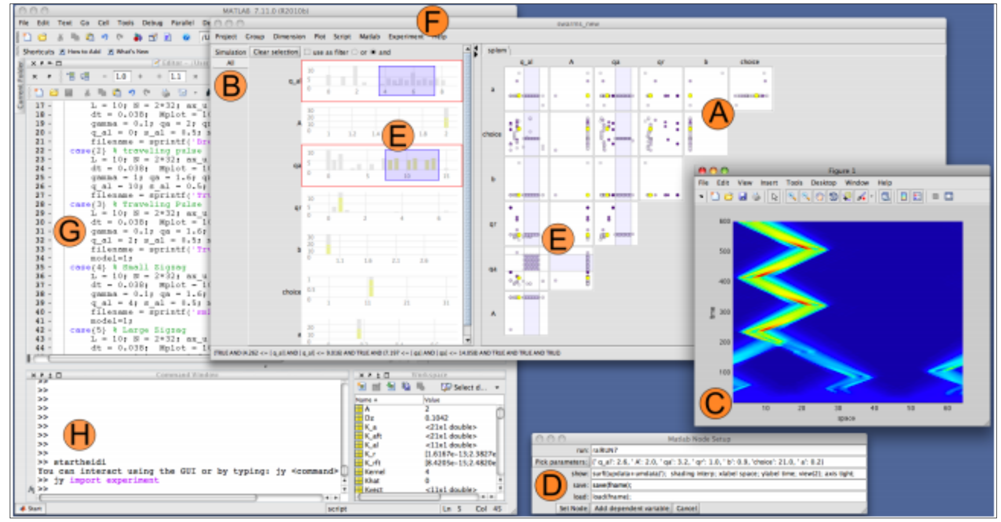
Booshehrian, “Vismon: Facilitating Risk Assessment and Decision Making In Fisheries Management”, (2012)

Vismon: Fisheries

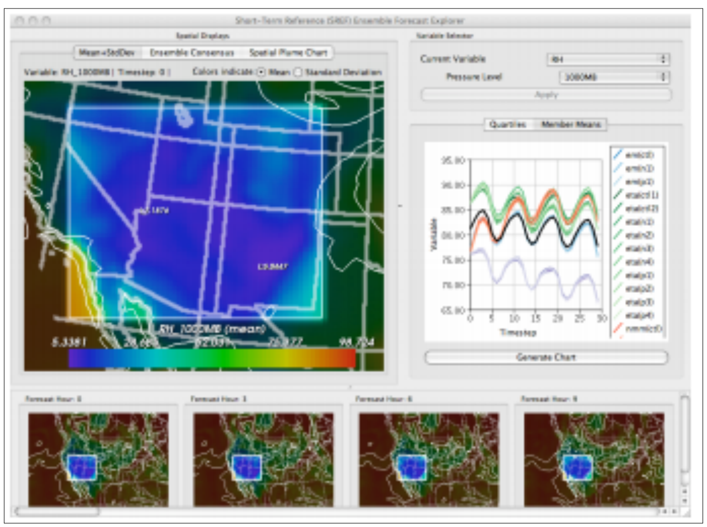




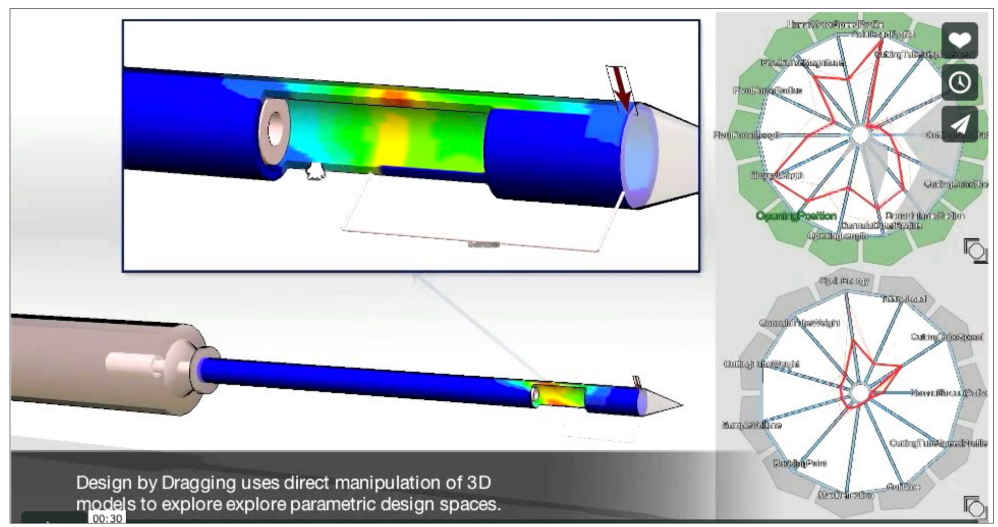
[Bruckner & Möller 2010]



[Bergner et al. 2013]



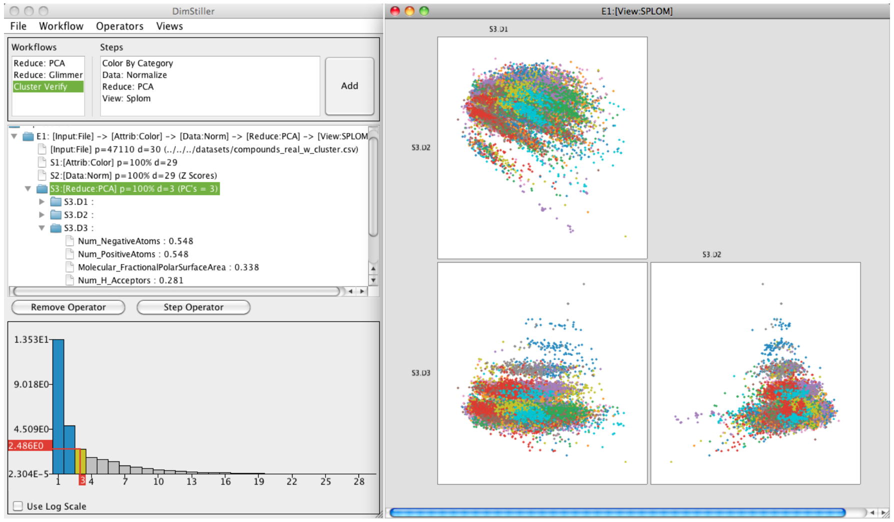
[Potter et al. 2009]



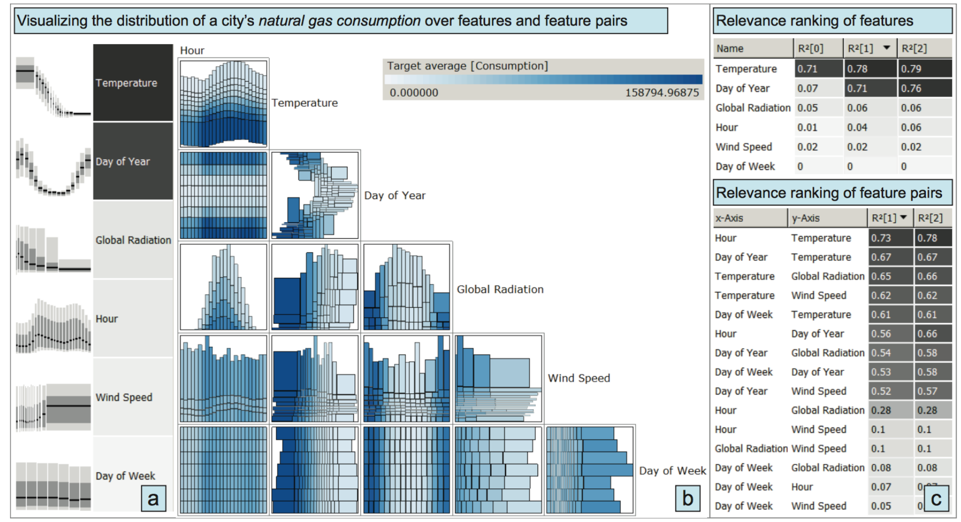
[Coffey et al. 2013]

Statistical Modeling

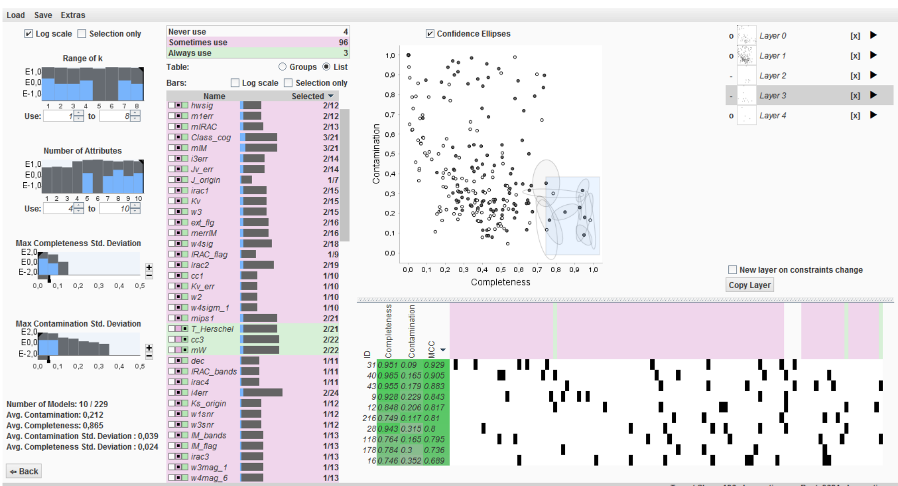
- "Mainstream" understanding of Data Science
- Classical (machine learning) approaches:
  - Clustering
  - Classification
  - Regression
  - (dimensionality reduction, outlier detection, etc)



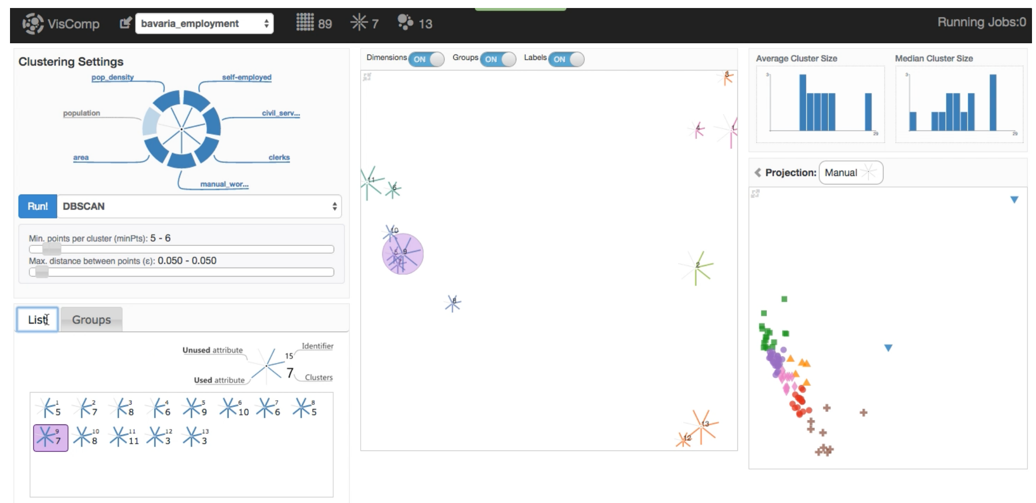
Dim reduction — [Ingram et al. 2010]



Regression — [Mühlbacher & Piringer 2013]



Classification — [Linhardt et al. 2016?]



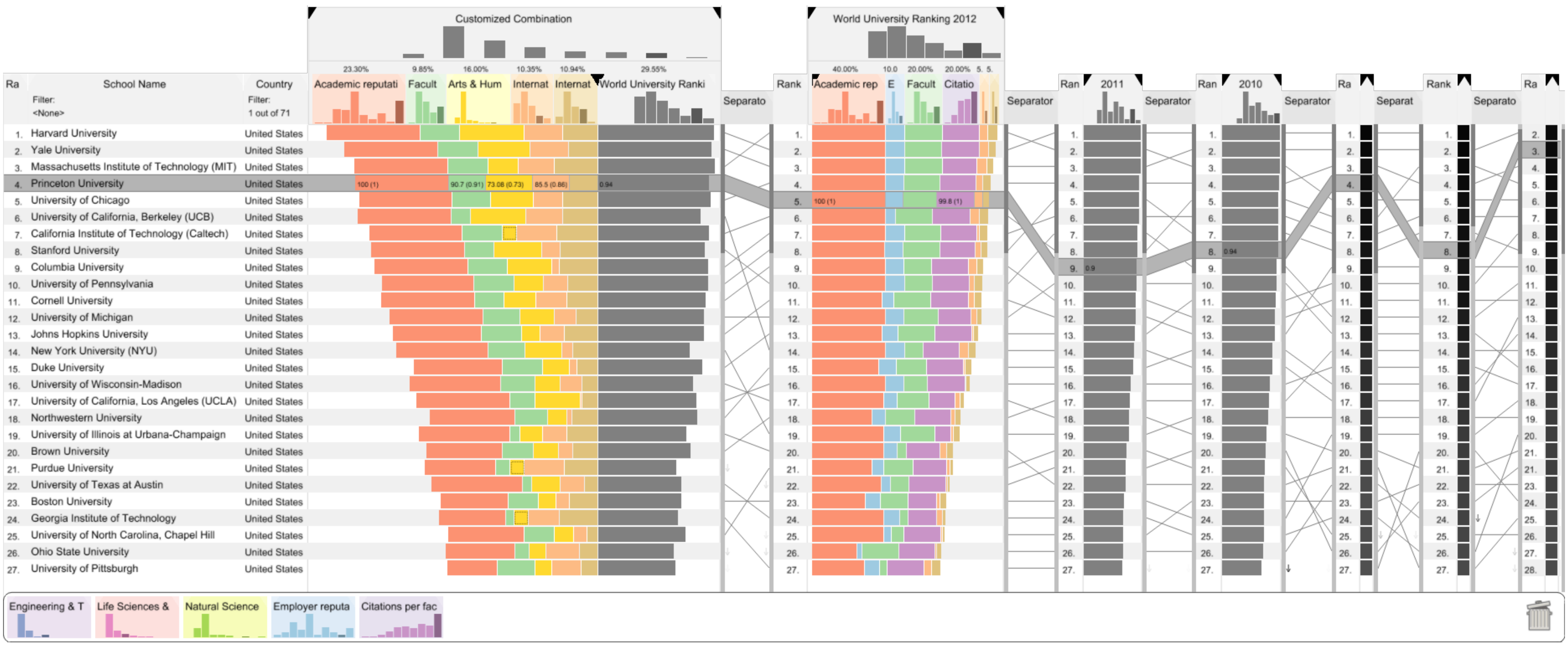
Clustering — [Sedlmair et al. 2016?]

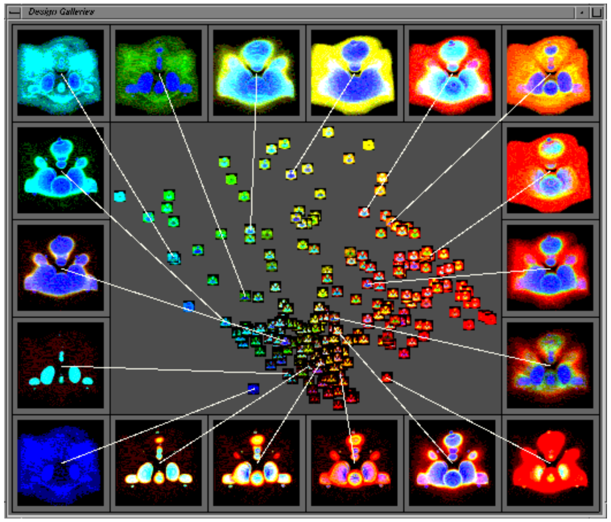
Empirical Modeling

- often no explicit modelling or only simple models, e.g.
  - linear models
  - weighted averages etc.
- examples: spreadsheets, rankings

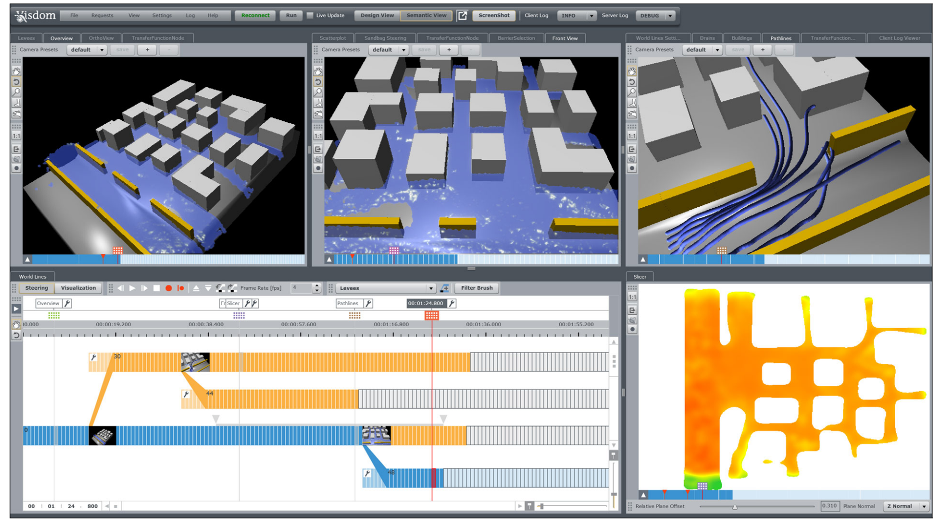
LineUp: Gratzl et al. 2013

LineUp: Gratzl et al. 2013

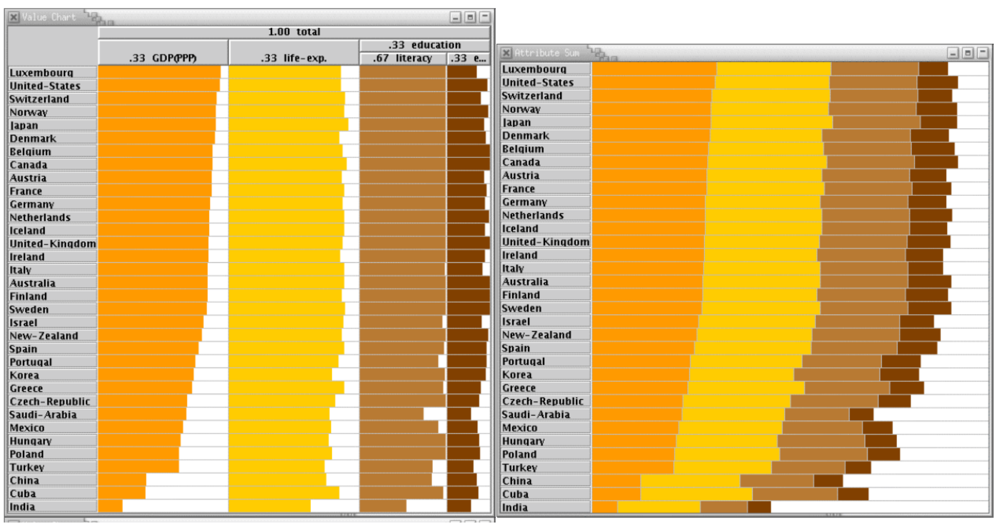




Design Galleries — [Marks et al. 1997]



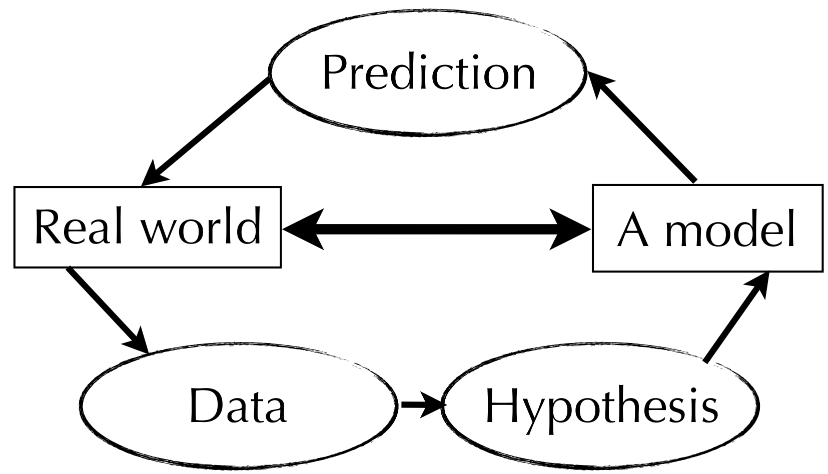
World Lines — [Waser et al. 2010]



ValueCharts — [Carenini et al. 2004]

Not just Labcoat Science

- valid for business, engineering, public policy
- general data analysis approach



Overview

- Data Science is all about modelling
- The three types of modelling
  - Computational modelling
  - Statistical modelling
  - Empirical modelling
- Challenges of Visual Data Science
- Conclusions

What is visual data science?

- **Visual** Data Science **is helping users** explore, abstract, and communicate complex systems through models from data.

Acting upon models

Building vs. Using

Data → Models (predictions) → Decisions

- building models
  - computational experts
  - bioinformaticians

- using models
  - decision makers
  - domain experts
  - biologists

Building vs. Using

Data → Models (predictions) → Decisions

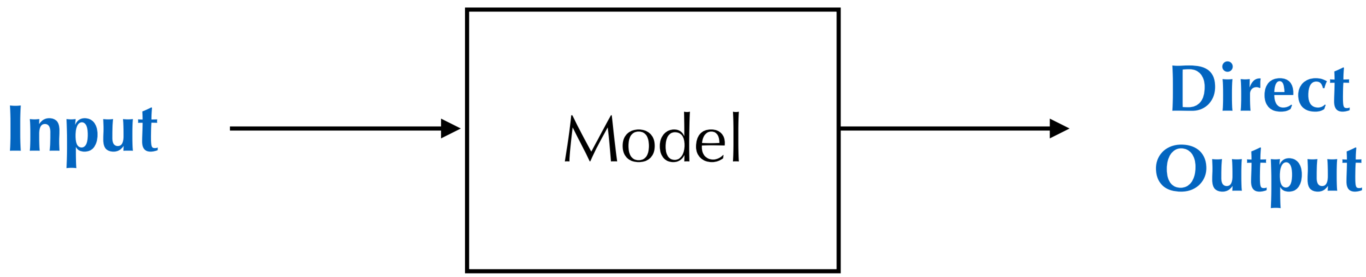
- building models
  - validation
  - uncertainty
- using models
  - trust
  - tradeoffs + risks

A modern microscope

Data → Models (predictions) → Decisions

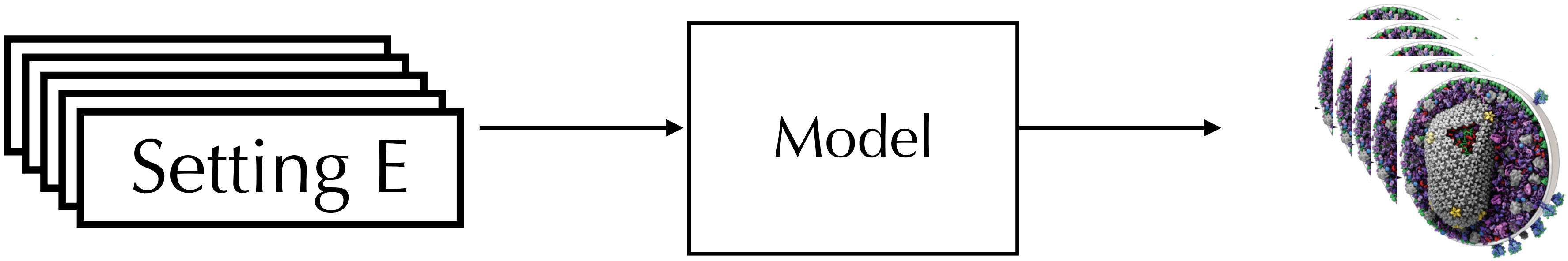
- making difficult algorithmic solutions accessible to a broad audience: enable model users to become model builders

What is a model?



- has input parameters
- creates outputs
- it's really "just" an algorithm

What is a model?



- paradigm shift:
  - from single input/output exploration to input ranges and ensemble outputs

Supporting the user

Data → Models (predictions) → Decisions

- hypothesis creation
- uncertainty / risk analysis
- sensitivity analysis / model uncertainty
- decision making / sense making

Conclusions

What is visual data science?

- **Visual** Data Science **is helping users** explore, abstract, and communicate complex systems **through models** from data.

Three types of modelling

- computational
- statistical
- empirical

A modern microscope

Data → Models (predictions) → Decisions

- making difficult algorithmic solutions accessible to a broad audience: enable model users to become model builders

Modern microscope

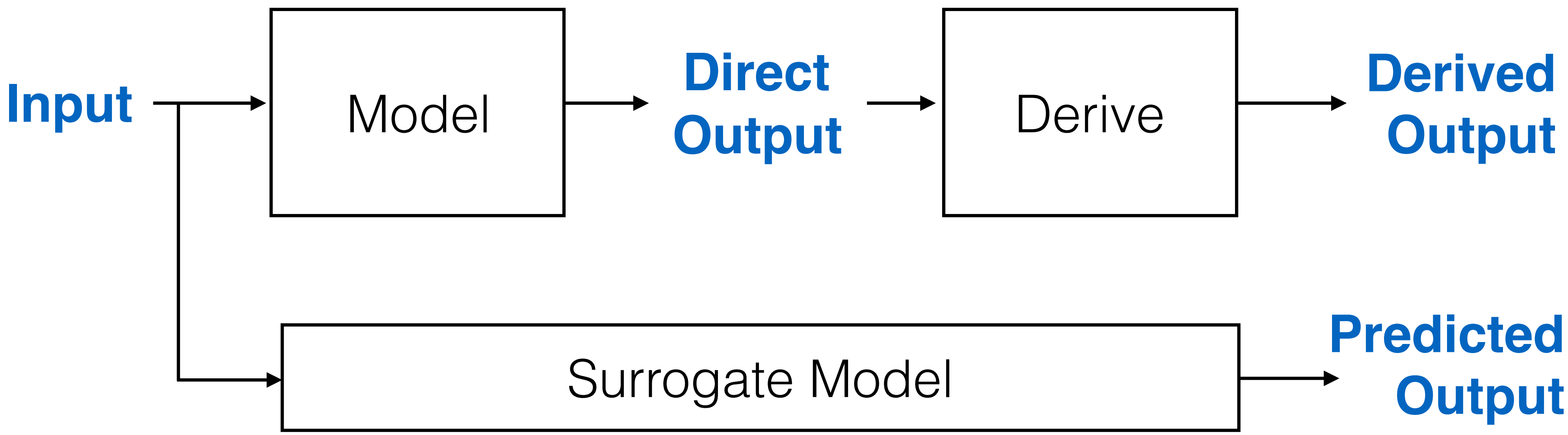
Visual Data Science

=

=

Making modelling techniques accessible to a broad set of users without requiring a PhD in Stats/ML.

Key ingredient

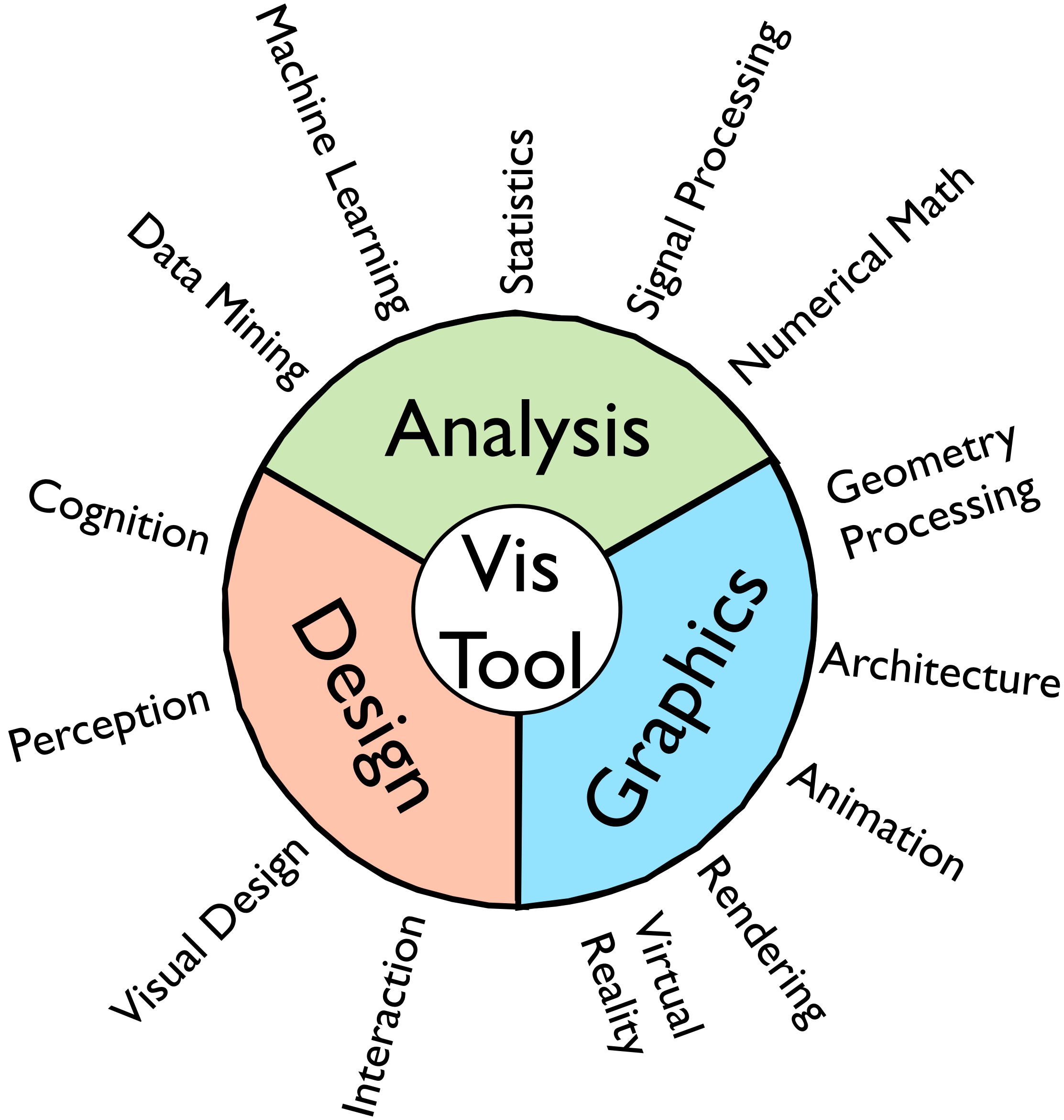


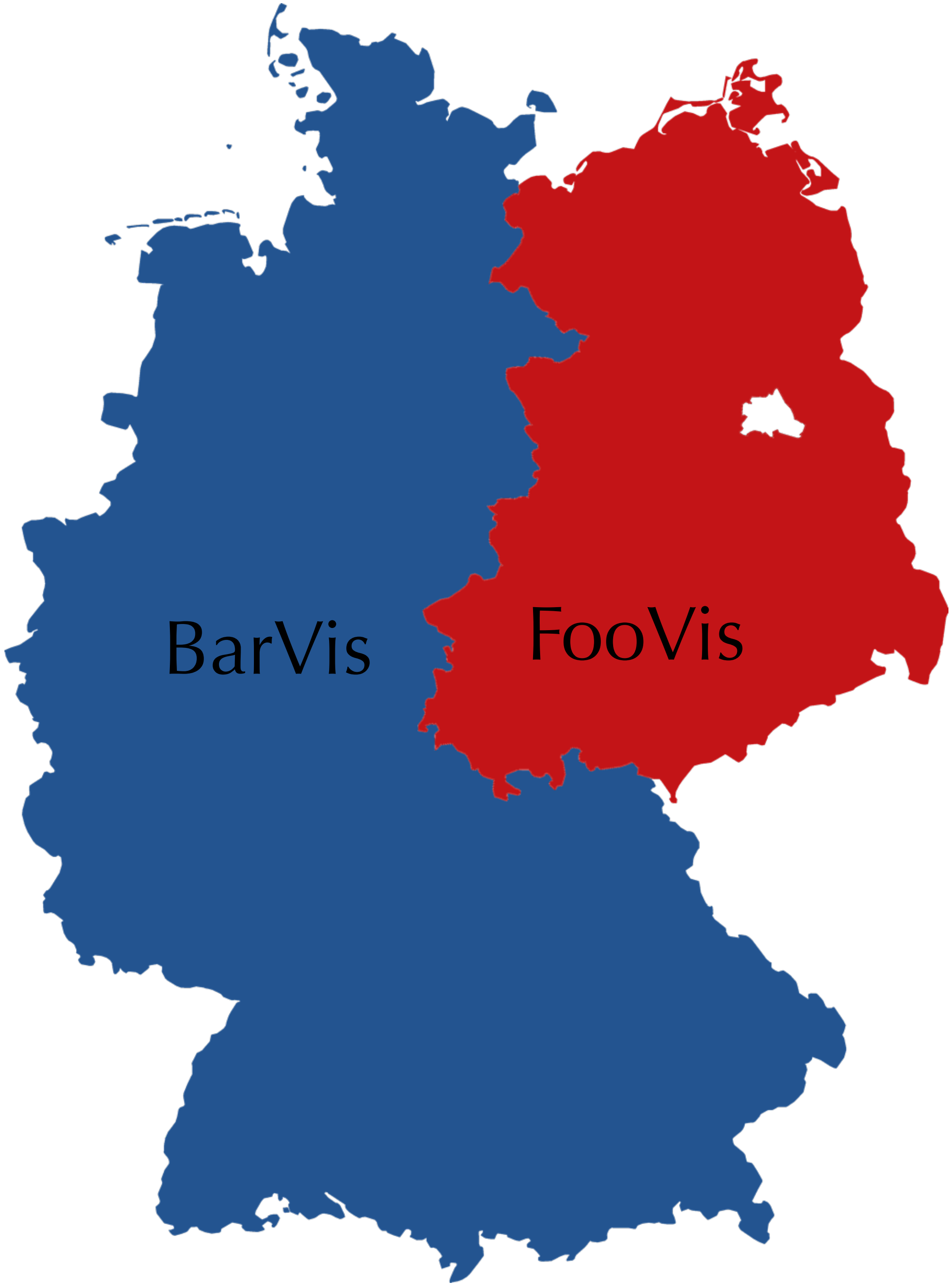
What is Visualization?

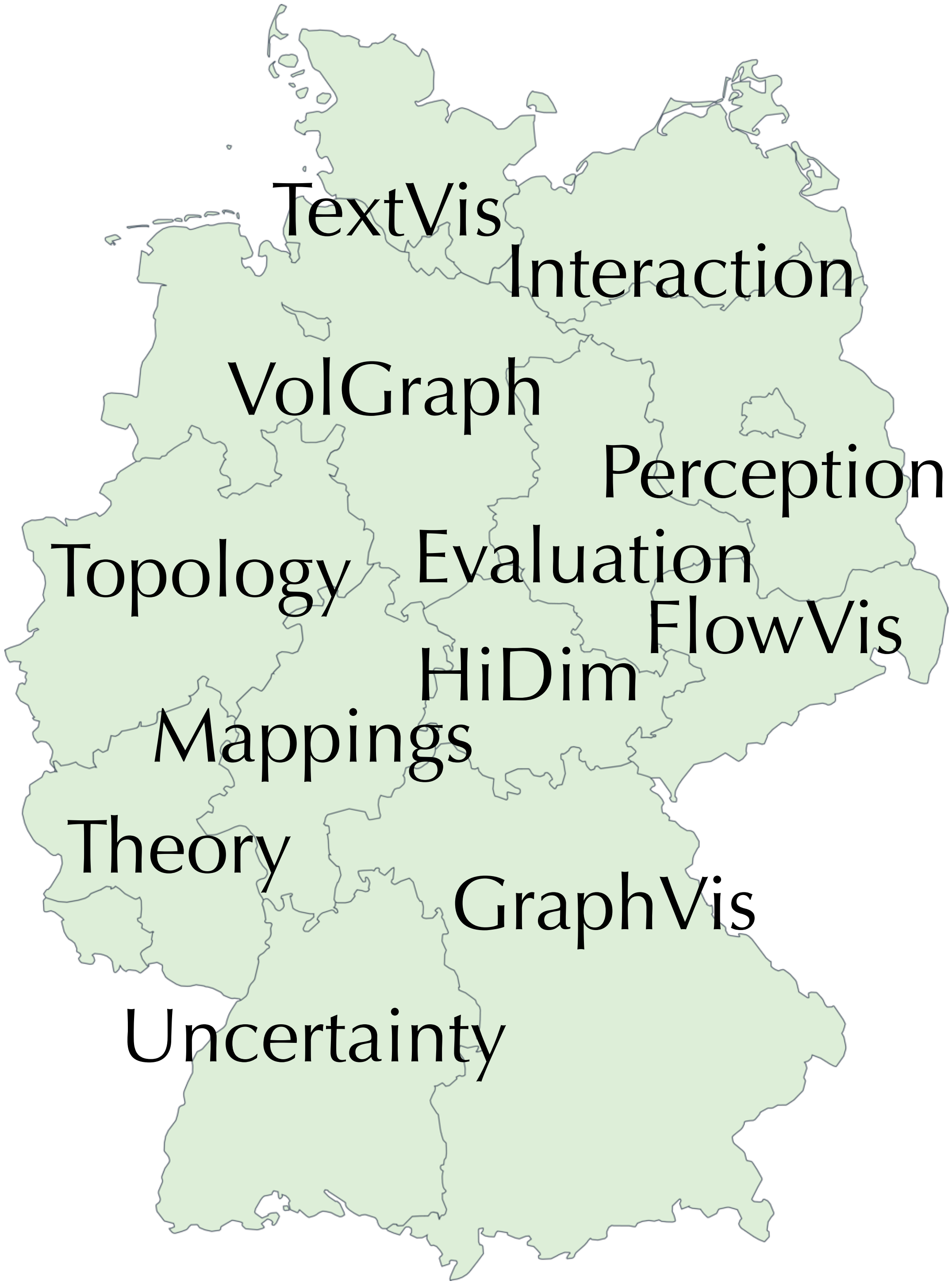
Tamara Munzner 2011:

> "Computer-based visualization systems provide visual representations of datasets intended to help people carry out some task more effectively."

Visualization




BarVis
FooVis


TextVis
Interaction
VolGraph
Perception
Topology
Evaluation
FlowVis
HiDim
Mappings
Theory
GraphVis
Uncertainty

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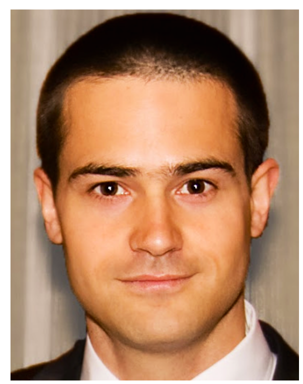

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VRVis

Michael Sedlmair
U of Vienna

Patrick Wolf
Software Dev

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- Visual Parameter Space Analysis: A Conceptual Framework. Michael Sedlmair, Christoph Heinzl, Stefan Bruckner, Harald Piringer, Torsten Möller, IEEE Transactions on Visualization and Computer Graphics (Proceedings InfoVis 2014), 20, pp. 2161-2170, 2014.
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Questions?

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