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

Plan the human-centred design process

Designed solution meets user requirements

Understand and specify the context of use

Iterate, where appropriate

Evaluate the designs against requirements

Specify the user requirements

Produce design solutions to meet user requirements

general Design process

- **Ask:** Identify the need & constraints
- **Research the problem**
- **Improve:** Redesign as needed
- **Test and evaluate prototype**
- **Create:** Build a prototype
- **Plan:** Select a promising solution
- **Imagine:** Develop possible solutions

[https://www.teachengineering.org/engrdesignprocess.php](https://www.teachengineering.org/engrdesignprocess.php)
Munzner’s Nested model

Domain situation

Data/task abstraction

Visual encoding/interaction idiom

Algorithm
Munzner’s Nested model

- **Domain situation**
  - What are people doing?
  - What are their goals?

- **Data/task abstraction**

- **Visual encoding/interaction idiom**

- **Algorithm**
Munzner’s Nested model

- **Domain situation**
- **Data/task abstraction**
- **Visual encoding/interaction idiom**
- **Algorithm**

What are data/tasks to accomplish these goals?
Munzner’s Nested model

- Domain situation
- Data/task abstraction
- Visual encoding/interaction idiom
- Algorithm

How do I show/interact with the data?
Munzner’s Nested model

- Domain situation
- Data/task abstraction
- Visual encoding/interaction idiom
- Algorithm

How do I make this all work?
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

1. **Domain situation**
   Observe target users using existing tools

2. **Data/task abstraction**

3. **Visual encoding/interaction idiom**
   Justify design with respect to alternatives

4. **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
Workflow for designing a tool
Making the right tool

Questions -> Data -> Tasks -> Vis researcher
Making the right tool

Questions

Data

Tasks

Design study methodology
Design study methodology

PRECONDITION
personal validation

CORE
inward-facing validation

ANALYSIS
outward-facing validation

Learn → Winnow → Cast → Discover → Design → Implement → Deploy → Reflect → Write

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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Geilo Winterschool, Jan 2016

Torsten Möller
Design study methodology

What tools/techniques are available?

- Read vis papers
- Read vis books
- Talk to vis practitioners
A crucial precondition for conducting an effective design study is a solid knowledge of the visualization literature, including visual metaphors and techniques. This visualization knowledge will inform all later stages: in coding and interaction techniques, design guidelines, and evaluation methods. This visualization knowledge will inform all later stages: in coding and interaction techniques, design guidelines, and evaluation methods.

The precondition stages of a design study are shown in Figure 2, with gray arrows implying these dynamics.

**PRECONDITION**
- **personal validation**

**CORE**
- **inward-facing validation**

**ANALYSIS**
- **outward-facing validation**

**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?

The diagram shows a two-dimensional axis system with axes labeled 'Task Clarity' and 'Information Location'. The axes are further divided into 'Crisp' and 'Fuzzy' categories, and 'Head' and 'Computer' categories. The diagram illustrates the suitability of design studies in different scenarios based on the combination of task clarity and information location.

- **NOT ENOUGH DATA**
  - The red area on the left side of the diagram represents situations where there is not enough data available.

- **ALGORITHM AUTOMATION POSSIBLE**
  - The blue triangle on the top right side of the diagram indicates situations where automatic algorithmic solutions are possible.

- **DESIGN STUDY METHODOLOGY SUITABLE**
  - The large yellow area in the middle of the diagram represents situations where design studies are suitable.

The diagram suggests that design studies are most useful when there is a clear and defined task (Crisp) and the data or metadata is available (Head), and least useful when the task is ill-defined and lacks data (Computer).

The diagram is labeled with Torsten Möller and includes a reference to Sedlmair:2012.
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 a lot of code)
- Breaking bugs vs annoying bugs
- Fast usability testing
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

PRECONDITION
personal validation

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outward-facing validation

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

Design study methodology

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learn winnow cast discover design implement deploy reflect write

Geilo Winterschool, Jan 2016
Torsten Möller
Where are design studies?

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Measure adoption
Pitfalls
Pitfalls

#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

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

early 2009  mid 2010  April 2012
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 …

...etc.
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…etc.
Much recent attention in vPSA

- comprehensive study of 21 different tools

...etc.
Data Flow Model
Build an estimator

sample points → segmenter → design points → objective function → ground truth

response 1 → \( f_1(x) \)
response 2 → \( f_2(x) \)
estimation
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)

Input Parameters

\[
\begin{array}{ccc}
1.0 & 2.1 & 3.7 \\
6.3 & 3.3 & 5.2 \\
2.2 & 2.1 & 2.0 \\
1.1 & 5.6 & 7.8 \\
\end{array}
\]

Outputs

\[
\begin{array}{ccc}
& & \\
& & \\
& & \\
& & \\
\end{array}
\]

[Torsney-Weir et al. 2011]
Derive objective measures

[Diagram with blocks labeled 'Model' and 'Derive' connected by arrows, with values [1.0, 2.1, 3.7] and 7.1]
Surrogate models

1.5    2.5    3.5

expensive!
Surrogate models

Model → Surrogate Model → Derive

Surrogate Model
Data flow model

Input -> Model -> Direct Output -> Derive -> Derived Output

Surrogate Model -> Predicted Output
Navigation Strategies
Navigation strategies

• Trial and error (traditional approach)
Navigation strategies

- Trial and error (traditional approach)
- 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 $\rightarrow$ global tweaking
- Global $\rightarrow$ 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**: Find the best parameter combination given some objectives.
- Partitioning
- Fitting
- Outliers
- Uncertainty
- Sensitivity

*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?*

Model \(\rightarrow\) Derive

ground truth

*in 9/21 papers*
Analysis tasks

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

What outputs are special?

Model

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?

Model

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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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.”

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

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Scientific Method

after Hans Christian Ørsted, "First Introduction to General Physics" (1811)
Validation ➔ Prediction

Real world ➔ Observation ➔ Hypothesis ➔ A model

Validation ➔ Hypothesis ➔ Observation ➔ Real world
4 Paradigms of Science

- empirical: observe, then derive

4 Paradigms of Science

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

4 Paradigms of Science

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

---


Jim Gray, 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
Vismon: Fisheries Science

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

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<th>School Name</th>
<th>Country</th>
<th>Faculty/student ratio</th>
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<th>Citations per faculty</th>
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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

Diagram:
- Prediction
- Real world
- A model
- Data
- Hypothesis

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Torsten Möller
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

- building models
  - computational experts
  - bioinformaticians
- using models
  - decision makers
  - domain experts
  - biologists
Building vs. Using

- 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

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

- 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

Input → Model → Direct Output → Derive → Derived Output

Input → Surrogate Model → Predicted Output
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
Acknowledgments

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Geilo Winterschool, Jan 2016
References


Questions?

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