PANEL: Visual Data Science and its role in Computational Medicine

Visual data science vs. Classical science
Computational vs. Interactive visual approaches
The role of the human in visual data science
Medicine and the “new” computational disciplines

Data Science  ‘producing insights’  e.g. explorative and longitudinal data analysis

Machine Learning  ‘producing predictions’  e.g. biomarkers  treatment response

Artificial Intelligence  ‘producing actions’  e.g. image guided and robot assisted surgery

Assist surgery in twin-to-twin transfusion syndrome

Arvid Lundervold, UiB

Visual Data Science and its role in Computational Medicine

Delft Data Science Seminar – Visual Data Science and its role in Computational Medicine, Panel discussion, TU Delft 6-Feb-2018 (Arvid Lundervold)
Multiscale, multimodal - modeling and visualization in health and disease

Gene networks

Pathway models

Stochastic models

Ordinary Differential Equations

Continuum models (Partial Differential Equations)

Systems models

Atom

Protein

Cell

Tissue

Organ

Organ system & organism

10^{-12} m

10^{-9} m

10^{-6} m

10^{-3} m

10^0 m

Anatomy

Brain

Spinal cord

Peripheral nerves

10^{-6} s

10^{-3} s

10^0 s

10^3 s

10^6 s

10^9 s

molecular events (ion channel gating)
diffusion cell signalling
motility
mitosis
protein turnover
human lifetime

Hypothesis driven
Data driven
Discovery science
Hybrid approaches
Modeling + ML

Arvid Lundervold, UiB

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Visual Data Science and its role in Computational Medicine

• Hypothesis driven
• Data driven
• Discovery science

• Hybrid approaches
  Modeling + ML

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Labeling data - visualization - understanding deep convolutional networks in computational medicine

- Understanding CNN
- Visualizing the data gradient and friends
- Reconstructing original images based on CNN Codes
- How much spatial information is preserved?
- Plotting performance as a function of image attributes
- Fooling ConvNets
- Neuroscience-inspired AI

http://cs231n.github.io/understanding-cnn

Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps
http://playground.tensorflow.org

Visualizing and Understanding Convolutional Networks
Understanding Deep Image Representations by Inverting Them
Deep Neural Networks in Computational Neuroscience
Explaining and Harnessing Adversarial Examples

Artificial neuroscience + Visual data science = “Artificial neuroimaging”

Real NN
Artificial NN
Real imaging
Artificial imaging

Sidetack (DL & CNN):

A. Zhong Hua. Department of Molecular Biology & Genetics, Johns Hopkins University School of Medicine, Baltimore, Maryland. Subject: Peripheral nerves in E11.5 mouse embryo; Technique: Confocal; Magnification: X20;
B. https://github.com/donglaiw/mNeuron

DeepMind / Hassabis

Wacom Cints QHD 2704D

Labeling tools
User interaction

Visualization support

Input Segment (Low resolution)
Convolutions Layers
Fully Connected Layers
Classification Layers
Input to semi-supervised labeling

Low Resolution
Upsampling
Normal Resolution
Morphology cleaning
filling holes closing opening

http://vision03.csail.mit.edu/cnn_art/index.html

Different layers (AlexNet)
UNIVERSITY OF TWENTE.

CYBER-SECURITY RESEARCH AND EDUCATION

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ABOUT ME

- Technische Universität Darmstadt, Germany 2003-2015
  - BSc and Diploma in Computer Science
  - PhD in Cryptography
  - Post-Doc in IT-Security
- University of Birmingham, UK 2015-2017
  - Lecturer in Cyber-Security
- University of Twente, NL 2017
  - Assistant-Professorship in Cyber-Security
\[ c = m^e \mod n \]

(\text{cc}) Wikipedia and others
THERE IS ALWAYS A TRADEOFF

High risks

Great opportunities

No risks

No opportunities
DIFFERENT VIEWS OF PRIVACY
CONCLUSION

- Everyone wants a better life, without risks of course.
- Depending on who you are, you are more or less concerned about privacy (you should be!)
- Having both is possible, but requires additional resources.
- Science should support that to make it as easy as possible.
The role of the human in visual data science

Jean-Daniel Fekete, Inria
automated analysis

Statistical Analysis
Data Mining
Data Management
Compression & Filtering

Semantics-based approaches

Human-centered computing

Human Cognition
Perception
Visual Intelligence
Decision Making Theory

“The best of both sides”

Information Visualization
Graphics and Rendering

human analysis
Confirm vs. Explore

**Confirmatory Analysis**
- Start with a hypothesis about the data
- Confirm that it is true

**Exploratory Analysis**
- Likely no a-priori information about the data
- Not sure about patterns and information present
- Explore to create hypotheses & confirm later

Focus of fully automated analysis methods
Focus of visual analytics
Automated vs. Human Driven

- Understanding is human
- Responsibility is human
- Steering an algorithm is human
- Deciding is human (most of the time)
- Finding theories is human
- Relating to real-life is human
  - Appropriateness
  - Plausibility
  - Acceptability

- Fitting is done by machines
- Modeling can be done with ML
- Computing is done by machines
- Storing and retrieving data is well done by machine

Overfitting or extrapolating is dangerous

But humans have pitfalls that should be controlled
Important issues

Technical
- Learn important methods on visualization
- Learn Visual Analytics
- Learn Machine Learning
- Learn Statistics

Humans
- Learn about cognitive biases
- Understand cognitive abilities and limitations
Examples of cognitive biases

- Base rate fallacy or Base rate neglect
- Anchoring
  - Human tendency to rely too heavily on the first piece of information offered when making decisions
- Framing
  - Drawing different conclusions from the same information, depending on how that information is presented
Improving visualization to assist users

- Exploration is typically done in depth-first manner
- Voyager 2 helps in providing suggestions
  - More help is needed
- More support for knowing what which of the data has been explored and which needs to be
- Improve guidance, data literacy and visualization literacy

https://idl.cs.washington.edu/papers/voyager2/