Andreas Holzinger

185.A83 Machine Learning for Health Informatics

2019S, VU, 2.0 h, 3.0 ECTS

Lecture 02 – Dienstag, 19.03.2019

From Clinical Decision Support to Causal Reasoning and explainable AI

andreas.holzinger AT tuwien.ac.at

https://hci-kdd.org/machine-learning-for-health-informatics-class-2019

Keywords

- Decision support system (DSS)
- MYCIN – Rule Based Expert System
- GAMUTS in Radiology
- Reasoning under uncertainty
- Example: Radiotherapy planning
- Example: Case-Based Reasoning
- Explainable Artificial intelligence
- Re-trace > Understand > Explain
- Transparency > Trust > Acceptance
- Fairness > Transparency > Accountability
- Causality > Causability
- (Some) Methods of Explainable AI

Advance Organizer (1/2)

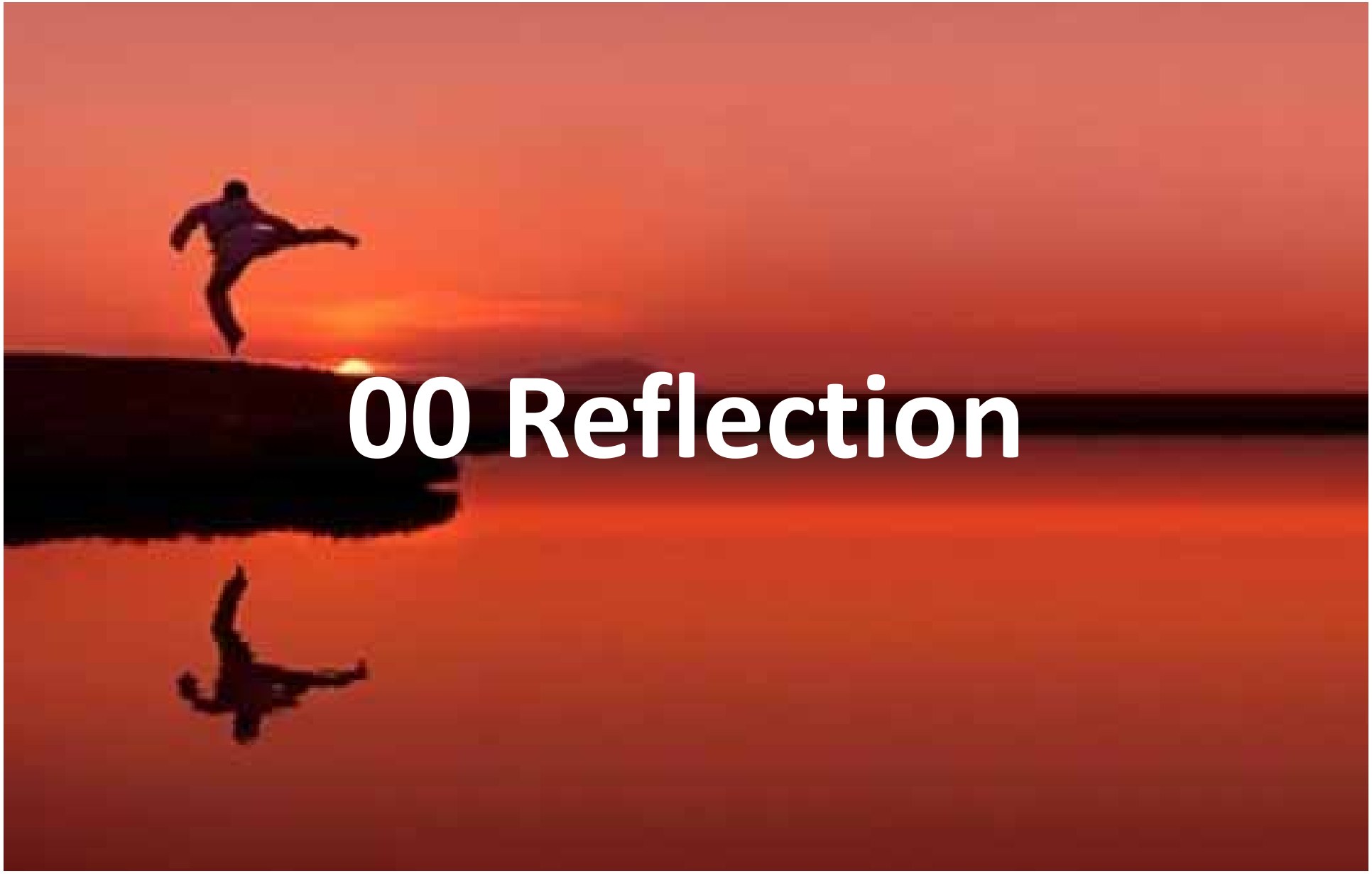
- **Causality** = fundamental relationship between cause and effect
- Causability = similar to the concept of usability the property of a human explanation
- **Case-based reasoning (CBR)** = process of solving new problems based on the solutions of similar past problems;
- **Certainty factor model (CF)** = a method for managing uncertainty in rule-based systems;
- **CLARION =** Connectionist Learning with Adaptive Rule Induction ON-line (CLARION) is a cognitive architecture that incorporates the distinction between implicit and explicit processes and focuses on capturing the interaction between these two types of processes. By focusing on this distinction, CLARION has been used to simulate several tasks in cognitive psychology and social psychology. CLARION has also been used to implement intelligent systems in artificial intelligence applications.
- **Clinical decision support (CDS)** = process for enhancing health-related decisions and actions with pertinent, organized clinical knowledge and patient information to improve health delivery;
- **Clinical Decision Support System (CDSS)** = expert system that provides support to certain reasoning tasks, in the context of a clinical decision;
- **Collective Intelligence** = shared group (symbolic) intelligence, emerging from cooperation/competition of many individuals, e.g. for consensus decision making;
- Counterfactual = relating to or expressing what has not happened or is not the case
- **Crowdsourcing** = a combination of "crowd" and "outsourcing" coined by Jeff Howe (2006), and describes a distributed problem-solving model; example for crowdsourcing is a public software beta-test;
- **Decision Making** = central cognitive process in every medical activity, resulting in the selection of a final choice of action out of several alternatives;
- **Decision Support System (DSS)** = is an IS including knowledge based systems to interactively support decision-making activities, i.e. making data useful;

Advance Organizer (2/2)

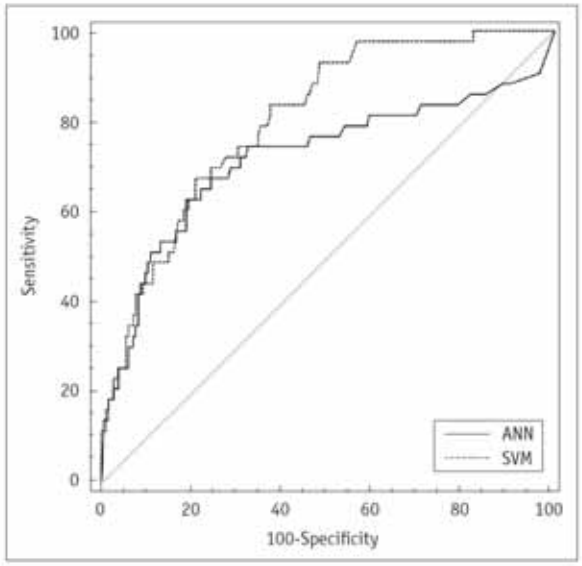
- **DXplain** = a DSS from the Harvard Medical School, to assist making a diagnosis (clinical consultation), and also as an instructional instrument (education); provides a description of diseases, etiology, pathology, prognosis and up to 10 references for each disease;
- Etiology = in medicine (many) factors coming together to cause an illness (see causality)
- Explainable AI = Explainability = upcoming fundamental topic within recent AI; answering e.g. **why** a decision has been made
- **Expert-System** = emulates the decision making processes of a human expert to solve complex problems;
- **GAMUTS** in Radiology = Computer-Supported list of common/uncommon differential diagnoses;
- **ILIAD** = medical expert system, developed by the University of Utah, used as a teaching and testing tool for medical students in problem solving. Fields include Pediatrics, Internal Medicine, Oncology, Infectious Diseases, Gynecology, Pulmonology etc.
- Interpretability = there is no formal technical definition yet, but it is considered as a prerequisite for trust
- **MYCIN** = one of the early medical expert systems (Shortliffe (1970), Stanford) to identify bacteria causing severe infections, such as bacteremia and meningitis, and to recommend antibiotics, with the dosage adjusted for patient's body weight;
- **Reasoning** = cognitive (thought) processes involved in making medical decisions (clinical reasoning, medical problem solving, diagnostic reasoning;
- **Transparency** = opposite of opacity of black-box approaches, and connotes the ability to understand how a model works (that does not mean that it should always be understood, but that – in the case of necessity – it can be re-enacted

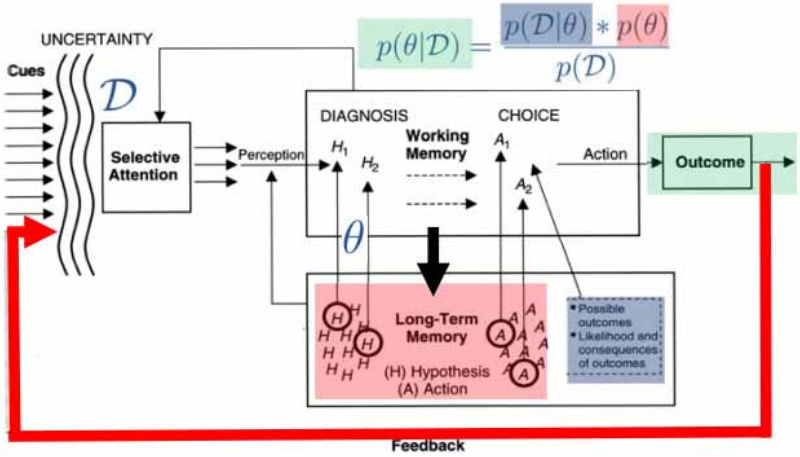
Agenda

- 00 Reflection – follow-up from last lecture
- 01 Decision Support Systems (DSS)
- 02 History of DSS = History of AI
- 03 Example: Towards Personalized Medicine
- 04 Example: Case Based Reasoning (CBR)
- 05 Causal Reasoning
- 06 Explainability – Causability
- 07 (Some) Methods of Explainable AI


00 Reflection

Reflection from last lectures





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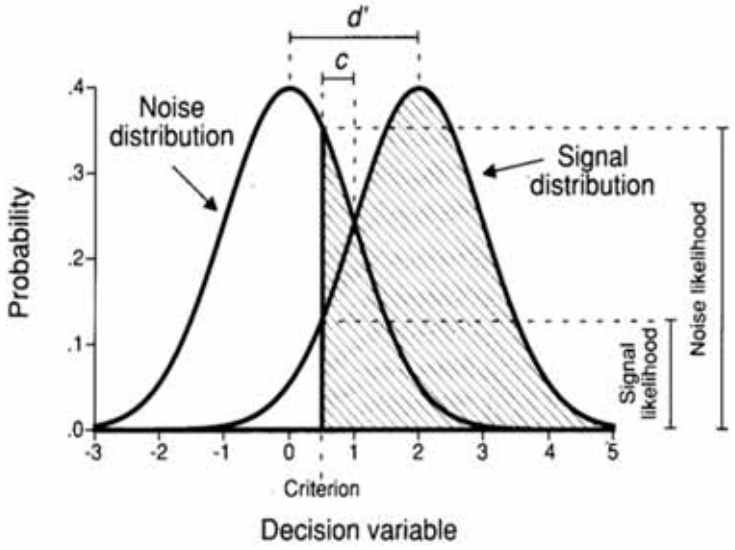

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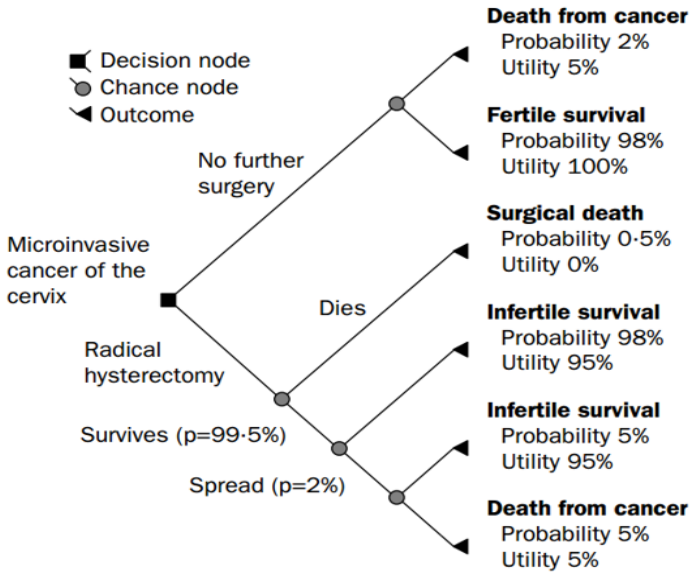

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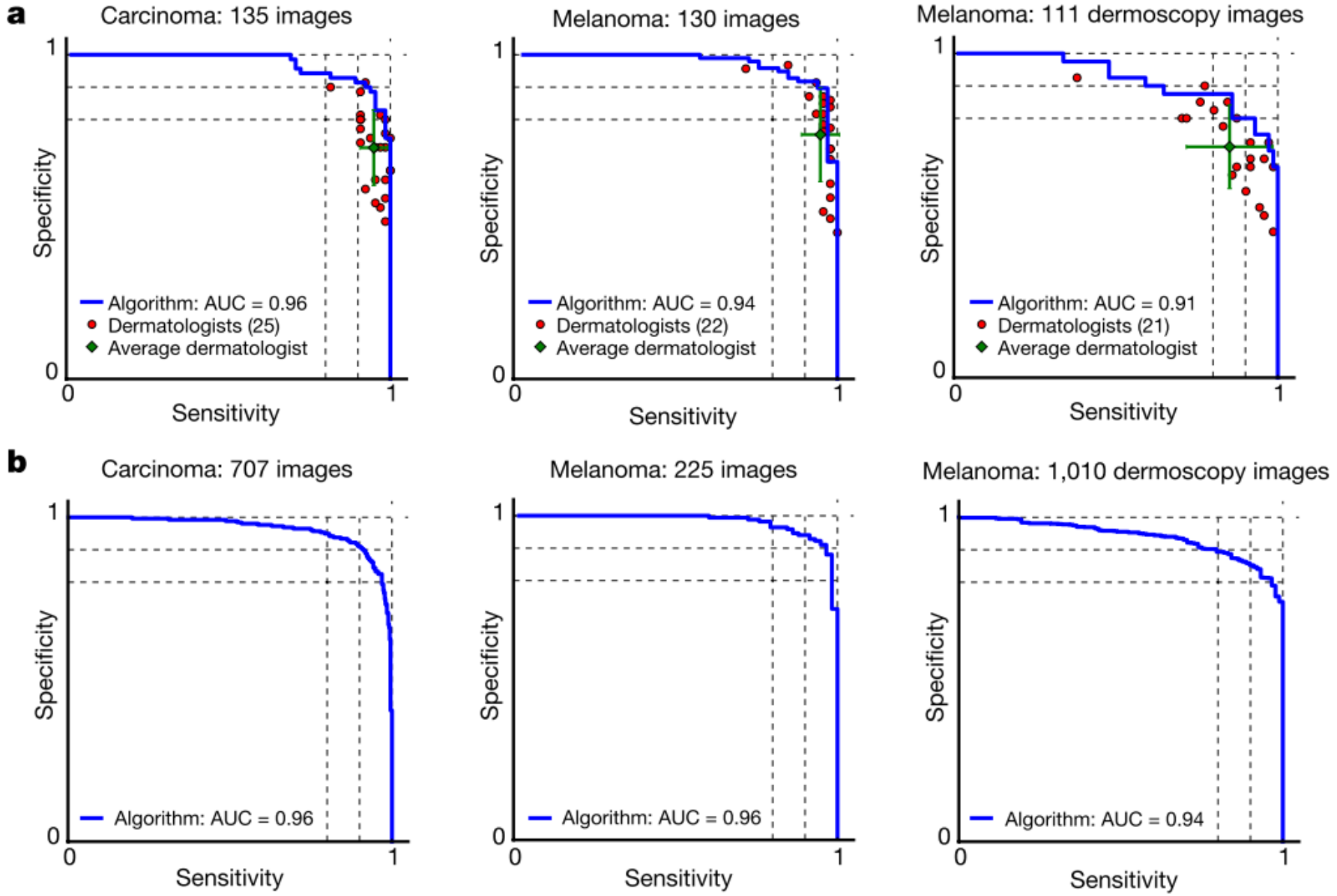
How do you explain this …

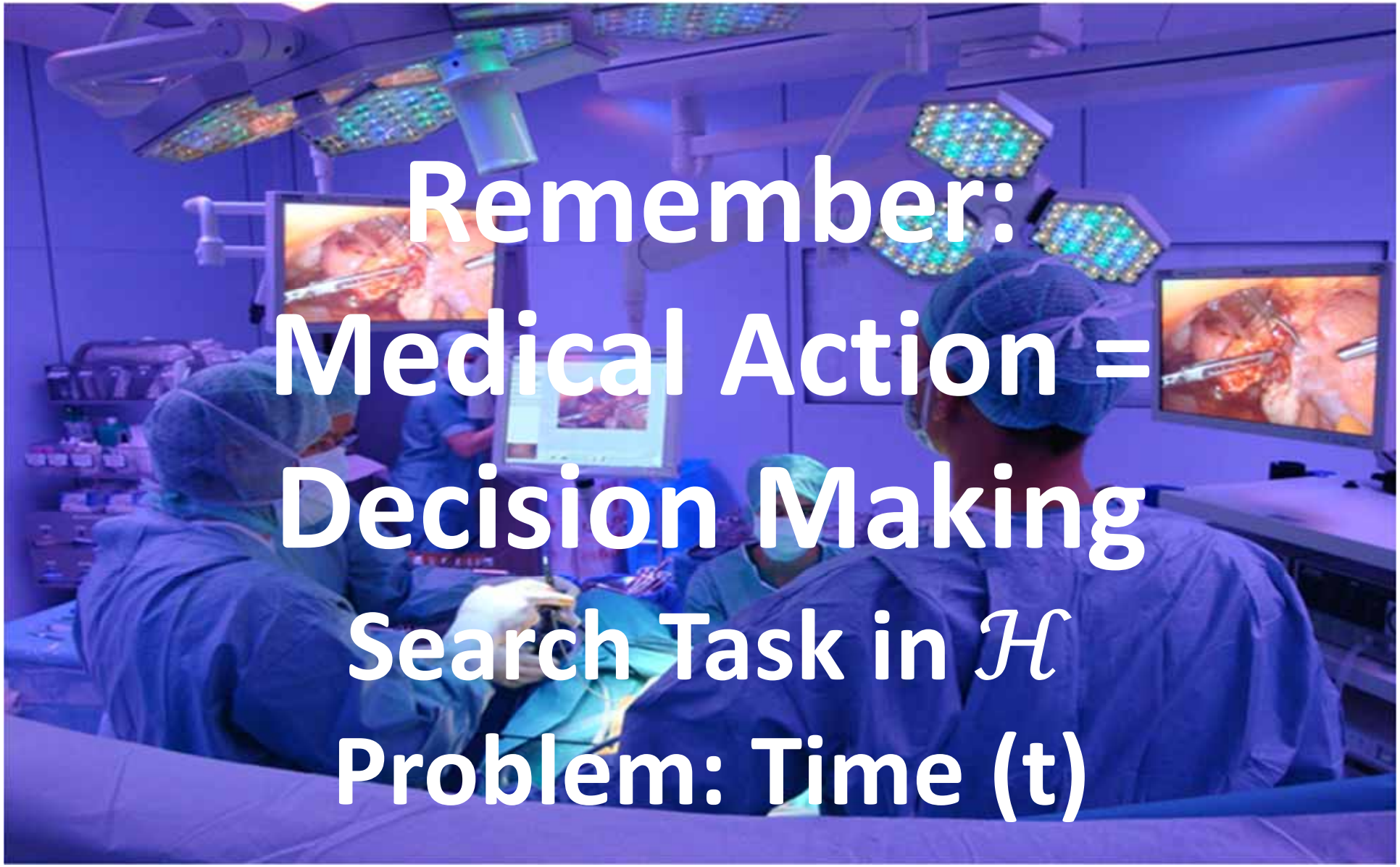


Andre Esteva, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau & Sebastian Thrun 2017. Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542, (7639), 115-118

Key Challenges

- Remember: Medicine is an complex application domain – dealing most of the time with **probable information!**
- Some challenges include:
- (a) defining hospital system architectures in terms of generic tasks such as diagnosis, therapy planning and monitoring to be executed for (b) medical reasoning in (a);
- (c) patient information management with (d) minimum uncertainty.
- Other challenges include: (e) knowledge acquisition and encoding, (f) human-ai interface and ai-interaction; and (g) system integration into existing clinical legacy and proprietary environments, e.g. the enterprise hospital information system; to mention only a few.

01 Decision Support Systems



Remember: Medical Action = Decision Making

Search Task in $\mathcal{H}$

Problem: Time (t)

Search in an arbitrarily high-dimensional space < 5 min.!

Decision Making is central in any (medical) work

Source: Cisco (2008). Cisco Health Presence Trial at Aberdeen Royal Infirmary in Scotland

The Medical Domain and Decision Making

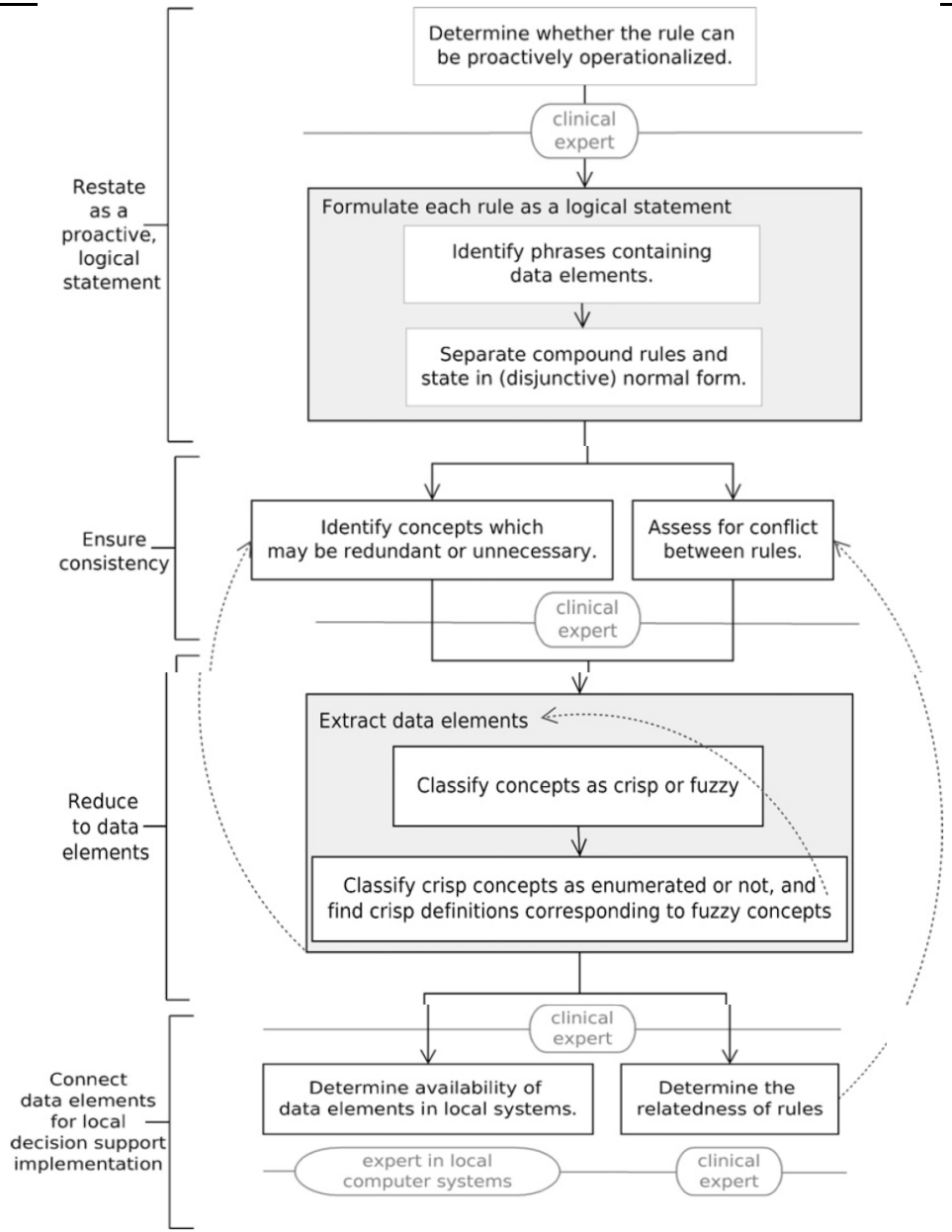
- 400 BC Hippocrates (460-370 BC), father of western medicine:
  - A medical record should accurately reflect the course of a disease
  - A medical record should indicate the probable cause of a disease
- **1890** William Osler (1849-1919), father of modern western medicine
  - **Medicine is a science of uncertainty and an art of probabilistic decision making**
- Today
  - Prediction models are based on data features, patient health status is modelled as high-dimensional feature vectors …

Digression: Clinical Guidelines as DSS & Quality Measure

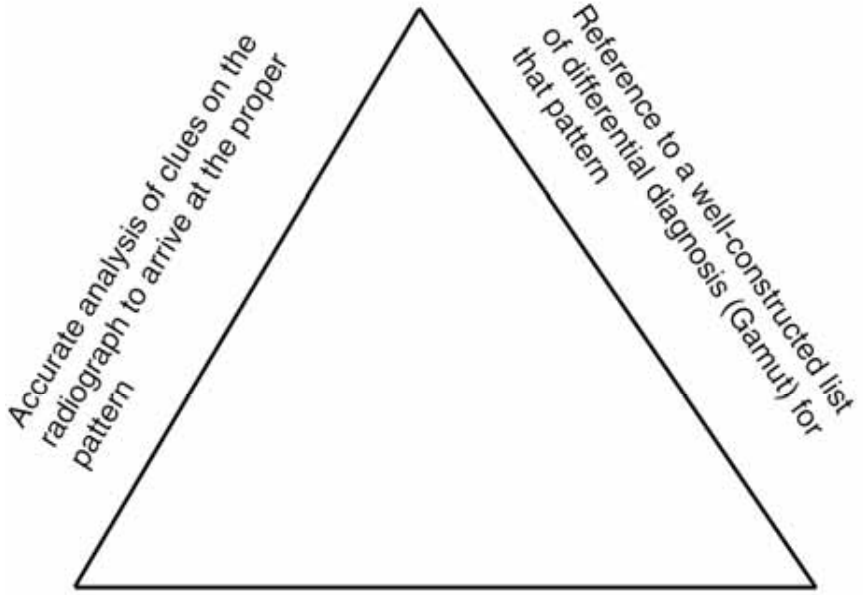
- Clinical guidelines are **systematically** developed documents to assist doctors and patient decisions about appropriate care;
- In order to build DS, based on a guideline, it is **formalized** (transformed from natural language to a logical algorithm), and
- **implemented** (using the algorithm to program a DSS);
- To increase the quality of care, they must be linked to a process of care, for example:
  - "80% of diabetic patients should have an HbA1c below 7.0" could be linked to processes such as:
  - "All diabetic patients should have an annual HbA1c test" and
  - "Patients with values over 7.0 should be rechecked within 2 months."
- **Condition-action rules** specify one or a few conditions which are linked to a specific action, in contrast to narrative guidelines which describe a series of branching or iterative decisions unfolding over time.
- Narrative guidelines and clinical rules are two ends of a continuum of clinical care standards.

Example: Clinical Guidelines

Medlock, S., Opondo, D., Eslami, S., Askari, M., Wierenga, P., de Rooij, S. E. & Abu-Hanna, A. (2011) LERM (Logical Elements Rule Method): A method for assessing and formalizing clinical rules for decision support. *International Journal of Medical Informatics, 80, 4, 286-295.*



Example: Triangulation to find diagnoses



Correlation of radiographic findings and Gamut with patients' clinical and lab findings to arrive at the most likely diagnosis

Reeder, M. M. & Felson, B. 2003. *Reeder and Felson's gamuts in radiology: comprehensive lists of roentgen differential diagnosis, New York, Springer Verlag.*

Gamut F-137

PHRENIC NERVE PARALYSIS OR DYSFUNCTION

COMMON

1. Iatrogenic (eg, surgical injury; chest tube; therapeutic avulsion or injection; subclavian vein puncture)
2. Infection (eg, tuberculosis; fungus disease; abscess)
3. Neoplastic invasion or compression (esp. carcinoma of lung)

UNCOMMON

1. Aneurysm$_g$, aortic or other
2. Birth trauma (Erb's palsy)
3. Herpes zoster
4. Neuritis, peripheral (eg, diabetic neuropathy)
5. Neurologic disease$_g$ (eg, hemiplegia; encephalitis; polio; Guillain-Barré S.)
6. Pneumonia
7. Trauma

Reference

1. Prasad S, Athreya BH: Transient paralysis of the phrenic nerve associated with head injury. JAMA 1976;236:2532–2533

Example - Gamuts in Radiology

GAMUT G-25
EROSIVE GASTRITIS*

COMMON

1. Acute gastritis (eg, alcohol abuse)
2. Crohn's disease I I
3. Drugs (eg, aspirin I I; NSAID I; steroids)
4. *Helicobacter pylori* infection I
5. Idiopathic
6. [Normal areae gastricae I]
7. Peptic ulcer; hyperacidity

UNCOMMON

1. Corrosive gastritis I
2. *Cryptosporidium* antritis
3. [Lymphoma]
4. Opportunistic infection (eg, candidiasis {moniliasis} I; herpes simplex; cytomegalovirus)
5. Postoperative gastritis
6. Radiation therapy
7. Zollinger-Ellison S. I; multiple endocrine neoplasia (MEN) S.

* Superficial erosions or aphthoid ulcerations seen especially with double contrast technique.

[ ] This condition does not actually cause the gamuted imaging finding, but can produce imaging changes that simulate it.

Reeder, M. M. & Felson, B. (2003) *Reeder and Felson's gamuts in radiology: comprehensive lists of roentgen differential diagnosis. New York, Springer*

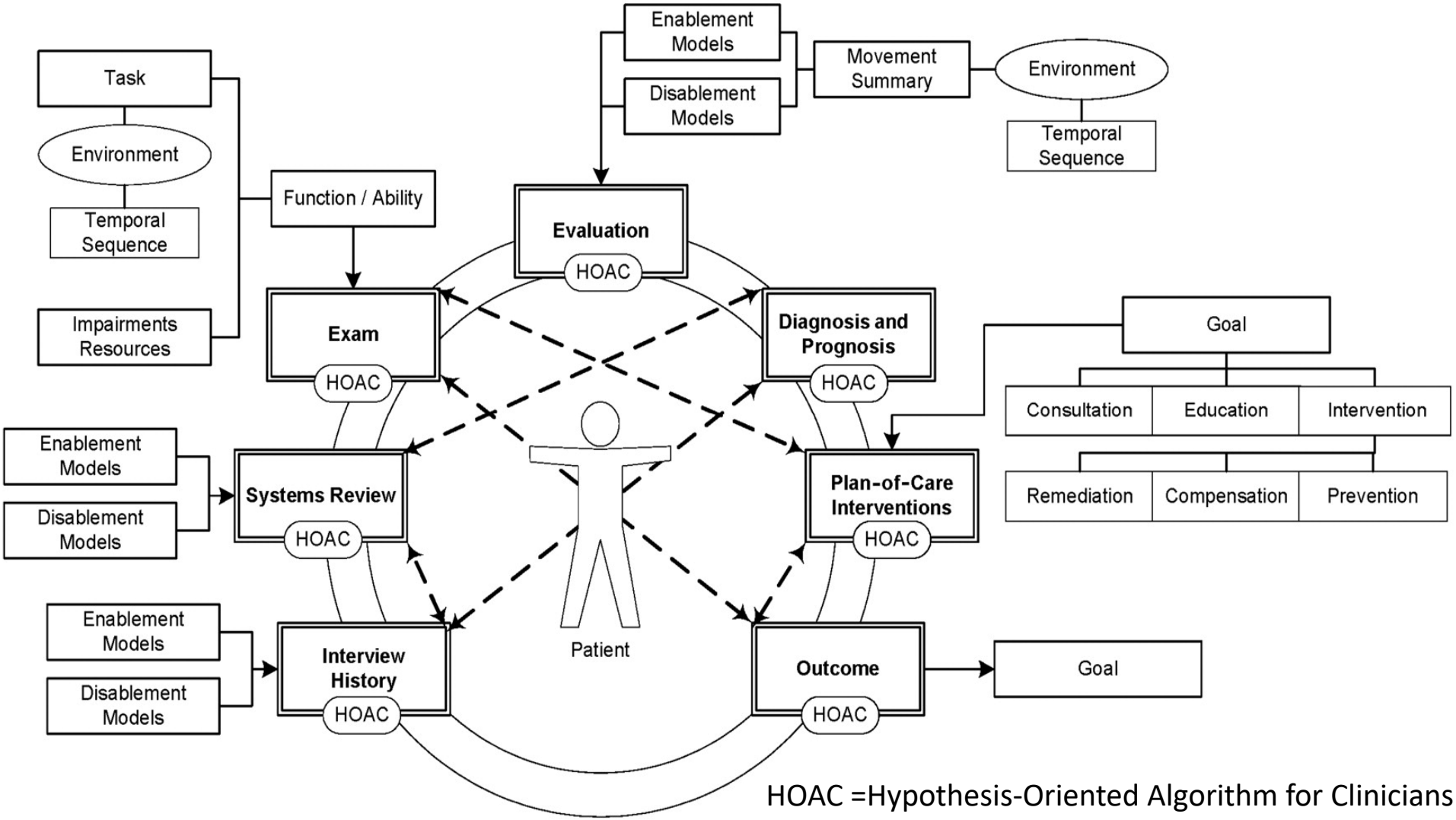
http://rfs.acr.org/gamuts/data/G-25.htm

Example: Triage Tags - International Triage Tags

Iserson, K. V. & Moskop, J. C. 2007. Triage in Medicine, Part I: Concept, History, and Types. Annals of Emergency Medicine, 49, (3), 275-281.

Image Source: http://store.gomed-tech.com

Example Clinical DSS: Hypothesis-Oriented Algorithm



HOAC =Hypothesis-Oriented Algorithm for Clinicians

Schenkman, M., Deutsch, J. E. & Gill-Body, K. M. (2006) An Integrated Framework for Decision Making in Neurologic Physical Therapist Practice. *Physical Therapy, 86, 12, 1681-1702.*

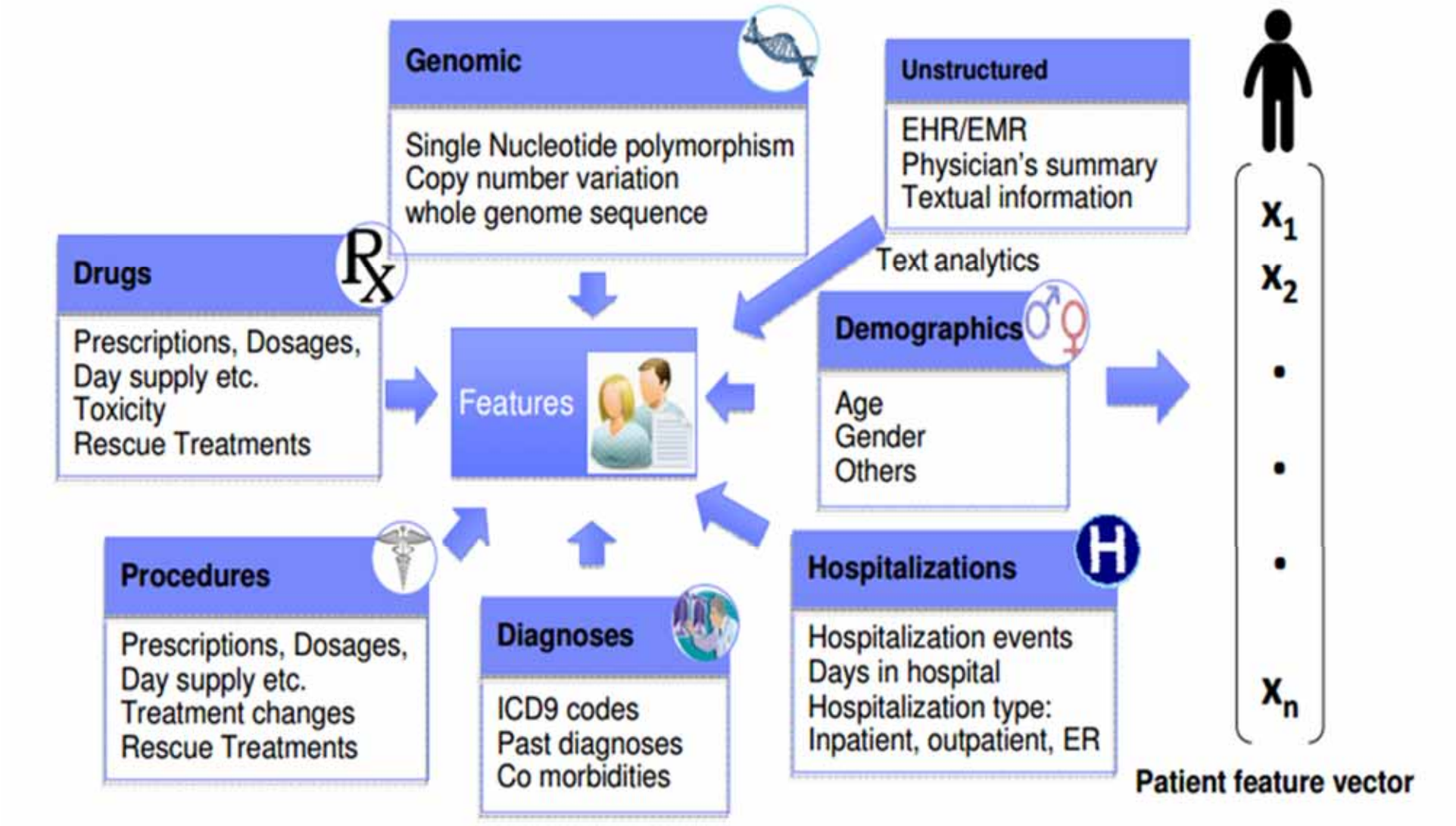
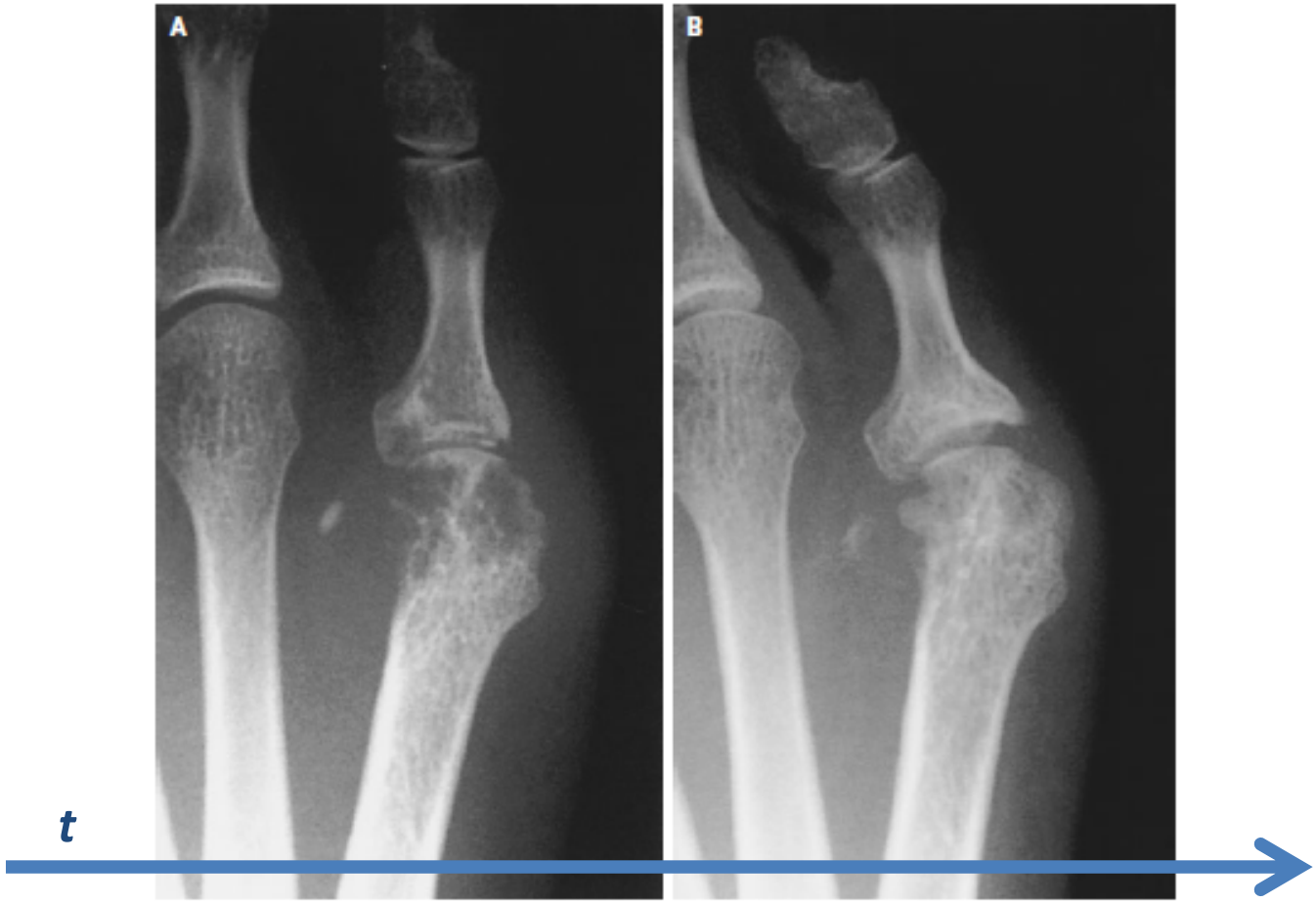


Image credit to Michal Rosen-Zvi

Example: Rheumatology

Chao, J., Parker, B. A. & Zvaifler, N. J. (2009) Accelerated Cutaneous Nodulosis Associated with Aromatase Inhibitor Therapy in a Patient with Rheumatoid Arthritis. *The Journal of Rheumatology, 36,* ***5, 1087-1088.***

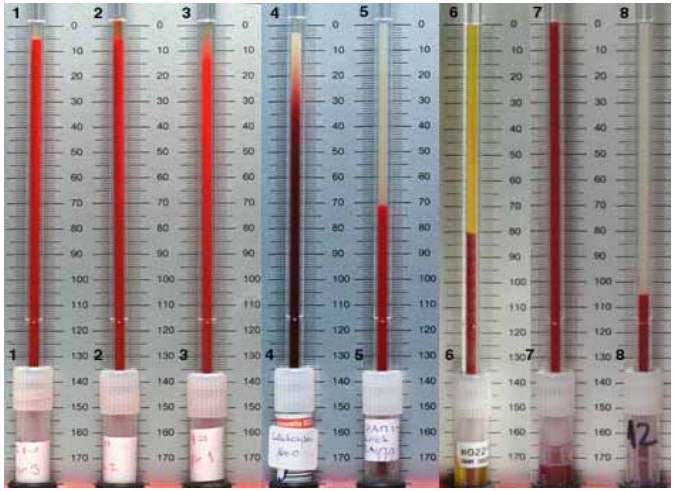
Bone Changes …

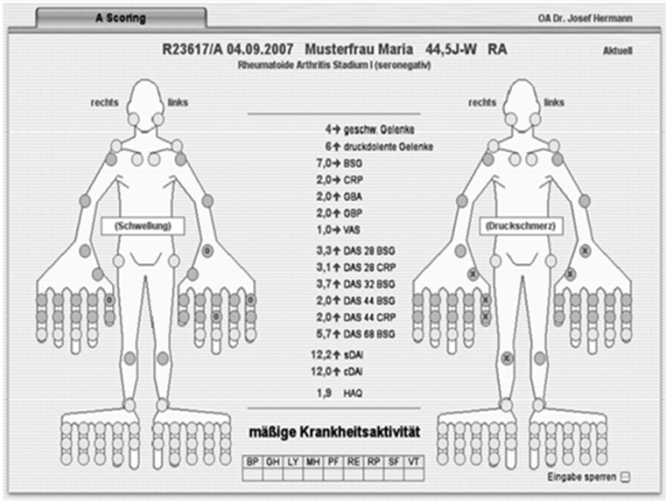


Ikari, K. & Momohara, S. (2005) Bone Changes in Rheumatoid Arthritis. *New England Journal of Medicine, 353,* ***15, e13.***

100+ clinical and functional parameter per Patient

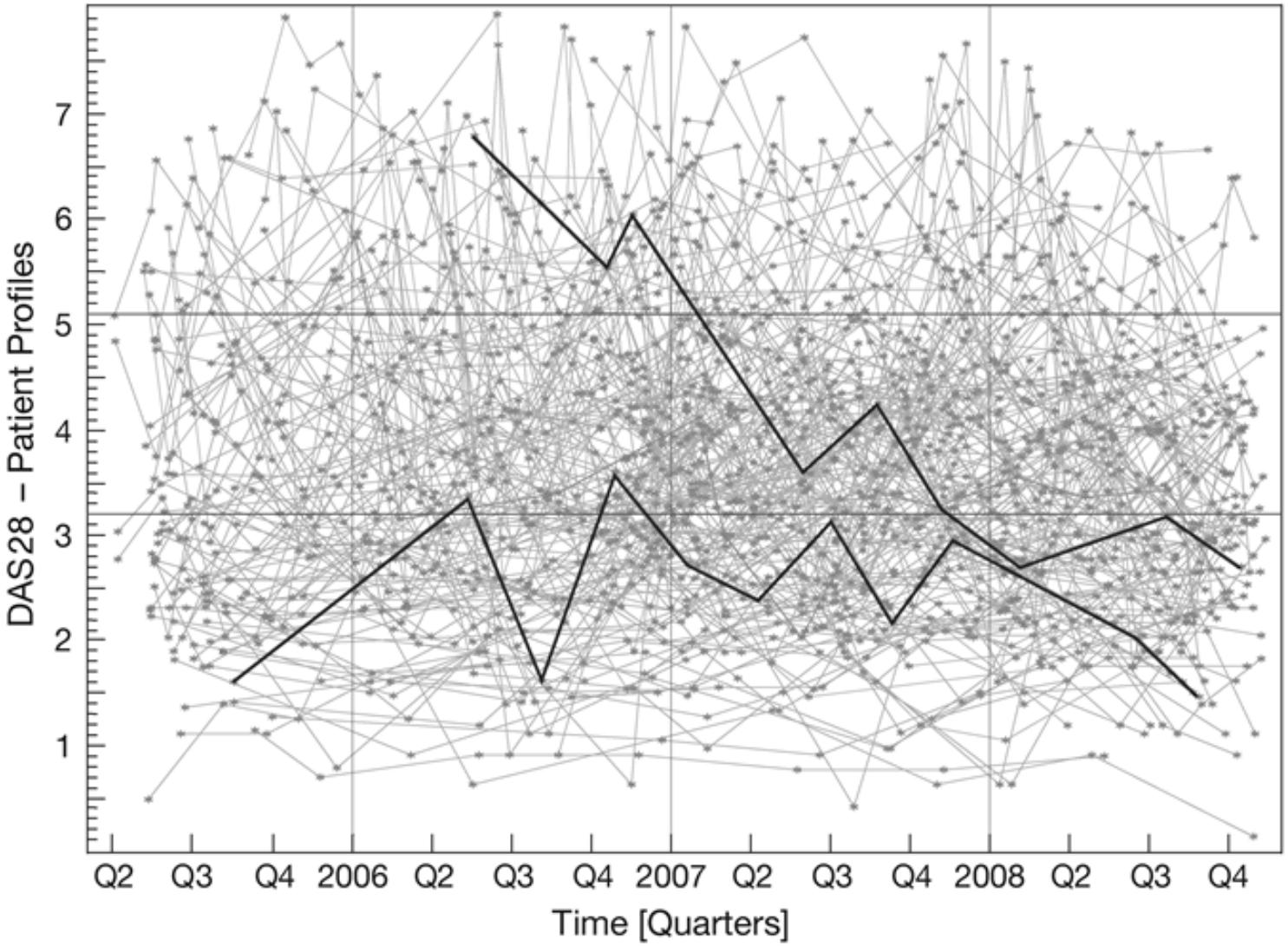
- 50+ Patients per day ~ 5000 data points per day …
- Aggregated with specific scores (Disease Activity Score, DAS)
- Current patient status is related to previous data
- = convolution over time
- ⇒ **time-series data**





Simonic, K. M., Holzinger, A., Bloice, M. & Hermann, J. (2011). *Optimizing Long-Term Treatment of Rheumatoid Arthritis with Systematic Documentation. Pervasive Health - 5th International Conference on Pervasive Computing Technologies for Healthcare, Dublin, IEEE, 550-554.*

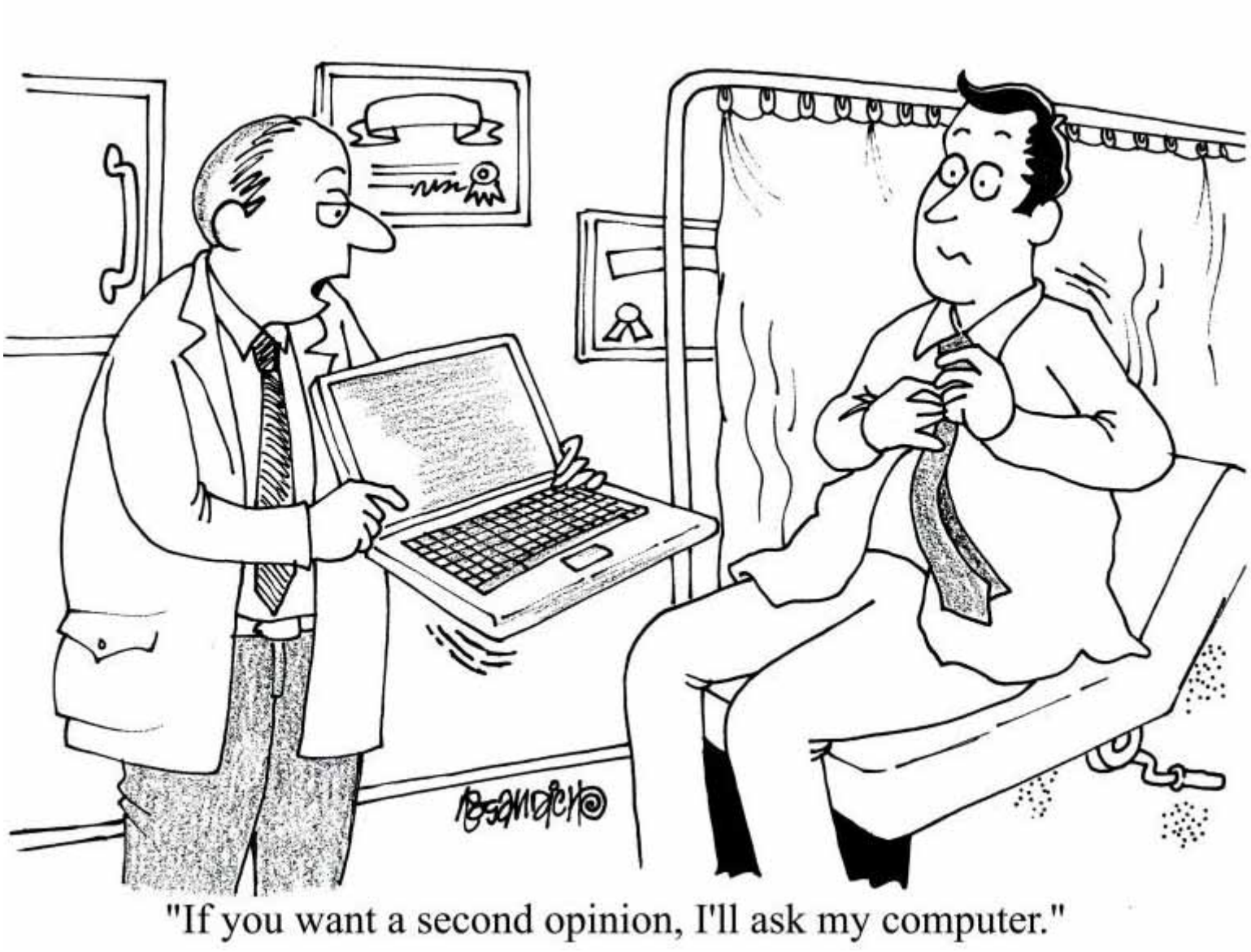
Gaining out Knowledge of time-series data



Simonic, K. M., Holzinger, A., Bloice, M. & Hermann, J. (2011). *Optimizing Long-Term Treatment of Rheumatoid Arthritis with Systematic Documentation. Pervasive Health - 5th International Conference on Pervasive Computing Technologies for Healthcare, Dublin, IEEE, 550-554.*

Can Computers help doctors to make better decisions?

Computers to help human doctors to make better decisions



http://biomedicalcomputationreview.org/content/clinical-decision-support-providing-quality-healthcare-help-computer

Augmenting Human Capabilities …

Two types of decisions (Diagnosis vs. Therapy)

- **Type 1 Decisions:** related to the **diagnosis,** i.e. AI/ML is used to assist in diagnosing a disease on the basis of the individual patient data. Questions include:
  - What is the probability that this patient has a myocardial infarction on the basis of given data (patient history, ECG, …)?
  - What is the probability that this patient has acute appendices, given the signs and symptoms concerning abdominal pain?
- **Type 2 Decisions:** related to **therapy,** i.e. AI/ML is used to select the best therapy on the basis of clinical evidence, e.g.:
  - What is the best therapy for patients of age x and risks y, if an obstruction of more than z % is seen in the left coronary artery?
  - What amount of insulin should be prescribed for a patient during the next 5 days, given the blood sugar levels and the amount of insulin taken during the recent weeks?

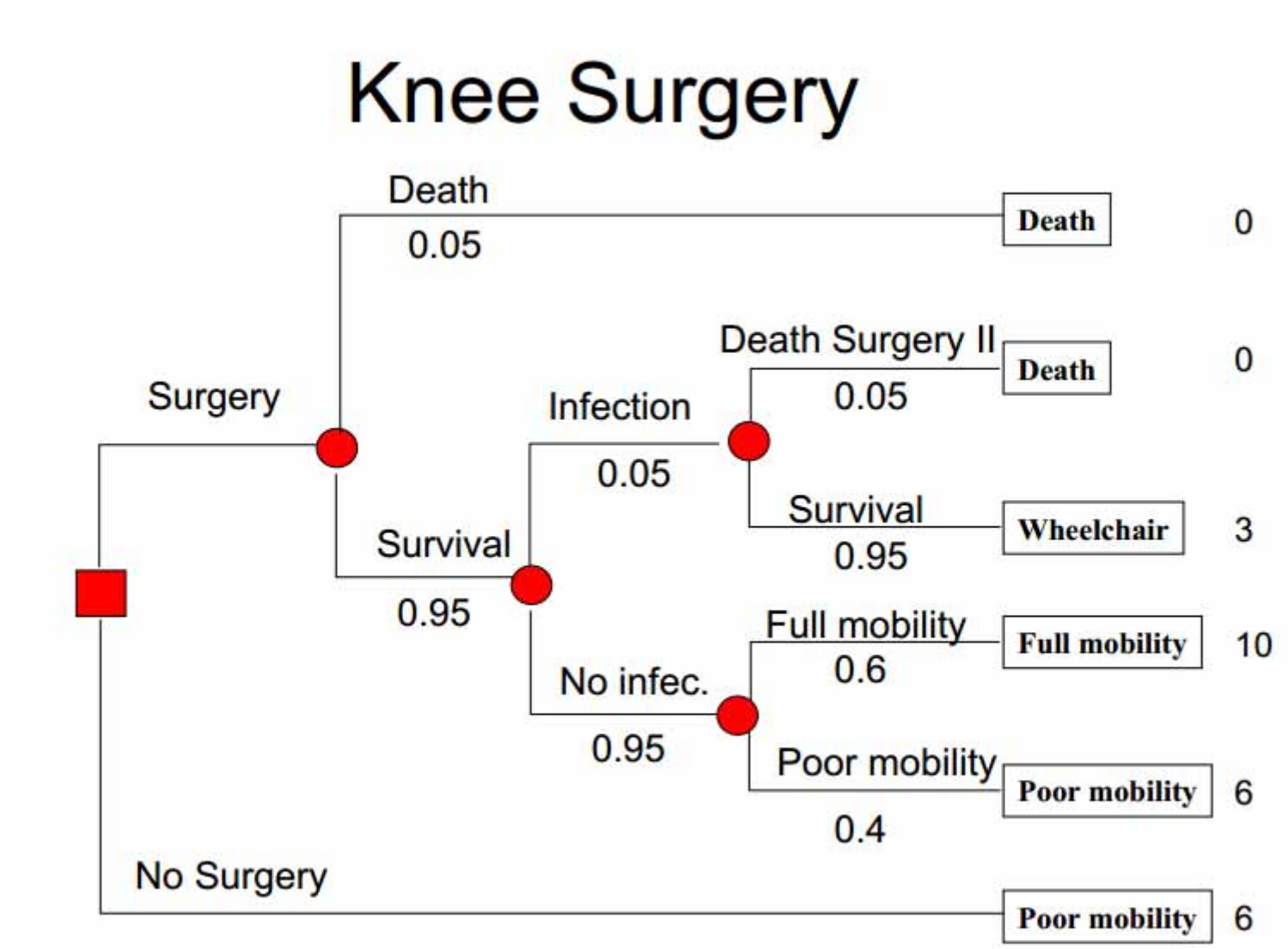
Bemmel, J. H. V. & Musen, M. A. 1997. *Handbook of Medical Informatics, Heidelberg, Springer.*

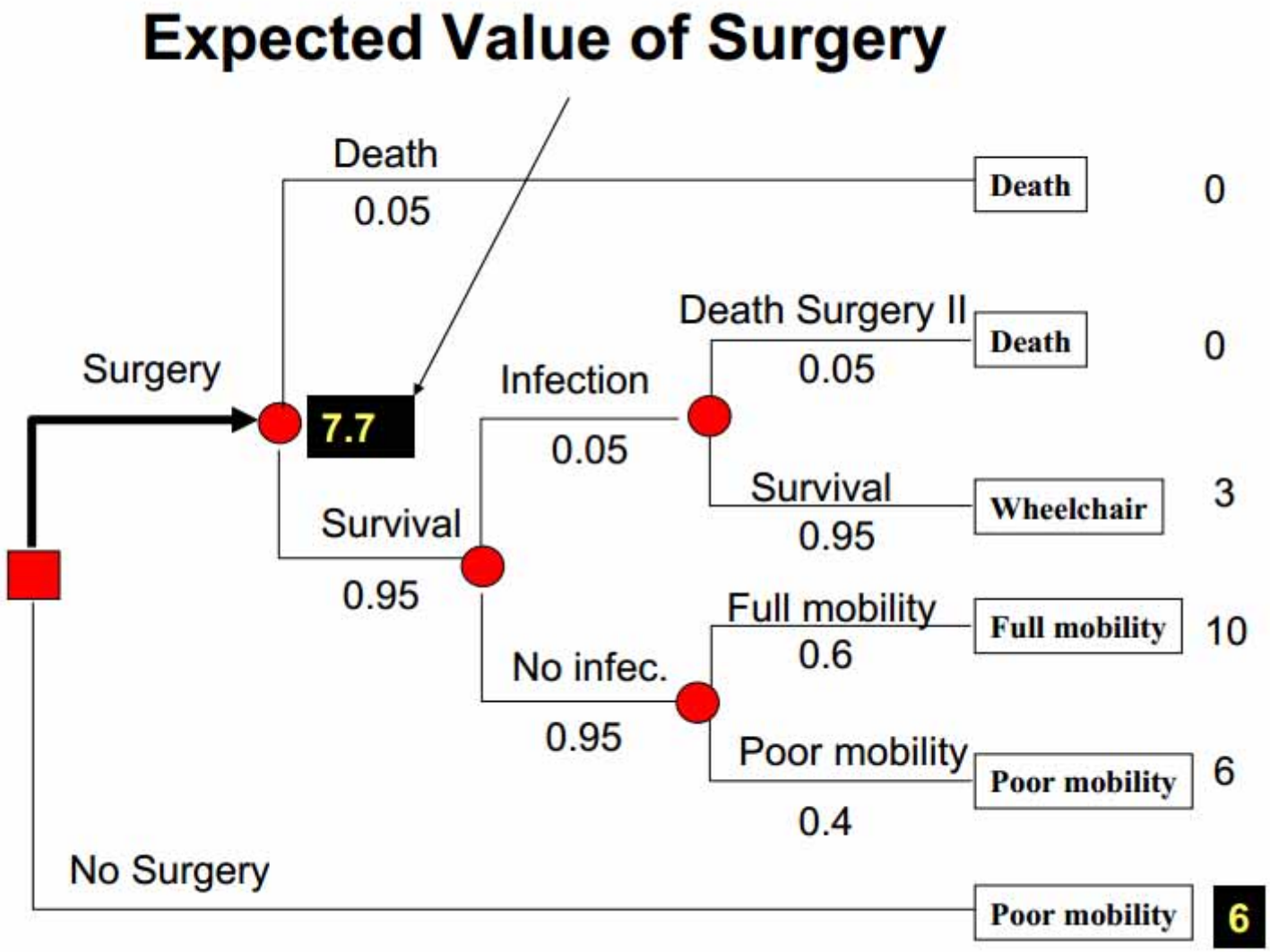
Example: Knee Surgery of a Soccer Player

- Example of a Decision Problem
- Soccer player considering knee surgery
- Uncertainties:
- Success: recovering full mobility
- Risks: infection in surgery (if so, needs another surgery and may loose more mobility)
- Survival chances of surgery

Harvard-MIT Division of Health Sciences and Technology
HST.951J: Medical Decision Support, Fall 2005
Instructors: Professor Lucila Ohno-Machado and Professor Staal Vinterbo

Decision Tree (this is known since Hippocrates!)




Expected Value of Surgery
Death
0.05
Death
0
Death Surgery II
0.05
Death
0
Surgery
7.7
Infection
0.05
Survival
0.95
Wheelchair
3
Survival
0.95
Full mobility
0.6
Full mobility
10
No infec.
0.95
Poor mobility
0.4
Poor mobility
6
No Surgery
Poor mobility
6

Remember: Expected Utility Theory $E\ (U|d)$

For a single decision variable an agent can select $D = d$ for any $d \in dom(D)$.

The expected utility of decision $D = d$ is

http://www.eoht.info/page/Oskar+Morgenstern

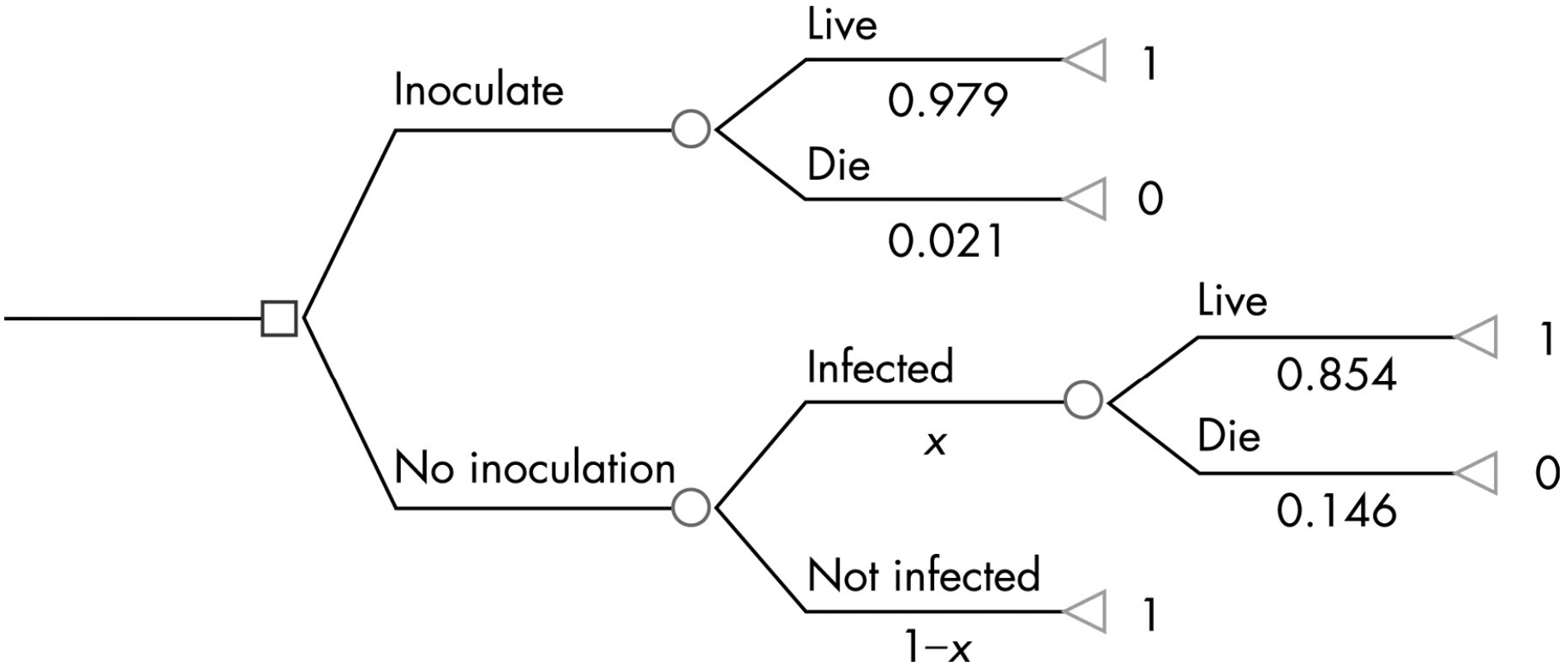
$$E(U \mid d) = \sum_{x_1,\ldots,x_n} P(x_1, \ldots, x_n \mid d) U(x_1, \ldots, x_n, d)$$

An optimal single decision is the decision $D = dmax$ whose expected utility is maximal:

$$d_{\max} = \arg \max_{d \in \mathrm{dom}(D)} E(U \mid d)$$

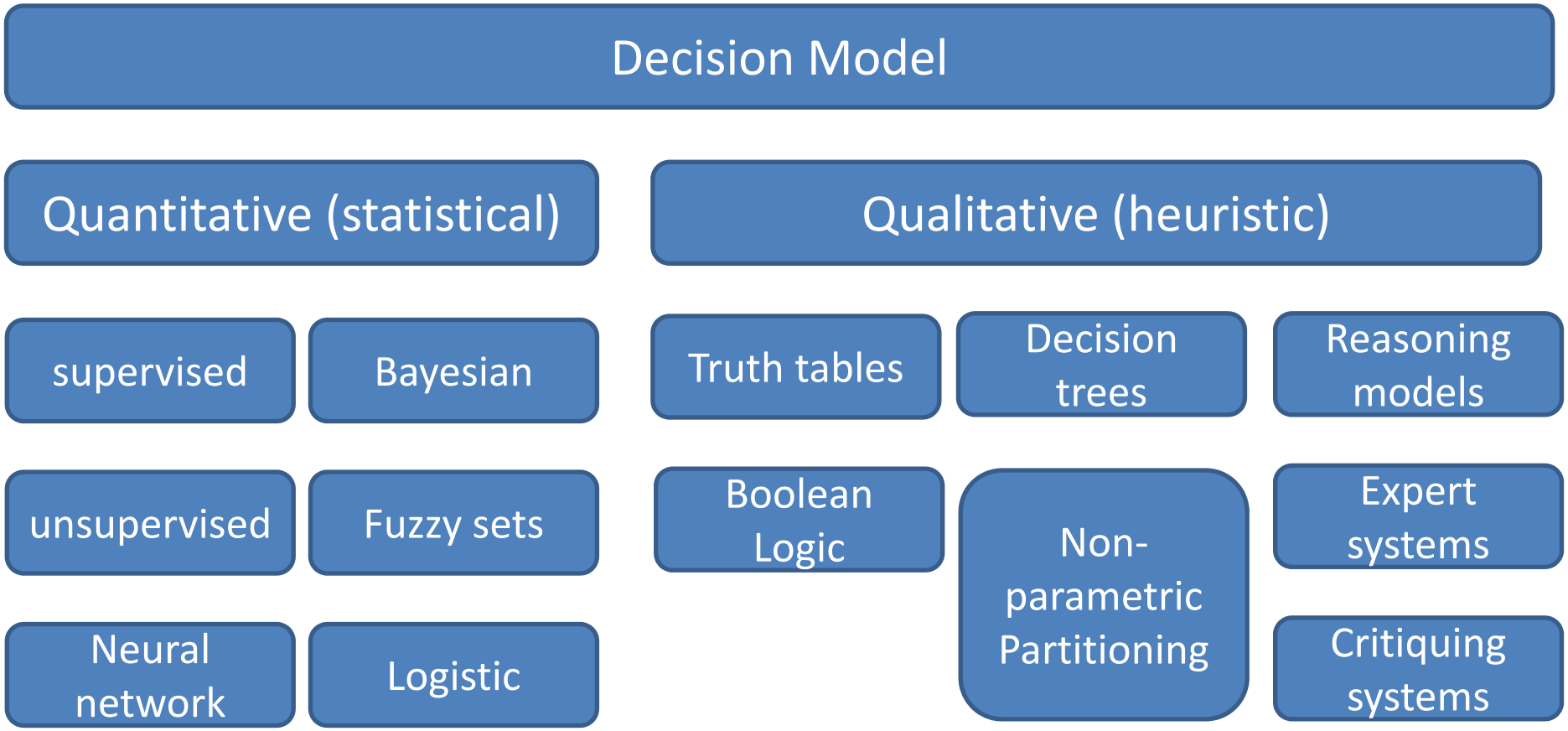
Von Neumann, J. & Morgenstern, O. 1947. Theory of games and economic behavior, Princeton university press.

Clinical Decision Tree (CDT) is still state-of-the-art



Ferrando, A., Pagano, E., Scaglione, L., Petrinco, M., Gregori, D. & Ciccone, G. (2009) A decision-tree model to estimate the impact on cost-effectiveness of a venous thromboembolism prophylaxis guideline. *Quality and Safety in Health Care, 18, 4, 309-313.*

Taxonomy of Decision Support Models



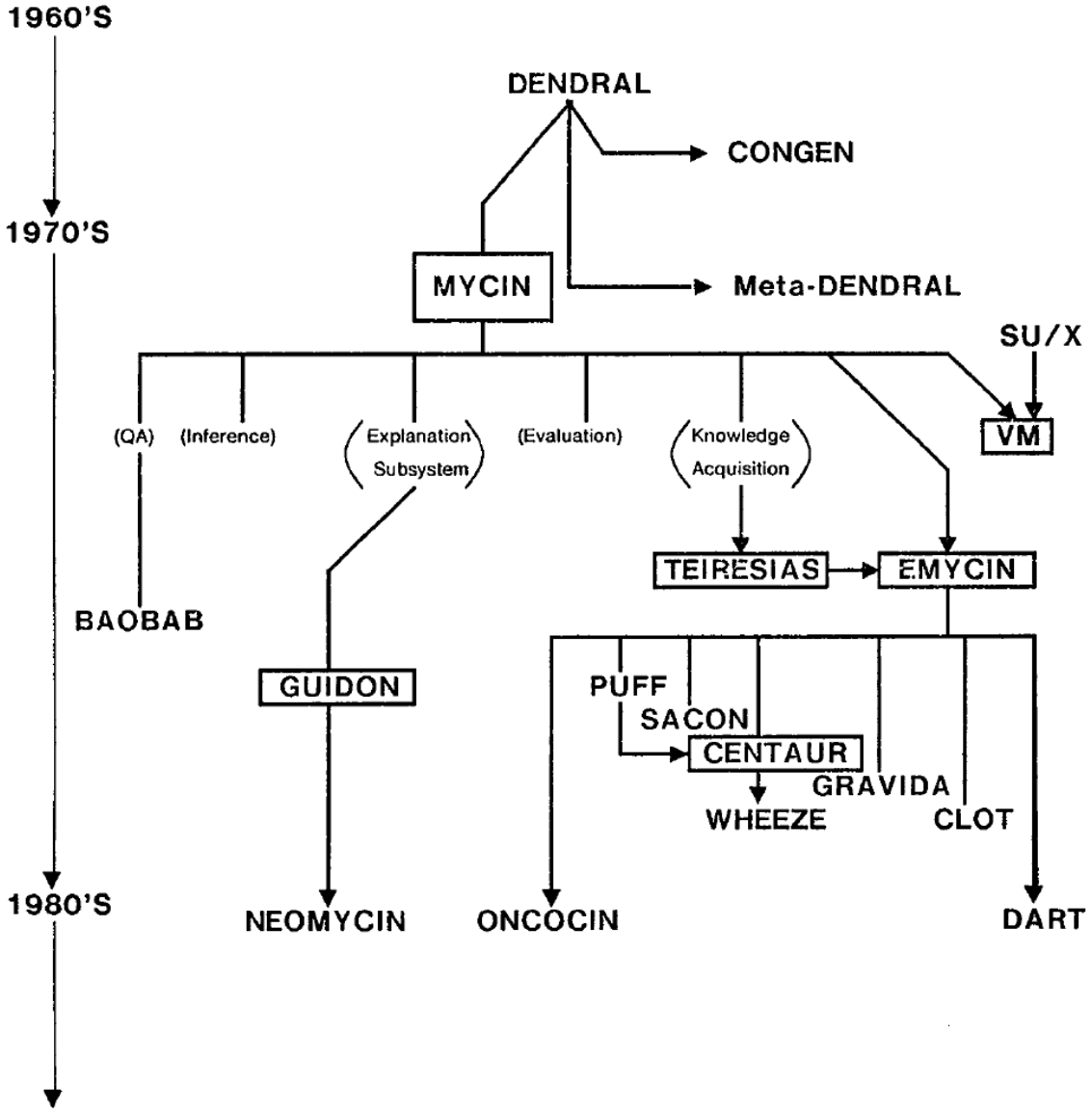
Extended by A. Holzinger after: Bemmel, J. H. v. & Musen, M. A. (1997) *Handbook of Medical Informatics. Heidelberg, Springer.*

02 History of DSS = History of AI

A ultrashort history of Early AI

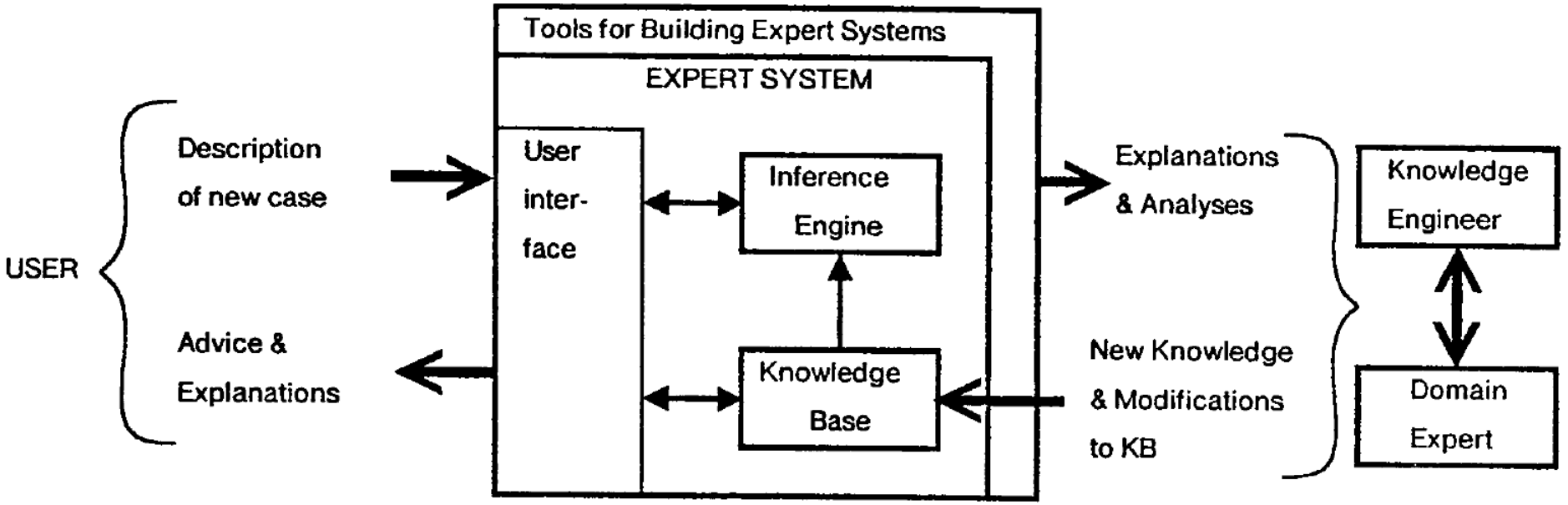
- **1943** McCulloch, W.S. & Pitts, W. A logical calculus of the ideas immanent in nervous activity. Bulletin of Mathematical Biology, 5, (4), 115-133, doi:10.1007/BF02459570.
- **1950** Turing, A.M. Computing machinery and intelligence. Mind, 59, (236), 433-460.
- 1958 John McCarthy Advice Taker: programs with common sense
- **1959** Samuel, A.L. Some studies in machine learning using the game of checkers. IBM Journal of research and development, 3, (3), 210-229, doi:10.1147/rd.33.0210.
- **1975** Shortliffe, E.H. & Buchanan, B.G. 1975. A model of inexact reasoning in medicine. Mathematical biosciences, 23, (3-4), 351-379, doi:10.1016/0025-5564(75)90047-4.
- 1978 Bellman, R. Can Computers Think? Automation of Thinking, problem solving, decision-making …

Evolution of Decision Support Systems (Expert Systems)



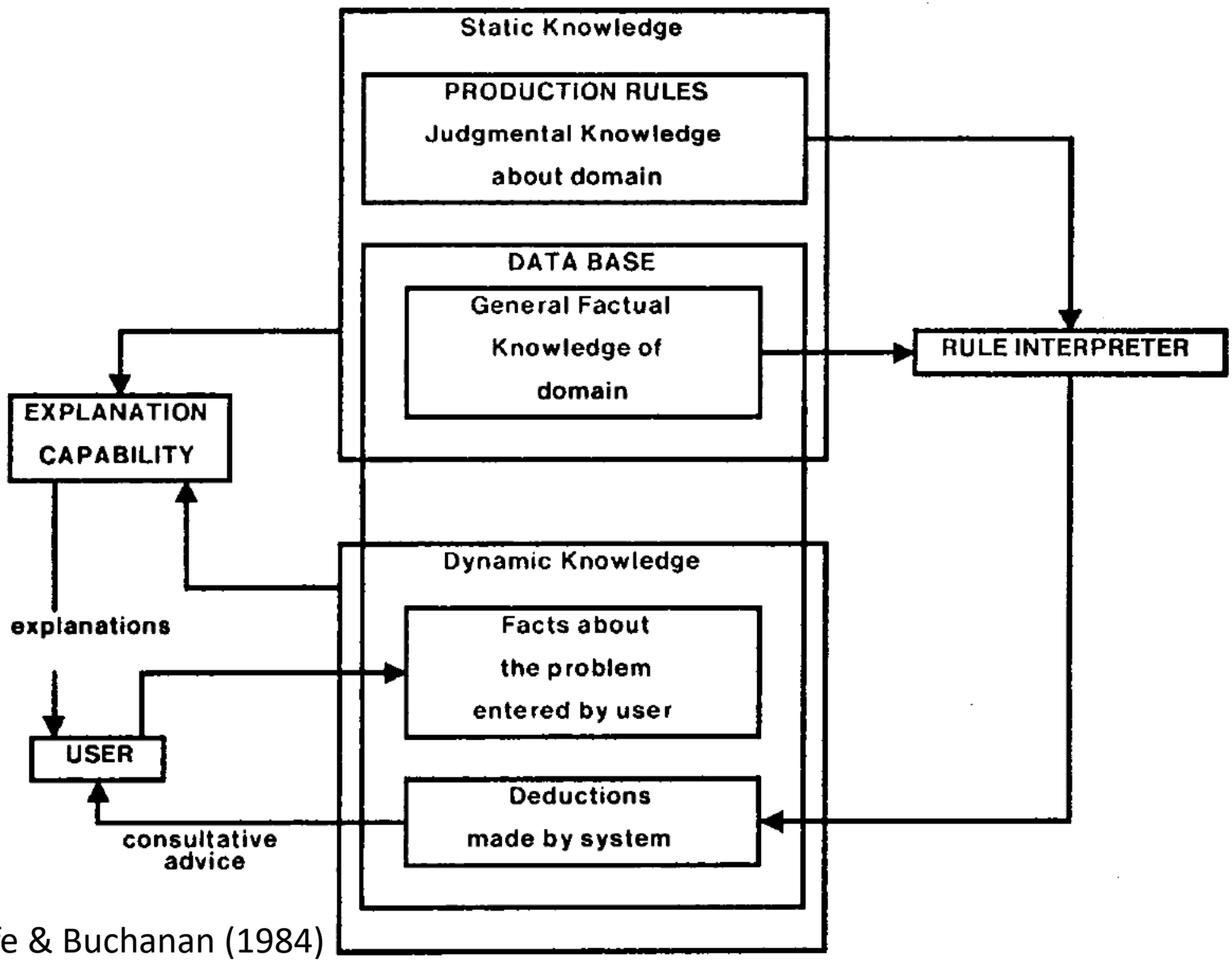
Shortliffe, E. H. & Buchanan, B. G. (1984) *Rule-based expert systems: the MYCIN experiments of the Stanford Heuristic Programming Project. Addison-Wesley.*

Early Knowledge Based System Architecture



Shortliffe, T. & Davis, R. (1975) Some considerations for the implementation of knowledge-based expert systems *ACM SIGART Bulletin, 55, 9-12.*

Static Knowledge versus dynamic knowledge



Shortliffe & Buchanan (1984)

Dealing with uncertainty in the real world

- The information available to humans is often imperfect – imprecise - uncertain.
- This is especially in the medical domain the case.
- An **human agent** can cope with deficiencies.
- Classical logic permits only **exact reasoning**:
- IF A is true THEN A is non-false and
  IF B is false THEN B is non-true
- Most real-world problems do not provide this exact information, mostly it is inexact, incomplete, uncertain and/or **un-measurable!**

MYCIN – rule based system - certainty factors

- MYCIN is a rule-based Expert System, which is used for therapy planning for patients with bacterial infections
- Goal oriented strategy (“Rückwärtsverkettung”)
- To every rule and every entry a certainty factor (CF) is assigned, which is between 0 und 1
- Two measures are derived:
- MB: measure of belief
- MD: measure of disbelief
- Certainty factor – CF of an element is calculated by:

$$CF[h] = MB[h] - MD[h]$$

- CF is positive, if more evidence is given for a hypothesis, otherwise CF is negative
- CF[h] = +1 -> h is 100 % true
- CF[h] = –1 -> h is 100% false

Original Example from MYCIN

h_1 = The identity of ORGANISM-1 is streptococcus
h_2 = PATIENT-1 is febrile
h_3 = The name of PATIENT-1 is John Jones

$CF[h_1,E] = .8$	:	There is strongly suggestive evidence (.8) that the identity of ORGANISM-1 is streptococcus
$CF[h_2,E] = -.3$	:	There is weakly suggestive evidence (.3) that PATIENT-1 is not febrile
$CF[h_3,E] = +1$	:	It is definite (1) that the name of PATIENT-1 is John Jones

Shortliffe, E. H. & Buchanan, B. G. (1984) *Rule-based expert systems: the MYCIN experiments of the Stanford Heuristic Programming Project. Addison-Wesley.*

MYCIN was *no* success in the clinical routine

However, AI was extremely popular in the 1970ies

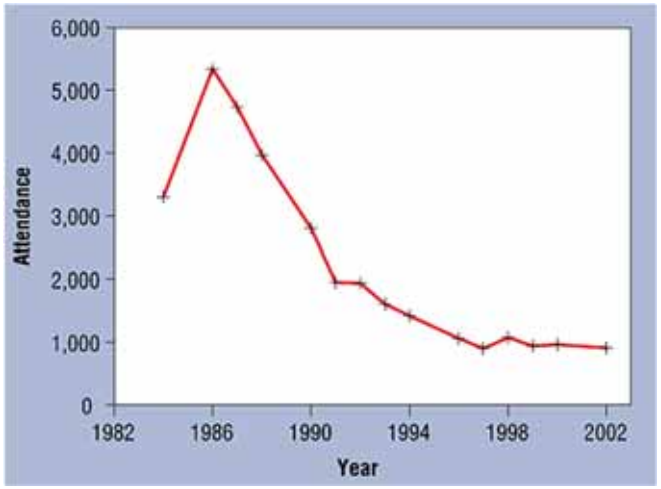
Image credit to Bernhard Schölkopf

Cybernetics was praised as the solution for everything

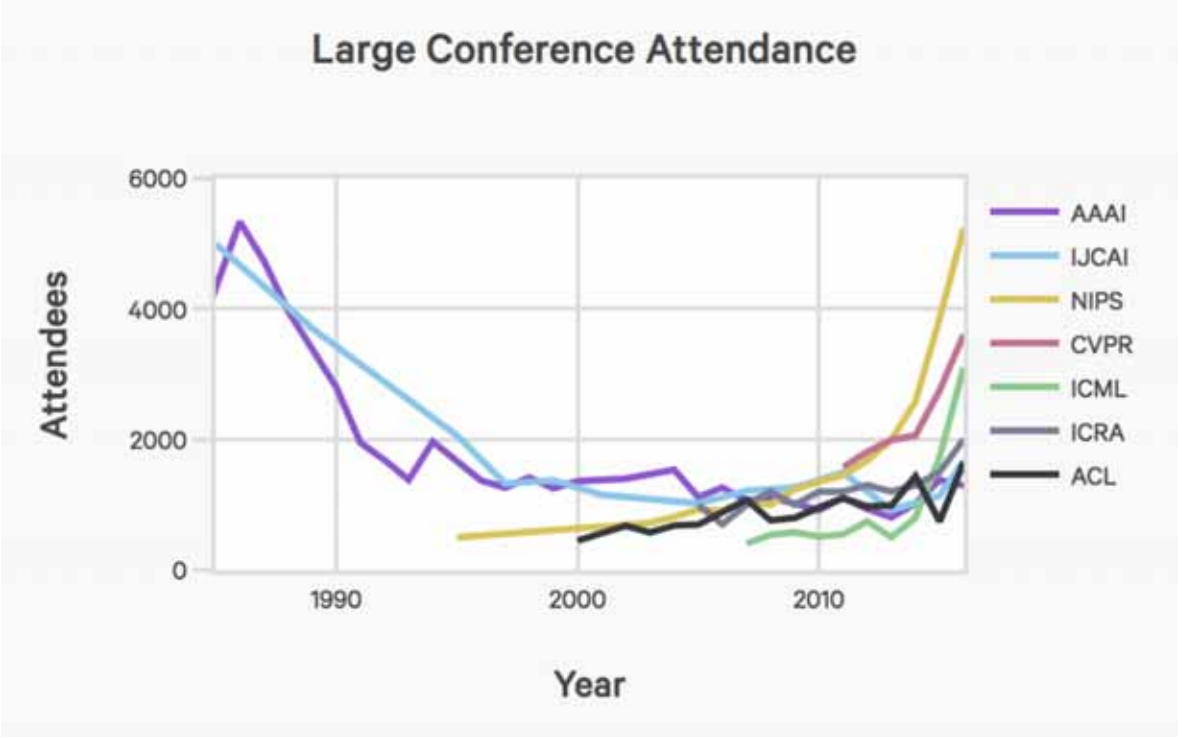
Image credit to Bernhard Schölkopf

The AI winter was bitter cold …

https://blogs.dxc.technology/2017/04/25/are-we-heading-toward-an-ai-winter/



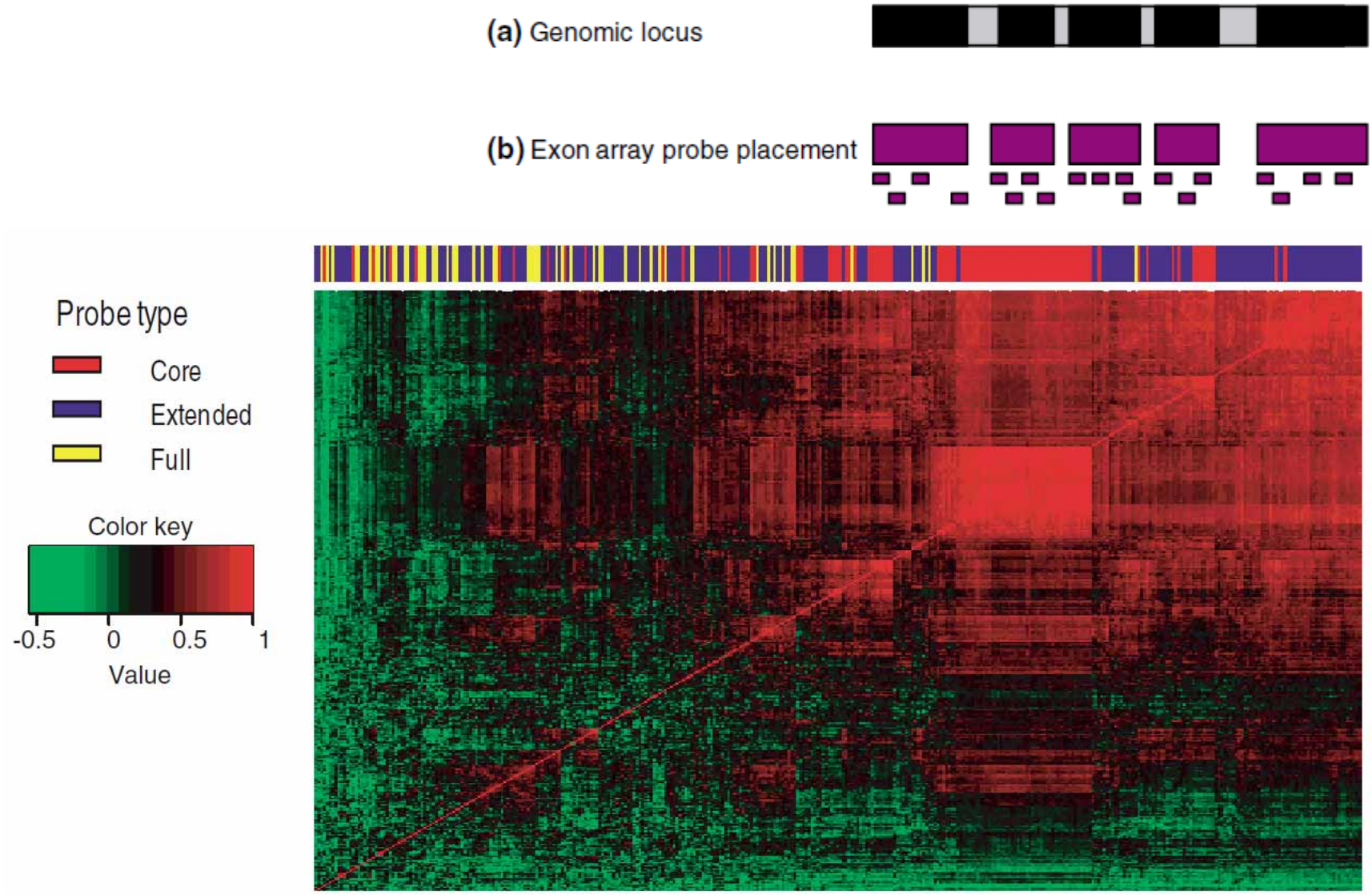
https://www.computer.org/csl/mags/ex/2003/03/x3018.html



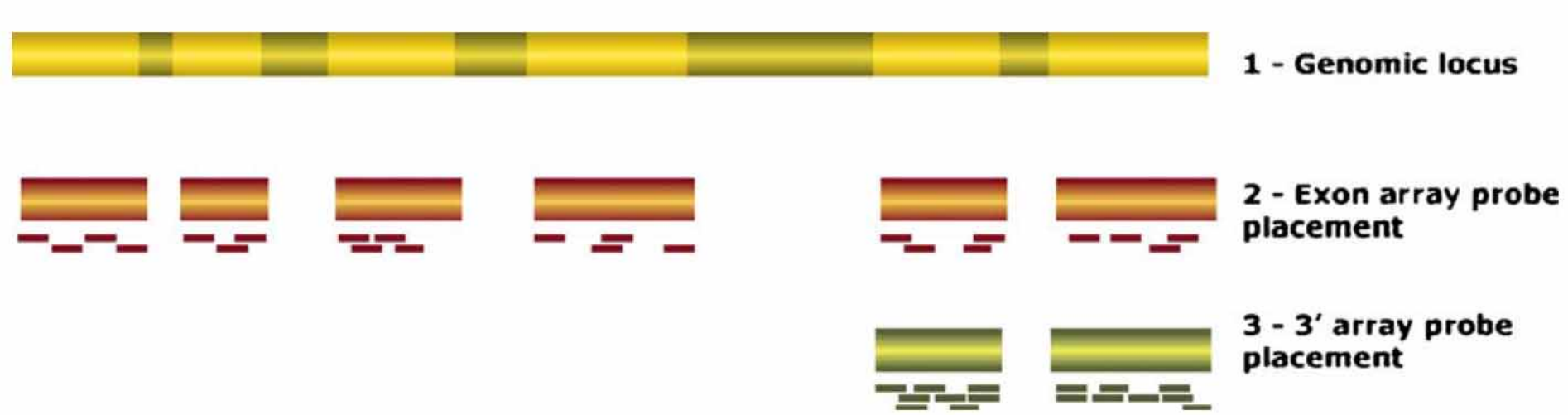
https://medium.com/machine-learning-in-practice/nips-accepted-papers-stats-26f124843aa0

03 Example: P4-Medicine

Slide 8-22 Example: Exon Arrays



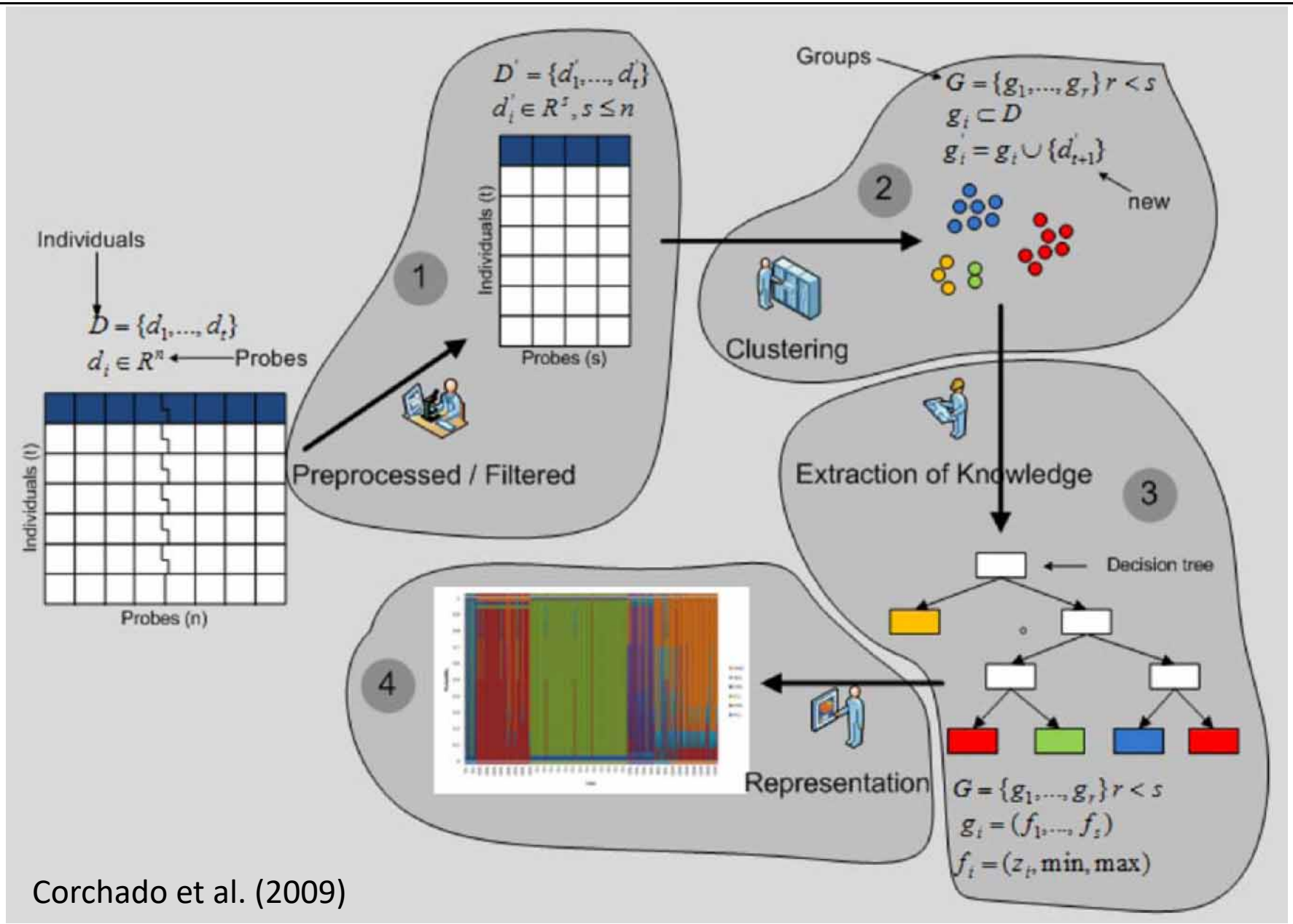
Kapur, K., Xing, Y., Ouyang, Z. & Wong, W. (2007) Exon arrays provide accurate assessments of gene expression. *Genome Biology, 8, 5, R82.*



Exon array structure. Probe design of exon arrays. (1) Exon—intron structure of a gene. Gray boxes represent introns, rest represent exons. Introns are not drawn to scale. (2) Probe design of exon arrays. Four probes target each putative exon. (3) Probe design of 30expression arrays. Probe target the 30end of mRNA sequence.

Corchado, J. M., De Paz, J. F., Rodriguez, S. & Bajo, J. (2009) Model of experts for decision support in the diagnosis of leukemia patients. *Artificial Intelligence in Medicine, 46, 3, 179-200.*

Slide 8-24 Computational leukemia cancer detection 2/6



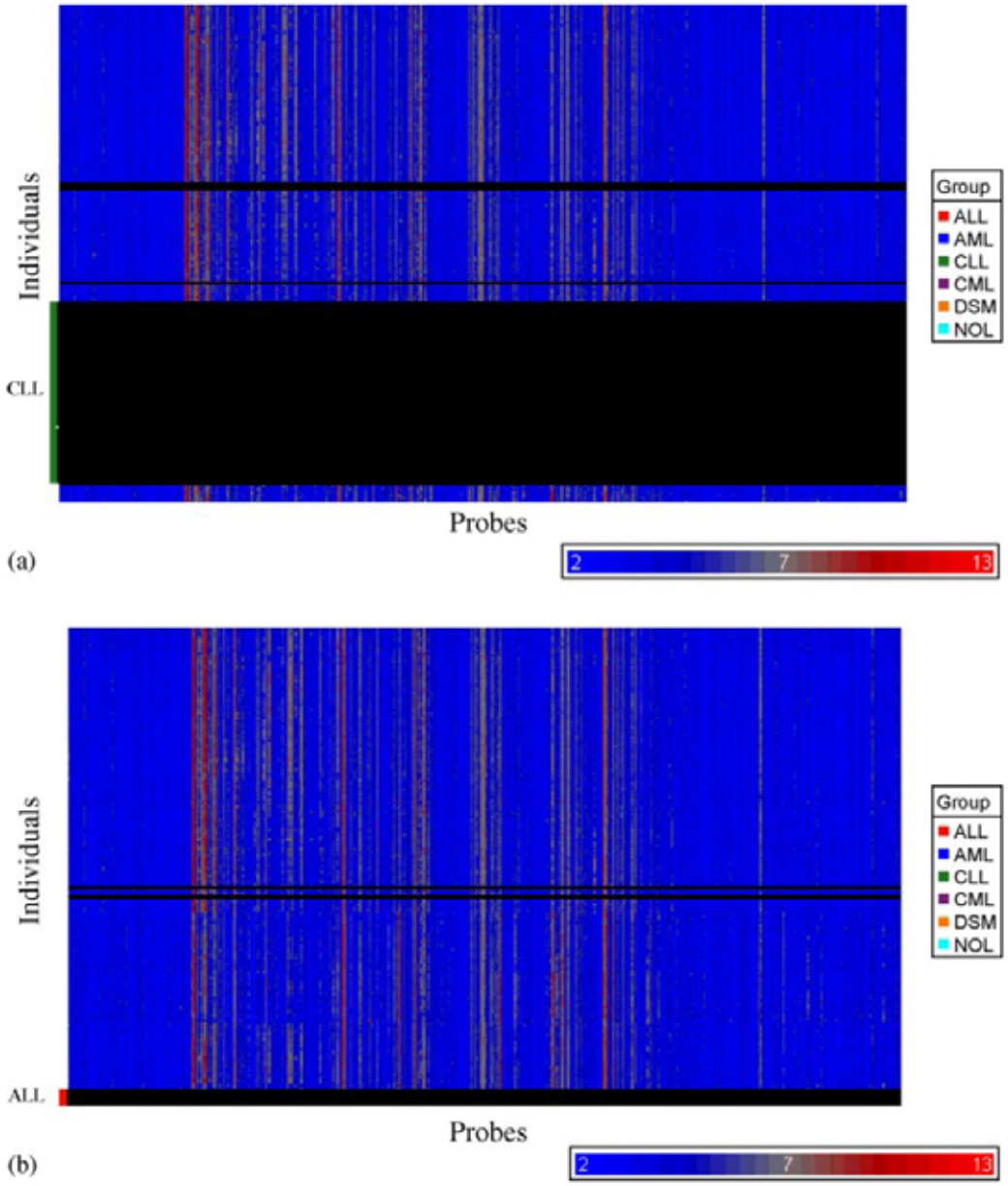
Corchado et al. (2009)

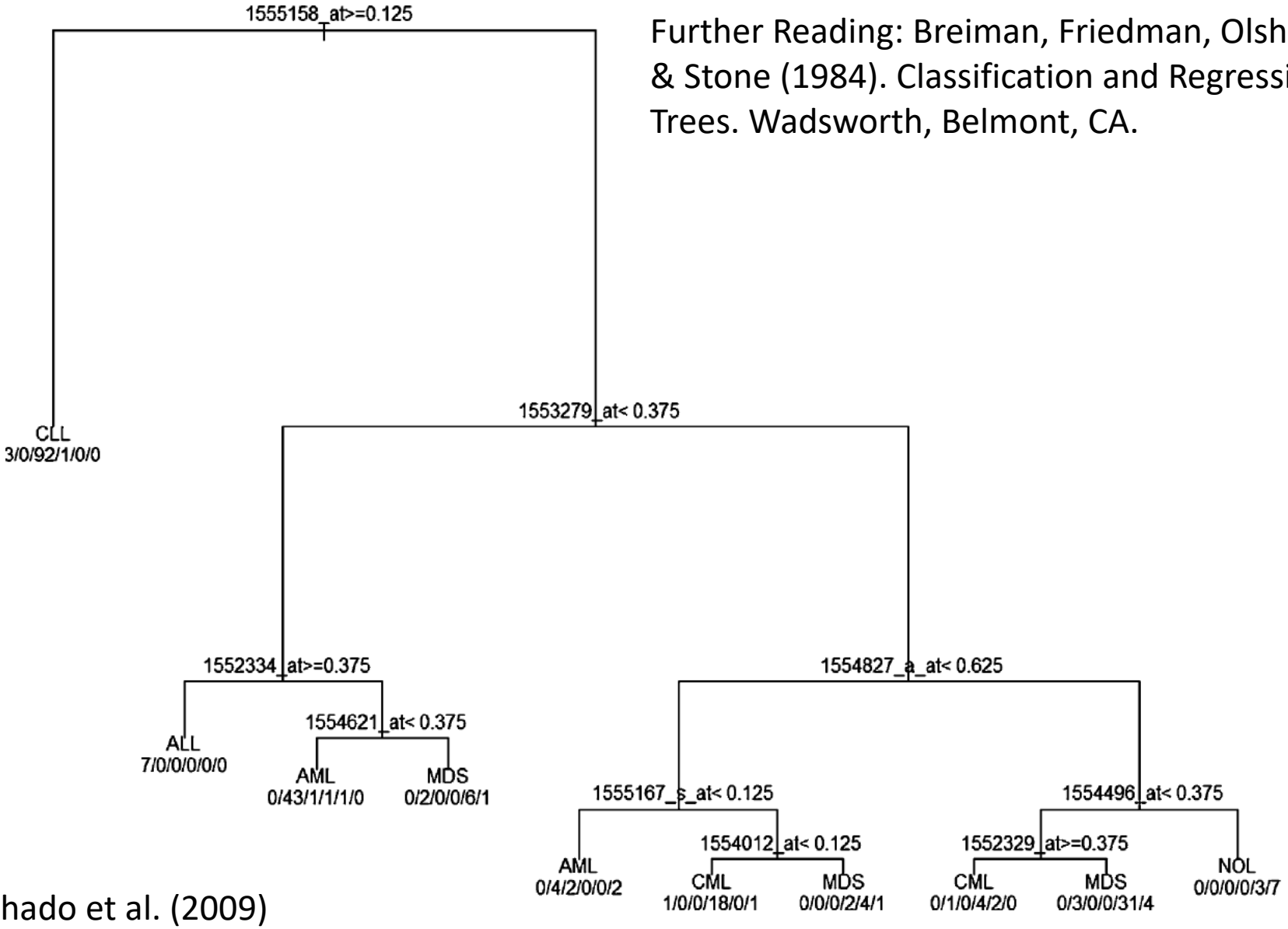
Slide 8-25 Computational leukemia cancer detection 3/6

A = acute, C = chronic,
L = lymphocytic, M = myeloid

- **ALL** = cancer of the blood AND bone marrow caused by an abnormal proliferation of lymphocytes.
- **AML** = cancer in the bone marrow characterized by the proliferation of myeloblasts, red blood cells or abnormal platelets.
- **CLL** = cancer characterized by a proliferation of lymphocytes in the bone marrow.
- **CML** = caused by a proliferation of white blood cells in the bone marrow.
- **MDS** (Myelodysplastic Syndromes) = a group of diseases of the blood and bone marrow in which the bone marrow does not produce a sufficient amount of healthy cells.
- **NOL** (Normal) = No leukemias

Corchado et al. (2009)

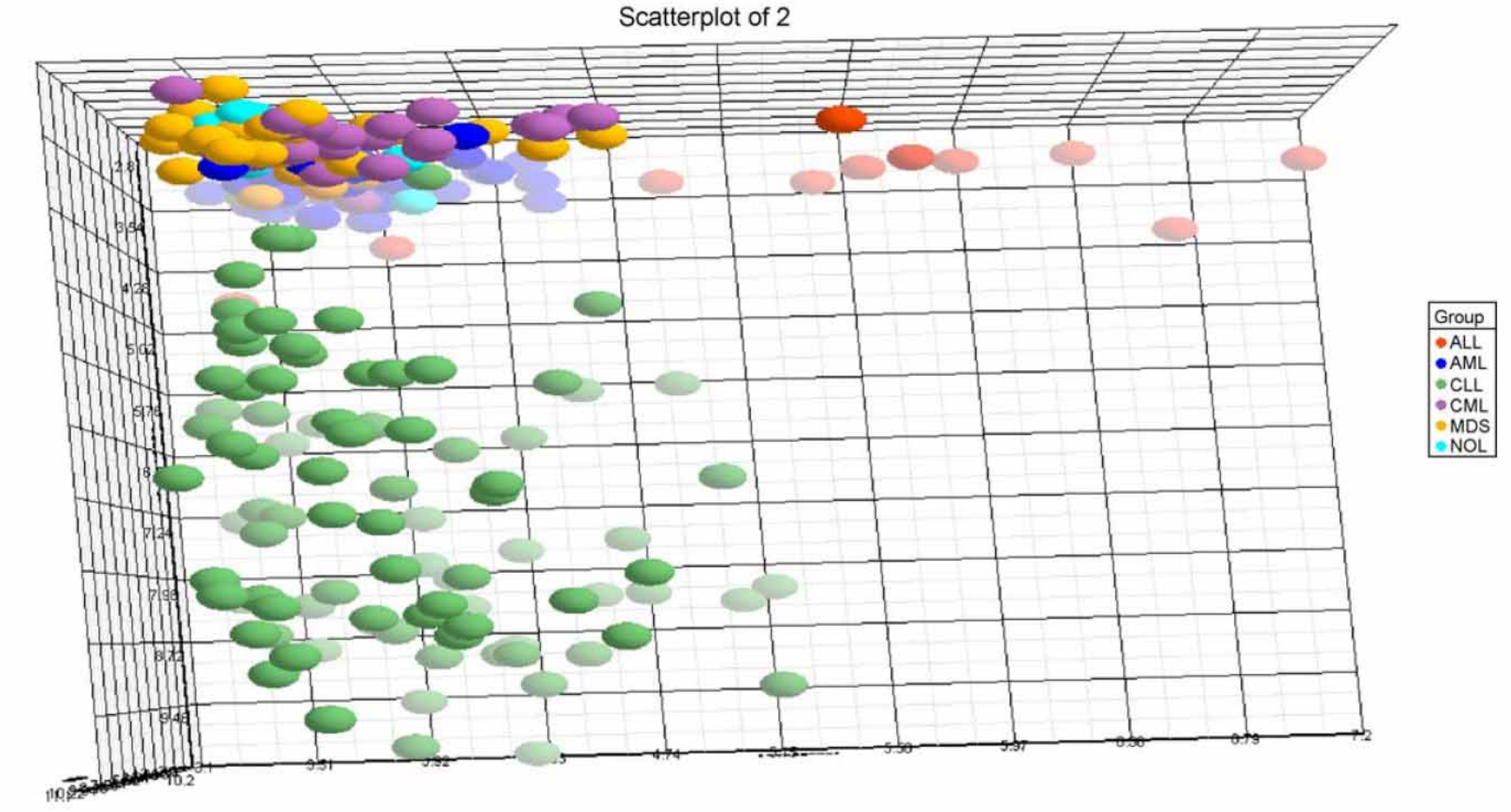




Further Reading: Breiman, Friedman, Olshen, & Stone (1984). Classification and Regression Trees. Wadsworth, Belmont, CA.

Corchado et al. (2009)

Classification CLL—ALL. Representation of the probes of the decision tree which classify the CLL and ALL to 1555158_at, 1553279_at and 1552334_at



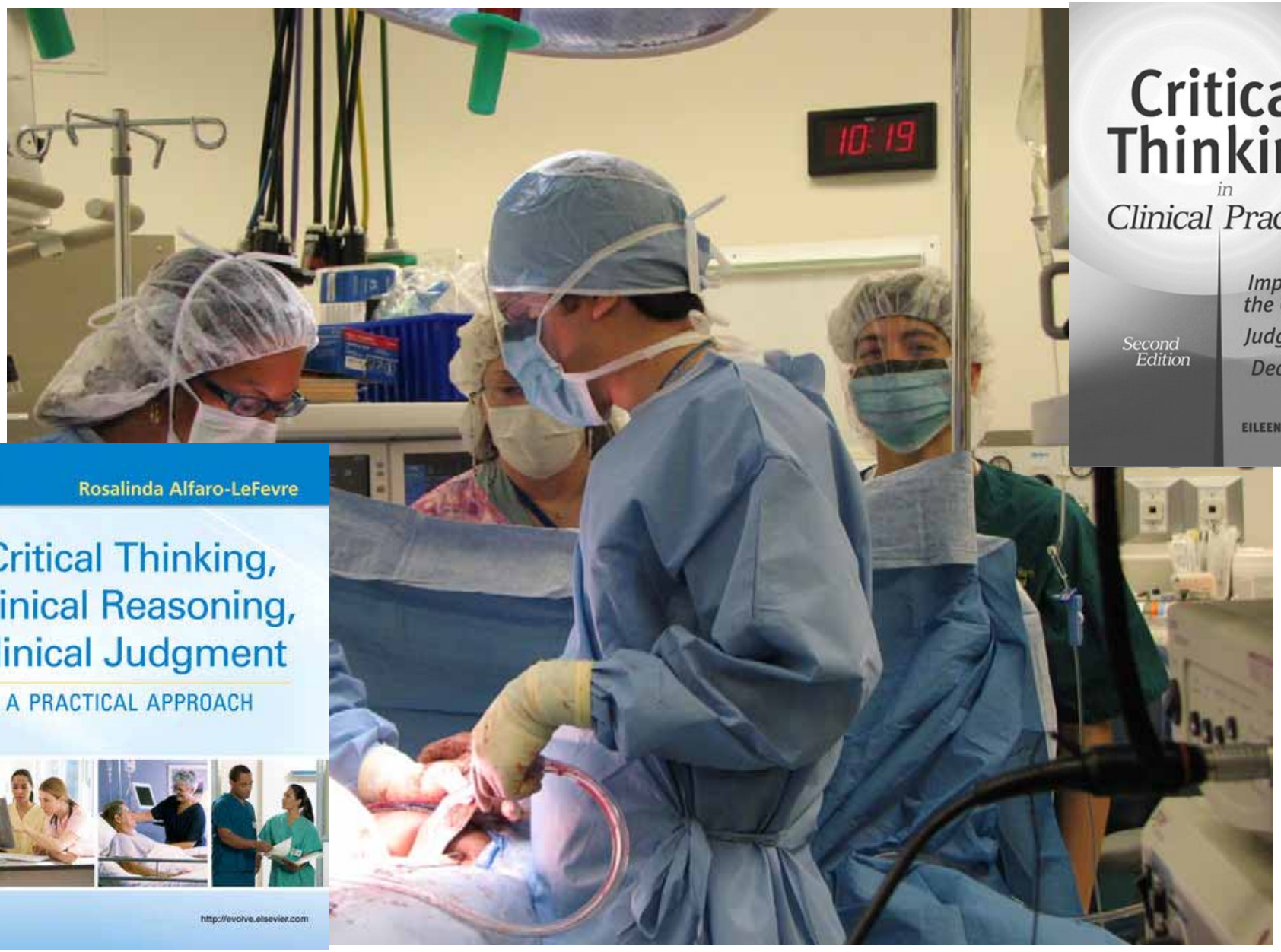
Corchado et al. (2009)

Computational leukemia cancer detection 6/6

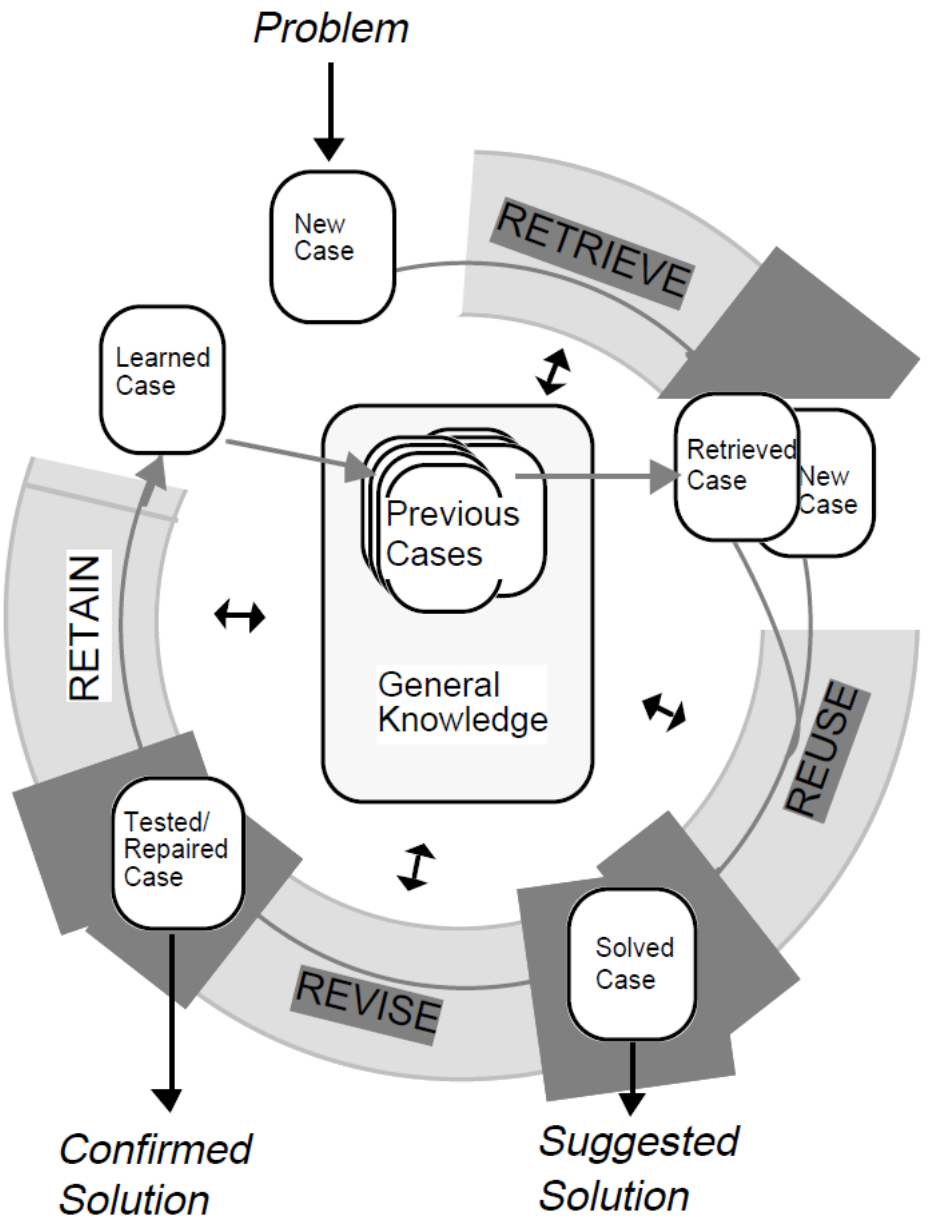
- The model of Corchado et al. (2009) combines:
- 1) methods to **reduce the dimensionality** of the original data set;
- 2) pre-processing and data filtering techniques;
- 3) a clustering method to classify patients; and
- 4) extraction of knowledge techniques
- The system reflects how human experts work in a lab, but
- 1) **reduces the time** for making predictions;
- 2) **reduces the rate of human error;** and
- 3) **works with high-dimensional data** from exon arrays

04 Example: Case Based Reasoning (CBR)

Slide 8-29 Thinking – Reasoning – Deciding – Acting

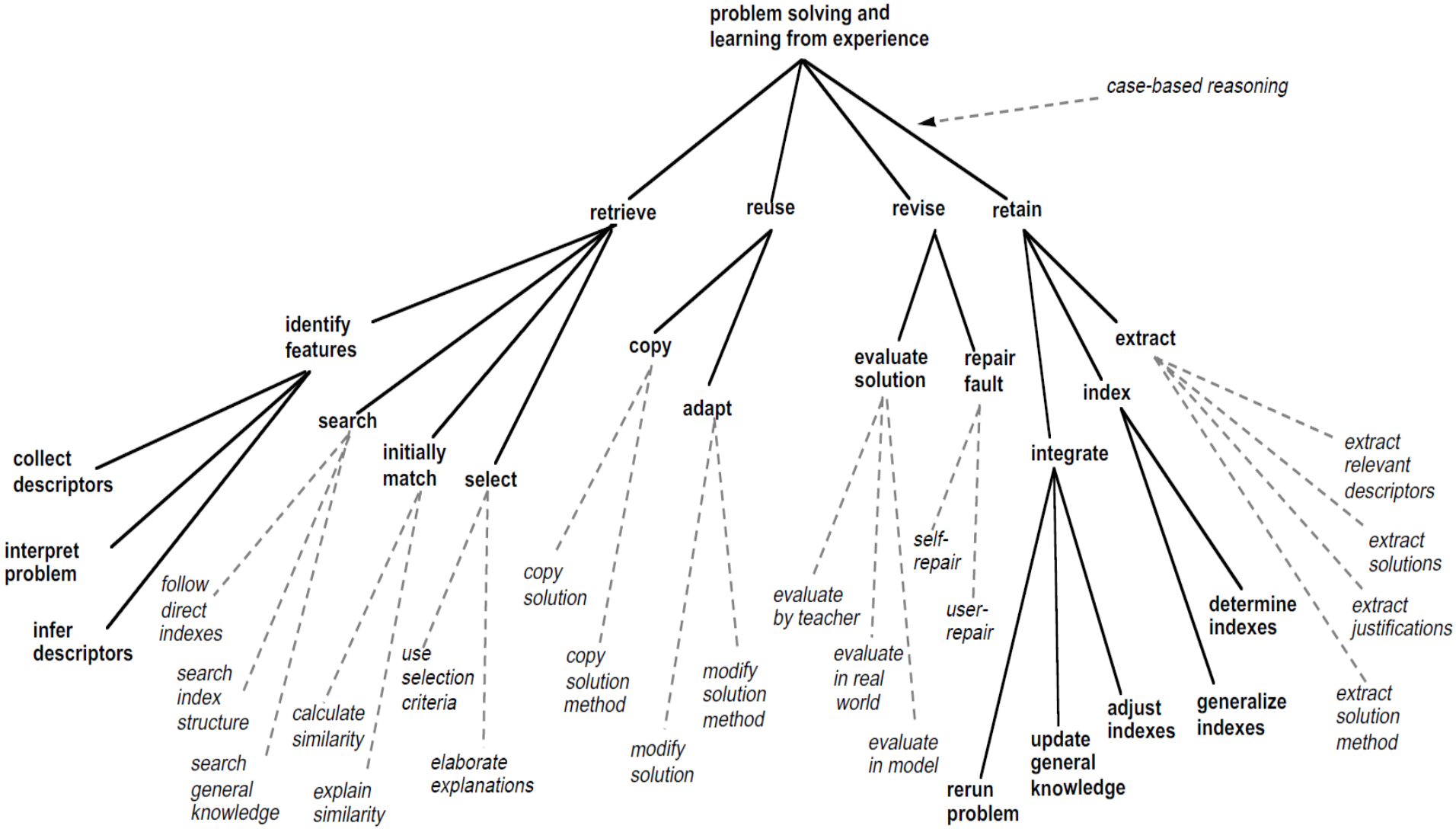


Slide 8-30 Case Based Reasoning (CBR) Basic principle



Aamodt, A. & Plaza, E. (1994) Case-based reasoning: Foundational issues, methodological variations, and system approaches. *AI Communications, 7, 1, 39-59.*

Slide 8-31 The task-method decomposition of CBR

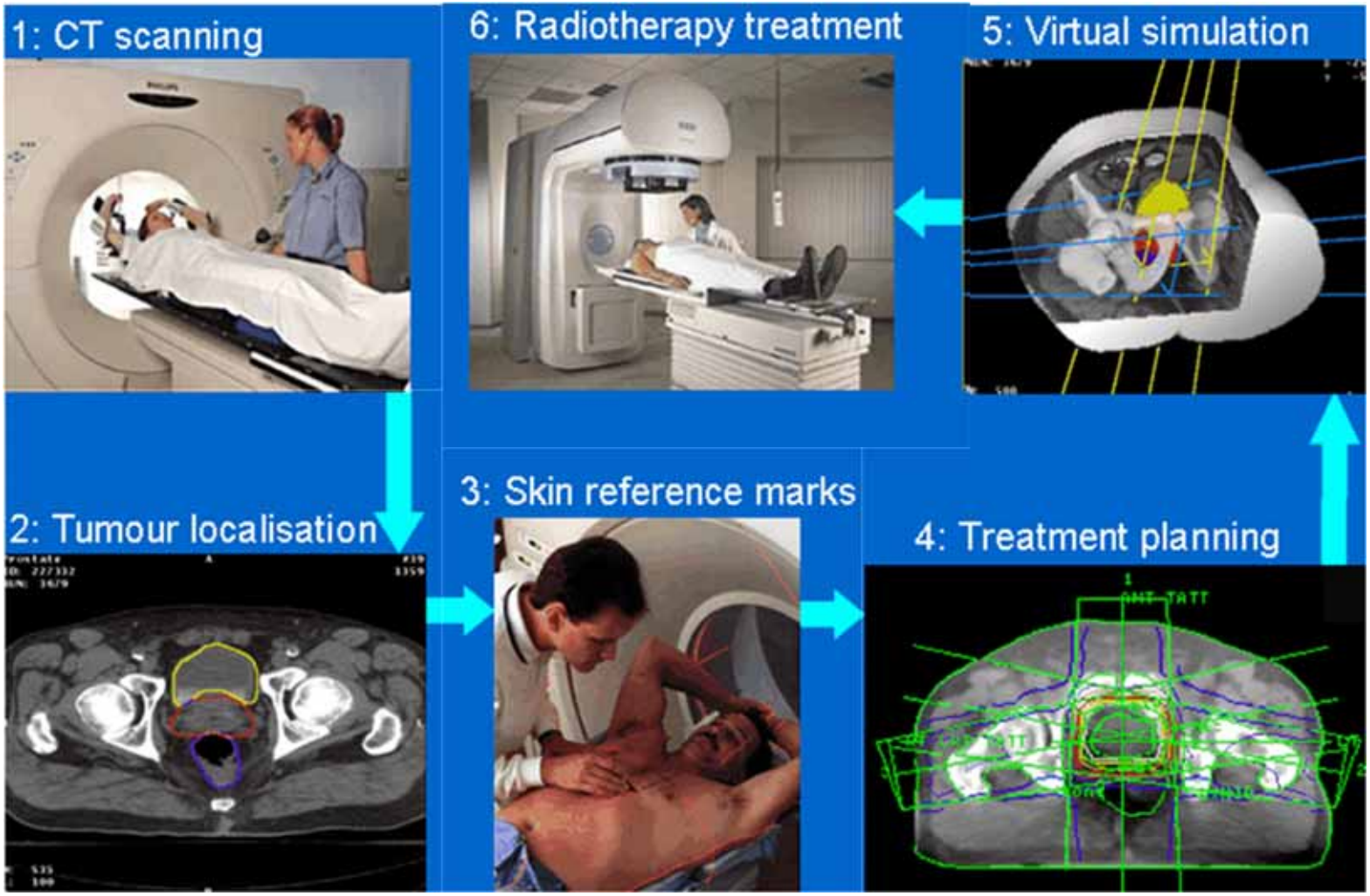


Aamodt & Plaza (1994)

Slide 8-32 CBR Example: Radiotherapy Planning 1/6

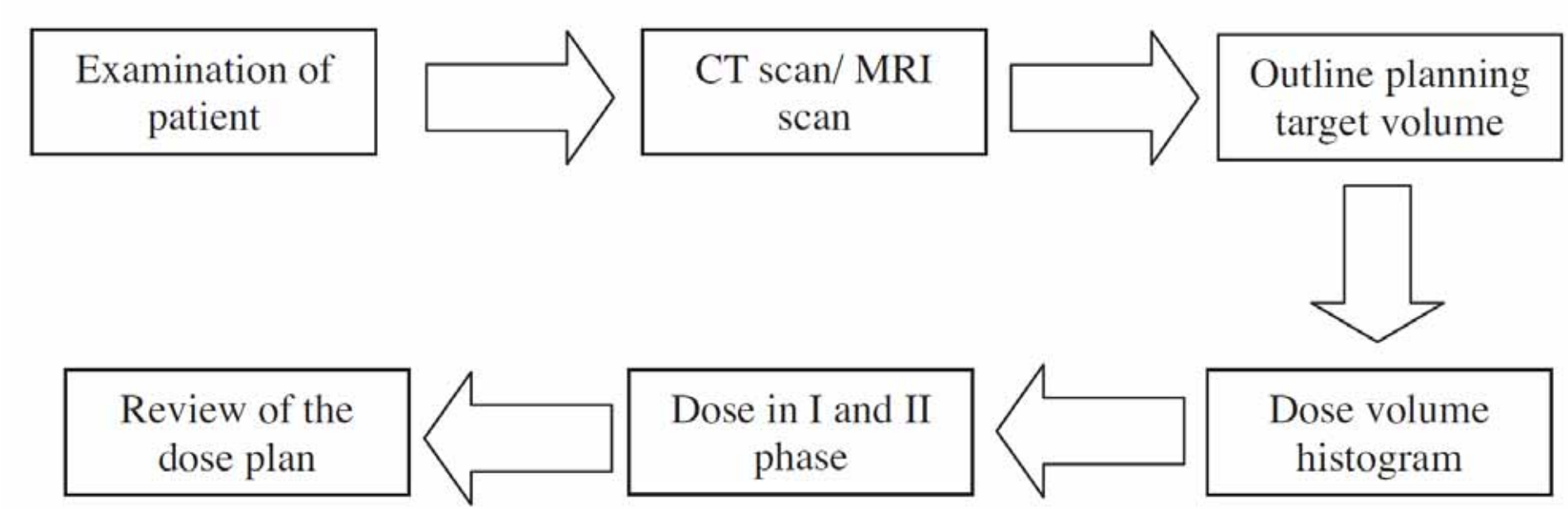
Source: http://www.teachingmedicalphysics.org.uk

Slide 8-33 CBR Example: Radiotherapy Planning 2/6



Source: Imaging Performance Assessment of CT Scanners Group, http://www.impactscan.org

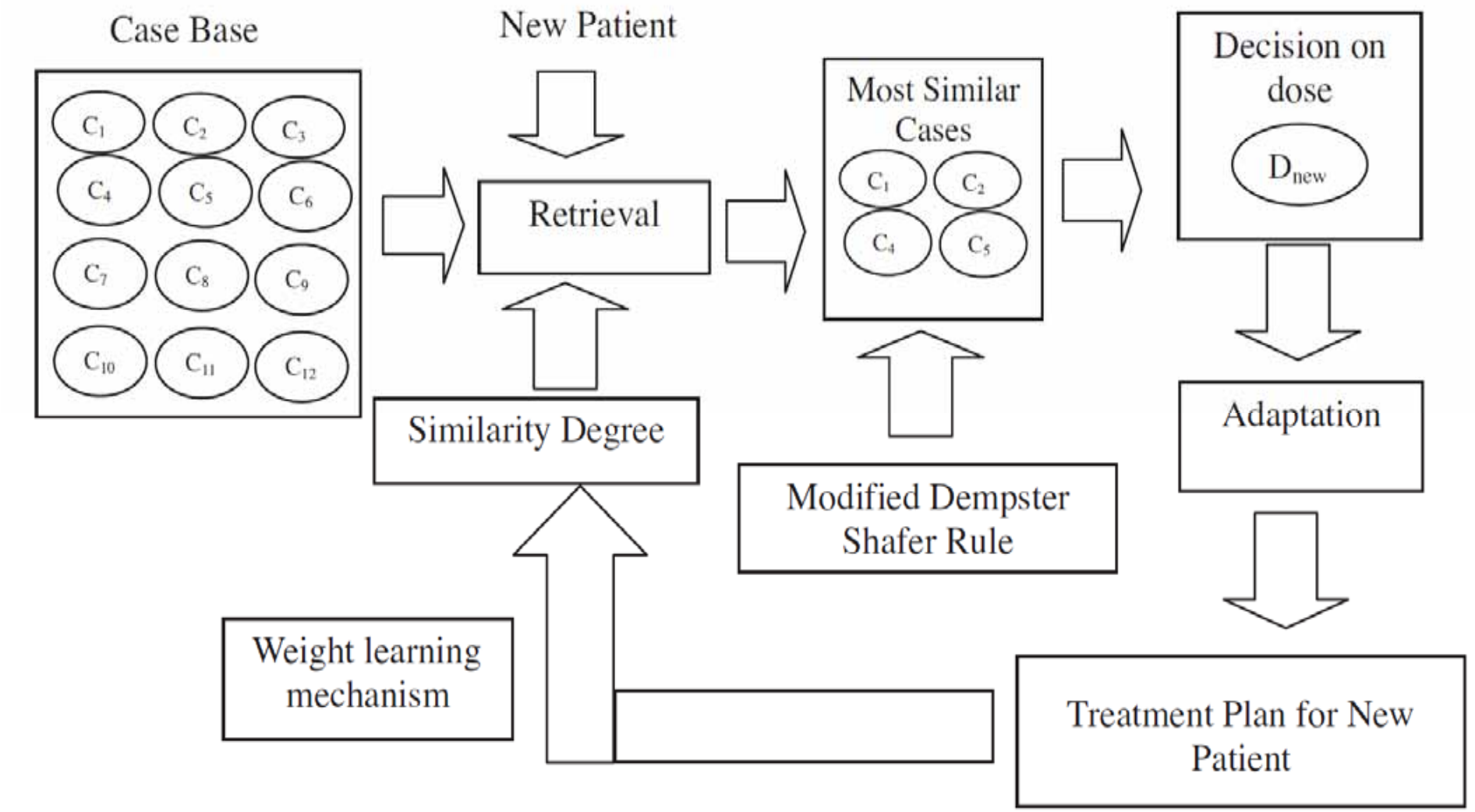
Slide 8-34 CBR Example: Radiotherapy Planning 3/6



Measures:

1) Clinical Stage = a labelling system
2) Gleason Score = grade of prostate cancer = integer between 1 to 10; and
3) Prostate Specific Antigen (PSA) value between 1 to 40
4) Dose Volume Histogram (DVH) = pot. risk to the rectum (66, 50, 25, 10 %)

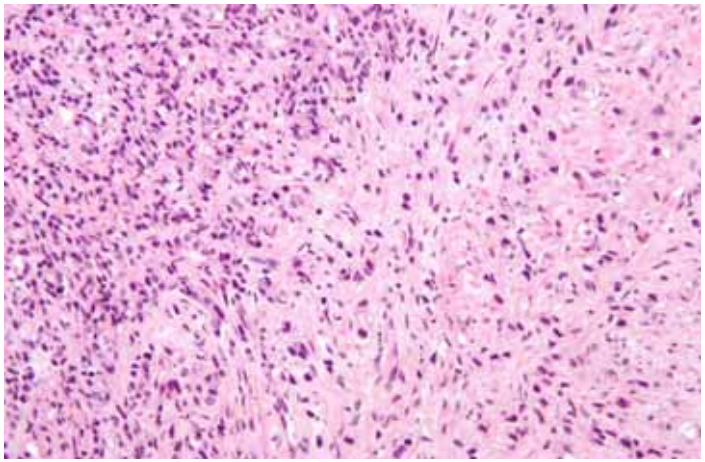
Petrovic, S., Mishra, N. & Sundar, S. (2011) A novel case based reasoning approach to radiotherapy planning. *Expert Systems With Applications, 38, 9, 10759-10769.*

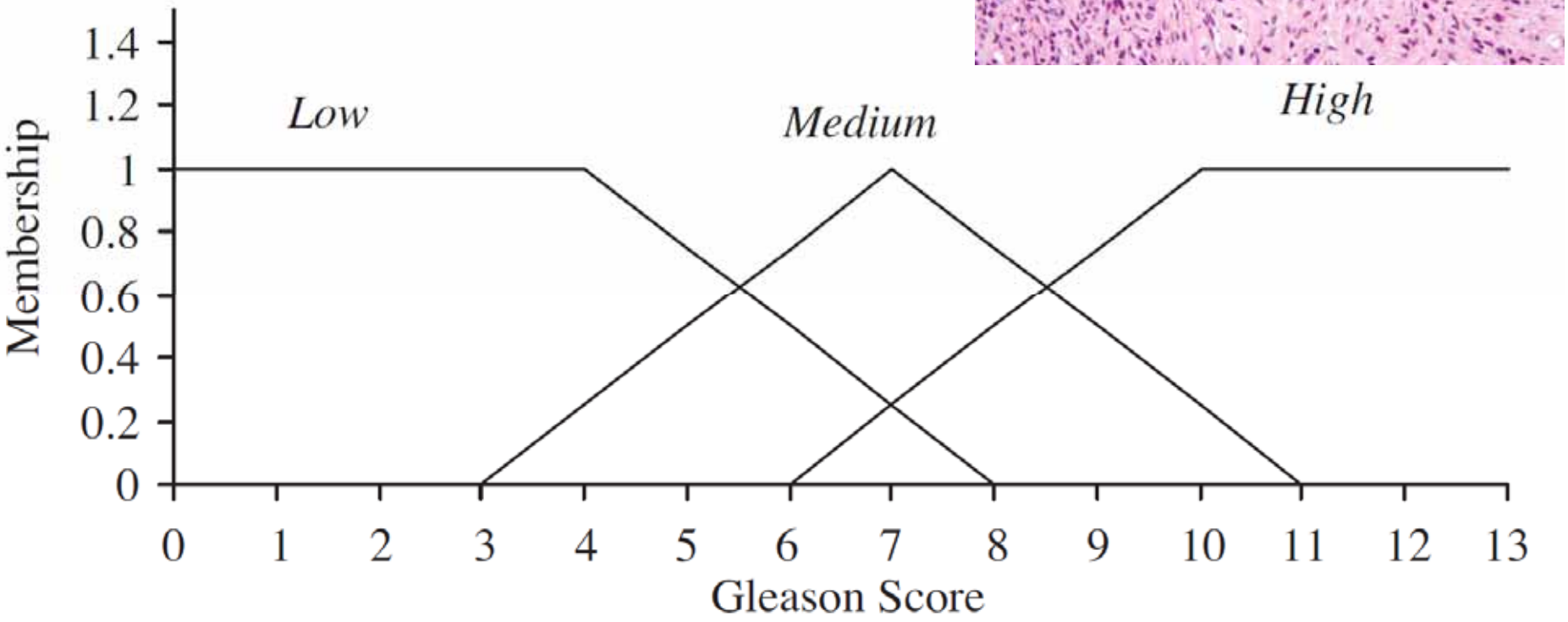


Petrovic, S., Mishra, N. & Sundar, S. (2011) A novel case based reasoning approach to radiotherapy planning. *Expert Systems With Applications, 38, 9, 10759-10769.*

Slide 8-36 Membership funct. of fuzzy sets Gleason score 5/6

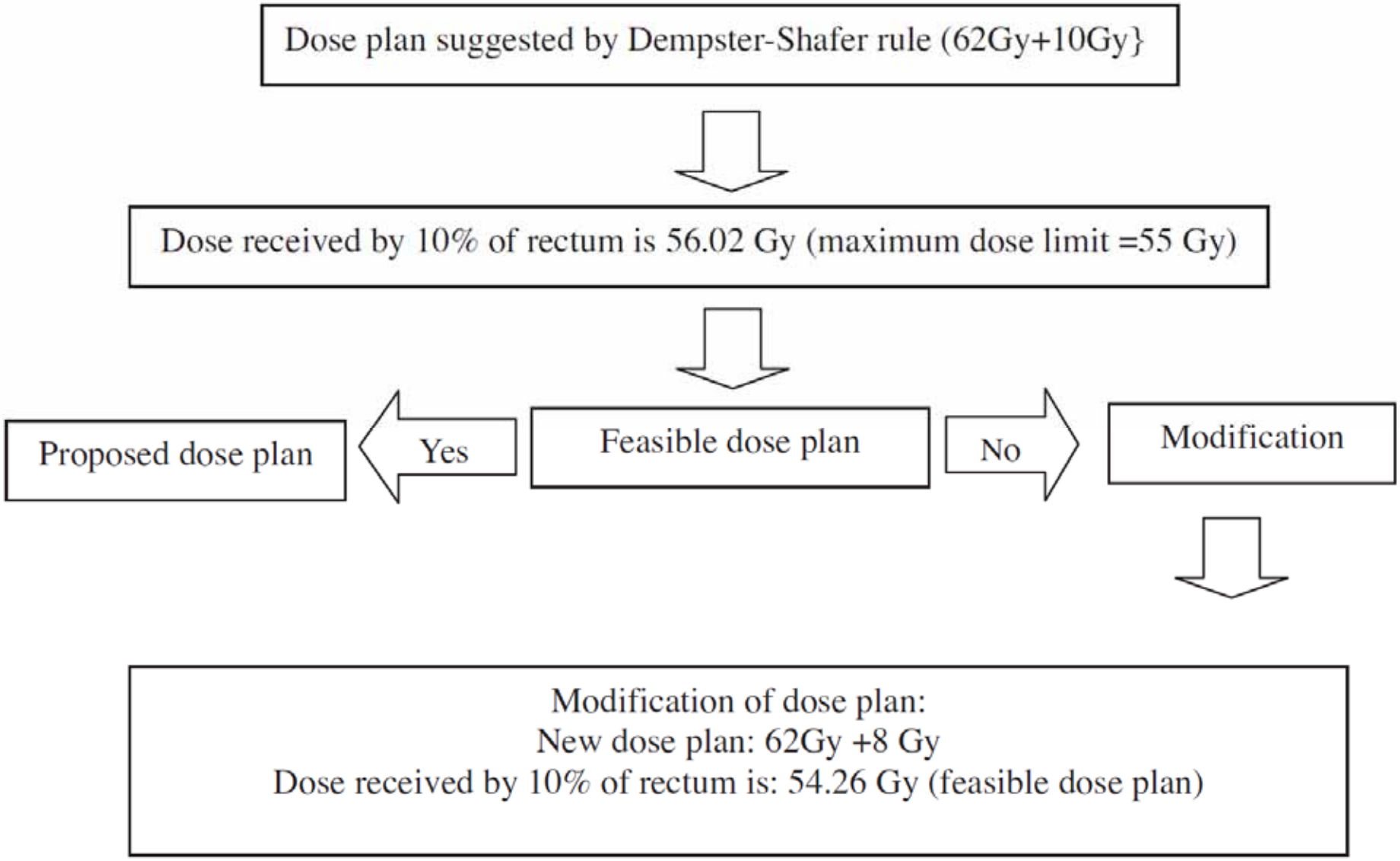
Gleason score evaluates the grade of prostate cancer. Values: integer within the range





Petrovic, S., Mishra, N. & Sundar, S. (2011) A novel case based reasoning approach to radiotherapy planning. *Expert Systems With Applications, 38, 9, 10759-10769.*

Petrovic et al. (2011)



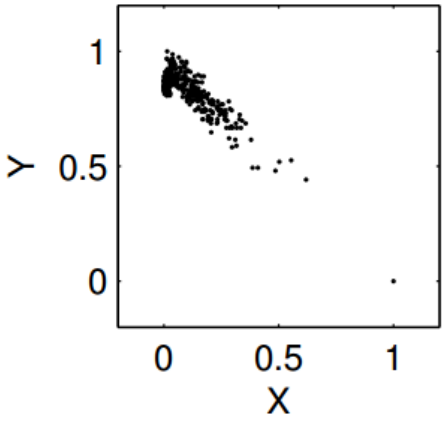
05 Causal Reasoning

- **"How do humans generalize from few examples?"**
  - Learning relevant representations
  - Disentangling the explanatory factors
  - Finding the shared underlying explanatory factors, in particular between $P(x)$ and $P(Y|X)$, with a causal link between $Y \rightarrow X$

Bengio, Y., Courville, A. & Vincent, P. 2013. Representation learning: A review and new perspectives. IEEE transactions on pattern analysis and machine intelligence, 35, (8), 1798-1828, doi:10.1109/TPAMI.2013.50.

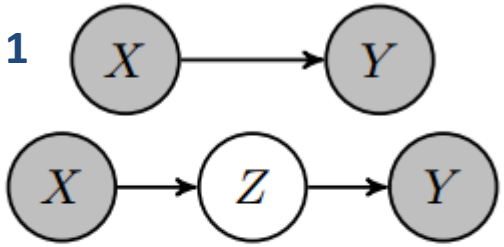
Tenenbaum, J. B., Kemp, C., Griffiths, T. L. & Goodman, N. D. 2011. How to grow a mind: Statistics, structure, and abstraction. Science, 331, (6022), 1279-1285, doi:10.1126/science.1192788.

Decide if X → Y, or Y → X using only observed data



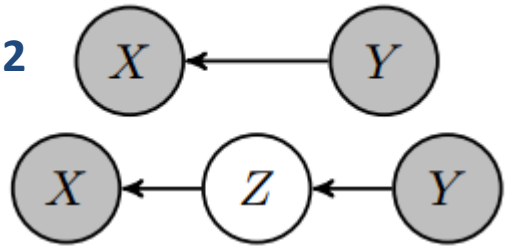
Joris M. Mooij, Jonas Peters, Dominik Janzing, Jakob Zscheischler & Bernhard Schölkopf 2016. Distinguishing cause from effect using observational data: methods and benchmarks. The Journal of Machine Learning Research, 17, (1), 1103-1204.

1



$$\mathbb{P}_Y \neq \mathbb{P}_{Y\,|\,\mathrm{do}(x)} = \mathbb{P}_{Y\,|\,x}$$
$$\mathbb{P}_X = \mathbb{P}_{X\,|\,\mathrm{do}(y)} \neq \mathbb{P}_{X\,|\,y}$$

2



$$\mathbb{P}_Y = \mathbb{P}_{Y\,|\,\mathrm{do}(x)} \neq \mathbb{P}_{Y\,|\,x}$$
$$\mathbb{P}_X \neq \mathbb{P}_{X\,|\,\mathrm{do}(y)} = \mathbb{P}_{X\,|\,y}$$

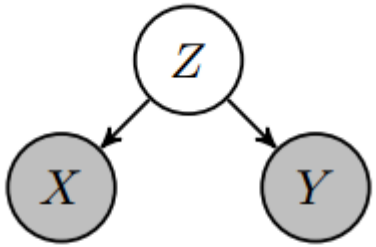
3

$$\mathbb{P}_Y = \mathbb{P}_{Y\,|\,\mathrm{do}(x)} = \mathbb{P}_{Y\,|\,x}$$
$$\mathbb{P}_X = \mathbb{P}_{X\,|\,\mathrm{do}(y)} = \mathbb{P}_{X\,|\,y}$$

4

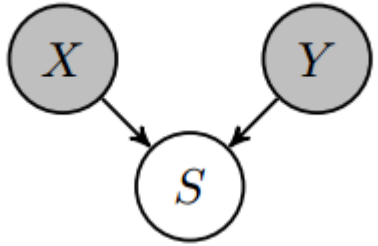
$$\mathbb{P}_Y \neq \mathbb{P}_{Y\,|\,\mathrm{do}(x)} \neq \mathbb{P}_{Y\,|\,x}$$
$$\mathbb{P}_X \neq \mathbb{P}_{X\,|\,\mathrm{do}(y)} \neq \mathbb{P}_{X\,|\,y}$$

5



$$\mathbb{P}_Y = \mathbb{P}_{Y\,|\,\mathrm{do}(x)} \neq \mathbb{P}_{Y\,|\,x}$$
$$\mathbb{P}_X = \mathbb{P}_{X\,|\,\mathrm{do}(y)} \neq \mathbb{P}_{X\,|\,y}$$

6



$$\mathbb{P}_{Y\,|\,s} \neq \mathbb{P}_{Y\,|\,\mathrm{do}(x),s} = \mathbb{P}_{Y\,|\,x,s}$$
$$\mathbb{P}_{X\,|\,s} \neq \mathbb{P}_{X\,|\,\mathrm{do}(y),s} = \mathbb{P}_{X\,|\,y,s}$$

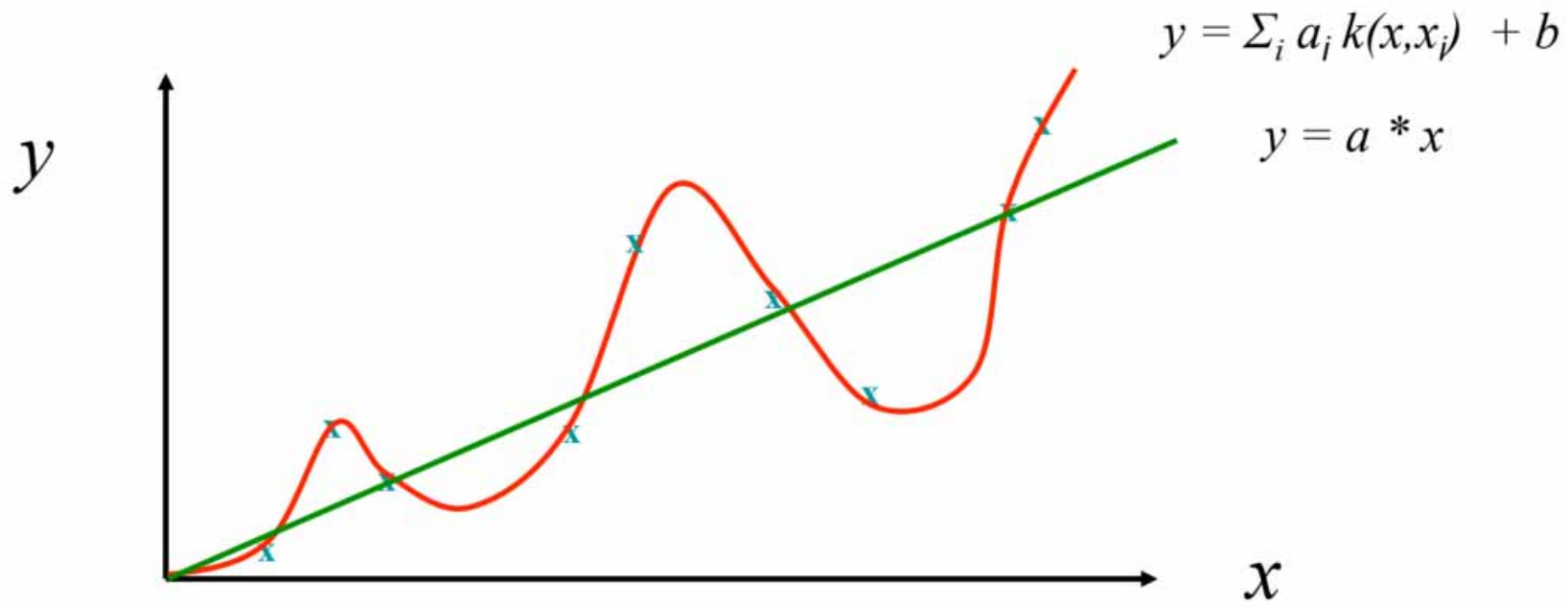
Remember: Reasoning = “Sensemaking”

- **Deductive Reasoning** = Hypothesis > Observations > Logical Conclusions
  - DANGER: Hypothesis must be correct! DR defines whether the truth of a conclusion can be determined for that rule, based on the truth of premises: A=B, B=C, therefore A=C
- **Inductive reasoning** = makes broad generalizations from specific observations
  - DANGER: allows a conclusion to be false if the premises are true
  - generate hypotheses and use DR for answering specific questions
- **Abductive reasoning** = inference = to get the best explanation from an incomplete set of preconditions.
  - Given a true conclusion and a rule, it attempts to select some possible premises that, if true also, may support the conclusion, though not uniquely.
  - Example: "When it rains, the grass gets wet. The grass is wet. Therefore, it might have rained." This kind of reasoning can be used to develop a hypothesis, which in turn can be tested by additional reasoning or data.

Important Definition: Ground truth

- := information provided by direct observation (empirical evidence) in contrast to information provided by inference
  - Empirical evidence = information acquired by observation or by experimentation in order to verify the truth (fit to reality) or falsify (non-fit to reality).
  - Empirical inference = drawing conclusions from empirical data (observations, measurements)
  - Causal inference = drawing a conclusion about a causal connection based on the conditions of the occurrence of an effect.
    - Causal inference is an example of causal reasoning.

Empirical Inference Example



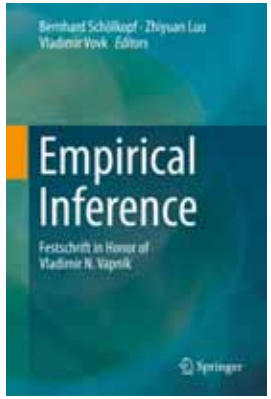
Gottfried W. Leibniz (1646-1716)

Hermann Weyl (1885-1955)

Vladimir Vapnik (1936-)

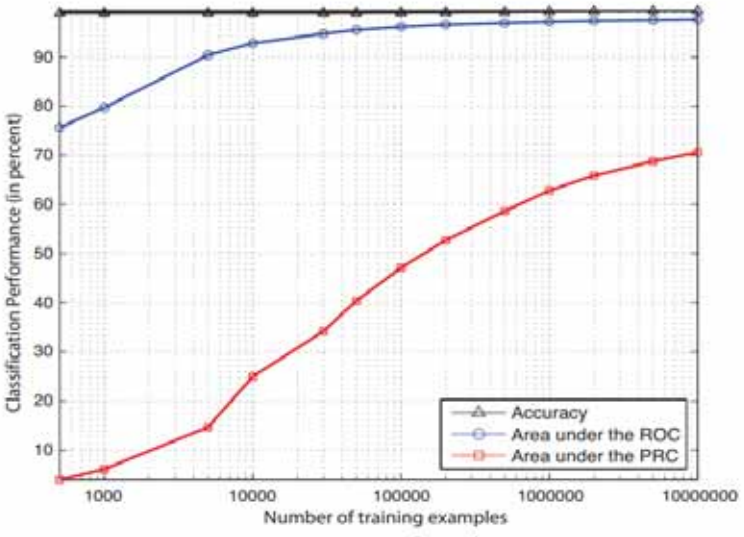
Alexey Chervonenkis (1938-2014)

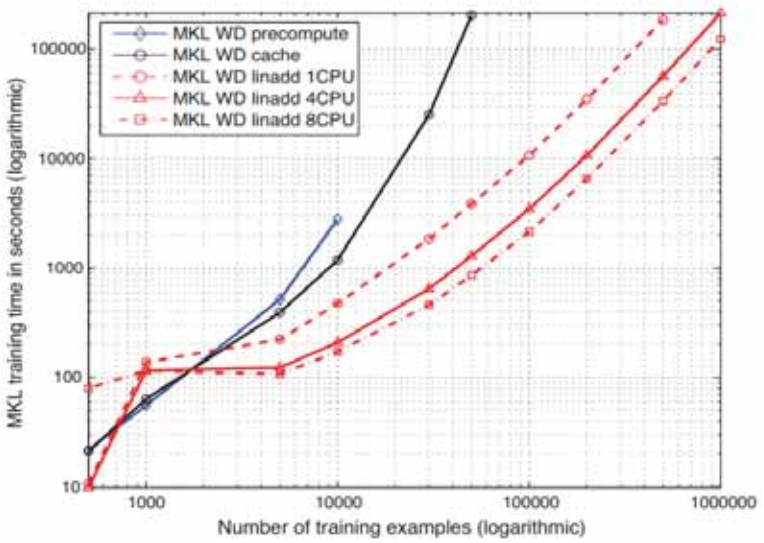
Gregory Chaitin (1947-)



Remember: hard inference problems

- High dimensionality (curse of dim., many factors contribute)
- Complexity (real-world is non-linear, non-stationary, non-IID *)
- Need of large top-quality data sets
- Little prior data (no mechanistic models of the data)
  - *) = Def.: a sequence or collection of random variables is independent and identically distributed if each random variable has the same probability distribution as the others and all are mutually independent





Sören Sonnenburg, Gunnar Rätsch, Christin Schaefer & Bernhard Schölkopf 2006. Large scale multiple kernel learning. Journal of Machine Learning Research, 7, (7), 1531-1565.

06 Explainability

Mastering the game of Go without human knowledge

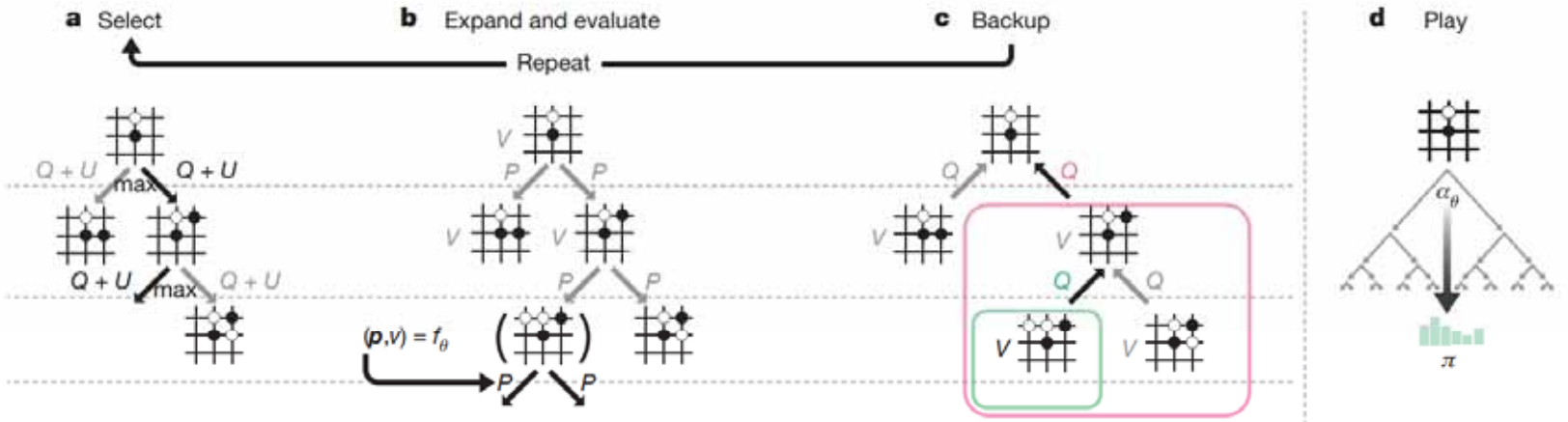


Figure 2 | MCTS in AlphaGo Zero. a, Each simulation traverses the tree by selecting the edge with maximum action value Q, plus an upper confidence bound U that depends on a stored prior probability P and visit count N for that edge (which is incremented once traversed). **b**, The leaf node is expanded and the associated position s is evaluated by the neural network $(P(s,\cdot),V(s))=f_\theta(s)$; the vector of P values are stored in the outgoing edges from s. **c**, Action value Q is updated to track the mean of all evaluations V in the subtree below that action. **d**, Once the search is complete, search probabilities π are returned, proportional to $N^{1/\tau}$, where N is the visit count of each move from the root state and τ is a parameter controlling temperature.

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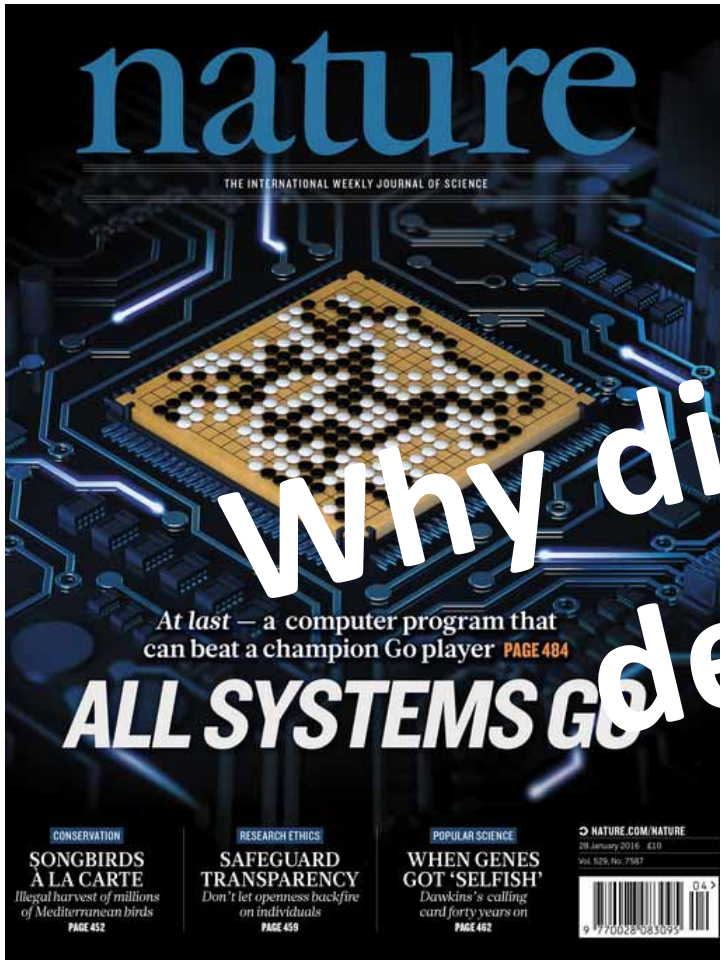
$$(\boldsymbol{p}, v) = f_\theta(s) \quad \text{and} \quad l = (z - v)^2 - \boldsymbol{\pi}^{\mathrm{T}} \log \boldsymbol{p} + c\|\theta\|^2$$

David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, Yutian Chen, Timothy Lillicrap, Fan Hui, Laurent Sifre, George Van Den Driessche, Thore Graepel & Demis Hassabis 2017. Mastering the game of go without human knowledge. Nature, 550, (7676), 354-359, doi:doi:10.1038/nature24270.



Why did it make this decision???

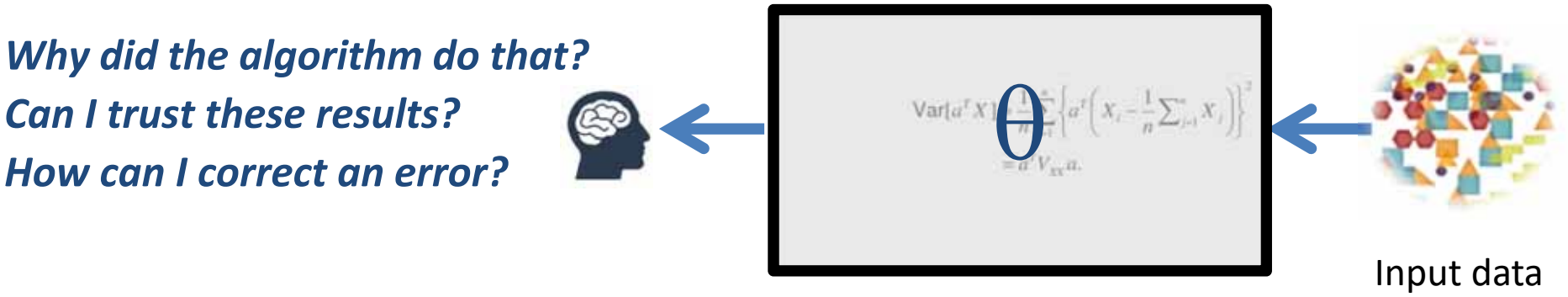
David Silver, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, Sander Dieleman, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel & Demis Hassabis 2016. Mastering the game of Go with deep neural networks and tree search. Nature, 529, (7587), 484-489, doi:10.1038/nature16961.

Causability :=
a property of a person
(Human Intelligence)

Explainability :=
a property of a system
(Artificial Intelligence)

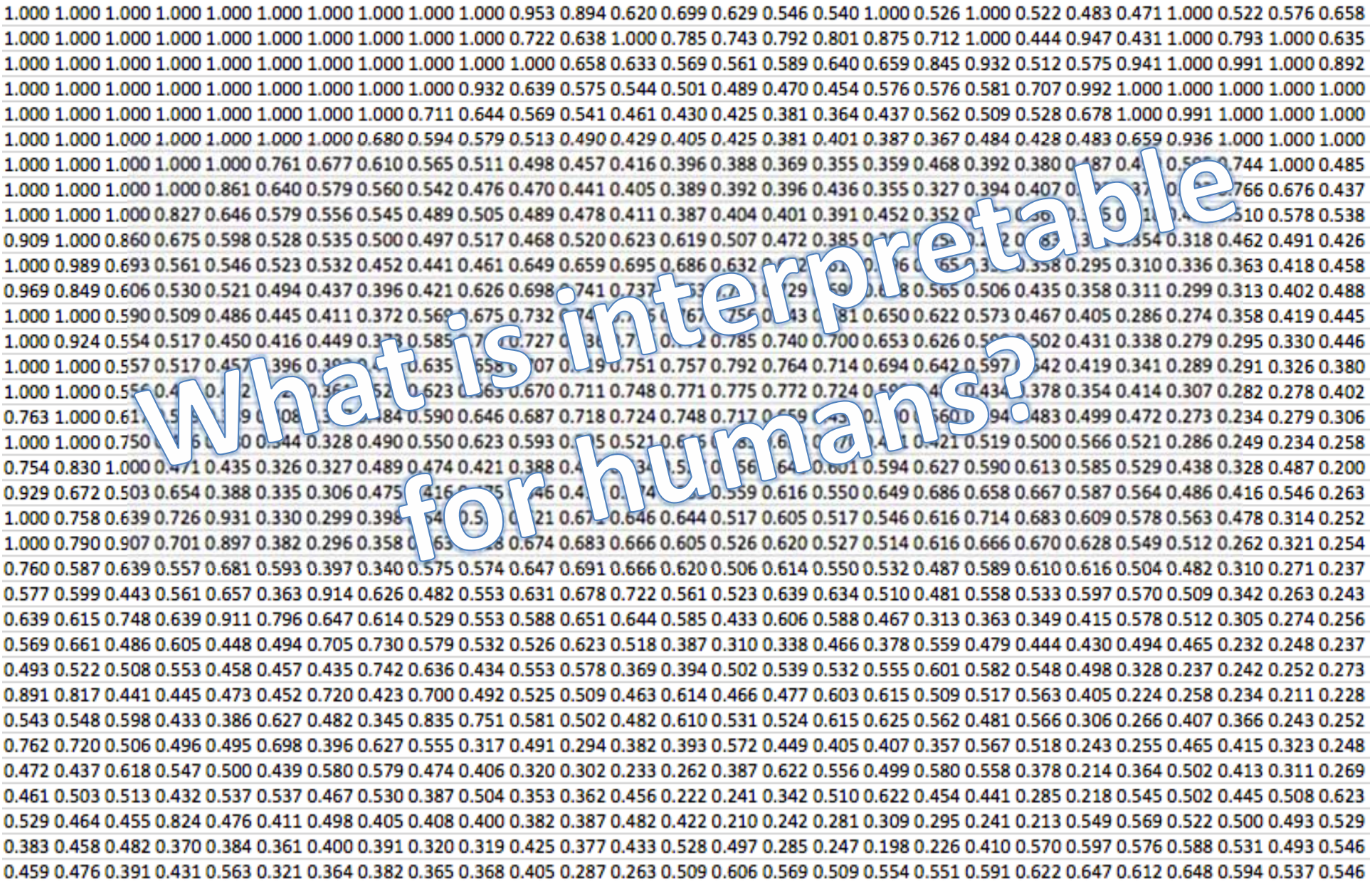
Andreas Holzinger et al. 2019. Causability and Explainability of AI in Medicine. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, doi:10.1002/widm.1312.

We need effective tools for Human-AI Interaction

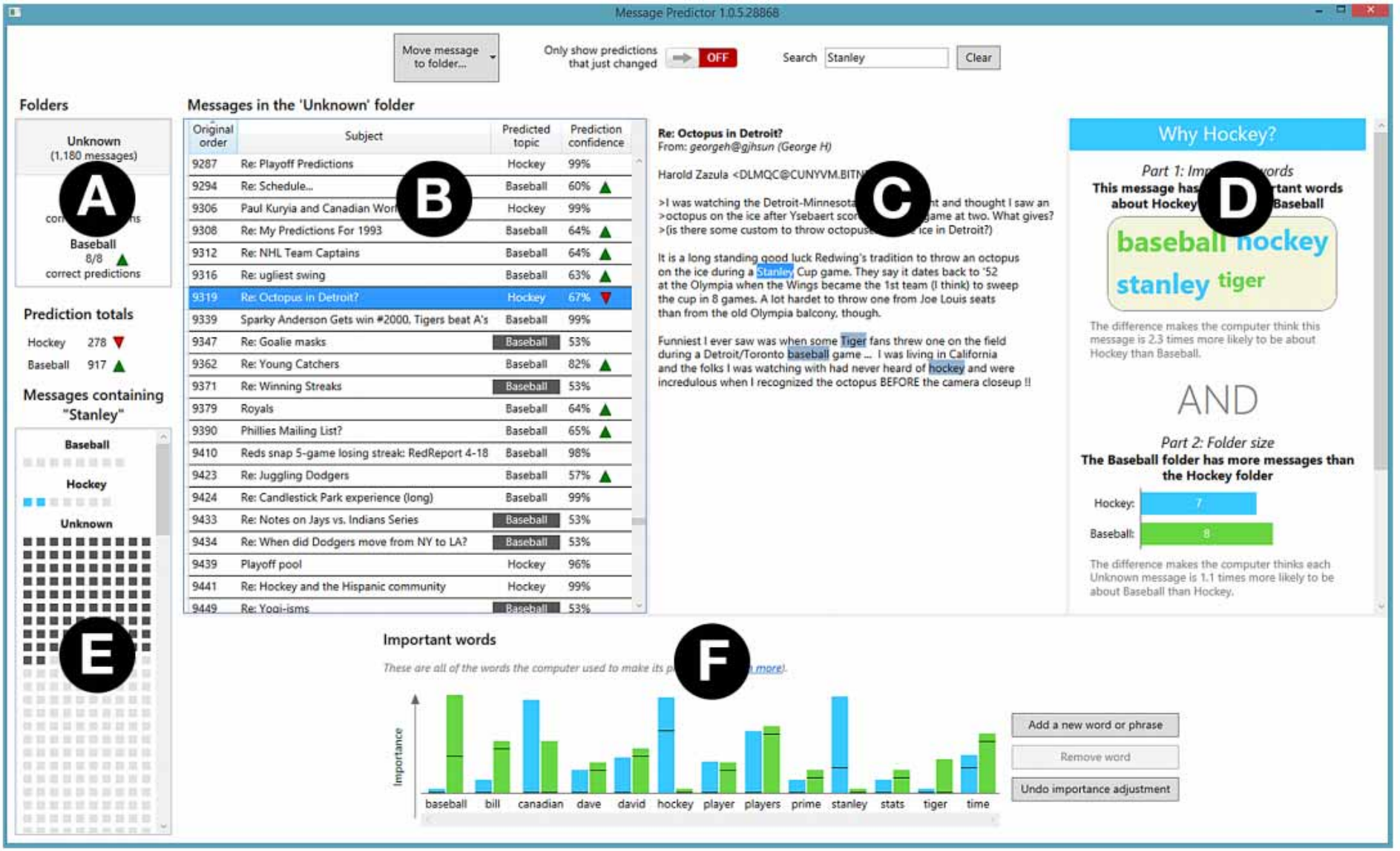


A possible solution

The domain expert can understand why …
The domain expert can learn and correct errors …
The domain expert can re-enact on demand …

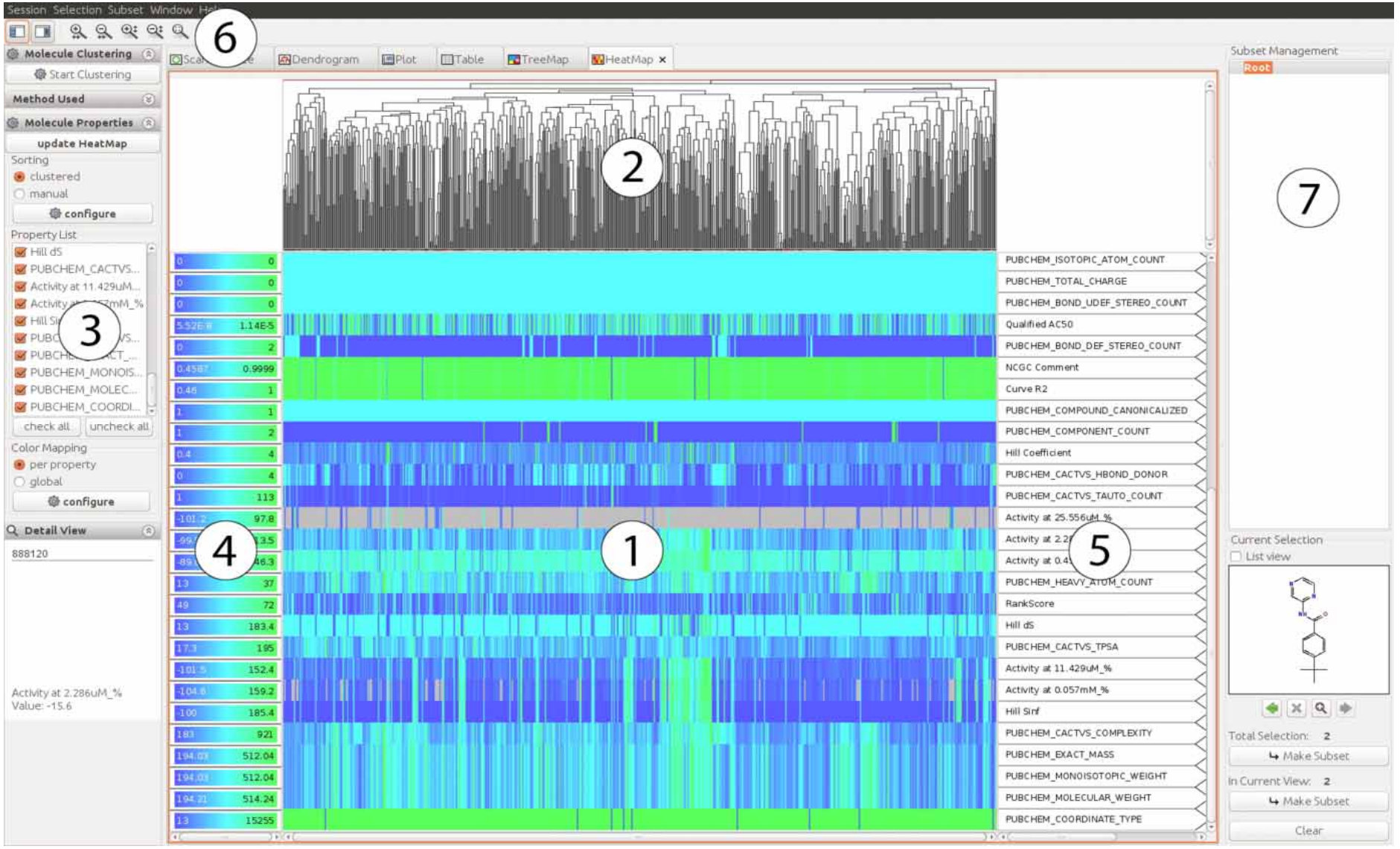

What is interpretable
for humans?

Example for an Explanation Interface



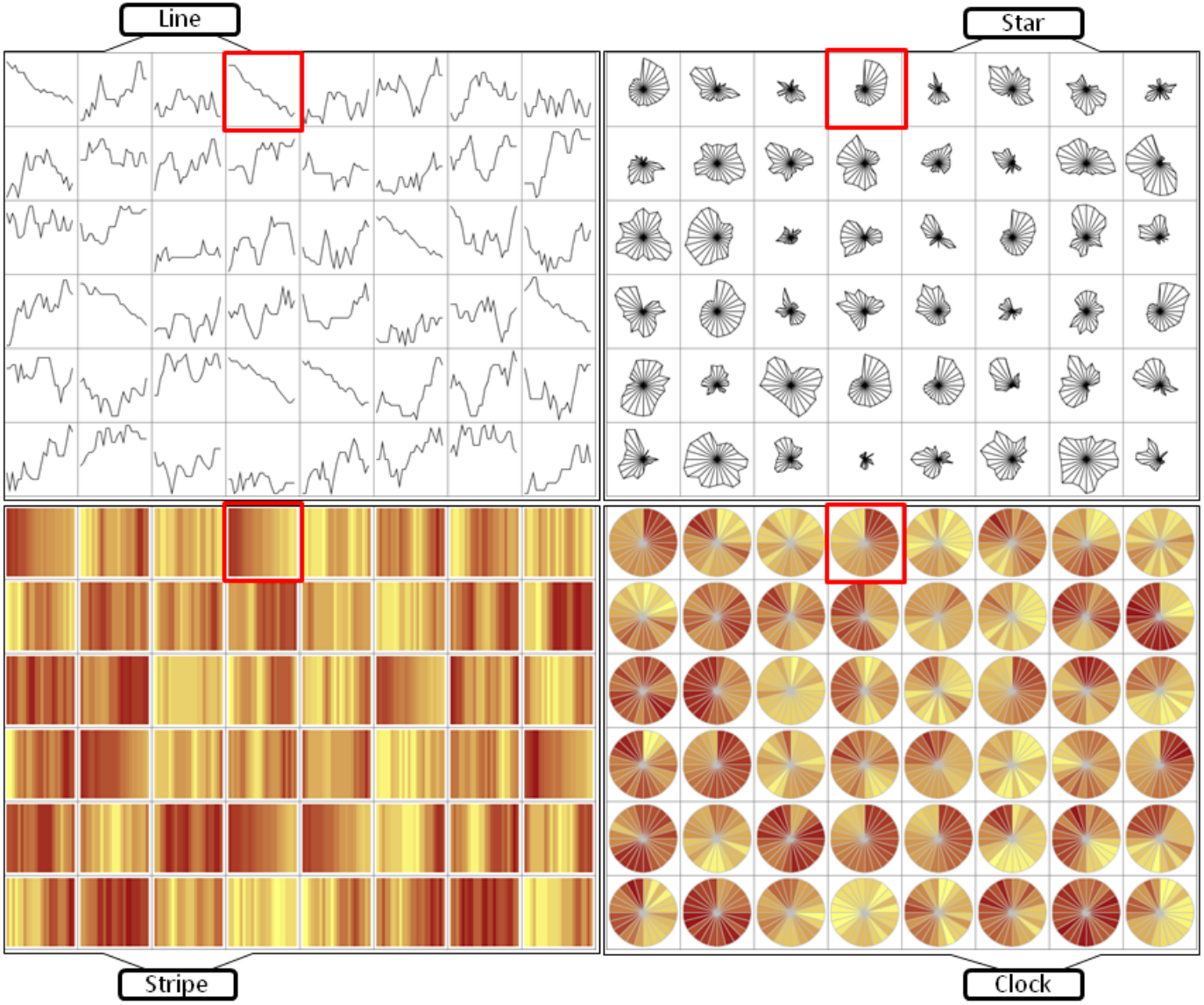
Todd Kulesza, Margaret Burnett, Weng-Keen Wong & Simone Stumpf. Principles of explanatory debugging to personalize interactive machine learning. Proceedings of the 20th International Conference on Intelligent User Interfaces (IUI 2015), 2015 Atlanta. ACM, 126-137, doi:10.1145/2678025.2701399.

Example for an Explanation Interface - open work ☺



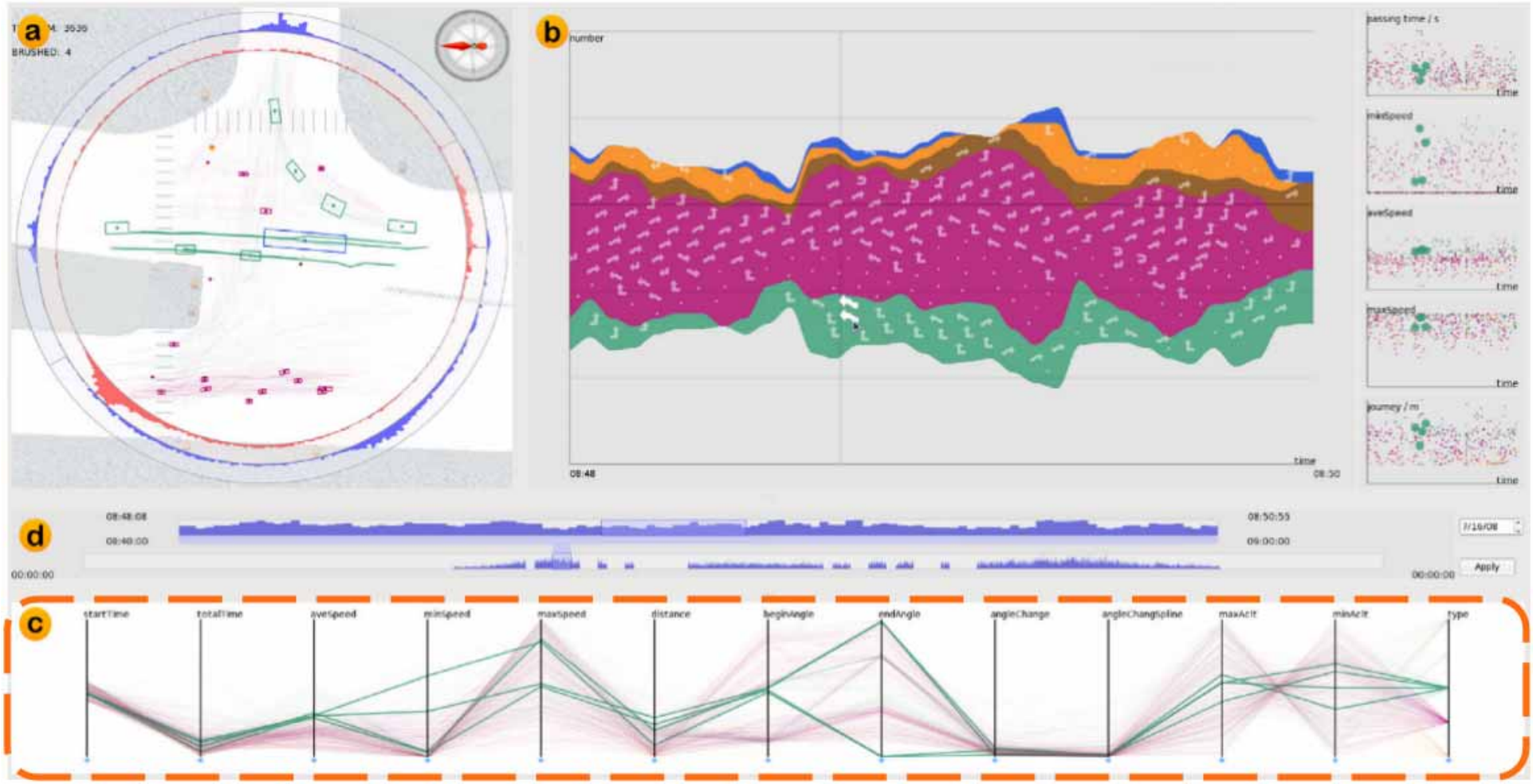
Werner Sturm, Till Schaefer, Tobias Schreck, Andeas Holzinger & Torsten Ullrich. Extending the Scaffold Hunter Visualization Toolkit with Interactive Heatmaps In: Borgo, Rita & Turkay, Cagatay, eds. EG UK Computer Graphics & Visual Computing CGVC 2015, 2015 University College London (UCL). Euro Graphics (EG), 77-84, doi:10.2312/cgvc.20151247.

What is understandable, interpretable, intelligible?

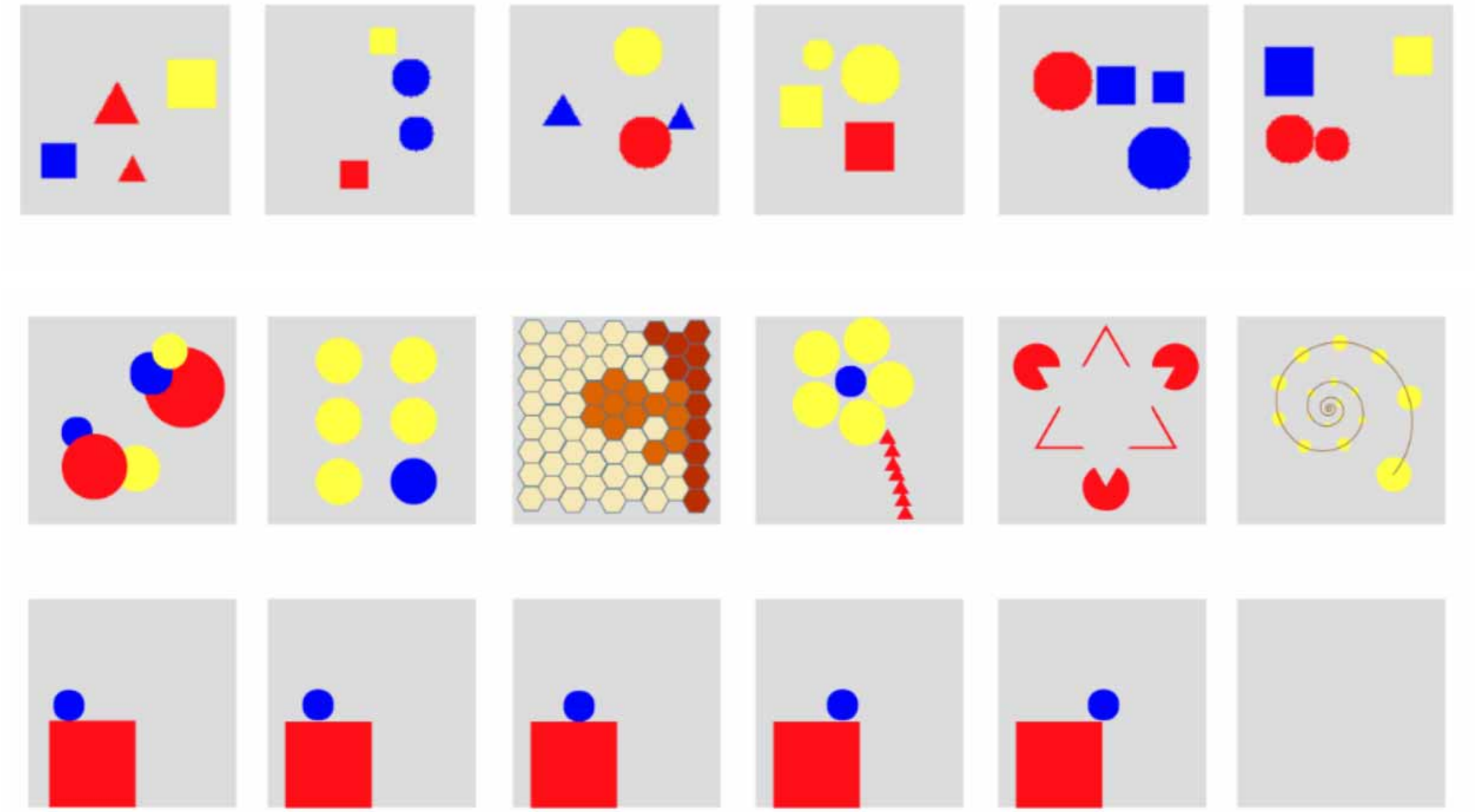


https://www.vis.uni-konstanz.de/en/members/fuchs/

Explainable AI is a huge challenge for visualization

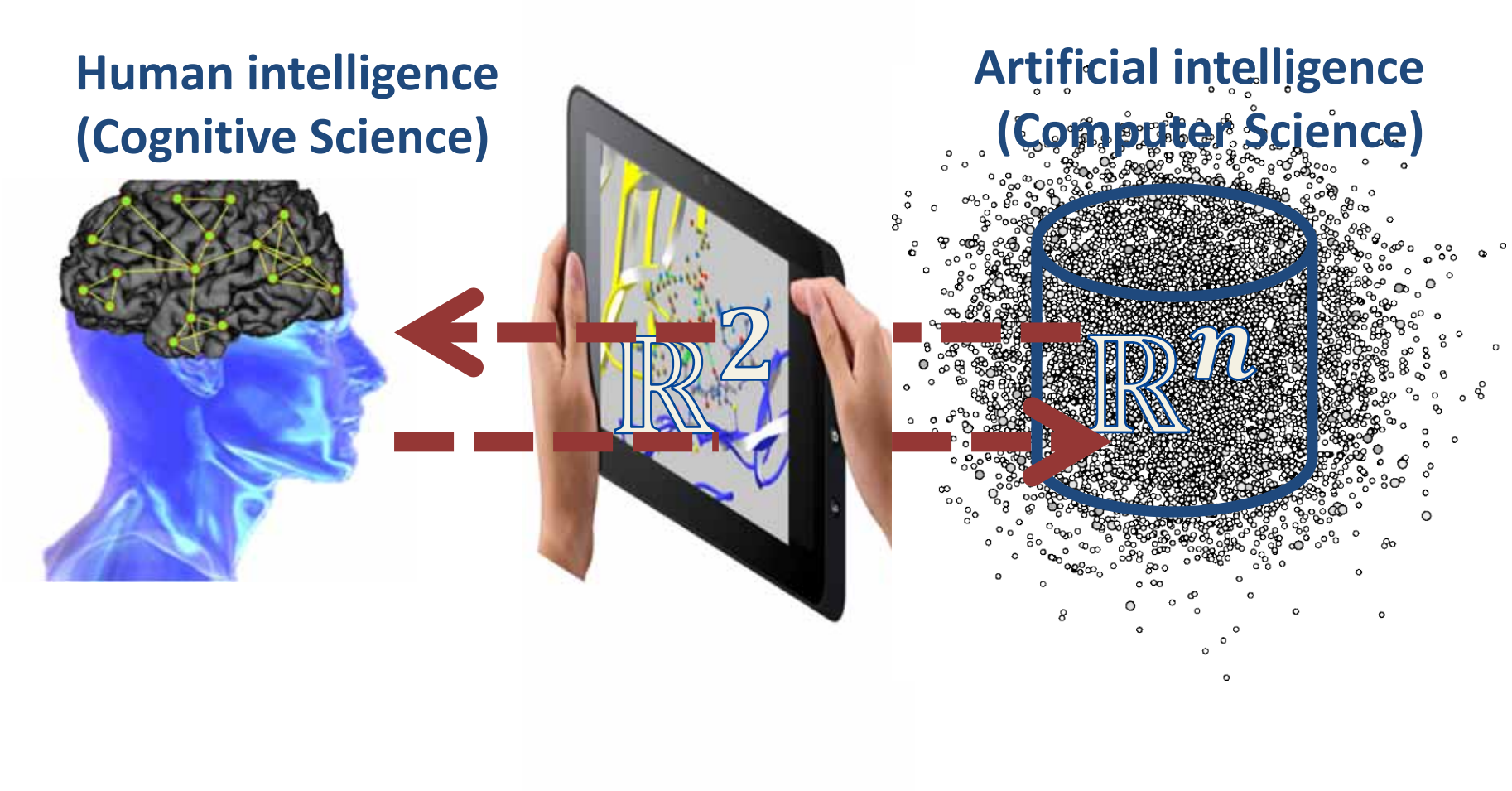


Kandinsky Patterns



07 Methods of Explainable AI

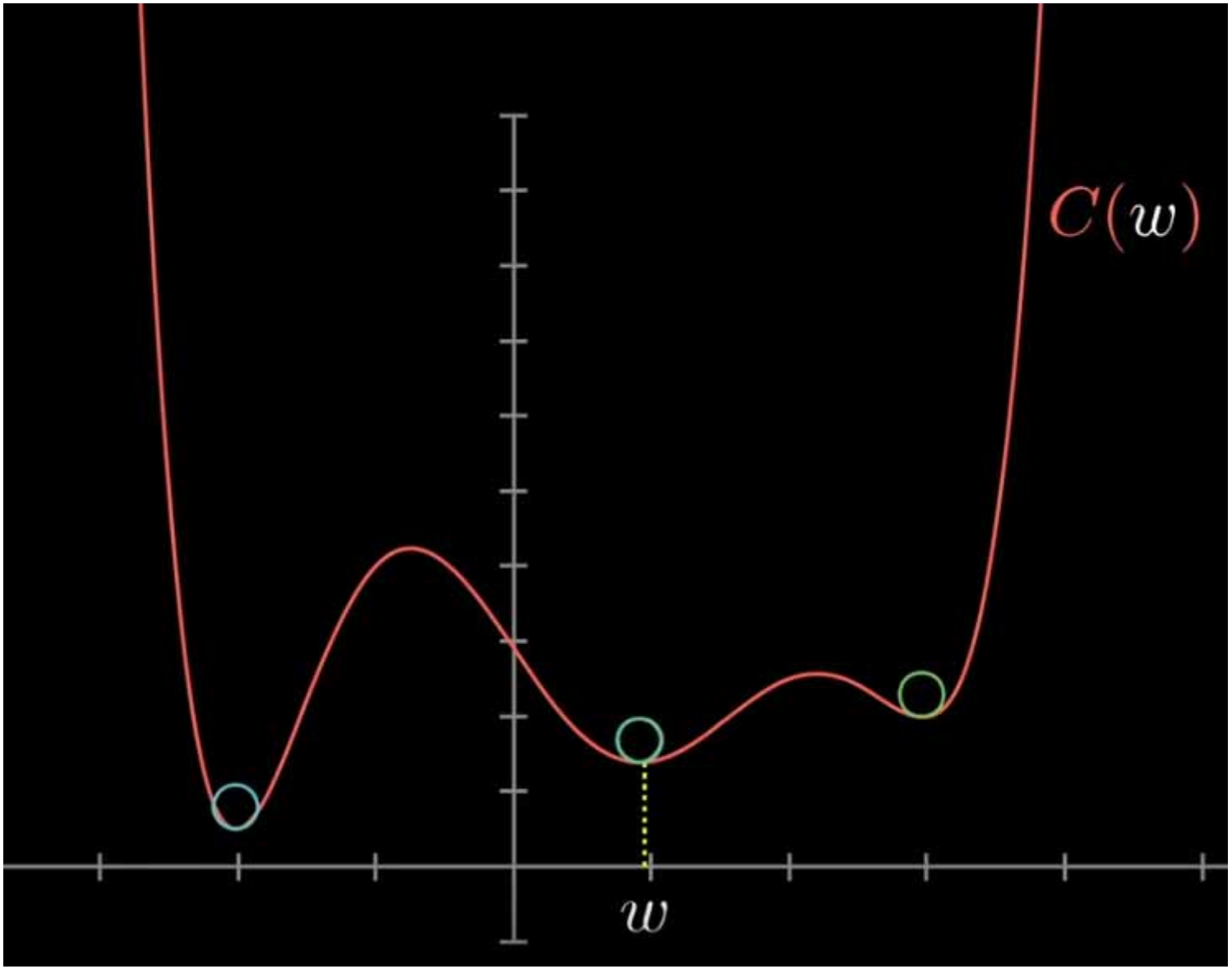
- Causability := a property of a person (Human)
- Explainability := a property of a system (Computer)



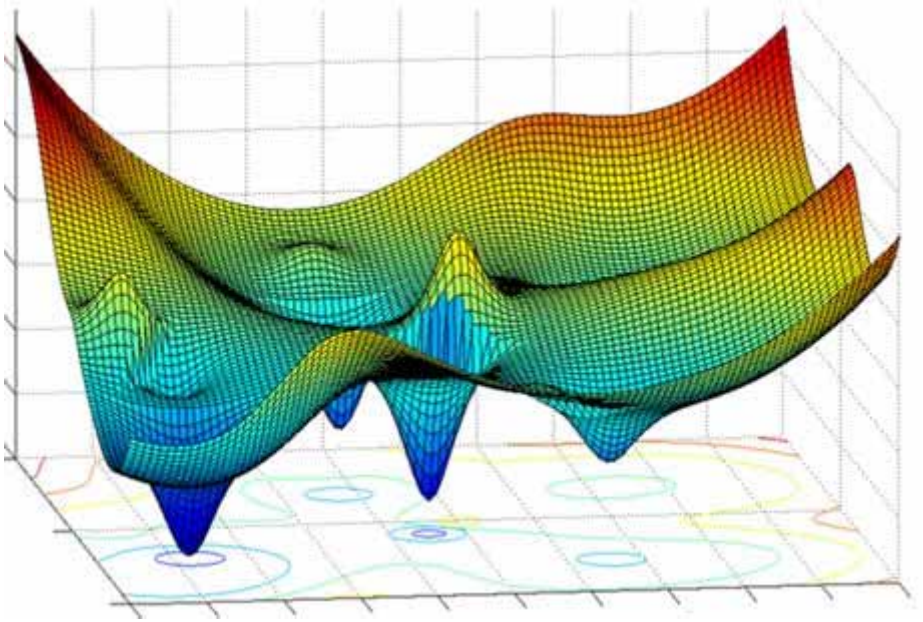
Methods of ex-AI

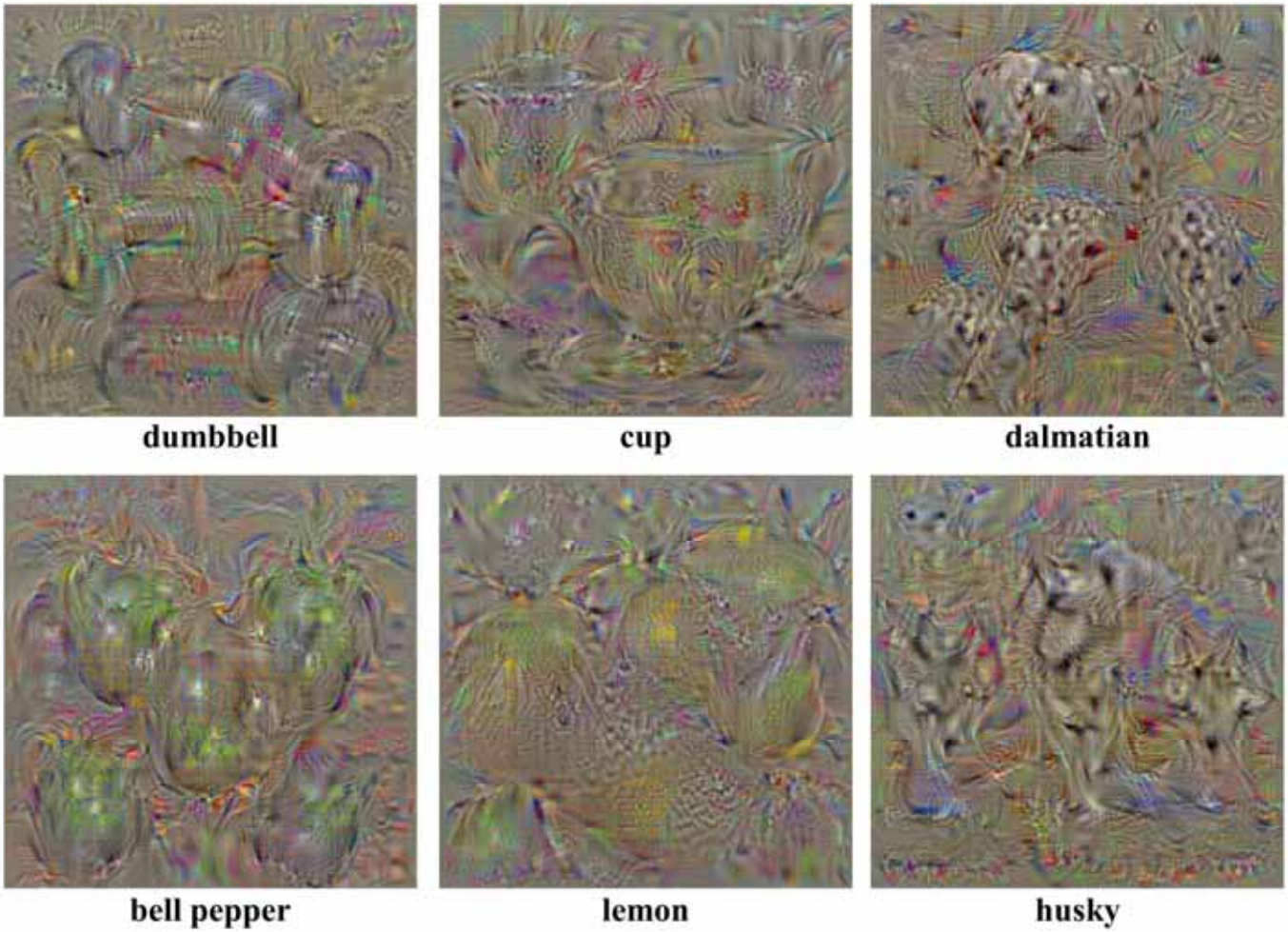
- 1) Gradients
- 2) Sensitivity Analysis
- 3) Decomposition Relevance Propagation (Pixel-RP, Layer-RP, Deep Taylor Decomposition, …)
- 4) Optimization (Local-IME – model agnostic, BETA transparent approximation, …)
- 5) Deconvolution and Guided Backpropagation
- 6) Model Understanding
  - Feature visualization, Inverting CNN
  - Qualitative Testing with Concept Activation Vectors TCAV
  - Network Dissection

Andreas Holzinger LV 706.315 From explainable AI to Causability, 3 ECTS course at Graz University of Technology https://hci-kdd.org/explainable-ai-causability-2019 (course given since 2016)


C(w)
w

Gradients



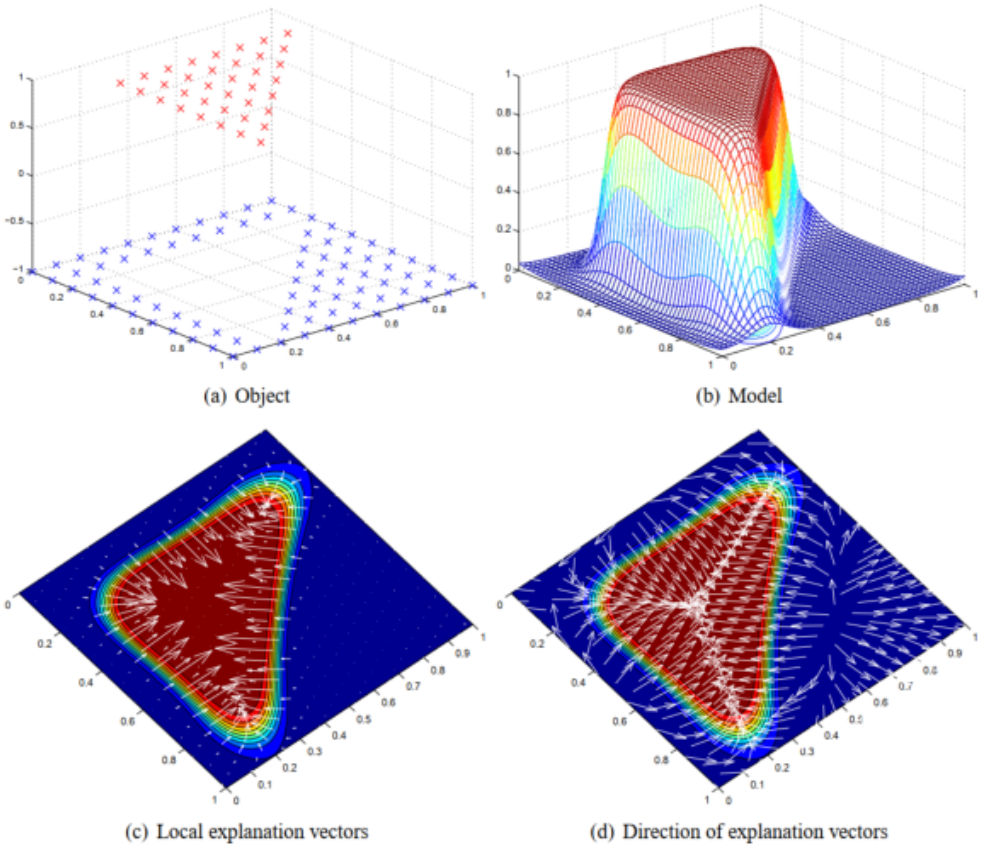


Karen Simonyan, Andrea Vedaldi & Andrew Zisserman 2013. Deep inside convolutional networks: Visualising image classification models and saliency maps. arXiv:1312.6034.

Gradients

For $\mathrm{var}_f(x_0) = k(x_0,x_0) - k_*^T(K+\Sigma)^{-1}k_*$ the derivative is given by[3]

$$\nabla \mathrm{var}_f(x)|_{x=x_0} = \frac{\partial \mathrm{var}_f}{\partial x_{0,j}} = \left(\frac{\partial}{\partial x_{0,j}} k(x_0,x_0)\right) - 2 * k_*^T(K+\Sigma)^{-1}\frac{\partial}{\partial x_{0,j}}k_* \quad \text{for } j \in \{1,\ldots,d\}.$$

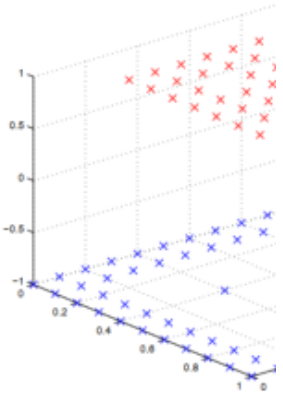


(a) Object (b) Model

(c) Local explanation vectors (d) Direction of explanation vectors

Figure 1: Explaining simple object classification with Gaussian Processes

Panel (a) of Figure 1 shows the training data of a simple object classification task and panel (b) shows the model learned using GPC.[4] The data is labeled -1 for the blue points and $+1$ for the red points. As illustrated in panel (b) the model is a probability function for the positive class which gives every data point a probability of being in this class. Panel (c) shows the probability gradient of the model together with the local gradient explanation vectors. Along the hypotenuse and at the corners of the triangle explanations from both features interact towards the triangle class while along



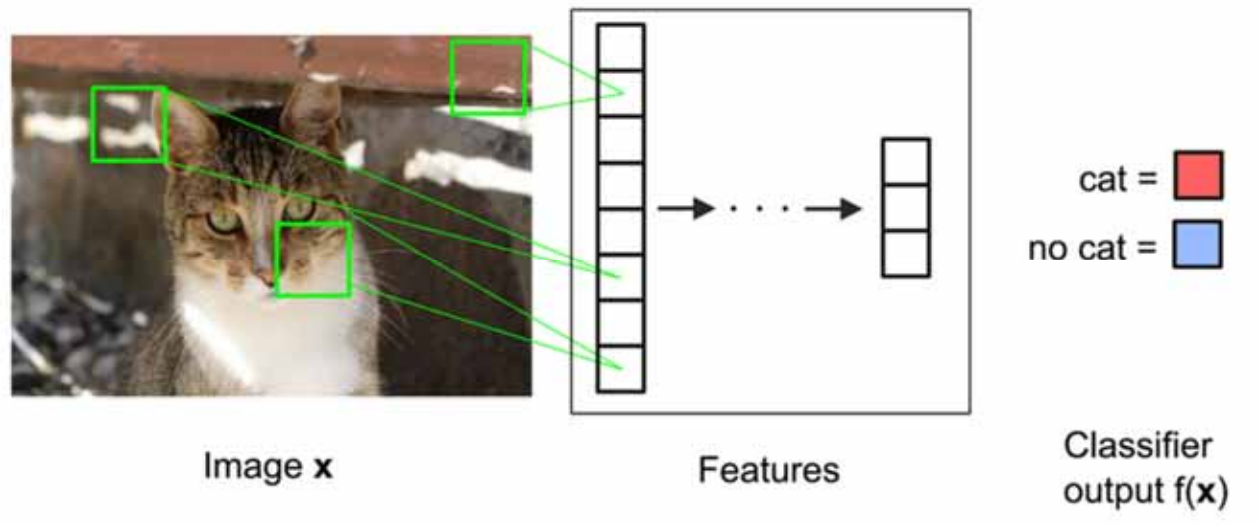
(a) outliers

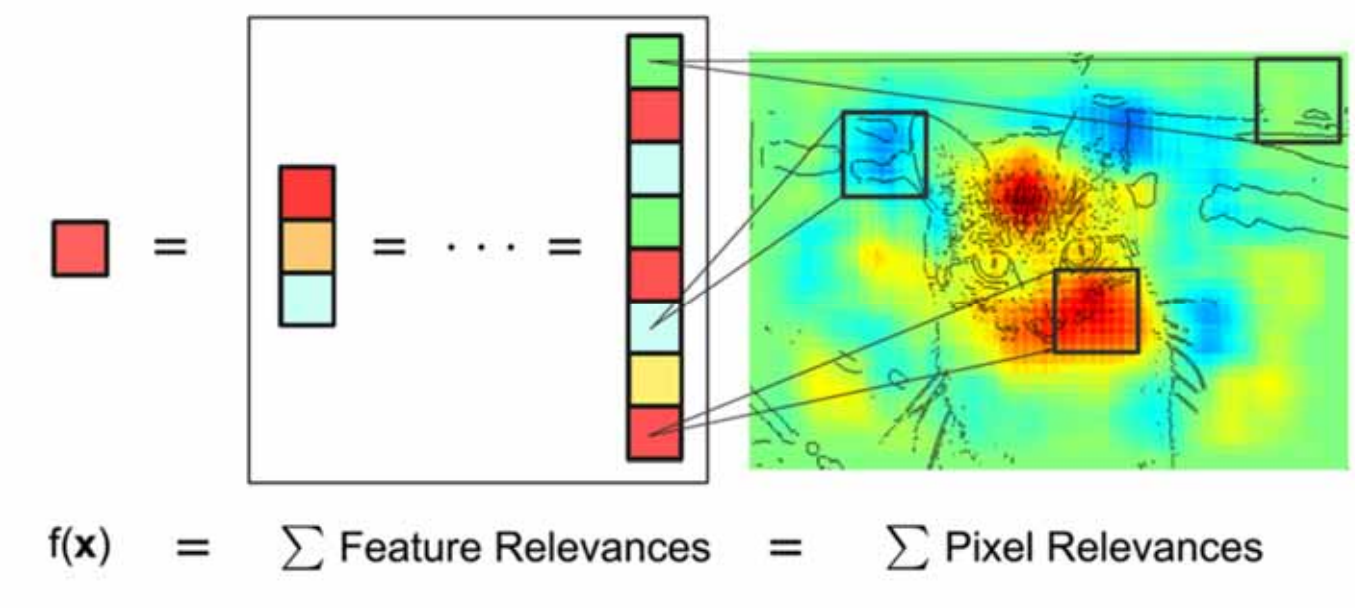
Figure 12

David Baehrens, Timor ·Robert Mueller 2010.
How to explain individ 11, (6), 1803-1831.

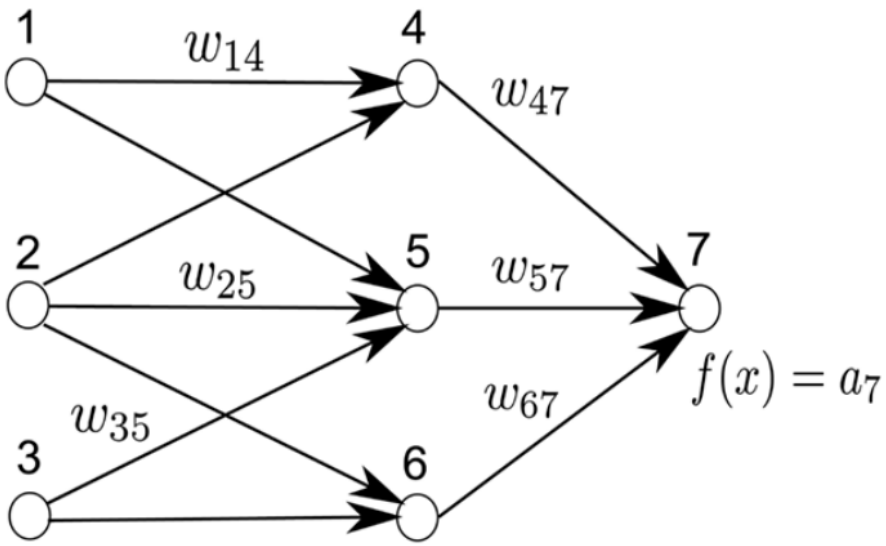
LRP Layer-Wise Relevance Propagation

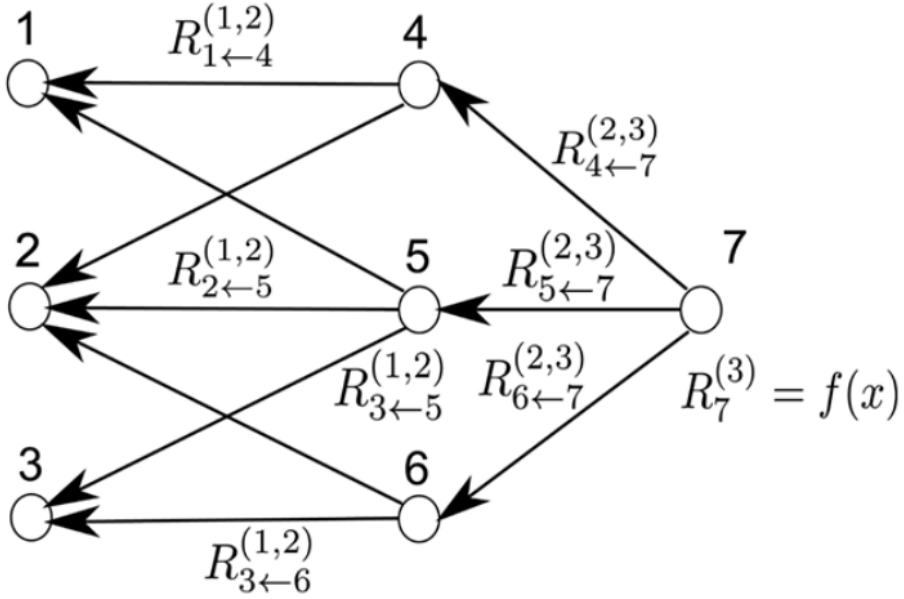
Sebastian Bach, Alexander Binder, Grégoire Montavon, Frederick Klauschen, Klaus-Robert Müller & Wojciech Samek 2015. On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. PloS one, 10, (7), e0130140, doi:10.1371/journal.pone.0130140.





A NN-classifier during prediction time





$$f(x) = \cdots = \sum_{d \in l+1} R_d^{(l+1)} = \sum_{d \in l} R_d^{(l)} = \cdots = \sum_{d} R_d^{(1)}$$

Sebastian Bach, Alexander Binder, Grégoire Montavon, Frederick Klauschen, Klaus-Robert Müller & Wojciech Samek 2015. On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. PloS one, 10, (7), e0130140, doi:10.1371/journal.pone.0130140.

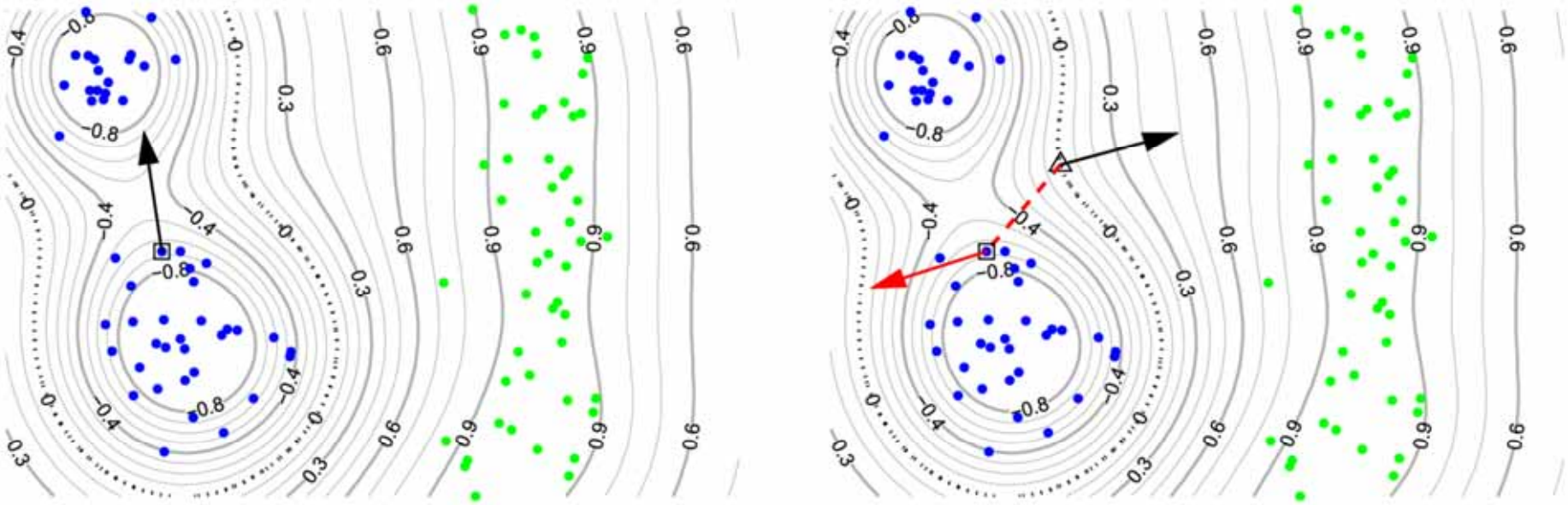


Fig 3. An exemplary real-valued prediction function for classification with the dashed black line being the decision boundary which separates the blue from the green dots. The blue dots are labeled negatively, the green dots are labeled positively. Left: Local gradient of the classification function at the prediction point. Right: Taylor approximation relative to a root point on the decision boundary. This figure depicts the intuition that a gradient at a prediction point x—here indicated by a square—does not necessarily point to a close point on the decision boundary. Instead it may point to a local optimum or to a far away point on the decision boundary. In this example the explanation vector from the local gradient at the prediction point x has a too large contribution in an irrelevant direction. The closest neighbors of the other class can be found at a very different angle. Thus, the local gradient at the prediction point x may not be a good explanation for the contributions of single dimensions to the function value $f(x)$. Local gradients at the prediction point in the left image and the Taylor root point in the right image are indicated by black arrows. The nearest root point x_0 is shown as a triangle on the decision boundary. The red arrow in the right image visualizes the approximation of $f(x)$ by Taylor expansion around the nearest root point x_0. The approximation is given as a vector representing the dimension-wise product between $Df(x_0)$ (the black arrow in the right panel) and $x - x_0$ (the dashed red line in the right panel) which is equivalent to the diagonal of the outer product between $Df(x_0)$ and $x - x_0$.

doi:10.1371/journal.pone.0130140.g003

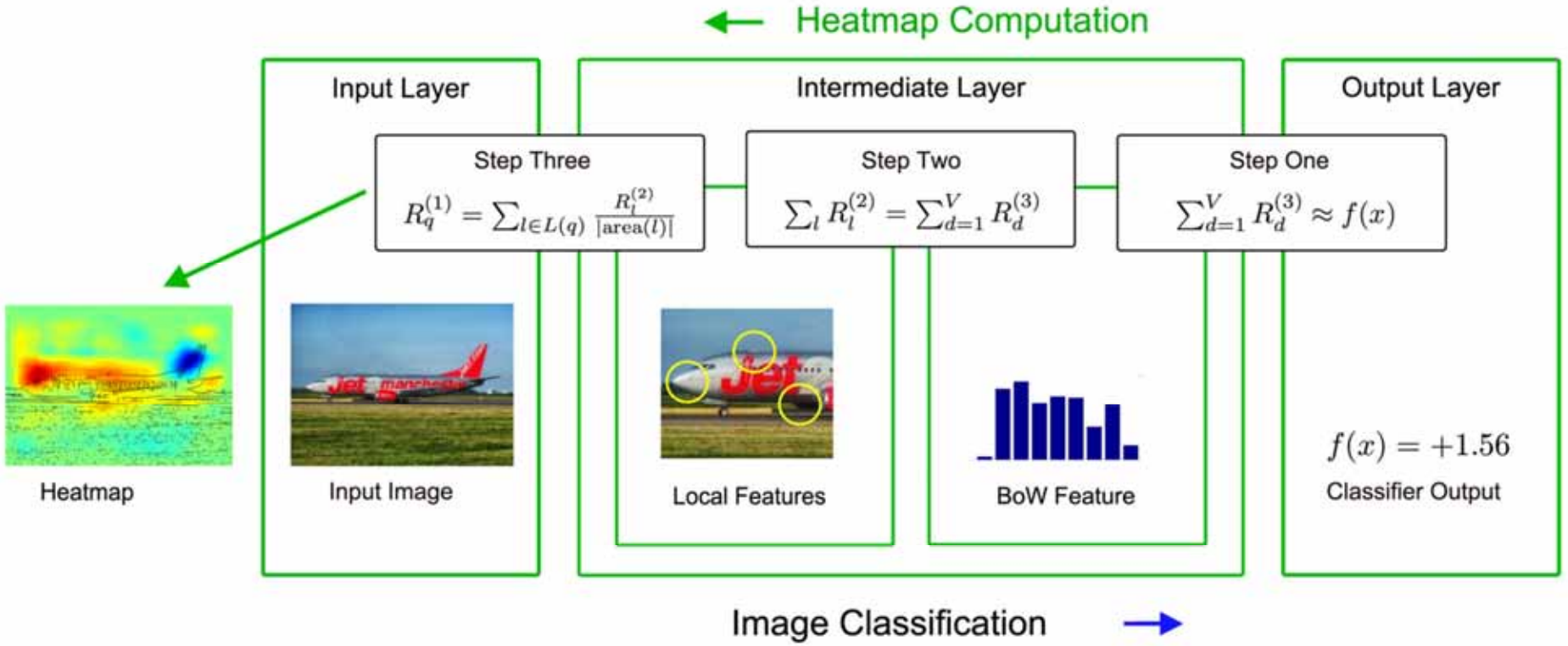
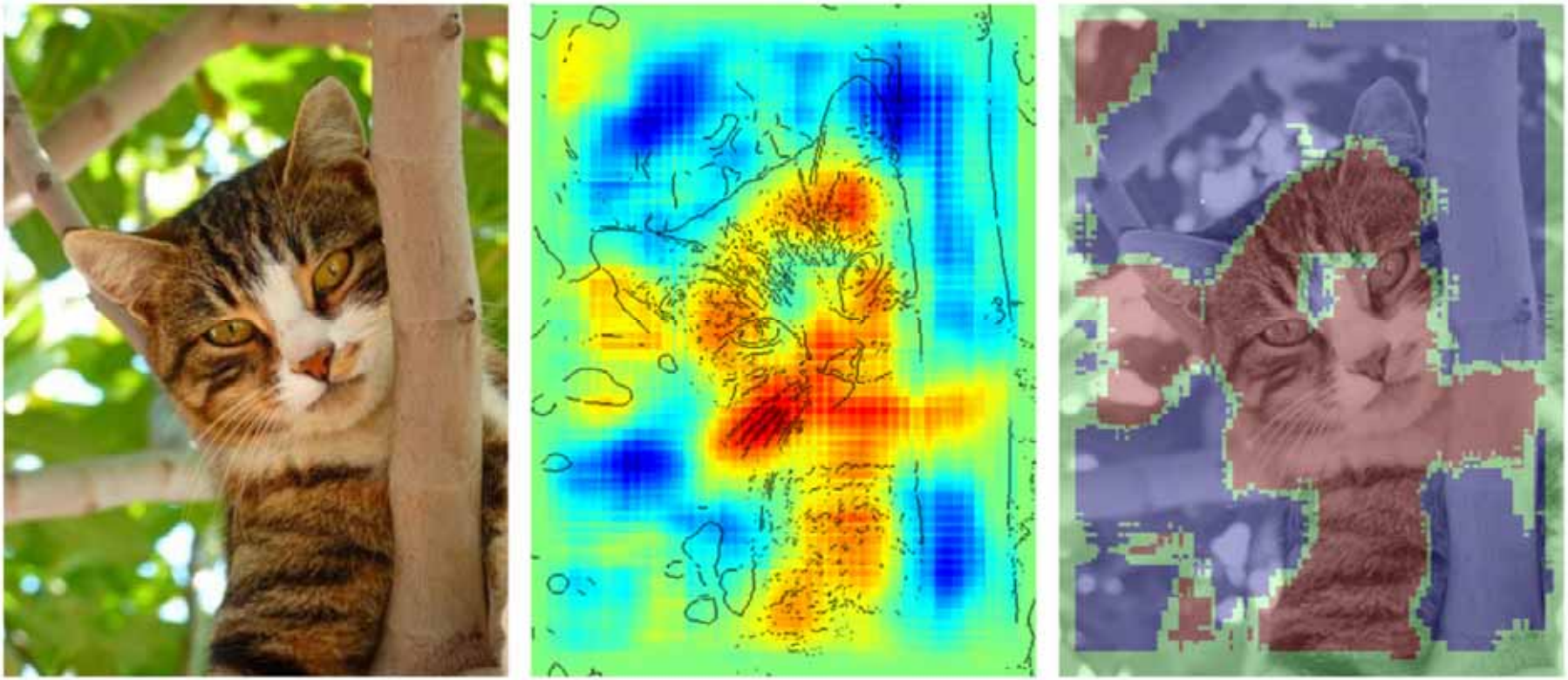


Fig 4. Local and global predictions for input images are obtained by following a series of steps through the classification- and pixel-wise decomposition pipelines. Each step taken towards the final pixel-wise decomposition has a complementing analogue within the Bag of Words classification pipeline. The calculations used during the pixel-wise decomposition process make use of information extracted by those corresponding analogues. Airplane image in the graphic by Pixabay user tpsdave.

doi:10.1371/journal.pone.0130140.g004



Definition 1. A heatmapping $\boldsymbol{R}(\boldsymbol{x})$ is *conservative* if the sum of assigned relevances in the pixel space corresponds to the total relevance detected by the model:

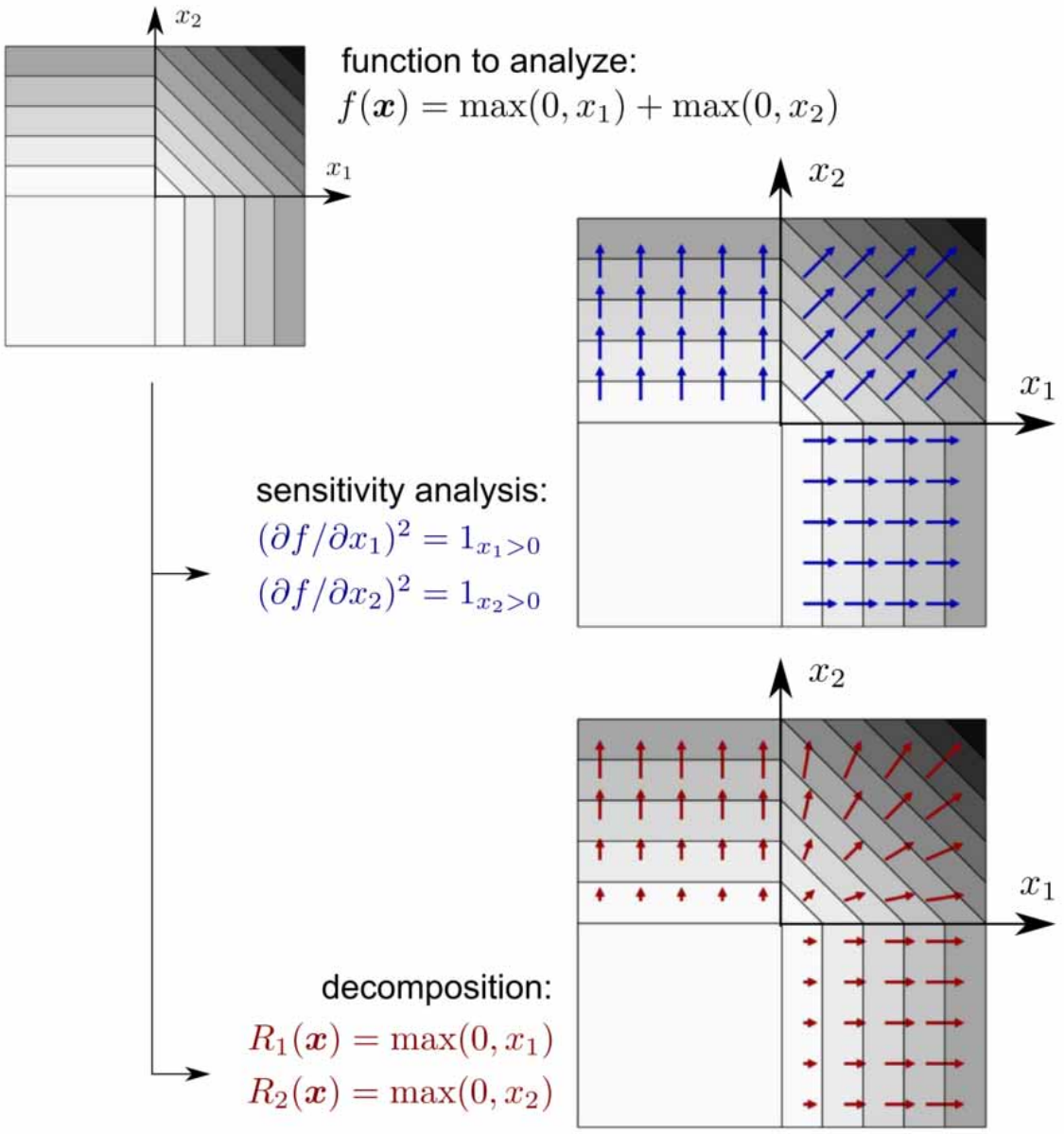
$$\forall\, \boldsymbol{x}\colon f(\boldsymbol{x}) = \sum_{p} R_p(\boldsymbol{x}).$$

Definition 2. A heatmapping $\boldsymbol{R}(\boldsymbol{x})$ is *positive* if all values forming the heatmap are greater or equal to zero, that is:

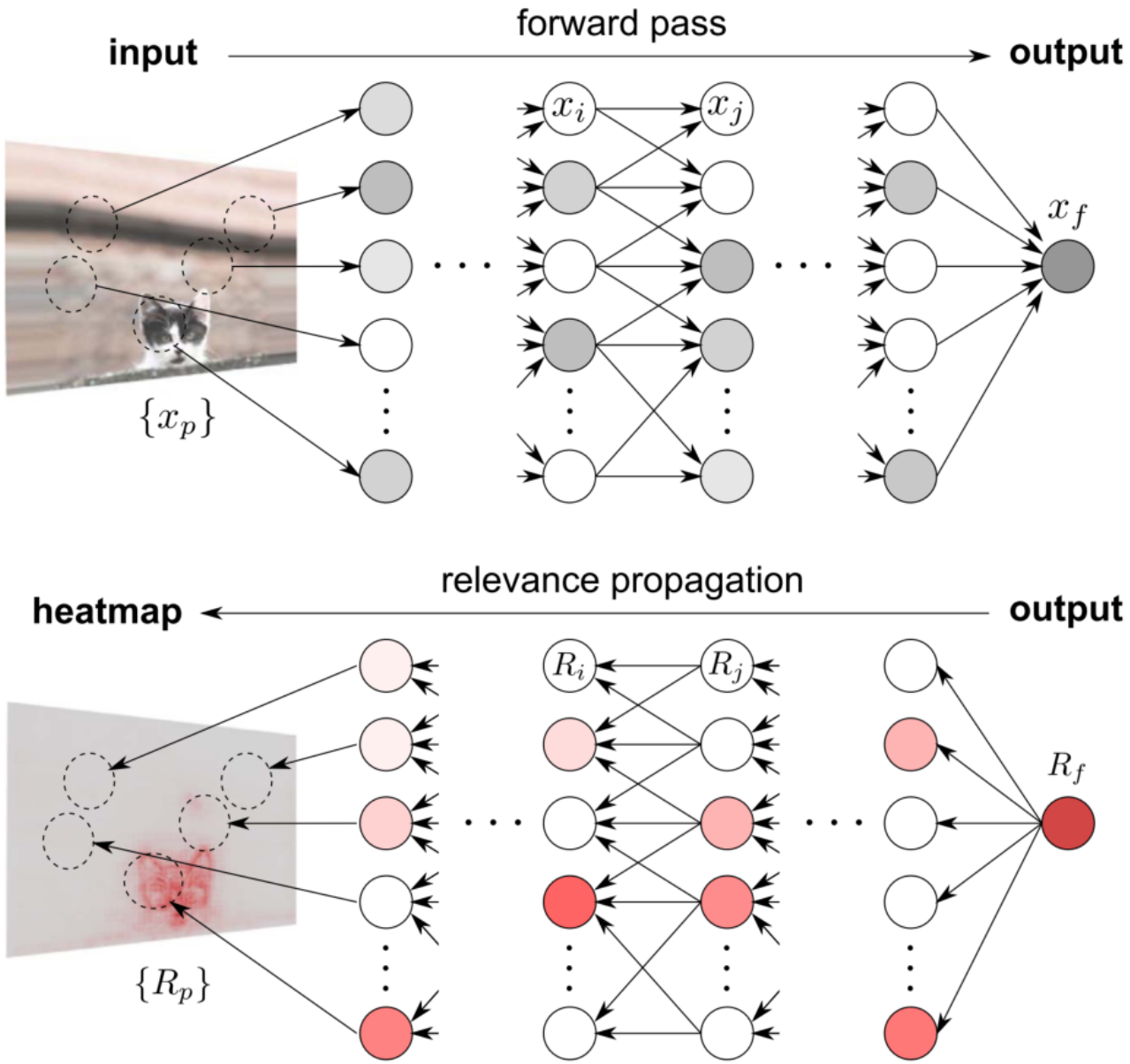
$$\forall\, \boldsymbol{x}, p\colon R_p(\boldsymbol{x}) \geq 0$$

Definition 3. A heatmapping $\boldsymbol{R}(\boldsymbol{x})$ is *consistent* if it is conservative *and* positive. That is, it is consistent if it complies with Definitions 1 and 2.

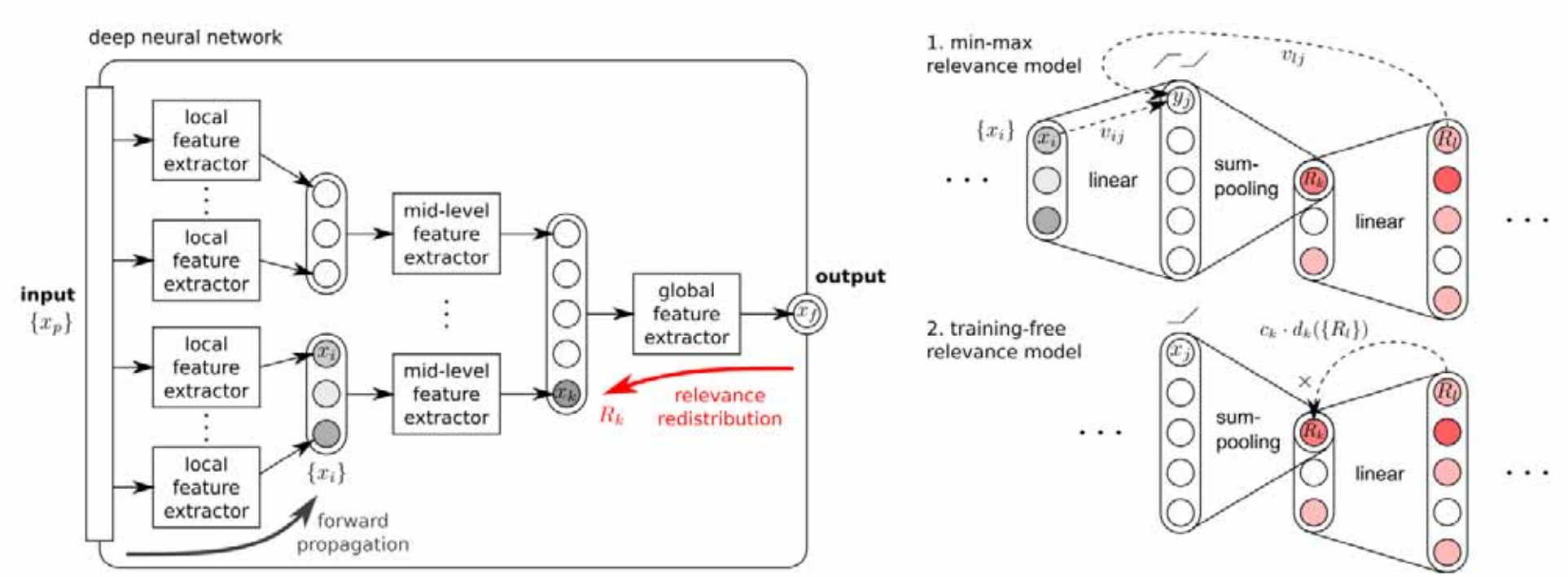
Gregoire Montavon, Sebastian Lapuschkin, Alexander Binder, Wojciech Samek & Klaus-Robert Müller 2017. Explaining nonlinear classification decisions with deep taylor decomposition. Pattern Recognition, 65, 211-222, doi:10.1016/j.patcog.2016.11.008.


x_2
x_1
function to analyze:
$f(\boldsymbol{x}) = \max(0, x_1) + \max(0, x_2)$
sensitivity analysis:
$(\partial f/\partial x_1)^2 = 1_{x_1>0}$
$(\partial f/\partial x_2)^2 = 1_{x_2>0}$
decomposition:
$R_1(\boldsymbol{x}) = \max(0, x_1)$
$R_2(\boldsymbol{x}) = \max(0, x_2)$

Relevance propagation



Relevance Redistribution



Example 1

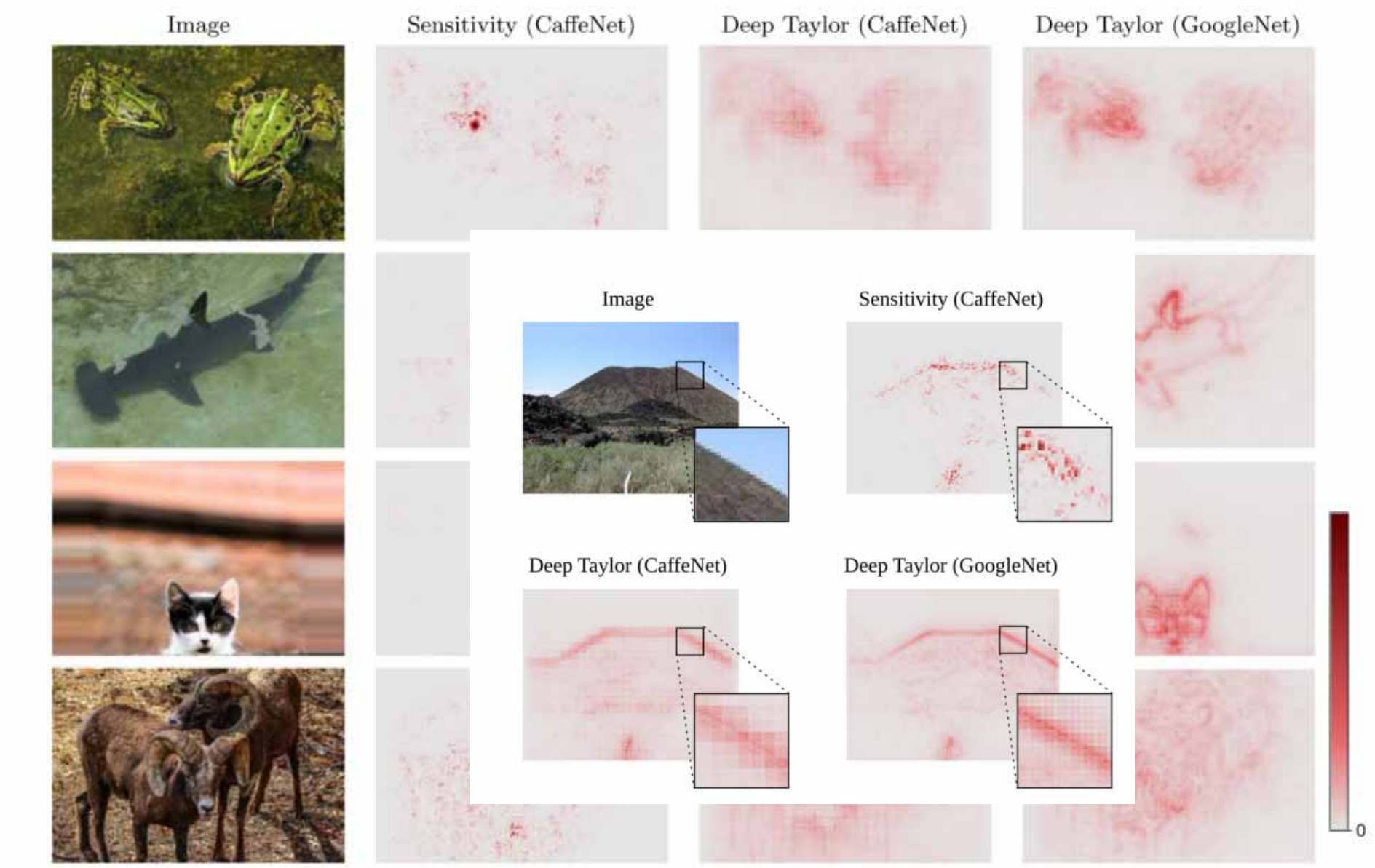
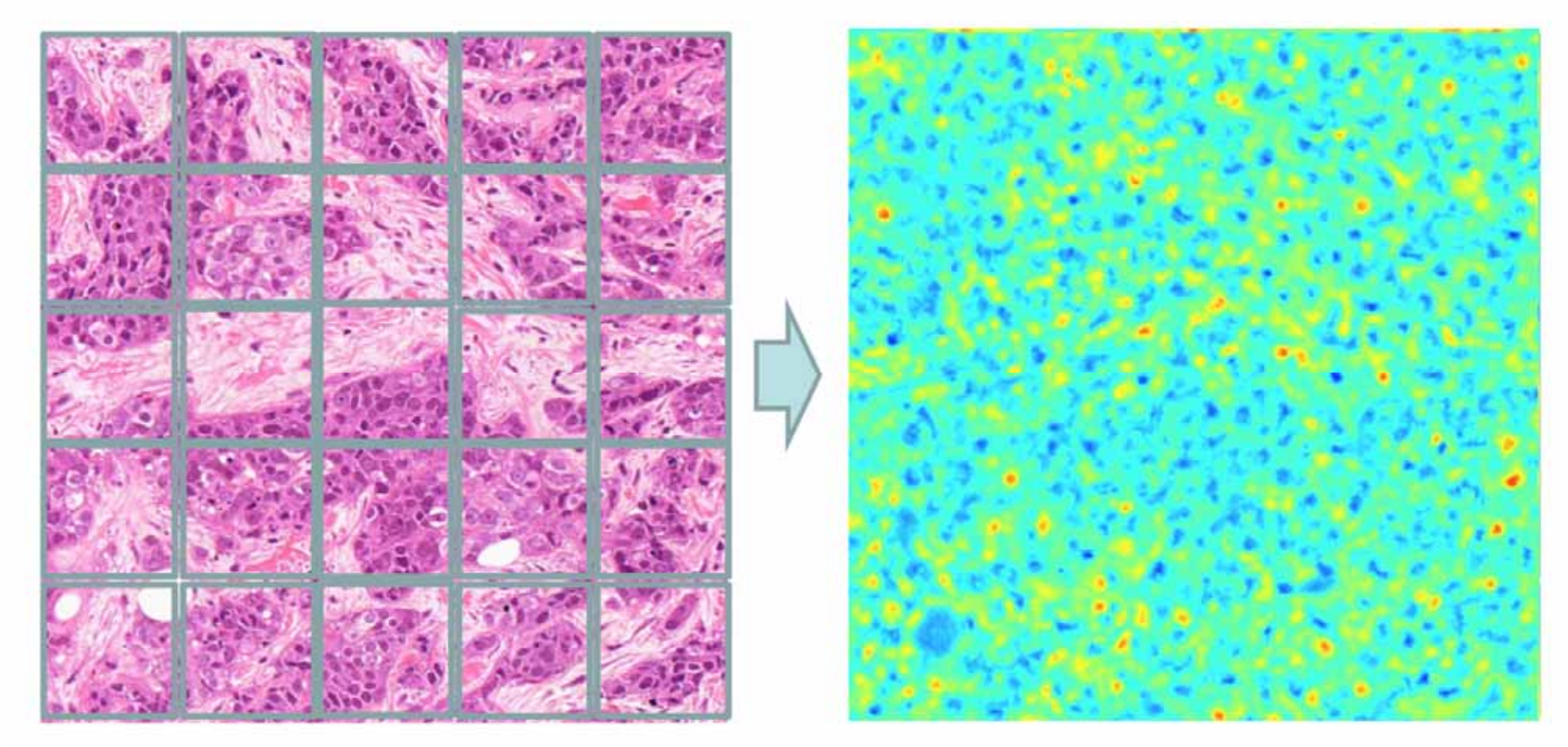


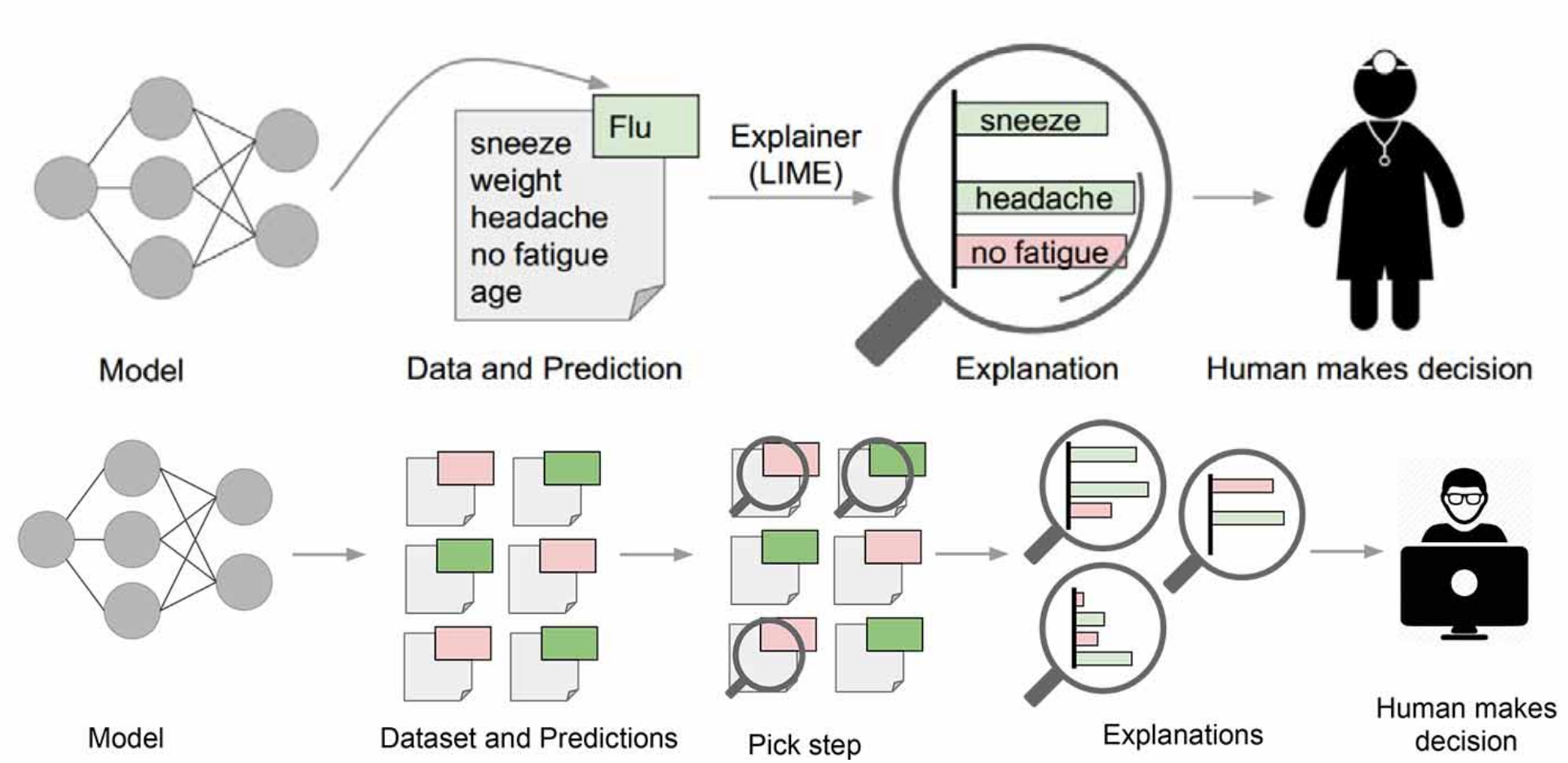
Image
Sensitivity (CaffeNet)
Deep Taylor (CaffeNet)
Deep Taylor (GoogleNet)
Image
Sensitivity (CaffeNet)
Deep Taylor (CaffeNet)
Deep Taylor (GoogleNet)
0

Example 2 Histopathology



Sebastian Bach, Alexander Binder, Grégoire Montavon, Frederick Klauschen, Klaus-Robert Müller & Wojciech Samek 2015. On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. PloS one, 10, (7), e0130140, doi:10.1371/journal.pone.0130140.

LIME – Local Interpretable Model Agnostic Explanations



Marco Tulio Ribeiro, Sameer Singh & Carlos Guestrin. Why should i trust you?: Explaining the predictions of any classifier. 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016. ACM, 1135-1144, doi:10.1145/2939672.2939778.

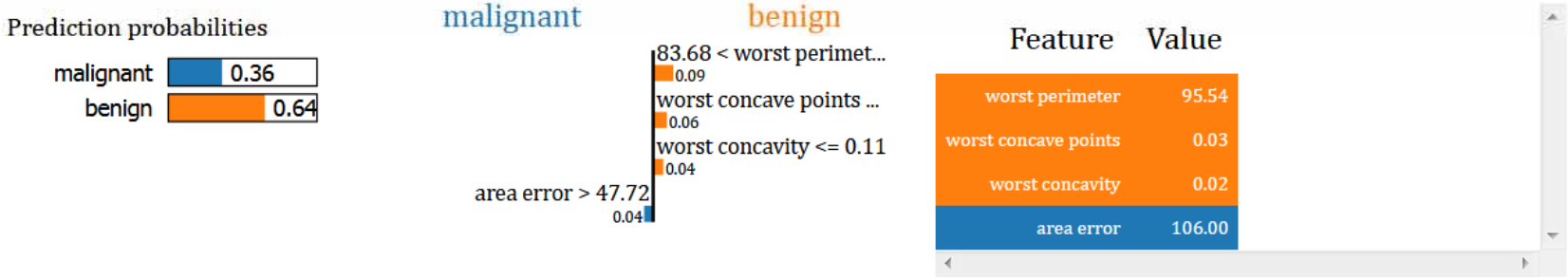
Example LIME – Model Agnostic Explanation

In [12]:
```
explainer = lime.lime_tabular.LimeTabularExplainer(X_train, feature_names=breast.feature_names, class_names=breast.targe
```

Here we will take a sample from the test set (in this case the sample at index 76) and create an explainer instance for this sample. This will let us see why the algorithm made its prediction visually.

In [18]:
```
# For this demonstration, let's take the same sample each time, in this case sample index 86
i = 76
# For a random sample uncomment out the following line
# i = np.random.randint(0, X_test.shape[0])

exp = explainer.explain_instance(X_test[i], random_forest.predict_proba, num_features=4)
exp.show_in_notebook(show_table=True, show_all=False)
```

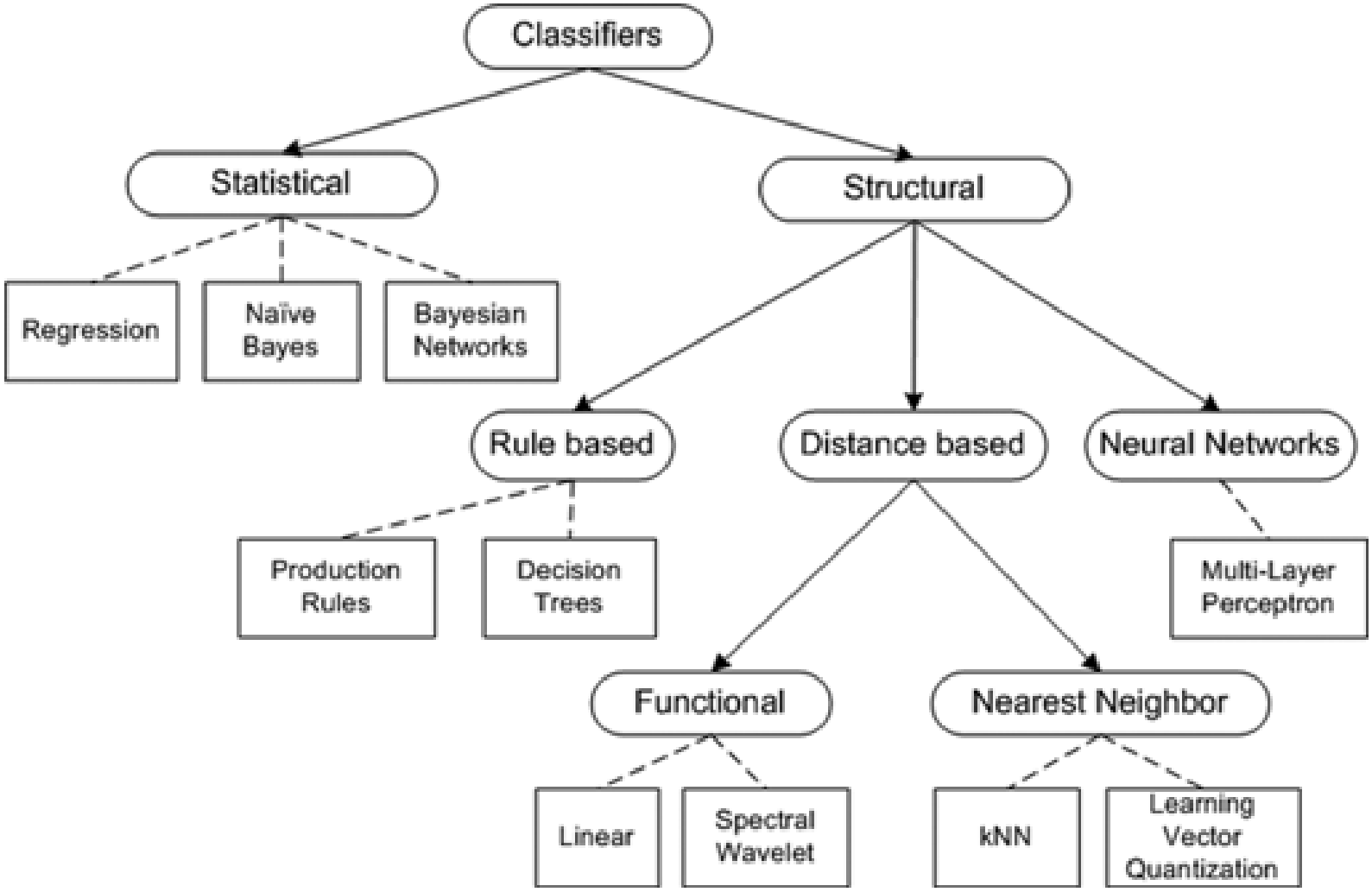


As you can see, the random forest algorithm has predicted with a probability of 0.64 that the sample at index 76 in the test set is malignant.

When using the explainer, we set the `num_features`parameter to 4, meaning the explainer shows the top 4 features that contributed to the prediction probabilities.

We chose 76 as it was a borderline decision. For example sample 86 is much more clear (this will we will set the `num_features` parameter to include all features so that we see each feature's contribution to the probability):

Remember: there are myriads of classifiers …



https://stats.stackexchange.com/questions/271247/machine-learning-statistical-vs-structural-classifiers

If Age <50 **and** Male =Yes:

If Past-Depression =Yes **and** Insomnia =No **and** Melancholy =No, **then** Healthy

If Past-Depression =Yes **and** Insomnia =Yes **and** Melancholy =Yes **and** Tiredness =Yes, **then** Depression

If Age ≥ 50 **and** Male =No:

If Family-Depression =Yes **and** Insomnia =No **and** Melancholy =Yes **and** Tiredness =Yes, **then** Depression

If Family-Depression =No **and** Insomnia =No **and** Melancholy =No **and** Tiredness =No, **then** Healthy

Default:

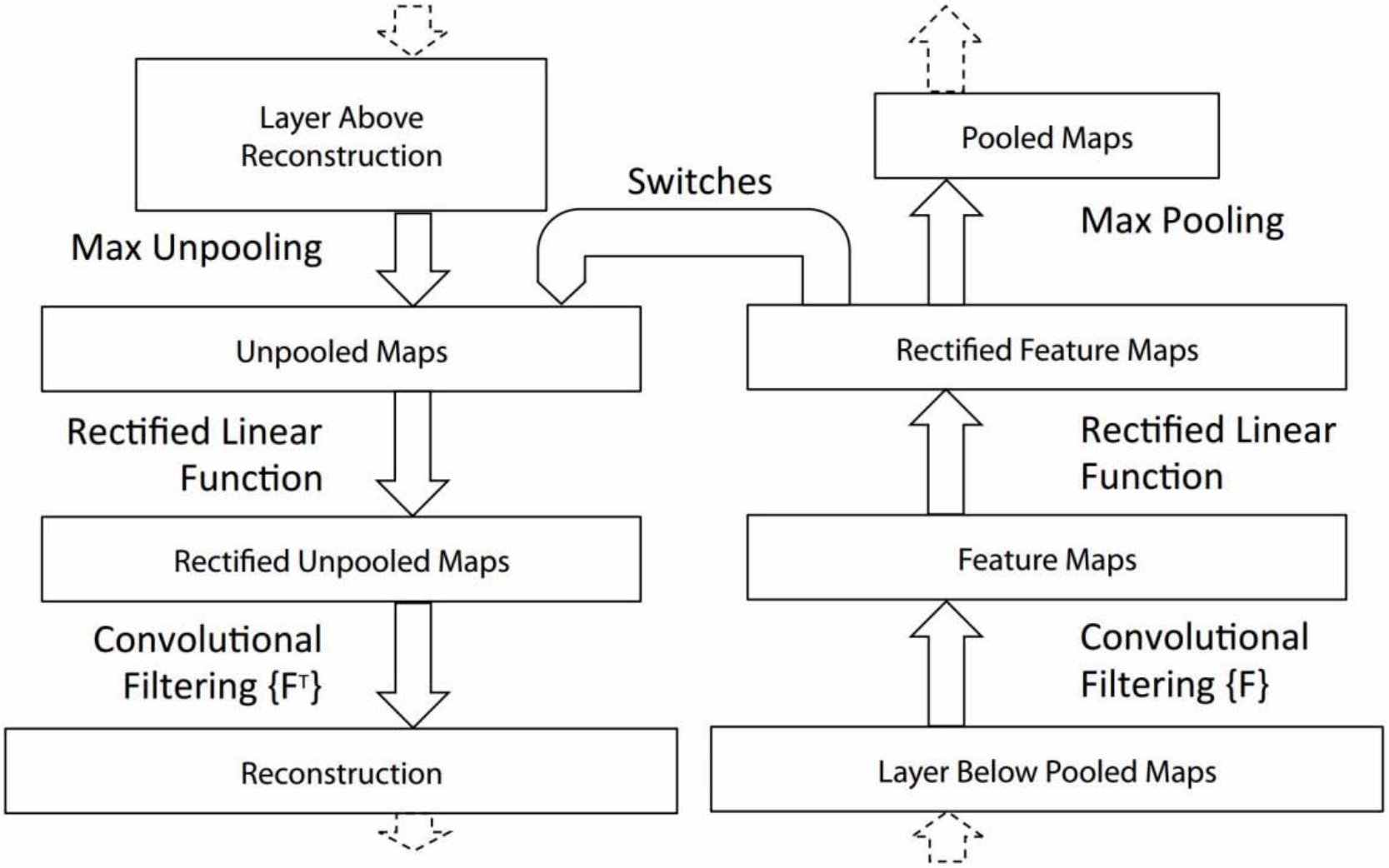
If Past-Depression =Yes **and** Tiredness =No **and** Exercise =No **and** Insomnia =Yes, **then** Depression

If Past-Depression =No **and** Weight-Gain =Yes **and** Tiredness =Yes **and** Melancholy =Yes, **then** Depression

If Family-Depression =Yes **and** Insomnia =Yes **and** Melancholy =Yes **and** Tiredness =Yes, **then** Depression

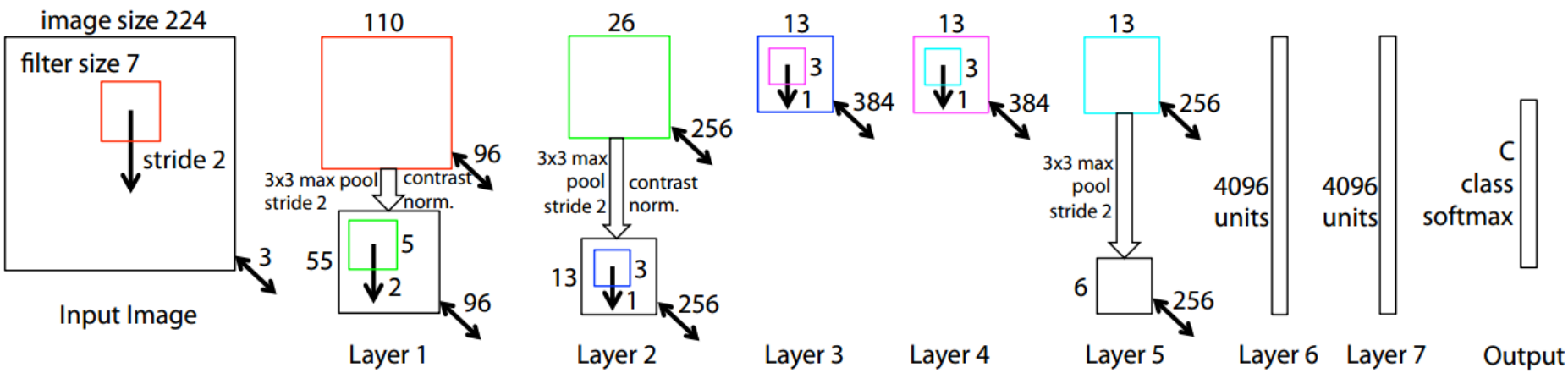
Himabindu Lakkaraju, Ece Kamar, Rich Caruana & Jure Leskovec 2017. Interpretable and Explorable Approximations of Black Box Models. arXiv:1707.01154.

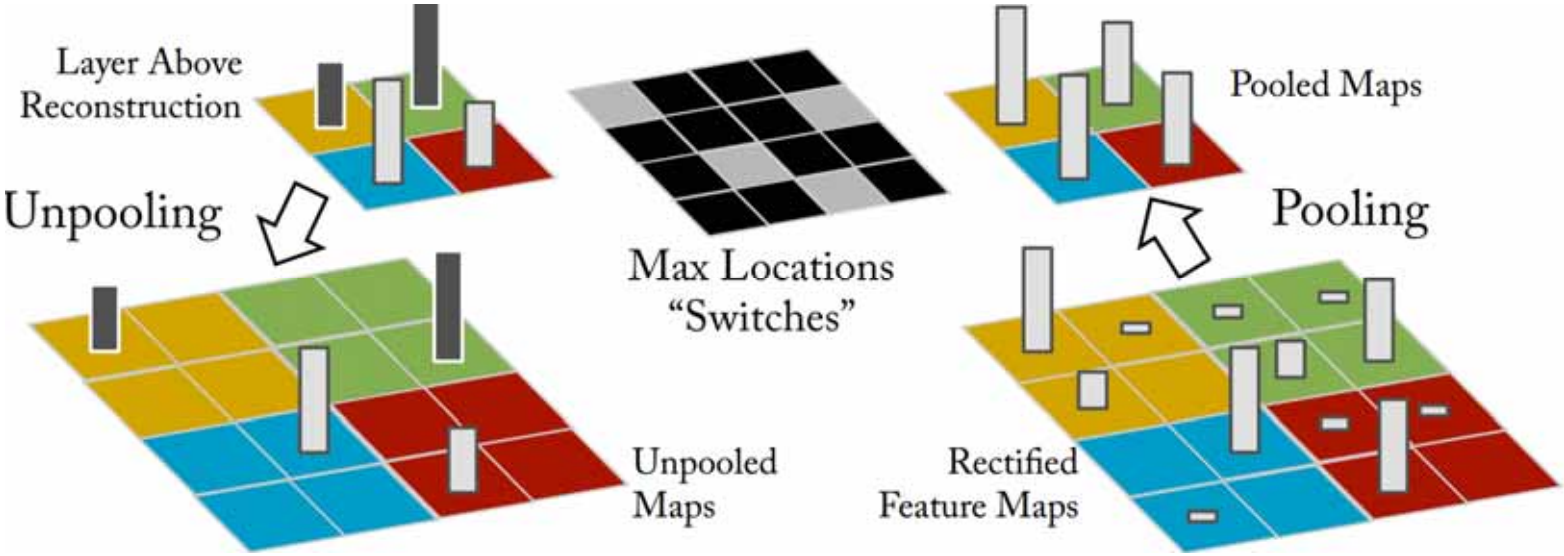
Example: Interpretable Deep Learning Model



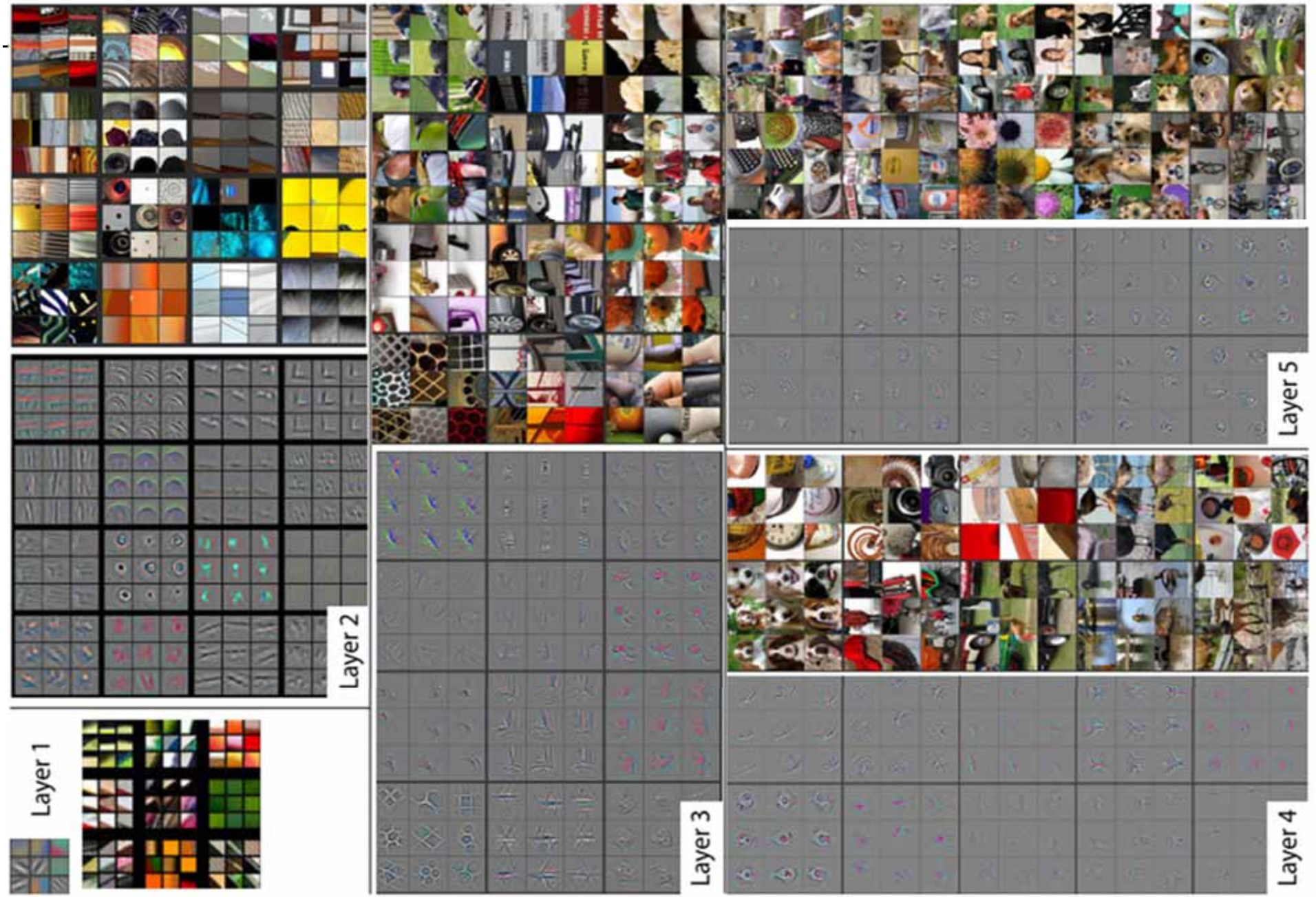
Matthew D. Zeiler & Rob Fergus 2013. Visualizing and Understanding Convolutional Networks. arXiv:1311.2901.

Visualizing a Conv Net with a De-Conv Net



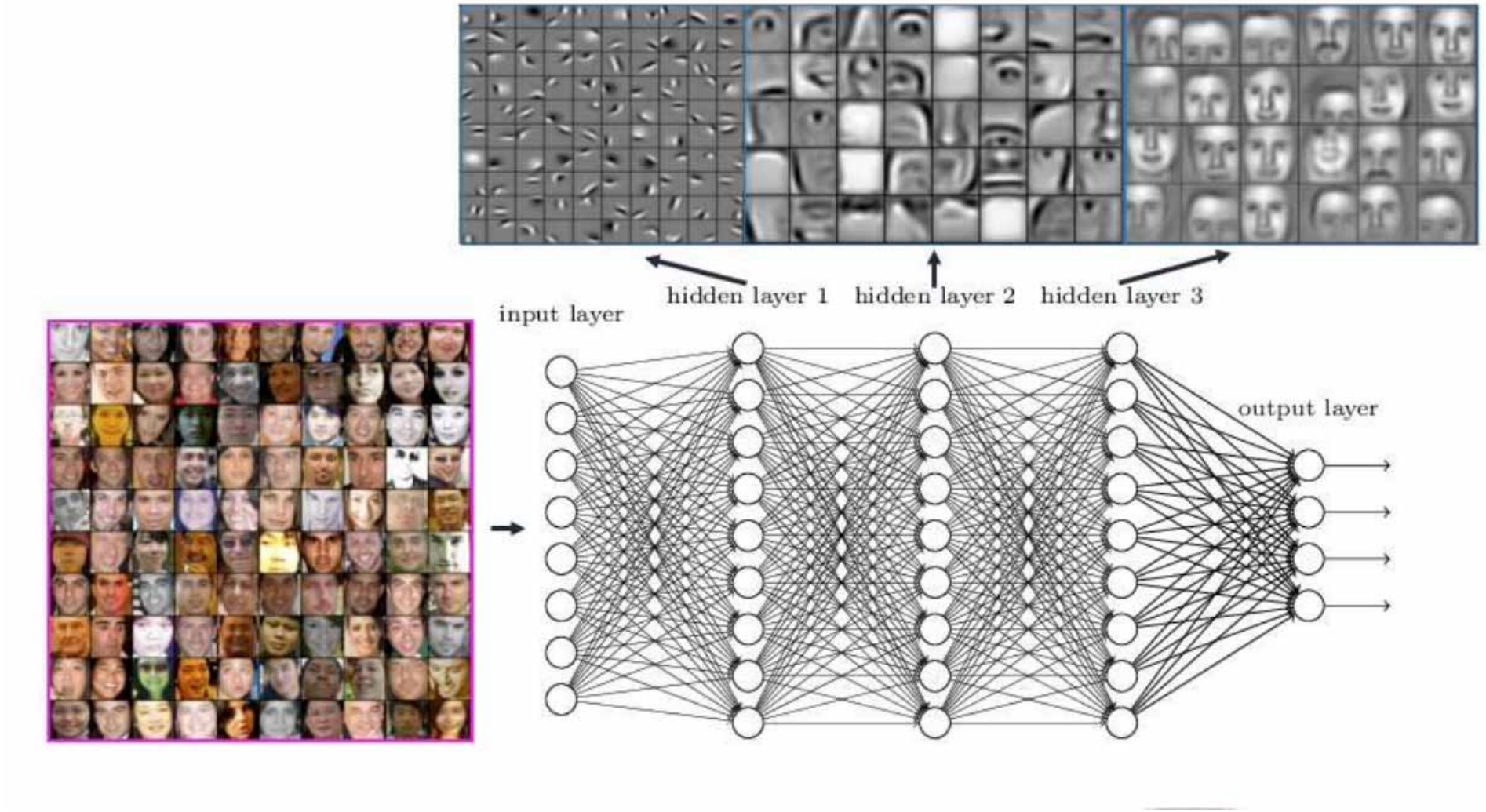


Matthew D. Zeiler & Rob Fergus 2014. Visualizing and understanding convolutional networks. In: D., Fleet, T., Pajdla, B., Schiele & T., Tuytelaars (eds.) ECCV, Lecture Notes in Computer Science LNCS 8689. Cham: Springer, pp. 818-833, doi:10.1007/978-3-319-10590-1_53.



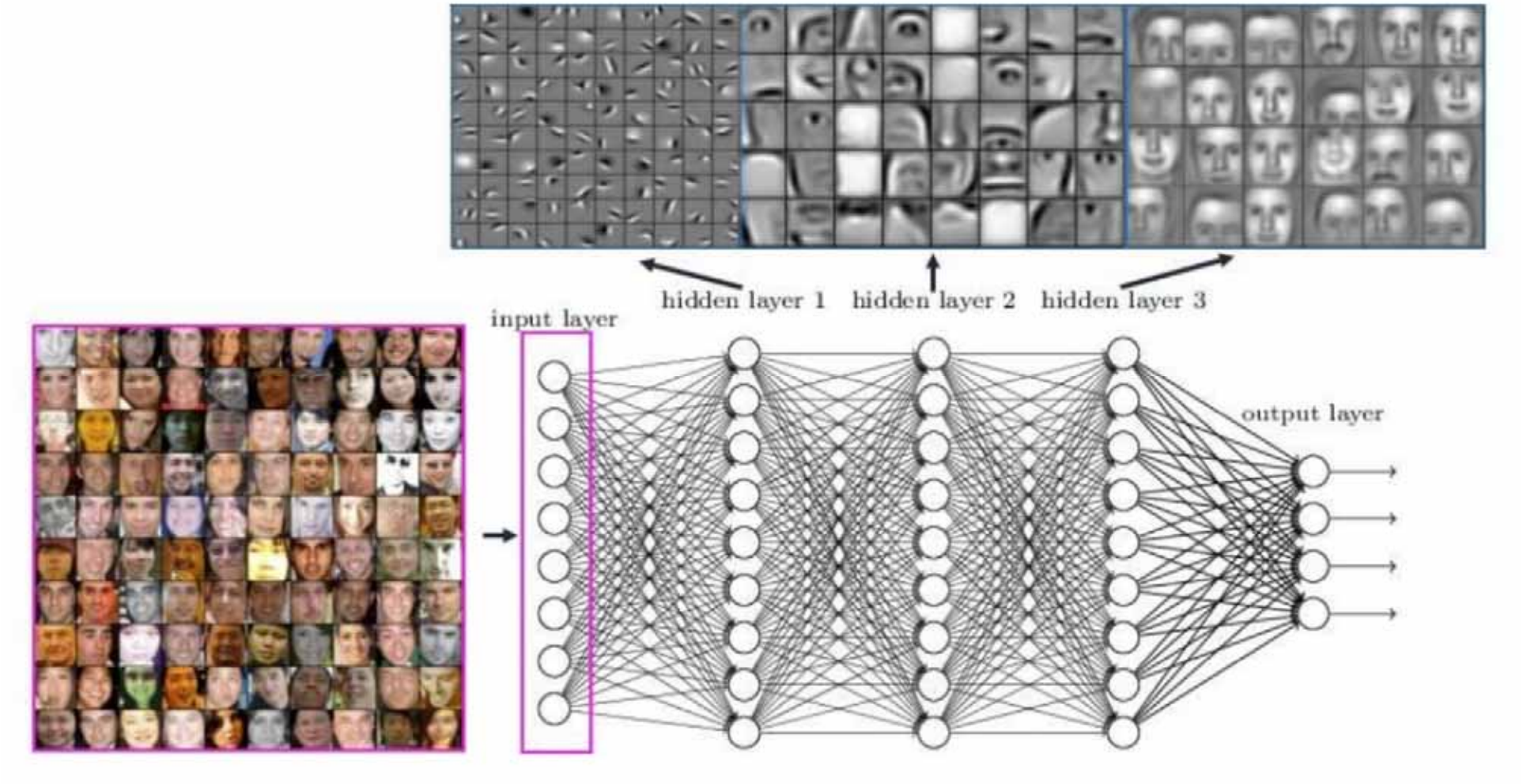
Matthew D. Zeiler & Rob Fergus 2013. Visualizing and Understanding Convolutional Networks. arXiv:1311.2901.

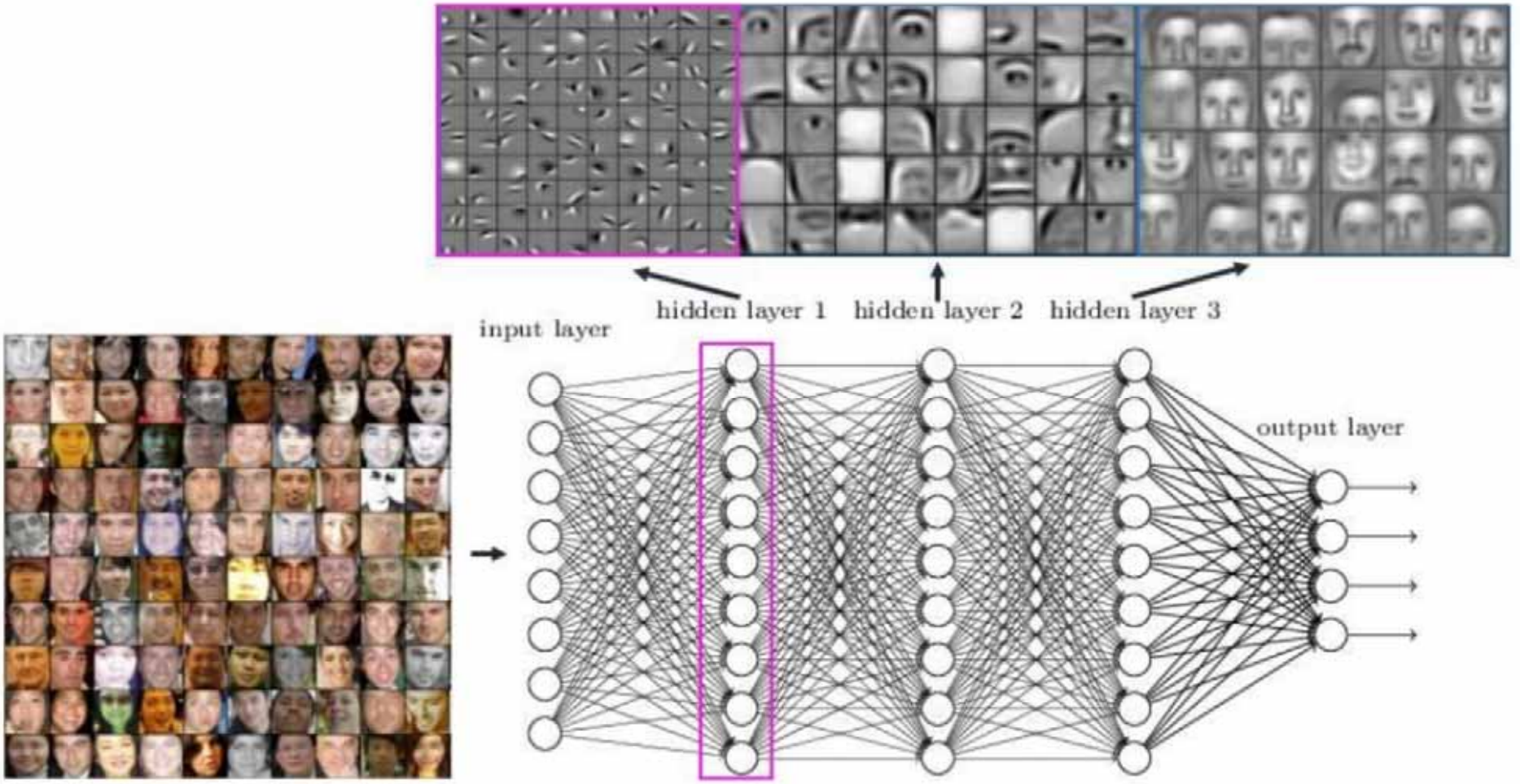
The world is compositional (Yann LeCun)

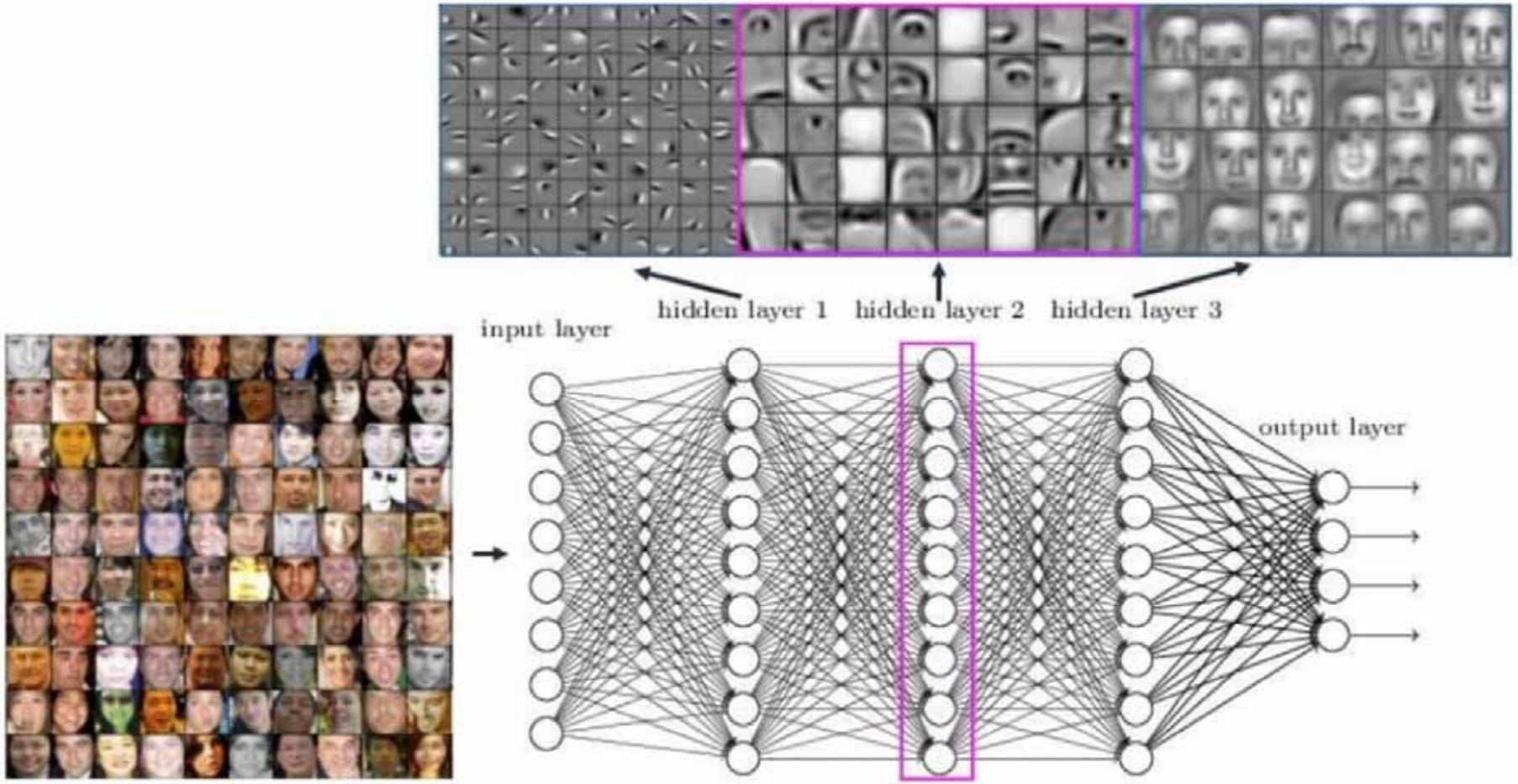


Matthew D. Zeiler & Rob Fergus 2013. Visualizing and Understanding Convolutional Networks. arXiv:1311.2901

The world is compositional (Yann LeCun)




hidden layer 1
hidden layer 2
hidden layer 3
input layer
output layer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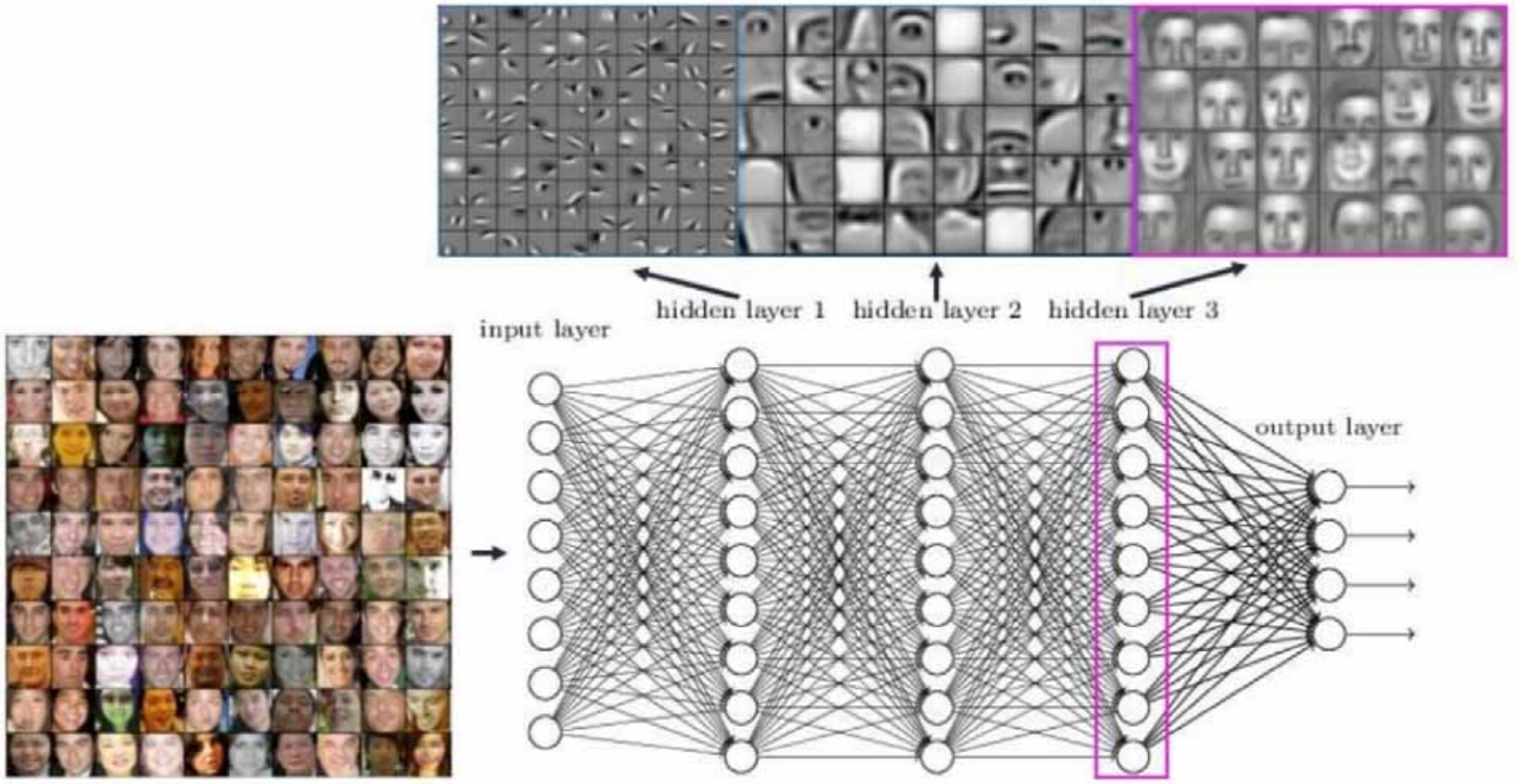
hidden layer 3
input layer
output layer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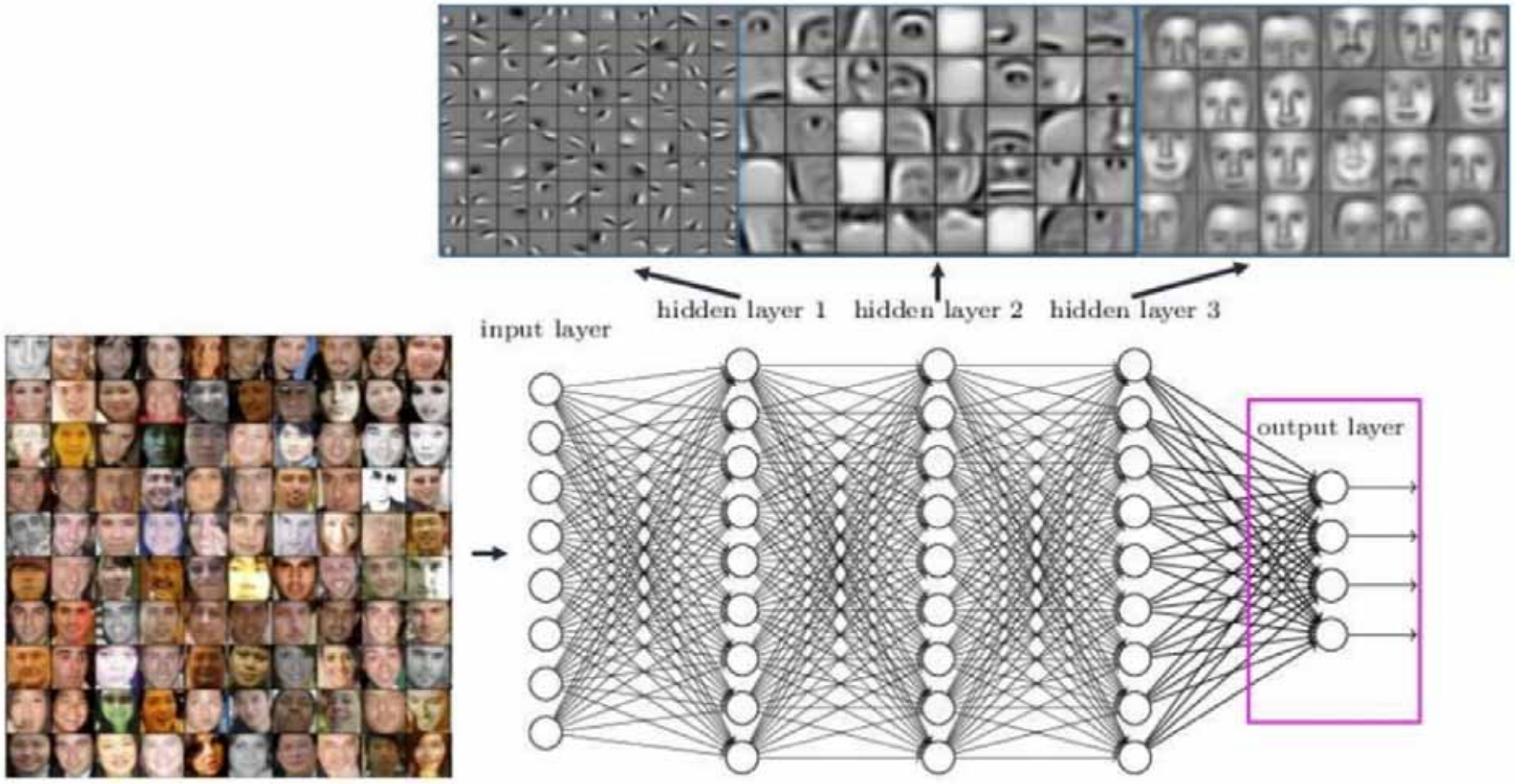
hidden layer 1
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input layer
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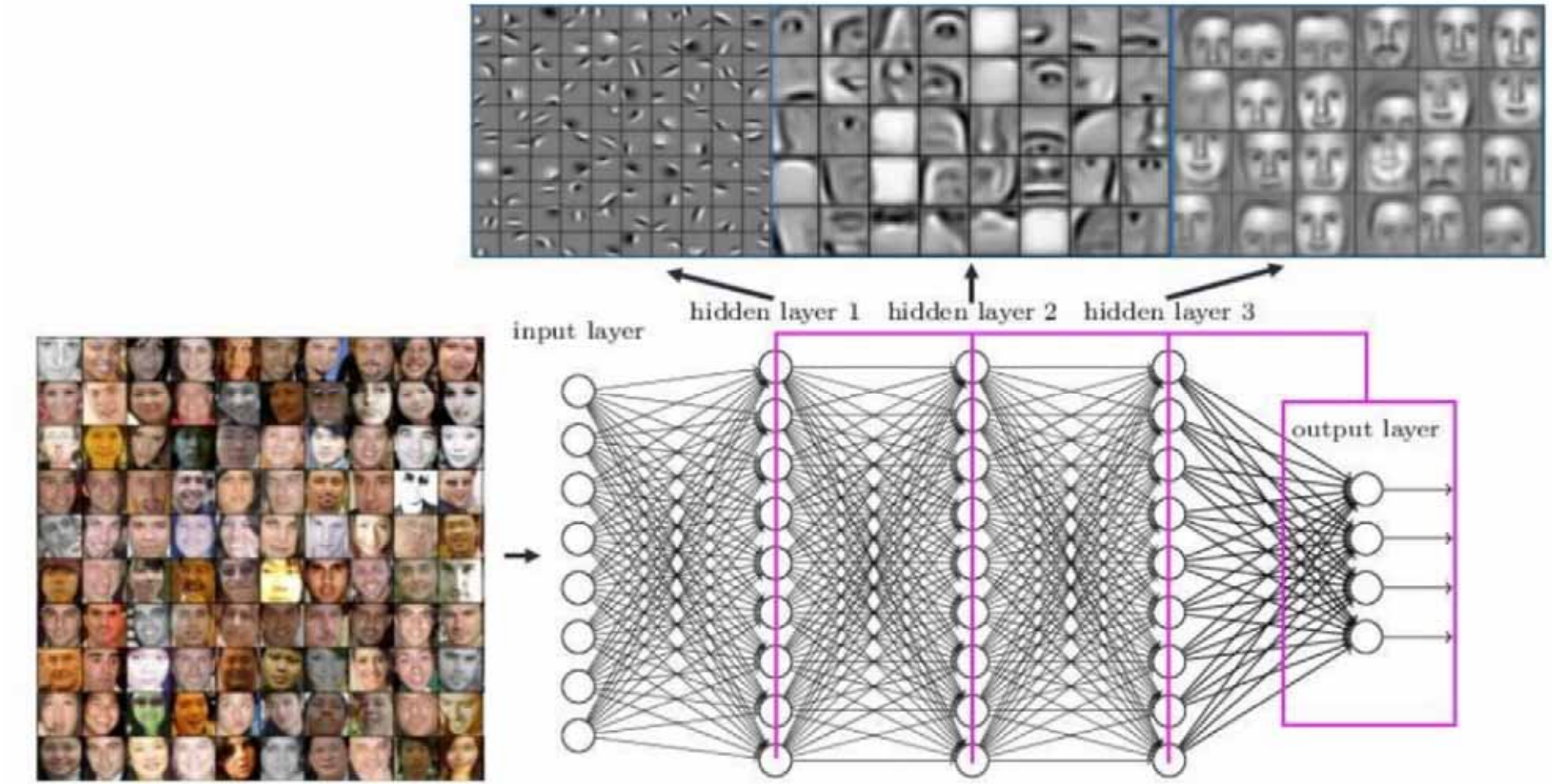
hidden layer 1
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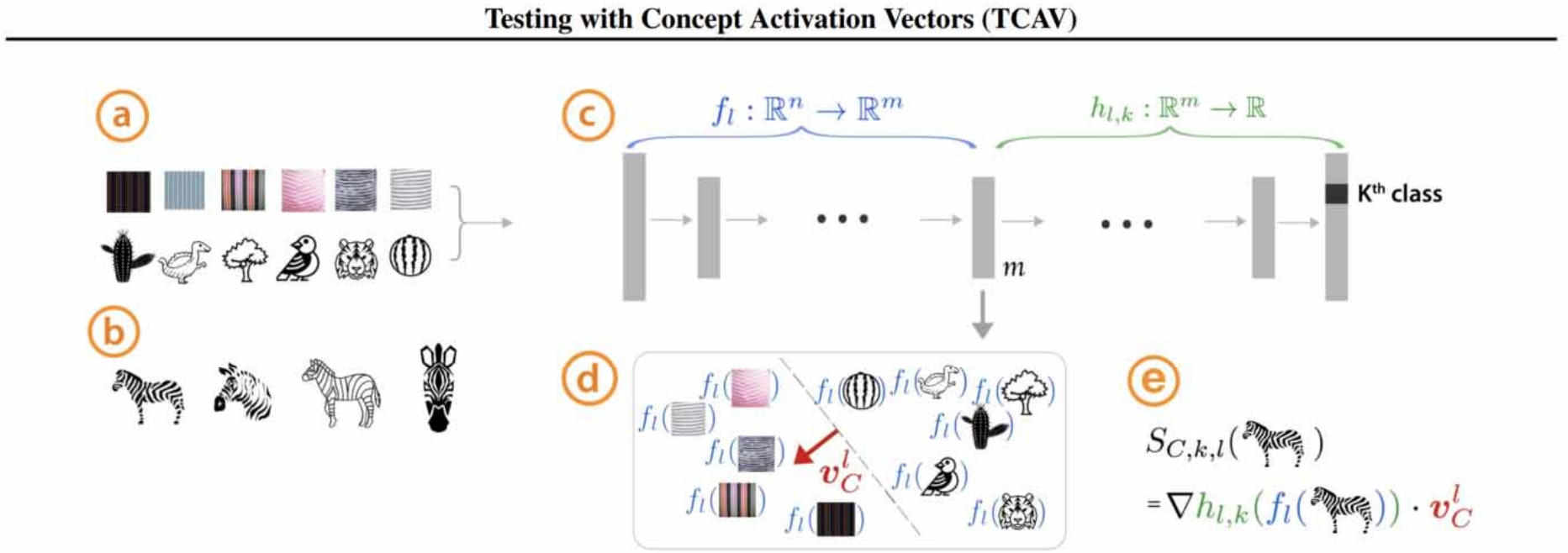
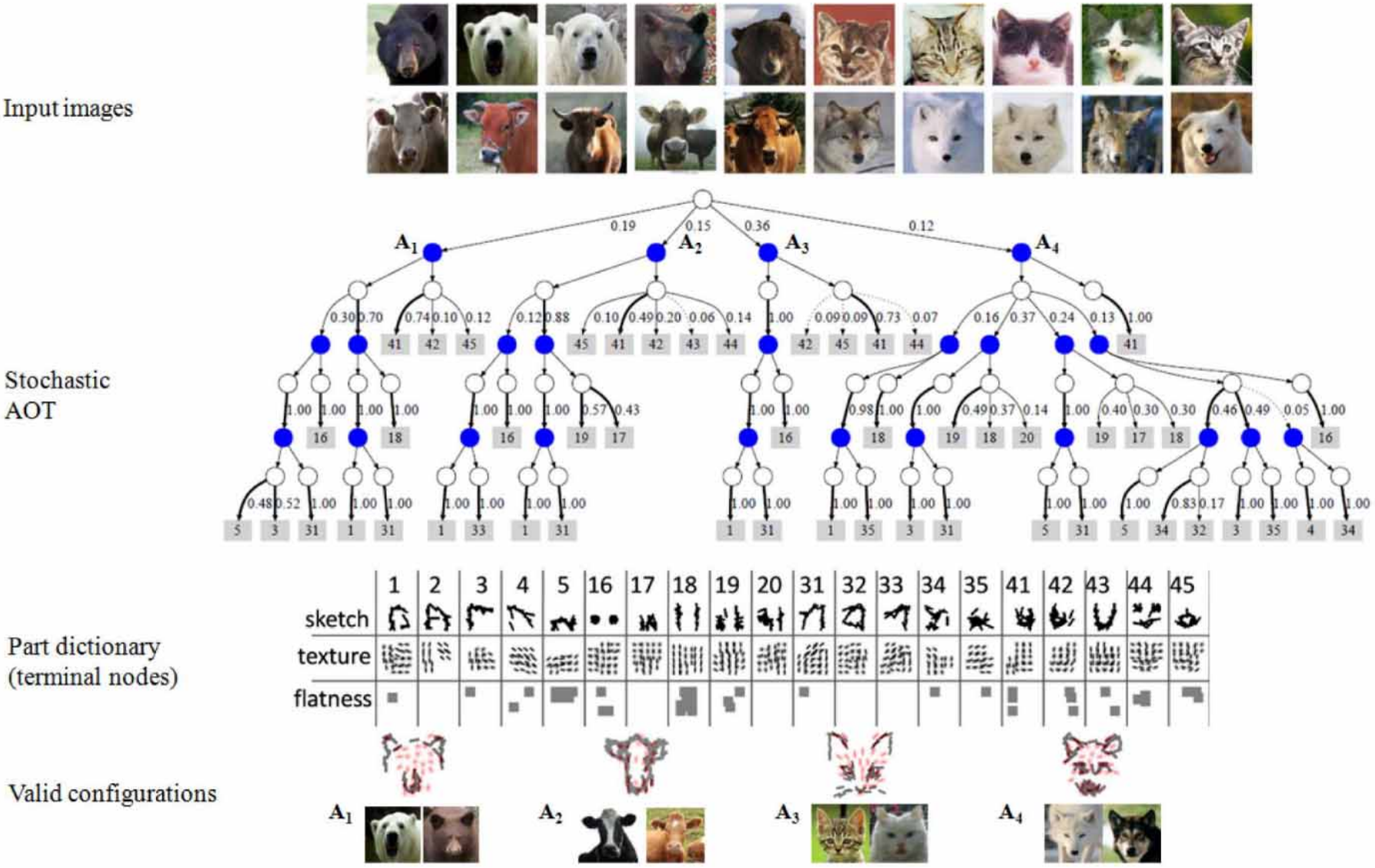


Figure 1. **Testing with Concept Activation Vectors:** Given a user-defined set of examples for a concept (e.g., 'striped'), and random examples ⓐ, labeled training-data examples for the studied class (zebras) ⓑ, and a trained network ⓒ, TCAV can quantify the model's sensitivity to the concept for that class. CAVs are learned by training a linear classifier to distinguish between the activations produced by a concept's examples and examples in any layer ⓓ. The CAV is the vector orthogonal to the classification boundary (v_C^l, red arrow). For the class of interest (zebras), TCAV uses the directional derivative $S_{C,k,l}(\boldsymbol{x})$ to quantify conceptual sensitivity ⓔ.

https://github.com/tensorflow/tcav

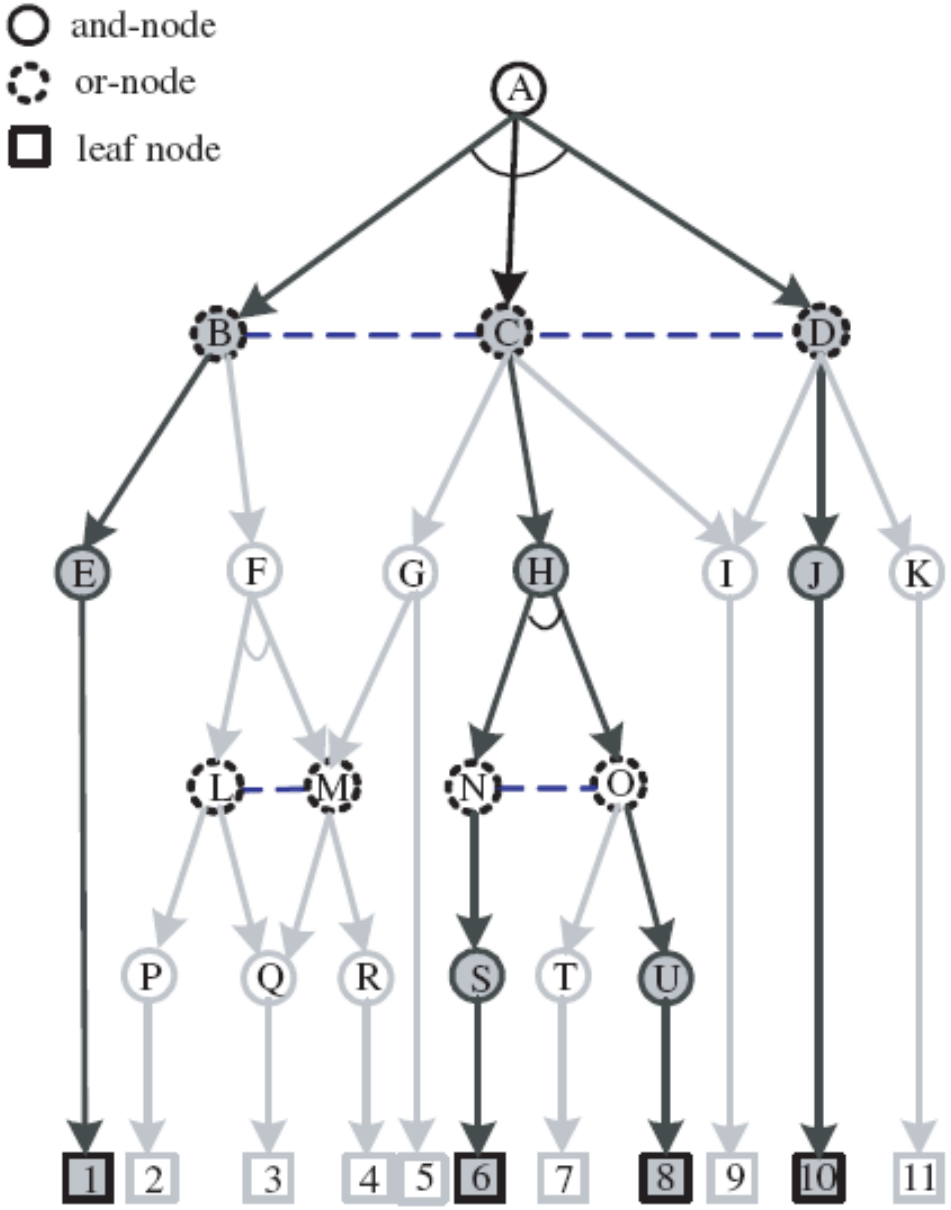
Been Kim, Martin Wattenberg, Justin Gilmer, Carrie Cai, James Wexler & Fernanda Viegas. Interpretability beyond feature attribution: Quantitative testing with concept activation vectors (TCAV). International Conference on Machine Learning (ICML), 2018. 2673-2682.

Stochastic AND-OR Templates for visual objects



Zhangzhang Si & Song-Chun Zhu 2013. Learning and-or templates for object recognition and detection. IEEE transactions on pattern analysis and machine intelligence, 35, (9), 2189-2205, doi:10.1109/TPAMI.2013.35.

Framework for vision: AND-OR Graphs



- Algorithm for this framework
  - Top-down/bottom-up computation
- Generalization of small sample
  - Use Monte Carlos simulation to synthesis more configurations
- Fill **semantic gap**

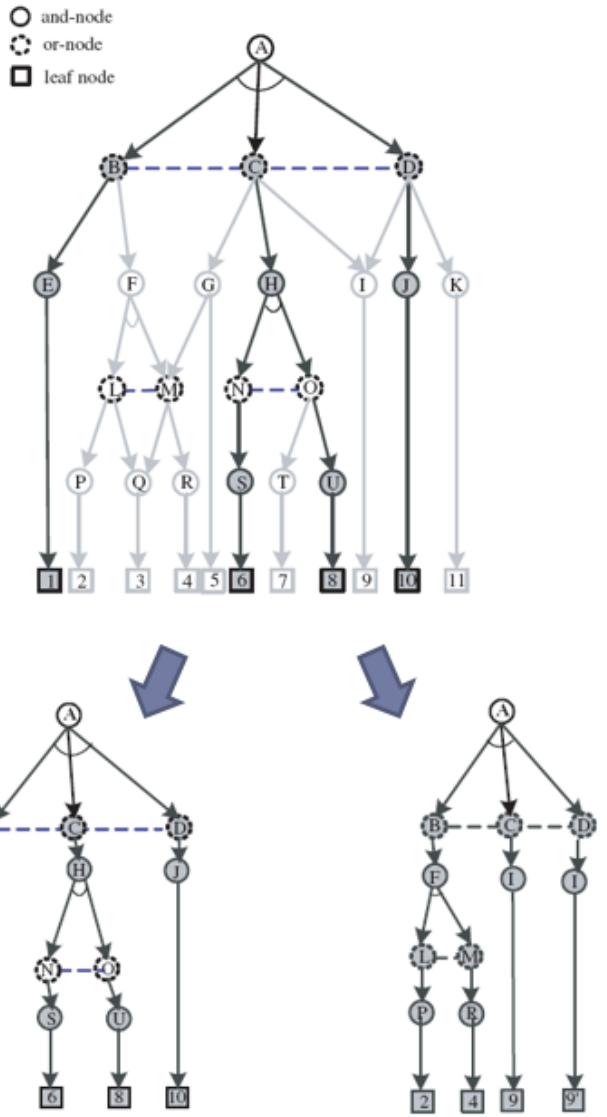
Images credit to Zhaoyin Jia (2009)

- Terminal (leaf) node: $T(pg)$
- And-Or node: $V^{or}(pg), V^{and}(pg)$
- Set of links: $E(pg)$
- Switch variable at Or-node: $w(t)$
- Attributes of primitives: $\alpha(t)$

$$p(pg;\Theta,R,\Delta)=\frac{1}{Z(\Theta)}\exp(-\xi(pg))$$

$$\xi(pg)=\sum_{v\in V^{Or}(pg)}\lambda_v(w(v))+\sum_{v\in V^{and}(pg)\cup T(pg)}\lambda_t(\alpha(t))$$

$$+\sum_{(i,j)\in E(pg)}\lambda_{ij}(v_i,v_j,\gamma_{ij},\rho_{ij})$$



- Terminal (leaf) node: $T(pg)$
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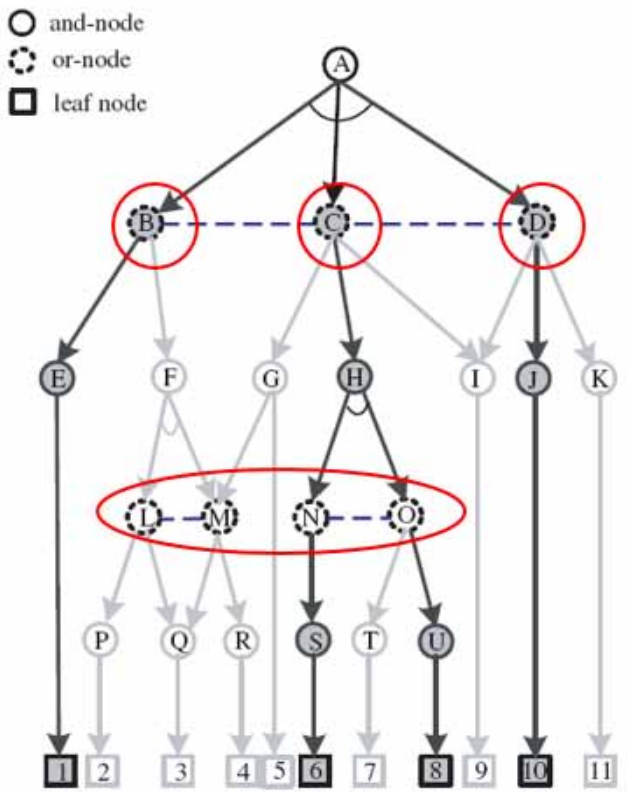


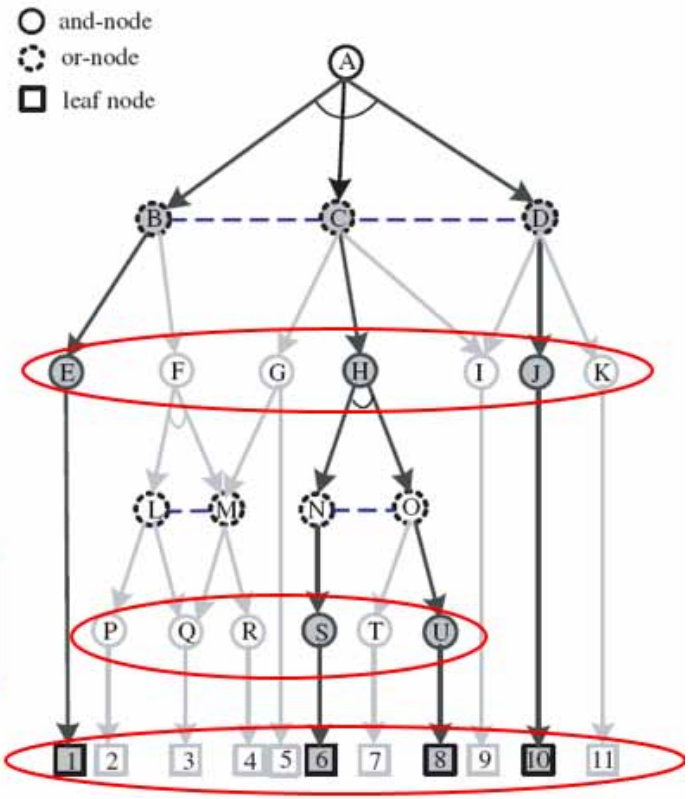
SCFG: weigh the frequency at the children of or-nodes

- Terminal (leaf) node: $T(pg)$
- And-Or node: $V^{or}(pg), V^{and}(pg)$
- Set of links: $E(pg)$
- Switch variable at Or-node: $w(t)$
- Attributes of primitives: $\alpha(t)$

$$p(pg;\Theta,R,\Delta)=\frac{1}{Z(\Theta)}\exp(-\xi(pg))$$

$$\xi(pg)=\sum_{v\in V^{Or}(pg)}\lambda_v(w(v))+\sum_{v\in V^{and}(pg)\cup T(pg)}\lambda_t(\alpha(t))$$

$$+\sum_{(i,j)\in E(pg)}\lambda_{ij}(v_i,v_j,\gamma_{ij},\rho_{ij})$$



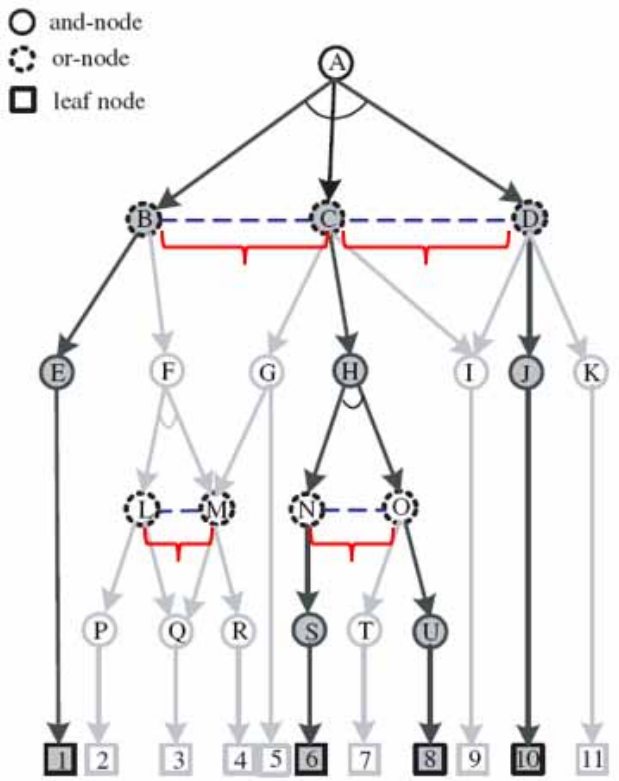
Weigh the local compatibility of primitives (geometric and appearance)

- Terminal (leaf) node: $T(pg)$
- And-Or node: $V^{or}(pg), V^{and}(pg)$
- Set of links: $E(pg)$
- Switch variable at Or-node: $w(t)$
- Attributes of primitives: $\alpha(t)$

$$p(pg;\Theta,R,\Delta)=\frac{1}{Z(\Theta)}\exp(-\xi(pg))$$

$$\xi(pg)=\sum_{v\in V^{Or}(pg)}\lambda_v(w(v))+\sum_{v\in V^{and}(pg)\cup T(pg)}\lambda_t(\alpha(t))$$

$$+\sum_{(i,j)\in E(pg)}\lambda_{ij}(v_i,v_j,\gamma_{ij},\rho_{ij})$$



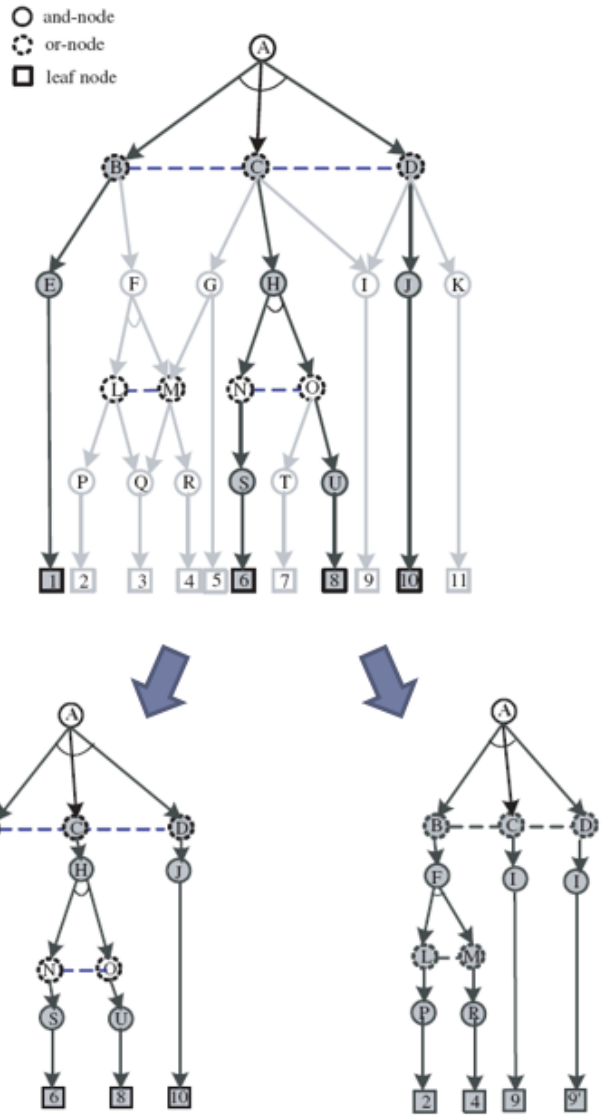
Spatial and appearance between primitives (parts or objects)

- Terminal (leaf) node: $T(pg)$
- And-Or node: $V^{or}(pg), V^{and}(pg)$
- Set of links: $E(pg)$
- Switch variable at Or-node: $w(t)$
- Attributes of primitives: $\alpha(t)$

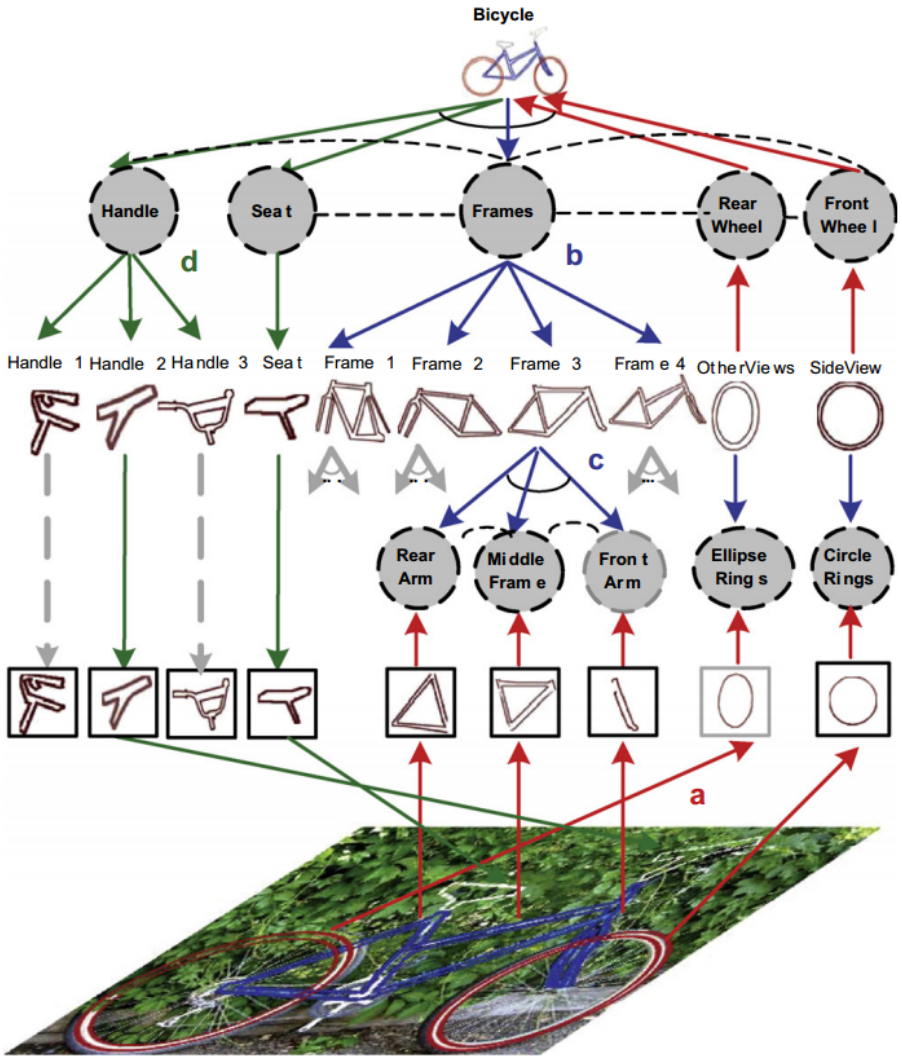
$$p(pg;\Theta,R,\Delta)=\frac{1}{Z(\Theta)}\exp(-\xi(pg))$$

$$\xi(pg)=\sum_{v\in V^{Or}(pg)}\lambda_v(w(v))+\sum_{v\in V^{and}(pg)\cup T(pg)}\lambda_t(\alpha(t))$$

$$+\sum_{(i,j)\in E(pg)}\lambda_{ij}(v_i,v_j,\gamma_{ij},\rho_{ij})$$



Stochastic graph grammar/comp. object representation



Input: an input image **I**, and a set of constructed And-Or graphs of compositional object categories.
Output: a parsing graph pg, of the scene that consists of the parsing graphs of detected objects.

- Repeat the following steps

1 Schedule the next node A to visit from the candidate parts.

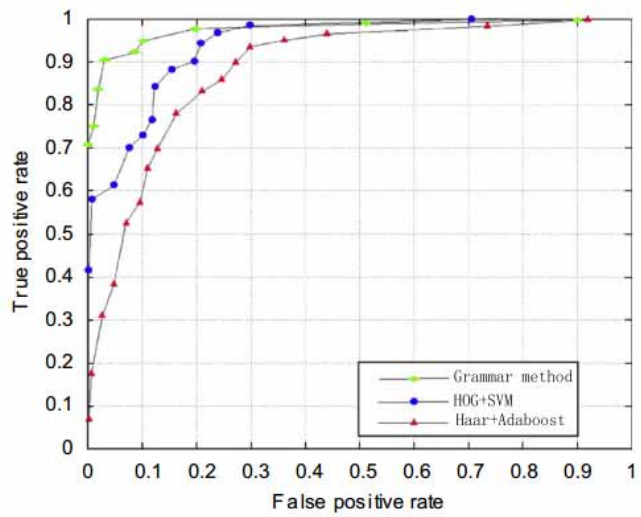
2 Call Bottom-up(A) to update A's **open** list.

i Detect terminal instances of A from the image.
ii Bind non-terminal instances of A from its children's **open** or **closed** lists

3 Call Top-down(A) to update A's **open** or **closed** lists.

i Accept hypotheses from A's **open** list to its **closed** list.
ii Remove (or disassemble) hypotheses from A's **closed** list.
iii Update the **open** lists for particles that overlap with node A.

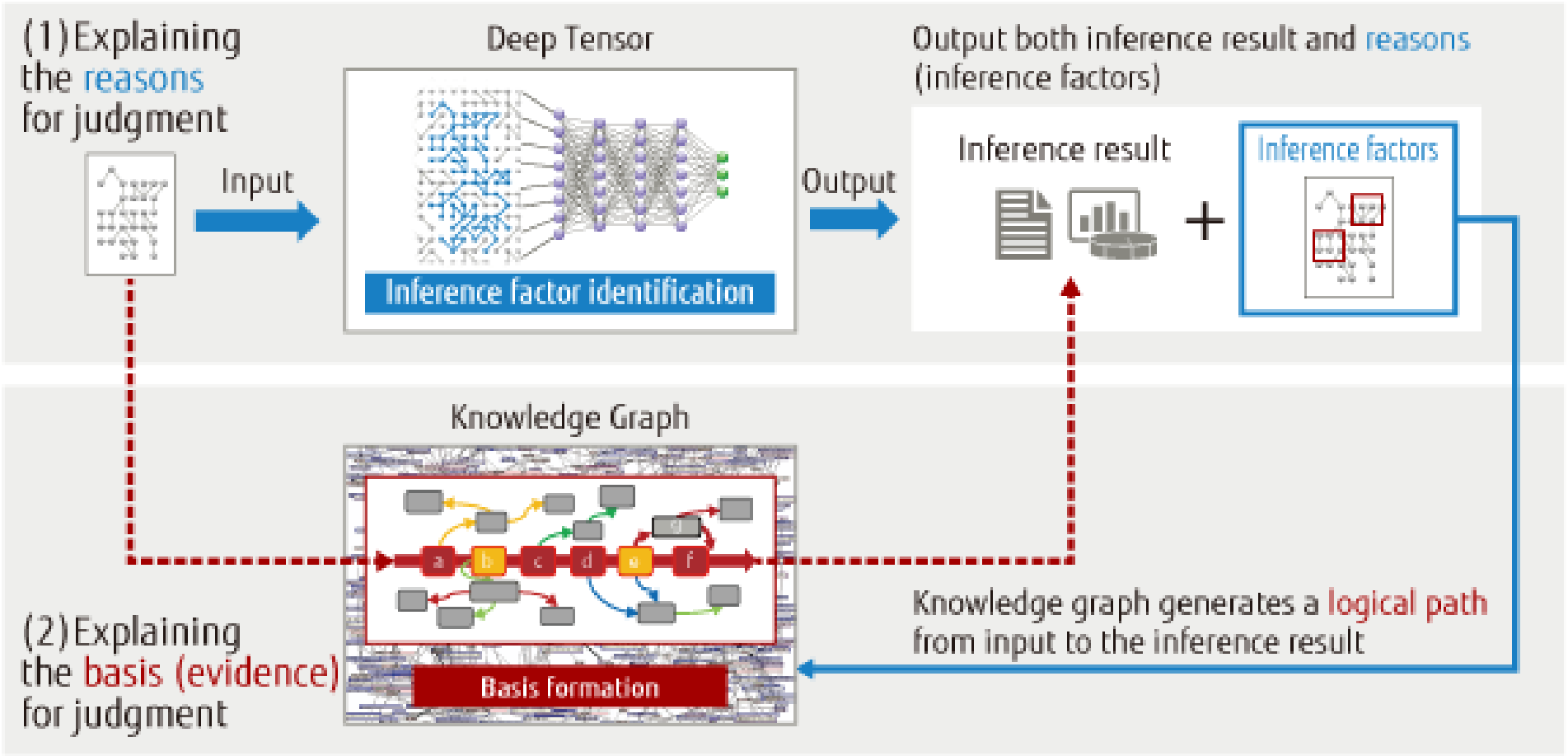
- Until the particles in **open** list with weights higher than the empirical threshold are exhausted. Output all parsing graphs whose root nodes are reached.



Liang Lin, Tianfu Wu, Jake Porway & Zijian Xu 2009. A stochastic graph grammar for compositional object representation and recognition. Pattern Recognition, 42, (7), 1297-1307, doi:10.1016/j.patcog.2008.10.033.

Future Work

Combination of Deep Learning with Ontologies



Explainable AI with Deep Tensor and Knowledge Graph

http://www.fujitsu.com/jp/Images/artificial-intelligence-en_tcm102-3781779.png

Seemingly trivial questions … ?

- What is a good explanation?
- (obviously if the other did understand it)
- Experiments needed!
- What is explainable/understandable/intelligible?
- When is it enough (Sättigungsgrad – you don't need more explanations – enough is enough)
- But how much is it …

Explanations in Artificial Intelligence will be necessary

IBM is doing it now: teaching meaningful explanations

Noel C.F. Codella, Michael Hind, Karthikeyan Natesan Ramamurthy, Murray Campbell, Amit Dhurandhar, Kush R. Varshney, Dennis Wei & Aleksandra Mojsilovic 2018. Teaching Meaningful Explanations. arXiv:1805.11648.

Teaching Meaningful Explanations

Noel C. F. Codella,* Michael Hind,* Karthikeyan Natesan Ramamurthy,*
Murray Campbell, Amit Dhurandhar, Kush R. Varshney, Dennis Wei,
Aleksandra Mojsilović
* These authors contributed equally.

IBM Research
Yorktown Heights, NY 10598
{nccodell,hindm,knatesa,mcam,adhuran,krvarshn,dwei,aleksand}@us.ibm.com

Abstract

The adoption of machine learning in high-stakes applications such as healthcare and law has lagged in part because predictions are not accompanied by explanations comprehensible to the domain user, who often holds ultimate responsibility for decisions and outcomes. In this paper, we propose an approach to generate such explanations in which training data is augmented to include, in addition to features and labels, explanations elicited from domain users. A joint model is then learned to produce both labels and explanations from the input features. This simple idea ensures that explanations are tailored to the complexity expectations and domain knowledge of the consumer. Evaluation spans multiple modeling techniques on a simple game dataset, an image dataset, and a chemical odor dataset, showing that our approach is generalizable across domains and algorithms. Results demonstrate that meaningful explanations can be reliably taught to machine learning algorithms, and in some cases, improve modeling accuracy.

1 Introduction

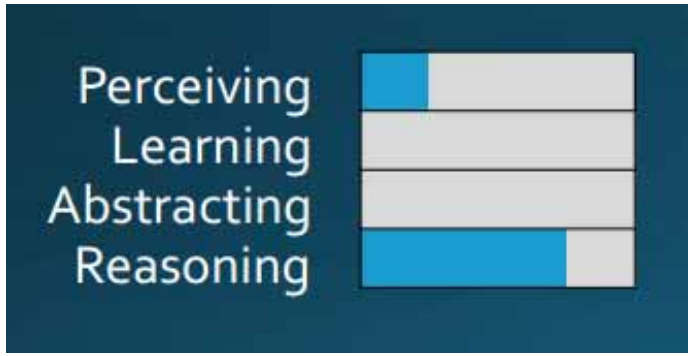
New regulations call for automated decision making systems to provide "meaningful information" on the logic used to reach conclusions [1–4]. Selbst and Powles interpret the concept of "meaningful information" as information that should be understandable to the audience (potentially individuals


Conclusion
This image is in the Public Domain

This is compatible to interactive machine learning

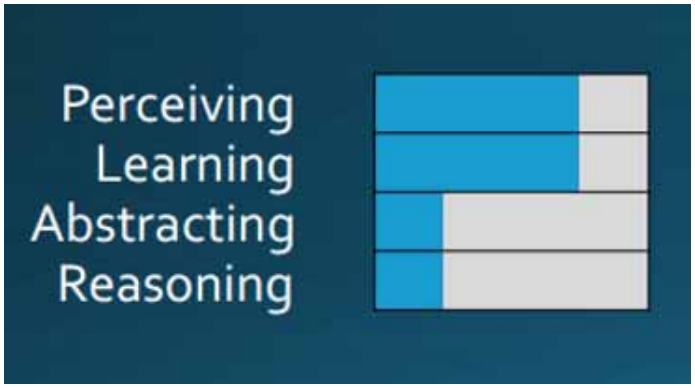
- Computational approaches can find in R^n what no human is able to see
- However, still there are many hard problems where a human expert in R^2 can understand the **context** and bring in experience, expertise, knowledge, intuition, …
- Black box approaches can not explain **WHY** a decision has been made …

The fist wave of AI (1943-1975): Handcrafted Knowledge



- Engineers create a set of logical rules to represent knowledge (Rule based Expert Systems)
- Advantage: works well in narrowly defined problems of well-defined domains
- Disadvantage: No adaptive learning behaviour and poor handling of $p(x)$

Image credit to John Launchbury



- Engineers create learning models for specific tasks and train them with “big data” (e.g. Deep Learning)
- Advantage: works well for standard classification tasks and has prediction capabilities
- Disadvantage: No contextual capabilities and minimal reasoning abilities

Image credit to John Launchbury

- A contextual model can perceive, learn and understand and abstract and reason
- Advantage: can use transfer learning for adaptation on unknown unknowns
- Disadvantage: Superintelligence …

Image credit to John Launchbury

- Myth 1a: Superintelligence by 2100 is inevitable!
- Myth 1b: Superintelligence by 2100 is impossible!
- **Fact: We simply don't know it!**
- Myth 2: Robots are our main concern

Fact: Cyberthreats are the main concern: it needs no body – only an Internet connection

- Myth 3: AI can never control us humans

Fact: Intelligence is an enabler for control: We control tigers by being smarter …

Our goal: Contextual adaptations can explain decisions

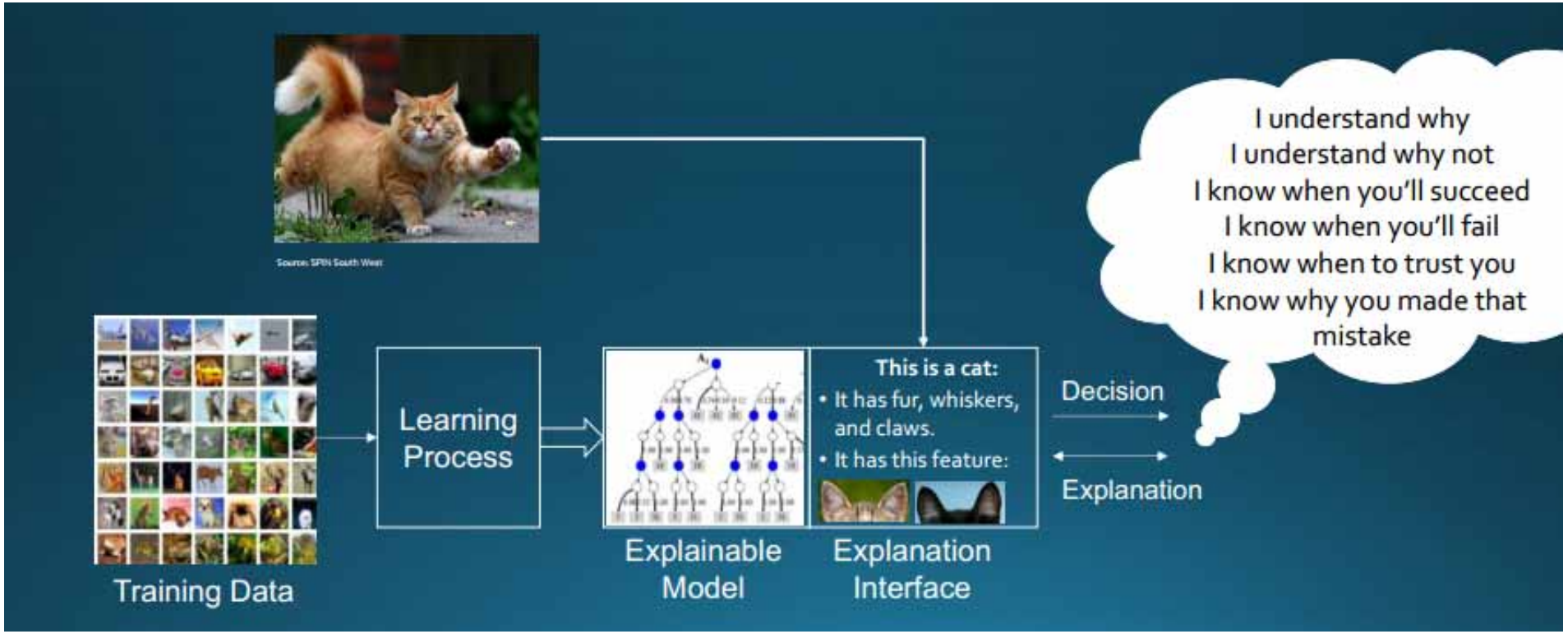


Image credit to John Launchbury

Thank you!