MAKE Decisions
Medical Information Science for Decision Support

EXECUTIVE ACADEMY

Assoc. Prof. Dr. Andreas HOLZINGER (Medical University Graz)

https://hci-kdd.org/mini-course-make-decisions-practice

Day 1 > Part 1 > 19.09.2018

Information Sciences meets Life Sciences

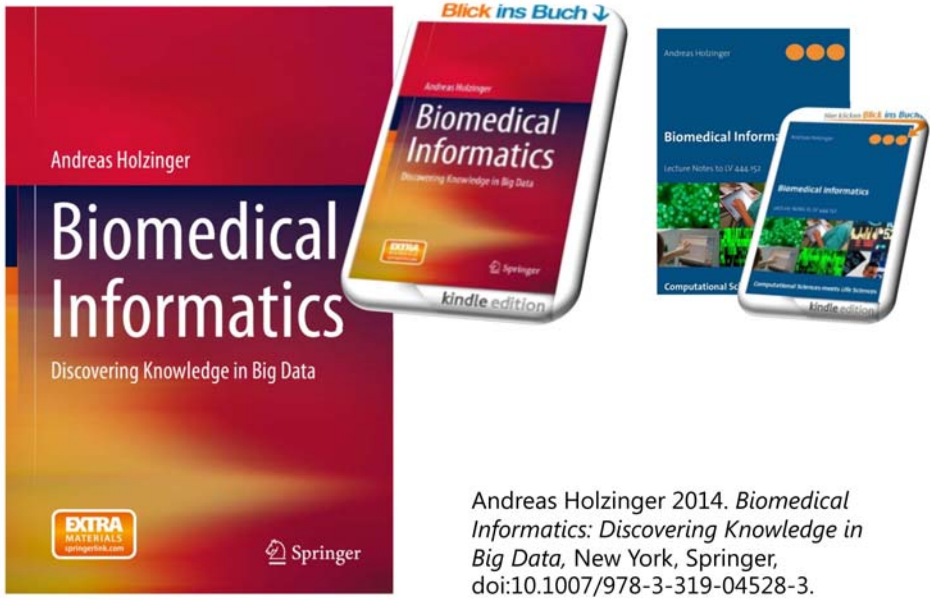
Andreas Holzinger: Background

- PhD in Cognitive Science 1998
- Habilitation Computer Science 2003
- Lead Holzinger Group HCI-KDD
  www.hci-kdd.org
- Visiting Professor for Machine Learning in Health Informatics: TU Vienna, Univ. Verona, UCL London, RWTH Aachen
- Research Statement see:
  Holzinger, A. (2016) Interactive Machine Learning for Health Informatics: When do we need the human-in-the-loop? Springer Brain Informatics, 3, 1-13, doi:10.1007/s40708-016-0042-6
- Most recent:
  Holzinger, A. 2018. Explainable AI (ex-AI). Informatik-Spektrum, doi:10.1007/s00287-018-1102-5

Mini-Course Syllabus

- At the end of this course you will …
- … be fascinated to see our world in **data sets;**
- … understand the differences between **data, information and knowledge**
- … be aware of some problems and challenges in **biomedical informatics**
- … understand the importance of the concept of **probabilistic information p(x)**
- … know what **AI/Machine Learning** can (not) do
- … have some fundamental insight into medical information science for **decision making**

Reading on Paper or on any electronic device



Andreas Holzinger 2014. *Biomedical Informatics: Discovering Knowledge in Big Data*, New York, Springer, doi:10.1007/978-3-319-04528-3.

Overview

Primer on Probability & Information

Day 1 - Fundamentals

- 01 Information Sciences meets Life Sciences
- 02 Data, Information and Knowledge
- 03 Decision Making and Decision Support
- 04 From Expert Systems to Explainable AI

Day 2 – Hot Topics

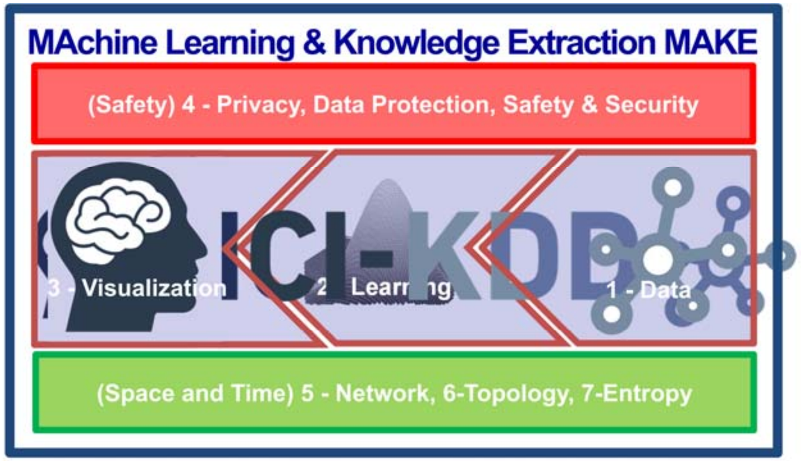
- 05 Methods of Explainable-AI
- Groupwork: Planning of a 500 bed Hospital - Bringing AI into the workflows
- Plenary: Presenting the developed concepts

Agenda

- 01 What is the HCI-KDD approach?
- 02 Application Area: Health Informatics
- 03 Probabilistic Information
- 04 Automatic Machine Learning
- 05 Interactive Machine Learning
- 06 Key Problems in Biomedical Informatics

01 What is the HCI-KDD approach?

- ML is a very practical field – algorithm development is at the core – however, successful ML needs a concerted effort of various topics …



Andreas Holzinger 2017. Introduction to Machine Learning and Knowledge Extraction (MAKE). *Machine Learning and Knowledge Extraction,* 1, (1), 1-20, doi:10.3390/make1010001.

Cognitive Science AND Computer Science

- Cognitive Science → human intelligence
- Computer Science → computational intelligence
- Human-Computer Interaction → the bridge

Andreas Holzinger 2013. Human–Computer Interaction and Knowledge Discovery (HCI-KDD): What is the benefit of bringing those two fields to work together? In: Springer Lecture Notes in Computer Science LNCS 8127. Heidelberg, Berlin, New York: Springer, pp. 319-328, doi:10.1007/978-3-642-40511-2_22.

To reach a level of usable intelligence we need to …

04

- 1) learn from prior data
- 2) extract knowledge
- 3) generalize, i.e. guessing where a probability mass function concentrates
- 4) fight the curse of dimensionality
- 5) disentangle **underlying explanatory factors of data**, i.e.
- 6) **understand** the data in the **context** of an application domain

Understanding Intelligence

"Solve intelligence – then solve everything else"

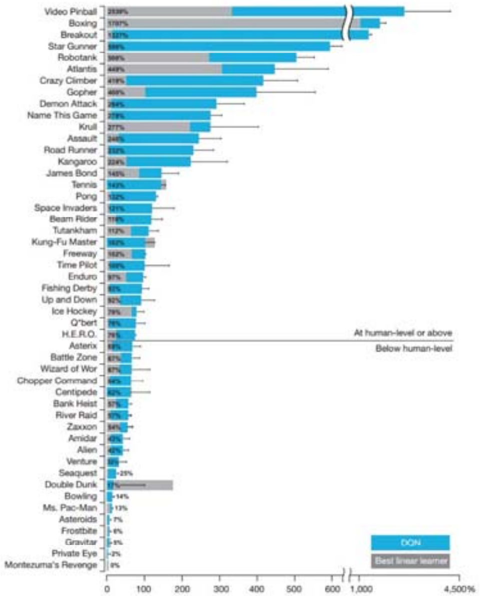
Demis Hassabis, 22 May 2015

The Royal Society,
Future Directions of Machine Learning Part 2

Google DeepMind

https://youtu.be/XAbLn66iHcQ?t=1h28m54s

Compare your best ML algorithm with a seven year old child …



Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S. & Hassabis, D. 2015. Human-level control through deep reinforcement learning. Nature, 518, (7540), 529-533, doi:10.1038/nature14236

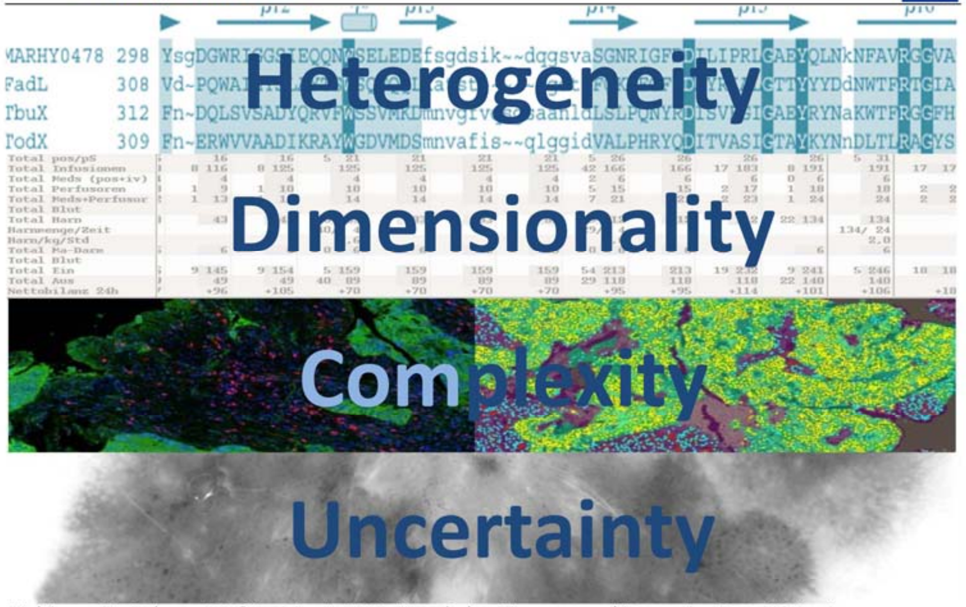
Why is this application area complex ?

In medicine we have two different worlds …

Our central hypothesis: Information may bridge this gap

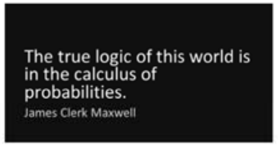
Holzinger, A. & Simonic, K.-M. (eds.) 2011. *Information Quality in e-Health. Lecture Notes in Computer Science LNCS 7058, Heidelberg, Berlin, New York: Springer.*

Main problems …



Holzinger, A., Dehmer, M. & Jurisica, I. 2014. Knowledge Discovery and interactive Data Mining in Bioinformatics - State-of-the-Art, future challenges and research directions. BMC Bioinformatics, 15, (S6), I1.

03 Probabilistic Information p(x)



The foundation for modern machine learning …

Probability theory is nothing but common sense reduced to calculation …

Pierre Simon de Laplace (1749-1827)

Analogies

- Newton, Leibniz, … developed calculus – mathematical language for describing and dealing with rates of change
- Bayes, Laplace, … developed probability theory - the mathematical language for describing and dealing with uncertainty
- Gauss generalized those ideas

Learning representations (θ, h) from observed data

Observed data: 

≈ Training data: $\mathcal{D} = x_{1:n} = \{x_1, x_2, ..., x_n\}$

Feature Parameter: θ **or hypothesis** h $h \in \mathcal{H}$

Prior belief ≈ prior probability of hypothesis h: $p(\theta)$ $p(h)$

Likelihood ≈ $p(x)$ **of the data that** h **is true** $p(\mathcal{D}|\theta)$ $p(d|h)$

Data evidence ≈ marginal $p(x)$ **that** h **= true** $p(\mathcal{D})$ $\sum_{h \in \mathcal{H}} p(d|h) * p(h)$

Posterior ≈ $p(x)$ **of** h **after seen ("learn") data** d $p(\theta|\mathcal{D})$ $p(h|d)$

$$posterior = \frac{likelihood * prior}{evidence} \quad p(\theta|\mathcal{D}) = \frac{p(\mathcal{D}|\theta) * p(\theta)}{p(\mathcal{D})}$$

$$p(h|d) = \frac{p(d|h) * p(h)}{\sum_{h \in H} p(d|h)\, p(h)}$$

Learning and Probabilistic Inference (Prediction)

04

d … data $\mathcal{H}$ … $\{H_1, H_2, ..., H_n\}$ $\forall\, h, d$ …

h … hypotheses

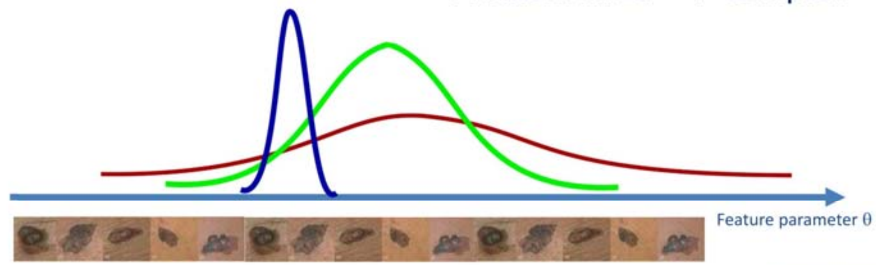
Likelihood

Prior Probability

$$\boxed{p(h|d)} = \frac{\boxed{p(d|h)} * \boxed{p(h)}}{\sum_{h \in H} p(d|h)\, p(h)}$$

Posterior Probability

Problem in $\mathbb{R}^n \rightarrow$ complex



Why is this relevant for health informatics?

Reasoning under uncertainty: Decision Making

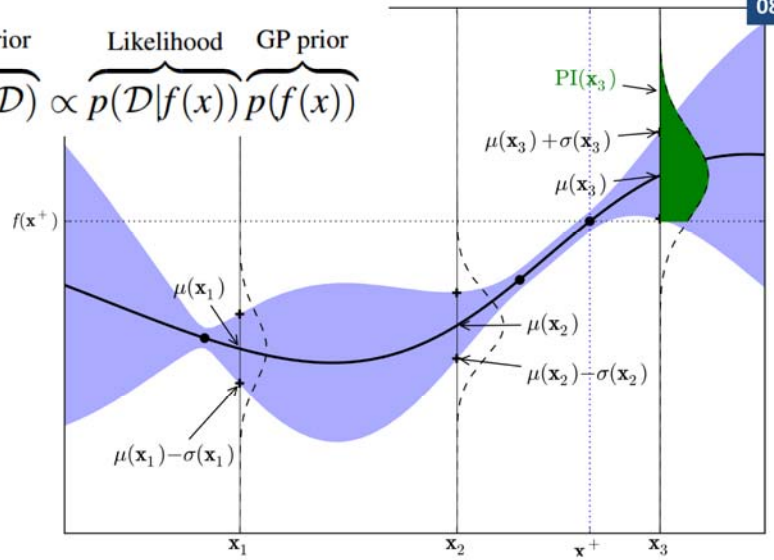
- Take patient information, e.g., observations, symptoms, test results, -omics data, etc. etc.
- Reach conclusions, and **predict** into the future, e.g. how likely will the patient be …
- Prior = belief before making a particular observation
- Posterior = belief after making the observation and is the prior for the next observation – intrinsically incremental

$$p(x_i|y_j) = \frac{p(y_j|x_i)p(x_i)}{\sum p(x_i, y_j)p(x_i)}$$

GP = distribution, observations occur in a cont. domain, e.g. t or space

08

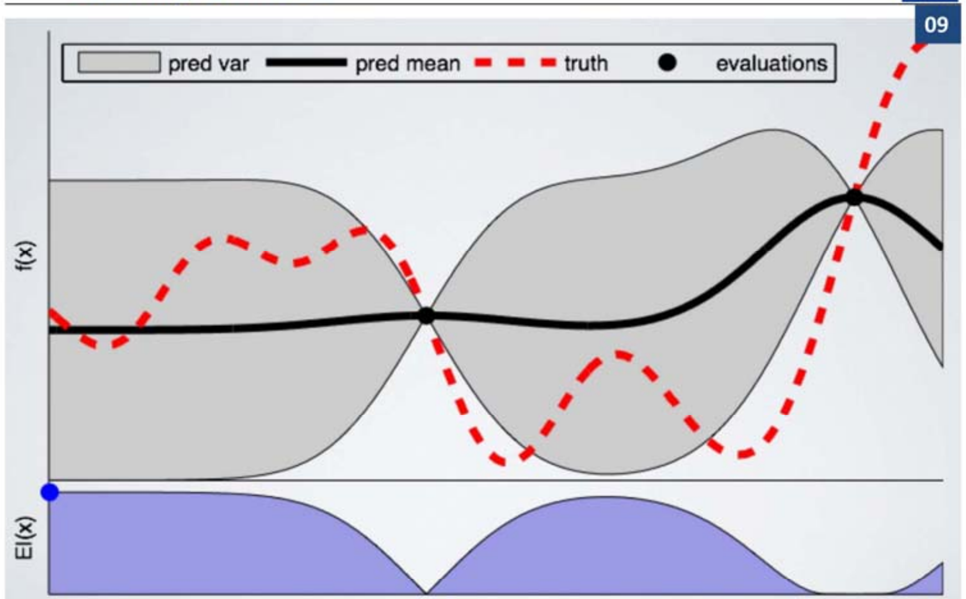
$$\overbrace{p(f(x)|\mathcal{D})}^{\text{GP posterior}} \propto \overbrace{p(\mathcal{D}|f(x))}^{\text{Likelihood}}\overbrace{p(f(x))}^{\text{GP prior}}$$



Brochu, E., Cora, V. M. & De Freitas, N. 2010. A tutorial on Bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning. arXiv:1012.2599.

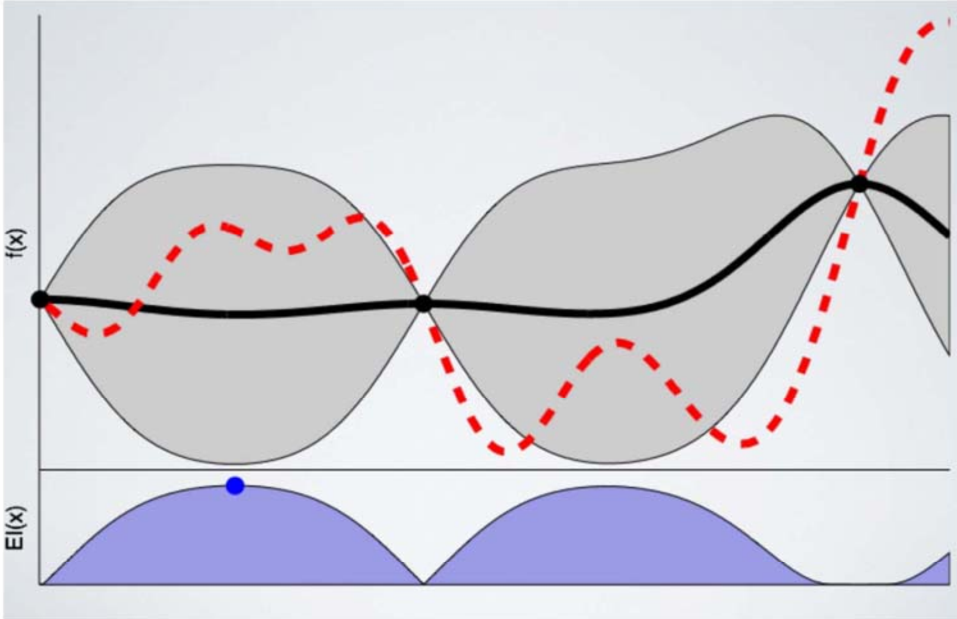
Learning from data

09

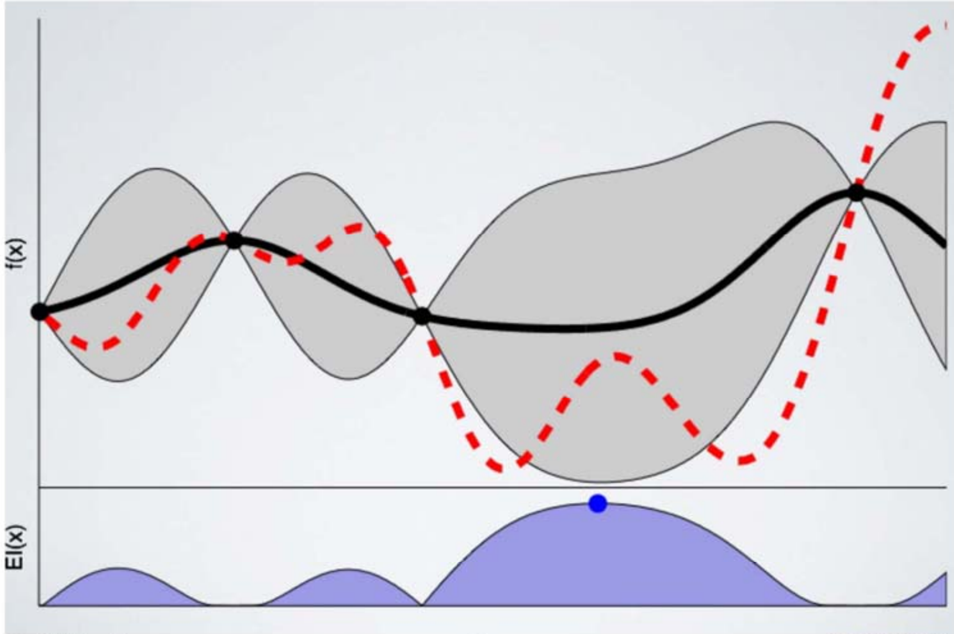


Snoek, J., Larochelle, H. & Adams, R. P. Practical Bayesian optimization of machine learning algorithms. Advances in neural information processing systems, 2012. 2951-2959.

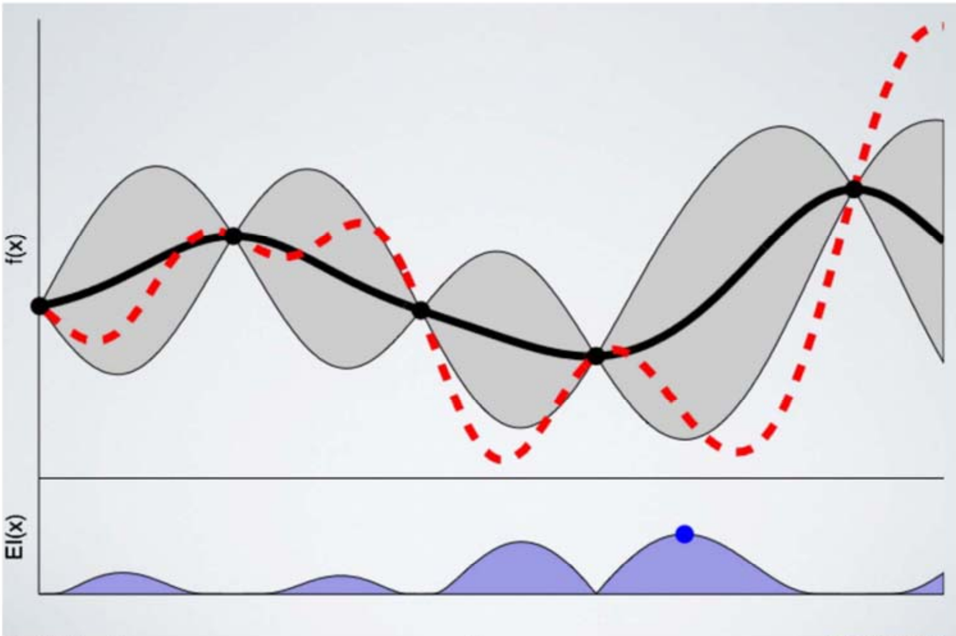
Bayesian Optimization 1



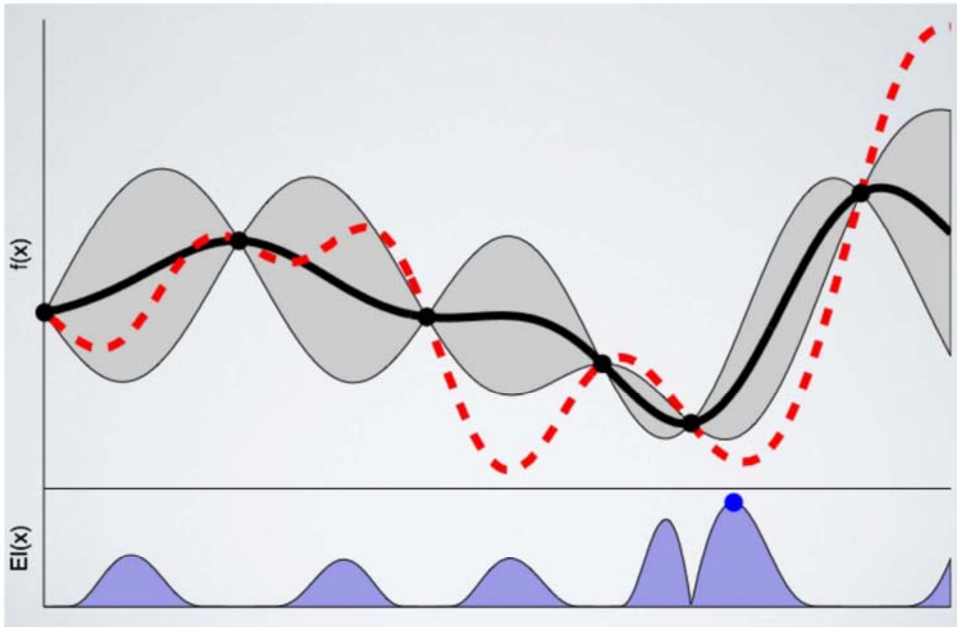
Bayesian Optimization 2



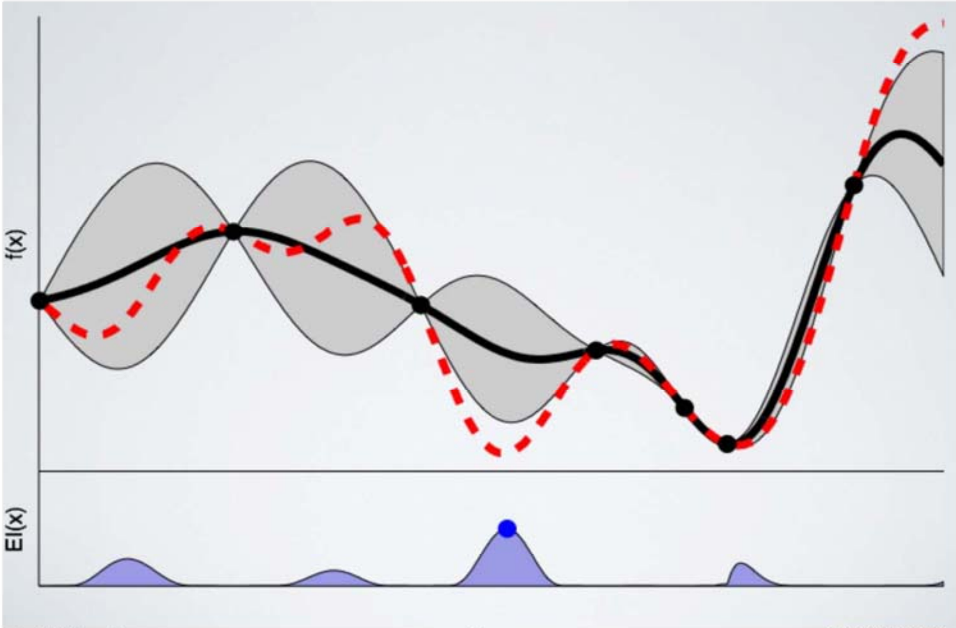
Bayesian Optimization 3



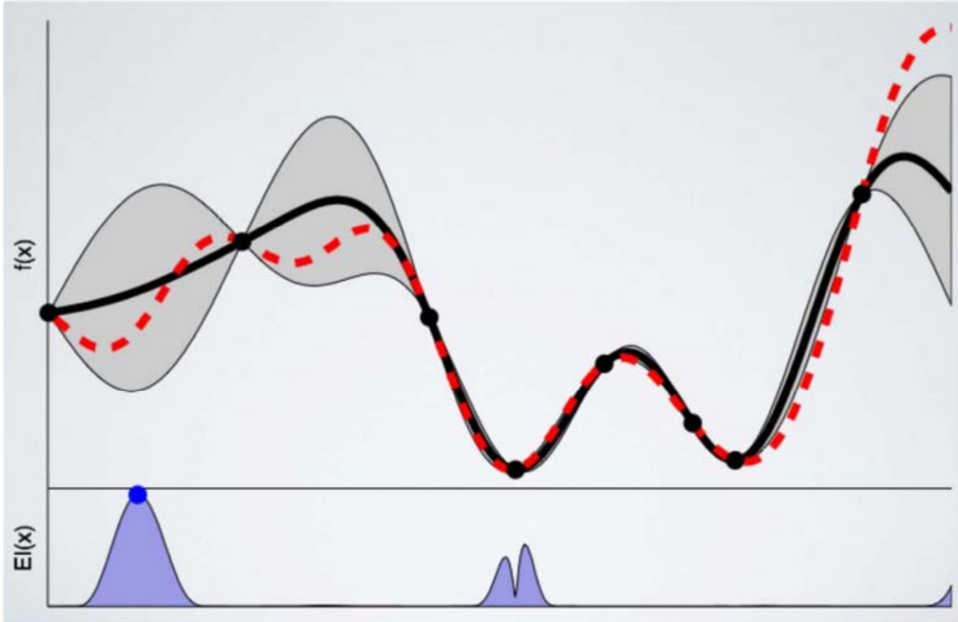
Bayesian Optimization 4



Bayesian Optimization 5



Bayesian Optimization 6



Scaling to high-dimensions is the holy grail in ML

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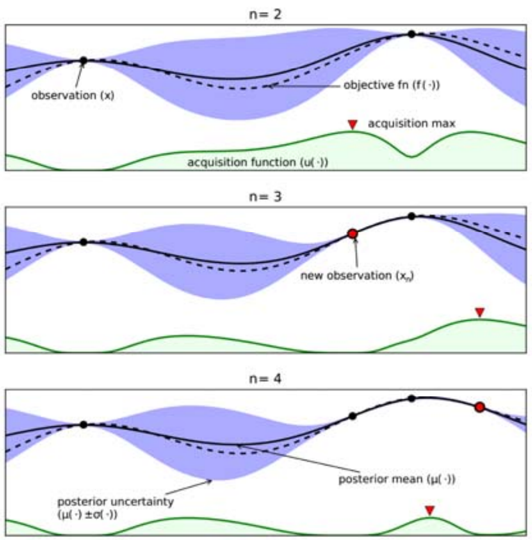
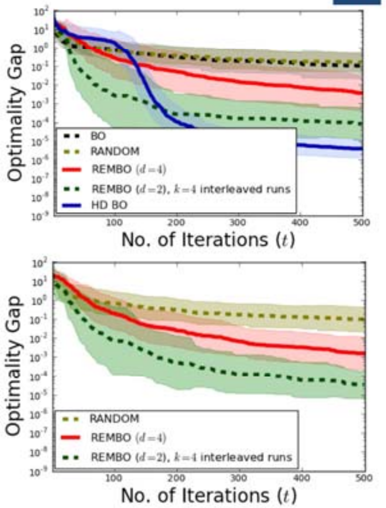
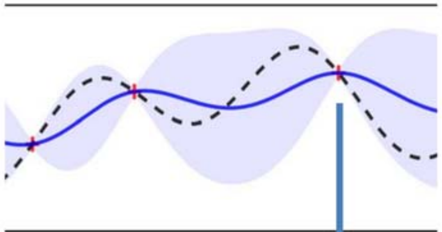




Wang, Z., Hutter, F., Zoghi, M., Matheson, D. & De Feitas, N. 2016. Bayesian optimization in a billion dimensions via random embeddings. Journal of Artificial Intelligence Research, 55, 361-387, doi:10.1613/jair.4806.

Fully automatic → Goal: Taking the human out of the loop

07

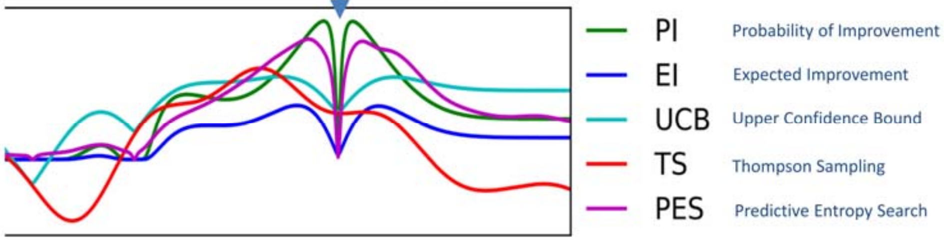


Algorithm 1 Bayesian optimization

for $n = 1, 2, \ldots$ **do**
  select new $\mathbf{x}_{n+1}$ by optimizing acquisition function α

$$\mathbf{x}_{n+1} = \arg\max_{\mathbf{x}} \alpha(\mathbf{x}; \mathcal{D}_n)$$

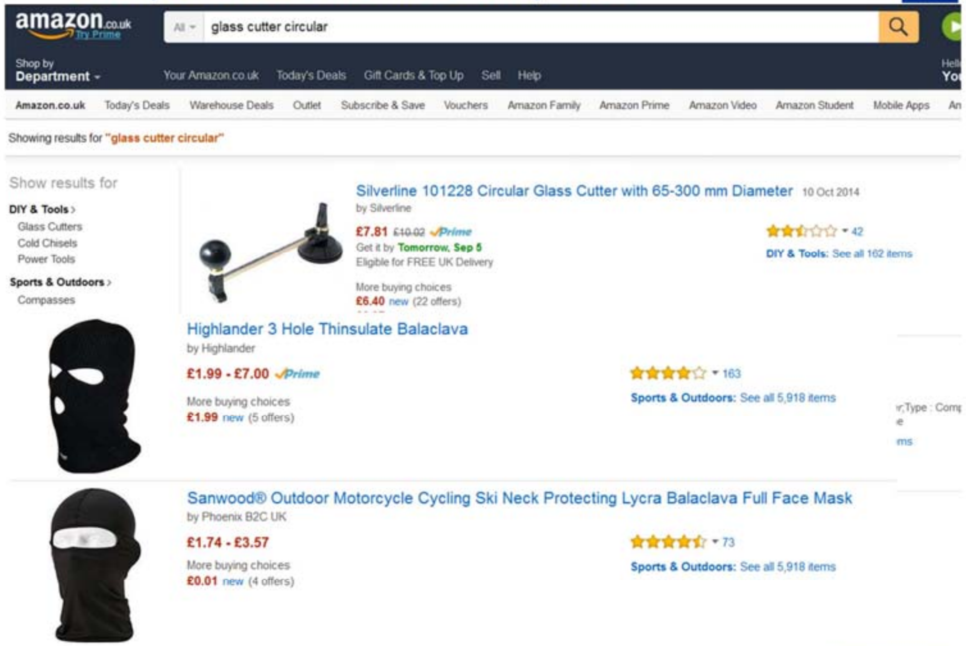
  query objective function to obtain y_{n+1}
  augment data $\mathcal{D}_{n+1} = \{\mathcal{D}_n, (\mathbf{x}_{n+1}, y_{n+1})\}$
  update statistical model
end for



Shahriari, B., Swersky, K., Wang, Z., Adams, R. P. & De Freitas, N. 2016. **Taking the human out of the loop:** A review of Bayesian optimization. *Proceedings of the IEEE*, 104, (1), 148-175, doi:10.1109/JPROC.2015.2494218.

04 aML

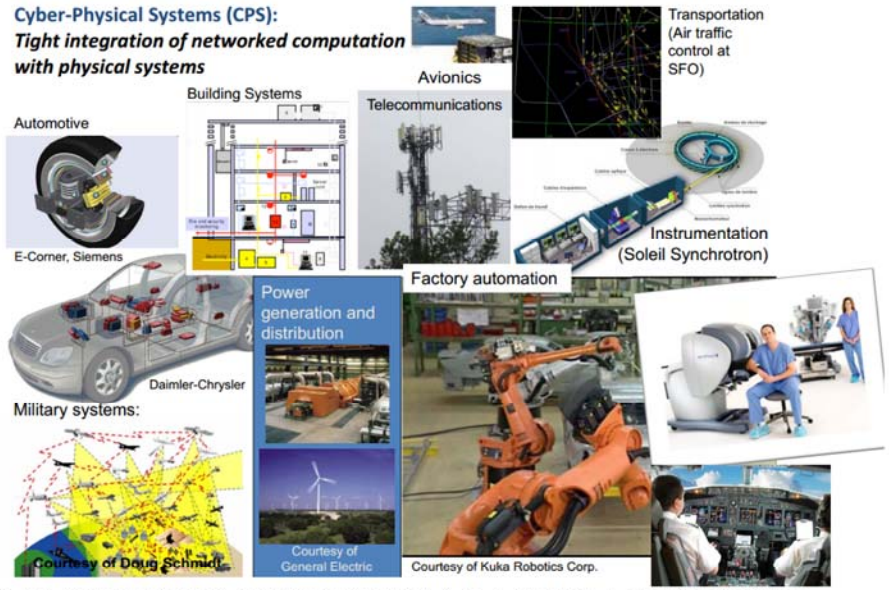
Example for aML: Recommender Systems



Fully automatic autonomous vehicles (Google car)

Dietterich, T. G. & Horvitz, E. J. 2015. Rise of concerns about AI: reflections and directions. Communications of the ACM, 58, (10), 38-40.

… and thousands of industrial aML applications …



Seshia, S. A., Juniwal, G., Sadigh, D., Donze, A., Li, W., Jensen, J. C., Jin, X., Deshmukh, J., Lee, E. & Sastry, S. 2015. Verification by, for, and of Humans: Formal Methods for Cyber-Physical Systems and Beyond. Illinois ECE Colloquium.

Big Data is necessary for aML !

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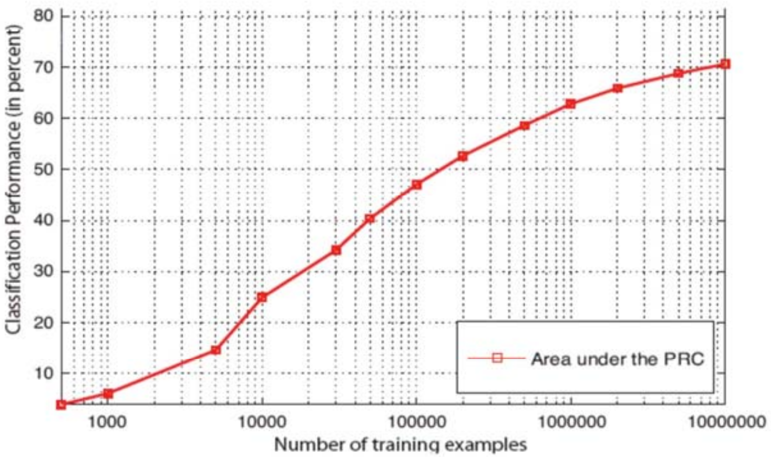
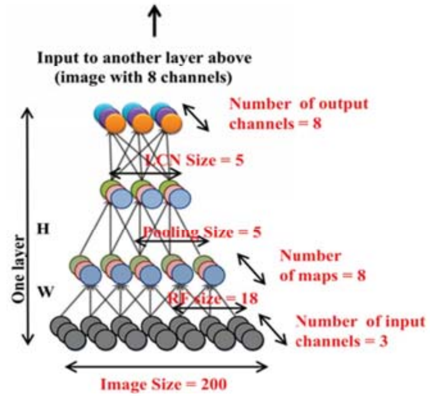


Sonnenburg, S., Rätsch, G., Schäfer, C. & Schölkopf, B. 2006. Large scale multiple kernel learning. Journal of Machine Learning Research, 7, (7), 1531-1565.

10 million 200 x 200 px images downloaded from Web



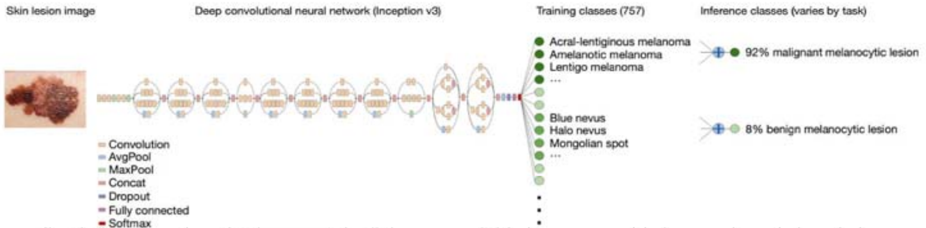
$$x^* = \arg\min_x f(x; W, H), \text{ subject to } ||x||_2 = 1.$$

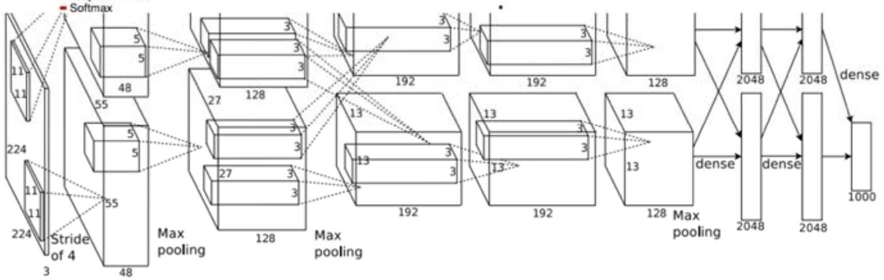
Le, Q. V., Ranzato, M. A., Monga, R., Devin, M., Chen, K., Corrado, G. S., Dean, J. & Ng, A. Y. 2011. Building high-level features using large scale unsupervised learning. arXiv preprint arXiv:1112.6209.

Le, Q. V. 2013. Building high-level features using large scale unsupervised learning. *IEEE Intl. Conference on Acoustics, Speech and Signal Processing ICASSP.* IEEE. 8595-8598, doi:10.1109/ICASSP.2013.6639343.

Deep Convolutional Neural Network Pipeline

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M. & Thrun, S. 2017. Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542, (7639), 115-118, doi:10.1038/nature21056.





Krizhevsky, A., Sutskever, I. & Hinton, G. E. Imagenet classification with deep convolutional neural networks. In: Pereira, F., Burges, C. J. C., Bottou, L. & Weinberger, K. Q., eds. Advances in neural information processing systems (NIPS 2012), 2012 Lake Tahoe. 1097-1105.

Limitations of Deep Learning approaches

- Computational resource intensive (supercomps, cloud CPUs, **federated learning,** …)
- Black-Box approaches – lack **transparency,** do not foster trust and acceptance among end-user, legal aspects make “black box” difficult!
- **Non-convex:** difficult to set up, to train, to optimize, needs a lot of expertise, error prone
- Very bad in dealing with **uncertainty**
- **Data intensive, needs often millions of training samples …**

When does aML fail …

- Sometimes we **do not have "big data"**, where aML-algorithms benefit.
- Sometimes we have
  - **Small amount of data sets**
  - Rare Events – **no training samples**
  - **NP-hard problems, e.g.**
    - Subspace Clustering,
    - k-Anonymization,
    - Protein-Folding, …

Holzinger, A. 2016. Interactive Machine Learning for Health Informatics: When do we need the human-in-the-loop? Springer Brain Informatics (BRIN), 3, (2), 119-131, doi:10.1007/s40708-016-0042-6.

Consequently …

Sometimes we (still) need a human-in-the-loop

05 iML

Definition of iML (Holzinger – 2016)

A6

- iML := algorithms which interact with agents***)** and can optimize their learning behaviour through this interaction

***) where the agents can be human**

Holzinger, A. 2016. Interactive Machine Learning (iML). Informatik Spektrum, 39, (1), 64-68, doi:10.1007/s00287-015-0941-6.

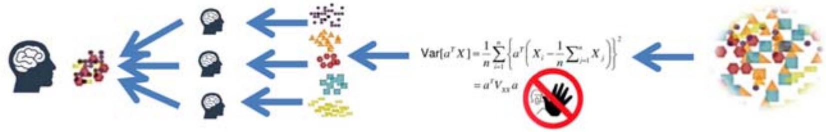
Sometimes we need a doctor-in-the-loop

A group of experts-in-the-loop

A crowd of people-in-the-loop

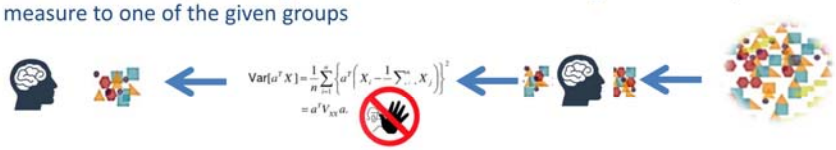
aML: taking the human-out-of-the-loop

A) Unsupervised ML: Algorithm is applied on the raw data and learns fully automatic – Human can check results at the end of the ML-pipeline



B) Supervised ML: Humans are providing the labels for the training data and/or select features to feed the algorithm to learn – the more samples the better – Human can check results at the end of the ML-pipeline

C) Semi-Supervised Machine Learning: A mixture of A and B – mixing labeled and unlabeled data so that the algorithm can find labels according to a similarity measure to one of the given groups



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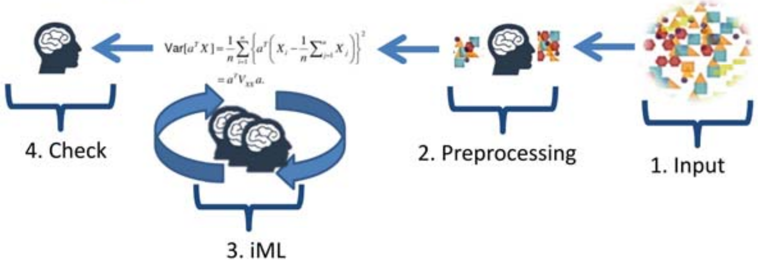
D) **Interactive Machine Learning:** Human is seen as an agent involved in the actual learning phase, step-by-step influencing measures such as distance, cost functions …



Constraints of humans: Robustness, subjectivity, transfer?
Open Questions: Evaluation, replicability, …

Holzinger, A. 2016. Interactive Machine Learning for Health Informatics: When do we need the human-in-the-loop? Brain Informatics (BRIN), 3, (2), 119-131, doi:10.1007/s40708-016-0042-6.

- **Example 1: Subspace Clustering**
- **Example 2: k-Anonymization**
- **Example 3: Protein Design**

Hund, M., Böhm, D., Sturm, W., Sedlmair, M., Schreck, T., Ullrich, T., Keim, D. A., Majnaric, L. & Holzinger, A. 2016. Visual analytics for concept exploration in subspaces of patient groups: Making sense of complex datasets with the Doctor-in-the-loop. Brain Informatics, 1-15, doi:10.1007/s40708-016-0043-5.

Kieseberg, P., Frühwirt, P., Weippl, E. & Holzinger, A. 2015. Witnesses for the Doctor in the Loop. In: Guo, Y., Friston, K., Aldo, F., Hill, S. & Peng, H. (eds.) Lecture Notes in Artificial Intelligence LNAI 9250. Springer, pp. 369-378, doi:10.1007/978-3-319-23344-4_36.

Lee, S. & Holzinger, A. 2016. Knowledge Discovery from Complex High Dimensional Data. In: Michaelis, S., Piatkowski, N. & Stolpe, M. (eds.) Solving Large Scale Learning Tasks. Challenges and Algorithms, Lecture Notes in Artificial Intelligence LNAI 9580. Springer, pp. 148-167, doi:10.1007/978-3-319-41706-6_7.

06 Key Problems in health informatics

Key Problems

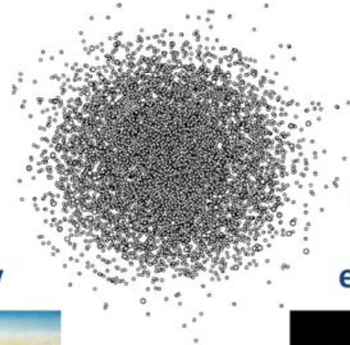
- **Zillions** of different biological species (humans, animals, bacteria, virus, plants, …);
- Enormous **complexity** of the medical domain [1];
- **Complex,** heterogeneous, high-dimensional, big data in the life sciences [2];
- Limited **time,** e.g. a medical doctor in a public hospital has only 5 min. to make a decision [3];
- Limited **computational power** in comparison to the complexity of life (and the natural limitations of the Von-Neumann architecture, …);

1. Patel VL, Kahol K, & Buchman T (2011) Biomedical Complexity and Error. *J. Biomed. Inform.* 44(3):387-389.
2. Holzinger A, Dehmer M, & Jurisica I (2014) Knowledge Discovery and interactive Data Mining in Bioinformatics - State-of-the-Art, future challenges and research directions. BMC Bioinformatics 15(S6):I1.
3. Gigerenzer G (2008) Gut Feelings: Short Cuts to Better Decision Making (Penguin, London).

Our World in Data - Macroscopic Structures

ESO, Atacama, Chile (2011)

Two thematic mainstreams in dealing with data …



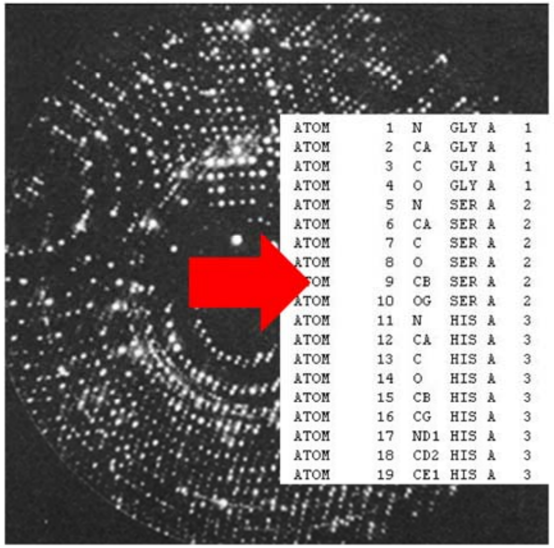
Time — e.g. Entropy

Dali, S. (1931) The persistence of memory

Space — e.g. Topology

Bagula & Bourke (2012) Klein-Bottle

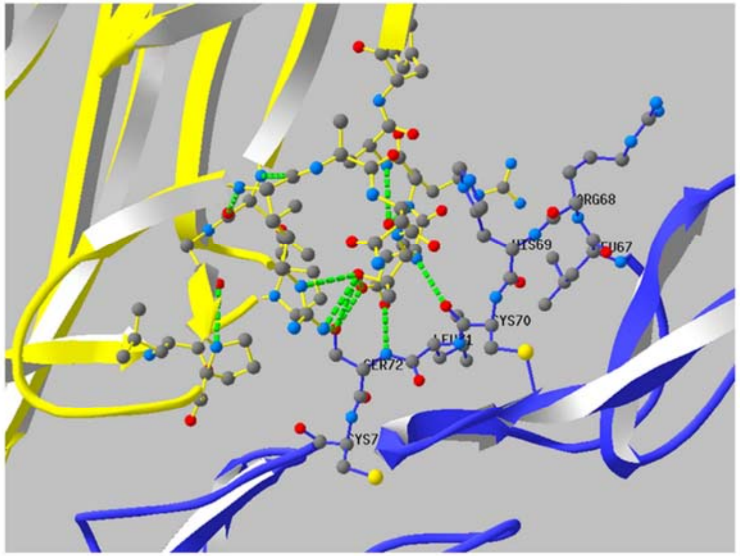
Our World in Data – Microscopic Structures



ATOM	1	N	GLY	A	1	44.842	51.034	101.284	0.01	27.20
ATOM	2	CA	GLY	A	1	45.640	50.230	100.389	0.01	26.99
ATOM	3	C	GLY	A	1	46.692	49.648	101.308	0.01	26.80
ATOM	4	O	GLY	A	1	46.895	50.222	102.381	0.01	26.91
ATOM	5	N	SER	A	2	47.283	48.516	100.951	1.00	26.26
ATOM	6	CA	SER	A	2	48.277	47.866	101.761	1.00	26.17
ATOM	7	C	SER	A	2	49.212	47.031	100.845	1.00	24.21
ATOM	8	O	SER	A	2	49.060	47.195	99.630	1.00	19.77
ATOM	9	CB	SER	A	2	47.438	47.091	102.800	1.00	26.31
ATOM	10	OG	SER	A	2	46.276	46.356	102.404	1.00	27.99
ATOM	11	N	HIS	A	3	50.147	46.186	101.370	1.00	23.93
ATOM	12	CA	HIS	A	3	51.129	45.389	100.609	1.00	21.44
ATOM	13	C	HIS	A	3	50.953	43.905	100.849	1.00	20.32
ATOM	14	O	HIS	A	3	50.530	43.595	101.950	1.00	22.00
ATOM	15	CB	HIS	A	3	52.555	45.674	100.990	1.00	19.69
ATOM	16	CG	HIS	A	3	52.940	47.090	100.611	1.00	21.44
ATOM	17	ND1	HIS	A	3	53.371	47.470	99.422	1.00	20.87
ATOM	18	CD2	HIS	A	3	52.956	48.175	101.433	1.00	21.69
ATOM	19	CE1	HIS	A	3	53.676	48.730	99.476	1.00	20.57

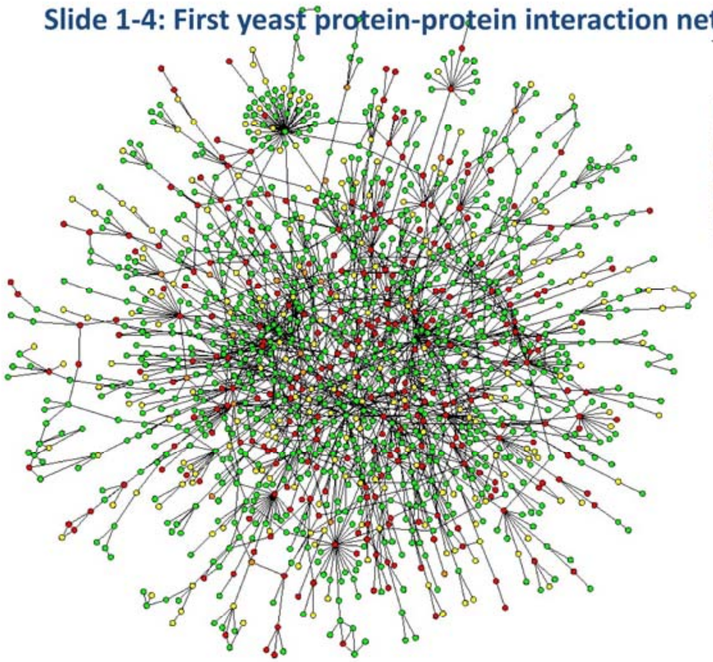
Wiltgen, M. & Holzinger, A. (2005) Visualization in Bioinformatics: Protein Structures with Physicochemical and Biological Annotations. In: *Central European Multimedia and Virtual Reality Conference. Prague, Czech Technical University (CTU), 69-74*

Knowledge Discovery from Data



Wiltgen, M., Holzinger, A. & Tilz, G. P. (2007) Interactive Analysis and Visualization of Macromolecular Interfaces Between Proteins. In: *Lecture Notes in Computer Science (LNCS 4799). Berlin, Heidelberg, New York, Springer, 199-212.*

Slide 1-4: First yeast protein-protein interaction network

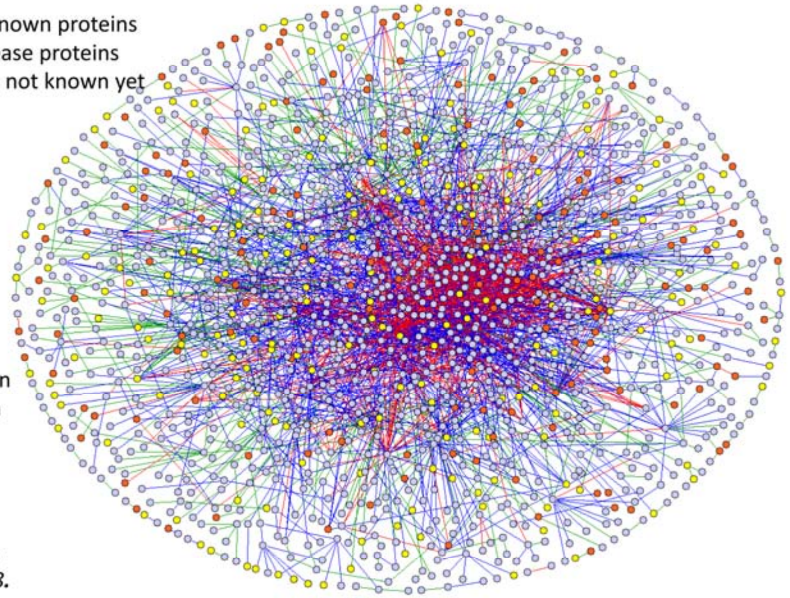


Nodes = proteins
Links = physical interactions (bindings)
Red Nodes = lethal
Green Nodes = non-lethal
Orange = slow growth
Yellow = not known

Jeong, H., Mason, S. P., Barabasi, A. L. & Oltvai, Z. N. (2001) Lethality and centrality in protein networks. *Nature, 411, 6833, 41-42.*

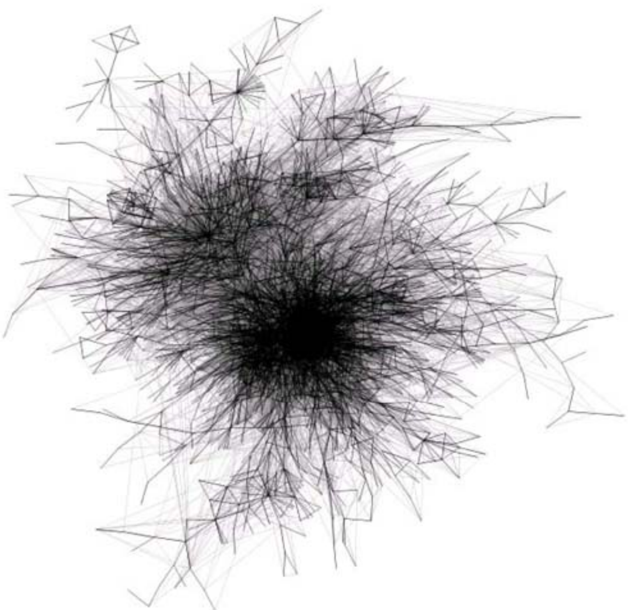
First human protein-protein interaction network

Light blue = known proteins
Orange = disease proteins
Yellow ones = not known yet



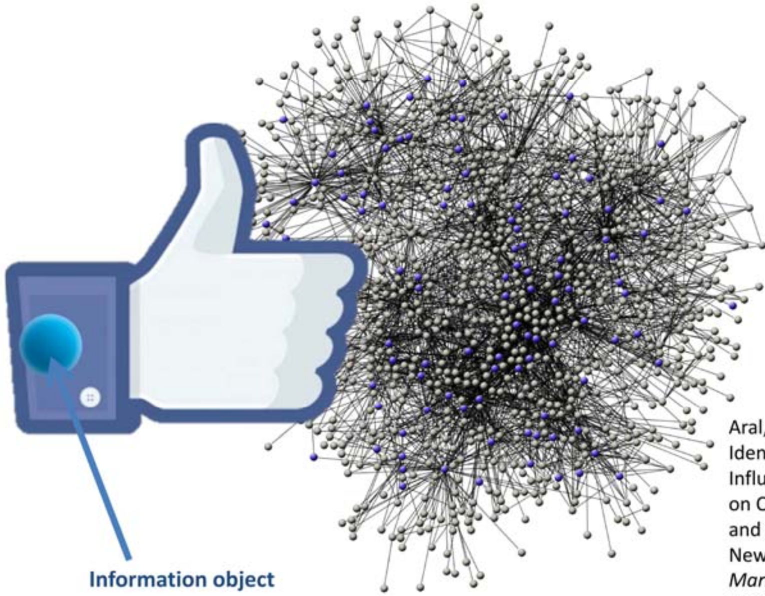
Stelzl, U. et al. (2005) A Human Protein-Protein Interaction Network: A Resource for Annotating the Proteome. *Cell, 122, 6, 957-968.*

Non-Natural Network Example: Blogosphere



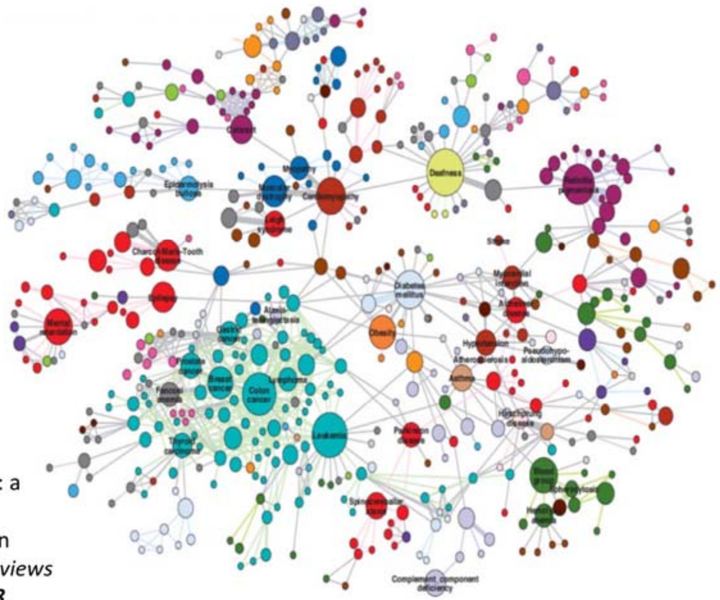
Hurst, M. (2007), Data Mining: Text Mining, Visualization and Social Media. Online available: http://datamining.typepad.com/data_mining/2007/01/the_blogosphere.html, last access: 2011-09-24

Social Behavior Contagion Network



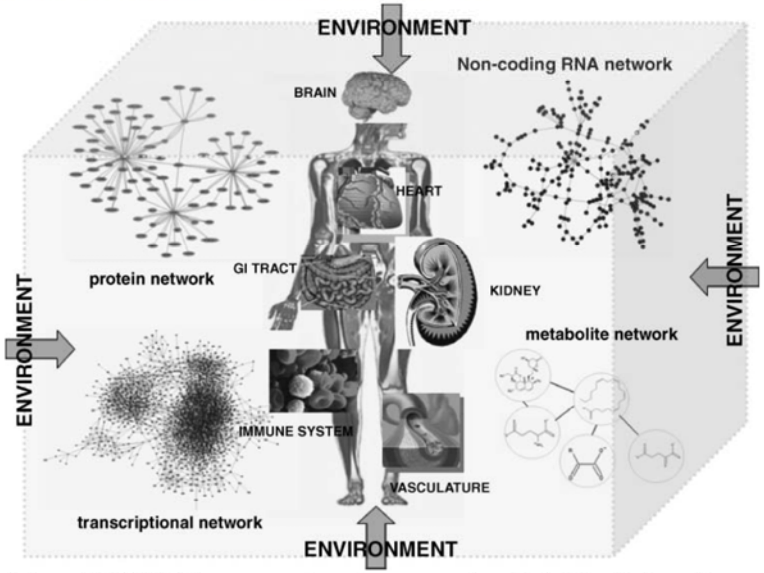
Aral, S. (2011) Identifying Social Influence: A Comment on Opinion Leadership and Social Contagion in New Product Diffusion. *Marketing Science, 30, 2, 217-223.*

Human Disease Network -> Network Medicine



Barabási, A. L., Gulbahce, N. & Loscalzo, J. 2011. Network medicine: a network-based approach to human disease. *Nature Reviews Genetics, 12*, ***56-68.***

Identifying Networks in Disease Research



Schadt, E. E. & Lum, P. Y. (2006) Reverse engineering gene networks to identify key drivers of complex disease phenotypes. *Journal of lipid research, 47, 12, 2601-2613.*

Conclusion: Five decades of Health Informatics

- 1960+ Medical Informatics (Early "AI")
  - Focus on data acquisition, storage, accounting (typ. "EDV"), Expert Systems
  - The term was first used in 1968 and the first course was set up 1978 !
- 1985+ Health Telematics (AI winter)
  - Health care networks, Telemedicine, CPOE-Systems, …
- 1995+ Web Era (AI is "forgotten")
  - Web based applications, Services, EPR, distributed systems, …
- 2005+ Success statistical learning (AI renaissance)
  - Pervasive, ubiquitous Computing, Internet of things, …
- 2010+ Data Era – Big Data (super for AI)
  - Massive increase of data – data integration, mapping, …
- 2020+ Information Era – (towards explainable AI)
  - Sensemaking, disentangling the underlying concepts, **causality,** …

Thank you!

Exam Questions

Appendix

Learning and Probabilistic Inference (Prediction)

04

d ... $data$

h ... $hypotheses$

$\mathcal{H}$ ... $\{H_1, H_2, \dots, H_n\}$ $\forall\, h, d$ ...

Likelihood

Prior Probability

$$p(h|d) = \frac{p(d|h) * p(h)}{\sum_{h \in H} p(d|h)\, p(h)}$$

Posterior Probability

Problem in $\mathbb{R}^n \rightarrow$ complex

$P(h)$: prior belief (probability of hypothesis h before seeing any data)

$P(d \mid h)$: likelihood (probability of the data if the hypothesis h is true)

$P(d) = \sum_h P(d \mid h) P(h)$: data evidence (marginal probability of the data)

$P(h \mid d)$: posterior (probability of hypothesis h after having seen the data d)

What is biomedical informatics?

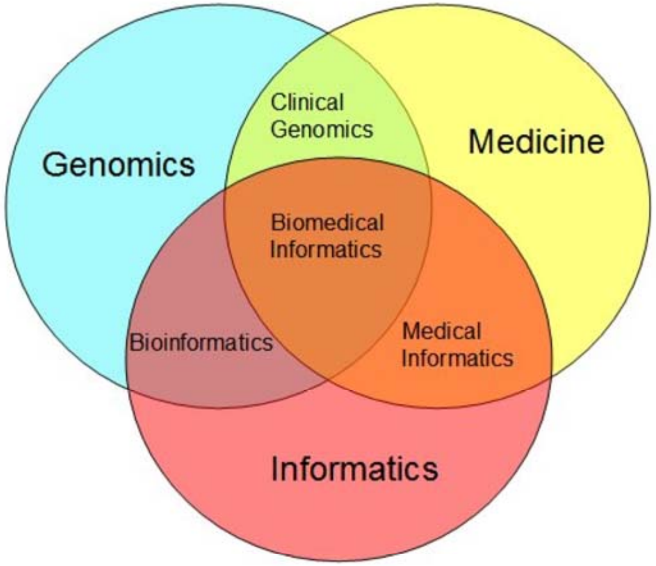
AMIA

INFORMATICS PROFESSIONALS. LEADING THE WAY.

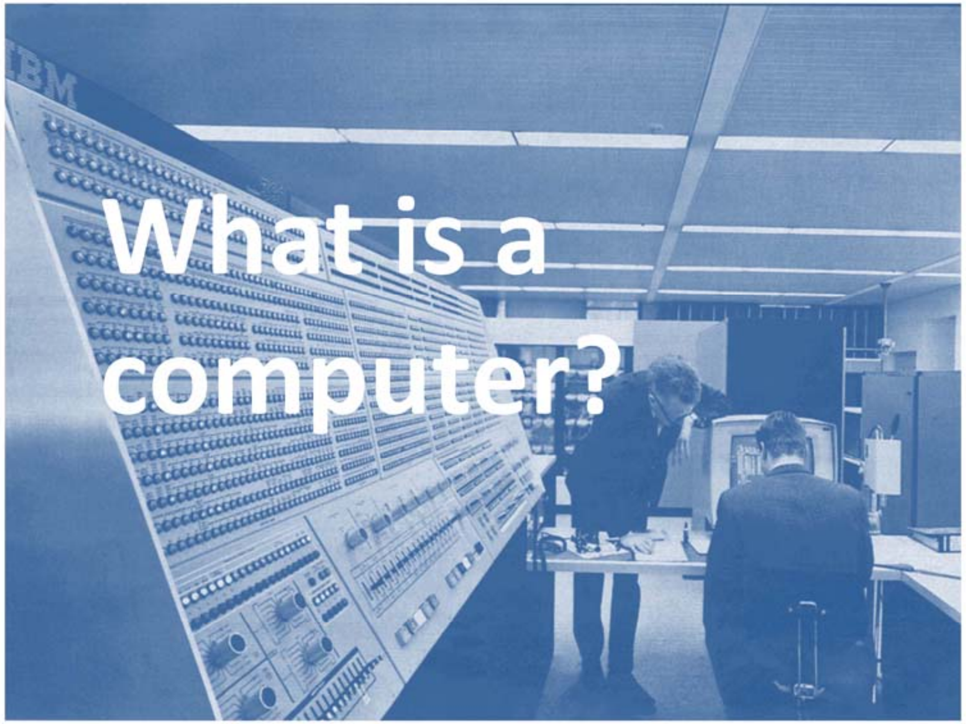
- ***Biomedical informatics*** **(BMI) is the interdisciplinary field that studies and pursues the effective use of biomedical data, information, and knowledge for scientific problem solving, and decision making, motivated by efforts to improve human health**

Shortliffe, E. H. (2011). Biomedical Informatics: Defining the Science and its Role in Health Professional Education. In A. Holzinger & K.-M. Simonic (Eds.), *Information Quality in e-Health. Lecture Notes in Computer Science LNCS 7058 (pp. 711-714). Heidelberg, New York: Springer.*

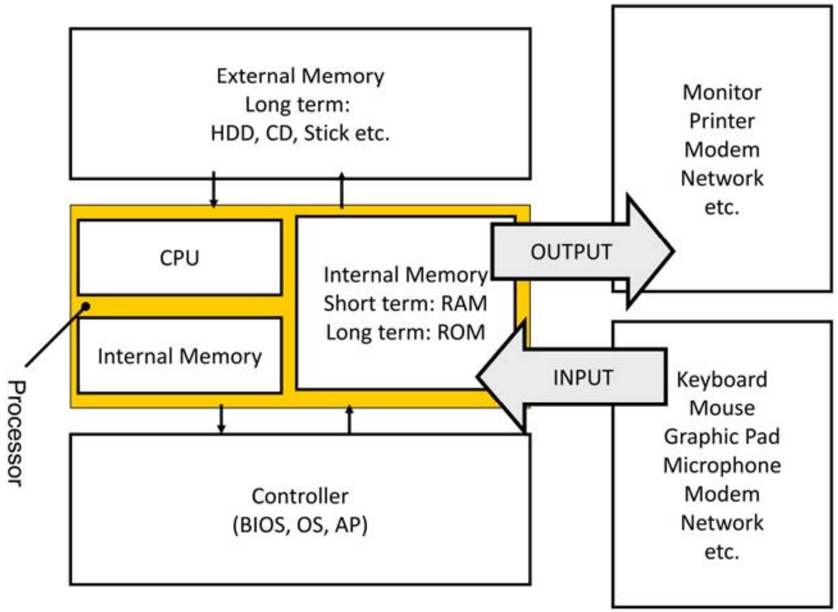
Computational Sciences meet Life Sciences



http://www.bioinformaticslaboratory.nl/twiki/bin/view/BioLab/EducationMIK1-2



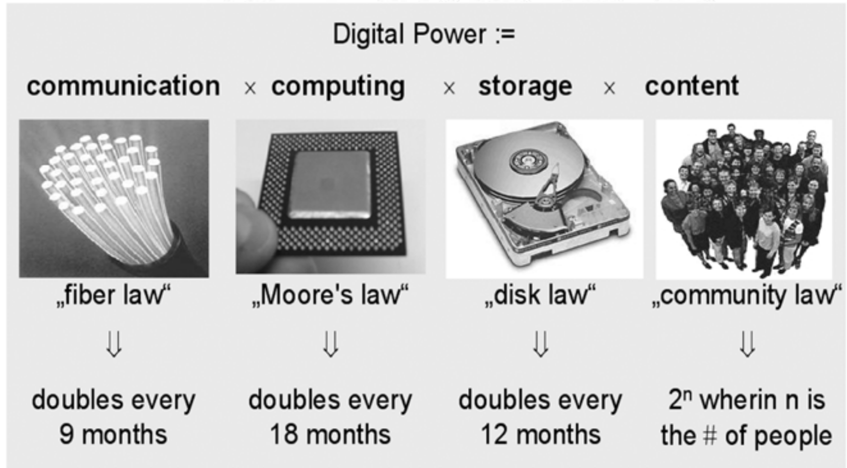
Computer: Von-Neumann Architecture



Holzinger (2002), 90-134

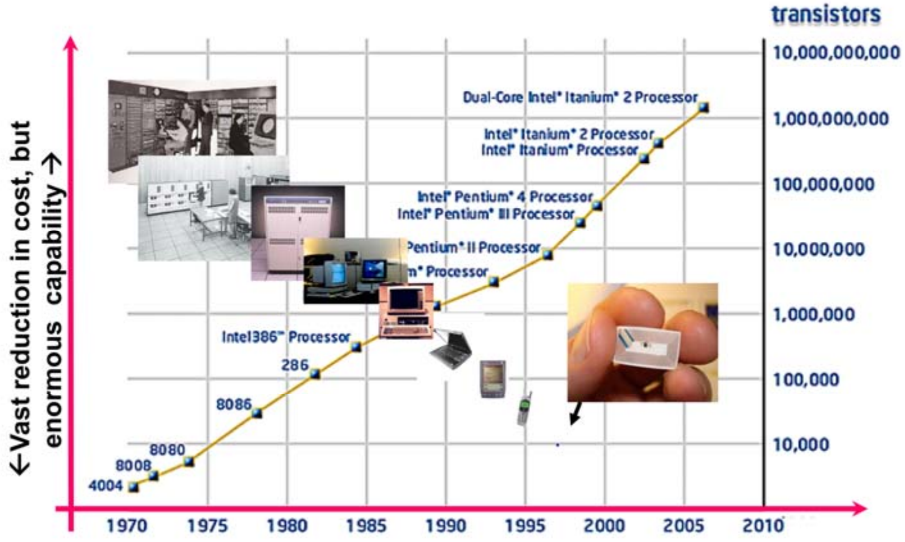
Technological Performance / Digital Power

Gordon E. Moore (1965, 1989, 1997)



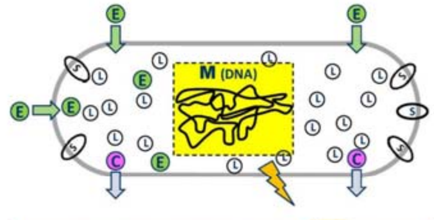
Holzinger, A. 2002. *Basiswissen IT/Informatik Band 1: Informationstechnik. Das Basiswissen für die Informationsgesellschaft des 21. Jahrhunderts, Wuerzburg, Vogel Buchverlag.*

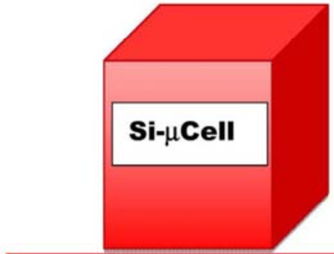
Computer cost/size versus Performance



Cf. with Moore (1965), Holzinger (2002), Scholtz & Consolvo (2004), Intel (2007)

Beyond Moore's Law -> biological computing





Memory:	10^7 bit
Logic:	$>10^6$ bit
Power:	10^{-13} W
Heat:	10^{-6} W/cm^2
Energy/task*:	10^{-10} J
Task time*:	2400s=40min

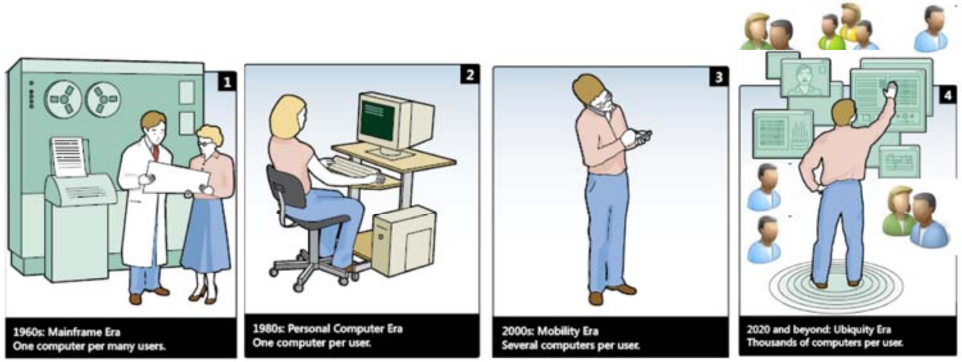
Memory:	$\sim 10^4$ bit
Logic:	~300–150,000 bit
Power:	$\sim 10^{-7}$ W
Heat:	~1 W/cm^2
Energy/task*:	$\sim 10^{-2}$ J
Task time*:	510,000 s ~ 6 days

*Equivalent to 10^{11} output bits

Cavin, R., Lugli, P. & Zhirnov, V. 2012. Science and Engineering Beyond Moore's Law. *Proc. of the IEEE, 100, 1720-49* (L=Logic-Protein; S=Sensor-Protein; C=Signaling-Molecule, E=Glucose-Energy)

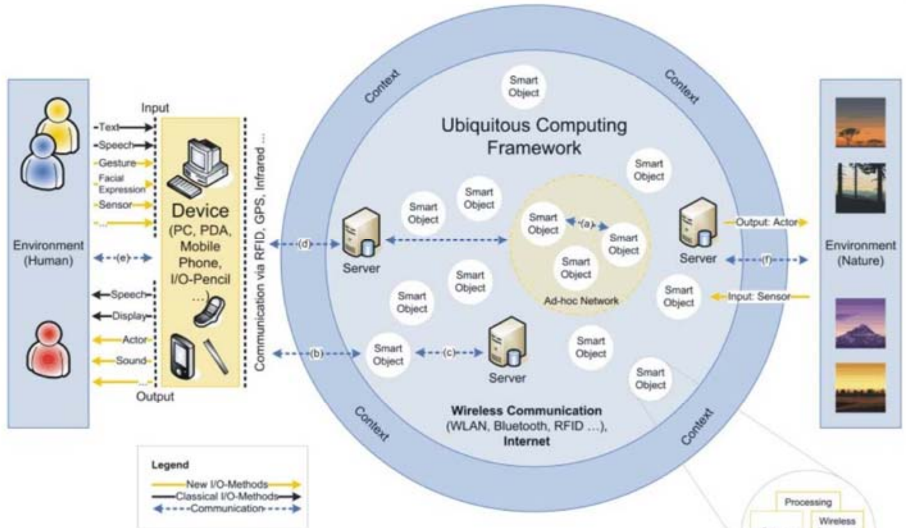
From mainframe to Ubiquitous Computing

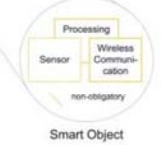
- … using technology to augment human capabilities for structuring, retrieving and managing information



Harper, R., Rodden, T., Rogers, Y. & Sellen, A. (2008) *Being Human: Human-Computer Interaction in the Year 2020. Cambridge, Microsoft Research.*

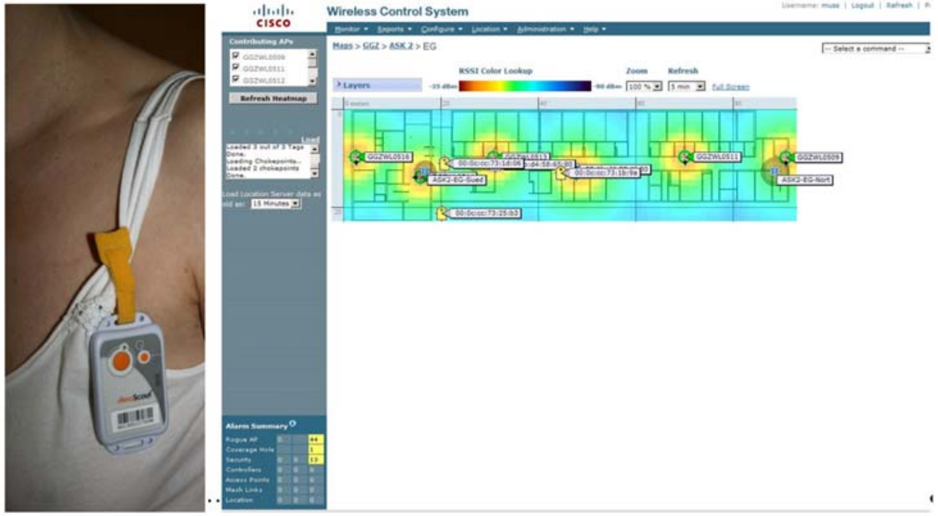
Ubiquitous Computing – Smart Objects





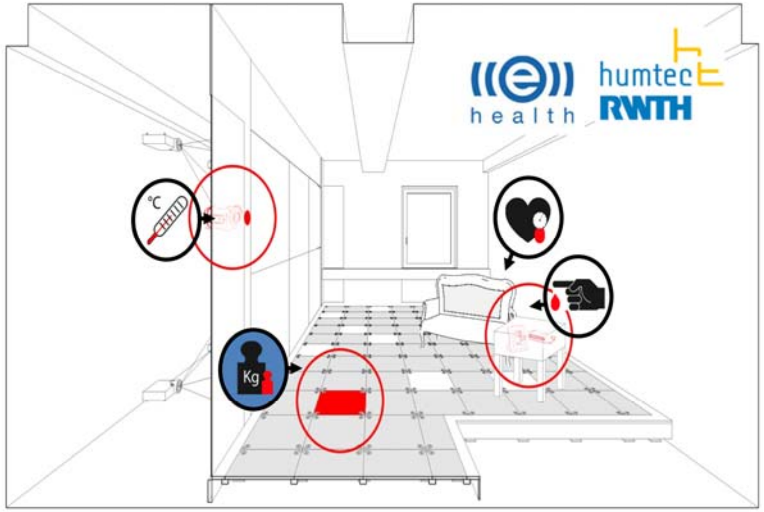
Holzinger, A., Nischelwitzer, A., Friedl, S. & Hu, B. (2010) Towards life long learning: three models for ubiquitous applications. *Wireless Communications and Mobile Computing, 10, 10, 1350-1365.*

Slide 1-34 Example: Pervasive Health Computing



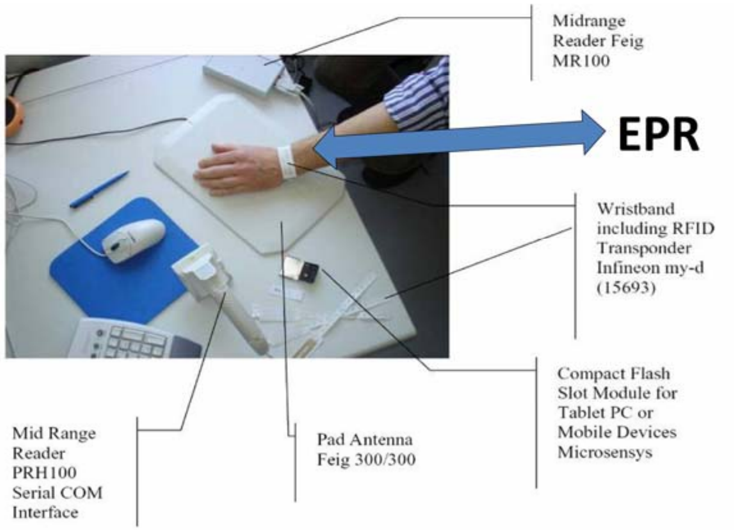
Holzinger, A., Schaupp, K. & Eder-Halbedl, W. (2008) An Investigation on Acceptance of Ubiquitous Devices for the Elderly in an Geriatric Hospital Environment: using the Example of Person Tracking In: *Lecture Notes in Computer Science (LNCS 5105). Heidelberg, Springer, 22-29.*

Ambient Assisted Living - pHealth



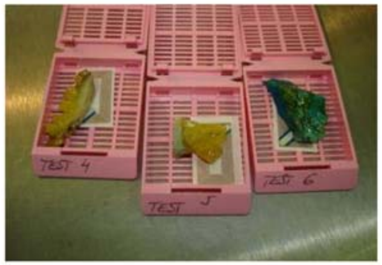
Alagoez, F., Valdez, A. C., Wilkowska, W., Ziefle, M., Dorner, S. & Holzinger, A. (2010) From cloud computing to mobile Internet, from user focus to culture and hedonism: The crucible of mobile health care and Wellness applications. *5th International Conference on Pervasive Computing and Applications (ICPCA). IEEE, 38-45.*

Example Pervasive Computing in the Hospital



Holzinger, A., Schwaberger, K. & Weitlaner, M. (2005) Ubiquitous Computing for Hospital Applications: RFID-Applications to enable research in Real-Life environments *29th Annual IEEE International Computer Software & Applications Conference (IEEE COMPSAC), 19-20.*

Smart Objects in the pathology




Holzinger et al. (2005)

The medical world is mobile (Mocomed)

Holzinger, A., Kosec, P., Schwantzer, G., Debevc, M., Hofmann-Wellenhof, R. & Frühauf, J. 2011. Design and Development of a Mobile Computer Application to Reengineer Workflows in the Hospital and the Methodology to evaluate its Effectiveness. *Journal of Biomedical Informatics, 44*, ***968-977.***

1970 Turning Knowledge into Data

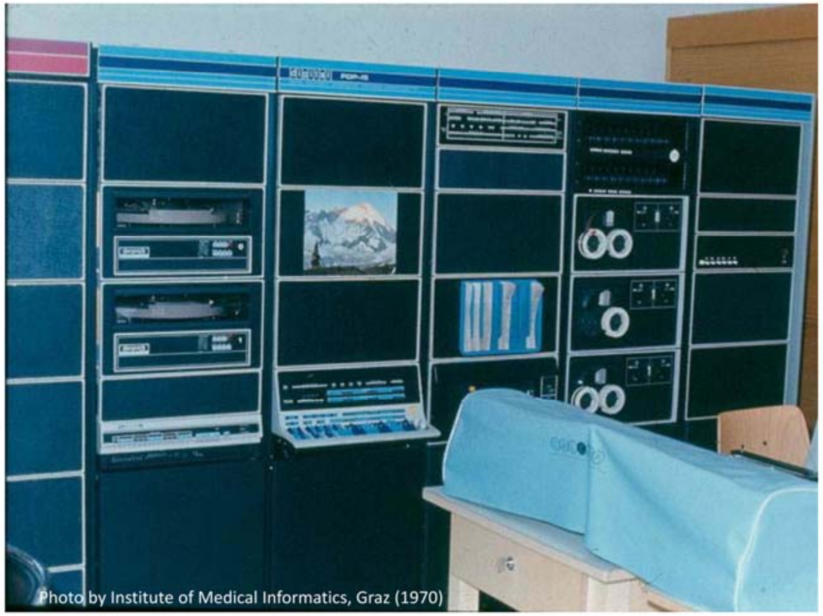


Photo by Institute of Medical Informatics, Graz (1970)

Overview

Primer on Probability & Information

Day 1 - Fundamentals

01 Information Sciences meets Life Sciences

02 Data, Information and Knowledge

03 Decision Making and Decision Support

04 From Expert Systems to Explainable AI