An Introduction to Machine Learning

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MindLAB Research Group - Universidad Nacional de Colombia

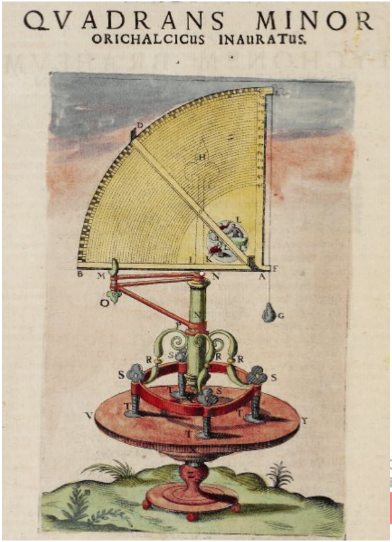
Introducción a los Sistemas Inteligentes

Outline

Observation and analysis

Tycho Brahe

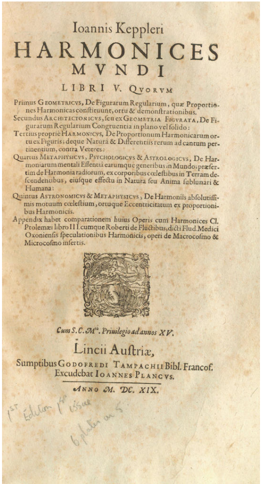

TYCHONIS BRAHE
ASTRONOMIÆ
INSTAURATÆ
MECHANICA
WANDESBVRGI
ANNO
Cum Cæsaris & Regum quorundam Privilegiis.

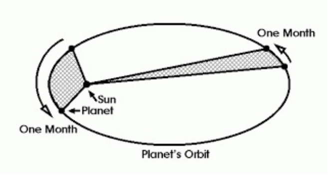

QVADRANS MINOR
ORICHALCICUS INAURATUS

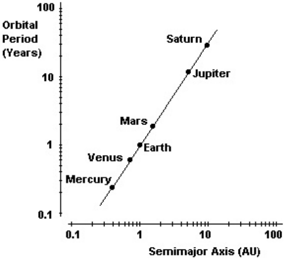
Tycho Brahe

	Date, Old Style			Longitude						Latitude			Mean Longitude			
	Year	Day	Month	H	M	D	M	S	Sign	D	M		S	D	M	S
I	1580	18	November	1	31	6	28	35	Gemeni	1	40	N.	1	25	49	31
II	1582	28	December	3	58	16	55	30	Cancer	4	6	N.	3	9	24	55
III	1585	30	January	19	14	21	36	10	Leo	4	32	N.	4	20	8	9
IV	1587	6	March	7	23	25	43	0	Virgo	3	41	N.	6	0	47	40
V	1589	14	April	6	23	4	23	0	Scorpio	1	12	N.	7	14	18	26
VI	1591	8	Jume	7	43	26	43	0	Sagitt.	4	0	S.	9	5	43	55
VII	1593	25	August	17	27	12	16	0	Pisces	6	2	S.	11	9	49	31
VIII	1595	31	October	0	39	17	31	40	Taurus	0	8	N.	1	9	55	4
IX	1597	13	December	15	44	2	28	0	Cancer	3	33	N.	2	23	11	56
X	1600	18	January	14	2	8	38	0	Leo	4	30	N.	4	4	35	50
XI	1602	20	Febuary	14	13	12	27	0	Virgo	4	10	N.	5	14	59	37
XII	1604	28	March	16	23	18	37	10	Libra	2	26	N.	6	27	0	12

Johannes Kepler


Ioannis Keppleri
HARMONICES MVNDI
LIBRI V. QVORVM
Primus GEOMETRICVS, De Figurarum Regularium, quæ Proportiones Harmonicas constituunt, ortu & demonstrationibus.
Secundus ARCHITECTONICVS, seu ex GEOMETRIA FIGVRATA, De Figurarum Regularium Congruentia in plano vel solido:
Tertius propriè HARMONICVS, De Proportionum Harmonicarum ortu ex Figuris; deque Naturâ & Differentiis rerum ad cantum pertinentium, contra Veteres:
Quartus METAPHYSICVS, PSYCHOLOGICVS & ASTROLOGICVS, De Harmoniarum mentali Essentiâ earumque generibus in Mundo; præsertim de Harmonia radiorum, ex corporibus cœlestibus in Terram descendentibus, eiusque effectu in Natura seu Anima sublunari & Humana:
Quintus ASTRONOMICVS & METAPHYSICVS, De Harmoniis absolutissimis motuum cœlestium, ortuque Eccentricitatum ex proportionibus Harmonicis.
Appendix habet comparationem huius Operis cum Harmonices Cl. Ptolemæi libro III. cumque Roberti de Fluctibus, dicti Flud Medici Oxoniensis speculationibus Harmonicis, operi de Macrocosmo & Microcosmo insertis.
Cum S. C. M^tis. Priuilegio ad annos XV.
Lincii Austriæ,
Sumptibus GODOFREDI TAMPACHII Bibl. Francof.
Excudebat IOANNES PLANCVS.
ANNO M. DC. XIX.





Data and models

Data

	Date, Old Style			Longitude						Latitude			Mean Longitude			
	Year	Day	Month	H	M	D	M	S	Sign	D	M		S	D	M	S
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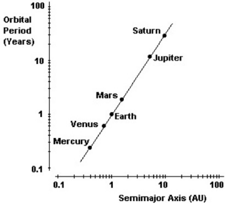
Model



Machine Learning

Data

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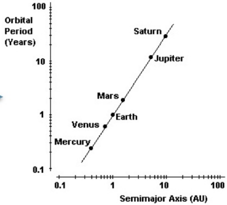
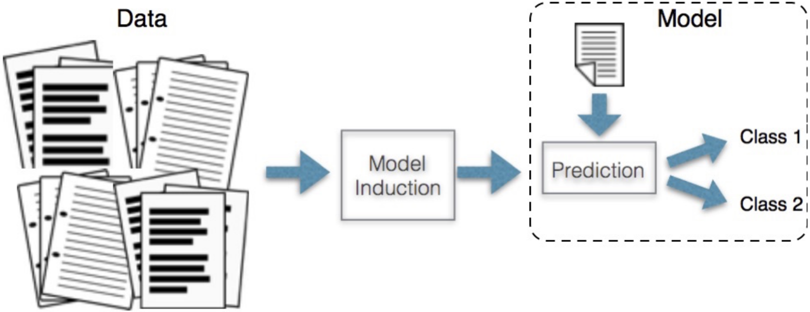
Learning/
Model
Induction

Model



Machine Learning with Text Data

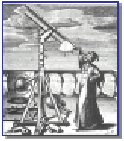


The fourth paradigm

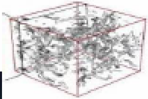
Emergence of a Fourth Research Paradigm

1. Thousand years ago – **Experimental Science**
   – Description of natural phenomena
2. Last few hundred years – **Theoretical Science**
   – Newton's Laws, Maxwell's Equations...
3. Last few decades – **Computational Science**
   – Simulation of complex phenomena
4. Today – **Data-Intensive Science**
   – Scientists overwhelmed with data sets from many different sources
     - Data captured by instruments
     - Data generated by simulations
     - Data generated by sensor networks

➢ eScience is the set of tools and technologies to support data federation and collaboration
- For analysis and data mining
- For data visualization and exploration
- For scholarly communication and dissemination



$$\left(\frac{\dot{a}}{a}\right)^2 = \frac{4\pi G\rho}{3} - K\frac{c^2}{a^2}$$



(With thanks to Jim Gray)

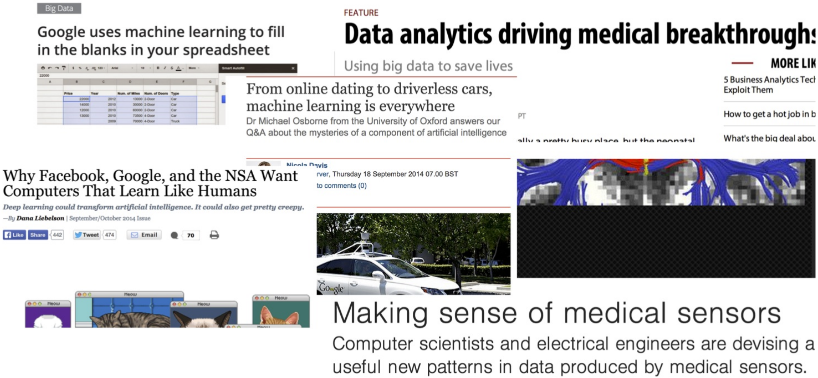
Machine Learning

- Construction and study of systems that can learn from data
- Main problem: to find patterns, relationships, regularities among data, which allow to build descriptive and predictive models.
- Related fields:
    - Statistics
    - Pattern recognition and computer vision
    - Data mining and knowledge discovery
    - Data analytics

Brief history

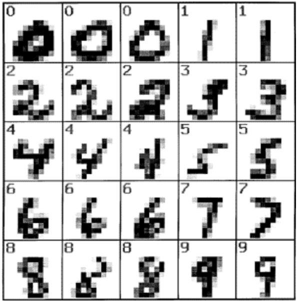
- Fisher's linear discriminant (Fisher, 1936)
- Artificial neuron model (MCCulloch and Pitts, 1943)
- Perceptron (Rosenblatt, 1957) (Minsky&Papert, 1969)
- Probably approximately correct learning (Valiant, 1984)
- Multilayer perceptron and back propagation (Rumelhart et al., 1986)
- Decision trees (Quinlan, 1987)
- Bayesian networks (Pearl, 1988)
- Support vector machines (Cortes&Vapnik, 1995)
- Efficient MLP learning, deep learning (Hinton et al., 2007)

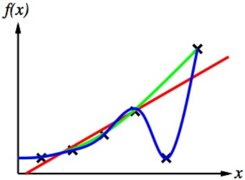
Machine Learning in the news



Supervised learning

- **Fundamental problem**: to find a function that relates a set of inputs with a set of outputs
- Typical problems:
    - Classification
    - Regression





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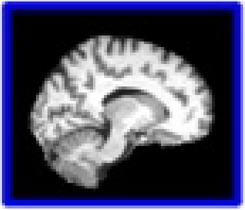
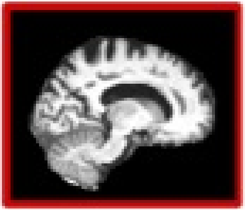
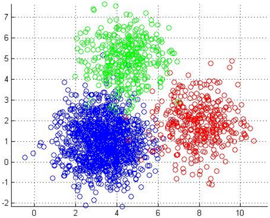




Non-supervised learning

- There are not labels for the training samples
- **Fundamental problem**: to find the subjacent structure of a training data set
- Typical problems: clustering, segmentation, dimensionality reduction, latent topic analysis
- Some samples may have labels, in that case it is called semi-supervised learning



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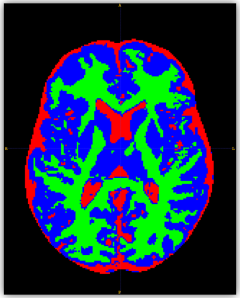
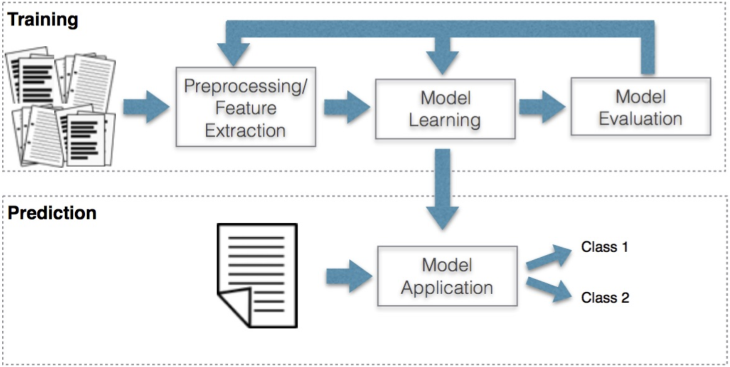
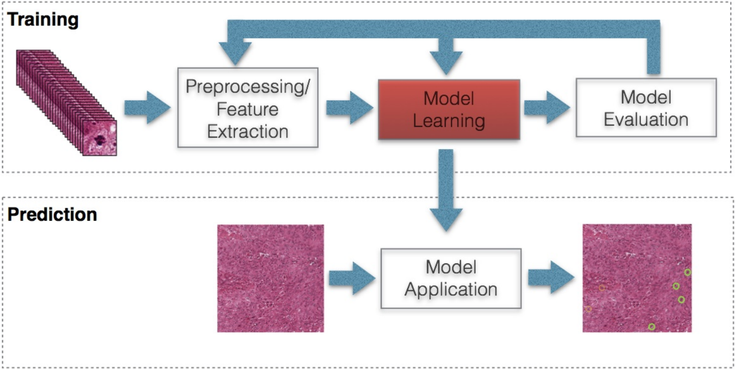


The machine Learning process



Model learning



Model induction from data

- Learning is an *ill-posed* problem (more than one possible solution for the same particular problem, solutions are sensitive to small changes on the problem)
- It is necessary to make additional assumptions about the kind of pattern that we want to learn
- **Hypothesis space**: set of valid patterns that can be learnt by the learning algorithm
- Occam's razor: "All things being equal, the simplest solution tends to be the best one."

Approaches to learning

- Probabilistic:
  - Generative models: model $P(Y, X)$
  - Discriminative models: model $P(Y|X)$
- Geometrical:
  - Manifold learning: model the geometry of the space where the data lives
  - Max margin learning: model the separation between the classes
- Optimization:
  - Energy/loss/risk minimization

Learning as optimization

- General optimization problem:

$$\min_{f \in H} L(f, D),$$

with H:hypothesis space, D:training data, L:loss/error

- Example, logistic regression:
  - Hypothesis space:

$$y(x) = P(C_+|x) = \sigma(w^T x)$$

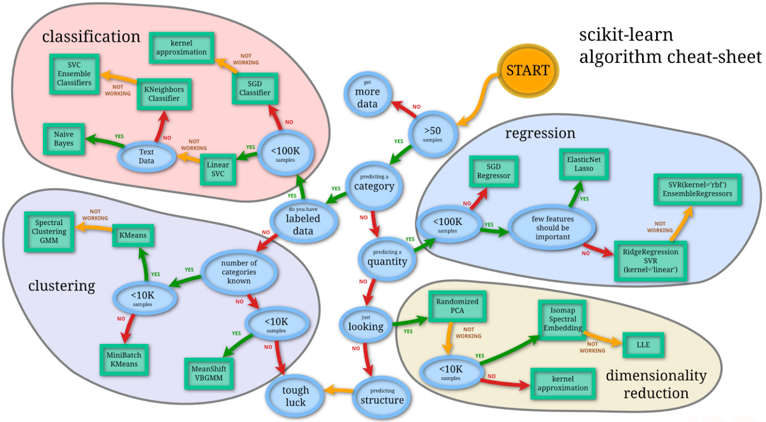
  - Cross-entropy error:

$$E(w) = -\ln p(\mathbf{t}|w) = -\sum_{n=1}^{\ell} [t_n \ln y_n + (1 - t_n) \ln(1 - y_n)]$$

Methods

- Supervised generative:
  - Naïve Bayes
  - Graphical models
  - Markov random fields
  - Hidden markov models
- Supervised discriminative:
  - Logistic regression
  - Ridge regression
  - Conditional random fields
- Supervised geometrical
  - Max margin classification (SVM)
  - k-nearest neighbors
- Non-supervised generative:
  - Latent semantic analysis
  - Latent Dirichlet allocation
  - Gaussian mixtures
- non-supervised geometrical:
  - k-means
  - PCA
  - Manifold learning
- Other
  - Neural networks (deep learning)
  - Decision tress
  - Association rules

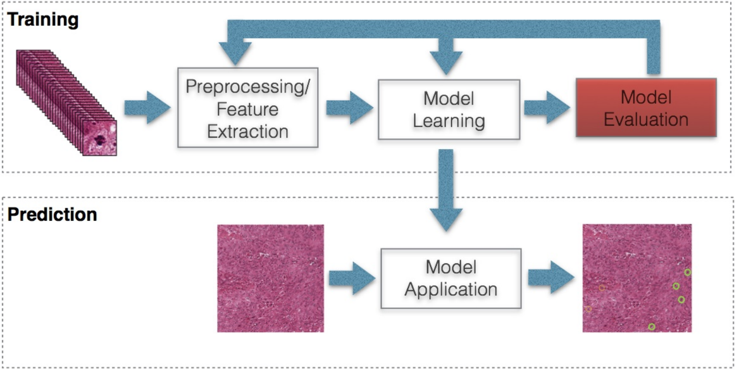
Methods


scikit-learn
algorithm cheat-sheet
START
>50 samples
get more data
predicting a category
do you have labeled data
<100K samples
SGD Classifier
kernel approximation
Linear SVC
Text Data
Naive Bayes
KNeighbors Classifier
SVC Ensemble Classifiers
classification
number of categories known
<10K samples
KMeans
Spectral Clustering GMM
MiniBatch KMeans
<10K samples
MeanShift VBGMM
clustering
tough luck
predicting a quantity
regression
<100K samples
SGD Regressor
few features should be important
ElasticNet Lasso
RidgeRegression SVR (kernel='linear')
SVR(kernel='rbf') EnsembleRegressors
just looking
predicting structure
Randomized PCA
<10K samples
Isomap Spectral Embedding
LLE
kernel approximation
dimensionality reduction
YES
NO
NOT WORKING

Strategies

- Optimization (non-linear, convex, etc)
- Stochastic gradient descent
- Kernel methods
- Maximum likelihood estimation
- Maximum a posteriori estimation
- Bayesian estimation (variational learning, Gaussian processes)
- Expectation maximization
- Maximum entropy models
- Sampling (Markov Chain Monte Carlo, particle filtering)

Evaluation


Training
Preprocessing/
Feature
Extraction
Model
Learning
Model
Evaluation
Prediction
Model
Application

Training error vs generalization error

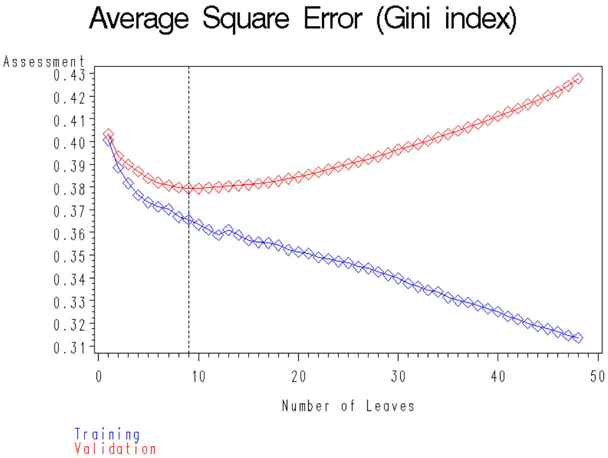
- Training error:

$$\sum_{i=1}^{\ell} L(f_w, S_i)$$

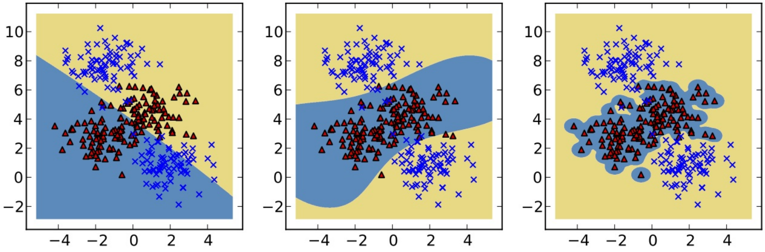
- Generalization error:

$$E[(L(f_w, S)]$$

Cross validation



Overfitting and underfitting

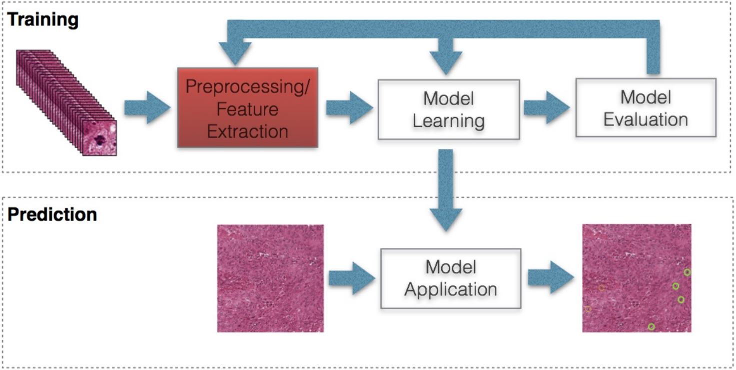


Regularization

$$\min_{w} -C \overbrace{\sum_{n=1}^{\ell} [t_n \ln y_n + (1 - t_n) \ln(1 - y_n)]}^{\text{original objective function}} + \overbrace{\|w\|^2}^{\text{regularizer}}$$

- Controls the complexity of a learned model
- Usually, the regularization term corresponds to a norm of the parameter vector (L_1 or L_2 the most common)
- In some cases, it is equivalent to the inclusion of a prior and finding a MAP solution.

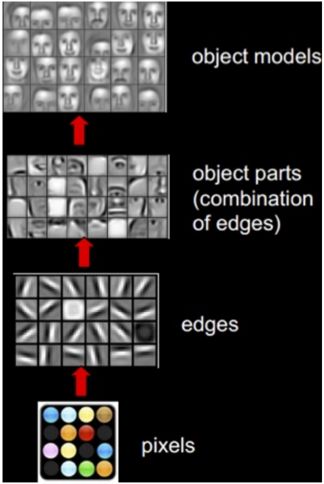
Feature extraction



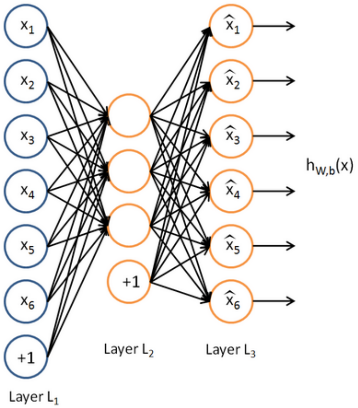
Features

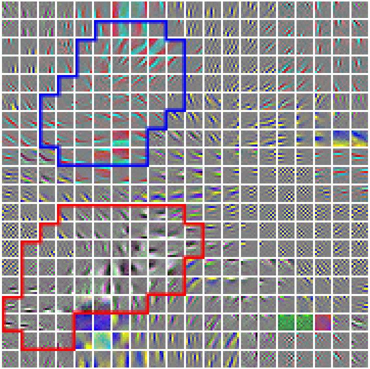
- Features represent our prior knowledge of the problem
- Depend on the type of data
- Specialized features for practically any kind of data (images, video, sound, speech, text, web pages, etc)
- Medical imaging:
    - Standard computer vision features (color, shape, texture, edges, local-global, etc)
    - Specialized features tailored to the problem at hand
- New trend: learning features from data

Feature learning



Unsupervised feature learning





AMIDA-MICCAI 2013 Challenge

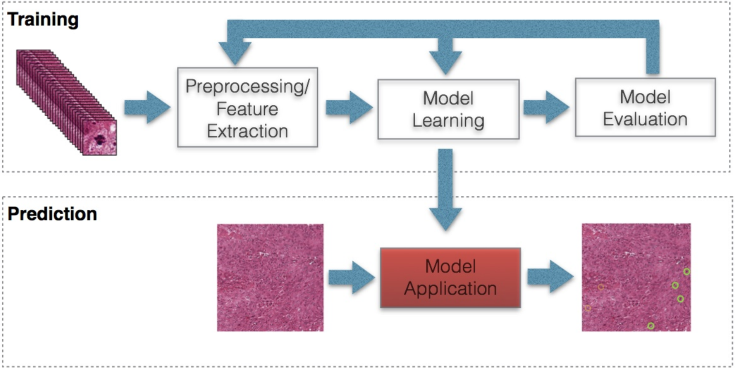
Team name	Precision	Recall	F_1-Score
IDSIA	0.610	0.612	0.611
DTU	0.427	0.555	0.483
SURREY	0.357	0.332	0.344
ISIK	0.306	0.351	0.327
PANASONIC	0.336	0.310	0.322
CCIPD/MINDLAB	0.353	0.291	0.319
WARWICK	0.171	0.552	0.261
POLYTECH/UCLAN	0.186	0.263	0.218
MINES	0.139	0.490	0.217
SHEFFIELD/SURREY	0.119	0.107	0.113
SEOUL	0.032	0.630	0.061
NTUST	0.011	0.685	0.022
UNI-JENA	0.007	0.077	0.013
NIH	0.002	0.049	0.003

→ UFL using deep-leranin

→ Donut like histograms—SVM

→ Shape, color, texture—SVM

Model application



High-throughput data analytics

- Large scale machine learning (big-data):
  - Large number of samples
  - Large samples (whole-slide images, 4D high-resolution volumes)
- Scalable learning algorithms (on-line learning)
- Distributed computing architectures (Hadoop, Spark)
- GPGPU computing and multicore architectures

Questions?

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http://www.mindlaboratory.org