TK8117: Multivariate Data Analysis

An enabler for Bigdatacybernetics

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Bigdatacybernetics

- Instructors
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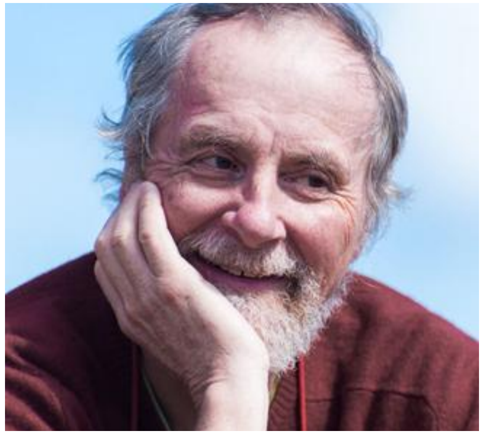
  - Frank Ove WESTAD
  - Adil RASHEED

Homework: Who is who ?



Expectations from today's lecture

- Why data analytics when first principle models are available in abundance?
- Why to take a course in Multivariate Data Analysis when so many courses on ML are available?
- What makes this course different from other courses on similar topics?
- Some taste of Bigdatacybernetics
- Get to know each other and encourage to prepare our own data
- Install Unscrambler, Python, Matlab
- Formal details about the course
- In-class performance analytics

Overview

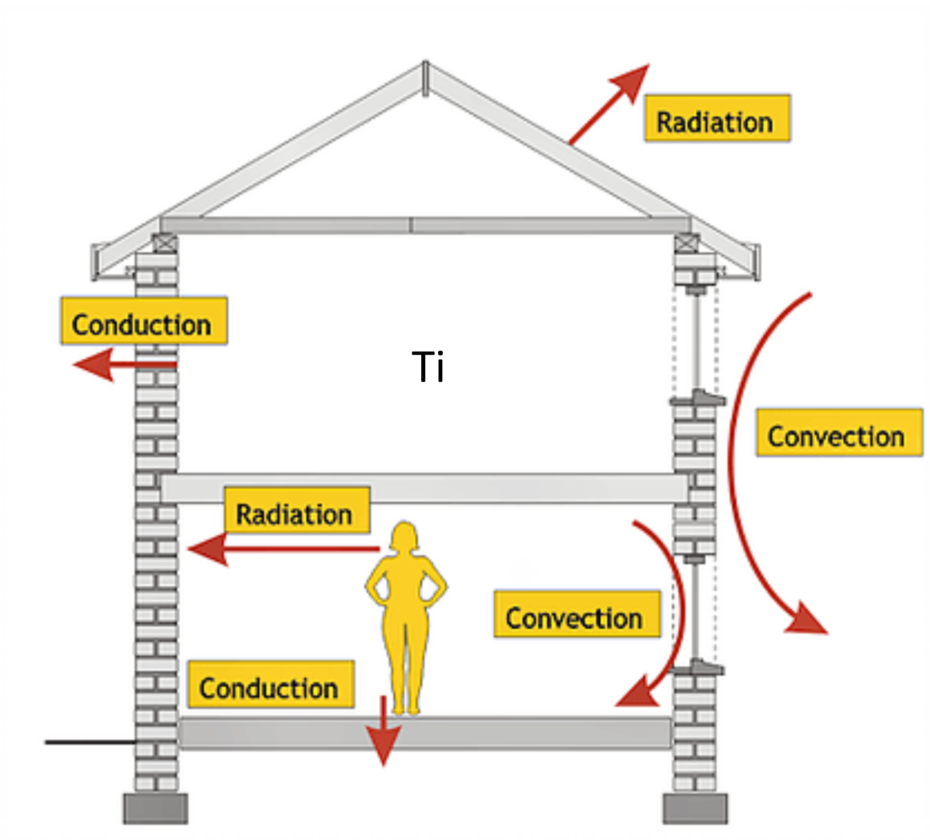
- Physics-based modeling
- Data-driven Modeling
- Bigdata Cybernetics

Physics-based modeling

Sample problem and modeling

Problem identification

To

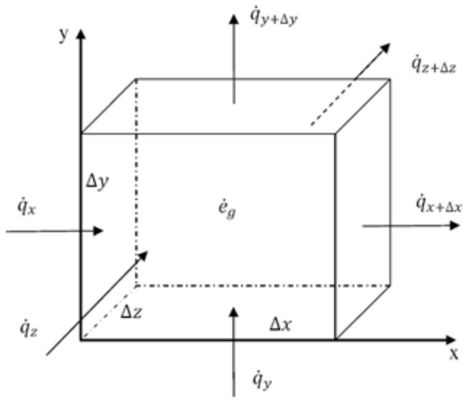


Modeling

$$\dot{q}_{x+dx} = \dot{q}_x + \frac{\partial \dot{q}_x}{\partial x} dx$$

or,

$$\dot{q}_x - \dot{q}_{x+dx} = -\frac{\partial \dot{q}_x}{\partial x} dx$$



Fourier's law of heat conduction

$$\dot{q}_x = -k\, dy\, dz \frac{\partial T}{\partial x}$$

$$\boxed{\dot{q}_x - \dot{q}_{x+dx} = \frac{\partial}{\partial x}\left(k \frac{\partial T}{\partial x}\right) dx\, dy\, dz}$$

$$\dot{q}_y - \dot{q}_{y+dy} = \frac{\partial}{\partial y}\left(k \frac{\partial T}{\partial y}\right) dx\, dy\, dz$$

and,

$$\dot{q}_z - \dot{q}_{z+dz} = \frac{\partial}{\partial z}\left(k \frac{\partial T}{\partial z}\right) dx\, dy\, dz$$

$$\boxed{\begin{aligned} &Rate\ of\ heat\ input + Rate\ of\ heat\ generation \\ &\qquad = Rate\ of\ heat\ output \\ &\qquad + Rate\ of\ change\ of\ heat\ energy\ within\ the\ body \end{aligned}}$$

$$\dot{u} = (\rho dx\, dy\, dz) c_p \left(\frac{\partial T}{\partial t}\right)$$

$$(\dot{q}_x + \dot{q}_y + \dot{q}_z) + (\dot{e}_g\, dx\, dy\, dz) = (\dot{q}_{x+dx} + \dot{q}_{y+dy} + \dot{q}_{z+dz}) + (\rho dx\, dy\, dz) c_p \left(\frac{\partial T}{\partial t}\right)$$

$$(\dot{q}_x - \dot{q}_{x+dx}) + (\dot{q}_y - \dot{q}_{y+dy}) + (\dot{q}_z - \dot{q}_{z+dz}) + (\dot{e}_g dx\, dy\, dz) = (\rho dx\, dy\, dz) c_p \left(\frac{\partial T}{\partial t}\right)$$

or,

$$\left\{\frac{\partial}{\partial x}\left(k \frac{\partial T}{\partial x}\right) + \frac{\partial}{\partial y}\left(k \frac{\partial T}{\partial y}\right) + \frac{\partial}{\partial z}\left(k \frac{\partial T}{\partial z}\right)\right\} (dx\, dy\, dz) + (\dot{e}_g\, dx\, dy\, dz) = (\rho dx\, dy\, dz) c_p \left(\frac{\partial T}{\partial t}\right)$$

or,

$$\left\{\frac{\partial}{\partial x}\left(k \frac{\partial T}{\partial x}\right) + \frac{\partial}{\partial y}\left(k \frac{\partial T}{\partial y}\right) + \frac{\partial}{\partial z}\left(k \frac{\partial T}{\partial z}\right)\right\} + \dot{e}_g = \rho c_p \left(\frac{\partial T}{\partial t}\right)$$

Model simplification

- Reducing dimensions (eg. Using symmetry)

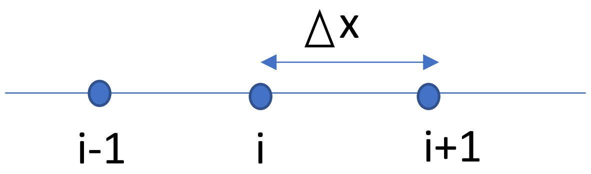
$$\boxed{\frac{\partial u}{\partial t} = \nu \frac{\partial^2 u}{\partial x^2}} \qquad \boxed{\frac{\partial u}{\partial t} = \nu \frac{\partial^2 u}{\partial x^2} + \nu \frac{\partial^2 u}{\partial y^2}}$$

- Approximating thermophysical properties
- Approximating shapes
- ....
- ....

Numerical Discretization

1D diffusion equation

$$\frac{\partial u}{\partial t} = \nu \frac{\partial^2 u}{\partial x^2}$$



$$u_{i+1} = u_i + \Delta x \left.\frac{\partial u}{\partial x}\right|_i + \frac{\Delta x^2}{2} \left.\frac{\partial^2 u}{\partial x^2}\right|_i + \frac{\Delta x^3}{3!} \left.\frac{\partial^3 u}{\partial x^3}\right|_i + O(\Delta x^4)$$

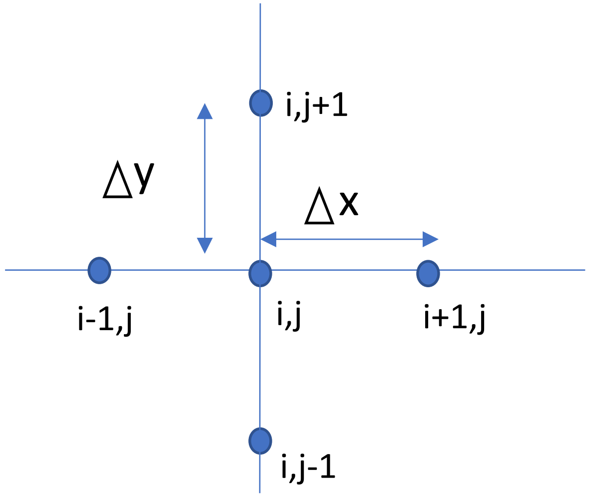
$$u_{i-1} = u_i - \Delta x \left.\frac{\partial u}{\partial x}\right|_i + \frac{\Delta x^2}{2} \left.\frac{\partial^2 u}{\partial x^2}\right|_i - \frac{\Delta x^3}{3!} \left.\frac{\partial^3 u}{\partial x^3}\right|_i + O(\Delta x^4)$$

$$\frac{\partial^2 u}{\partial x^2} = \frac{u_{i+1} - 2u_i + u_{i-1}}{\Delta x^2} + O(\Delta x^2)$$

$$\frac{u_i^{n+1} - u_i^n}{\Delta t} = \nu \frac{u_{i+1}^n - 2u_i^n + u_{i-1}^n}{\Delta x^2}$$

$$u_i^{n+1} = u_i^n + \frac{\nu \Delta t}{\Delta x^2}(u_{i+1}^n - 2u_i^n + u_{i-1}^n)$$

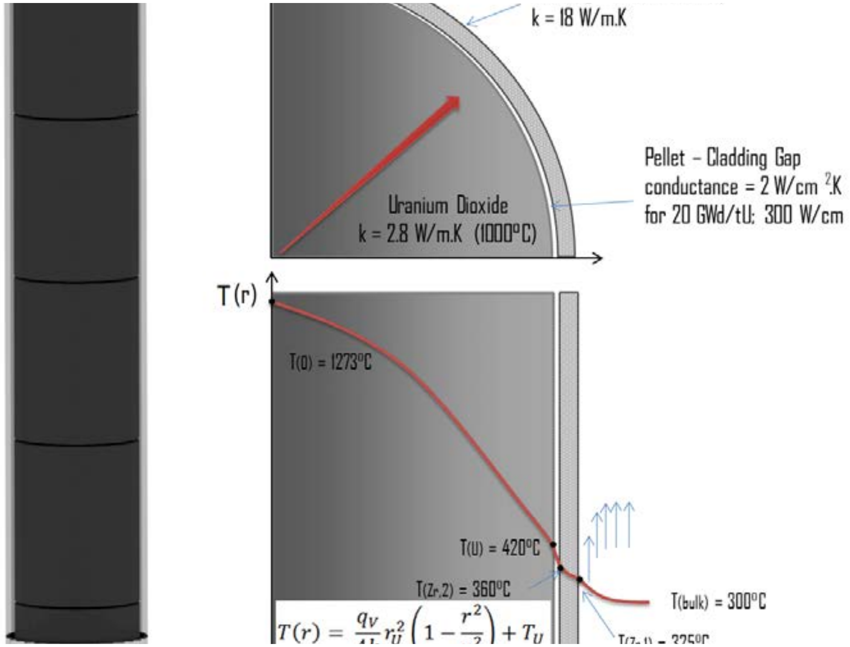
2D diffusion equation

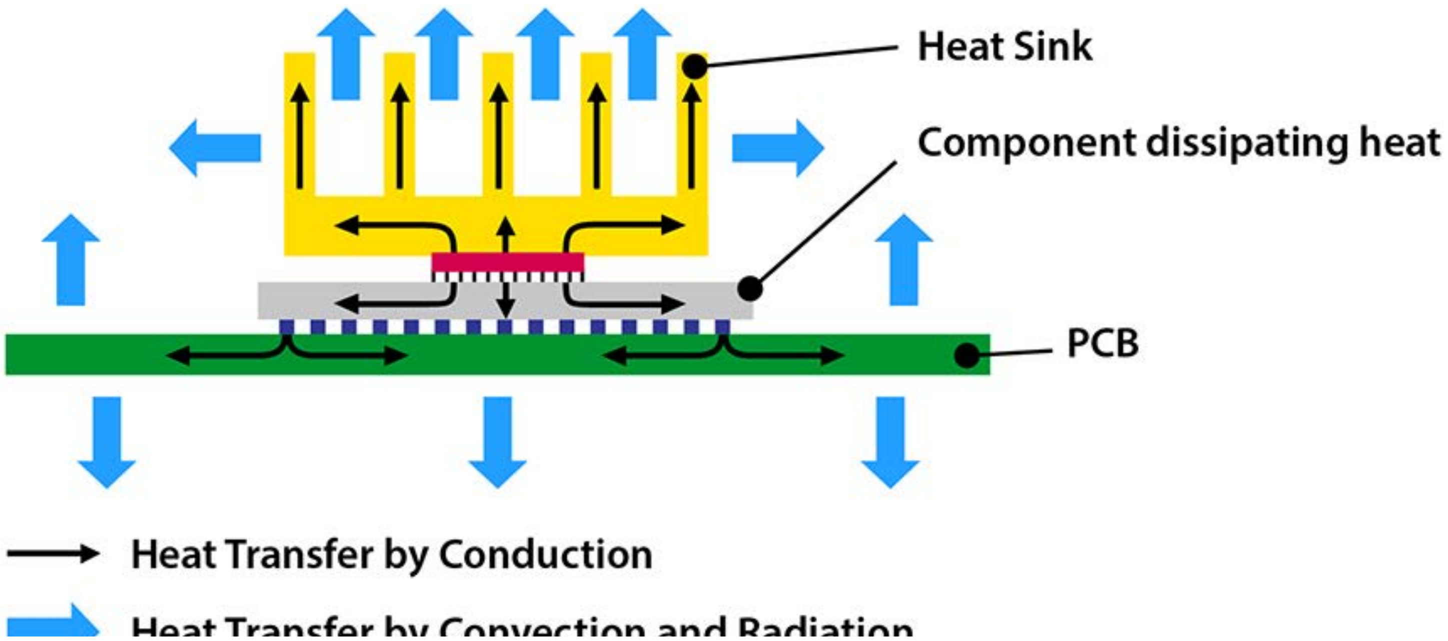


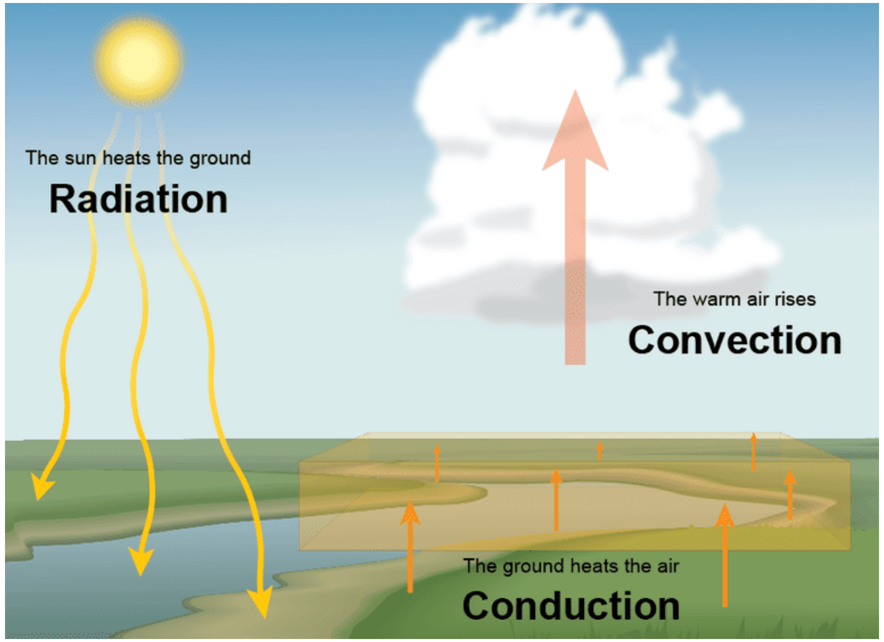
$$\frac{\partial u}{\partial t} = \nu \frac{\partial^2 u}{\partial x^2} + \nu \frac{\partial^2 u}{\partial y^2}$$

$$\frac{u_{i,j}^{n+1} - u_{i,j}^n}{\Delta t} = \nu \frac{u_{i+1,j}^n - 2u_{i,j}^n + u_{i-1,j}^n}{\Delta x^2} + \nu \frac{u_{i,j+1}^n - 2u_{i,j}^n + u_{i,j-1}^n}{\Delta y^2}$$

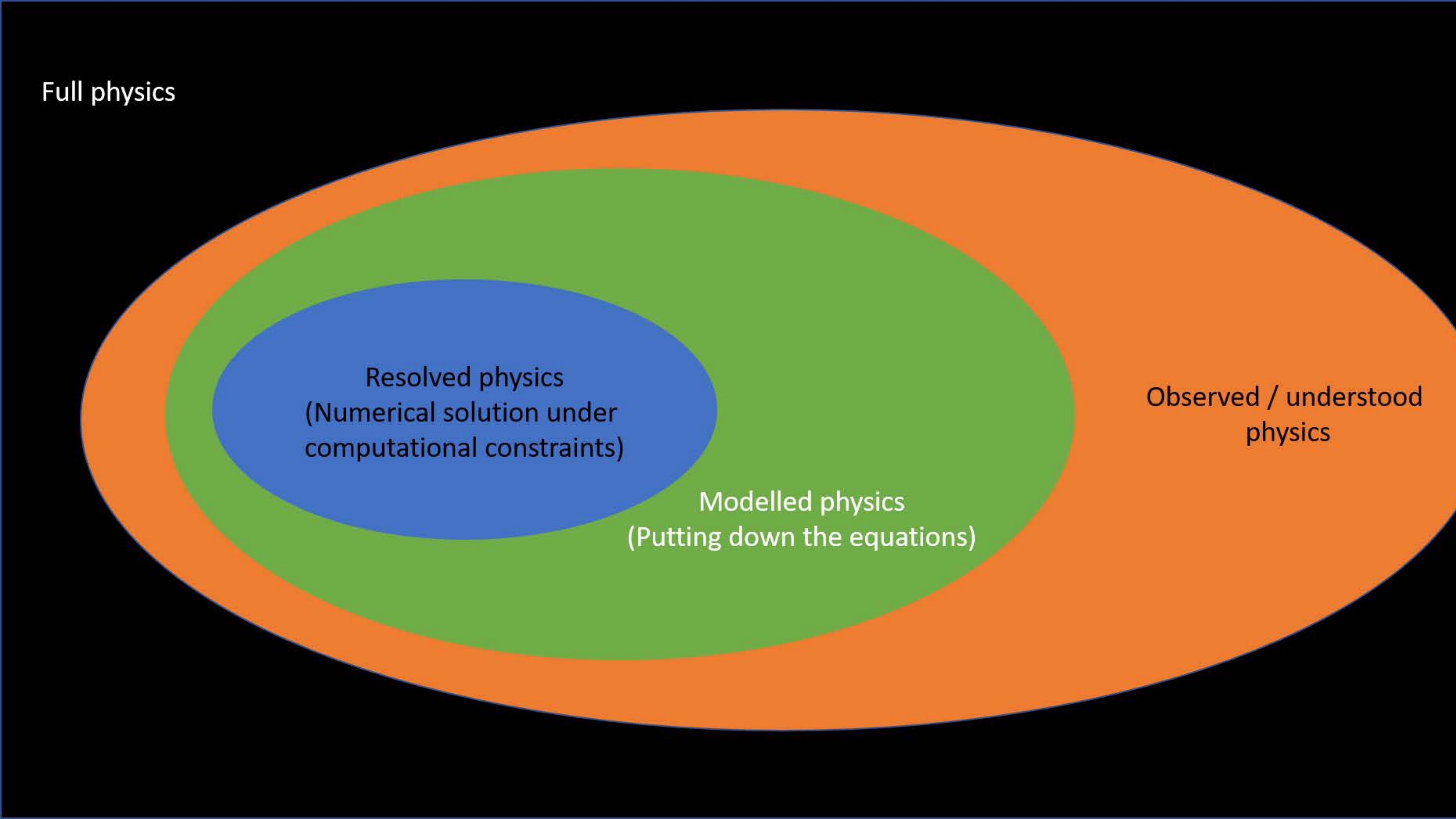
$$\begin{aligned} u_{i,j}^{n+1} = u_{i,j}^n &+ \frac{\nu \Delta t}{\Delta x^2}(u_{i+1,j}^n - 2u_{i,j}^n + u_{i-1,j}^n) \\ &+ \frac{\nu \Delta t}{\Delta y^2}(u_{i,j+1}^n - 2u_{i,j}^n + u_{i,j-1}^n) \end{aligned}$$







Extension to other applications

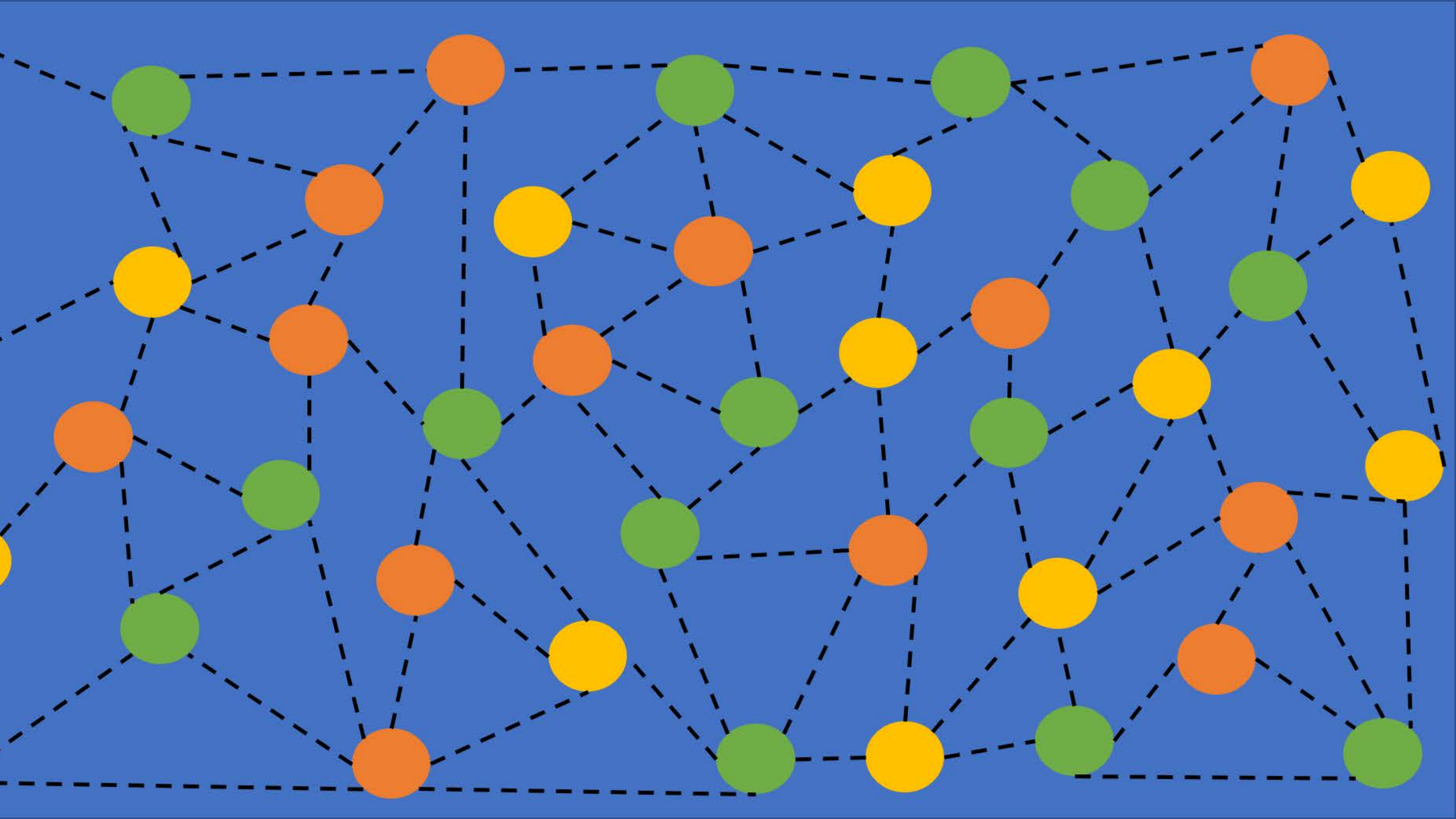

Full physics
Resolved physics
(Numerical solution under
computational constraints)
Modelled physics
(Putting down the equations)
Observed / understood
physics

Home work

- Figure out a phenomena governed by the 1D, 2D
- Decide on the initial condition and boundary condition
- Solve it using the numerical methods
- Convince yourself about the previous two slides

https://github.com/adil-rasheed/TK8117/blob/master/Lecture1/Physicsbased.ipynb

Data driven modeling



Data-driven modeling

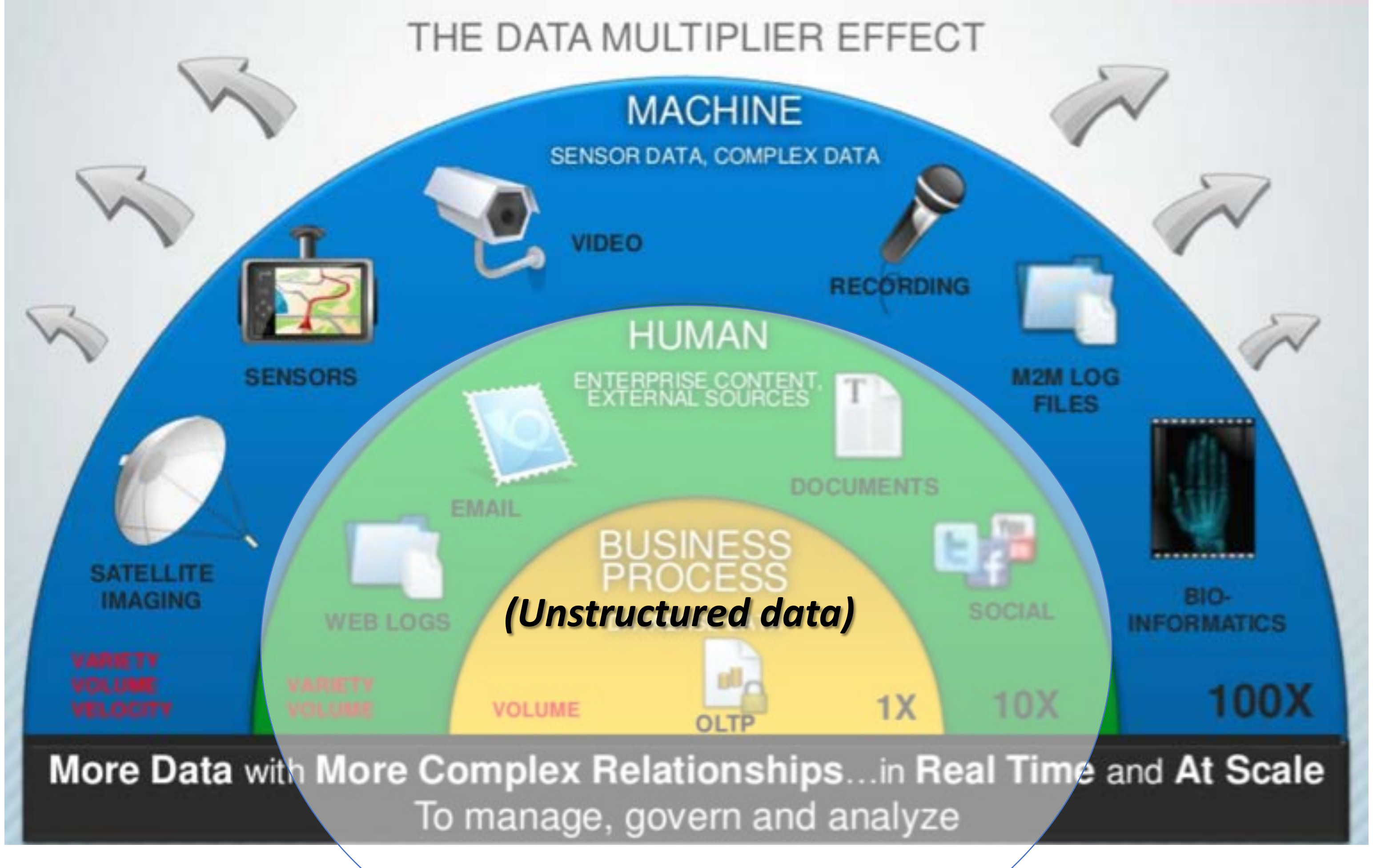
Technology Push

- New and existing algorithms
- Digitalization wave
- Cheap sensors and observation data (mobile data, cams)
- Easy-to-use software libraries
- Cheap GPU's and TPUs

Market Pull

- Digital Twin
- Internet of Things
- Smart Cities
- Autonomy
- Precision in predictions
- Real time control systems

Sources of Big Data Growth



Structured data **for**

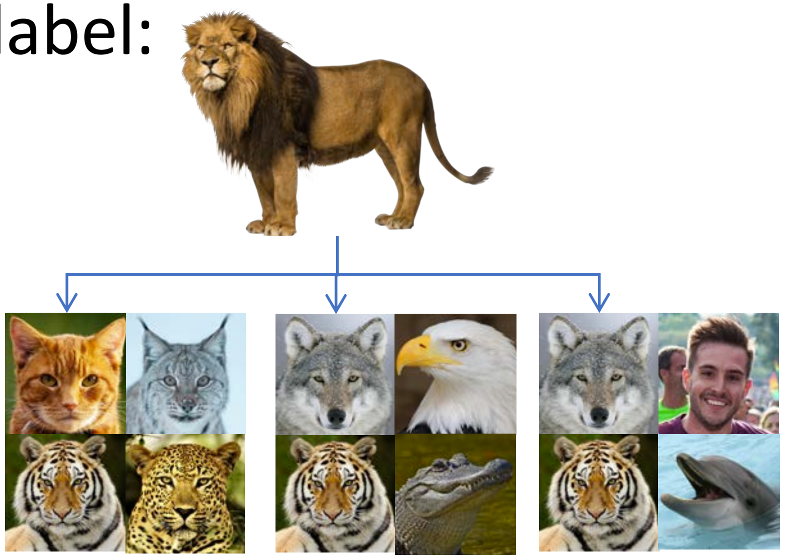
Big Data Cybernetics:

- Multichannel sensor data
- Web log data/log files
- Computer simulation data
- 4Vs

Supervised Learning

Classification

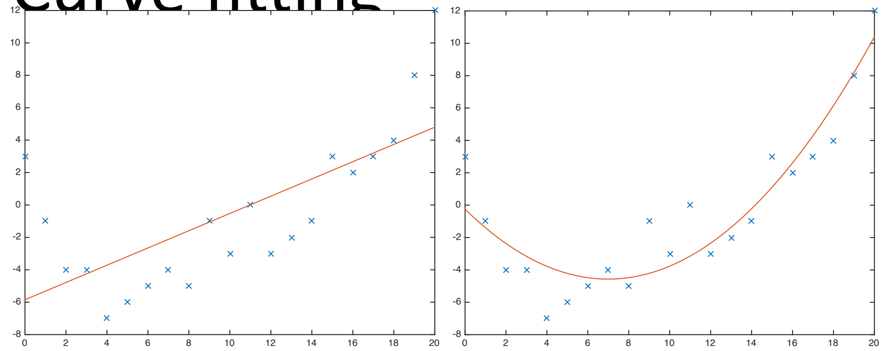
- Binary: 
- Multiclass: 
- Multilabel:

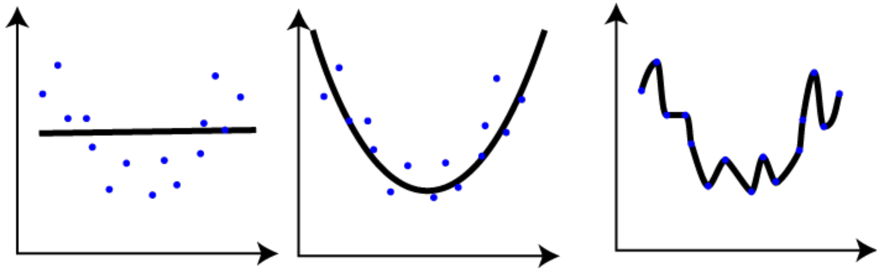


Cats Predators Mammals

Regression

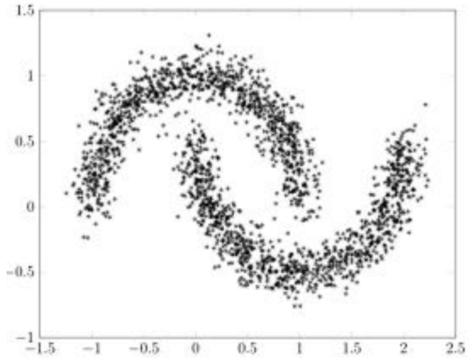
- Continuous output
- Curve fitting

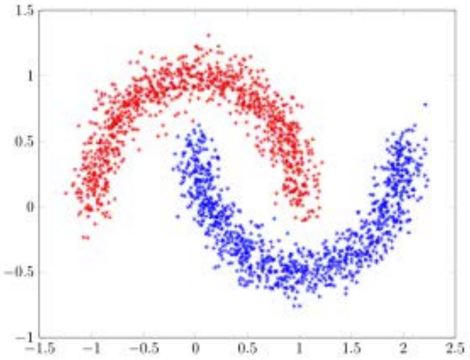




Unsupervised Learning

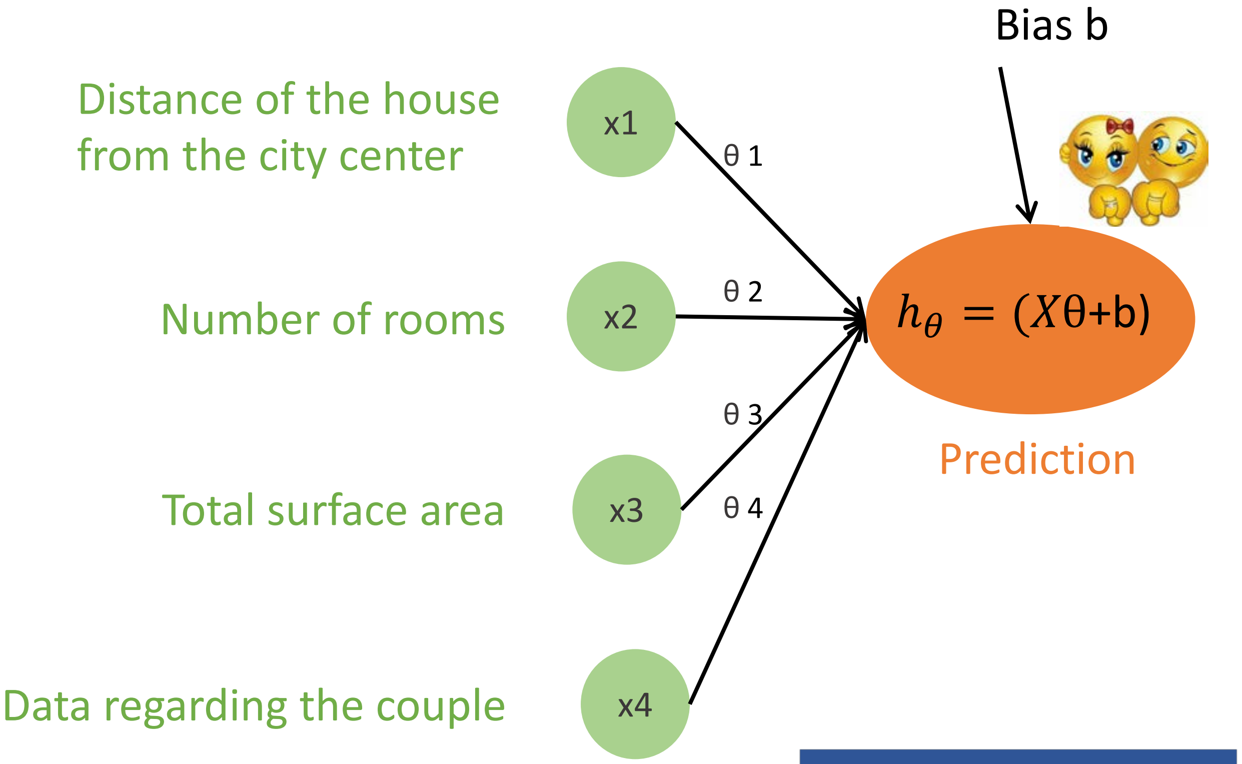
- Given an input X, find interesting structure in the data
- More general than a supervised approach
- Compares to human and animal learning





Linear Regression

x1	x2	x3	x4



Price

y
1.5MNOK
3MNOK
2.5MNOK
10MNOK
5MNOK

Mean squared error

$$J(\theta)= \frac{1}{2m} \sum_{i=1}^{m} (h_{\theta i} - yi)^2$$

Convince yourself about the interpretability of Linear Regression Model. Use the following notebook https://github.com/adil-rasheed/TK8117/blob/master/Lecture1/LinearRegression.ipynb

Batch Gradient Descent

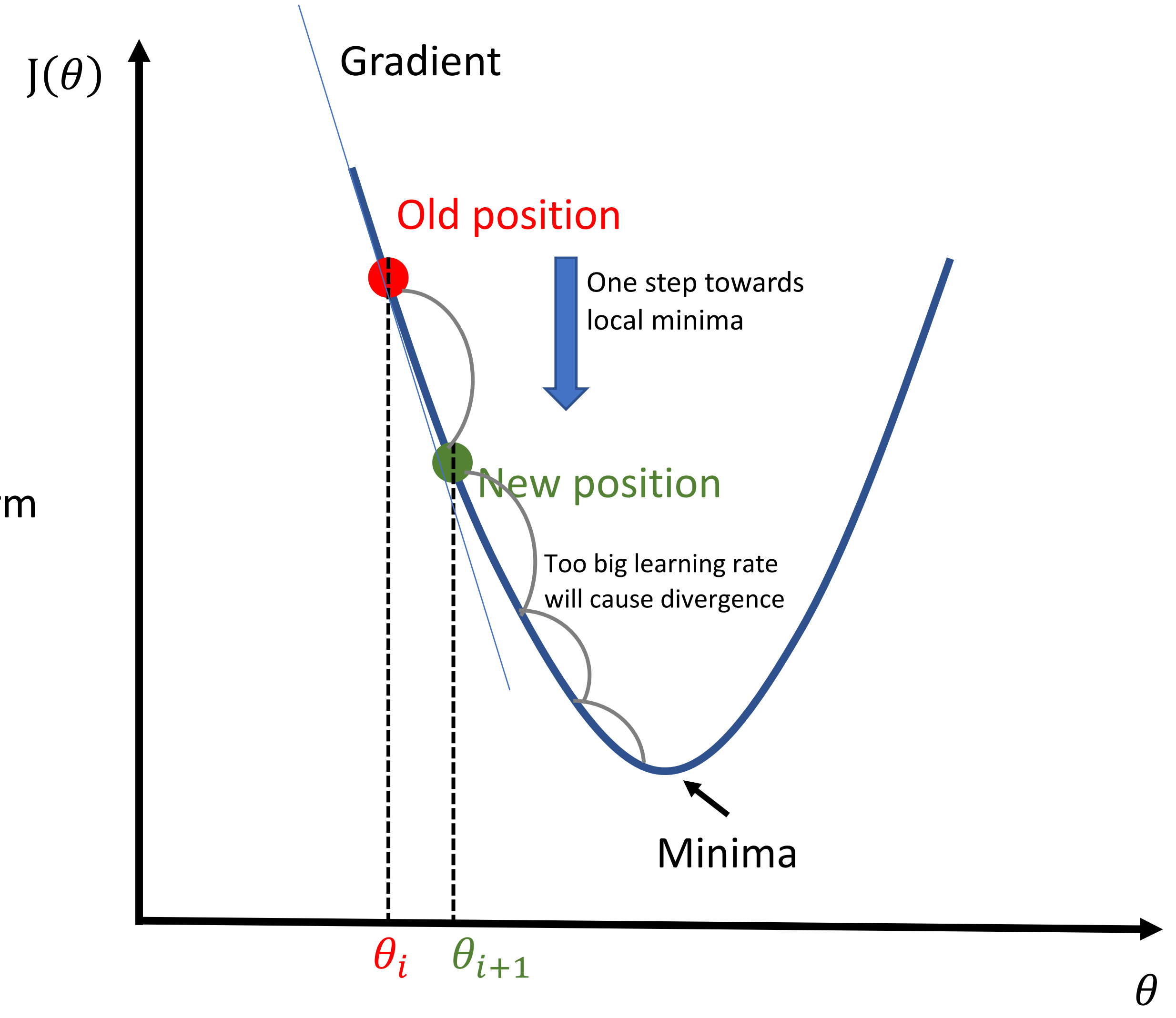
Learning rate

$$\theta_{i+1} = \theta_i - \alpha \nabla_\theta J(\theta)$$

New position after the step

Gradient term

Old position before the step



Logistic Regression

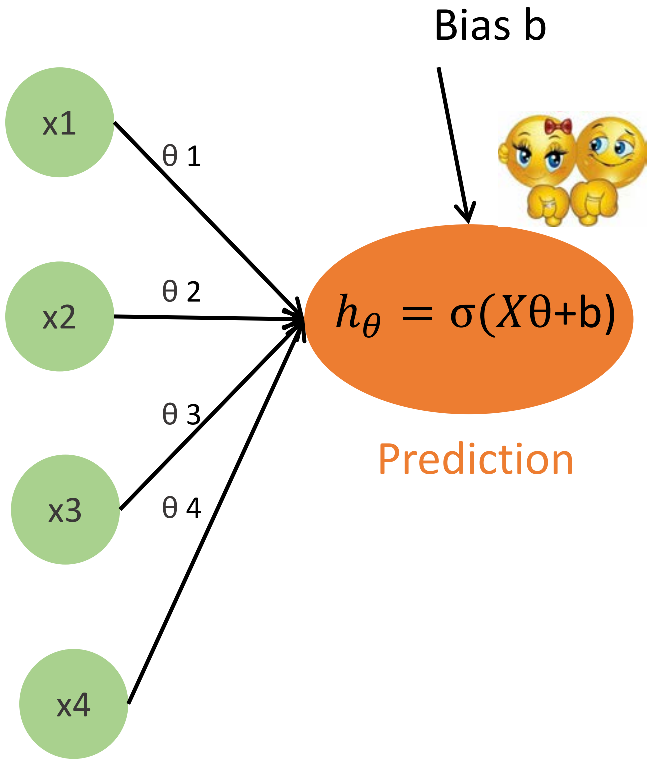
x1	x2	x3	x4

Distance of the house from the city center

Number of rooms

Total surface area

Data regarding the couple



Whether the couple bought the house ?

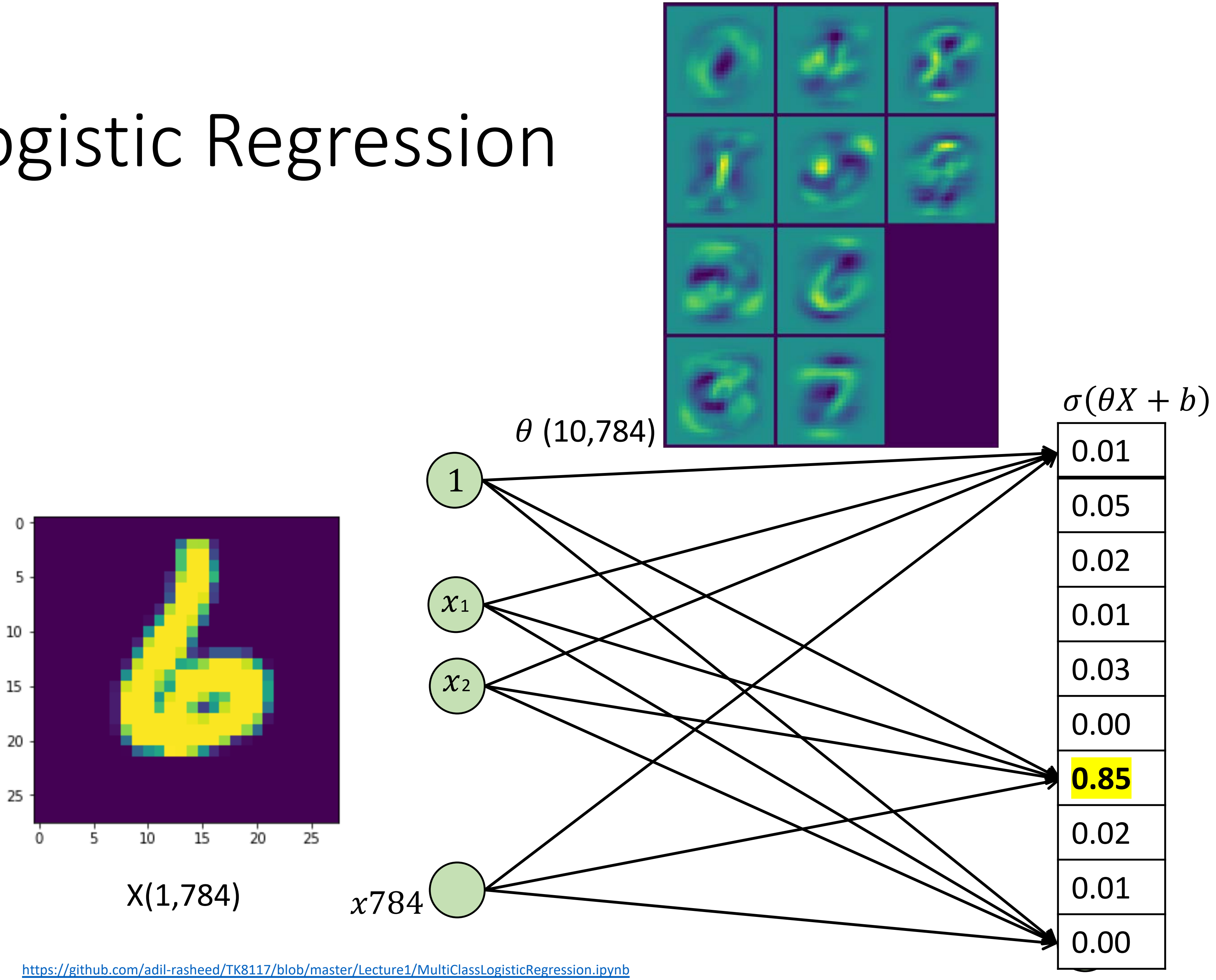
y
0
1
0
0
1

Categorically cross entropy loss

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^{(i)}log(h_\theta(x^{(i)})) + (1 - y^{(i)})log(1 - h_\theta(x^{(i)}))]$$

https://github.com/adil-rasheed/TK8117/blob/master/Lecture1/BinaryClassLogisticRegression.ipynb

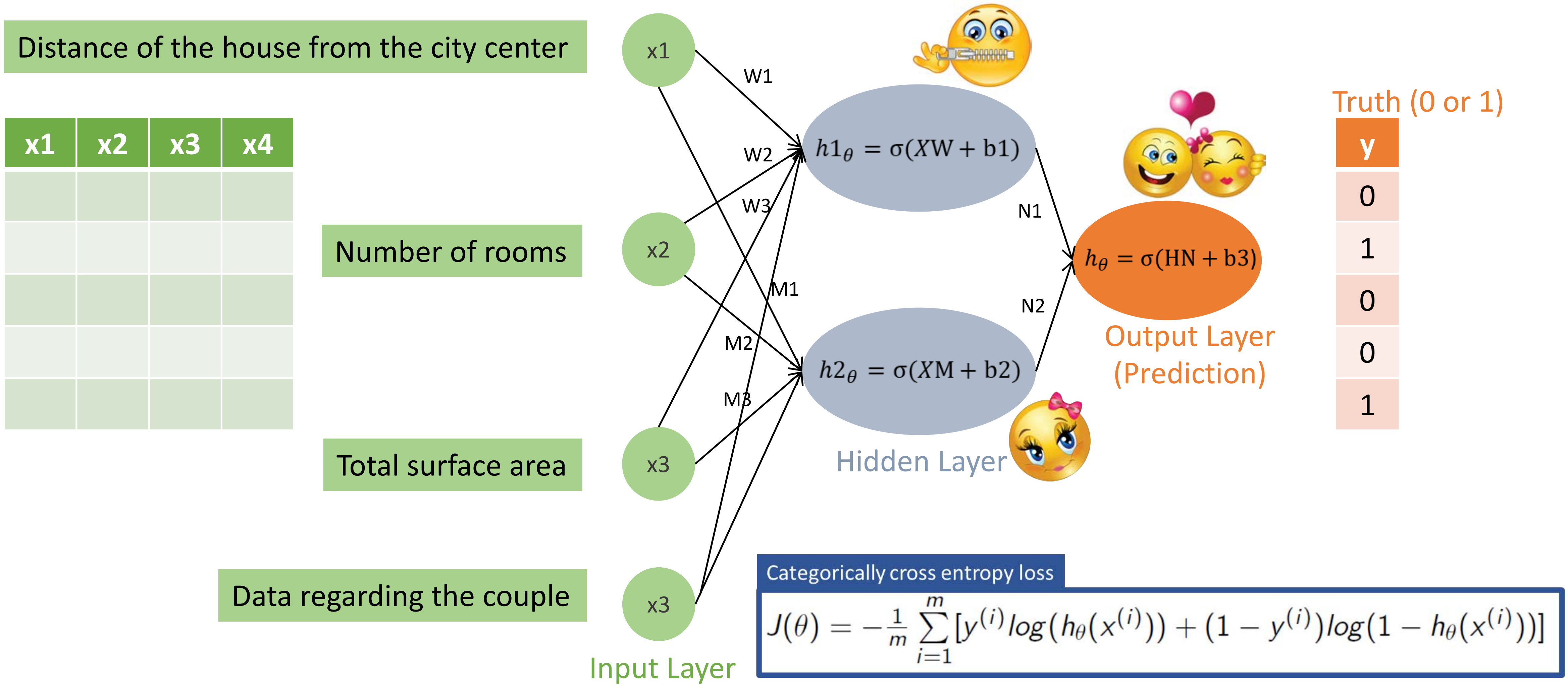
Logistic Regression



92% accuracy

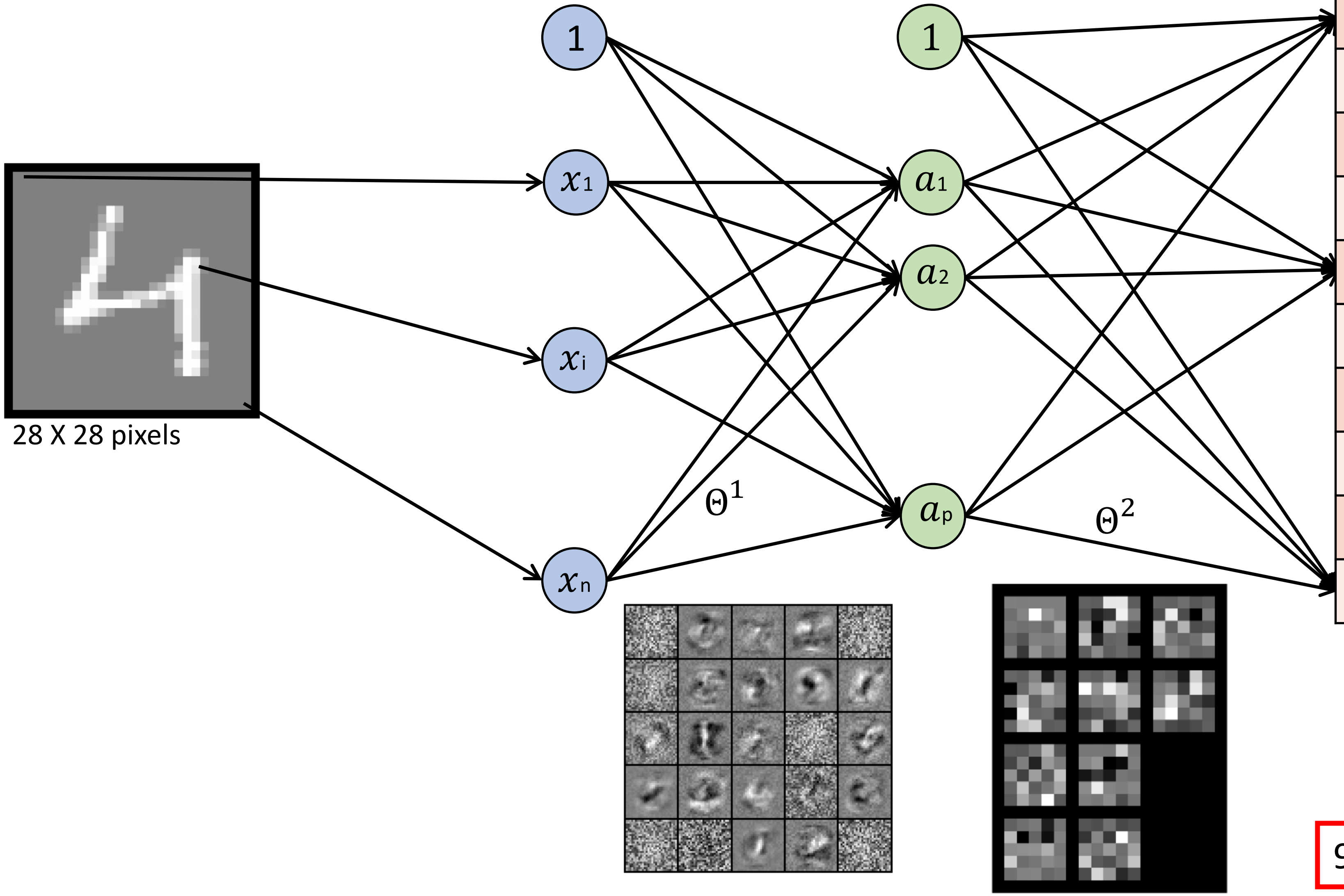
https://github.com/adil-rasheed/TK8117/blob/master/Lecture1/MultiClassLogisticRegression.ipynb

Artificial Neural Networks



https://github.com/adil-rasheed/TK8117/blob/master/Lecture1/Aritifial_Neural_Network.ipynb

Shallow neural network



Prediction	1-Hot-Encode	Label
0.05	0	0
0.01	0	1
0.02	0	2
0.05	0	3
0.8	**1**	**4**
0.1	0	5
0.04	0	6
0.01	0	7
0.04	0	8
0	0	9

96% accuracy

https://github.com/adil-rasheed/TK8117/blob/master/Lecture1/Aritificial_Neural_Network.ipynb

Deep Neural Networks

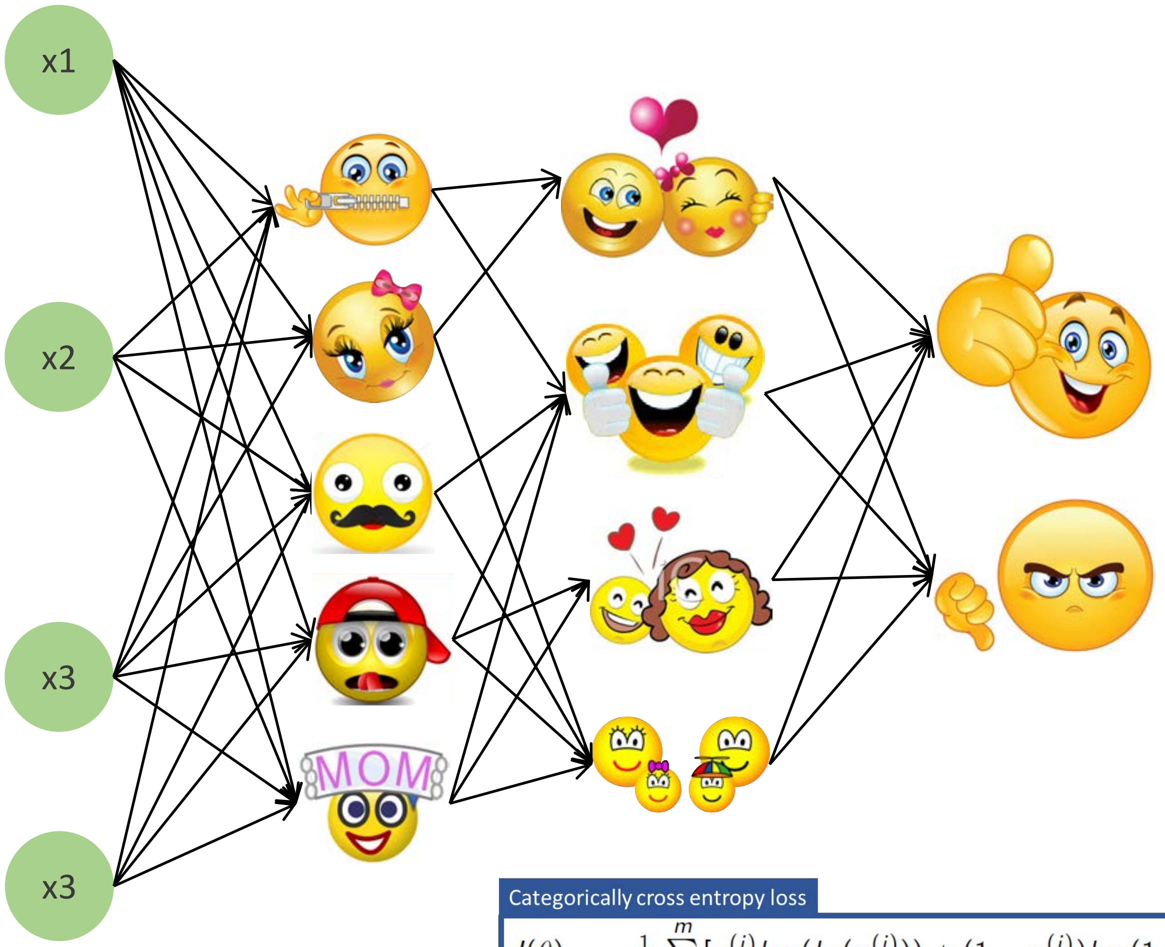
Distance of the house from the city center

x1	x2	x3	x4

Number of rooms

Total surface area

Data regarding the couple



Input Layer

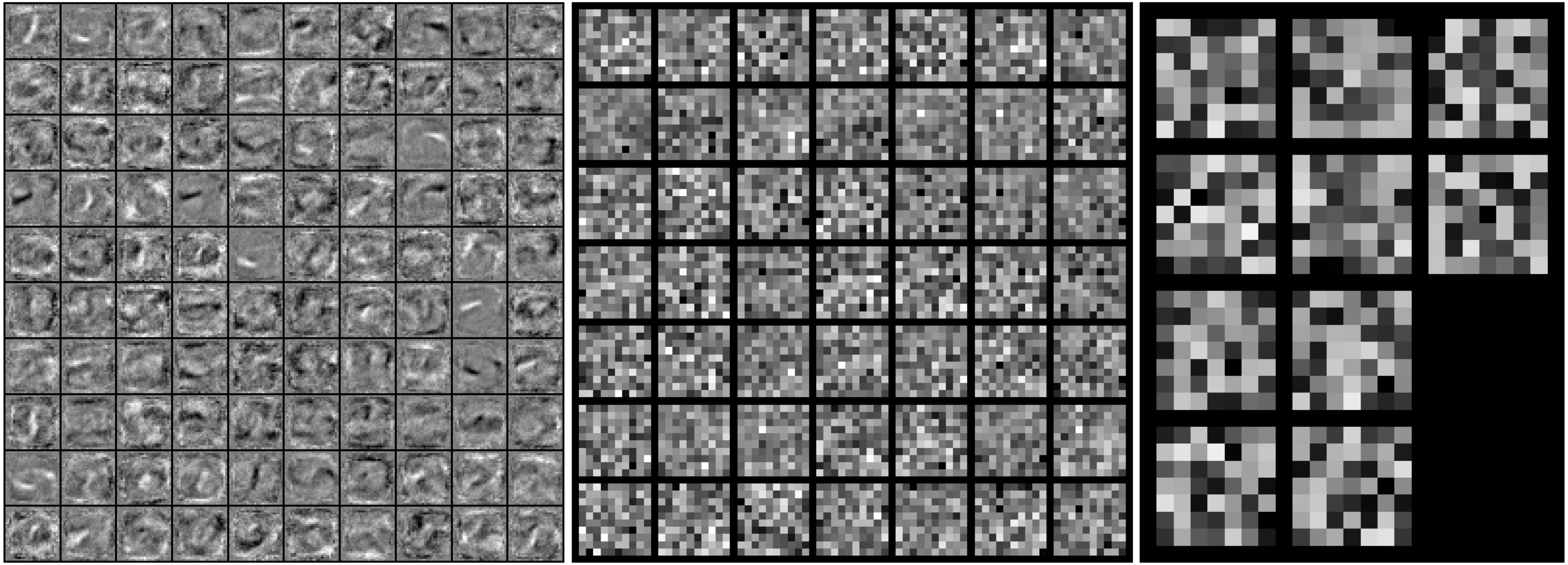
Truth

y
0
1
0
0
1

Categorically cross entropy loss

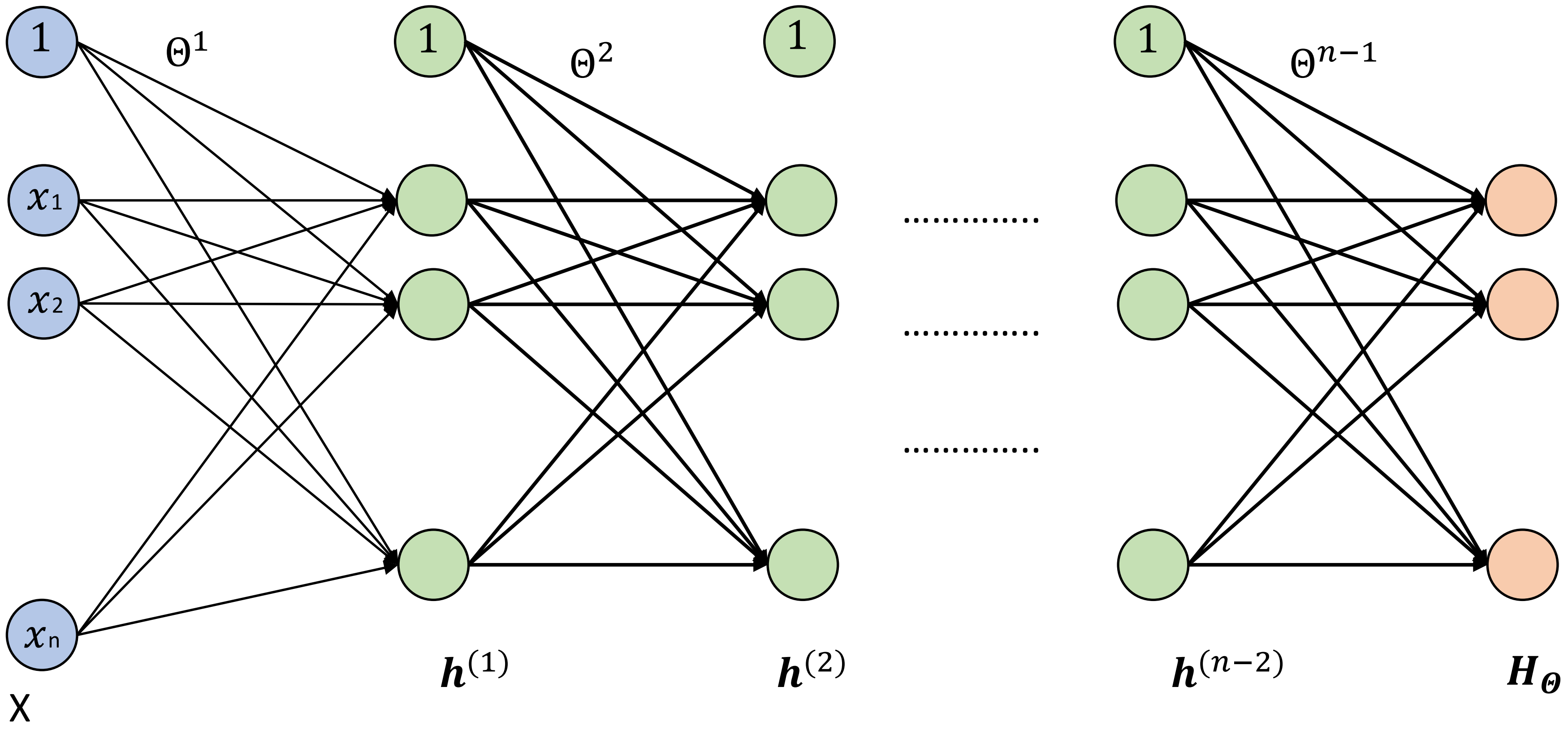
$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^{(i)}log(h_\theta(x^{(i)})) + (1-y^{(i)})log(1-h_\theta(x^{(i)}))]$$

How the weights look



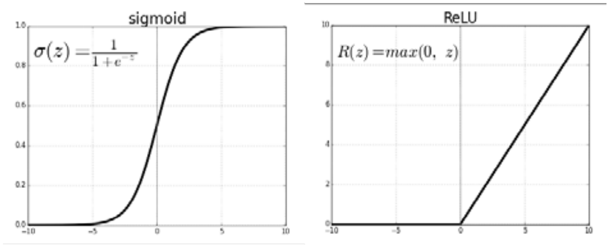
98% accuracy on the validation data

https://github.com/adil-rasheed/TK8117/blob/master/Lecture1/Aritifial_Neural_Network.ipynb



$p^{(i)}$ number of nodes in the ith layer

K = number of nodes in the output layer



σ

$$\mathbf{X} = [\mathbf{1}\ \mathbf{X}]$$
$$\mathbf{h}^{(1)} = \sigma(\mathbf{X}\boldsymbol{\Theta}^{\mathbf{1}})$$
$$\mathbf{h}^{(1)} = [\mathbf{1}\ \ \mathbf{h}^{(1)}]$$
$$\mathbf{h}^{(2)} = \sigma(\mathbf{h}^{(1)}\boldsymbol{\Theta}^{\mathbf{2}})$$
$$\mathbf{h}^{(2)} = [\mathbf{1}\ \ \mathbf{h}^{(2)}]$$
$$\mathbf{h}^{(3)} = \sigma(\mathbf{h}^{(2)}\boldsymbol{\Theta}^{\mathbf{3}})$$
$$\vdots$$
$$\mathbf{h}^{(n-2)} = \sigma(\mathbf{h}^{(n-3)}\boldsymbol{\Theta}^{\mathbf{n-2}})$$
$$\mathbf{h}^{(n-2)} = [\mathbf{1}\ \ \mathbf{h}^{(\mathbf{n-2})}]$$
$$\mathbf{H}_\Theta = \sigma(\mathbf{h}^{(n-2)}\boldsymbol{\Theta}^{\mathbf{n-1}})$$

$$J(\Theta) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{K}\left[y_k^{(i)} log(H_\Theta(x^{(i)})_k) + (1 - y_k^{(i)}) log(1 - H_\Theta(x^{(i)})_k)\right]$$

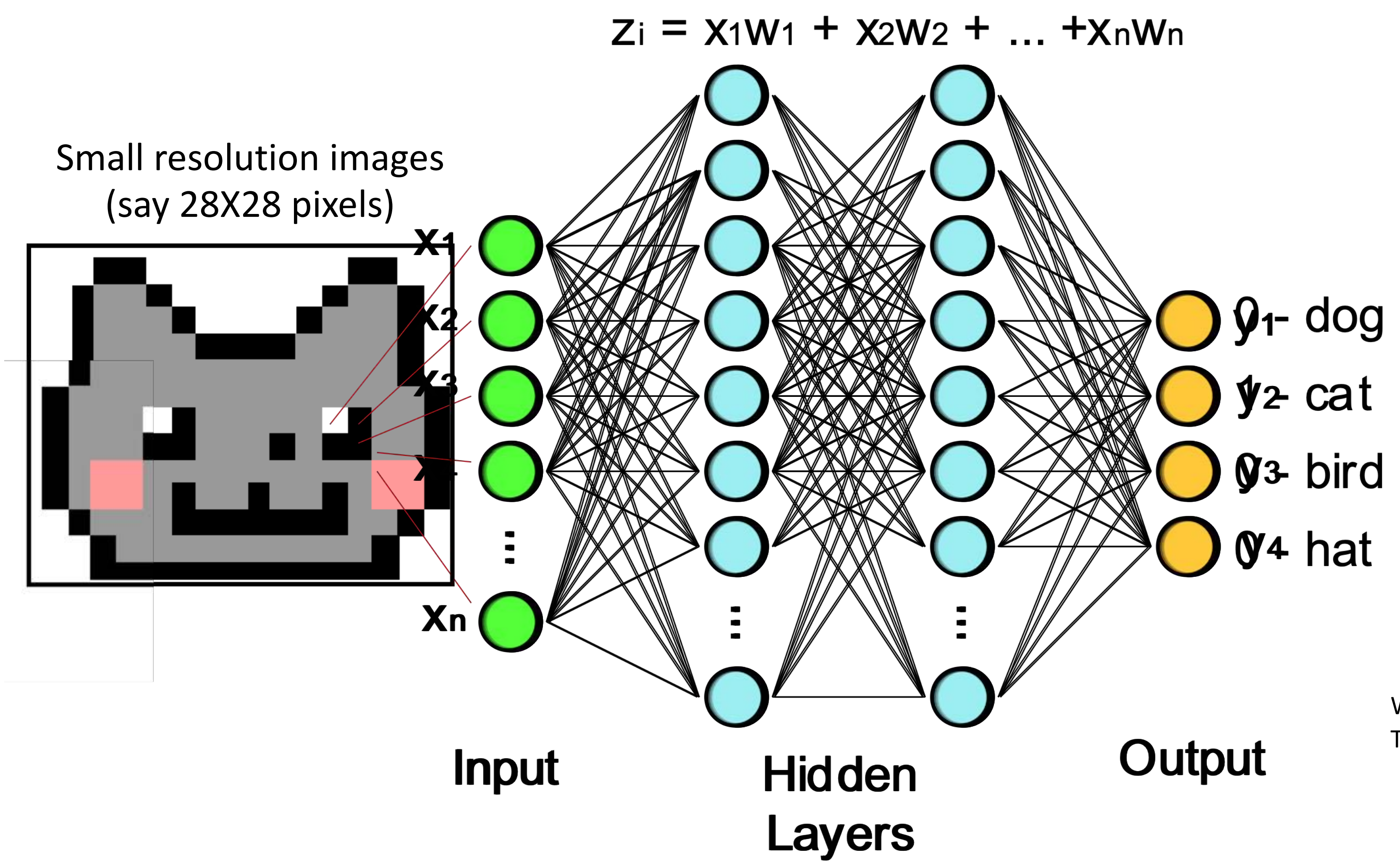
$$J(\Theta) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{K}\left[(y_k^{(i)} - H_\Theta(x^{(i)})_k)^2\right]$$

Minimize the function using Back Propagation

$$J(\Theta) = J(\Theta) + \boxed{\frac{\lambda}{2m}\sum_{i=1}^{n}\sum_{j=1}^{p^{(i)}-1}\sum_{q=1}^{p^{(i)}}(\Theta_{q,j}^{i})^2}$$

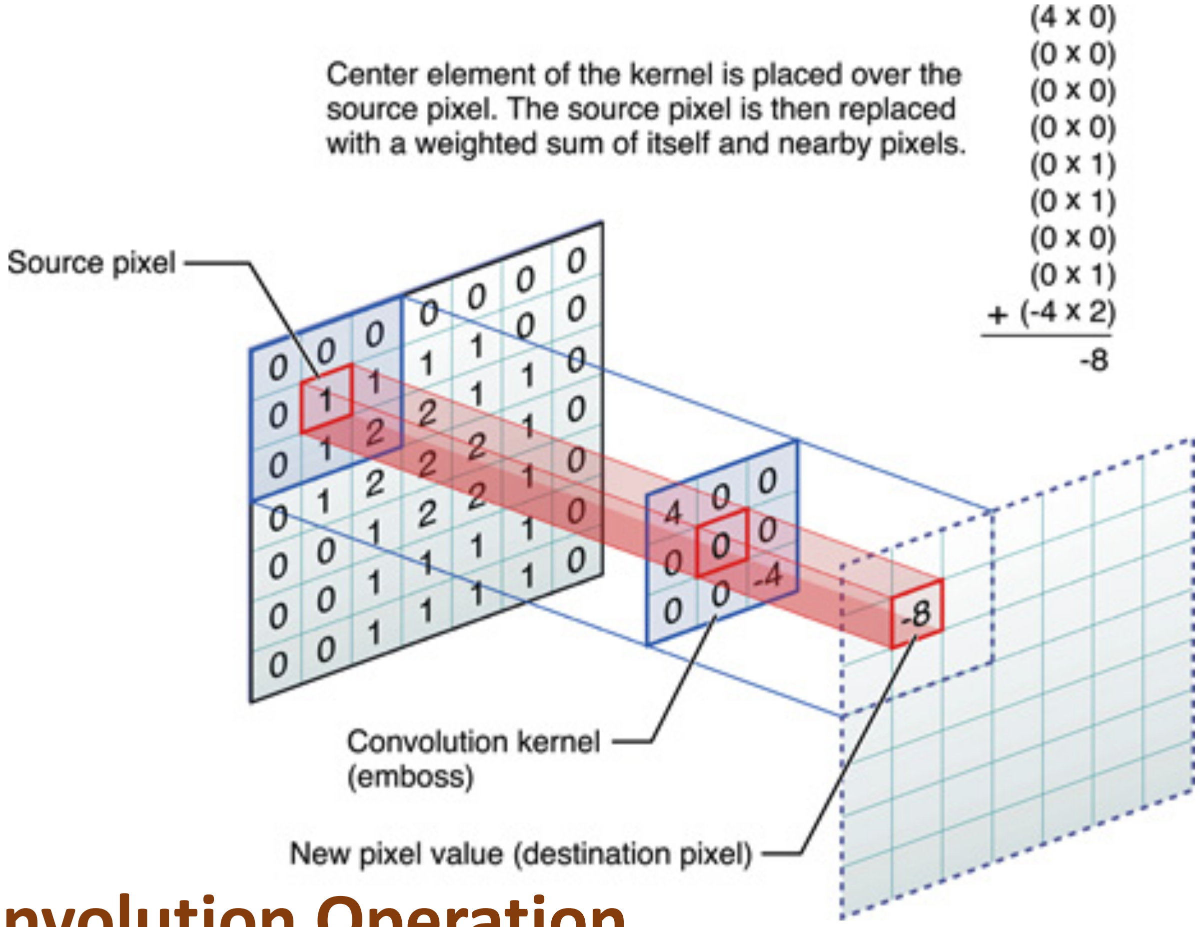
Regularization

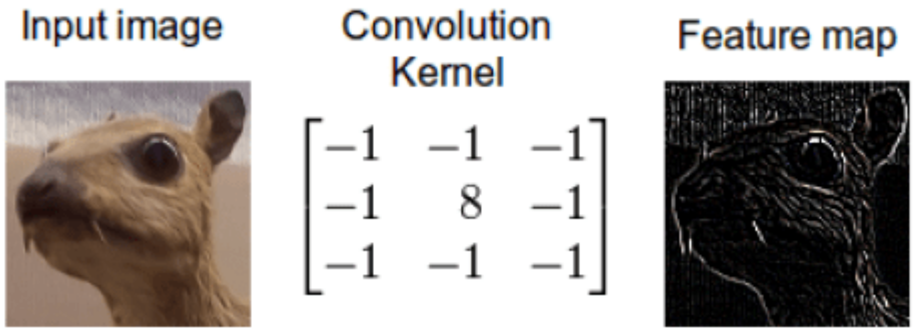
Algorithms: Deep Neural Networks



What to do when each image has millions of pixels
Thousands of images too ☹

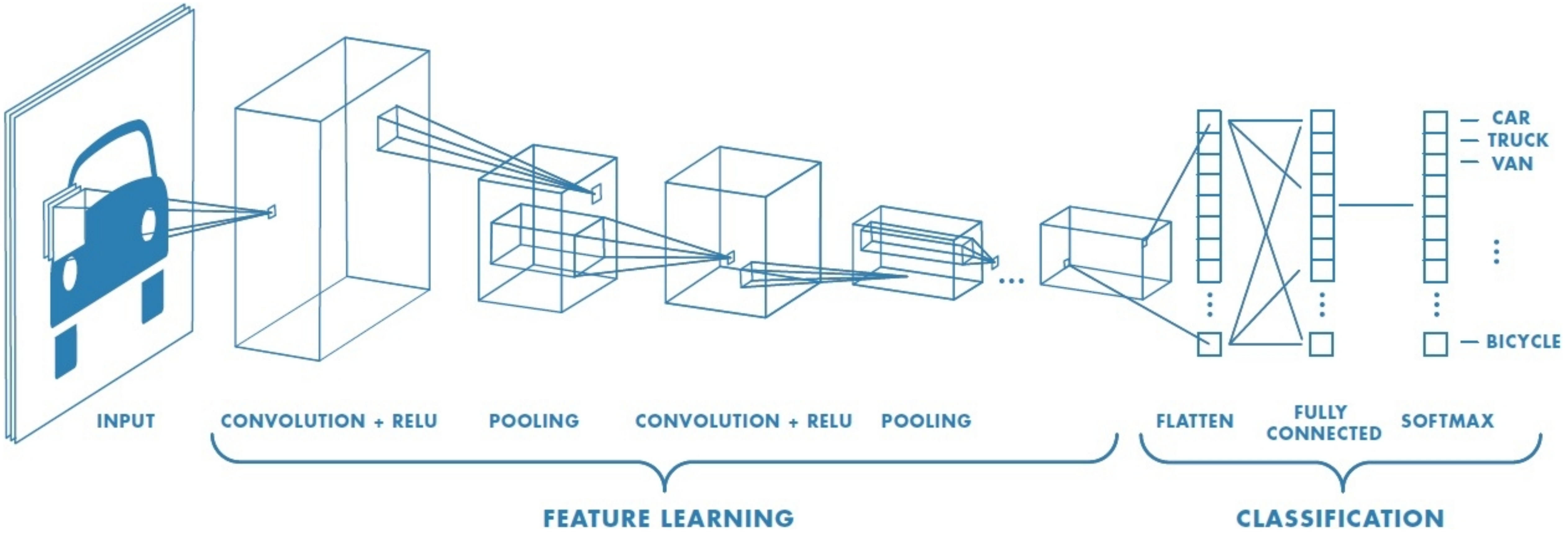
Algorithms: Convolution Neural Networks (CNN)





Convolution Operation

Convolutional Neural Network



Step by step guide to painting

- Step 1: Blocking big shapes (shadows)
- Step 2: Adding recognizable components (eyes)
- Step 3: Adding details (hair, skin texture etc.)

What does CNN do ?

Input image
(RGB channels)

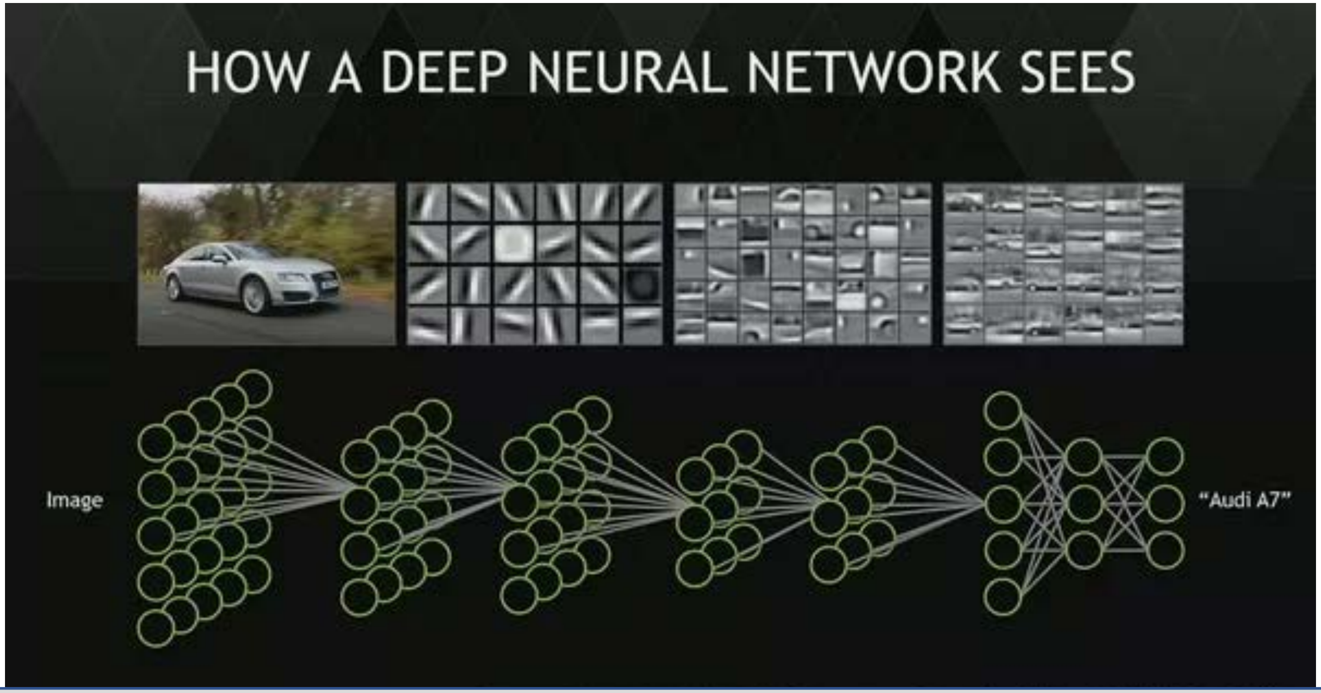
1st Layer

2nd Layer

3rd Layer

https://github.com/adil-rasheed/TK8117/blob/master/Lecture1/CNN-CatsVsDogs.ipynb

Algorithms: Understanding CNN



More complex features the deeper the network

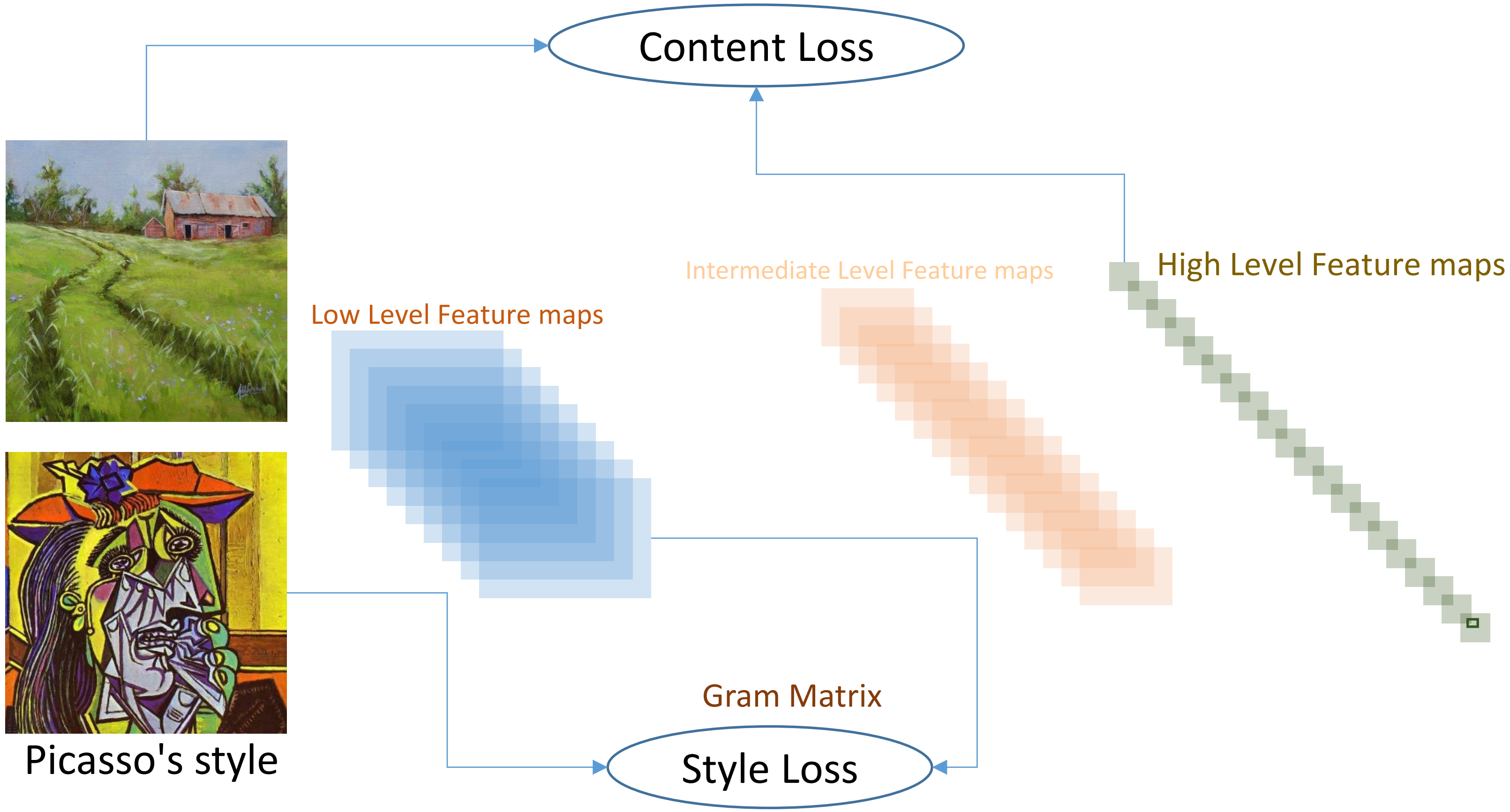
Level 0:
- Horizontal edges
- Vertical edges
- Mean values
- …

Level 1:
- Circles
- Boundaries
- Triangles
- …

Level 2:
- Windows
- Wheels
- Doors
- …

Level n:
- Car
- Truck
- Bus
- …

Style Transfer: Interpretation of the layers in CNN



$$\mathcal{L}_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{content}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{style}(\vec{a}, \vec{x})$$

p, a, x are the representations of the content, style and generated images

How to paint in the style of a famous painter ? Try prisma app on mobile.

Validation of the interpretation

My painting

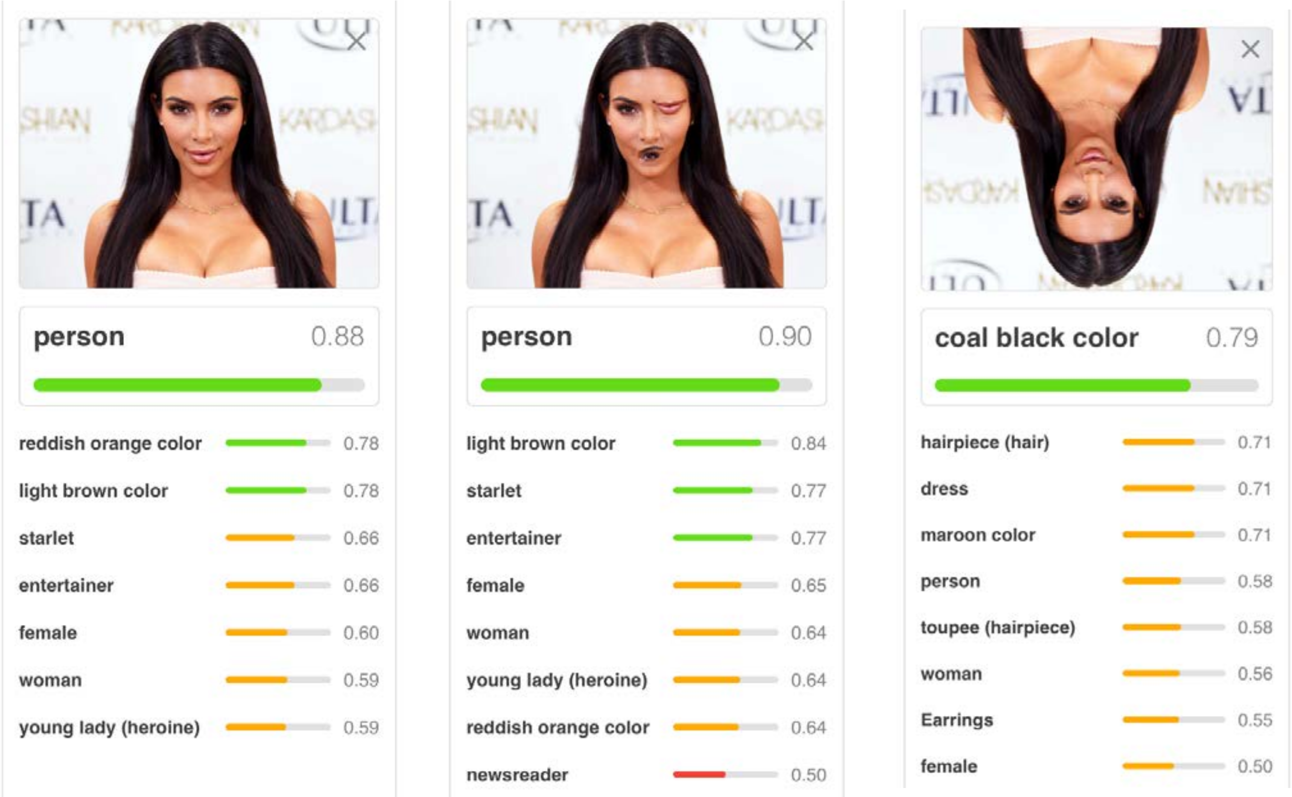
Picasso's painting

Style transferred painting

The resulting output has the content of my painting and the style of Picasso

Problems with CNN

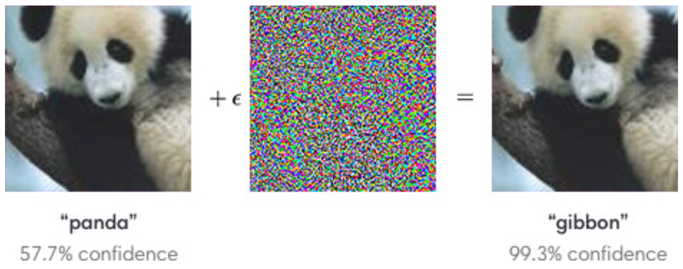
Maxpooling causes spatial invariance.
To make CNNs work we need to train the model with large number of transformed images.



Algorithms: Problems with CNN (Pixel Attack)

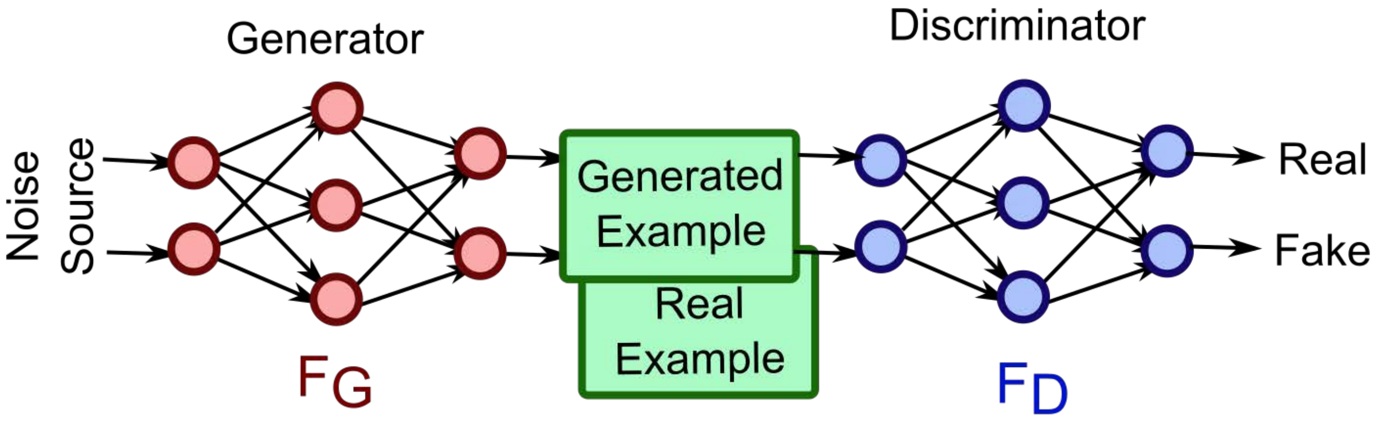
Recent research has revealed that the output of Deep Neural Networks (DNN) can be easily altered by adding relatively small perturbations to the input vector. In this paper, we analyze an attack in an extremely limited scenario where only one pixel can be modified. For that we propose a novel method for generating one-pixel adversarial perturbations based on differential evolution. It requires less adversarial information and can fool more types of networks. The results show that 70.97% of the natural images can be perturbed to at least one target class by modifying just one pixel with 97.47% confidence on average. Thus, the proposed attack explores a different take on adversarial machine learning in an extreme limited scenario, showing that current DNNs are also vulnerable to such low dimension attacks.

[*https://arxiv.org/pdf/1710.08864.pdf*](https://arxiv.org/pdf/1710.08864.pdf)



Goodfellow 2014 showed that one of the primary causes of this is excessive linearity.

Algorithms: Generative Adversarial Network



Invented by Ian Goodfellow, 2014

GANs is the most interesting idea in the last 10 years in ML
Yan Le cunn, Director Facebook

In a GANs solve a problem by training two separate networks with competitive goals.

- one network produces answers (generative)
- another network distinguishes between the real and the generated answers (adversarial)

The concept is to train these networks competitively, so that after some time, neither network can make further progress against the other. Or the generator becomes so effective that the adversarial network can not distinguish between real and synthetic solutions, even with unlimited time and substantial resources.

Trained a Conditional adversarial nets on NVIDIA GEFORCE 1080 Ti for 10 hours on 2000 images to come up with a model that can convert any grayscale image to its colored version.

Some other applications

- Converting summer scenes to winter
- Landscape images to sea scapes
- Convert boats into ships

Missing Pixels

Computer Generated

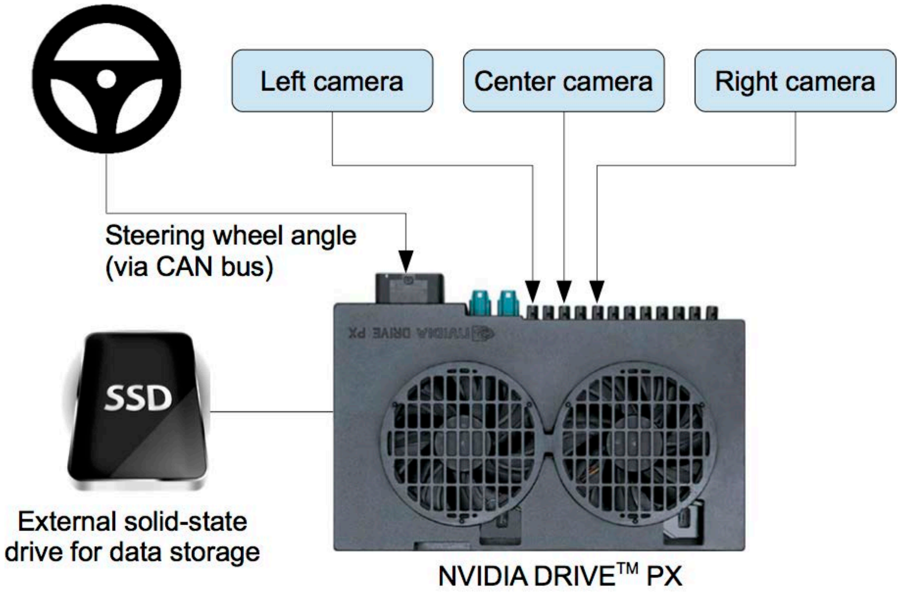
Original

Outline
Computer generated
Original

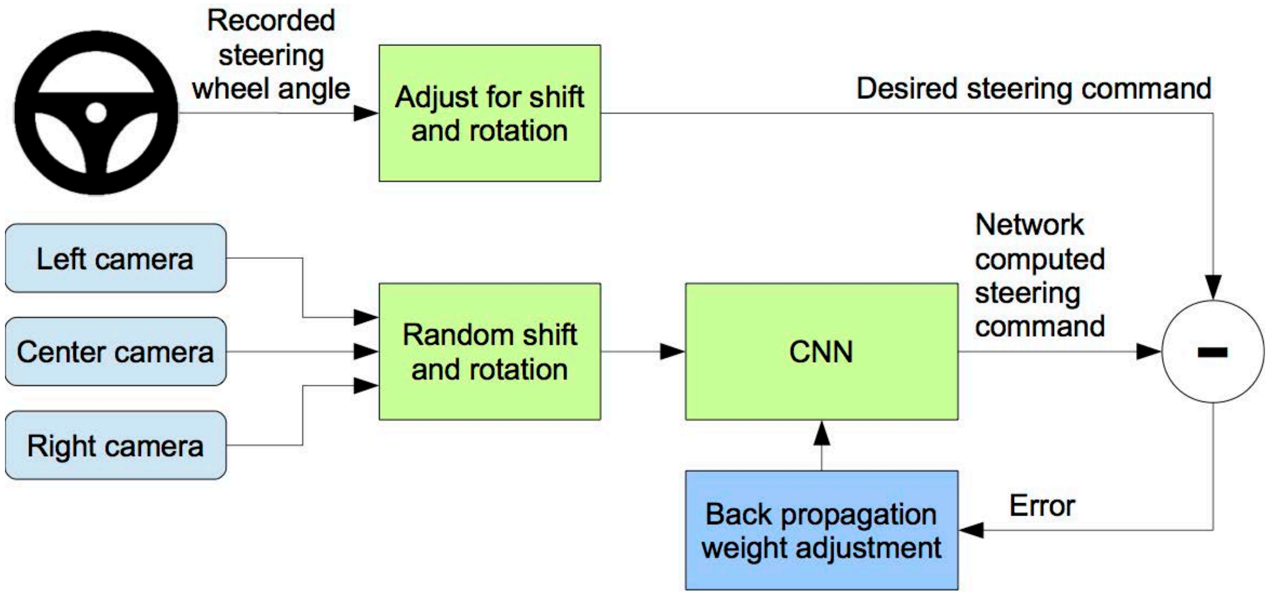
Algorithm: GANS for Content transformation

[Jun-Yan Zhu](Jun-Yan Zhu) et al

Behavioral Cloning: Mimicking behavior

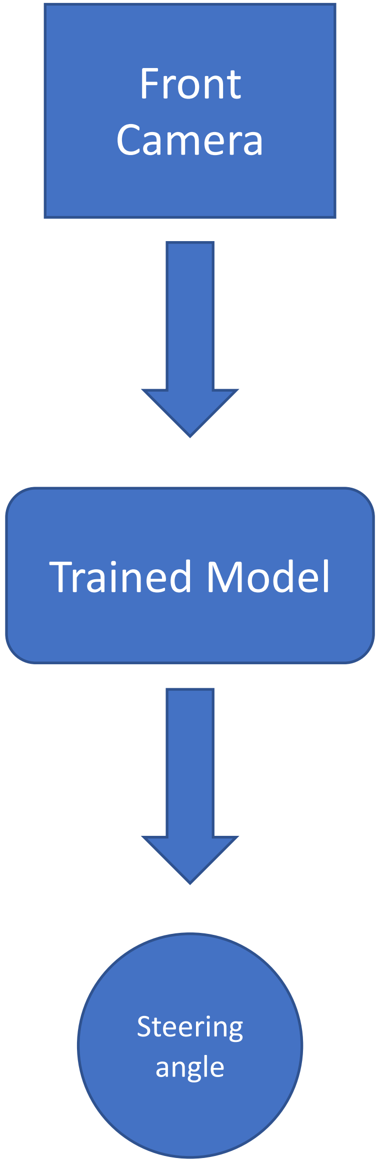


Hardware design

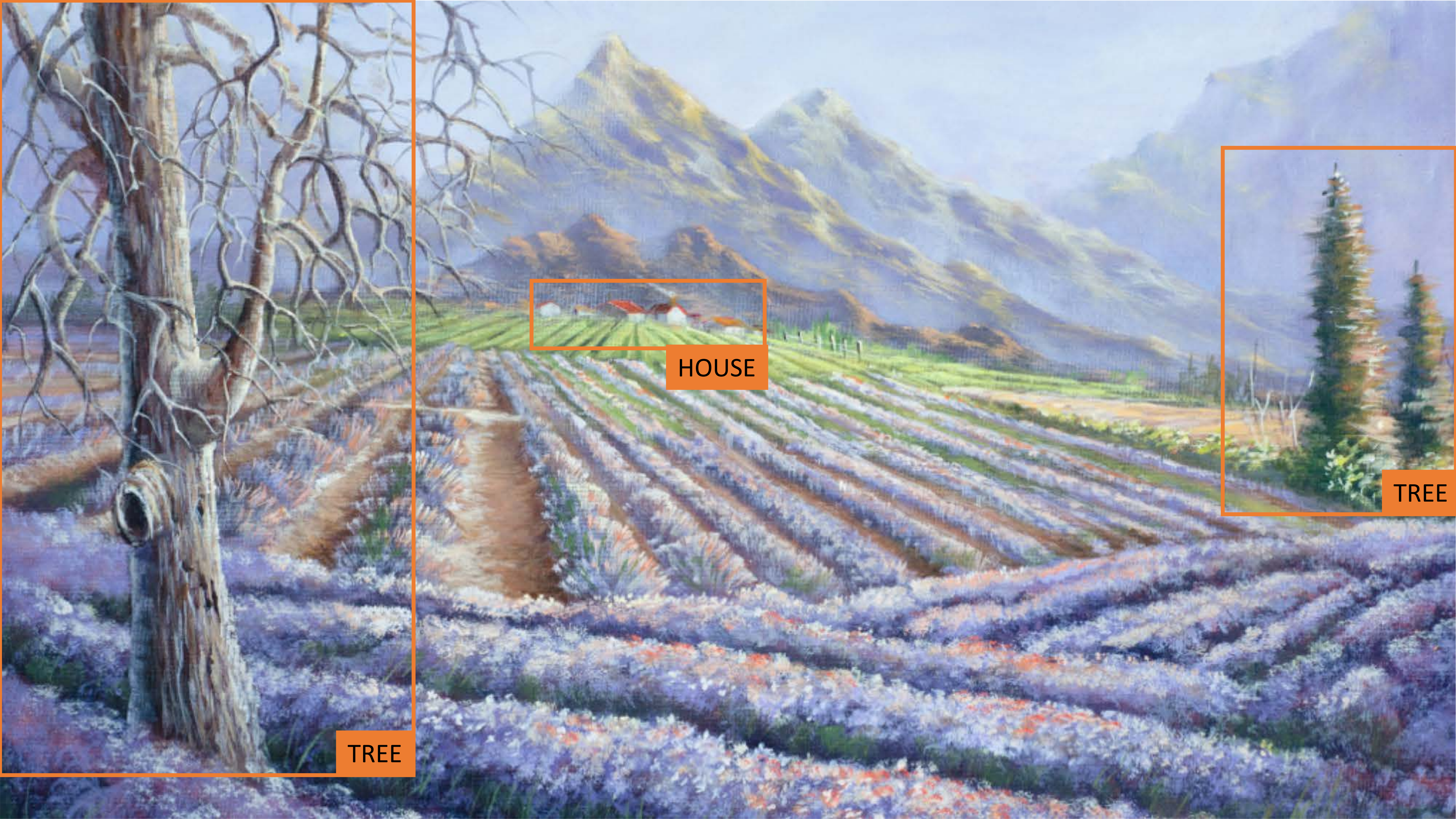


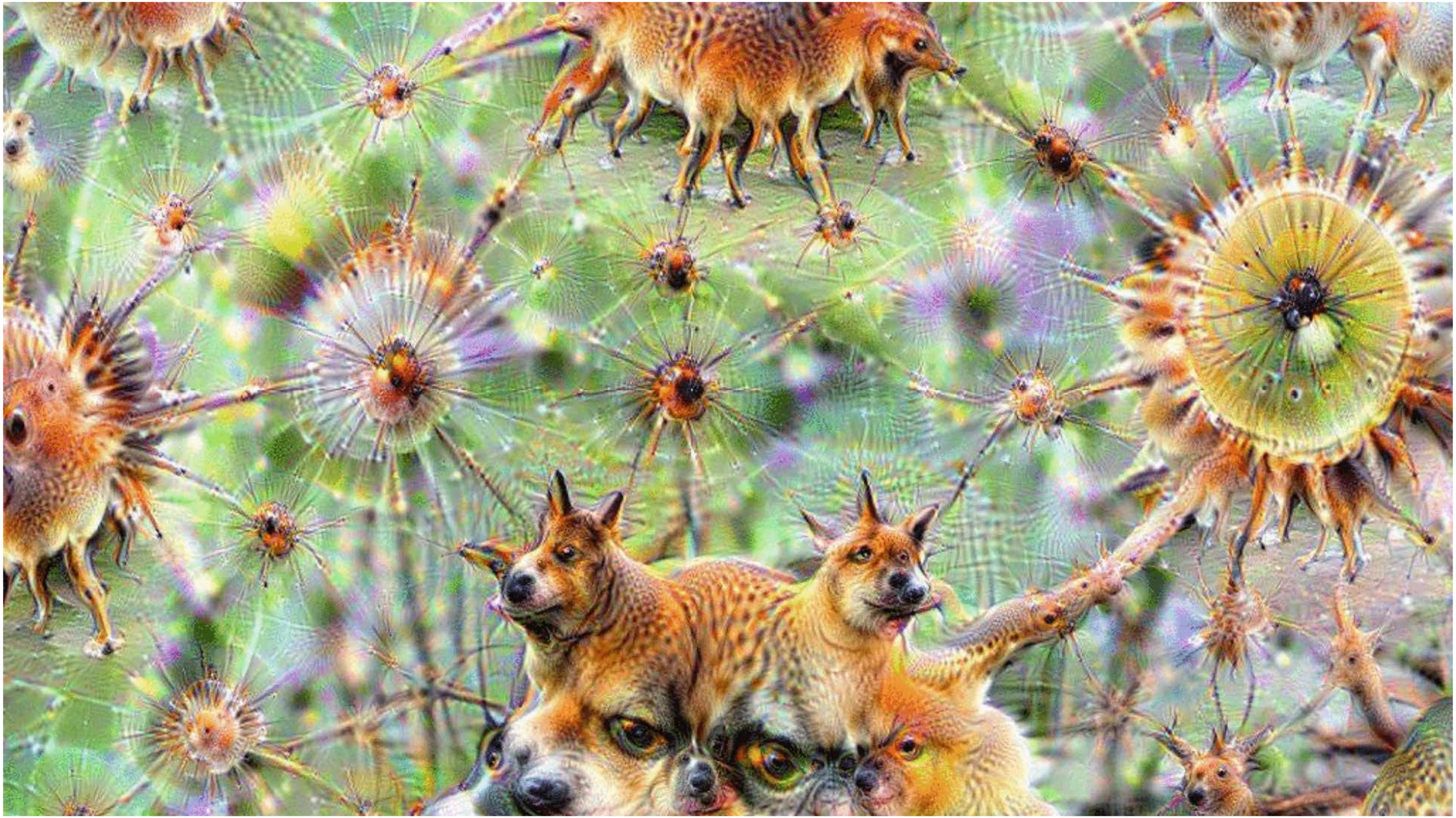
Software design

Self driving cars

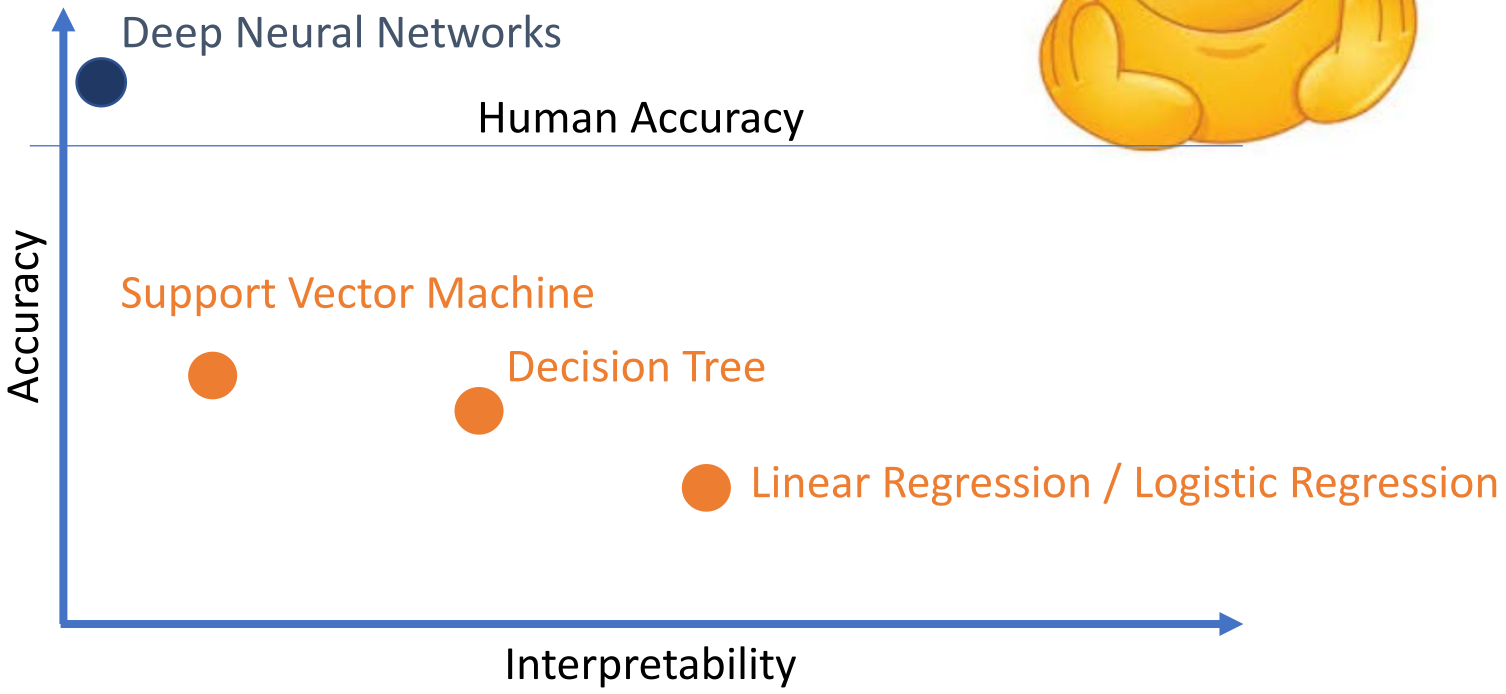


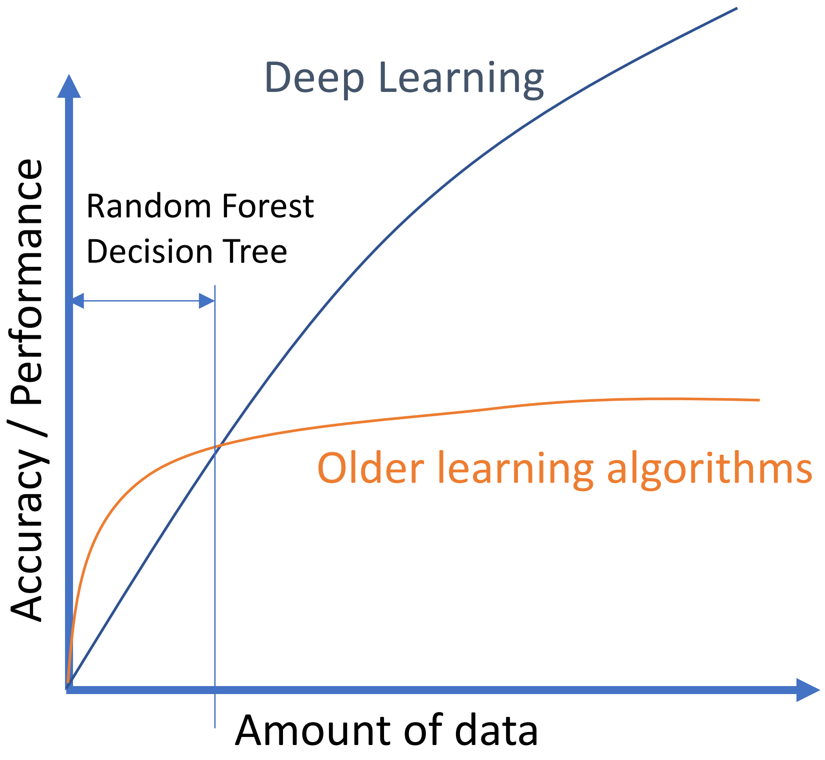
Udacity's opensource simulator


HOUSE
TREE
TREE



Accuracy vs Interpretability & Scalability





Physics based modelling vs Data driven Modeling

Physics based Modeling

+ Solid foundation based on physics and reasoning

− Difficult to assimilate very long term historical data into the computational models

− Sensitive and susceptible to numerical instability due to a range of reasons (boundary condition, initial conditions, uncertainties in the input parameters)

+ Errors / Uncertainties can be bounded and estimated

+ Less biases

+ Generalizes well to new problems with similar physics

Data Driven ML

− So far most of the algorithms have worked as black boxes (low interpretability)

+ Takes into account long term historical data and experiences

+ Once the model is trained, it is very stable for making predictions

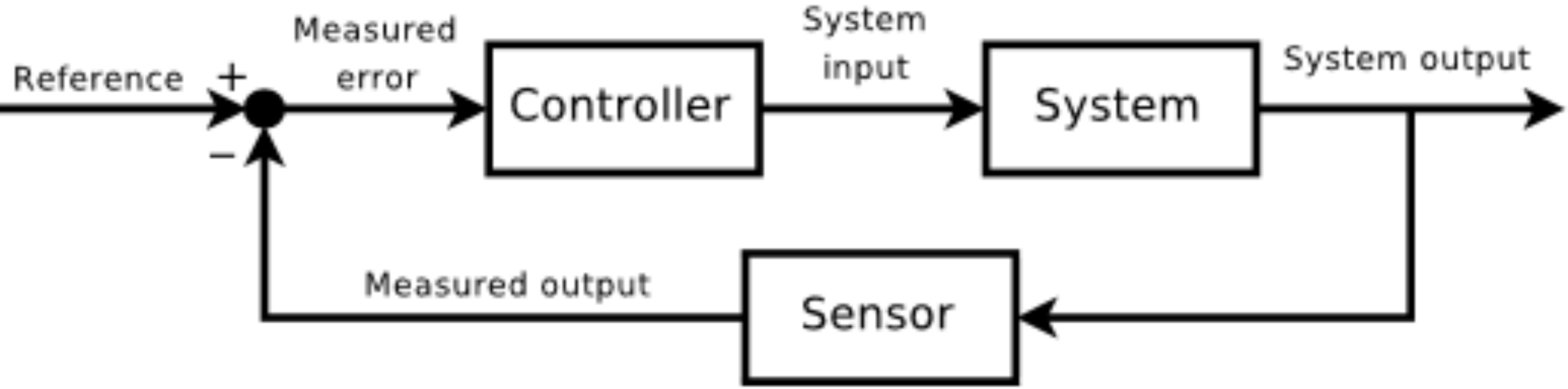
− Not possible to bound errors / uncertainties

− Bias in data is reflected in the prediction

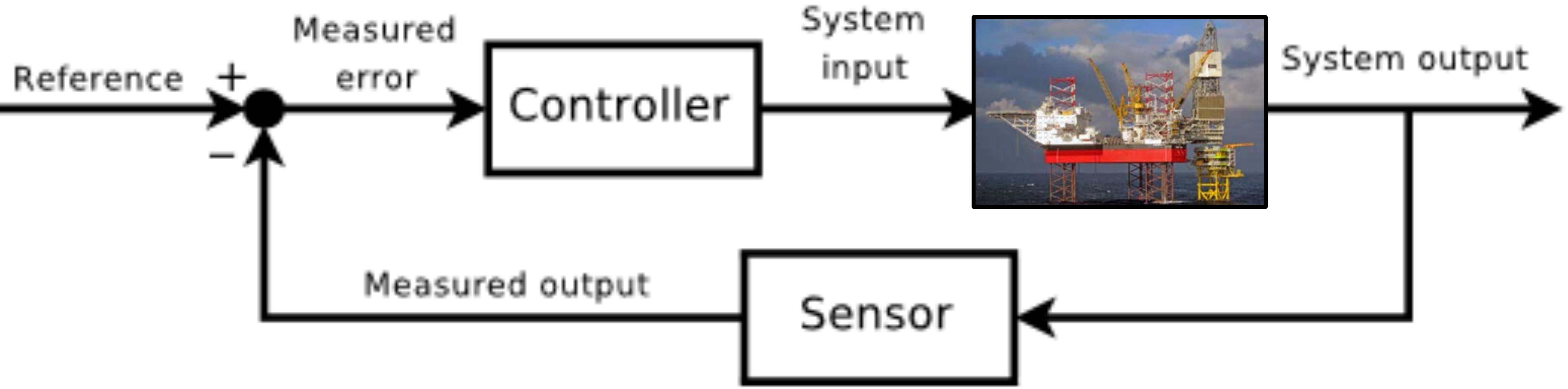
− Poor generalization on unseen problems

BIGDATACYBERNETICS

interpretable and transparent data analysis respecting physics and leveraging on domain knowledge



Modelling ***known*** **and** ***unknown*** **structures**
within the Framework of *Big Data Cybernetics*


Reference
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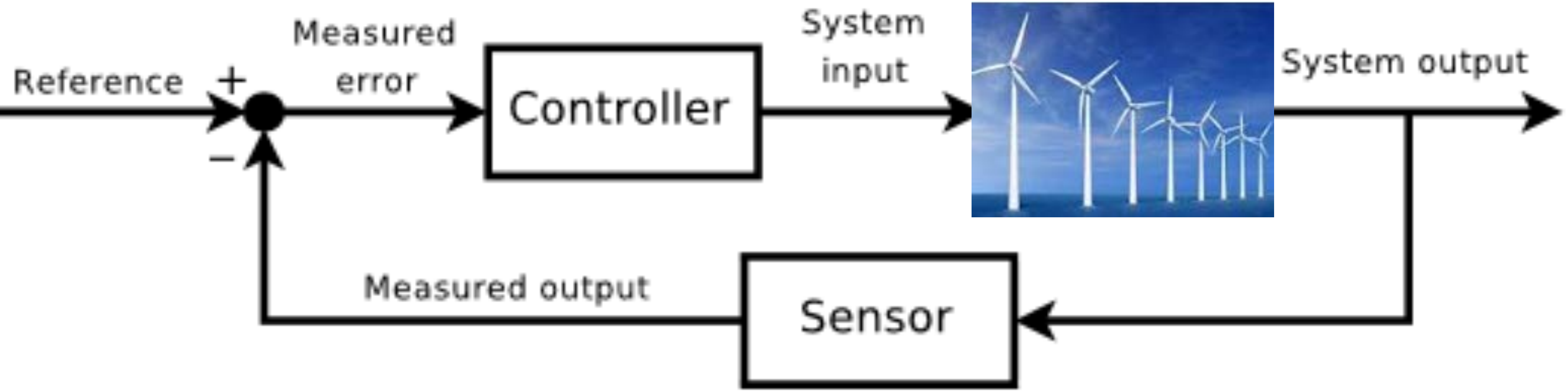
Measured
error
Controller
System
input
System output
Measured output
Sensor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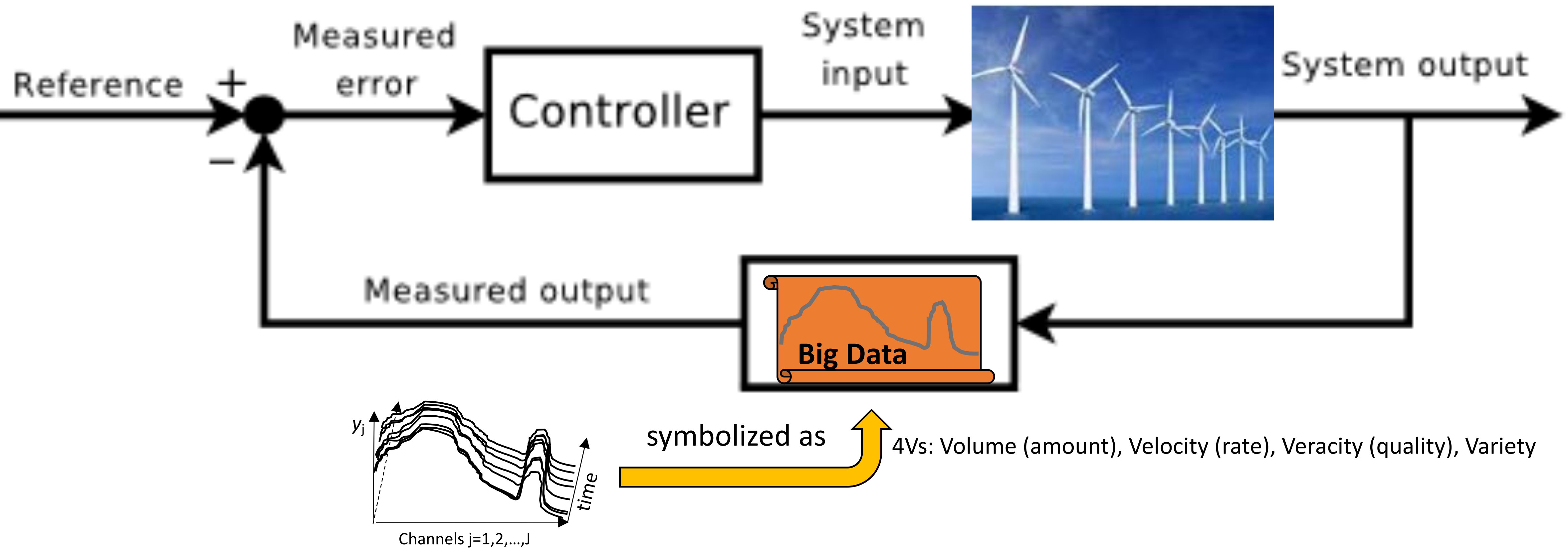

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System output
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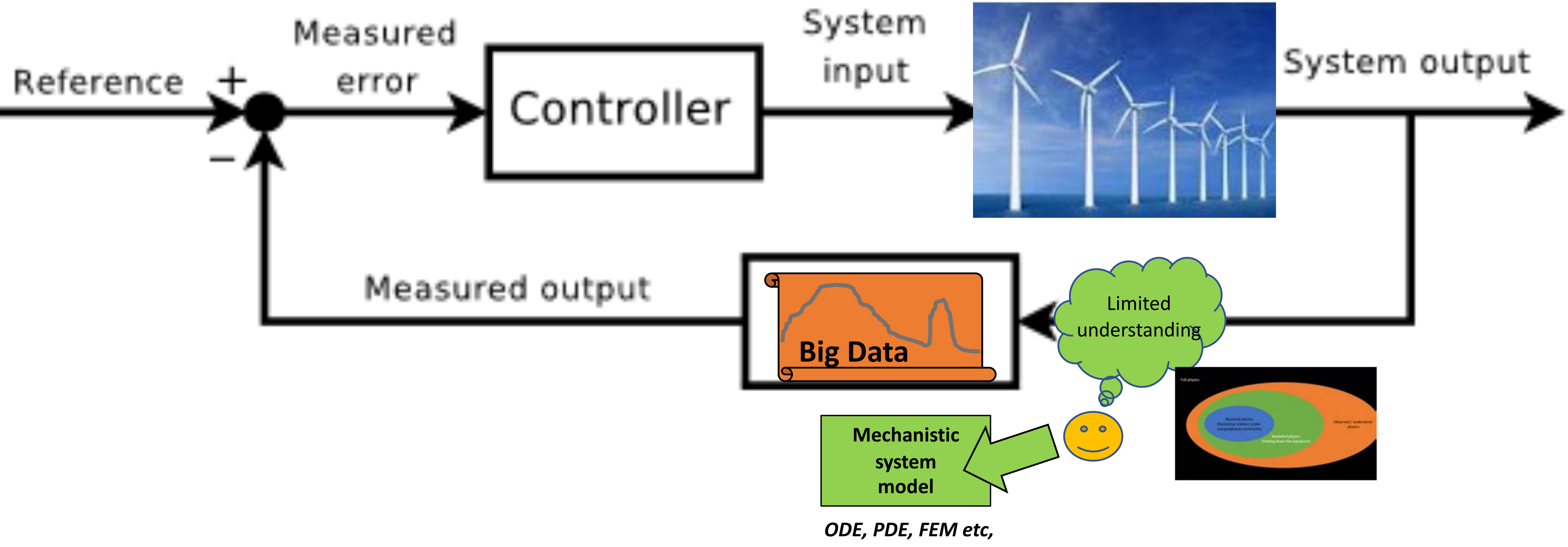
Big Data
y_j
time
Channels j=1,2,…,J
symbolized as
4Vs: Volume (amount), Velocity (rate), Veracity (quality), Variety



Reference
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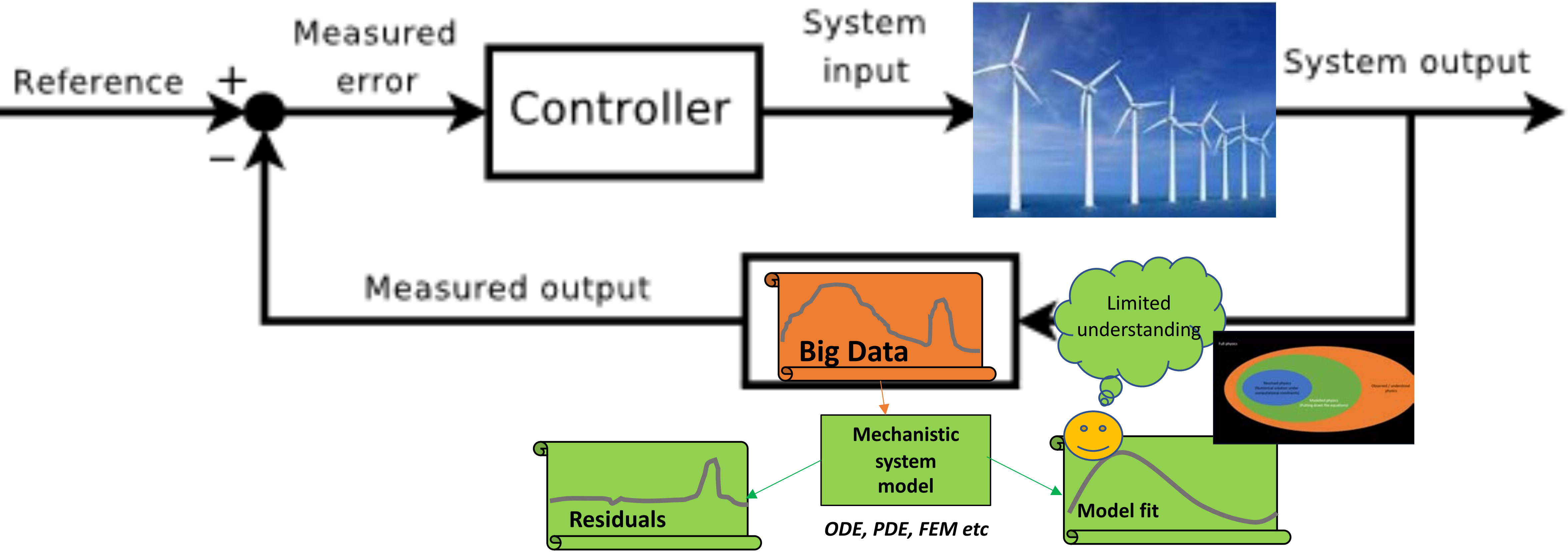
Big Data
Limited
understanding
Mechanistic
system
model
ODE, PDE, FEM etc,



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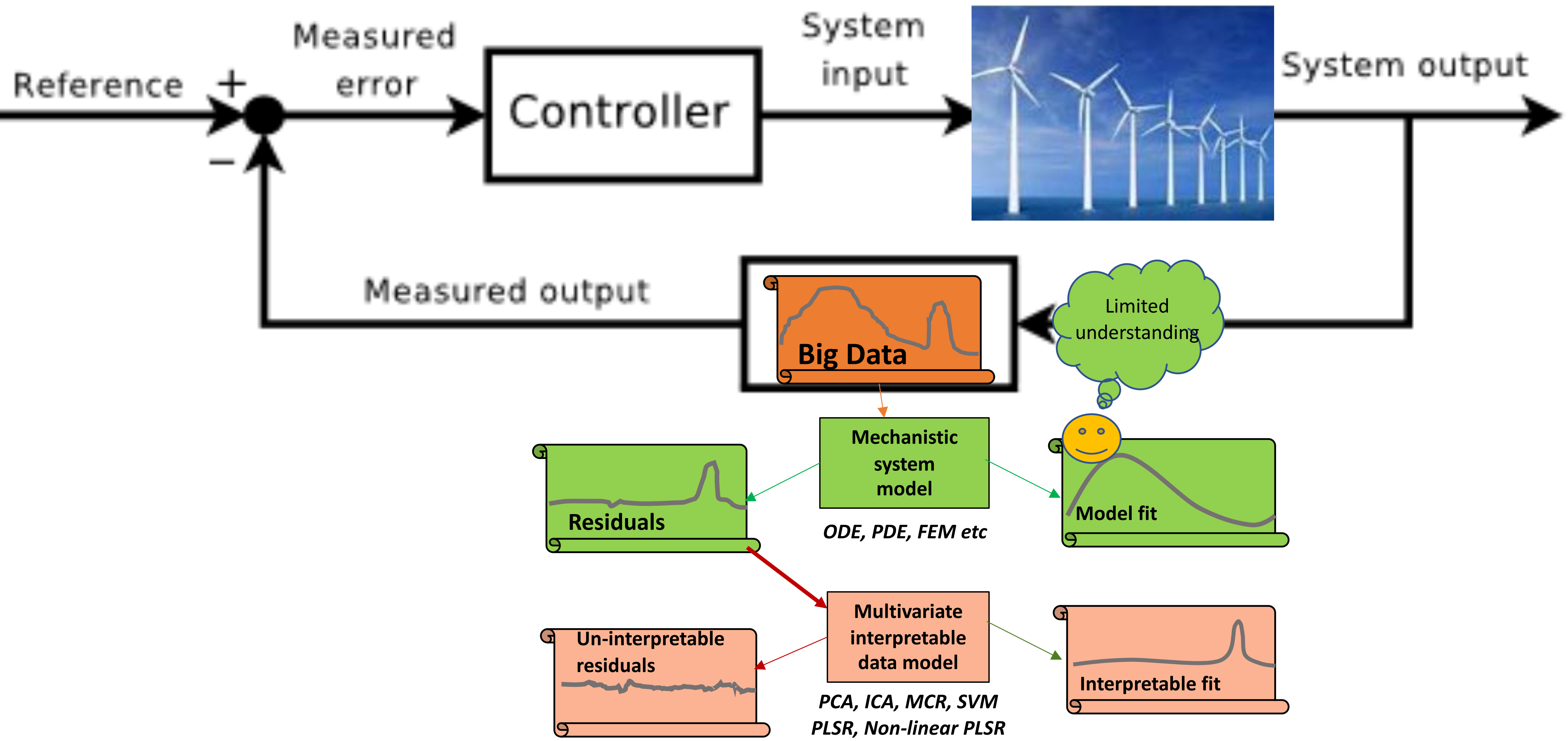
ODE, PDE, FEM etc
Residuals
Model fit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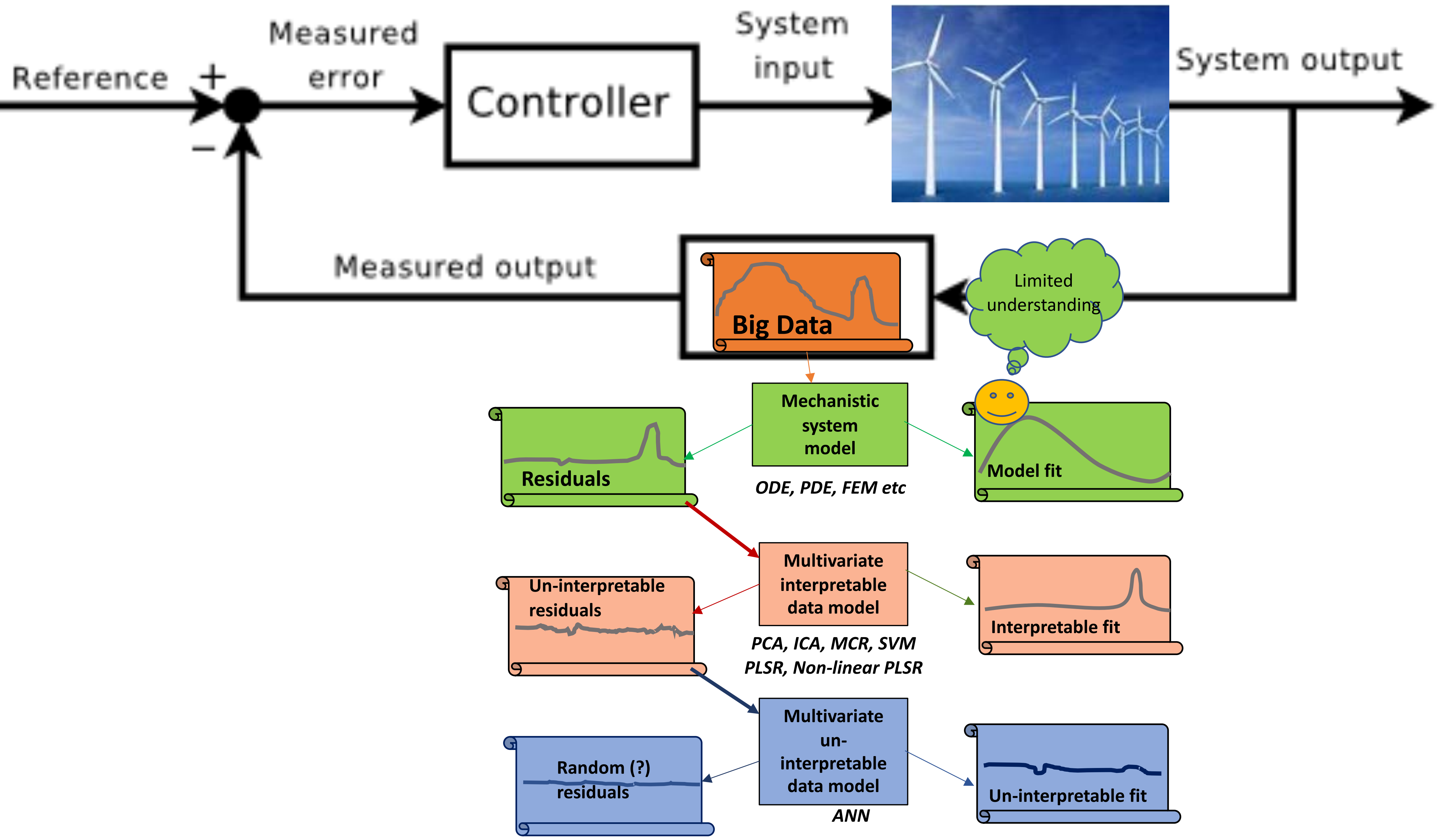
ODE, PDE, FEM etc
Residuals
Model fit
Multivariate
interpretable
data model
PCA, ICA, MCR, SVM
PLSR, Non-linear PLSR
Un-interpretable
residuals
Interpretable fit



Reference
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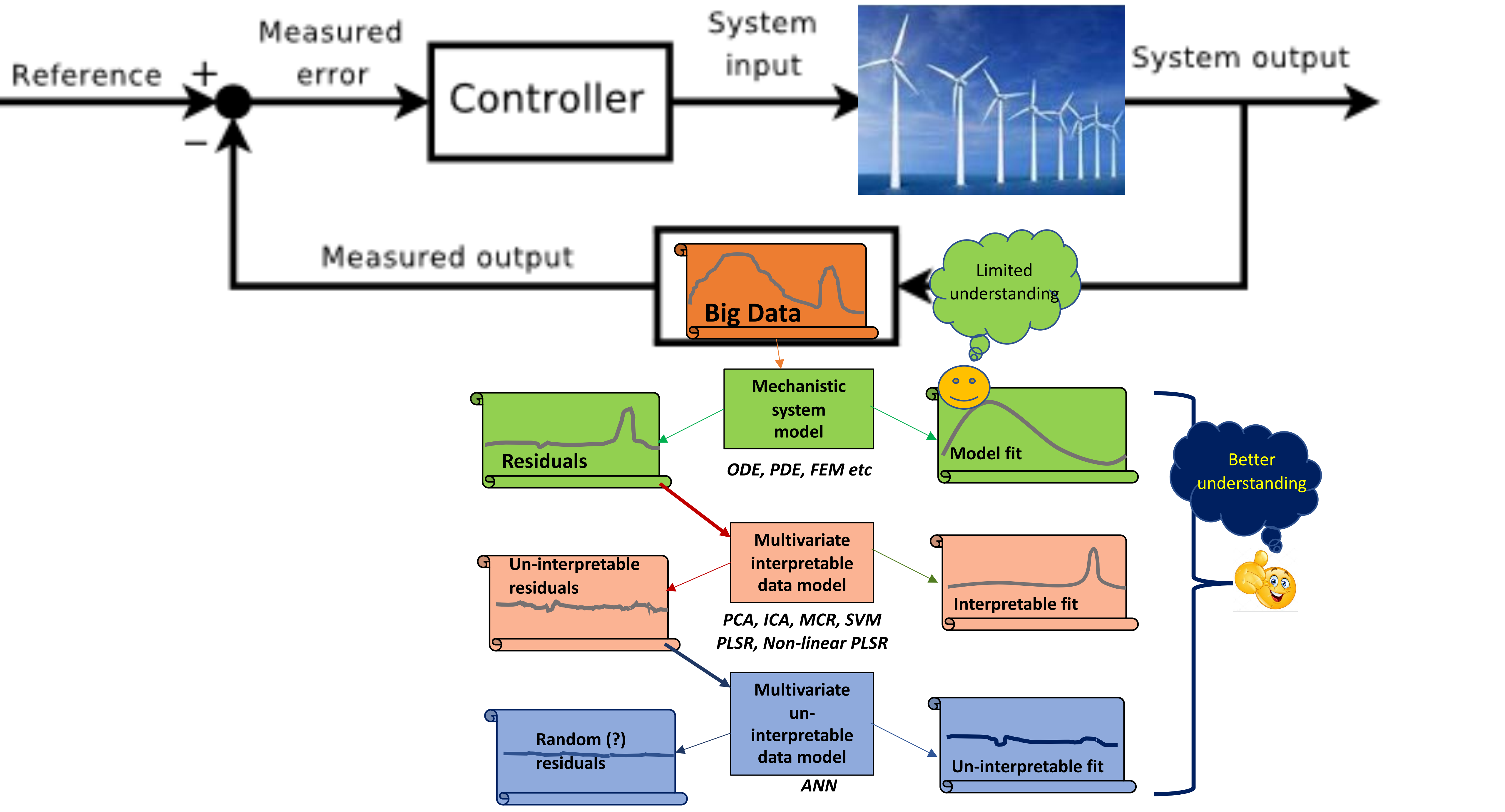
Measured error
Controller
System input
System output
Measured output
Big Data
Limited understanding
Mechanistic system model
ODE, PDE, FEM etc
Residuals
Model fit
Multivariate interpretable data model
PCA, ICA, MCR, SVM
PLSR, Non-linear PLSR
Un-interpretable residuals
Interpretable fit
Multivariate un-interpretable data model
ANN
Random (?) residuals
Un-interpretable fit



Reference
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System output
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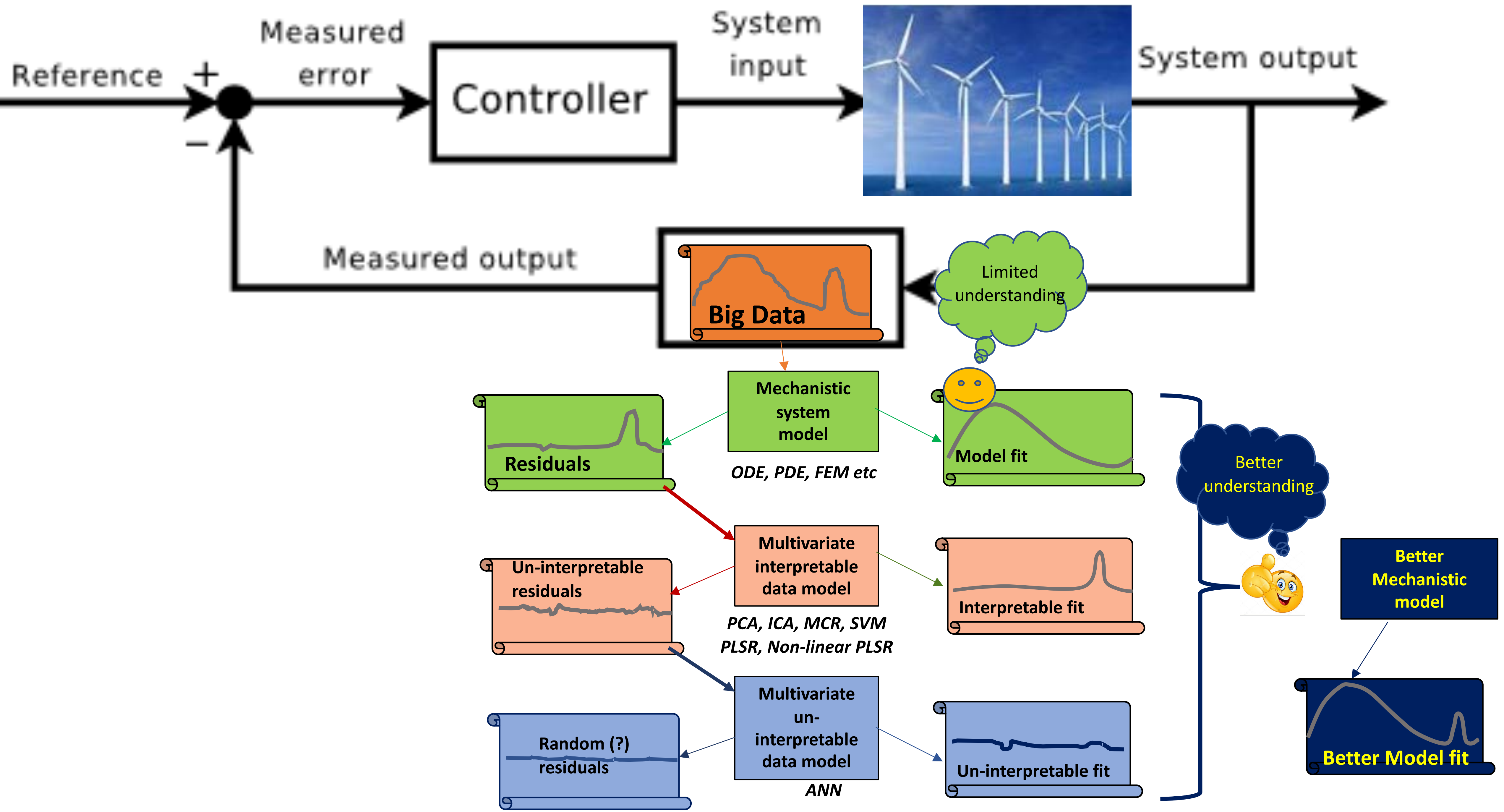
Random (?)
residuals
Un-interpretable fit



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Measured error
Controller
System input
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Measured output
Big Data
Limited understanding
Mechanistic system model
ODE, PDE, FEM etc
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Model fit
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Multivariate interpretable data model
PCA, ICA, MCR, SVM
PLSR, Non-linear PLSR
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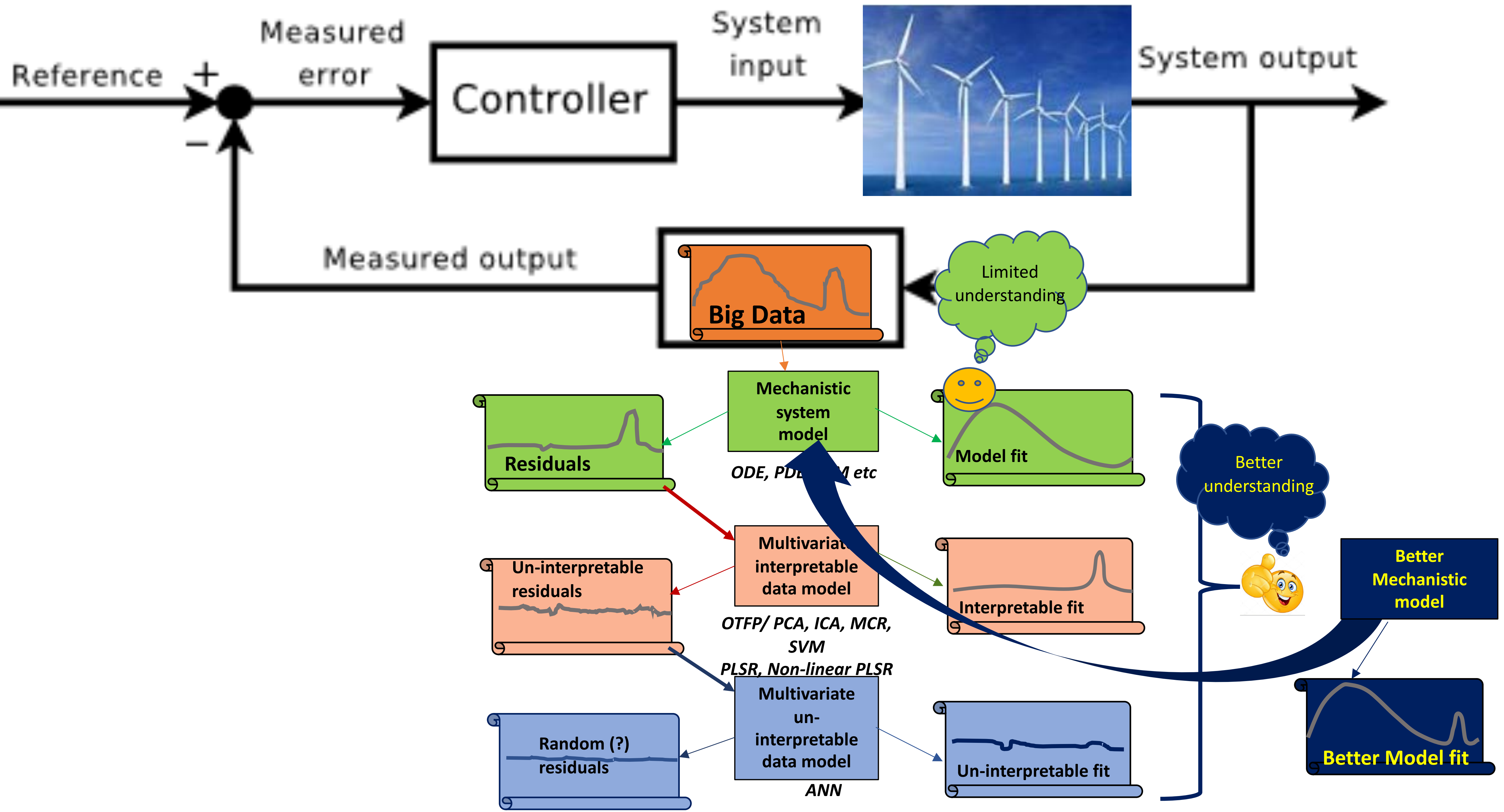
Interpretable fit
Better Mechanistic model
Multivariate un-interpretable data model
ANN
Random (?) residuals
Un-interpretable fit
Better Model fit



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System output
Measured output
Big Data
Limited
understanding
Mechanistic
system
model
ODE, PDE, M etc
Residuals
Model fit
Better
understanding
Multivariate
interpretable
data model
OTFP/ PCA, ICA, MCR,
SVM
PLSR, Non-linear PLSR
Un-interpretable
residuals
Interpretable fit
Better
Mechanistic
model
Multivariate
un-
interpretable
data model
ANN
Random (?)
residuals
Un-interpretable fit
Better Model fit

A process, e.g. an electrically powered metal production processes

idletechs

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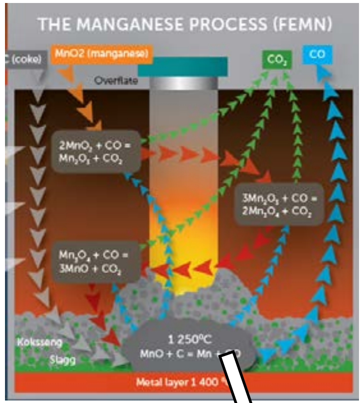
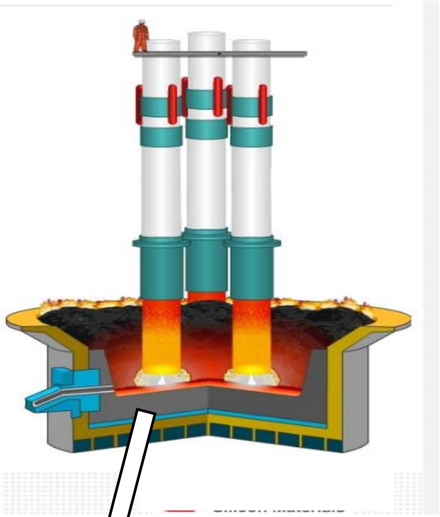
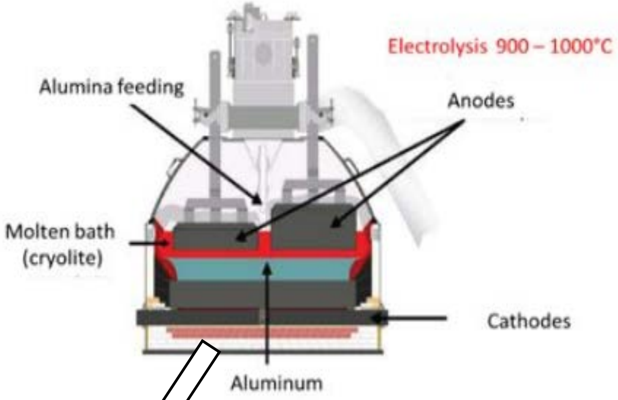


Fe, Si



Al, Mg



Few measurements

A process, e.g. an electrically powered metal production processes

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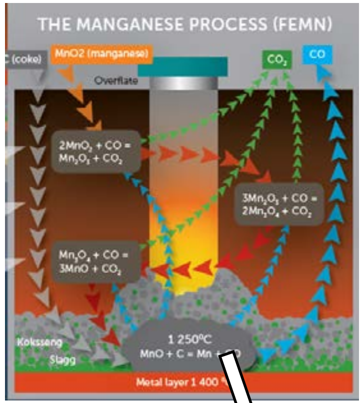
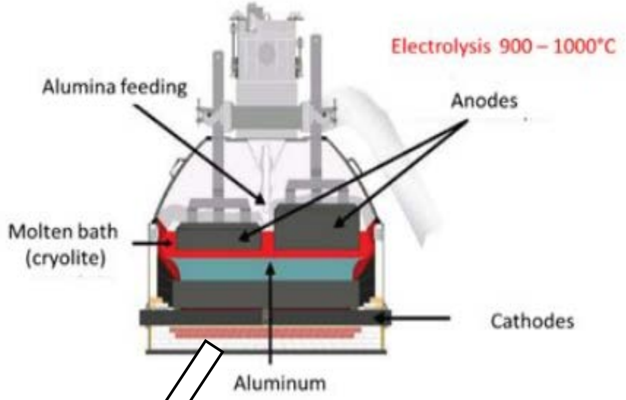


Fe, Si

Al, Mg



Few measurements

BAD process-understanding,
-control, -safety, - economy etc etc

PROBLEMS ?!

idletechs

A process, e.g. an electrically powered metal production processes

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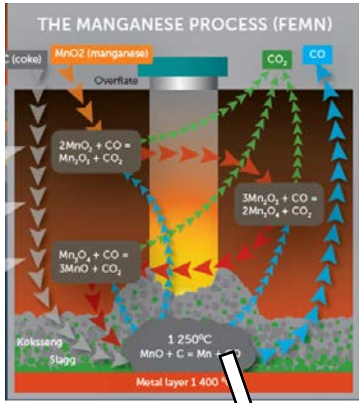
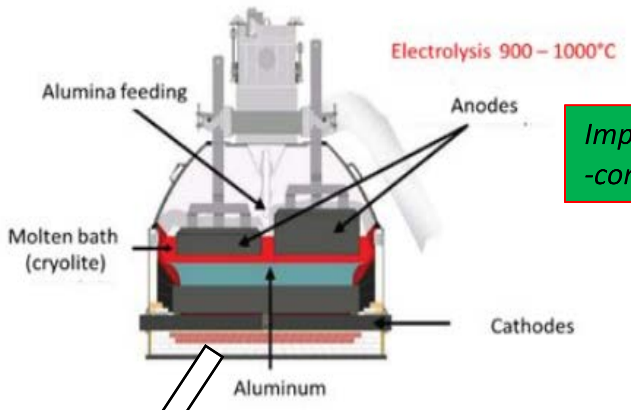


Fe, Si

Al, Mg



Improved process-understanding, -control, -safety, - economy etc etc

Few measurements

BAD process-understanding, -control, -safety, - economy etc etc

PROBLEMS ?!

A process, e.g. an electrically powered metal production processes

idletechs

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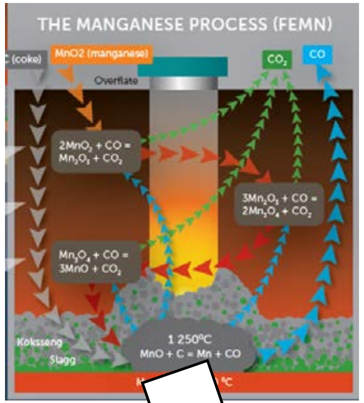
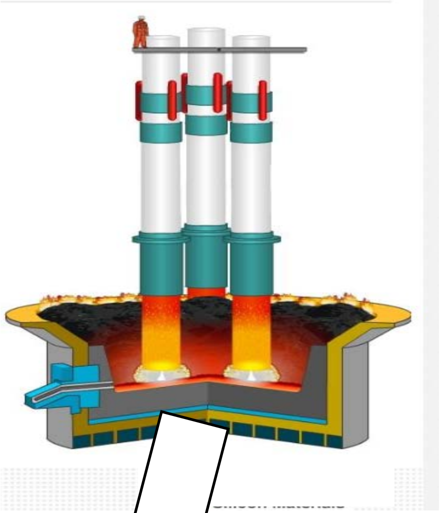
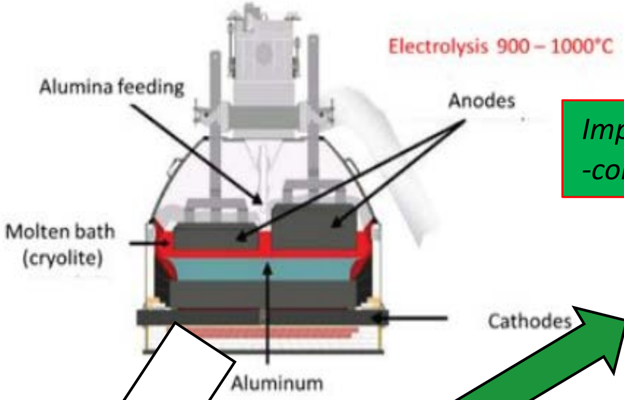


Fe, Si



Al, Mg



Improved process-understanding, -control, -safety, - economy etc etc

Multi-channel measurement streams (El./mech. vibrations, Temp.-video, Energy, Environmental, …)

A process, e.g. an electrically powered metal production processes

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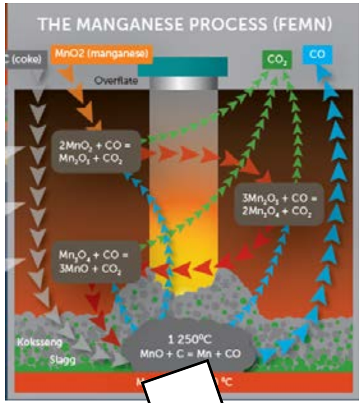

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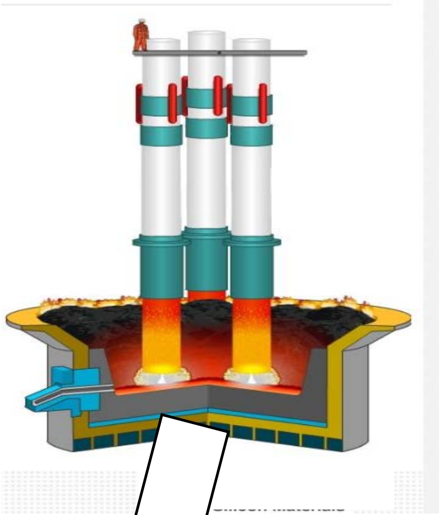
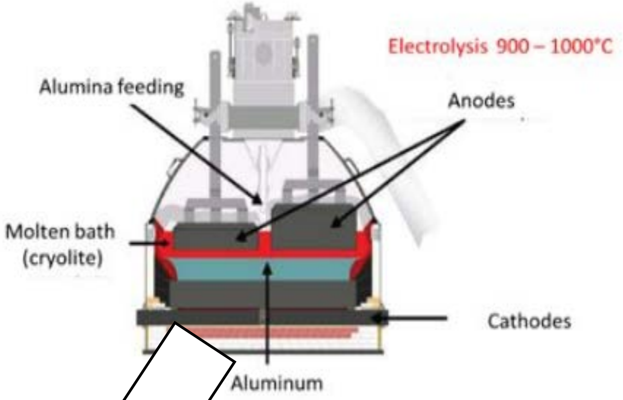


Al, Mg



Multi-channel measurement streams (El./mech. vibrations, Temp.-video, Energy, Environmental, …)

Too much data, not enough information

idletechs

A process, e.g. an electrically powered metal production processes

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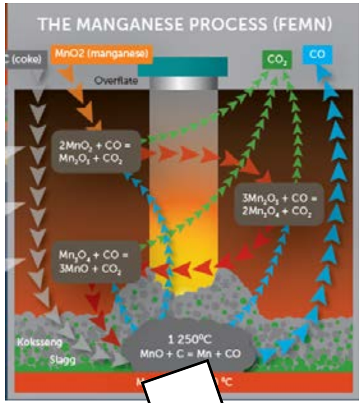

Fe, Si

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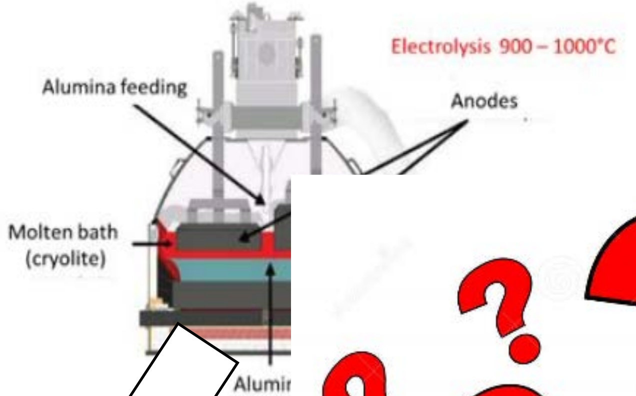

Multi-channel measurement streams (El./mech. vibrations, Temp.-video, Energy, Environmental,

Too much data, not enough information

Black box
AI

idletechs

A process, e.g. an electrically powered metal production processes

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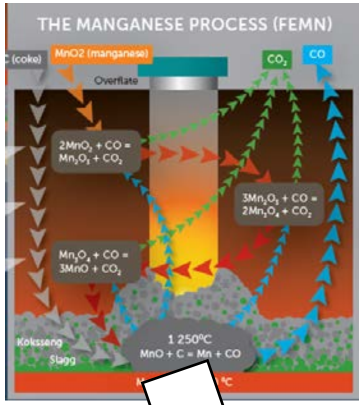

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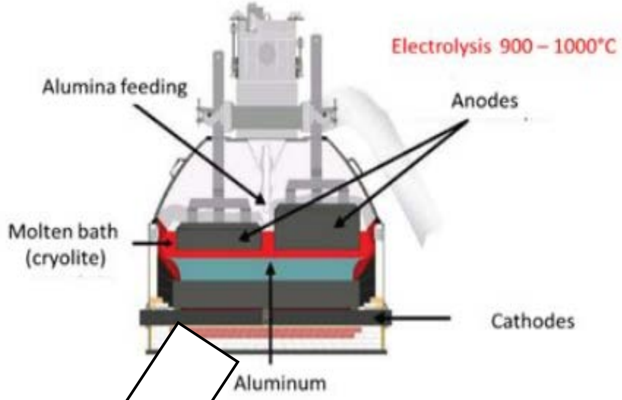


Multi-channel measurement streams (El./mech. vibrations, Temp.-video, Energy, Environmental, …)

Improved process-understanding, -control, -safety, - economy etc etc

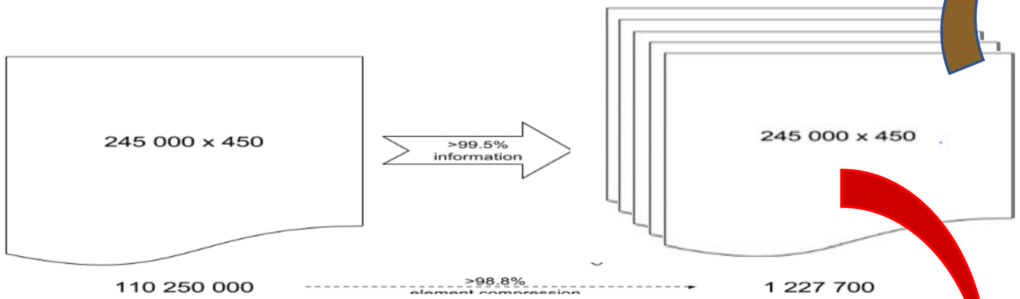
Instead: Big Data Cybernetics !

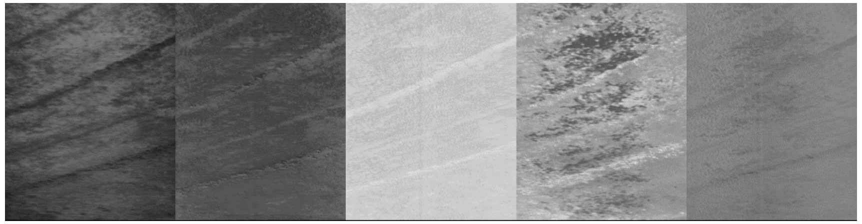
Hyper-spectral camera in small drone for environmental monitoring:

98.8% file reduction, only 0.5% loss (mostly noise)

File size reduced, with improved quality

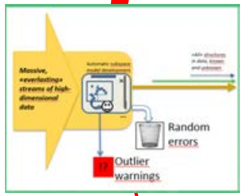
Measured Automatic model





Reconstructions in 5 principal components

Measured Reconstructed



Joao Fortuna, Tor Arne Johansen, Thor Inge Fossen, Harald Martens (2017):

AZORE ISLANDS VEGETATION seen by drone

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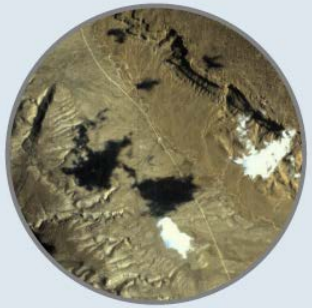
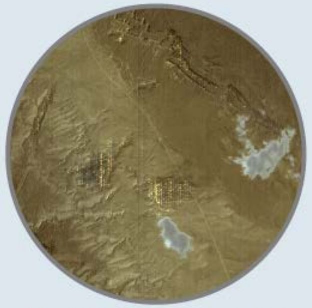
Satellite imaging

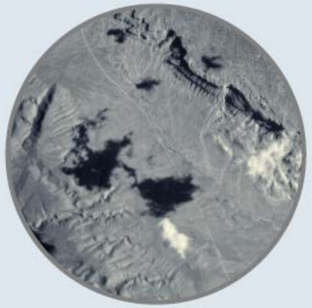
Multivariate, interpretable self-modelling of «everlasting» high-dimensional data streams:
OnTheFlyProcessing (OTFP)

Earth Observing-1

Data from the Hyperion instrument onboard the EO-1 Satellite. Data contains 200 bands in the VIS-NIR region. Clouds were the main source of shadows in this dataset.


Input data Y, in RGB


Deshadowed image, in RGB


"Shadow" (illumination change) image, $\widehat{CS}^{T}$, in RGB

AVIRIS

Airborne visible/infrared imaging spectrometer data from high altitude flights onboard the NASA ER-2 jet. Data contains 224 bands in the VIS-NIR region. Topology was the main source of shadows.


Input data Y, in RGB

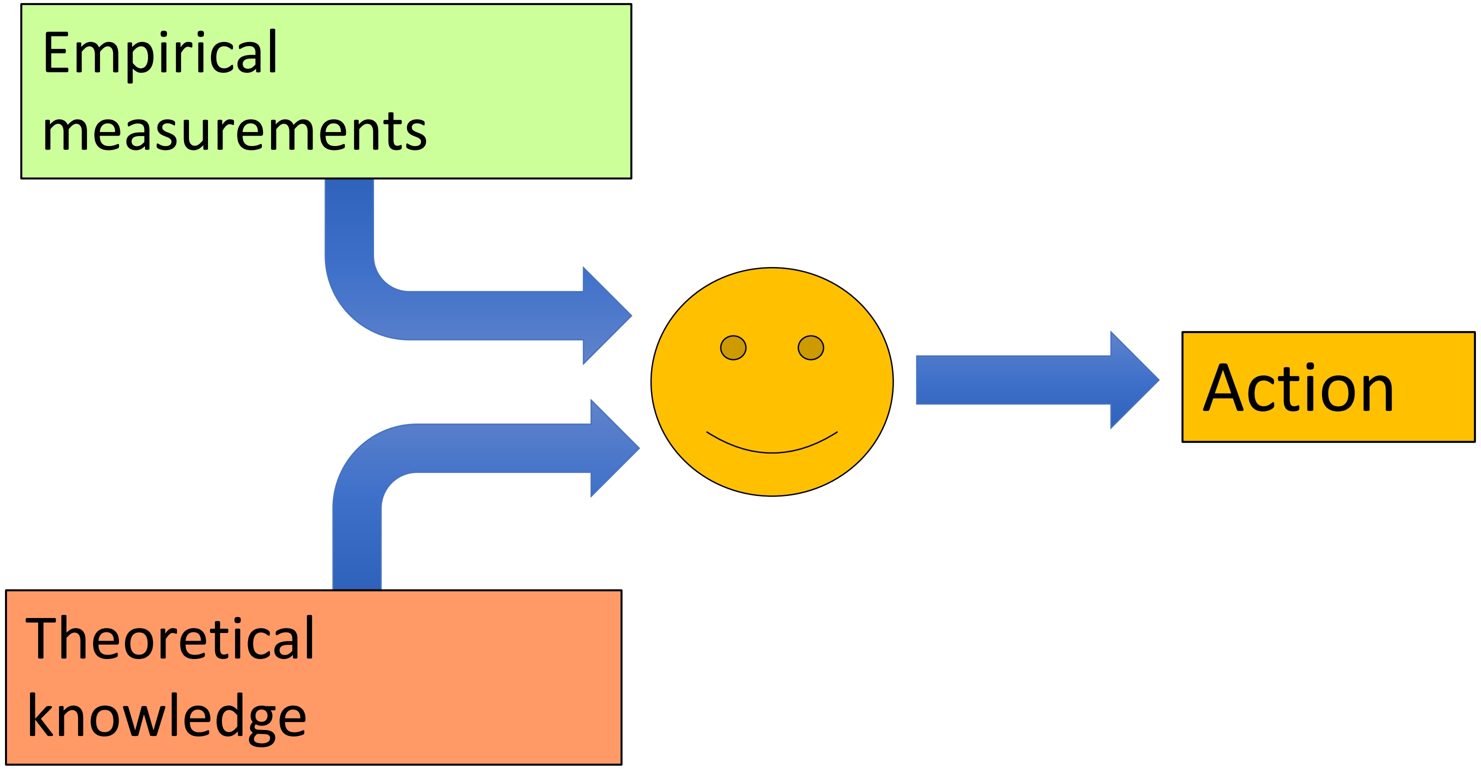

Deshadowed image, in RGB


"Shadow" (illumination change) image, $\widehat{CS}^{T}$, in RGB

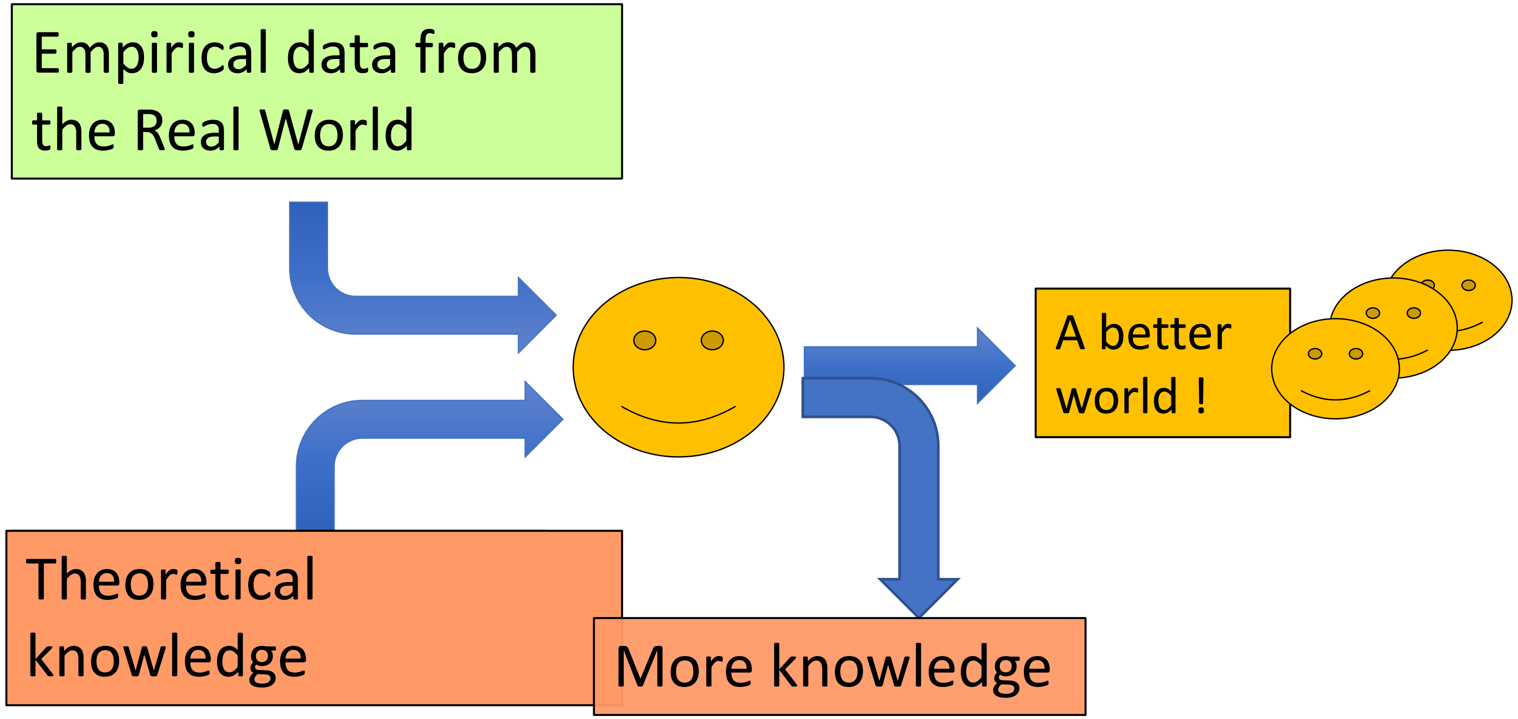
Compact Deshadowing Of Aerial Hyperspectral Images

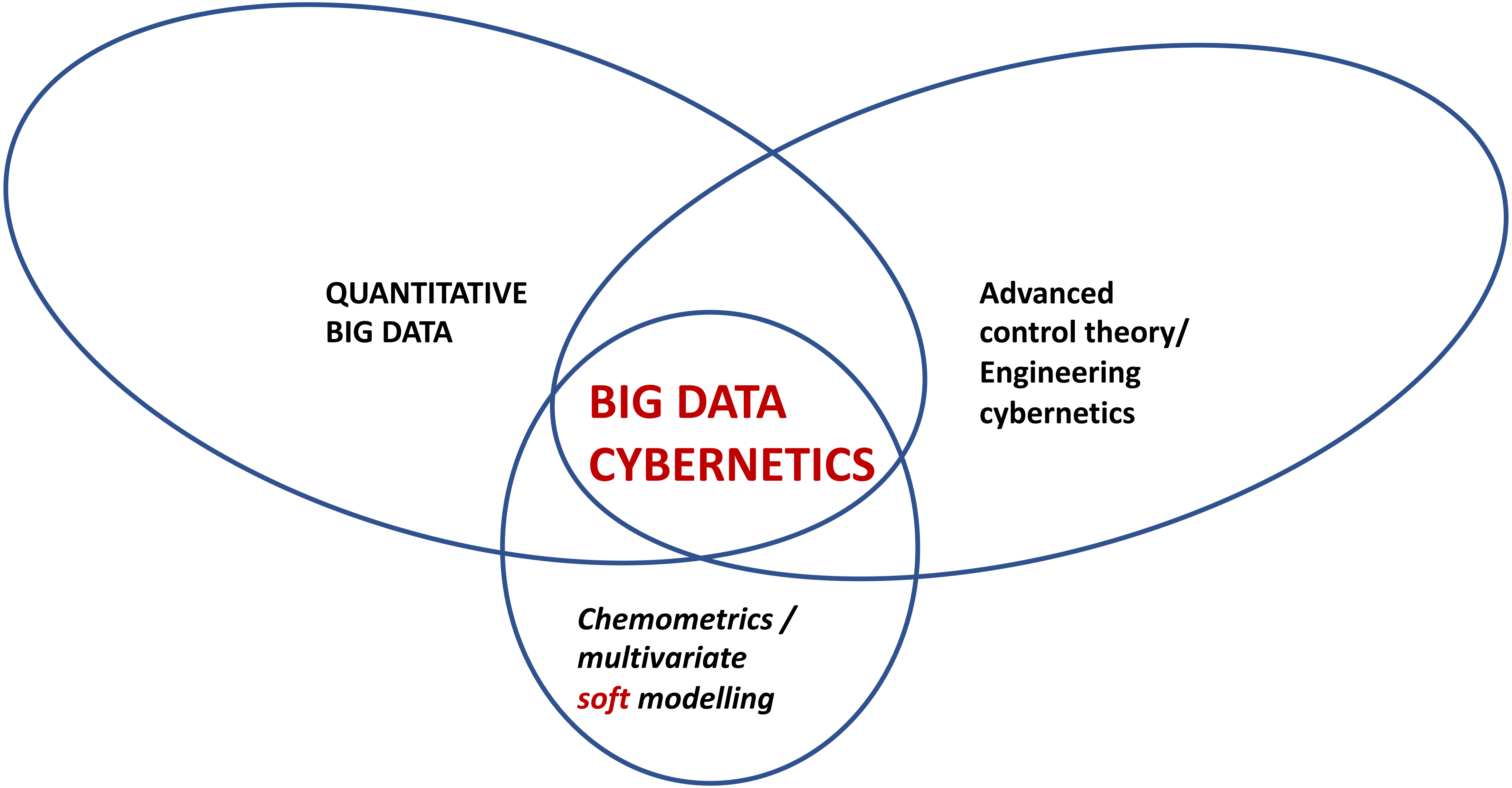
João Fortuna[a,b,c] and Harald Martens[a,c]
[a]Department of Engineering Cybernetics, Norwegian University of Science and Technology (NTNU)
[b]Centre for Autonomous Marine Operations and Systems (NTNU AMOS)
[c]Idletechs AS
Trondheim, Norway

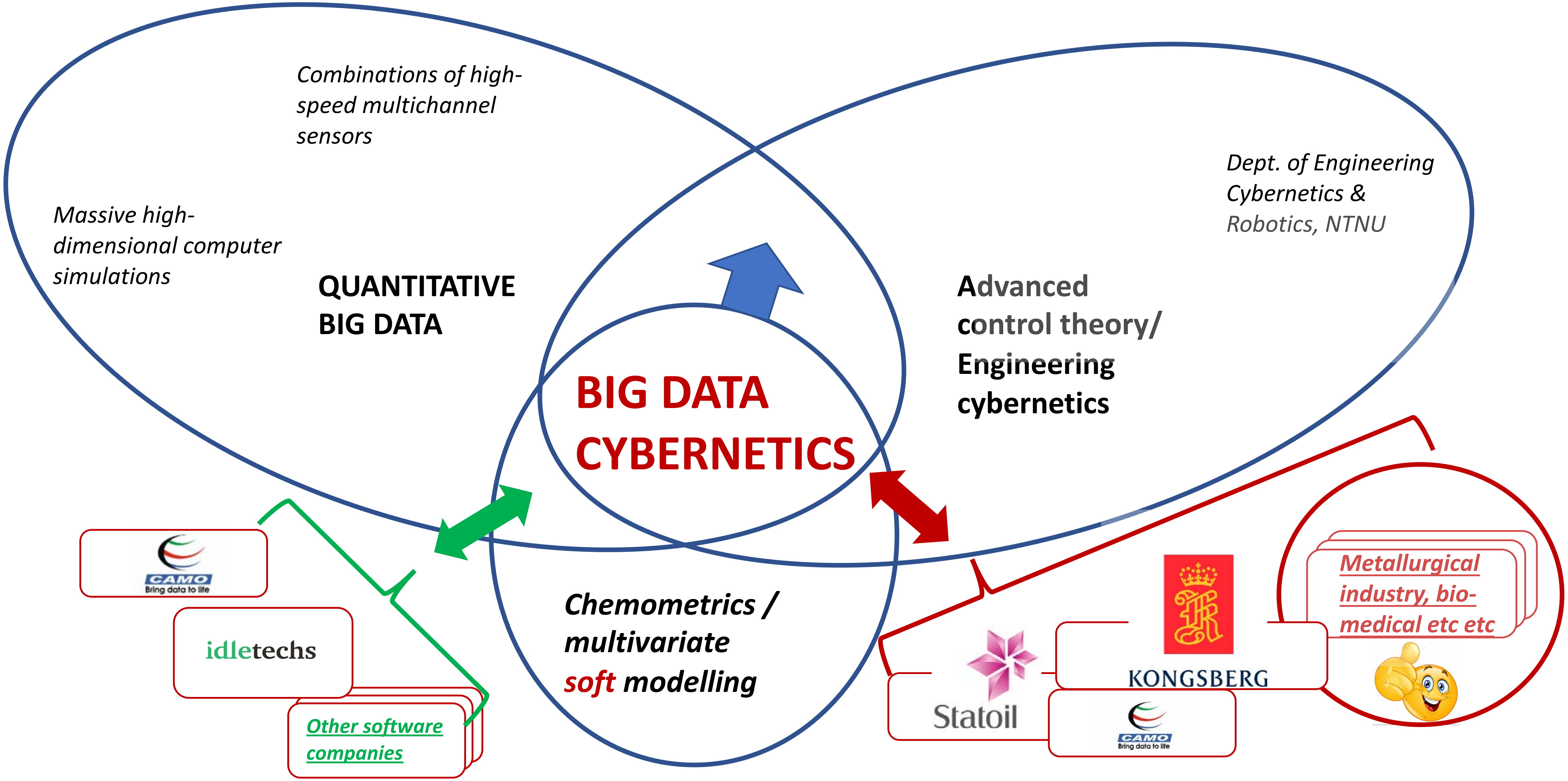
Source of knowledge at any given moment



NTNU´s visjon: Kunnskap for en bedre verden




QUANTITATIVE
BIG DATA
Advanced
control theory/
Engineering
cybernetics
BIG DATA
CYBERNETICS
Chemometrics /
multivariate
soft modelling

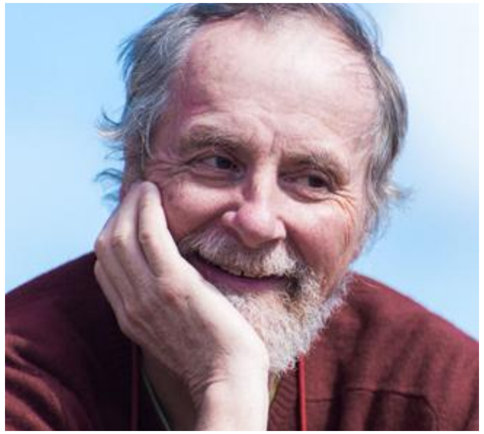


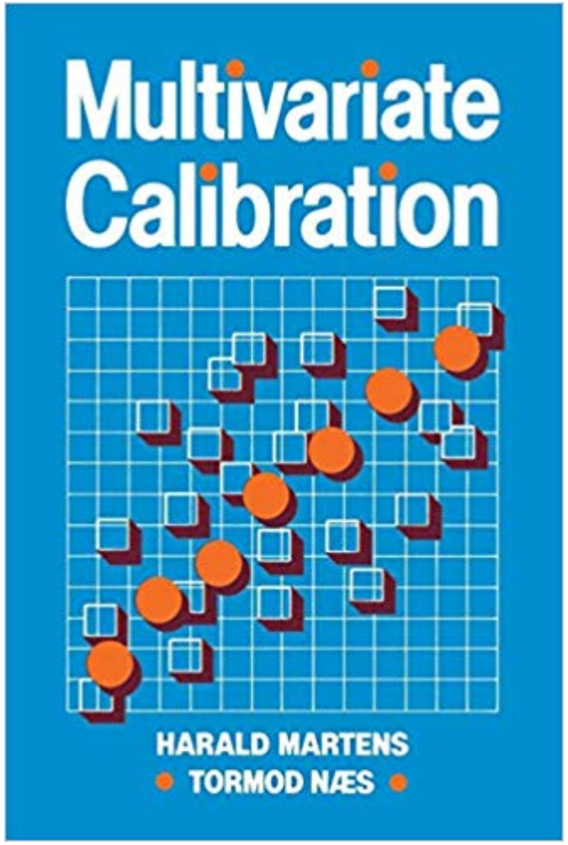
Combinations of high-speed multichannel sensors
Massive high-dimensional computer simulations
QUANTITATIVE BIG DATA
Dept. of Engineering Cybernetics & Robotics, NTNU
Advanced control theory/ Engineering cybernetics
BIG DATA CYBERNETICS
Chemometrics / multivariate soft modelling
CAMO Bring data to life
idletechs
Other software companies
Statoil
KONGSBERG
CAMO Bring data to life
Metallurgical industry, bio-medical etc etc

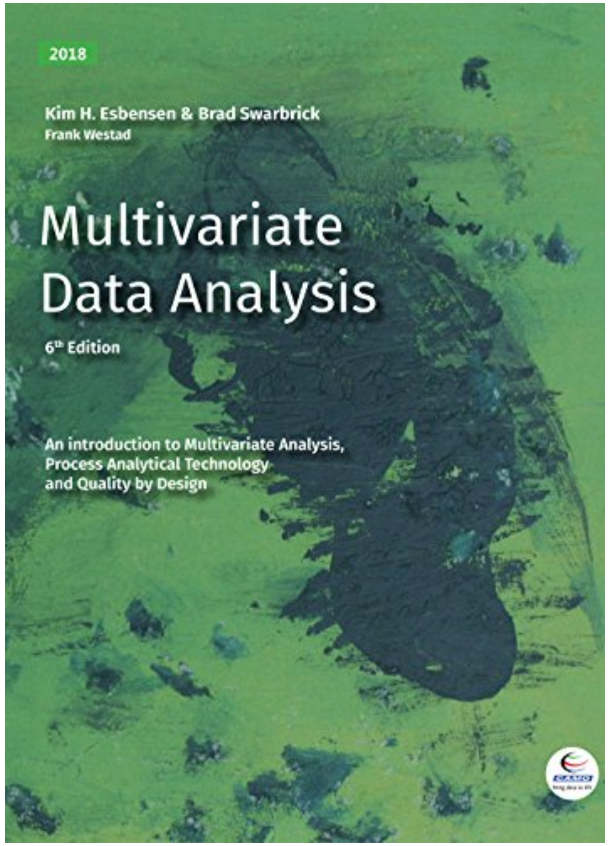
Bigdatacybernetics

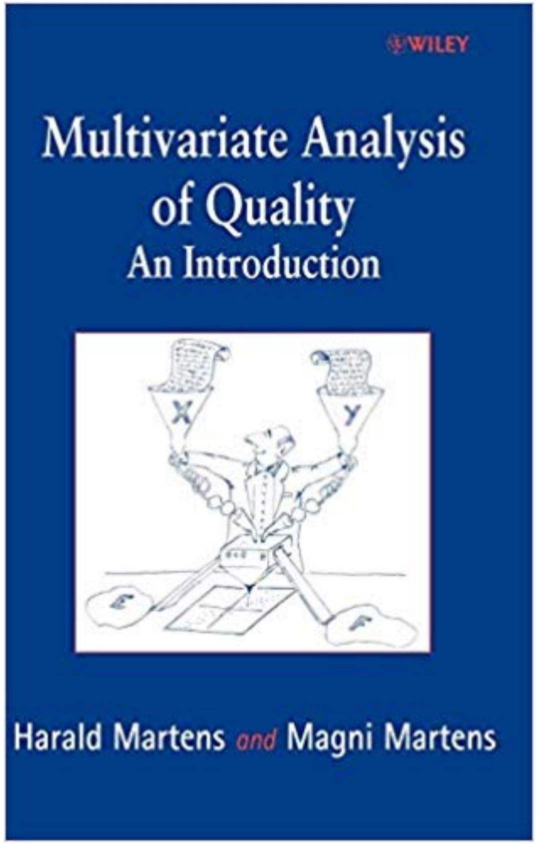
- Instructors
  - Harald MARTENS
  - Øivind RIIS
  - Kristin TØNDEL
  - Damiano VARAGNOLO
  - Frank Ove WESTAD
  - Adil RASHEED

Homework: Who is who ?







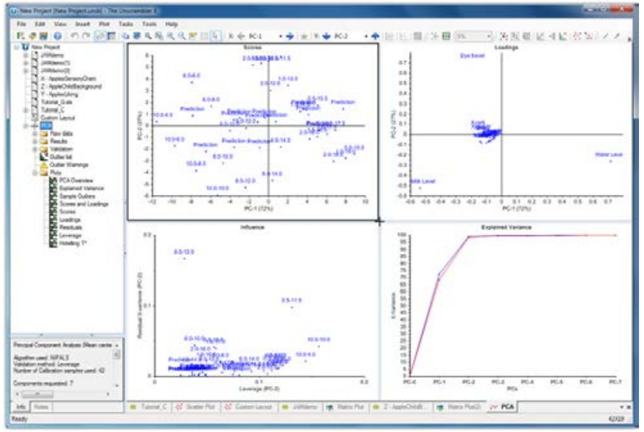


Books

Additional papers will be shared as and when required

Software

- UNSCRAMBLER (Frank)
- PYTHON (Adil)
- MATLAB (Damiano)



To do list

- Install Unscrambler, python and matlab
- Try the python notebook on github for Lecture 1 to convince the need for interpretable data analytics
- Prepare some data from your own research field to work with

Lecture schedule

lesson 1	motivations -- why this course? introductory test + personality test	Adil / Damiano	20.aug
lesson 2	DoE	Harald	27.aug
lesson 3	PCA	Damiano	03.sep
lesson 4	PCA - outliers and optimization	Damiano	10.sep
lesson 5	Multivariate regression and classification	Adil	17.sep
lesson 6	Validation	Adil / Damiano	24.sep
lesson 7	Multivariate regression and classification	Adil / Damiano	01.okt
lesson 8	Project presentation part 1	all - F2F + Skype	08.okt
lesson 9	Time dependent data and real time prediction	Frank	15.okt
lesson 10	IDLE models and interpretable ML	Harald	22.okt
lesson 11	multiblock data and introduction to sensor-fusion	Damiano	29.okt
lesson 12	nonlinearities and metamodelling, with demonstrations	Adil	05.nov
lesson 13	3-dimensional data and multiway methods (PARAFAC)	Kristin	12.nov
lesson 14	advanced assessment of data quality and detection of outliers	Adil	19.nov
lesson 15	feature extraction in multivariate models	Frank	26.nov

To do list

Lecture 1: Excercise / Convince yourself

https://github.com/adil-rasheed/TK8117

Prepare a one page description of the dataset and the project each of us will be working on

Lesson 1 - part 2
TK8117

Damiano Varagnolo

August 20, 2019

Agenda

1. active teaching and learning
2. continuous assessments: why, what and how

Active teaching and learning: main ingredients

flipped classrooms

peer instructions

Active teaching and learning: main ingredients

ScalableLearning

Kahoot!

Traditional vs. flipped classrooms

	traditional	*flipped*
in class		
at home		

Traditional vs. flipped classrooms

	traditional	*flipped*
in class	deliver lectures	
at home		

Traditional vs. flipped classrooms

	traditional	*flipped*
in class	deliver lectures	
at home	fixing notes & exercises	

Traditional vs. flipped classrooms

	traditional	*flipped*
in class	deliver lectures	
at home	fixing notes & exercises	as before *plus* watch online lectures

Traditional vs. flipped classrooms

	traditional	*flipped*
in class	deliver lectures	exercises, quizzes & discussions
at home	fixing notes & exercises	as before *plus* watch online lectures

Scalable learning

Scalable learning - how to enroll in the portal

1. register an account in `https://www.scalable-learning.com/#/users/login` using your institutional email (i.e., `xxx@ntnu.no`)
2. go to `https://www.scalable-learning.com/#/courses/enroll?id=WREQD-29680` and follow the instructions
3. in case the portal asks, use `WREQD-29680` as the course enrollment key

course Link:

`https://www.scalable-learning.com/#/courses/4108/course_information`

Scalable learning - TODOs for you

1. enroll
2. do module 1.1

we will use this data as an example during the course

?

Peer instructions

aim = foster:

- discussions among and with students
- sharpen focus and understanding

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algorithm:

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1. the teacher poses one question

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2. students think individually and then provide an individual answer

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algorithm:

1. the teacher poses one question
2. students think individually and then provide an individual answer
3. the teacher shows the aggregate responses, without giving the correct answer

Peer instructions

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algorithm:

1. the teacher poses one question
2. students think individually and then provide an individual answer
3. the teacher shows the aggregate responses, without giving the correct answer
4. students form small groups,

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algorithm:

1. the teacher poses one question
2. students think individually and then provide an individual answer
3. the teacher shows the aggregate responses, without giving the correct answer
4. students form small groups, discuss the question,

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algorithm:

1. the teacher poses one question
2. students think individually and then provide an individual answer
3. the teacher shows the aggregate responses, without giving the correct answer
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algorithm:

1. the teacher poses one question
2. students think individually and then provide an individual answer
3. the teacher shows the aggregate responses, without giving the correct answer
4. students form small groups, discuss the question, then provide again an *individual* answer
5. the teacher shows the new aggregate responses,

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algorithm:

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Peer instructions

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1. the teacher poses one question
2. students think individually and then provide an individual answer
3. the teacher shows the aggregate responses, without giving the correct answer
4. students form small groups, discuss the question, then provide again an *individual* answer
5. the teacher shows the new aggregate responses, then gives the correct answer, then takes and responds to questions

examples

?

Bonus material

`http://folk.ntnu.no/damianov/matlab.html`

Continuous assessments: why should we do it?

Continuous assessments: what does it mean?

Continuous assessments: what does it mean?

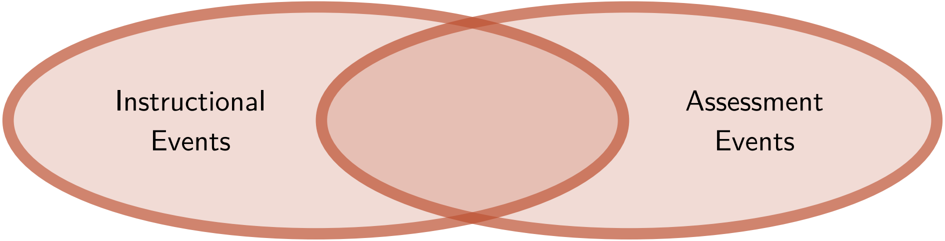
the Knowledge, Learning and Instruction framework

Goal of the KLI framework

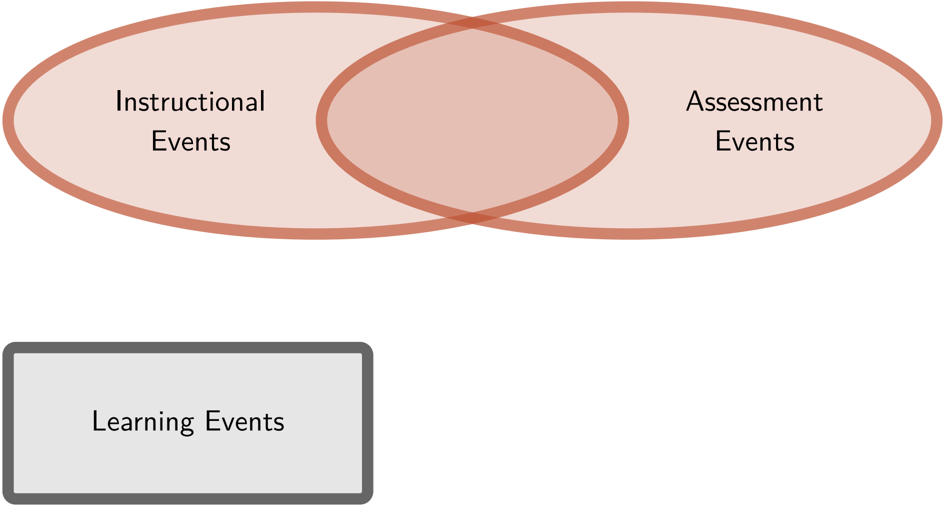
enable discussing quantitatively
how teaching affects the learning performance
and how to give each other some feedback

Graphical representation of the KLI framework

Graphical representation of the KLI framework



Graphical representation of the KLI framework



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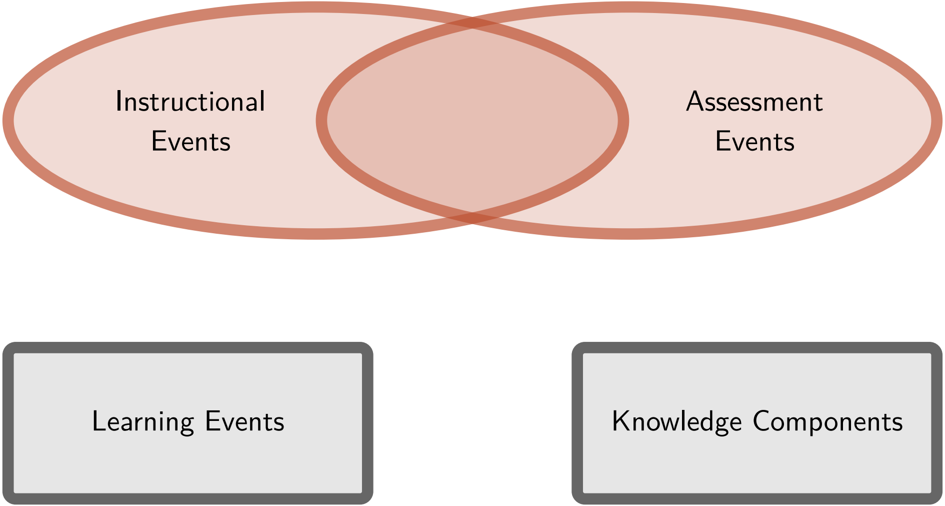

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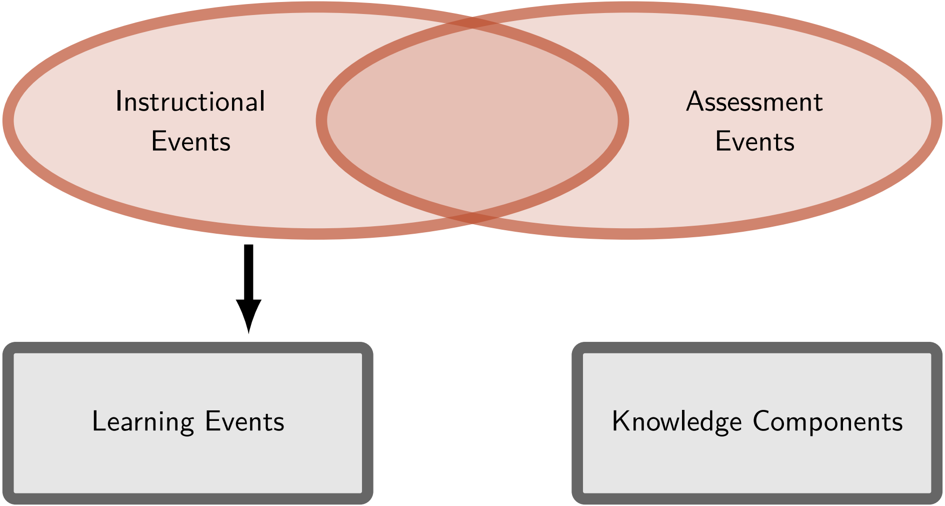

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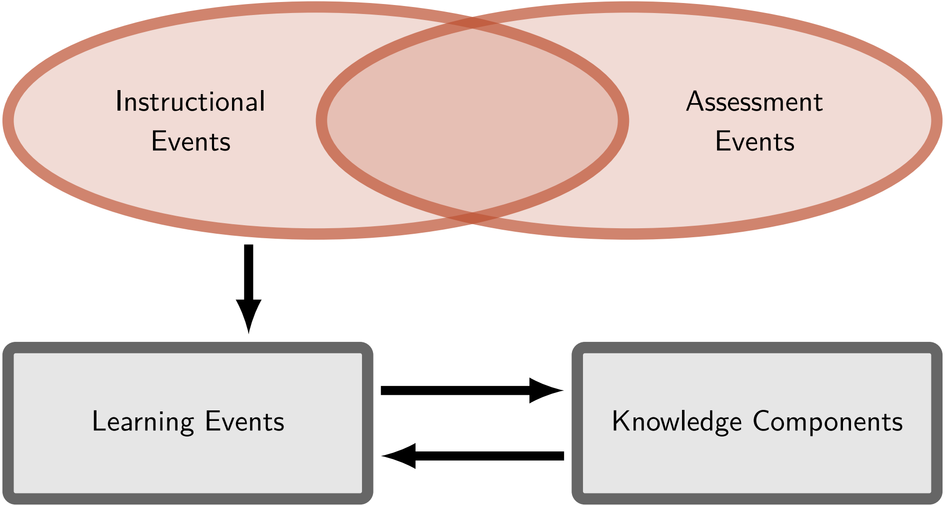

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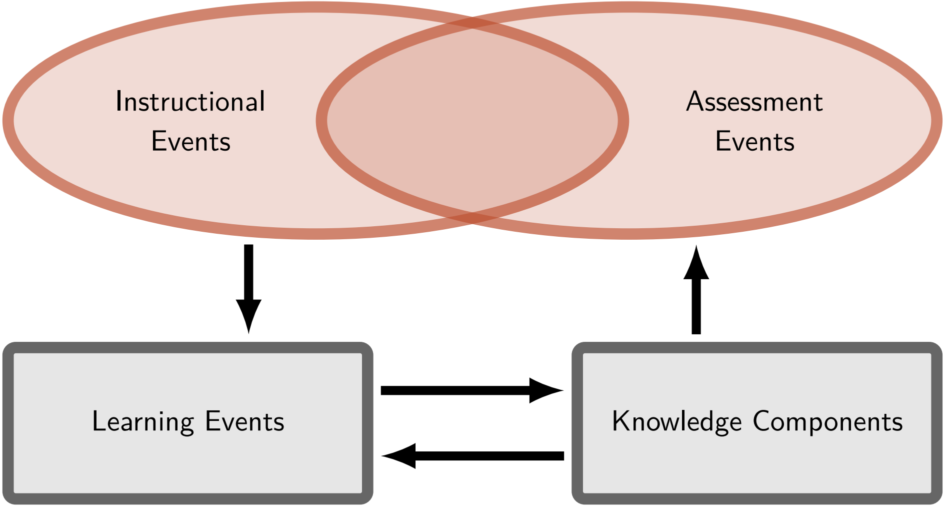

To enable quantitative discussions we need quantitative descriptions of the atomic units

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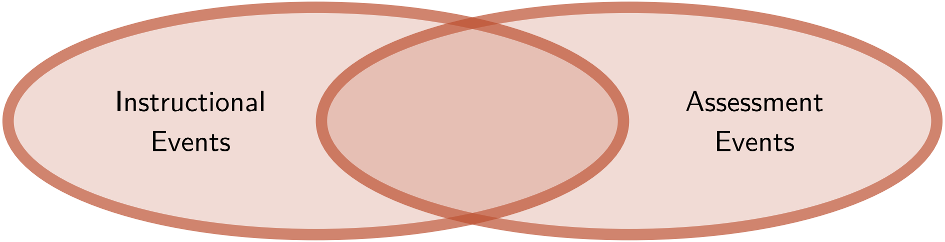

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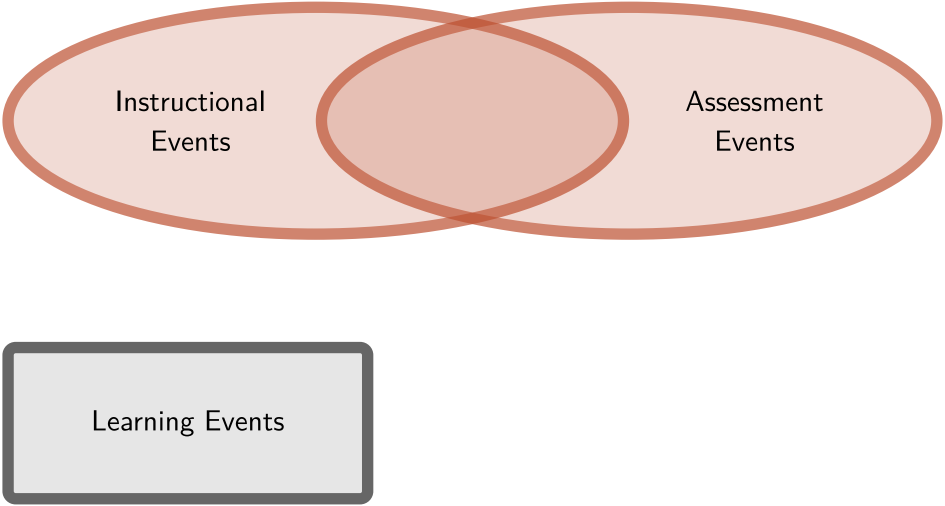

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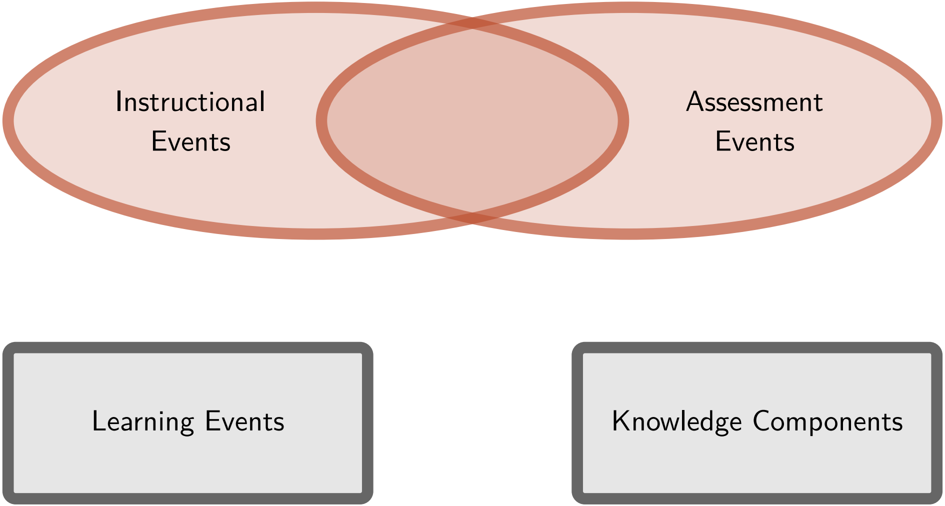

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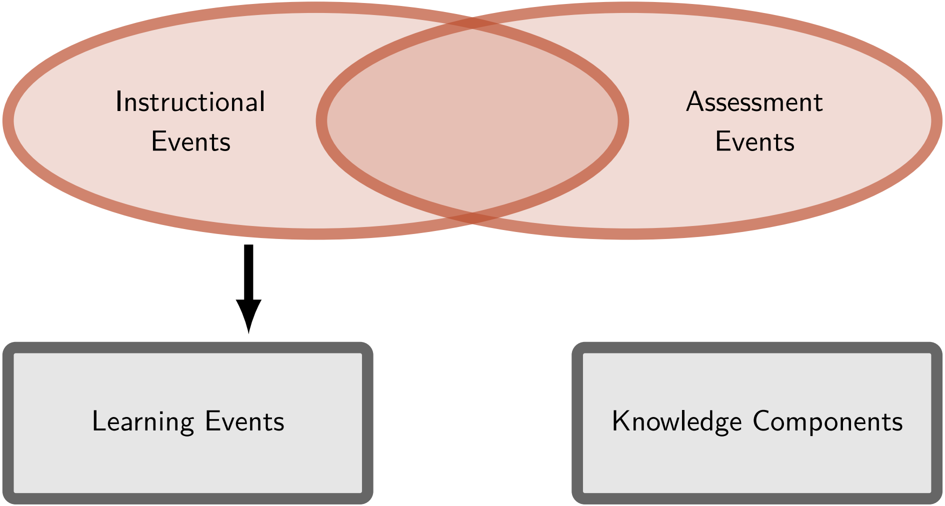

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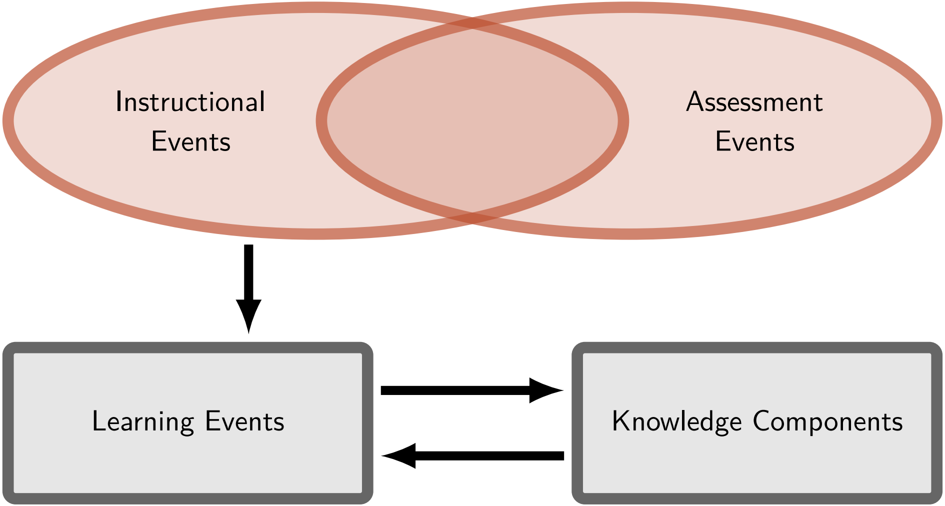

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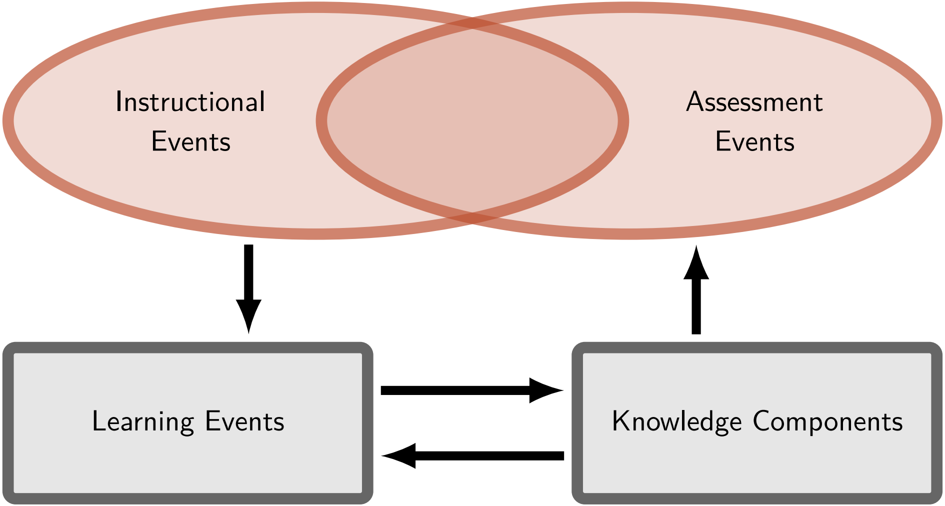


Towards a taxonomy for the KCs

- can the KC be used?
- can the KC be explained?

How to describe a taxonomy level for a given KC

2-dimensional vector (u, e) with $u, e \in \{0, 1, 2, 3\}$ *(e.g., $(2, 3)$ or $(1, 0)$* where u indicates the *using* component and e indicates the *explaining* component as follows:

$$u = \begin{cases} 0 \leftrightarrow & \text{the KC cannot be used at all} \\ 1 \leftrightarrow & \text{the KC can be used in AEs asking to use that KC explicitly and always in the same way} \\ 2 \leftrightarrow & \text{the KC can be used in AEs asking to use that KC explicitly without specifying how} \\ 3 \leftrightarrow & \text{the KC can be used in AEs that do not ask explicitly to use that KC} \end{cases}$$

$$e = \begin{cases} 0 \leftrightarrow & \text{the KC can not be verbalized nor rationalized} \\ 1 \leftrightarrow & \text{the KC can be verbalized, but not rationalized} \\ 2 \leftrightarrow & \text{the KC can be rationalized, but not verbalized} \\ 3 \leftrightarrow & \text{the KC can be both verbalized and rationalized} \end{cases}$$

?

Where are we now?

a taxonomy
for the IEs

a list of
typical AEs

a taxonomy
for the LEs

taxonomy for the KCs:
$(u, e) \in \{(0,0), \ldots, (3,3)\}$

Taxonomy for the Learning Events

(in terms of knowledge acquisition processes)

Taxonomy for the Learning Events

(in terms of knowledge acquisition processes)

1. memory and fluency-building processes

Taxonomy for the Learning Events

(in terms of knowledge acquisition processes)

1. memory and fluency-building processes
2. induction and refinement processes

Taxonomy for the Learning Events

(in terms of knowledge acquisition processes)

1. memory and fluency-building processes
2. induction and refinement processes
3. understanding and sense-making processes

Connections between the taxonomies for the LEs and the KCs

explaining

$$\begin{array}{cccc}
(0,3) & (1,3) & (2,3) & (3,3) \\
(0,2) & (1,2) & (2,2) & (3,2) \\
(0,1) & (1,1) & (2,1) & (3,1) \\
(0,0) & (1,0) & (2,0) & (3,0)
\end{array}$$

using

Connections between the taxonomies for the LEs and the KCs

explaining

$(0,3)$	$(1,3)$	$(2,3)$	$(3,3)$
$(0,2)$	$(1,2)$	$(2,2)$	$(3,2)$
$(0,1)$	$(1,1)$	$(2,1)$	$(3,1)$
$(0,0)$	$(1,0)$	$(2,0)$	$(3,0)$

using

memory and fluency building processes

Connections between the taxonomies for the LEs and the KCs

induction and refinement processes

Connections between the taxonomies for the LEs and the KCs

explaining

$(0,3)$	$(1,3)$	$(2,3)$	$(3,3)$
$(0,2)$	$(1,2)$	$(2,2)$	$(3,2)$
$(0,1)$	$(1,1)$	$(2,1)$	$(3,1)$
$(0,0)$	$(1,0)$	$(2,0)$	$(3,0)$

using

understanding and sense-making processes

Connections between the taxonomies for the LEs and the KCs

explaining

$\boxed{(0,3)}$	$\boxed{(1,3)}$	$(2,3)$	$(3,3)$
$\boxed{(0,2)}$	$\boxed{(1,2)}$	$(2,2)$	$(3,2)$
$\boxed{(0,1)}$	$(1,1)$	$(2,1)$	$(3,1)$
$\boxed{(0,0)}$	$(1,0)$	$(2,0)$	$(3,0)$

using

not covered because not meaningful

Where are we now?

a taxonomy
for the IEs

a list of
typical AEs

taxonomy for the LEs:
1) memory &
fluency building
2) induction & refinement
3) understanding
& sense making

taxonomy for the KCs:
$(u, e) \in \{(0,0), \ldots, (3,3)\}$

Taxonomy for the Instructional Events

1. memory and fluency enhancing IEs
2. induction and refinement enhancing IEs
3. understanding and sense making enhancing IEs

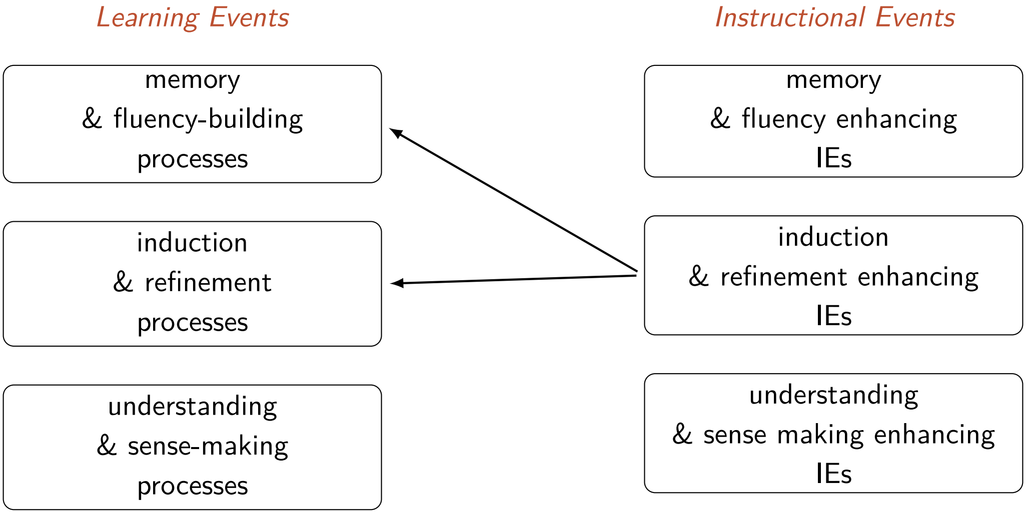
Important: the connections between the IEs and LEs taxonomies are asymmetric!

Learning Events	*Instructional Events*
memory & fluency-building processes	memory & fluency enhancing IEs
induction & refinement processes	induction & refinement enhancing IEs
understanding & sense-making processes	understanding & sense making enhancing IEs

Important: the connections between the IEs and LEs taxonomies are asymmetric!

Learning Events		*Instructional Events*
memory & fluency-building processes	←	memory & fluency enhancing IEs
induction & refinement processes		induction & refinement enhancing IEs
understanding & sense-making processes		understanding & sense making enhancing IEs

Important: the connections between the IEs and LEs taxonomies are asymmetric!



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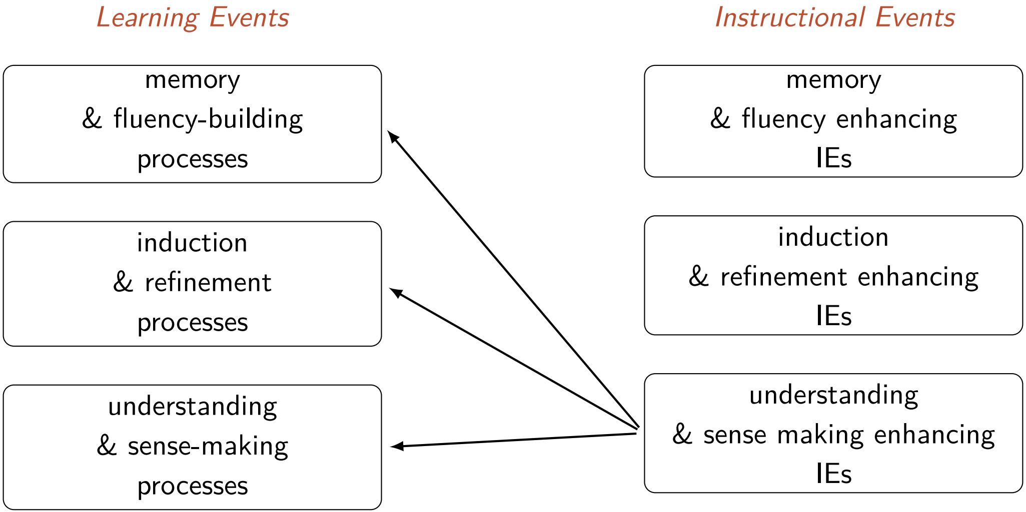

Where are we now?

taxonomy for the IEs:
1) memory & fluency building
2) induction & refinement
3) understanding & sense making

a list of typical AEs

taxonomy for the LEs:
1) memory & fluency building
2) induction & refinement
3) understanding & sense making

taxonomy for the KCs:
$(u, e) \in \{(0,0), \ldots, (3,3)\}$

Where are we now?

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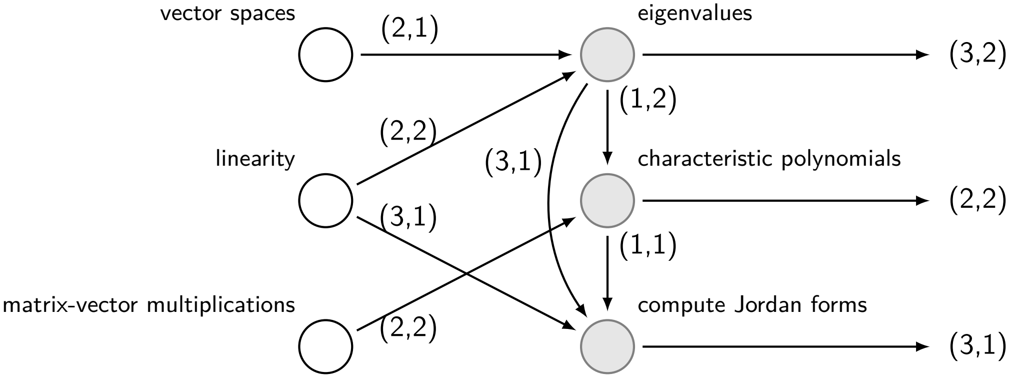
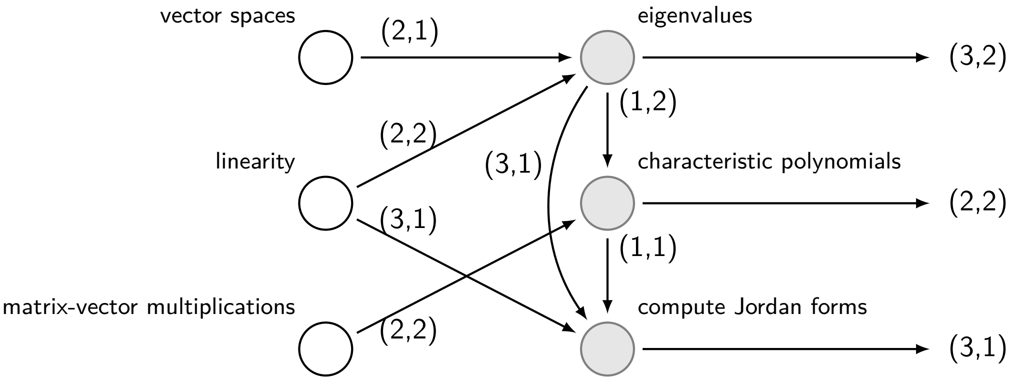
Knowledge Components Graphs



Take home message 1:
learn how to read (course-wide) Knowledge Components Graphs



Take home message 2: use the KLI framework to provide feedback