



Data-Driven Mechanics: Constitutive Model-Free Approach

$$\inf_{y \in D} \inf_{z \in E} \|y - z\| = \inf_{z \in E} \inf_{y \in D} \|y - z\|$$

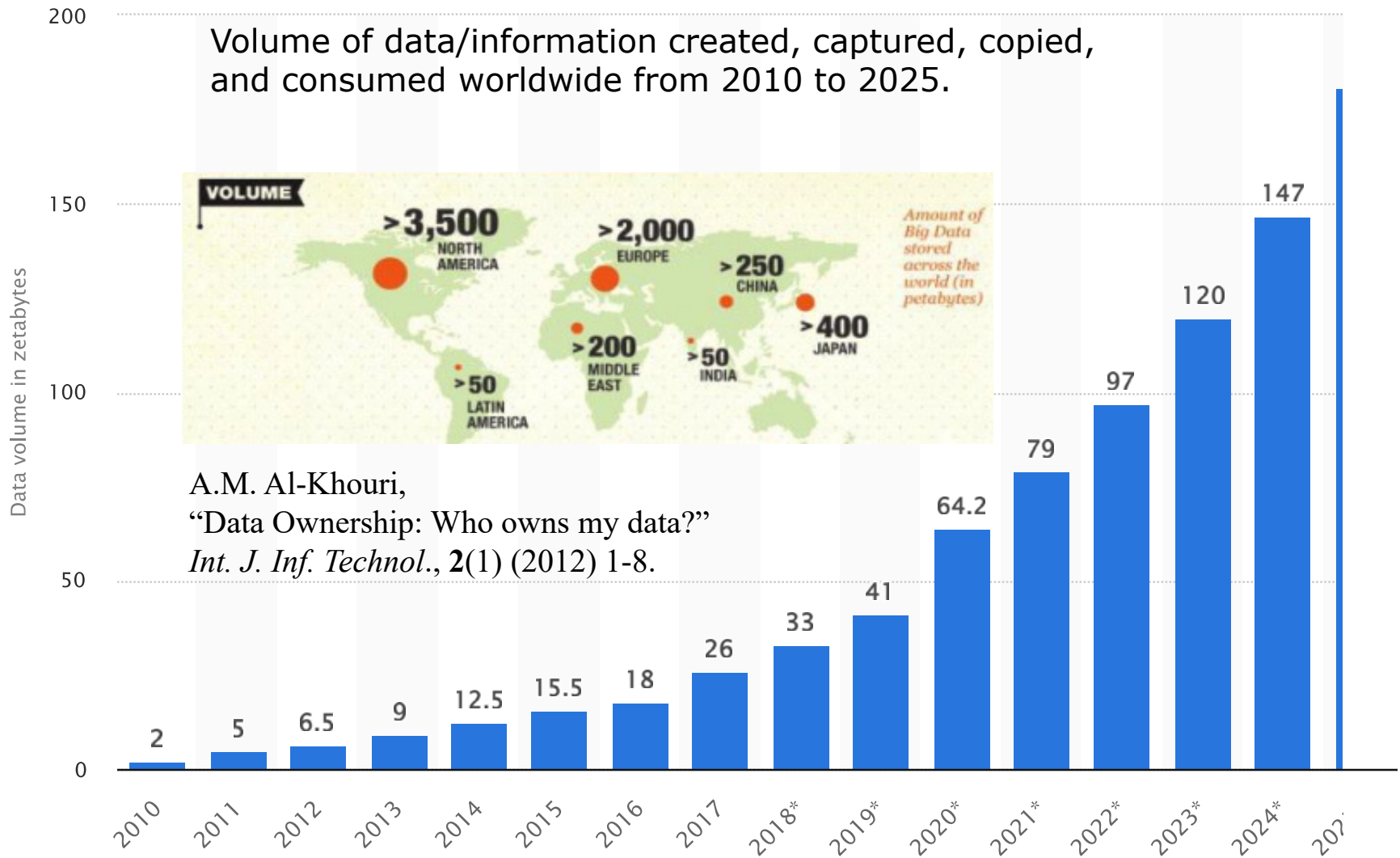
Michael Ortiz – Lecture 1
California Institute of Technology and
Rheinische Friedrich-Wilhelms Universität Bonn

Centre International des Sciences Mécaniques (CSIM)
Udine (Italy), October 10-14, 2022

Why Data-Driven Computing Now?

- The world's data volume has increased dramatically over the past ~ 20 years.

Why Data-Driven Computing Now?



<https://www.statista.com/statistics/871513/worldwide-data-created/>

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- The world's data volume has increased dramatically over the past ~ 20 years.
- With the advent of *cloud infrastructure* circa 2000, previous limits on storage became obsolete.
- As billions of new users gained *internet access* across the globe, data generation increased enormously.

Why Data-Driven Computing Now?

A DAY IN DATA 1EB/DAY!

The exponential growth of data is undisputed, but the numbers behind this explosion - fuelled by internet of things and the use of connected devices - are hard to comprehend, particularly when looked at in the context of one day

DEMISTIFYING DATA UNITS

From the more familiar "KB" or "megabyte", larger units of measurement are more frequently being used to explain the masses of data.

Unit	Value	Size
B	0 or 1	1/8 of a byte
b	8 bits	1 byte
KB	1,000 bytes	1,000 bytes
MB	1,000 ² bytes	1,000,000 bytes
GB	1,000 ³ bytes	1,000,000,000 bytes
TB	1,000 ⁴ bytes	1,000,000,000,000 bytes
PB	1,000 ⁵ bytes	1,000,000,000,000,000 bytes
EB	1,000 ⁶ bytes	1,000,000,000,000,000,000 bytes
ZB	1,000 ⁷ bytes	1,000,000,000,000,000,000,000 bytes
YB	1,000 ⁸ bytes	1,000,000,000,000,000,000,000,000 bytes

*In some cases "T" is used as an abbreviation for tera, while an uppercase "T" represents tera.

463EB

of data will be created every day by 2025

SAC

95m

photos and videos are shared on Instagram

Instagram Business

65bn

messages sent over WhatsApp and two billion minutes of voice and video calls made

Facebook

28PB

to be generated from wearable devices by 2020

Statista

4PB

of data created by Facebook, including

350m photos
100m hours of video watch time

Facebook Research

4TB

of data produced by a connected car

Intel

ACCUMULATED DIGITAL UNIVERSE OF DATA

4.4ZB

44ZB

PwC

2013

2020

500m

tweets are sent every day

Twitter

294bn

billion emails are sent

Radicati Group

320bn

emails to be sent each day by 2021

306bn

emails to be sent each day by 2020

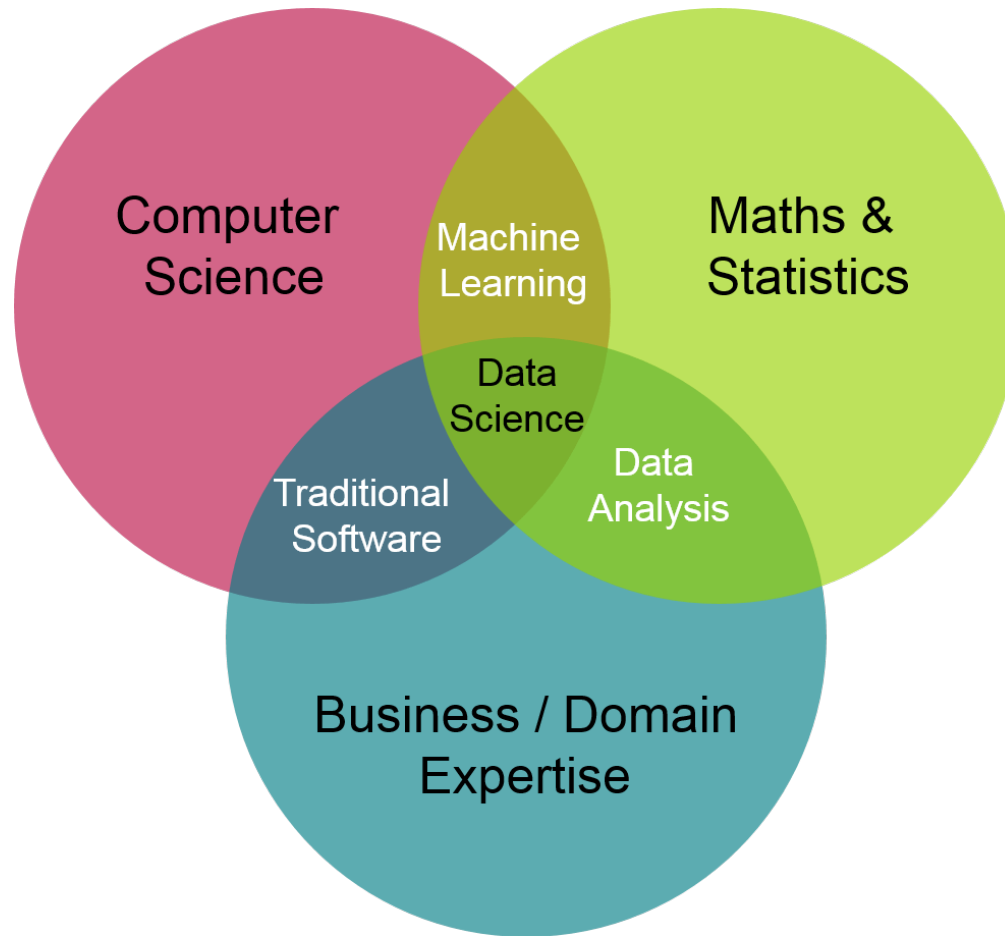
3.9bn

people use emails

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- Soon, companies around the world adopted *Big-Data* strategies, developed tools.
- Tools, algorithms, for learning—and making predictions, decisions—from big-data sets are now generically referred to as *Machine Learning*.
- Machine Learning is a modern version of *statistical analysis* (regression, testing, inference...) and *data mining* (discovering patterns in data).

Why Data-Driven Computing Now?



Great Learning Team,
What is Data Science and How Does it Work:
A Complete Beginner's Guide, Jan 11, 2022.

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- Machine Learning is a modern version of *statistical analysis* (regression, testing, inference...) and *data mining* (discovering patterns in data).
- Key enablers (what is old? what is new?):
 - i) Advent of *high-performance and distributed computing*.
 - ii) *Cost of storing* and managing big data sets dramatically lowered.
 - iii) *Commercial data sets* available (weather, social media, medical).
 - iv) Tools available through *open-source communities* with large user bases.
- *Sea-change* in the way data is generated, managed and utilized! Here to stay, cannot be ignored by the scientific computing community.

The anatomy of a field theory

- How does Data Science intersect with *scientific computing*?
- Scientific computing deals with the *field theories* of physics.

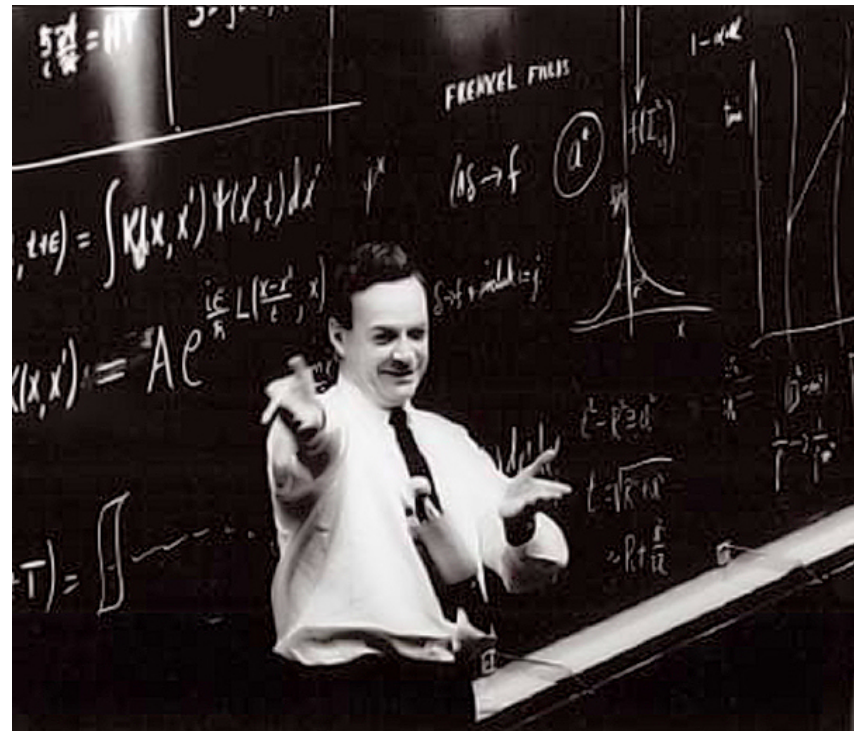
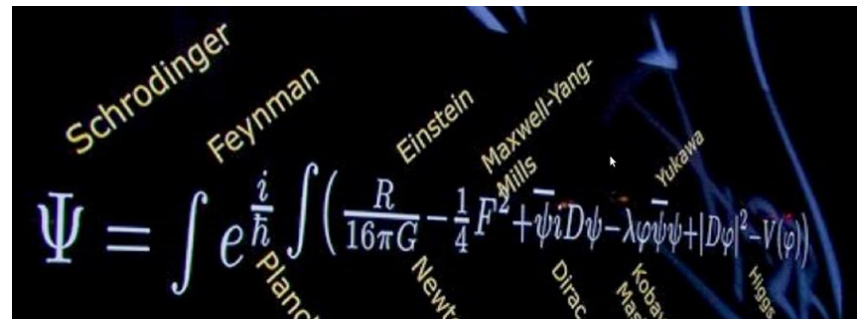
The anatomy of a field theory



James Clerk Maxwell
June 13, 1831 (Edinburgh)
November 5, 1879 (Cambridge)

$$\mathcal{L} = -\frac{1}{4\mu_0} F_{\mu\nu} F^{\mu\nu} - A_\mu J^\mu$$

NB: Duality structure!



Richard Feynman
May 11, 1918 (New York City)
February 15, 1988 (Los Angeles)

The anatomy of a field theory

- How does Data Science intersect with *scientific computing*?
- Scientific computing deals with the *field theories* of physics.
- Field theories describe how a *field* evolves in time or depends on other variables.
- Field theories often constructed by writing a *Lagrangian* or a *Hamiltonian* of the field and treating it as a classical or quantum system with a finite or infinite number of degrees of freedom.
- The resulting field theories are referred to as classical or quantum field theories and have a particular mathematical structure expressed in terms of *field equations*:

Field	Potential	Conservation	Material law
Gravitation	$g = -\nabla\phi$	$\nabla \cdot f + 4\pi\rho = 0$	$f = g/G$ (Newton)
Electrostatics	$E = -\nabla V$	$\nabla \cdot D = 4\pi\rho$	$D = \epsilon E$
Electromagnetics	$B = \nabla \times A$	$\nabla \times H = J$	$H = B/\mu$
Diffusion	$g = -\nabla c$	$\nabla \cdot J + s = 0$	$J = D g$ (Fick)
Heat transfer	$g = -\nabla T$	$\nabla \cdot J + s = 0$	$J = \kappa g$ (Fourier)
Elasticity	$\epsilon = \text{sym}\nabla u$	$\nabla \cdot \sigma + f = 0$	$\sigma = \mathbb{C} \epsilon$ (Hooke)
General	$\epsilon = \delta u$	$\partial\sigma + f = 0$??

- Field equations are exactly known, *only material law is determined from data!*

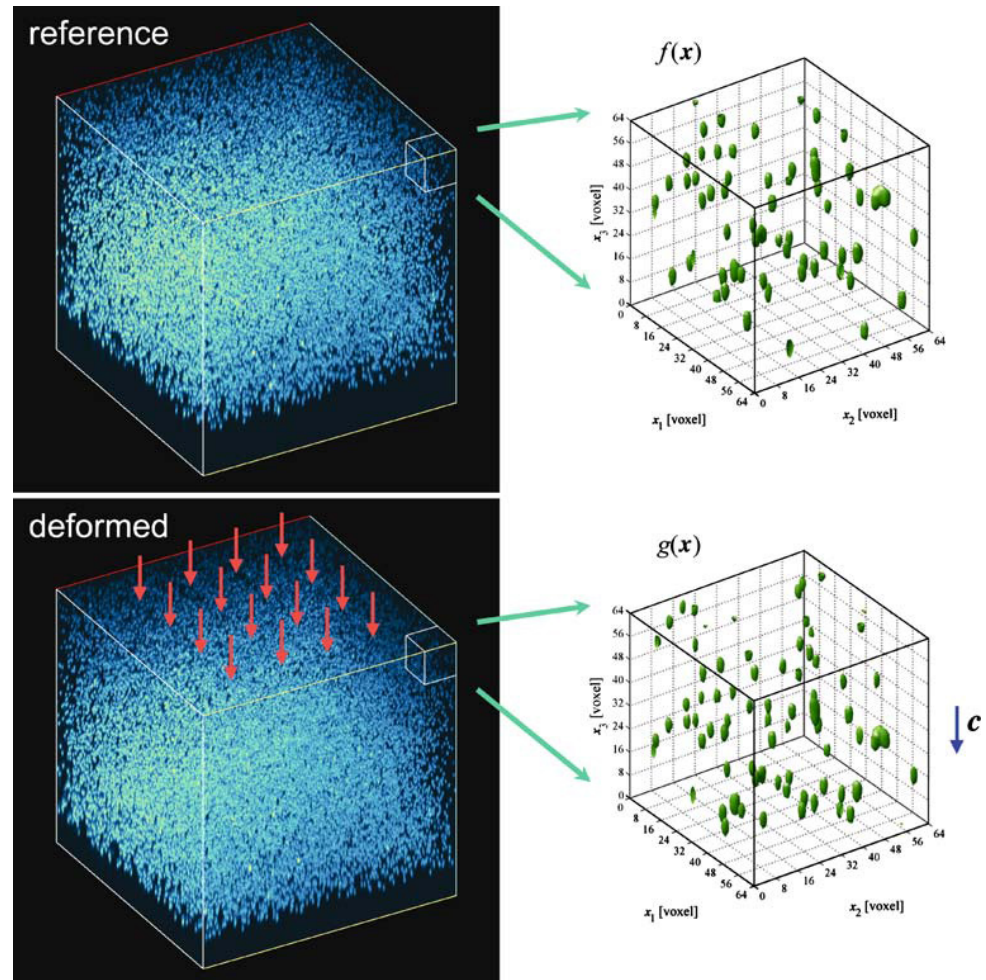
Why Data-Driven Computing Now?

- How does Data-Science intersect with *computational mechanics*?
- *Material data is currently plentiful* due to dramatic advances in experimental science (DIC, EBSD, microscopy, tomography...) and multiscale computing (DFT → MD → DDD → SM → Hom)

Digital Volume Correlation

(DVC): Two confocal volume images of an agarose gel with randomly dispersed fluorescent particles before and after mechanical loading. The full displacement vector field is measured using 3D volume correlation methods.

C. Franck, S. Hong, S.A. Maskarinec,
D.A. Tirrell and G. Ravichandran,
Experimental Mechanics (2007)
47:427–438.



Why Data-Driven Computing Now?

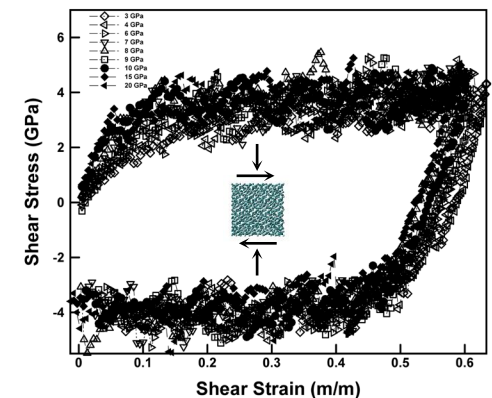
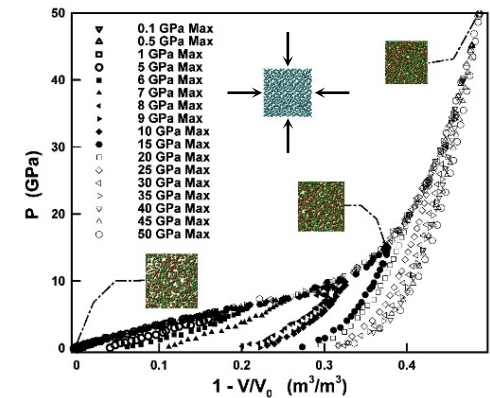
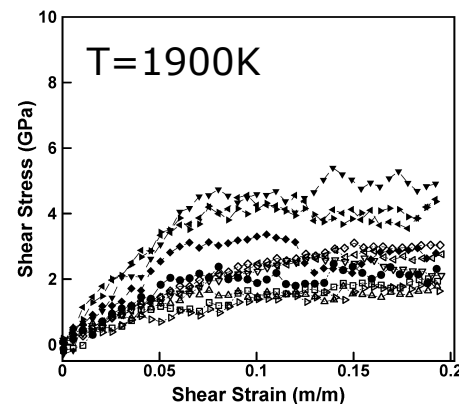
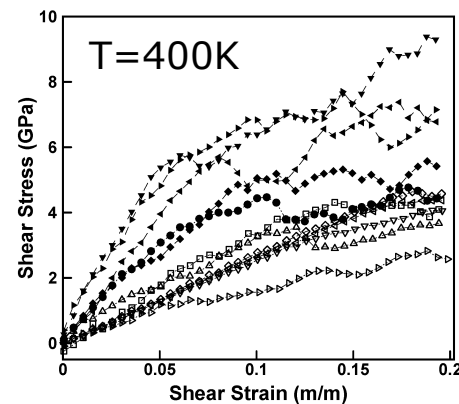
- Material data can also be generated in large volumes from high-fidelity *micromechanical calculations* (DFT, MD, DD...)
- New role for *multiscale analysis*: Data generation

Amorphous SiO_2 glass:

LAMMPS MD calculations of amorphous silica glass under *pressure-shear* loading over a range of *temperatures* and *strain rates*. RVEs are quenched from the melt, then analyzed using the BKS potential with Ewald summation.

Schill, W., Heyden, S., Conti, S.
& MO, *JMPS*, **113** (2018) 105-125.

Schill, W., Mendez, J.P., Stainier, L.
& MO, *JMPS*, **140** (2020) 103940.



Why Data-Driven Computing Now?

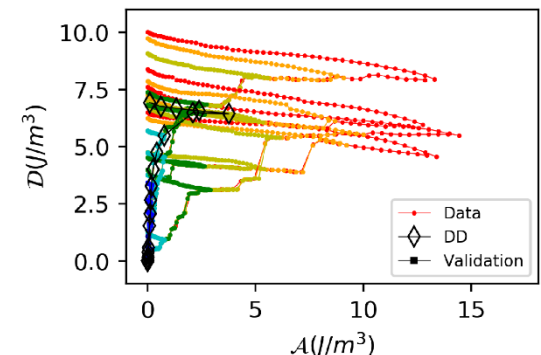
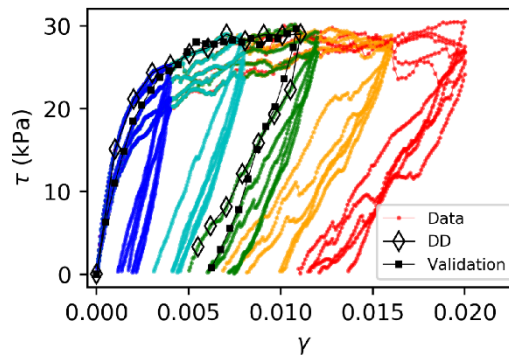
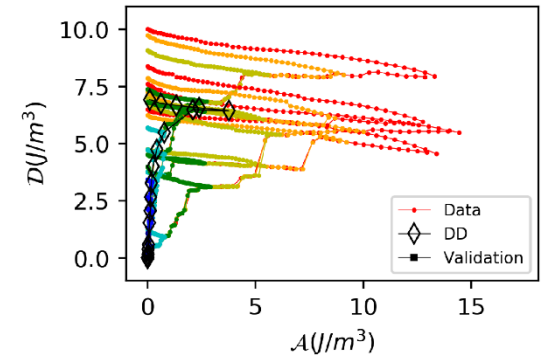
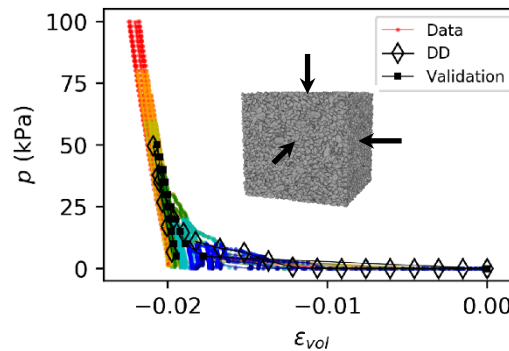
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Granular matls. (dry sand):

Level-Set Discrete Element Method (LS-DEM) simulation of granular material samples. 3D irregular *rigid particles* interact through *frictional contact*. Particle morphology described by level-set functions. Note calculation of *dissipation and free energy*.

Karapiperis, K., Harmon, J., And, E.,
Viggiani, G. & Andrade, J.E.,
JMPS, **144** (2020) 104103.

Karapiperis, K., Stainier, L., Ortiz, M.
& Andrade, J.E., *JMPS*, **147** (2021) 104239.

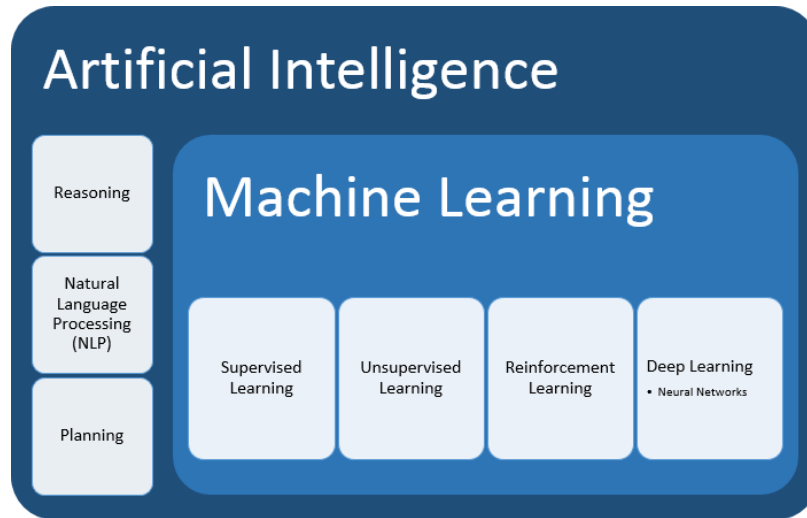


Model-Free Data-Driven Computing

- Mechanics of materials is presently *data rich*: Challenge and opportunity!
- *Data-Driven Computing*: Forge a closer connection between data and predictions.
- *Model-Based* (supervised) vs. *Model-Free* (unsupervised) Data-Driven computing:

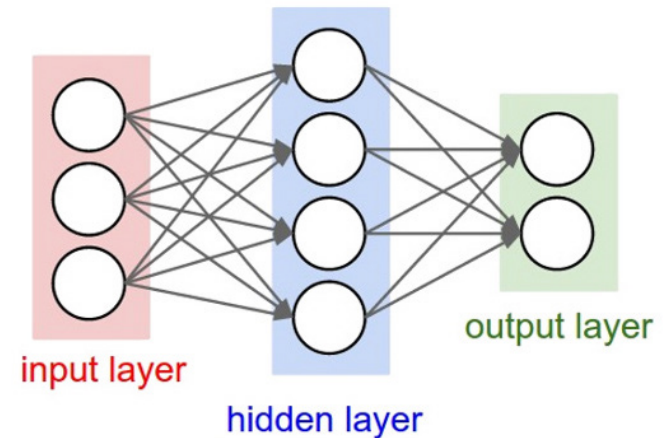
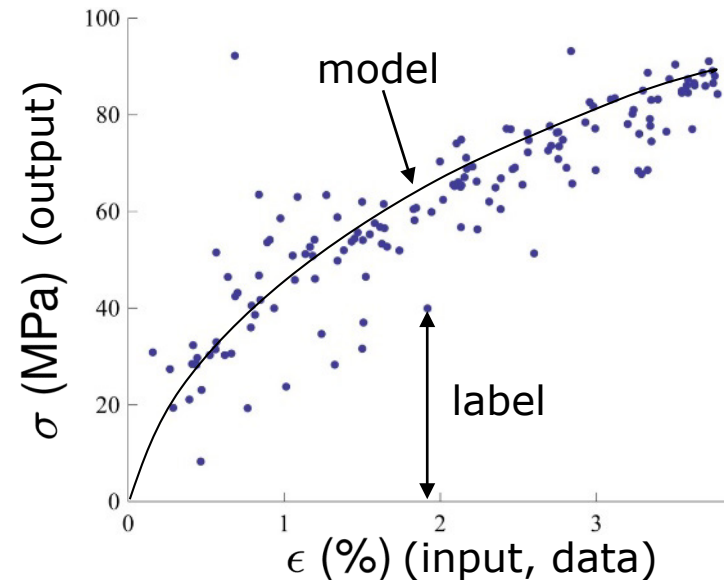
Model-Based Data-Driven computing:	Data	→	Model	→	Prediction
Model-Free Data-Driven computing:	Data		→		Prediction

Model-Free Data-Driven Computing



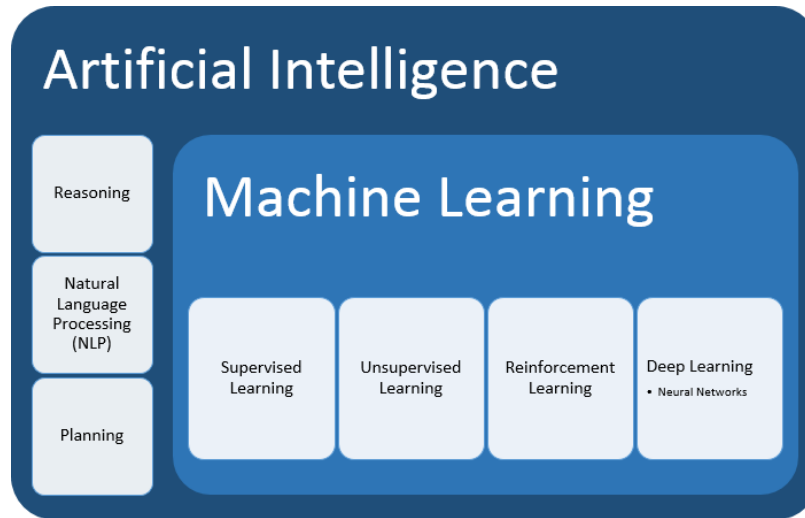
Supervised learning: Find (e.g., by *regression*) a function (e.g., *deep Neural Network*) from data containing both inputs and outputs (labels).

J. Hurwitz & D. Kirsch, *Machine Learning*, John Wiley & Sons, 2018.



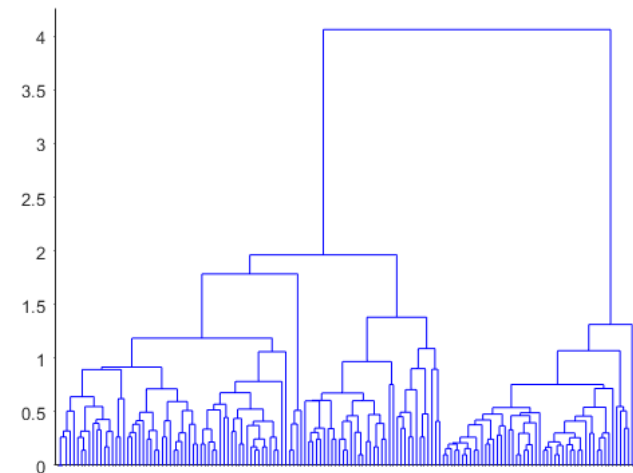
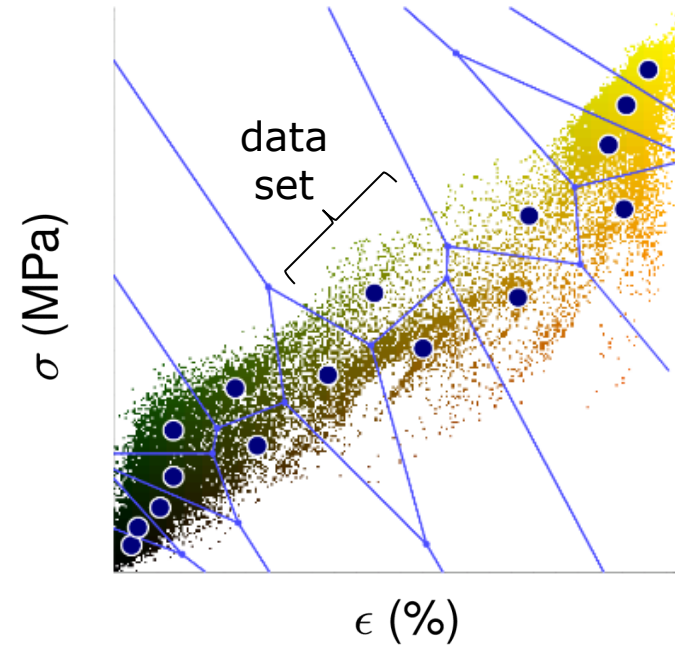
Deep Neural Network
representation, regression

Model-Free Data-Driven Computing



Unsupervised learning: Find structure in *unlabeled data* sets (e.g., grouping, clustering, density), make predictions directly from *data structures*.

J. Hurwitz & D. Kirsch, *Machine Learning*, John Wiley & Sons, 2018.



Hierarchical k-means representation, set based

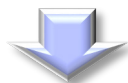
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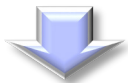
- Critique of Model-Based Data-Driven computing:
 - i) Modeling is *lossy* (information in model < information in data).

Modern
microscopy:
*massive
data sets*

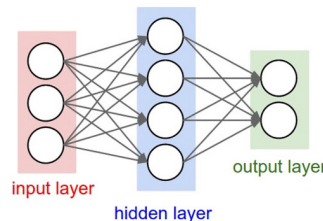
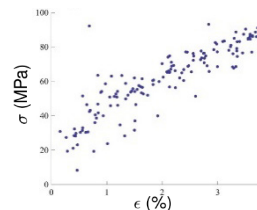
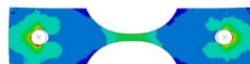


Modelling:
*massive
loss of
information!*

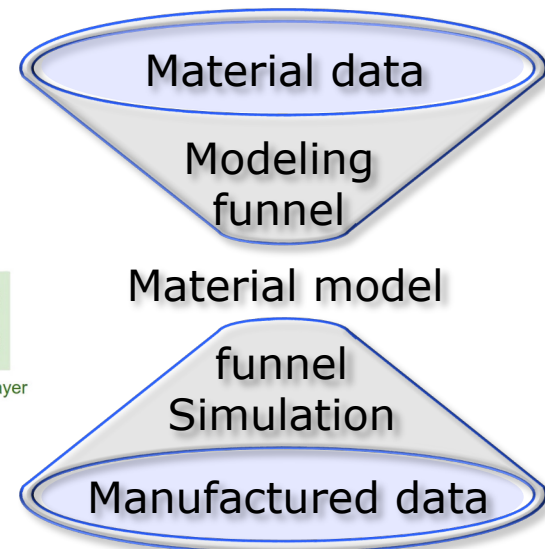
$$\sigma = \hat{\sigma}(\epsilon)$$



FE analysis:
*garbage in
garbage out*



(BVP)

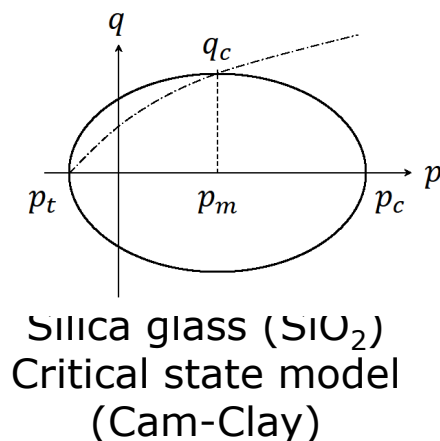
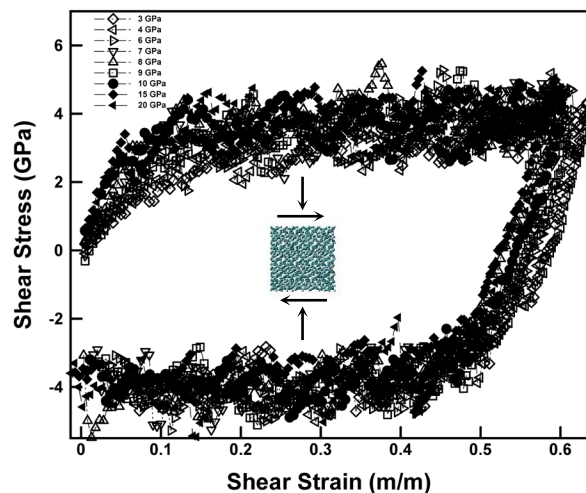


Model-Free Data-Driven Computing

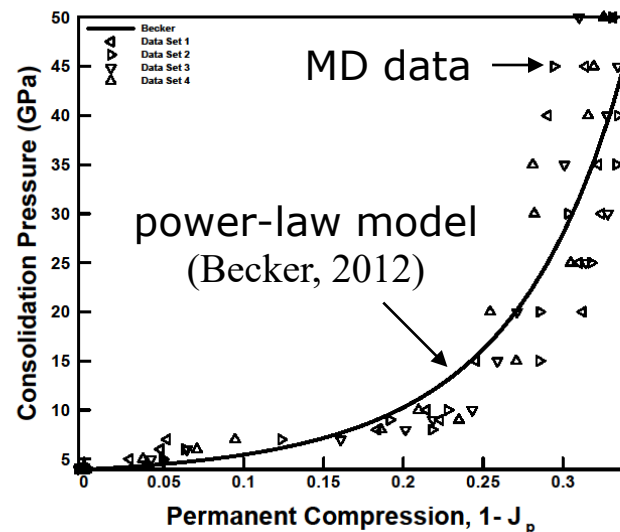
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 - ii) Modeling is *ad hoc* (involves arbitrary decisions, sausage making).
 - iii) Modeling introduces *biases, modeling error, epistemic uncertainty*.



W. Schill *et al.*, *JMPS*,
 113 (2018) 105-125.

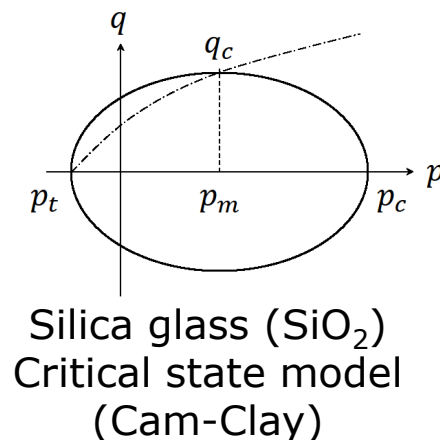
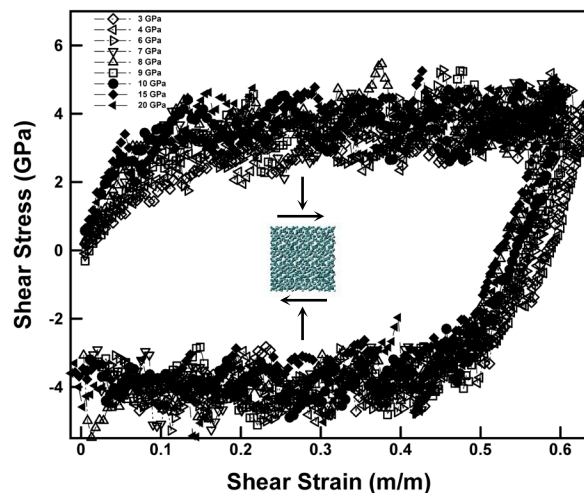


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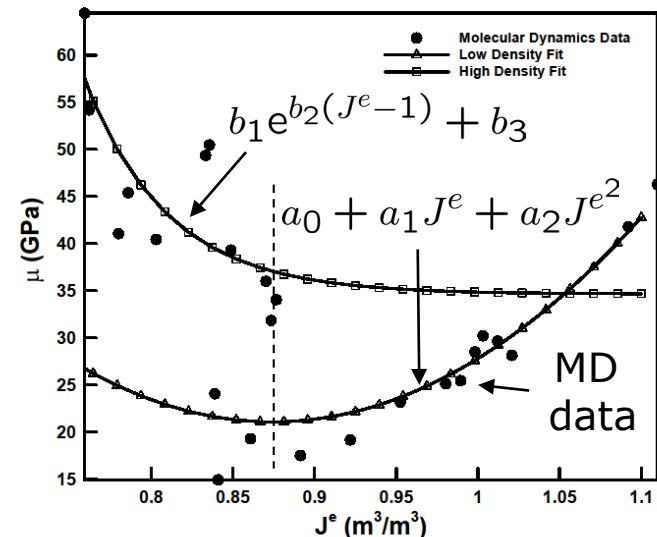
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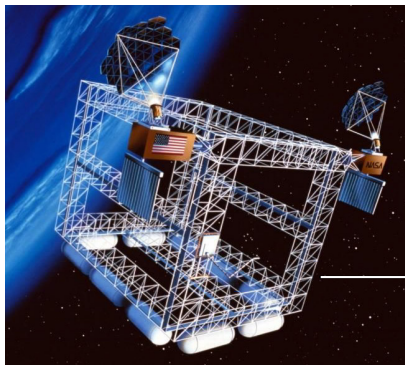


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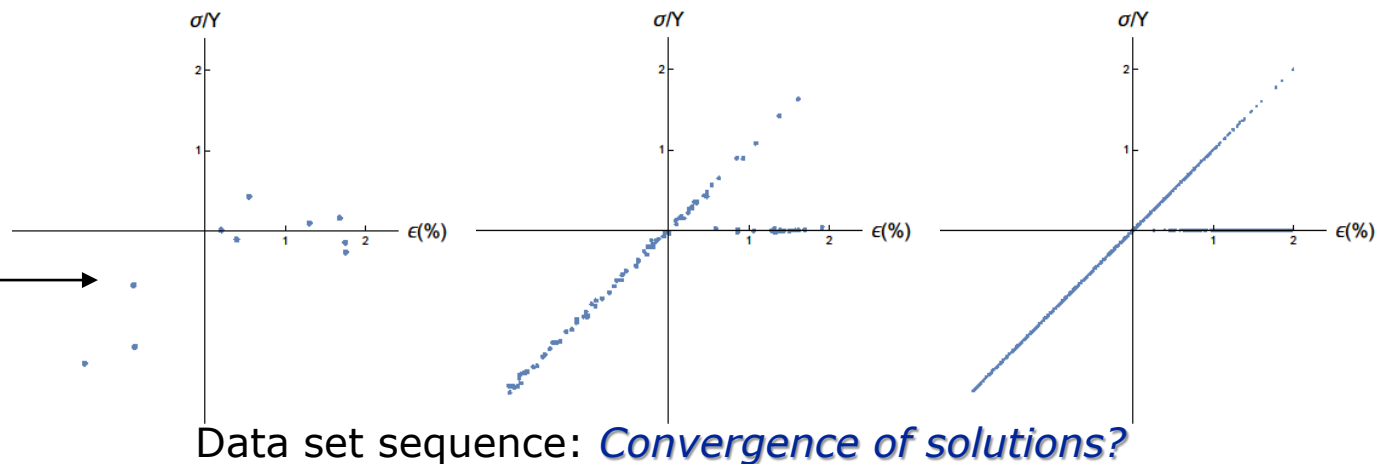
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NASA L89-14711



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 - iv) Modeling is *ill-posed* (no notion of continuity, convergence, with respect to data).
- Cut-out the middleman! Model-Free Data-Driven computing: Make predictions directly from the data.

The data, all the data, nothing but the data

How?

Why Data-Driven Computing Now?

- It is possible to formulate boundary-value problems, convergent approximation schemes, *based directly on material data*, without the intermediate step of constitutive modeling
- The *Model-Free Data-Driven paradigm* forges a direct connection between material data and solutions of boundary-value problems, in the spirit of unsupervised learning
- Results extend to *infinite-dimensional problems* (linear, finite elasticity)
- *Solvers*? Data structures, searching? Connections to Machine Learning?
- Extension to *time-dependent problems*? (e.g., dynamics)
- Extension to *inelasticity*? (viscoelasticity, viscoplasticity, plasticity)
- *Probability? Inference?* (scatter, random materials, random loads...)
- *Where does the data come from?*
 - *Multiscale* Data-Driven schemes
 - Data-Driven *Material Identification*

Why Data-Driven Computing Now?

TIME TABLE

TIME	Monday	Tuesday	Wednesday	Thursday	Friday
	October 10	October 11	October 12	October 13	October 14
09.00 - 09.45	Registration	Schönlieb	Stainier	Doblaré	Doblaré
09.45 - 10.30	Ortiz	Schönlieb	Stainier	Doblaré	Doblaré
11.00 - 11.45	Ortiz	Ortiz	Schönlieb	Stainier	Doblaré
11.45 - 12.30	Ortiz	Ortiz	Schönlieb	Stainier	Ortiz
14.00 - 14.45	Réthoré	Schönlieb	Reese	Stainier	
14.45 - 15.30	Réthoré	Schönlieb	Reese	Reese	
16.00 - 16.45	Réthoré	Réthoré	Stainier (DDCM)	Reese	
16.45 - 17.30	Réthoré (DIC)	Réthoré (DDI)	Poster Session	Reese	
18.00	Welcome aperitif				

Why Data-Driven Computing Now? – Lecture plan



- MD: Physically-informed neural networks in predictive physics
- MO: Fundamentals of (model-free) Data-Driven mechanics
- JR: Data-Driven material identification, experimental methods
- SR: Data structures, solvers, algorithmic strategies, plasticity
- CBS: Imaging, mathematical approaches, hybrid modeling
- LS: Extensions to finite elasticity, multiscale analysis, design

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to be continued...