



## Machine Learning Unveiled as a Bridge-building Trailblazer *(really a set of bridging paths falling under the AI\* umbrella!)*



**A. ML Essentials: roots in data analysis methods**

**B. Computational Strategies: varied forms of  
'learning' and applying 'learning' algorithms...**

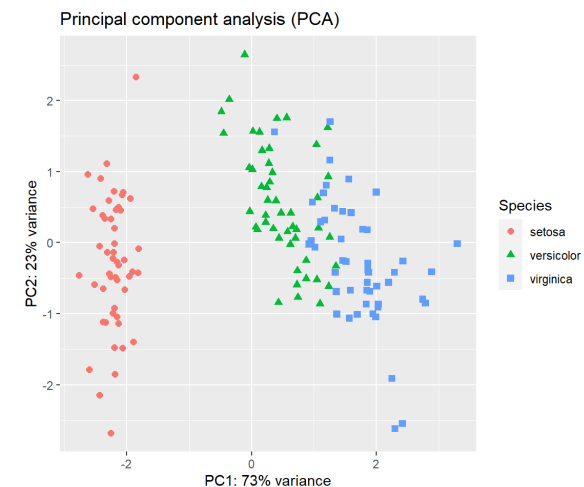
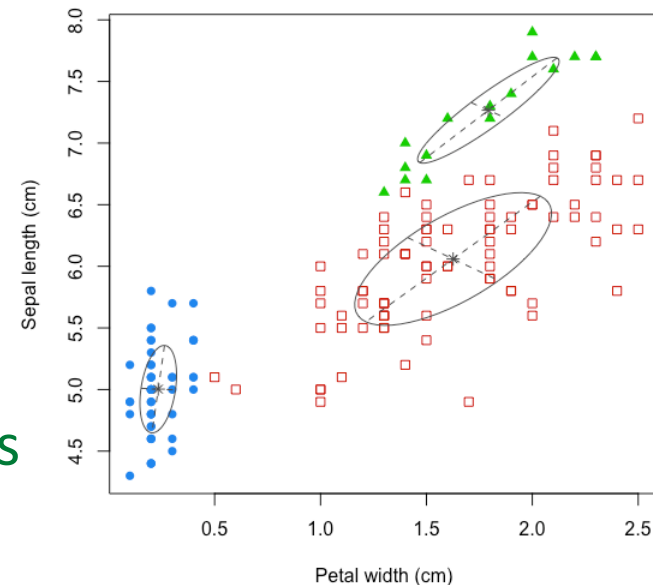
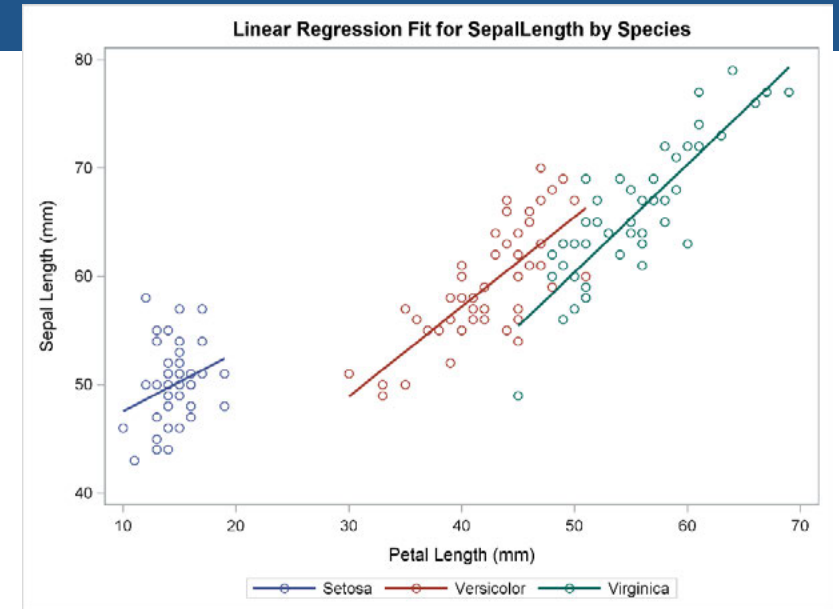
\* Recall *cynical* definition offered at recent NIH meeting: if it *actually* works in practice somehow, it's 'machine learning' otherwise it may just be termed 'artificial intelligence' that still has more to learn...



# ML Essentials: roots in data analysis methods

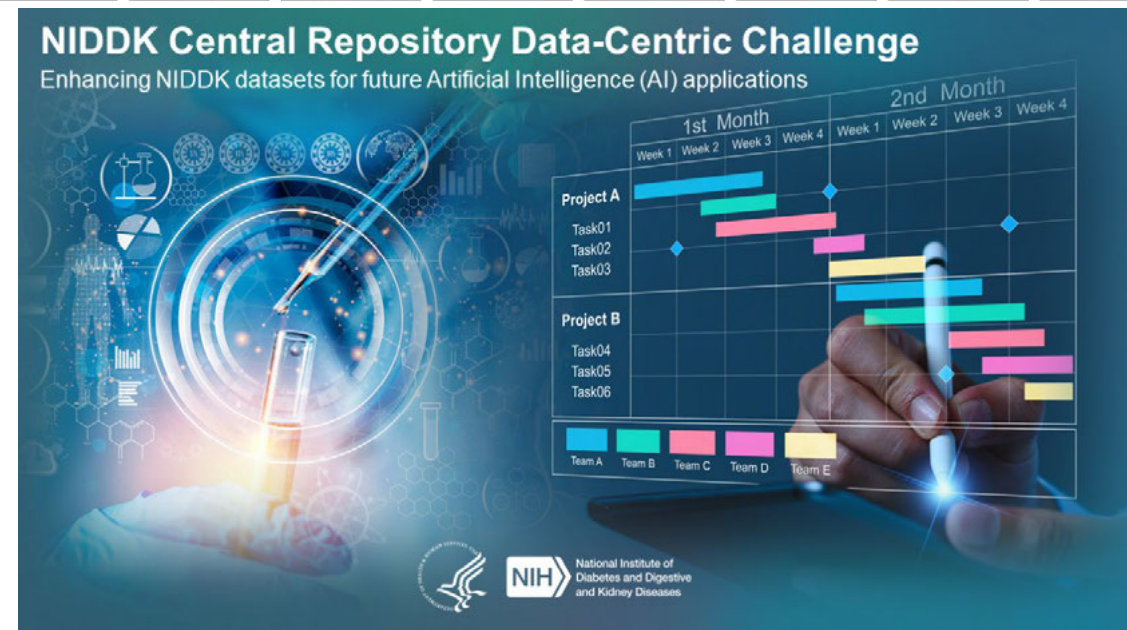
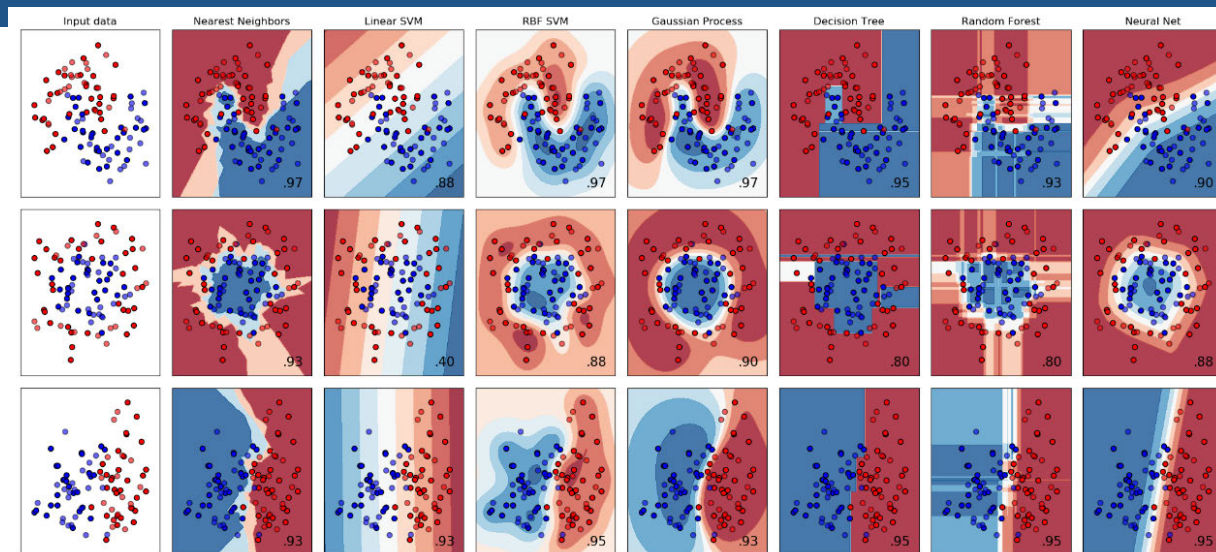


- Data analysis methods to ‘learn’ how to predict patterns in data
  - Classic iris flower regression example
- Data analysis methods to ‘learn’ *novel* patterns in data: clustering & ‘mixture modeling’
  - Discover ‘clusters’ by length measures
  - Data reduction by principal components



# ML Essentials: roots in data analysis methods

- Data analysis methods to ‘learn’ how to predict patterns in data
- Data analysis methods to ‘learn’ *novel* patterns in data: clustering
- Relates to UN-supervised v. semi-supervised v. Supervised learning
  - Hearken back to prior SchARe Think-a-thon
  - Underway: PHASE 2 of NIDDK CR Data-Centric Challenge (till Jan 22, 2024)

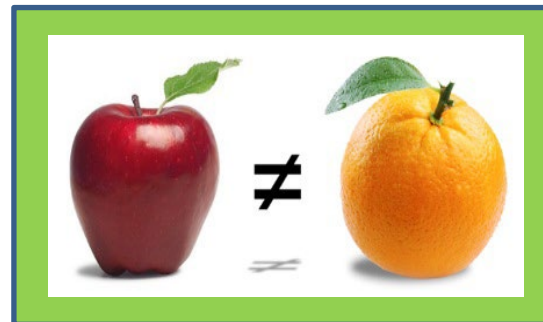




# ML Essentials: supervised v. semi-supervised v. unsupervised learning

*‘Machine Learning’ as a tool for Data Science (thus, for health equity research)*

- *Does one term cover all approaches? Types of ML, matching use cases & data*
- *e.g. (extent of ‘supervision’; goals of analysis)*
- *What does “extent of ‘supervision’” mean in this context?*



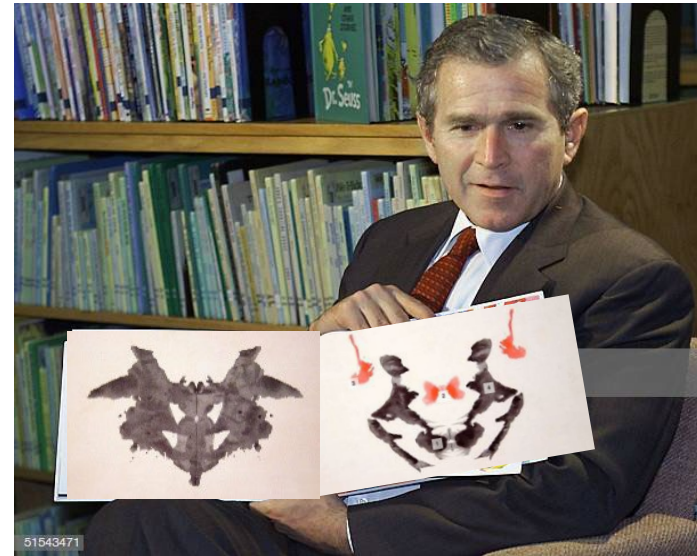
*Supervised Learning*

Supervision here:  
*each instance is given exactly 1 ‘label’ to distinguish*

# ML Essentials: supervised v. semi-supervised v. unsupervised learning

*‘Machine Learning’ as a tool for Data Science (thus, for health equity research)*

- *Does one term cover all approaches? Types of ML, matching use cases & data*
- *e.g. (extent of ‘supervision’; goals of analysis)*
- *What does “extent of ‘supervision’” mean in this context?*



*Semi-supervised Learning*

**RED** color shows up on the **RIGHT**  
No picture lacks a ‘mirror’ image

Supervision here:  
*Only some instances given a ‘label’ to distinguish ‘labeling’ pattern overall...*

# ML Essentials: supervised v. semi-supervised v. unsupervised learning

*‘Machine Learning’ as a tool for Data Science (thus, for health equity research)*

- *Does one term cover all approaches? Types of ML, matching use cases & data*
- *e.g. (extent of ‘supervision’; goals of analysis)*
- *What does “extent of ‘supervision’” mean in this context?*



**Four-eyed Fox**  
**Four-eyed Wolf**  
Red kidneys & butterflies around a 2 person drum circle

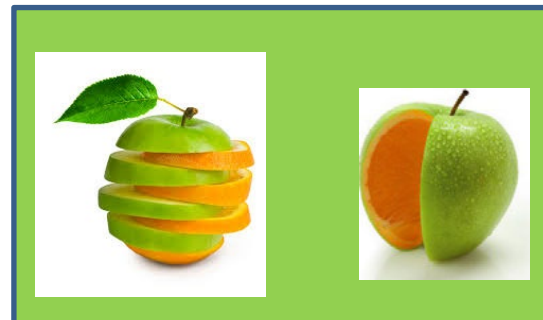
*Unsupervised Learning*

Supervision here:  
*Only intrinsic parts of instances used to ‘label’ them, elicit any pattern overall...*

# ML Essentials: supervised v. semi-supervised v. unsupervised learning

*‘Machine Learning’ as a tool for Data Science (thus, for health equity research)*

- *Does one term cover all approaches? Types of ML, matching use cases & data*
- *e.g. (extent of ‘supervision’; goals of analysis)*
- *What does “extent of ‘supervision’” mean in this context?*



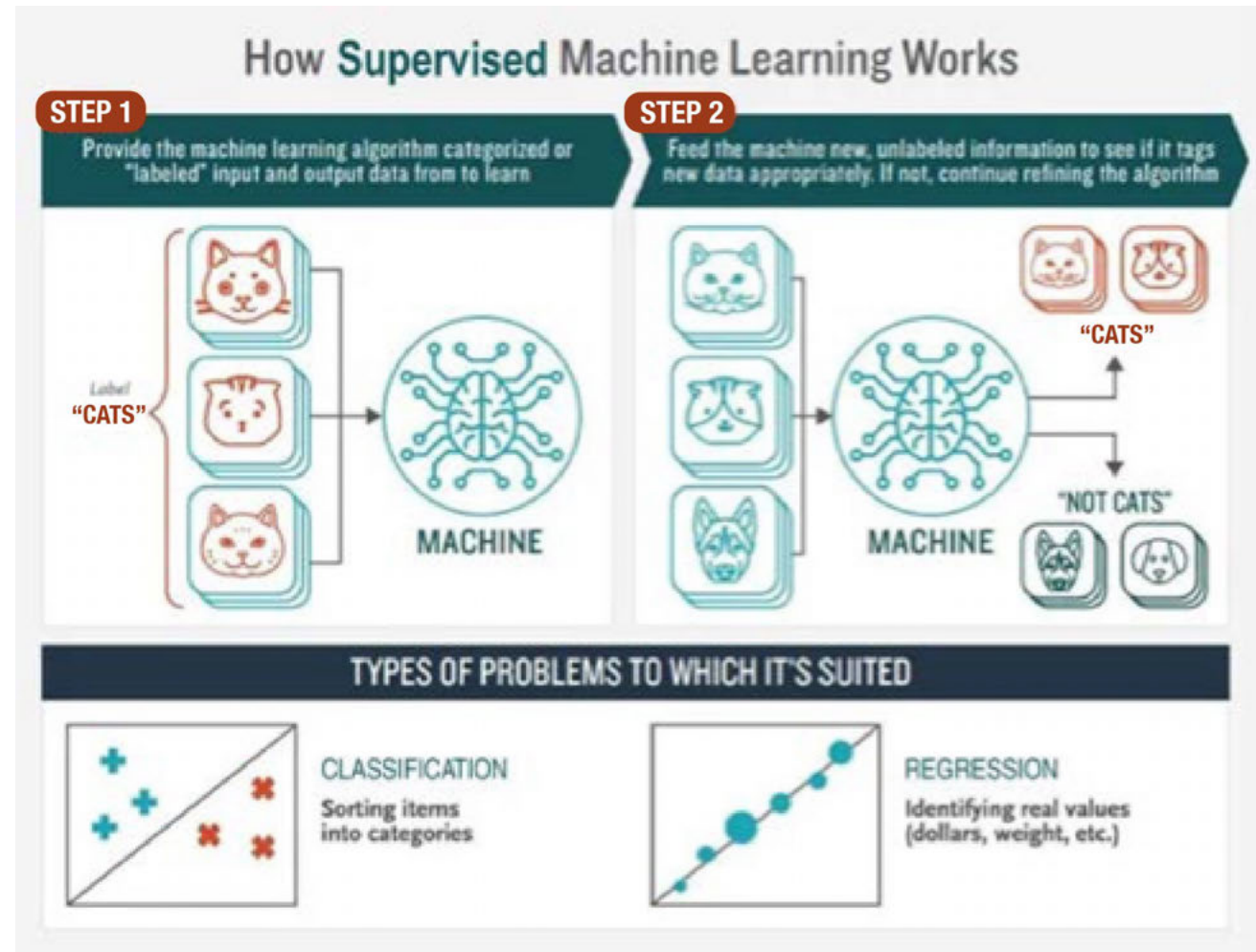
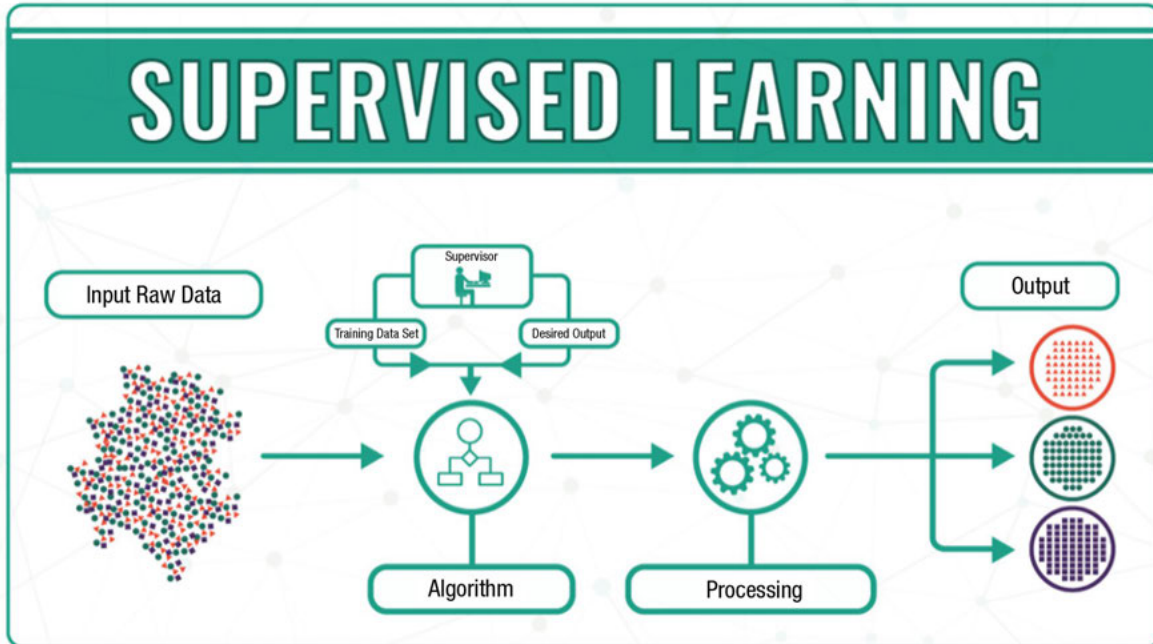
*Unsupervised Learning*

Supervision here:  
*LACK of such can elicit patterns NOT typically within human intuition*



# ML Essentials: supervised v. semi-supervised v. unsupervised learning

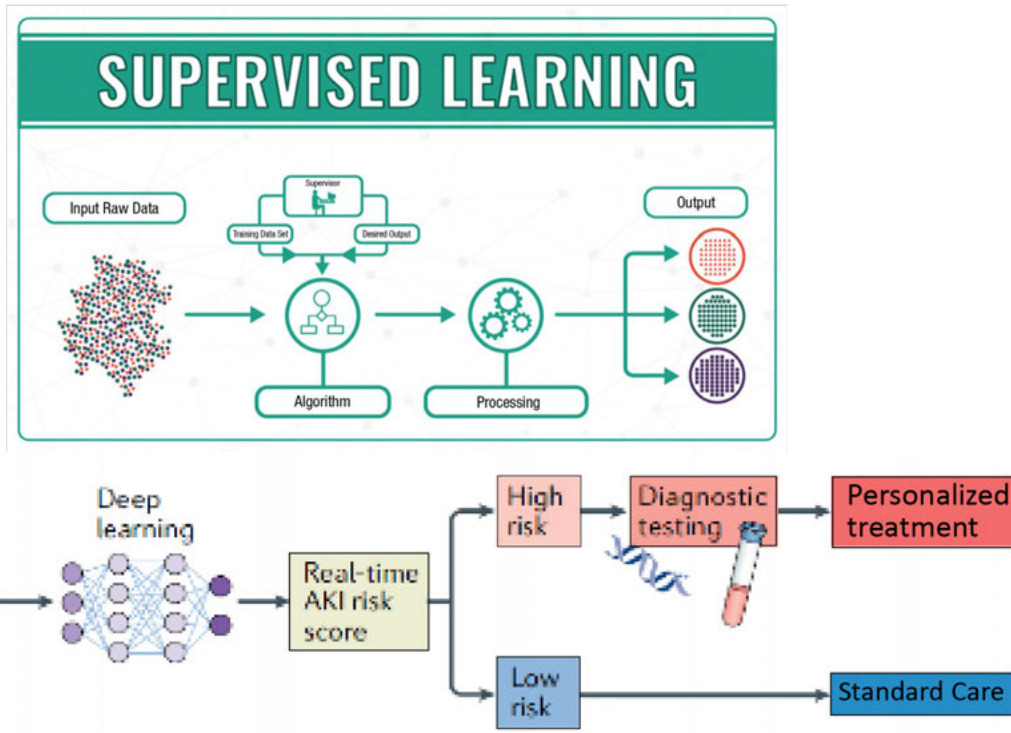
- From Booz Allen Team for CKD





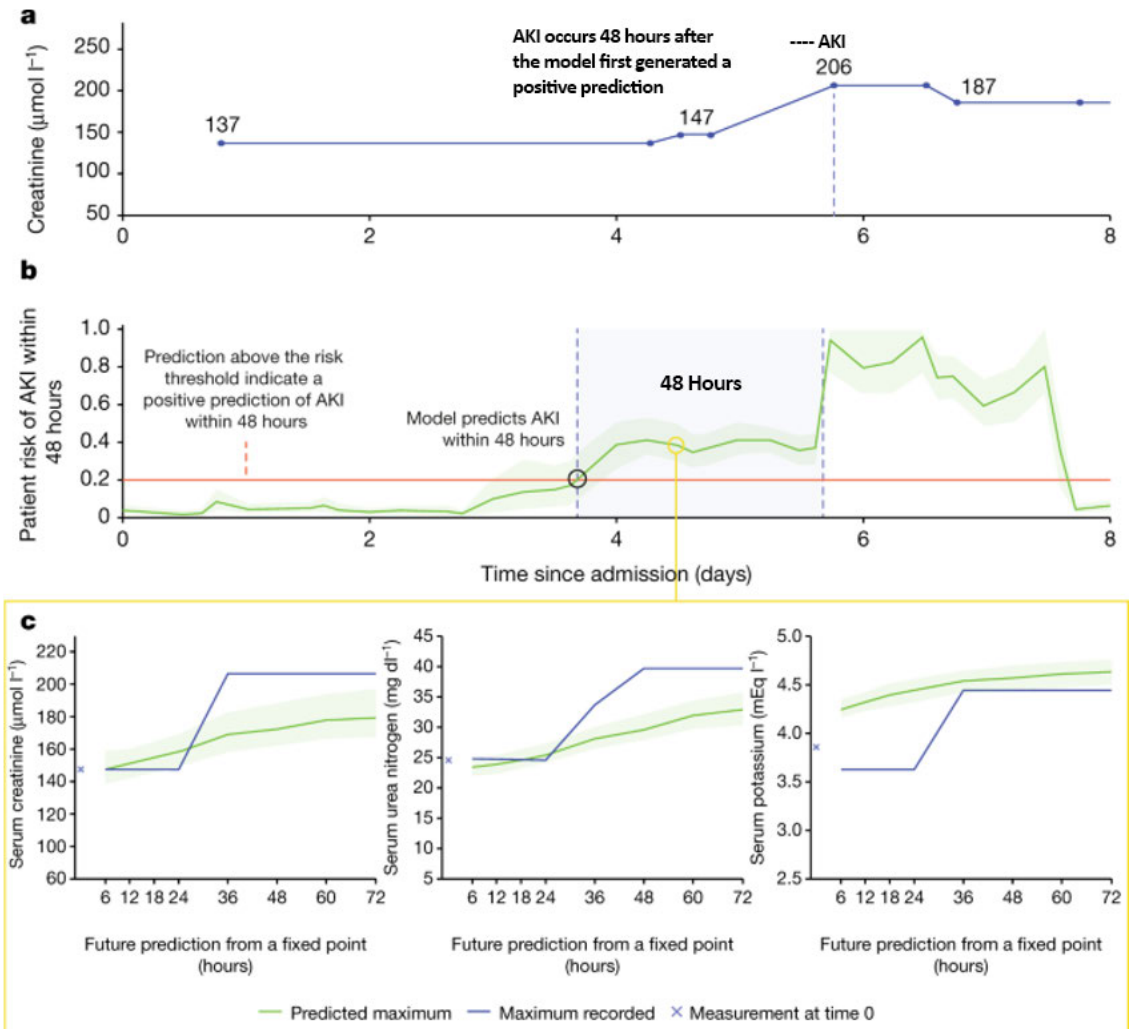
# ML Essentials: supervised v. semi-supervised v. unsupervised learning

- From non-NIH-funded team



**Fig. 1 | Implementation of deep learning algorithms to identify patients at high risk of AKI.** Deep learning algorithms developed to support clinical decisions in real time should be based on integrated patient information, including electronic health records (EHRs) with detailed medical history (including ongoing problems and procedures), physiological parameters (such as vital signs and laboratory results) and medication details. Acute kidney injury (AKI) risk scores derived from such an algorithm would stratify patients and inform clinical decisions, including the use of additional diagnostics to enable personalized treatment.

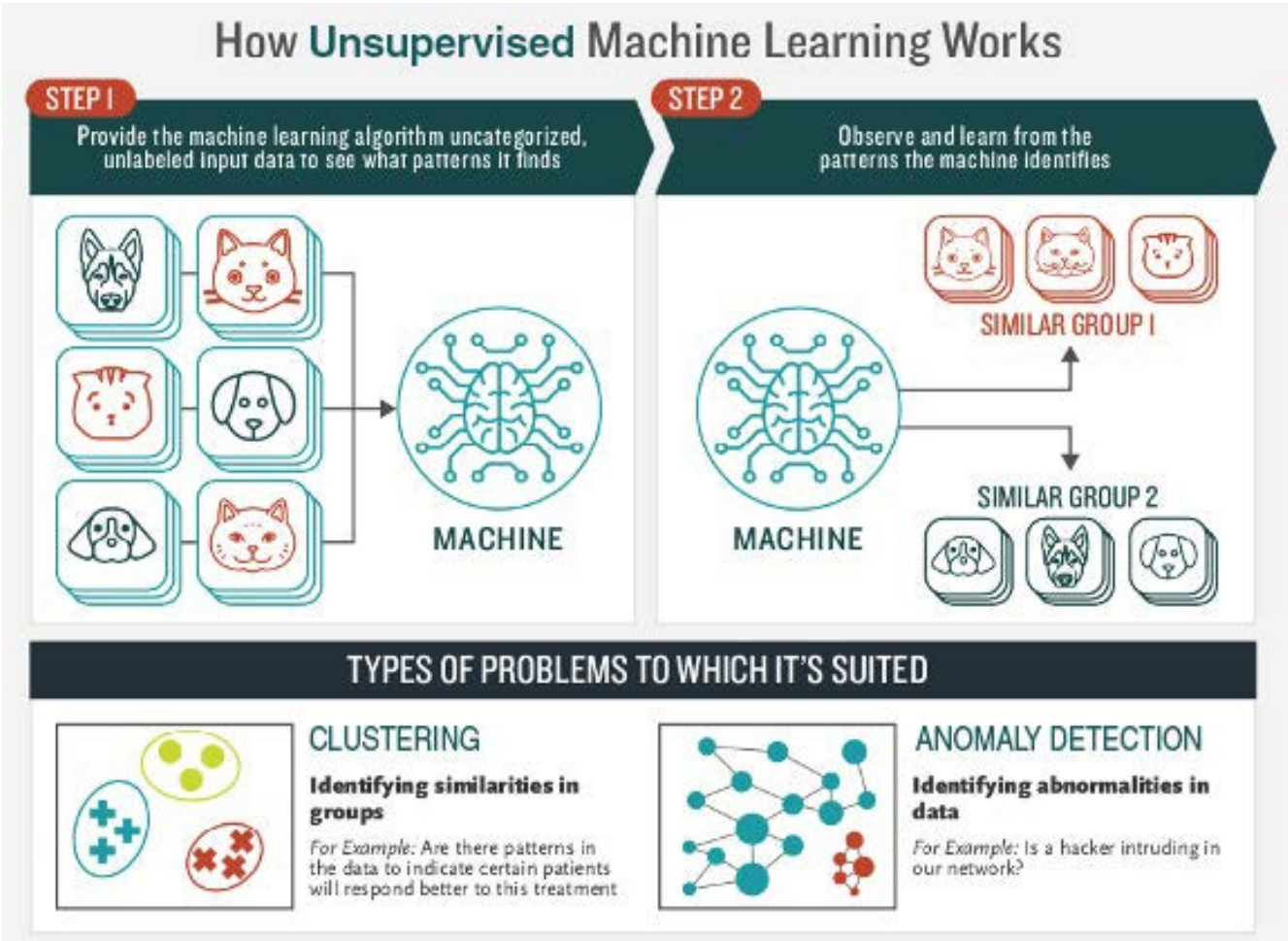
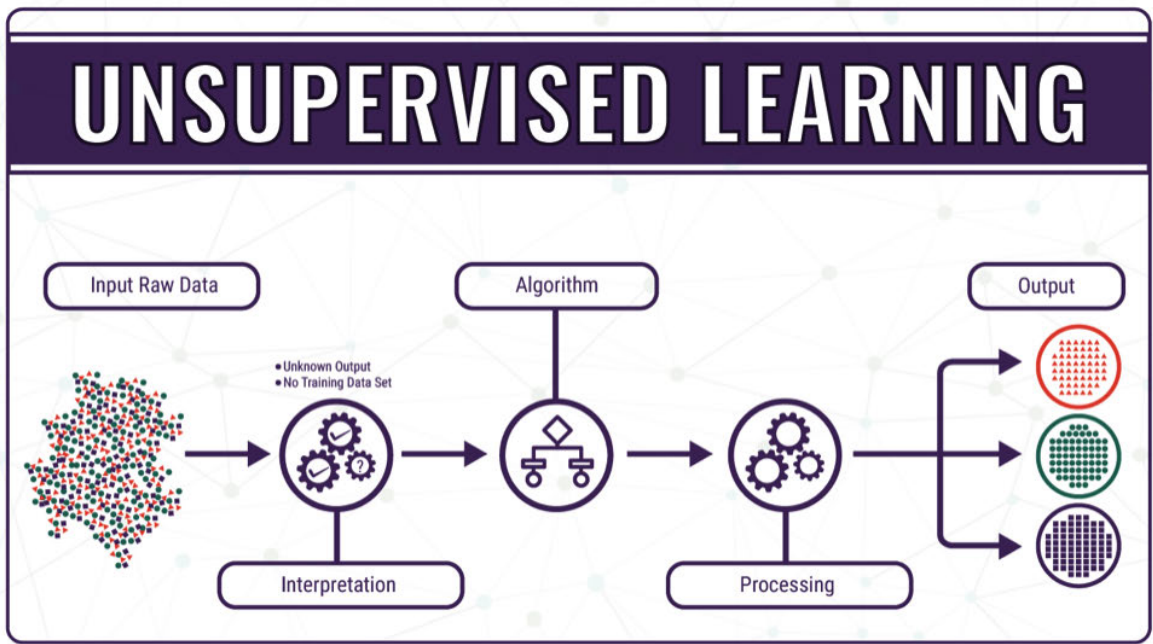
Figures 1 from editorial on and paper of DeepMind's AKI approach in Tomašev, N. et al. A clinically applicable approach to continuous prediction of future acute kidney injury. *Nature* 572, 116–119 (2019).



"We make use of several open-source libraries to conduct our experiments: the machine learning framework TensorFlow (<https://github.com/tensorflow/tensorflow>) along with the TensorFlow library Sonnet (<https://github.com/deepmind/sonnet>)"

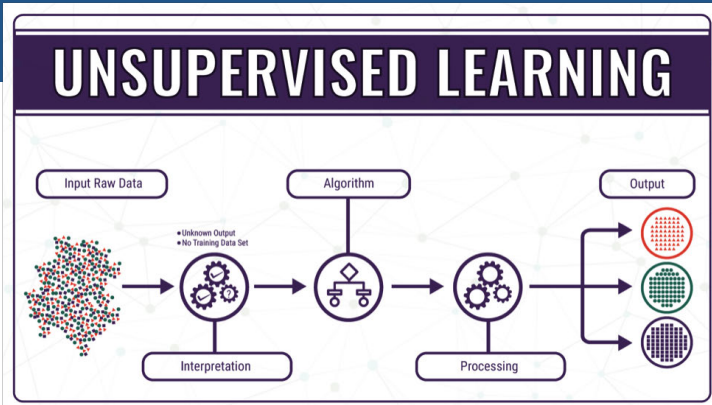
# ML Essentials: supervised v. semi-supervised v. unsupervised learning

- From Booz Allen Team for CKD



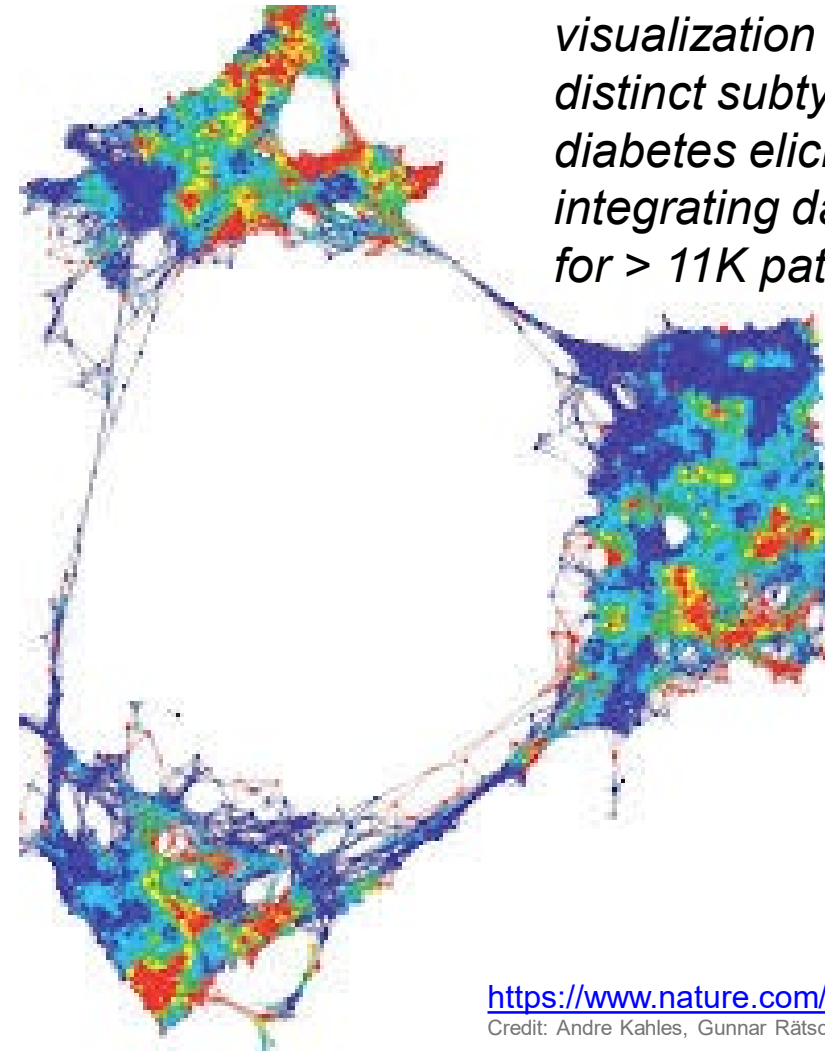
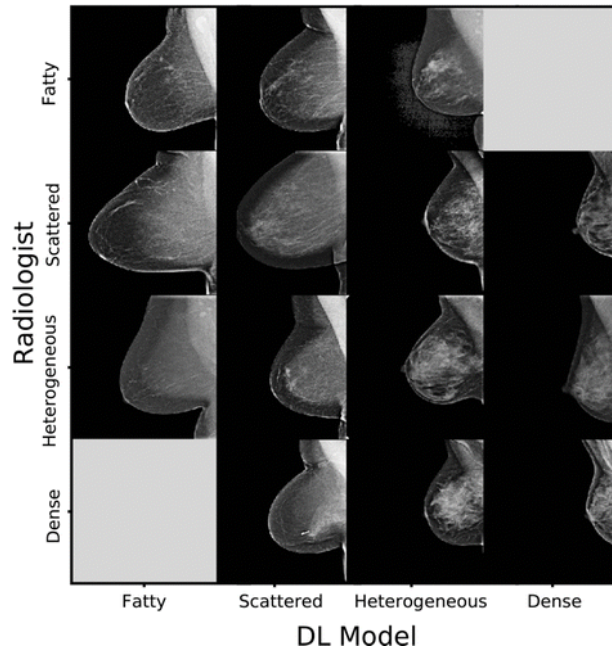


# ML Essentials: supervised v. semi-supervised v. unsupervised learning



- From NIDDK-funded team →
- From other NIH-funded team ↓
  - Mammograms
  - Role of density
  - Blend: un+sup

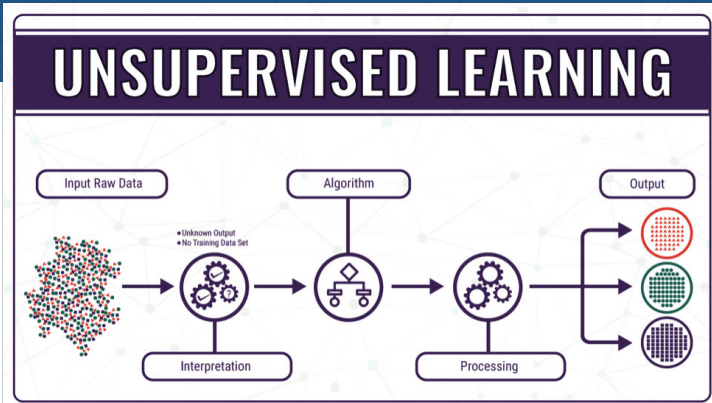
**Figure 1d:** Test set assessment. Comparison of the original interpreting radiologist assessment with the deep learning (DL) model assessment for (a) binary and (c) four-way mammographic breast density classification. (b, d) Corresponding examples of mammograms with concordant and discordant assessments by the radiologist and with the DL model.



From NIDDK report: *network visualization showing 3 distinct subtypes of Type 2 diabetes elicited after integrating data from EHRs for > 11K patients*



# ML Essentials: supervised v. semi-supervised v. unsupervised learning

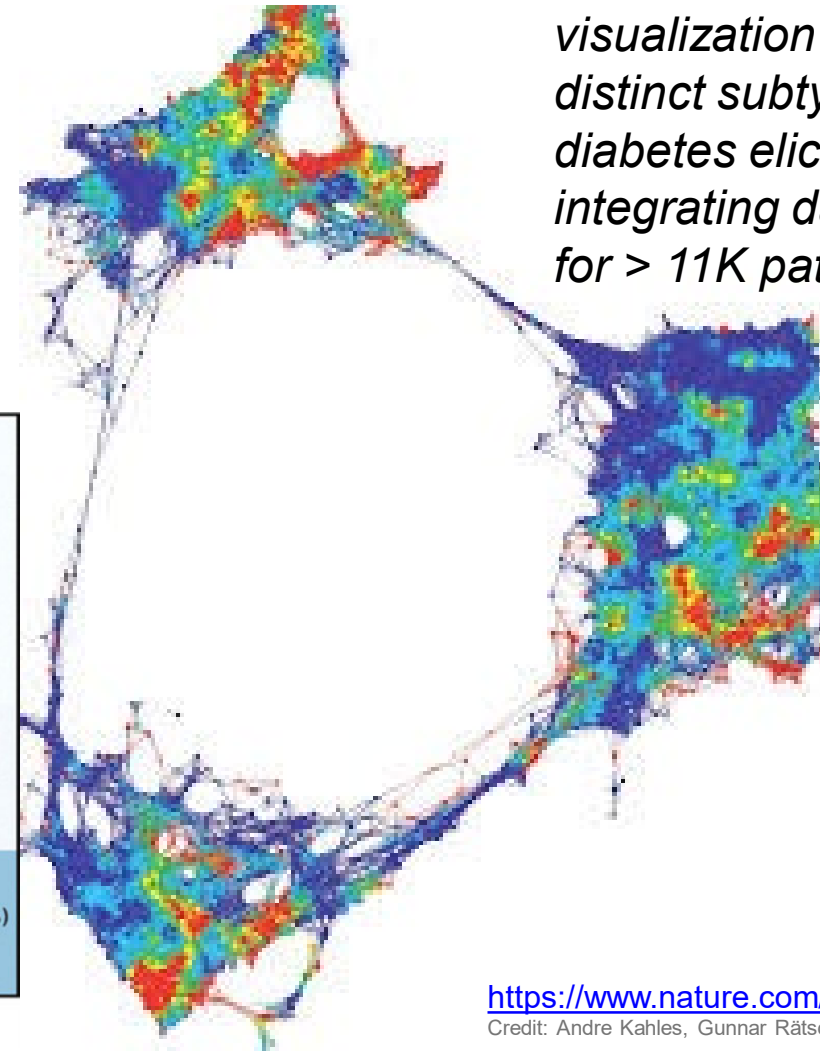


- From NIDDK-funded team →
- From other NIH-funded team ↓
  - Mammograms
  - Role of density
  - Blend: un+sup

**Figure 1d:** Test set assessment. Comparison of the original interpreting radiologist assessment with the deep learning (DL) model assessment for (a) binary and (c) four-way mammographic breast density classification. (b, d) Corresponding examples of mammograms with concordant and discordant assessments by the radiologist and with the DL model.

	Fatty	Scattered	Heterogeneous	Dense
Fatty	444 (56.1%)	345 (43.6%)	3 (0.4%)	0 (0.0%)
Scattered	221 (5.0%)	3631 (82.6%)	543 (12.4%)	1 (0.0%)
Heterogeneous	1 (0.0%)	562 (18.2%)	2477 (80.0%)	56 (1.8%)
Dense	0 (0.0%)	4 (1.0%)	267 (66.3%)	132 (32.8%)
	Fatty	Scattered	Heterogeneous	Dense

DL Model



From NIDDK report: *network visualization showing 3 distinct subtypes of Type 2 diabetes elicited after integrating data from EHRs for > 11K patients*

# Machine Learning Computational Strategies

- We now engage participants to check our mutual understanding