

Machine Learning in Seismology

turning data into insights

Qingkai Kong

<http://seismo.berkeley.edu/qingkaikong/>



Seismological Research Letters

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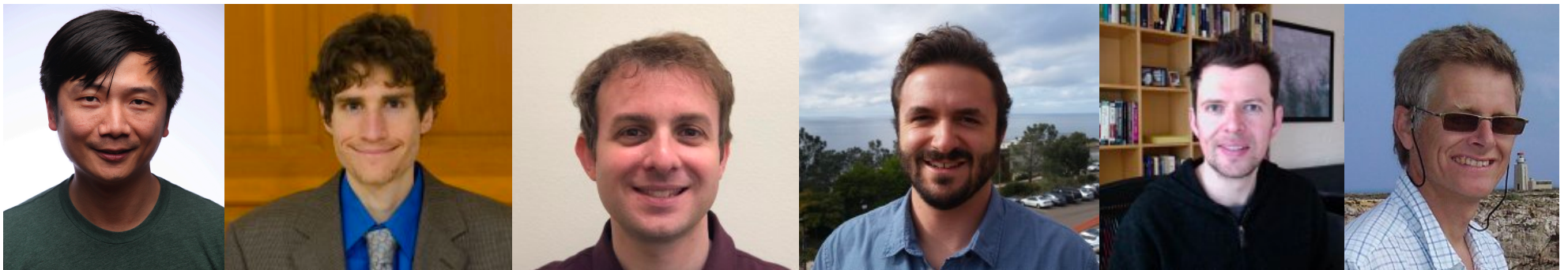
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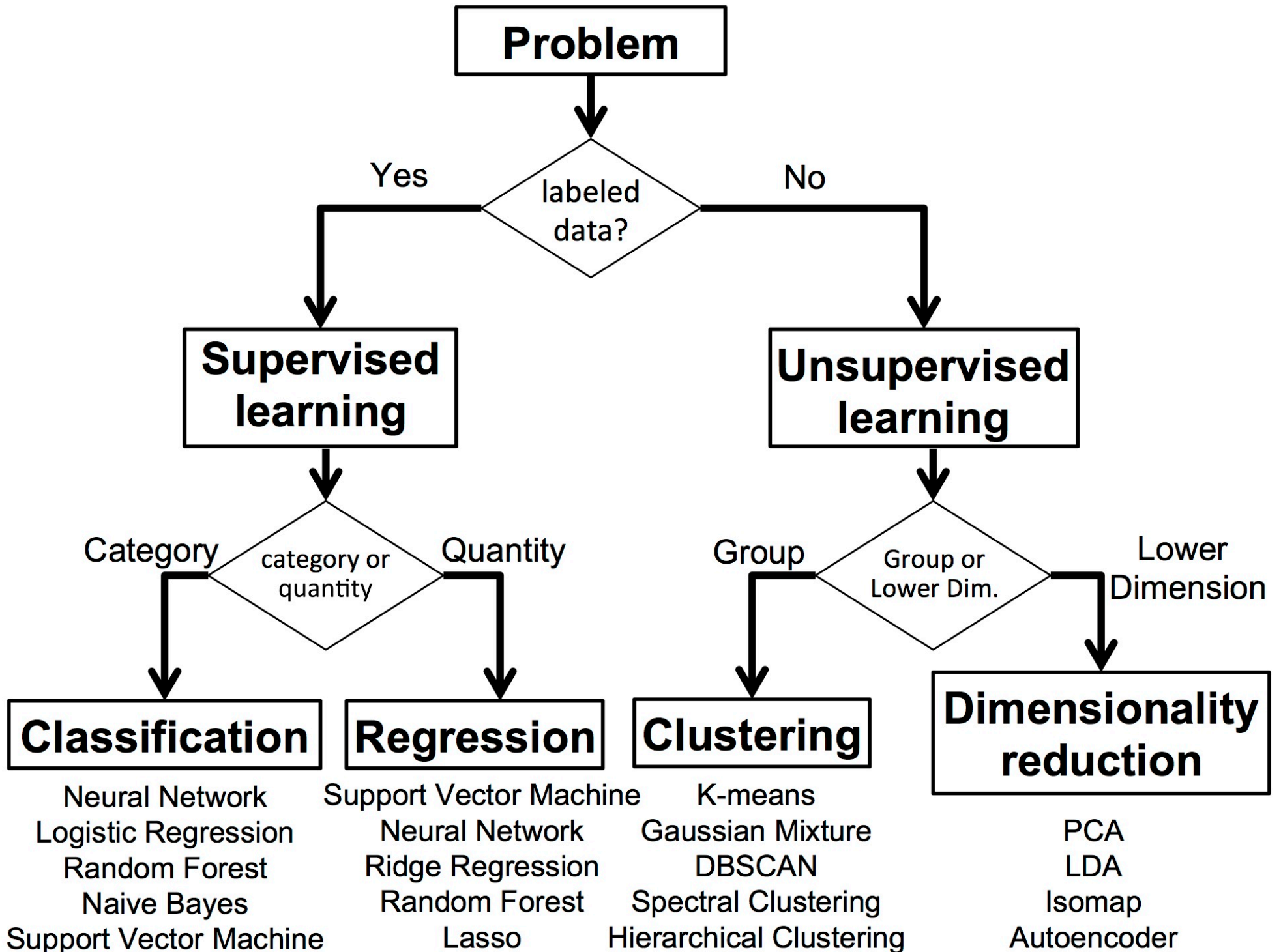
Machine Learning in Seismology: Turning Data into Insights ✓

Qingkai Kong; Daniel T. Trugman; Zachary E. Ross; Michael J. Bianco; Brendan J. Meade; Peter Gerstoft

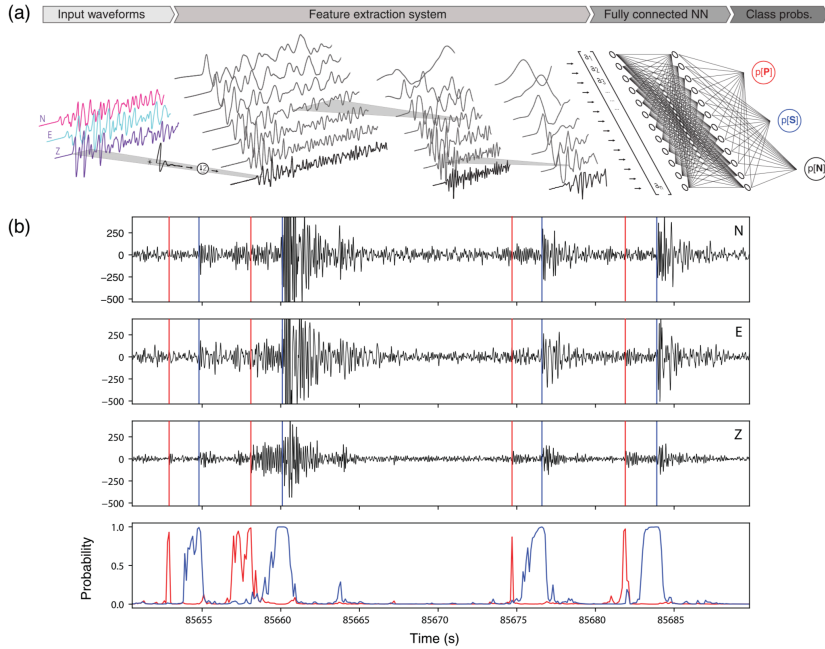
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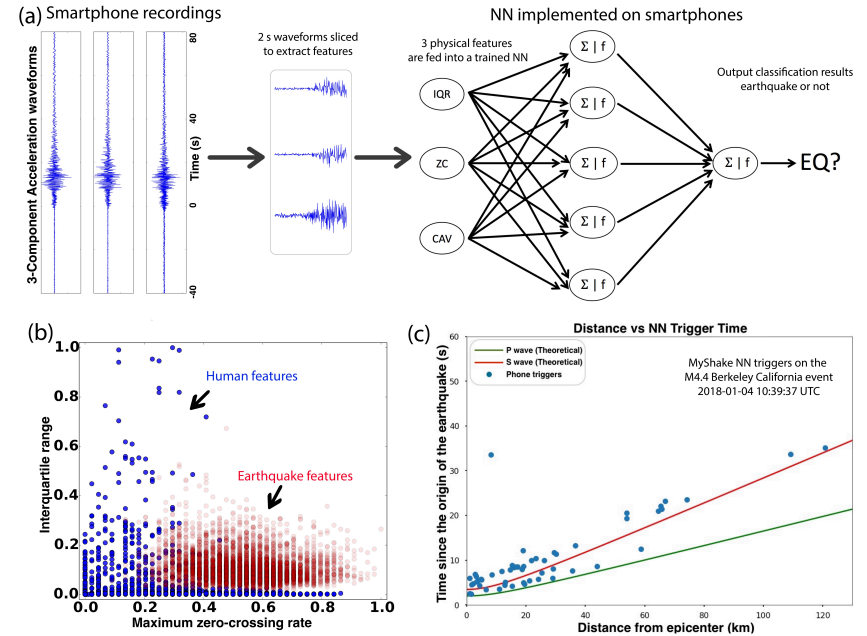




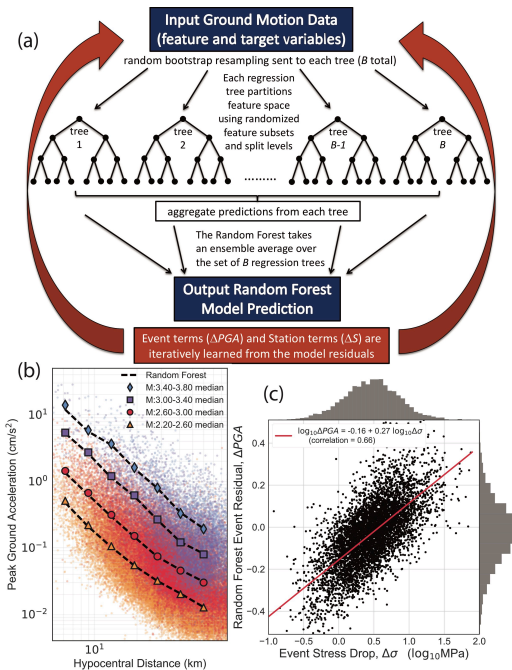
Earthquake detection



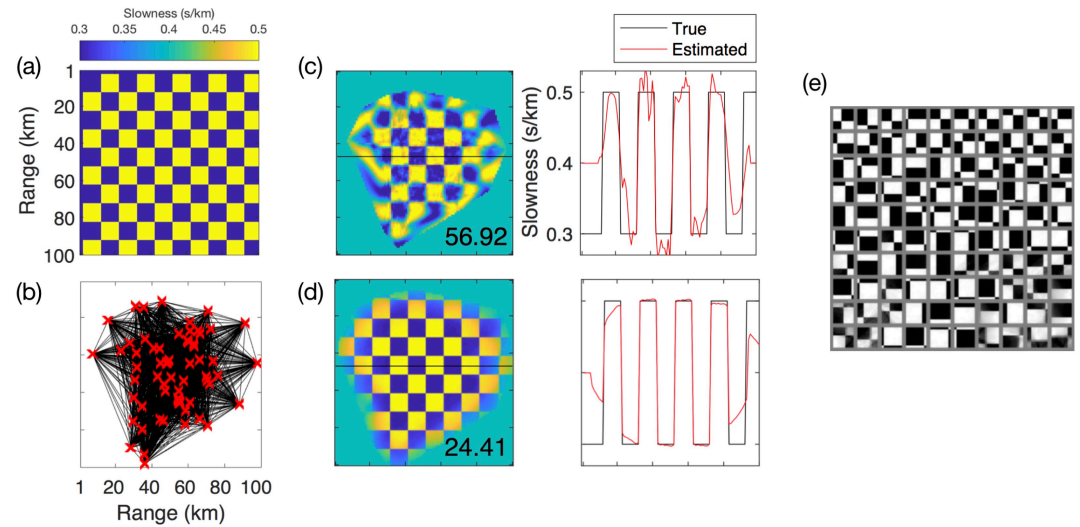
Earthquake Early Warning



Ground motion Prediction



Tomography



Earthquake geodesy and other applications

Panel 2: Next Practical Steps to Accelerate and Broaden Use of ML in the Geosciences

Moderator: Thorsten Becker

Guiding questions:

- *What are the opportunities and challenges for ML and DL for the next 5-10 years in the solid Earth geosciences?*
- *ML and DL are often being used as a black box -- how do we move beyond the current situation into a deeper understanding of the techniques and into physical insight?*
- *What steps do we need to take as a community to move ML and DL forward?*

I want to show some of my thoughts based on my experience and reading (may not be right), and hope to generate more discussions in this workshop

Panel 2: Next Practical Steps to Accelerate and Broaden Use of ML in the Geosciences

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My Talk Today ...

- Some limitations of current machine learning
- Some examples on combining ML with physics model
- Moving forward

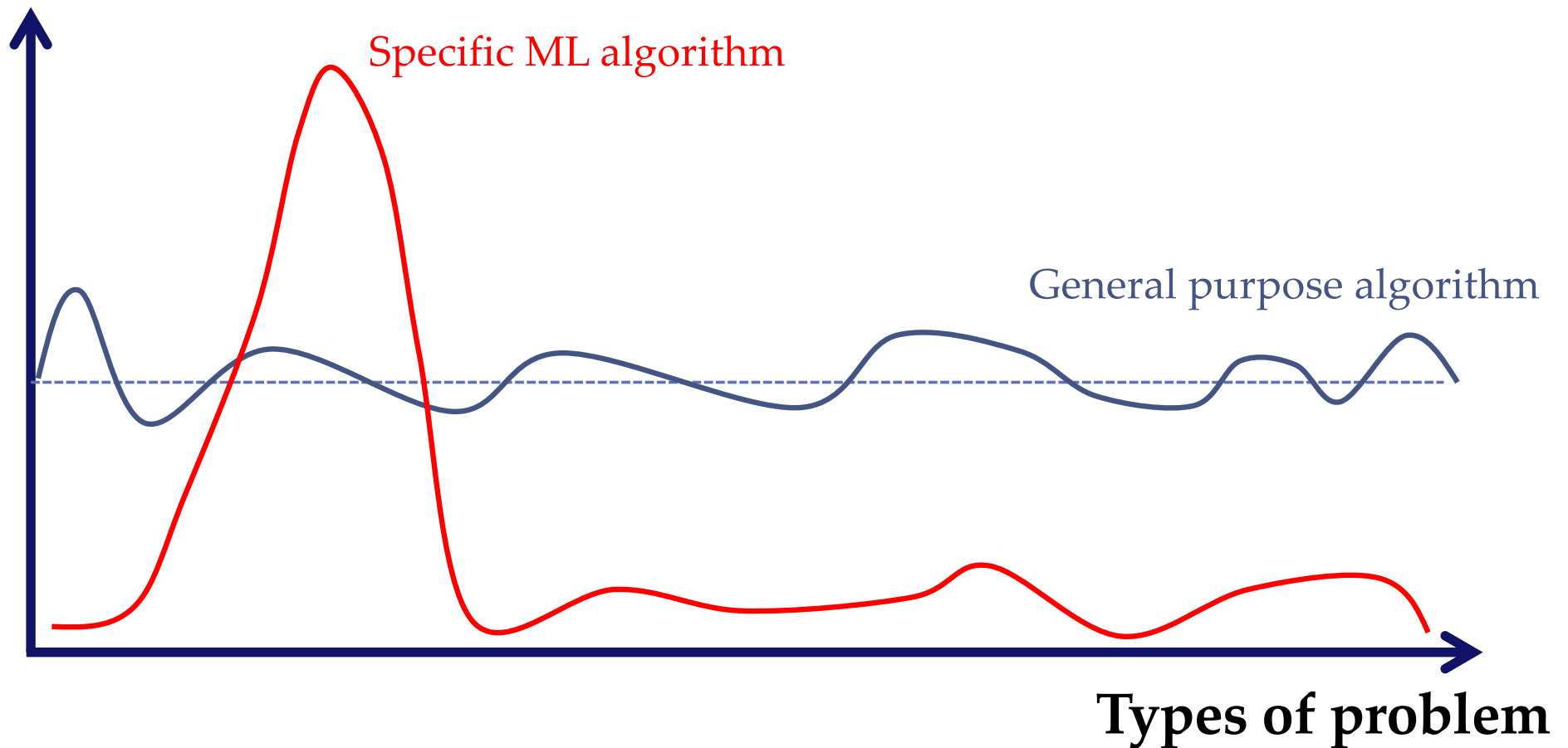
Some limitations on current ML

Not magic



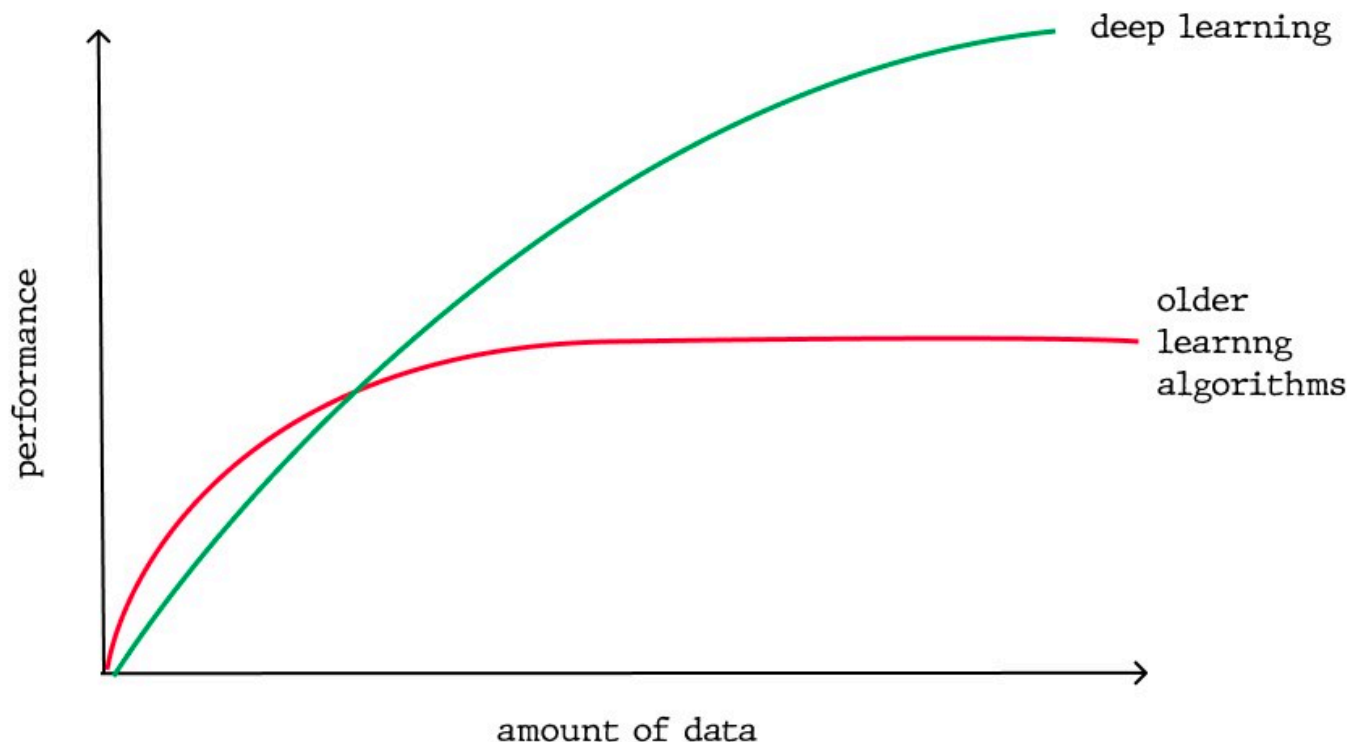
ML algorithms are narrow

Performance



Need a lot of data

- Lots of structured data, or lots of good data
- Labels (time tedious)
- Some problems in our field are small data problems





As the old saying ...

Garbage in,
Garbage out

still applies

Bias in the data

- Bias in the data are difficult to identify

How AI systems amplify bias

Image recognition systems that use biased machine learning data sets will inadvertently magnify that bias. Researchers are examining ways to reduce the effects.



COOKING

ROLE	VALUE
AGENT	▶ WOMAN
FOOD	▶ PASTA
HEAT	▶ STOVE
TOOL	▶ SPATULA
PLACE	▶ KITCHEN



COOKING

ROLE	VALUE
AGENT	▶ WOMAN
FOOD	▶ FRUIT
HEAT	▶ —
TOOL	▶ KNIFE
PLACE	▶ KITCHEN



COOKING

ROLE	VALUE
AGENT	▶ WOMAN
FOOD	▶ MEAT
HEAT	▶ GRILL
TOOL	▶ TONGS
PLACE	▶ OUTSIDE



COOKING

ROLE	VALUE
AGENT	▶ WOMAN
FOOD	▶ VEGETABLES
HEAT	▶ STOVE
TOOL	▶ TONGS
PLACE	▶ KITCHEN



COOKING

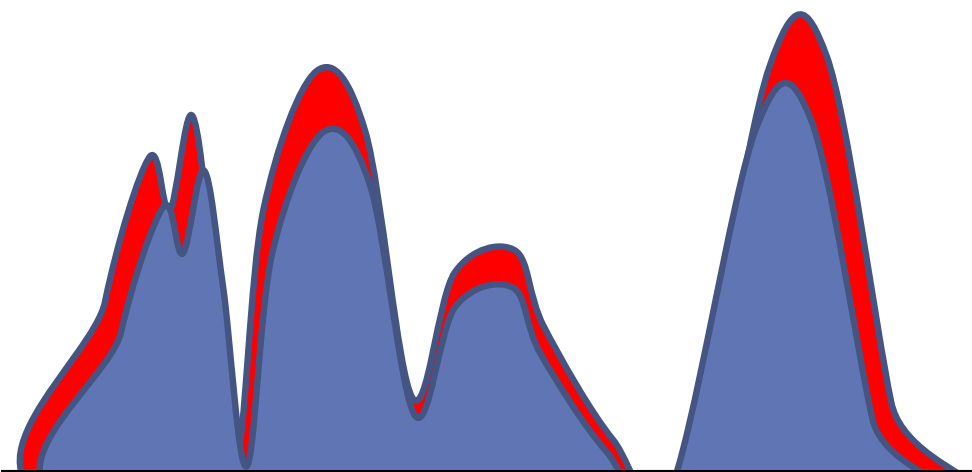
ROLE	VALUE
AGENT	▶ MAN
FOOD	▶ —
HEAT	▶ STOVE
TOOL	▶ SPATULA
PLACE	▶ KITCHEN

In this example of gender bias, adapted from a report published by researchers from the University of Virginia and the University of Washington, a visual semantic role labeling system has learned to identify a person cooking as female, even when the image is male.

Generalization ...

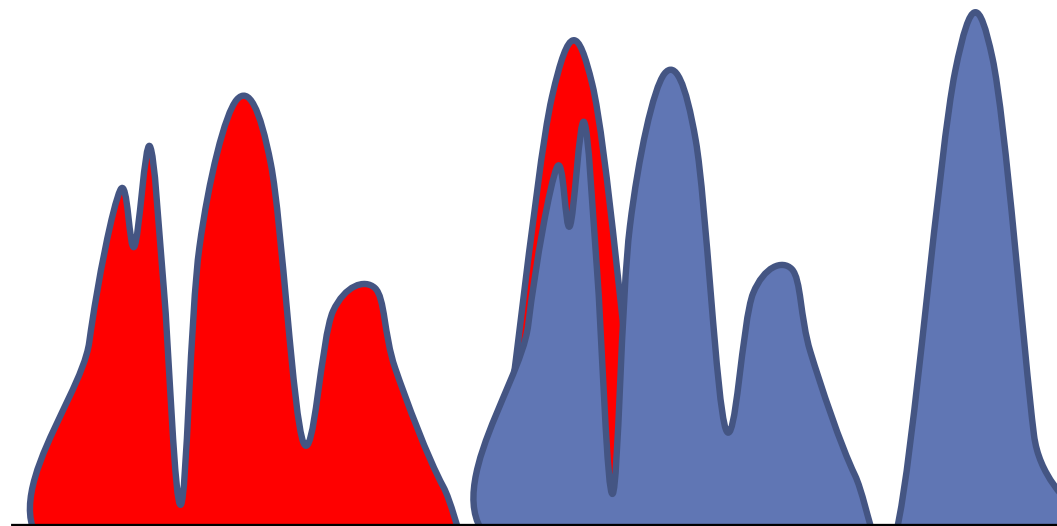
Generalization usually refers to a ML model's ability to perform well on new unseen data rather than just the training data.

Weak generalization
May work



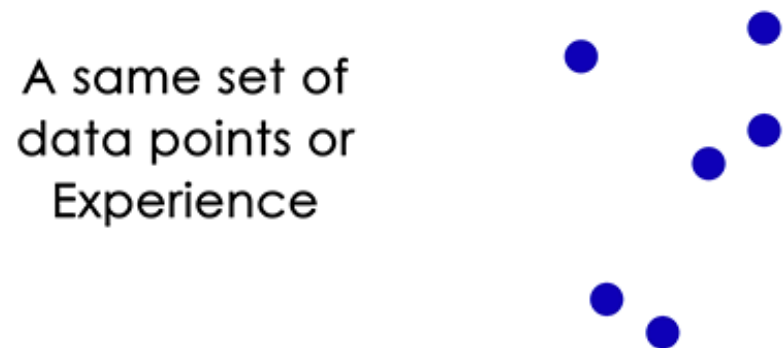
Training distribution
New distribution

Strong generalization
not work

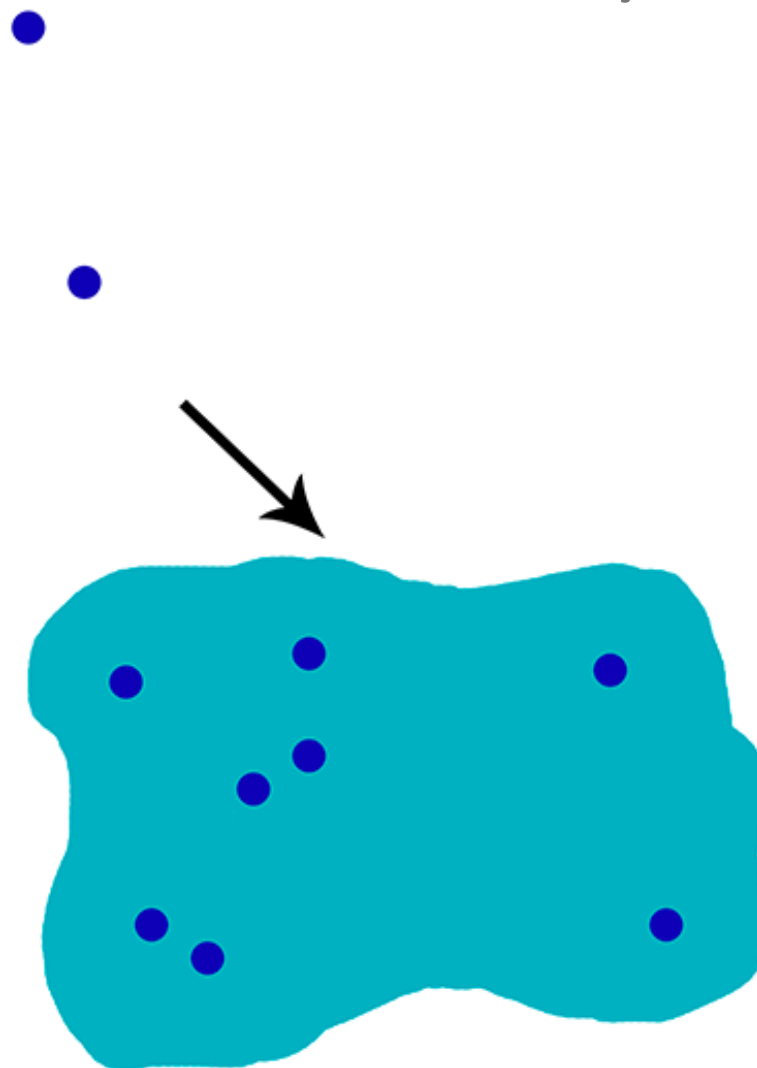


Training distribution
New distribution

A same set of
data points or
Experience

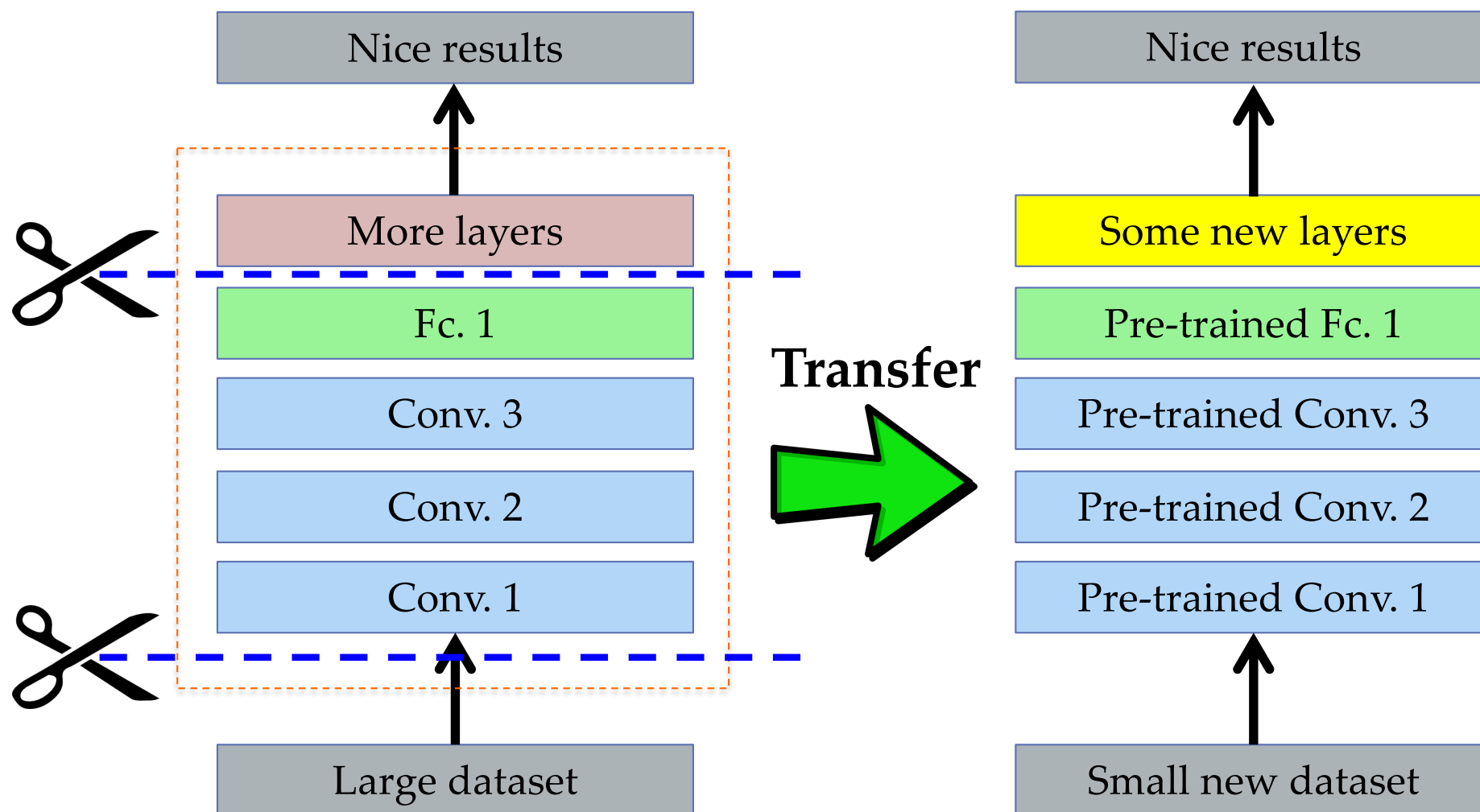


Local generalization:
Generalization power of
pattern recognition

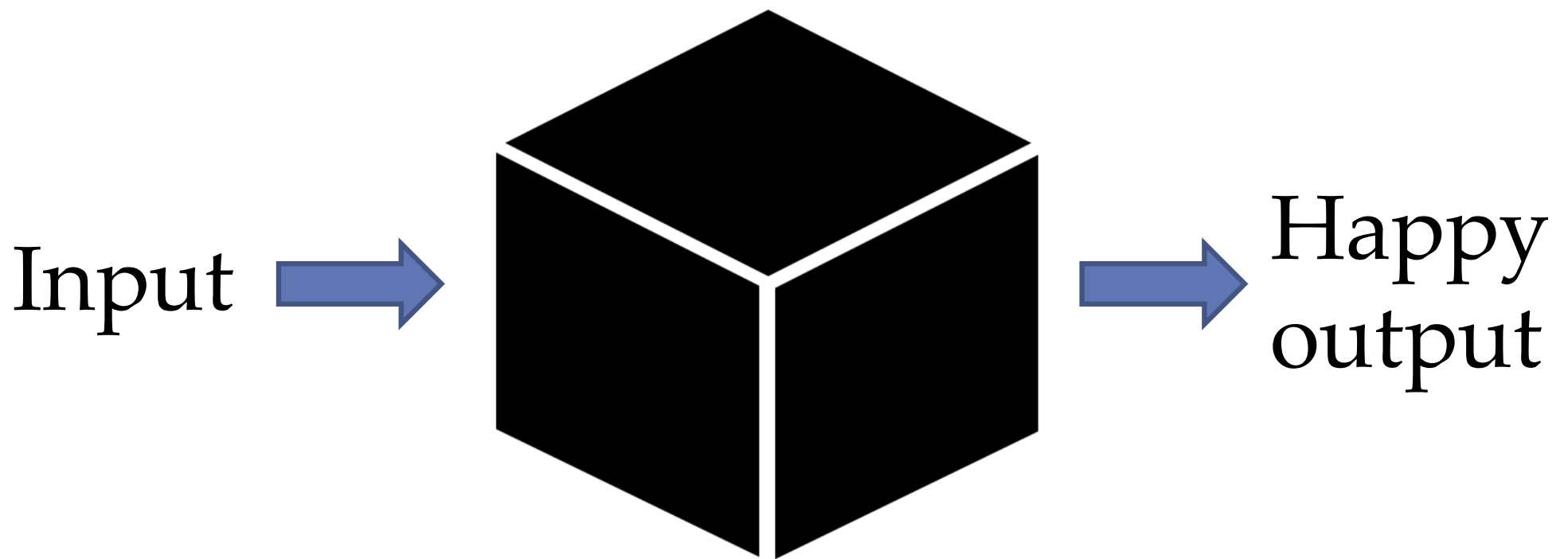


Extreme generalization:
Generalization power
achieved via
abstraction and reasoning

Transfer learning



Missing physics ...



Missing physics ...

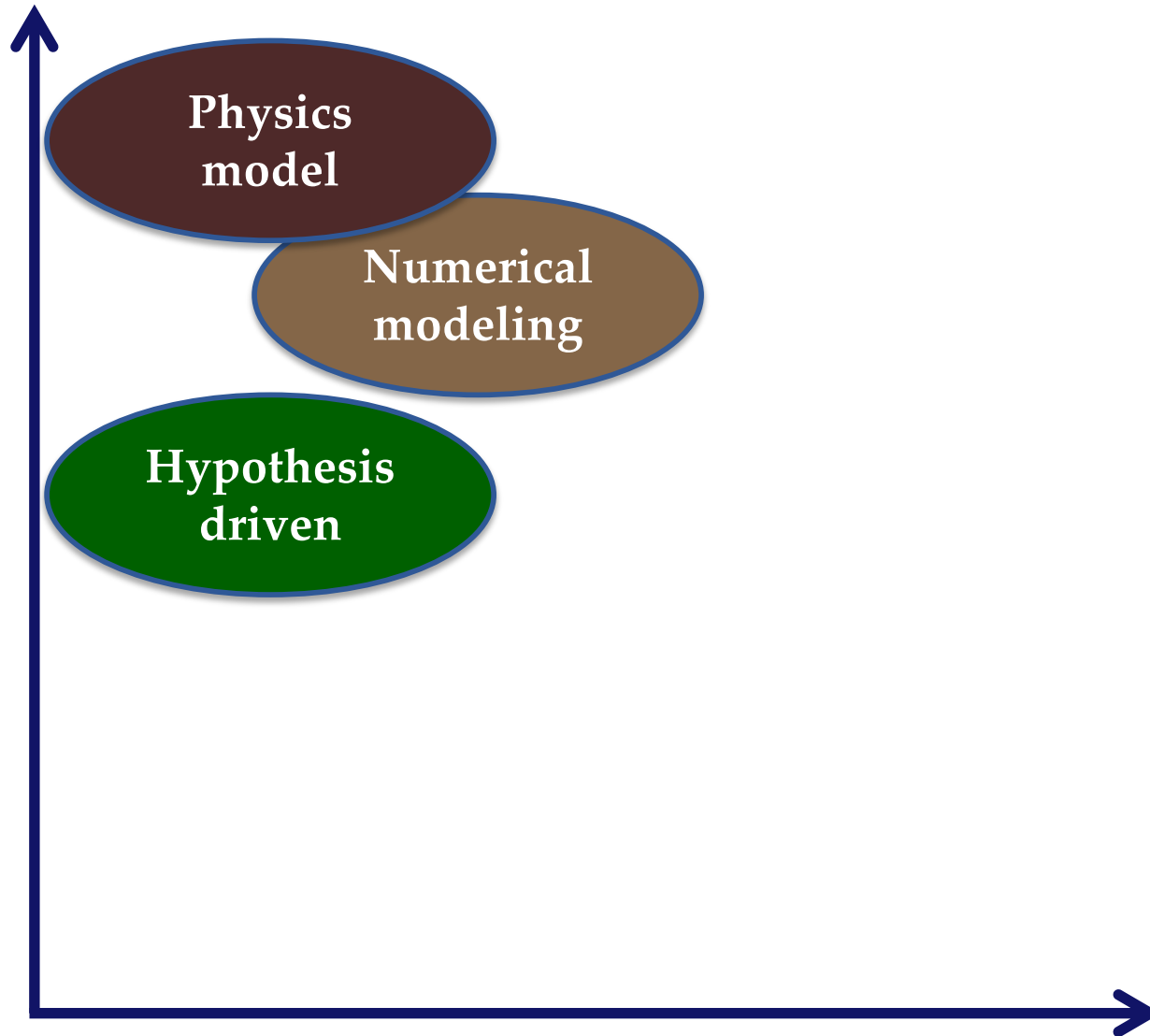
- Difficult to interpret how it works well
- May not bound by the existing laws

There are more limitations ...

- [One pixel attack for fooling deep neural networks](#)
- Not easy to learn in real-time (even though we have online learning)
- Misapplication - [AAAS: Machine learning 'causing science crisis'](#)
- ...

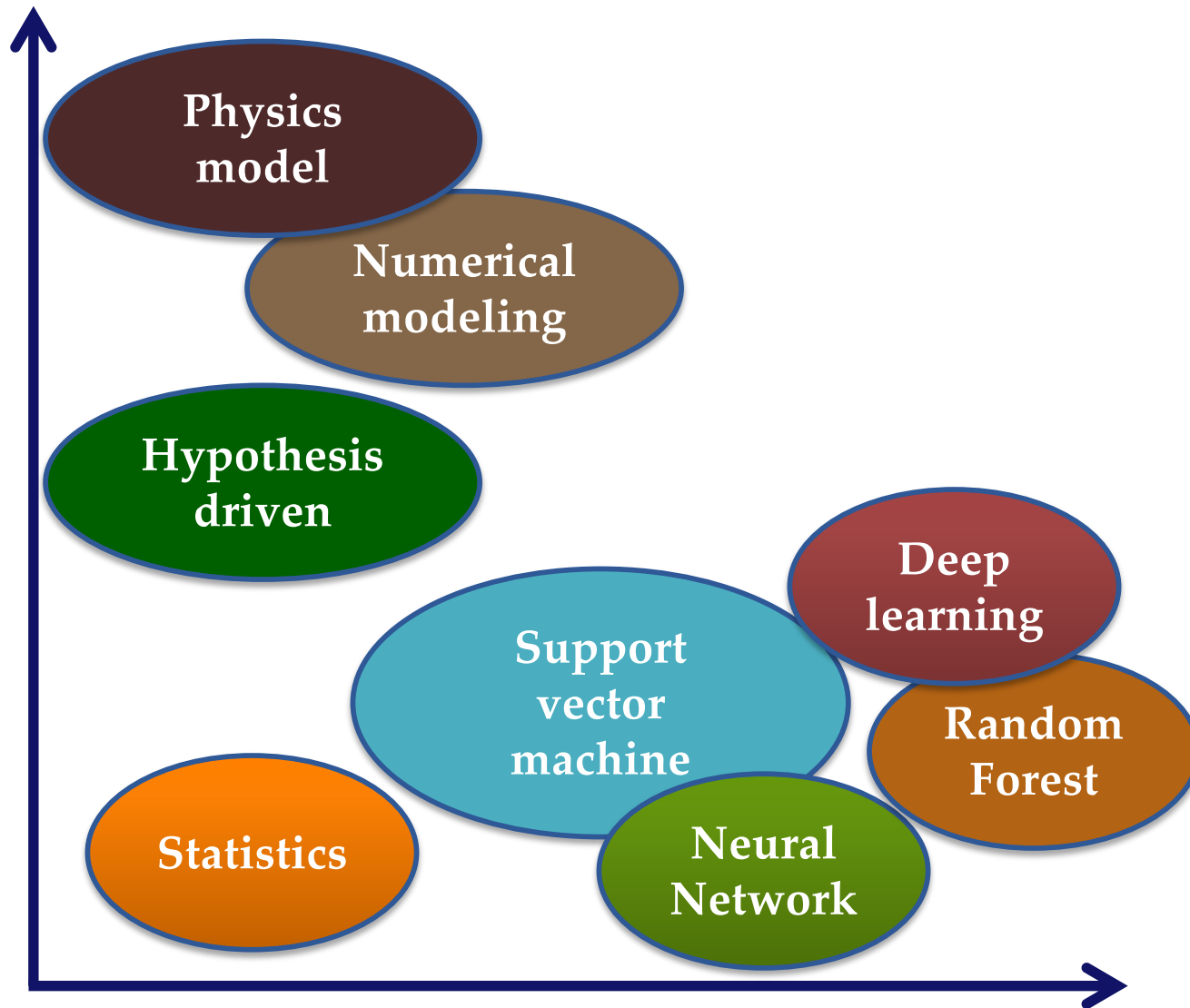
Some examples on
combining physics

Domain-driven approaches



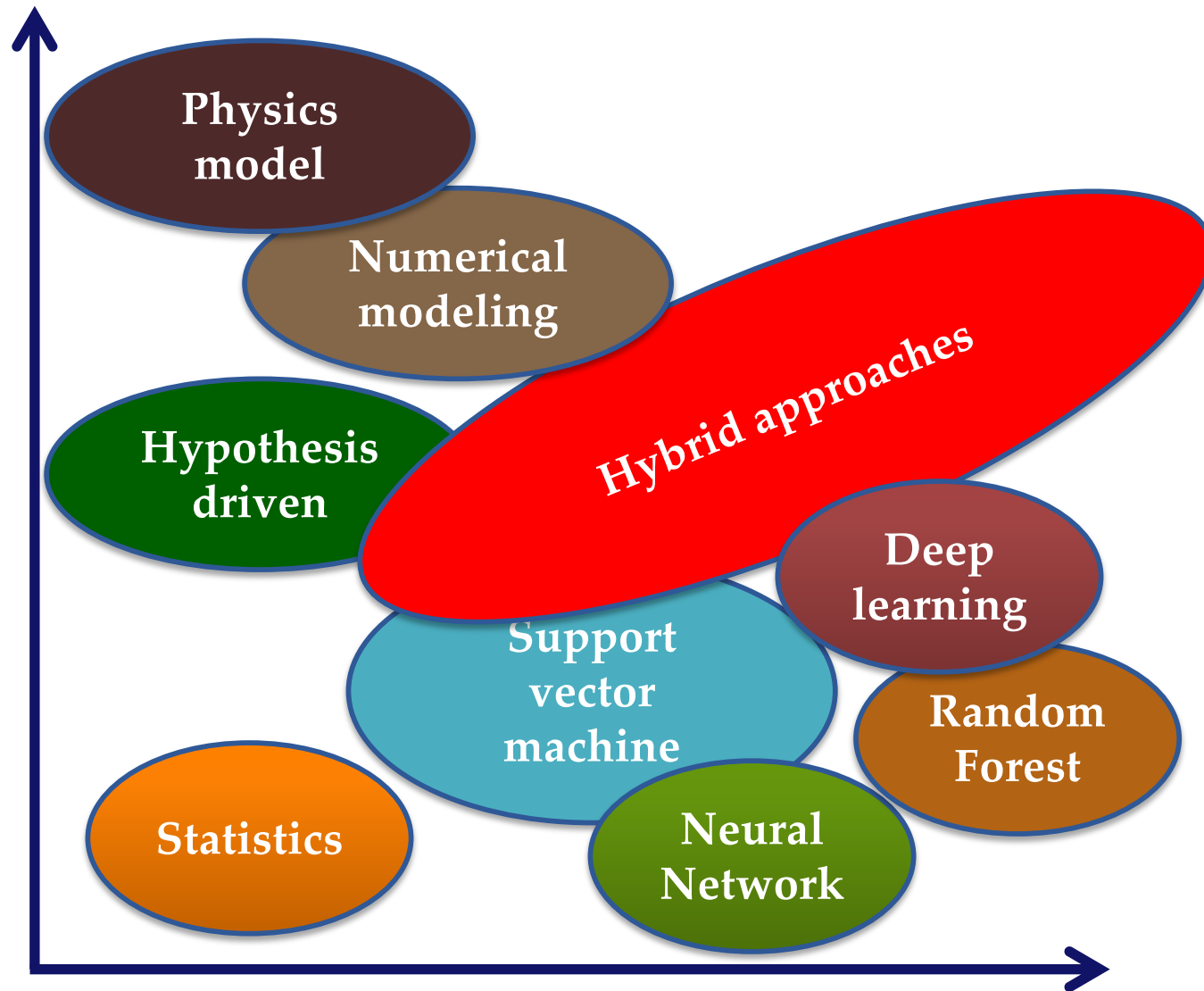
Data-driven approaches

Domain-driven approaches



Data-driven approaches

Domain-driven approaches



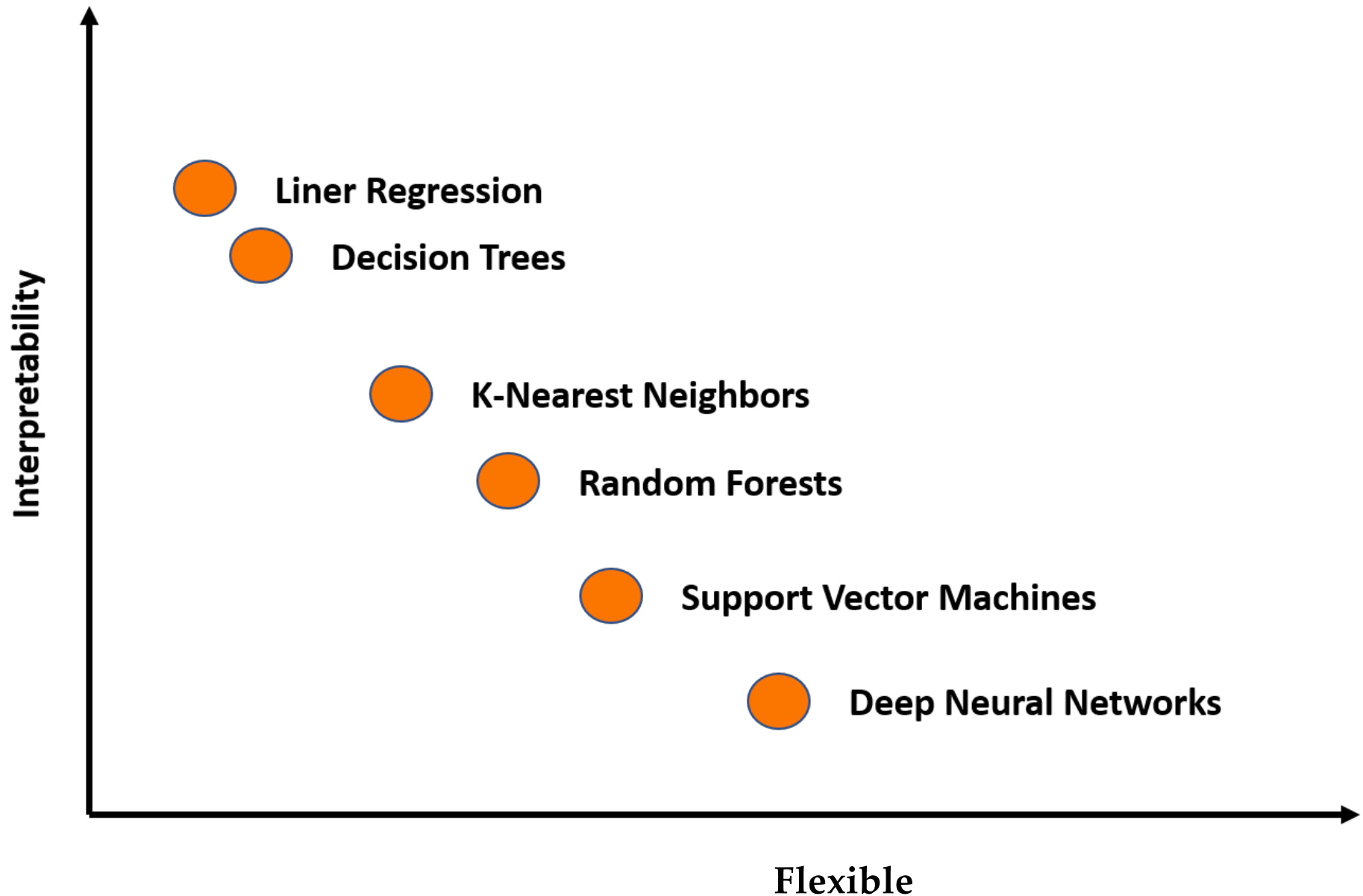
Data-driven approaches

Luckily, more researchers
are working on this

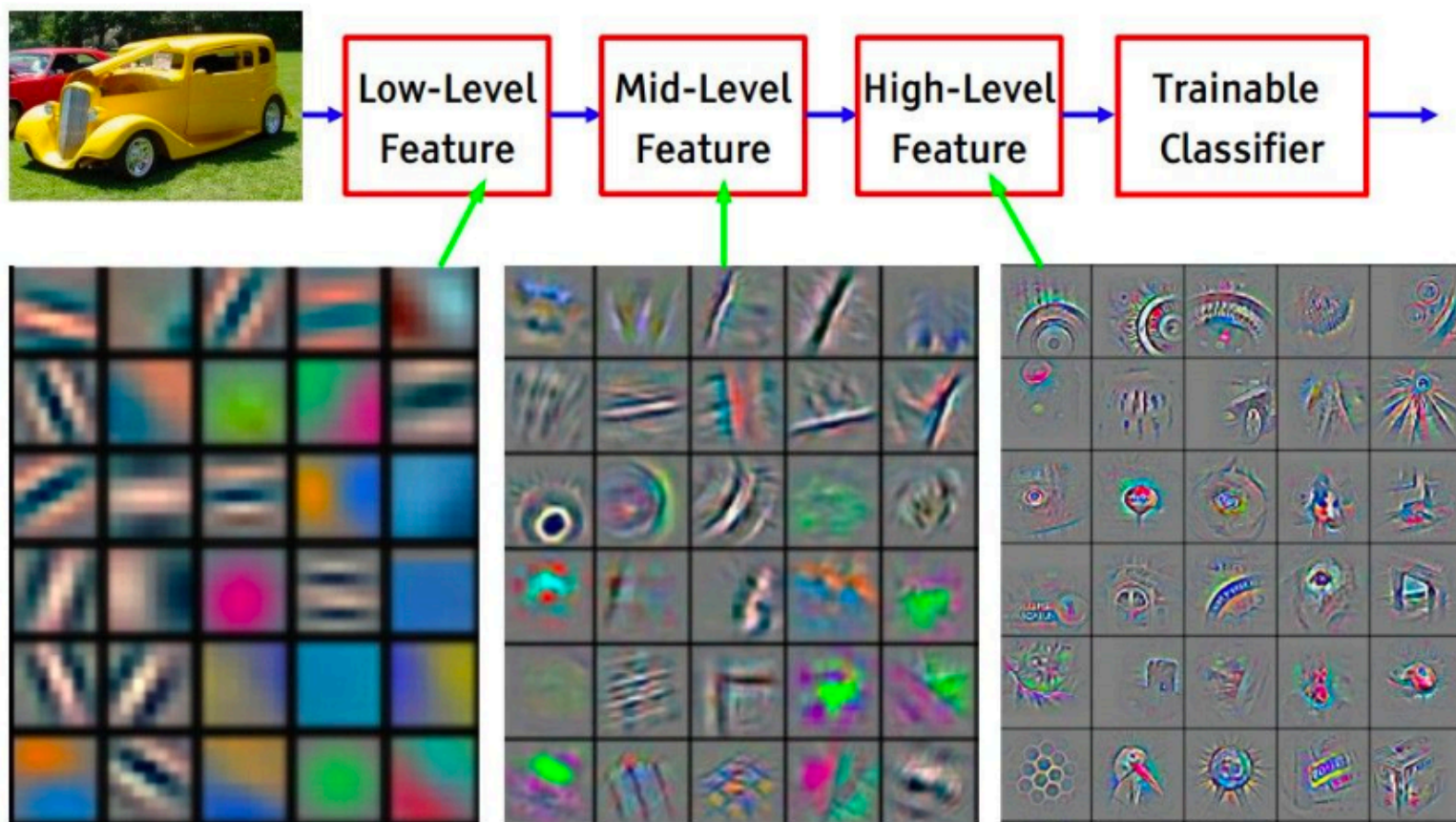
Let me get a start ...

- Better understanding what we learned
- Use physics generated data
- Encode the physics laws to a ML algorithm
- Finding physics concepts
- ...

What we learned ...

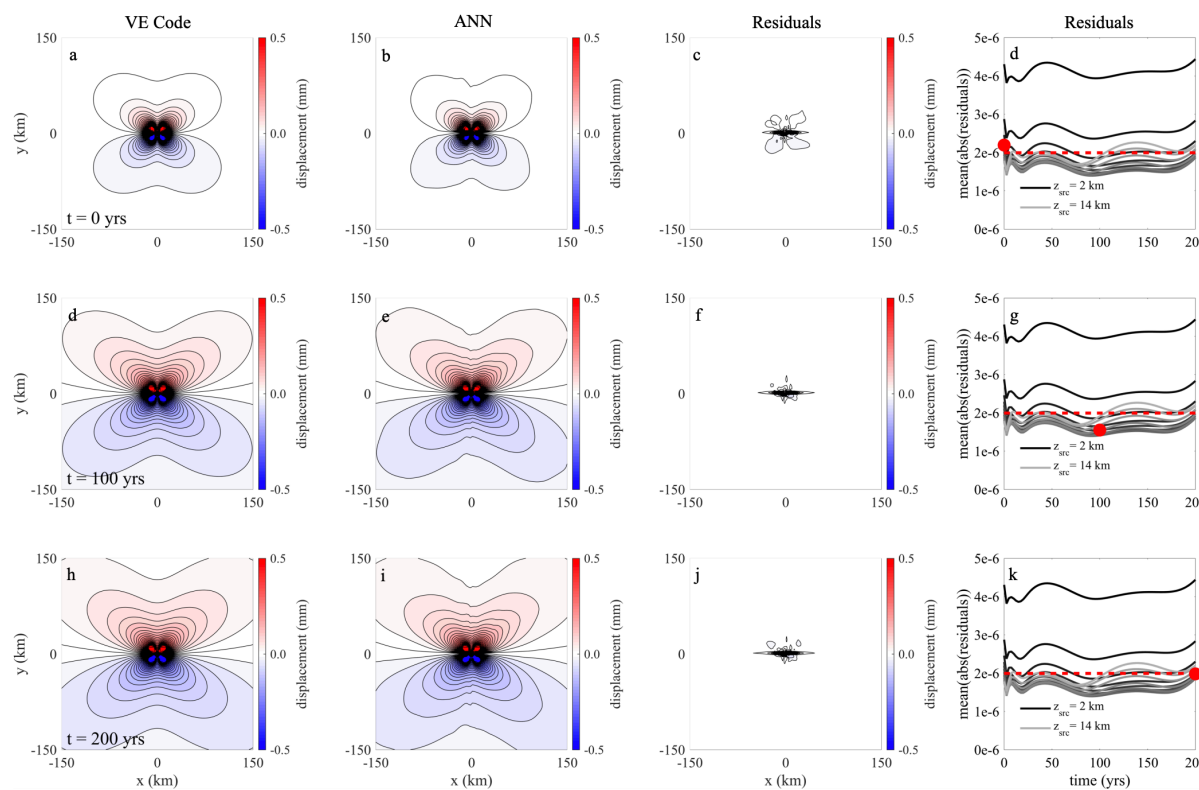


We shouldn't stop when we just have a good model



Using synthetic data ...

- Diego's presentation if there is not enough observation data
- Usually this can reduce the simulation computation cost



Enabling large-scale viscoelastic calculations via neural network acceleration, DeVries et al. 2017

- Generating seismograms with deep neural networks, Krischer et al 2017

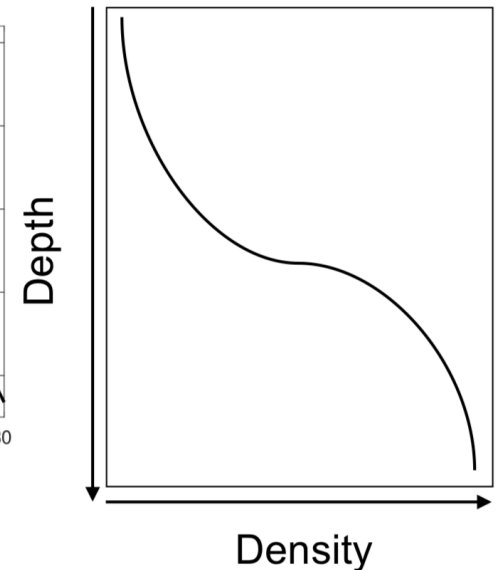
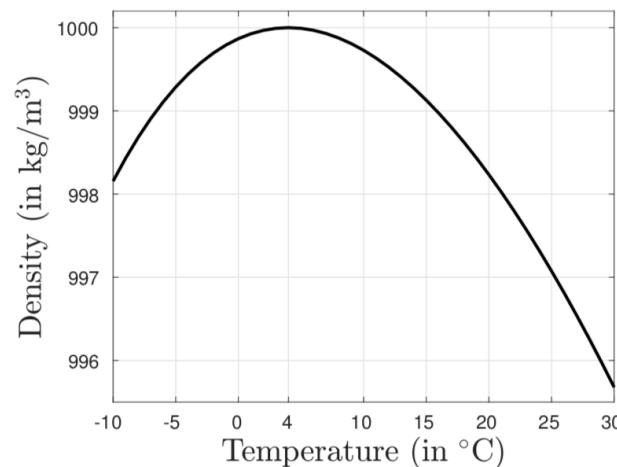
ML approach accelerates viscoelastic calculations by more than 50,000%

Encode physics laws into ML

➤ Add to cost function

$$\alpha Error_{ML-obs} + \lambda Error_{ML-phy}$$

	Input Drivers
1	Day of Year (1 – 366)
2	Depth (in m)
3	Short-wave Radiation (in W/m ²)
4	Long-wave Radiation (in W/m ²)
5	Air Temperature (in °C)
6	Relative Humidity (0 – 100 %)
7	Wind Speed (in m/s)
8	Rain (in cm)
9	Growing Degree Days [14]
10	Is Freezing (True or False)
11	Is Snowing (True or False)



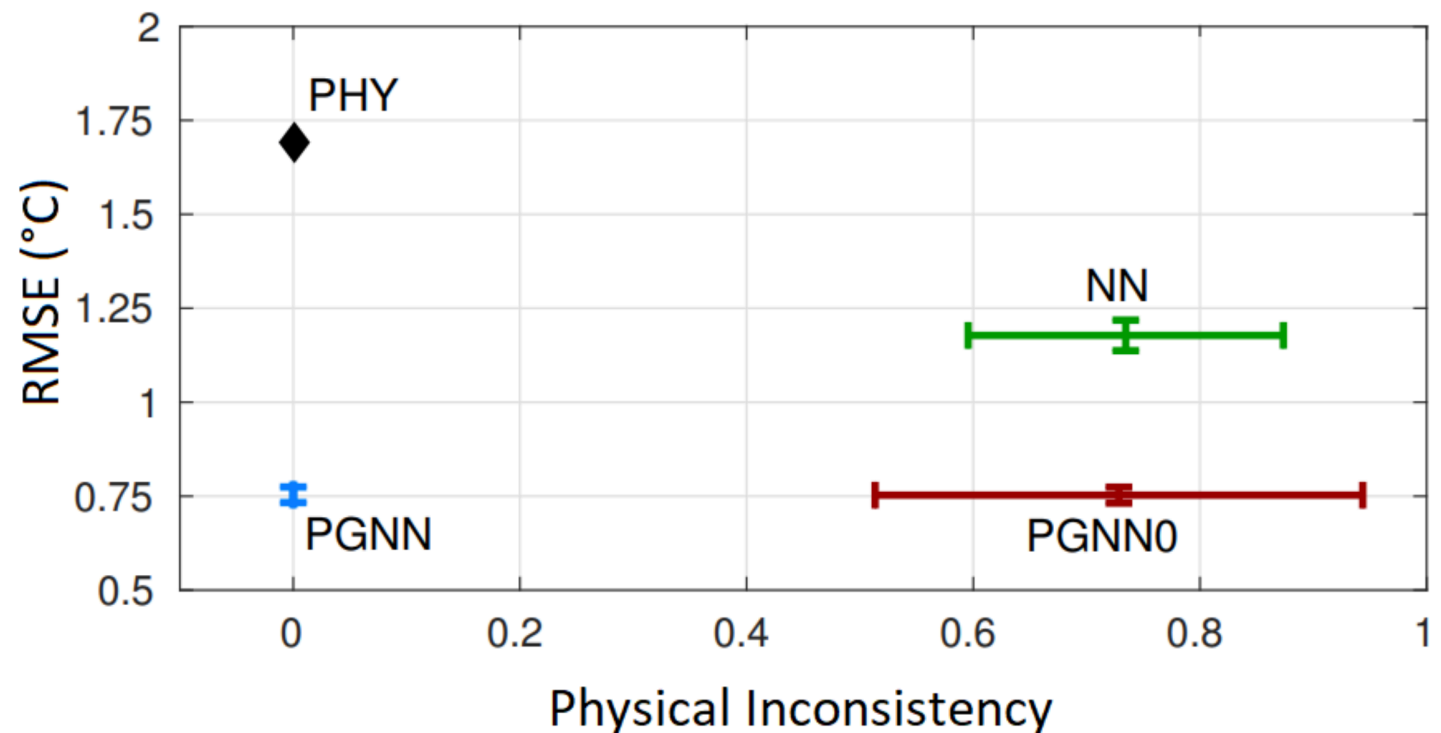
Physics-guided Neural Networks (PGNN):

An Application in Lake Temperature Modeling Karpatne et al 2018

Encode physics laws into ML

- Add to cost function

$$\arg \min_f \underbrace{Loss(\hat{Y}, Y) + \lambda R(f)}_{\text{Typical loss function}} + \underbrace{\lambda_{PHY} Loss.PHY(\hat{Y})}_{\text{Physical Inconsistency}}$$



Physics-guided Neural Networks (PGNN):
An Application in Lake Temperature Modeling -
Karpatne et al 2018

Encode physics laws into ML

➤ Respecting law of physics by nonlinear PDE

differentiate neural networks with respect to their input coordinates and model parameters to obtain physics informed neural networks

Burger's equation along with Dirichlet boundary conditions

$$u_t + uu_x - (0.01/\pi)u_{xx} = 0, \quad x \in [-1, 1], \quad t \in [0, 1],$$

$$u(0, x) = -\sin(\pi x),$$

$$u(t, -1) = u(t, 1) = 0.$$

$$f := u_t + uu_x - (0.01/\pi)u_{xx},$$

Physics Informed Deep Learning: Data-driven
Solutions of Nonlinear Partial Differential
Equations – Raissi et al 2017

Encode physics laws into ML

➤ Respecting law of physics by nonlinear PDE

differentiate neural networks with respect to their input coordinates and model parameters to obtain physics informed neural networks

Burger's equation along with Dirichlet boundary conditions

$$f := u_t + uu_x - (0.01/\pi)u_{xx},$$

```
def u(t, x):  
    u = neural_net(tf.concat([t,x],1), weights, biases)  
    return u
```

Correspondingly, the *physics informed neural network* $f(t, x)$ takes the form

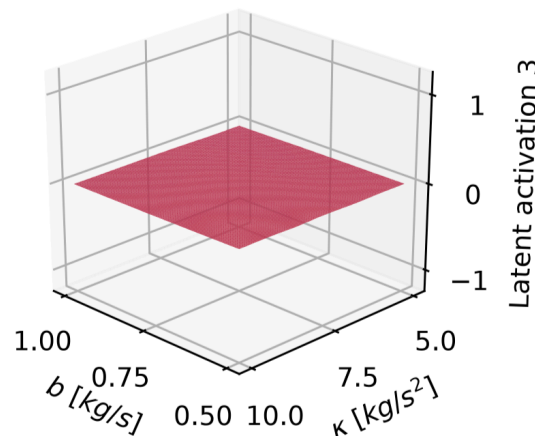
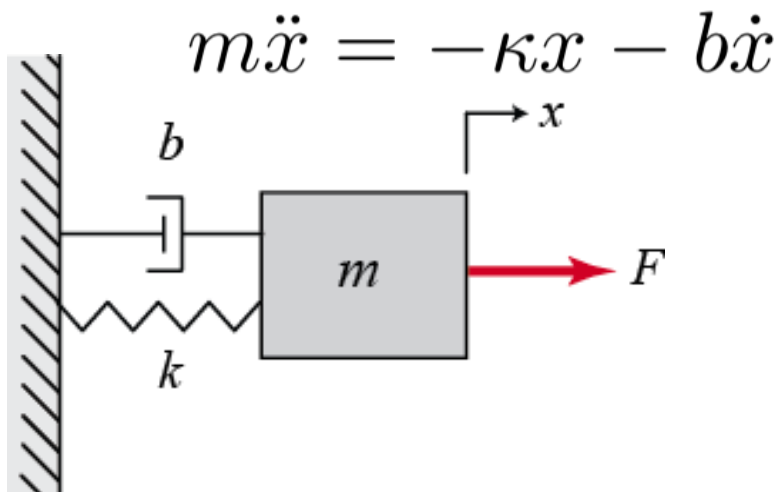
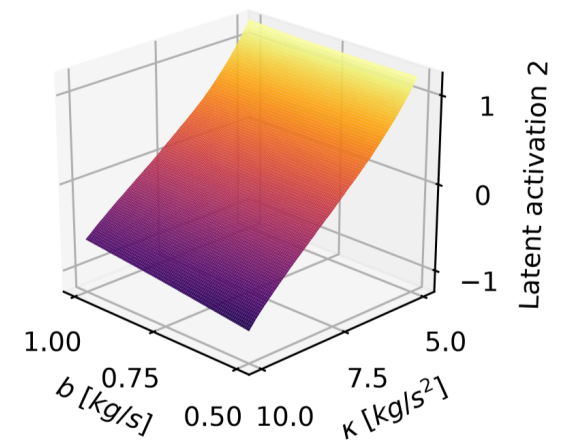
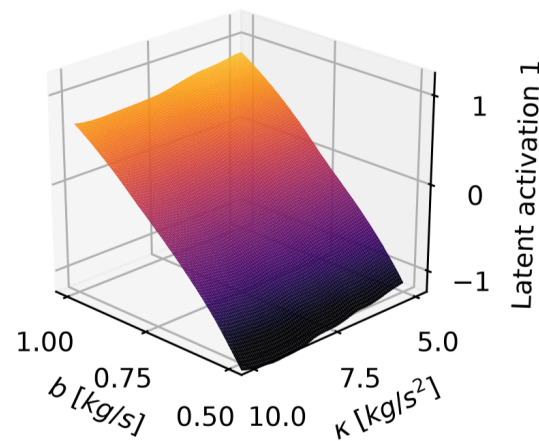
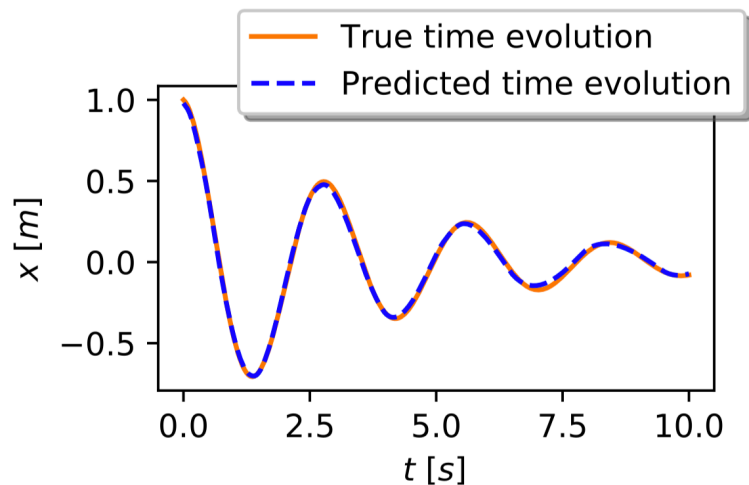
```
def f(t, x):  
    u = u(t, x)  
    u_t = tf.gradients(u, t)[0]  
    u_x = tf.gradients(u, x)[0]  
    u_xx = tf.gradients(u_x, x)[0]  
    f = u_t + u*u_x - (0.01/tf.pi)*u_xx  
    return f
```

Physics Informed
Deep Learning:
Data-driven
Solutions of
Nonlinear Partial
Differential
Equations –
Raissi et al 2017

$$MSE = MSE_u + MSE_f,$$

Finding physics concepts ...

➤ Learning from existing physics systems



Discovering physical concepts with neural networks
Iten et al 2018

More to learn ...

➤ Bayesian approach

- Bayesian inversion – Minson et al 2013
- Bayesian based detection – Net-Visa, Sig-Visa - Stuart Russell
- Bayesian based early warning – Tom Heaton's group

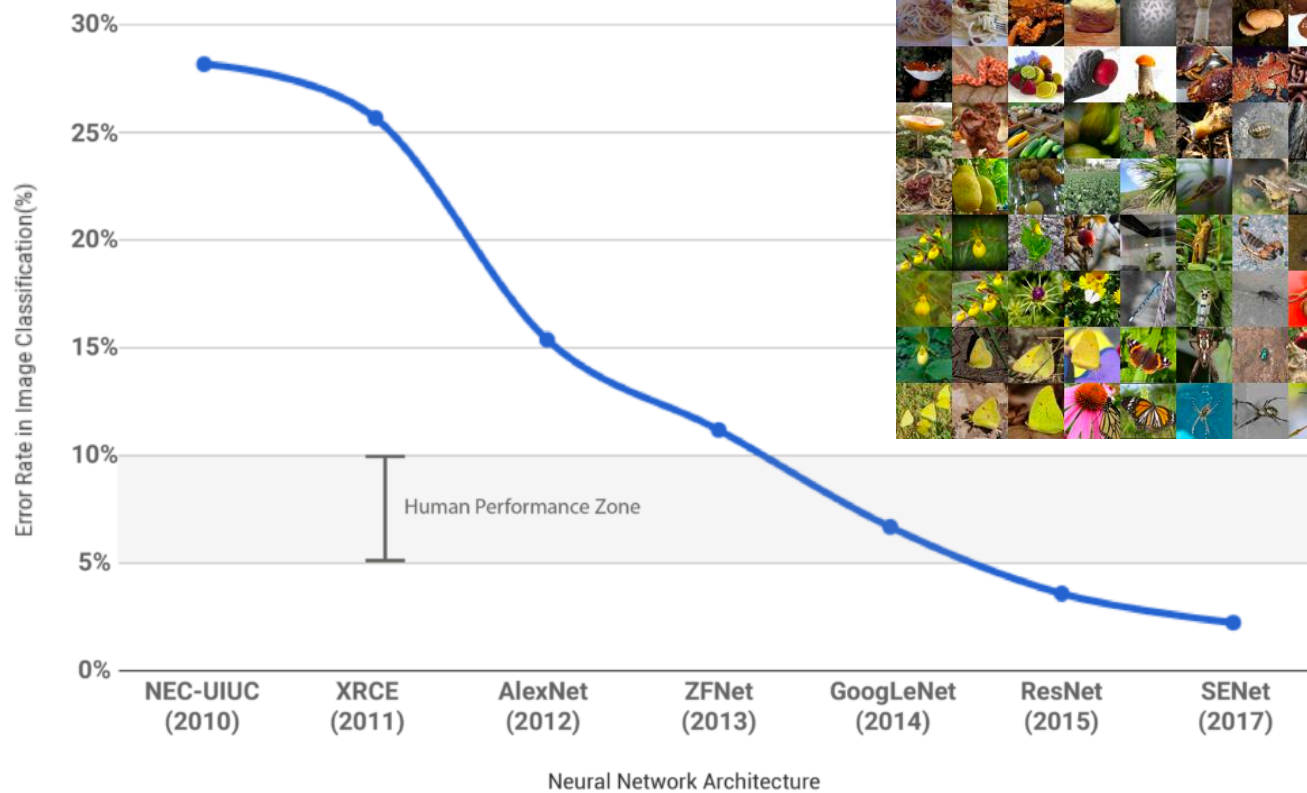
➤ Bayesian deep learning

➤ Physics in GAN model

Moving forward

- Benchmark datasets
- Open science
- New data sources
- The new model, new architecture
- Geoscience curriculum

Benchmark datasets



New data sources - fusion

- Remote sensing, smartphones, social media, fiber optic, etc.

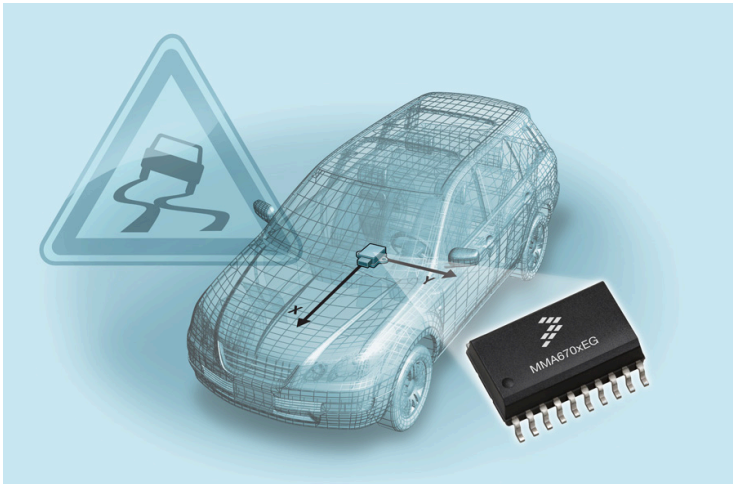


How to use
different
types of
data

half million
downloads
last week

Future data source

Large-scale arrays



Thank you so much!

Qingkai Kong

<http://seismo.berkeley.edu/qingkaikong/>

