311 Introduction to Machine Learning

Fall 2025

Instructor: Ioannis Konstantinidis

Overview

- What topics will we focus on in this introductory class?
- DETOUR: what topics are beyond the introductory level?
- The two flavors of AI: symbolic vs. connectionist

Topics we will focus on in this introductory class

Data: Structured, Toy Examples

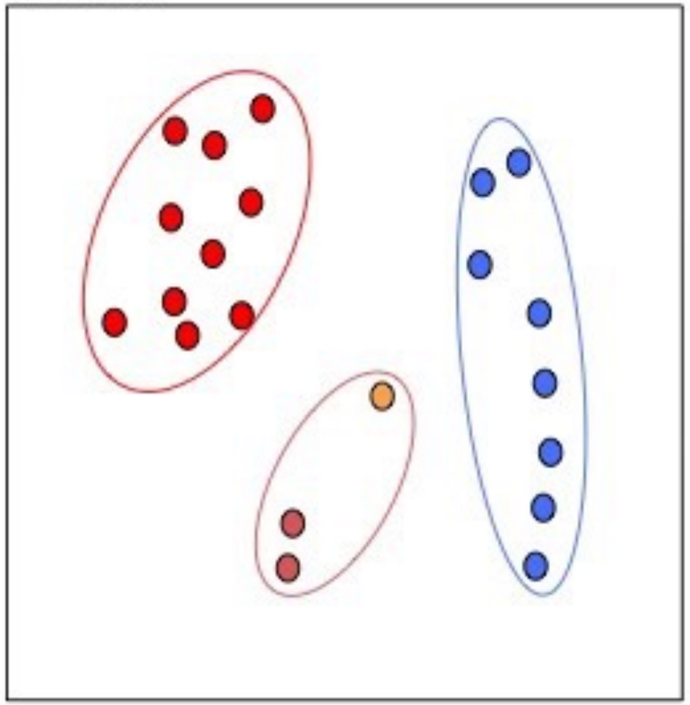
- Flat, static CSV files
- Tidy (normalized, tabular)
- Clean; no parts
    - incomplete,
    - incorrect,
    - inaccurate, or
    - irrelevant

Models: training and evaluation

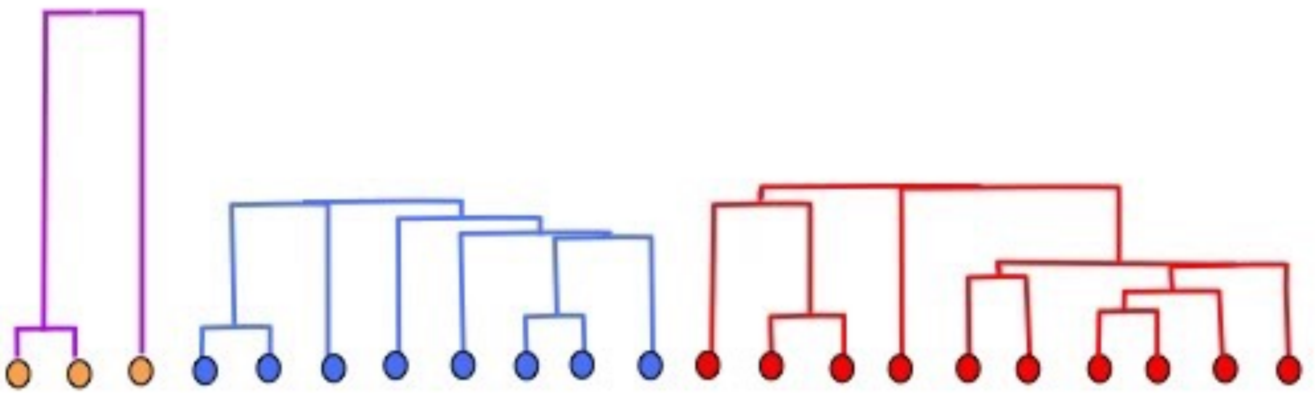
- Regularization
- Cross-validation
- Objective functions
- Scoring methods

Models: mostly for supervised learning

Models: also a few unsupervised learning ones

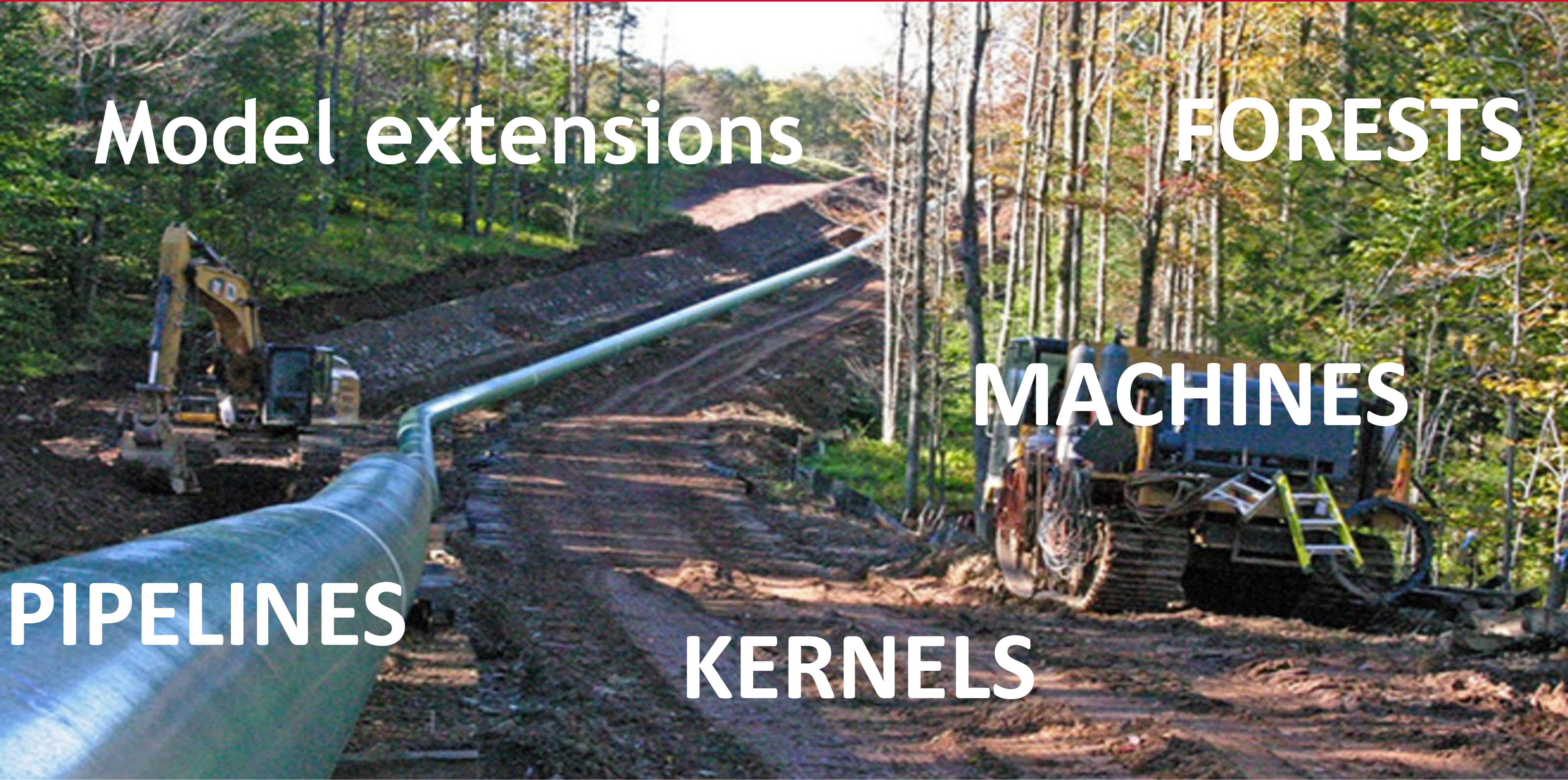


K-means

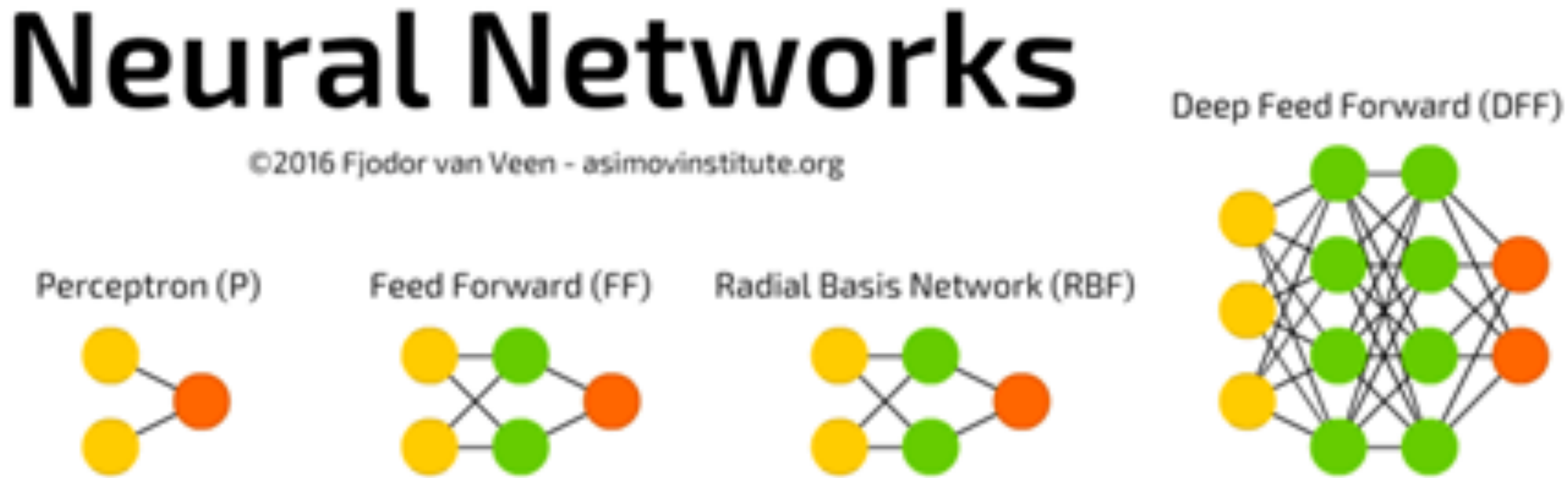


Hierarchical clustering

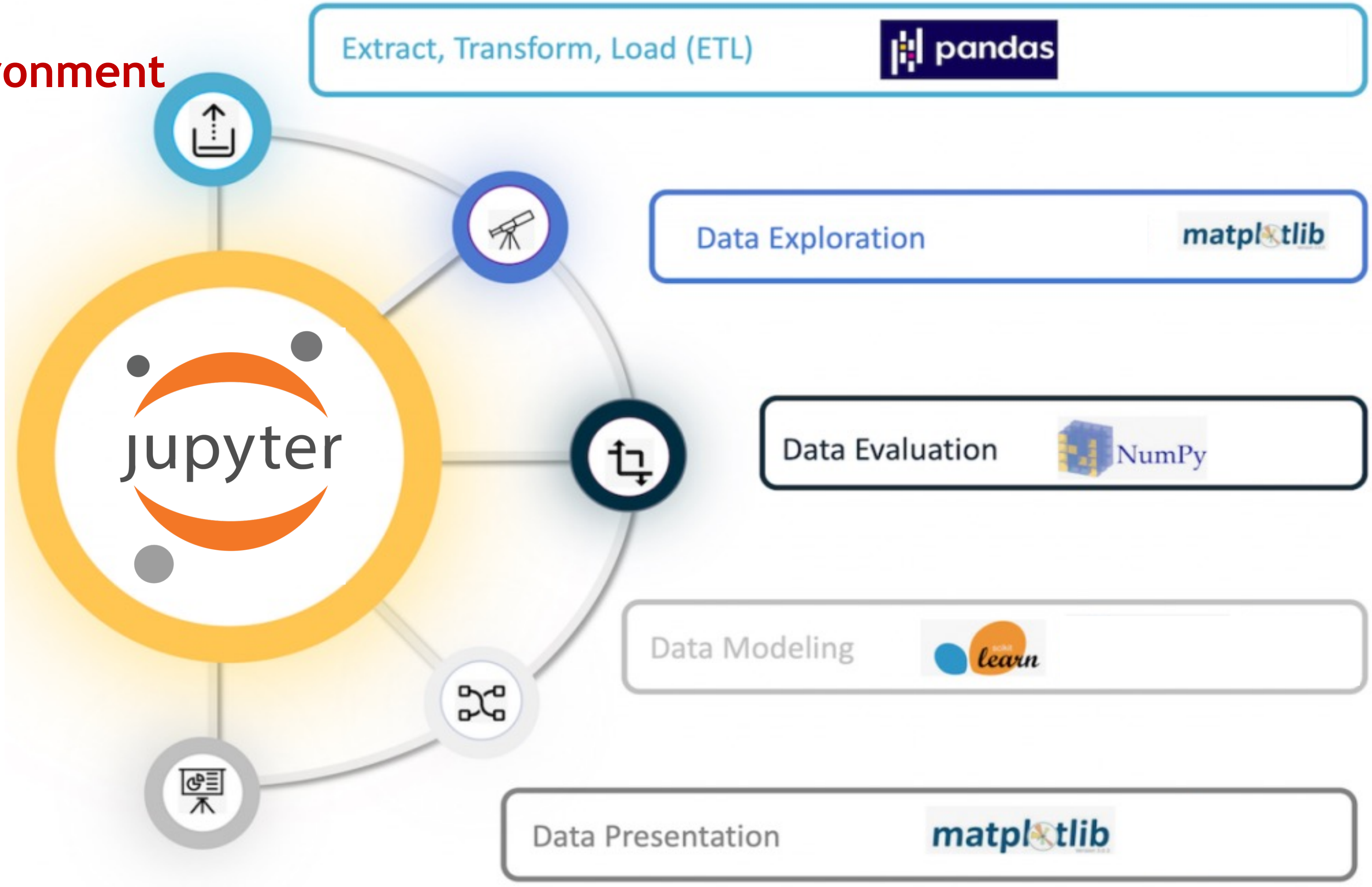
Model extensions



Deep Learning: A small taste of



Software Environment



That’s plenty for five weeks! There’s a lot more that we will not have time to cover

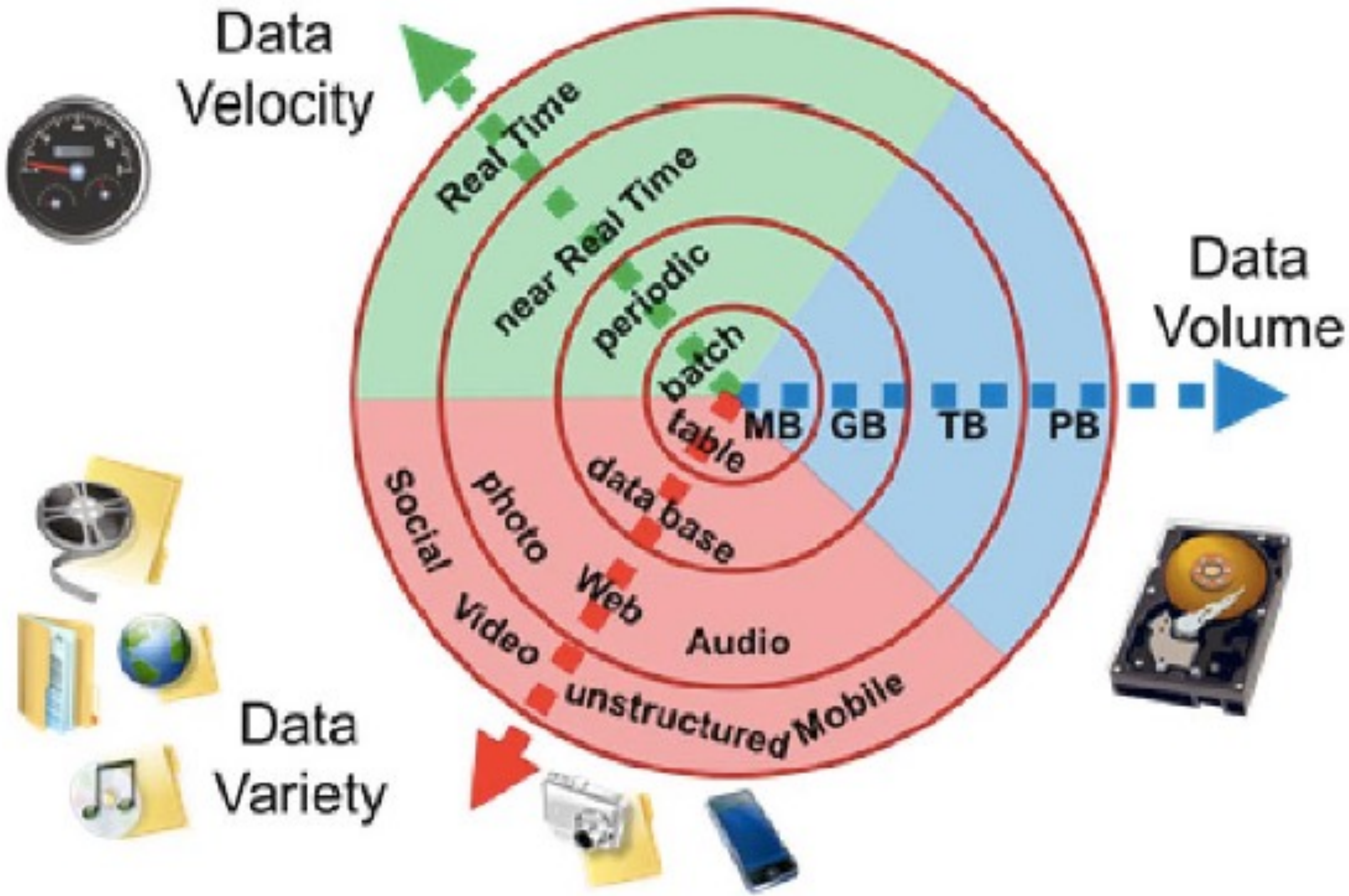
Hewlett Packard Enterprise Data Science Institute
UNIVERSITY OF HOUSTON

DATA: Variety

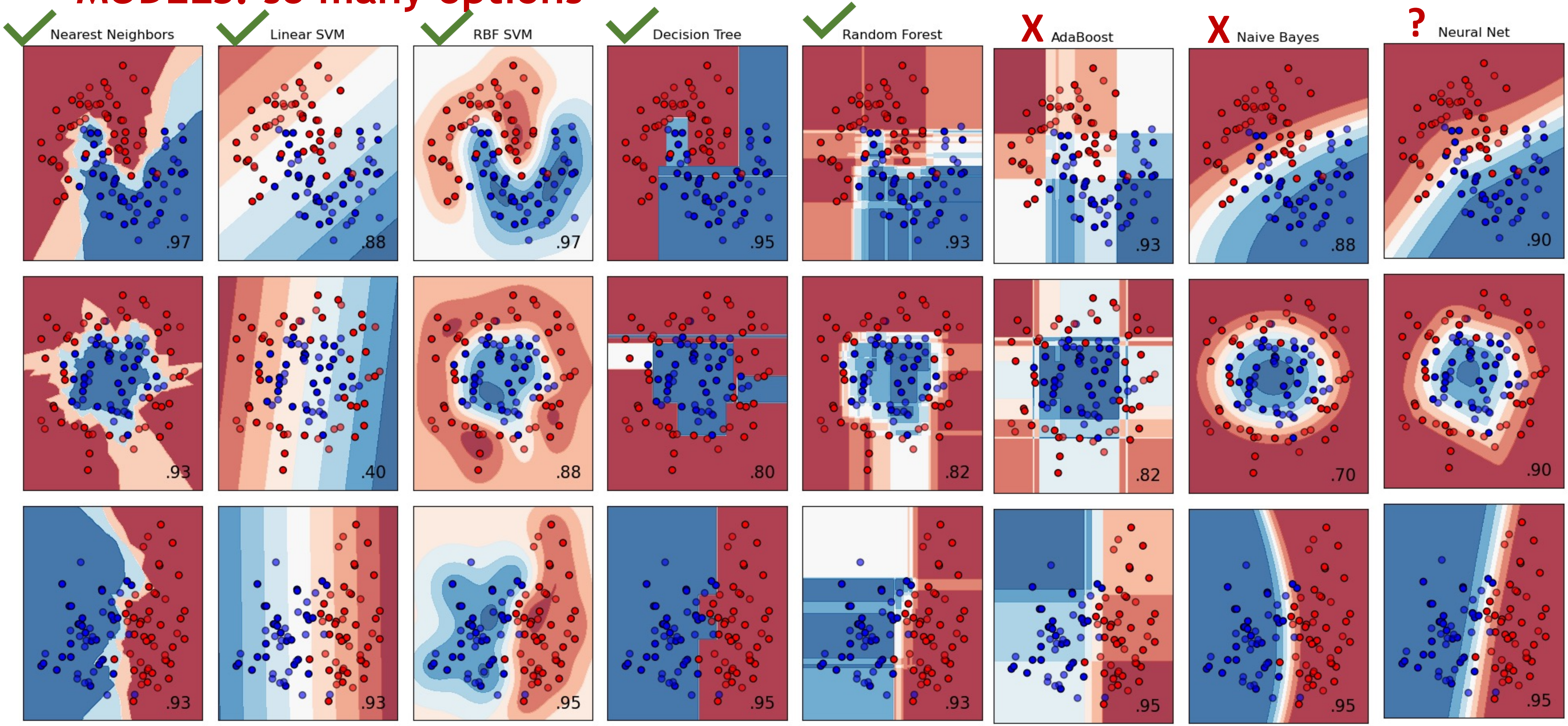
Data Format

Data Source	Structured	Unstructured
Internal	**Human-Generated** • Survey ratings • Aptitude testing **Machine-Generated** • Web metrics from Web logs • Product purchase from sales Records • Process control measures	**Human-Generated** • Emails, letters, text messages • Audio transcripts • Customer comments • Voicemails • Corporate video/communications • Pictures, illustrations • Employee reviews
External	**Human-Generated** • Number of Retweets, Facebook likes, Google Plus +1s • Ratings on Yelp • Patient ratings ratings **Machine-Generated** • GPS for tweets • Time of tweet/updates/postings	**Human-Generated** • Content of social media updates • Comments in online forums • Comments on Yelp • Video reviews • Pinterest images • Surveillance video

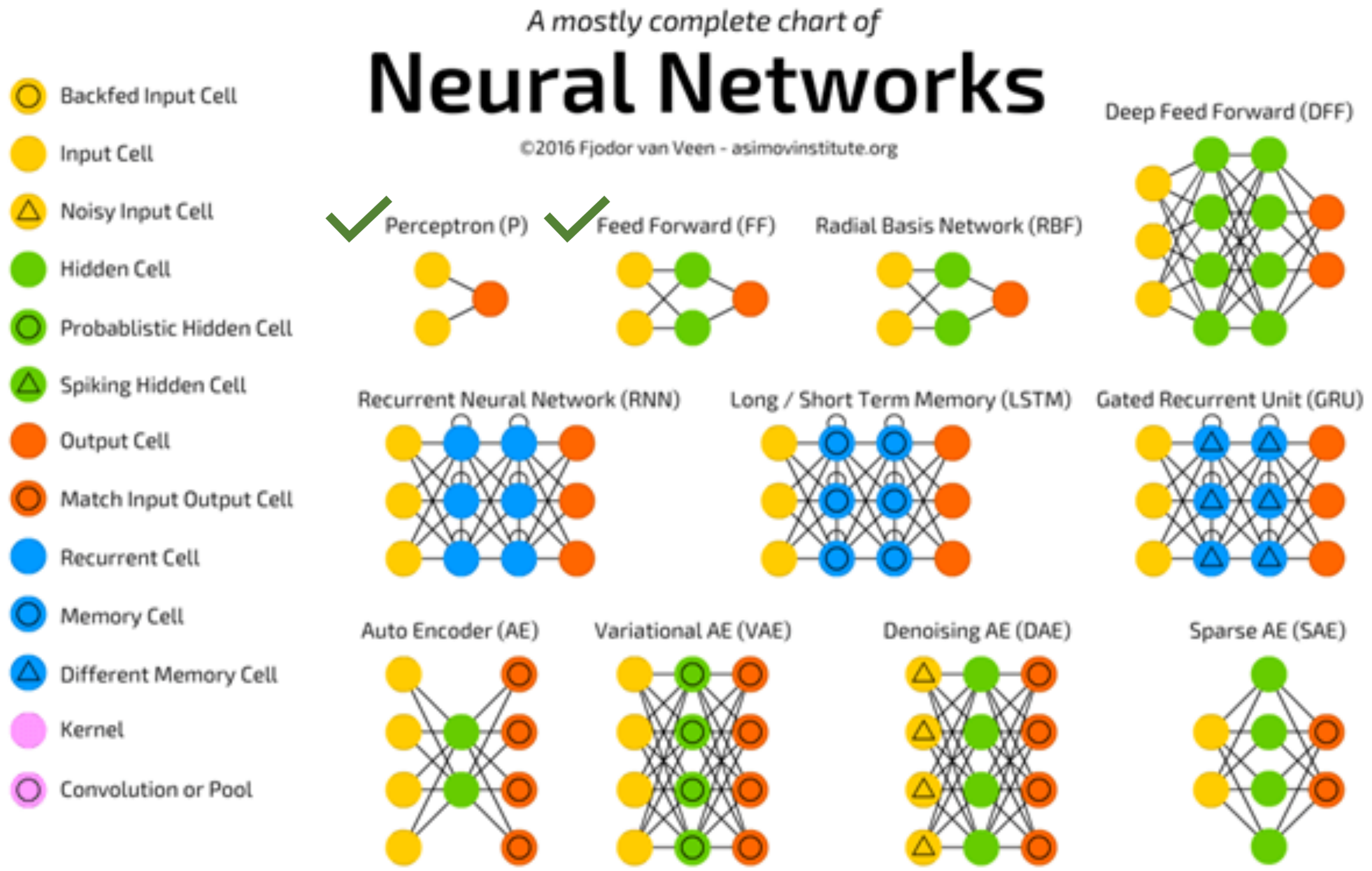
DATA: 3Vs

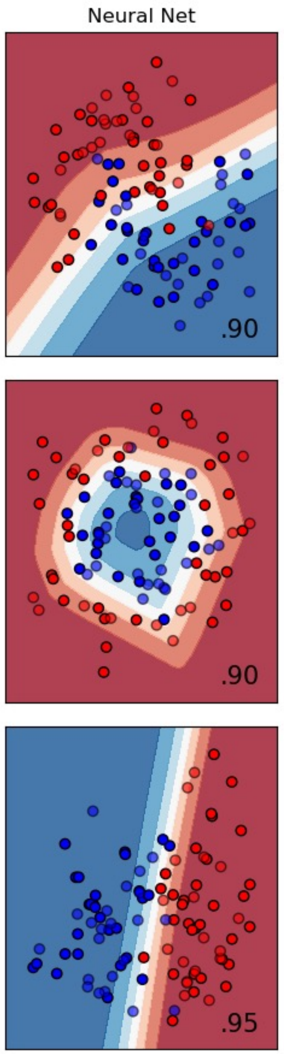

Data
Velocity
Real Time
near Real Time
periodic
batch
Data
Volume
MB
GB
TB
PB
table
data base
photo
Web
Audio
Social
Video
unstructured
Mobile
Data
Variety

MODELS: so many options



MODELS: so many options with so many variations





SOFTWARE TOOLS: UI/UX

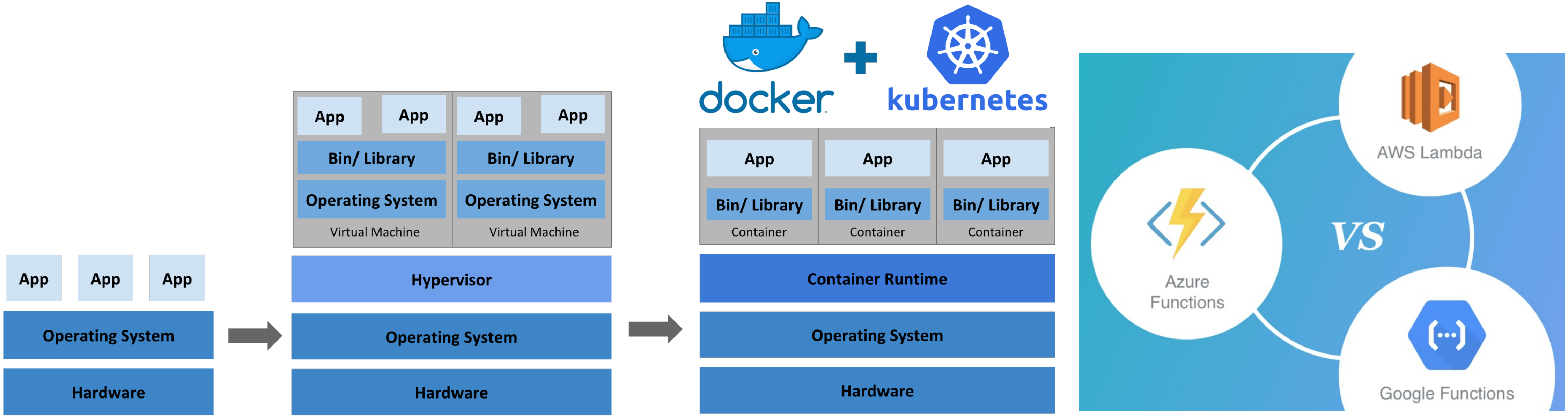
- Dashboards (Plotly/Dash/Tableau)
- Javascript dataviz (React + D3)
- Web apps (Gradio, Flask, Streamlit)

SOFTWARE TOOLS: Parallelization

- across multiple cores on a single machine
- using GPUs (e.g. CUDA/OpenCL)
- across multiple nodes in a cluster (e.g. MLlib on Spark, Mahout on Hadoop/Mapreduce)

Carya @ HPEDSI

SOFTWARE TOOLS: Production Deployment



Servers
Deploy in months

Virtual Machines
Deploy in minutes

Containers
Deploy in seconds

Serverless
Deploys in milliseconds


END
DETOUR

“The Road Not Taken”, by Robert Frost

Two roads diverged in a yellow wood
And sorry I could not travel both
And be one traveler, …

https://www.flickr.com/photos/yooperann/6212927553

AI is not new: the road taken in 1956

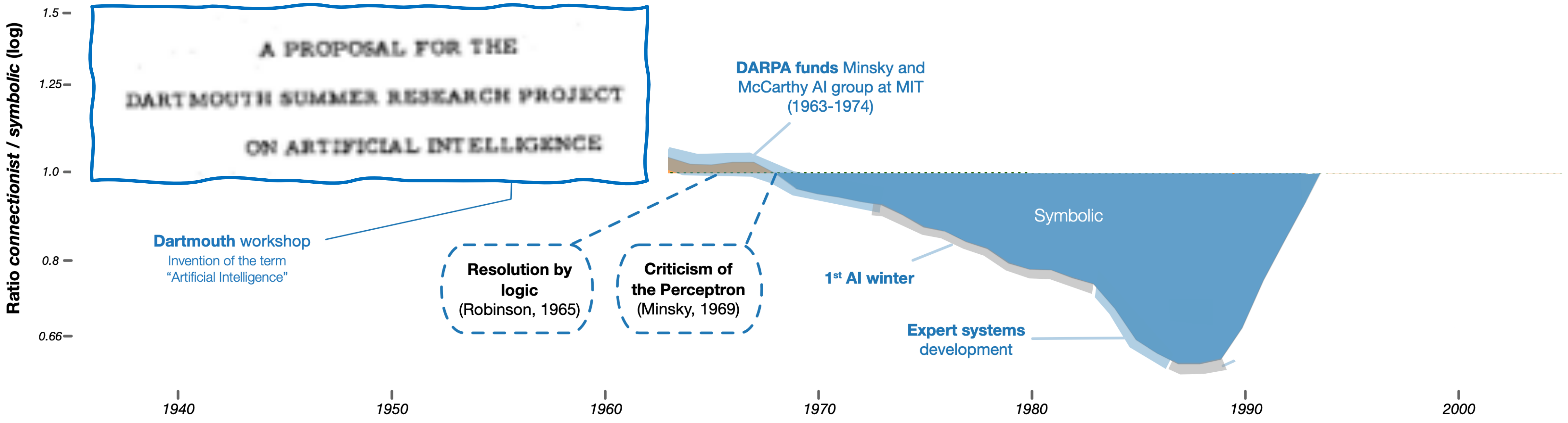
A PROPOSAL FOR THE
DARTMOUTH SUMMER RESEARCH PROJECT
ON ARTIFICIAL INTELLIGENCE

"The study is to proceed on the basis of the conjecture
that every aspect of learning or
any other feature of intelligence
can in principle be so **precisely described** that
a machine can be made to simulate it."

J. McCarthy, Dartmouth College
M. L. Minsky, Harvard University
N. Rochester, I. B. M. Corporation
C. E. Shannon, Bell Telephone Laboratories

AI is not new: the road taken in 1956

Symbolic AI:
explicit rules, based on
expert knowledge



https://neurovenge.antonomase.fr/

Early chatbot example of AI

Symbolic AI:
explicit rules, based on expert knowledge

Joseph Weizenbaum's program ELIZA, published in 1966, simulated conversation by using a "pattern matching" and substitution methodology. **Directives on how to interact** were provided by "scripts", which allowed ELIZA to process user inputs and engage in discourse following the **rules and directions of the script**, using pre-prepared or pre-programmed responses.

For example:

EXPERT KNOWLEDGE: the meaning of the word ‘FAMILY’ is broader than the meaning of the word ‘MOTHER’

RULE: Respond to any input that contains the word 'MOTHER’ with 'TELL ME MORE ABOUT YOUR FAMILY’

https://sites.google.com/view/elizagen-org/try-eliza

Modern chatbot example of AI

~~Syn AI:~~
~~explicit r ased on~~
~~ex t know dge~~

Modern chatbot example of AI

Connectionist AI: patterns inferred from data examples

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Modern chatbot example of AI

Connectionist AI: patterns inferred from data examples

Collect as many conversations as possible

For any given input,

find the closest match among the inputs in the collected data, and
respond with the matching response text from the collected data

Modern chatbot example of AI

Connectionist AI: patterns inferred from data examples

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For any given input,

find the closest match among the inputs in the collected data, and
respond with the matching response text from the collected data

CAUTION: this is an extremely oversimplified example, not an actual detailed blueprint for how generative NLP systems work (for that, see DSI312 ☺)

Modern chatbot example of AI

Connectionist AI: patterns inferred from data examples

Everything old is new again!

I.—COMPUTING MACHINERY AND INTELLIGENCE

By A. M. Turing

1. *The Imitation Game.*

AKA the Turing Test

I PROPOSE to consider the question, 'Can machines think ?' This should begin with definitions of the meaning of the terms 'machine' and 'think'. The definitions might be framed so as to

ML skews to the "patterns" flavor of AI

Artificial Intelligence (AI)

Symbolic AI:
Refers to techniques that rely on **explicit rules, based on expert knowledge** about data ontologies

Machine Learning (ML):
refers to (mostly connectionist) techniques that rely on **patterns inferred from data examples**

ML skews to the "patterns" flavor of AI

Start with **THEORY** to **construct** MODEL

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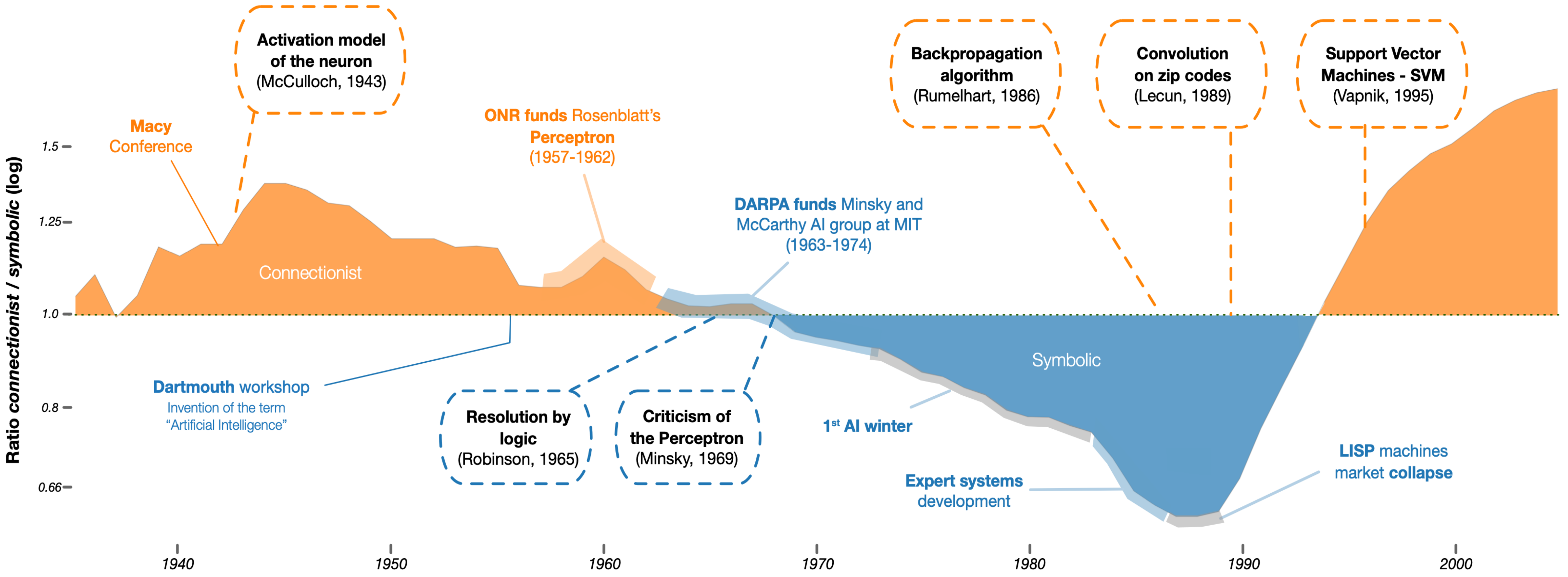
Start with **DATA** to **fit** MODEL

Two roads diverged … - A brief timeline



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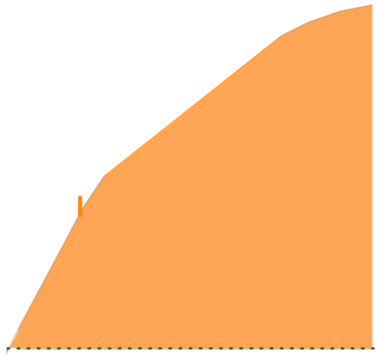
Deep Learning: Walking further down the ML path



We are here

2000

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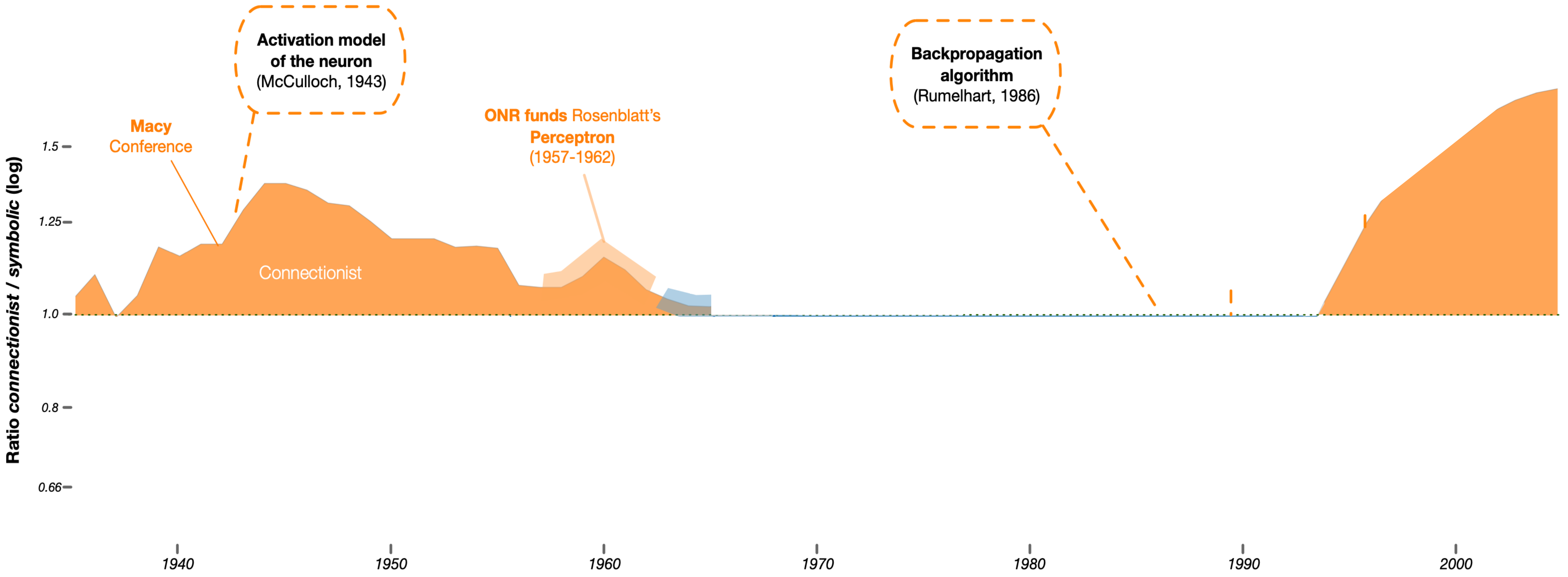
Deep Learning: Walking further down the ML path, using two early ideas



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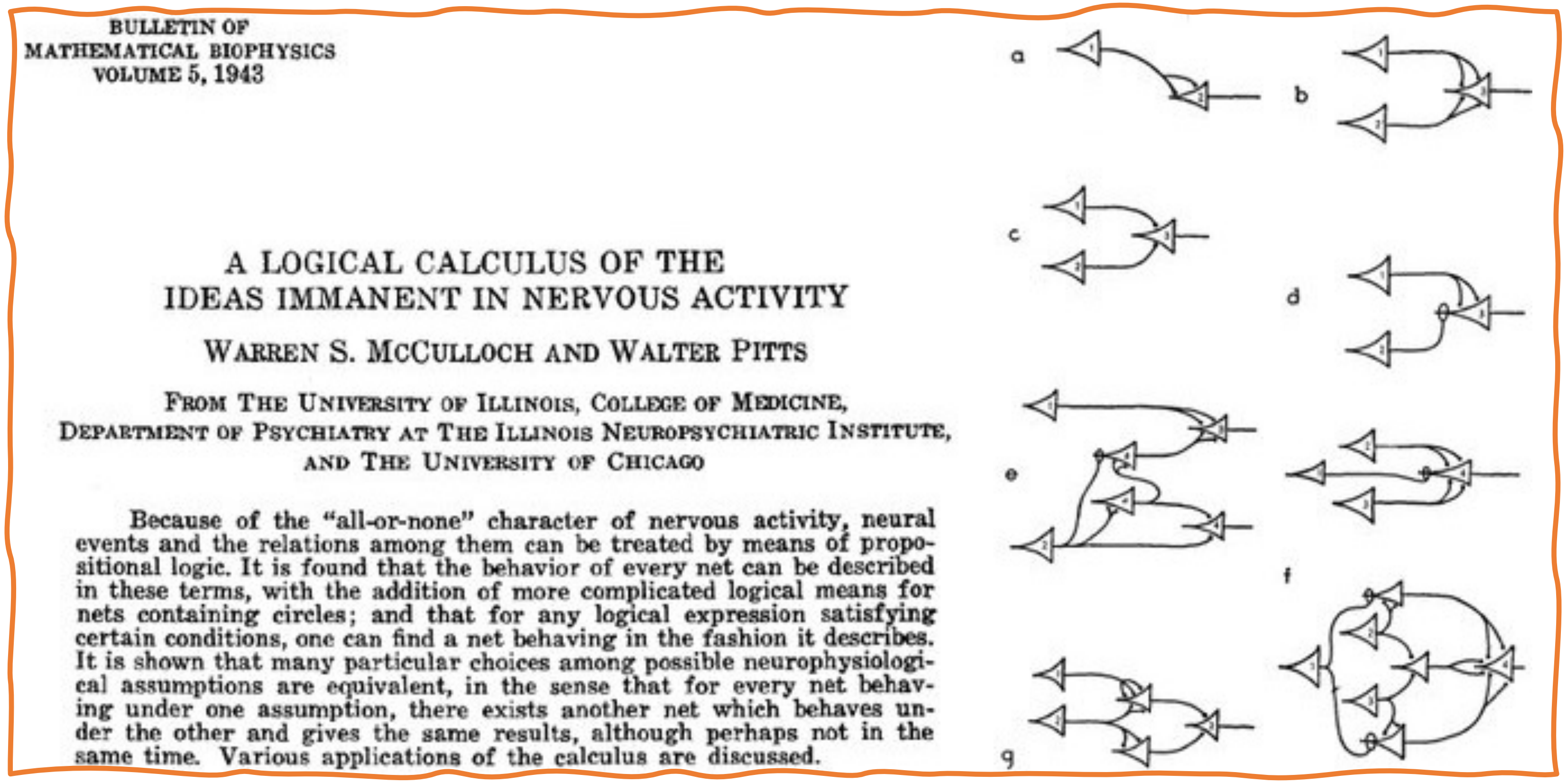
Deep Learning: Walking further down the ML path, using two early ideas

Neural Networks (1940s)



BULLETIN OF
MATHEMATICAL BIOPHYSICS
VOLUME 5, 1943

A LOGICAL CALCULUS OF THE
IDEAS IMMANENT IN NERVOUS ACTIVITY

WARREN S. MCCULLOCH AND WALTER PITTS

FROM THE UNIVERSITY OF ILLINOIS, COLLEGE OF MEDICINE,
DEPARTMENT OF PSYCHIATRY AT THE ILLINOIS NEUROPSYCHIATRIC INSTITUTE,
AND THE UNIVERSITY OF CHICAGO

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

Deep Learning: Walking further down the ML path, using two early ideas

Error Backpropagation (1980s)

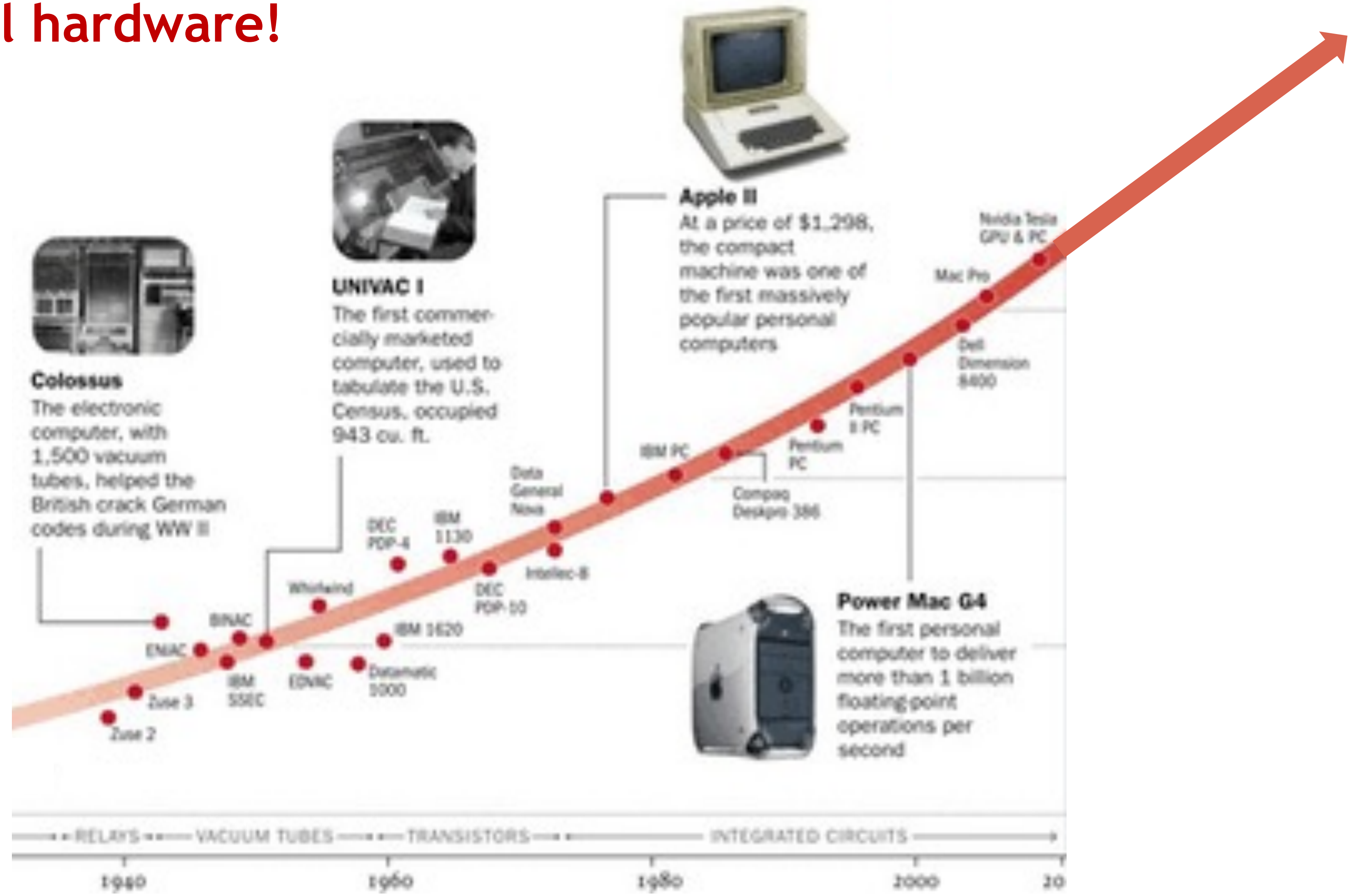
Learning representations by back-propagating errors

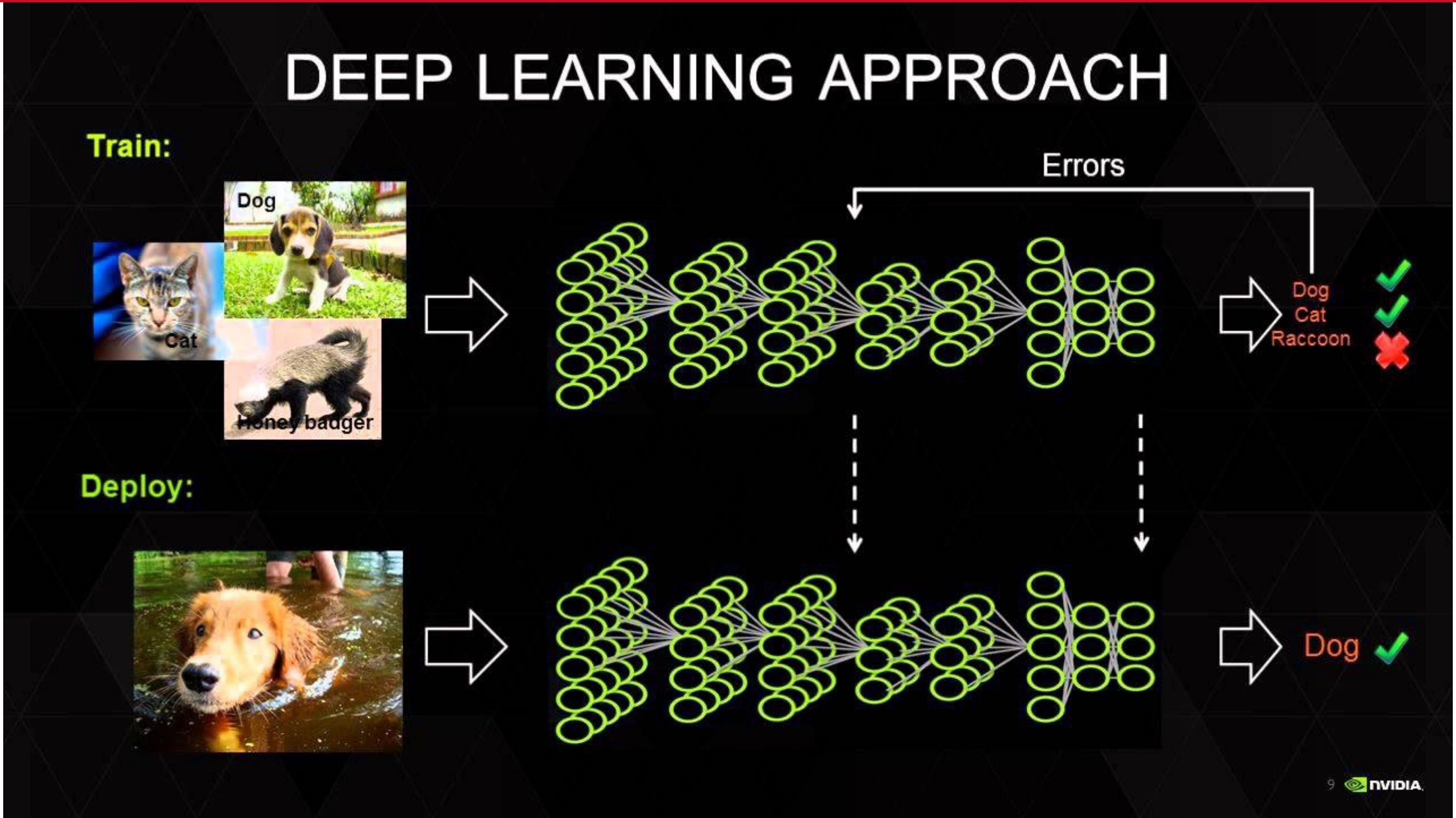
David E. Rumelhart*, Geoffrey E. Hinton† & Ronald J. Williams*

* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA

We describe a new learning procedure, back-propagation, for networks of neurone-like units. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal 'hidden' units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure[1].

Deep Learning: Walking further down the ML path, using two early ideas on powerful hardware!




DEEP LEARNING APPROACH
Train:
Dog
Cat
Honey badger
Errors
Dog
Cat
Raccoon
Deploy:
Dog
9
NVIDIA

Deep ML = Data + Computing *at Scale*

Artificial Intelligence (AI)

Symbolic AI:
Refers to techniques that rely on **explicit rules based on expert knowledge** about data ontologies

Machine Learning (ML):

Deep Learning relies on fitting LARGE models (million+ parameters)

Deep ML = Data + Computing *at Scale*

The technology (CPUs+GPUs) and dataset sizes (Big Data) needed for practical implementations of Deep Learning algorithms did not mature until the 21st century