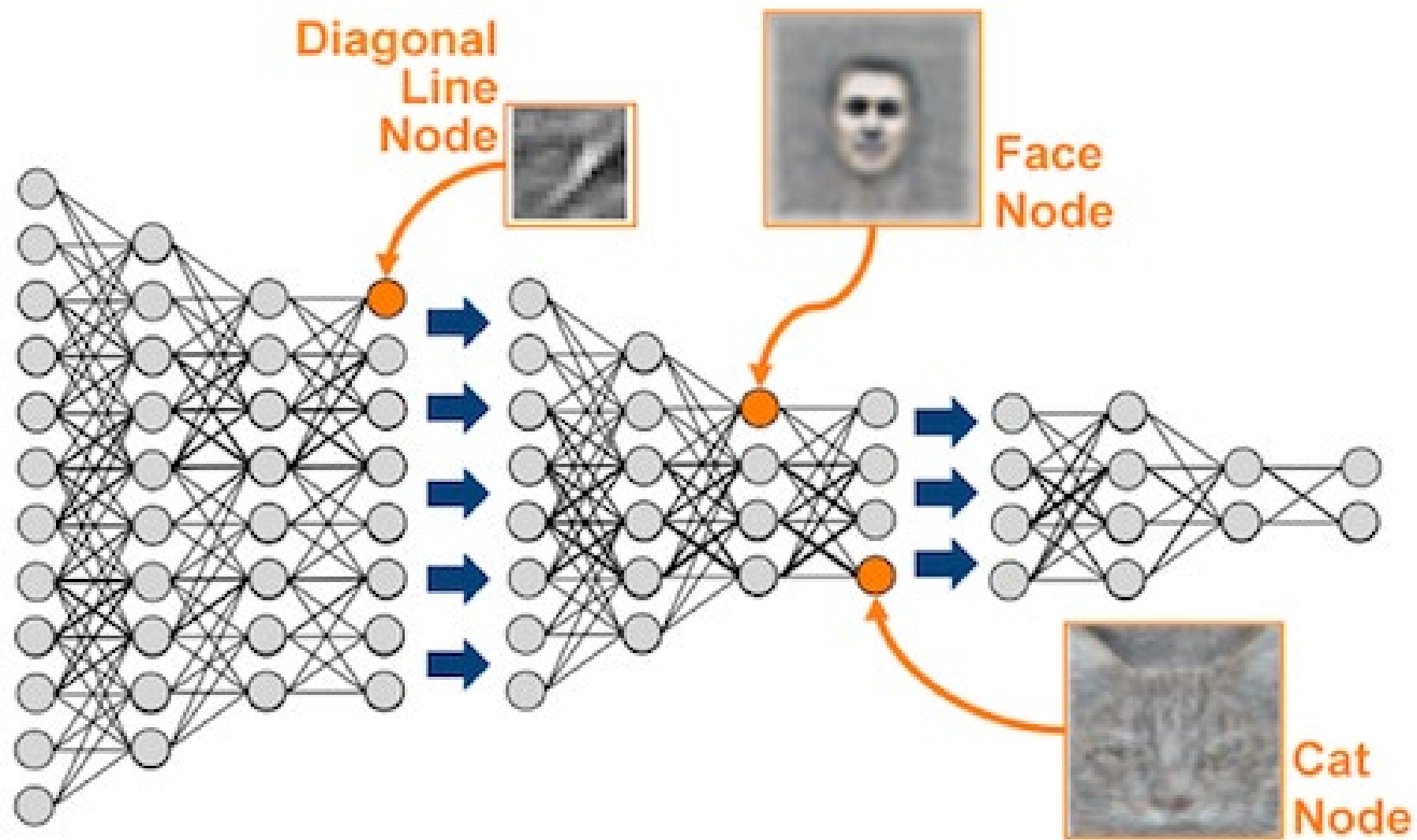




On Representation Learning

Alexander G. Ororbia II
Introduction to Machine Learning
CSCI-736
2/4/2025

Companion reading:
Chapter 15 of Deep Learning textbook
















On the plethora of model structures...

THE SPACE OF NEURAL ARCHITECTURES

A mostly complete chart of Neural Networks

Deep zoo!

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-  Backfed Input Cell
-  Input Cell
-  Noisy Input Cell
-  Hidden Cell
-  Probabilistic Hidden Cell
-  Spiking Hidden Cell
-  Output Cell
-  Match Input Output Cell
-  Recurrent Cell
-  Memory Cell
-  Different Memory Cell
-  Kernel
-  Convolution or Pool

Perceptron (P)



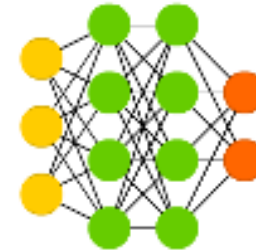
Feed Forward (FF)



Radial Basis Network (RBF)



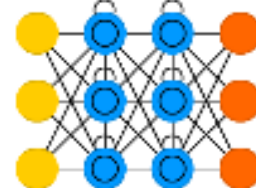
Deep Feed Forward (DFF)



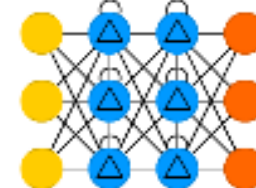
Recurrent Neural Network (RNN)



Long / Short Term Memory (LSTM)



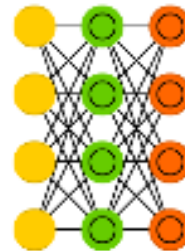
Gated Recurrent Unit (GRU)



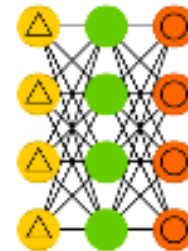
Auto Encoder (AE)



Variational AE (VAE)



Denoising AE (DAE)



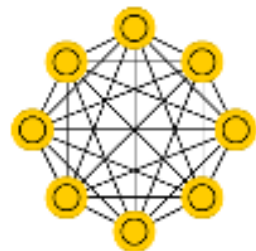
Sparse AE (SAE)



Markov Chain (MC)



Hopfield Network (HN)



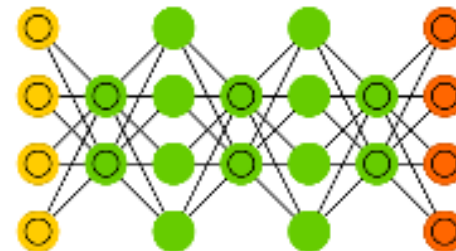
Boltzmann Machine (BM)



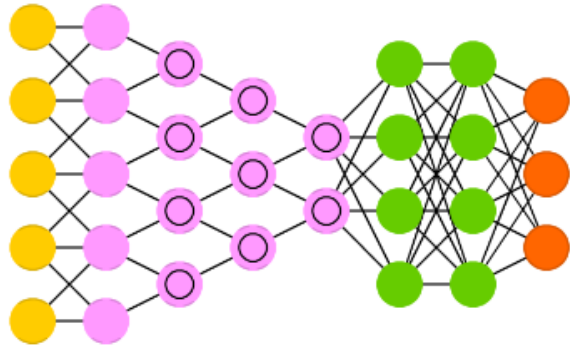
Restricted BM (RBM)



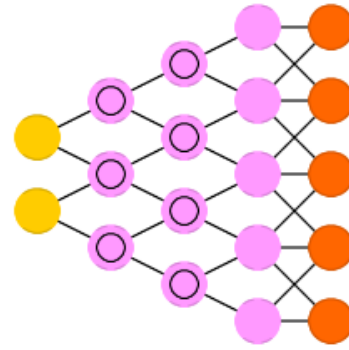
Deep Belief Network (DBN)



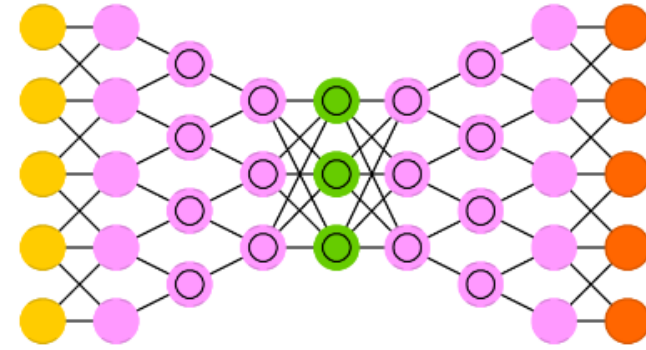
Deep Convolutional Network (DCN)



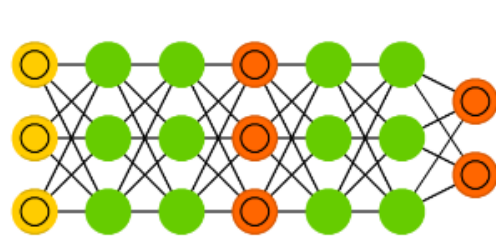
Deconvolutional Network (DN)



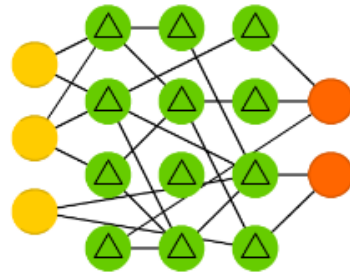
Deep Convolutional Inverse Graphics Network (DCIGN)



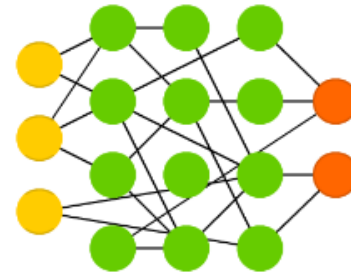
Generative Adversarial Network (GAN)



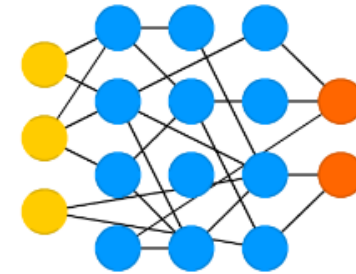
Liquid State Machine (LSM)



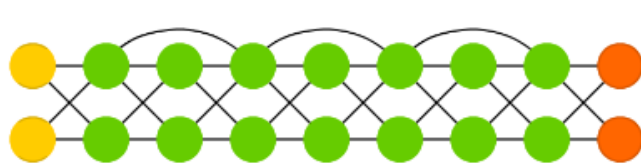
Extreme Learning Machine (ELM)



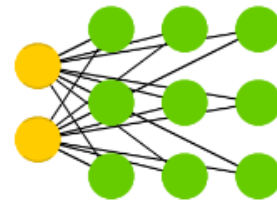
Echo State Network (ESN)



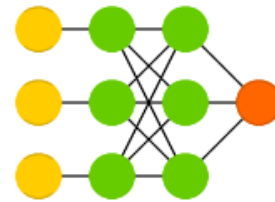
Deep Residual Network (DRN)



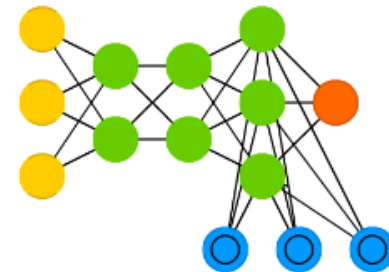
Kohonen Network (KN)



Support Vector Machine (SVM)



Neural Turing Machine (NTM)



What is Representation Learning?

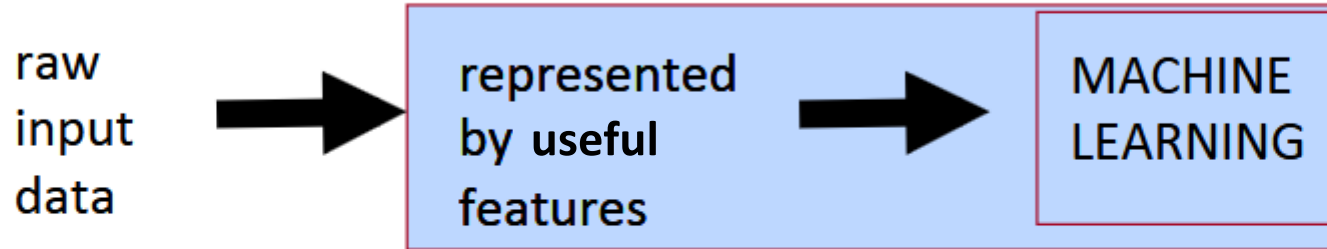
- Learn features automatically
 - Find a transformation of raw data input to a representation / space that can be effectively exploited in machine learning tasks
- Can be viewed as complementary to machine learning
 - “Automatic” pre-processing (or automated feature engineering)
- What makes one representation better than another?
 - ***Good representation*** = one that makes a subsequent learning task easier (choice of representation depends on the choice of subsequent learning task)



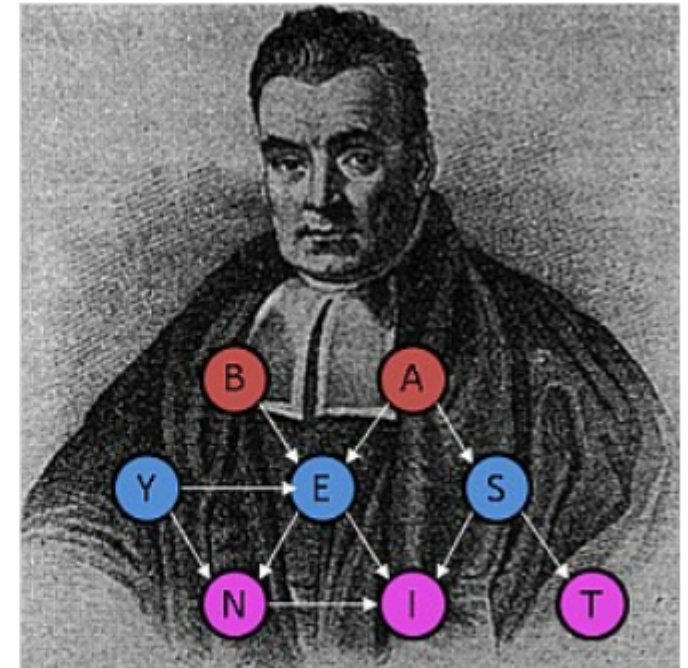
Why?

- *Intelligent systems need:*
 - Knowledge (constraints/priors)
 - Learning (optimization/search)
 - Generalization
(guessing where probability mass concentrates)
 - Ways to fight off curse of dimensionality
(exponentially many configurations of variables to consider)
 - Needs to disentangle underlying explanatory factors
(making sense of data)

- Good **features** essential for successful ML: 90% of effort



- Handcrafting features vs learning them
- Good representation?
- **guesses**
the features / factors / causes

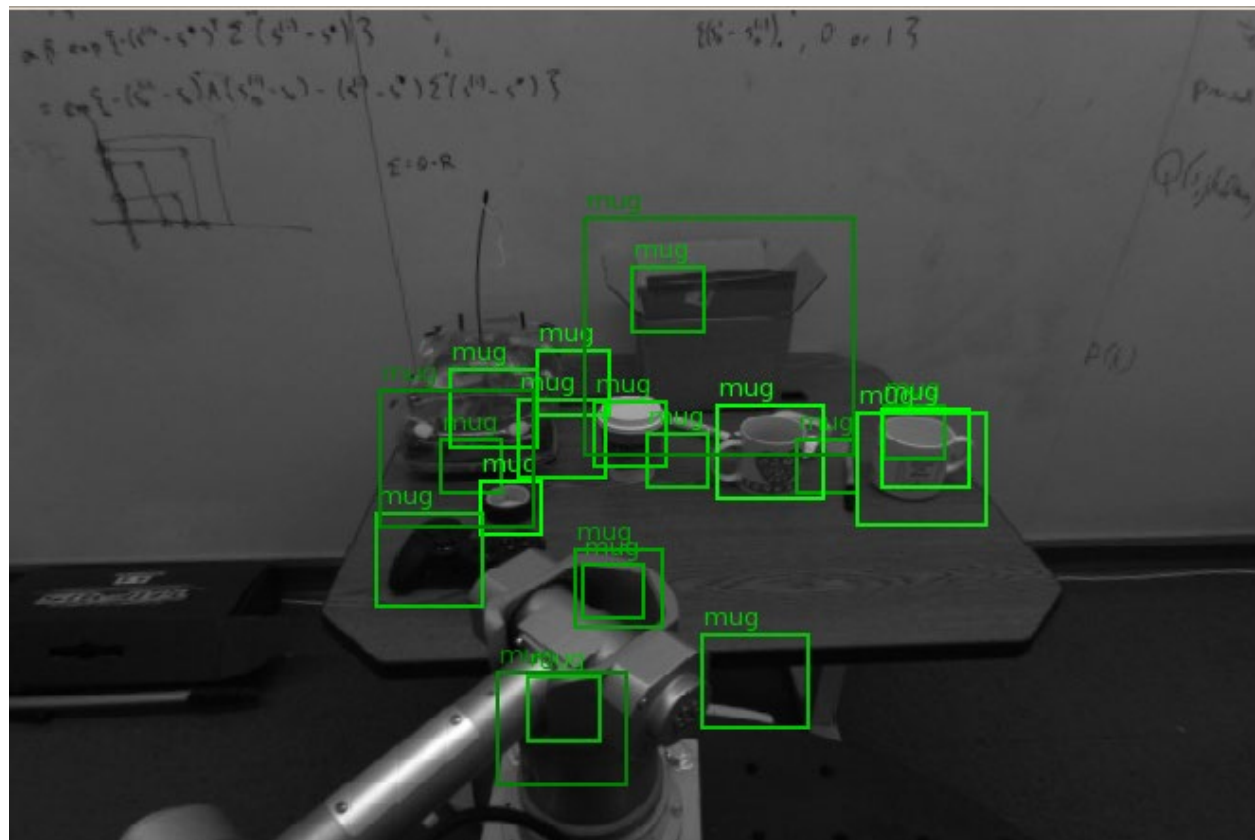


(Courtesy of Yoshua Bengio)

How do humans generalize from very few examples?

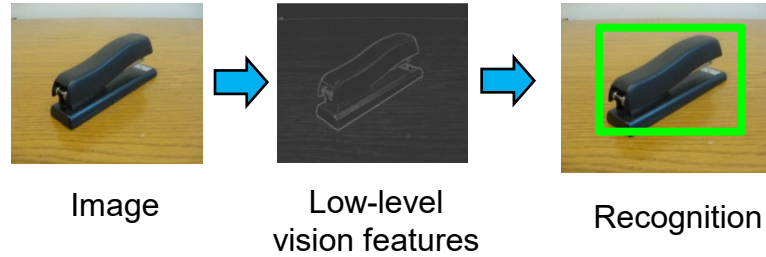
- They **transfer** knowledge from previous learning:
 - **Abstract** (i.e. deep) representations
 - Explanatory factors
- Previous learning from: unlabeled data
 - + labels for other tasks

Computer Vision is Hard

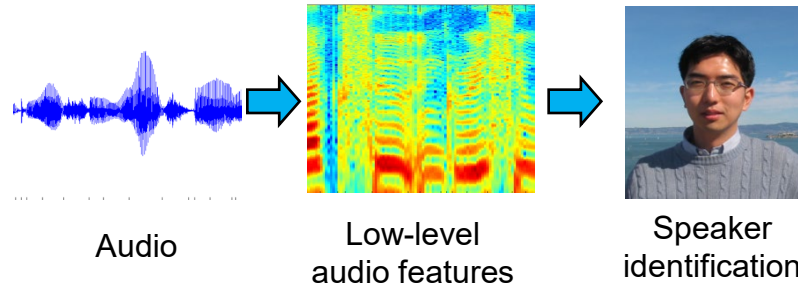


How is Computer Perception Done?

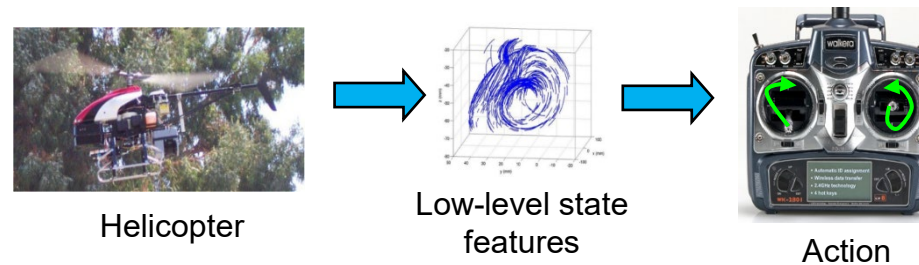
Object
detection



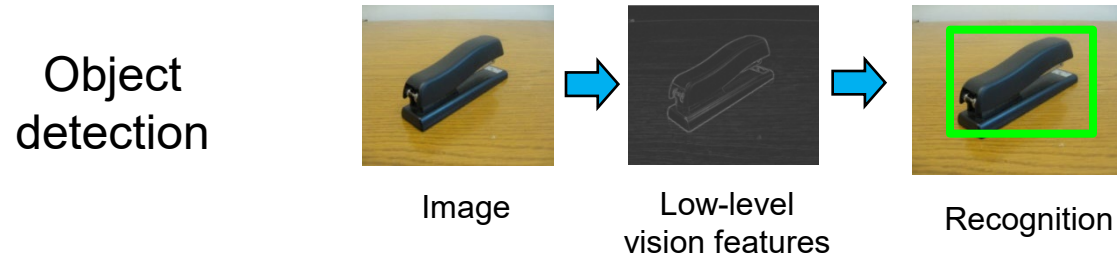
Audio
classification



Helicopter
control



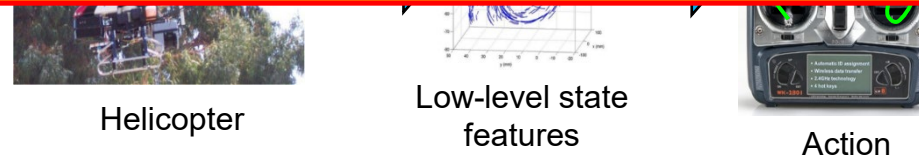
How is Computer Perception Done?



Al
class

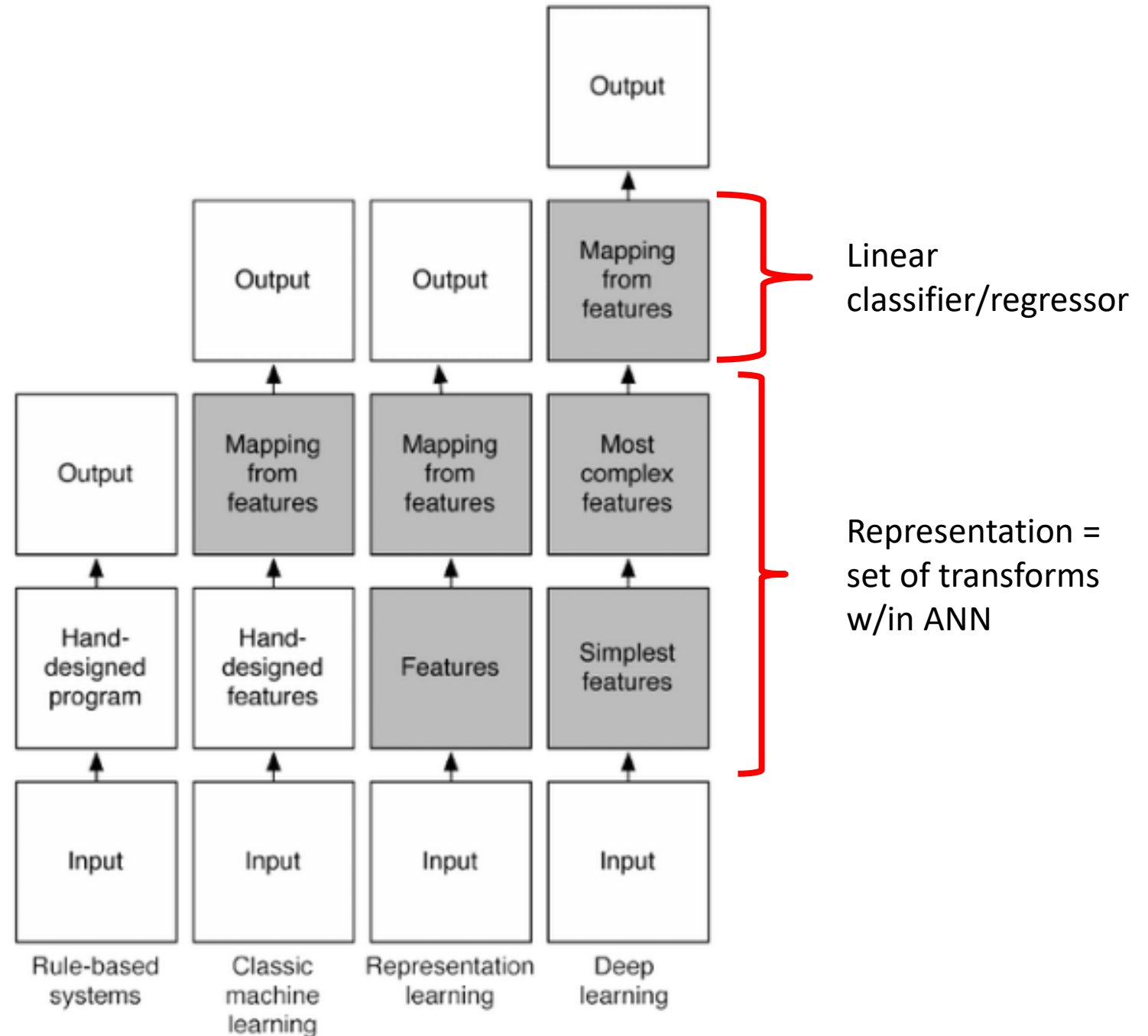
- Problems of hand-tuned features
1. Needs expert knowledge
 2. Time-consuming and expensive
 3. Does not generalize to other domains

Helic
control



In the context of a deep ANN:

Training w/ supervised criterion naturally leads to representation at every hidden layer (more so near top hidden layer) taking on properties that make discriminative/task-centric learning easier



Deep Architectures are More Expressive

Theoretical arguments:

2 layers of {
Logic gates
Formal neurons
RBF units

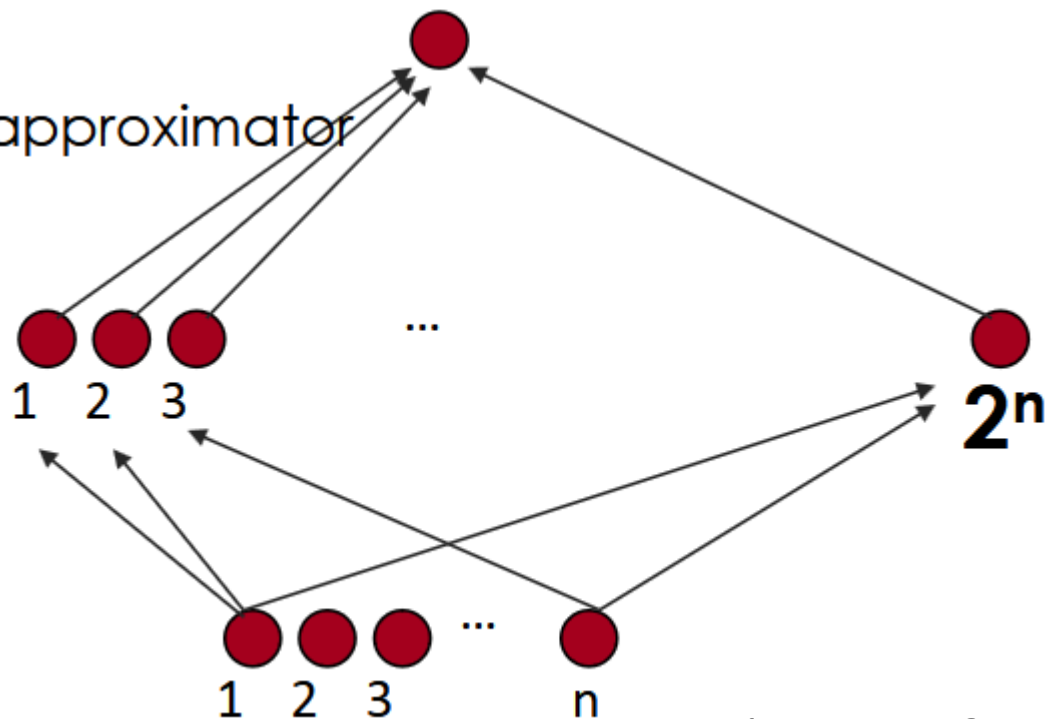
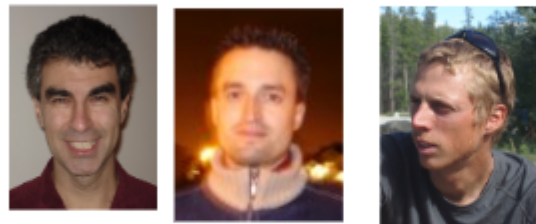
= universal approximator

RBM's & auto-encoders = universal approximator

Theorems on advantage of depth:

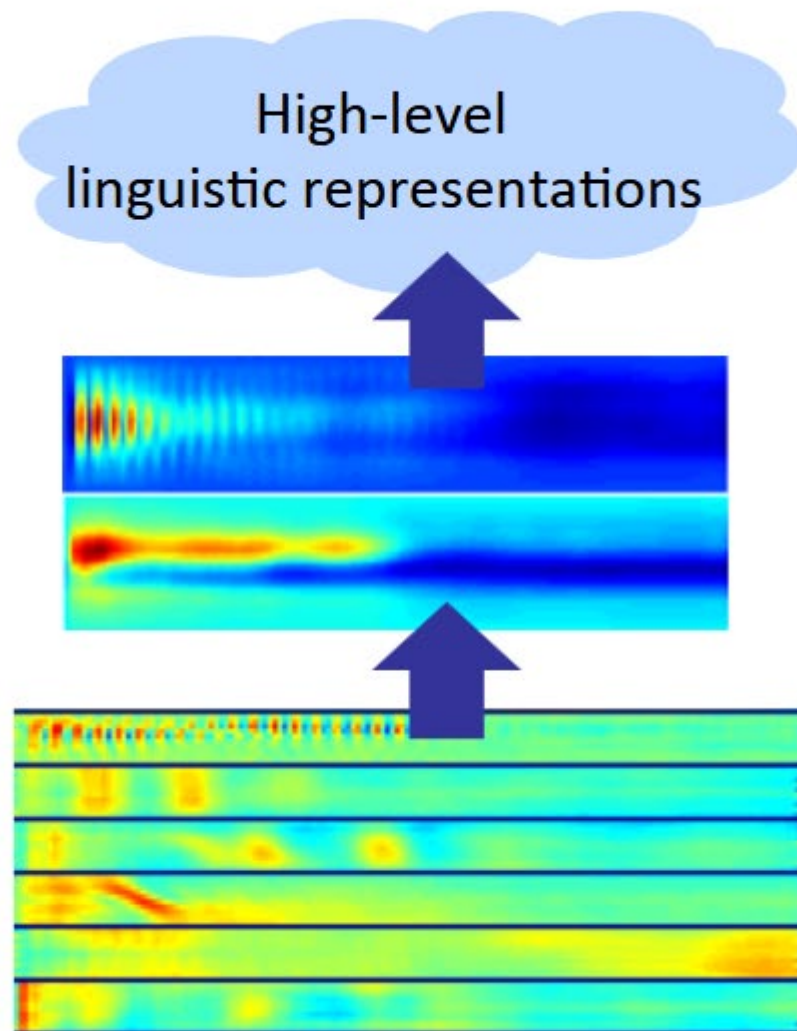
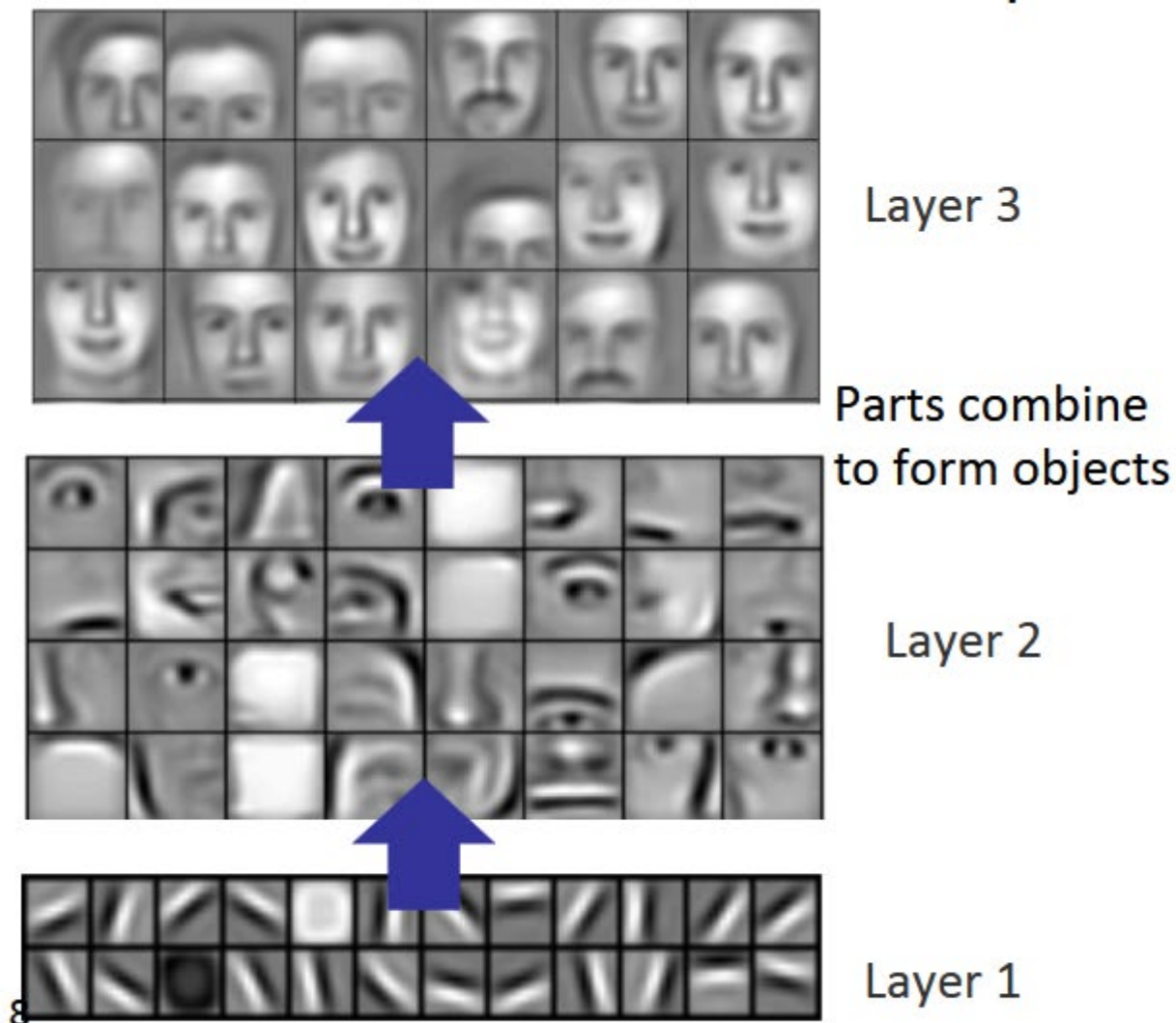
(Hastad et al 86 & 91, Bengio et al 2007, Bengio & Delalleau 2011, Braverman 2011)

Some functions compactly represented with k layers may require exponential size with 2 layers



(Courtesy of Yoshua Bengio)

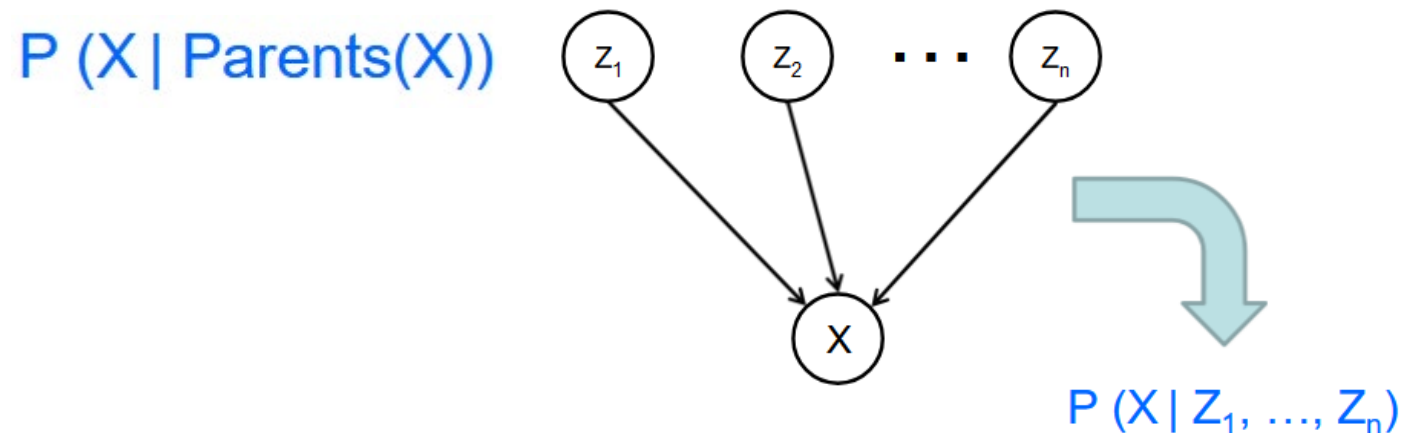
Successive model layers learn deeper intermediate representations



Prior: underlying factors & concepts compactly expressed w/ multiple levels of abstraction

The Problem of Representation Learning

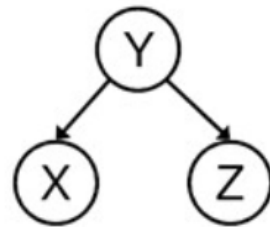
- Representation learning problems face trade-off between preserving as much information about input (as possible) and attaining nice properties
 - Models (supervised or unsupervised) have main training objective but learn a representation as a “side effect”
- Offers pathway to facilitate semi-supervised learning
 - **Hypothesis**: unlabeled data can be used to learn a good representation



The Problem of Representation Learning

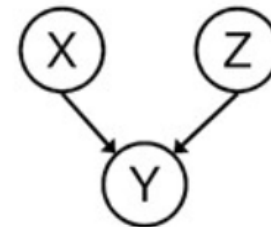
- Representation learning problems face trade-off between preserving as much information about input (as possible) and attaining nice properties, e.g., might want things like independence of detectors
- Often add constraints to shape representation in some cases
 - Density estimation – encourage elements of representation/latent vector \mathbf{z} to be independent (distributions w/ more independencies are easier to model)

Common cause



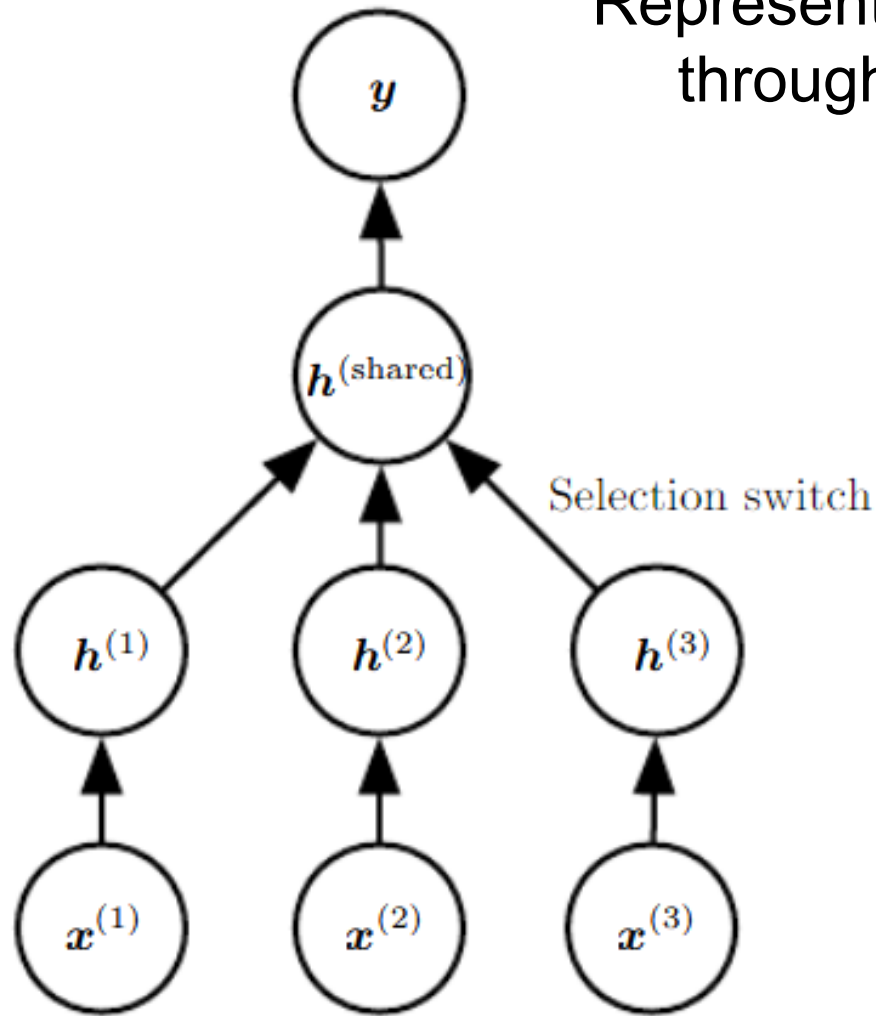
Y: Project due
X: Newsgroup
busy
Z: Lab full

Common effect

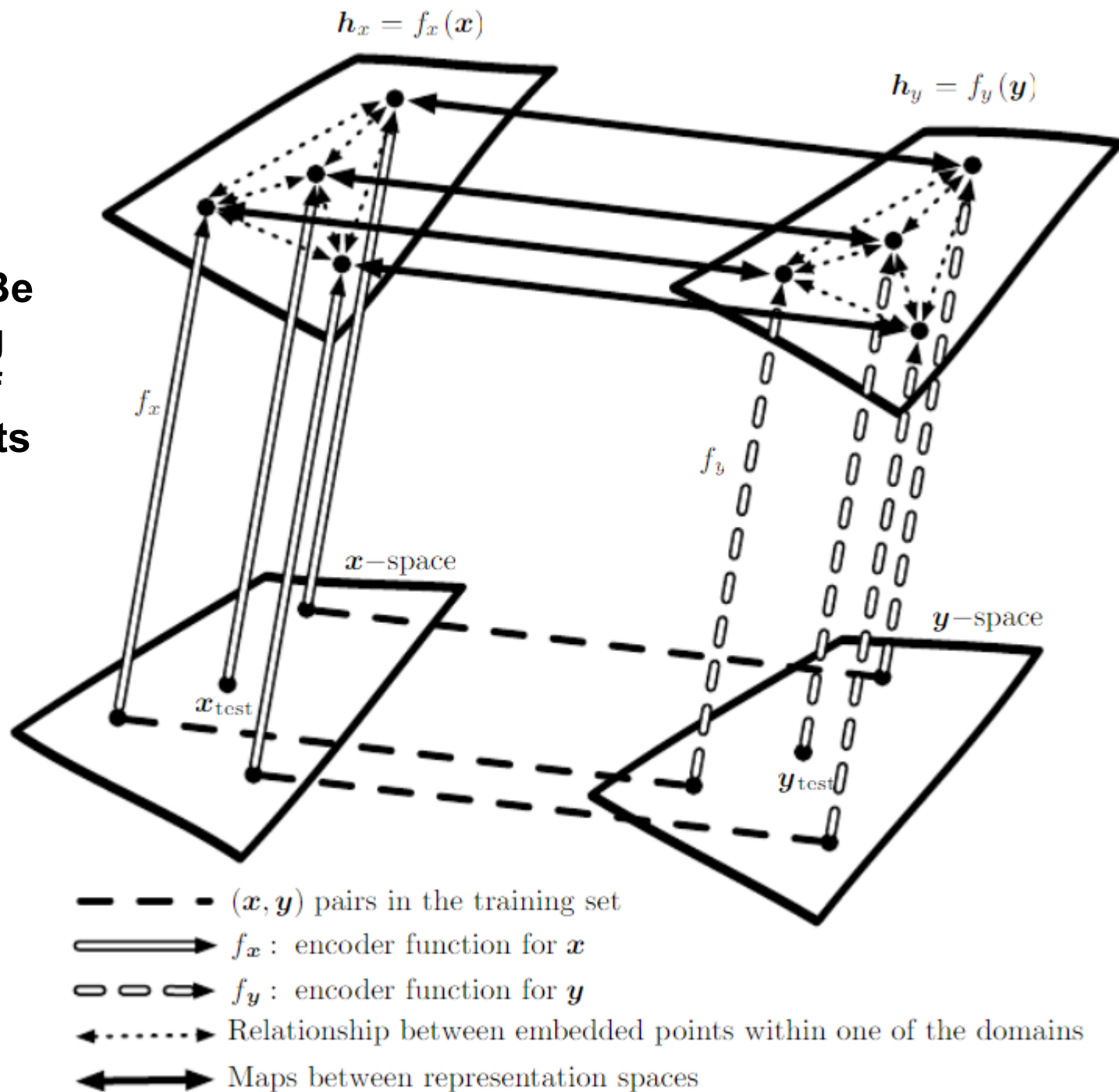


X: Raining
Z: Ballgame
Y: Traffic

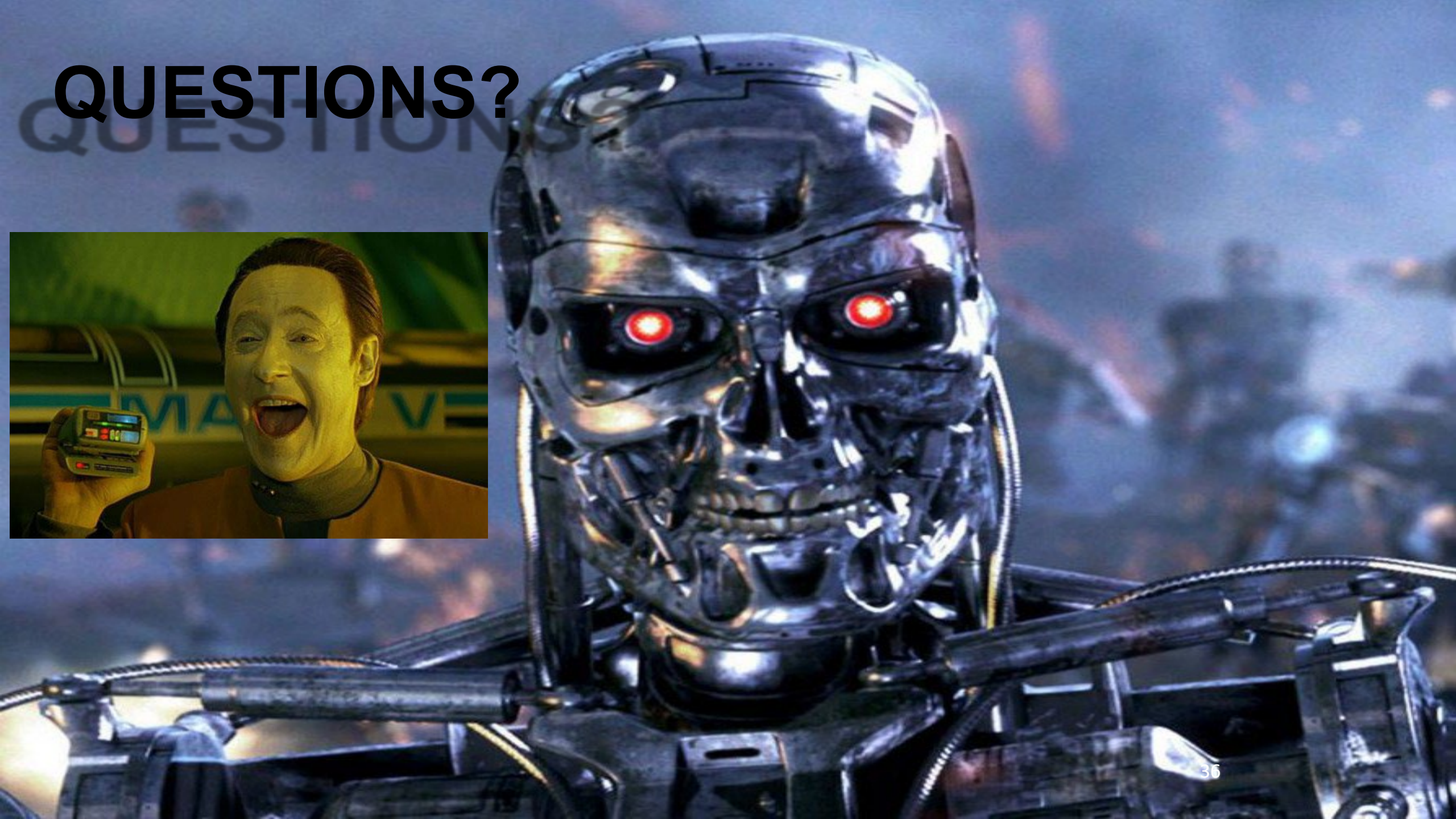
Representations Can Be Acquired
through Multi-Task Learning



Representations Can Be
Acquired by Mapping
Across Encodings of
Modalities/Variable Sets



QUESTIONS?



Unsupervised Feature Learning



Find a better way to represent images (or low-level data in general) than pixels (or low-level/raw sensory features).