Universität Potsdam

Deep Learning for NLP

Deep Learning Basics

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Additional Resources

- Deep Learning textbook:
  - http://www.deeplearningbook.org/
    An MIT Press book by Ian Goodfellow, Yoshua Bengio and Aaron Courville, 2016.

- standard ML textbooks:
  - Tom Mitchell: *“Machine Learning”*, McGraw Hill, 1997.
  - Christopher M. Bishop: *“Pattern Recognition and Machine Learning”*, Springer, 2007.

Additional Resources

- online lectures:
  - https://www.coursera.org/course/neuralnets
    Geoffrey Hinton: *“Neural Networks for Machine Learning”*, Coursera, 2012.
  - http://cs224d.stanford.edu/
    Richard Socher: *“Deep Learning for Natural Language Processing”*, Standford, 2015.
- generally useful:
  - http://deeplearning.net/

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Machine Learning Basics

Motivation

"lazy engineer" approach:

How to program a machine <u>to learn</u> to solve task XY?

- generalizes to new / similar problems

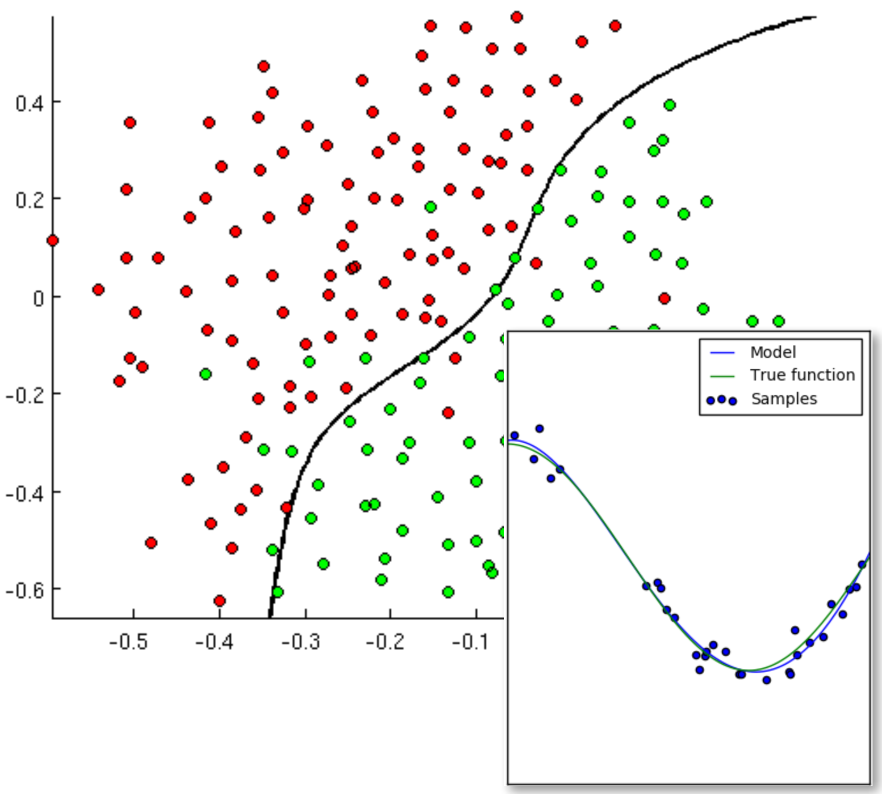
Defining Learning

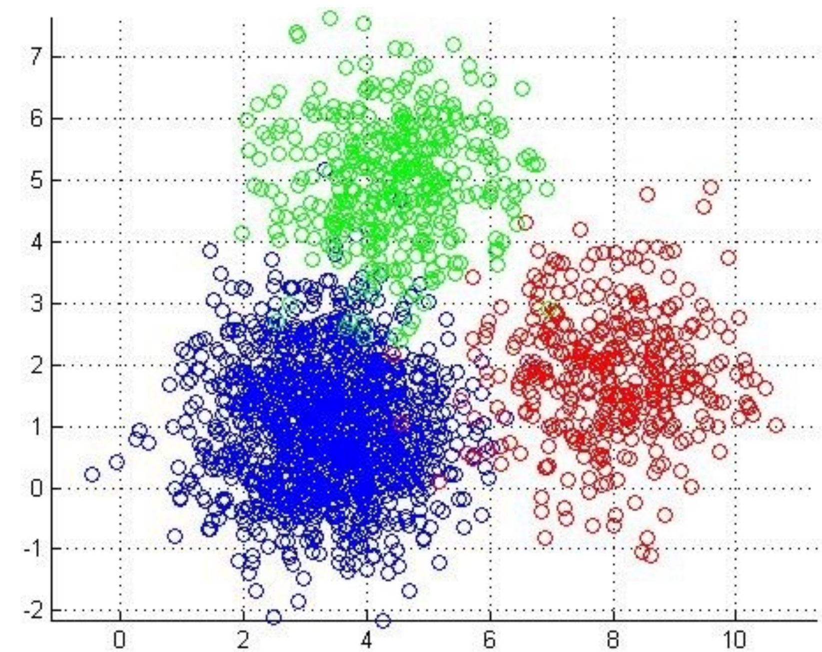
[Mitchell 1997]

- Learning:
  – Improving with experience at some task

- Formal definition:
  – Improve over task T,
  – with respect to performance measure P,
  – based on experience E.

Machine Learning Tasks:
Supervised vs. Unsupervised





Defining Learning

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generalization on unseen (test) data

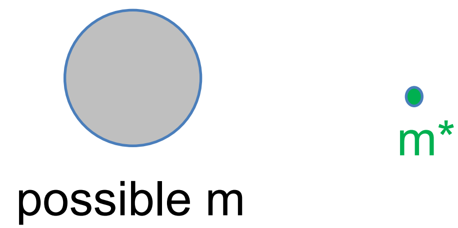
training examples

Bias-Variance Trade-Off

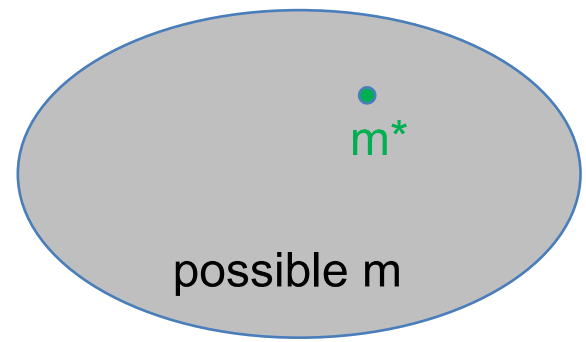
- conflict: choose model that
  - accurately captures the training data regularities
  - generalizes well to unseen data
- bias
  - error from (implicit or explicit) assumption of the learning algorithm => underfitting
- variance
  - error from fitting to small fluctuations => overfitting

Bias-Variance Trade-Off

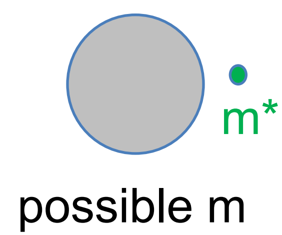
- high bias, low variance:



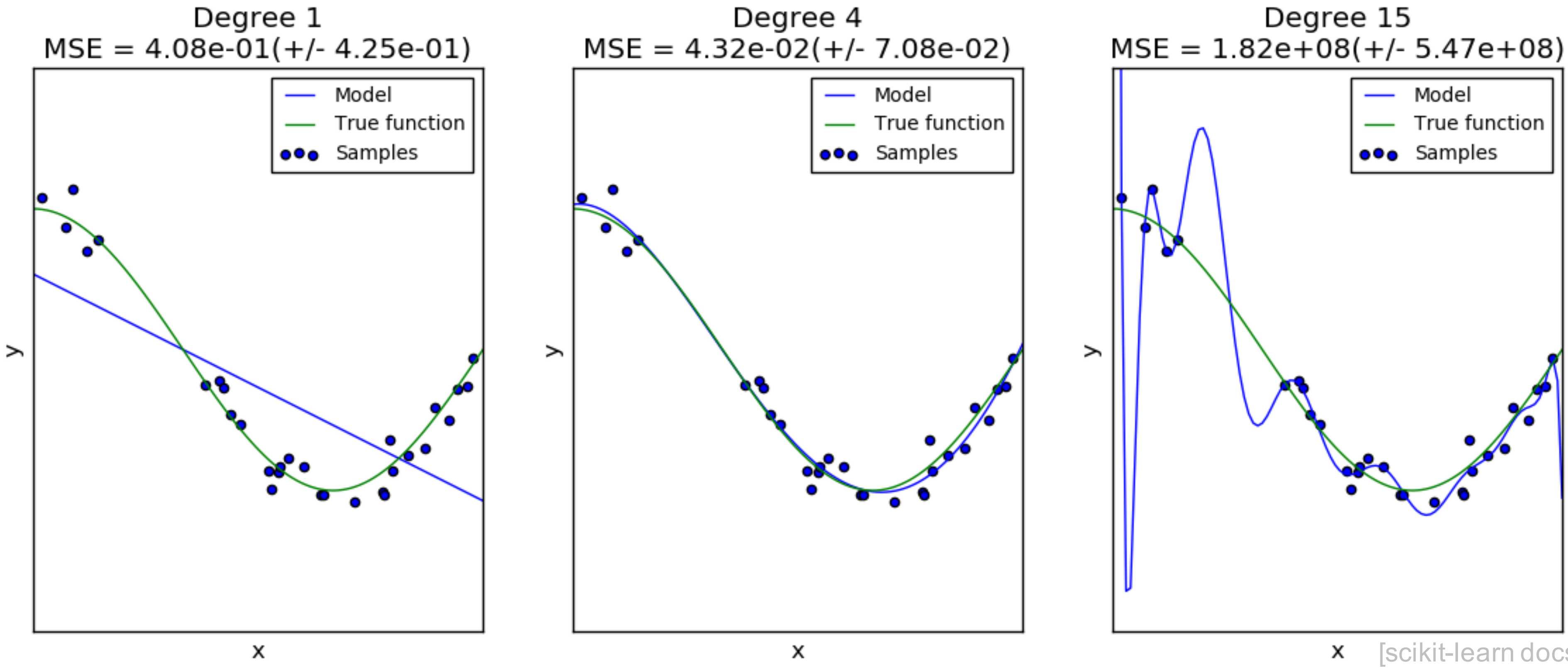
- low bias, high variance:



- good trade-off:



Under- vs. Overfitting



[scikit-learn docs]

How to improve generalization performance?

- underfitting: more training or increase model *capacity*
- overfitting: less training or decrease model *capacity*

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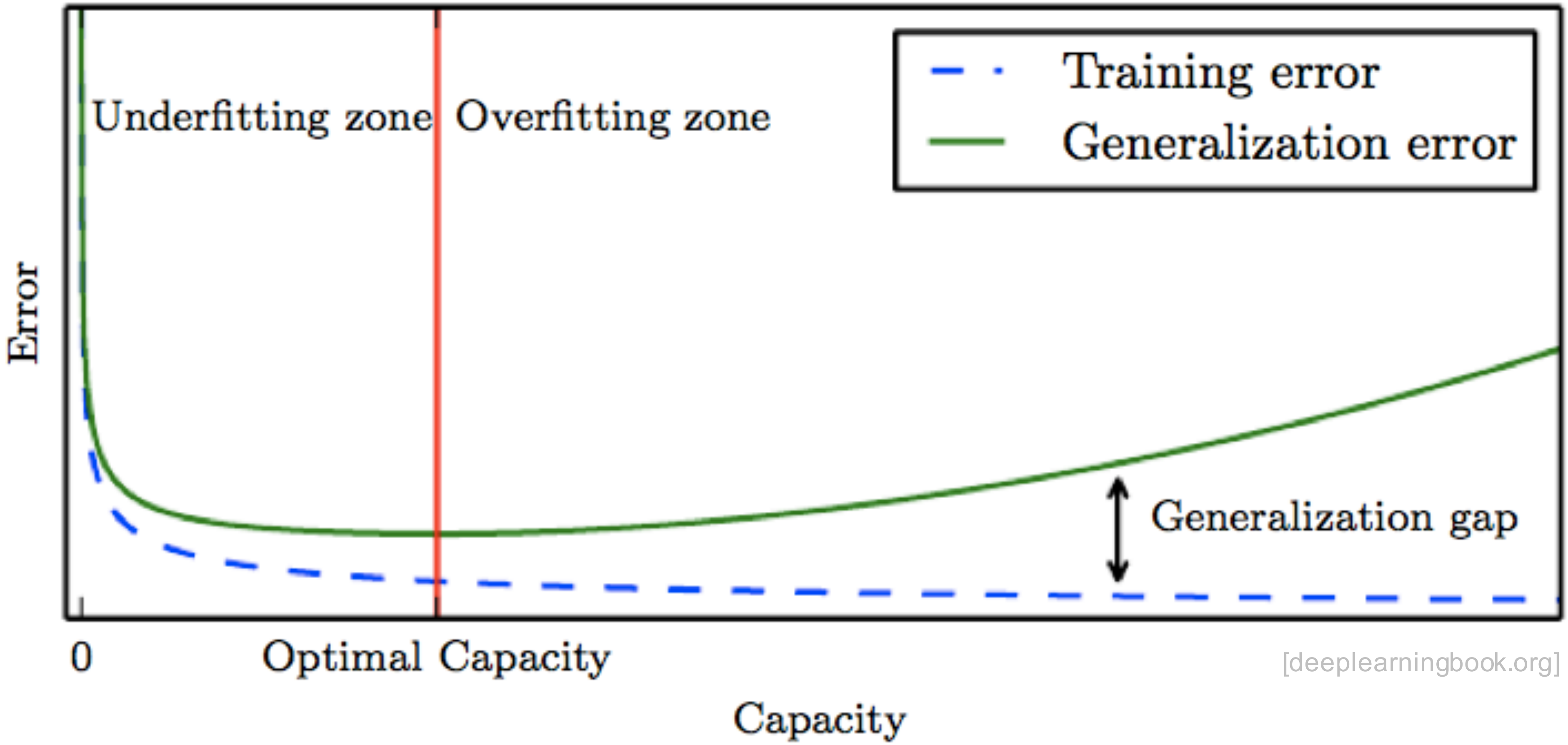
Model Capacity



[deeplearningbook.org]

- decide when to stop based on validation set

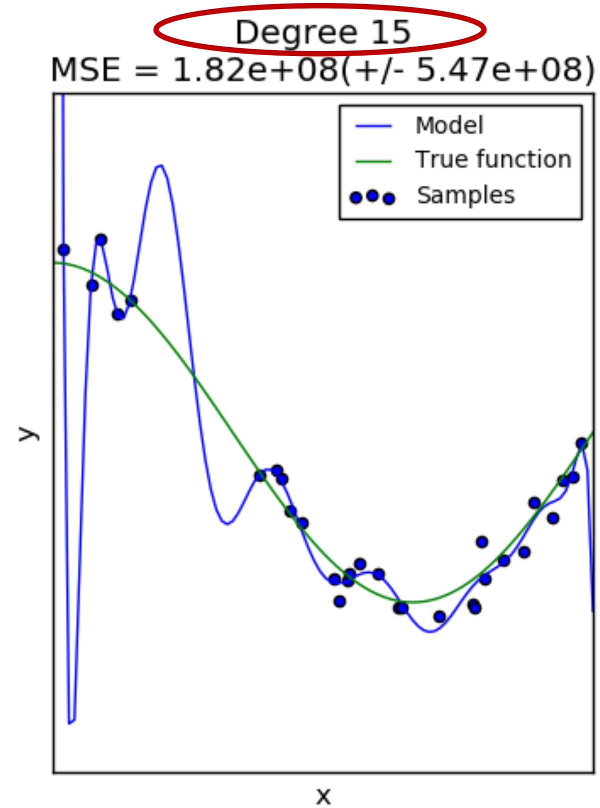
Model Capacity

- intuitive definition: model's ability to fit
- statistical learning theory: VC dimension

- optimal performance when model capacity appropriate for task complexity
  – higher-capacity models can solve harder tasks but are more prone to overfitting
- effective capacity may be reduced by limits of the learning algorithm => in deep learning

Hyper-Parameters

- set before training starts
- typical roles:
  - determine (representational) model capacity, including regularization params
  - control training algorithm (effective capacity)
- important: Never use the test set to tune hyper-parameters!

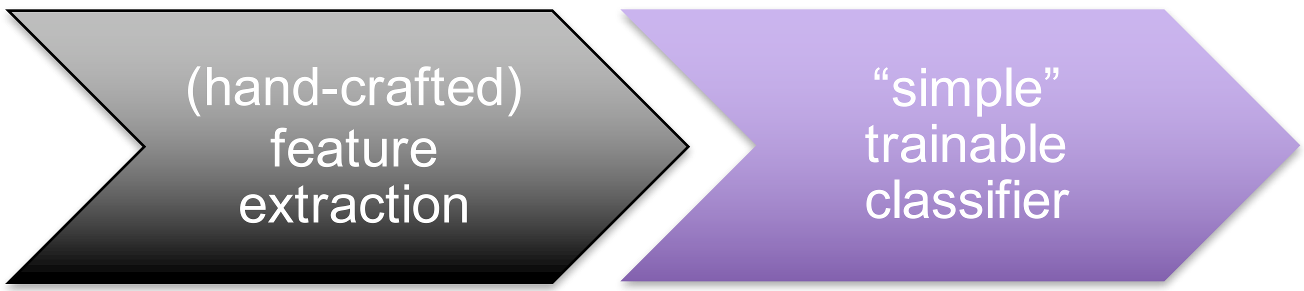


From Machine Learning to Deep Learning

Typical Machine Learning Workflow (for Classification)

make use of domain knowledge from experts

data



predicted labels

train with labeled data (supervised)

Typical Deep Learning Workflow (for Classification)

make use of abundant data and (GPU) compute power

data

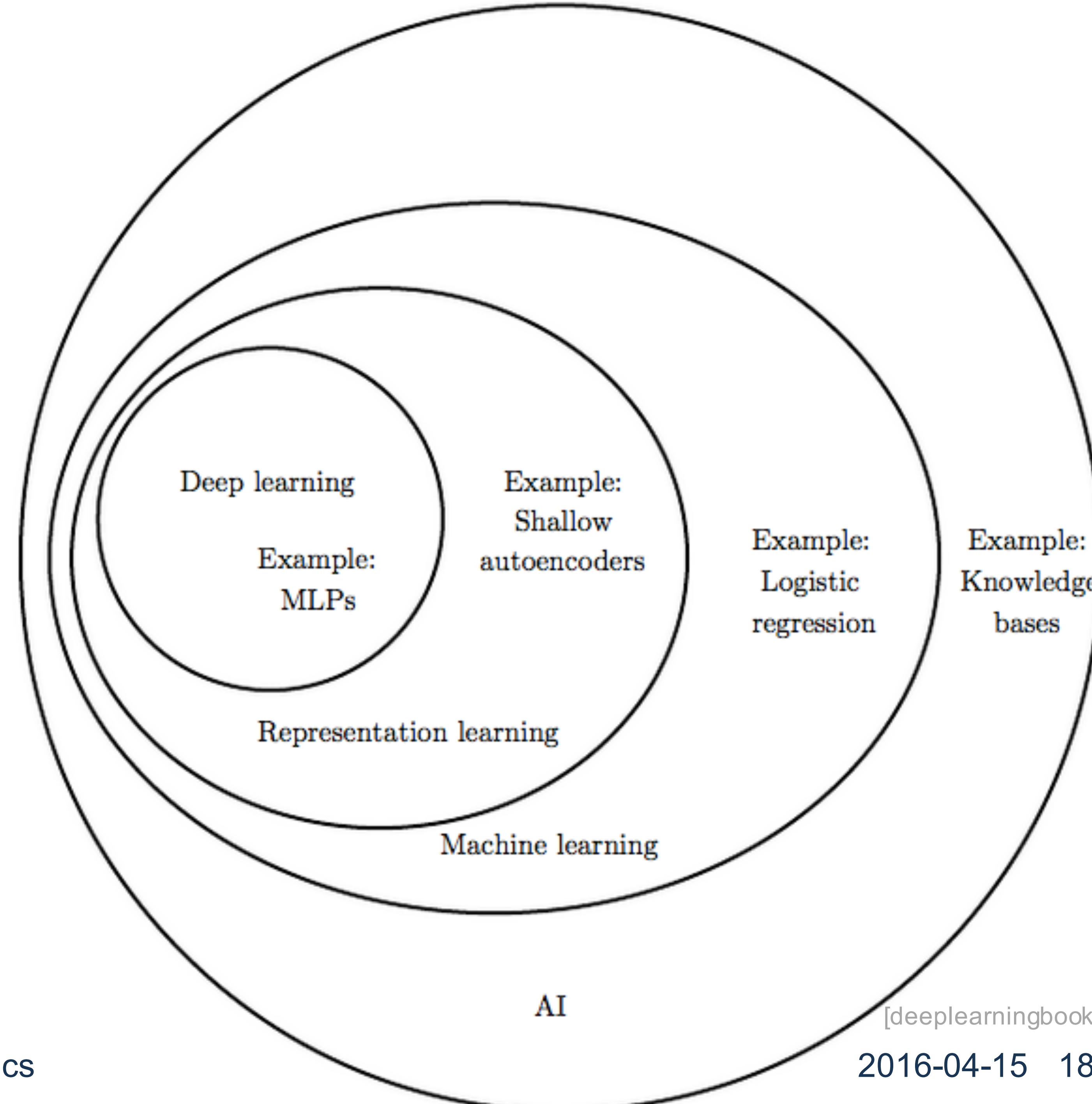
trainable feature transform(s)

trainable classifier

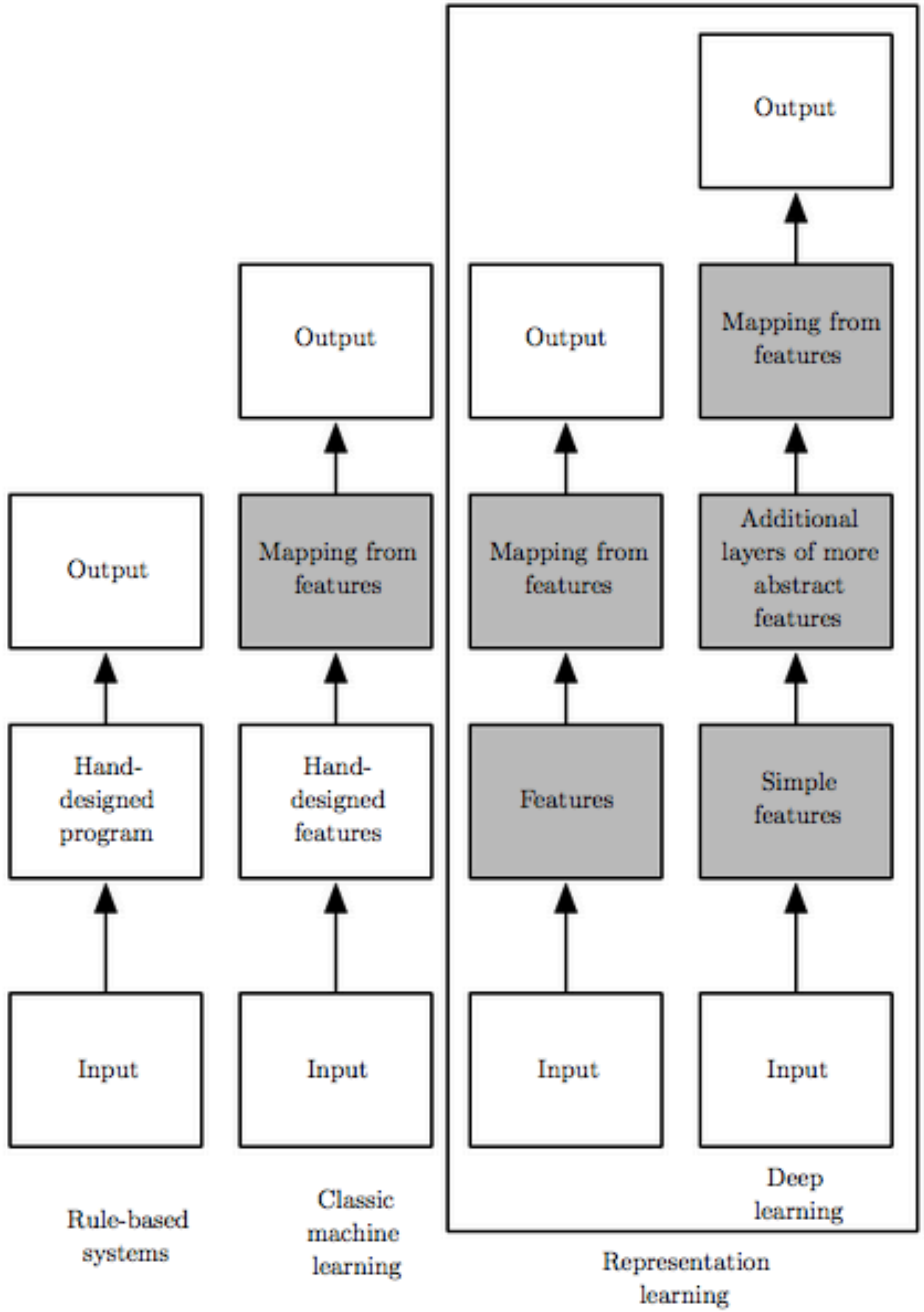
predicted labels

“pre-train” with unlabeled data (unsupervised)

train with labeled data (supervised)



[deeplearningbook.org]



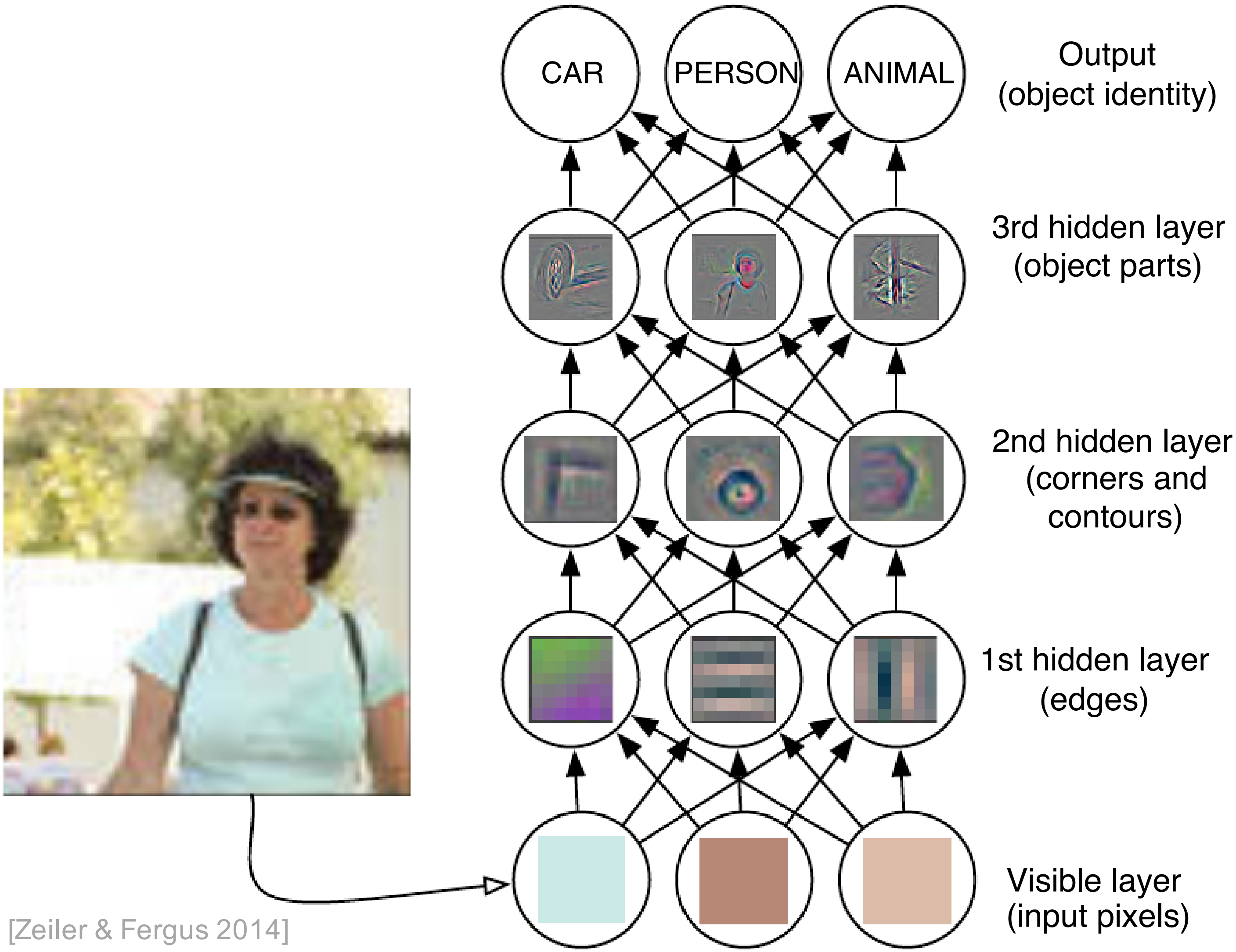
[deeplearningbook.org]

The Promise of Deep Learning

- learn suitable feature representations along with the actual learning task

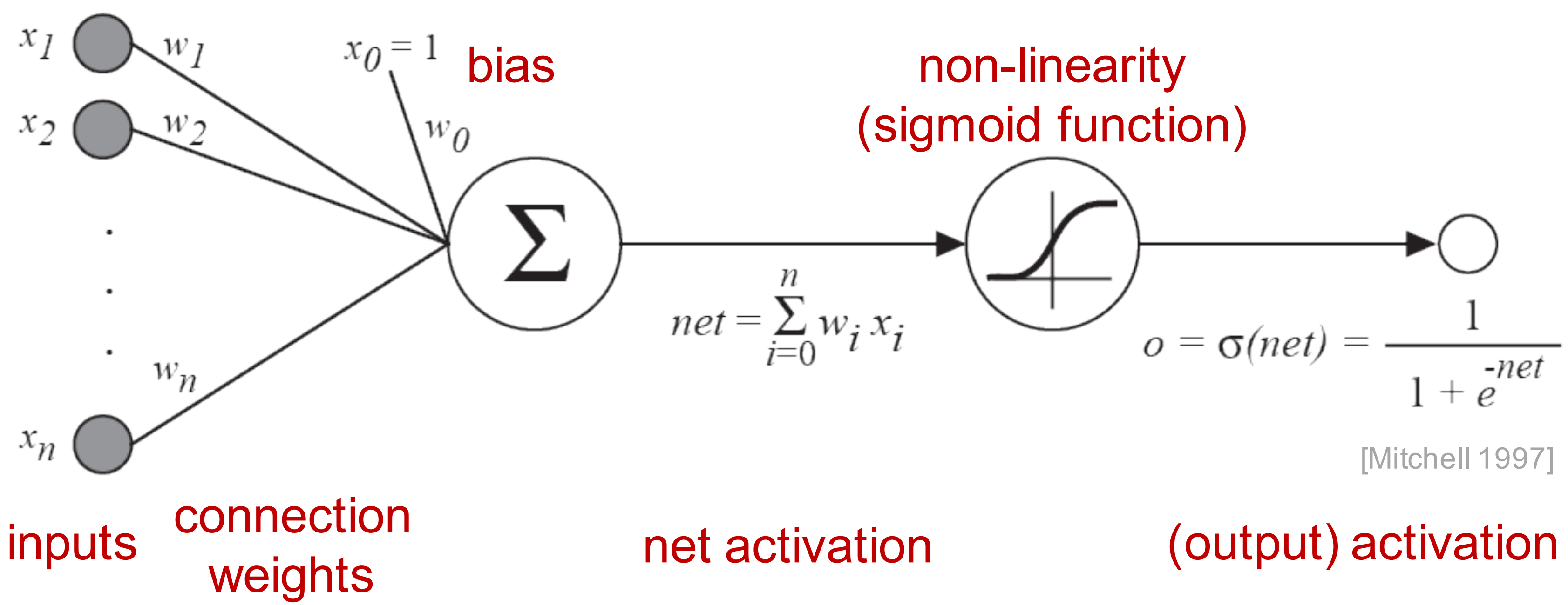
- using a general-purpose learning procedure

An Example Deep Net

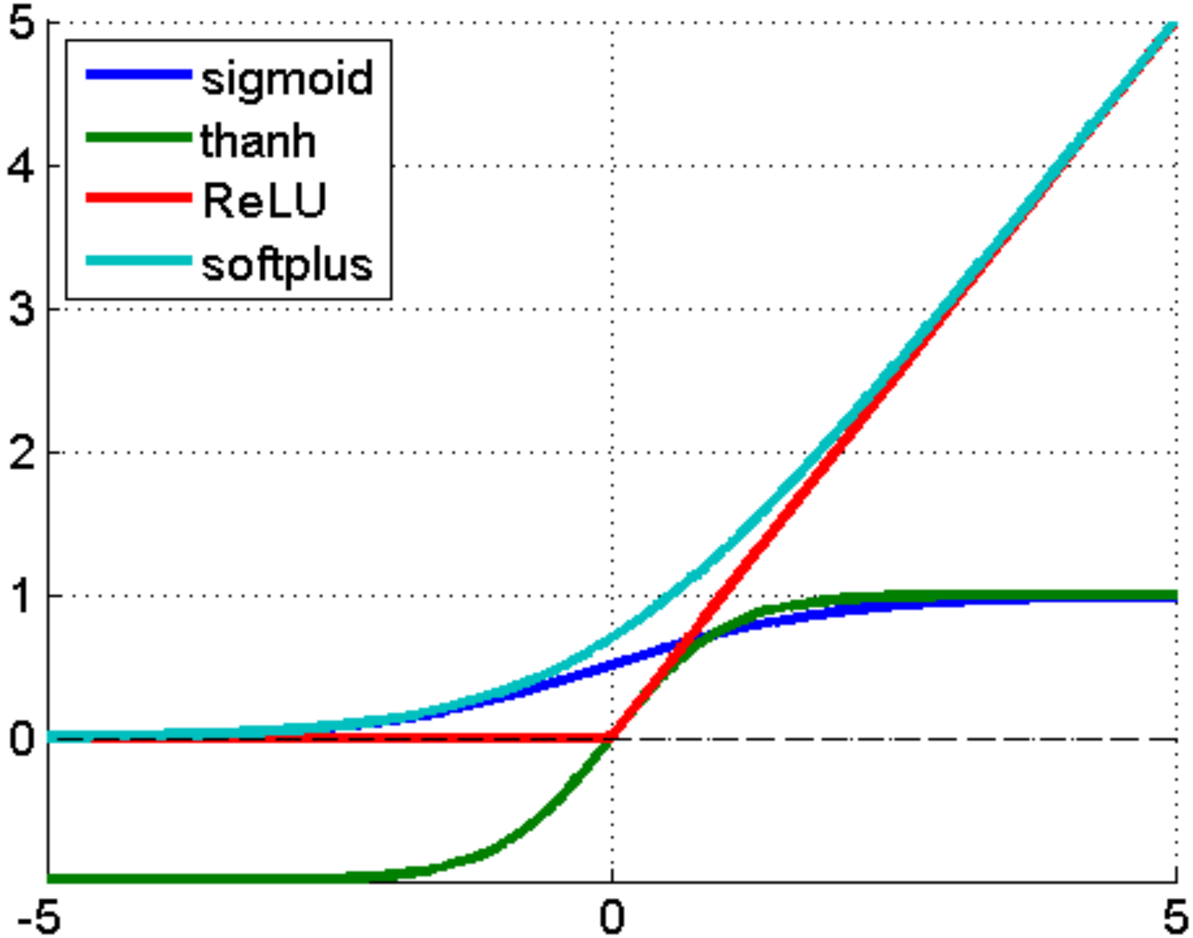


[Zeiler & Fergus 2014]

Neuron (Sigmoid Unit)

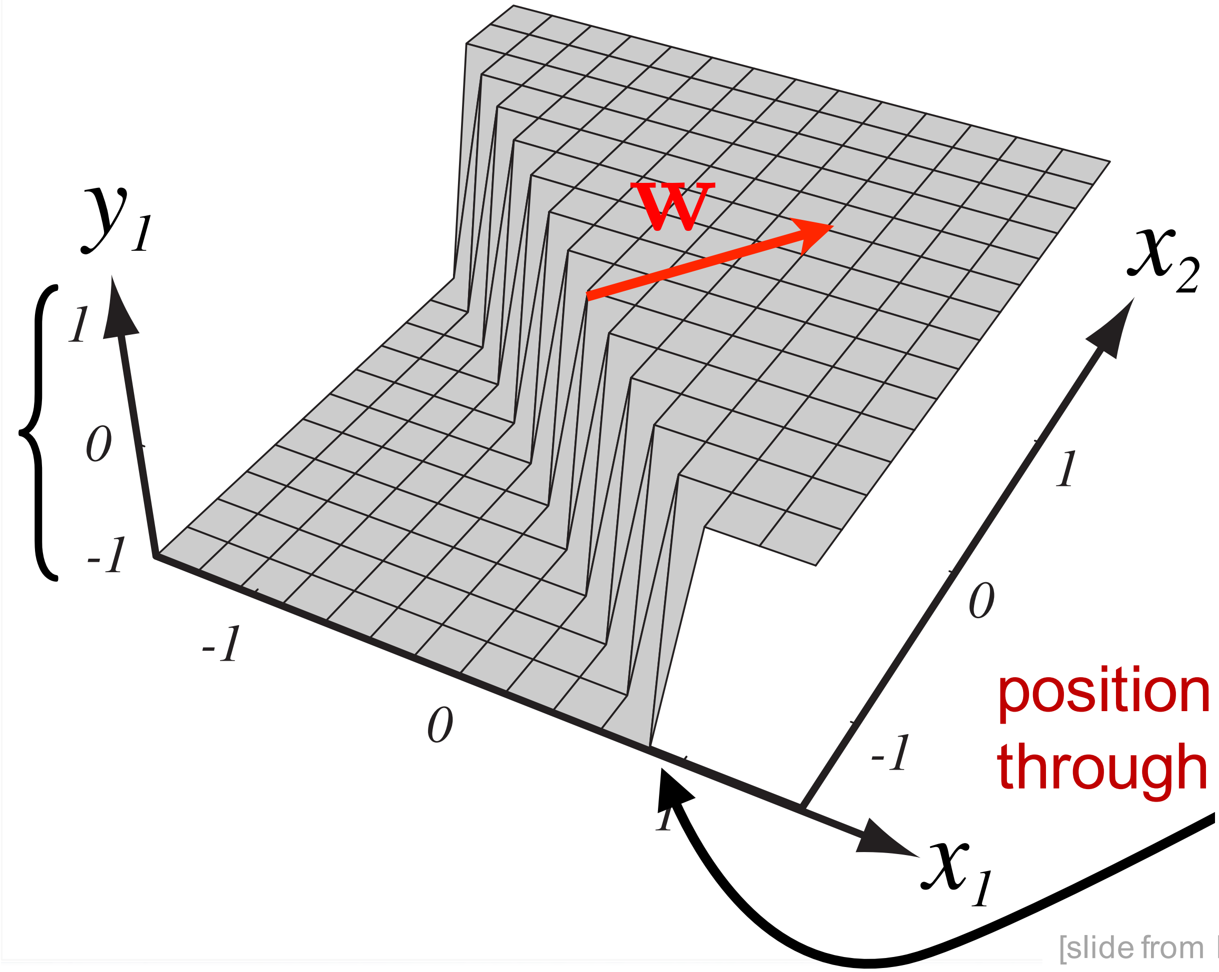


Common Activation Functions



Single Neuron Capacity

range depends on act()



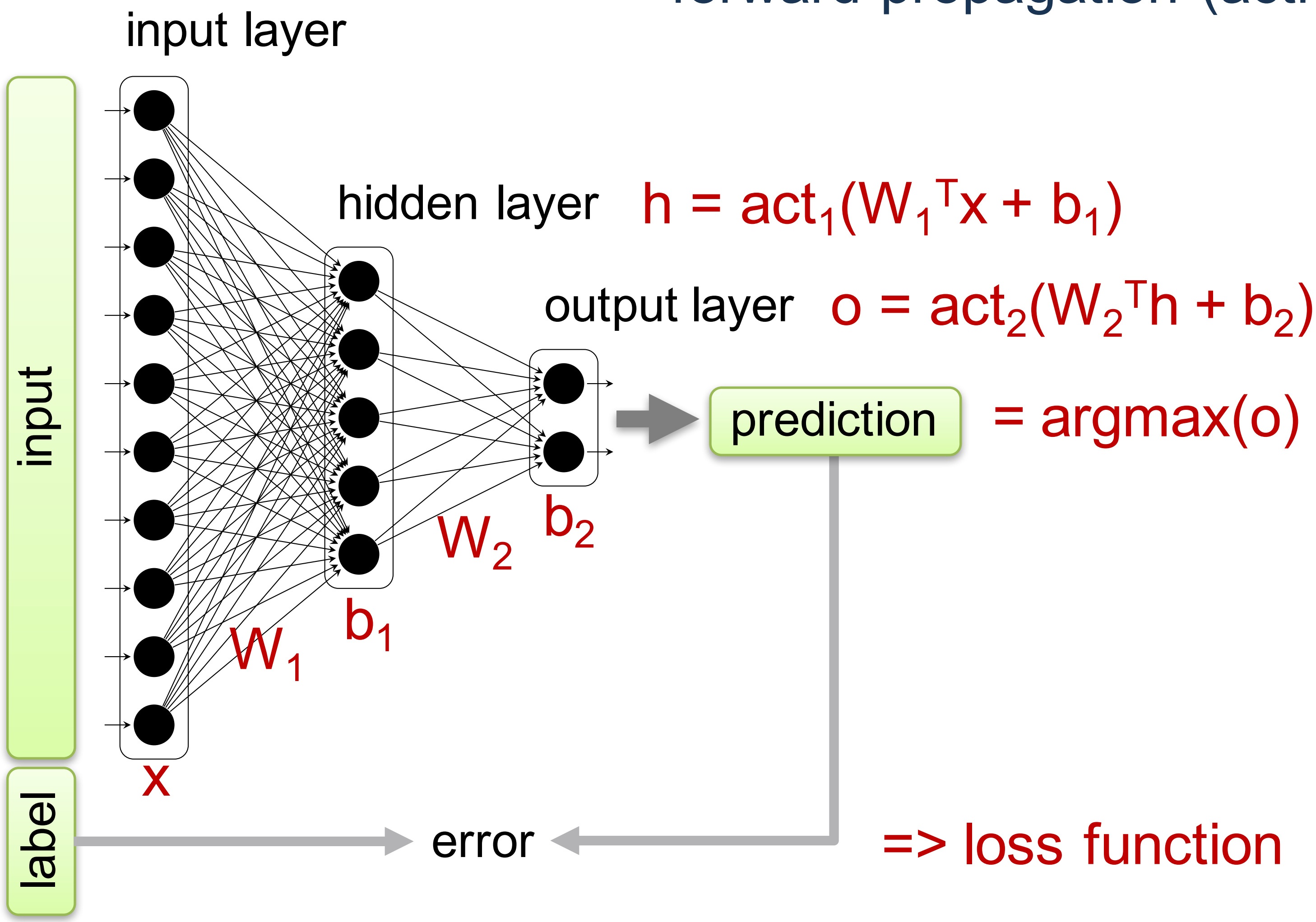
position controlled through bias b

[slide from Hugo Larochelle]

=> linearly separable problems

Multi-Layer Perceptron

forward propagation (activations)



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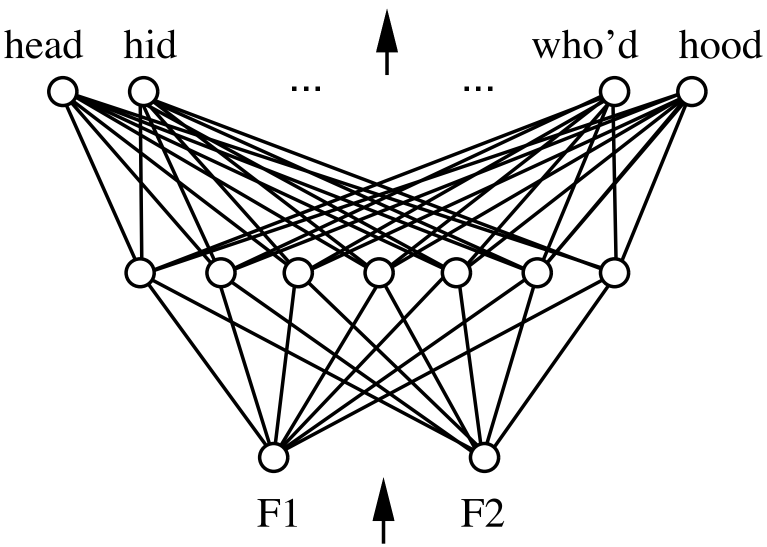
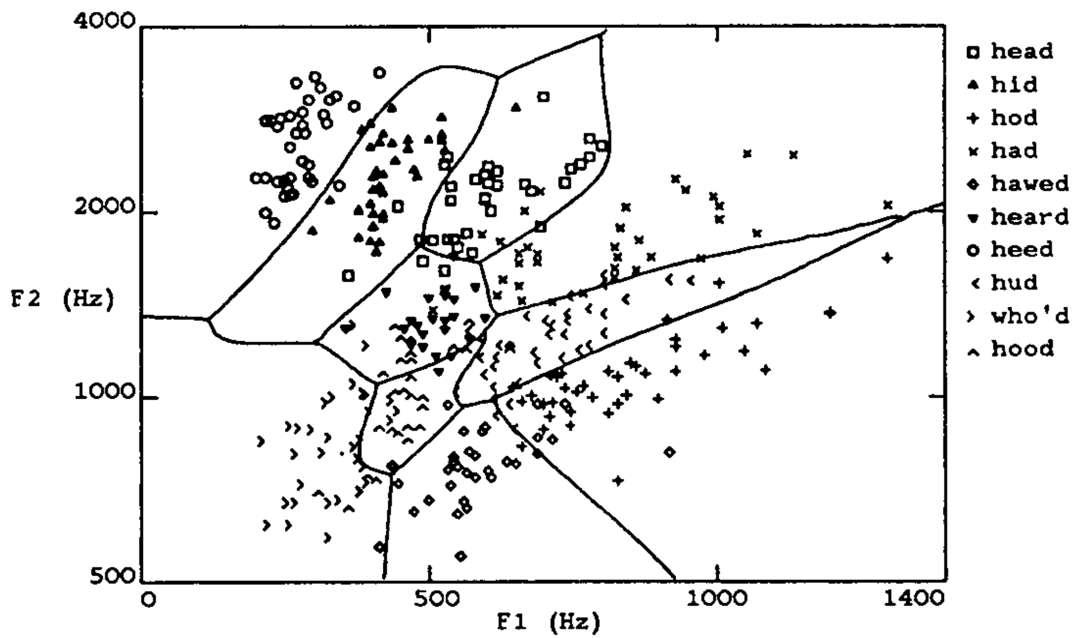
MLP Capacity





[Mitchell 1997]

- with enough hidden units
  => arbitrarily complex but smooth functions
- but: may become infeasibly large! => go deeper!

Softmax (Output) Layer

"softargmax"

- used for multi-class classification
  - 1 output neuron per class
  - (optional) linear transform: $z = W^T x + b$
  - interpret z as unnormalized conditional log probabilities given input x, i.e. $z_i = \log P'(y=i \mid x)$

$$\text{softmax}(\boldsymbol{z})_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

normalization (sum = 1)

  - predict class with highest probability (winner-take-all principle)

Quiz

- How could a real *softmax* be obtained? (I.e. a soft version of the *max* function)

Cost Function

- goal: maximize log likelihood of target class i
  i.e. maximize log(P(y=i | z)) = softmax(z)$_i$

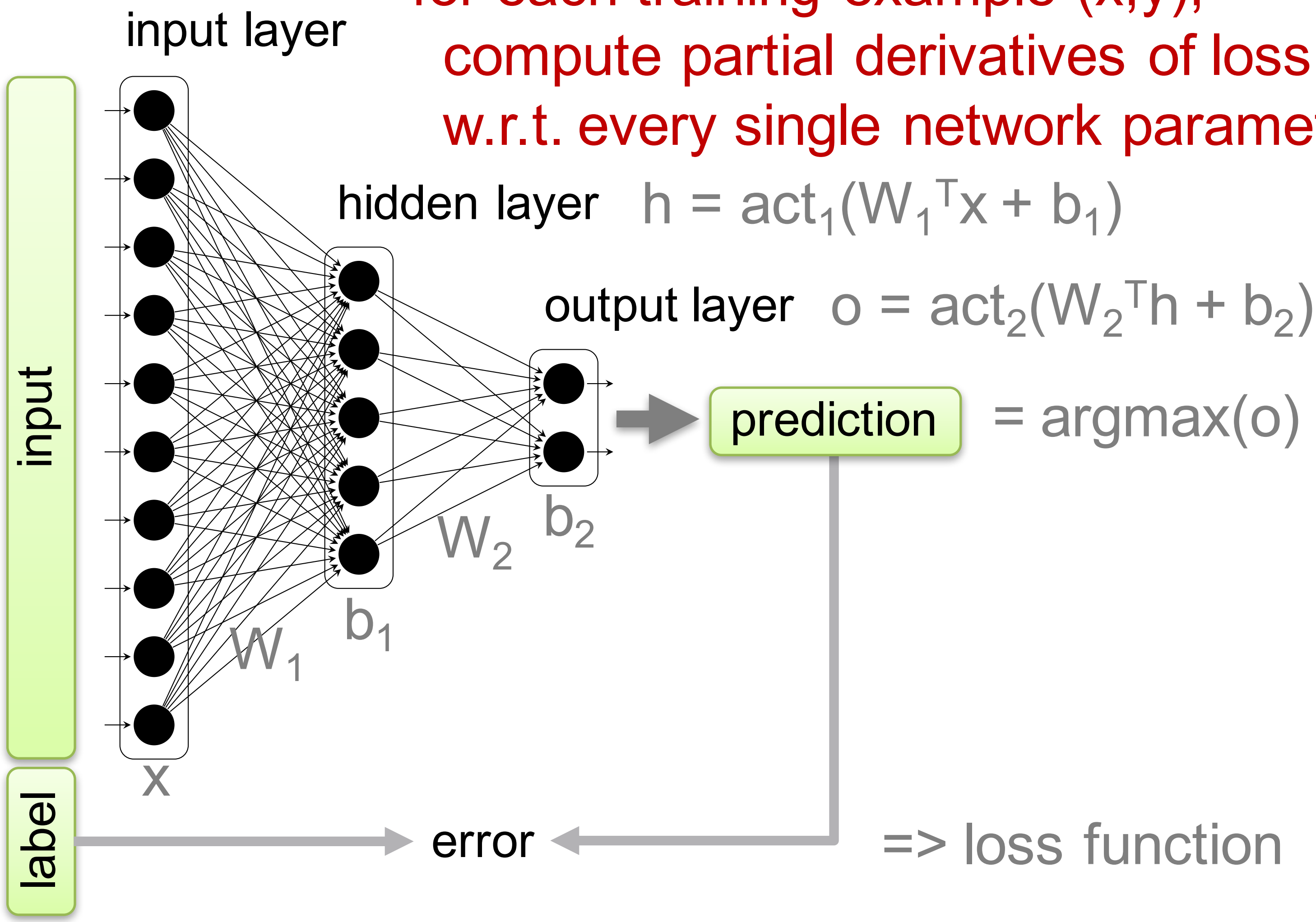
$$\log \operatorname{softmax}(\boldsymbol{z})_i = z_i - \log \sum_j \exp(z_j)$$

- convert into a loss function:
  minimize **negative log likelihood (NLL)**

(also referred to as ”Cross Entropy”)

Error Backpropagation

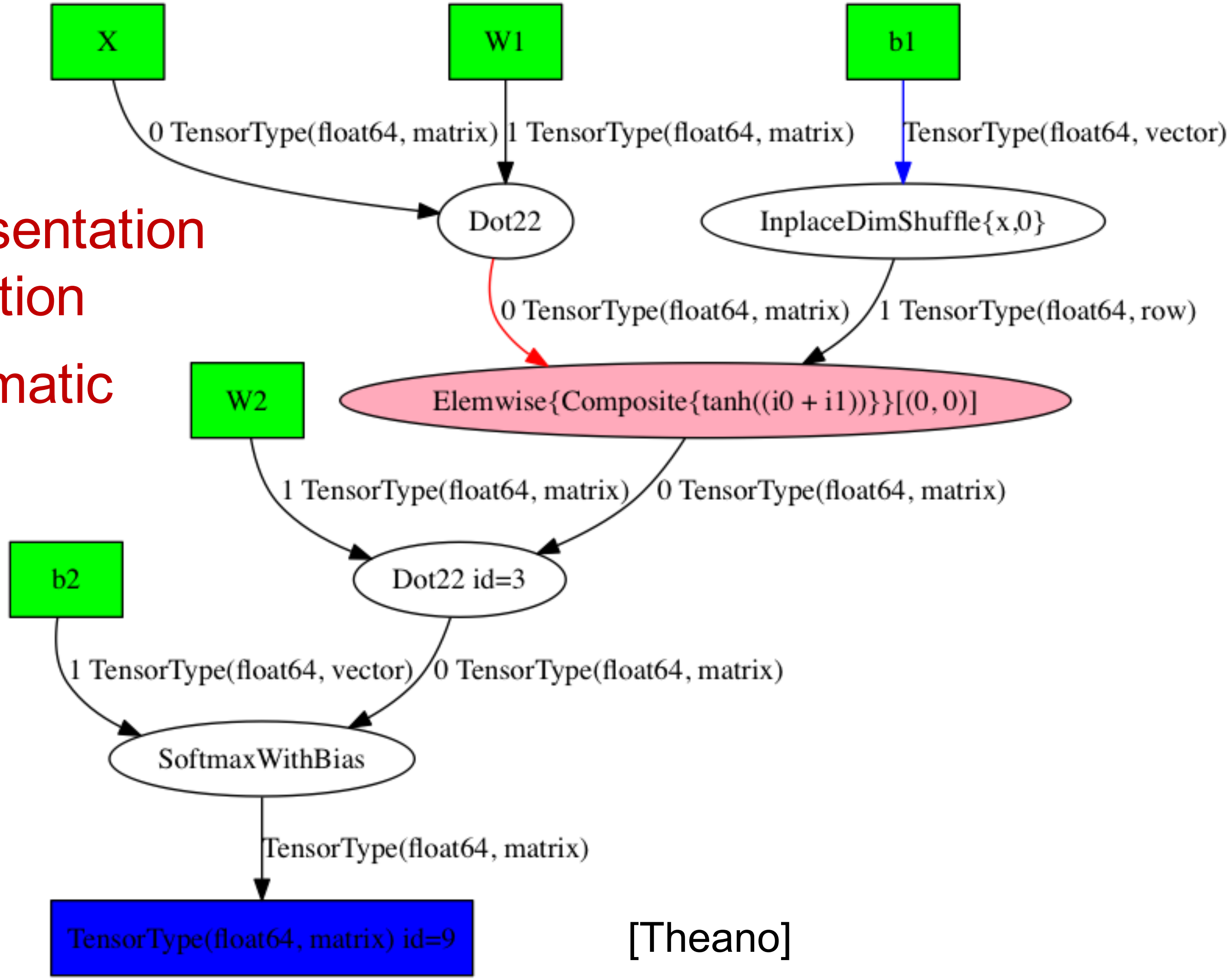
for each training example (x,y),
compute partial derivatives of loss function
w.r.t. every single network parameter (W,b)



Computation Graph

symbolic representation of the loss function

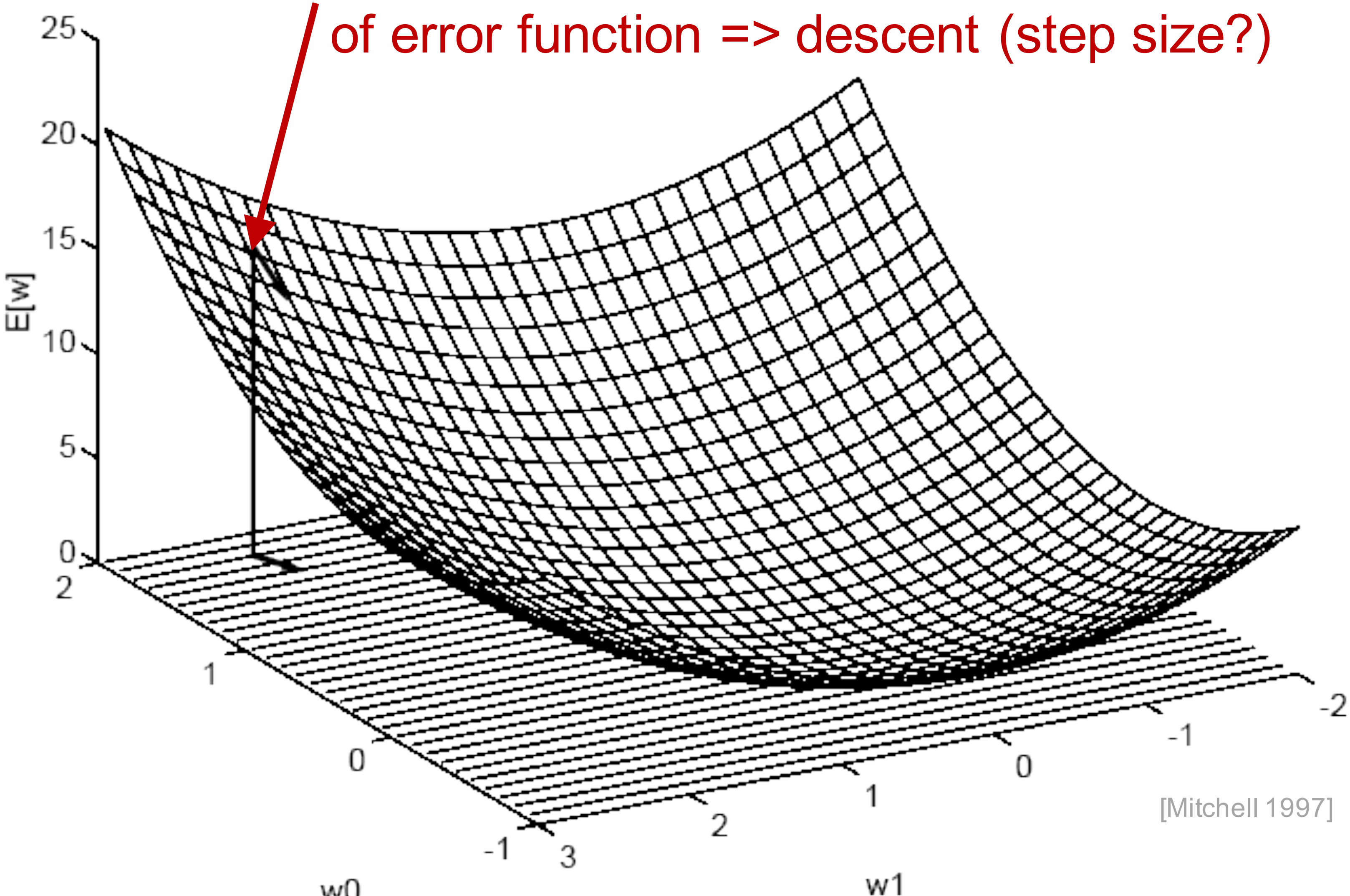
=> allows automatic differentiation



[Theano]

Gradient Descent

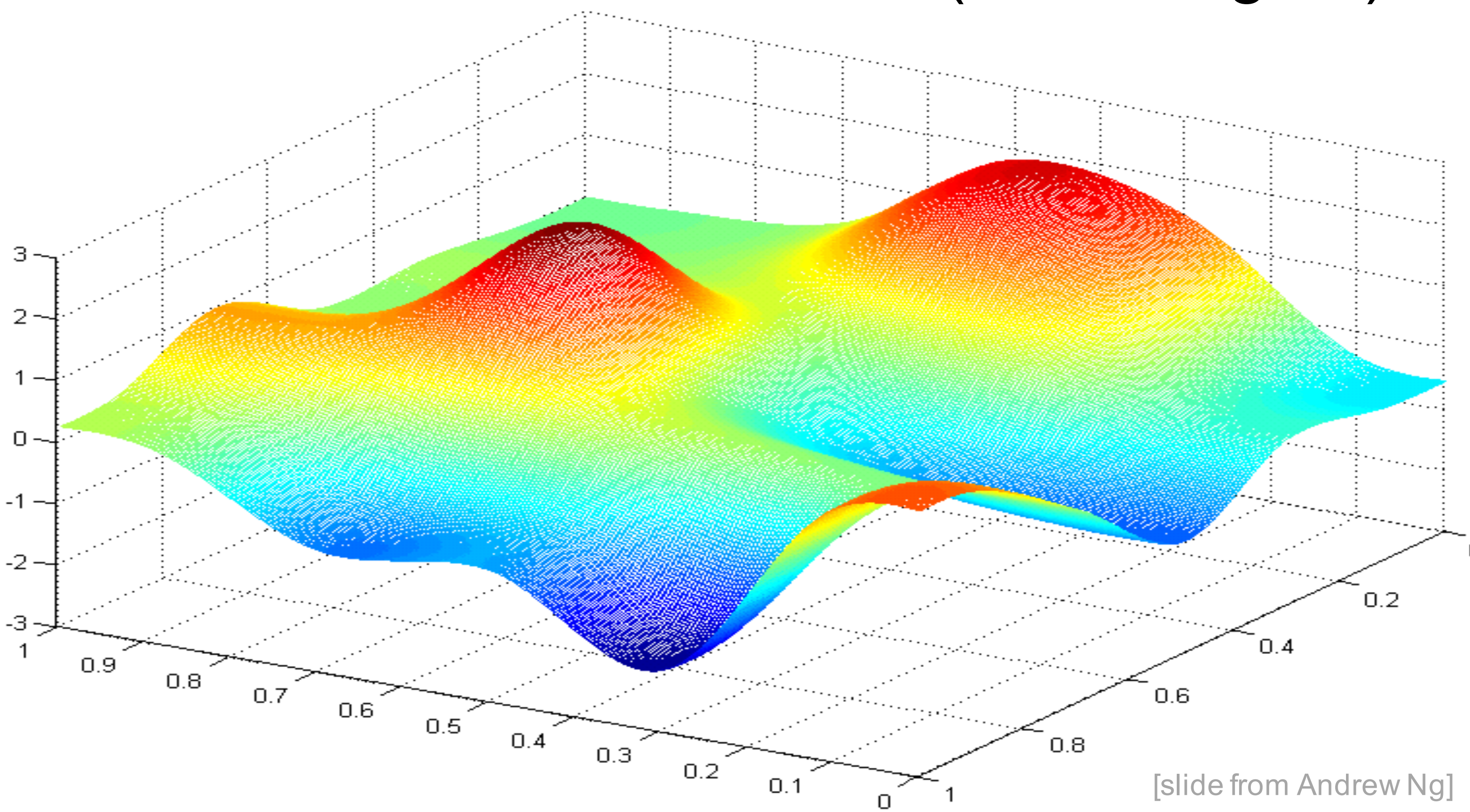
gradient at <u>one point</u> (current parameters) of error function => descent (step size?)



[Mitchell 1997]

Gradient Descent

a more realistic error function (for 2 weights)



[slide from Andrew Ng]

=> can get stuck in local minima!

Gradient Descent

- for all training examples (batch training)
  - can take very long
  - possible aggregation effects
- for each training example (online training)
  - less chance of getting stuck in local minima
  - can be very “jumpy”
- good trade-off: minibatch training

Deep Net Training Building Blocks

Datasets

- features (network inputs)
  - topology (flat, structured, …)
  - variable length?

- targets (desired network outputs)
  - encoding (one-hot, plain labels, structured, …)

- optional meta-data

Datasets (2)

- partitioning
  - training set : train model
  - validation set : choose hyper-parameters
  - test set : estimate generalization performance
- normalization
- storage
  - in memory (on GPU?), DB
  - generated on-the-fly

Model Structure

- hidden layer types and dimensions
  - e.g. fully connected, convolutional, recurrent
- biases?
- activation functions
- output layer (e.g. softmax, linear, …)

Model Initialization

- general rule of thumb:
  - start with linear model behavior
- constant, identity
- random (uniform, Gaussian, …)
- sparse
- orthogonal
- pre-trained
- model domain knowledge

Why is simply setting everything to 0 a bad idea?

Cost Function

also: objective or loss function

- measures model quality
  - How much has it improved / learned?
  - How well does it generalize?

- very common choices:
  - cross entropy (supervised training)
  - reconstruction error (unsupervised training)

Regularization

- early stopping
- weight regularization / “weight decay”
  - L1 = penalize non-zero values
  - L2 = penalize extreme weights
- sparse activation
- Dropout = randomly set activations to zero
  - separate effects from correlated features
- DropConnect = randomly set weights to zero

Training Algorithm

- (full) batch gradient descent
  - update after seeing all examples (= 1 epoch)
- stochastic gradient descent (SGD)
  - update after each example
- minibatch SGD
  - update after each batch of examples
- second-order methods
  - Hessian-free optimization

Learning Rule

- scale
- Momentum
- AdaDelta
- AdaGrad
- RMSProp
- Adam

Termination Criterion

- fixed number of epochs
- fixed maximum runtime
- monitoring-based
  – weights change below threshold
  – training error
  – early stopping (validation error)

- combinations

Training Extensions

- monitoring
  - errors
  - gradients
  - weights
- plotting
- parameter adjustments
- save model
  - keep track of best model so far