# EE482/682: DSP APPLICATIONS

## OVERVIEW OF ML AND NEURAL NETWORKS

Géron Chapter 1 + 10

# OUTLINE

- Géron Chapter 1 – Machine Learning (ML) Landscape
  - What is ML
  - Why use ML
  - Types of ML systems
  - Challenges
- Géron Chapter 10 – Intro Artificial Neural Networks (ANNs)
  - Biological inspiration
  - Perceptron
  - Multilayer perceptron (MLP)

# WHAT IS ML?

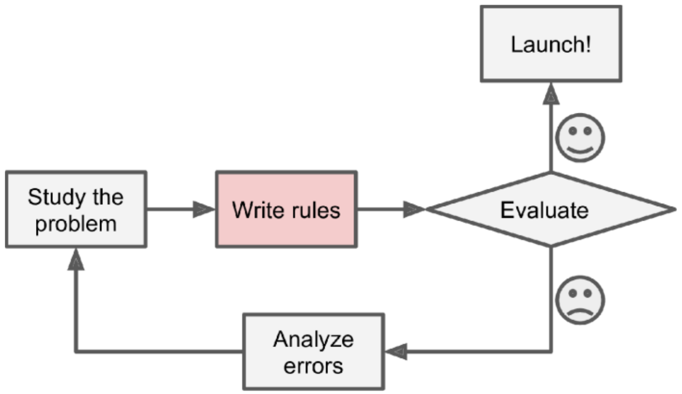
- [Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed. – Arthur Samuel, 1959

- A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E. – Tom Mitchell, 1997

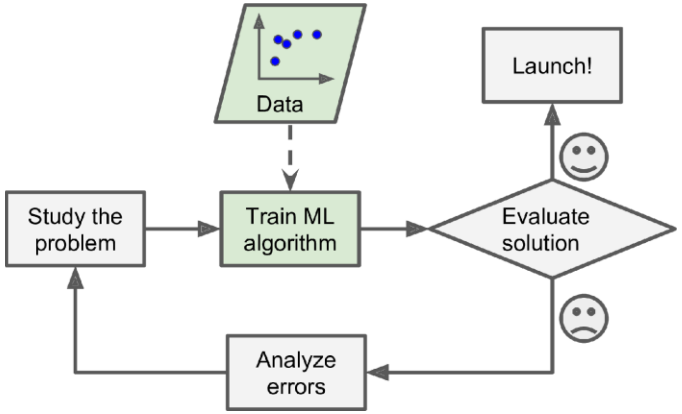
- Machine Learning is the science (and art) of programming computers so they can learn from data
  - Not enough to have lots of data, must be able to use data to solve a task

# WHY USE ML?

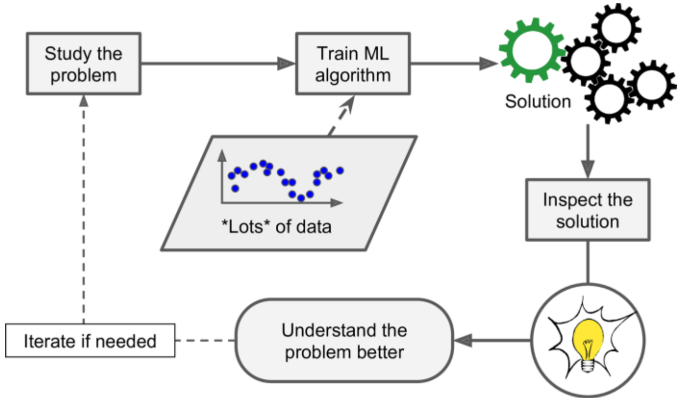
- Traditional approach has complex rules and difficult to maintain



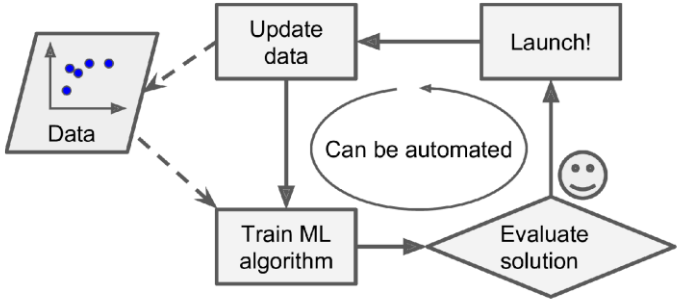

- ML learns from data making code shorter, easier to maintain, and more accurate




- Can inform humans of what was learned for new insight into a problem




- Can automatically be updated to changes



# EXAMPLE APPLICATIONS

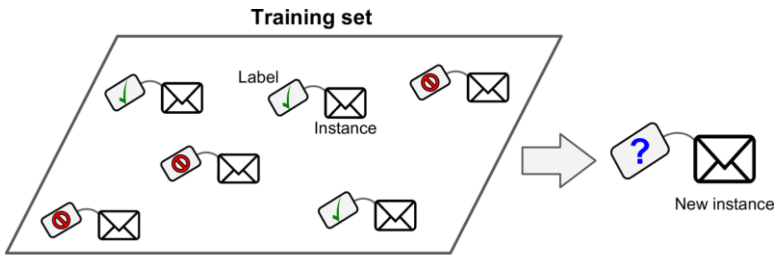
- Analyzing production line images to classify or detecting tumors in brain scans
  - Chapter 14 – convolutional neural networks (CNNs)
- Visual representation of complex, high-dimensional data
  - Chapter 8 – data visualization and data reduction
- Intelligent bot for a game
  - Chapter 18 – reinforcement learning (RL)
- Forecasting future company revenue
  - Chapter 4, 5, 7, 10, 15, 16 – regression using classical (linear/polynomial regression, SVM, Random Forest or deep learning methods)
- News article classification, flagging offensive comments, long document summarization, chatbot creation
  - Chapter 16 – natural language processing (NLP)
- Making an app react to voice commands
  - Chapter 15/16 – recurrent neural networks (RNNs), CNNs, Transformers
- Detecting credit card fraud, segmenting customers for marketing strategy
  - Chapter 9 – anomaly detection, clustering
- Product recommendations based on past purchases
  - Chapter 10 – ANN

# TYPES OF ML SYSTEMS

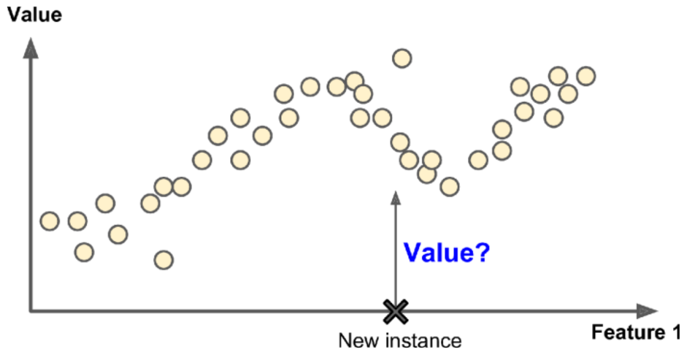
- Broad categories:
  - Training with human supervision (supervised, unsupervised, semi-supervised, and reinforcement learning)
  - Learning incrementally or on the fly (online vs batch learning)
  - Comparison with known data points or by finding patterns in training data to build predictive models (instance-based vs model-based learning)
- Criteria are not exclusive and can be combined

# SUPERVISED LEARNING

- Training with data and labels (desired solutions)
- Typical tasks
  - Classification: determine data class
    - Spam filter: data=emails, label={spam, not-spam}



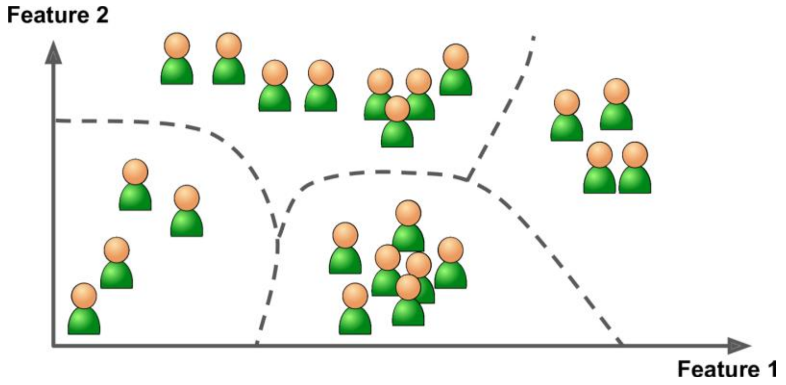

  - Regression: predict target numeric value
    - Price of car: data=features (mileage, age, brand, etc.) label=price

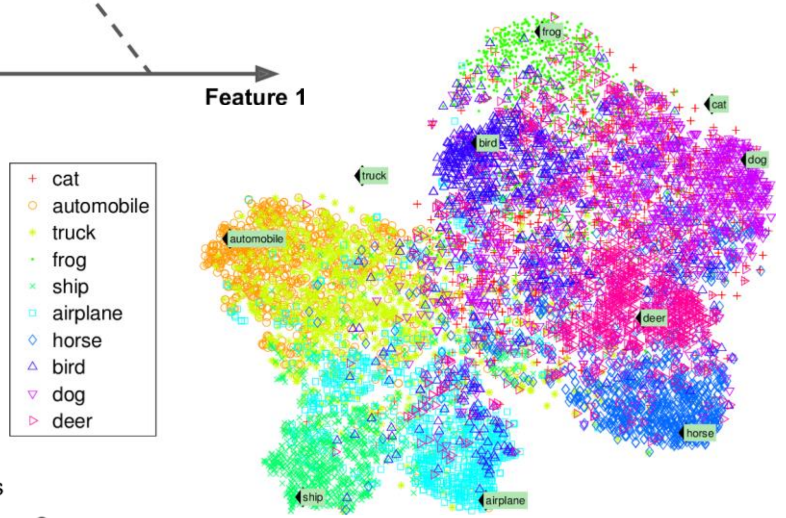


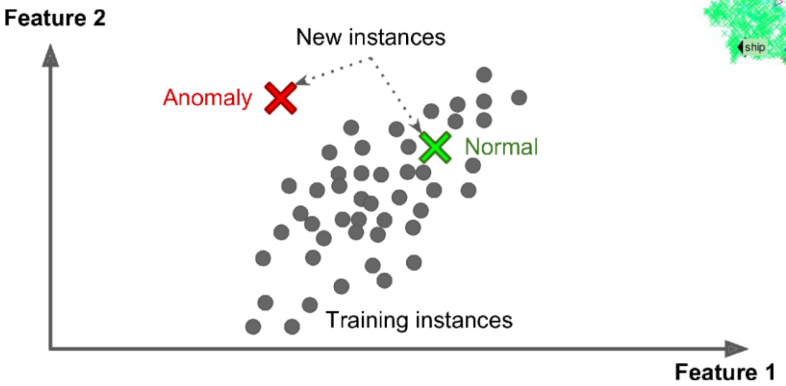

- Important algorithms
  - k-NN, linear and logistic regression, SVM, decision trees and random forests, neural networks

# UNSUPERVISED LEARNING

- Training with unlabeled data (no teacher)
- Important algorithms
  - Clustering – discovering groups
    - K-means, DBSCAN
  - Visualization and dimensionality reduction – reduce feature dimension and maintain structure
    - (Kernel) principle component analysis (PCA), LLE, t-SNE
  - Anomaly/novelty detection – find unusual test data
    - One-class SVM, isolation forest
  - Association rule learning – find relations between features
    - Apriori, Eclat

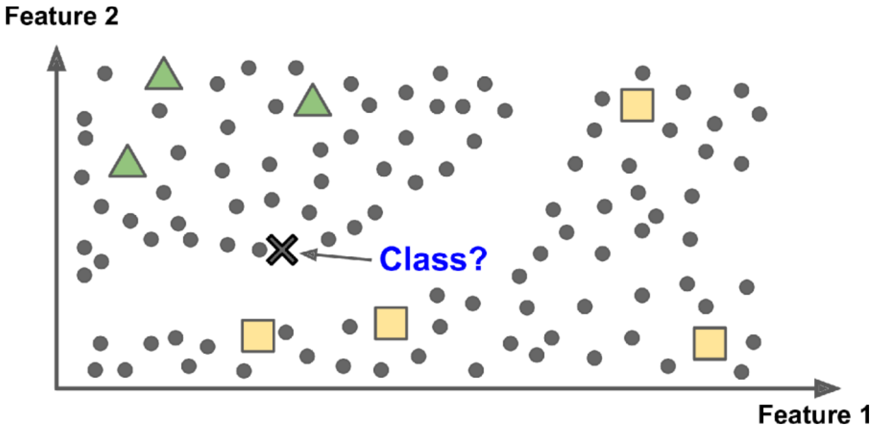


# SEMI-SUPERVISED LEARNING

- Training with partially labeled data
  - Lots of unlabeled and few labeled instances

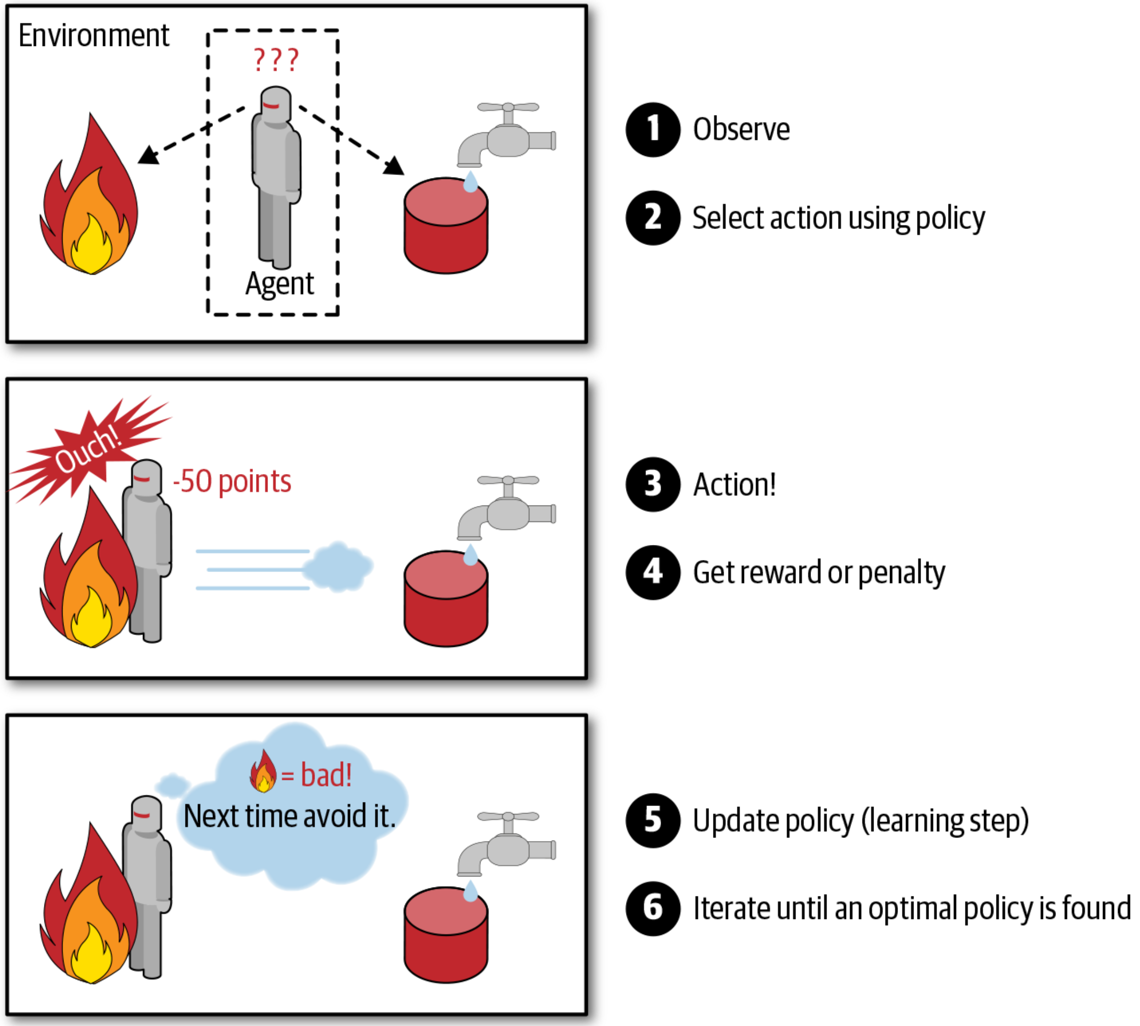



- Most are combination of unsupervised and supervised algorithms
  - Deep belief networks (DBNs) are based on stacked unsupervised restricted Boltzmann machines (RBMs) that are fine-tuned using supervised learning techniques

- Example: Google Photos
  - Given large personal photo library
  - Automatically cluster photos into groups of people
  - Supervision when specify name of group
    - Need to merge and split groups to fine-tune

# REINFORCEMENT LEARNING

- Agent-based learning paradigm
  - Agent – learning system that can observe environment, select and perform actions, and get rewards
  - Rewards/penalties – "value" associated with actions
  - Policy – strategy, action to choose which is learned to maximize reward over time
- Popular for robotics and game playing
  - E.g. DeepMind's [Q-Learning Atari Breakout]() or [AlphaGo]()

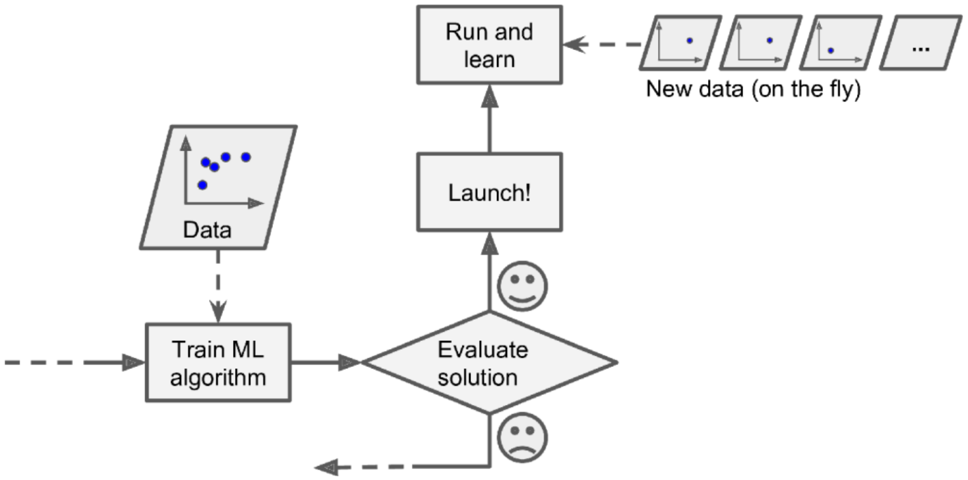


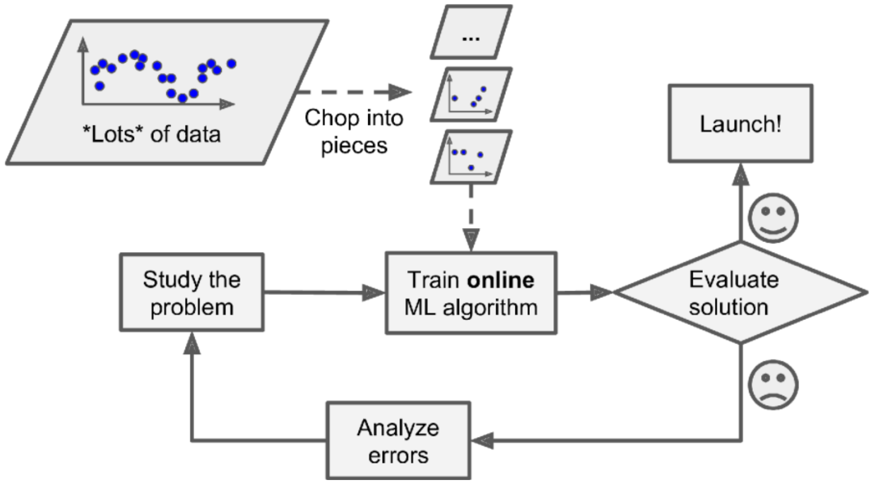
# BATCH LEARNING

- Learning uses all available data
- Offline learning – train then launched into production with no more training
  - Often because of heavy time and resource requirements
- Can update model fairly easily by incorporating new data (say every 24 hours)
- Does not work in many situations
  - Rapidly changing data – need to adapt more quickly
  - Big data and computational restrictions – too costly to train, too large to batch, or not enough resources (mobile phone or Mars rover)

# ONLINE LEARNING

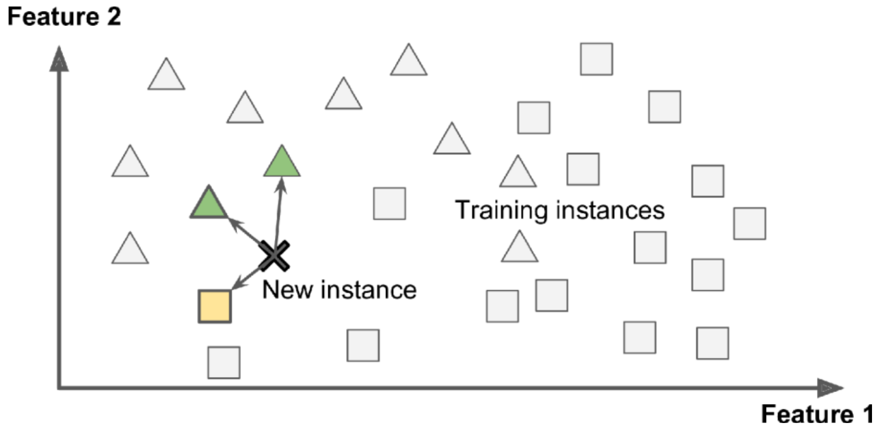
- Incremental training by feeding data instances sequentially
  - Use of mini-batch – small groupings of data
- Well-suited for streaming data or limited computing resources
  - Can react/adapt quickly to changes autonomously
  - Can discard samples after incorporating into model
  - Out-of-core learning for large datasets that do not fit in memory
- Learning-rate – how fast to adapt to changing data
  - High: quickly adapt, but forget old
  - Low: less sensitive to noise/outliers but slower to update (inertia)
- Major challenge: graceful degradation over time
  - How to handle bad data that comes in?



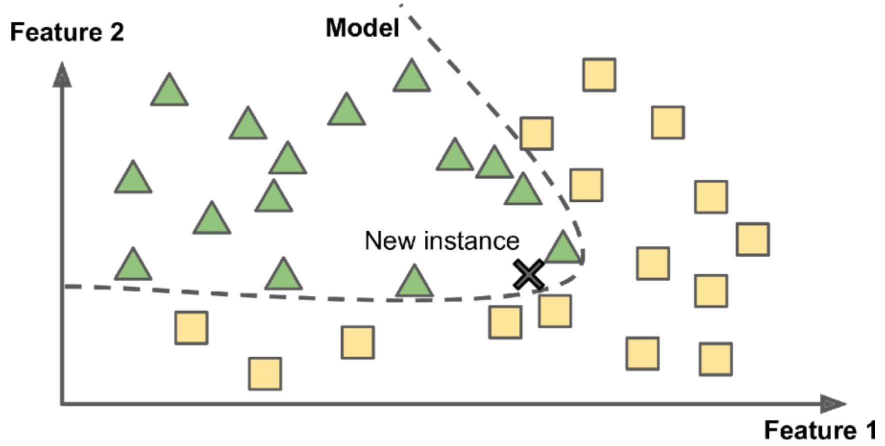
# INSTANCE-BASED LEARNING

- System learns examples by-heart, then generalizes to new cases using a similarity measure
  - Simple learning method (e.g k-NN)
  - Needs to store instances (database)
  - Define meaningful similarity measure



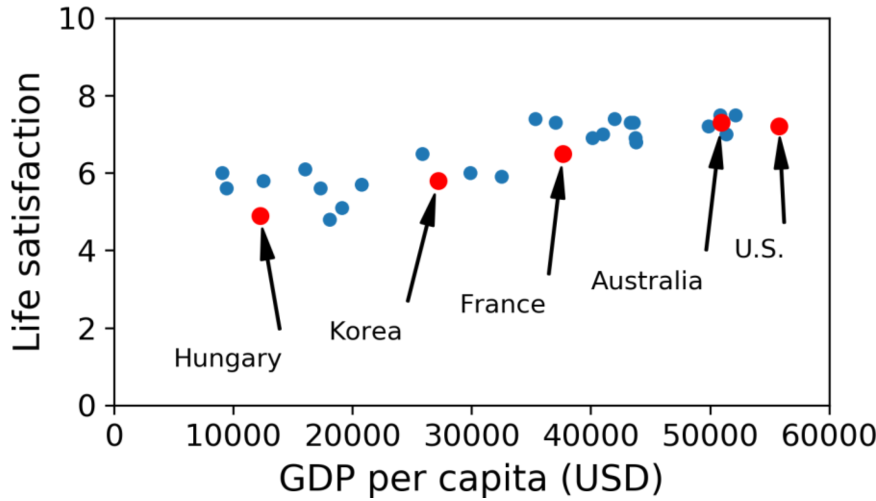
# MODEL-BASED LEARNING

- Build model of examples and use model to make predictions

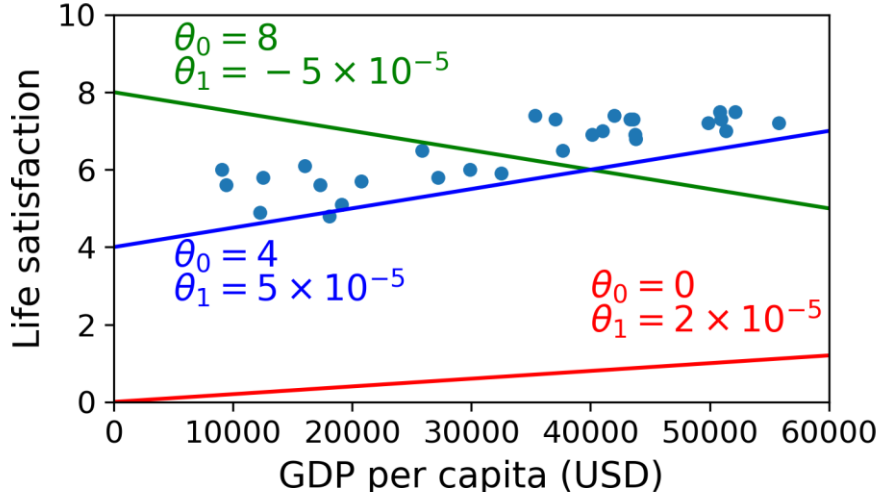



- Need to choose a "model"
- Tune parameters for good fit
  - Define utility/fitness function for goodness or cost function for badness of fit

- Data




- Linear model

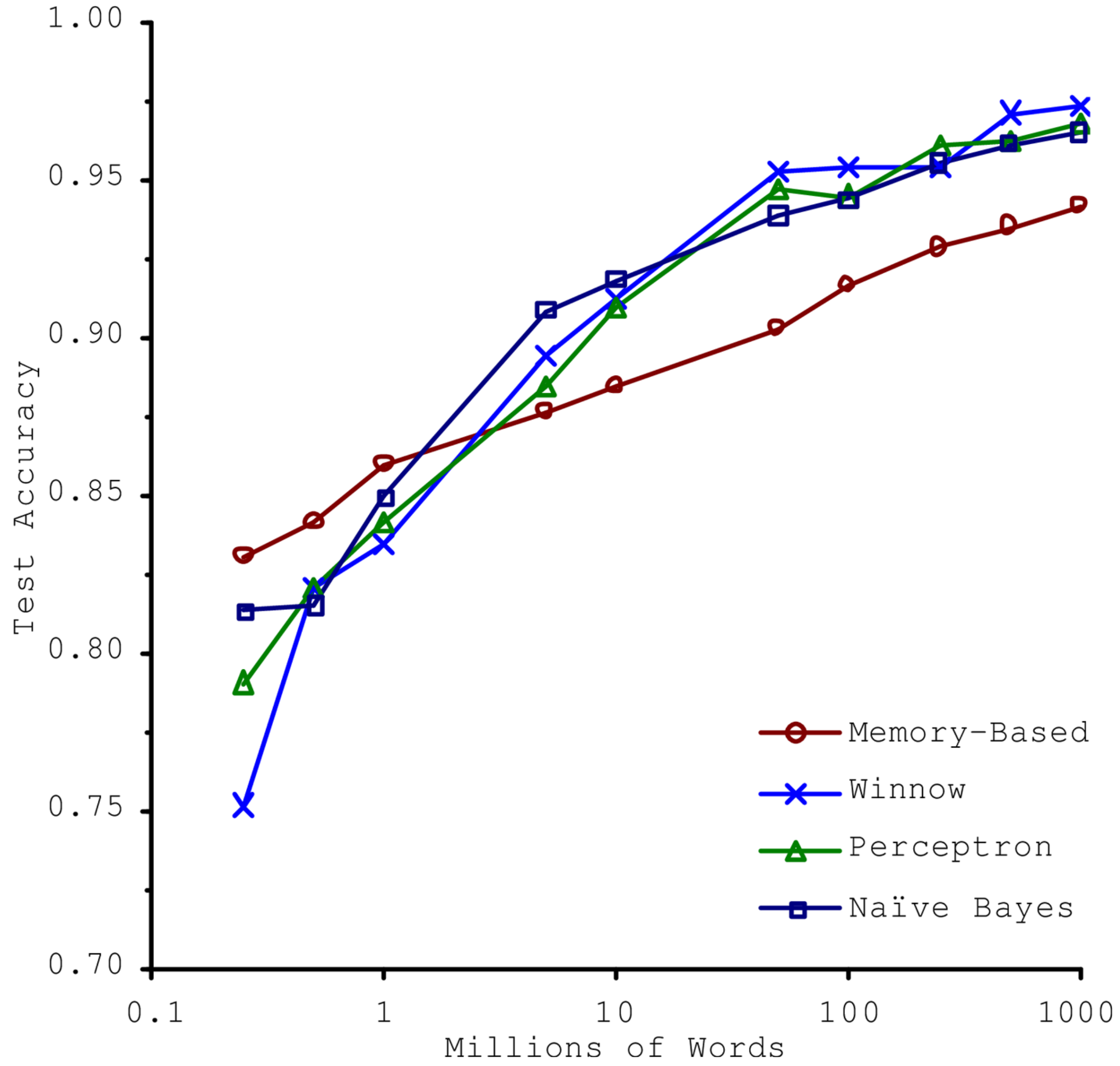


# MAIN CHALLENGES OF ML

- "Bad Data"
  - Insufficient quantity of data – not enough
  - Non-representative data – biased data
  - Poor quality data – errors, noise, outliers
  - Irrelevant features – not measuring the right things
- "Bad Algorithms"
  - Overfitting – overreliance on limited training data
  - Underfitting – not enough model capacity

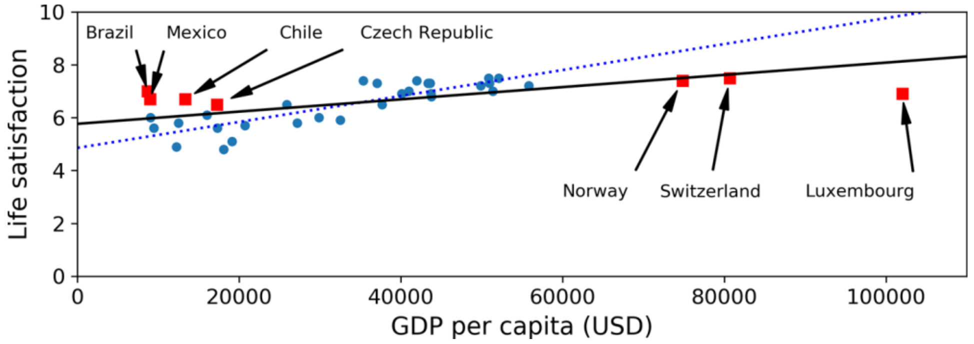
# INSUFFICIENT QUANTITY OF TRAINING DATA

- ML still requires a lot of data to work properly
  - 1000s or more (millions for image/speech)
- The Unreasonable Effectiveness of Data
  - Given enough data, very different ML algorithms (including fairly simple) all perform similarly
  - "Reconsider trade-off between spending time and money on algorithm development versus spending it on corpus development"
    - Has led to much of modern ML and computer vision → massive datasets
    - Do we now have enough (too much) data?



# NONREPRESENTITIVE TRAINING DATA

- Training data must be representative of test cases to generalize well




  - Dashed blue old model using blue dots
  - Solid line trained using also red squares
  - Poor performance with old model
    - Especially with poor and rich countries

- Sampling noise – nonrepresentative sample data due to chance
- Sampling bias – training samples have systematic issue in collection which produces non-uniformity (or mis-matching of underlying distribution)
  - E.g. facial recognition systems performing poorly on darker skin tones

# POOR-QUALITY DATA

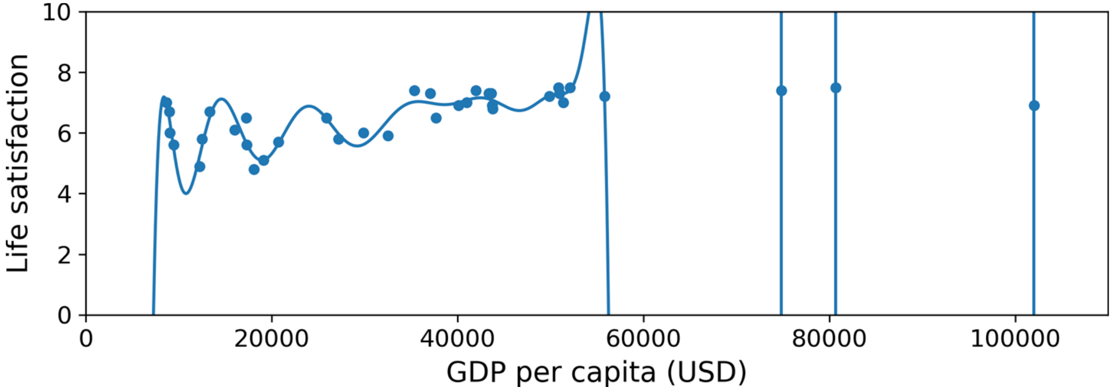
- Data full of errors, outliers, and noise (e.g., due to poor-quality measurements)
  - Will make it harder to detect underlying patterns and less likely to perform well
- Data scientist spend significant time to cleaning up data
  - Clear outliers – discard or manually fix errors
  - Missing a few features – decide to ignore attribute, instances with "holes", fill in missing value, or train multiple models (with/without missing features)

# IRRELEVANT FEATURES

- Garbage in, garbage out
  - Can only learn if features are relevant, not too much irrelevant info
- Feature engineering – process of determining a good set of features to train on
  - Feature selection – select most useful features among all available/existing features
  - Feature extraction – combining existing features to produce more useful ones
  - Creating new features by gathering new data
- Classical ML uses "hand-crafted" features while deep learning has data-driven features

# OVERFITTING THE TRAINING DATA

- Overgeneralizing based on limited data
  - Model is too complex relative to the amount of noisiness in the training data → modeling noise
  - Good performance on training but poor generalization (bad performance on test)

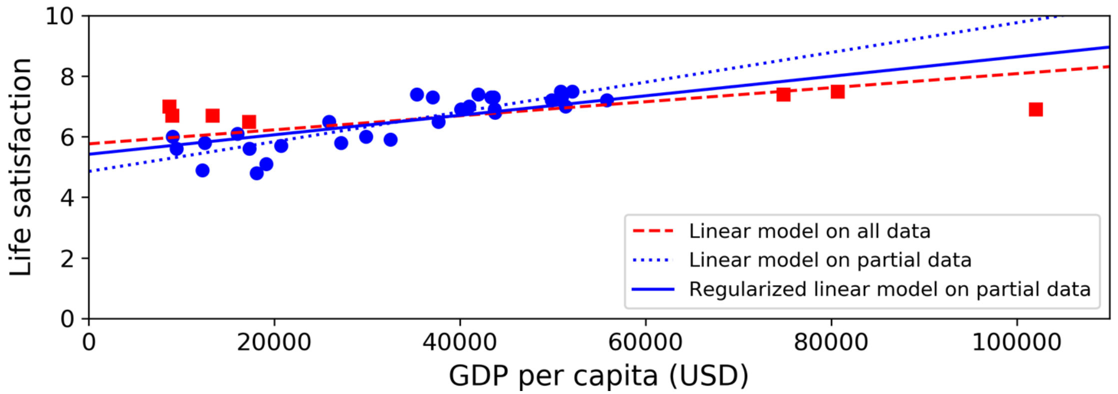



- Options to address problem
  - Simplify model by selecting one with fewer parameters, reducing the number of features, or constraining model
  - Gather more training data
  - Reduce noise in training data (e.g., fix data errors and remove outliers)

High degree polynomial with overfitting

# REGULARLIZATION

- Constraining a model to make it simpler and reduce the risk of overfitting
  - E.g. constrain parameters to limit search space
- Hyperparameter – parameter of a learning algorithm (not model) to control regularlization
  - Constant set prior to training
  - Not affected by the learning parameter itself




- Will have to tune (train) hyperparameters for best performance

# UNDERFITTING THE TRAINING DATA

- Occurs when your model is too simple to learn the underlying structure of the data
  - Data is more complex that your selected model
  - Predictions will be poor, even on training data
- Options to address the problem
  - Select a more powerful model, with more parameters
  - Use better features (feature engineering)
  - Reduce the constraints on the model (e.g., reduce regularization hyperparameter)

# BIG PICTURE

- ML – making machines get better at a task by learning from data rather than explicitly coding rules
- ML comes in many flavors: un/supervised, batch/online, instance/model-based
- ML steps
  - Select modeling approach
  - Feed data to learning algorithm
  - Tune parameters to fit model to training data
- ML systems do not perform well if:
  - Training data is too small
  - Data is too noisy or polluted with irrelevant features
  - Model is too simple or too complex

# TESTING AND VALIDATION

- Most important goal for ML is to generalize well
  - Model should behave as expected to new unseen cases
  - Evaluate and fine-tune models to be sure it works well
- Split training into training and test sets
  - Training data – used to train model
  - Test data – test model on unseen data and measure the error rate (generalization or out-of-sample error) to estimate how well model performs
- Low training and test error is desired
  - Low training error but high test error means the model is overfitting

# HYPERPARAMETER TUNING AND MODEL SELECTION

- Must select a model with various # parameters (e.g. linear and polynomial) and add regularization to avoid overfitting
- Can use test set for model generalization but not for regularization parameter tuning (test set tuning)

- Use a validation (val or development or dev set) for holdout validation
  - Subset of training data used specifically for model and hyper parameter tuning
  - Train full model on train+val and get generalization error on test set

- Cross-validation (multiple train/val data splits) can be used for better characterization with smaller datasets by averaging performance across splits
  - Val too small → imprecise model evaluations
  - Val too large → not enough training data

# DATA MISMATCH

- Data must be representative
  - Don't want to train on magazine/professional (web) images if the use case are coming from user cell phones
- Makes sure val/test sets match use case
- Train-dev set is split of training data used to determine if model is overfitting or if there is data mismatch
  - Poor val performance → data mismatch
  - Poor train-dev performance → overfit and need to simplify model, add regularization, get more data, or clean data

# NO FREE LUNCH THEOREM

- If you make absolutely no assumptions about the data, then there is no reason to prefer one model over any other – David Wolpert 1996
- A priori, there is no model guaranteed to work better
  - Cannot test all possible models
  - Must make reasonable assumptions about the data and evaluate only a few reasonable models
    - Simple tasks – linear models with regularization
    - Complex tasks – neural networks

# OUTLINE

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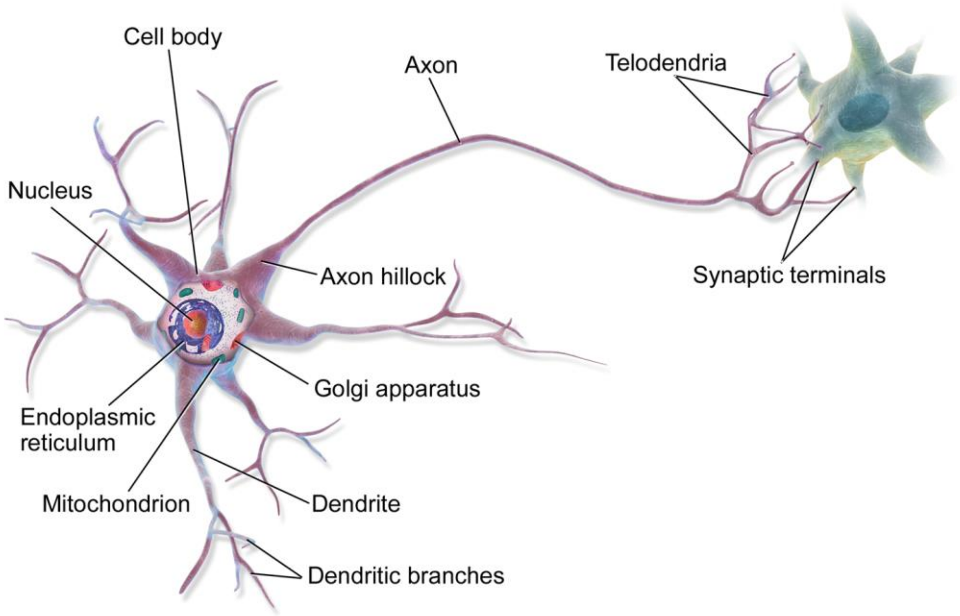
  - Biological inspiration
  - Perceptron
  - Multilayer perceptron (MLP)

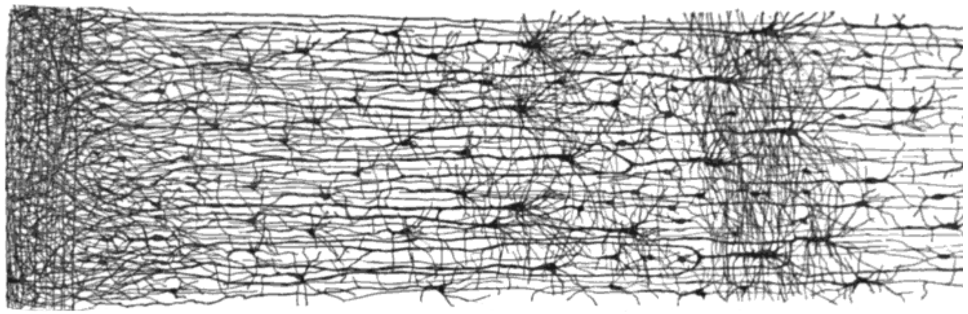
# FROM BIOLOGICAL TO ARTIFICIAL NEURONS

- Artificial neural networks (ANNs) first introduced in 1943
- Excitement with ANNs waned in the 1960s
- 1980s had renewed interest but was overtaken in the 1990s with ML techniques such as SVM
- Since 2010s major renewed interest
  - Huge quantities of data are available to train networks
  - Major computing power increases for reduced training times (GPU and cloud)
  - Improved training algorithms
  - Local optima issue rare
  - Lots of funding in ANNs (Artificial Intelligence/Deep Learning)

# BIOLOGICAL NEURONS

- Cell mostly found in animal brains
- Produce short electrical impulses (action potentials, APs, or signals) to make synapses release chemical signals (neurotransmitters)
- When a neuron receives enough neurotransmitters it fires its own electrical pulses
- Individual neurons are simple but arranged into vast networks of billions
  - Each neuron connected to thousands of other neurons
  - Neurons seem to be organized in consecutive layers

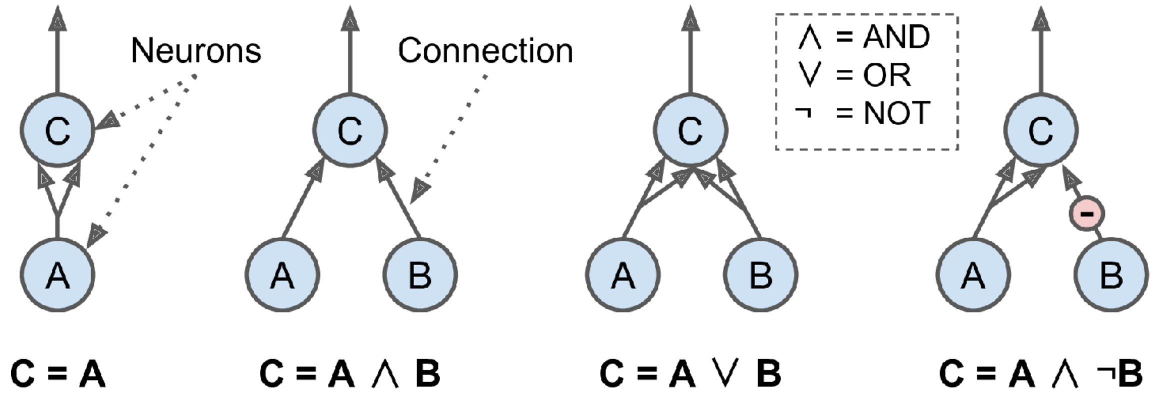


# LOGICAL COMPUTATIONS WITH NEURONS

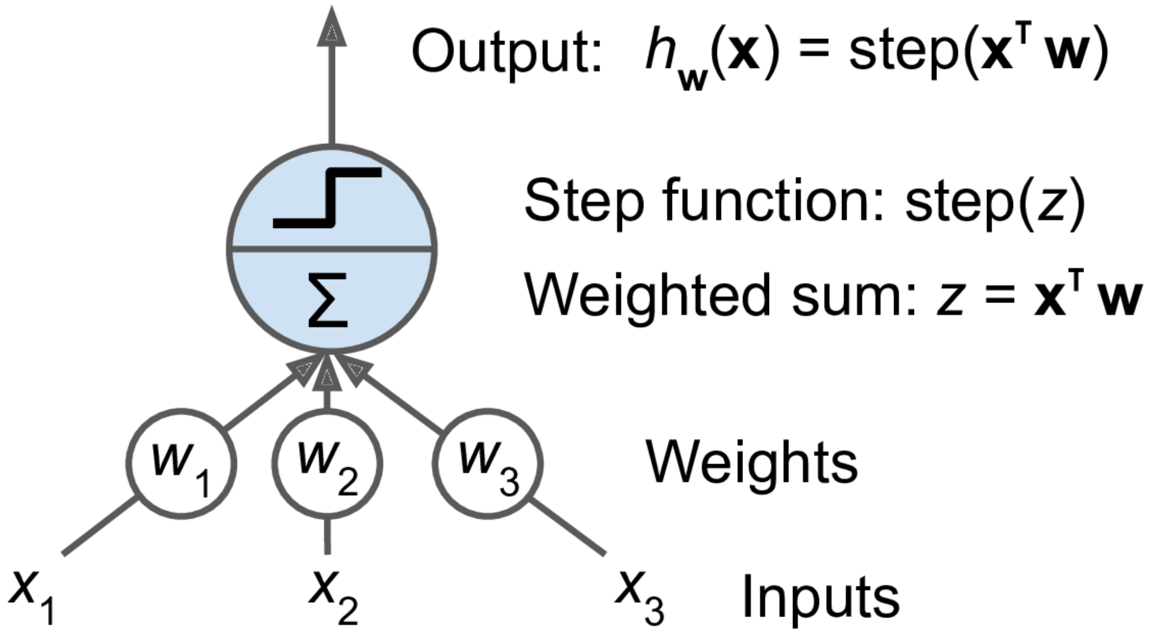
- Artificial neuron proposed by McCulloch and Pitts
  - Simple binary inputs and one binary output
  - Activates output when certain number of inputs on/active
- Even with the simple model, any logical proposition can be computed
- Basic building block networks can be combined for more complex logical expressions

- Building block networks
  - Implement basic logic functions



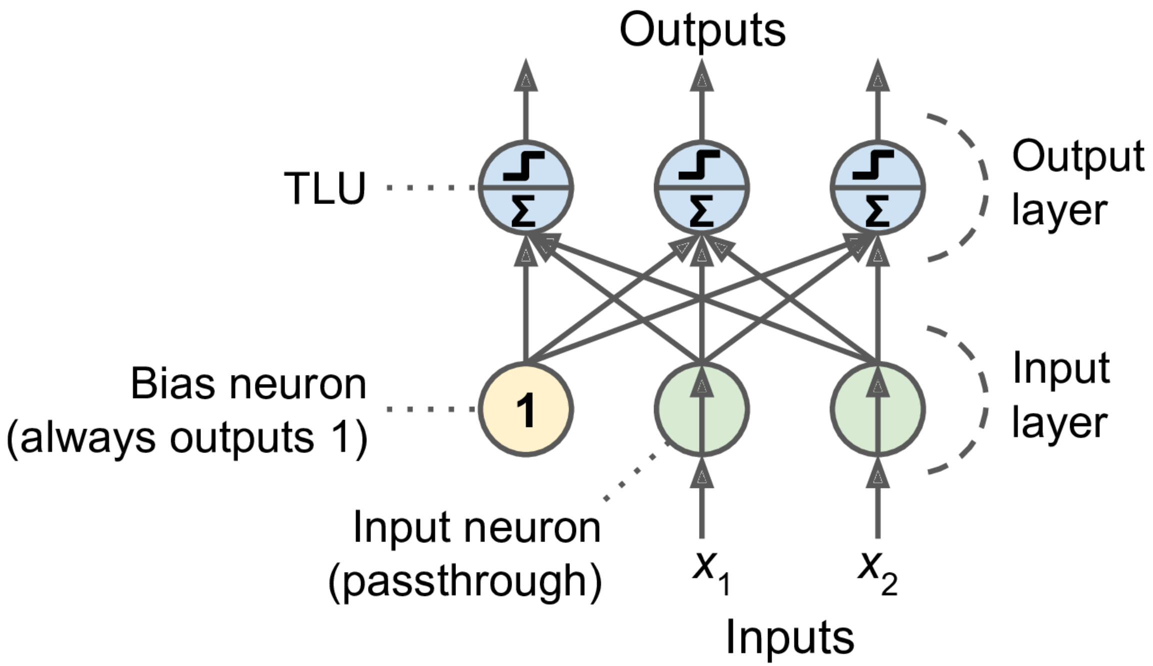
# THE PERCEPTRON I (TLU)

- Invented by Frank Rosenblatt in 1957
- Inputs/outputs are numbers (instead of binary)
- Based on threshold logic unit (TLU) or linear threshold unit
- Inputs associated with a weight
- TLU computes weighted sum of input
  - $z = w_1 x_1 + w_2 x_2 + w_3 x_3$
- Output after a step (threshold) function
  - Heavyside of sign function
- TLU can be used as a simple linear binary classifier



# THE PERCEPTRON II

- Perceptron is a layer for TLU
  - Fully connected (dense) layer – all inputs connected to all neurons
- Input neuron – pass value through unchanged
- Bias neuron – always outputs 1




- Example: Multilabel classifier
  - 2 inputs 3 outputs
  - Can classify into three binary classes based on two input values

# THE PERCEPTRON III

- Output of fully connected layer

$$h_{W,b}(X) = \phi(XW + b)$$

  - $X$ – matrix of input features
  - $W$ – weight matrix (all weights between input and neurons)
    - One row per input neuron
    - One column per neuron layer
  - $b$ – bias (weights) vector
  - $\phi$ – activation function (e.g. step)

- Produces linear (non-complex) decision boundary

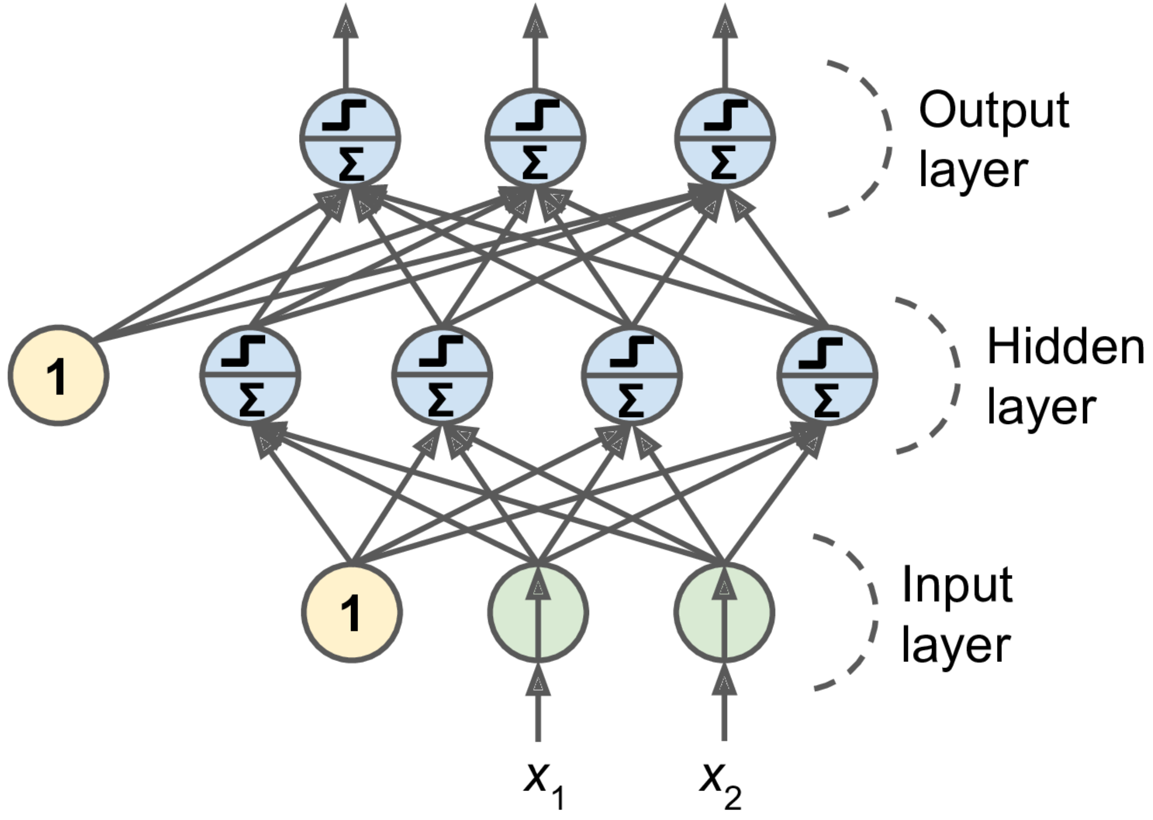
- Perceptron training – reinforce connections that reduce prediction error

$$w_{i,j}^{(next\ step)} = w_{i,j} + \eta(y_j - \hat{y}_j)x_i$$

  - $w_{i,j}$ - connection weight between ith input and jth output neuron
  - $x_i$ - ith input value
  - $\hat{y}_j$ - perceptron output of jth neuron
  - $y_j$ - target (ground truth) output of jth neuron
  - $\eta$ – learning rate

# MULTILAYER PERCEPTRON (MLP)

- Stack TLU layers for more complicated functions
  - Input layer - passthrough
  - Hidden layer – intermediate TLU layer
  - Output layer – final fully connected TLU layer
- Lower layers – closer to input
- Upper layers – closer to output
- Deep neural network (DNN) has many hidden layers



# BACKPROPAGATION I

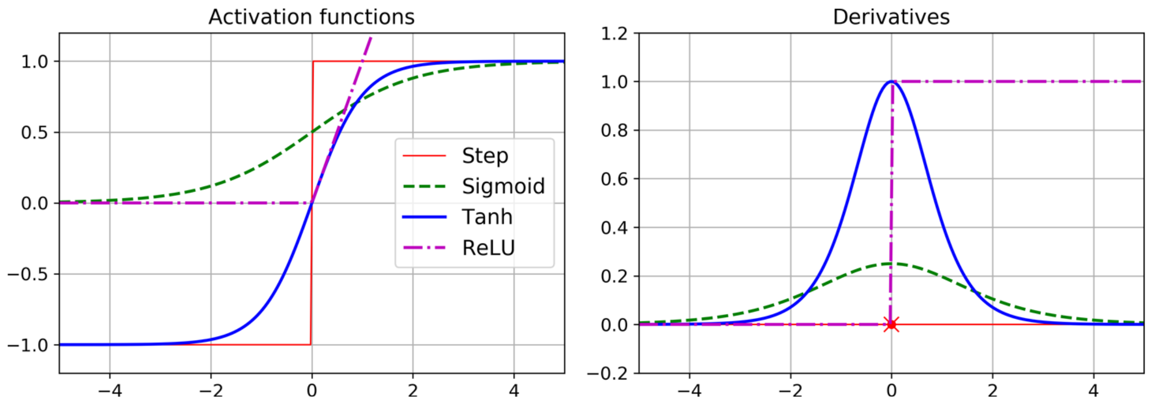
- Effective method to train a MLP developed in 1986
  - Gradient Descent method with efficient gradient computation technique
  - Single forward-backward pass through network to compute gradient of network error for all model parameters
    - Can update all connection weights and bias terms
- Backpropagation uses reverse-mode autodiff to automatically compute gradients (Appendix D)

# BACKPROPAGATION II

- Process full dataset each epoch
  - Use mini-batch at each iteration – larger more efficient and more stable gradient but requires more memory
- Mini-batch of input is sent through the MLP in a forward pass (from input to output prediction)
  - All intermediate results (from hidden layers) are saved for backward pass
- Measure current network prediction error
  - Use of loss function to define error metric
- Compute contribution of each connection to the total error
  - Performed backward from output through hidden layers back to input using the chain rule
- Perform Gradient Descent step to adjust all connection weights
  - Using the error gradients from the backward pass

# ACTIVATION FUNCTIONS

- Cannot use step for activation since it has no gradient information
- Sigmoid (logistic) function
  - $\sigma(z) = 1/(1 + \exp(-z))$
  - S-shaped between [0, 1]
- Hyperbolic tangent function
  - $\tanh(z) = 2\sigma(2z) - 1$
  - Output between [-1,1] helps speed convergence
- Rectified Linear Unit function
  - $ReLU(z) = \max(0, z)$
  - Not differentiable, but works well and fast so popular




**Activation functions add non-linearity!**

# REGRESSION MLPs

- Single output neuron
  - Mulivariate regression requires an output neuron for each output dimension
    - 2: (x,y) for center of object
    - 4: (x,y,h,w) for a bounding box around object
- Output activation
  - No activation – no limits on output range of value
  - ReLU or softplus (smooth ReLU) – positive output only
  - Scaled sigmoid/tanh – fixed output range
- Loss function
  - Mean squared error (L2 norm)
  - Mean absolute error (L1 norm) when there are a lot of outliers
  - Huber loss is a combination
- Regression MLP summary

*Table 10-1. Typical regression MLP architecture*

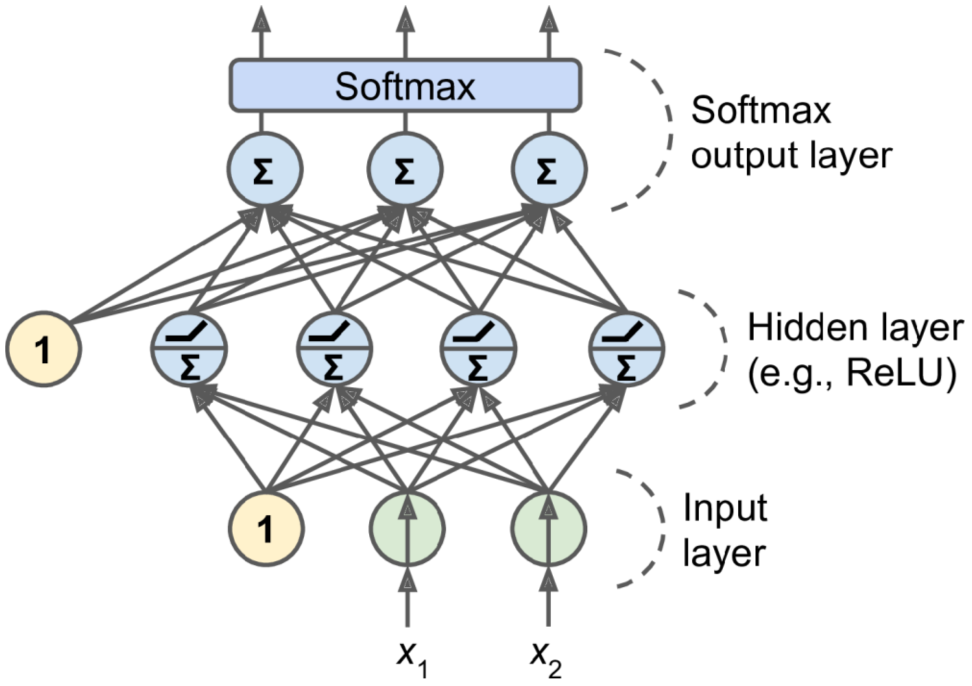
| Hyperparameter | Typical value |
|---|---|
| # input neurons | One per input feature (e.g., 28 x 28 = 784 for MNIST) |
| # hidden layers | Depends on the problem, but typically 1 to 5 |
| # neurons per hidden layer | Depends on the problem, but typically 10 to 100 |
| # output neurons | 1 per prediction dimension |
| Hidden activation | ReLU (or SELU, see Chapter 11) |
| Output activation | None, or ReLU/softplus (if positive outputs) or logistic/tanh (if bounded outputs) |
| Loss function | MSE or MAE/Huber (if outliers) |

# CLASSIFICATION MLPs I

- Single class (binary) – single output neuron
  - Output between [0,1] using sigmoid
  - Estimate probability of positive class (confidence)
- Multilabel binary – output neuron for every binary classification
  - Output between [0,1] using sigmoid
  - Output probabilities do not sum to one
  - Combinational output space

# CLASSIFICATION MLPs II

- Multiclass classification – multiple possible classes (e.g. number 0-9)
  - Each input instance can only belong to a single class (>2)
  - One output neuron per class
  - Softmax activation on the full output layer (Chapter 4 pg 148)
    - $\hat{p}_k = \sigma\left(s(x)\right)_k = \frac{\exp\left(s_k(x)\right)}{\sum_j \exp\left(s_j(x)\right)}$
    - $s_k(x) = \left(\theta^{(k)}\right)^T x$
    - Estimated probabilities between [0,1] and sum to 1
- Cross entropy loss
  - $J(\theta) = -\frac{1}{m}\sum_i \sum_k y_k^{(i)} \log\left(\hat{p}_k^{(i)}\right)$
  - Penalizes models with low probability estimate for the ground truth class




- Classification summary

*Table 10-2. Typical classification MLP architecture*

| Hyperparameter | Binary classification | Multilabel binary classification | Multiclass classification |
|---|---|---|---|
| Input and hidden layers | Same as regression | Same as regression | Same as regression |
| # output neurons | 1 | 1 per label | 1 per class |
| Output layer activation | Logistic | Logistic | Softmax |
| Loss function | Cross entropy | Cross entropy | Cross entropy |

# FINE-TUNING HYPERPARAMETERS

- Many hyperparameters must be tweaked for good model performance
- Grid search can evaluate different hyperparameter combinations → slow
  - Book gives other libraries for hyperparam optimization
  - These typically explore more in good hyperparameter space
- Number of hidden layers → deeper is better
  - Transfer learning – reuse lower layers from network trained on large dataset (good initialization and avoid cost of learning from scratch)
- Number of neurons per hidden layers → use fixed size
- Activation function → ReLU works well
- Learning rate – very important parameter, need learning schedule
- Optimizer – more than just mini-batch gradient descent (e.g. Adam)
- Batch size – significant impact on model performance and training time
  - Large batch – efficiently process for reduced training time → maximize for GPU with learning rate warm-up (schedule)
  - Small batch – more stable early in learning and good generalization