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Deep Learning: Building Neural Networks Using Deeplearning4j

This is the main title page for the book

It is generated from the top level README.md

Welcome to the Course

In the following days we will have a great time

Page 2

In the following days we will have a great time

Page 3

In the following days we will have a great time

This is the Readme

THis is where the Readme per chapter goes

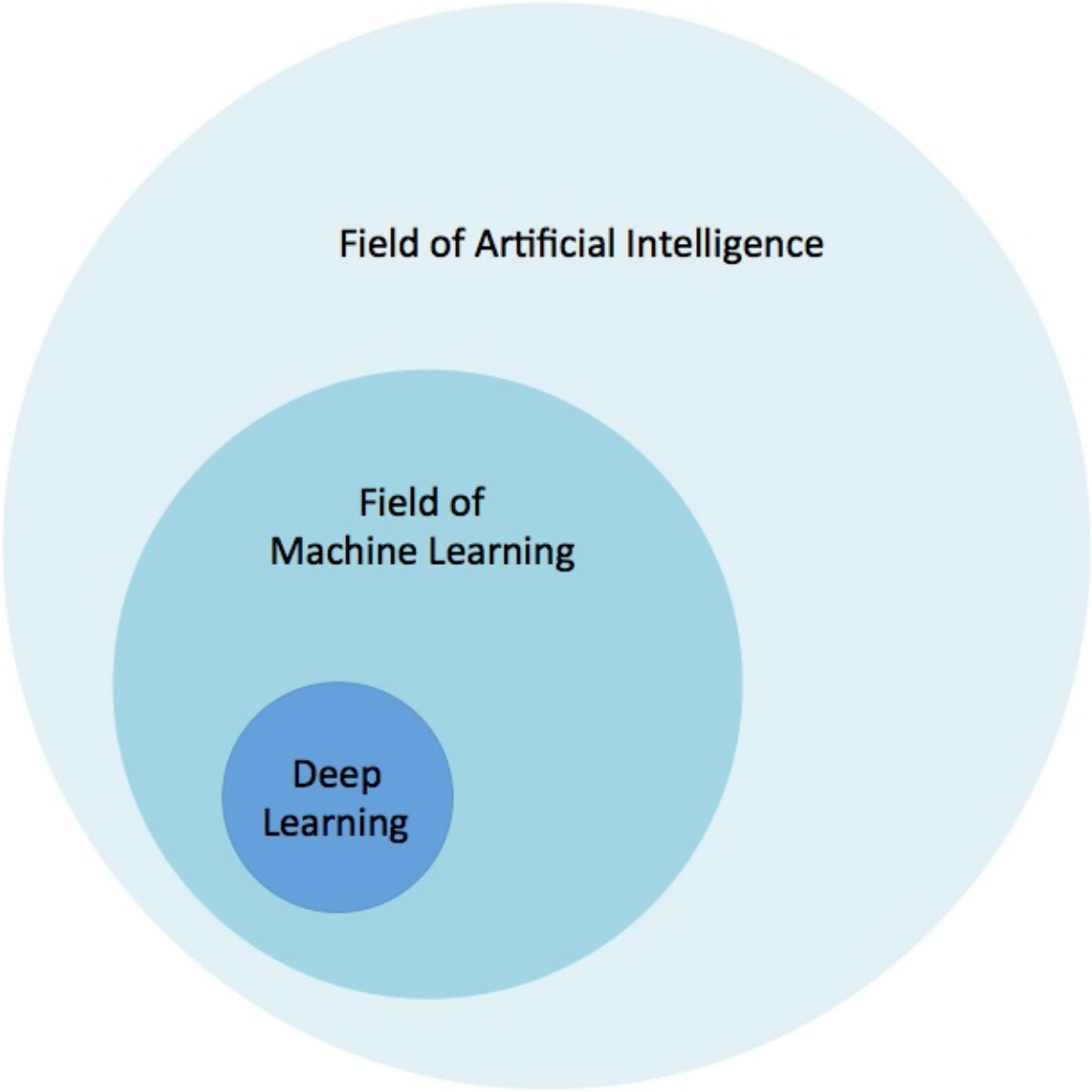
About this Course

This content comes from the 01.md per directory

3 Day Hands on Course

- Neural Networks
- More Neural Networks

A Diagram


Field of Artificial Intelligence
Field of
Machine Learning
Deep
Learning

Introduction to Machine Learning

This section provides an introduction to Machine Learning and DeepLearning concepts.

Introduction to Neural Networks with DeepLearning4J

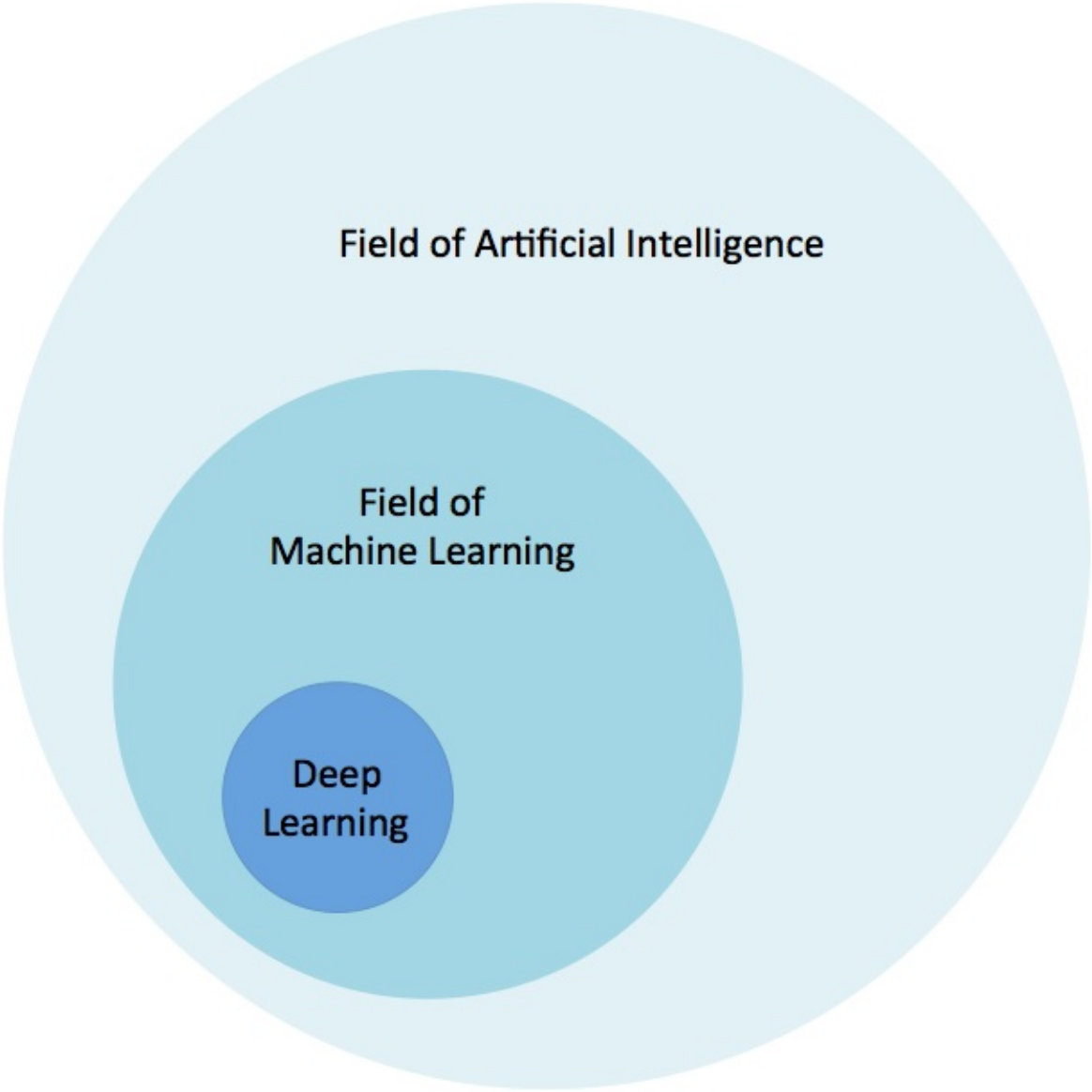
Table of Contents

1. Fundamentals of Machine Learning
2. Something else

What is Machine Learning?

- Extracting Knowledge from raw data in the form of a model
  - Decision trees
  - Linear Models
  - Neural Networks
- Arthur Samuel quote
  - "Field of study that gives computers the ability to learn without being explicitly programmed"

A Diagram


Field of Artificial Intelligence
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Machine Learning Compared to Data Science/Mining

- Data Mining
  - The process of extracting information from the data
  - Uses Machine Learning
- Data Science
  - Data Mining from the lens of a statistician
  - Venn Diagrams
  - A way to get a raise
  - A more agreeable Actuary
  - A statistician using a Mac

Framing the Questions

- To build models we have to define
  - What is our training data (“evidence”)?
  - What kind of model (“hypothesis”) is appropriate for this data?
  - What kind of answer (“inference”) would we like to get from the model?
- These questions frame all machine learning workflows

Ax = b

- In neural networks we're solving systems of (non-linear) equations of the form
  - Ax = b
- A matrix
  - This is our set of input data converted into an array of vectors
- x vector
  - The parameter vector of weights representing our model
- b vector
  - Vector of output values or labels matching the rows in the A matrix

Ax = b Visually

Let’s Talk Linear Algebra

- Scalars
  - Elements in a vector
  - In compsci synonymous with the term “variable”
- Vectors
  - For a positive integer n, a vector is an n-tuple, ordered (multi)set, or array of n numbers, called elements or scalars
- Matricies
  - Group of vectors that have the same dimension (number of columns)

Solving Systems of Equations

- Two general Methods
  - Direct method
  - Iterative methods
- Direct method
  - Fixed set of computation gives answer
  - Data fits in memory
  - Ex: Gaussian Elimination, Normal Equations
- Iterative methods
  - Converges after a series of steps
  - Stochastic Gradient Descent (SGD)

Vectorization

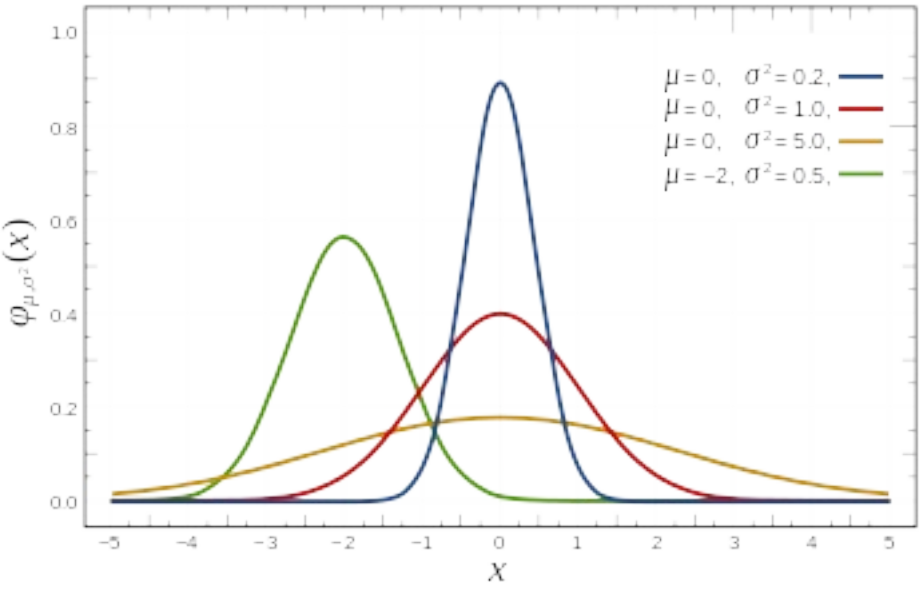
- To solve$Ax = b$ with optimization methods such as SGD
  - We have to get raw data into the vectors and matrices
- This ends up being a lot of work
  - most folks never consider this phase to be *sniff* “real machine learning”
- Actually it's pretty key to building good models

Quick Statistics Review: Probability

- Probability
  - We define probability of an event E as a number always between 0 and 1.
  - In this context the value 0 infers that the event E has no chance of occurring and the value 1 means that the event E is certain to occur.
- The Canonical Coin Example
  - Fair coin flipped, looking for heads/tails (0.5 for each side)
  - Probability of sample space is always 1.0
  - P(Heads) = 0.5 every time

Probability Distributions

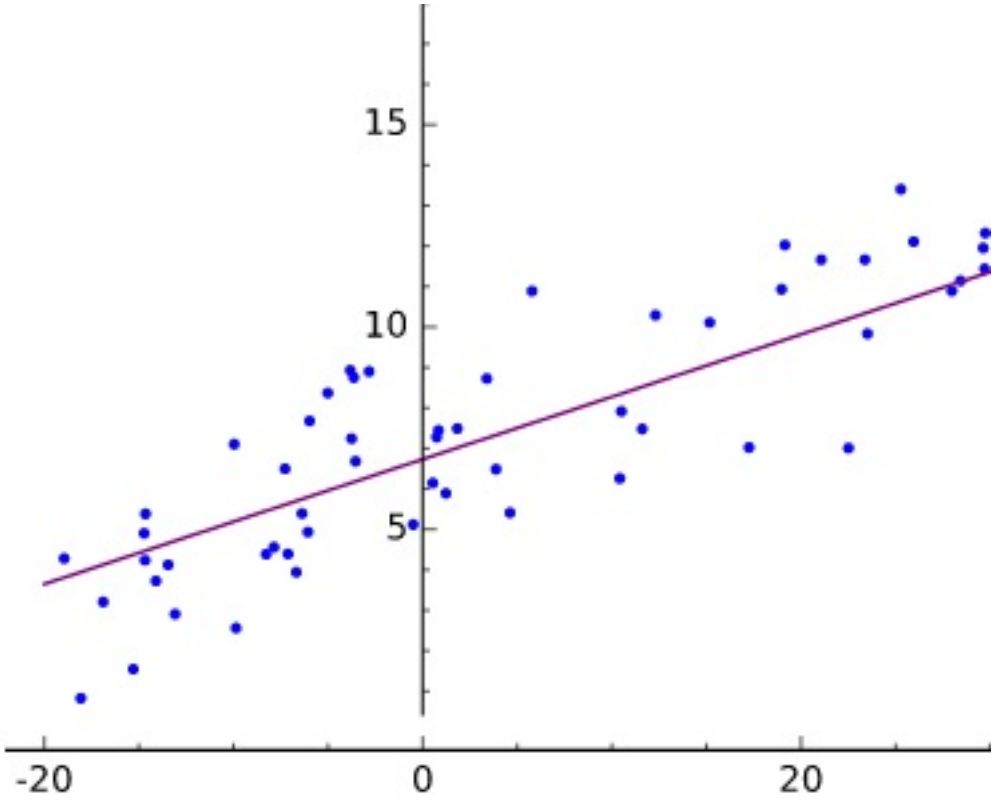
- A specification of the stochastic structure of random variables
- In statistics we rely on making assumptions about how the data is distributed
  - To make inferences about the data
- We want a formula specifying how frequent values of observations in the distribution are
  - And how values can be taken by the points in the distribution



High-Level Machine Learning

- Determine
  - Output desired (“question to be answered”)
  - Input data to build model (“evidence”)
  - Appropriate model (“hypothesis”)
- Setup data in Ax = b form
  - For linear models and neural networks
- Then Optimize the x parameter vector

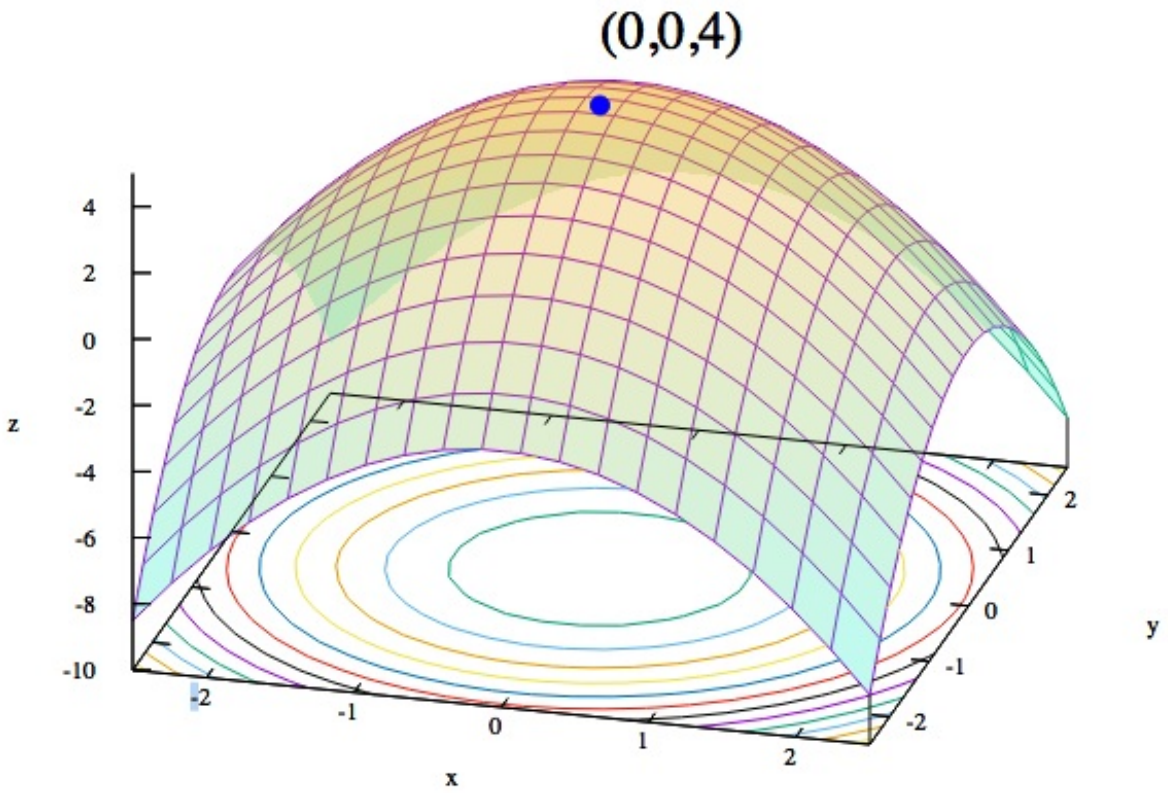
Fitting the Training Data



Optimization

- Iteratively adjust the values of the x parameter vector
  - Until we minimize the error in the model
- Error = prediction – actual
- Loss functions measure error
  - simple/common loss function:
  - “mean squared error”
- How do we make choices about the next iterative “step”?
  - Where “step” is how we change the x parameter vector

Convex Optimization



Gradient Descent

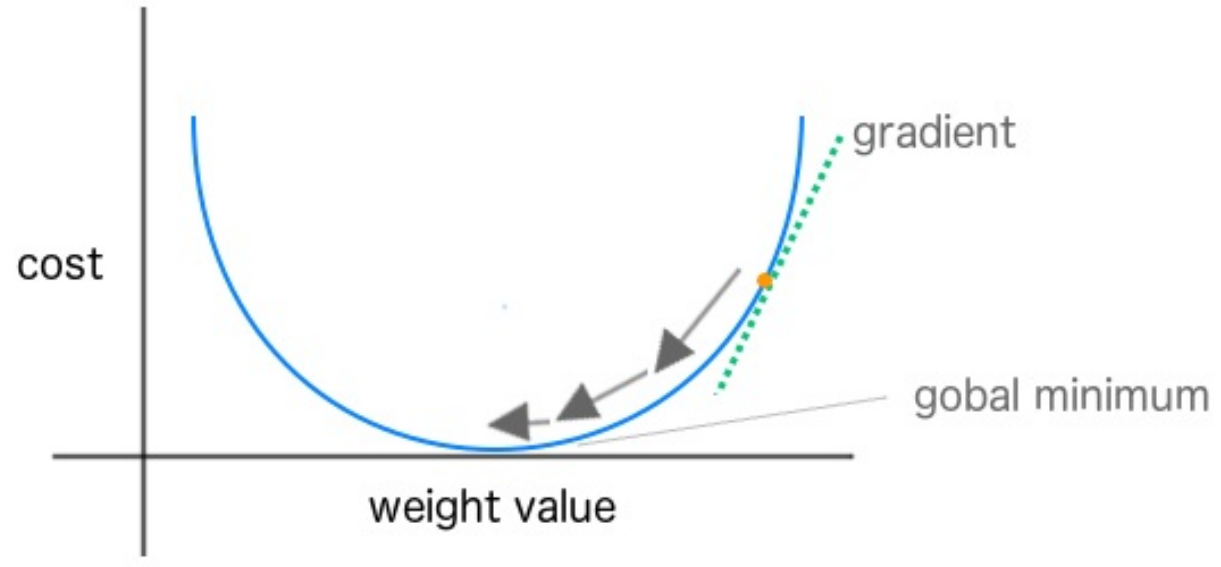
- Optimization method where we consider parameter space as
  - “hills of error”
  - Bottom of the loss curve is the most “accurate” spot for our parameter vector
- We start at one point on the curved error surface
  - Then compute a next step based on local information
- Typically we want to search in a downhill direction
  - So we compute the gradient
    - The derivative of the point in error-space
    - Gives us the slope of the curve

Stochastic Gradient Descent

- With basic Gradient Descent we look at every training instance before computing a “next step”
- With SGD with compute a next step after every training instance
  - Sometimes we’ll do a mini-batch of instances

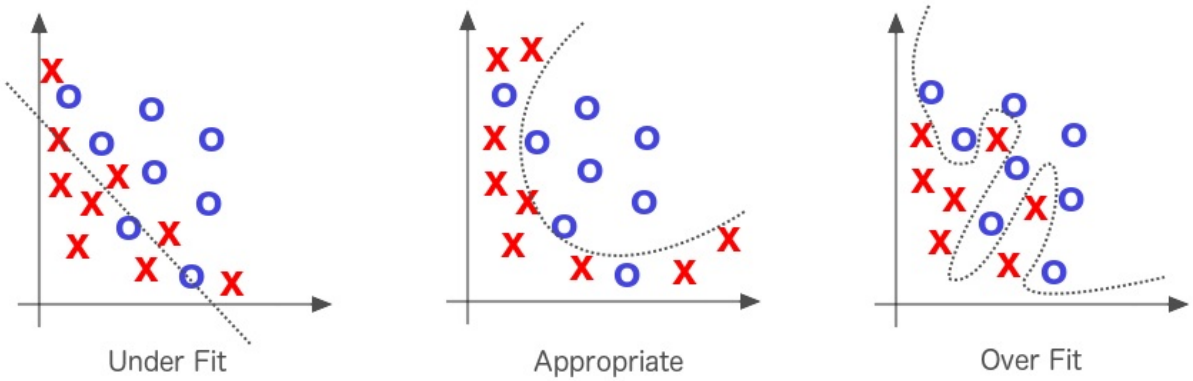
TH-clean this up

SGD Visually Explained



Underfitting and Overfitting

- Underfitting
  - Our model does not learn the structure of the training data well enough
  - Doesn’t perform on new data as well as it could
- Overfitting
  - Our model gives tremendous accuracy scores on training data
  - However, our model performs poorly on test data and other new data



Classification

- A type of answer we can get from a model
- Example:
  - “Is this an image of a cat or a dog?”
  - Binary classification
  - Classes: { cat, dog }
- Binary classification is where we have only 2 labels
  - Example: { positive, negative }
- Multi-Label Classification
  - N number of labels

Supervised vs Unsupervised Learning

- Supervised Learning
  - We give the training process labels (“outputs”) for every training input data row
  - Model learns to associate input data with output value
- Unsupervised Learning
  - No labels
  - Model attempts to learn structure in the data

Regression

- Where we seek a continuous value output from the model
- Example: “predict the temperature for tomorrow”
  - Output: 75F
- Example: “predict price of house based on square footage”
  - Output: $250,000.00

Clustering

- Typically unsupervised learning
  - “K-Means Clustering”
- Example
  - “cluster K groups of similar news articles together”

Logistic Regression

- 3 parts to Logistic Regression Model
  - Hypothesis (logistic function): $\frac{1}{1+e^{-\theta x}}$
    - Gives us a prediction based on the parameter vector x and the input data features
  - Cost Function
    - Example: “max likelihood estimation”
    - Tells us how far off the prediction from the hypothesis is from the actual value
  - Update Function
    - Derivative of the cost function
    - Tells us what direction / how much of step to take [more notes, gradient, etc]

Evaluation and The Confusion Matrix

- Table representing
  - Predictions vs Actual Data
- We count these answers to get
  - True Positives
  - False Positives
  - True Negatives
  - False Negatives
- Allows us to evaluate the model beyond “average accurate” percent
  - Can look at well a model can perform when it needs to be more than just “accurate a lot”

	P’ (Predicted)	N’ (Predicted)
P (Actual)	True Positive	False Negative
N (Actual)	False Positive	True Negative