ChicagoKUG – Many Types of AI

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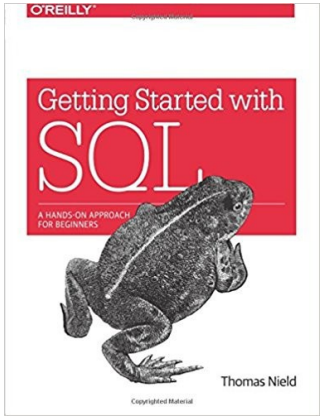
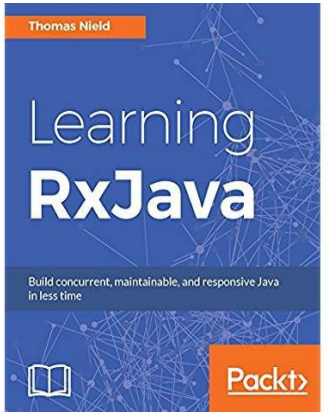
Getting Started with SQL by O'Reilly

Learning RxJava by Packt





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Thomas Nield

The Monty Hall Problem

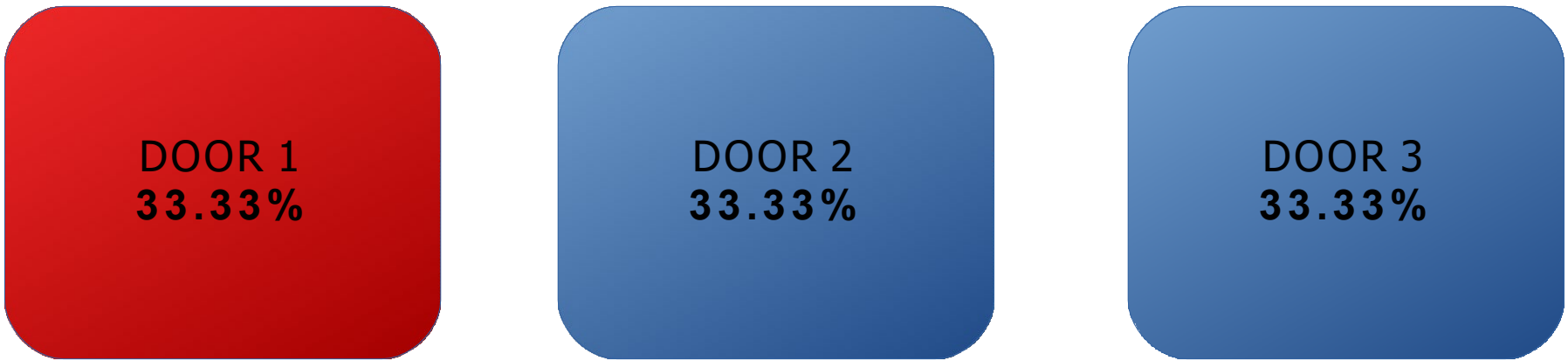
The Monty Hall Problem

Choose a door, one has a prize.
Two others have goats.

The Monty Hall Problem

You choose **Door 1**.
What is the probability it has the prize?

The Monty Hall Problem



You choose **Door 1**.
What is the probability it has the prize? **33%**

The Monty Hall Problem

Twist! **Door 3** was just opened. It's a goat.
Did you want to switch from **Door 1** to **Door 2**?

The Monty Hall Problem

DOOR 1
?%

DOOR 2
?%

What is the prize probability of each door now?

The Monty Hall Problem

DOOR 1
?%

DOOR 2
?%

HINT: The prize probability of either door is not 50%

The Monty Hall Problem

DOOR 1
33.33%

DOOR 2
66.66%

The probability of **Door 1** is **33.33%** while **Door 2** is now **66.66%**.
You should switch! But why?

The Monty Hall Problem

33.33%

66.66%

33.33%

The Monty Hall Problem

According to Bayes Theorem...

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$$P(P_1|D_2) = \frac{P(D_2|P_1)P(P_1)}{P(D_2)} = \frac{(.5)(.33)}{(.5)} = .33$$

$$P(P_2|D_2) = \frac{P(D_2|P_2)P(P_2)}{P(D_2)} = \frac{(1)(.33)}{(.5)} = .66$$

The Monty Hall Problem

D_2 = Probability of door 2 being left = .5

P_1 = Probability door 1 contains prize = .33

P_2 = Probability door 2 contains prize = .5

$P(P_1|D_2)$ = Probability door 1 contains prize given door 2 is left = .33

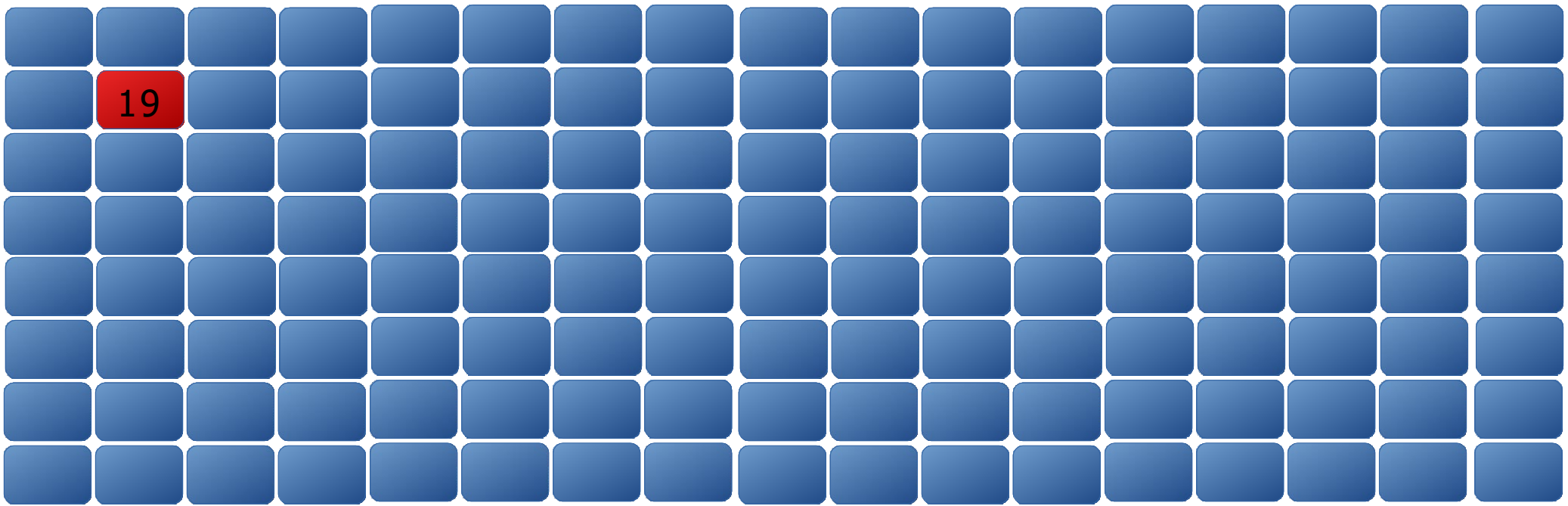
$P(P_2|D_2)$ = Probability door 2 contains prize given door 2 is left = .66

$P(D_2|P_1)$ = Probability door 2 is left given door 1 has prize = .5

$P(D_2|P_2)$ = Probability door 2 is left given door 2 has prize = 1.0

The Monty Hall Problem

Still confused? Hyperbolize! Imagine you had 1000 doors, and you chose **Door #19**.



The Monty Hall Problem

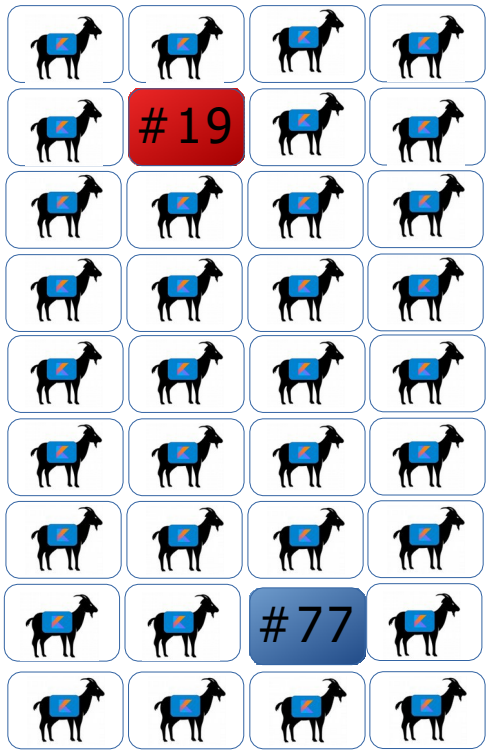
All other doors are opened but yours and **Door #77**. Inclined to switch now?

The Monty Hall Problem

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$$P(P_{19}|D_{77}) = \frac{P(D_{77}|P_{19})P(P_{19})}{P(D_{77})} = \frac{\frac{1}{999} * \frac{1}{1000}}{\frac{1}{1000}} = \frac{1}{999}$$

$$P(P_{77}|D_{77}) = \frac{P(D_{77}|P_{77})P(P_{77})}{P(D_{77})} = \frac{\frac{999}{1000} * \frac{1}{1000}}{\frac{1}{1000}} = \frac{999}{1000}$$



Yes, you should switch!

Monty Hall Simulation

Monte Carlo simulation of the Monty Hall Problem
https://gist.github.com/thomasnield/95443be4d5255929a0d716933df29de7

Why Am I Showing This?

The Monty Hall problem encapsulates the critical (and misunderstood) nuances of probability.

- Sometimes we only have incomplete data, but we need to make a decision anyway.
- When new partial data is available, we must merge (not abandon) the data we previously had.

Businesses often want certainty and exactness.

But the valuable, high-profile problems today often tackle uncertainty and approximation.

- Users and businesses expect "smarter" applications that will predict what they want.
- Machine learning and optimization is nondeterministic and unavoidably has error.
- Many search spaces are too large to exhaustively explore.

What Is Mathematical Optimization?

Optimization is a space of algorithms that tries to find a feasible or optimal solution to a constrained problem.

- Scheduling classrooms, staff, transportation, sports teams, and manufacturing
- Finding an optimal route for vehicles to visit multiple destinations
- Optimizing manufacturing operations
- Solving a Sudoku
- Minimizing loss for a machine learning algorithm

Mathematical optimization is a mixed bag of algorithms and techniques, which can be built from scratch or with the assistance of a library.

Traveling Salesman Problem

The Traveling Salesman Problem (TSP) is one of the most elusive and studied computer science problems since the 1950's.

Objective: Find the shortest round-trip tour across several geographic points/cities.

The Challenge: Just ***60*** cities = ***8.3 x 10^{81}*** possible tours

That's more tour combinations than there are observable atoms in the universe!

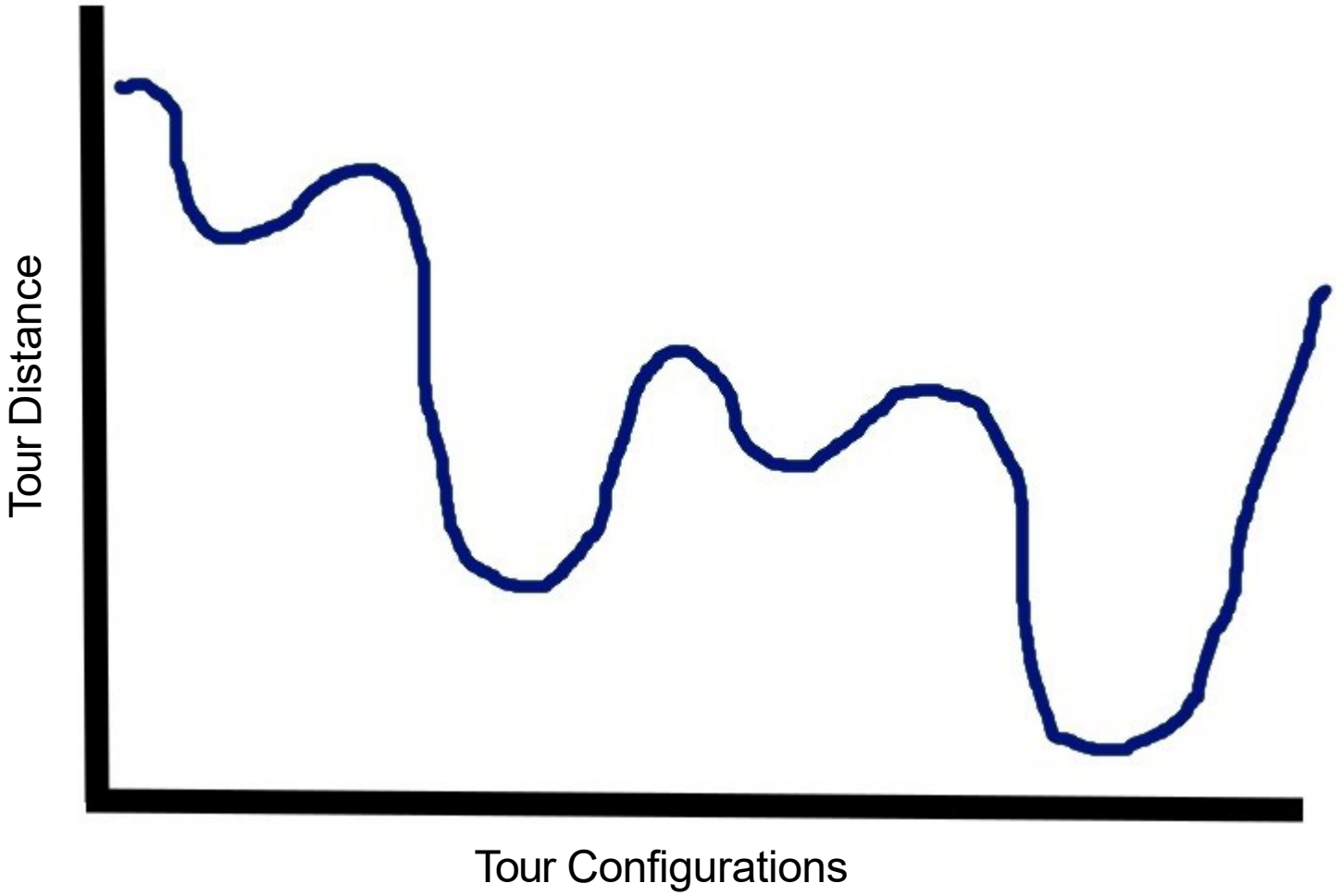
Metaheuristic – Hill Climbing

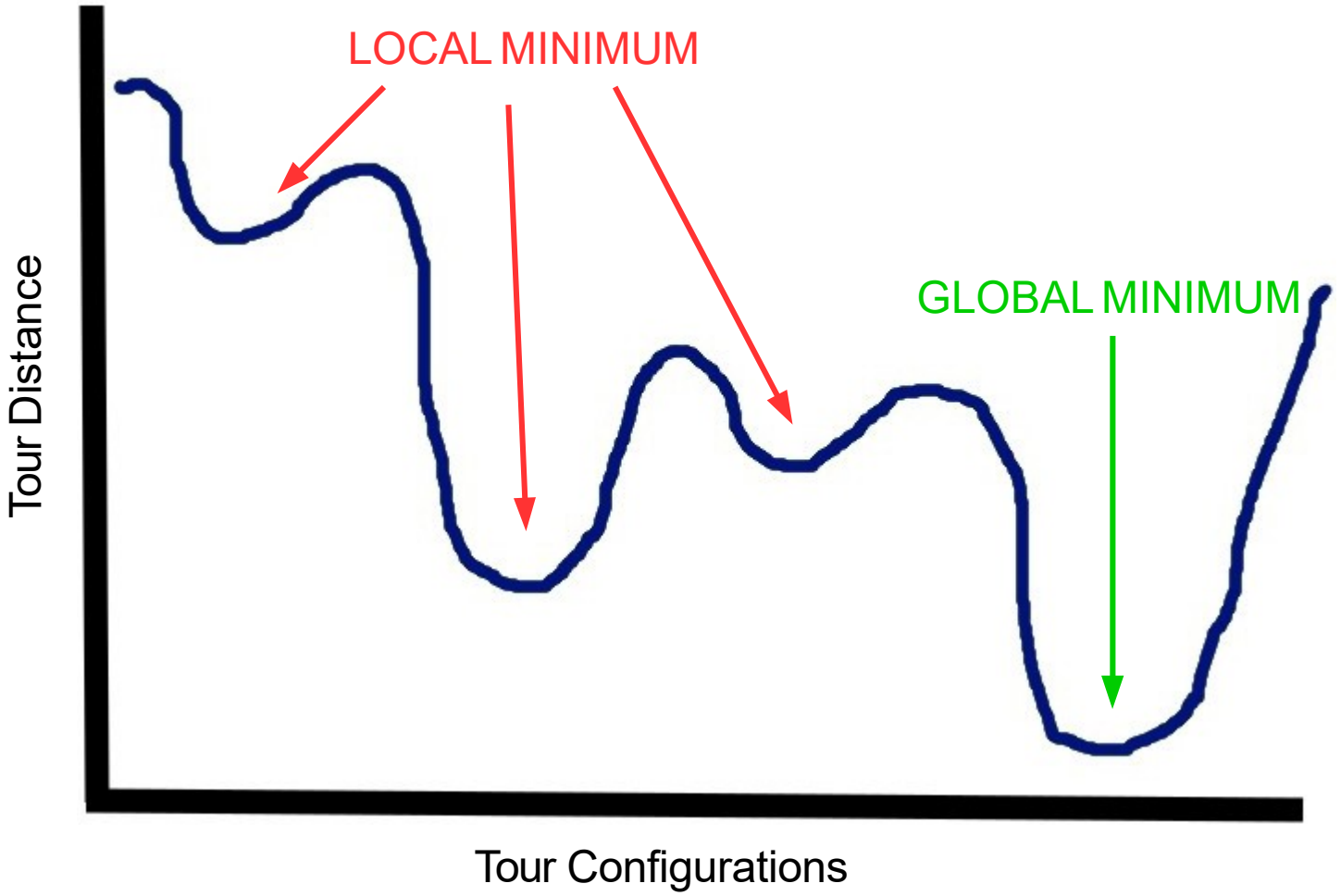
1) **Start with a random solution, even if it is poor quality.**

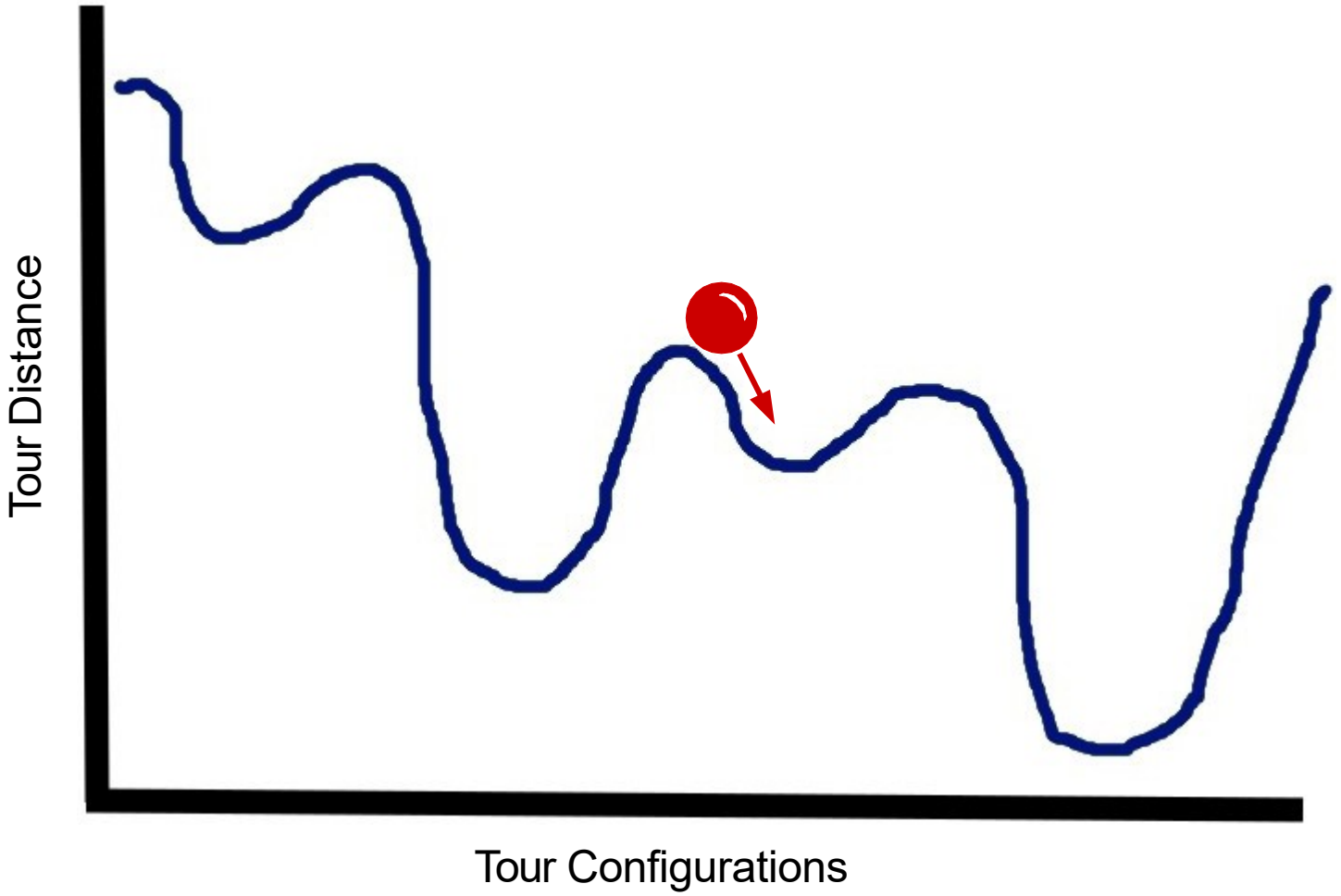
2) **Repeat the following steps for a number of iterations and/or until the solution cannot improve anymore.**

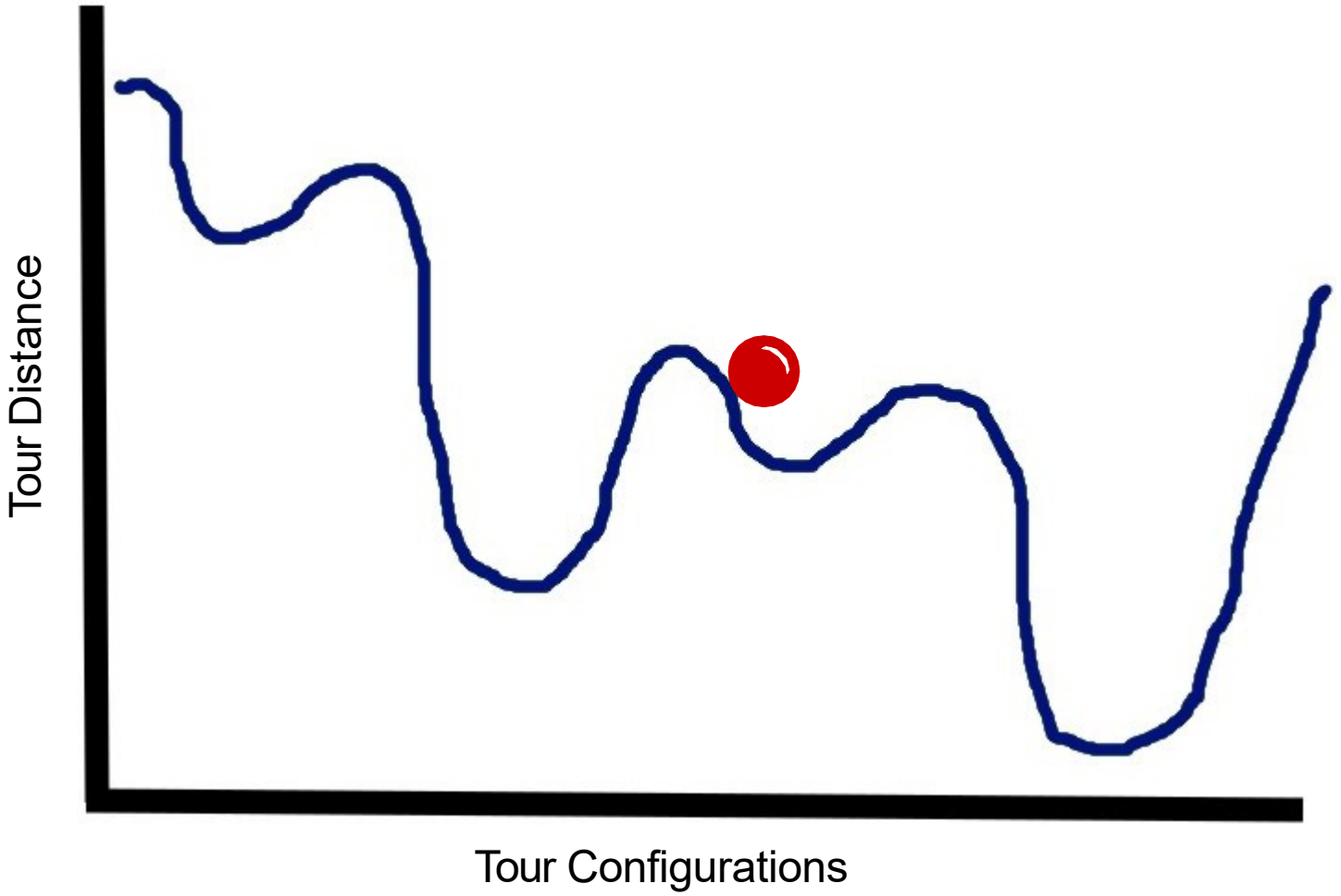
    1. Select a random part of the solution and change it.
    2. If that results in an improvement, keep it.

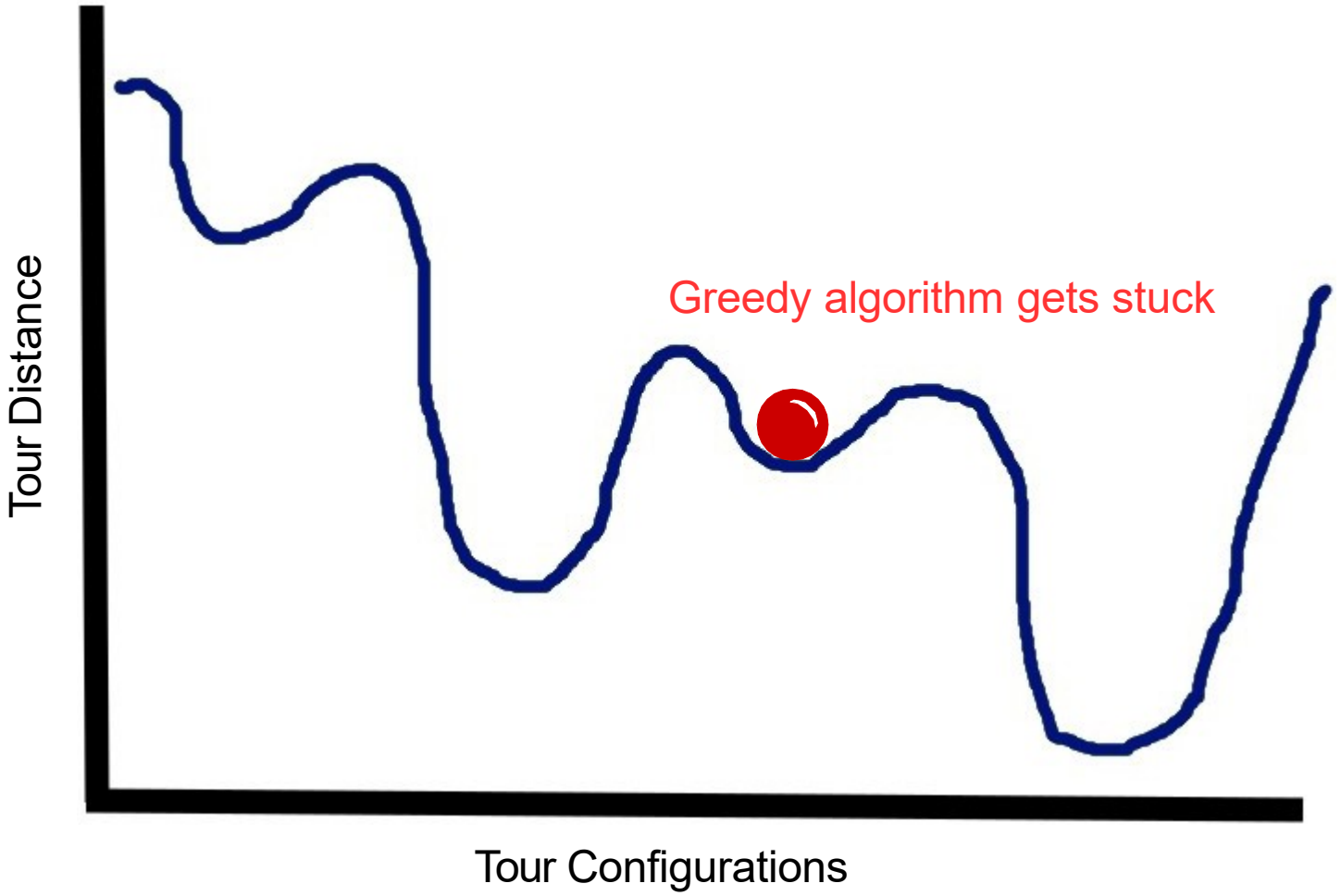
Easy, right? But there is a problem…

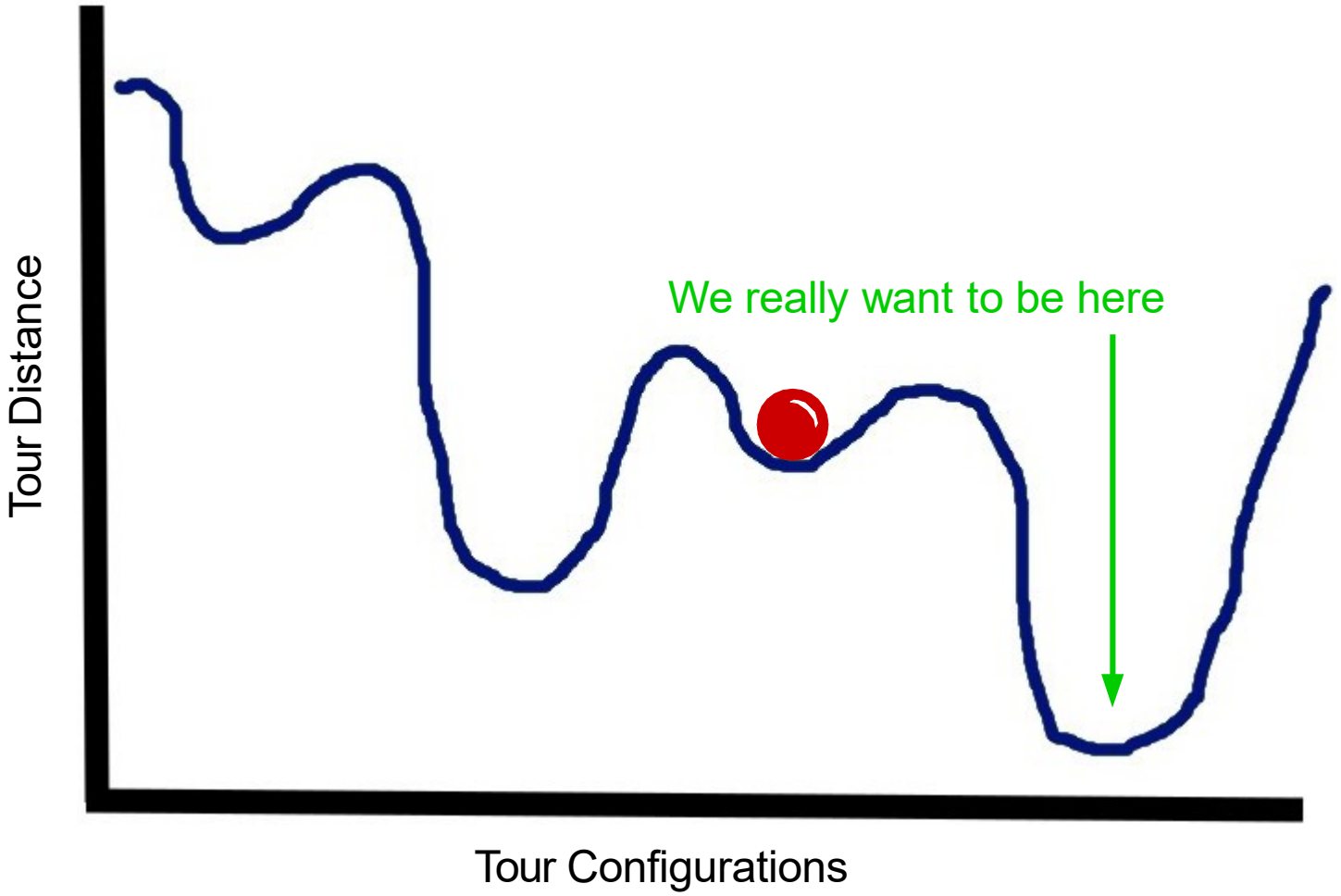

Tour Distance
Tour Configurations

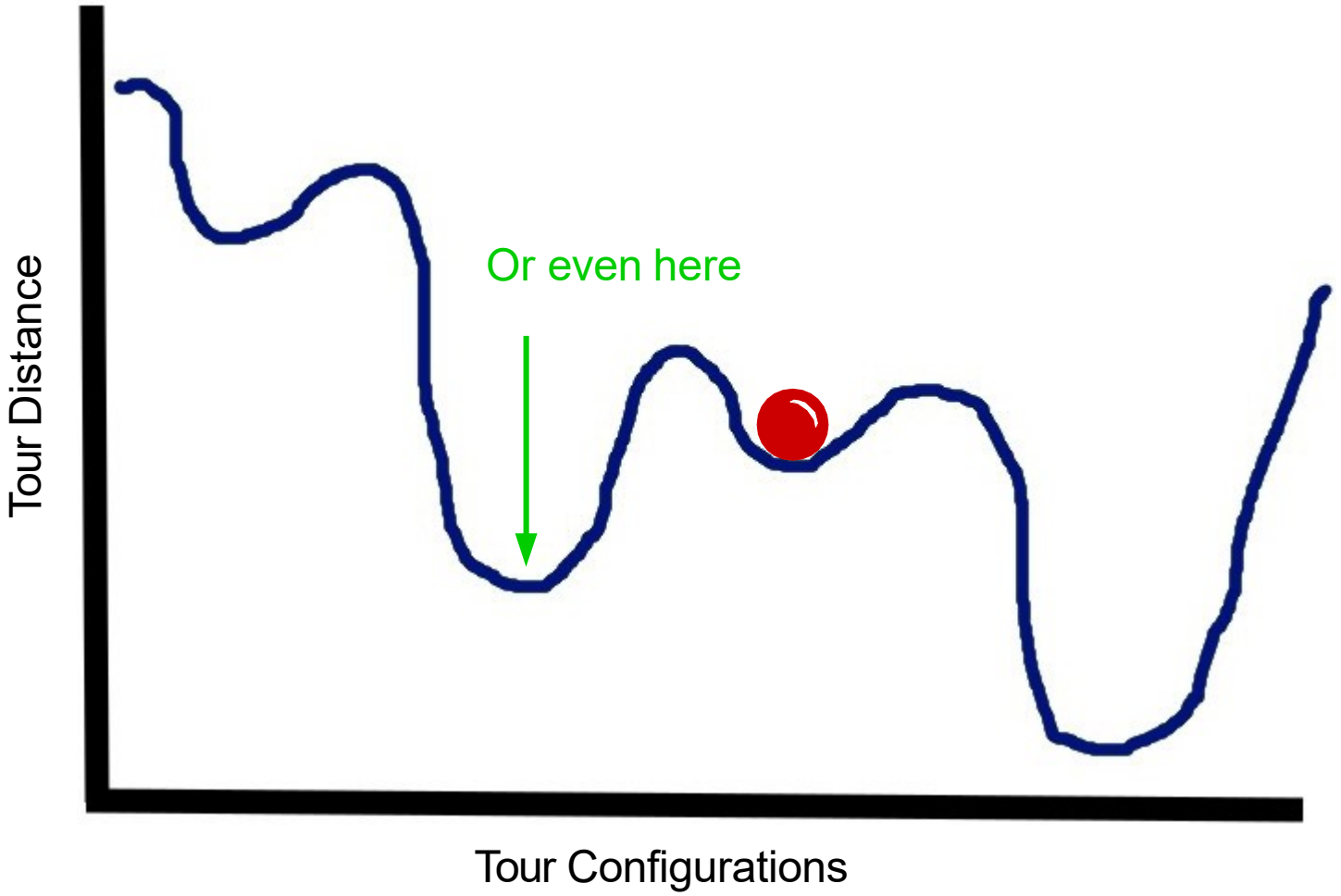

LOCAL MINIMUM
GLOBAL MINIMUM
Tour Distance
Tour Configurations

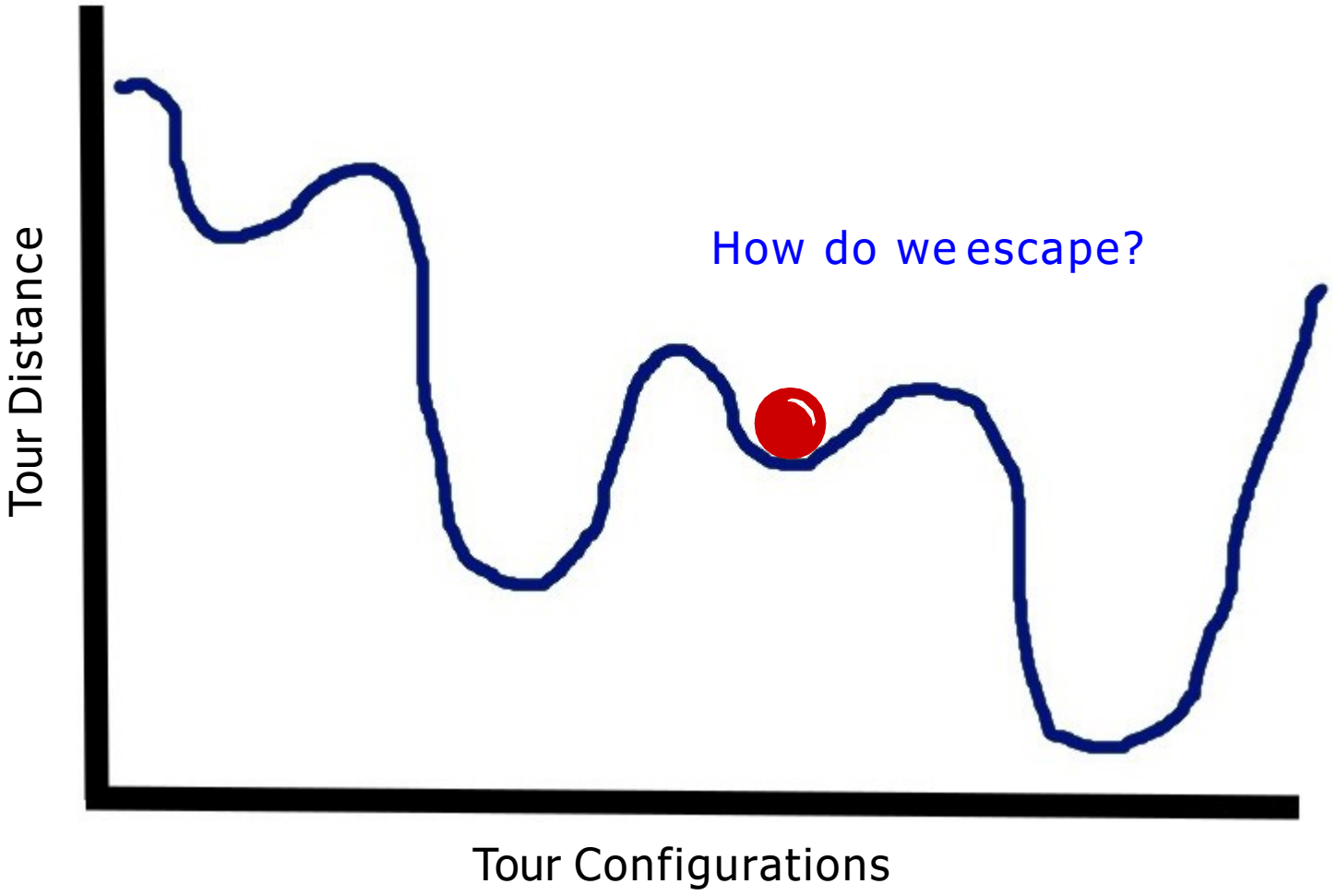

Tour Distance
Tour Configurations

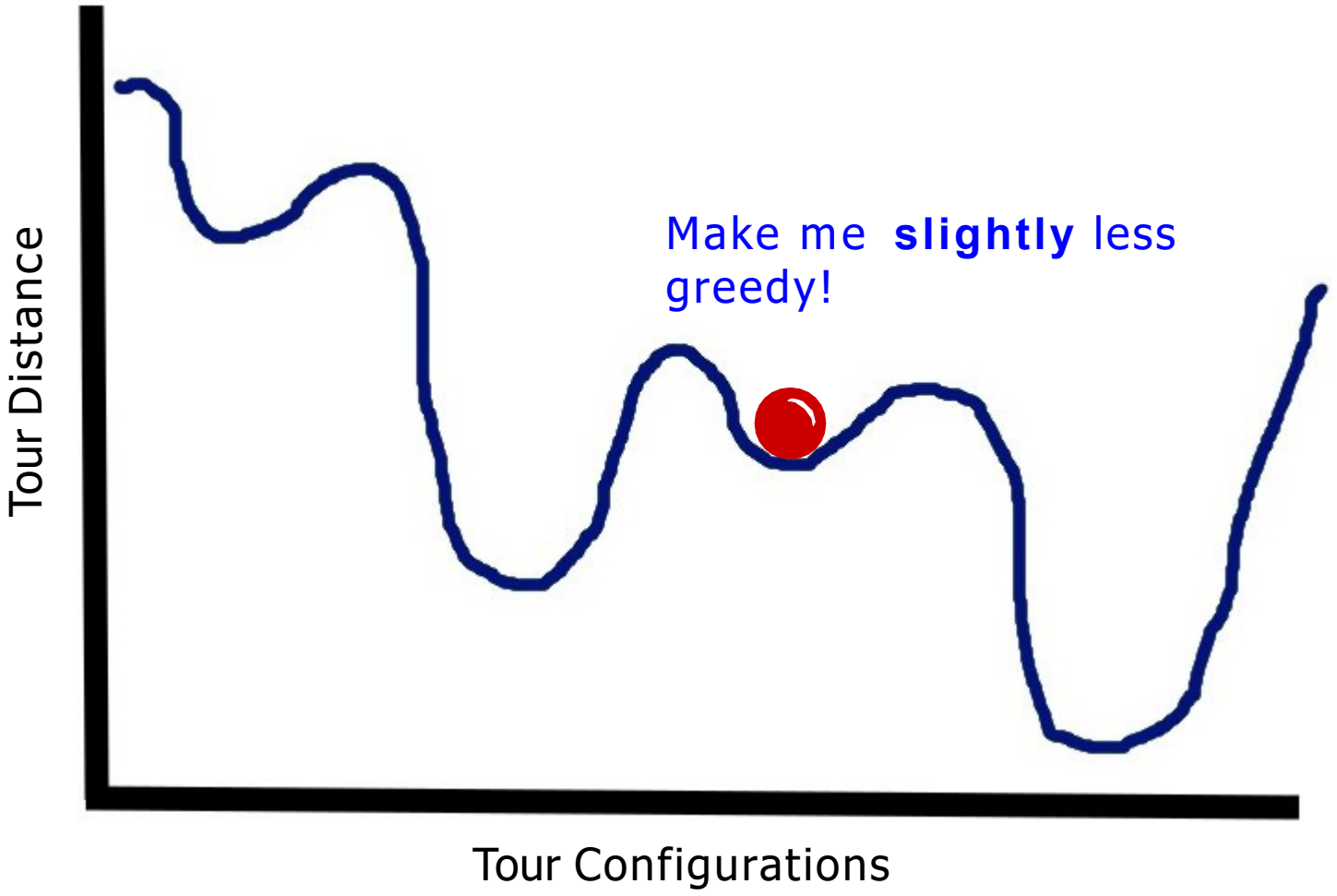

Tour Distance
Tour Configurations

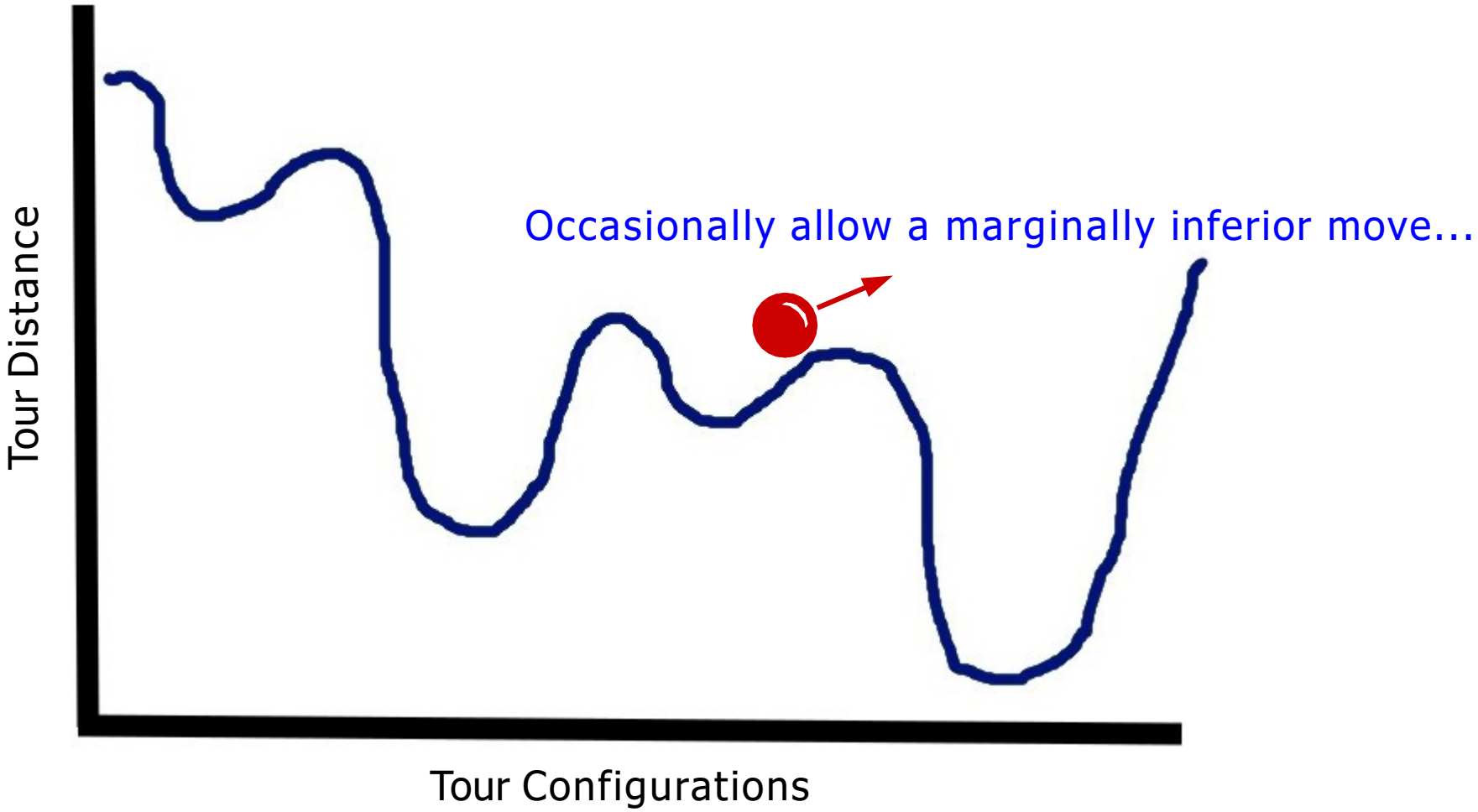

Greedy algorithm gets stuck
Tour Distance
Tour Configurations

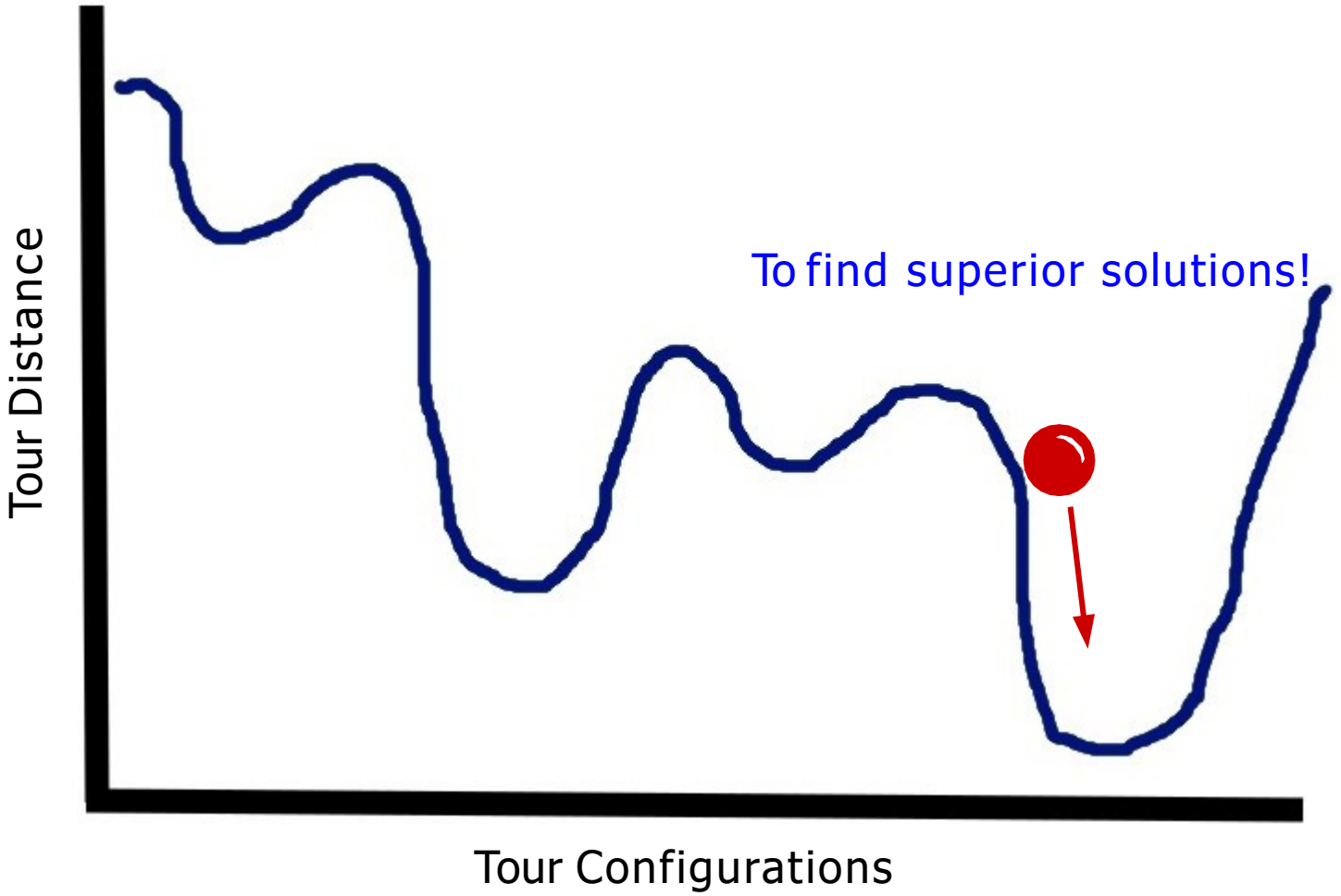

Tour Distance
We really want to be here
Tour Configurations

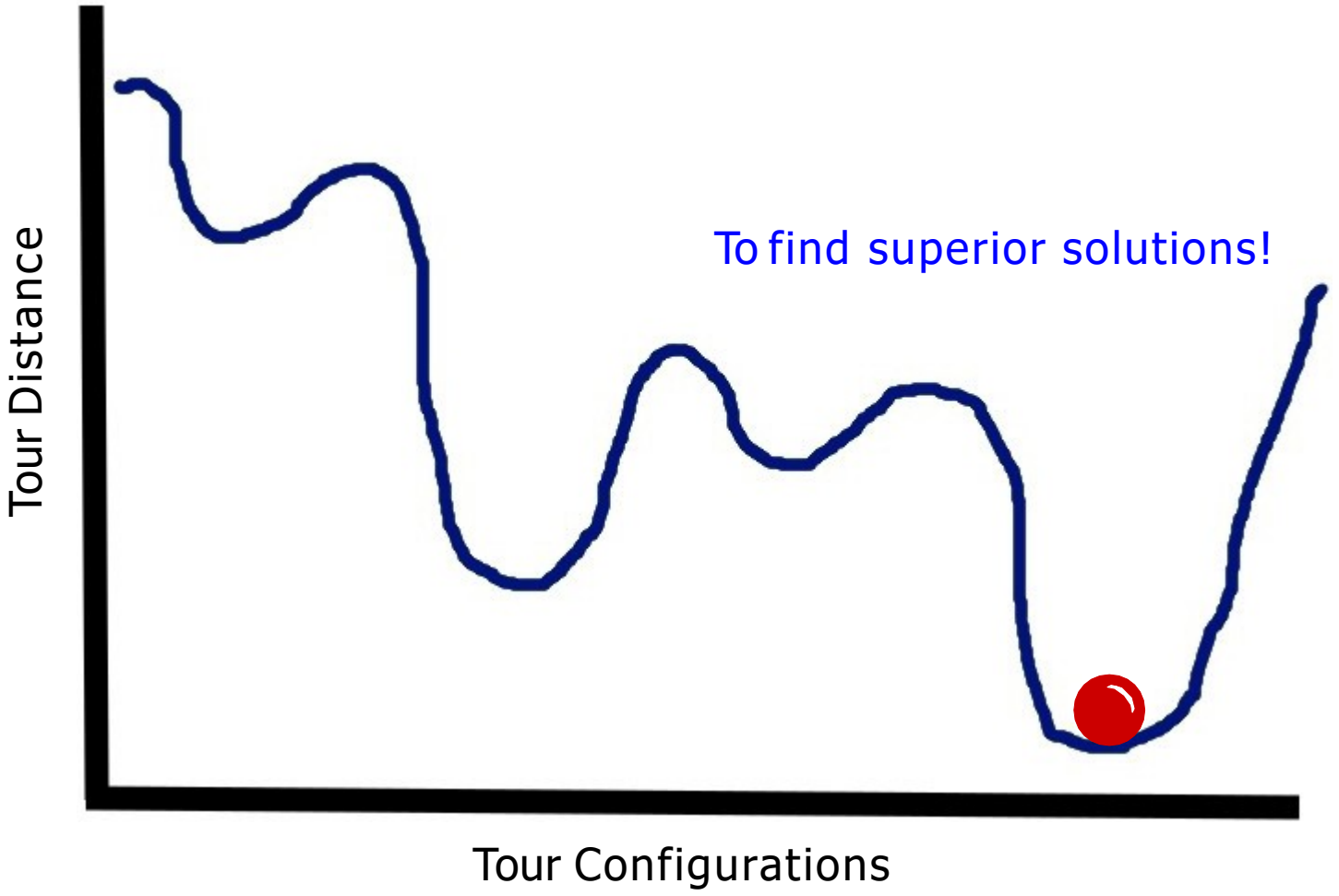

Tour Distance
Or even here
Tour Configurations


How do we escape?
Tour Distance
Tour Configurations


Tour Distance
Make me **slightly** less greedy!
Tour Configurations


Occasionally allow a marginally inferior move...
Tour Distance
Tour Configurations


Tour Distance
To find superior solutions!
Tour Configurations


Tour Distance
To find superior solutions!
Tour Configurations

Simulated Annealing

Simulated annealing **is another metaheuristic similar to hill-climbing, but it periodically allows inferior moves hoping it will lead to better solutions.**

It can be surprisingly versatile, and used to optimize problems ranging from the Traveling Salesman to tuning neural networks.

So how do you determine whether to keep an inferior move?

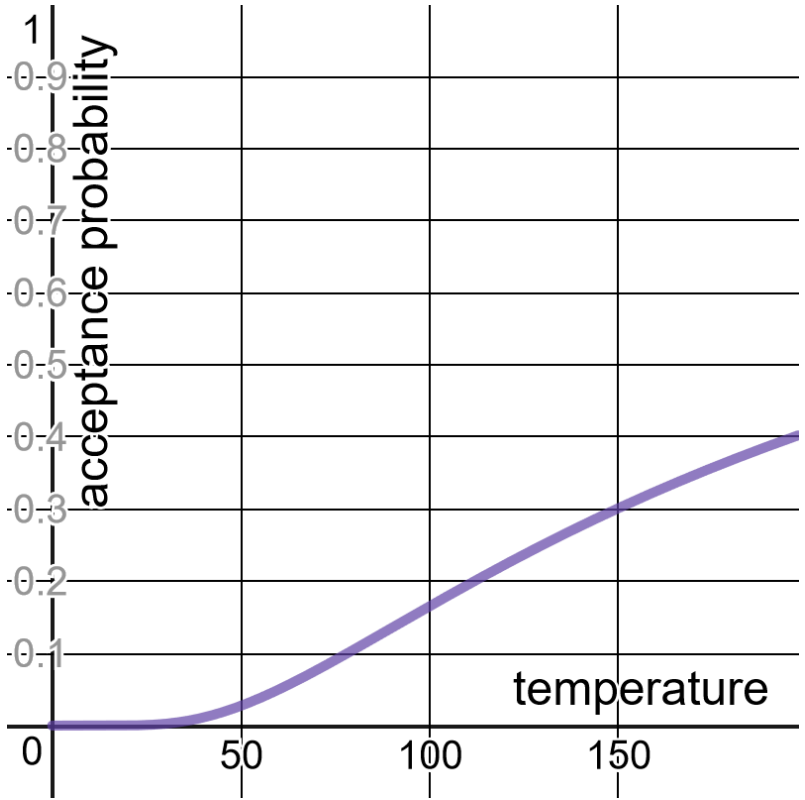
- A temperature schedule throttles periodically between greediness (don't accept an inferior move) and randomness (accept an inferior move).
- A given temperature on the given iteration will result in a weighted coin flip, and that coin flip will determine whether the inferior move is accepted or not.

Calculating the Weighted Coin Flip Probability

*Where **x** is a given temperature, here is how to convert it into a probability of accepting an inferior move.*

***d*_{degrading}** *and* ***d*_{current}** *reflect the inferior distance and current distance of the move respectively.*

$$\exp\left(\frac{-\left(d_{degrading}-d_{current}\right)}{x}\right)$$



https://www.desmos.com/calculator/rpfpfiq7ce

Metaheuristic – Simulated Annealing

1) **Start with a random solution, even if it is poor quality.**

2) **At each given temperature/iteration, do the following steps:**
   1. Select a random variable in the solution and change it.
   2. If that results in an improvement, keep it.
   3. If the result is inferior, *flip a weighted coin* based on the temperature and degradation of the move to determine whether to keep it.

3) **If your solution is not acceptable, modify your temperature schedule and try again.**

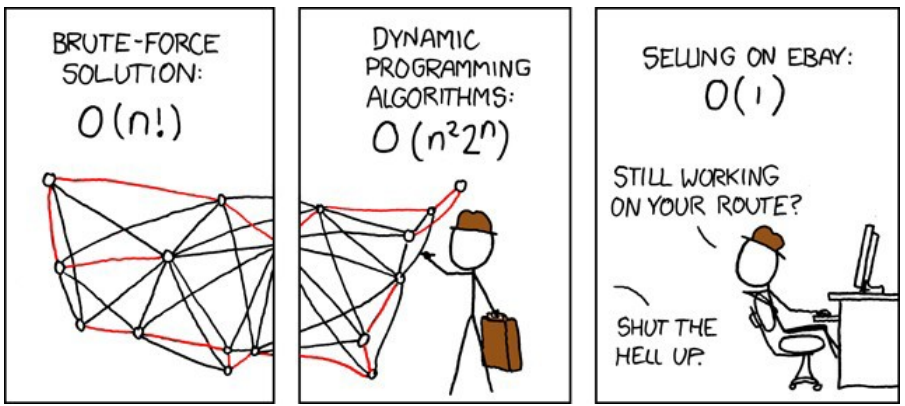
Source Code

Traveling Salesman Demo

https://github.com/thomasnield/traveling_salesman_demo

Traveling Salesman Plotter

https://github.com/thomasnield/traveling_salesman_plotter



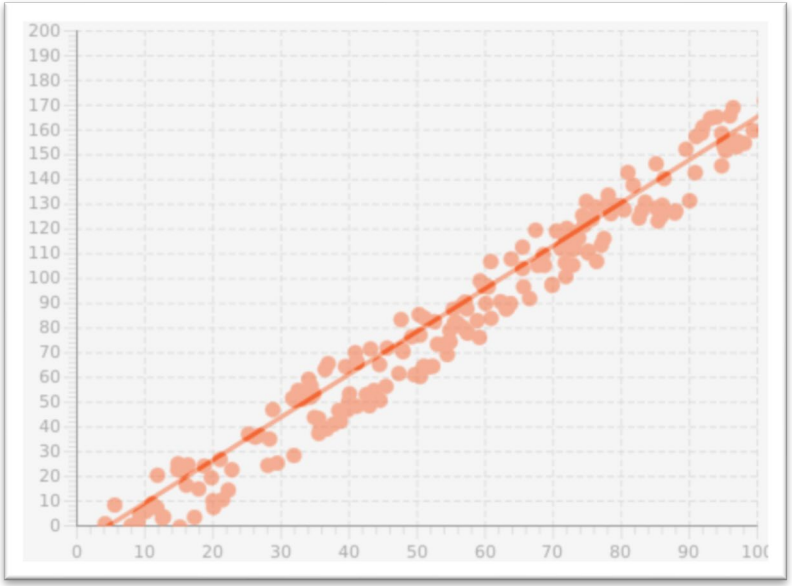
SOURCE: xkcd.com

Metaheuristics for Linear Regression

Let's use hill climbing/simulated annealing for a simple problem with continuous variables: linear regression.

A simple linear regression fits a line of the form **y = mx + b**, where we find the best **m** and **b** values that fit the points, minimizing the sum of least squared differences.

Note: For an intuitive graph demonstration sum of least squares fitting:
https://www.desmos.com/calculator/lywhybetzt

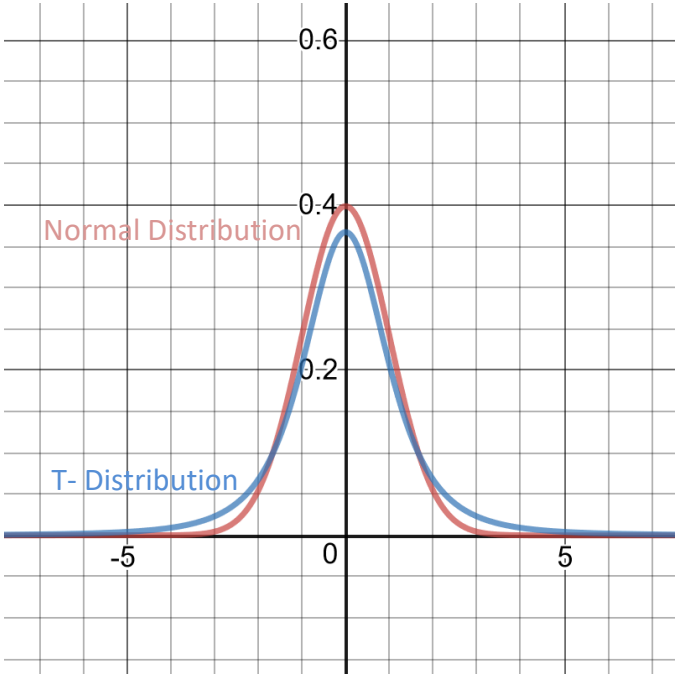


Metaheuristics for Linear Regression

Since they are continuous and not discrete, how do we randomly change values for m or b?

- We randomly increase/decrease **m** and **b** with random values from a standard normal distribution, or even better a T-Distribution which has fatter tails.
- Fatter tails = more smaller/larger values = more diverse moves.

We can use these random adjustments to m and b as our moves in hill climbing and simulated annealing.



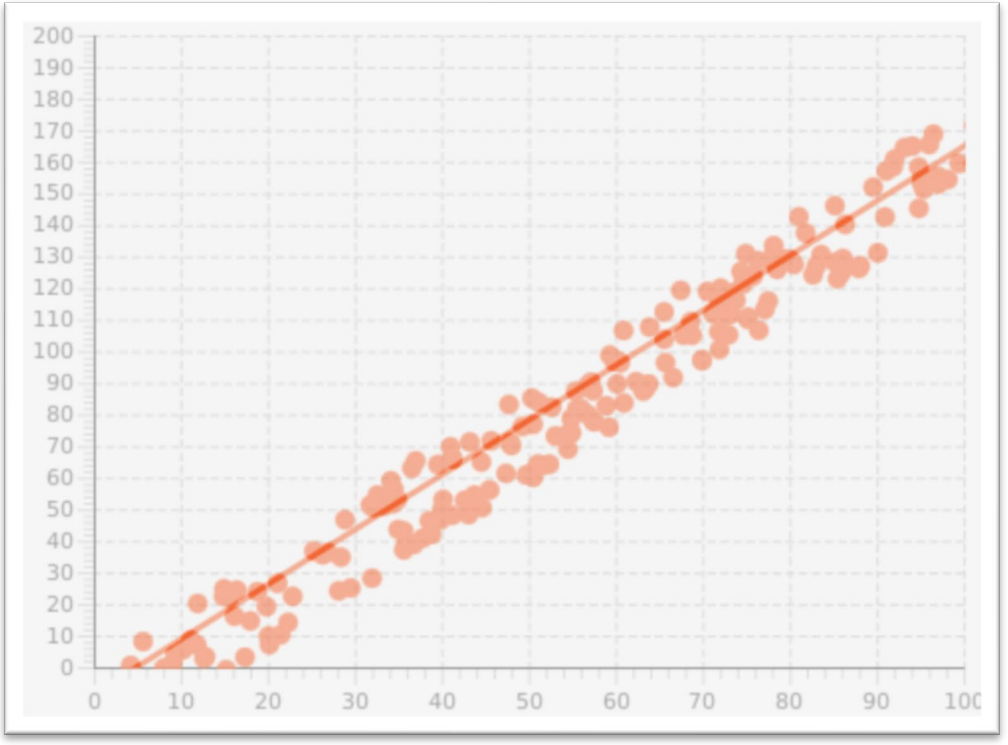
https://www.desmos.com/calculator/xm56tvvalh

Metaheuristics for Quantile Regression

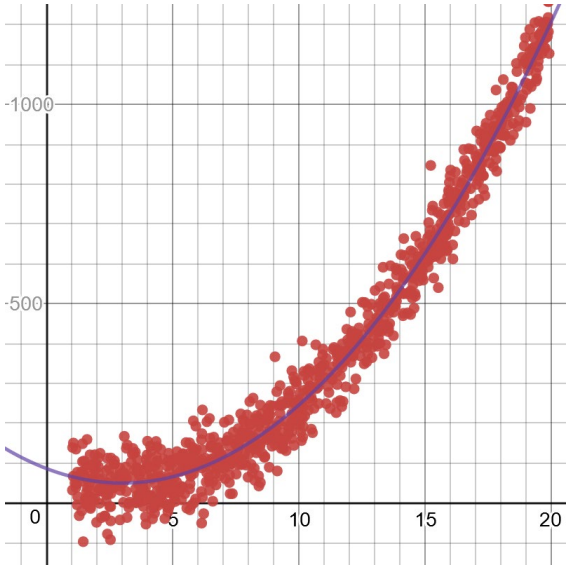
What's cool about building search algorithms is we can pursue weird, niche, and even nonlinear objectives often needed in real-world problems, even if we don't know how to mathematically implement them.

This may not yield the most efficient or precise approach, but it can be effective nonetheless. For example, quantile regression is just like linear regression, but it puts a percentage of points under the line.

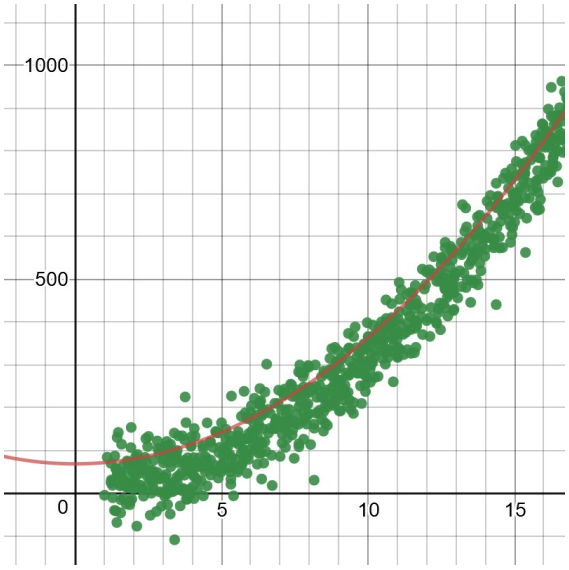
If you want 80% of the point to fall under the line, you can quickly build a search algorithm seeking that objective rather than having to deep dive into niche Calculus concepts.



Use Metaheuristics for Nonlinear Regressions Too!



Regression for $f(x) = ax^2 + b$
https://www.desmos.com/calculator/zdlsp6erjq



80% quantile regression for $f(x) = ax^2 + b$
https://www.desmos.com/calculator/4yp5m3lj5h

Python Code:
https://bit.ly/2VQAjnn

Other Metaheuristics Algorithms

Hill Climbing and Simulated Annealing are practical workhorses for a lot of optimization problems
There are many other metaheuristics algorithms, some of which you might have heard of:

- Genetic algorithms
- Tabu search
- Ant colony optimization
- Evolutionary algorithms
- K-Opt

Go down the rabbit hole: https://en.wikipedia.org/wiki/Metaheuristic

Using Randomness for Simulation

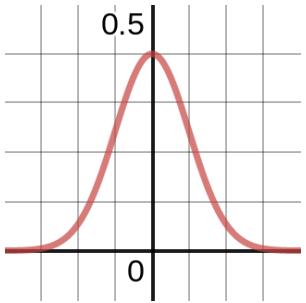
You may be familiar with random number generators

When any number is equally likely to be generated, this is known as a *Uniform* distribution

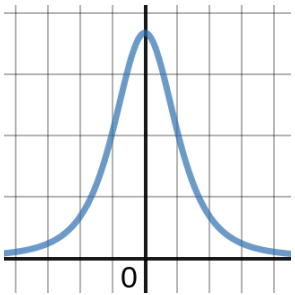
But what if we wanted some numbers to be generated more likely than others?

This can be a powerful tool and can be used to create simulations.

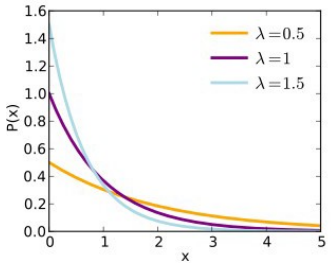
Some Useful Distributions



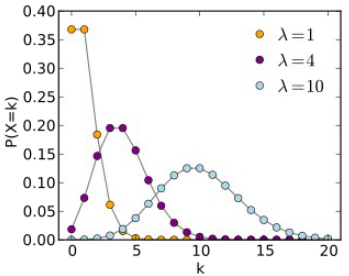
Normal



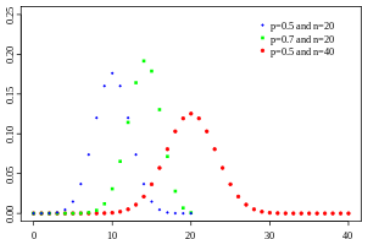
T-Distribution



Exponential



Poisson



Binomial

Learn More:

https://www.coursera.org/learn/introductiontoprobability

Generating a Schedule

You need to generate a schedule for a single classroom with the following classes:

Psych 101 (1 hour, 2 sessions/week)
English 101 (1.5 hours, 2 sessions/week)
Math 300 (1.5 hours, 2 sessions/week)
Psych 300 (3 hours, 1 session/week)
Calculus I (2 hours, 2 sessions/week)
Linear Algebra I (2 hours, 3 sessions/week)
Sociology 101 (1 hour, 2 sessions/week)
Biology 101 (1 hour, 2 sessions/week)
Supply Chain 300 (2.5 hours, 2 sessions/week)
Orientation 101 (1 hour, 1 session/week)

Available scheduling times are Monday through Friday, 8:00AM-11:30AM, 1:00PM-5:00PM
Slots are scheduled in 15 minute increments.

Generating a Schedule

Visualize a grid of each 15-minute increment from Monday through Sunday, intersected with each possible class.

Each cell will be a 1 or 0 indicating whether that's the start of the first class.

	MON	MON	MON	MON	MON	MON	MON	MON		SUN
	12:00 AM	12:15 AM	12:30 AM	12:45 AM	1:00 AM	1:15 AM	1:30 AM	1:45 AM	...	11:55 PM
Psych 101	0	0	0	0	0	0	0	0	...	0
English 101	0	0	0	0	0	0	0	0	...	0
Math 300	0	0	0	0	0	0	0	0	...	0
Psych 300	0	0	0	0	0	0	0	0	...	0
Calculus I	0	0	0	0	0	0	0	0	...	0
Linear Algebra I	0	0	0	0	0	0	0	0	...	0
Sociology 101	0	0	0	0	0	0	0	0	...	0
Biology 101	0	0	0	0	0	0	0	0	...	0
Supply Chain 300	0	0	0	0	0	0	0	0	...	0
Orientation 101	0	0	0	0	0	0	0	0	...	0

Generating a Schedule

Next visualize how overlaps will occur.

Notice how a 9:00AM Psych 101 class will clash with a 9:15AM Sociology 101.

We can sum all blocks that affect the 9:45AM block and ensure they don't exceed 1.

		MON	MON	MON	MON	MON	MON	MON	MON		SUN
	...	9:00 AM	9:15 AM	9:30 AM	9:45 AM	10:00 AM	10:15 AM	10:30 AM	10:45 AM	...	11:55 PM
Psych 101	...	1	0	0	0	0	0	0	0	...	0
English 101	...	0	0	0	0	0	0	0	0	...	0
Math 300	...	0	0	0	0	0	0	0	0	...	0
Psych 300	...	0	0	0	0	0	0	0	0	...	0
Calculus I	...	0	0	0	0	0	0	0	0	...	0
Linear Algebra I	...	0	0	0	0	0	0	0	0	...	0
Sociology 101	...	0	1	0	0	0	0	0	0	...	0
Biology 101	...	0	0	0	0	0	0	0	0	...	0
Supply Chain 300	...	0	0	0	0	0	0	0	0	...	0
Orientation 101	...	0	0	0	0	0	0	0	0	...	0

Sum of affecting slots = 2
FAIL, sum must be <=1

Generating a Schedule

Next visualize how overlaps will occur.

Notice how a 9:00AM Psych 101 class will clash with a 9:30AM Sociology 101.

We can sum all blocks that affect the 9:45AM block and ensure they don't exceed 1.

		MON	MON	MON	MON	MON	MON	MON	MON		SUN
	...	9:00 AM	9:15 AM	9:30 AM	9:45 AM	10:00 AM	10:15 AM	10:30 AM	10:45 AM	...	11:55 PM
Psych 101	...	1	0	0	0	0	0	0	0	...	0
English 101	...	0	0	0	0	0	0	0	0	...	0
Math 300	...	0	0	0	0	0	0	0	0	...	0
Psych 300	...	0	0	0	0	0	0	0	0	...	0
Calculus I	...	0	0	0	0	0	0	0	0	...	0
Linear Algebra I	...	0	0	0	0	0	0	0	0	...	0
Sociology 101	...	0	0	1	0	0	0	0	0	...	0
Biology 101	...	0	0	0	0	0	0	0	0	...	0
Supply Chain 300	...	0	0	0	0	0	0	0	0	...	0
Orientation 101	...	0	0	0	0	0	0	0	0	...	0

Sum of affecting slots = 2
FAIL, sum must be <=1

Generating a Schedule

Next visualize how overlaps will occur.

Notice how a 9:00AM Psych 101 class will clash with a 9:45AM Sociology 101.

We can sum all blocks that affect the 9:45AM block and ensure they don't exceed 1.

		MON	MON	MON	MON	MON	MON	MON	MON		SUN
	...	9:00 AM	9:15 AM	9:30 AM	9:45 AM	10:00 AM	10:15 AM	10:30 AM	10:45 AM	...	11:55 PM
Psych 101	...	1	0	0	0	0	0	0	0	...	0
English 101	...	0	0	0	0	0	0	0	0	...	0
Math 300	...	0	0	0	0	0	0	0	0	...	0
Psych 300	...	0	0	0	0	0	0	0	0	...	0
Calculus I	...	0	0	0	0	0	0	0	0	...	0
Linear Algebra I	...	0	0	0	0	0	0	0	0	...	0
Sociology 101	...	0	0	0	1	0	0	0	0	...	0
Biology 101	...	0	0	0	0	0	0	0	0	...	0
Supply Chain 300	...	0	0	0	0	0	0	0	0	...	0
Orientation 101	...	0	0	0	0	0	0	0	0	...	0

Sum of affecting slots = 2
FAIL, sum must be <=1

Generating a Schedule

If the "sum" of all slots affecting a given block are no more than 1, then we have no conflicts!

		MON	MON	MON	MON	MON	MON	MON	MON		SUN
	...	9:00 AM	9:15 AM	9:30 AM	9:45 AM	10:00 AM	10:15 AM	10:30 AM	10:45 AM	...	11:55 PM
Psych 101	...	1	0	0	0	0	0	0	0	...	0
English 101	...	0	0	0	0	0	0	0	0	...	0
Math 300	...	0	0	0	0	0	0	0	0	...	0
Psych 300	...	0	0	0	0	0	0	0	0	...	0
Calculus I	...	0	0	0	0	0	0	0	0	...	0
Linear Algebra I	...	0	0	0	0	0	0	0	0	...	0
Sociology 101	...	0	0	0	0	1	0	0	0	...	0
Biology 101	...	0	0	0	0	0	0	0	0	...	0
Supply Chain 300	...	0	0	0	0	0	0	0	0	...	0
Orientation 101	...	0	0	0	0	0	0	0	0	...	0

Sum of affecting slots = 1
SUCCESS!

Generating a Schedule

For every "block", we must sum all affecting slots (shaded below) which can be identified from the class durations.

This sum must be no more than 1.

		MON	MON	MON	MON	MON	MON	MON	MON	MON	MON	MON	MON	MON		SUN
	...	7:00 AM	7:15 AM	7:30 AM	7:45 AM	8:00 AM	8:15 AM	8:30 AM	8:45 AM	9:00 AM	9:15 AM	9:30 AM	9:45 AM	10:00 AM	...	11:55 PM
Psych 101	...	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0
English 101	...	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0
Math 300	...	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0
Psych 300	...	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0
Calculus I	...	0	0	0	0	1	0	0	0	0	0	0	0	0	...	0
Linear Algebra I	...	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0
Sociology 101	...	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0
Biology 101	...	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0
Supply Chain 300	...	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0
Orientation 101	...	0	0	0	0	0	0	0	0	0	0	0	0	0	...	0

Generating a Schedule

Taking this concept even further, we can account for all recurrences.

The “affected slots” for a given block can query for all recurrences for each given class.

View image here.

Generating a Schedule

Plug these variables and *feasible* constraints into the optimizer or a tree search algorithm (which I'll show next), and you will get a solution.

Most of the work will be finding the affecting slots for each block.

Hold that Thought, Let's Talk About State Space Search

Imagine you are presented a Sudoku.

Rather than do an exhaustive brute-force search, think in terms of constraint programming to reduce the search space.

First, sort the cells by the count of possible values they have left:

5	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

Solving a Sudoku

[4,4] →5
[7,7] →3
[8,6] →4
[1,4] →2, 5
[0,7] →2, 3
[3,2] →2, 3
[4,2] →3, 4
[5,2] →2, 4
[3,5] →5, 9
[5,5] →1, 4
[4,6] →3, 5
[5,8] →2, 6
[6,7] →3, 6
[2,6] →1,7
[0,2] →1, 2, 3
[1,3] →1, 2, 5
…
[2,6] →1,3,4,5,7,9

Put cells in a list sorted by possible candidate count

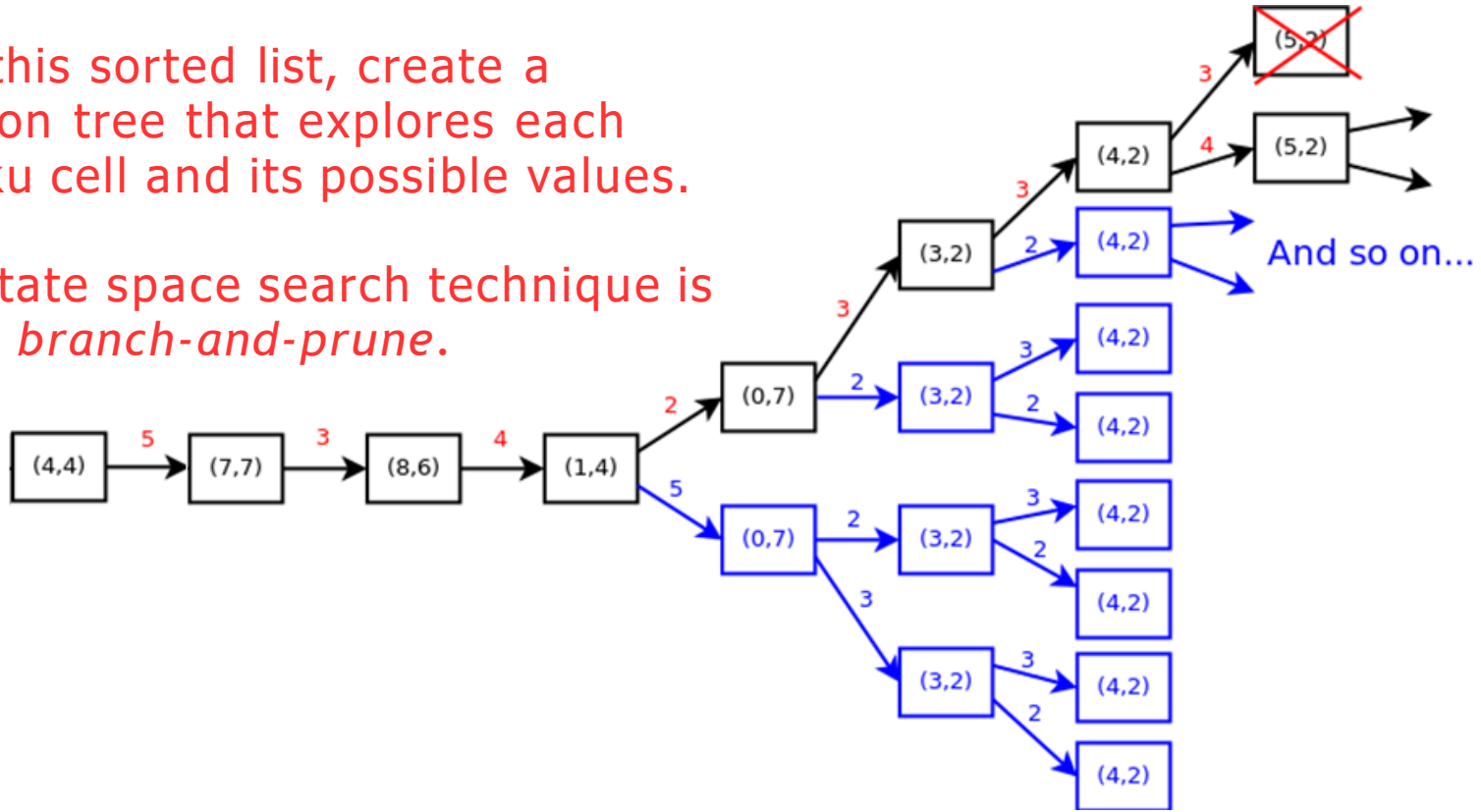
	0	1	2	3	4	5	6	7	8
0	5	3			7				
1	6			1	9	5			
2		9	8					6	
3	8				6				3
4	4			8		3			1
5	7				2				6
6		6					2	8	
7				4	1	9			5
8					8			7	9

Solving a Sudoku

[4,4] →5
[7,7] →3
[8,6] →4
[1,4] →2, 5
[0,7] →2, 3
[3,2] →2, 3
[4,2] →3, 4
[5,2] →2, 4
[3,5] →5, 9
[5,5] →1, 4
[4,6] →3, 5
[5,8] →2, 6
[6,7] →3, 6
[2,6] →1,7
[0,2] →1, 2, 3
[1,3] →1, 2, 5
…
[2,6] →1,3,4,5,7,9

With this sorted list, create a decision tree that explores each Sudoku cell and its possible values.

This state space search technique is called *branch-and-prune*.



Solving a Sudoku

A branch should terminate immediately when it finds an infeasible configuration, and then explore the next branch.

After we have a branch that provides a feasible value to every cell, we have solved our Sudoku!

Unlike many optimization problems, Sudokus are trivial to solve because they constrain their search spaces quickly.

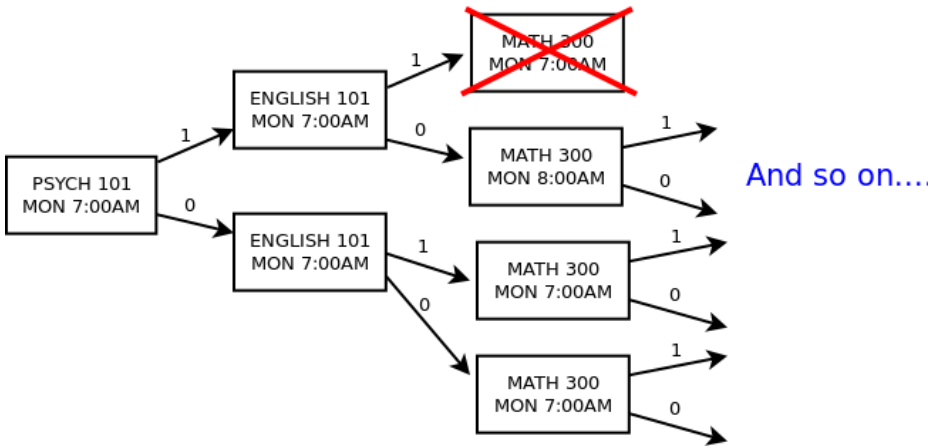
5	3	4	6	7	8	9	1	2
6	7	2	1	9	5	3	4	8
1	9	8	3	4	2	5	6	7
8	5	9	7	6	1	4	2	3
4	2	6	8	5	3	7	9	1
7	1	3	9	2	4	8	5	6
9	6	1	5	3	7	2	8	4
2	8	7	4	1	9	6	3	5
3	4	5	2	8	6	1	7	9

Branch-and-Prune for Scheduling

You could solve the scheduling problem from scratch with branch-and-prune.

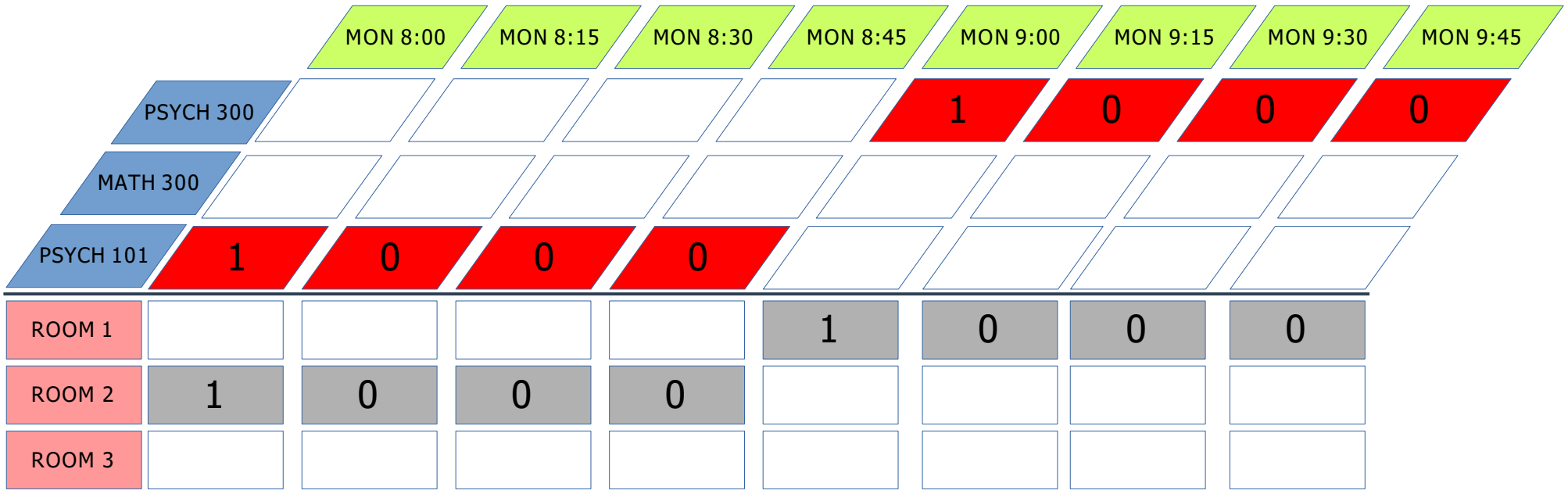
Start with the most "constrained" slots first to narrow your search space (e.g. slots fixed to zero first, followed by Monday slots for 3-recurrence classes).

HINT: Proactively prune the tree as you go, eliminating any slots ahead that must be zero due to a "1" decision propagating an occupied state.

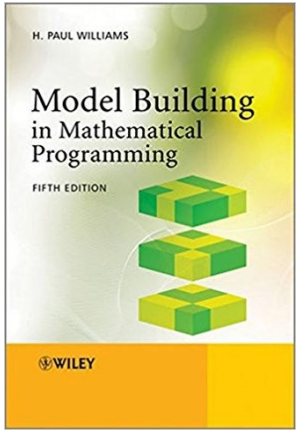


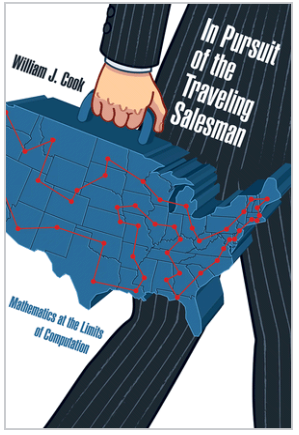
Generating a Schedule

If you want to schedule against multiple rooms, plot each variable using three dimensions.

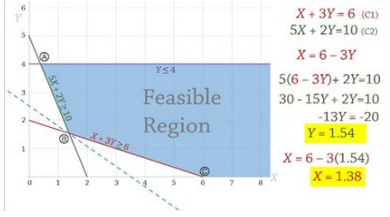


Learn More

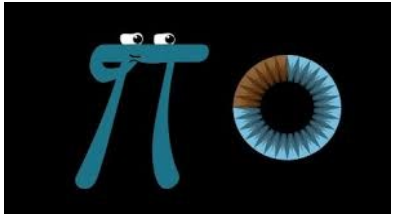




PatrickJMT on YouTube



Joshua Emmanuel on YouTube



3Blue1Brown on YouTube

Classifying Things

Probably the most common task in machine learning is classifying data:

- How do I identify images of ***dogs*** vs ***cats***?
- What ***words*** are being said in a piece of audio?
- Is this email ***spam*** or ***not spam***?
- What attributes define ***high-risk***, ***medium-risk***, and ***low-risk*** loan applicants?
- How do I predict if a shipment will be ***late,*** **early**, or ***on-time***?

There are many techniques to classify data, with pros/cons depending on the task:

- Neural Networks
- Support Vector Machines
- Decision Trees/Random Forests
- Naive Bayes
- Linear/Non-linear regression

Naive Bayes

Let's focus on Naive Bayes because it is simple to implement and effective for a common task: *text categorization*.

Naive Bayes is an adaptation of Bayes Theorem that can predict a category ***C*** for an item ***T*** with *multiple* features **F**.

A common usage example of Naive Bayes is email spam, where each word is a feature and **spam/not spam** are the possible categories.

Implementing Naive Bayes

Naive Bayes works by mapping probabilities of each individual feature occurring/not occurring for a given category (e.g. a word occurring in ***spam***/***not spam***).

A category can be predicted for a new set of features by...

1) For a given category, combine the probabilities of each feature ***occuring*** and ***not occuring*** by multiplying them.

$$\text{Occur Product} = P_{f1} * P_{f2} * \ldots P_{fn}$$

$$\text{Not Occur Product} = !P_{f1} * !P_{f2} * \ldots !P_{fn}$$

2) Divide the products to get the probability for that category.

$$\text{Combined Probability} = \frac{(\text{Occur Product})}{(\text{Occur Product}) + (\text{Not Occur Product})}$$

Implementing Naive Bayes

3) Calculate this for every category, and select the one with highest probability.

Dealing with floating point underflow.

A big problem is multiplying small decimals for a large number of features may cause a floating point underflow.

To remedy this, transform each probability with **log()** or **ln()** and sum them, then call **exp()** to convert the result back!

$$\text{Occur Product} = exp(ln(P_{f1}) + ln(P_{f2}) + \ldots ln(P_{fn}))$$

$$\text{Not Occur Product} = exp(ln(!P_{f1}) + ln(!P_{f2}) + \ldots ln(!P_{fn}))$$

Implementing Naive Bayes

One last consideration, never let a feature have a 0 probability for any category!

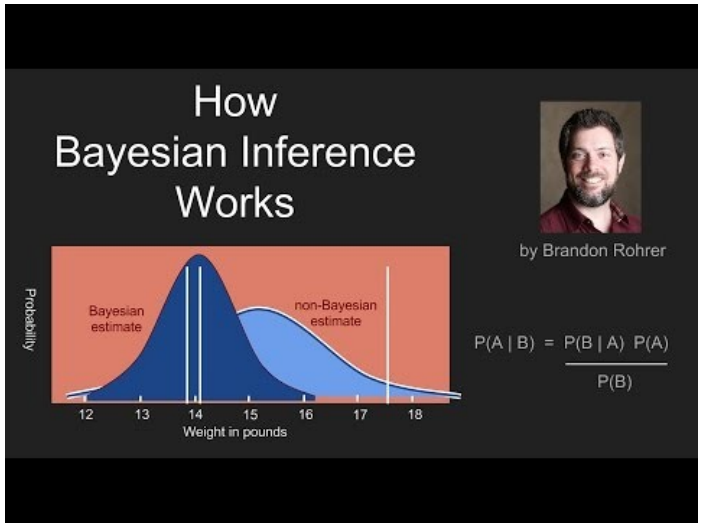
Always leave *a little* possibility it could belong to any category so you don't have *0* multiplication or division mess anything up.

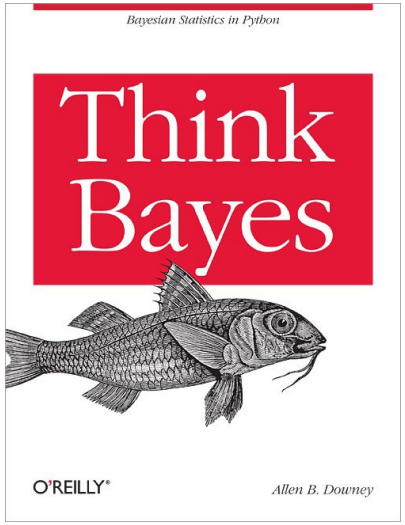
This can be done by adding a small value to each probability's numerator and denominator (e.g. *0.5* and *1.0*).

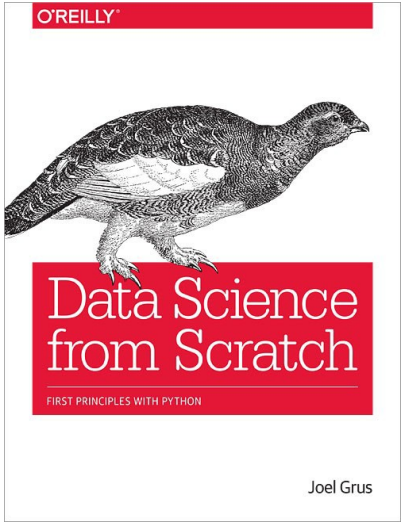
$$CombinedProbability = \frac{0.5 + (\text{Occur Product})}{1.0 + (\text{Occur Product}) + (\text{Not Occur Product})}$$

Learn More About Bayes

Brandon Rohrer - YouTube







Source Code

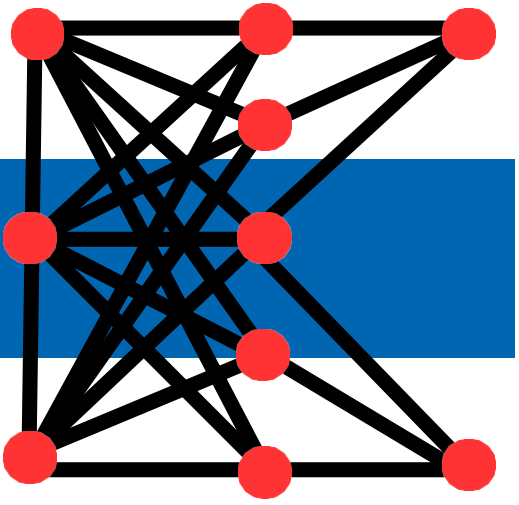
Bank Transaction Categorizer Demo

https://github.com/thomasnield/bayes_user_input_prediction

Email Spam Classifier Demo

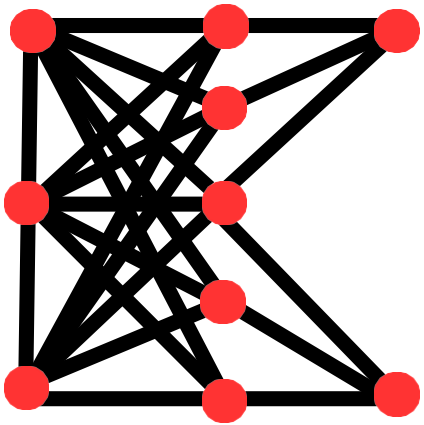
https://github.com/thomasnield/bayes_email_spam

Part III:
Neural Networks



What Are Neural Networks?

Neural Networks are a machine learning tool that takes numeric inputs and predicts numeric outputs.



A series of multiplication, addition, and nonlinear functions are applied to the numeric inputs.

The mathematical operations above are iteratively tweaked until the desired output is met.

The Problem

Suppose we wanted to take a background color (in RGB values) and predict a light/dark font for it.

Hello Hello

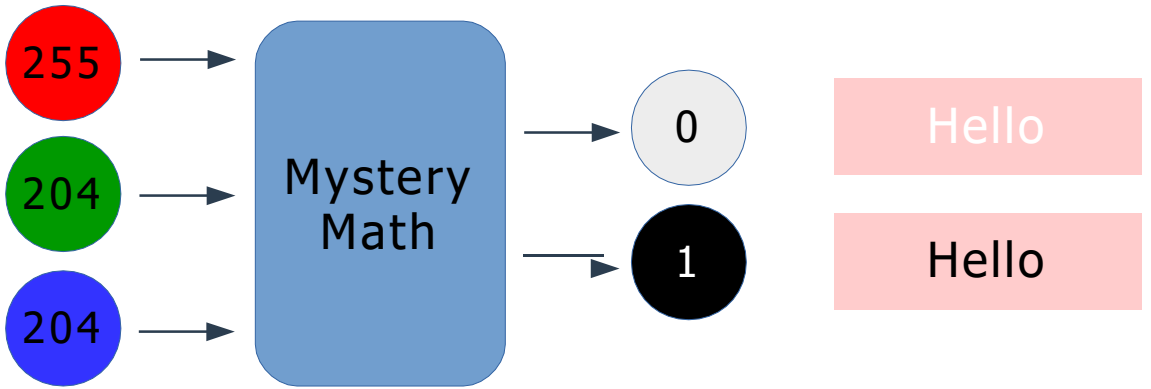
If you search around Stack Overflow, there is a nice formula to do this:

$$L = (.299R + .587G + .114B)/255$$

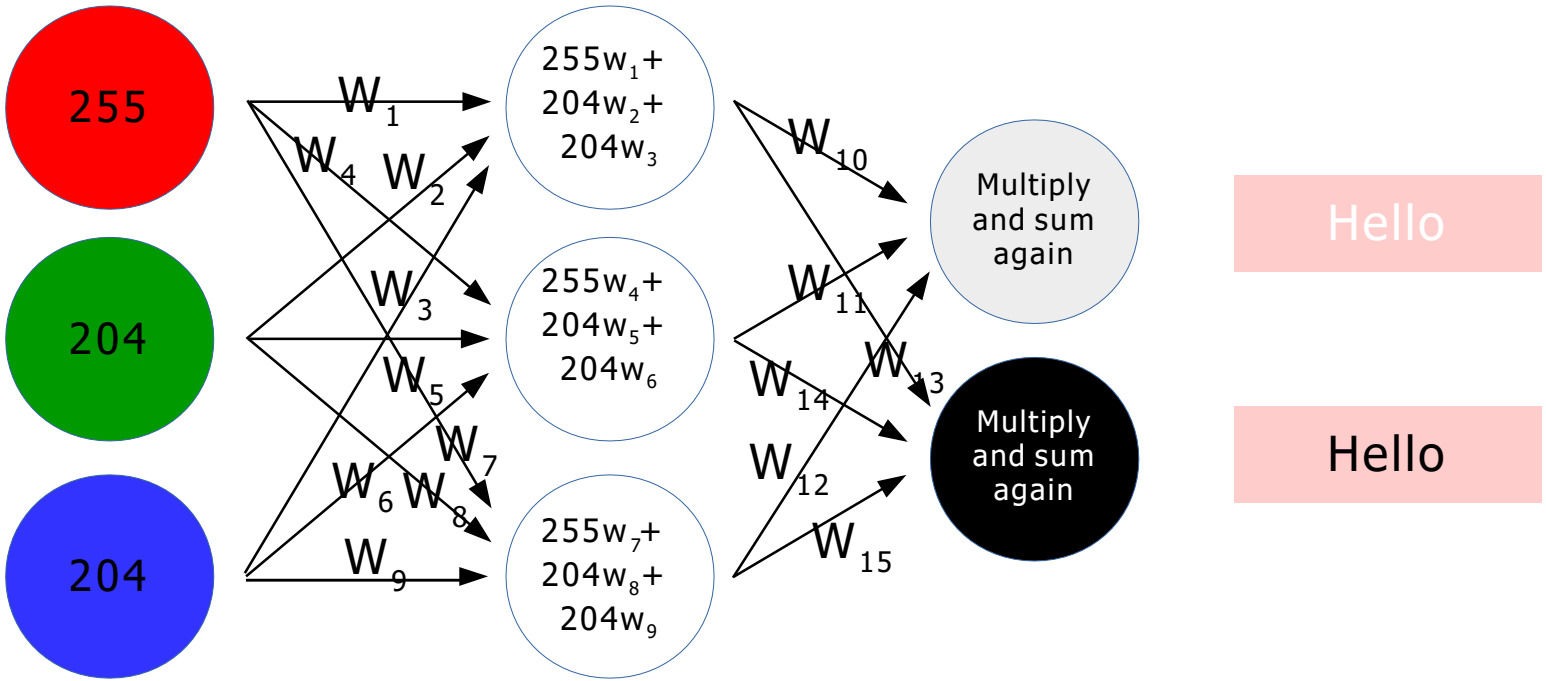
But what if we do not know the formula? Or one hasn't been discovered?

A Simple Neural Network

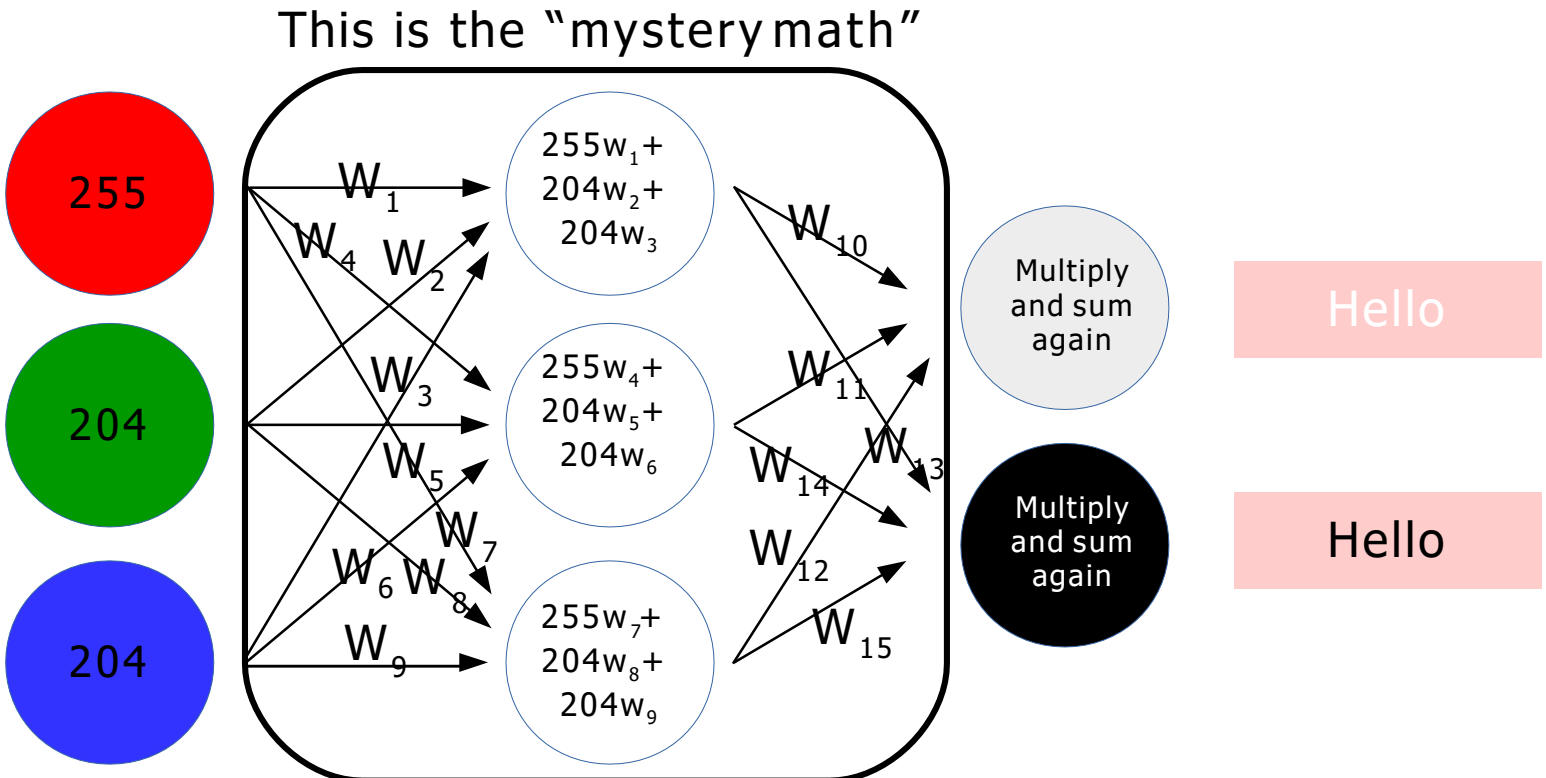
Let's represent background color as 3 numeric RGB inputs, and predict whether a DARK/LIGHT font should be used.



A Simple Neural Network

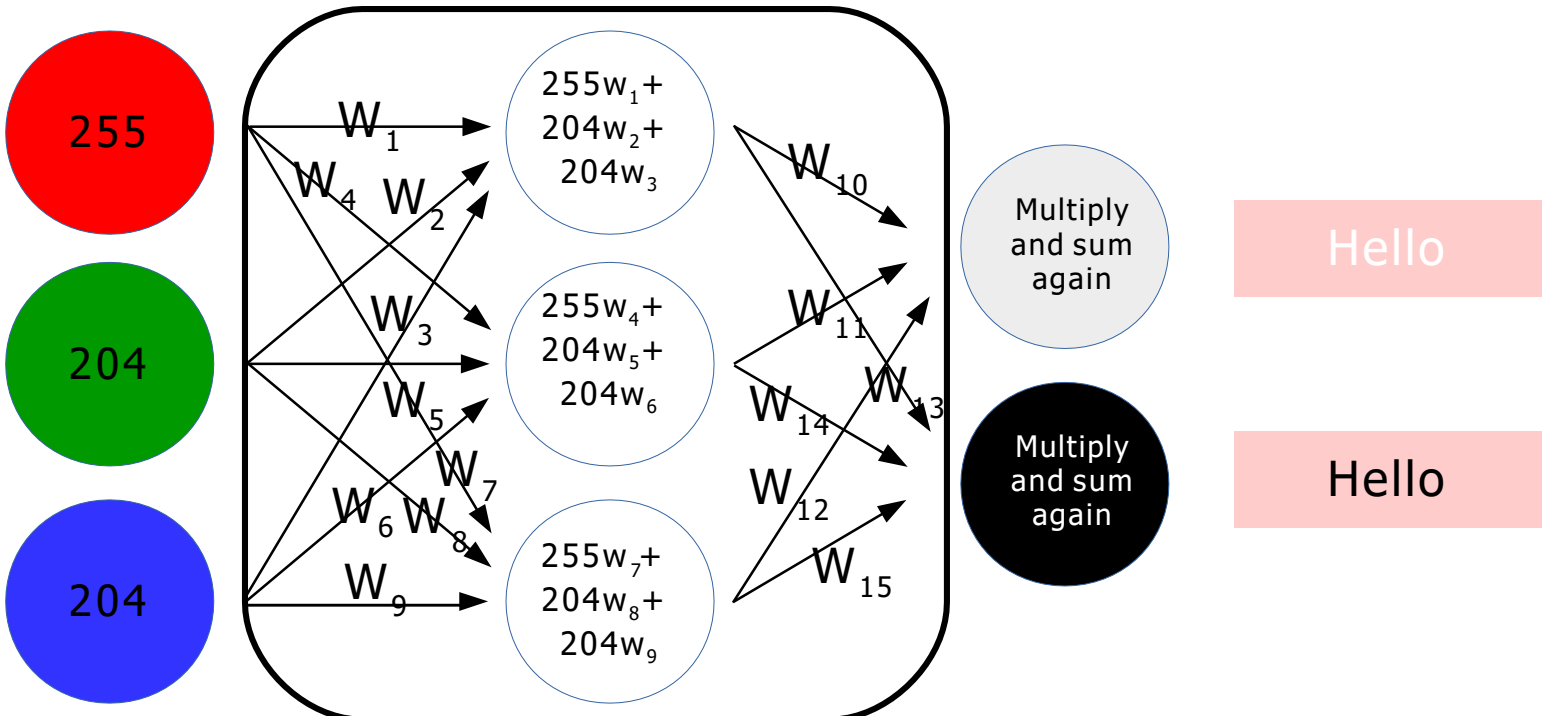


A Simple Neural Network



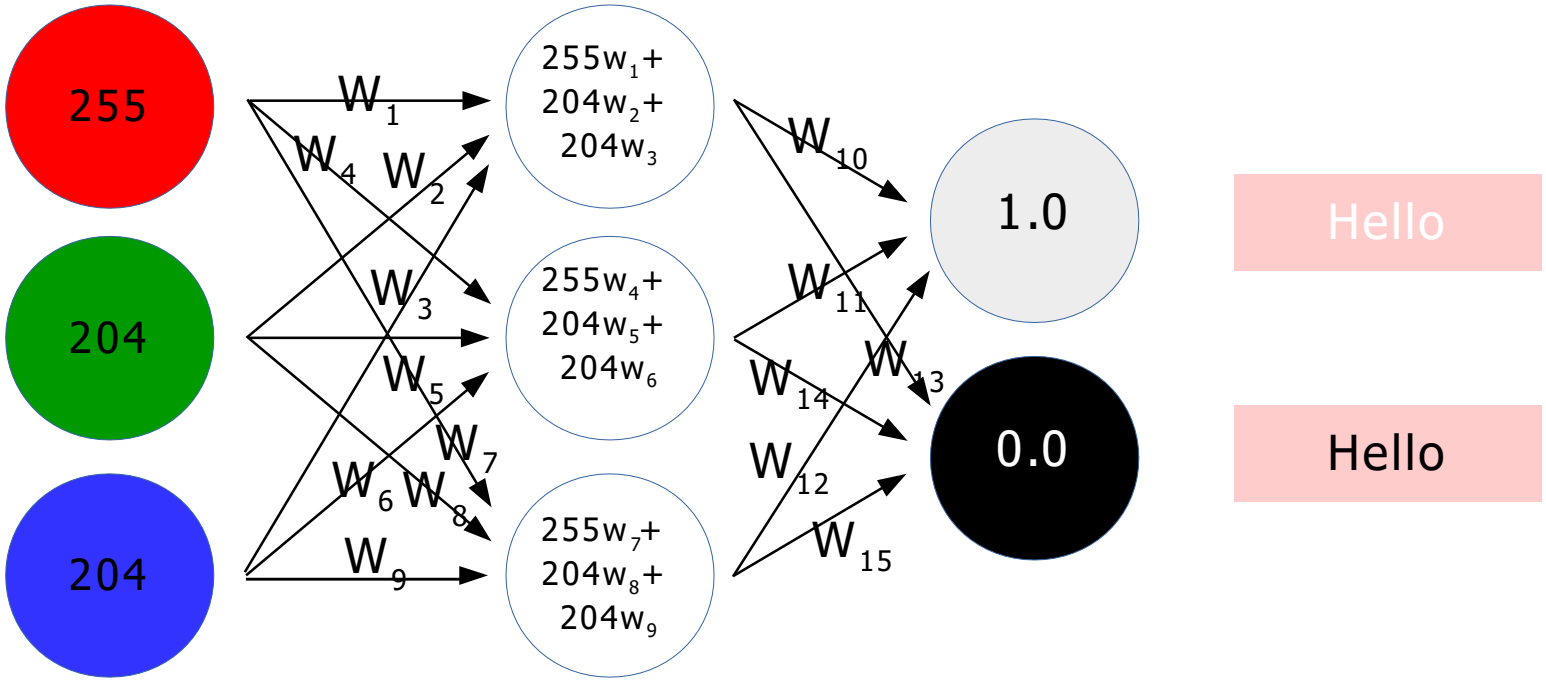
A Simple Neural Network

Each weight w_x value is between -1.0 and 1.0



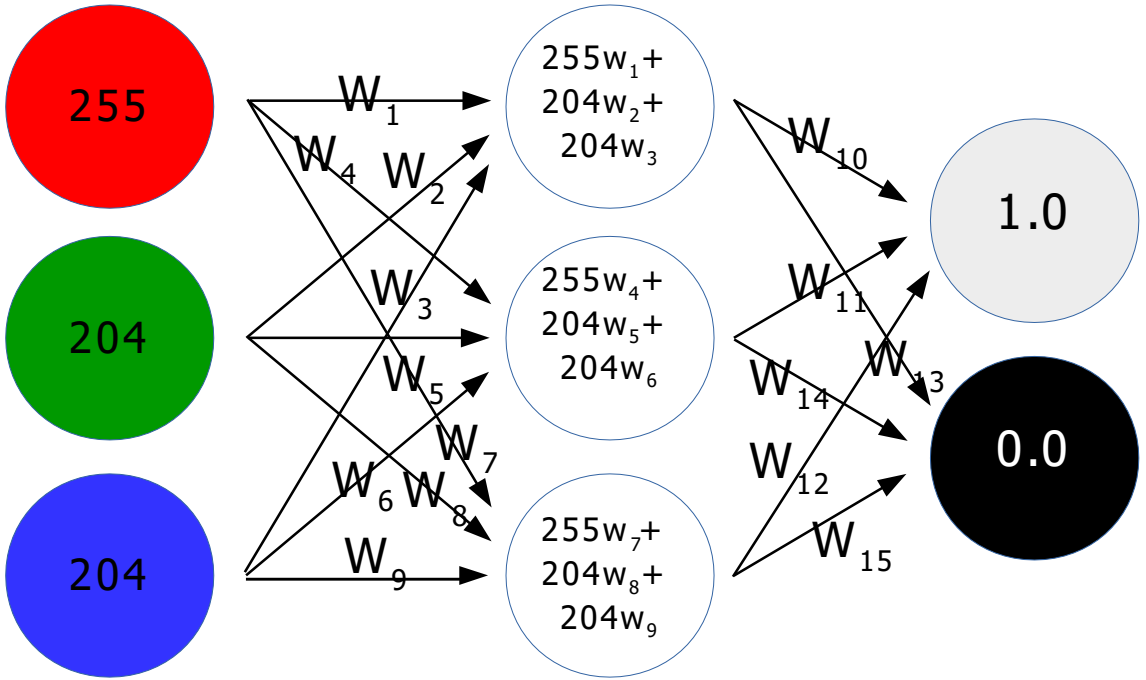
A Simple Neural Network

Million Dollar Question:
What are the *optimal* weight values to get the desired output?



A Simple Neural Network

Million Dollar Question:
What are the *optimal* weight values to get the desired output?

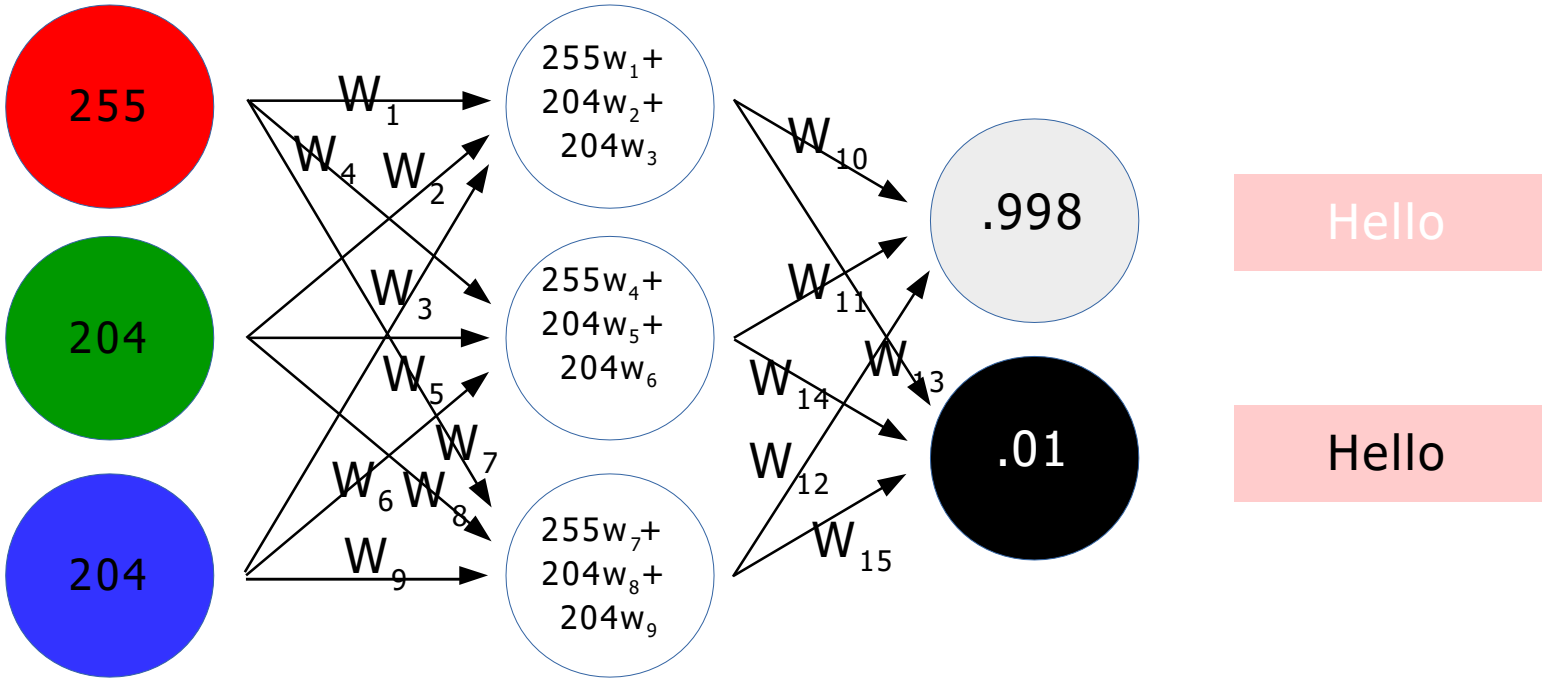


Hello

Hello

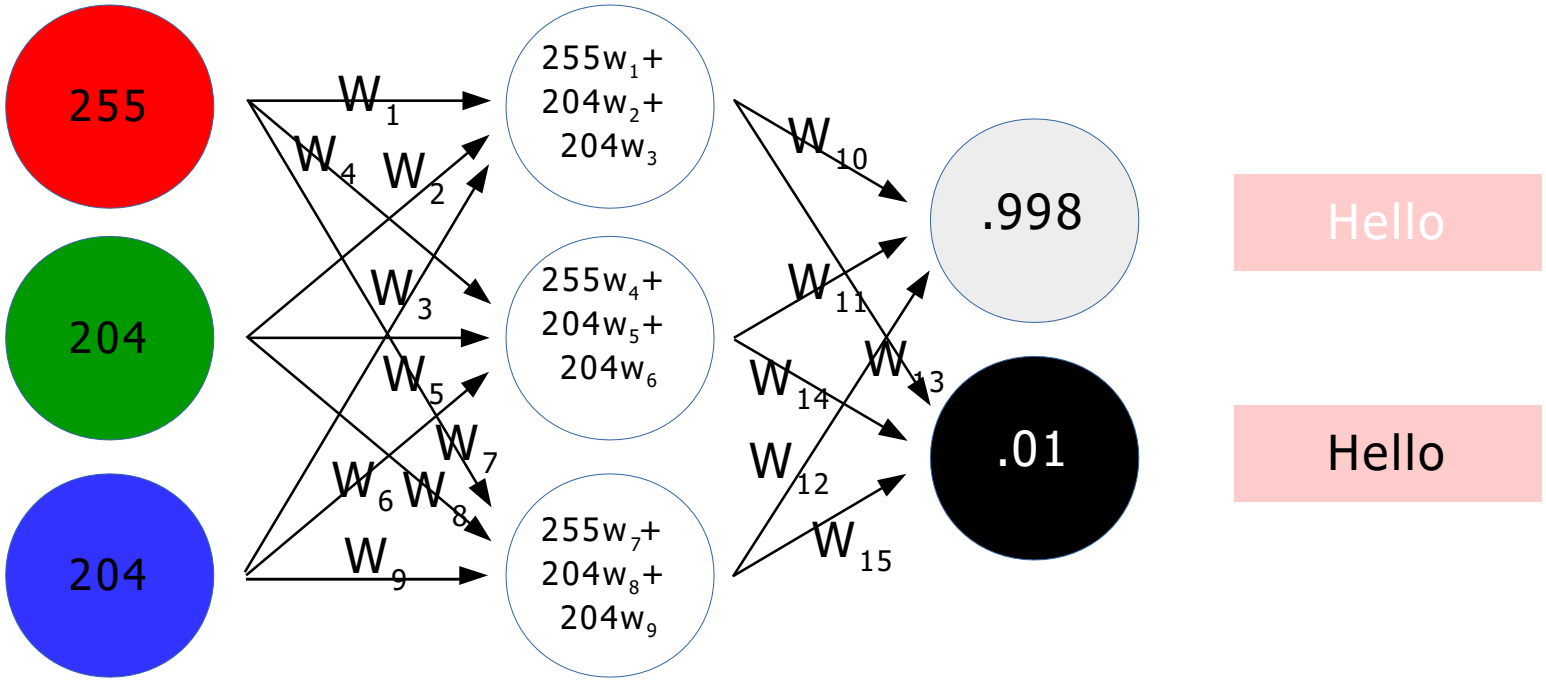
A Simple Neural Network

Answer:
This is an optimization problem!

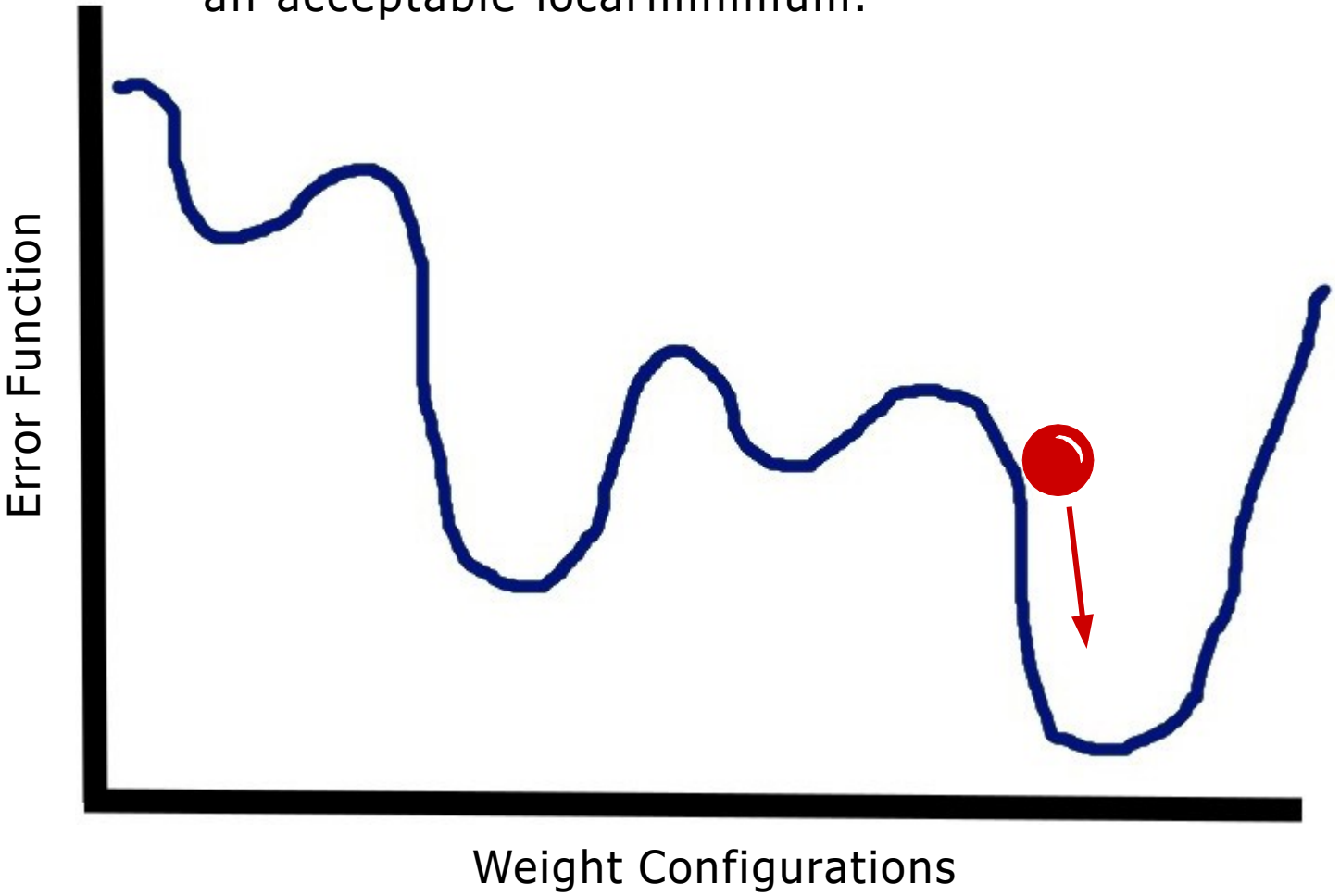


A Simple Neural Network

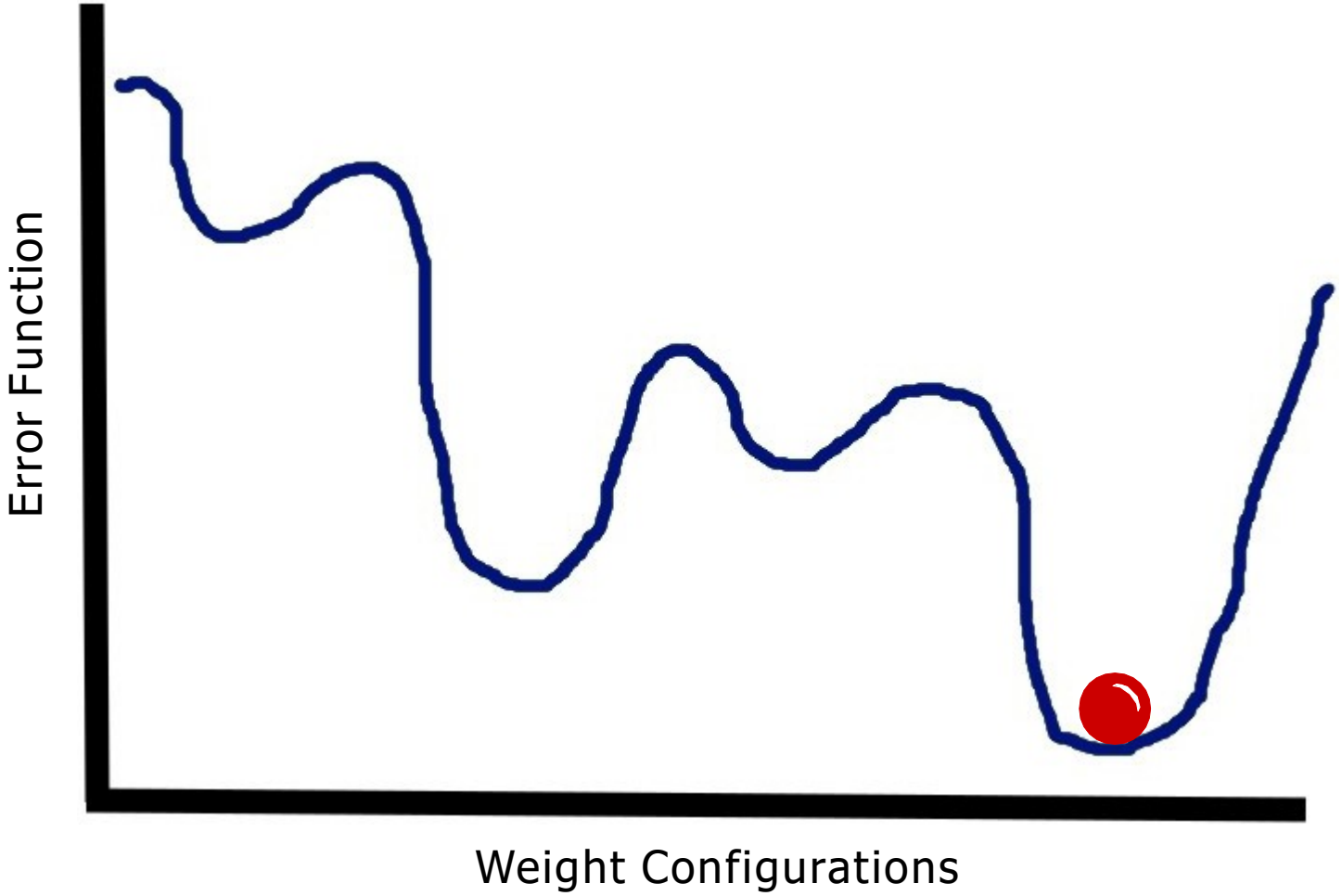
We need to solve for the weight values that gets our training colors as close to their desired outputs as possible.



Just like the Traveling Salesman Problem, you need to explore configurations seeking an acceptable local minimum.



Stochastic gradient descent, *simulated annealing*, and other optimization techniques can help tune a neural network.

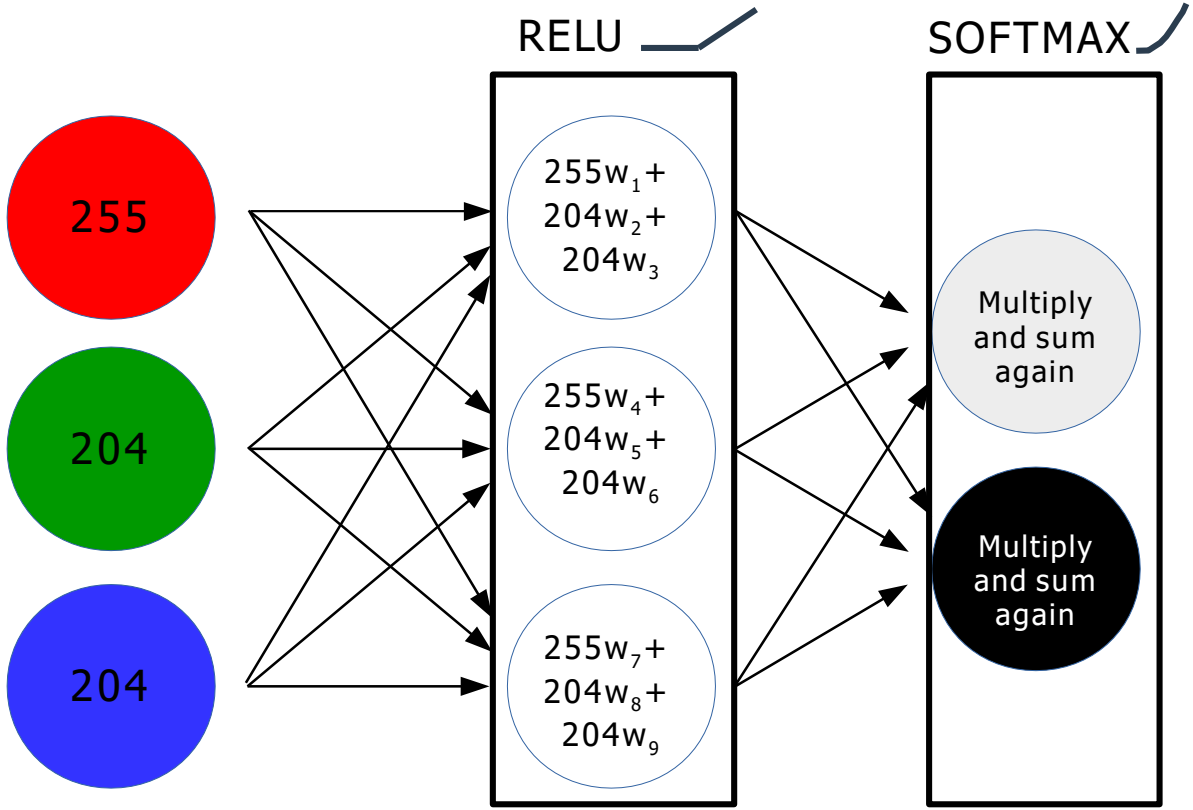


Activation Functions

You might also consider using **activation functions** on each layer.

These are nonlinear functions that smooth, scale, or compress the resulting sum values.

These make the network operate more naturally and smoothly.



Activation Functions

Four common neural network activation functions implemented using kotlin-stdlib

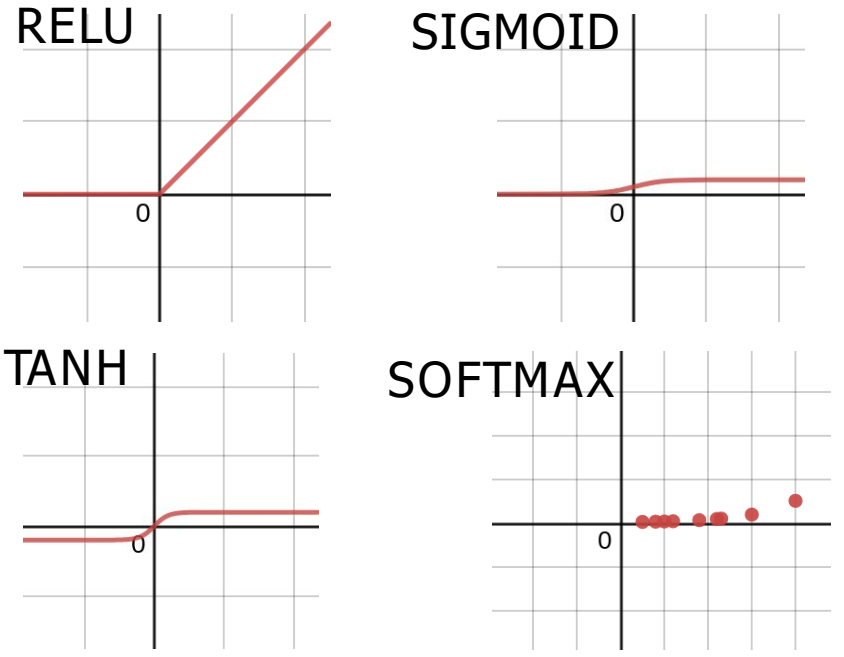
```
import kotlin.math.exp
import kotlin.math.max


fun sigmoid(x: Double) = 1.0 / (1.0 + exp(-x))

fun relu(x: Double) = max(0.0, x)

fun softmax(x: Double, allValues: DoubleArray) =
        exp(x) / allValues.map { exp(it) }.sum()

fun tanh(x: Double) = kotlin.math.tanh(x)
```



https://www.desmos.com/calculator/jwjn5rwfy6

Other Design Decisions

While optimizing weights is a core part of neural networks, there are other components to consider too:

How many middle *layers* are needed?

How many *nodes* are needed in each layer?

What *activation functions* should be applied to each layer?

Middle Layers - Should the layers be recurrent, recursive, convolutional, etc?

Loss function – How should we measure error?

Learning Rate - How aggressively should the optimization move towards the local minimum?

The Practicality of Neural Networks

Despite some seemingly intelligent applications like image recognition, neural networks have drawbacks:

Requires **LOTS** of labeled data fortraining.

Difficult for the data scientist to understand convoluted layers and nodes.

Has a quick diminishing return for problem spaces outside of image and natural language processing.

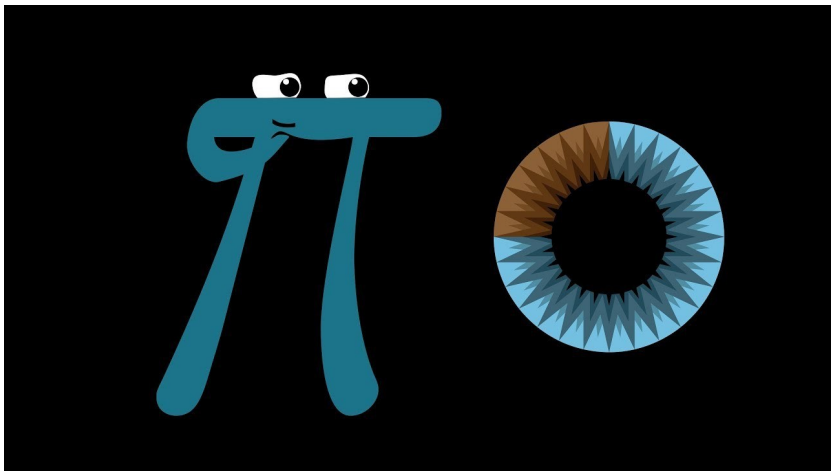
Neural networks generate excitement because many believe they will generalize solutions to most problems one day.

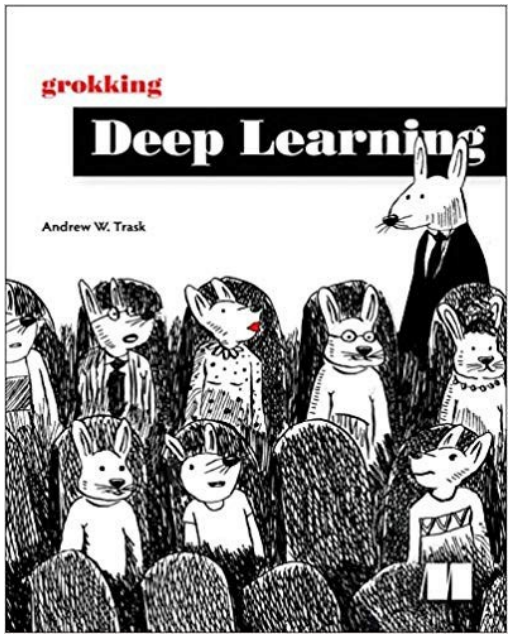
In reality, specialized and incumbent algorithms will outperform neural networks for most practical problems.

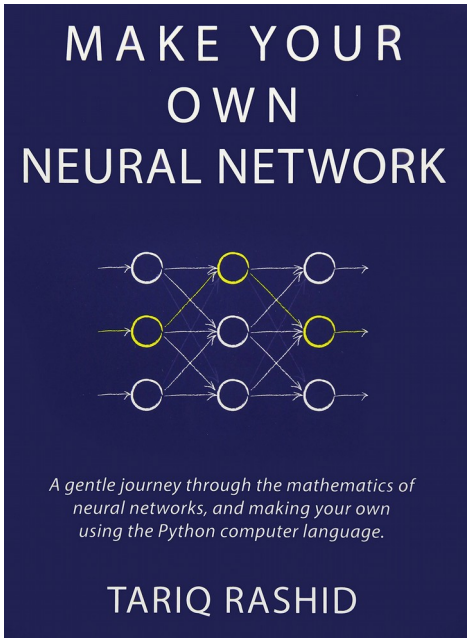
There are many academic papers citing research applying neural networks to the Traveling Salesman Problem and while this is interesting, the results are underwhelming.

Learn More About Neural Networks

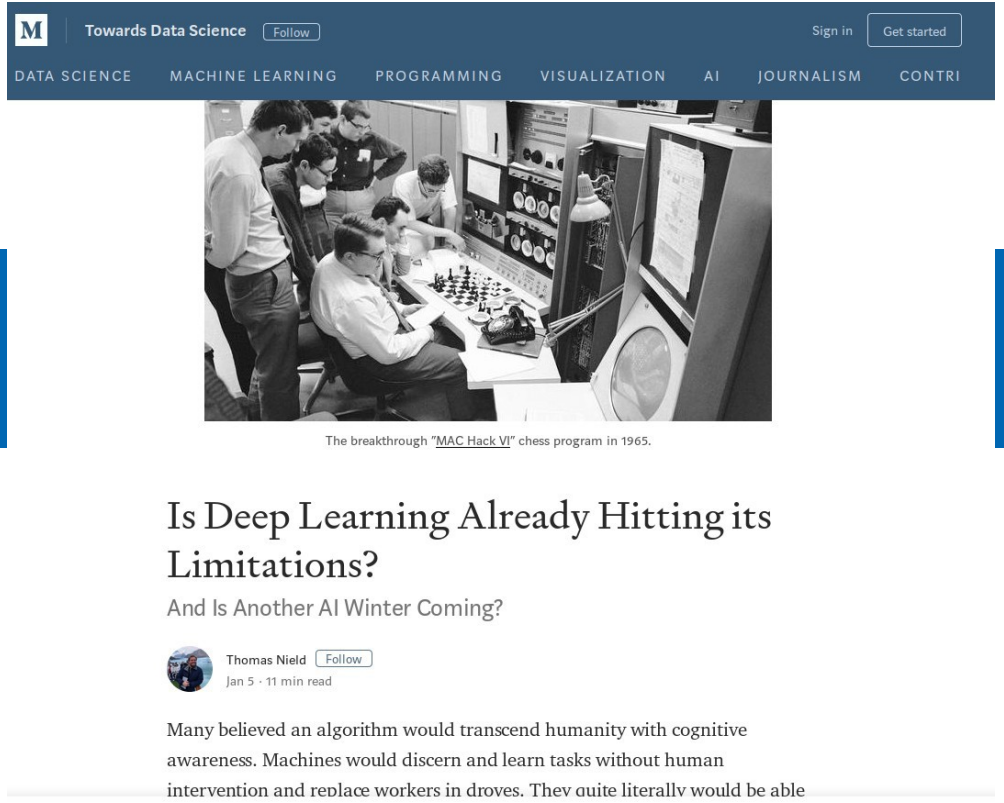
3Blue1Brown - YouTube







Also Read My Recent Blog Article



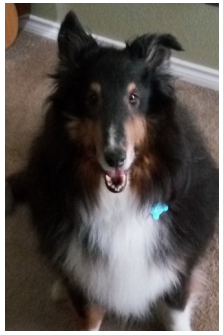
Source Code

Kotlin Neural Network Example

https://github.com/thomasnield/kotlin_simple_neural_network

Use the Right "AI" for the Job

Neural Networks



- **Image/Audio/Video Recognition**
  "Cat" and "Dog" photo classifier
- **Natural language processing**
- **Any fuzzy, difficult problems that have no clear model but *lots* of data**
  Self-driving vehicles
  Difficult nonlinear regressions
  Problems w/ mysterious unknowns

Bayesian Inference

- **Text classification**
  Email spam, sentiment analysis, document categorization
- **Document summarization**
- **Probability inference**
  Disease diagnosis, updating predictions

Mathematical Optimization

- **Routing and Scheduling**
  Staff, transportation, classrooms, sports tournaments, server jobs
- **On-Time Optimization**
  Transportation, manufacturing
- **Industry**
  Manufacturing, farming, nutrition, energy, engineering, finance

Appendix

Pop Culture

Traveling Salesman **(2012 Movie)**
http://a.co/d/76UYvXd

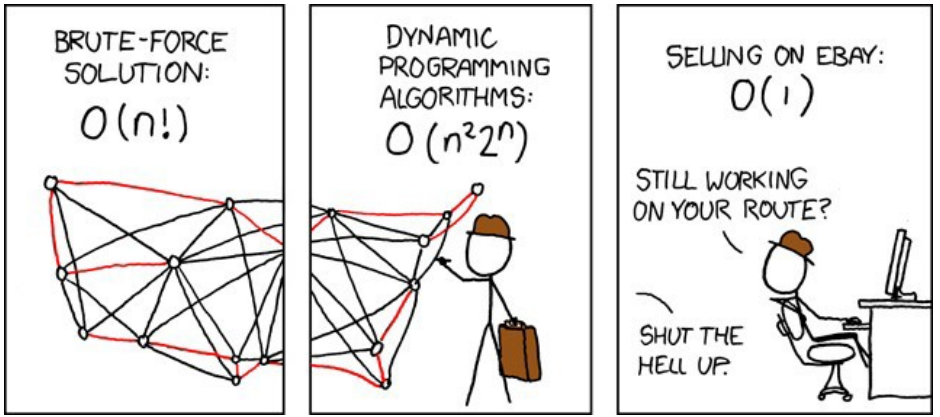
Silicon Valley (HBO) **–The "Not Hotdog" App**
https://youtu.be/vIci3C4JkL0

Silicon Valley (HBO) **–Making the "Not Hotdog" App**
https://tinyurl.com/y97ajsac

XKCD – Traveling Salesman Problem
https://www.xkcd.com/399/

XKCD – NP-Complete
https://www.xkcd.com/287/

XKCD – Machine Learning
https://xkcd.com/1838/



SOURCE: xkcd.com

Areas to Explore

Machine Learning

- Linear Regression
- Nonlinear Regression
- Neural Networks
- Bayes Theorem/Naive Bayes
- Support Vector Machines
- Decision Trees/Random Forests
- K-means (nearest neighbor)
- XGBoost

Optimization

- Discrete Optimization
- Linear/Integer/Mixed Programming
- Dynamic Programming
- Constraint programming
- Metaheuristics

Online Class Resources

Coursera – Discrete Optimization

https://www.coursera.org/learn/discrete-optimization/home/

Coursera – Machine Learning

https://www.coursera.org/learn/machine-learning/home/welcome

YouTube Channels and Videos

Thomas Nield
https://youtu.be/F6RiAN1A8n0

Brandon Rohrer
https://www.youtube.com/c/BrandonRohrer

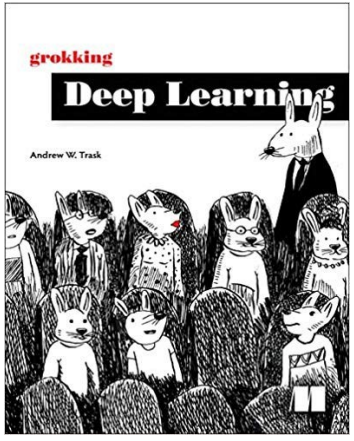
3Blue1Brown
https://www.youtube.com/channel/UCYO_jab_esuFRV4b17AJtAw

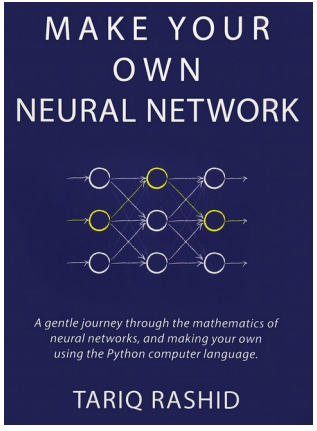
YouTube –P vs NP and the Computational Complexity Zoo
https://youtu.be/YX40hbAHx3s

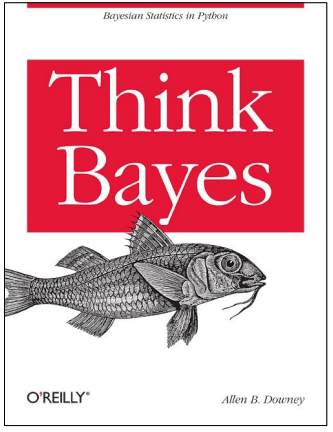
The Traveling Salesman Problem Visualization
https://youtu.be/SC5CX8drAtU

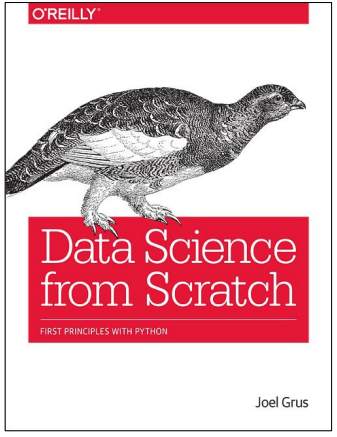
The Traveling Salesman w/ 1000 Cities (Video)
https://youtu.be/W-aAjd8_bUc

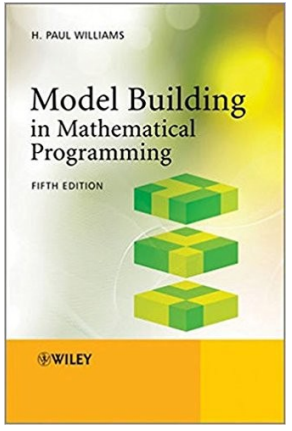
Books


grokking
Deep Learning
Andrew W. Trask


MAKE YOUR
OWN
NEURAL NETWORK
A gentle journey through the mathematics of neural networks, and making your own using the Python computer language.
TARIQ RASHID


Bayesian Statistics in Python
Think Bayes
O'REILLY
Allen B. Downey


O'REILLY
Data Science from Scratch
FIRST PRINCIPLES WITH PYTHON
Joel Grus


H. PAUL WILLIAMS
Model Building in Mathematical Programming
FIFTH EDITION
WILEY

Interesting Articles

Does A.I. Include Constraint Solvers?

https://www.optaplanner.org/blog/2017/09/07/DoesAIIncludeConstraintSolvers.html

Can You Make Swiss Trains Even More Punctual?

https://medium.com/crowdai/can-you-make-swiss-trains-even-more-punctual-ec9aa73d6e35

The SkyNet Salesman

https://multithreaded.stitchfix.com/blog/2016/07/21/skynet-salesman/

Interesting Articles

Essential Math for Data Science

https://towardsdatascience.com/essential-math-for-data-science-why-and-how-e88271367fbd

The Unreasonable Reputation of Neural Networks

http://thinkingmachines.mit.edu/blog/unreasonable-reputation-neural-networks

Mario is Hard, and that's Mathematically Official

https://www.newscientist.com/article/mg21328565.100-mario-is-hard-and-thats-mathematically-official/

Interesting Papers

The Lin-Kernighan Traveling Salesman Heuristic

http://akira.ruc.dk/~keld/research/LKH/LKH-1.3/DOC/LKH_REPORT.pdf

The Traveling Salesman: A Neural Network Perspective

http://www.iro.umontreal.ca/~dift6751/paper_potvin_nn_tsp.pdf

The Interplay of Optimization and Machine Learning Research

http://jmlr.org/papers/volume7/MLOPT-intro06a/MLOPT-intro06a.pdf