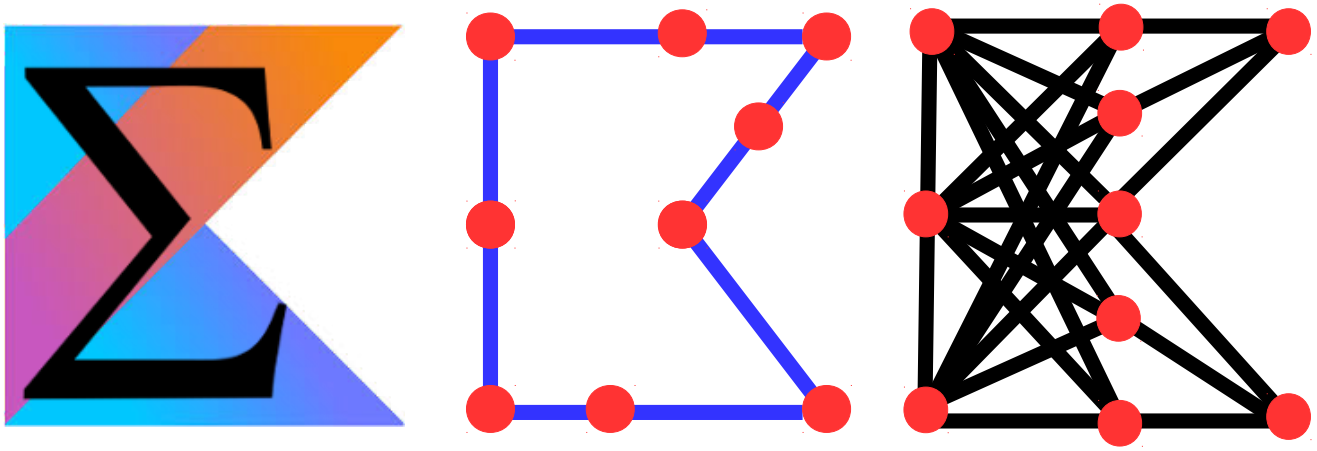
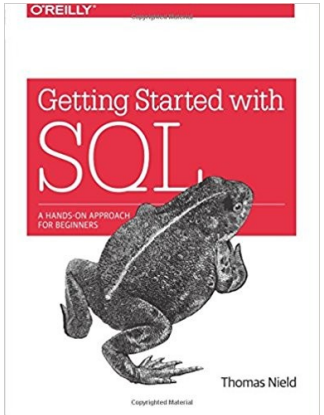


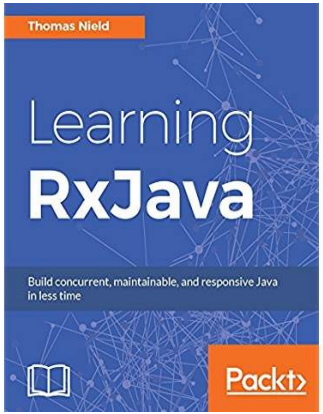
Thomas Nield
KotlinConf 2018

Thomas Nield

Business Consultant at Southwest Airlines
Dallas, Texas

Author
Getting Started with SQL by O'Reilly
Learning RxJava by Packt





Trainer and content developer at O'Reilly Media

OSS Maintainer/Collaborator

RxKotlin	TornadoFX	RxJavaFX
Kotlin-Statistics	RxKotlinFX	

thomasnield9727

https://github.com/thomasnield

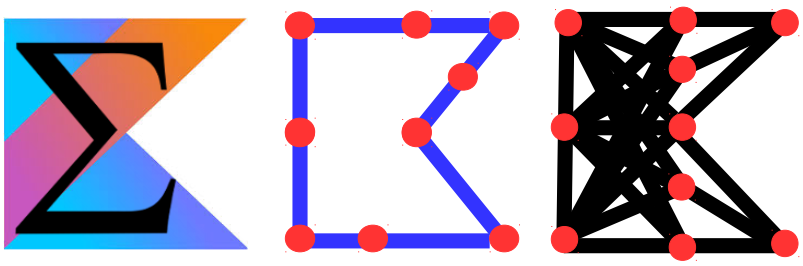
Thomas Nield

Agenda

Why Learn Mathematical Modeling?

Discrete Optimization

- Traveling Salesman
- Classroom Scheduling
- Solving a Sudoku



Machine Learning

- Naive Bayes
- Neural Networks

Part I:
Why Learn Mathematical Modeling?

What is Mathematical Modeling?

Mathematical modeling is a broad discipline that attempts to solve real-world problems using mathematical concepts.

Applications range broadly, from *biology* and *medicine* to *engineering, business,* and *economics*.

Mathematical Modeling is used heavily in optimization, machine learning, and data science.

Real-World Examples

Product recommendations
Dynamic pricing
Sport event planning
Staff/resource scheduling
Image/audio recognition
Game "AI" (Sudoku, Chess)
Text categorization
DNA sequencing
Disaster Management

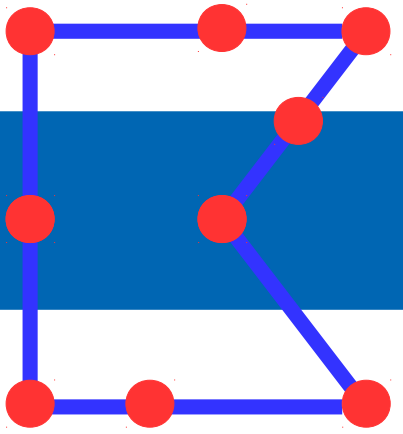
Why Learn Mathematical Modeling?

As programmers, we thrive in certainty and exactness.

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

Technologies, frameworks, and languages come and go… but math never changes.

Part II:
Discrete Optimization



What Is Discrete Optimization?

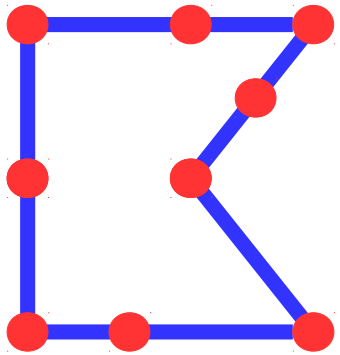
Discrete optimization is a space of algorithms that tries to find a feasible or optimal solution to a constrained problem.

- Scheduling classrooms, staff, transportation, sports teams, and manufacturing
- Finding an optimal route for vehicles to visit multiple destinations
- Optimizing manufacturing operations
- Solving a Sudoku or Chess game

Discrete 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

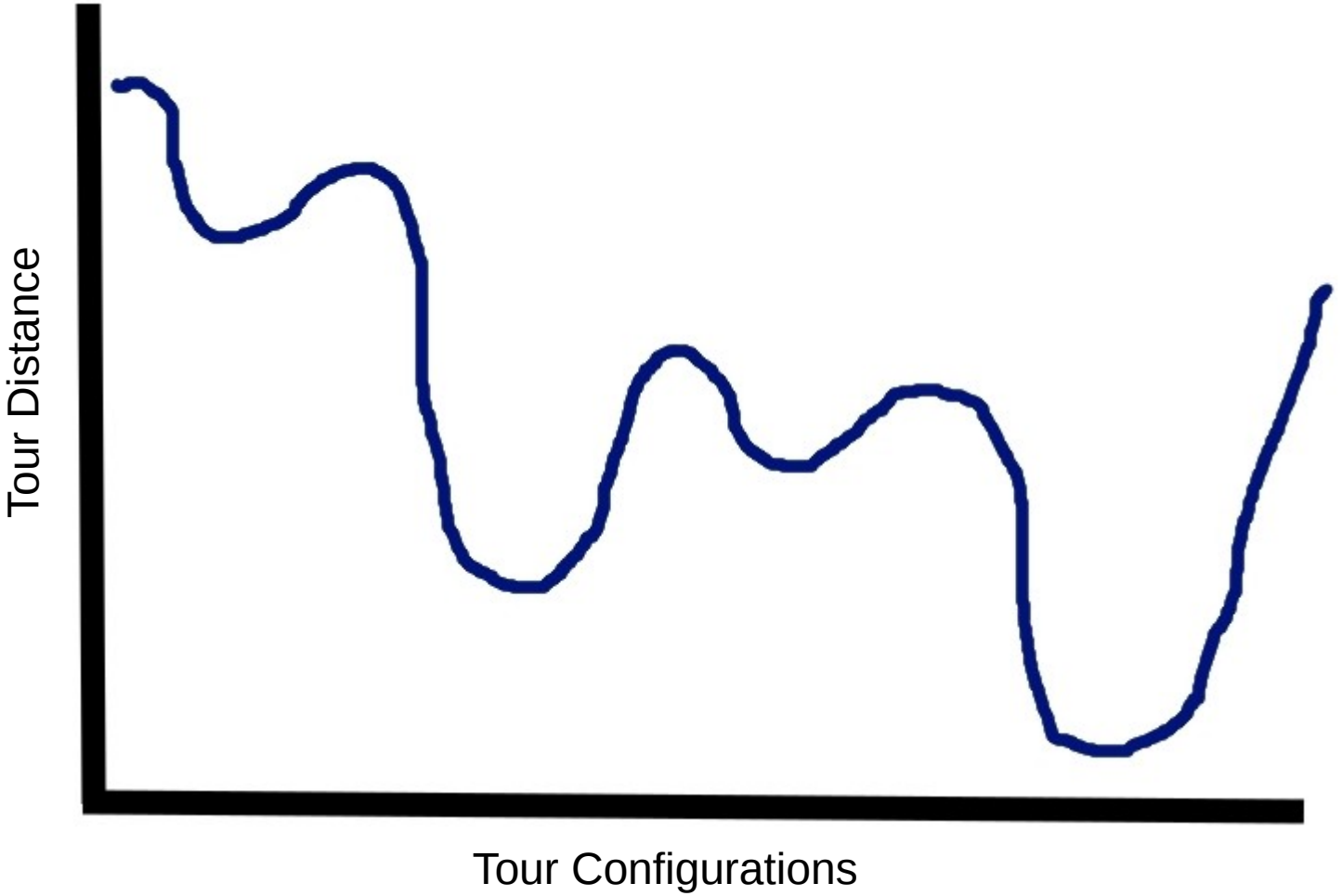
The Traveling Salesman Problem (TSP) is one of the most elusive and studied computer science problems since the 1950's.

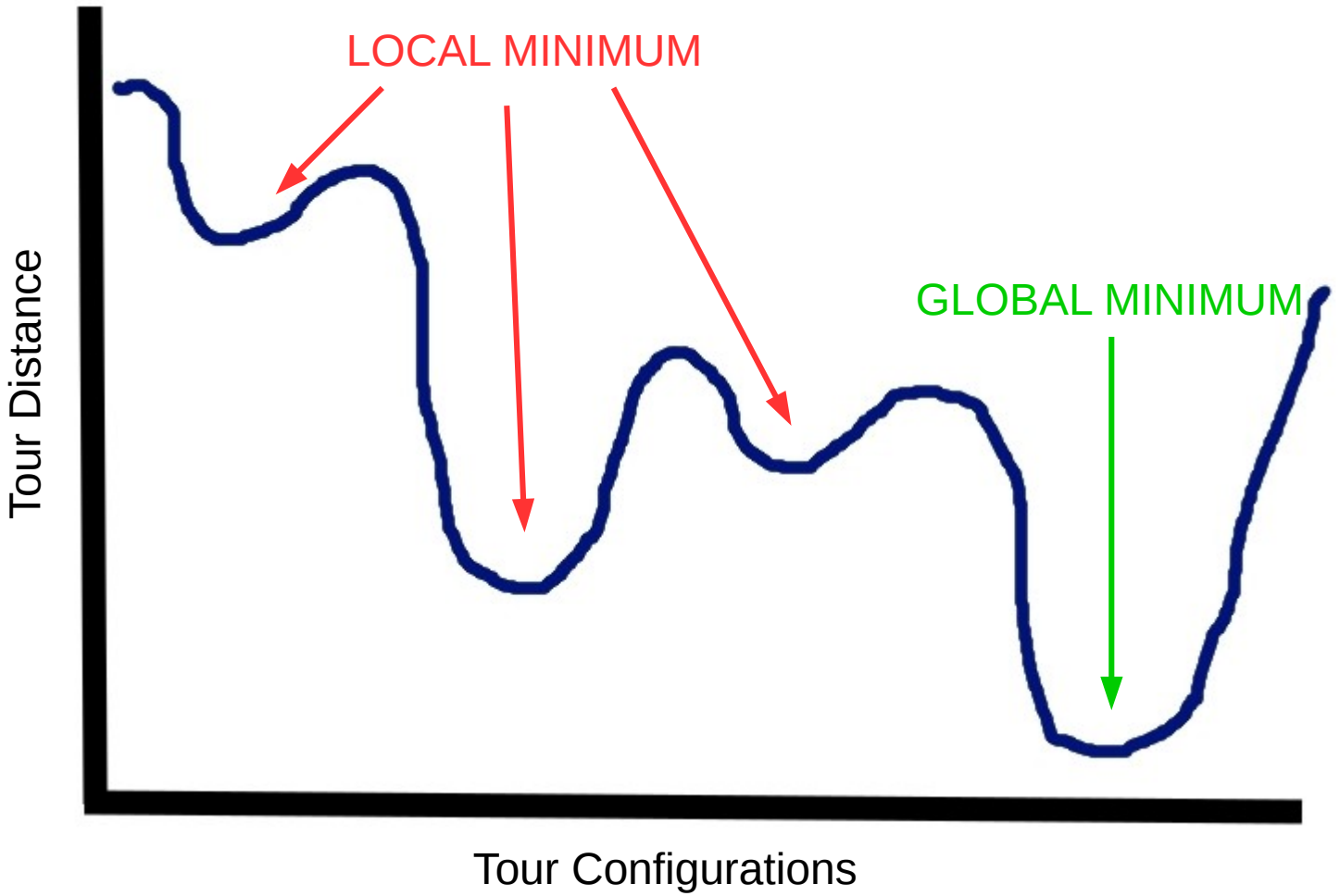


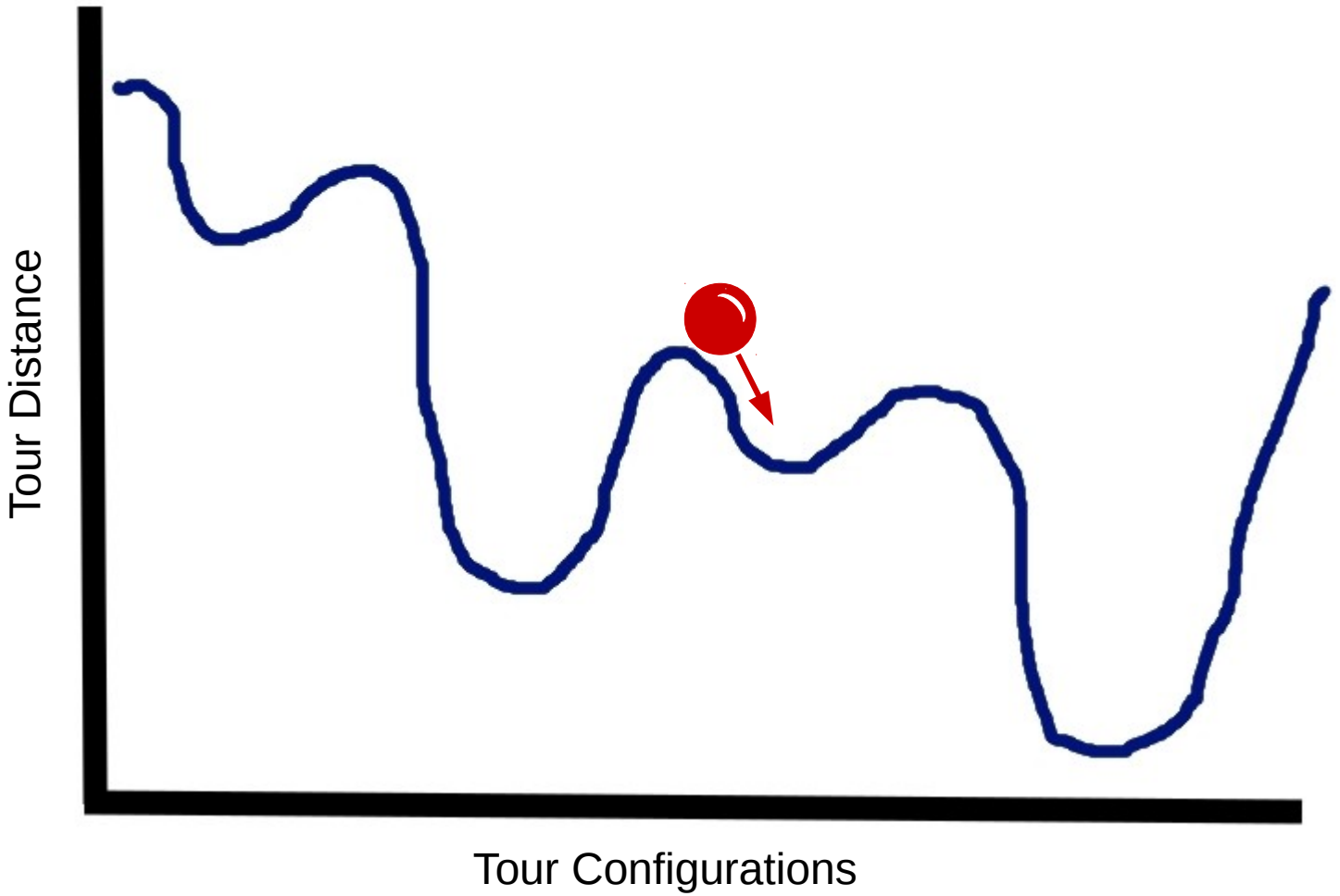
Objective: Find the shortest round-trip tour across several geographic points/cities.

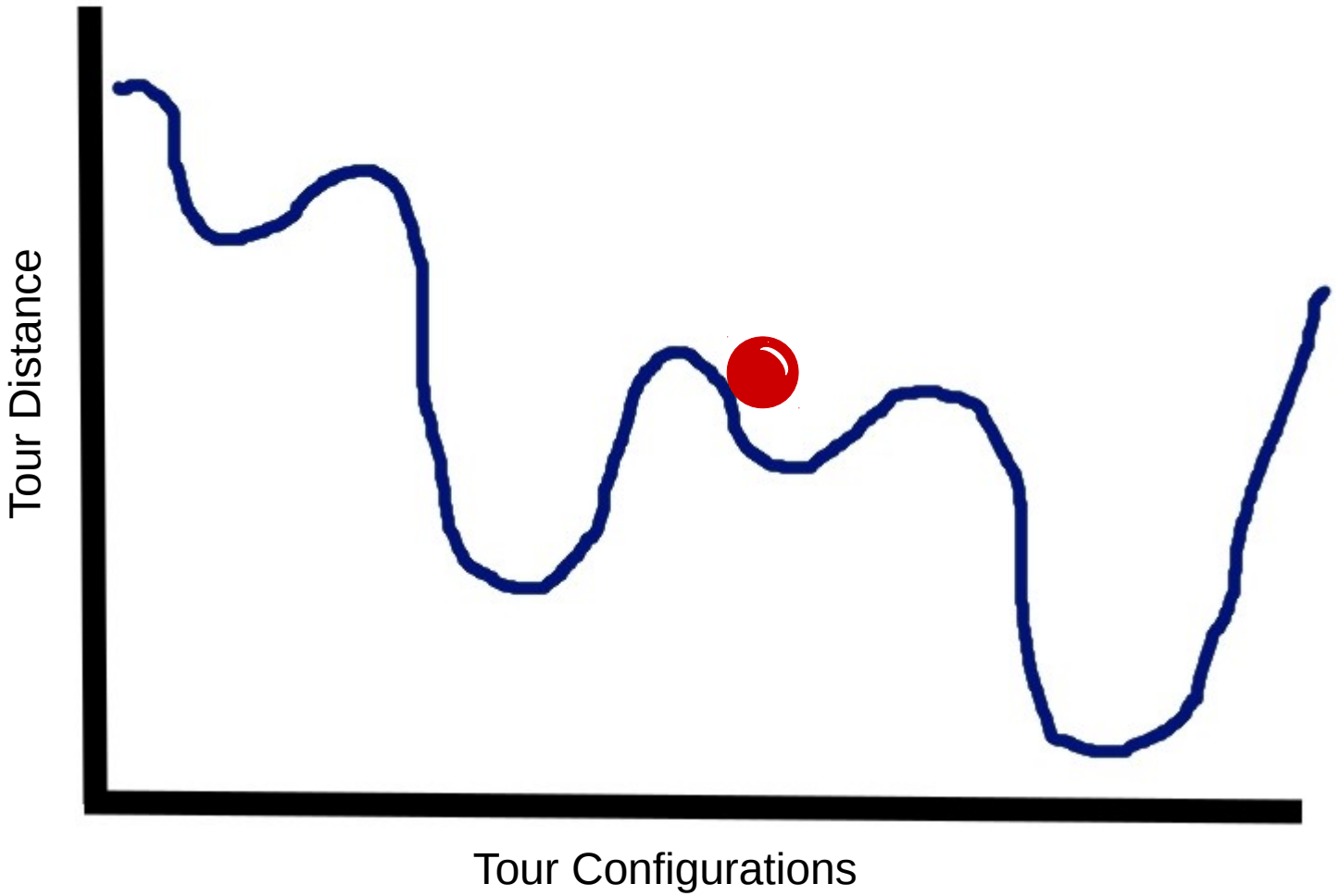
The Challenge: Just ***60*** cities = ***8.3 x 10^{81}*** possible tours

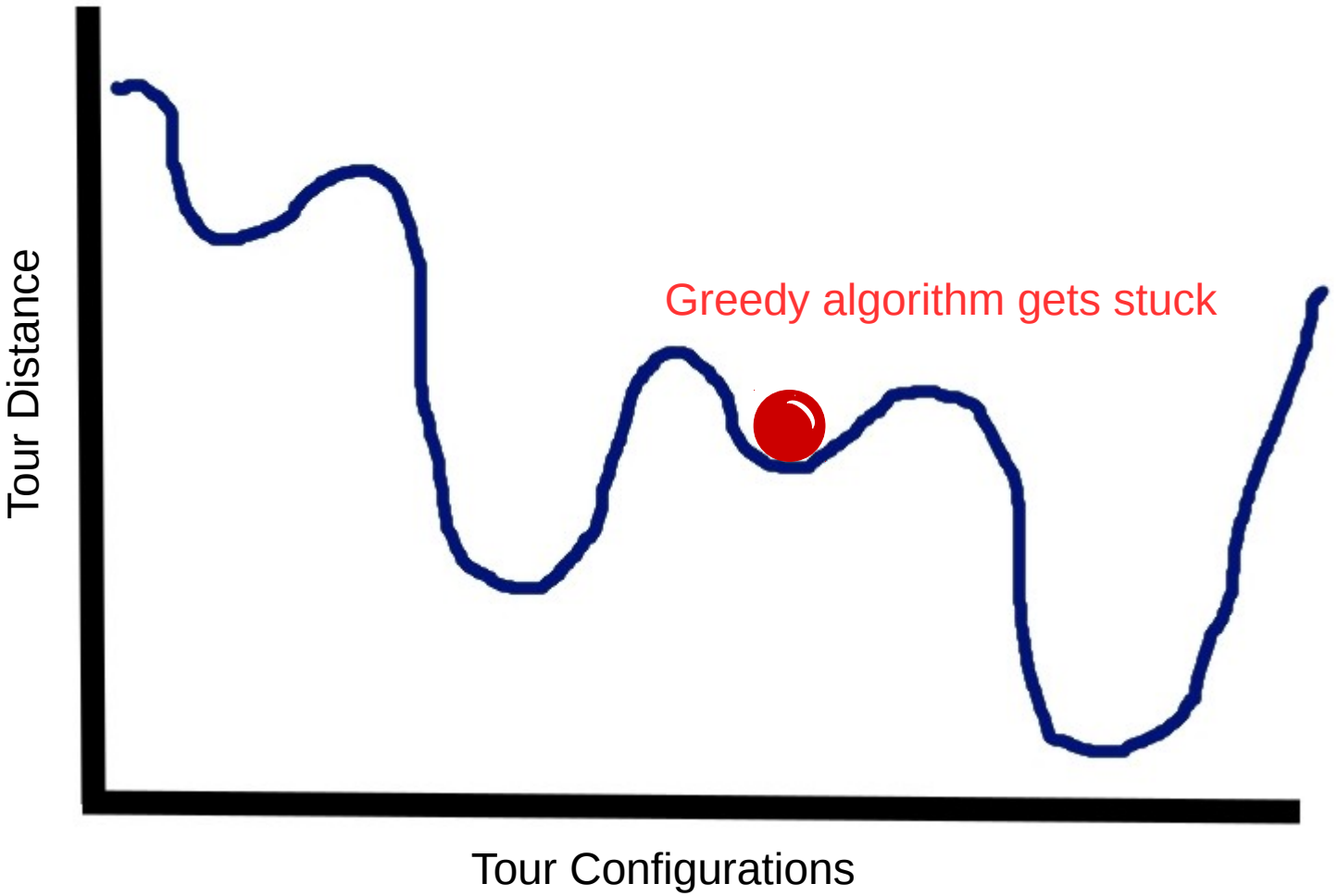
That's more tour combinations than there are observable atoms in the universe!

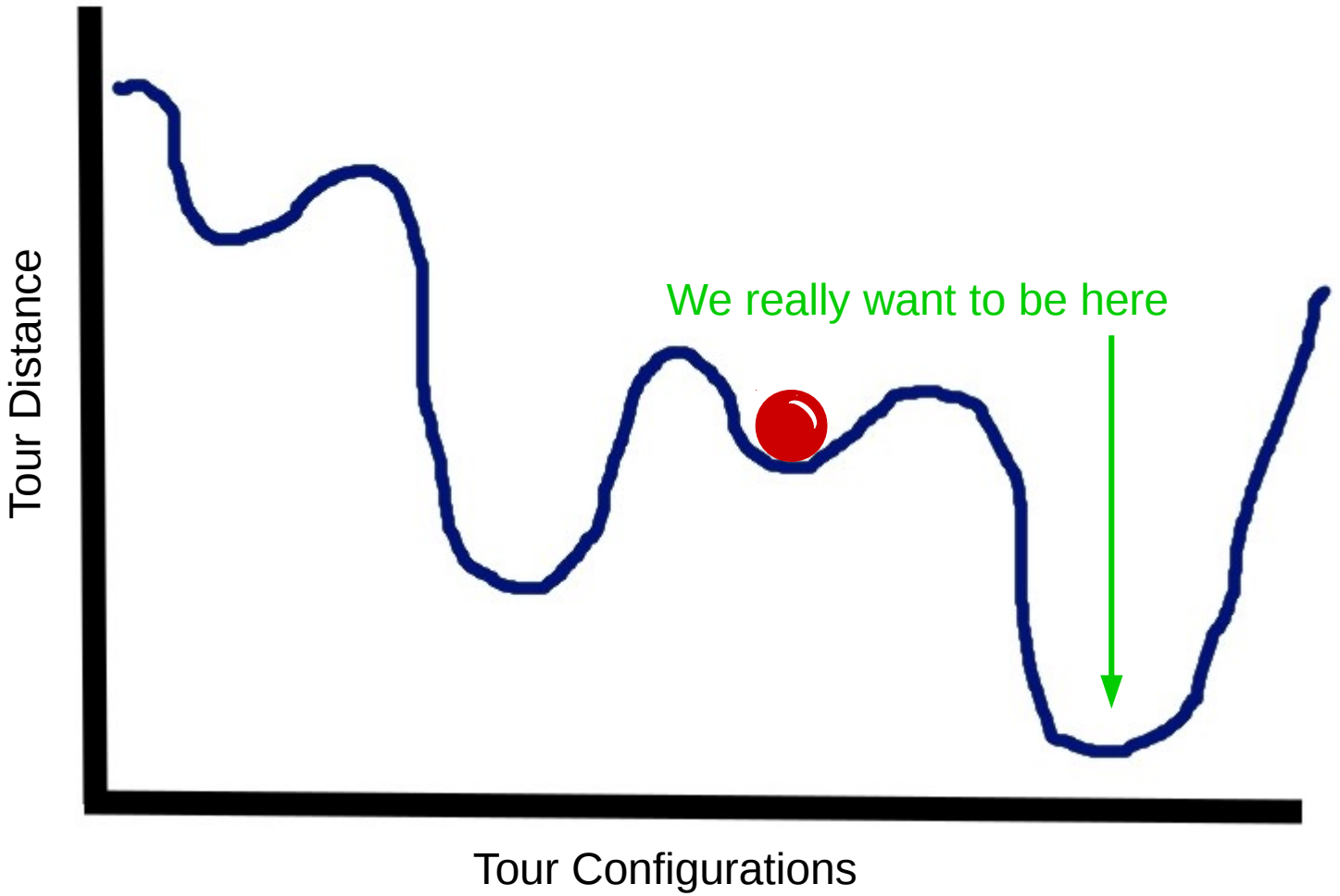

Tour Distance
Tour Configurations

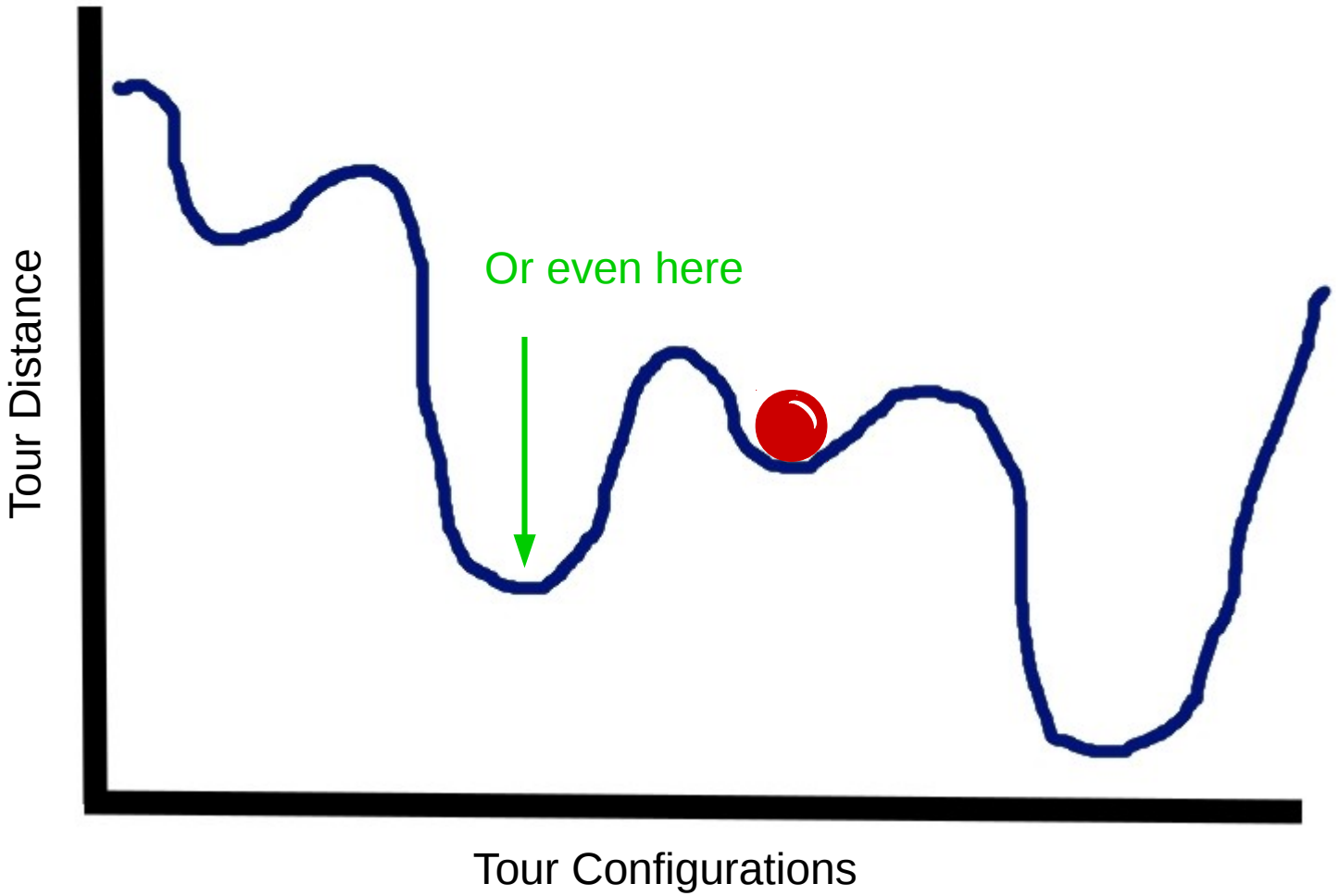

LOCAL MINIMUM
GLOBAL MINIMUM
Tour Distance
Tour Configurations

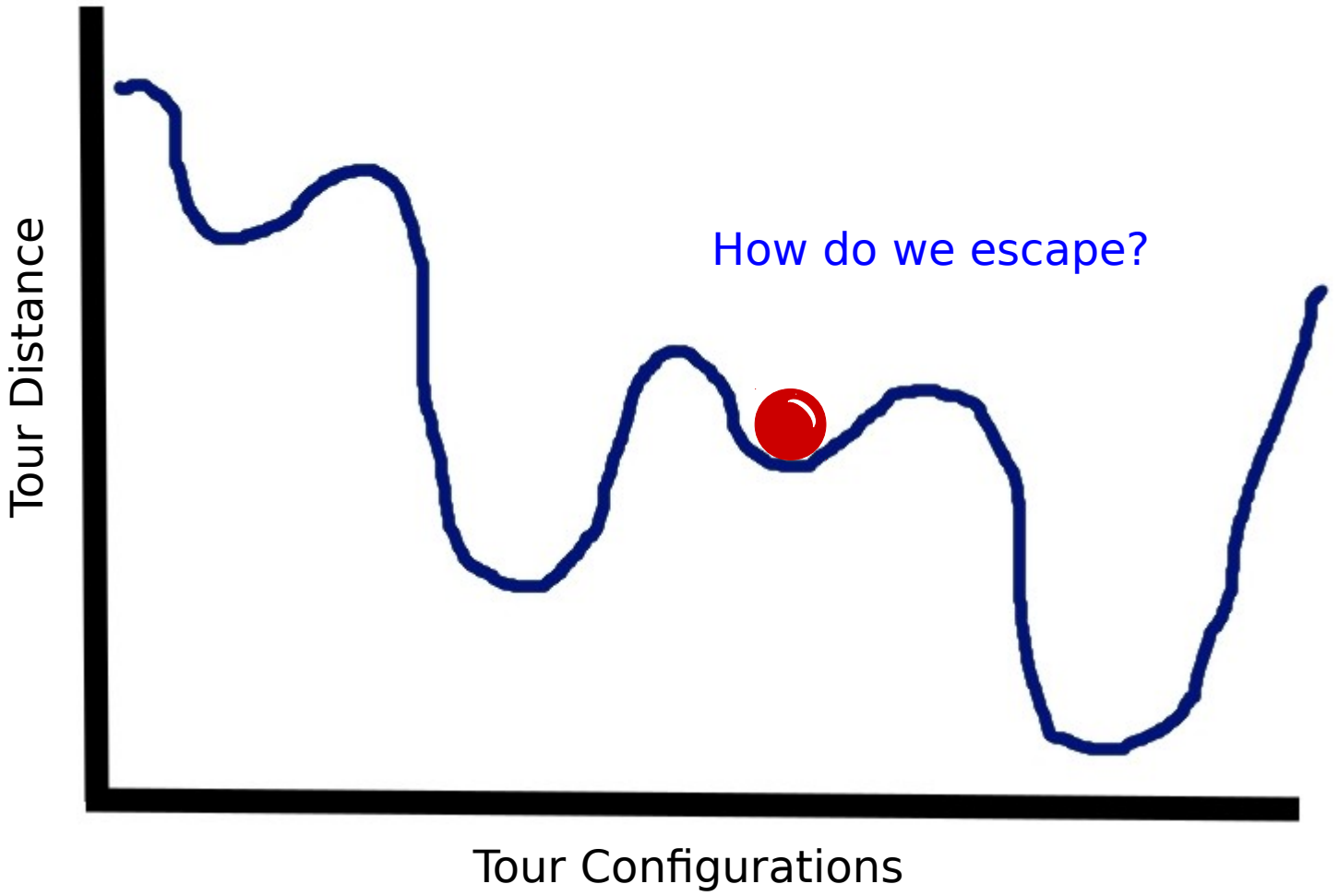

Tour Distance
Tour Configurations

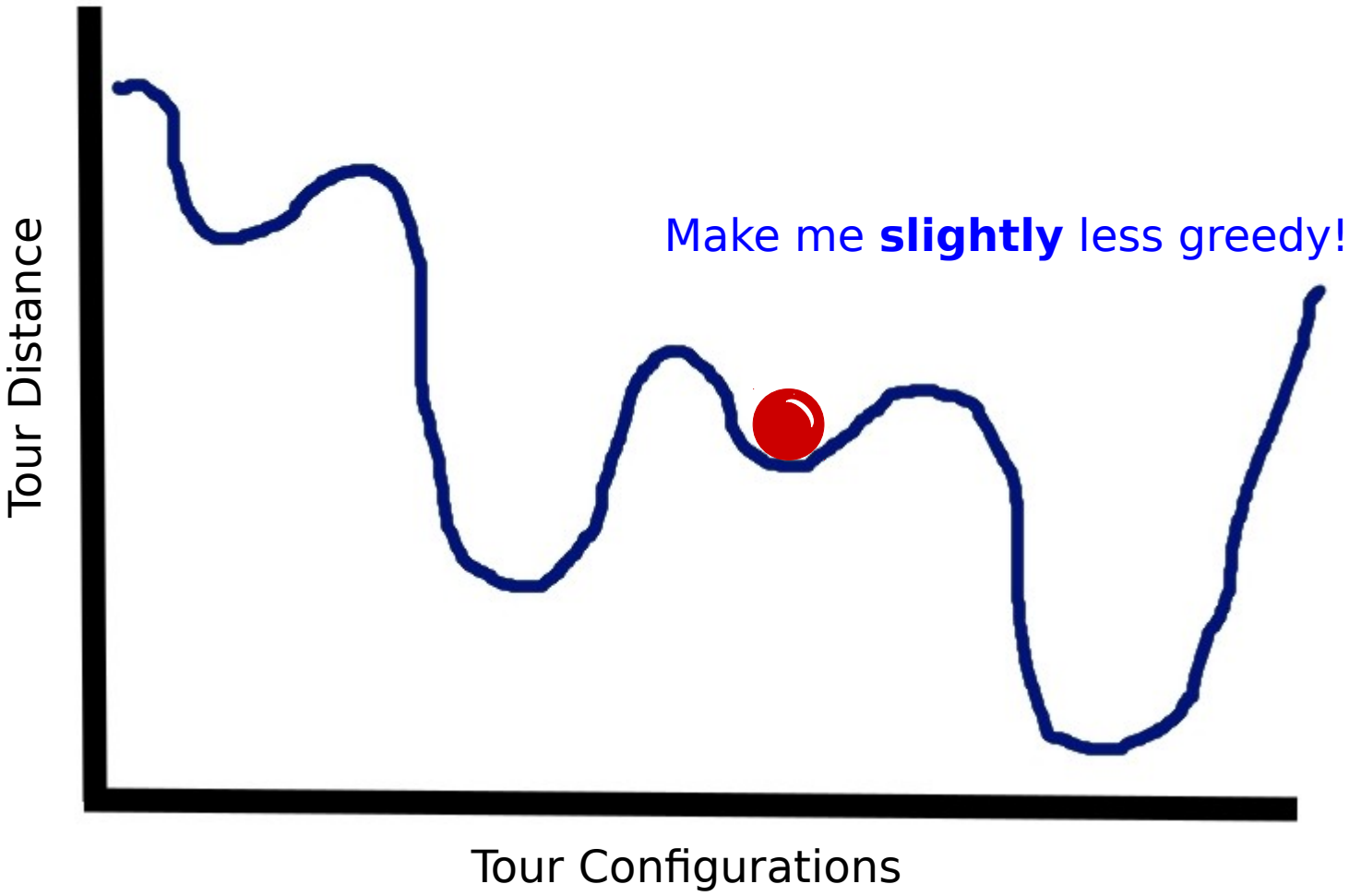

Tour Distance
Tour Configurations

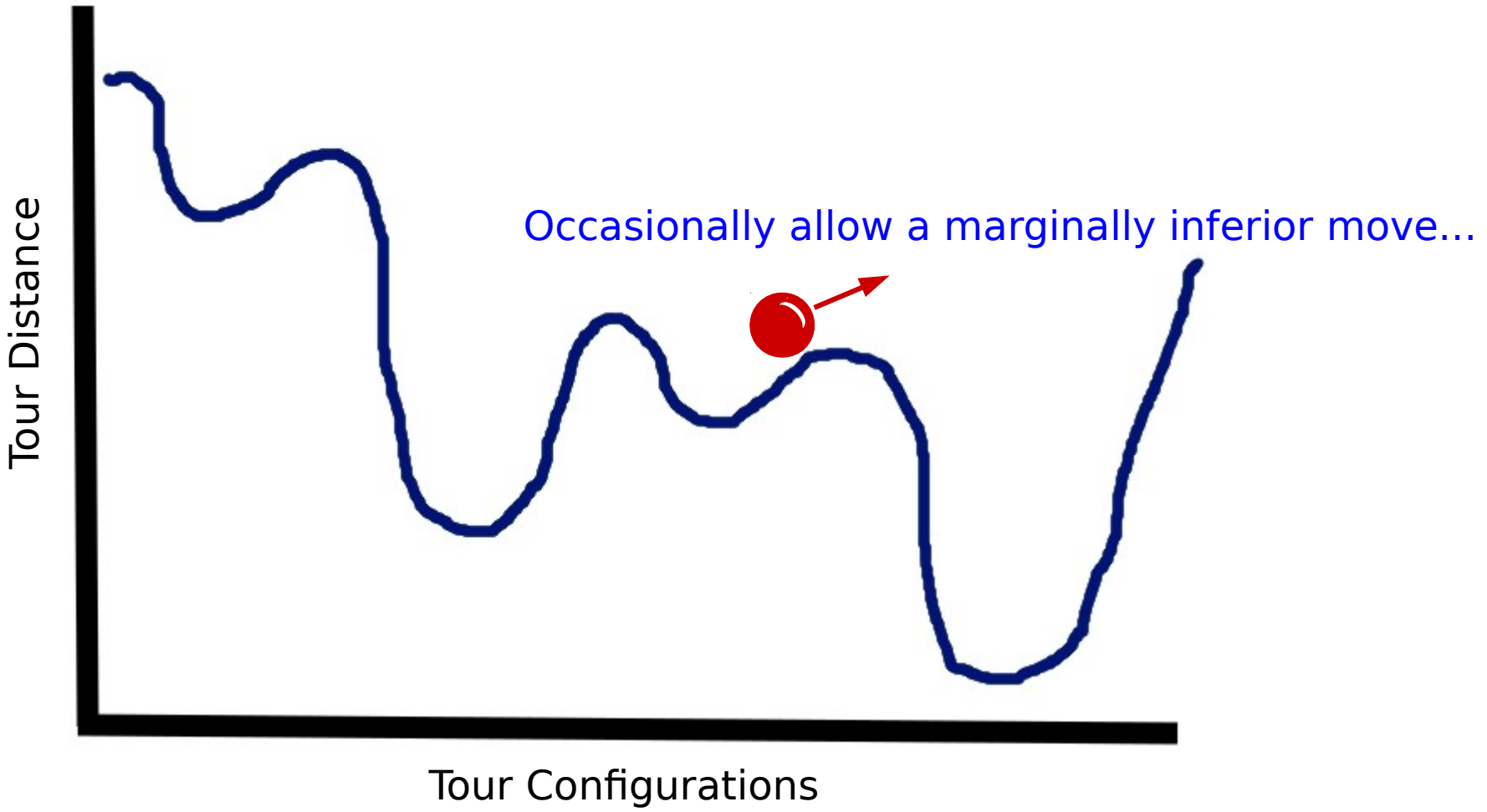

Greedy algorithm gets stuck
Tour Distance
Tour Configurations

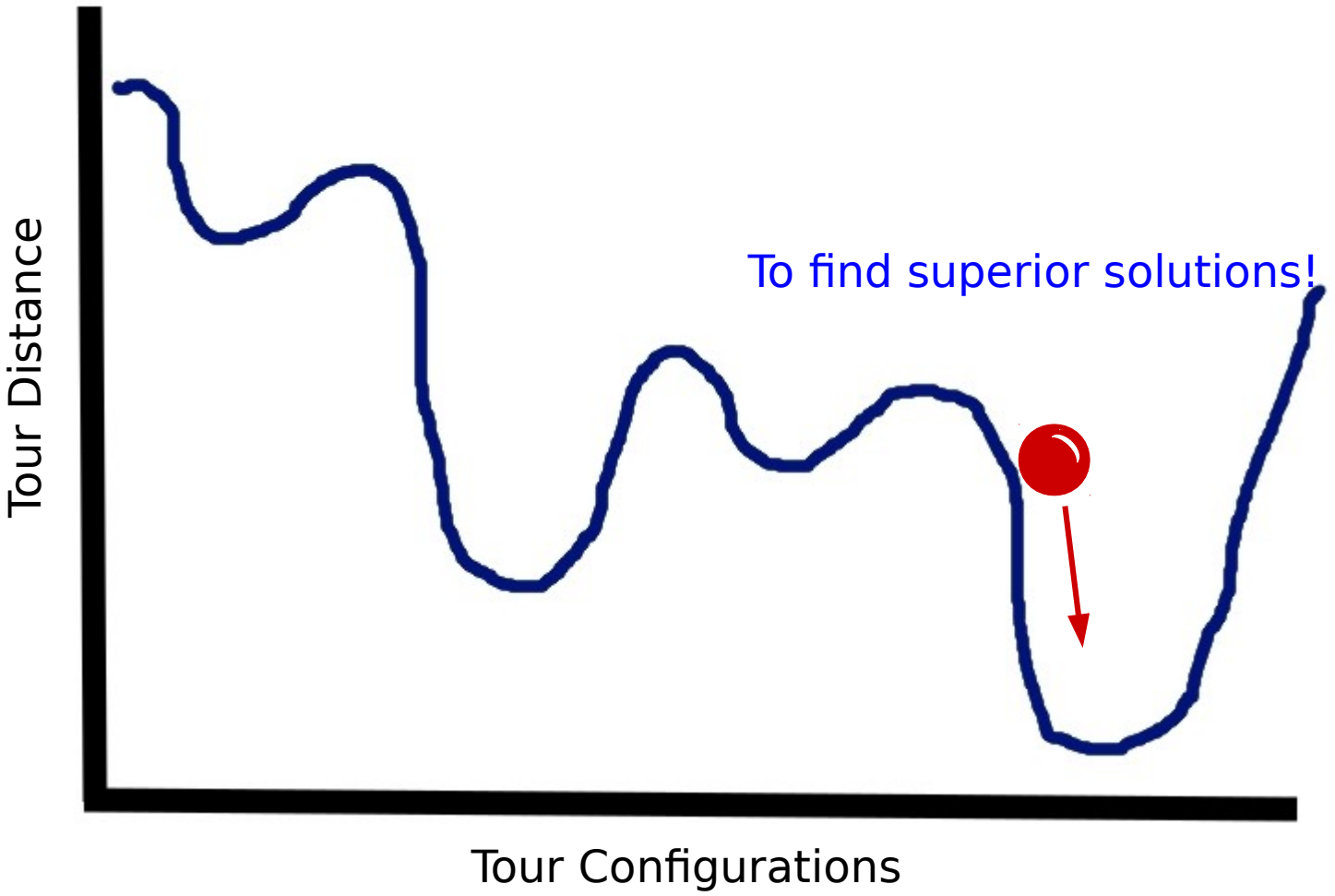

Tour Distance
We really want to be here
Tour Configurations

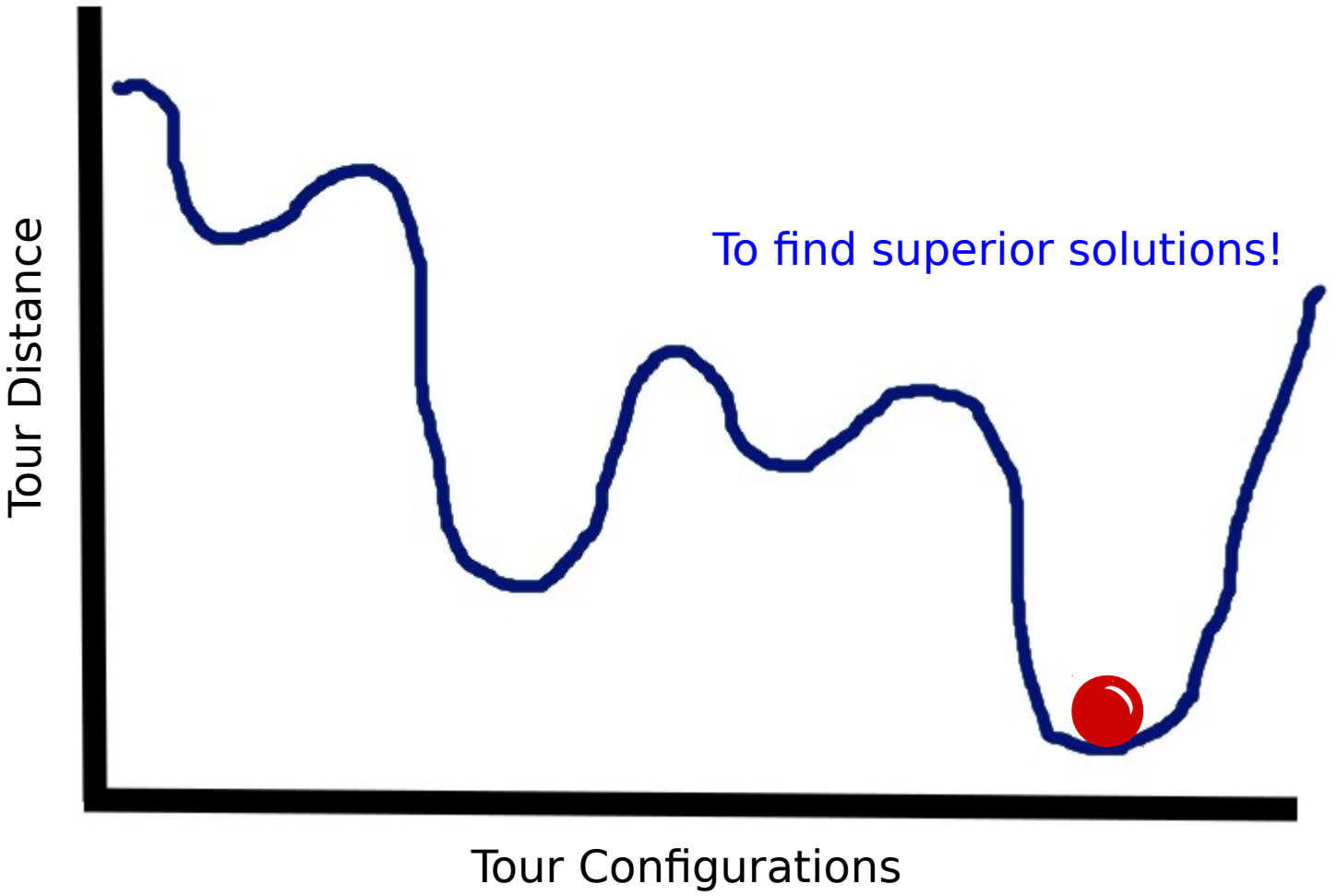

Tour Distance
Or even here
Tour Configurations


How do we escape?
Tour Distance
Tour Configurations


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

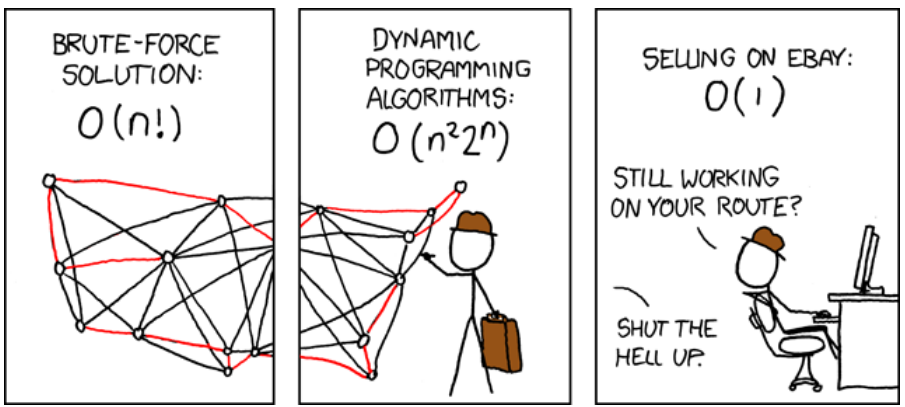
Source Code

Traveling Salesman Demo

https://github.com/thomasnield/traveling_salesman_demo

Traveling Salesman Plotter

https://github.com/thomasnield/traveling_salesman_plotter



SOURCE: xkcd.com

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.

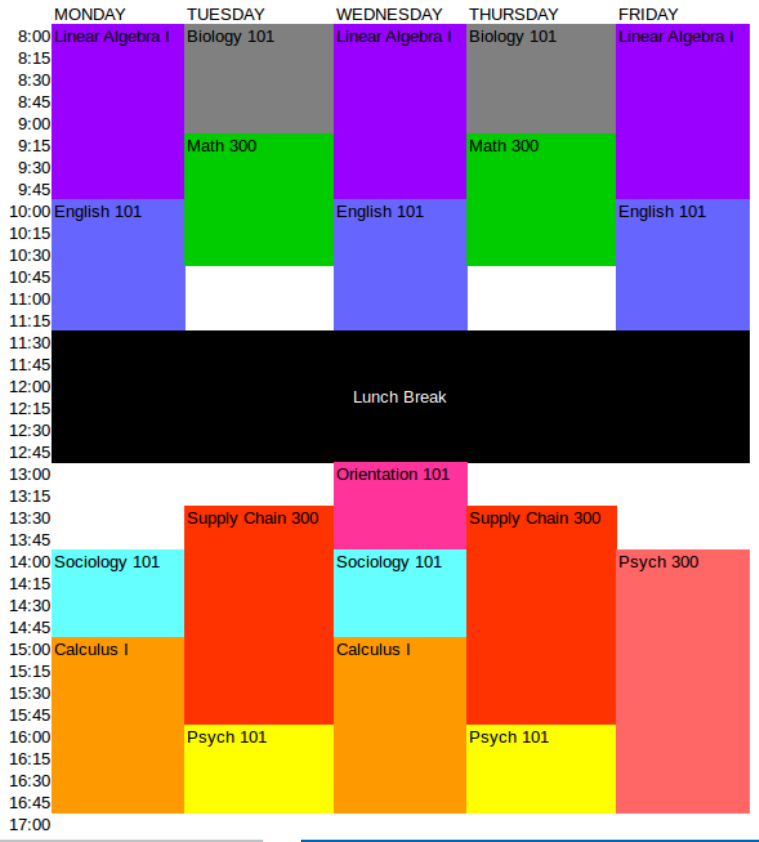
The “affected slots” for a given block can query for all recurrences for each given class.

View image here.

Generating a Schedule

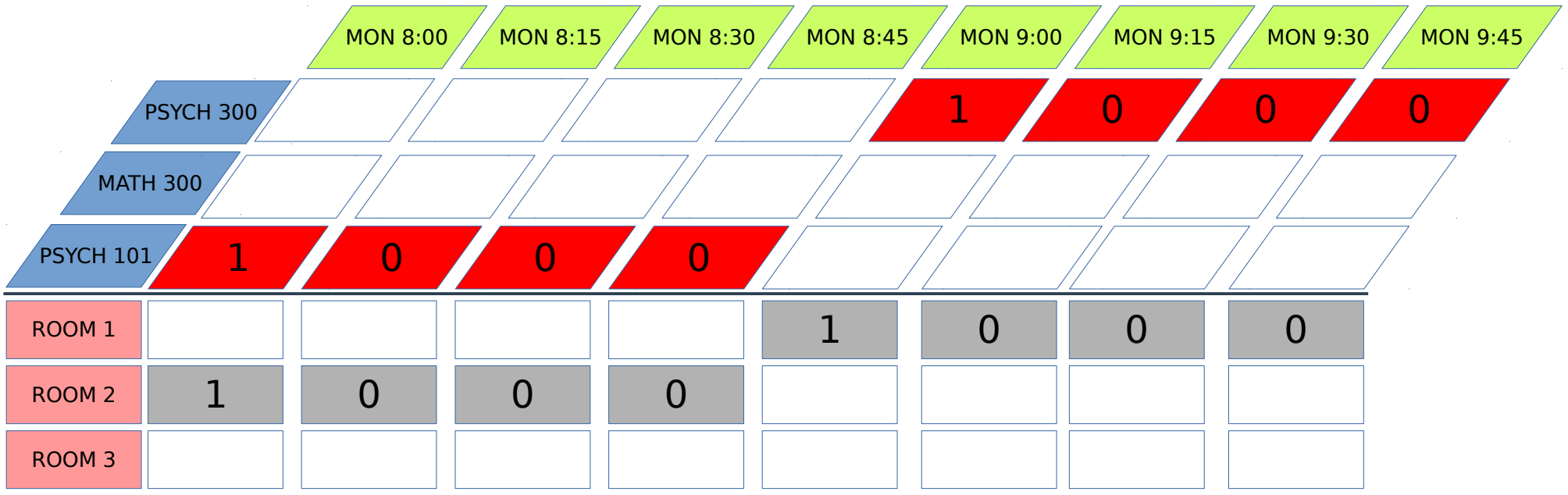
Plug these variables and *feasible* constraints into the optimizer, and you will get a solution.

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



Generating a Schedule

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



Source Code

Classroom Scheduling Optimizer

https://github.com/thomasnield/optimized-scheduling-demo

Solving a Sudoku

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
[2,6] → 7
[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
[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

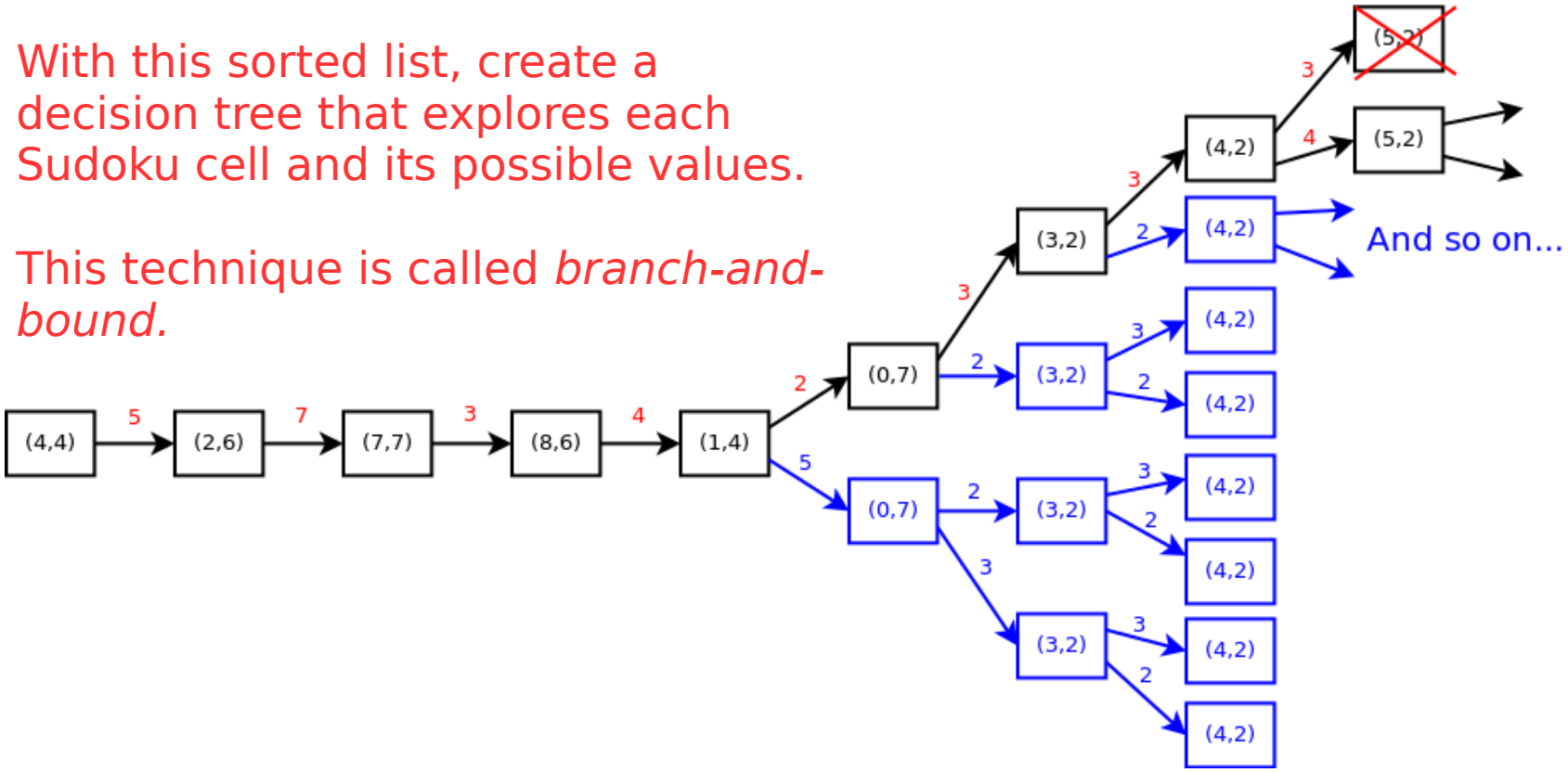
	0	1	2	3	4	5	6	7	8
0	5	3			7				
1	6			1	9	5			
2		9	8					6	
3	8				6				3
4	4			8		3			1
5	7				2				6
6		6					2	8	
7				4	1	9			5
8					8			7	9

Solving a Sudoku

[4,4] → 5
[2,6] → 7
[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
[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 technique is called *branch-and-bound.*



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.

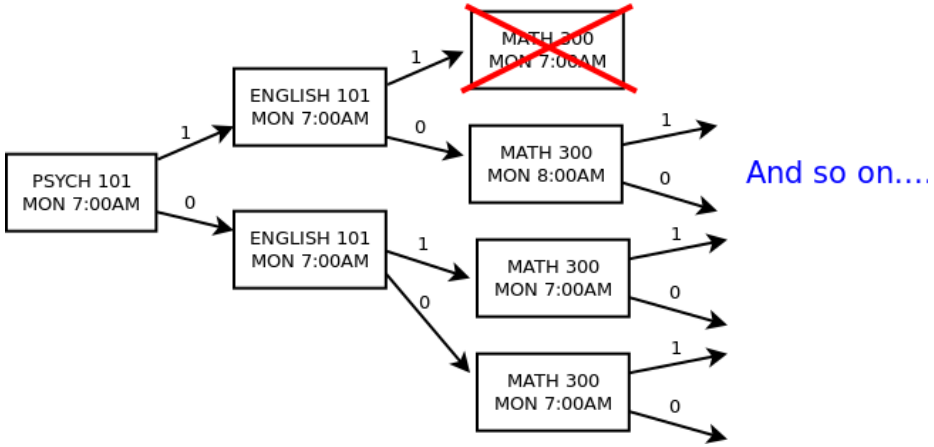
5	3	4	6	7	8	9	1	2
6	7	2	1	9	5	3	4	8
1	9	8	3	4	2	5	6	7
8	5	9	7	6	1	4	2	3
4	2	6	8	5	3	7	9	1
7	1	3	9	2	4	8	5	6
9	6	1	5	3	7	2	8	4
2	8	7	4	1	9	6	3	5
3	4	5	2	8	6	1	7	9

Branch-and-Bound for Scheduling

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

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.



Source Code

Kotlin Sudoku Solver

https://github.com/thomasnield/kotlin-sudoku-solver

Discrete Optimization Summary

Discrete Optimization is a best-kept secret well-known in operations research.

Machine learning itself is an optimization problem, finding the right values for variables to minimize an error function.

Many folks misguidedly turn to neural networks and other machine learning when discrete optimization would be more appropriate.

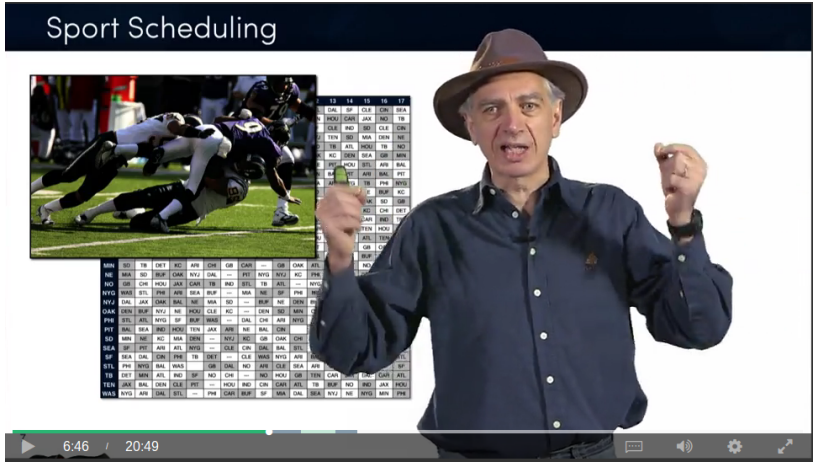
Recommended Java Libraries:

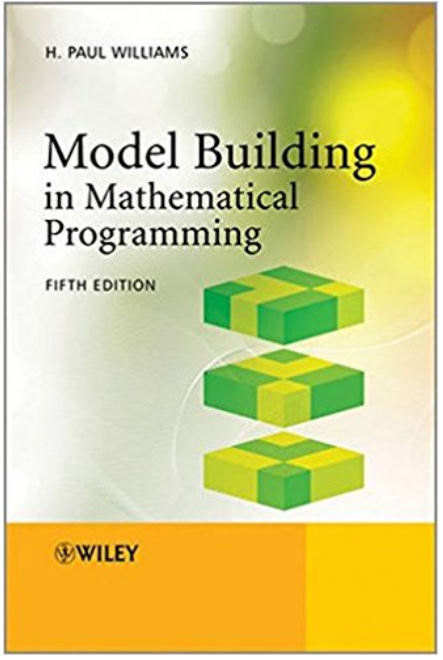
OjAlgo!

OptaPlanner

Learn More About Discrete Optimization

coursera *Discrete Optimization*





Part III:
Classification w/ Naive Bayes

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!

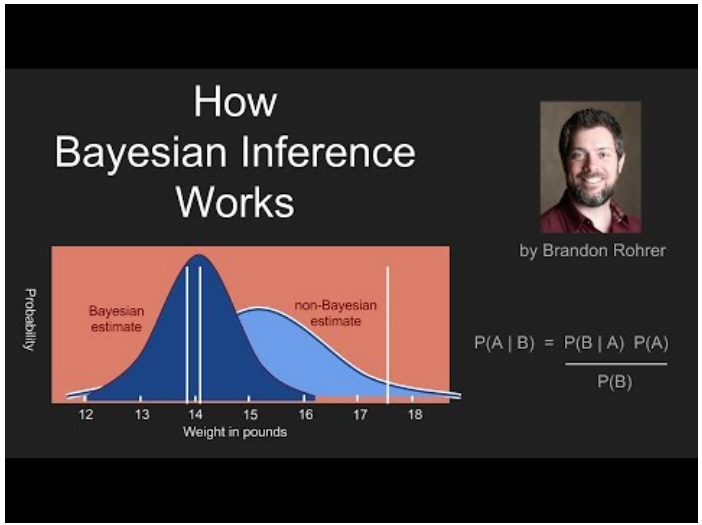
Always leave *a little* possibility it could belong to any category so you don't have *0* multiplication or division mess anything up.

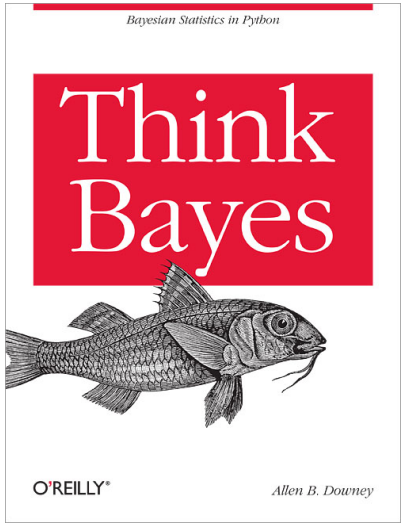
This can be done by adding a small value to each probability's numerator and denominator (e.g. *0.5* and *1.0*).

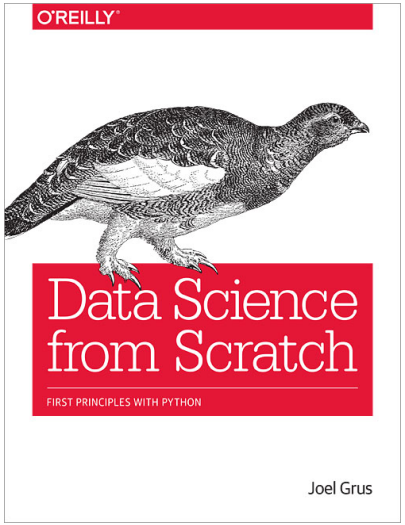
$$CombinedProbability = \frac{0.5 + (\text{Occur Product})}{1.0 + (\text{Occur Product}) + (\text{Not Occur Product})}$$

Learn More About Bayes

Brandon Rohrer - YouTube







Source Code

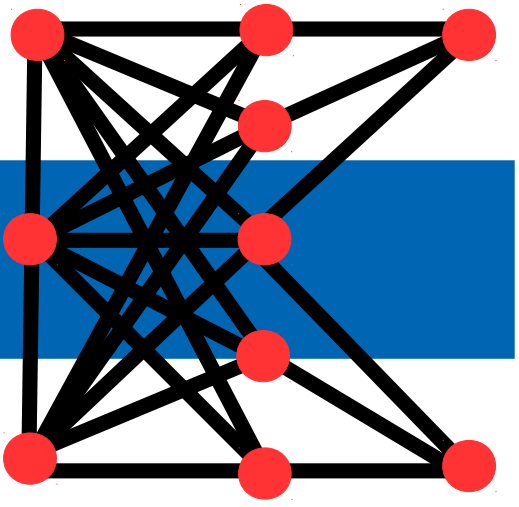
Bank Transaction Categorizer Demo

https://github.com/thomasnield/bayes_user_input_prediction

Email Spam Classifier Demo

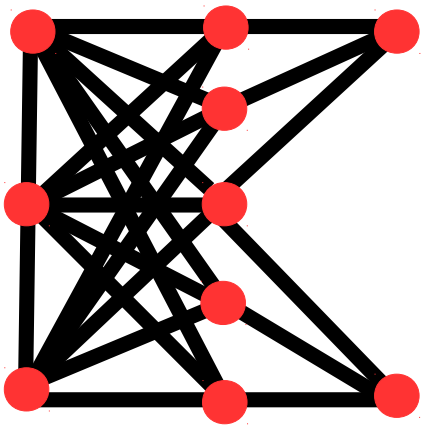
https://github.com/thomasnield/bayes_email_spam

Part V:
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

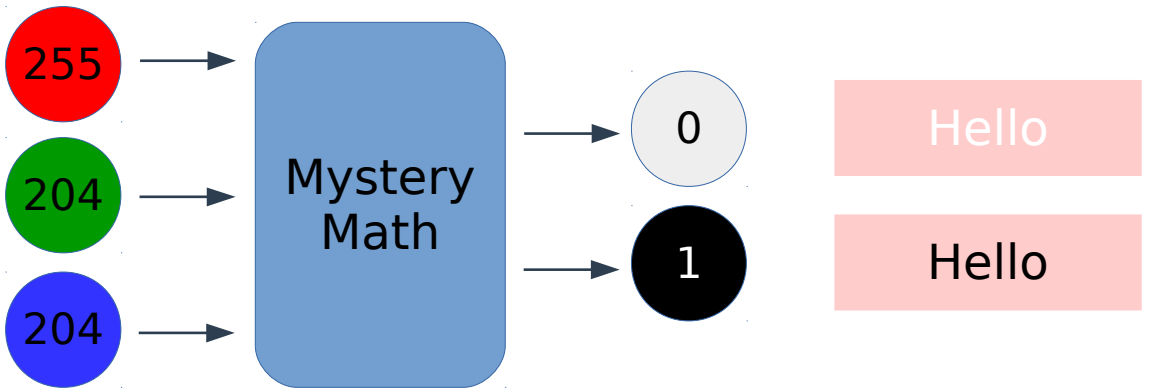
If you search around Stack Overflow, there is a nice formula to do this:

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

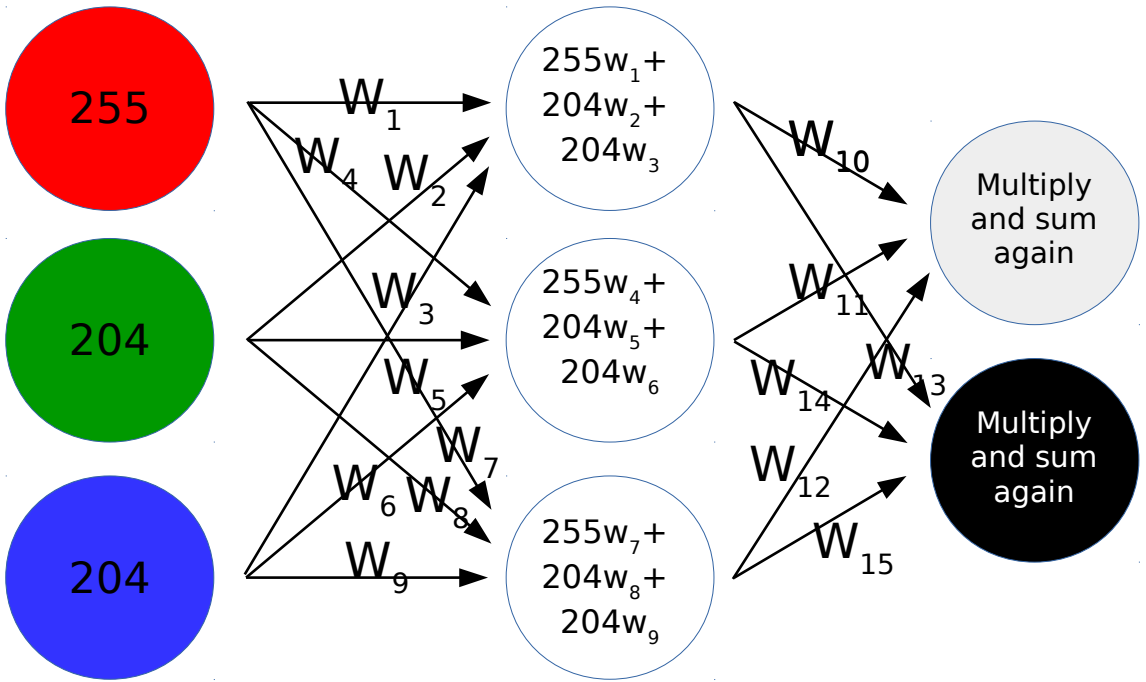
But what if we do not know the formula? Or one hasn't been discovered?

A Simple Neural Network

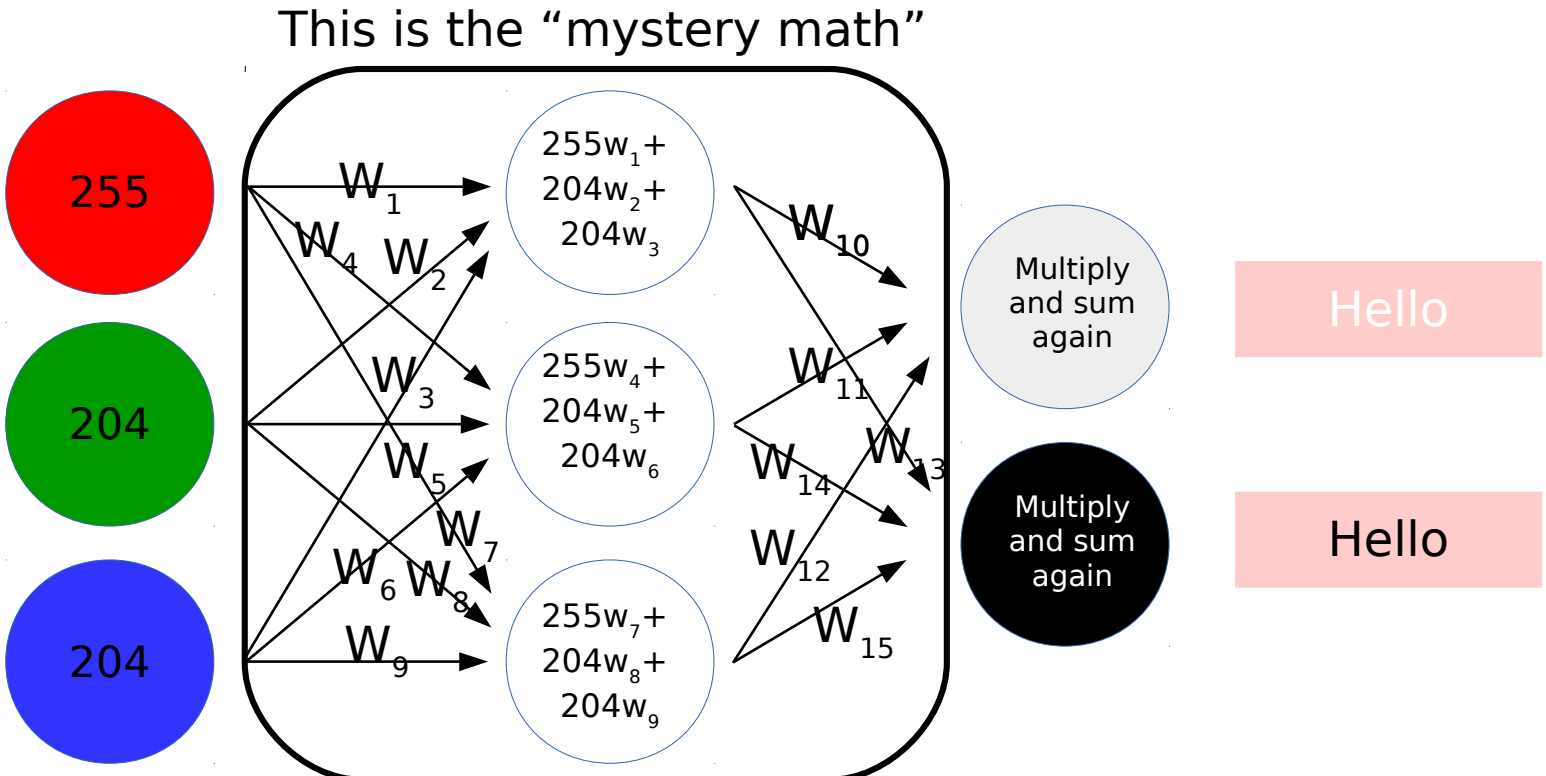
Let’s represent background color as 3 numeric RGB inputs, and predict whether a DARK/LIGHT font should be used.



A Simple Neural Network

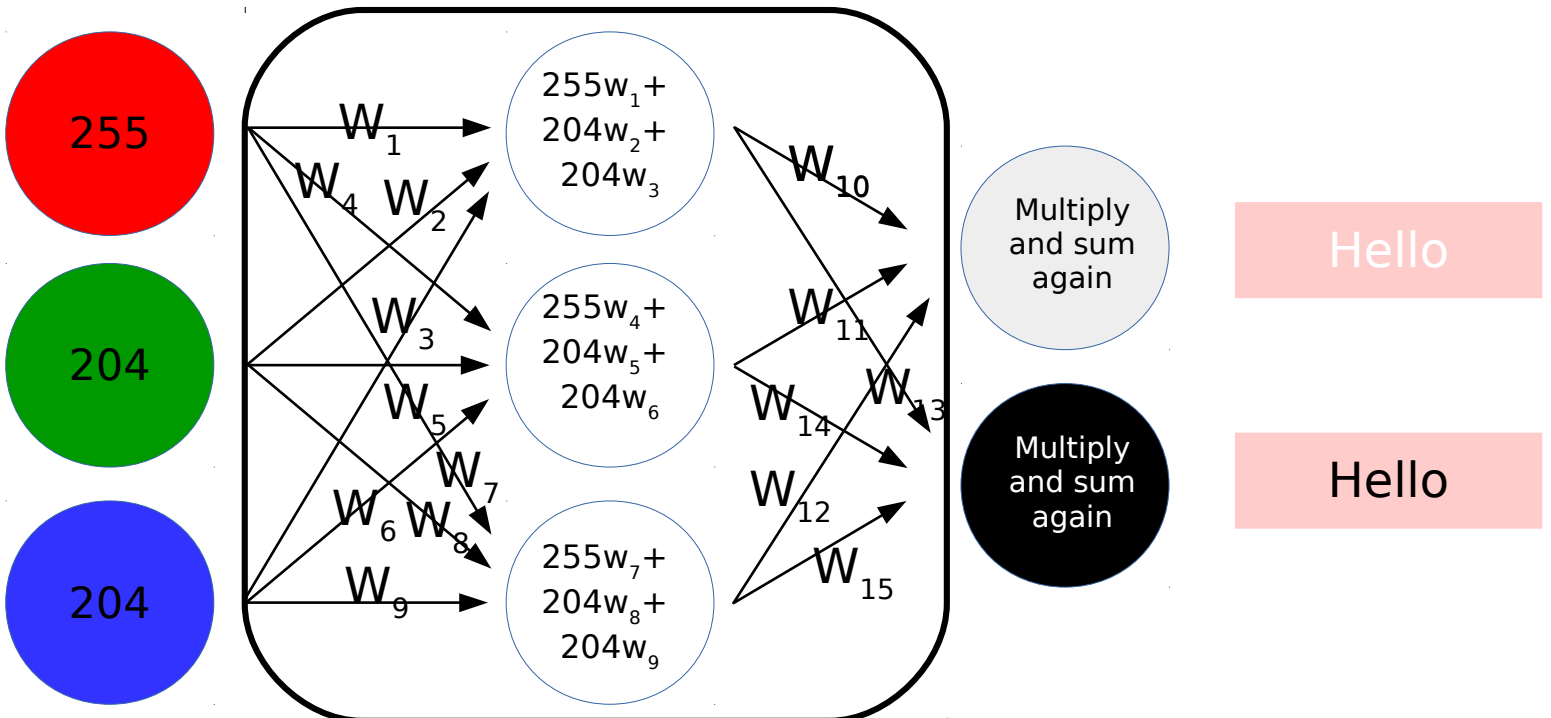


A Simple Neural Network



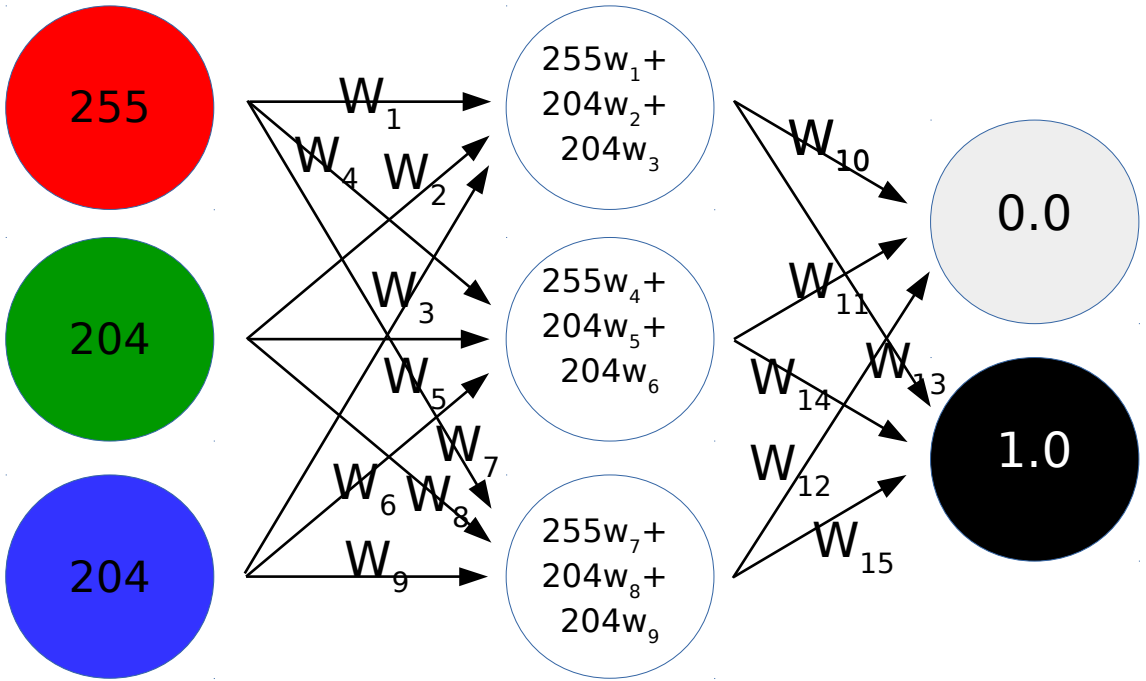
A Simple Neural Network

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?

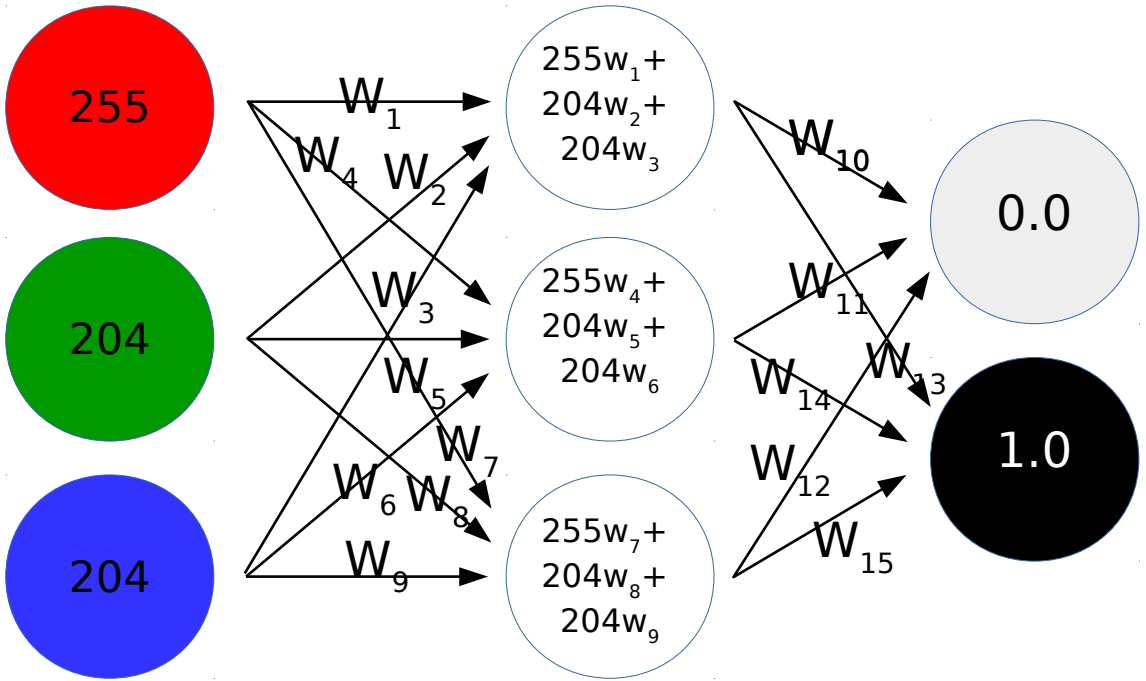


Hello

Hello

A Simple Neural Network

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

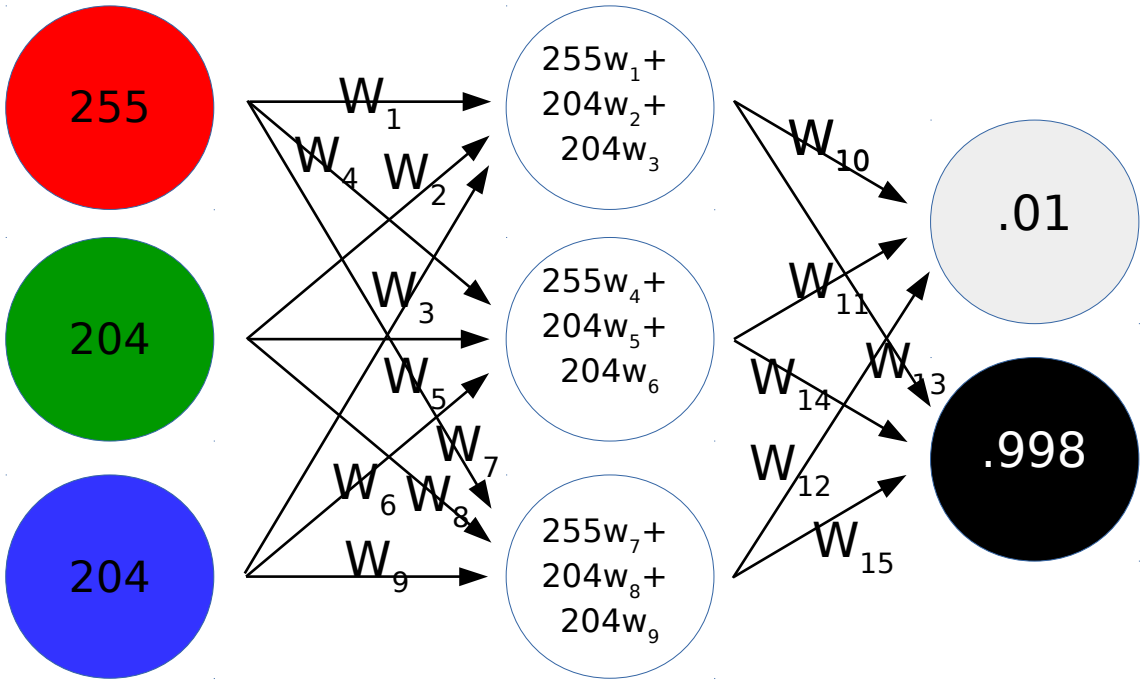


Hello

Hello

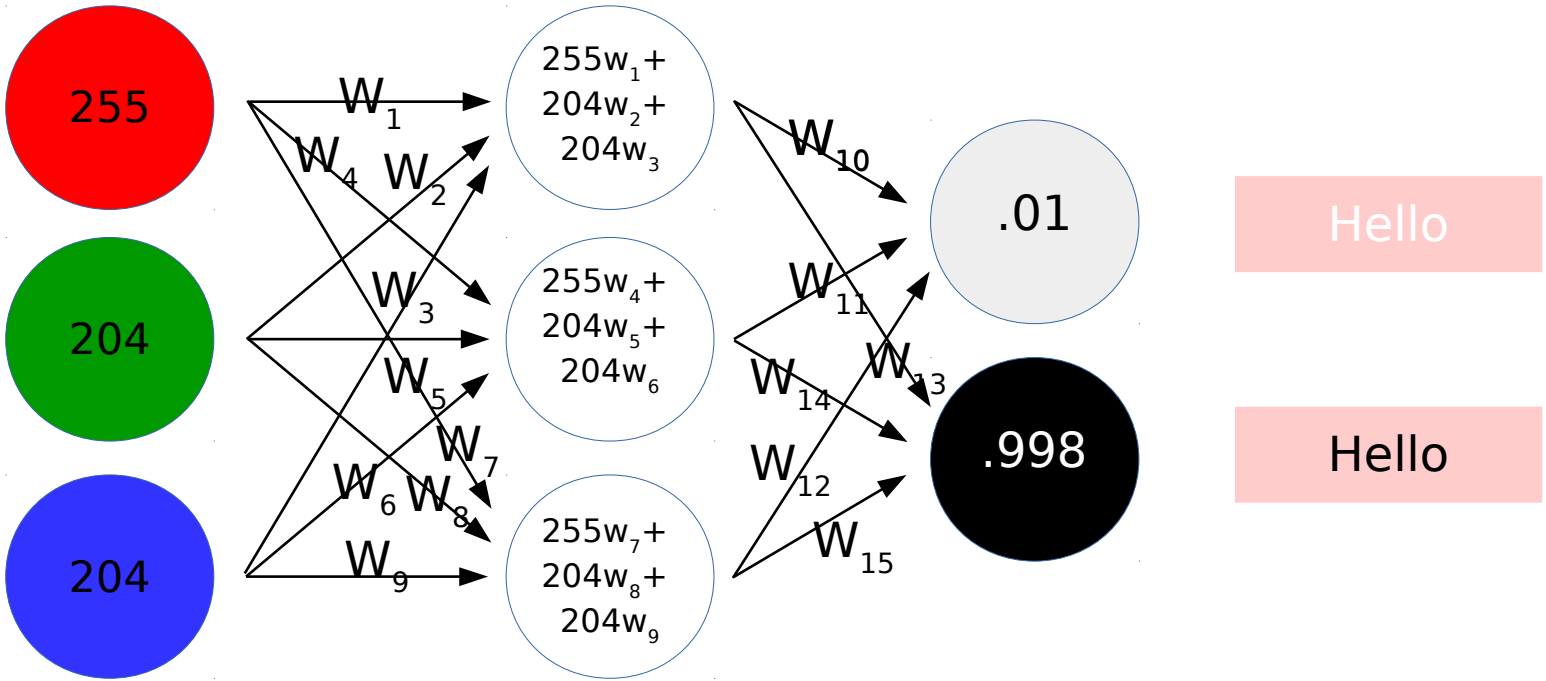
A Simple Neural Network

Answer:
This is an optimization problem!

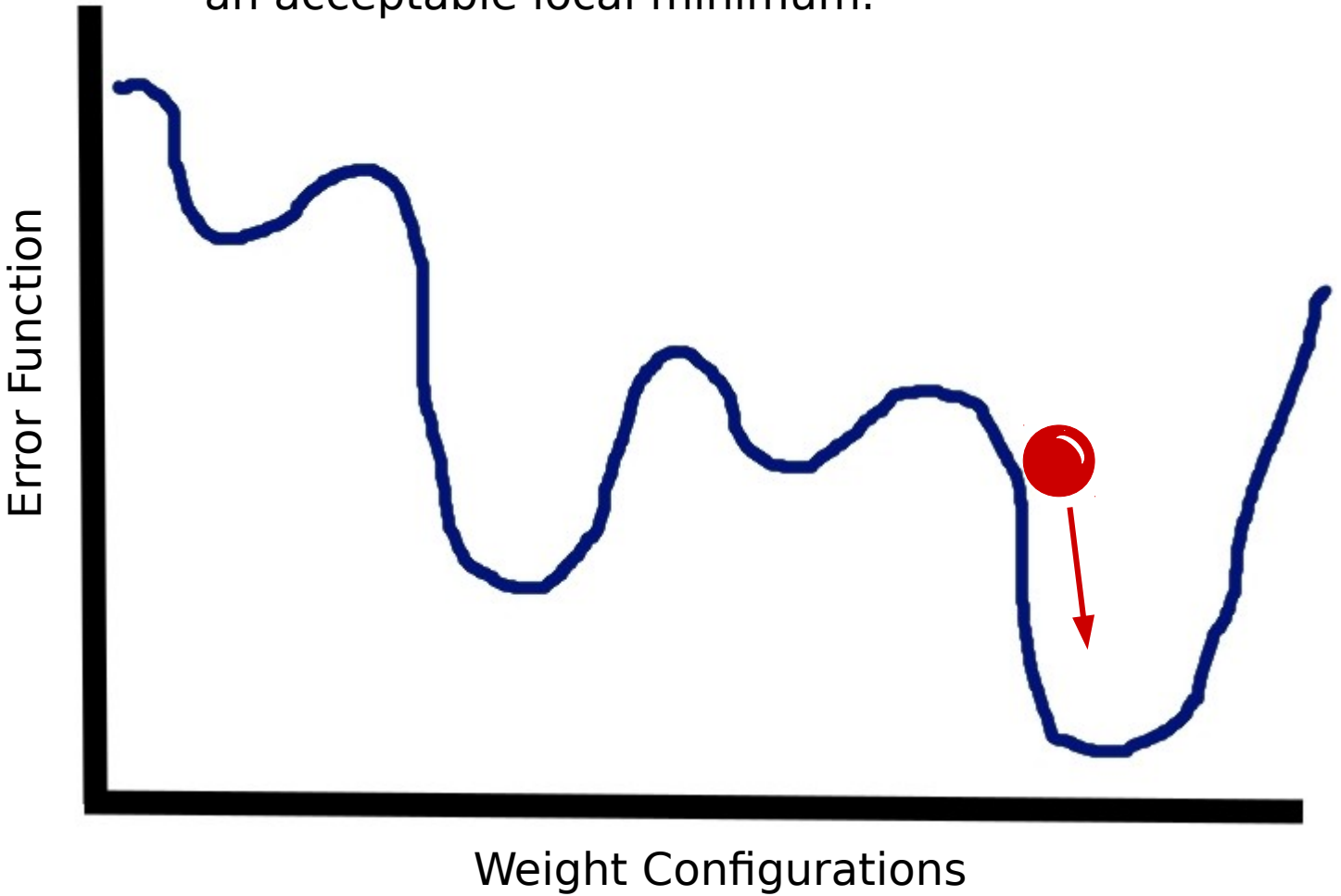


A Simple Neural Network

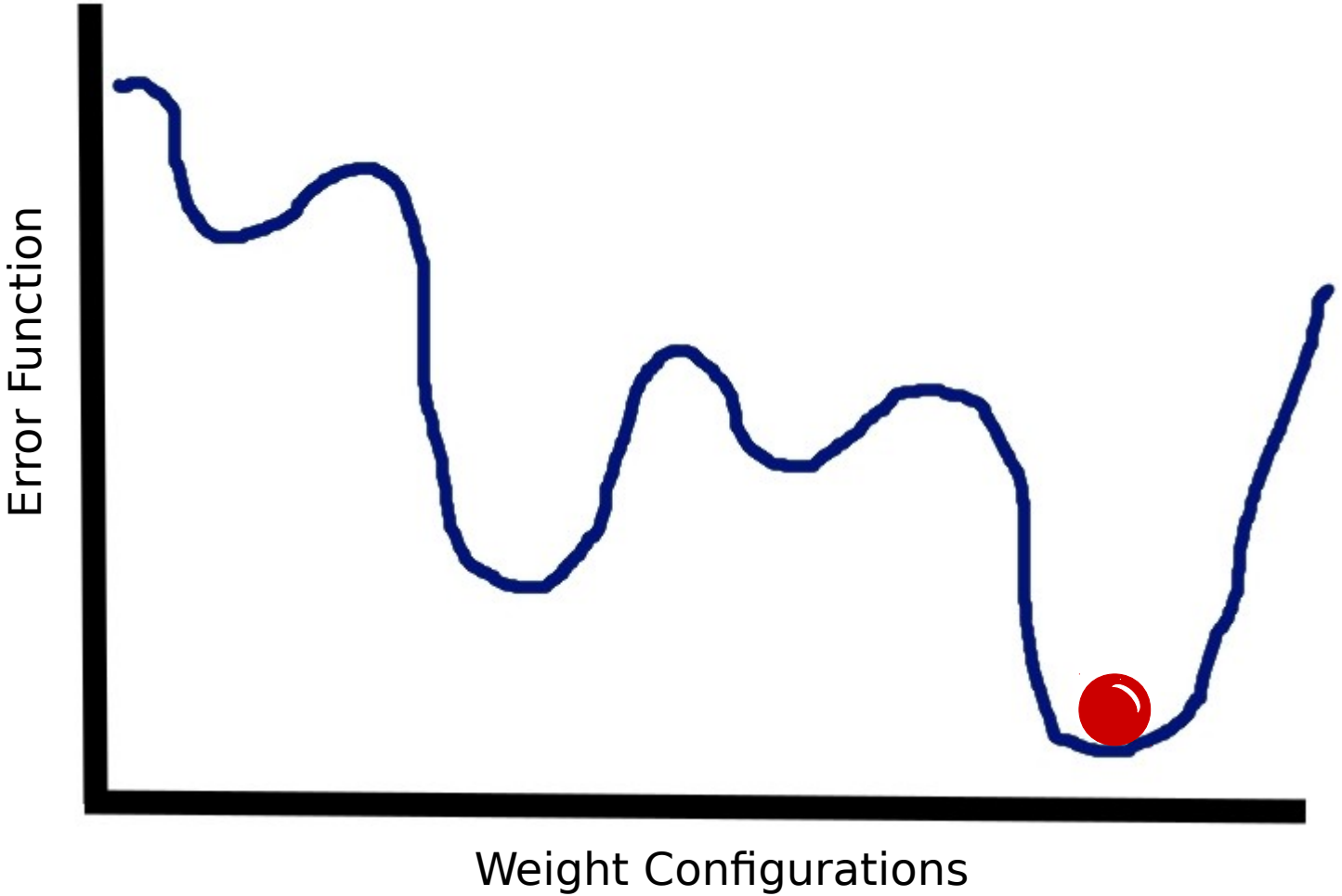
We need to solve for the weight values that gets our training colors as close to their desired outputs as possible.



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



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

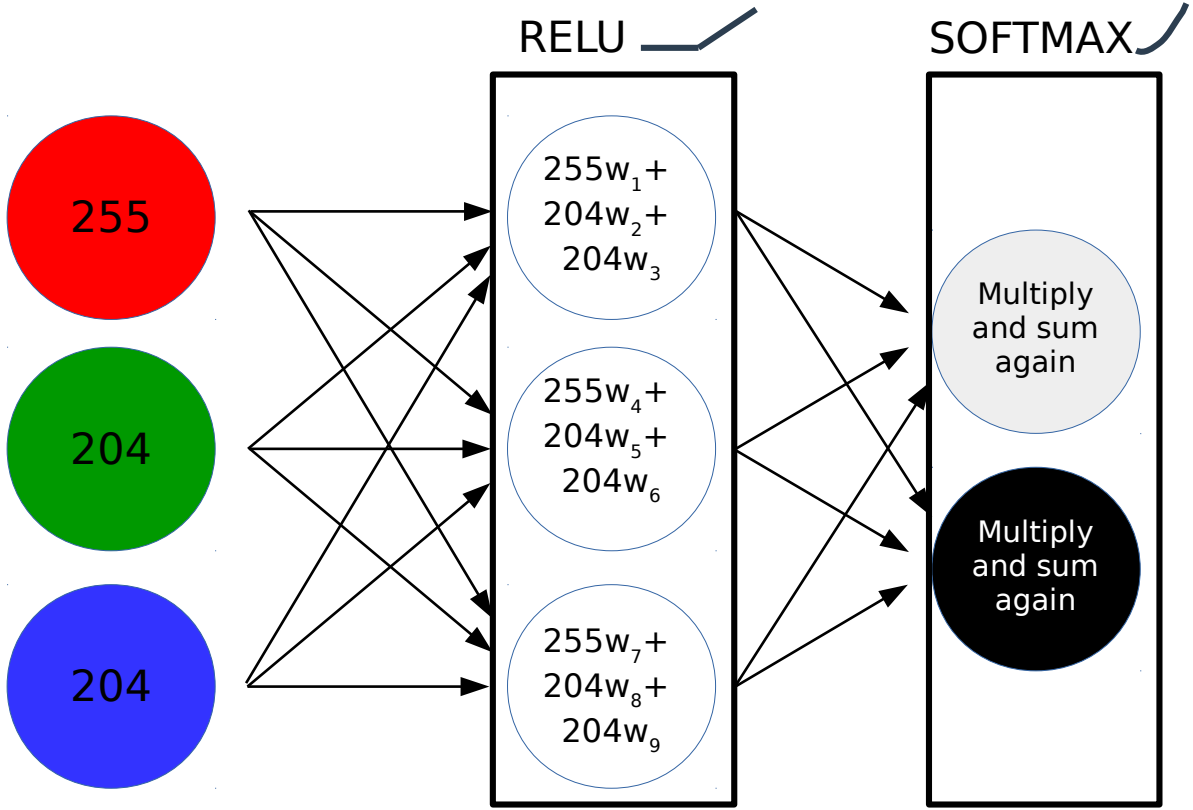


Activation Functions

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

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

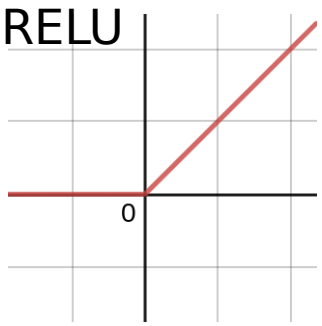
These make the network operate more naturally and smoothly.

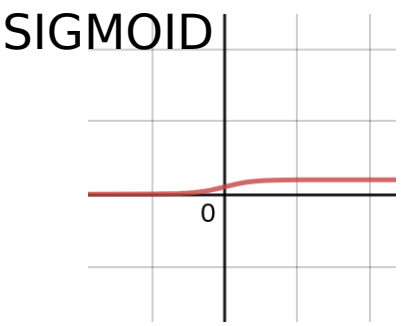


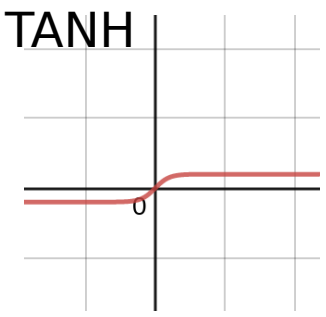
Activation Functions

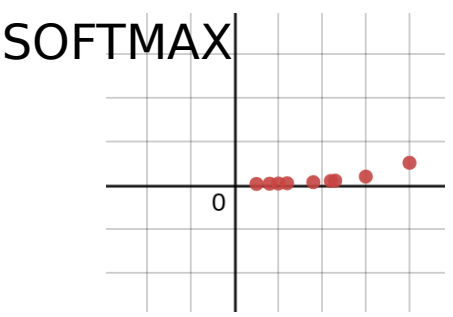
Four common neural network activation functions implemented using kotlin-stdlib

```kotlin
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)
```





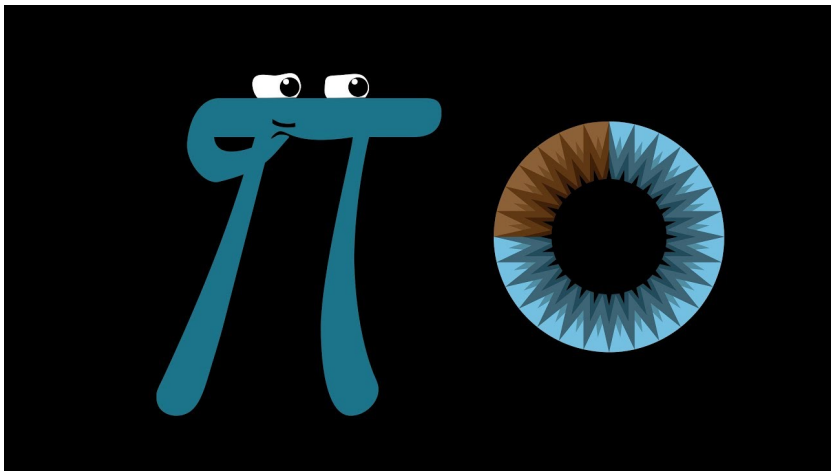


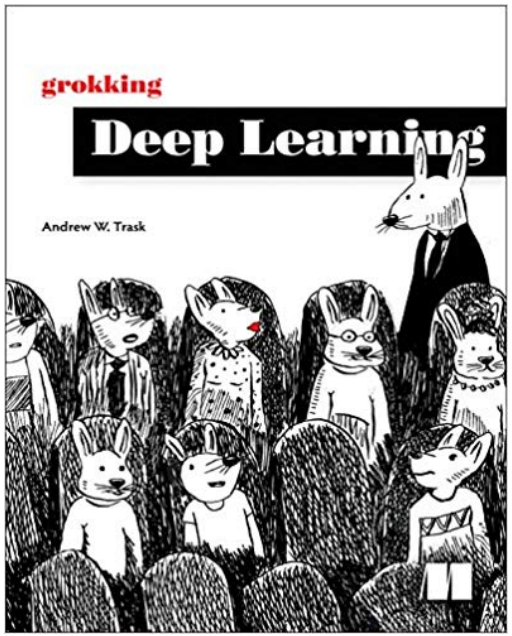


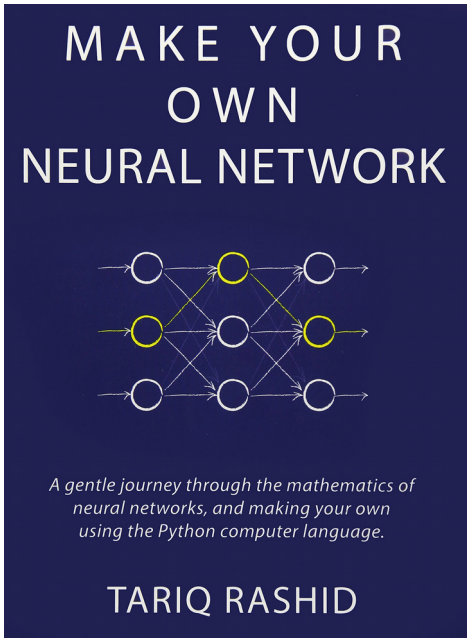
https://www.desmos.com/calculator/jwjn5rwfy6

Learn More About Neural Networks

3Blue1Brown - YouTube







Source Code

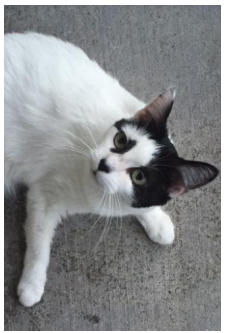
Kotlin Neural Network Example

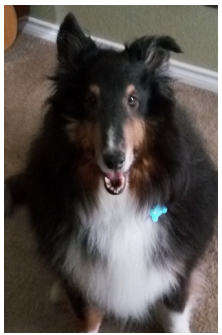
https://github.com/thomasnield/kotlin_simple_neural_network

Going Forward

Use the Right “AI” for the Job

Neural Networks





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

Bayesian Inference

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

Discrete Optimization

- **Scheduling**
  Staff, transportation, classrooms, sports tournaments, server jobs
- **Route Optimization**
  Transportation, communications
- **Industry**
  Manufacturing, farming, nutrition, energy, engineering, finance

GitHub Page for this Talk

Slides have links to code examples

https://github.com/thomasnield/kotlinconf-2018-mathematical-modeling

Appendix

The Best Way to Learn

The best way to become proficient in machine learning, optimization, and mathematical modeling is to have *specific projects*.

Instead of chasing vague objectives, pursue specific curiosities like:

- Sports tournament optimization
- Recognizing handwritten characters
- Creating a Chess A.I.
- Sentiment analysis of political candidates on social media

Turn these specific curiosities into self-contained projects or apps.

You will be surprised by how much you learn, and develop insight in which solutions work best for a given problem.

Pop Culture

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

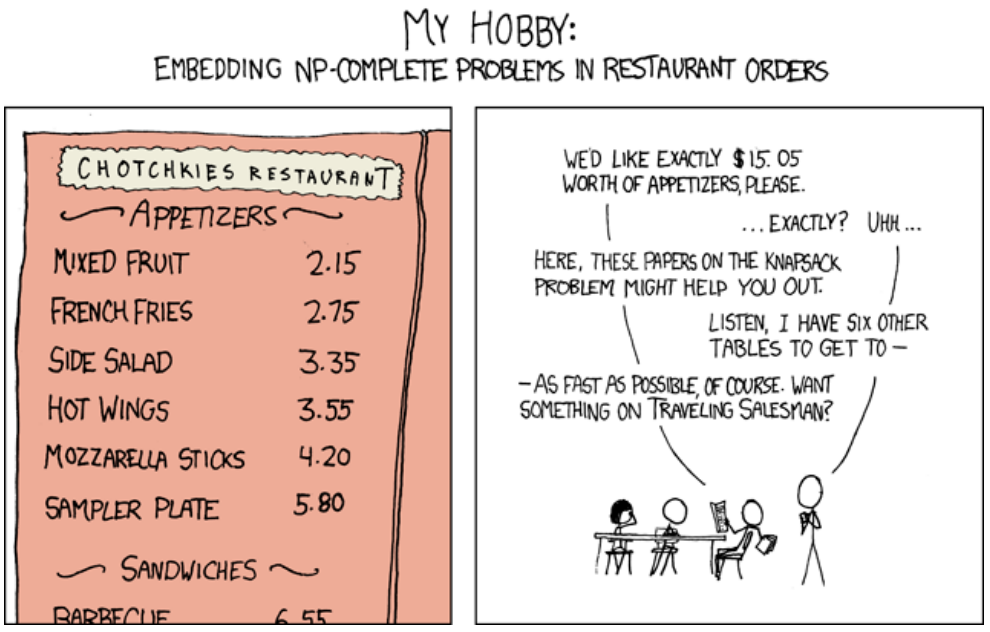
***Silicon Valley (HBO)* – The "Not Hotdog" App**
https://youtu.be/vIci3C4JkL0

***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

Java/Kotlin ML and Optimization Libraries

Java/Kotlin Library	Python Equivalent	Description
ND4J / Koma / ojAlgo	NumPy	Numerical computation Java libraries
DeepLearing4J	TensorFlow	Deep learning Java/Scala/Kotlin library
SMILE	scikit-learn	Comprehensive machine learning suite for Java
ojAlgo / OptaPlanner	PuLP	Optimization libraries for Java
Apache Commons Math	scikit-learn	Math, statistics, and ML for Java
TableSaw / Krangl	Pandas	Data frame libraries for Java/Kotlin
Kotlin-Statistics	scikit-learn	Statistical/probability operators for Kotlin
JavaFX / Data2Viz / Vegas	matplotlib	Charting libraries

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 (Channel)
https://youtu.be/F6RiAN1A8n0

Brandon Rohrer (Channel)
https://www.youtube.com/c/BrandonRohrer

3Blue1Brown (Channel)
https://www.youtube.com/channel/UCYO_jab_esuFRV4b17AJtAw

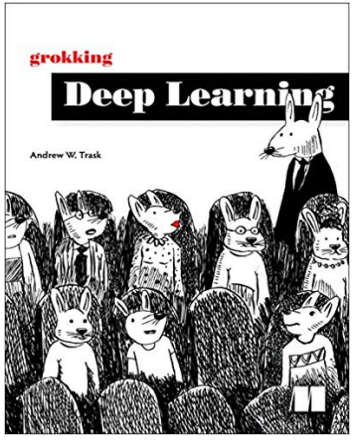
YouTube – P vs NP and the Computational Complexity Zoo (Video)
https://youtu.be/YX40hbAHx3s

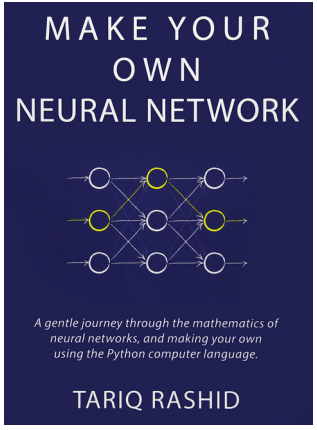
The Traveling Salesman Problem Visualization (Video)
https://youtu.be/SC5CX8drAtU

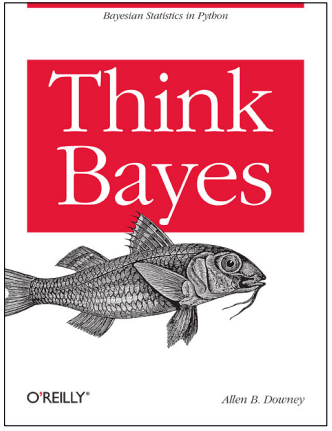
The Traveling Salesman w/ 1000 Cities (Video)
https://youtu.be/W-aAjd8_bUc

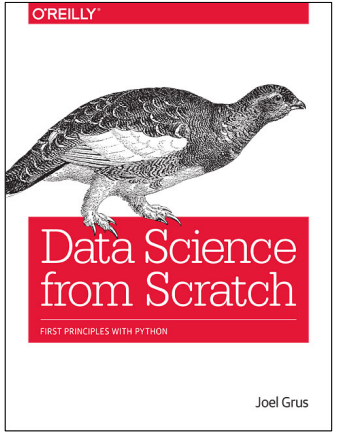
Writing My First Machine Learning Game (Video)
https://youtu.be/ZX2Hyu5WoFg

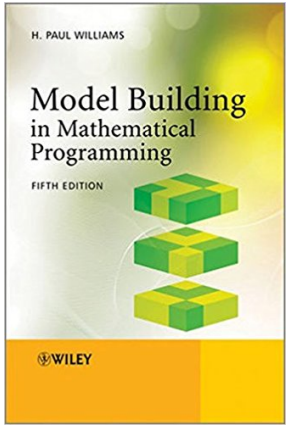
Books


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
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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

Building a Simple Chess A.I.

https://medium.freecodecamp.org/simple-chess-ai-step-by-step-1d55a9266977

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

The Hard Thing About Deep Learning

https://www.oreilly.com/ideas/the-hard-thing-about-deep-learning

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 (A powerful TSP algorithm)

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