Probability for HACKERS

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Pycon India 2017

< About me >

- Machine Learning Engineer @Juxt-Smart Mandate
- AI and ML Enthusiast
- Likes to crack puns- Ni..pun (^-^)
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- More on website:

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#Questions:

1. How many of you are from heavy mathematical background?
   E.g. Engineering, Physics

2. How many of you have used ML libraries like sklearn in your work?

3. How many of you want to get into following fields?
   - Artificial Intelligence
   - Machine Learning
   - Deep Learning
   - Data Science

MOTIVATION #1

Prerequisite for any famous AI and ML course/Book

CS229
Machine Learning
Autumn 2016

Course Information

Instructors:

Andrew Ng, John Duchi

Course Description

This course provides a broad introduction to machine learning and statistical
(generative/discriminative learning, parametric/non-parametric learning, neur
dimensionality reduction, kernel methods); learning theory (bias/variance trad
control. The course will also discuss recent applications of machine learning,
bioinformatics, speech recognition, and text and web data processing.

Prerequisites

Students are expected to have the following background:

- Knowledge of basic computer science principles and skills, at a level suf
- Familiarity with the probability theory. (CS 109 or STATS 116)
- Familiarity with linear algebra (any one of Math 104, Math 113, or CS 20

Deep Learning

An MIT Press book

Ian Goodfellow and Yoshua Bengio and Aaron Courville

Deep Learning

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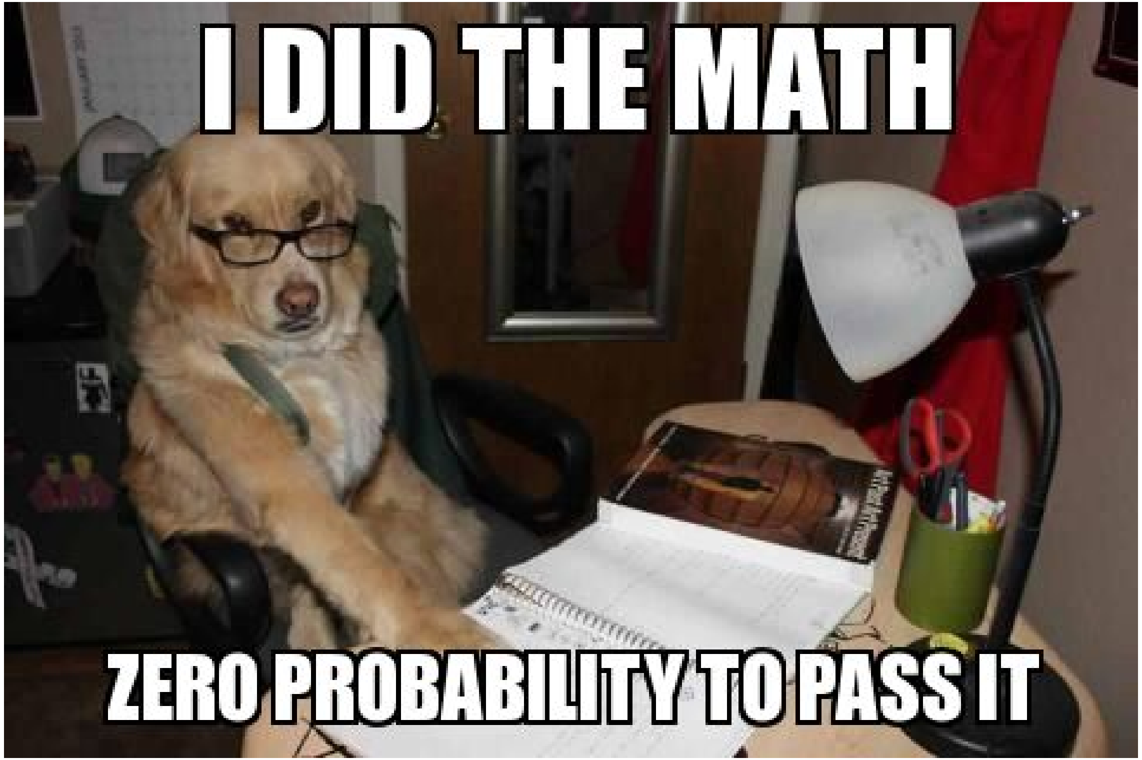
Those who struggle with math be like:



😈 Hackers' approach to learn Math

- Math is difficult but through coding, we can make it more interactive and intuitive.

- I like this quote:

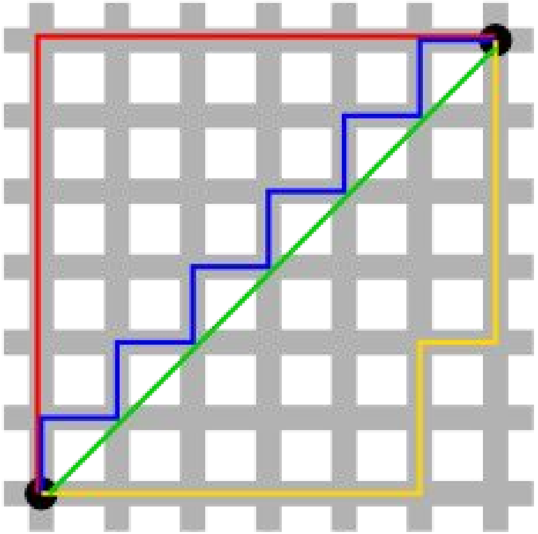
  "Statistics is Hard.
  Using programming skills it can be easy"
  – *Jake VanderPlas (Statistics for Hackers - Pycon 2016)*
  [Same for Probability]

- Though, I want you to focus more on concepts and not on code (Code is available on GitHub. Have a look at it later)

MOTIVATION #2

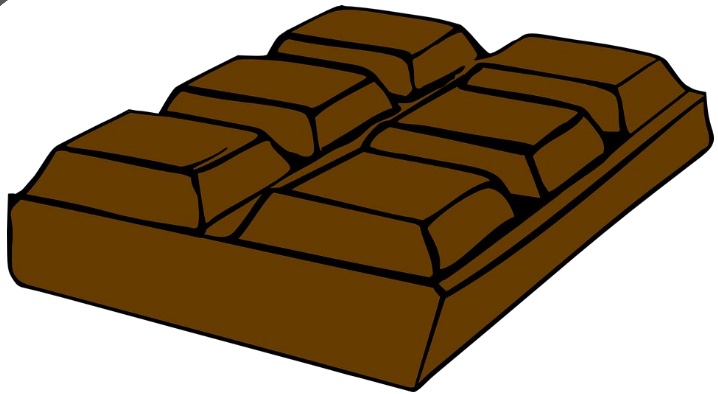
Modern AI

"Study and design of any agent that behaves in an intelligent way"



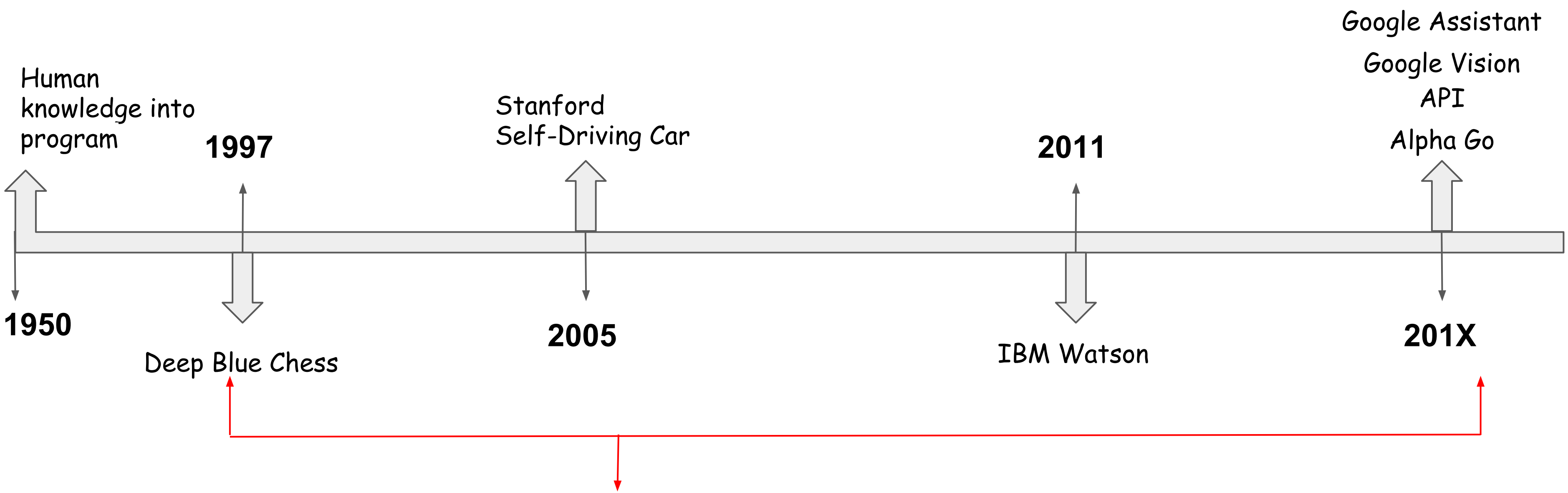
Demo Time! 🕒

WHO LIKES CHOCOLATES HERE?



MOTIVATION #2

HISTORY OF AI



Uses two revolutionary ideas:

1. Probability with Examples
2. Artificial Neurons

Conclusion

"Not once, but twice AI was revolutionized by people who understood Probability Theory"

- Stanford University | CS 109: Probability for Computer Scientists

TARGET

To be able to understand following math

$$p(C_k \mid \mathbf{x}) = \frac{p(C_k)\, p(\mathbf{x} \mid C_k)}{p(\mathbf{x})}$$

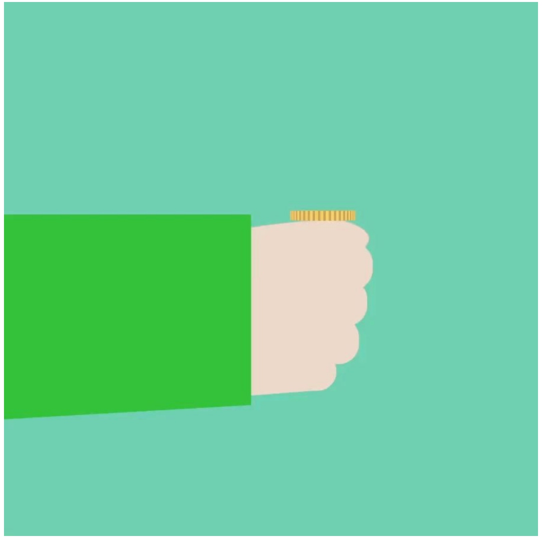
$$\begin{aligned} p(C_k \mid x_1, \dots, x_n) &\propto p(C_k, x_1, \dots, x_n) \\ &\propto p(C_k)\, p(x_1 \mid C_k)\, p(x_2 \mid C_k)\, p(x_3 \mid C_k) \cdots \\ &\propto p(C_k) \prod_{i=1}^{n} p(x_i \mid C_k)\,. \end{aligned}$$

"Naive" conditional independence assumptions

$$\hat{y} = \underset{k \in \{1,\dots,K\}}{\operatorname{argmax}}\ p(C_k) \prod_{i=1}^{n} p(x_i \mid C_k).$$

Diving into Probability

Obligatory coin toss experiment (interactive way)



Using:

1. Virtual Coin with jQuery
2. Comparing theoretical Vs experimental probability with D3
3. Simulating experiment with Python

[Introduction to Probability.ipynb]

Ingredients to Modelling Uncertainty

1. Sample space:

   The set of all possible outcomes for the experiment

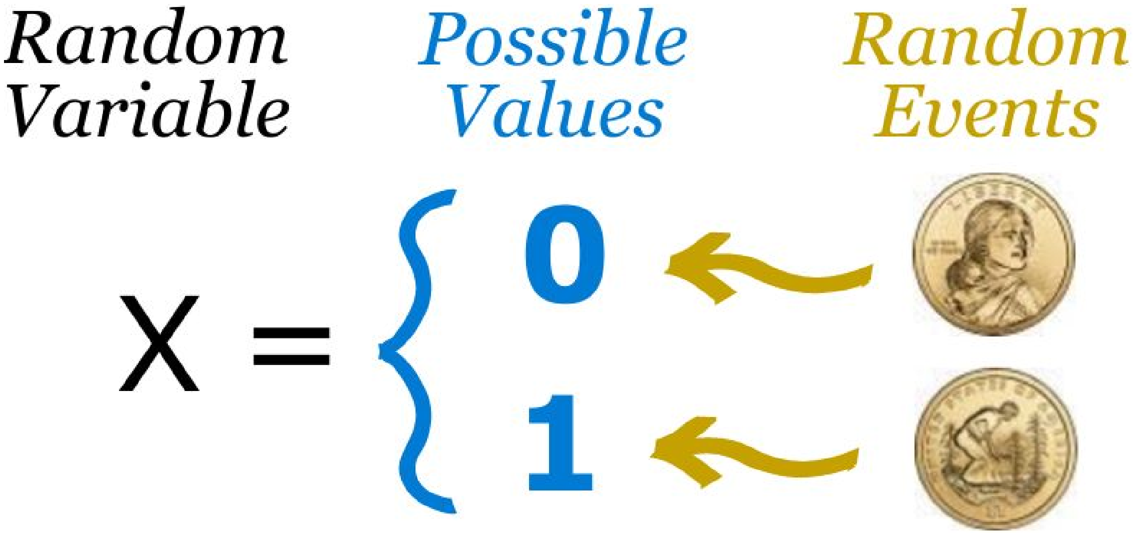
   $$\Omega = \{\text{heads}, \text{tails}\}$$

2. The probability of each outcome:

   For each possible outcome, assign a probability that is at least 0 and at most 1. For the fair coin flip:

   $$\mathbb{P}(\text{heads}) = \frac{1}{2} \text{ and } \mathbb{P}(\text{tails}) = \frac{1}{2}$$

Introduction to Random Variables



Introducing Random Variables.ipynb

Relation between Random Variables

1. Joint Probability
2. Marginal Probability
3. Conditional Probability
4. Dependence & Independence

Demystifying Bayes theorem

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

Application of Probability Theory learnt so far in Machine learning

Naive Bayes
Algorithm
As a Spam filter

Take Away:

- Mathematics is Hard, using programming skills it can be easy

- Intuition of Probability theory behind simple yet fast Naive Bayes algorithm

~ Thank you! ~

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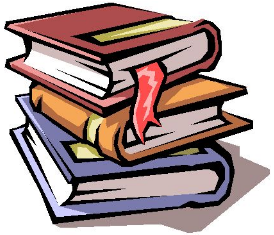

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3. Prob140: Probability for Data Science, UC Berkeley
4. Mathsisfun.com
5. https://en.wikipedia.org/wiki/Naive_Bayes_classifier
6. Seeing Theory, Brown University
7. https://github.com/wintersummermint/coin-flip-javascript