

# Reinforcement Learning for Autonomous Driving - Week 1

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# Overview

1. Basics of probability theory: Bayes Theorem, Conditional Probability, classifiers: supervised and unsupervised learning (Plenty of material via Google search).
2. Markov Chain and decision theory and automata theory (Posted on Piazza)
3. Reinforcement Learning: look for different papers: Google Scholar, arXiv, IEEEXplore
4. Meta-learning: Curated list of meta-learning papers: <https://github.com/dragen1860/awesome-meta-learning>
5. Ebook on meta-learning: <https://www.packtpub.com/big-data-and-business-intelligence/hands-meta-learning-python> (Don't need to buy, there is a 10-days trial period, which I believe should be enough, but do it at the very end when you know you can finish it. It is okay if you want to buy though)
6. ROS: <http://wiki.ros.org/>
7. <http://gazebosim.org/tutorials>
8. <http://sdformat.org/spec?ver=1.6&elem=world>

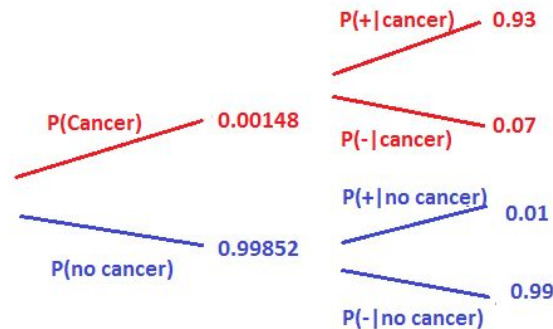
# Bayes Theorem

- Given two events A and B, what is the probability that event A will occur given that event B will occur as well?
- Common Example: Patients getting treated for cancer

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

↑ THE PROBABILITY OF "A" BEING TRUE GIVEN THAT "B" IS TRUE

↓ THE PROBABILITY OF "B" BEING TRUE



# Applications to Machine Learning

- Naive Bayes Classifier
  - Supervised
  - All features are independent of each other
- Based on the feature vector (data) for a given data point, what should it be classified as?
- Recursive Calculation

GAUSSIAN  
NAIVE BAYES  
CLASSIFIER

"Gaussian" because this is a normal distribution

This is our prior belief

$$P(\text{class} | \text{data}) = \frac{P(\text{data} | \text{class}) \times P(\text{class})}{P(\text{data})}$$

We don't calculate this in naive bayes classifiers

Chris Albon

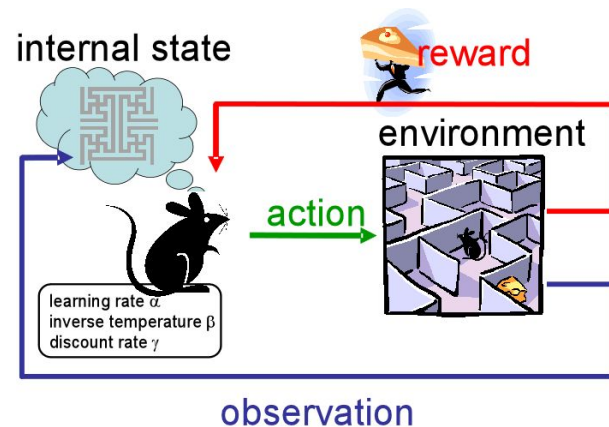
Now, the numerator of the fraction on right-hand side of the equation above is

$$P(x_1, x_2, \dots, x_n | C_i) \cdot P(C_i) = P(x_1, x_2, \dots, x_n, C_i)$$

$$\begin{aligned} P(x_1, x_2, \dots, x_n, C_i) &= P(x_1 | x_2, \dots, x_n, C_i) \cdot P(x_2, \dots, x_n, C_i) \\ &= P(x_1 | x_2, \dots, x_n, C_i) \cdot P(x_2 | x_3, \dots, x_n, C_i) \cdot P(x_3, \dots, x_n, C_i) \\ &= \dots \\ &= P(x_1 | x_2, \dots, x_n, C_i) \cdot P(x_2 | x_3, \dots, x_n, C_i) \dots P(x_{n-1} | x_n, C_i) \cdot P(x_n | C_i) \cdot P(C_i) \end{aligned}$$

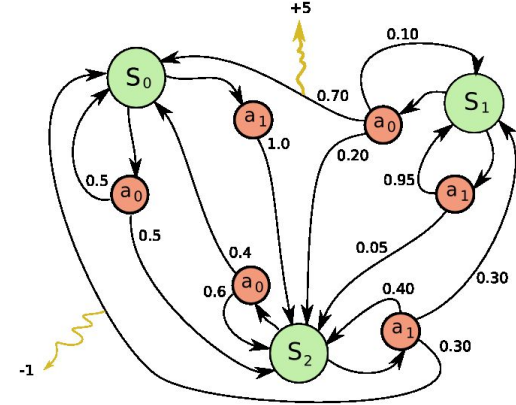
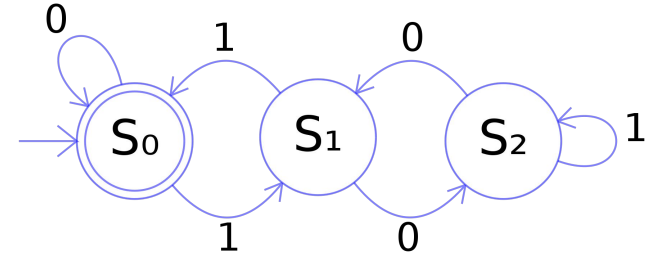
# Reinforcement Learning

- A way for programming agents to be rewarded and punished without needing to specify how a task is to be achieved.
- Problems faced with trial and error learning interactions with the programming agents.
- The first is to search in the space of behaviors in order to find one that performs well in the environment.
- The second is to use statistical techniques and dynamic programming methods to estimate the utility of taking actions in states of the world.



# Markov Chain, Decision Theory and Automata Theory

- An automata is a model of computation; it describes how an input is processed.
- A Markov Decision Process (MDP) is a stochastic finite automata; given a state and action, there are probabilities associated with what state is entered next.
- Decision Theory is the study of how to make an optimal decision with associated rewards and penalties.



# Meta Learning

Source: the book "Hands-On Meta Learning with Python"

Meta learning is the process of learning to learn, where an AI optimizes one or several other AIs.



# Types of Meta Learning

## 1/ Learning the metric space:

Learn about similarity between 2 images by computing distances of features. (Siamese networks, prototypical networks, and relation networks.)

## 2/ Learning the initializations:

Learn optimal initial parameter values. (MAML, Reptile, and Meta-SGD)

## 3/ Learning the optimizer:

We will have two networks: a base network that actually tries to learn and a meta network that optimizes the base network.

# Some Problems of Meta Learning

## **Credit assignment problem:**

-Computer needs to recognize what part of the action actually leads to the reward  
=> need to have a ton of time to train.

## **Shape reward function:**

-not scalable

-the computer may find the way to have that partial reward, not the way we want it to do.

# What's Next?

- Consolidate our knowledge, make sure that we're all on the same page
- Continue Literature Review, specifically looking for papers related to Reinforcement learning in Autonomous Vehicles
  - Challenges that other people faced, Implementation Methods, etc.
  - We were told that there isn't too much literature to review, so it's possible that we will have to create our own implementation
- Understand how to implement a model in a simulation using tools such as ROS and Gazebo for testing our design

# References

- Bayes Theorem and Cancer Screening -  
<https://www.youtube.com/watch?v=j2tNxlaGpR4>
- Naive Bayes and Machine Learning -  
<https://www.youtube.com/watch?v=sjUDIJfdnKM>
- Supervised vs Unsupervised vs Reinforcement Learning -  
<https://www.youtube.com/watch?v=xtOg44r6dsE>
- Reinforcement Learning -  
<https://www.jair.org/index.php/jair/article/view/10166>
- \section{Meta Learning}
- Meta Learning: It introduces realistic class imbalances. This varies the number of classes in each task and the size of the training set.
- \end{document}