

Probabilities Determinism v/s Non Determinism 09/24/2019

Sets, Conditional Probabilities.

$$P(A|B) = \frac{P(A \cap B)}{P(B)}, P(B) \neq 0$$

$$P(A \cap B) = P(A|B) P(B) - (1) \quad (1) = (2)$$

$$P(B|A) = \frac{P(B \cap A)}{P(A)}, P(B \cap A) = P(B|A) P(A) - (2)$$

- Dependent & Independent Events.

Probability Tree Diagrams Bayes Theorem.

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

Law of Total Probability

(marginal Probabilities)

posterior = likelihood × prior
evidence

(Q- ~~Actual~~)

~~P(+ | user) = 99%~~

No. of people = 1000

$$\text{Users of drug} = \frac{5}{1000} \times 1000 = 5$$

$$\frac{5}{1000} \times$$

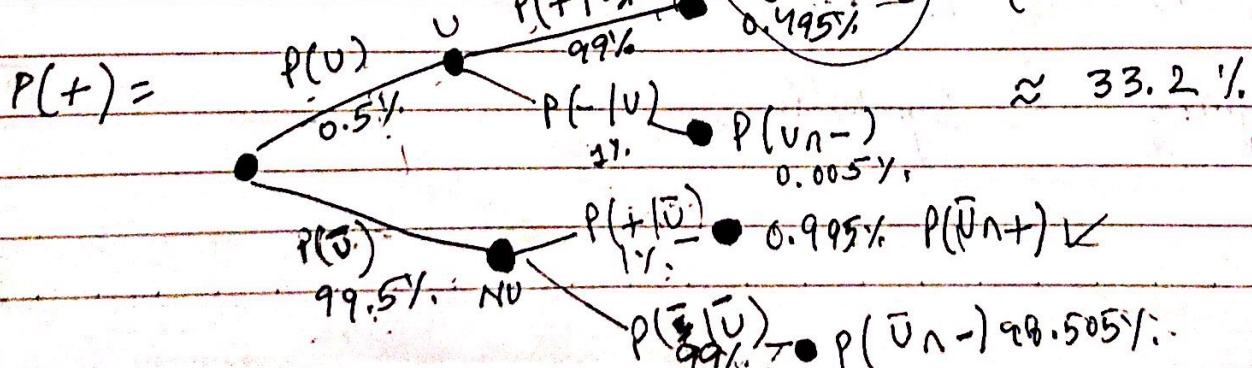
sensitivity
 $P(+ | \text{user}) = 99\%$

$$P(\text{user}) = 0.5\%$$

specific
 $P(- | \text{non-user}) = 99\% \approx 0.995$

$$P(\text{user} | +) = \frac{P(+ | \text{user}) P(\text{user})}{P(+)} \rightarrow$$

$$= \frac{99\% \times 0.5\%}{(0.5 \times 99\%) + (0.495 \times 0.005)} \times 100$$



UCI M/C learning dataset

Bayes Classifier

(Iris)

09/26/2019

Continuous

Discrete

Random Variables

Mean?

10/01/2019

→ Normal Distribution

→ Monte Carlo Integration

→ Pseudorandom number generators Linear congruential generator.

$$M = 9, C = 4$$

$$a = 7, x_0 = 3$$

modulus m

multiplier a ($2 \leq a < m$)

increment c ($0 \leq c \leq m$)

$$x_{n+1} = (ax_0 + c) \bmod m$$

seed x_0

random()

seed(a) - initializes

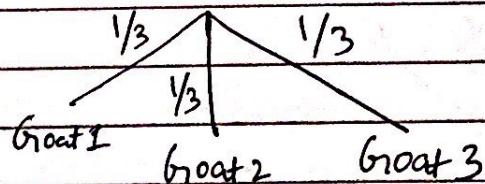
randint(a,b)

random as rand

matplotlib.pyplot as plt

rand.seed(0)

⇒ Monte Carlo Algorithms



→ Monty Hall Problem

car doors

random

1, 2, 3

Player choice

random

1, 2, 3

Simulation

Car - 1

Player - 2

$\times \times \rightarrow \text{open}$
1, 2, (3)

→ Monty fall Problem

10/03/2019

K-armed bandit problem

$$\frac{601 \times 100}{1000} + 0.999 \times 0 - 1$$

$$\cdot 1 + (-1) = -0.9$$

$$\frac{x}{6} - \frac{7}{8}$$

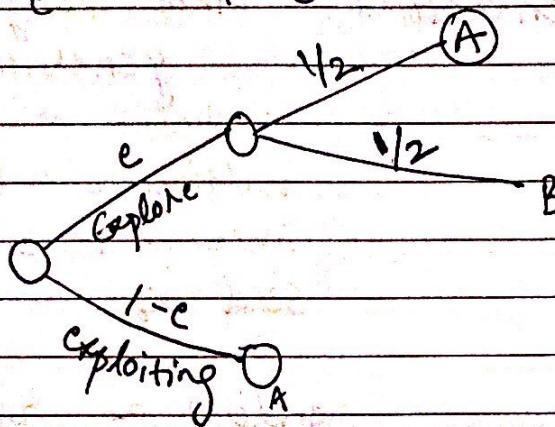
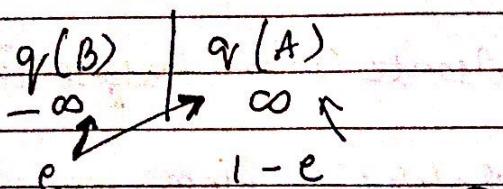
Constant decay

constant Rate decay

Exponential decay

Incremental Update Rule

A simple Bandit Algo.



$$\begin{aligned} & 1 \times (1-e) + e \times \frac{1}{2} \\ & (1-e) + e \times \frac{1}{2} \end{aligned}$$

$$(1 - 0.1) + \frac{1}{10} \cdot 9 + 0.01 \cdot 10$$

$$(1 - 0.01) + 0.01$$

$$.91$$

$$.99 + .001$$

$$.991$$

$$91\%$$

Abstract Bandit Algo.

a	1	2
$Q_t(a)$	1	2

$$P(a) = \frac{e^{Q_t(a)/\tau}}{\sum_{b=1}^n e^{Q_t(b)/\tau}}$$

$$P(1) = \frac{e^{Q_t(1)/\tau}}{e + e^2} = \frac{e}{e + e^2} = 0.27$$

$$P(2) = \frac{e^{0+2)/1}}{e+e^2} = \frac{e^2}{e+e^2} = 0.73$$

$$\tilde{c} = 1/20$$

$$P(1) = \frac{e^{20}}{e^{20} + e^{40}} \approx 0 \quad P(2) = \frac{e^{40}}{e^{20} + e^{40}} \approx 1$$

Upper Confidence Bound (UCB) action selection 10/08/2019

Update Rule Stationarity vs non-Stationarity

$$\begin{aligned} Q_{n+1} &= Q_n + \alpha [R_n - Q_n] && \text{Stochastic} \\ &= \alpha R_n + (1-\alpha) Q_n && \text{Approximation Theorem} \end{aligned}$$

$$= (1-\alpha)^n Q_1 + \sum_{i=1}^n \alpha(1-\alpha)^{n-i} R_i$$

Gradient Bandit Algorithms * Gradient Descent Tutorial.

→ Optimization - Selection of best element
1st order iterative optimization algo. for finding the min. or max.

→ Gradient vector $z = f(x, y) = x^2 + xy + y^2$

$$\frac{\partial f}{\partial x} = 2x + y, \quad \frac{\partial f}{\partial y} = 2y + x$$

$$\nabla f = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right) = (2x+y, 2y+x)$$

$$\text{cut}_x = 3$$

$$\text{prev. } z = 3$$

$$\text{cut}_x = 3 - 0.01 \times \nabla f (4x^3 - 9x^2)$$

Ascent / Gradient Descent Variants

10/10/2019

Batch

Stochastic <http://ruder.io/optimizing-gradient-descent/>
Mini Batch

→ Initialization Rule

10/15/2019

Probabilities

Set - Collection of objects - No repetition or ordering

set Cardinality L - no. of elements in set.

Power set - 2^L (no. of elements)

$$0 \leq P(A) \leq 1$$

$$P(A \cup B) = P(A) + P(B) - P(A \cap B), \quad P(A') = 1 - P(A)$$

- Conditional Probabilities

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

$P(A|B)$ Prob. of event A given that the event B has already occurred.

$$P(A \cap B) = P(A|B) \cdot P(B)$$

$$P(B \cap A) = P(B|A) \cdot P(A)$$

chain rule.

$$\begin{aligned} P(A \cap B) &= P(A|B) \cdot P(B) \\ &= P(B|A) \cdot P(A) \end{aligned}$$

Independent Events - If occurrence of one does not affect the prob. of occurrence of the other

Dependent Events - dependent on one another

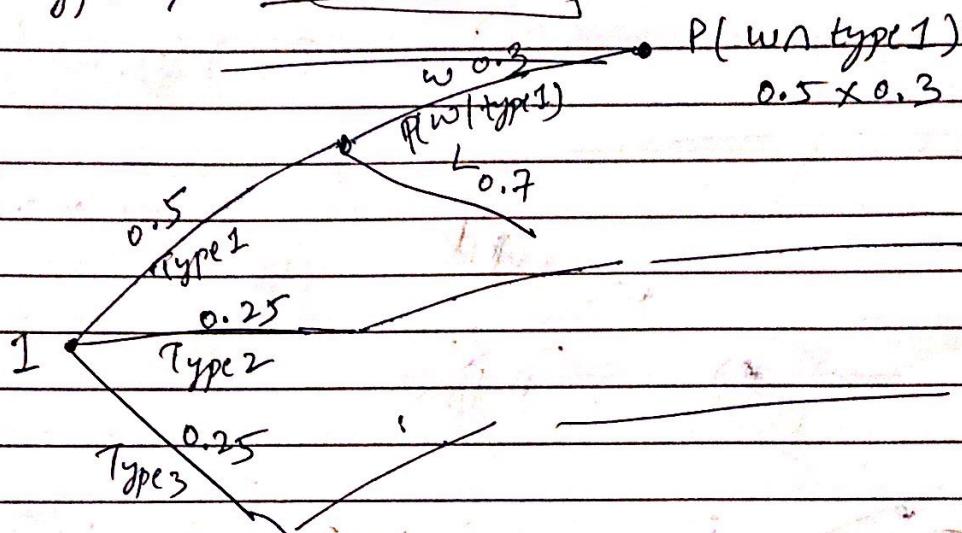
$$\begin{aligned} P(\text{Type 1}) &= 0.5 \\ P(\text{Type 2}) &= 0.25 \\ P(\text{Type 3}) &= 0.25 \end{aligned}$$

$$\begin{aligned} P(W | \text{Type 1}) &= 0.3 \\ P(W | \text{Type 2}) &= 0.4 \\ P(W | \text{Type 3}) &= 0.5 \end{aligned}$$

$$P(W \cap \text{Type 1}) = \underbrace{0.3 \times 0.5}_{+} \quad 1$$

$$P(W \cap \text{Type 2}) = \underbrace{0.4 \times 0.25}_{+}$$

$$P(W \cap \text{Type 3}) = \underbrace{0.5 \times 0.25}_{+}$$



Independent $P(A|B) = P(A)$

$$P(B|A) \Rightarrow P(A|B)$$

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

$$P(A \cup B) = P(A) + P(B) - P(A)P(B)$$

$$P(A \cap B) = P(A) \cdot P(B)$$

— independent

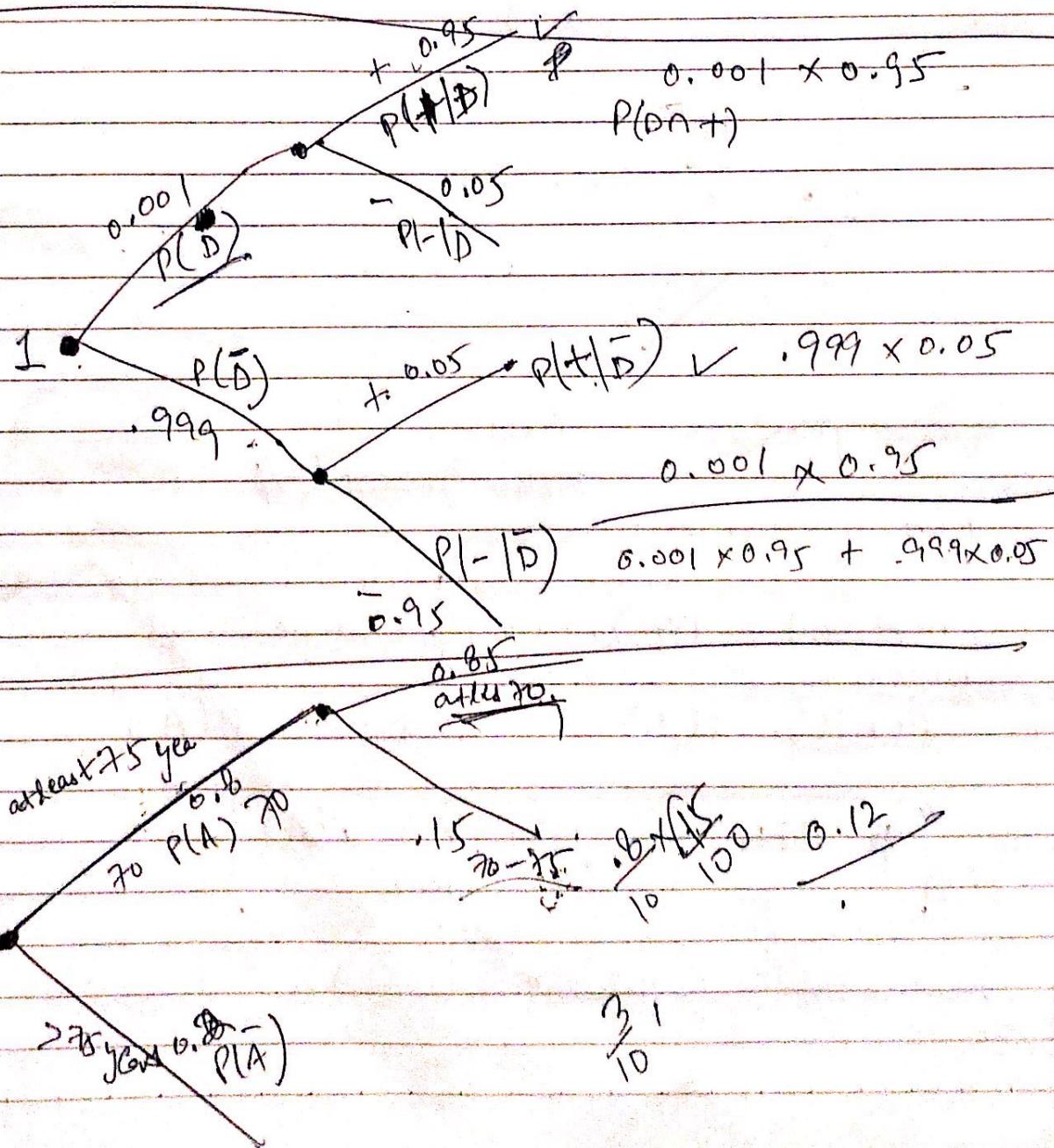
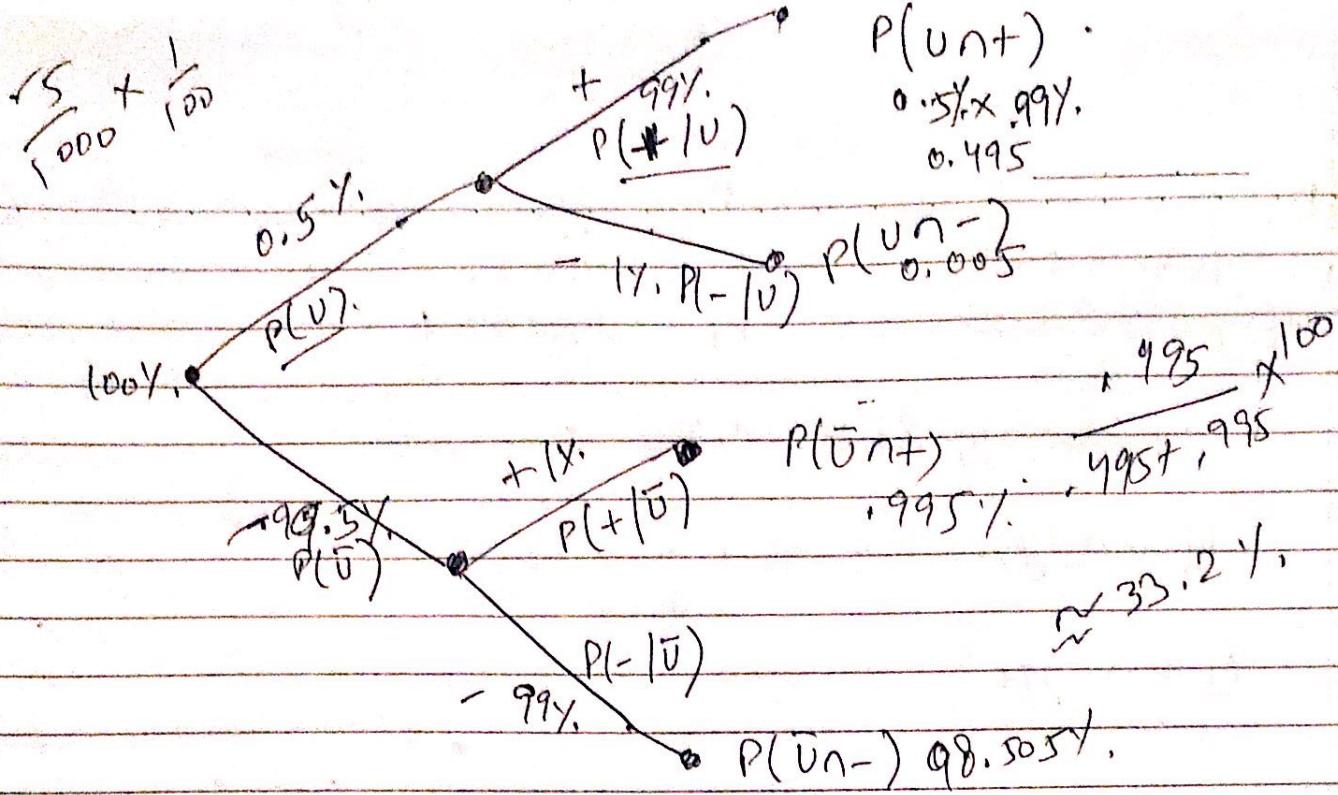
Bayes

$$P(A|B) \cdot P(B) = P(B|A) \cdot P(A)$$

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

Mutually Exclusive

$$P(A \cap B) = 0$$



$$P(\text{at least 70 years old}) = 0.85$$

$$P(\text{at least 75 years old}) = 0.8$$

$$\frac{3}{10} \times \frac{3}{10}$$

10 suspects.

$$P(L) = \frac{4}{10} \quad \frac{1}{10}$$

max. of 2 rolls is 2

$$\cancel{(1,1)}, (1,2), (2,1) \quad \frac{3}{16}$$

min. of 2 rolls is 2

$$\cancel{(2,2)}, (2,1), (2,3), (1,2,3) \\ (3,2), (4,1) \quad \frac{5}{16}$$

$$P(A \cap B) = \frac{1}{16}$$

$$\frac{1}{16} \neq \frac{3}{16} \times \frac{5}{16} \quad \frac{\frac{3}{4} + \frac{8}{6}}{18+12} = \frac{30}{24} \times 100$$

$$\frac{3}{4} \times \frac{3}{4} + \frac{5}{6} \times \frac{5}{6}$$

$$\frac{9}{16} + \frac{25}{36} = \frac{9+12}{24}$$

$$\frac{9}{40} + \frac{18}{60} = \frac{9+12}{40}$$

$$\frac{3}{10} \times \frac{3}{10} + \frac{3}{10} \times \frac{3}{6} + \frac{3}{10} \times \frac{3}{6}$$

$$\frac{21}{100} \times \frac{100}{2} = 105$$

$$\frac{9}{40} + \frac{9}{60} = P(A \cup B) = \frac{3}{4} + \frac{3}{6}$$

$$\frac{540+360}{240} = \frac{9}{10}$$

$$\frac{6}{10}$$

$$\frac{840}{360} = \frac{900}{720}$$

$$\frac{1}{10} \times \frac{3}{9} \times \frac{2}{8} + \underbrace{\frac{6}{10} \times \frac{5}{9} \times \frac{4}{8}}$$

$$\frac{24 + 120}{10 \times 9 \times 8} = \frac{144}{10 \times 9 \times 8} = 20 \text{ Y.}$$

(1)

$P(\text{Type 1}) = 0.5$	$P(w \text{Type 1}) = 0.3$
$P(\text{Type 2}) = 0.25$	$P(w \text{Type 2}) = 0.4$
$P(\text{Type 3}) = 0.25$	$P(w \text{Type 3}) = 0.5$

$$P(w | \text{Type}) = \frac{P(w \cap \text{Type 1})}{P(\text{Type 1})}$$

$$\frac{25}{100} = \frac{1}{4}$$

$$P(w \cap \text{Type 1}) = 0.3 \times 0.5 = .15$$

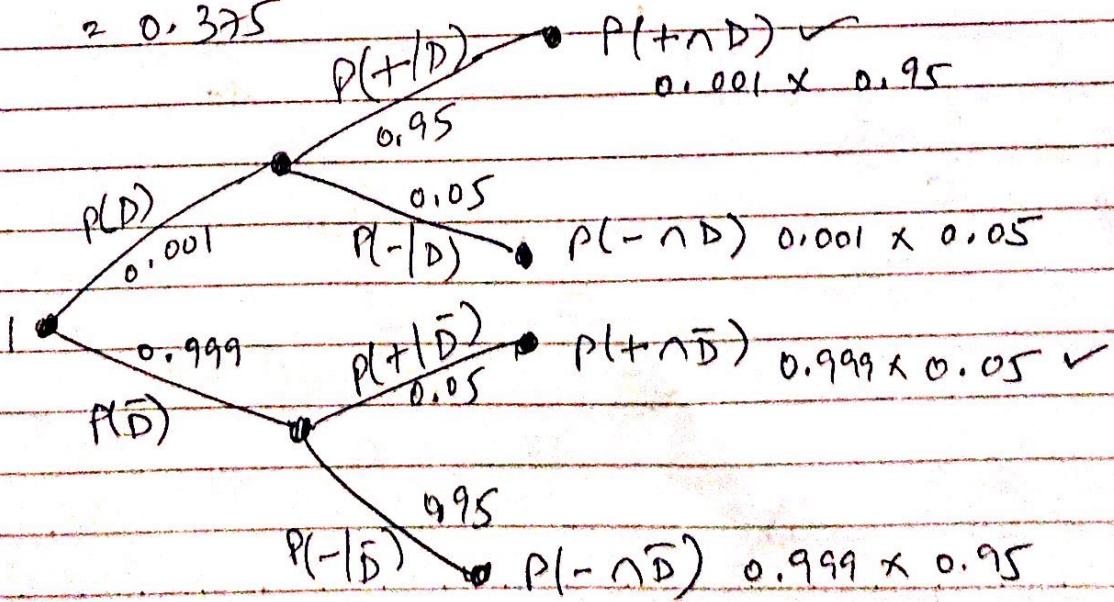
$$P(w \cap \text{Type 2}) = 0.4 \times .25 = 0.1$$

$$P(w \cap \text{Type 3}) = 0.5 \times .25 = 0.125$$

$$\frac{.15}{125} = \frac{15}{1000}$$

$$P(w) = 0.15 + 0.1 + 0.125 = 0.375$$

(2)



$$0.001 \times 0.95 + 0.999 \times 0.05 = 0.00095 + 0.04995 = 0.0187$$

③ Sample Space equal prob. = $1/16$

- (1,1), (1,2), (1,3), (1,4)
- (2,1), (2,2), (2,3), (2,4)
- (3,1), (3,2), (3,3), (3,4)
- (4,1), (4,2), (4,3), (4,4)

(a) $P(A \cap B) = 1/16$

$$P(A) = \text{# 1st roll results in } 1 = 4/16 = 1/4$$

$$P(B) = \text{# 2nd roll results in } 1 = 4/16 = 1/4$$

$P(A \cap B) = P(A|B) \cdot P(B)$ → for independent events = $P(A)$

$$= P(A) \cdot P(B) = 1/4 \times 1/4 = 1/16$$

independent events.

(b) $P(A \cap B) = 1/16 \quad P(A \cap B) = P(A) \cdot P(B)$

$$P(A) = 4/16 = 1/4 \quad = 1/4 \times 1/4$$

$$P(B) = 4/16 = 1/4 \quad \text{independent} = 1/16$$

(c) $P(A \cap B) = 1/16 \quad P(A \cap B) = P(A) \cdot P(B)$

$$P(A) = 3/16 \quad 1/16 \neq 3/16 \times 5/16$$

$$P(B) = 5/16 \quad \text{Not independent}$$

Assignment

9

115

③ 10 snipe or. $\frac{4}{10} \times \frac{3}{9} \times \frac{2}{8} + \frac{6}{10} \times \frac{5}{9} \times \frac{4}{8}$

$$\frac{24 + 120}{10 \times 9 \times 8} = \frac{144}{10 \times 9 \times 8} \times 100\% = 20\%$$

Compound event - subset of sample space consisting of more than 1 outcome.

Simple event - subset with single outcome.

Random variable - Needs to be a number.

$x=1$ (Head) $x=0$ (Tail)

Discrete Random Variable - countable no. of distinct values

Continuous Random Variable - any value within a range of values

$F(x)$ cdf - cumulative distribution func?

w	0	1	2	3	
$p(w)$	0.02	0.27	0.33	0.38	pmf
$F(w)$	0.02	0.29	0.62	1	cdf

$$\mu \text{ (mean)} = \sum (x) \cdot p(x)$$

$$\sigma^2 = v(x) \text{ (variance)} = \sum (x - \mu)^2 \cdot p(x)$$

$$\sigma = \sqrt{\sigma^2} \text{ (standard deviation)}$$

$$pdf = f(x) = \frac{d}{dx} F(x)$$

$$cdf = \int_{-\infty}^x f(t) dt$$

Pseudo Random Number generators

Algo. that produce Random no.s.

Bandits. K-armed bandit problem.

Action A_t from K possibilities \rightarrow receive reward R_t
finite sequence of time steps $t = 1, 2, 3, \dots$

goal is to max. expected total reward.

$$q^*(a) = E(R_t | A_t = a), \quad \forall a \in \{1, 2, \dots, K\}$$

$$E[x_a] = \$0.7$$

$$E[x_b] = \$0.5 \quad \Rightarrow \quad q^*(b) = \$0.5$$

$$E[x_c] = \$0.4$$

greedy action selection - always choose the action with best value estimate

$$A_t^* = \operatorname{argmax}_a Q_t(a) \quad \text{exploitation}$$

Randomly choose when ties.

Random action selection -

$$A_t^{\text{uni}} = \text{uniform}(\{a_1, a_2, \dots, a_K\}) \quad \text{exploration.}$$

- ϵ -greedy action selection $\epsilon = 0.1$

$$A_t = \begin{cases} A_t^* = \operatorname{argmax}_a Q_t(a) & \text{with prob. } 1-\epsilon \\ A_t^{\text{uni}} = \text{uniform}(\{a_1, a_2, \dots, a_K\}) & \text{with prob. } \epsilon \end{cases}$$

$$\text{constant decay}$$

- Decaying ϵ -greedy action selection ϵ ~~constant decay~~ ~~exp. decay~~

At some point there is no need to explore anymore
switch to greedy after some pt. in time.

$$A_t = \begin{cases} A_t^* = \operatorname{argmax}_a Q_t(a) & \text{with prob. } 1-\epsilon \\ A_t^{\text{uni}} = \text{uniform}(\{a_1, a_2, \dots, a_K\}) & \text{with prob. } \epsilon \end{cases}$$

$$\text{const. rate decay}$$

0.1

$$0.005 \frac{1+0.5}{\alpha}$$

$$Q + \frac{\gamma}{\alpha} [1 - Q]$$

Incremental update rule

$$Q_n = \underbrace{R_1 + R_2 + \dots + R_{n-1}}_{n-1} =$$

$$Q_{n+1} = Q_n + \frac{1}{n} [R_n - Q_n] = \text{stationary}$$

$$-0.1 + \frac{1}{3} [-0.4 + 0.1] \quad \text{non-stationary}$$

$$Q_{n+1} = Q_n + \alpha [R_n - Q_n]$$

$$Q_2 = Q_1 + \frac{0.2}{0+} [1 - 0]$$

Initialize, for $a=1$ to k :

$$Q(a) \leftarrow 0$$

$$N(a) \leftarrow 0$$

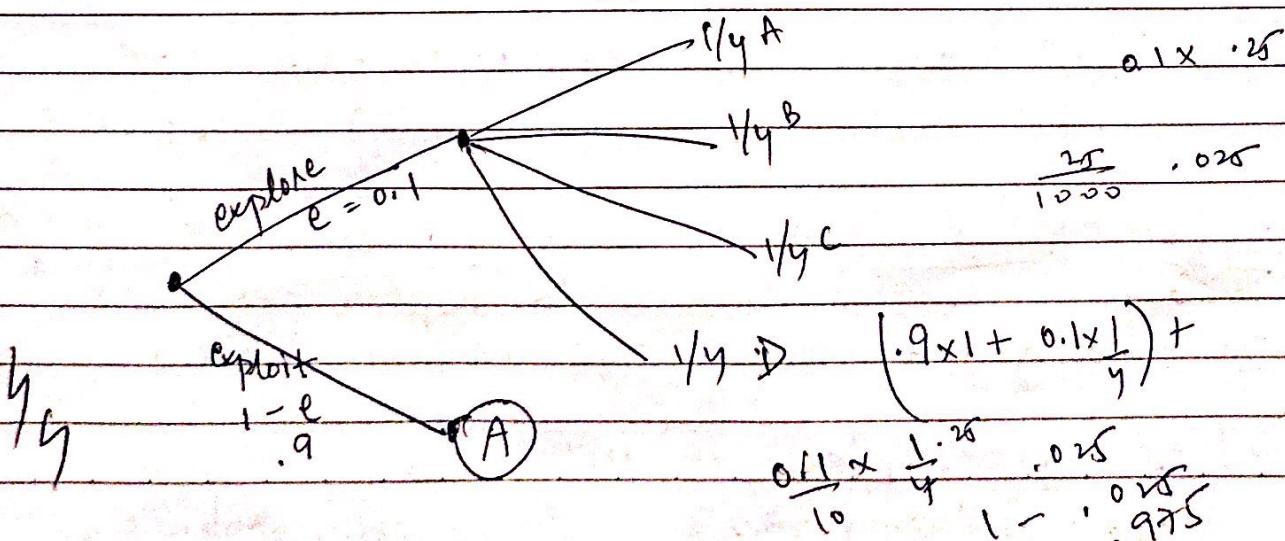
Repeat forever:

$$A \leftarrow \begin{cases} \underset{a}{\operatorname{argmax}} Q(a) \text{ with prob. } 1-\epsilon \\ \text{random action with prob. } \epsilon \end{cases}$$

$$R \leftarrow \text{bandit}(A)$$

$$N(A) \leftarrow N(A) + 1$$

$$Q(A) \leftarrow Q(A) + \frac{1}{N(A)} [R - Q(A)]$$

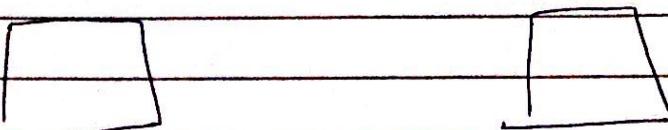


formulas.

$$R_1 = \frac{a}{1} + \frac{b}{Q_1} \cdot c \cdot d \quad 1(1-e) + P(e)$$

$$Q_1 = \frac{0 + 10[1-0]}{12} = 5 \quad 1(1-0.1) + \frac{0+1}{2} = 0.99 + 0.01$$

$$(1-\alpha)^K Q_1 + \sum_{i=1}^K \alpha (1-\alpha)^{K-i} R_i$$



$$q_t(a) = 0.1$$

$$q_t(b) = 0.2$$

0.5

$$q_t(a) = 0.9$$

$$q_t(b) = 0.8$$

0.5

UCB

value of bound is max. then we play on that m/c.

$$A_t = \operatorname{argmax}_a [Q_t(a) + C \sqrt{\frac{\log t}{N_t(a)}}]$$

Initial value bias

$$n = 1$$

$$Q_{nt+1} = Q_t + \alpha [R_t - Q_t] = \alpha R_t + (1-\alpha) Q_t$$

Softmax.

$$P(a) = \frac{e^{Q_t(a)/T}}{\sum_{b=1}^K e^{Q_t(b)/T}}$$

design
performance
comparing