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#1

a) $p(X = 2 \land Y = A) = p(x|y) * p(y)$ formula

$= \alpha * P(y = a)$

$= \alpha * p(2/10)$

$p(X = 2 \land Y = A)$ **$= 0.2\alpha$**

b)

$p(X = 2 \land Y = B) = p(x=2 \mid y = b) * p(y=b)$ formula

$= p(X = 2 \land Y = B) = \beta * P(5/10)$

$= p(X = 2 \land Y = B) = 0.5*\beta$

$p(X = 2 \land Y = B)$ **$= 0.5*\beta$**

c)

$p(X = 2 \land Y = C) = p(x=2 \mid y = b) * p(y=C)$ formula

$= p(X = 2 \land Y = C) = \gamma * p(y=c)$

$= p(X = 2 \land Y = C) = \gamma * p(y=c)$

$= p(X = 2 \land Y = C) = \gamma * p(3/10) = 0.3* \gamma$

$p(X = 2 \land Y = C)$ **$= 0.3* \gamma$**

d)

Marginalization and product rule

p(X = 2) = SUM_y p(x=2,Y= y)

we don't need this latter part for product ruel SUM_y p(Y= y | x=2) * p(x=2)

$0.2\alpha + 0.5\beta + 0.3\gamma$ is the $p(X = 2)$, because we Marginalization over all values of Y

0.2α + 0.5β + 0.3γ = p(X = 2)

e)

p(Y =A|X =2) = (P(X =2|Y =A) * p(Y =A)) / (p(X =2) formula

We know that p(X = 2 ∧ Y = A) **= 0.2α**

p(X = 2|Y = A) = α

p(Y = a |x =2) = α * P(Y=A) / p(X =2)

p(Y = a |x =2) = 0.2*α / p(X =2)

p(Y = a |x =2) = **0.2α / (0.2α + 0.5β + 0.3γ)**

f)

tten as

$$p(\mathcal{C}_1|\mathbf{x}) = \frac{p(\mathbf{x}|\mathcal{C}_1)p(\mathcal{C}_1)}{p(\mathbf{x}|\mathcal{C}_1)p(\mathcal{C}_1) + p(\mathbf{x}|\mathcal{C}_2)p(\mathcal{C}_2)}$$

$$\begin{aligned} p(\mathcal{C}_k|\mathbf{x}) &= \frac{p(\mathbf{x}|\mathcal{C}_k)p(\mathcal{C}_k)}{\sum_j p(\mathbf{x}|\mathcal{C}_j)p(\mathcal{C}_j)} \\ &= \frac{\exp(a_k)}{\sum_j \exp(a_j)} \end{aligned}$$

As we can see, our numerator is p(x|c_k) = P(c_k)

The P(c =a) is much higher than p(c = b). this compensates for class be being physical closer

<u>I expect the ? to be predicted as class A.</u>

#2 a)

a_1 = 0.2 * 0.3 + 0.04

a_2 = -0.1 *0.3 + 0.01

a_3 = 0.7 * RELU(a_1) + 0.7 RELU(a_2) + 0.08

a_3 = 0.7 * RELU(0.2 * 0.3 + 0.04) + 0.7 RELU(-0.1 *0.3 + 0.01) + 0.08

a_3 = 0.7 * RELU(0.1) + 0.7* RELU(-0.02) + 0.08

a_3 = 0.7 * (0.1) + 0.7 * (0.02) + 0.08 = 0.164

z_3 = σ(a_3) = 1 / (1 + e^-0.164) = 0.5409

z_3 = 0.5409

I am not sure what ‘in terms of e’ means in the context.

- ➔ ~~1 / (1 + e^-0.164) * [(1 + e^-0.164)] = 0.5409 * [(1 + e^-0.164)]~~
- ➔ ~~1 = 0.5409 *(1 + e^-0.164)~~
- ➔ ~~1 = 0.5409 + 0.5409 * e^-0.164)~~
- ➔ ~~0.8487 = e^-0.164)~~

$$Z_3 = \frac{e}{5.02547943882} = 0.19898599 * e = 0.5409$$

$$Z_3 = 0.19896e = 0.5409$$

b) loss function take in Z_3

B_21 goes to Z_3, goes to loss function

$$\frac{\mathbf{\delta L}}{\mathbf{\delta b_{21}}} = \frac{\mathbf{\delta L}}{\mathbf{\delta Z_3}}\frac{\mathbf{\delta Z_3}}{\mathbf{\delta b_{21}}}$$

c) loss function take in Z_3

B_12 goes to Z_2, goes to W_22, goes to Z_3, goes to the loss

$$\frac{\mathbf{\delta L}}{\mathbf{\delta b_{12}}} = \frac{\mathbf{\delta L}}{\mathbf{\delta Z_3}}\frac{\mathbf{\delta Z_3}}{\mathbf{\delta W_{22}}}\frac{\boldsymbol{\delta W_{22}}}{\mathbf{\delta Z_2}}\frac{\mathbf{\delta Z_2}}{\mathbf{\delta B_{12}}}$$

#3 a) Write down the factorized form of the joint distribution over all of the variables, *P*(*S; CV; D; C; F; N; Z*).

$$P(S; CV; D; C; F; N; Z) =$$

$$= \mathrm{P}(S)P(CV|S)P(D|S)P(N|D)P(N|Z)P(F|D)P(F|CV)P(Z|F)P(C|CV)$$

b) What is the probability that one has the Coronavirus, when no prior information is known?

Want, P(CV = True)

Have, P(CV|S)

$P(S = \text{winter})$	$P(S = \text{summer})$
0.5	0.5

	$P(\text{CV} = \text{true} \mid S)$	$P(\text{CV} = \text{false} \mid S)$
$S = \text{winter}$	0.4	0.6
$S = \text{summer}$	0.1	0.9

P(CV = True) = P(CV =true, S = any)

P(CV = True) = SUM_i [P(CV =true**,** S_i)] use marginalization

P(CV = True) = SUM_i [P(CV =true **|** S_i) * P(s_i)] use marginalization

P(CV = True) = 0.4*0.5 + 0.1 *0.5

P(CV = True) = 0.25

c) What is the probability that one has the Coronavirus, given that it is winter, that one is fatigued, and that one is dehydrated?

Want $P(CV = True \mid S = Winter, F = True, D = True)$

I will use this:

- Bayes' rule:

$$p(Y|X) = \frac{p(X|Y)p(Y)}{p(X)} = \alpha p(X|Y)p(Y)$$

- Marginalization:

$$p(X) = \sum_y p(X, Y = y) \quad \text{or} \quad p(X) = \int p(X, Y = y)dy$$

- Product rule:

$$p(X, Y) = p(X)p(Y|X)$$

$want, P(CV = True \mid S = Winter, F = True, D = True)$

Reshape the problem,

$$= \frac{P(CV = True, S = Winter, F = True, D = True)}{P(S = Winter, F = True, D = True)}$$

$$= \frac{0.9 * 0.4 * 0.1 * 0.5}{0.9 * 0.4 * 0.1 * 0.5 + 0.8 * 0.6 * 0.1 * 0.5} = 0.42857142857$$

$$P(CV = True \mid S = Winter, F = True, D = True) = 0.42857142857$$

#4

Given,

γ = 0.7,

The Q-learning rate is α = 0.2

the target policy is the greedy policy

Want,

The new Q value after one update for the agent attempting right at state 22

You may assume that the Q value for only this state and action pair – and no other state and action pair – is being updated.

Qn(s,a) ← (1−a_n) * Q_n−1(s,a)+ a2_n [R(s1)+ MAX_a` * Q_n−1(s` ,a`)]

- $Q(s,a) \leftarrow Q(s,a) + \alpha\left(r(s,a) + \gamma \max_{a'} Q(s',a') - Q(s,a)\right)$

21	AL	3
22	AR	2
22	AD	-1
22	AU	1
22	AL	-3
23	AR	-2

Q(22,AR) ← Q(22,2) * 0.2 (-0.1 + 0.7 * MAX_A Q(s`,a`) – Q(s,a)

Plug in γ and α,

Q(22,AR) ← 2 * 0.2 (-0.1 + 0.7 * (10 – 2)

Becomes,

Q(22,AR) ← 2.2

I ran out of time, lost 15mins due to technical issue with canvas