Image Model

Name	Dharini Baskaran
Identity Key	dhba5060

	Level	Completed
	Beginner	14
	Intermediate	6
	Advanced	0
	Expert	0

Goal	
4722	16
5722	18
Total Completed	
20	

Image Model

CSCI 5722/4722: Computer Vision

Spring 2024

Dr. Tom Yeh

Dr. Mehdi Moghari

ROC Curve

CSCI 5722/4722 Computer Vision

University of Colorado Boulder

Discriminator = Binary Classifier

1*

1	0	1
0	1	1

1*

1	1	-3

Pred	.7	.1	.5	.7	.1	.3	.7	0	0	.1

Target	1	1	0	1	0	1	0	1	0	0

Threshold vs. TPR / FPR

.7	.7	.7	.9	1	1	1
.5	.5	.5	.7 +	.9	+	1
.3	.3	.3	.5 −	+	.9	1
.1	− .1	.1	+	.5	− .7	.9
0	+	0 −	.1 −	.3	.5	.7
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7

.7	.7	.7	.9	1	1	1
.5	.5	.5	.7 +	.9	+	1
.3	.3	.3	.5 −	+	.9	1
.1	− .1	.1	+	.5	− .7	.9
0	+	0 −	.1 −	.3	.5	.7
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7

.7	.7	.7	.9	1	1	1
.5	.5	.5	.7 +	.9	+	1
.3	.3	.3	.5 −	+	.9	1
.1	− .1	.1	+	.5	− .7	.9
0	+	0 −	.1 −	.3	.5	.7
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7

.7	.7	.7	.9	1	1	1
.5	.5	.5	.7 +	.9	+	1
.3	.3	.3	.5 −	+	.9	1
.1	− .1	.1	+	.5	− .7	.9
0	+	0 −	.1 −	.3	.5	.7
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7

Threshold vs. TPR / FPR

.7	.7	.7	.9	1	1	1
.5	.5	.5	+	.9	+	1
.3	.3	.3	−	+	.9	1
.1	−	.1	+	.5	−	.9
0	+	0	−	.3	.5	.7
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7

.7	.7	.7	.9	1	1	1
.5	.5	.5	+	.9	+	1
.3	.3	.3	−	+	.9	1
.1	−	.1	+	.5	−	.9
0	+	0	−	.3	.5	.7
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7

.7	.7	.7	.9	1	1	1
.5	.5	.5	+	.9	+	1
.3	.3	.3	−	+	.9	1
.1	−	.1	+	.5	−	.9
0	+	0	−	.3	.5	.7
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7

.7	.7	.7	.9	1	1	1
.5	.5	.5	+	.9	+	1
.3	.3	.3	−	+	.9	1
.1	−	.1	+	.5	−	.9
0	+	0	−	.3	.5	.7
0	0	0	.1	.3	.5	.7
0	0	0	.1	.3	.5	.7

>=.7

.5	.5	.7 +	.9	.7
.3	.3 −	.5 −	.7 +	.5
.1	.1	.3 +	.5 +	.3 −
0	0 −	.1 −	.3	.1
0	0	0	.1	0

a

TPR = $\frac{2}{4} = 0.5$

d

FPR = $\frac{0}{5} = 0$

>=.5

.5	.5	.7 +	.9	.7
.3	.3 −	.5 −	.7 +	.5
.1	.1	.3 +	.5 +	.3 −
0	0 −	.1 −	.3	.1
0	0	0	.1	0

b

TPR = $\frac{3}{4} = 0.75$

e

FPR = $\frac{1}{5} = 0.2$

>=.3

.5	.5	.7 +	.9	.7
.3	.3 −	.5 −	.7 +	.5
.1	.1	.3 +	.5 +	.3 −
0	0 −	.1 −	.3	.1
0	0	0	.1	0

c

TPR = $\frac{4}{4} = 1$

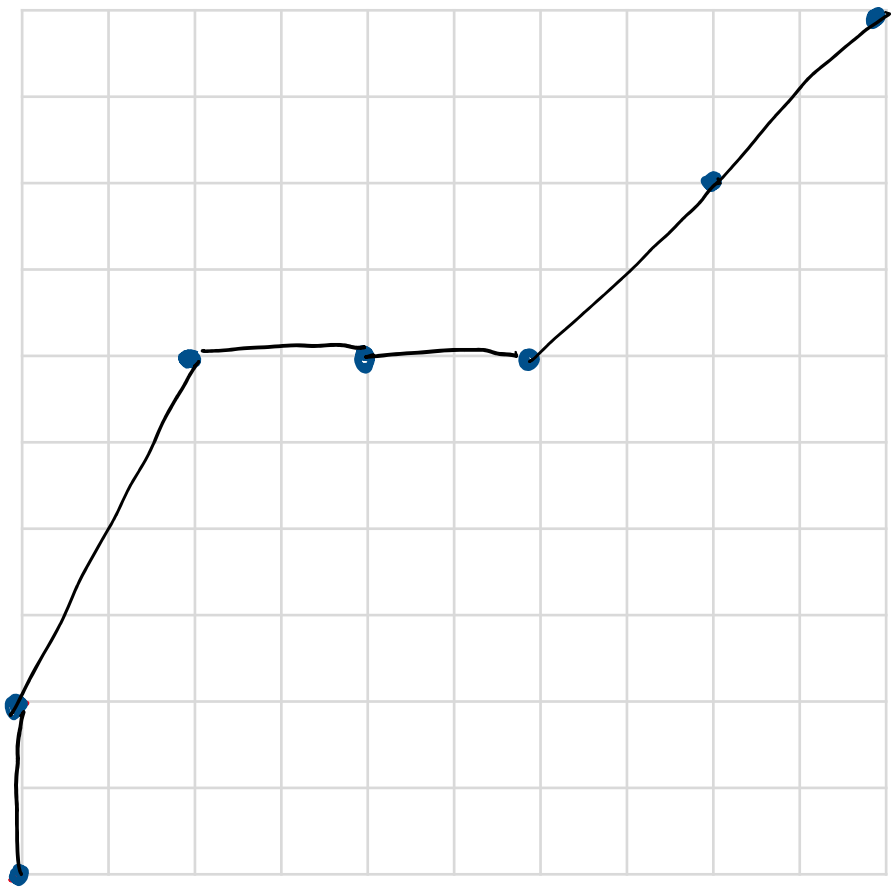
f

FPR = $\frac{3}{5} = 0.6$

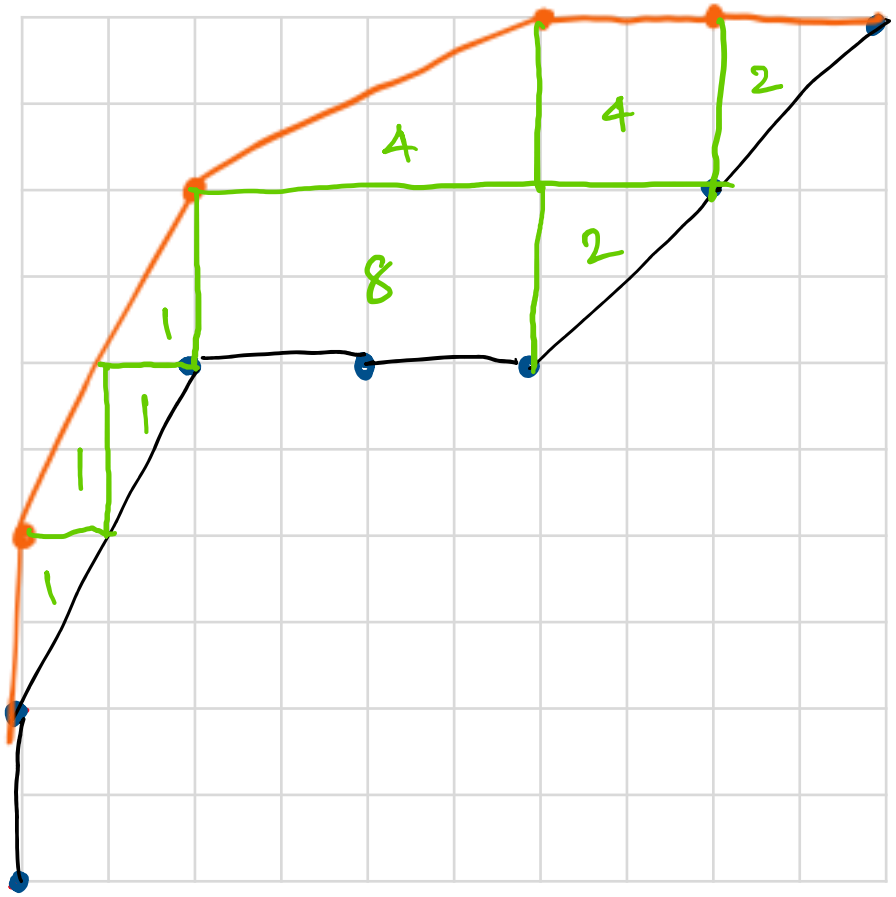
🔑 a+b+c = 2.25; d+e+f = ~~1~~ 0.8

Receiver Operating Characteristic (ROC) Curve

Area Under ROC Curve (AUC)



Calculate the improvement in AUC

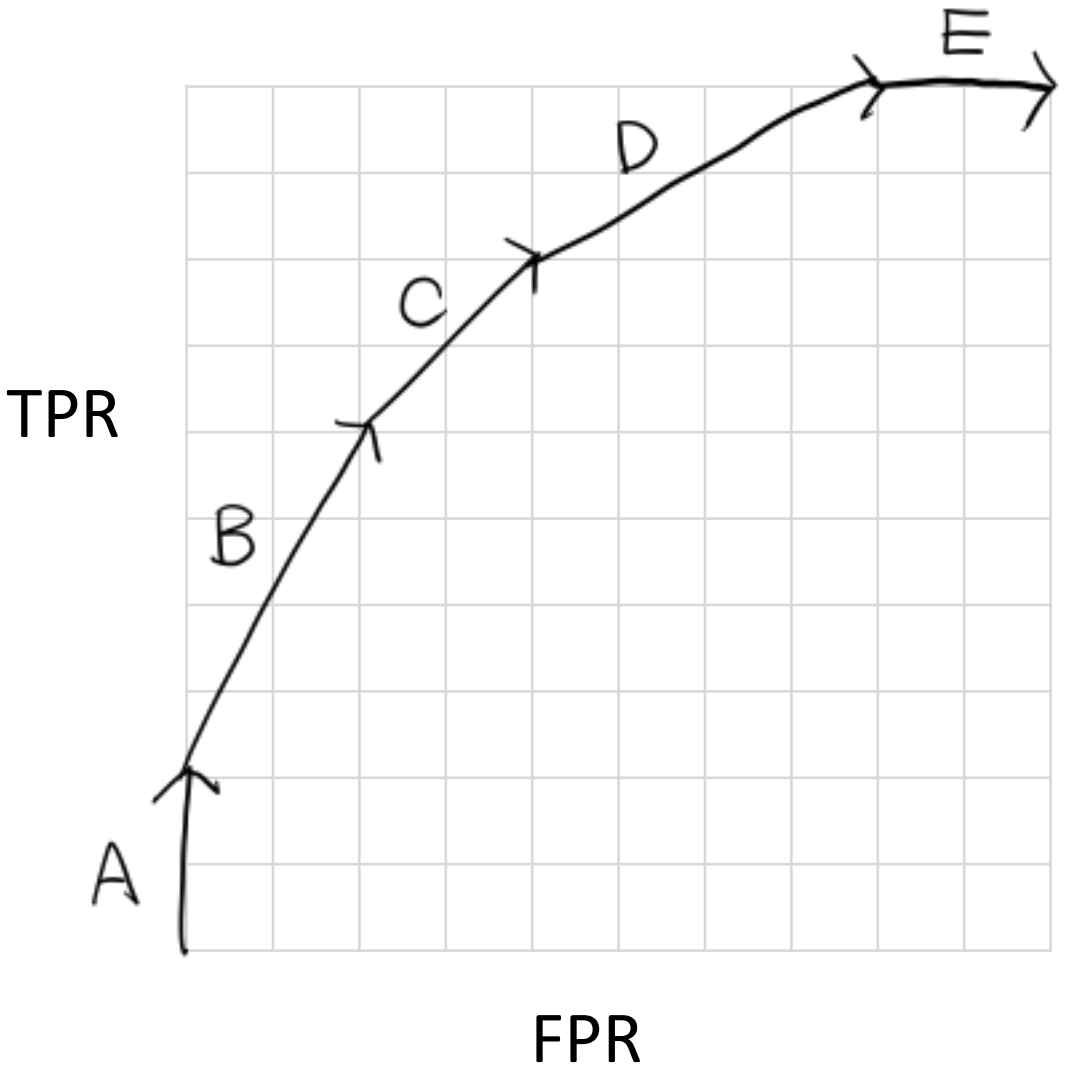


a

Answer = 24

a mod 7 = 3

Match each movement segment to the correct interpretation of the changes in TP and FP



1. More true positives but at the cost of a lot more false positives. D
2. More true positives without any new false positives. A
3. No more true positives, just more false positives. E
4. More true positives, but at the cost of about the same number of false positives. C
5. More true positives at the cost of additional, but relatively fewer false positives. B

Probabilities

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1: Correct, 0: Incorrect

A. How are you?	
B. How do you do?	
C. Howdy?	
D. How are you doing?	
E. How is you?	
F. How am you?	

3: very high, 2: high, 1: low, 0: wrong

A. How are you?	
B. How do you do?	
C. Howdy?	
D. How are you doing?	
E. How is you?	
F. How am you?	

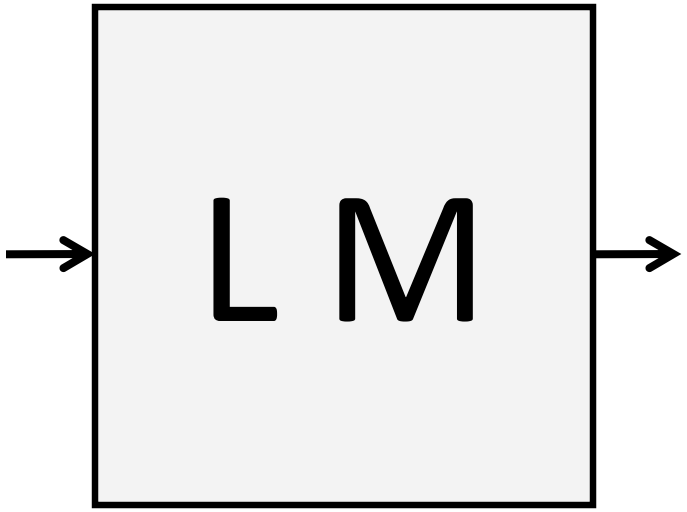
Context: Texas +2

	A. How are you?	3
	B. How do you do?	2
	C. Howdy?	1
	D. How are you doing?	3
	A. How are you?	3
	B. How do you do?	2
	C. Howdy?	1
	D. How are you doing?	3

Context: Formal +1, Texas +2

	Texas	A. How are you?	3
		B. How do you do?	2
		C. Howdy?	1
		D. How are you doing?	3
	!Texas	A. How are you?	3
		B. How do you do?	2
		C. Howdy?	1
		D. How are you doing?	3
	Texas	A. How are you?	3
		B. How do you do?	2
		C. Howdy?	1
		D. How are you doing?	3
	!Texas	A. How are you?	3
		B. How do you do?	2
		C. Howdy?	1
		D. How are you doing?	3

Language Model: Input and Output



Aggregate

Formal	Texas	A. How are you?	3
		B. How do you do?	3
		C. Howdy?	3
		D. How are you doing?	3
	!Texas	A. How are you?	3
		B. How do you do?	3
		C. Howdy?	1
		D. How are you doing?	3
!Formal	Texas	A. How are you?	3
		B. How do you do?	2
		C. Howdy?	2
		D. How are you doing?	3
	!Texas	A. How are you?	3
		B. How do you do?	2
		C. Howdy?	1
		D. How are you doing?	3

Joint probability

Formal 22	Texas 12	A. How are you?	3			
		B. How do you do?	3			
		C. Howdy?	3			
		D. How are you doing?	3			
	!Texas 10	A. How are you?	3			
		B. How do you do?	3			
		C. Howdy?	1			
		D. How are you doing?	3			
!Formal 19	Texas 10	A. How are you?	3			
		B. How do you do?	2			
		C. Howdy?	2			
		D. How are you doing?	3			
	!Texas 9	A. How are you?	3			
		B. How do you do?	2			
		C. Howdy?	1			
		D. How are you doing?	3			

41

Conditional probability

Formal 22	Texas 12	A. How are you?	3	3/41	
		B. How do you do?	3	3/41	
		C. Howdy?	3	3/41	
		D. How are you doing?	3	3/41	
	!Texas 10	A. How are you?	3	3/41	
		B. How do you do?	3	3/41	
		C. Howdy?	1	1/41	
		D. How are you doing?	3	3/41	
!Formal 19	Texas 10	A. How are you?	3	3/41	
		B. How do you do?	2	2/41	
		C. Howdy?	2	2/41	
		D. How are you doing?	3	3/41	
	!Texas 9	A. How are you?	3	3/41	
		B. How do you do?	2	2/41	
		C. Howdy?	1	1/41	
		D. How are you doing?	3	3/41	

41

Joint probability

$p(x_3 | x_2, x_1)$

$p(x_1, x_2, x_3)$

Formal 22	Texas 12			A. How are you?	3	3/41	3/12
				B. How do you do?	3	3/41	3/12
				C. Howdy?	3	3/41	3/12
				D. How are you doing?	3	3/41	3/12
	!Texas 10			A. How are you?	3	3/41	3/10
				B. How do you do?	3	3/41	3/10
				C. Howdy?	1	1/41	1/10
				D. How are you doing?	3	3/41	3/10
!Formal 19	Texas 10			A. How are you?	3	3/41	3/10
				B. How do you do?	2	2/41	2/10
				C. Howdy?	2	2/41	2/10
				D. How are you doing?	3	3/41	3/10
	!Texas 9			A. How are you?	3	3/41	3/9
				B. How do you do?	2	2/41	2/9
				C. Howdy?	1	1/41	1/9
				D. How are you doing?	3	3/41	3/9

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Conditional probability

		$p(x_1, x_2)$			$p(x_3 \mid x_2, x_1)$	$p(x_1, x_2, x_3)$
Formal 22	Texas 12	$\frac{12}{41}$		A. How are you?	3	3/41	3/12
				B. How do you do?	3	3/41	3/12
				C. Howdy?	3	3/41	3/12
				D. How are you doing?	3	3/41	3/12
	!Texas 10	$\frac{10}{41}$		A. How are you?	3	3/41	3/10
				B. How do you do?	3	3/41	3/10
				C. Howdy?	1	1/41	1/10
				D. How are you doing?	3	3/41	3/10
!Formal 19	Texas 10	$\frac{10}{41}$		A. How are you?	3	3/41	3/10
				B. How do you do?	2	2/41	2/10
				C. Howdy?	2	2/41	2/10
				D. How are you doing?	3	3/41	3/10
	!Texas 9	$\frac{9}{41}$		A. How are you?	3	3/41	3/9
				B. How do you do?	2	2/41	2/9
				C. Howdy?	1	1/41	1/9
				D. How are you doing?	3	3/41	3/9

41

Probability

			$p(x_1, x_2)$	$p(x_2 \mid x_1)$			$p(x_1, x_2, x_3)$	$p(x_3 \mid x_2, x_1)$
Formal 22		Texas 12	$\frac{12}{41}$	$\frac{12}{22}$	A. How are you?	3	3/41	3/12
					B. How do you do?	3	3/41	3/12
					C. Howdy?	3	3/41	3/12
					D. How are you doing?	3	3/41	3/12
		!Texas 10	$\frac{10}{41}$	$\frac{10}{22}$	A. How are you?	3	3/41	3/10
					B. How do you do?	3	3/41	3/10
					C. Howdy?	1	1/41	1/10
					D. How are you doing?	3	3/41	3/10
!Formal 19		Texas 10	$\frac{10}{41}$	$\frac{10}{19}$	A. How are you?	3	3/41	3/10
					B. How do you do?	2	2/41	2/10
					C. Howdy?	2	2/41	2/10
					D. How are you doing?	3	3/41	3/10
		!Texas 9	$\frac{9}{41}$	$\frac{9}{19}$	A. How are you?	3	3/41	3/9
					B. How do you do?	2	2/41	2/9
					C. Howdy?	1	1/41	1/9
					D. How are you doing?	3	3/41	3/9

41

Calculate Joint Probabilities $p(x_1, x_2)$

x_1	x_2	Freq	$p(x_1, x_2)$	
!Angry 80	A. woof	40	0.4	a
	B. growl	20	0.2	b
	C. bark	20	0.2	c
Angry 20	A. woof	4	0.04	d
	B. growl	8	0.08	e
	C. bark	8	0.08	f

🔑 a+b+c+d+e+f = 1; b + d + f = .32

Calculate Conditional Probabilities $p(x_2|x_1)$

x_1	x_2	Freq	$p(x_2 \mid x_1)$	
!Angry 80	A. woof	40	0.5	a
	B. growl	20	0.25	b
	C. bark	20	0.25	c
Angry 20	A. woof	4	0.2	d
	B. growl	8	0.4	e
	C. bark	8	0.4	f

a+b+c+d+e+f = 2; b + d + f = .85

Calculate p(home?)

(Simplify the fractions)

!Home 15	!Angry 10	A. woof	3
		B. growl	2
		C. bark	5
	Angry 5	A. woof	1
		B. growl	3
		C. bark	1

Home 30	!Angry 20	A. woof	12
		B. growl	4
		C. bark	4
	Angry 10	A. woof	2
		B. growl	5
		C. bark	3

a p(home) = $\frac{2}{3}$

b p(!home) = $\frac{1}{3}$

🔑 numerator(a) + denominator(b) = ~~4~~ 5; a + b = 1

Calculate p(angry? | home?)

(Simplify the fractions)

!Home 15	!Angry 10	A. woof	3
		B. growl	2
		C. bark	5
	Angry 5	A. woof	1
		B. growl	3
		C. bark	1

Home 30	!Angry 20	A. woof	12
		B. growl	4
		C. bark	4
	Angry 10	A. woof	2
		B. growl	5
		C. bark	3

a p(angry| !home) = $\frac{1}{3}$

b p(!angry| home) = $\frac{2}{3}$

🔑 numerator(a) + denominator(b) = 4; a + b = 1

Calculate p(angry?, home?)

(Simplify the fractions)

!Home 15	!Angry 10	A. woof	3
		B. growl	2
		C. bark	5
	Angry 5	A. woof	1
		B. growl	3
		C. bark	1

Home 30	!Angry 20	A. woof	12
		B. growl	4
		C. bark	4
	Angry 10	A. woof	2
		B. growl	5
		C. bark	3

a p(angry, !home) = $\frac{1}{9}$

b p(!angry, home) = $\frac{4}{9}$

🔑 (a + b) * 153 % 13 = 7

Calculate p(sound?, angry?, home?)

(Simplify the fractions)

!Home 15	!Angry 10	A. woof	3
		B. growl	2
		C. bark	5
	Angry 5	A. woof	1
		B. growl	3
		C. bark	1

Home 30	!Angry 20	A. woof	12
		B. growl	4
		C. bark	4
	Angry 10	A. woof	2
		B. growl	5
		C. bark	3

a

p(growl, angry, !home) = $\frac{1}{15}$

b

p(woof, angry, !home) = $\frac{1}{45}$

c

p(woof, angry, home) = $\frac{2}{45}$

d

p(bark, !angry, home) = $\frac{4}{45}$

🔑 numerator(a) + denominator(b) + numerator(c) + denominator(d) = 93

Calculate p(sound? | angry?, home?)

(Simplify the fractions)

!Home 15	!Angry 10	A. woof	3
		B. growl	2
		C. bark	5
	Angry 5	A. woof	1
		B. growl	3
		C. bark	1

Home 30	!Angry 20	A. woof	12
		B. growl	4
		C. bark	4
	Angry 10	A. woof	2
		B. growl	5
		C. bark	3

a

p(growl| angry, !home) = $\frac{3}{5}$

3/5

b

p(woof| angry, !home) = $\frac{1}{5}$

1/5

c

p(woof| angry, home) = $\frac{1}{5}$

2/10

d

p(bark| !angry, home) = $\frac{1}{5}$

4/20

🔑 numerator(a) + denominator(b) + numerator(c) + denominator(d) = 14

The Chain Rule of Probabilities

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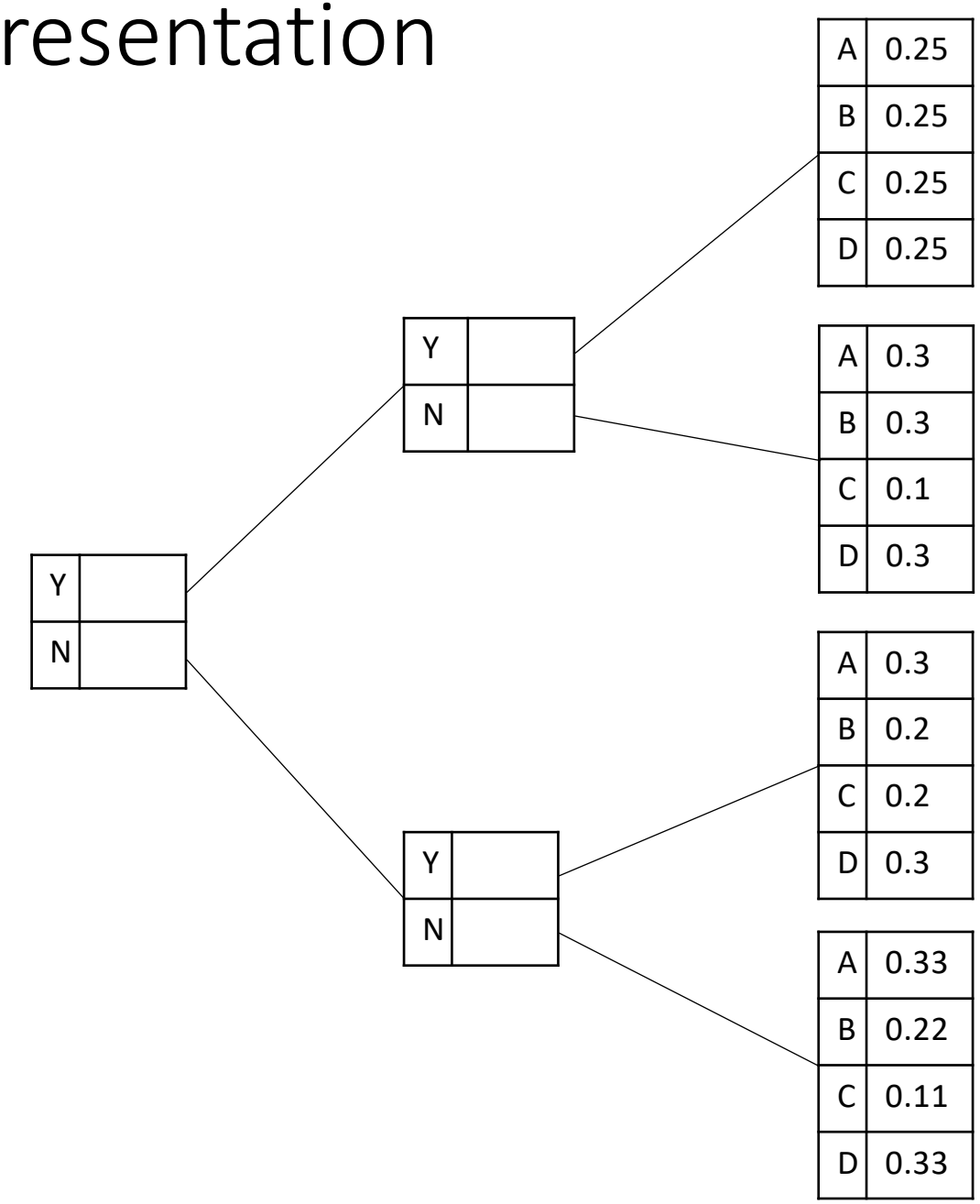
Conditional → Joint Probabilities

$p(x_1)$		$p(x_1, x_2)$	$p(x_2 \mid x_1)$		$p(x_3 \mid x_2, x_1)$	$p(x_1, x_2, x_3)$
Formal 22	Texas 12	$\frac{12}{41}$	$\frac{12}{22}$	A. How are you?	3	3/41	3/12
				B. How do you do?	3	3/41	3/12
				C. Howdy?	3	3/41	3/12
				D. How are you doing?	3	3/41	3/12
	!Texas 10	$\frac{10}{41}$	$\frac{10}{22}$	A. How are you?	3	3/41	3/10
				B. How do you do?	3	3/41	3/10
				C. Howdy?	1	1/41	1/10
				D. How are you doing?	3	3/41	3/10

Tree Representation



Probability Distribution vs. Values

$P(x_1)$ =

Y	0.54
N	0.46

$P(x_1 = Y)$ =

$P(x_1 = N)$ =

Conditional Probability Distributions

$P(x_2 \mid x_1 = Y) =$

Y	0.55
N	0.45

Y	0.54
N	0.46

$P(x_2 \mid x_1 = N) =$

Y	0.53
N	0.47

Conditional Probability Values

Y	0.54
N	0.46

Y	0.55
N	0.45

Y	0.53
N	0.47

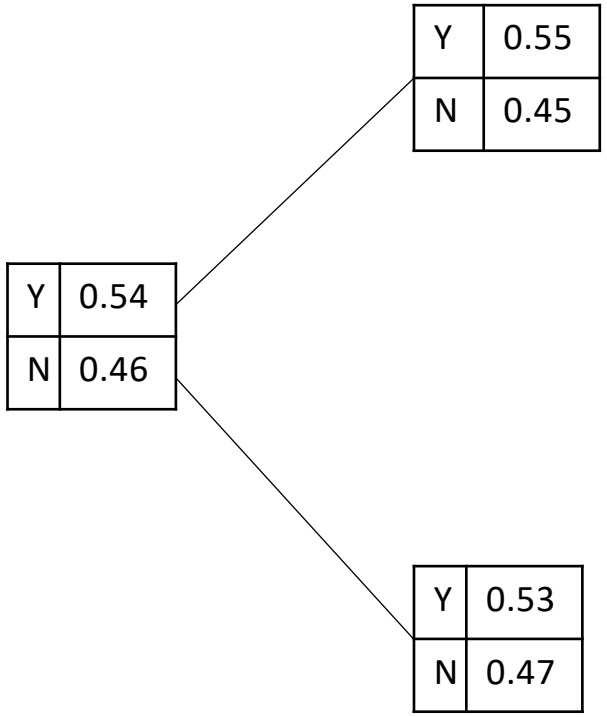
$$P(x_2 \mid x_1 = Y) = \begin{pmatrix} .55 \\ .54 \end{pmatrix}$$

$$P(x_2 = Y \mid x_1 = Y) =$$

$$P(x_2 \mid x_1 = N) = \begin{pmatrix} .53 \\ .47 \end{pmatrix}$$

$$P(x_2 = N \mid x_1 = N) =$$

Joint Probability "Values" by the Chain Rule



Joint Probability of x1, x2

= p(_____, _____)

= p(_____) x p(_____)

$P(x_1 = Y, x_2 = N\ ) =$

$P(x_1 = N, x_2 = Y\ ) =$

Joint Probability "Distributions" by the Chain Rule

Y	0.54
N	0.46

Y	0.55
N	0.45

Y	0.53
N	0.47

$P(x_1 = Y, x_2\ ) =$

$P(x_1 = N, x_2) =$

Conditional Probability Distributions

Y	0.54
N	0.46

Y	0.55
N	0.45

Y	0.53
N	0.47

A	0.25
B	0.25
C	0.25
D	0.25

A	0.3
B	0.3
C	0.1
D	0.3

A	0.3
B	0.2
C	0.2
D	0.3

A	0.33
B	0.22
C	0.11
D	0.33

$$P(x_3 \mid x_1 = N, x_2 = Y) =$$

$$P(x_3 \mid x_1 = Y, x_2 = N) =$$

Conditional Probability Values

Y	0.54
N	0.46

Y	0.55
N	0.45

Y	0.53
N	0.47

A	0.25
B	0.25
C	0.25
D	0.25

A	0.3
B	0.3
C	0.1
D	0.3

A	0.3
B	0.2
C	0.2
D	0.3

A	0.33
B	0.22
C	0.11
D	0.33

$$P(x_3 \mid x_1 = N, x_2 = Y) = \begin{pmatrix} .3 \\ .2 \\ .2 \\ .3 \end{pmatrix}$$

$$P(x_3 = C \mid x_1 = N, x_2 = Y) =$$

$$P(x_3 \mid x_1 = Y, x_2 = N) = \begin{pmatrix} .3 \\ .3 \\ .1 \\ .3 \end{pmatrix}$$

$$P(x_3 = D \mid x_1 = Y, x_2 = N) =$$

Joint Probability "Values" by the Chain Rule

Y	0.54
N	0.46

Y	0.55
N	0.45

Y	0.53
N	0.47

A	0.25
B	0.25
C	0.25
D	0.25

A	0.3
B	0.3
C	0.1
D	0.3

A	0.3
B	0.2
C	0.2
D	0.3

A	0.33
B	0.22
C	0.11
D	0.33

Joint Probability of x1, x2, x3

= p(_____, _____, _____)

= p(_____) x p(_____) x p(_____)

$P(x_1 = Y, x_2 = N, x_3 = A) =$

$P(x_1 = N, x_2 = N, x_3 = B) =$

Joint Probability "Distributions" by the Chain Rule

Y	0.54
N	0.46

Y	0.55
N	0.45

Y	0.53
N	0.47

A	0.25
B	0.25
C	0.25
D	0.25

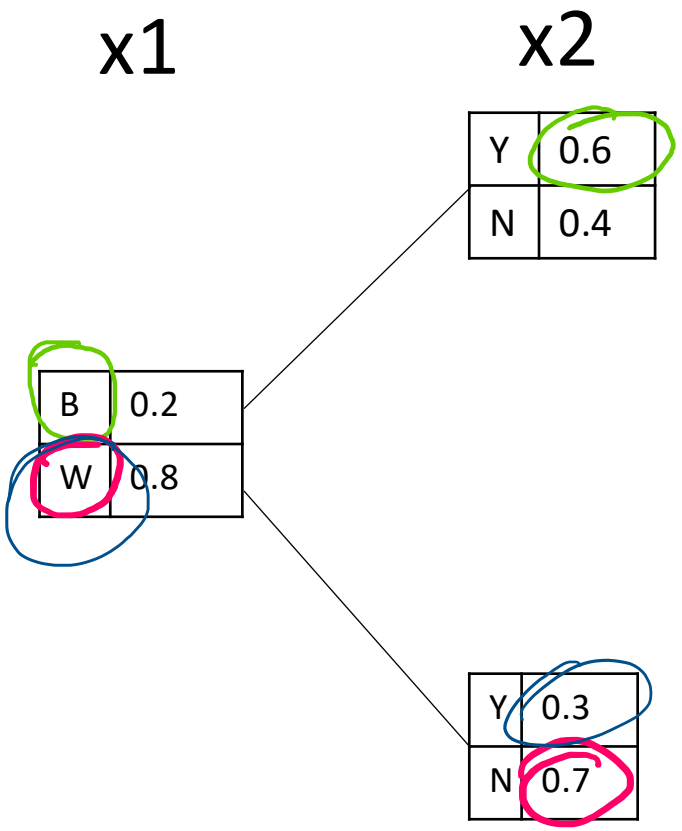
A	0.3
B	0.3
C	0.1
D	0.3

A	0.3
B	0.2
C	0.2
D	0.3

A	0.33
B	0.22
C	0.11
D	0.33

$P(x_1 = Y, x_2 = N, x_3) =$

Calculate Joint Probability



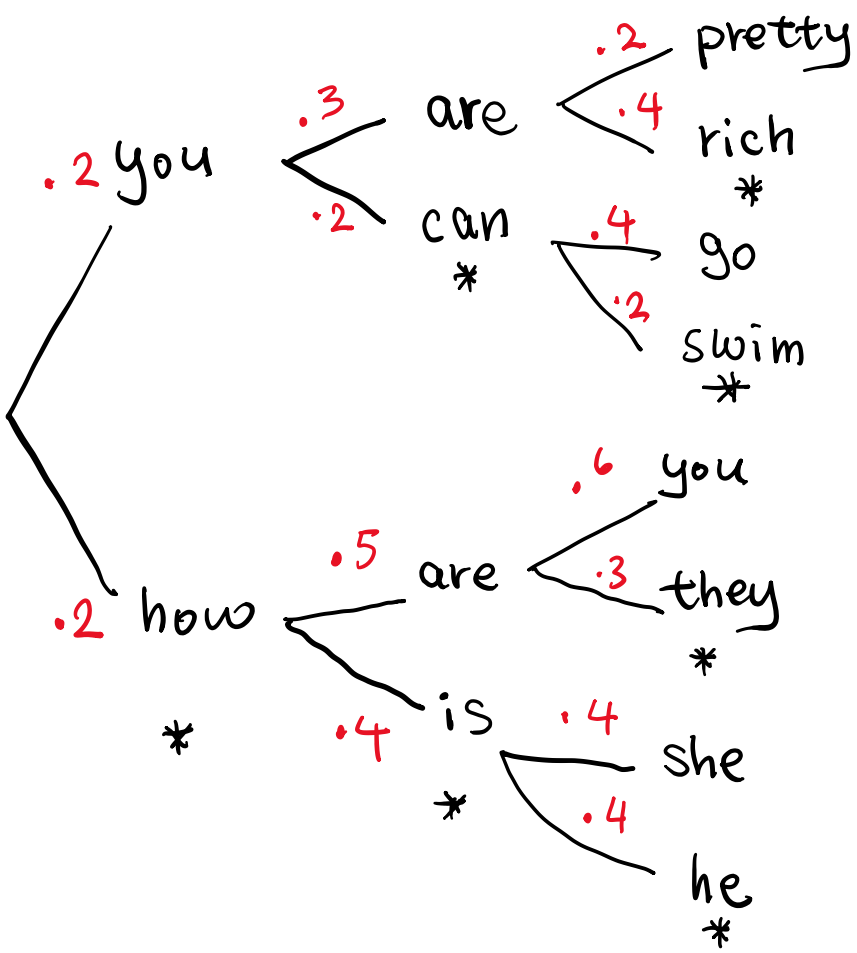
a p(x1=B, x2=Y) = 0.6 x 0.2 = 0.12

b p(x1=W, x2=N) = 0.7 x 0.8 = 0.56

c p(x1=W, x2=Y) = 0.3 x 0.8 = 0.24

🔑 1000 * sum(a+b+c) % 13 = ~~4~~ 10

Calculate Conditional Probability



a p("rich" | "you are") = 0.4

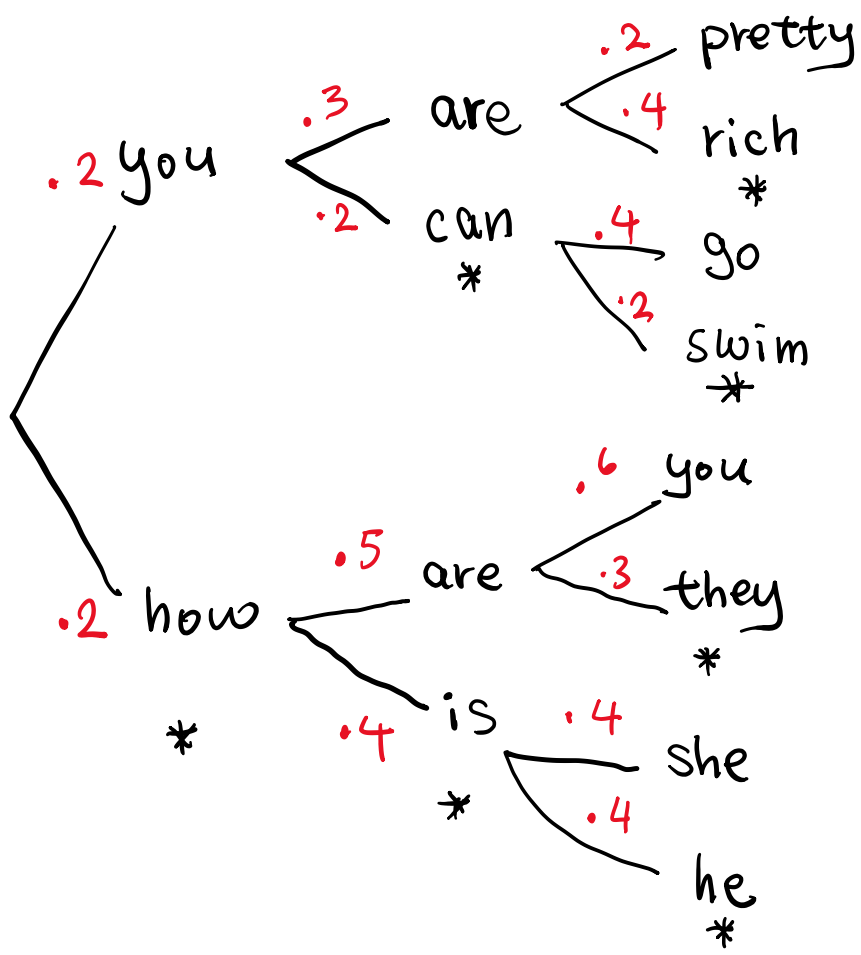
b p("swim" | "you can") = 0.2

c p("she" | "how is") = 0.4

d p("he" | "how is") = 0.4

🔑 1000 * sum(a+b+c+d) % 13 = 9

Calculate Joint Probability



a p("you are rich") = 0.2×0.3×0.4 = 0.024

b p("you can swim") = 0.2×0.2×0.2 = 0.008

c p("how is she") = 0.2×0.4×0.4 = 0.032

d p("how is he") = 0.2×0.4×0.4 = 0.032

🔑 1000 * sum(a+b+c+d) % 13 = 5

Pixel-based Image Model

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Color Image

C	C	B	A
B	B	B	A
B	C	B	A
B	B	B	B

Part Labels

1 = skin, 2 = hair

2	2	2	1
1	1	1	2
1	1	1	1
1	1	1	1

Generative Image Model (Joint Probability)

C	C	B	A
B	B	B	A
B	C	B	A
B	B	B	B

1 = skin, 2 = hair

2	2	2	1
1	1	1	2
1	1	1	1
1	1	1	1

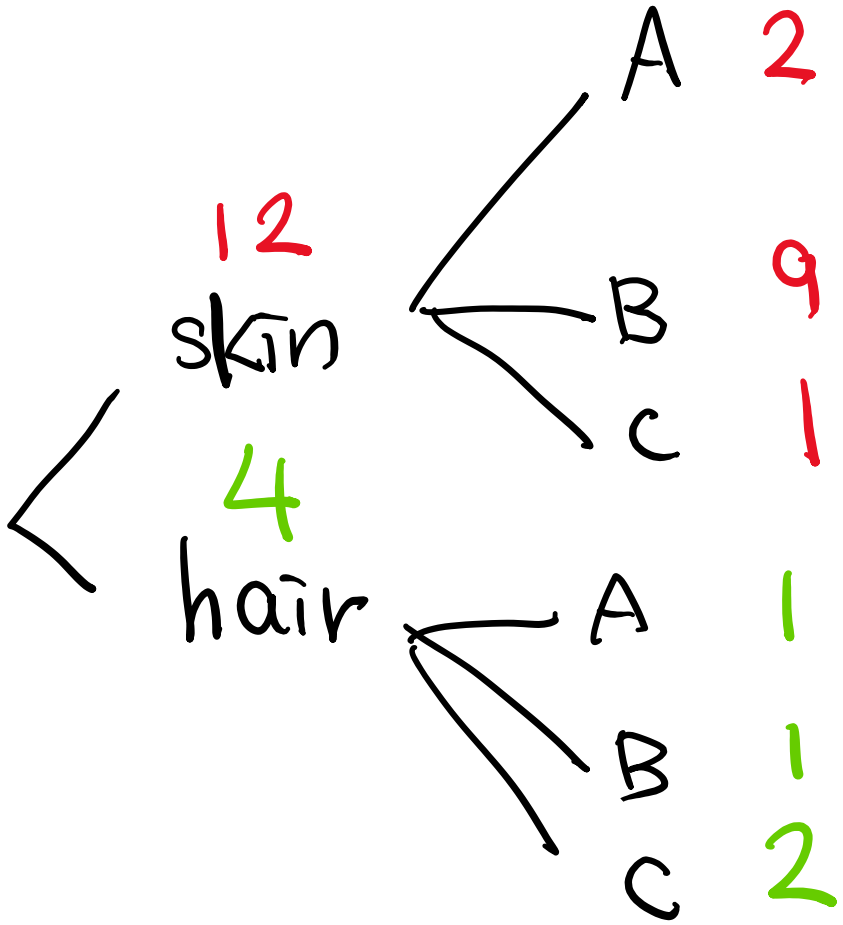
Tree Representation

C	C	B	A
B	B	B	A
B	C	B	A
B	B	B	B

1 = skin, 2 = hair

2	2	2	1
1	1	1	2
1	1	1	1
1	1	1	1

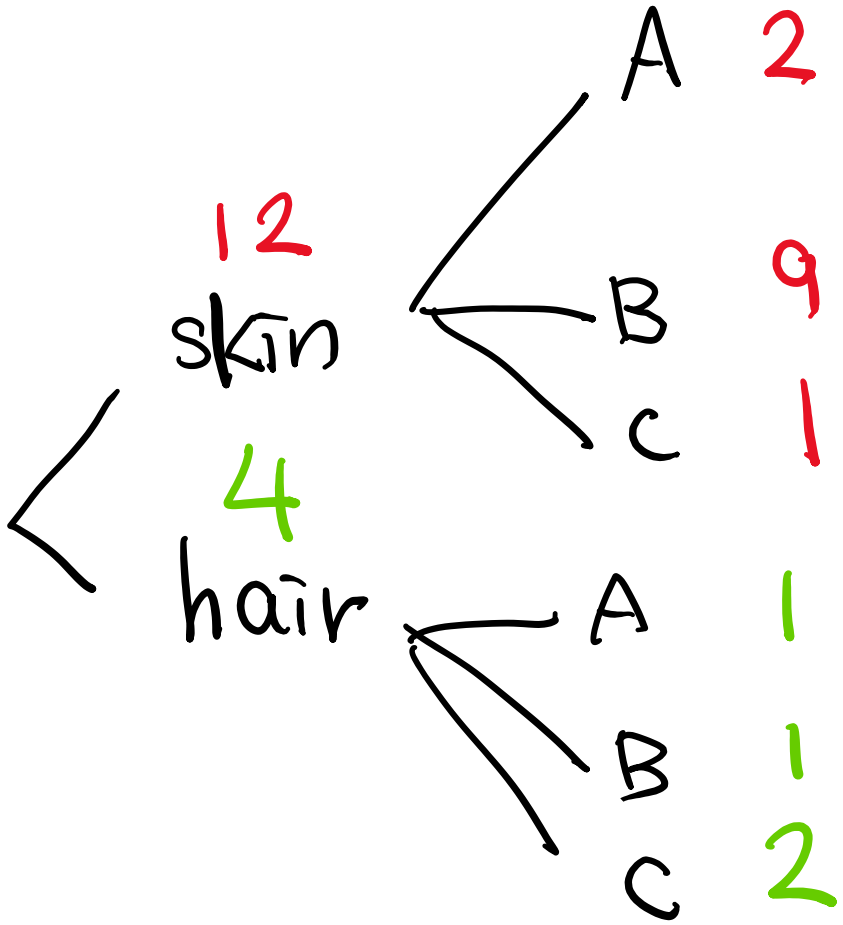
Conditional Probability Distribution



p(color | part = skin) =

p(color | part = hair) =

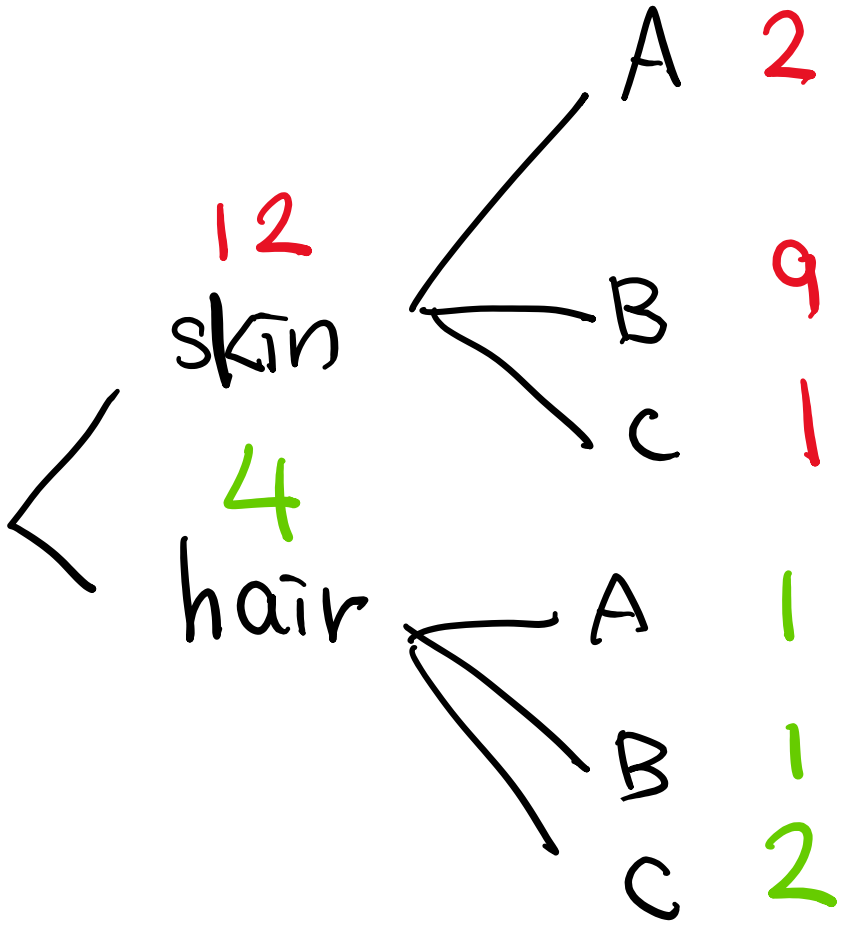
Conditional Probability Values



p(color = A | part = skin) =

p(color = B | part = hair) =

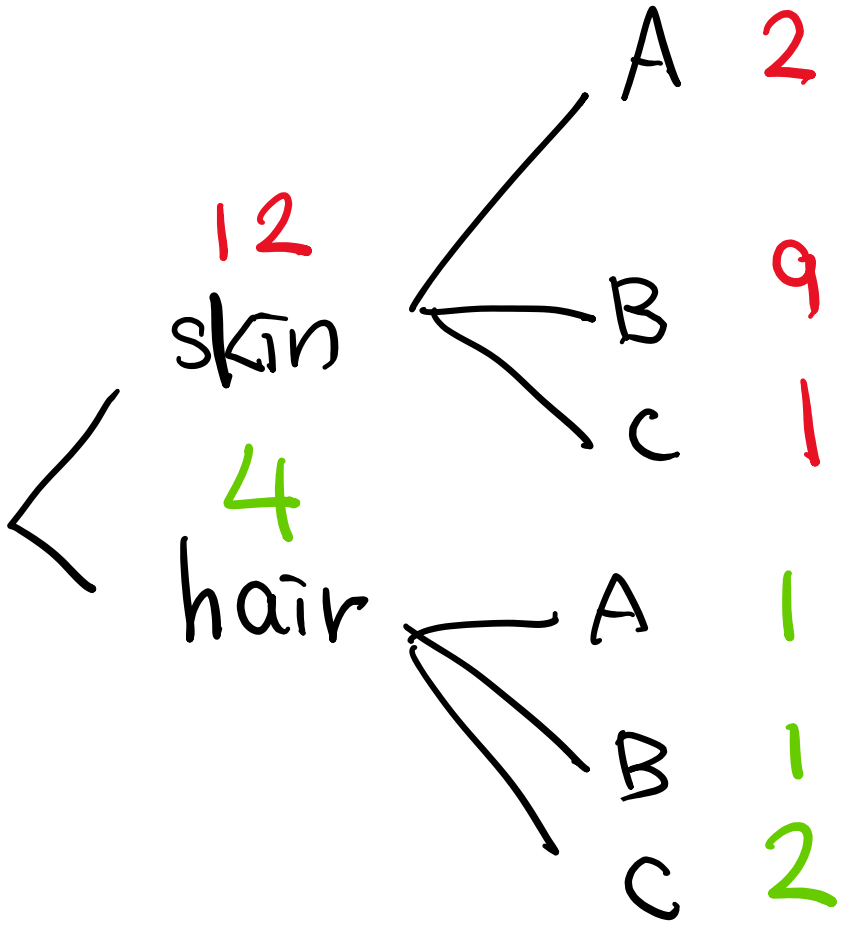
Joint Probability Distribution



p(color, part = skin) =

p(color, part = hair) =

Joint Probability Values



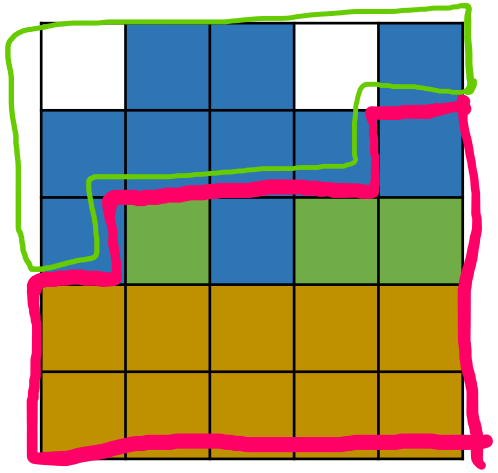
p(color = A, part = skin) =

p(color = B, part = hair) =

Fill the aggregation tree

1 = sky, 2 = land

1	1	1	1	1
1	1	1	1	2
1	2	2	2	2
2	2	2	2	2
2	2	2	2	2



a

sky	10
land	15

b

white	2
blue	8
green	0
brown	0

c

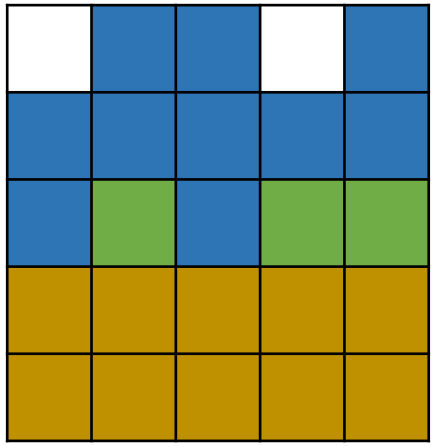
white	0
blue	2
green	3
brown	10

too easy

Conditional Probability Values

1 = sky, 2 = land

1	1	1	1	1
1	1	1	1	2
1	2	2	2	2
2	2	2	2	2
2	2	2	2	2



a p(color = blue| part = sky) = $\frac{4}{5}$

b p(color = blue| part = land) = $\frac{2}{15}$

c p(color = white| part = sky) = $\frac{1}{5}$

d p(color = green| part = land) = $\frac{1}{5}$

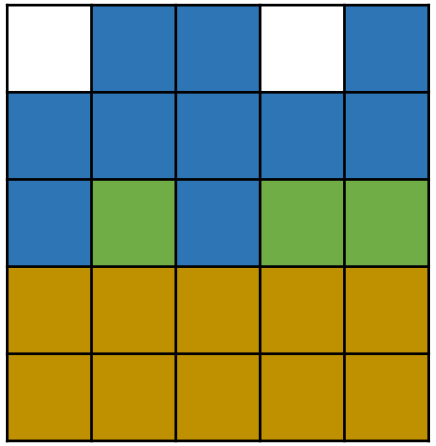
🔑 numerator(a) + denominator(b) + numerator(c) + denominator(d) = ~~13~~ -> 25

Joint Probability Values

(Simplify the fractions)

1 = sky, 2 = land

1	1	1	1	1
1	1	1	1	2
1	2	2	2	2
2	2	2	2	2
2	2	2	2	2



a p(color = blue, part = sky) = $\frac{8}{25}$

$\frac{2}{5} \times \frac{4}{5}$

b p(color = blue, part = land) = $\frac{2}{25}$

$\frac{\cancel{2}}{5} \times \frac{2}{\cancel{5}\,5}$

c p(color = white, part = sky) = $\frac{2}{25}$

$\frac{2}{5} \times \frac{1}{5}$

d p(color = green, part = land) = $\frac{3}{25}$

$\frac{3}{5} \times \frac{1}{5}$

🔑 numerator(a) + denominator(b) + numerator(c) + denominator(d) = ~~40~~ -> 60

Autoregressive Image Model

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What would AI draw next?

Prompt: First, describe the scene in this photo. Second, add the most probable object to the scene.

Input Image

Text Response

First, the photo depicts a child lying on the snow with arms and legs spread out, likely making a snow angel. The child is wearing a blue jacket with a hood and black snow pants. The sun is shining, and the sky seems clear, suggesting it's a bright winter day. The child's expression is difficult to discern, but they appear to be looking directly at the camera. There are traces of previous activity in the snow around the child, including what seem to be footprints and marks in the snow.

Second, the most probable object to add to this scene would be a pair of brightly colored mittens on the child's hands, which are commonly worn during snow play to keep hands warm and dry. Let's proceed with adding this object to the scene.

The scene has been enhanced with the addition of a pair of bright red mittens on the child's hands, contributing to the playful and colorful aspect of the winter activity.

Generated Image

What would AI draw next?

Input Image

Generated Image

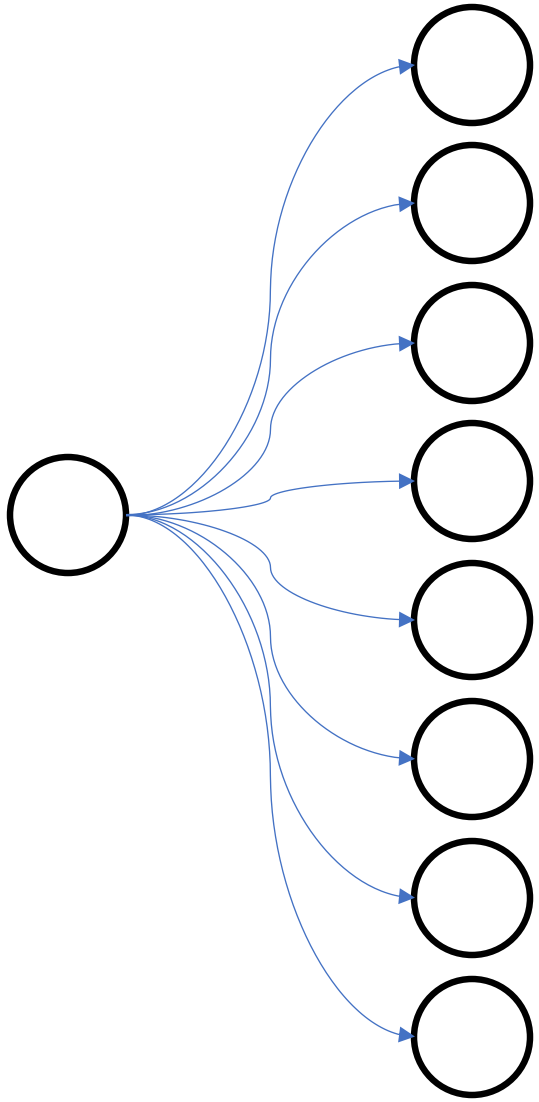
shared in the post

Share your finding

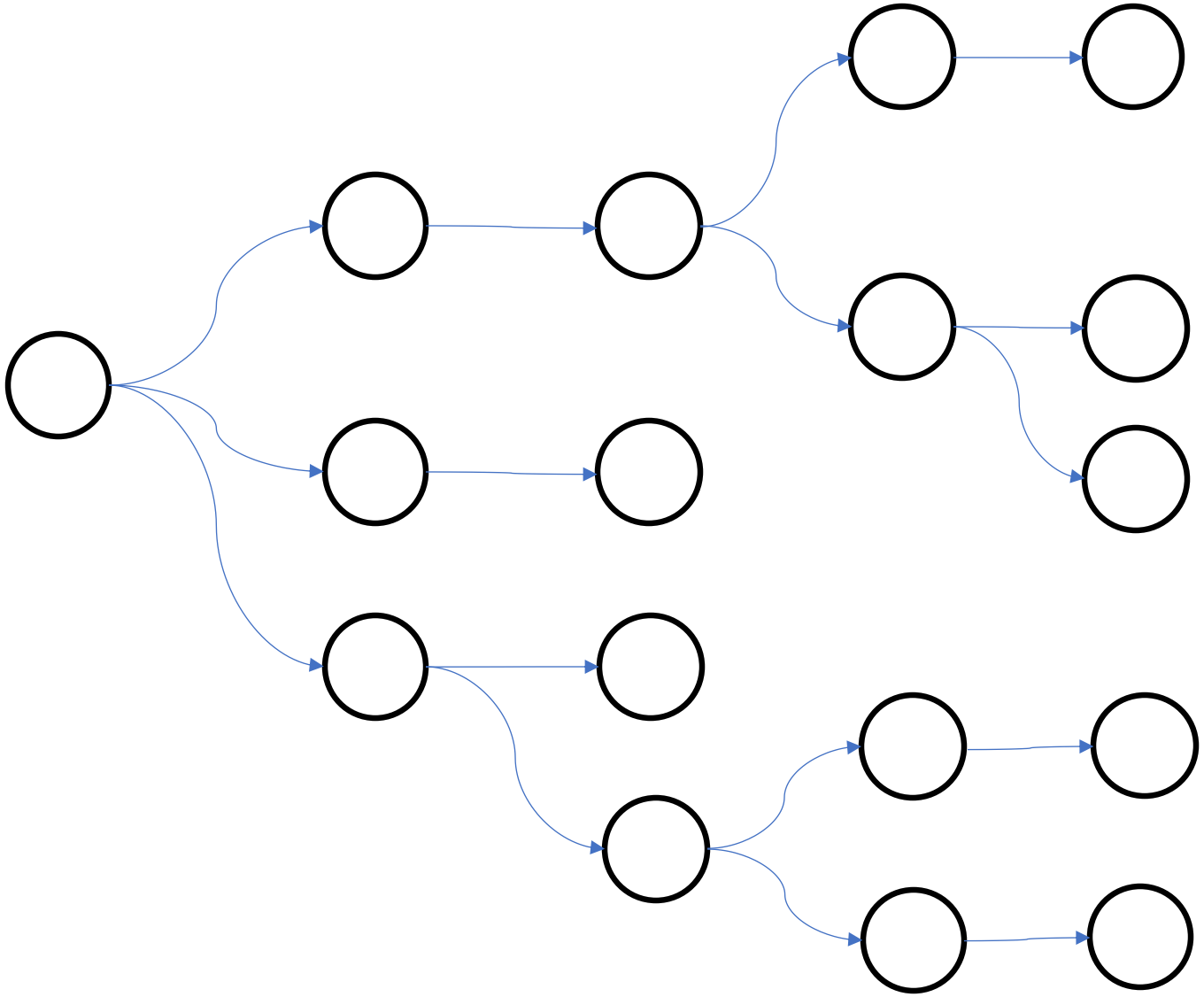
1. Export the previous slide with your images as a PNG image
2. Increase the width to 1440 so that the image can be seen more clearly.
3. Add a comment to the activity post
4. Attach your image to the comment

Note: This counts as a separate activity. It is entirely up to you whether or not you want to share.

What to draw next?



Sketch Tree

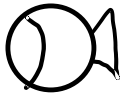


Conditional Probability

p(|)=

p(x4 |)=

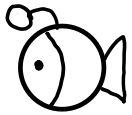
p(|)=

p(x4 | )=

Joint Probability

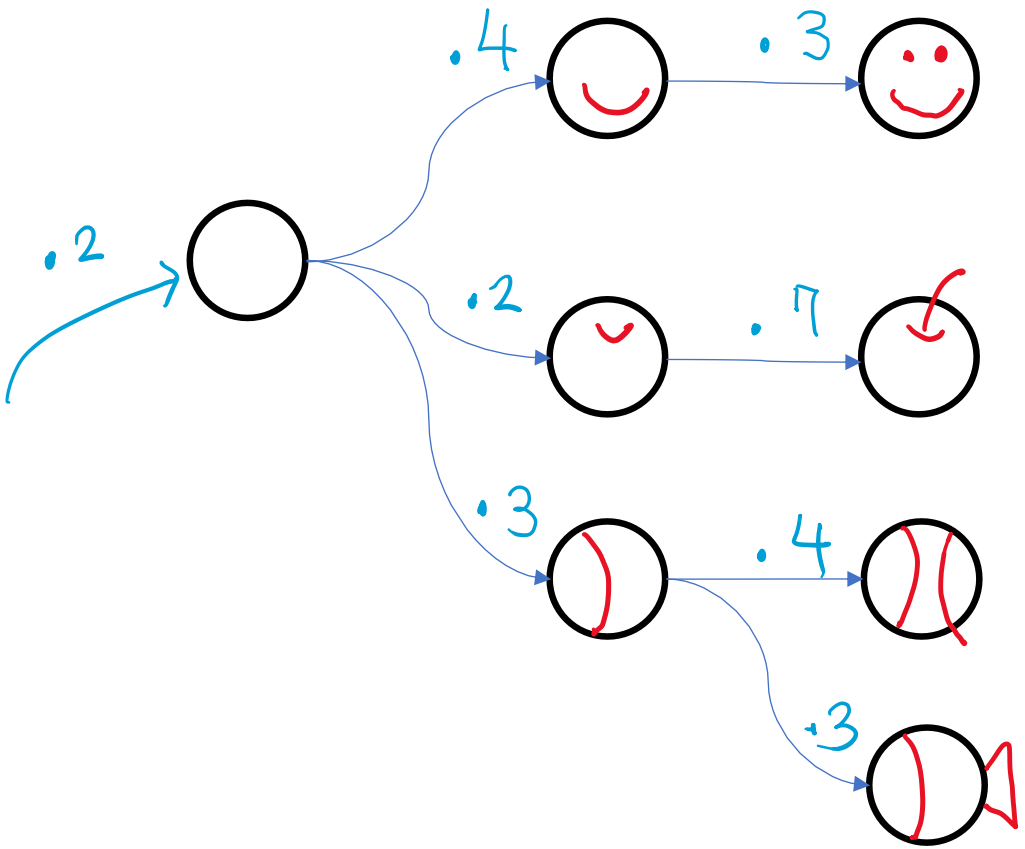
p( )=

p( )=

p()=

p( )=

Joint Probability



a p( ) = 0.2 x 0.4 x 0.3 = 0.024

b p( ) = 0.2 x 0.2 x 0.7 = 0.028

c p( ) = 0.2 x 0.3 x 0.4 = 0.024

d p( ) = 0.2 x 0.3 x 0.3 = 0.018

🔑 (a + b + c + d) * 1000 % 13 =

3

NumPy by Hand ✍️ [Entropy]

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Cross Entropy by @

1. g = -1 * np.log(q)
2. pt = np.transpose(p)
3. CE = pt @ g

p	q
.7	.3
0	.5
.3	.1
0	.1

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

Cross Entropy by *

1. g = -1 * np.log(q)
2. pg = p * g
3. CE = np.sum(b)

p	q
.7	.3
0	.5
.3	.1
0	.1

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

Categorical CE

1. g = -1 * np.log(q)
2. pt = np.transpose(p)
3. CE = pt @ g

p	q
0	.3
1	.5
0	.1
0	.1

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

Categorical CE

1. g = -1 * np.log(q)
2. pg = p * g
3. CE = np.sum(pg)

p	q
0	.3
1	.5
0	.1
0	.1

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

Batch Categorical CE

1. g = -1 * np.log(q)
2. pg = p * g
3. CE = np.sum(pq)

q

.3	.1	.1
.5	.5	.1
.1	.3	.5
.1	.1	.3

p

1	0	0
0	1	0
0	0	0
0	0	1

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

Batch Categorical CE

```
1.  q1 = q[c, [0,1,2]]
2.  g = np.log(q1)
3.  CE = np.sum(g)
```

q

.3	.1	.1
.5	.5	.1
.1	.3	.5
.1	.1	.3

c

0	1	3

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

Binary Cross Entropy

1. q = np.vstack((y, 1 – y))
2. p = np.vstack((t, 1-t))
3. g = -np.log(q)
4. pg = p * g
5. CE = np.sum(pg)

y .7

t 1

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

Batch BCE

1. q = np.vstack((y, 1 – y))
2. p = np.vstack((t, 1-t))
3. g = -np.log(q)
4. pg = p * g
5. CE = np.sum(pg)

y	.7	.3	.9
t	1	0	1

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

BCE

1. q = np.vstack((y, 1 – y))
2. p = np.vstack((t, 1-t))
3. g = -np.log(q)
4. pg = p * g
5. CE = np.sum(pg)

y	.3	.1	.7	.9	0	1
t	1	0	0	0	1	1
q	.3	.1	.7	.9	0	1
	.7	.9	.3	.1	1	0
p	1	0	0	0	1	1
	0	1	1	1	0	0
g	2	3	.5	.2	32	0
	.5	.2	2	3	0	32
pg	2	0	0	0	32	0
	0	.2	2	3	0	0
					CE	39.2

-log(0) ≈32
-log(0.1) ≈ 3
-log(0.3) ≈ 2
-log(0.5) ≈ 1
-log(0.7) ≈ 0.5
-log(0.9) ≈ 0.2
-log(1) = 0

39.2 × 10
= ~~392~~ 56

Show your work

CE * 10 % 7 = ~~3~~ 0