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Part B

1)

a. Given 2 random variables A and B

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

b.

Let $p(D)$ be the probability of observing the given data and $p(h)$ be probability of the hypothesis h holding true.

according to baye's theorem:

$$p(h/D) = \frac{p(D/h) \cdot p(h)}{p(D)}$$

$$\boxed{h_{MAP} = \underset{h \in H}{\operatorname{argmax}} \; p(h/D)}$$

$$\boxed{h_{ML} = \underset{h \in H}{\operatorname{argmax}} \; p(D/h)}$$

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2) Find S algorithm :

a. Initialize h to the most specific hypothesis, φ for every attribute.

b. For ~~all~~ every positive training example x,

for each attribute a,

if the attribute a DOES NOT satisfy the constraint, replace the attribute a by the next more general constraint in h.

initially, h = <φ, φ, φ, φ, φ, φ>

E1 : (sunny, Warm, high, Strong, Cool, change)

h = < Sunny, warm, high, strong, cool, change >

E2 : (Sunny, warm, High, strong, warm, Same)

h = < Sunny, warm, high, strong, ?, ? >

E3 ignored as -ve training

E4 : (Sunny, warm, normal, Light, warm, Same)

$\boxed{h = < \text{Sunny, warm, ?, ?, ?, ?} >}$

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Part - C

3)

a) → The general boundary G with respect to hypothesis space H and training data D is the set of maximally general hypothesis consistent with D in H.

→ The specific boundary S with respect to H and D is set of maximally specific hypotheses consistent with D in H.

$G = \{ g \in H \mid consistent(g, D)$ and $\neg (\exists g' \in H)[g' >_g g$ and $consistent(g', D)] \}$

$S = \{ s \in H \mid consistent(s, D)$ and $\neg (\exists s' \in H) [s >_g s'$ and $consistent(s', D)] \}$

b) using candidate elimination algorithm,

$S_0 = \{ < \phi, \phi, \phi > \}$
$G_0 = \{ < ?, ?, ? > \}$

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T_1 : (Big, Red, circle) - NO

consistent with ~~S_0~~ $\forall s \in S_0$

$\boxed{S1 = \{ \langle \phi, \phi, \phi \rangle \}}$

~~G1~~ ~~G0~~ T1 is inconsistent with ~~G0~~

~~g0~~ : $\langle ?, ?, ? \rangle$

minimally more ~~general~~ specific ~~which are~~ than $\langle ?, ?, ? \rangle$ consistent are

$\langle$ Small, ?, ? $\rangle$, $\langle$?, Blue, ? $\rangle$, $\langle$ ~~Tri~~ ?, ?, Triangle $\rangle$.

~~$\forall$~~ $\exists s \in S1$ are more specific than above hypotheses.

$\boxed{G1 = \{ \langle \text{small}, ?, ? \rangle, \langle ?, \text{Blue}, ? \rangle, \langle ?, ?, \text{Triangle} \rangle \}}$

T2 : (Small, Red, circle) - YES.

only $\langle$Small, ?, ?$\rangle$ is CONSISTENT

$\Rightarrow$ ~~G2 = \{ $\langle$small, Red, circle$\rangle$ \}~~

~~S2 = \{~~

$$\boxed{\begin{aligned} G2 &= \{ \langle \text{small}, ?, ? \rangle \} \\ S2 &= \{ \langle \text{small}, \text{Red}, \text{circle} \rangle \} \end{aligned}}$$

T3 : (Small, Red, Triangle) – NO.

$\forall s \in S2$ are consistent with T3.

$\Rightarrow$ S3 = \{ $\langle$Small, Red, Circle$\rangle$ \}

$\langle$Small, ?, ?$\rangle$ is NOT CONSISTENT

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minimally more ~~general~~ specific hypotheses of <small, ?, ?> consistent with T3 are { <φ, ?, ?> , <small, Blue, ?> , <small, ?, circle> }

<small, Blue, ?> & <φ, ?, ?> are NOT more general than specific boundary.

$$\Rightarrow \boxed{\begin{array}{l} G3 = \{ \langle small, ?, circle \rangle \} \\ S3 = \{ \langle small, Red, circle \rangle \} \end{array}}$$

T4 : (Big Blue Triangle) - NO

T4 is consistent with $\forall s \in S3$ & $\forall g \in G3$.

$$\Rightarrow \boxed{\begin{array}{l} S4 = S3 \\ G4 = G3 \end{array}}$$

T5 : (small, Blue, Circle) - YES

T5 is consistent with $\forall g \in G4$
G5 = { <small, ?, circle> }
<small, Red, Circle> ∈ S4 is ~~not~~ inconsistent with T5.

$$\Rightarrow \boxed{\begin{array}{l} S5 = \{ \langle small, ?, circle \rangle \} \\ \quad = G5 \end{array}}$$

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Thus, candidate elimination has CONVERGED.

Final $VS_{H,D} \equiv \{ < small, ?, circle > \}$

c.

version space is CONVERGED.

i. (Big Blue circle) is classified as NO

ii) (small Blue Triangle) is also classified as NO

5)

a) Inductive bias of a learning algorithm is the set of assumptions sufficient to deductively justify inductive inference performed by learning algorithm.

Formally,

$$(B \wedge D_c \wedge x_i) \vdash L(x_i, D_c)$$

B : inductive bias (set of assumptions)
D_c : Training data
x_i : unseen example
L : learning algorithm

$x \vdash y$ means y can be deduced ~~deductively~~ ~~[illegible]~~ from x.

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b)

There are 2 assumptions under which the CANDIDATE ELIMINATION algorithm can converge to the target concept. These assumptions are the inductive bias

1) The target concept c is contained in hypothesis space. $(c \in H)$
2) All training examples are error free.

c)

i) ID3 searches the complete hypothesis space, where the hypothesis is a finite discrete valued function. Candidate elimination searches only an INCOMPLETE hypothesis space.

ii) ID3 searches its H incompletely (from simpler - complex until termination condition is true) but candidate elimination COMPLETELY searches its hypothesis space.

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Thus, ~~the~~ the inductive bias of ID3 is a preference bias and that of Candidate elimination is restriction bias.