Exercise 3

1. Explain why it is a good heuristic to choose the variable that is most constrained but the value that is least constraining in a CSP search.

The most constrained variable makes sense because it chooses a variable that is likely to cause an early failure, and it is more efficient to fail as early as possible. Also called Fail First heuristic or Minimum Remaining Values.

The least constraining value heuristic makes sense because it allows the most chances for future assignments to avoid a conflict. Once a variable is selected (MRV), increase the chance to find a solution.

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Init: Put all the arcs of the csp in a queue

While the queue is not empty

Take an arc out of the queue (X_i, X_j)

Check if a domain value of X_i must be removed

If a domain value is removed check whether the domain of X_i is empty. If yes, stop Put all arcs of neighbors of X_i in the queue

Finished if the queue is empty

4. For each of the following statements, either proof it is true or give a counterexample.

- If $P(a|b,c) = P(b|a,c)$, then $P(a|c) = P(b|c)$
- If $P(a|b,c) = P(a)$, then $P(b|c) = P(b)$
- If $P(a|b) = P(a)$, then $P(a|b,c) = P(a|c)$

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5. It is quite often useful to consider the effect of some specific propositions in the context of some general background evidence that remains fixed, rather than in the complete absence of information. The following questions ask you to prove more general versions of the product rule, with respect to some background evidence e. Prove the conditionalized version of the general product rule:

 $P(A,B|E) = P(A|B,E) P(B|E)$.

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

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

6. This exercise investigates the way in which conditional independence relationships affect the amount of

 \rightarrow P(A,B|E) = P(A|B,E) P(B|E)

16 information needed for probabilistic calculations. a) Suppose we wish to calculate $P(H | E_1, E_2)$ and we have no conditional independence information. Which of the following set of numbers are sufficient for the calculation? **I.** $P(E_1, E_2)$, $P(H)$, $P(E_1 | H)$, $P(E_2 | H)$ II. $P(E_1, E_2)$, $P(H)$, $P(E_1, E_2 | H)$ **III.** $P(H)$, $P(E_1|H)$, $P(E_2|H)$ b) Suppose we know that $P(E_1 | H, E_2) = P(E_1 | H)$ for all values of H, E_1 , E_2 . Now which of the three sets are sufficient? $P(H|E_1, E_2) = \frac{P(E_1, E_2|H)P(H)}{P(E_1, E_2)}$ $\frac{P(Y|X)P(X)}{P(E_1, E_2)}$ Bayes rule: $P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}$ Clearly II. is sufficient Intuitively III. is insufficient, because it provides no information about correlations of E_1 and E_2 . Suppose H has m , E_1 has n and E_2 has o possible values. $P(H | E_1, E_2)$ contains $(m-1)*n*o$ independent values III. has $(m-1)+m*(n-1)+m*(o-1)$ I. has $(n *o-1)$ + $(m-1)$ + $m * (n-1)$ + $m * (o-1)$ $P(Y)$

 \rightarrow if *m, n, o* are large enough, I. and III. are insufficient.

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