# LAB on OJ

Exact Inference

- http://10.88.3.60/
- 1003 Exact Inference

# Review on exact inference algorithm

• Example: MaryCall, JohnCall in Ch14

- Enumeration algorithm:
  - Step 1: Select the entries consistent with the evidence
  - Step 2: Sum out hidden vars to get joint of Query and evidence
  - Step 3: Normalize
- Elimination algorithm:
  - Make factors
  - Join all factors and eliminate all hidden vars.

# Review on exact inference algorithm

• Example: MaryCall, JohnCall in Ch14

- Enumeration algorithm:
  - Def enumeration\_ask(X, e, bn):
  - Def enumeration all(X, e, bn):
- Elimination algorithm:
  - Def elimination ask(X, e, bn):

# Problem description – sample in

\*\*\*

0.9 +

0.05 -

\*\*\*

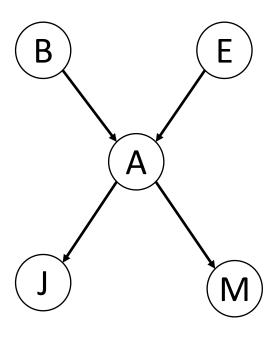
0.7 +

0.01 -

John | Alarm

Mary | Alarm

```
P(Earthquake = -)
P(Burglary = + | John = +, Mary = +)
*****
Burglary
0.001
***
Earthquake
0.002
***
Alarm | Burglary Earthquake
0.95 + +
0.94 + -
0.29 - +
0.001 - -
```



# Problem description – sample out

```
probability by enumeration: 1.0 probability by elimination: 1.0 *******

probability by enumeration: 0.28 probability by elimination: 0.28
```

\*\*\*\*\*

#### Classes

```
used in building the BayesNet
class BayesNet:
  def init (self, node specs=[]):
  def add(self, node spec):
  def variable node(self, var):
  def variable values(self, vars):
class BayesNode:
                                              used in building the BayesNet
  """A conditional probability distribution for a boolean variable, P(X \mid parents).
Part of a BayesNet."""
  def init (self, x, parents, cpt):
  def p(self, value, event):
```

#### Classes

```
class ProbDist:
                              used in the computation for probability distribution
  def init (self, varname='?', freqs=None):
  def normalize(self):
class Factor:
                              used in elimination algorithm
  def init (self, variables, cpt):
  def pointwise product(self, other):
  def sum out(self, var):
  def p(self, e):
  def normalize(self):
```

#### Procedure

- First read the input and bulid bn = BayesNet()
  by bn.add((node, parents, cpt))
- Discuss (1) joint/ marginal distribution
  (2) conditional distribution

- (1): def joint\_probability():

  Call enumerate\_all() and elimination\_ask() respectively
- (2): def conditional\_probability():

  Call *enumerate ask*() and *elimination ask*() respectively

### pseudocode

• Enumeration algorithm

Figure 14.9

```
function ENUMERATION-ASK(X, \mathbf{e}, bn) returns a distribution over X
   inputs: X, the query variable
            e, observed values for variables E
             bn, a Bayes net with variables \{X\} \cup \mathbf{E} \cup \mathbf{Y} / \star \mathbf{Y} = hidden \ variables \ \star /
   \mathbf{Q}(X) \leftarrow a distribution over X, initially empty
   for each value x_i of X do
       \mathbf{Q}(x_i) \leftarrow \text{ENUMERATE-ALL}(bn.\text{VARS}, \mathbf{e}_{x_i})
            where \mathbf{e}_{x_i} is \mathbf{e} extended with X = x_i
   return Normalize(\mathbf{Q}(X))
function ENUMERATE-ALL(vars, e) returns a real number
  if EMPTY?(vars) then return 1.0
   Y \leftarrow \text{FIRST}(vars)
   if Y has value y in e
       then return P(y \mid parents(Y)) \times \text{ENUMERATE-ALL(REST}(vars), \mathbf{e})
       else return \sum_{y} P(y \mid parents(Y)) \times ENUMERATE-ALL(REST(vars), \mathbf{e}_y)
            where \mathbf{e}_{y} is \mathbf{e} extended with Y = y
```

The enumeration algorithm for answering queries on Bayesian networks.

# pseudocode

#### • Elimination algorithm

```
function ELIMINATION-ASK(X, \mathbf{e}, bn) returns a distribution over X inputs: X, the query variable \mathbf{e}, observed values for variables \mathbf{E} bn, a Bayesian network specifying joint distribution \mathbf{P}(X_1, \dots, X_n) factors \leftarrow [] for each var in ORDER(bn.VARS) do factors \leftarrow [MAKE-FACTOR(var, \mathbf{e})|factors] if var is a hidden variable then factors \leftarrow SUM-OUT(var, factors) return NORMALIZE(POINTWISE-PRODUCT(factors))
```

Figure 14.10 The variable elimination algorithm for inference in Bayesian networks.