L13-14 Probability based Reasoning under Uncertainty

- Uncertainty（不確実性）
- The axioms of probability（確実論の公理）
- Bayes rule (ベイズ規則)
- Belief network/Bayes net (新念ネットワーク)
- Joint Probability and Conditional Probability
- Try to edit Bayes net

Uncertainty

No matter in proposition logic or first order logic reasoning, it is assumed that

assumed
仮定した

- facts are known to be true,
- facts are known to be false,
- or nothing is known.

In general, however, people are not sure what the relevant facts are true or false and thing becomes unpredictable due to

unpredictable
予知できない

- partial observation (e.g. road state, other driver's plan)
- noisy sensors (Radio traffic report)
- uncertainty in action outcome (flat tire, accident)

→ Rules may give unreliable conclusions

unreliable信頼
できない

e.g. A_t = Leaving for airport t minutes before flight, will A_t get me airport on time??

toothache → cavity?? gum disease??

Probabilistic Reasoning

- Probability theory provides a way of dealing rationally with uncertainty – assigning a numerical degree of belief between 0 and 1 to sentences.

  e.g. P(cavity) = 0.1 indicates a patient having cavity with a probability of 0.1 (a 10% chance).

- Degree of truth, as opposed to degree of belief, is the subject of fuzzy logic.

- Probabilistic reasoning may be used in the following three types of situations:

  - The world is really random
  - The relevant world is not random given enough data, but it is not always have access to that much data
  - The world appears to be random because we have not describe it at the right level.

Probability theory
確率論

cavity
虫歯

Fuzzy logic
ファジー論理

Belief
信じること

Necessary formulas

- Definition of conditional probability

Conditional probability
条件確率

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

Where, P(A|B) is read as "the probability of A given that all we know is B"

for example, P(Sore-throat|Cold)=0.8

means the probability of the patient having Sore Throat will be 0.8 (a 80% chance)

under the condition of getting Cold is TRUE.

- Product rule gives an alternative formulation

alternative
代わりの

Product
(掛け算の)積

$$P(A \wedge B)=P(A|B)P(B)$$

it comes from the fact that for A and B to be true, we need B to be true,

and then A to be true given B. You can also write

$$P(A \wedge B)=P(B|A)P(A)$$

The axioms of probability

For any propositions, A, B

axiom
公理

- $0 \le P(A) \le 1$

  all probabilities are between 0 and 1

- $P(True) = 1$ and $P(False) = 0$

  Necessary true propositions have probability 1, and

  necessary false propositions have probability 0.

assign
与える

- $P(A \vee B) = P(A) + P(B) - P(A \wedge B)$

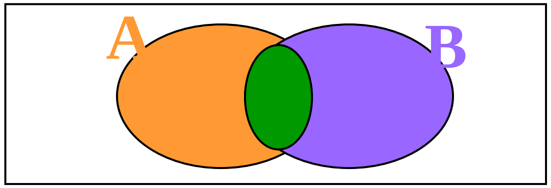
  The total probability of $A \vee B$ is seen to be the sum of the

  probabilities assigned to A and B, but with $P(A \wedge B)$

  subtracted out so that those cases are not counted twice.

subtract
引く

True



$A \wedge B$

$P(A \vee B) = P_{orange\_color} + P_{purple\_color} + P_{green\_color}$

覚えておくべき式

- 条件付き確率

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

- 積の法則

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

- ベイズの法則

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

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

$$P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A|\neg B)P(\neg B)}$$

Work in class

問4. 予防接種をうけてインフルエンザにかからない確率は0.75、予防接種を受けずにインフルエンザにかからない確率は0.01であったとする。このとき、予防接種を受けない確率を0.60とすると次の確率を求めよ。(既約分数で示せ。)

① インフルエンザにかからない確率を求めよ。

② インフルエンザにかからなかった時に、予防接種を受けていた確率と予防接種を受けていなかった確率の比を求めよ。

Joint Probability (結合確率)

- It is derived by successive application of product rule:

successive
継続的な

derive
得る

$$P(X_1, \ldots, X_n) = P(X_n | X_{n-1}, \ldots, X_1)\, P(X_{n-1}, \ldots, X_1)$$

$$= P(X_n | X_{n-1}, \ldots, X_1)\, P(X_{n-1} | X_{n-2}, \ldots, X_1)\, P(X_{n-2}, \ldots, X_1)$$

$$= \ldots$$

$$= P(X_n | X_{n-1}, \ldots, X_1)\, P(X_{n-1} | X_{n-2}, \ldots, X_1) \ldots P(X_2 | X_1)\, P(X_1)$$

$$= \Pi^n_{i=1} P(X_i | X_{i-1}, \ldots, X_1)$$

$= P(X_1, \wedge \ldots, \wedge X_n)$

Work in class: Please finish the following formulae

$P(X_1, X_2) = ?$

$P(X_1, X_2, X_3) = ?$

Joint Probability (結合確率) –例

$P(X_1, \ldots, X_n) = \Pi^n_{i=1} P(X_i | X_{i-1}, \ldots, X_1)$

$= P(X_1)P(X_2|X_1) \ldots P(X_{n-1}| X_{n-2}, \ldots, X_1)P(X_n| X_{n-1}, \ldots, X_1)$

n=5,

$P(X_1, X_2, X_3, X_{4,} X_5) = P(X_1)P(X_2|X_1) P(X_3| X_2, X_1)P(X_4| X_3, X_{2,} X_1) P(X_5| X_4, X_3, X_{2,} X_1)$

- For example, we can calculate the probability of the event that the alarm has sounded but neither a burglary nor an earthquake has occurred, and both John and Mary call.

$P(\neg B \wedge \neg E \wedge A \wedge J \wedge M)$

$= P (\neg B) P (\neg E|\neg B) P (A| \neg E \neg B) P(J|A \wedge \neg B \wedge \neg E) P(M|J \wedge A \wedge \neg B \wedge \neg E)$

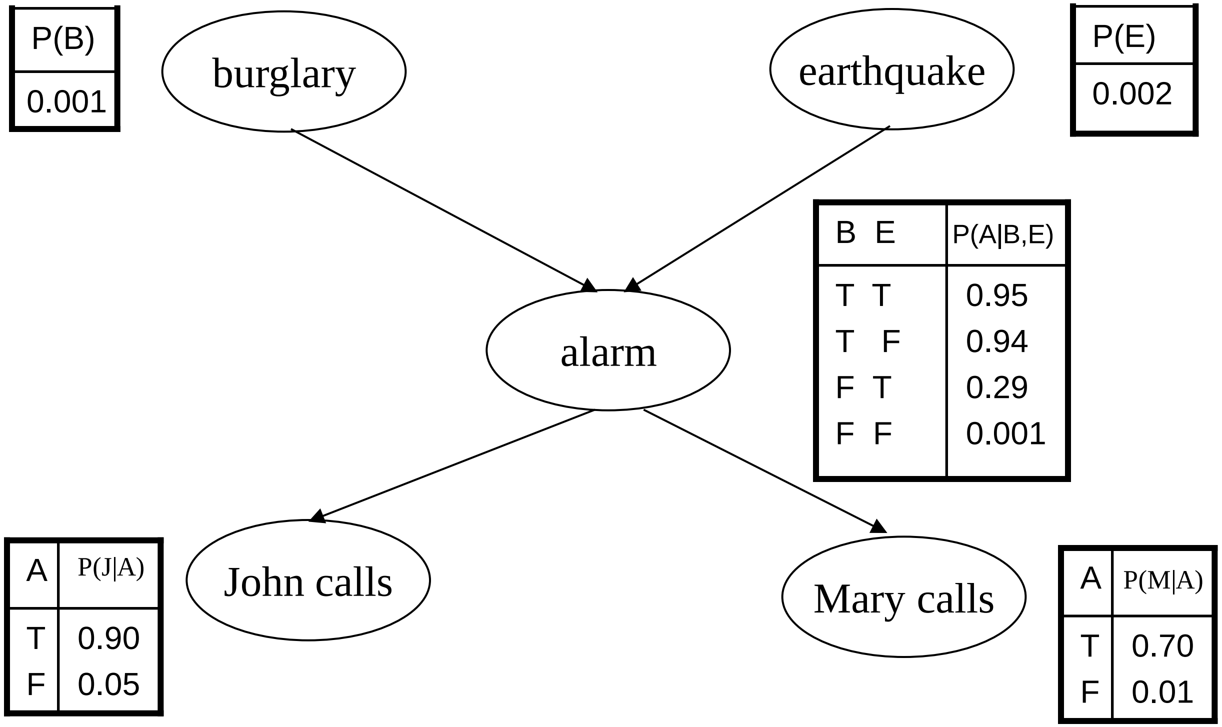
(referring to Belief network/Bayes net in next page for conditional probability)

$= P(\neg B)P(\neg E)P(A| \neg B \wedge \neg E) P(J|A)P(M|A)$

(referring to the conditional probability values in next page)

$= 0.999 \times 0.998 \times 0.001 \times 0.90 \times 0.70$

$= 0.00062$



P(B)
0.001

P(E)
0.002

B E	P(A|B,E)
T T	0.95
T F	0.94
F T	0.29
F F	0.001

A	P(J|A)
T	0.90
F	0.05

A	P(M|A)
T	0.70
F	0.01

$P(\neg B \wedge \neg E \wedge A \wedge J \wedge M)$

$= P(\neg B)\, P(\neg E|\neg B)\, P(A| \neg E \neg B)\, P(J|A \wedge \neg B \wedge \neg E)\, P(M|J \wedge A \wedge \neg B \wedge \neg E)$

(referring to Belief network/Bayes net in next page for conditional probability)

$= P(\neg B)P(\neg E)P(A| \neg B \wedge \neg E)\, P(J|A)P(M|A)$

(referring to the conditional probability values in next page)

$= 0.999 \times 0.998 \times 0.001 \times 0.90 \times 0.70$

$= 0.00062$

Independence

- Two random variables *A B* are (absolutely) independent iff

  $P(A|B) = P(A)$

  or $P(A, B) = P(A|B)P(B) = P(A)P(B)$

  e.g., A and B are two coin flips

  $P(A=\text{head}, B=\text{head}) = P(A=\text{head})P(B=\text{head})=0.5 \times 0.5 = 0.25$

flip (勝負を決めるため)硬貨を空中へはじき上げること

- If *n* Boolean variables are independent, the full joint is

  $P(X_1, \ldots, X_n) = \Pi^n_{i=1} P(X_i)$

Absolute independence is a very strong requirement, seldom met!

- Conditional independence

  $P(A|B, C) = P(A|C)$

  we say that A is conditionally independent of B given C

  e.g., $P(J|A, \neg B, \neg E) = P(J|A)$

  $P(\neg E|\neg B) = P(\neg E)$

Belief network/Bayes net

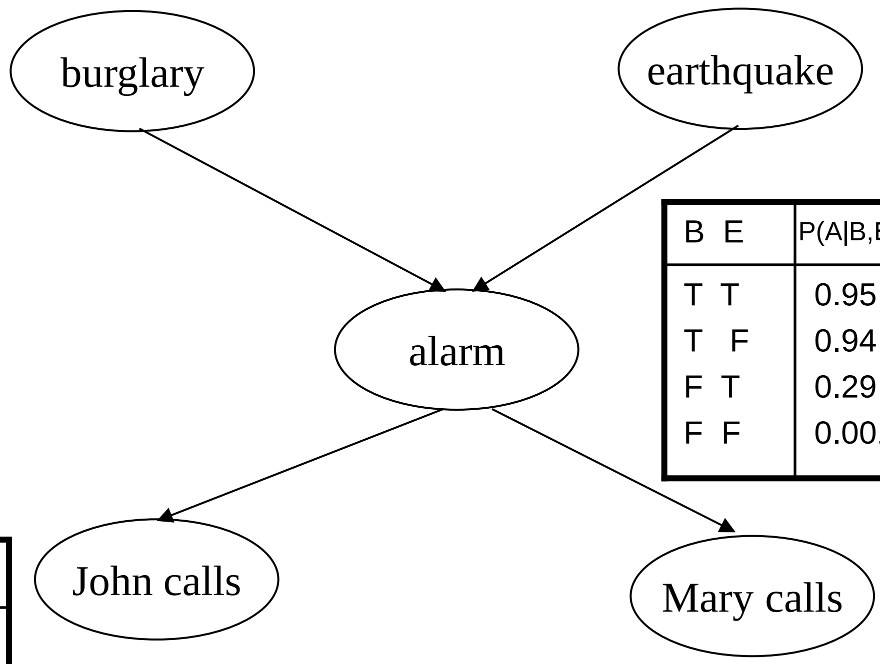
- A simple, graphical notation for conditional independence assertions and hence for compact specification of full joint distributions.
- Belief networks are also called “causal nets”, “Bayes nets”, or “influence diagrams”.

For example, the following figure shows a belief network.

Variables: Burglary, Earthquake, Alarm, JohnCallas, MaryCalls

P(B)
0.001

P(E)
0.002



B	E	P(A|B,E)
T	T	0.95
T	F	0.94
F	T	0.29
F	F	0.001

A	P(J|A)
T	0.90
F	0.05

A	P(M|A)
T	0.70
F	0.01

Syntax and Semantics

direct

(ある方向に)向ける

influence
影響

Syntax:

- A set of nodes, one per variable
- a directed, a cyclic graph (link shows "directly influences")
- a conditional probability distribution for each node given its parents:

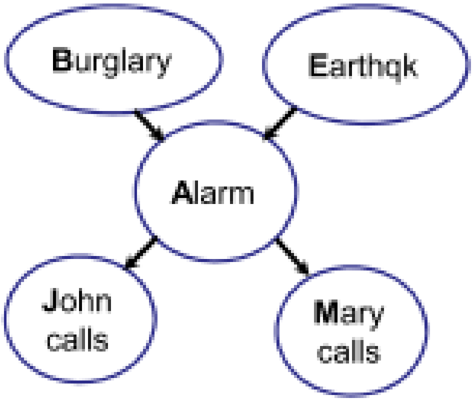
probability distribution
確率分布

$P(X_i|Parents(X_i))$

Semantics:

- "Global" semantics defines the full joint probability distribution as the product of the local conditional distributions:

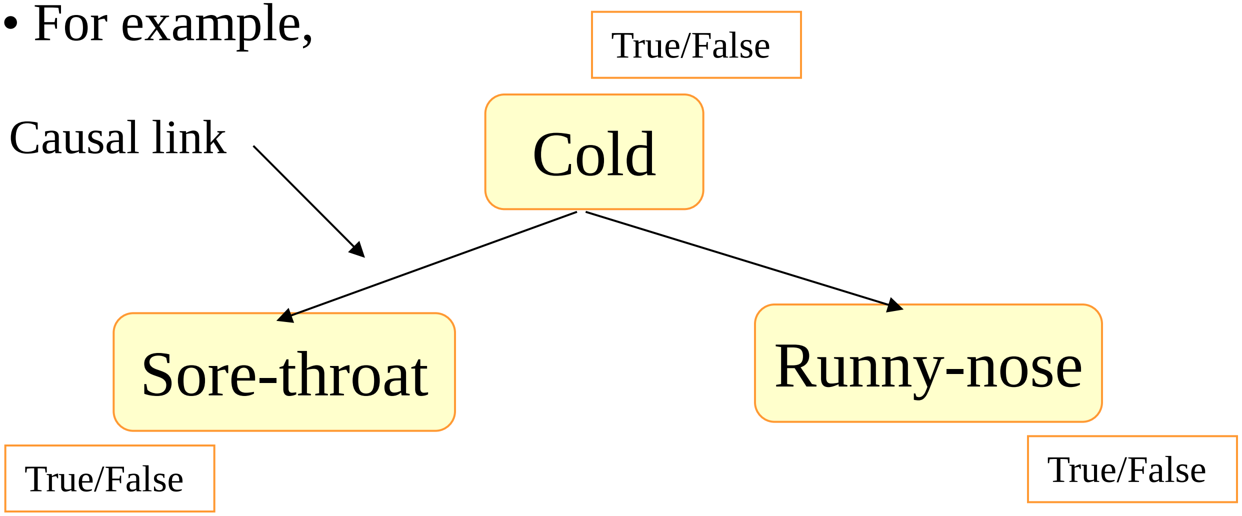
$P(X_1, \ldots, X_n) = \Pi^n_{i=1} P(X_i|Parents(X_i))$



e.g., $P(J \wedge M \wedge A \wedge \neg B \wedge \neg E) = P(\neg B)P(\neg E)P(A| \neg B \wedge \neg E) P(J|A)P(M|A)$

Belief networks/Bayes Nets

- It is also called “Causal nets”, “belief networks”, and “influence diagrams”.
- Bayes nets provide a general technique for computing probabilities of causally related random variables given evidence for some of them.
- For example,

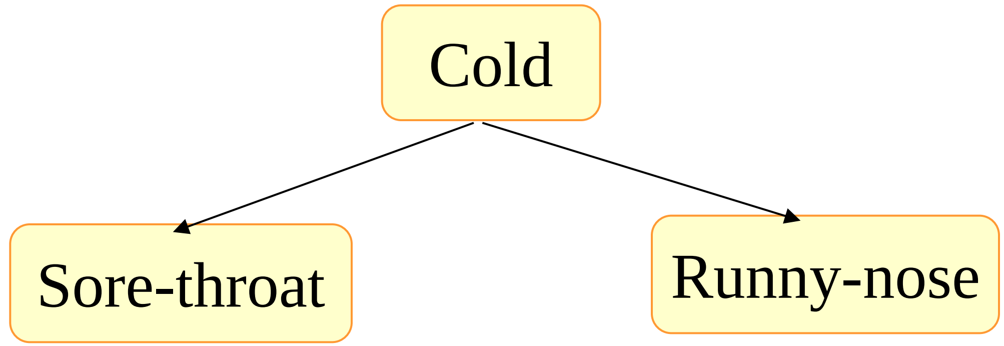


- ? Joint distribution: P(Cold, Sore-throat, Runny-nose)

For nets with a unique root

? Joint distribution: P(Cold, Sore-throat, Runny-nose)

The joint probability distribution of all the variables in the net equals the probability of the root times the probability of each non-root node given its parents.



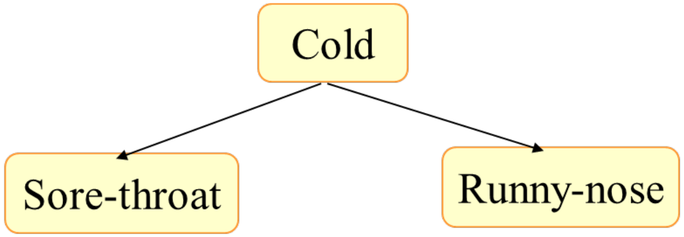
P(Cold, Sore-throat, Runny-nose) =

P(Cold)P(Sore-throat|Cold)P(Runny-nose|Cold)

? Prove it

Proof

For the “Cold” example, from the Bayes nets we can assume that Sore-throat and Runny-nose are irrelevant, thus we can apply conditional independence.



P(Sore-throat | Cold, ~~Runny-nose~~) = P(Sore-throat | Cold)

P(Runny-nose | Cold, ~~Sore-throat~~) = P(Runny-nose | Cold)

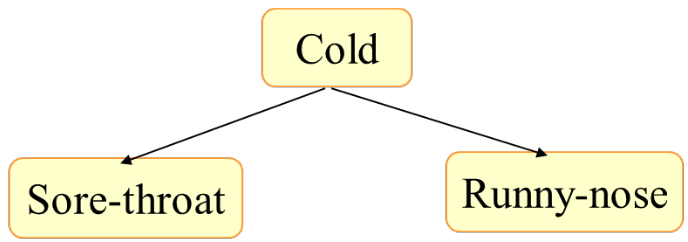
compute

P(Cold, Sore-throat, Runny-nose)

= ?

Proof

For the “Cold” example, from the Bayes nets we can assume that Sore-throat and Runny-nose are irrelevant, thus we can apply conditional independence.



P(Sore-throat | Cold, ~~Runny-nose~~) = P(Sore-throat | Cold)

P(Runny-nose | Cold, ~~Sore-throat~~) = P(Runny-nose | Cold)

compute

P(Cold, Sore-throat, Runny-nose)

= P(Runny-nose | Sore-throat, Cold) P(Sore-throat | Cold)P(Cold)

= P(Runny-nose | Cold) P(Sore-throat | Cold)P(Cold)

Further observations

- If there is no path that connects 2 nodes by a sequence of causal links, the nodes are conditionally independent with respect to root. For example, Sore-throat, Runny-nose are two independently events.
- Since Bayes nets assumption is equivalent to conditional independence assumptions, posterior probabilities in a Bayes net can be computed using standard formulas from probability theory

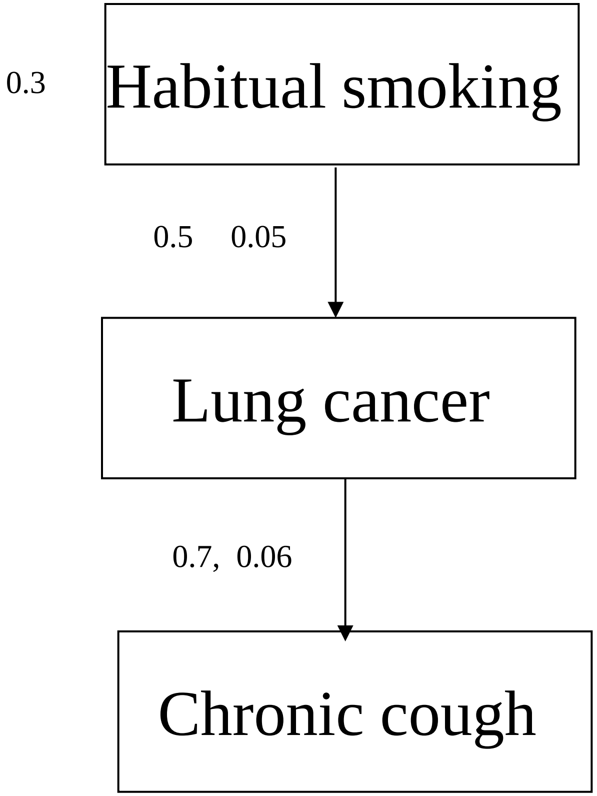
$$P(B|A) = \frac{P(A|B)P(B)}{P(A)}$$

$$P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A|\neg B)P(\neg B)}$$

Using
A = Sore-throat
B = Cold
We obtain

$$\text{P(Cold | Sore-throat)} = \frac{\text{P(Sore-throat | Cold) P(Cold)}}{\text{P(Sore-throat | Cold) P(Cold)} + \text{P(Sore-throat} \mid \neg\text{Cold) P(}\neg\text{Cold)}}$$

An example



$P(S) = 0.3$

$P(L|S) = 0.5$, $P(L|\neg S) = 0.05$

$P(C|L) = 0.7$, $P(C|\neg L) = 0.06$

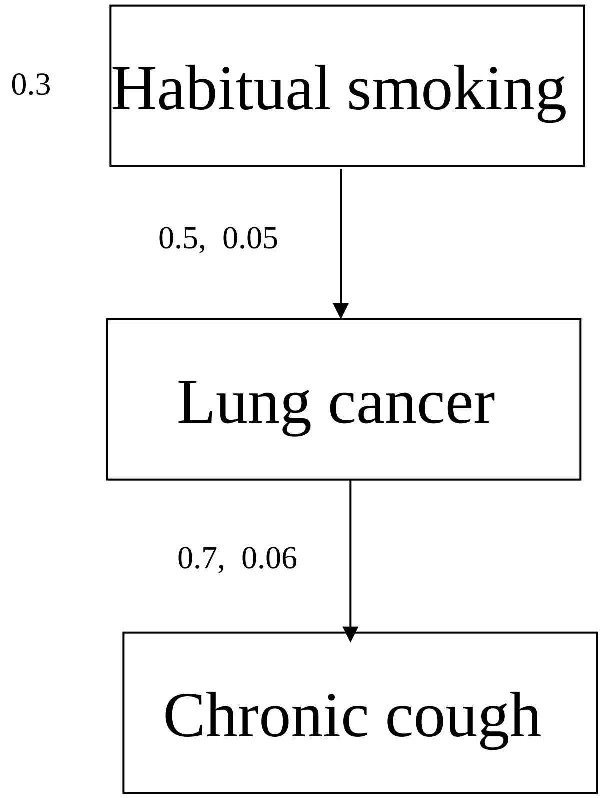
Joint probability distribution:

$$P(S, L, C) = P(S)\, P(L|S) P(C|L)$$

$$= 0.3 * 0.5 * 0.7 = 0.105$$

? P(L|C)

Compute P(L|C)



$P(S) = 0.3$

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Joint probability distribution:

$P(S, L, C) = P(S)\, P(L|S) P(C|L)$

$= 0.3 * 0.5 * 0.7 = 0.105$

$P(L|C) = (P(C|L)P(L)) / (P(C))$

$P(C) = P(C/L)P(L) + P(C/\neg L)P(\neg L)$

$P(L) = P(L/S)P(S) + P(L/\neg S)P(\neg S) = 0.5*0.3 + 0.05*(1-0.3) = 0.185$

$P(\neg L) = (1-0.185) = 0.815$

$P(C) = 0.7*0.185 + 0.06*0.815 = 0.1784$

$P(L|C) = 0.7*0.185 / 0.1784 = 0.7258968$

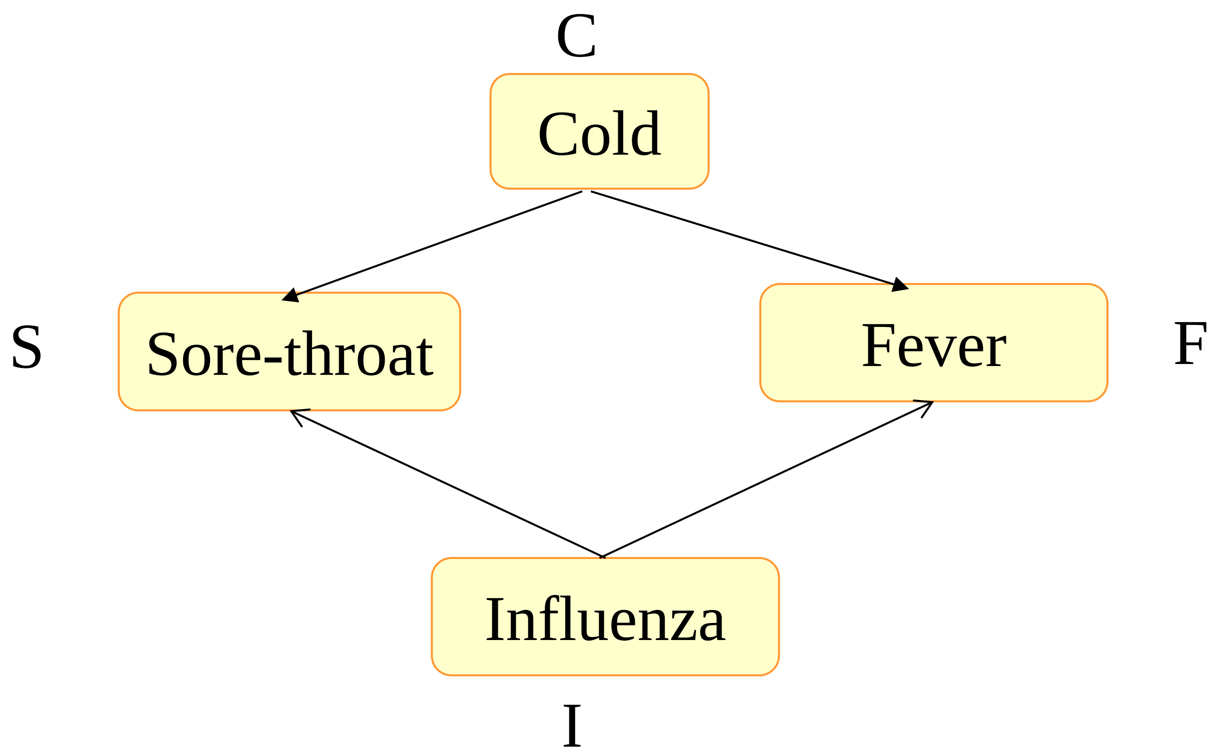
General way of computing any conditional probability:

1. Express the conditional probabilities for all the nodes
2. Use the Bayes net assumption to evaluate the joint probabilities.
3. $P(A) + P(\neg A) = 1$

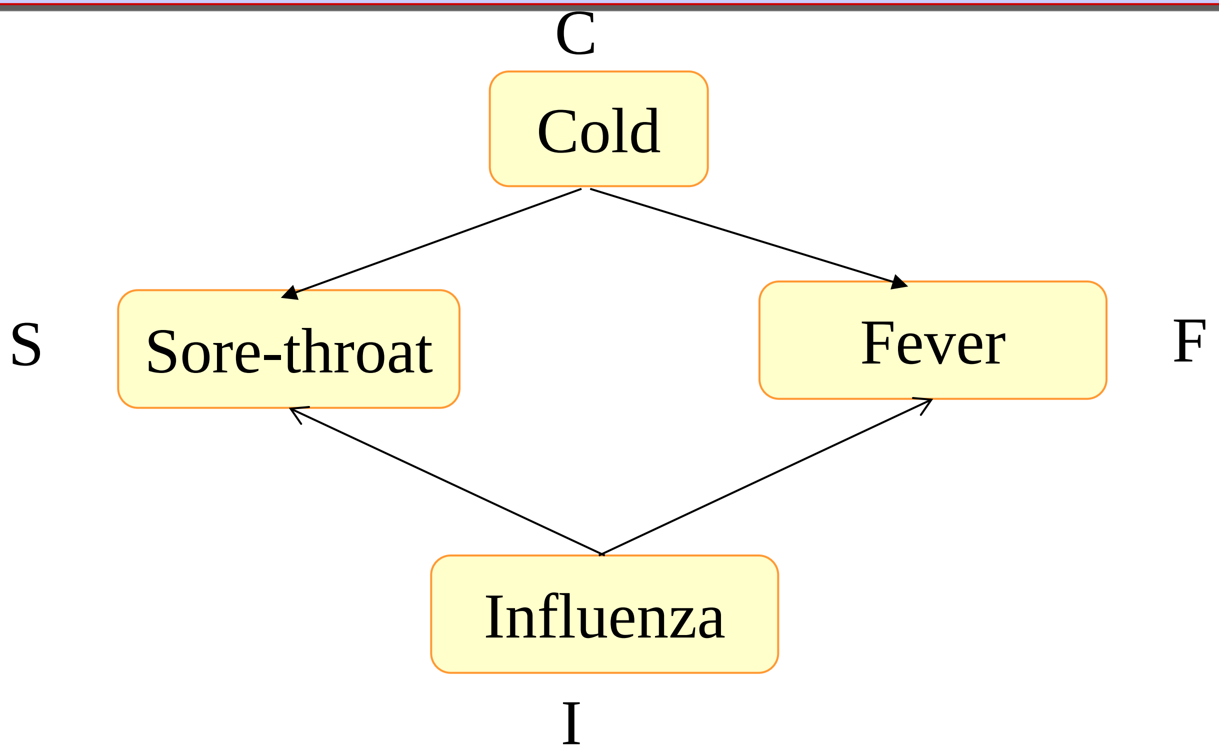
Work in class – No. 1

Could you write down the formulas to compute

P(C, S, F, I)



以下を計算する数式を書きなさい P(C, S, F, I)



$$P(C,S,F,I) = P(C)P(I)P(S|C,I)P(F|C,I)$$

Work in class – No. 2

Could you calculate P(S|L) in page 18.

P(S|L)の計算

0.3

習慣性喫煙
Smoke (S)

0.5, 0.05

肺癌
Lung cancer (L)

0.7, 0.06

慢性的な咳
Cough (C)

P(S) = 0.3

P(L|S) = 0.5, P(L|¬S) = 0.05

P(C|L) = 0.7, P(C| ¬L) = 0.06

結合確率:

P(S, L, C) = P(S) P(L|S)P(C|L)

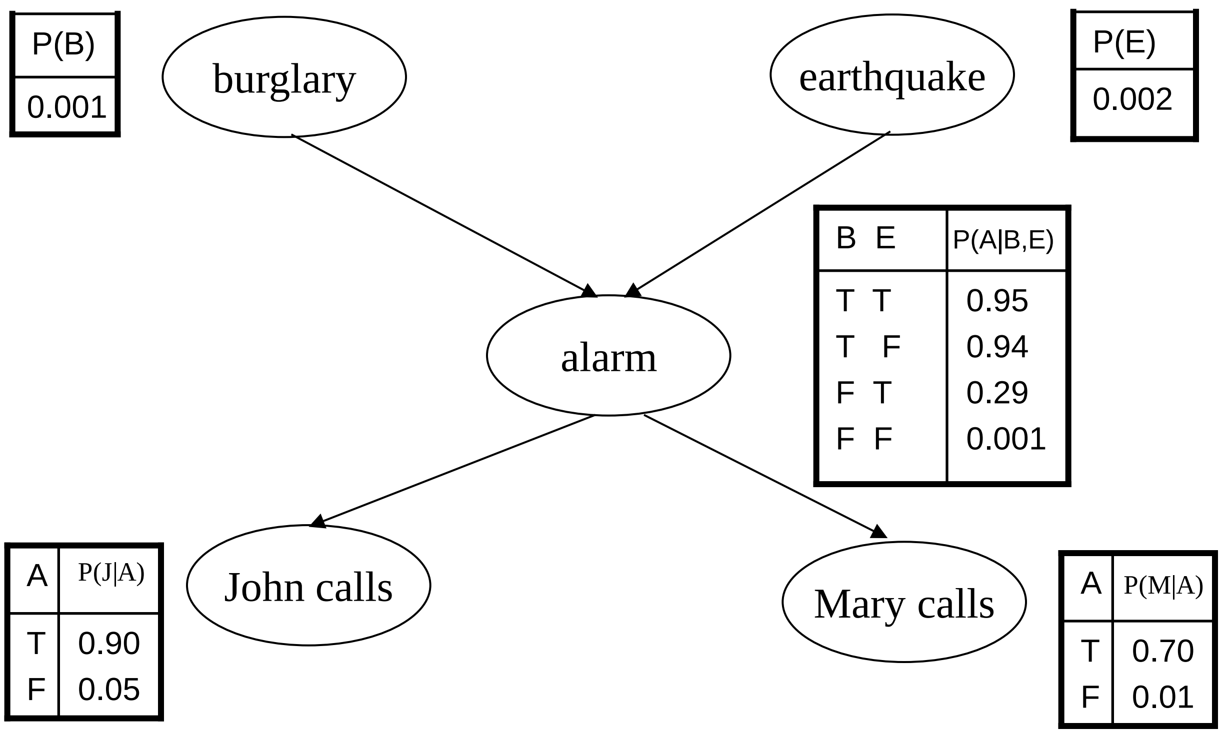
= 0.3*0.5 *0.7 = 0.105

P(S|L) = (P(L|S)P(S)) / (P(L))

P(L) = P(L/S)P(S) + P(L/ ¬S)P(¬S) = 0.5*0.3 + 0.05*(1-0.3) = 0.185

P(S|L) = 0.5*0.3 / 0.185 = ?

Example: One is at work, neighbors John and Mary call to say his alarm at home is ringing. Sometimes it's set off by minor earthquakes or in the case of burglar.



P(B)
0.001

P(E)
0.002

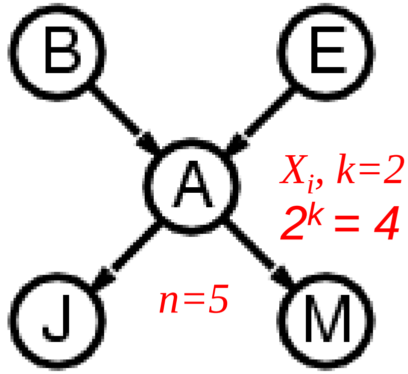
B	E	P(A|B,E)
T	T	0.95
T	F	0.94
F	T	0.29
F	F	0.001

A	P(J|A)
T	0.90
F	0.05

A	P(M|A)
T	0.70
F	0.01

Bayes Nets

Compactness



X_i, $k=2$

$2^k = 4$

Variables (each node is a avaible):

Burglary, Earthquake, Alarm, JohnCalls, MaryCalls

B	E	P(A|B,E)
T	T	0.95
T	F	0.94
F	T	0.29
F	F	0.001

- A CPT for Boolean X_i with k Boolean parents has 2^k rows for the combinations of parent values
- Each row requires one number p for X_i = *true* (the number for X_i = *false* is just $1-p$)
- If each variable has no more than k parents, the complete network requires $O(n \cdot 2^k)$ numbers
- I.e., grows linearly with n, vs. $O(2^n)$ for the full joint distribution
- For burglary net, 1 + 1 + 4 + 2 + 2 = 10 numbers (vs. 2^5-1 = 31)

独立性

- 2つの確率変数 A B が(絶対に) 独立している場合

$$P(A|B) = P(A)$$

or $P(A, B) = P(A|B)P(B) = P(A)P(B)$

- もしn 個のブール変数が独立している場合、完全な結合は以下のようになる

$$P(X_1, \ldots, X_n) = \Pi^n_{i=1} P(X_i)$$

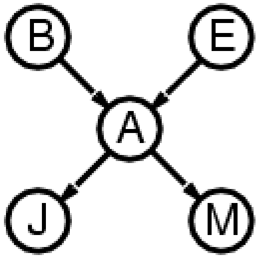
- 条件付き独立性

$$P(A|B, C) = P(A|C)$$

上式を満たすときAはCが与えられた下でBに対して条件付き独立性があるという

Semantics

The full joint distribution is defined as the product of the local conditional distributions:



$$\mathbf{P}(X_1, \ldots, X_n) = \pi_{i=1}^{n} \mathbf{P}(X_i \mid Parents(X_i))$$

e.g., $\mathbf{P}(j \wedge m \wedge a \wedge \neg b \wedge \neg e)$

$= \mathbf{P}(j \mid a)\, \mathbf{P}(m \mid a)\, \mathbf{P}(a \mid \neg b, \neg e)\, \mathbf{P}(\neg b)\, \mathbf{P}(\neg e)$

Constructing Bayesian networks

- 1. Choose an ordering of variables $X_1, \ldots, X_n$
- 2. For i = 1 to n
  - add X_i to the network
  - select parents from $X_1, \ldots, X_{i-1}$ such that

$$\mathbf{P}(X_i \mid Parents(X_i)) = \mathbf{P}(X_i \mid X_1, \ldots X_{i-1})$$

This choice of parents guarantees:

$$\mathbf{P}(X_1, \ldots, X_n) = \pi_{i=1}^{n} \mathbf{P}(X_i \mid X_1, \ldots, X_{i-1})$$

(chain rule)

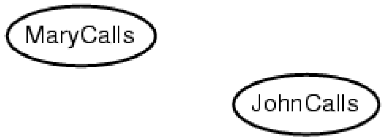
$$= \pi_{i=1}^{n} \mathbf{P}(X_i \mid Parents(X_i))$$

(by construction)

Example

- Suppose we choose the ordering *M, J, A, B, E*

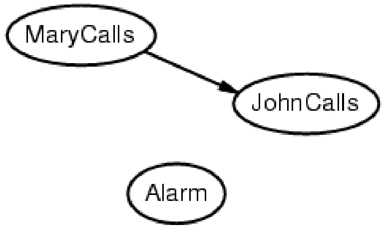
From conditional probability table (CPT)
to check dependence of variables



P$(J \mid M) =$ ***P***(J)?

Example

- Suppose we choose the ordering *M, J, A, B, E*
-

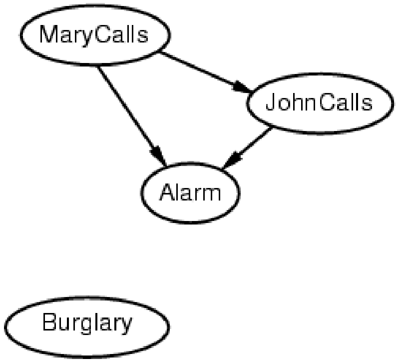


P$(J \mid M) =$ ***P***(J)? **No** *(J depends on M)*

P$(A \mid J, M) =$ ***P***$(A \mid J)$? ***P***$(A \mid J, M) =$ ***P***(A)?

Example

- Suppose we choose the ordering *M, J, A, B, E*
-



$\mathbf{P}(J \mid M) = \mathbf{P}(J)$? **No**

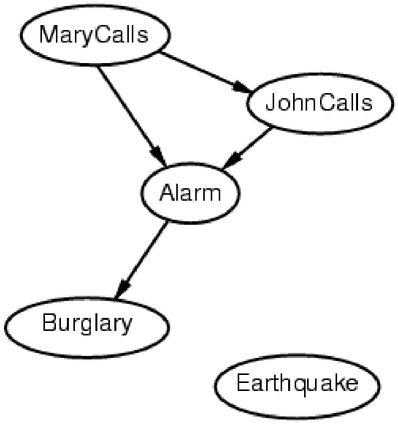
$\mathbf{P}(A \mid J, M) = \mathbf{P}(A \mid J)$? $\mathbf{P}(A \mid J, M) = \mathbf{P}(A)$? **No** *(A depends on M, J)*

$\mathbf{P}(B \mid A, J, M) = \mathbf{P}(B \mid A)$?

$\mathbf{P}(B \mid A, J, M) = \mathbf{P}(B)$?

Example

- Suppose we choose the ordering M, J, A, B, E



P*(J | M)* = ***P****(J)?* **No**

P*(A | J, M)* = ***P****(A | J)*? ***P****(A | J, M)* = ***P****(A)*? **No**

P*(B | A, J, M)* = ***P****(B | A)*? **Yes** *(B does not depend on J, M)*

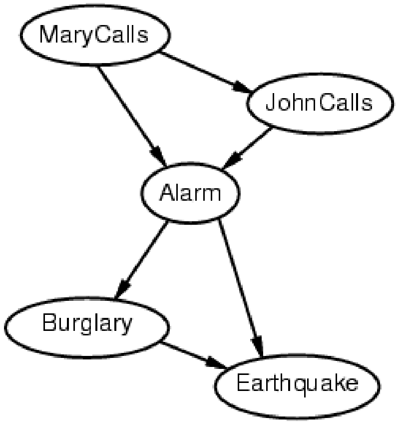
P*(B | A, J, M)* = *P(B | A)* = ***P****(B)*? **No** *(B depends on A)*

P*(E | B, A ,J, M)* = ***P****(E | A)*?

P*(E | B, A, J, M)* = ***P****(E | A, B)*?

Example

- Suppose we choose the ordering M, J, A, B, E



$\mathbf{P}(J \mid M) = \mathbf{P}(J)$? **No**

$\mathbf{P}(A \mid J, M) = \mathbf{P}(A \mid J)$? $\mathbf{P}(A \mid J, M) = \mathbf{P}(A)$? **No**

$\mathbf{P}(B \mid A, J, M) = \mathbf{P}(B \mid A)$? **Yes**

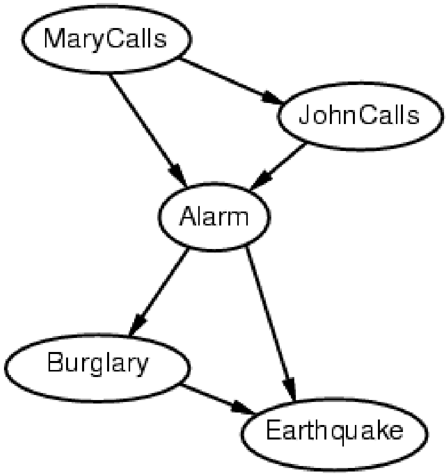
$\mathbf{P}(B \mid A, J, M) = P(B \mid A) = \mathbf{P}(B)$? **No**

$P(E \mid A, B, J, M) = P(E \mid A, B)$? **Yes** *(E does not depend on M, J)*

$\mathbf{P}(E \mid A, B, J, M) = P(E \mid A, B) = \mathbf{P}(E \mid B)$? **No** *(E depends on A)*

$P(E \mid A, B, J, M) = P(E \mid A, B) = P(E \mid A)$? **No** *(E depends on B)*

Example contd.



- Deciding conditional independence is hard in noncausal directions
-
- (Causal models and conditional independence seem hardwired for humans!)
-
- Network is less compact: 1 + 2 + 4 + 2 + 4 = 13 numbers needed
-

- Suppose we choose the ordering B, E, A, J, M
  to construct a Bayesian Network

  From Bayesian Network
  to check dependence of variables

- Work in class

  $\mathbf{P}(B \mid E) = \mathbf{P}(B)$? *yes or no (why?)*

  $\mathbf{P}(A \mid B, E) = \mathbf{P}(A \mid B)$? *yes or no (why?)*

  $\mathbf{P}(A \mid B, E) = \mathbf{P}(A \mid E)$? *yes or no (why?)*

  $\mathbf{P}(J \mid A, B, E) = \mathbf{P}(J \mid A)$? *yes or no (why?)*

  $\mathbf{P}(J \mid A, B, E) = \mathbf{P}(J)$? *yes or no (why?)*

  $\mathbf{P}(M \mid J, A, B, E) = \mathbf{P}(M \mid A)$? *Yes or no (why?)*

- Suppose we choose the ordering B, E, A, J, M to construct a Bayesian Network

- Work in class

  P(*B* | *E* = ***P***(*B*)? Yes

  P(*A* | *B*, *E*) = ***P***(*A* | *B*)? No

  P(*A* | *B*, *E*) = ***P***(*A* | *E*)? No

  P(*J* | *A*, *B*, *E*) = ***P***(*J* | *A*)? Yes

  P(*J* | *A*, *B*, *E*) =*P*(*J* | *A*) = ***P***(*J*)? No

  P(*M* | *J*, *A* ,*B*, *E*) = ***P***(*M* | *A*)? Yes

A Video Lecture:

http://www.youtube.com/watch?v=TPp33LJWncI

Given by Stefan Conrady

This 30-minute webinar will provide a brief overview of the basic concepts behind Bayesian networks. You will see how a few simple and intuitive ideas can form a marvelous framework for inference and reasoning.

In particular, pay attention to examples in the lecture.

Using Bayes net editor in Weka

New name for node

Node1

hair-c

OK 取消

Node1 → rename (hair-c)
Node2 → rename (eye-c)

Node hair-c

New name for value Value1

black

OK 取消

Node1 → rename value
value1 → black
value 2

Probability Distribution Table For eye-color

hair-color	Brown	Blue	Hazel	Green
black	0.61	0.2	0.16	0.03
brown	0.37	0.31	0.19	0.13
red	0.37	0.22	0.2	0.21
blond	0.05	0.75	0.11	0.09

Randomize Ok Cancel

Probability Distribution Table For eye-c

hair-c	Value1	Value2	Value3	Value4
black	0.656	0.177	0.003	0.163
Value2	0.453	0.132	0.054	0.361
Value3	0.472	0.093	0.161	0.274
Value4	0.42	0.217	0.112	0.251

Randomize Ok Cancel

eye-c → edit CPT

Change random data
to an example

An example CPT

Probability Distribution Table For eye-color

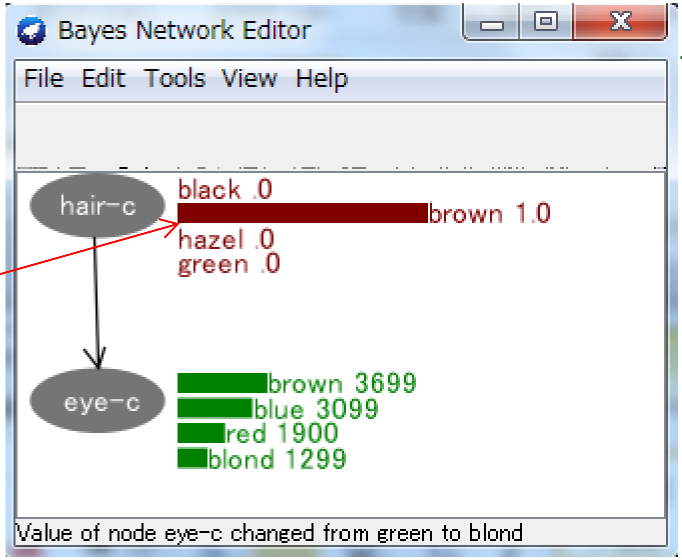
hair-color	Brown	Blue	Hazel	Green
black	0.61	0.2	0.16	0.03
brown	0.37	0.31	0.19	0.13
red	0.37	0.22	0.2	0.21
blond	0.05	0.75	0.11	0.09

Randomize Ok Cancel

Tools → show margins

Hair-c node → set evidence (brown)

an example



Try more (Work in class)

Add node -- node 3

rename node 3 → skin-c

rename value 1 → black

value 2 → white

value 3 → yellow

value 4 → brown

add parent hair-c

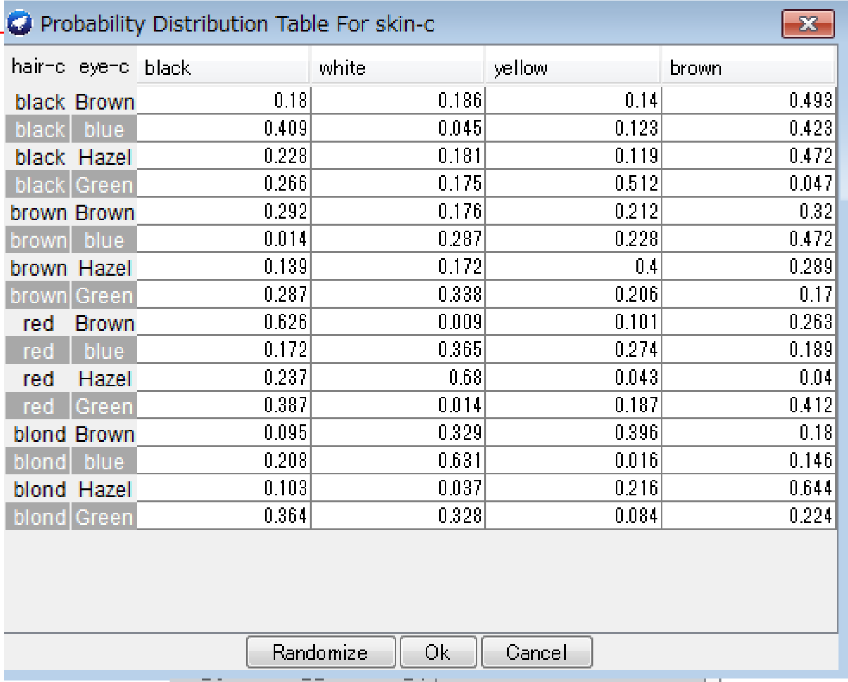
add parent eye-c

edit CPT

(you can edit the table)

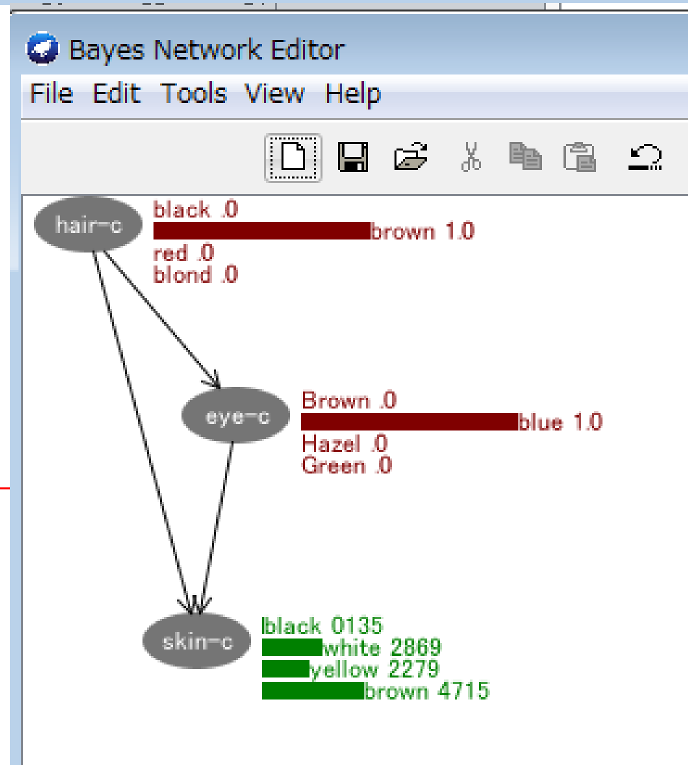
to a particular example

or randomize the table.



Probability Distribution Table For skin-c

hair-c	eye-c	black	white	yellow	brown
black	Brown	0.18	0.186	0.14	0.493
black	blue	0.409	0.045	0.123	0.423
black	Hazel	0.228	0.181	0.119	0.472
black	Green	0.266	0.175	0.512	0.047
brown	Brown	0.292	0.176	0.212	0.32
brown	blue	0.014	0.287	0.228	0.472
brown	Hazel	0.139	0.172	0.4	0.289
brown	Green	0.287	0.338	0.206	0.17
red	Brown	0.626	0.009	0.101	0.263
red	blue	0.172	0.365	0.274	0.189
red	Hazel	0.237	0.68	0.043	0.04
red	Green	0.387	0.014	0.187	0.412
blond	Brown	0.095	0.329	0.396	0.18
blond	blue	0.208	0.631	0.016	0.146
blond	Hazel	0.103	0.037	0.216	0.644
blond	Green	0.364	0.328	0.084	0.224



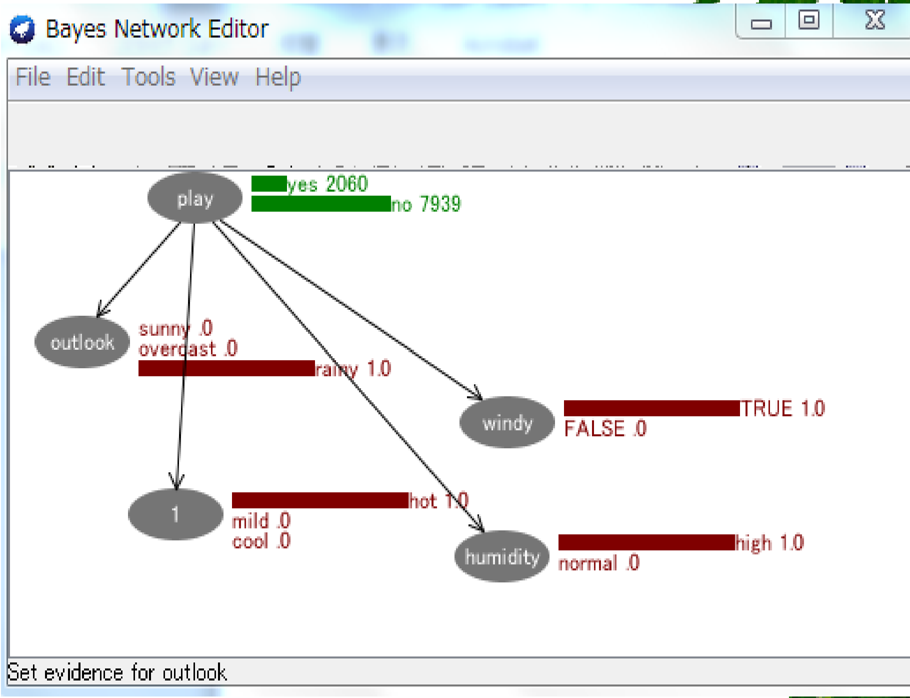
Work in Class:

Use training dataset to get Bayes Net and then to make Bayesian Inference

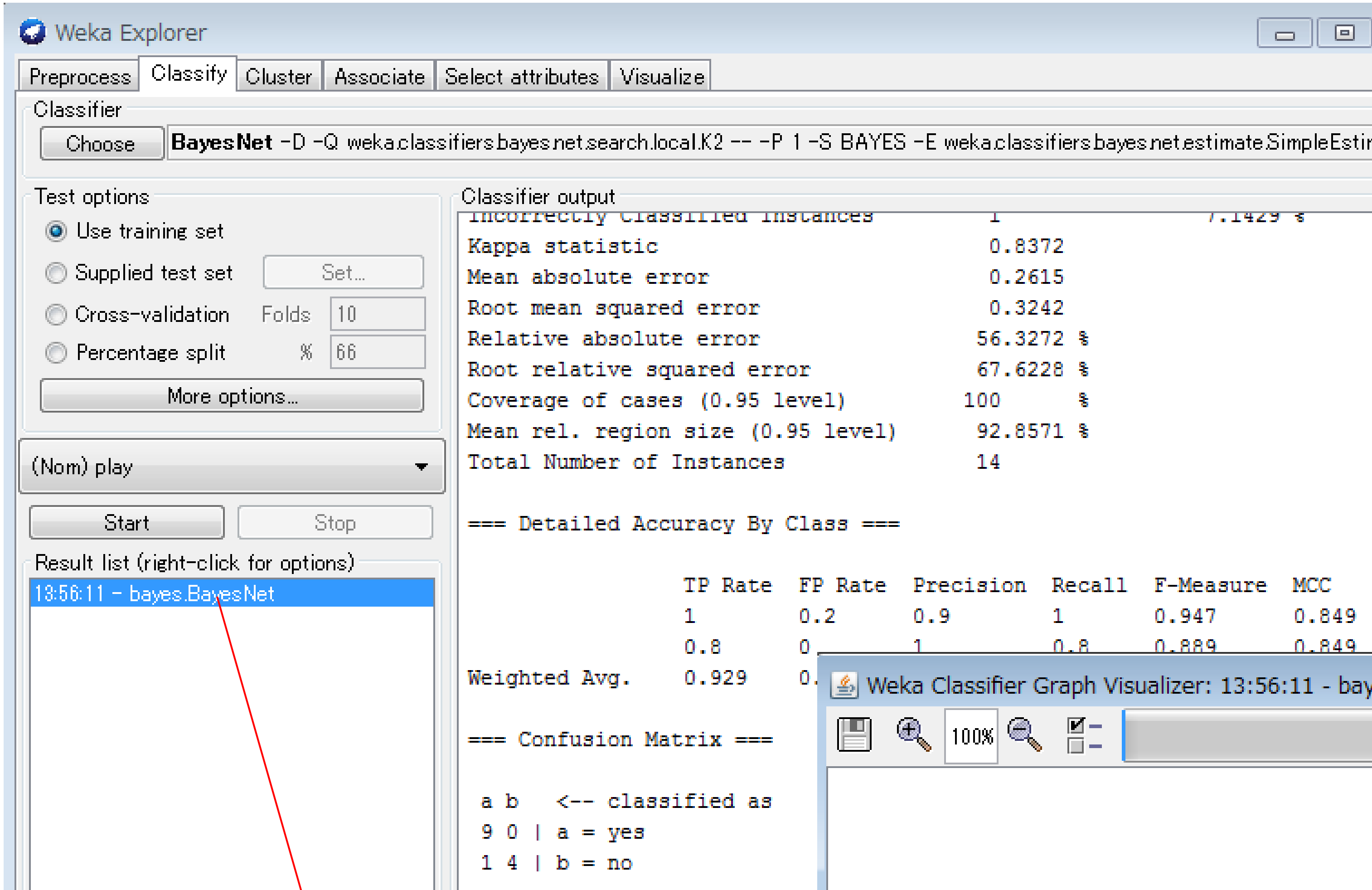
Explore → Open (weather.nominal.arff) → classify → choose (BayesNet) → Use training set → Start

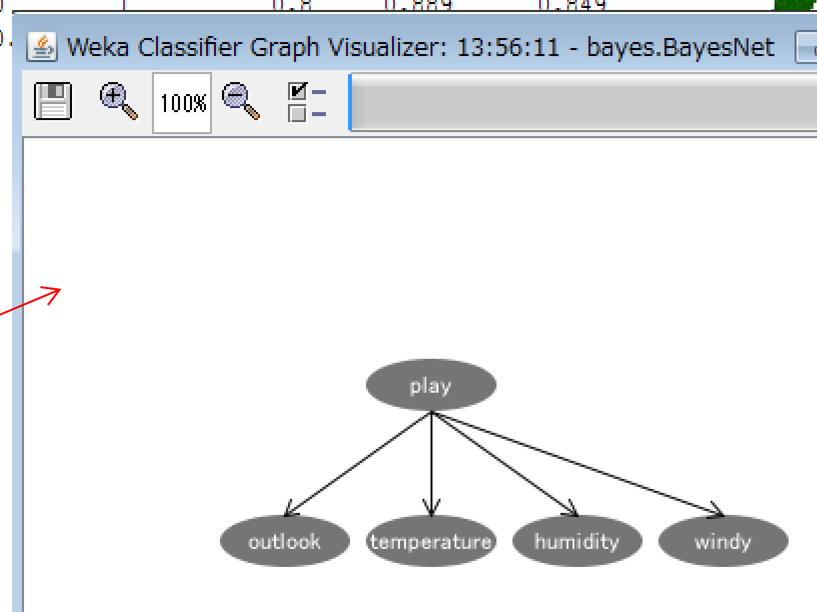
Bayes Net→ Visualize graph → Save Graph (as XML BIF file)

Bayes Net editor → load (.xml)



Tools → Show Margins
Set evidences
(windy is true
humidity is high
temperature is hot
outlook is raining) →





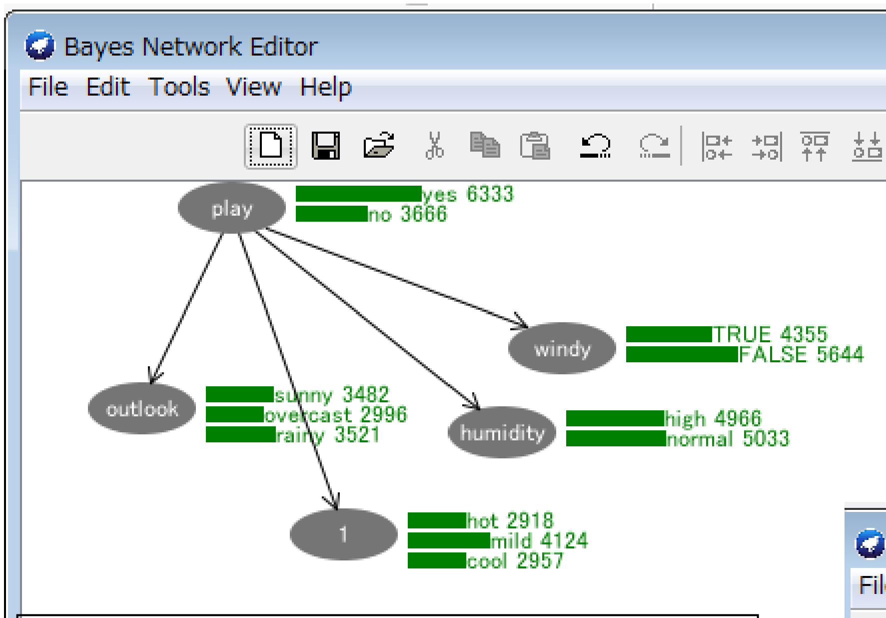
Visualize bayes BayesNet

→ visualize Graph

In Visualize graph → Save Graph (as XML BIF file)

Bayes Net editor → load (.xml)

Tools → Show Margins



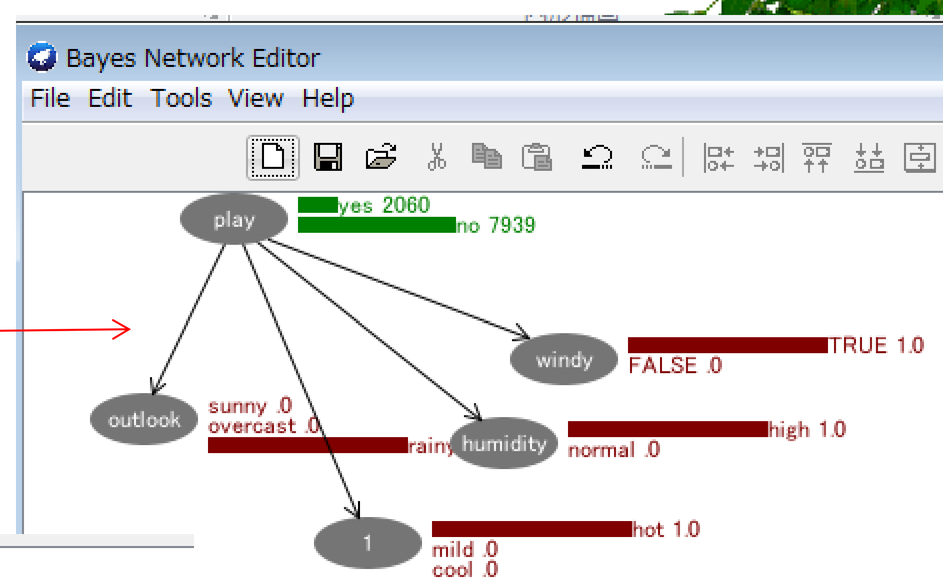
Set evidences

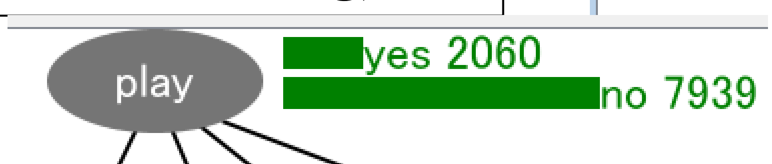
(windy is true

humidity is high

temperature is hot

outlook is raining)

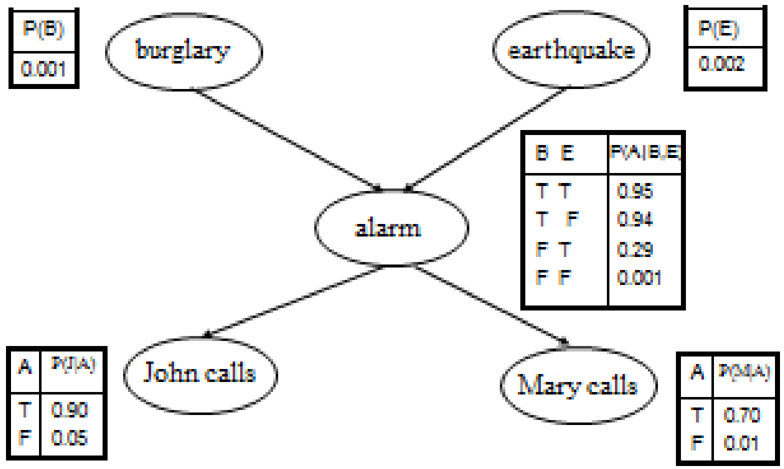




Home Work:

You may try to use Weka for the Bayes net below.

Example: One is at work, neighbors John and Mary call to say his alarm at home is ringing. Sometimes it's set off by minor earthquakes or in the case of burglar.



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