Data Mining and Machine Learning
Introduction

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September 15, 2021

Outline

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- Pass the test covering the material of the semester

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- You can miss a maximum of 3 lab sessions

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- Bayesian networks

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- Any other environment of your choice

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- We will be using Jupyter most of the time, although you are welcomed to do scripting
- What is Jupyter? → "Project Jupyter exists to develop open-source software, open-standards, and services for interactive computing across dozens of programming languages."

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- EDA can be done with: Pandas, Numpy, Matplotlib, Seaborn, etc.
- An automated EDA tool: Sweetviz

Bayesian networks – I.

Bayes' theorem:

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

$$P(A \wedge B) = P(B \mid A) \cdot P(A)$$

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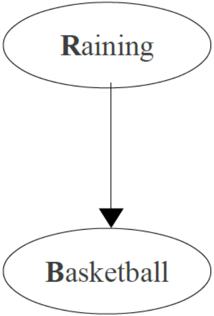
First set of exercises:

$$P(\boldsymbol{R} = T) = \quad ?$$

$$P(\boldsymbol{B} = T) = \quad ?$$

$$P(\boldsymbol{B} = T \wedge \boldsymbol{R} = T) = \quad ?$$



P(**R**=T)
0.1

r	P(**B**=T | **R**=r)
T	0.2
F	0.7

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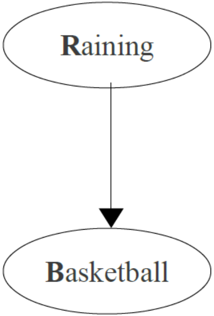
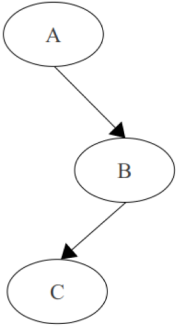


P(**R**=T)
0.1

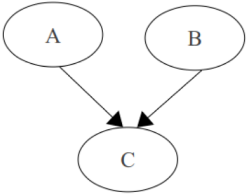
r	P(**B**=T | **R**=r)
T	0.2
F	0.7

Solutions: 0.1, 0.65, 0.02.

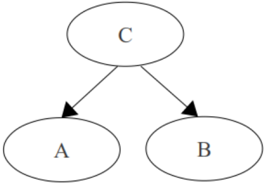
Bayesian networks – II.



1.
If event B is known:
A and C are independent.
$$P(C|A \wedge B) = P(C|B)$$
$$P(C \wedge A|B) = P(C|B) \cdot P(A|B)$$



2.
If event C is <u>not</u> known:
A and B are independent.
$$P(A \wedge B) = P(A) \cdot P(B)$$



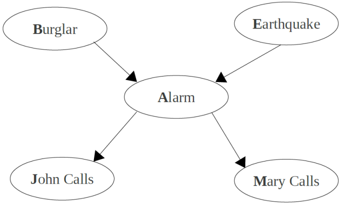
3.
If event C is known:
A and B are independent.
$$P(A|C \wedge B) = P(A|C)$$
$$P(A \wedge B|C) = P(A|C) \cdot P(B|C)$$

Second set of exercises:

$$P(J \wedge M \wedge A \wedge \neg B \wedge \neg E) = \quad ?\,, \quad P(B \mid J) = \quad ?\,, \quad P(J) = \quad ?$$

P(**B**=T)
0.001

P(**E**=T)
0.002



b	e	P(**A**=T | **B**=b ^ **E**=e)
T	T	0.950
T	F	0.940
F	T	0.290
F	F	0.001

a	P(**J**=T | **A**=a)
T	0.900
F	0.050

a	P(**M**=T | **A**=a)
T	0.700
F	0.010

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Bayesian networks – III.

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

$$\begin{aligned} P(J \wedge M \wedge A \wedge \neg B \wedge \neg E) &= P(J \wedge M \mid A \wedge \neg B \wedge \neg E) \cdot P(A \wedge \neg B \wedge \neg E) = \\ &= P(J \wedge M \mid A) \cdot P(A \mid \neg B \wedge \neg E) \cdot P(\neg B \wedge \neg E) = \end{aligned}$$

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&= P(J \mid A) \cdot P(M \mid A) \cdot P(A \mid \neg B \wedge \neg E) \cdot P(\neg B) \cdot P(\neg E) =
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&= P(J \mid A) \cdot P(M \mid A) \cdot P(A \mid \neg B \wedge \neg E) \cdot P(\neg B) \cdot P(\neg E) = \\
&= 0.9
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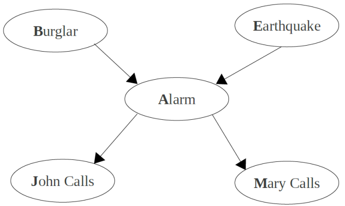

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Solutions: 0.00063, 0.00085, 0.016.