

# Uncertainty modelled using Probability, applications of Bayes formula for conditional prob.

Plus: Solutions to exercises from last time  
Written assignments (!)

Henning Christiansen

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# Program of today

- Presentation of solutions to exercises 3 and 5 from last time
- Probability: Short intro and working in groups with exercises
- Written assignments, we need to get everyone started!

# Exercises from last time

Ex. 1. Robots walking in 2D space.

```
trip(To) --> trip(point(0,0),To).
```

```
trip(Here,Here) --> [].
```

```
trip(point(FromX,FromY),To) -->  
  step(vector(DeltaX,DeltaY)),  
  { NewFromX is FromX + DeltaX,  
    NewFromY is FromY + DeltaY },  
  trip(point(NewFromX,NewFromY),To).
```

```
step(vector(1,0)) --> [forward].
```

```
step(vector(-1,0)) --> [back].
```

```
step(vector(0,1)) --> [up].
```

```
step(vector(0,-1)) --> [down].
```

```
step(vector(0,0)) --> [think].
```

## Ex 5. Pronoun resolution using assumptions

`discourse --> ss.`

`ss --> [].`

`ss --> s, ss.`

`s --> np(_,Who), [shoots], np(_,Whom),  
{event(shooting,Who,Whom)}.`

`np(Gender,Who) --> pro(Gender,Who),`

`np(Gender,Who) --> name(Gender,Who),`

`name(masc,luckyLuke) --> [luckyLuke]. % ...`

`name(fem,calamityJane) --> [calamityJane]. % ...`

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- (there are other, more or less ad-hoc weighting mechanisms applied in expert systems, etc. ...)

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- Important: Probability function  $P(V=\dots)$  is a **mathematical definition**, which has nothing to do with “average of ...”
- However: Probabilities should reflect reality, e.g., be defined from statistics.... which is a different matter!

# Operations on events: $\cup$ and $\cap$

Corresponds to set operations on events

$$P(V=x_1 \cup V=x_2) = P(V=x_1) + P(V=x_2) \text{ if } x_1 \neq x_2$$

$$P(V=x_1 \cap V=x_2) = 0 \text{ if } x_1 \neq x_2, \dots \text{ not interesting}$$

More interesting when applied for different rand. var's

$$P(V=x \cap W=y)$$

requires joint distribution given (as math. def.).

We could (but do not) write as  $P(VW=(x,y))$ .

Important: No a priori relationship

$$P(V=x \cap W=y) = P(V=x) \text{ ??? } P(W=y)$$

# Conditional probabilities

Informally  $P(A|B)$  means probability of event  $A$  given that  $B$  has occurred (been observed)

Example:  $P(\text{red-haired} \mid \text{girl})$  which abbreviates  $P(V=\text{red-haired} \mid W=\text{girl})$

where possible values are  $W \in \{\text{boy}, \text{girl}\}$ ,  $V \in \{\dots\}$

## ***Definition:***

$$P(A|B) = P(A \cap B) / P(B)$$

Fits with intuition of Prob  $\approx$  Relative Frequency:

$$\begin{aligned} P(\text{rh} \mid \text{g}) &\approx \left( \#(\text{rh} \cap \text{g}) / \#(\text{b} \cup \text{g}) \right) / \left( \# \text{g} / \#(\text{b} \cup \text{g}) \right) \\ &= \#(\text{rh} \cap \text{g}) / \# \text{g} \end{aligned}$$

## Dependent and independent events

**Definition:** Random variables  $V$  and  $W$  are *indep't* if

$$P(V=x \cap W=y) = P(V=x) \times P(W=y) \text{ for all } x, y$$

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**Example:** What do the following mean intuitively?

$$P(\text{red-haired} \cap \text{girl}) = P(\text{red-haired}) \times P(\text{girl})$$

$$P(\text{red-haired} \mid \text{girl}) = P(\text{red-haired})$$



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$$P(\text{red-haired} \mid \text{girl}) = P(\text{red-haired})$$

**Definition:** Two random variables are *dependent* if they are not independent ;-)

## **Now you do the work**

Exercises in section 2.1 + 2.2 of the note  
"Examples and exercises for conditional  
probabilities and Bayesian reasoning"

If you have not done it already, start reading text  
of section 2.1

NB: Notice also new concept of "exhaustive set  
of events" and Bayes' formula (3.11), plus sum  
versions 3.12–13.

# Bayesian reasoning

Bayes' formula: Twisting conditional probabilities

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

Correction: Swap A  
and B here • and here •.

Splitting up  $p(B)$  in two cases, conditioned with A  
and  $\neg A$ :

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

***Example with A=woman, B=read-haired ....***

## An example ...

A red-haired person is seen running away from scene of crime...

Police has two suspects in custody, both red-haired, a man and a woman.

Who did it (probably):

$$P(\text{woman}|\text{red}) = \frac{P(\text{red}|\text{woman}) \times P(\text{woman})}{P(\text{red}|\text{woman}) \times P(\text{woman}) + P(\text{red}|\text{man}) \times P(\text{man})}$$

Well, if we know  $P(\text{man})$ ,  $P(\text{woman})$ , how many men typically are red-haired and do. for women...

***Some definitions and clarification: ...***



# Prior and posterior probabilities

Correction: Swap A and B here •.

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

Probabilities  $P(A)$  and  $P(\neg A)$  are called **prior** probabilities as they refer to probabilities that are given before any event has been observed

Probability  $P(A|B)$  and  $P(\neg A|B)$  are called **posterior** probabilities as they are calculated after event has been observed

***Back to the example ...***

Consider again:

$$P(\text{woman}|\text{red}) = \frac{P(\text{red}|\text{woman}) \times P(\text{woman})}{P(\text{red}|\text{woman}) \times P(\text{woman}) + P(\text{red}|\text{man}) \times P(\text{man})}$$

We may have  $P(\text{woman})=0.6$  and  $P(\text{man})=0.4$ .

But add now "80% of all criminal are men"...  
changes  $P(\text{woman})=0.2$  and  $P(\text{man})=0.8$ , so  
with new prior probabilities, new posteriori are  
calculated...

## **Now you do the work**

Exercises in section 3 of the note

"Examples and exercises for conditional probabilities and Bayesian reasoning"

If you have not done it already, start reading text of section 3

1. Work with the red-haired woman/man example
2. More natural example about medical tests

## **On written assignments (see docu on course web)**

- Work in groups of 1-3 persons
- Make appointment with teacher about who and what
- Prepare
  - report of. say, 4-7 pages, latest 10 nov
  - short presentation for fellow student, 15 nov
- Report must be approved by teacher
  - let us discuss problems, progress and preliminary versions fo report, as...
  - there is no time for reject-rewrite-approve
- Warning: Level of ambition ...



## **Possible topics** (see note for details)

Should be related to course material

- may be extended exercise or "project" mentioned in earlier notes
- may be a topic you find interesting or have some background
- implementation+perspectives or overview

### Examples

- Abductive reasoning
- Language analysis
- Fuzzy logic/fuzzy expert systems
- Bayes reasoning/Bayes network and learning
- Neural nets, an application with specific system
- Evolutionary computing
- ....



