Neuroinformatics Lecture (L2)

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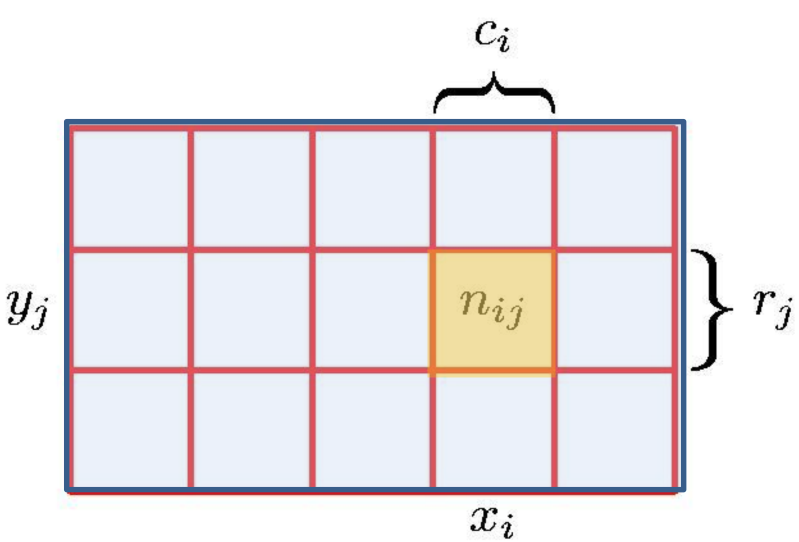
Rehearsal

R

Classes of events x and y i.e. :

Classes x: Color: Red or Blue
Classes y: Fruit: Apple or Orange



$$N = \sum_{i,j} n_{i,j} \qquad c_i = \sum_j n_{i,j}$$

Marginal Probability

(Probability of X=x irrespective of class y)

$$p(X = x_i) = \frac{c_i}{N}.$$

Conditional Probability

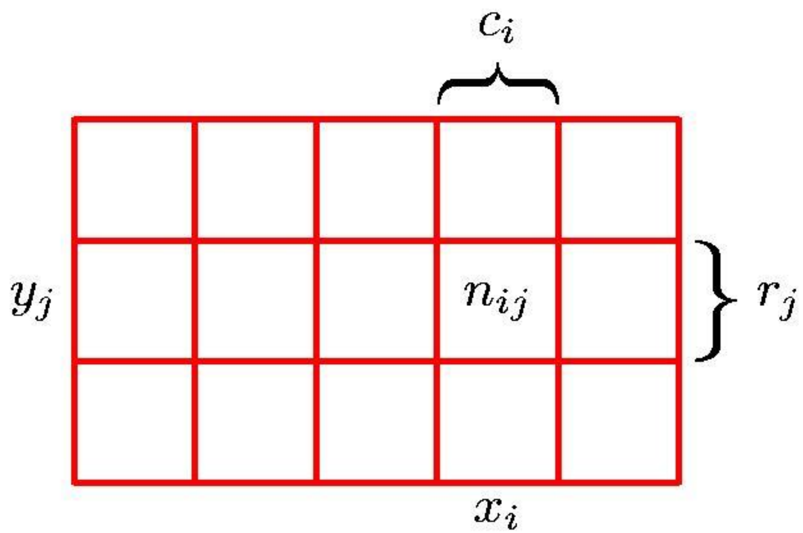
(Probability of Y=y given class X=x)

$$p(Y = y_j | X = x_i) = \frac{n_{ij}}{c_i}$$

Joint Probability

(Probability of X=x and Y=y)

$$p(X = x_i, Y = y_j) = \frac{n_{ij}}{N}$$



Sum Rule

marginal probability

$$\boxed{p(X = x_i) = \frac{c_i}{N}} = \frac{1}{N}\sum_{j=1}^{L} n_{ij}$$

$$= \sum_{j=1}^{L} p(X = x_i, Y = y_j)$$

joint probability

Product Rule

$$\boxed{p(X = x_i, Y = y_j)} = \frac{n_{ij}}{N} = \frac{n_{ij}}{c_i} \cdot \frac{c_i}{N}$$

$$= p(Y = y_j | X = x_i)\, p(X = x_i)$$

joint probability

conditional probability

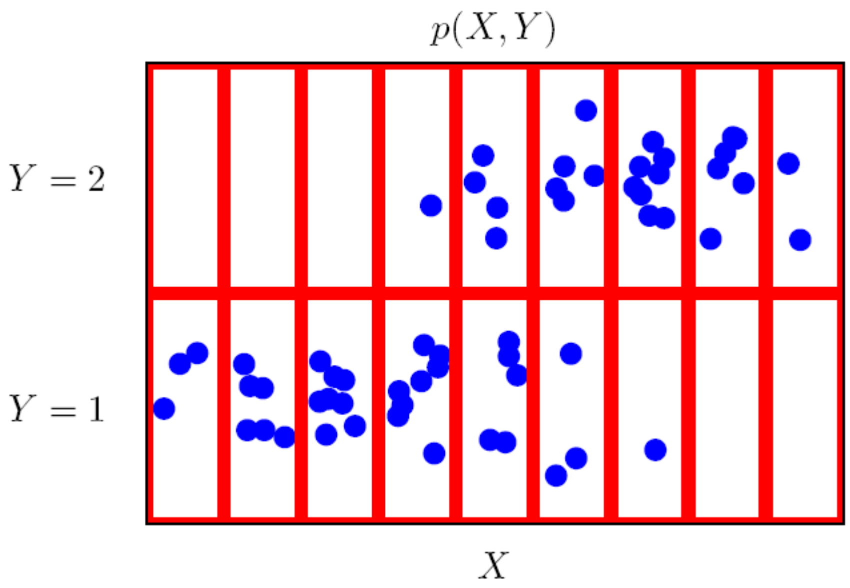
marginal probability

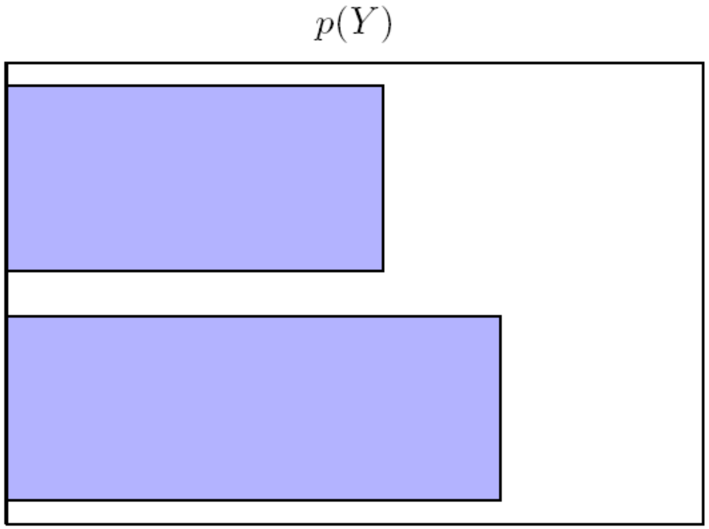
Sum Rule

$$p(X) = \sum_Y p(X,Y)$$

Product Rule

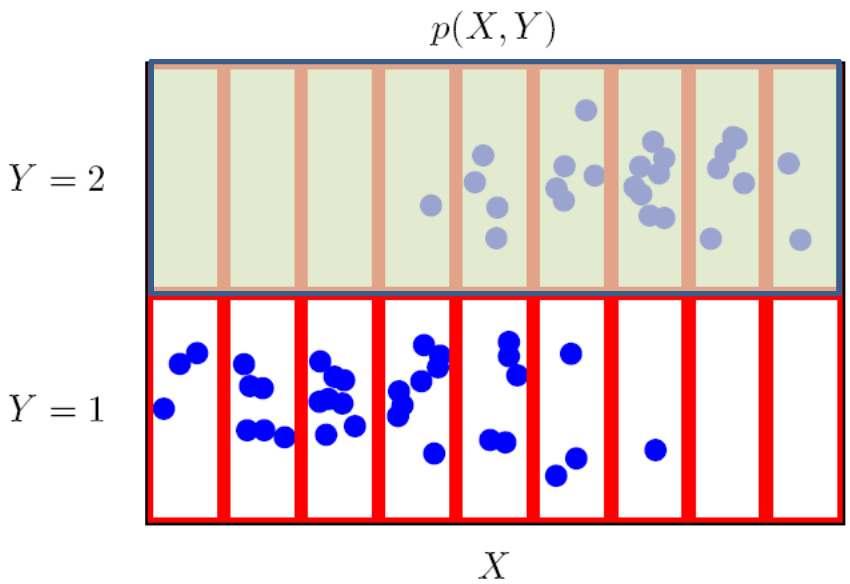
$$p(X,Y) = p(Y|X)p(X)$$

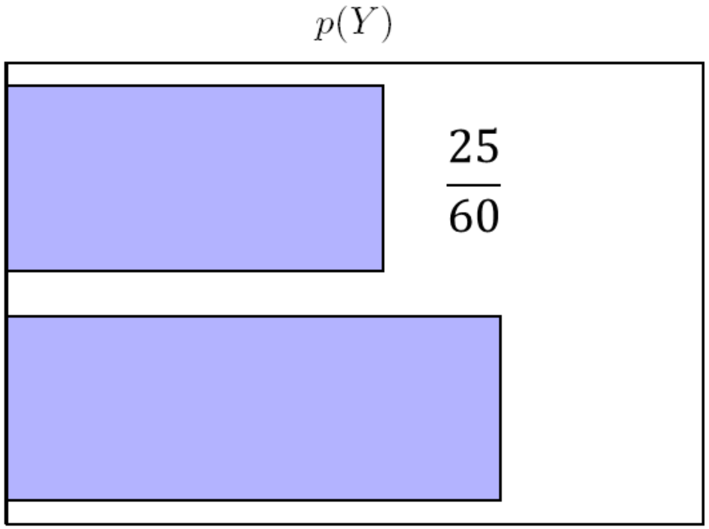




Given p(x,y) we can compute the marginal prob. p(x) and p(y) using the sum rule, e.g.

$$p(y) = \sum_x p(x,y)$$

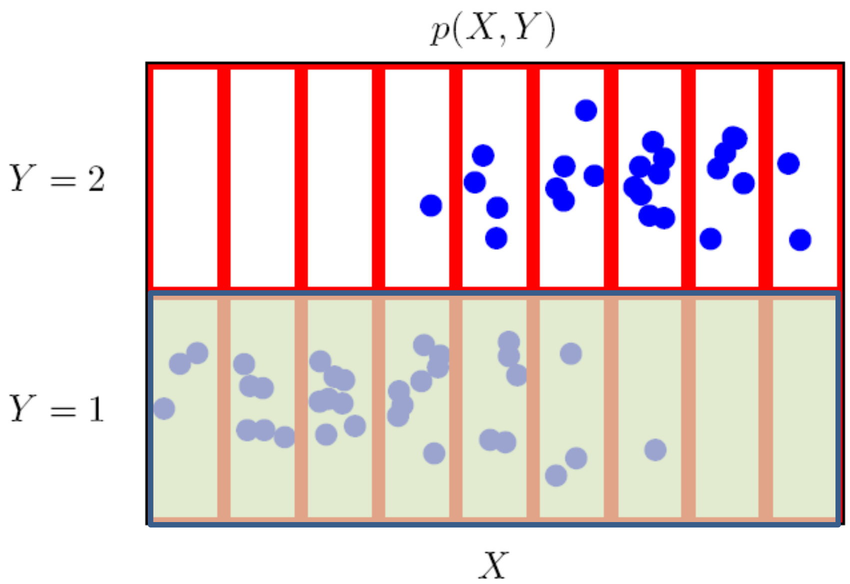


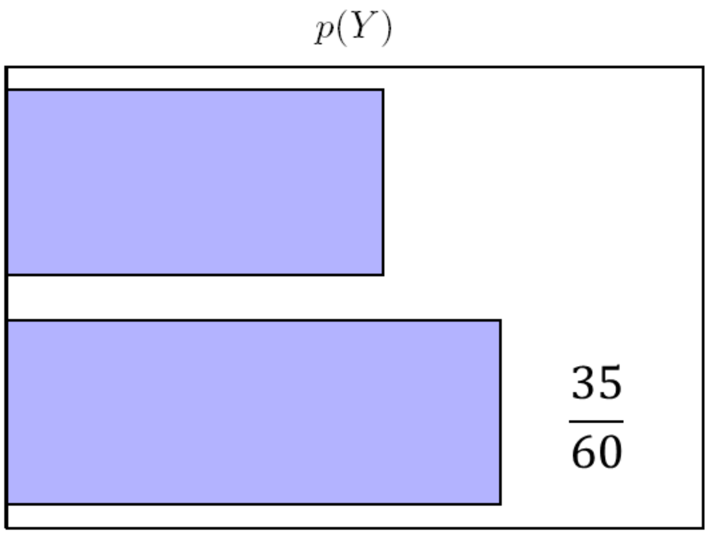


Given p(x,y) we can compute the marginal prob. p(x) and p(y) using the sum rule, e.g.

$$p(Y=2)=\frac{0}{60}+\frac{0}{60}+\frac{0}{60}+\frac{1}{60}+\frac{4}{60}+\frac{5}{60}+\frac{8}{60}+\frac{5}{60}+\frac{2}{60}$$

$$p(y)=\sum_x p(x,y)$$

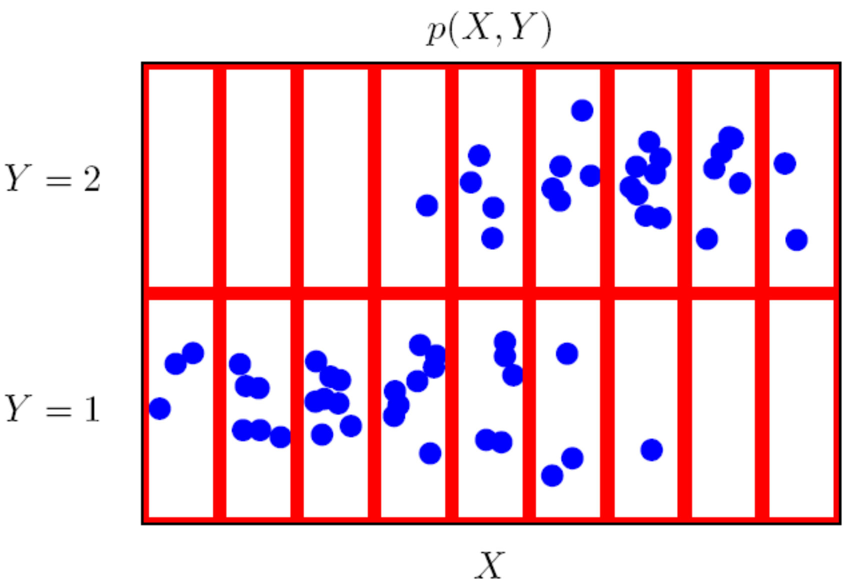


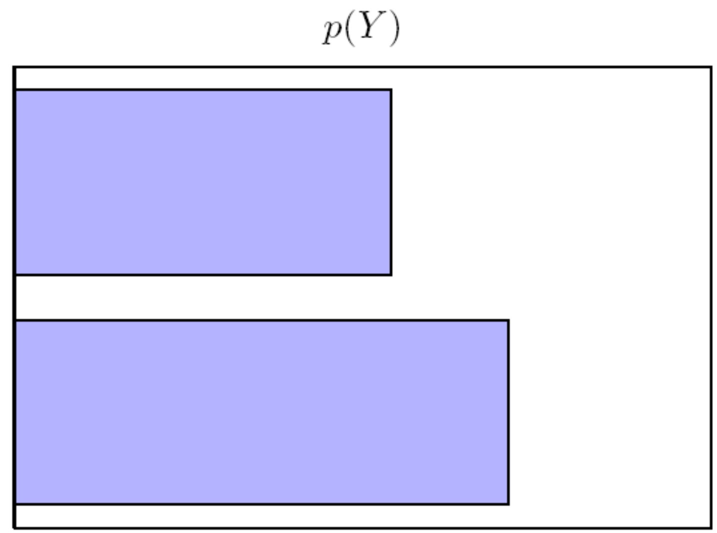


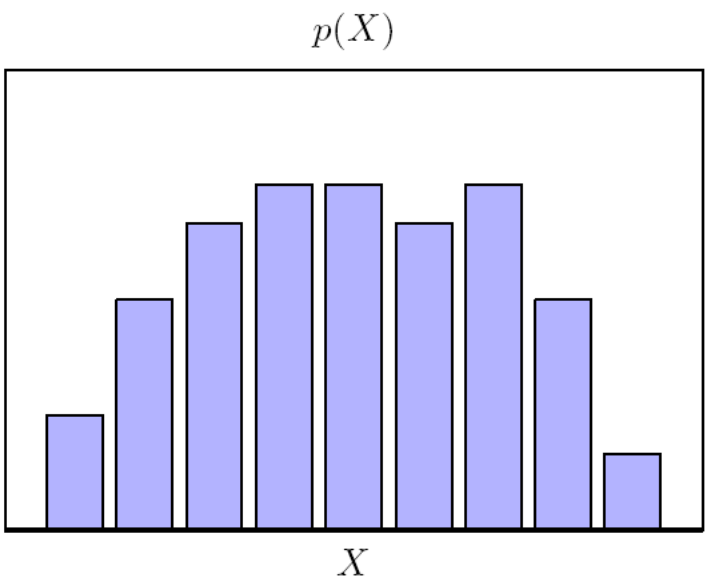
$$p(Y=1)=\frac{3}{60}+\frac{6}{60}+\frac{8}{60}+\frac{9}{60}+\frac{5}{60}+\frac{3}{60}+\frac{1}{60}+\frac{0}{60}+\frac{0}{60}$$

Given p(x,y) we can compute the marginal prob. p(x) and p(y) using the sum rule, e.g.

$$p(y)=\sum_x p(x,y)$$

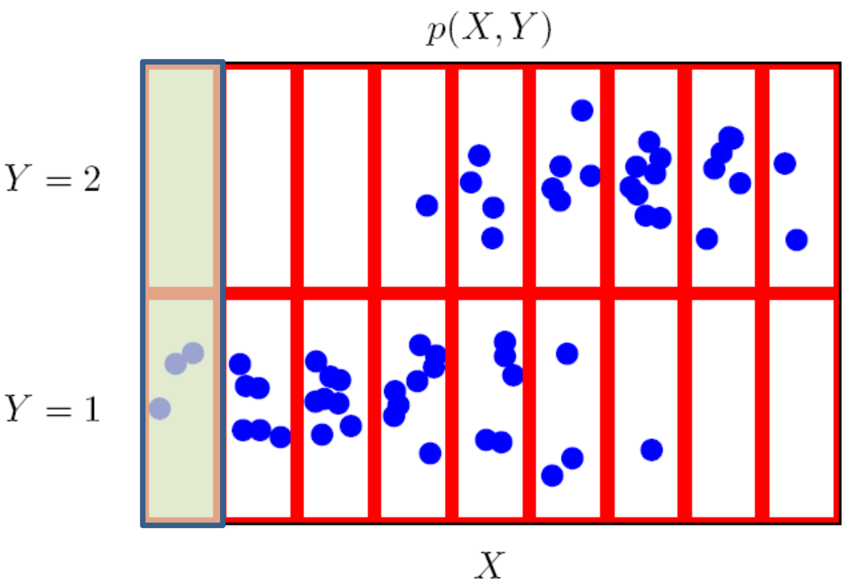


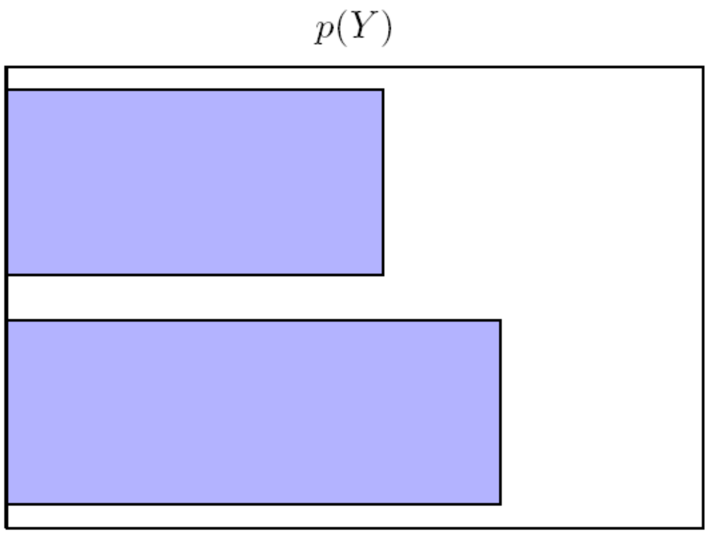


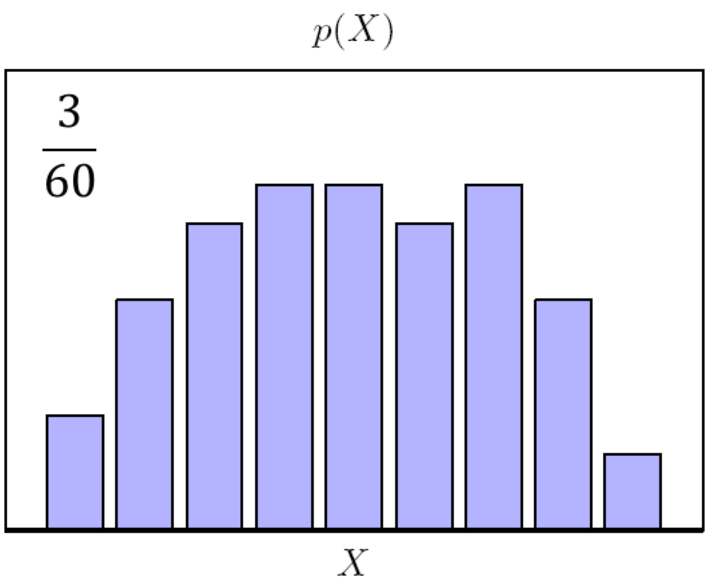


Given p(x,y) we can compute the marginal prob. p(x) and p(y) using the sum rule, e.g.

$$p(X) = \sum_{Y} p(X,Y)$$







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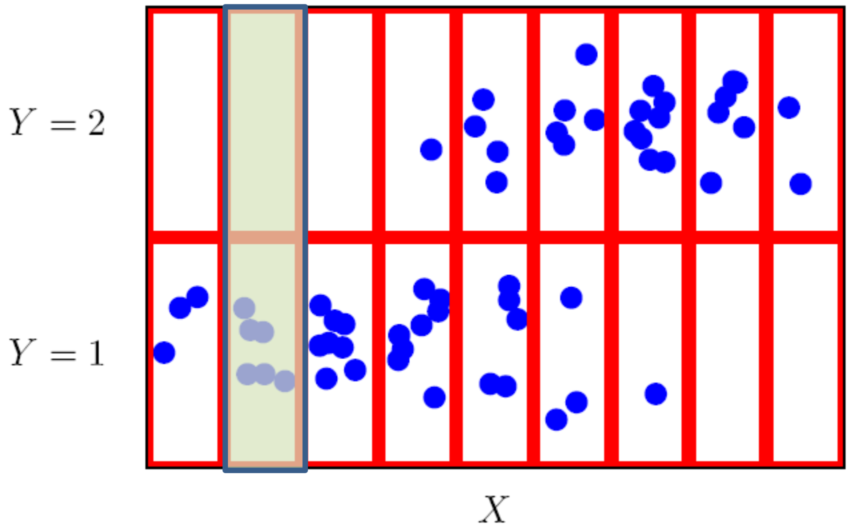
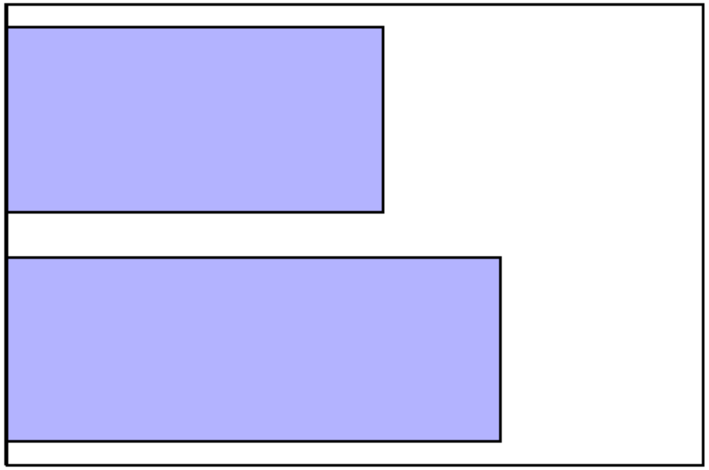
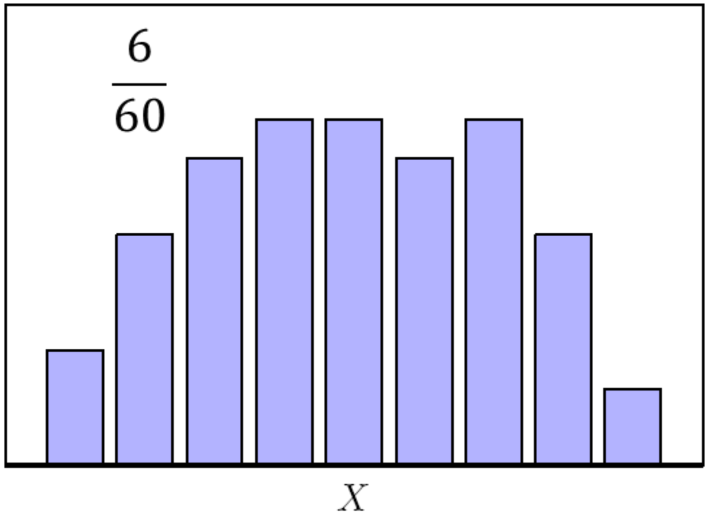
$p(X,Y)$



$p(Y)$



$p(X)$



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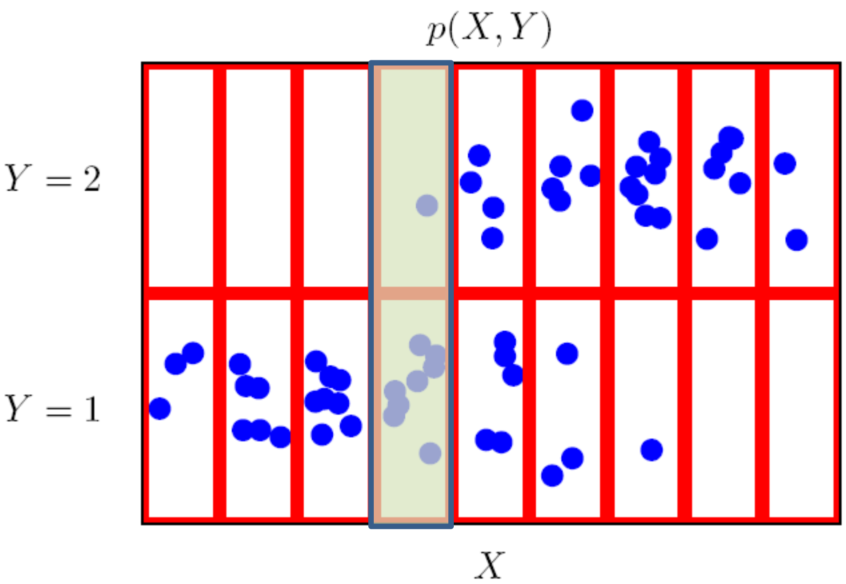

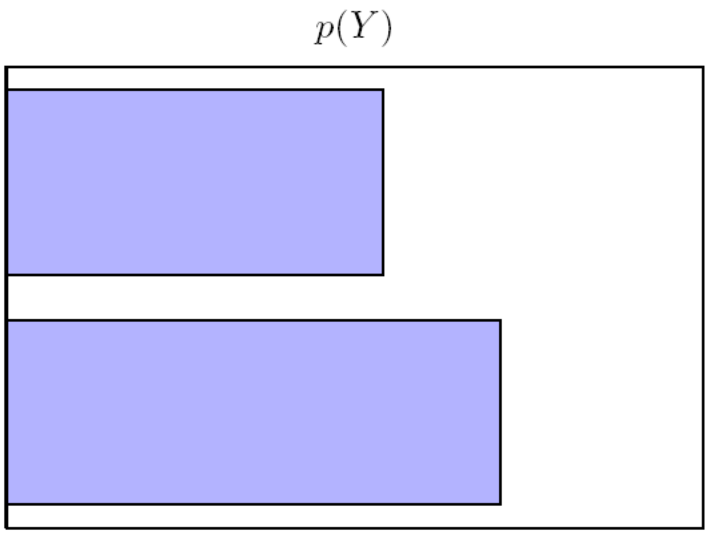

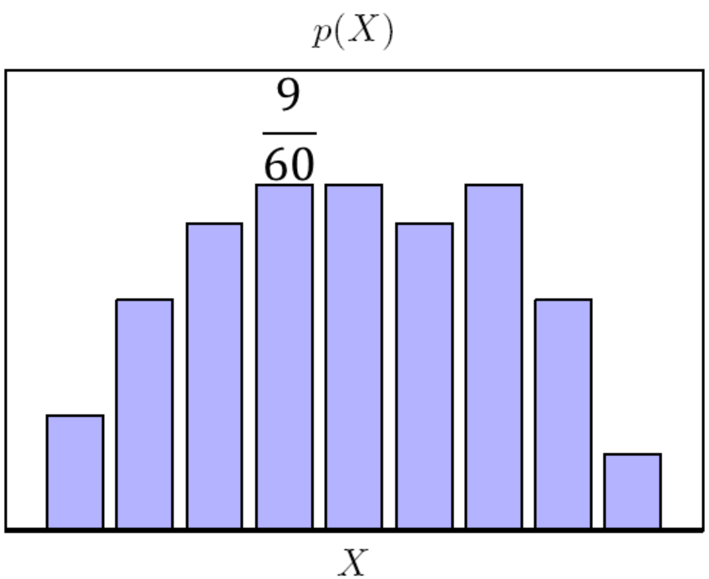

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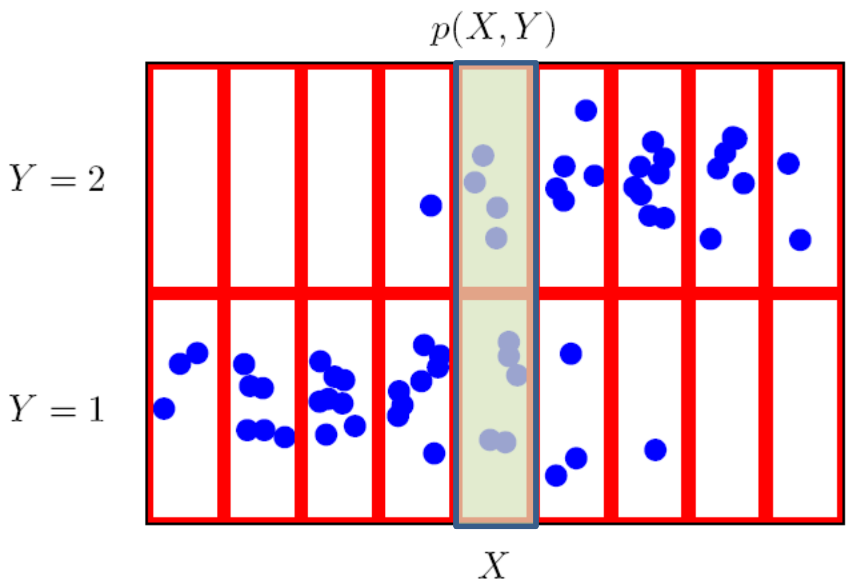

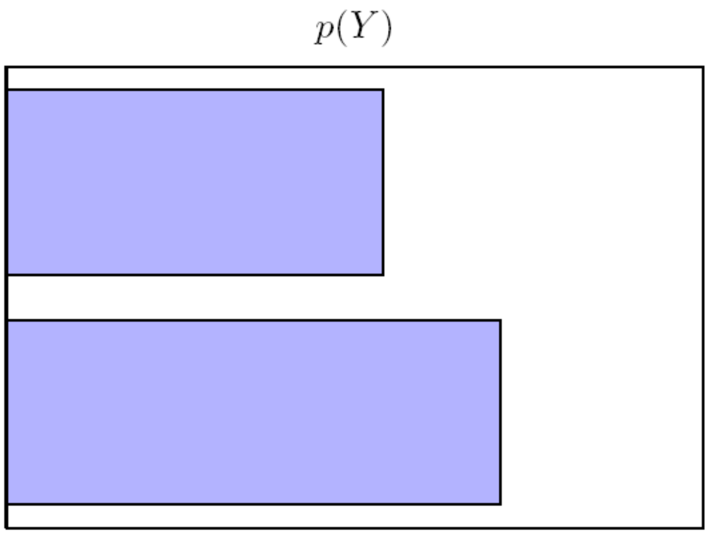

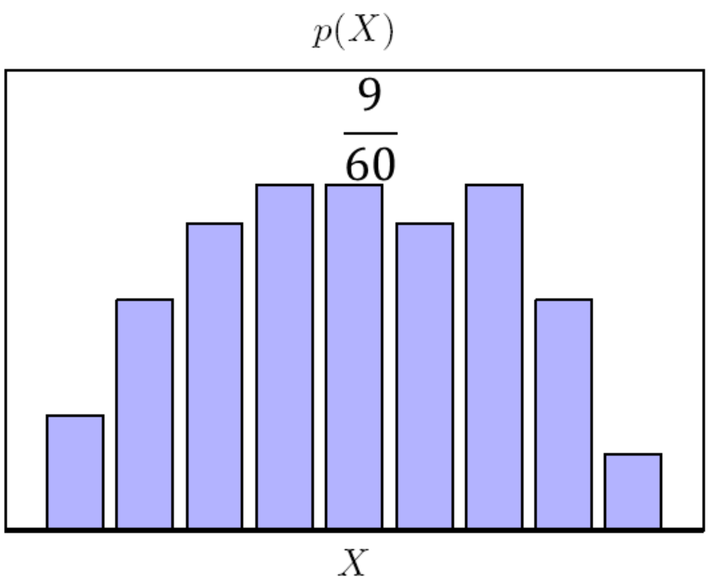

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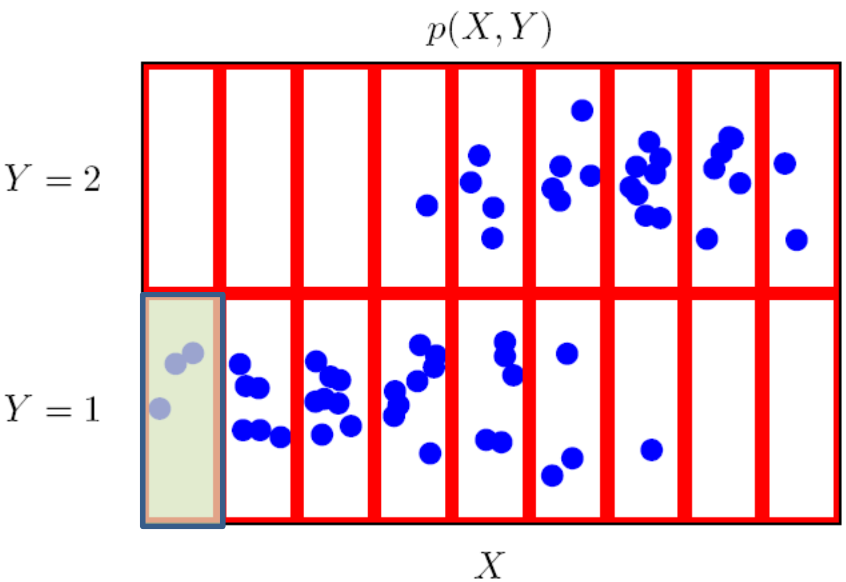
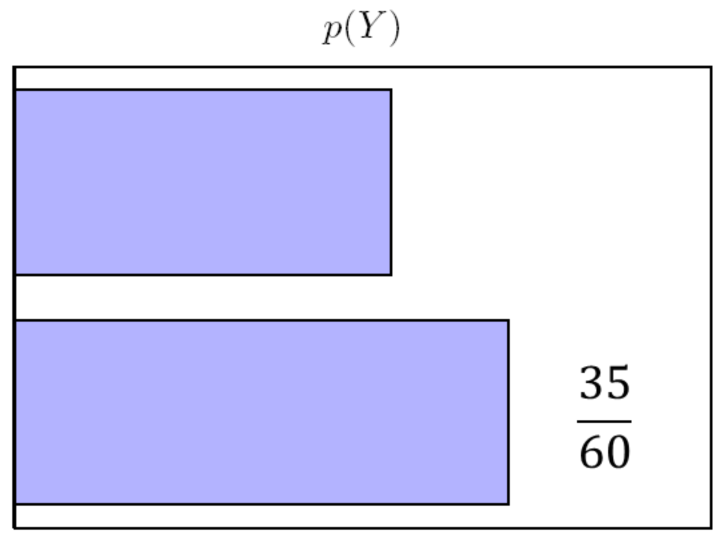
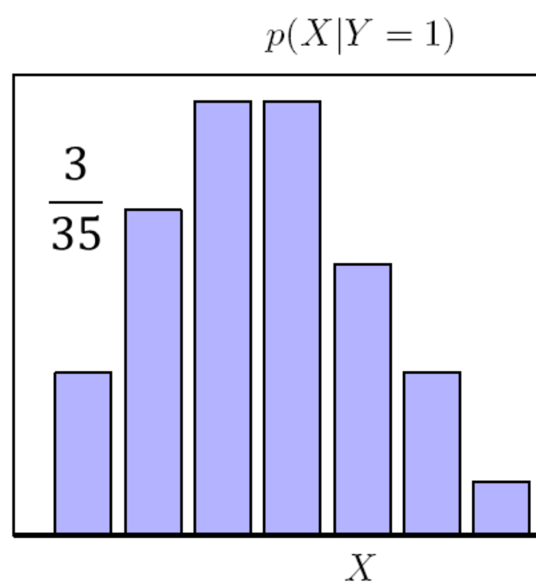






$$\frac{3}{60} : \frac{35}{60} =$$

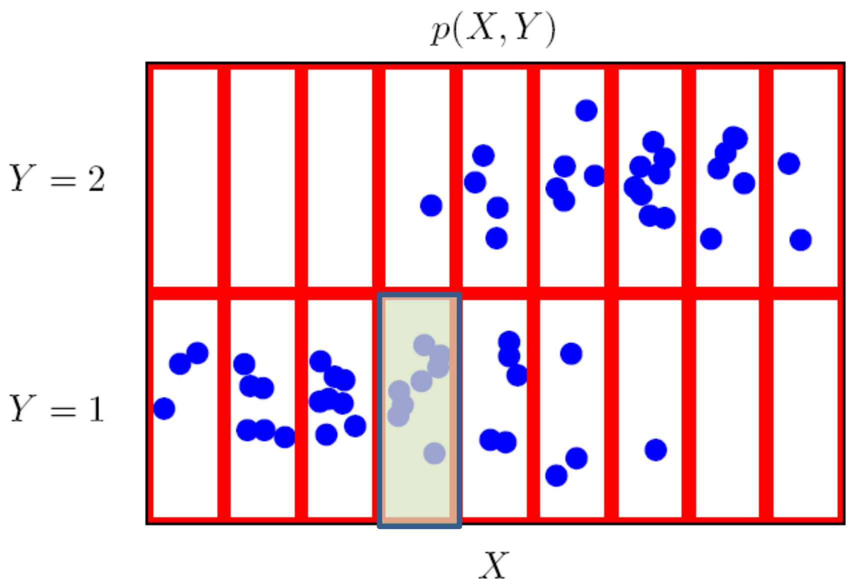
$$\frac{3}{60}\frac{60}{35} =$$

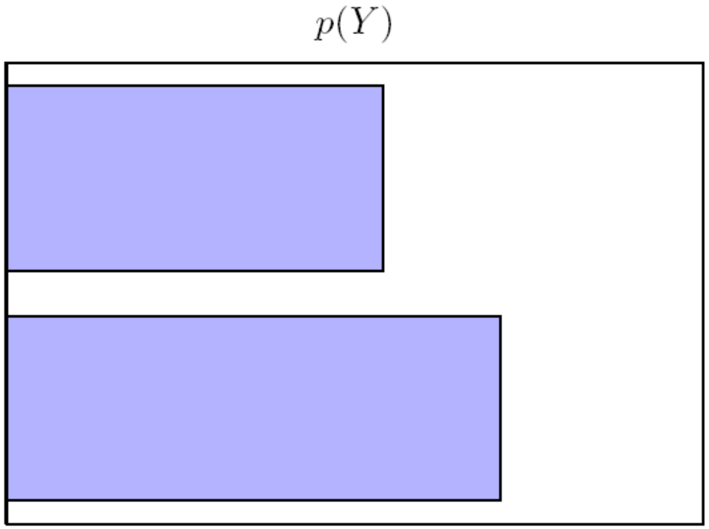
$$\frac{3}{35}$$

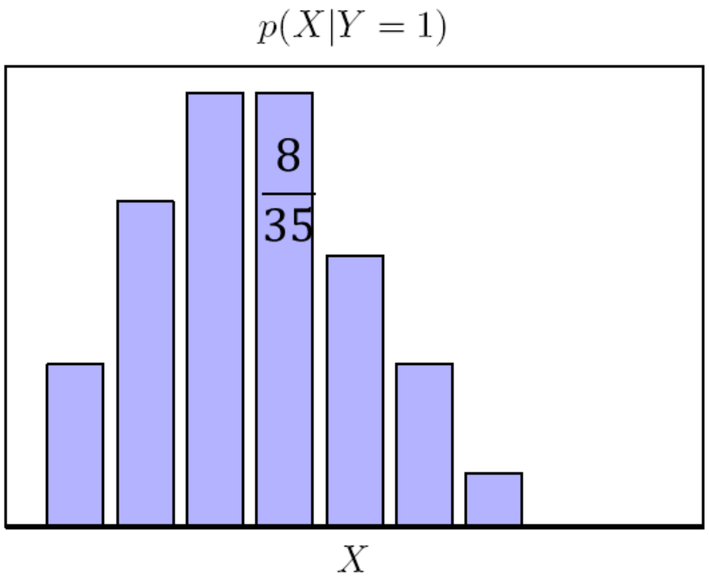
Given p(x,y) and p(x) we can compute p(x|y) using the product rule

$$p(x, y) = p(x|y)p(y)$$

$$p(x, y)/p(y) = p(x|y)$$







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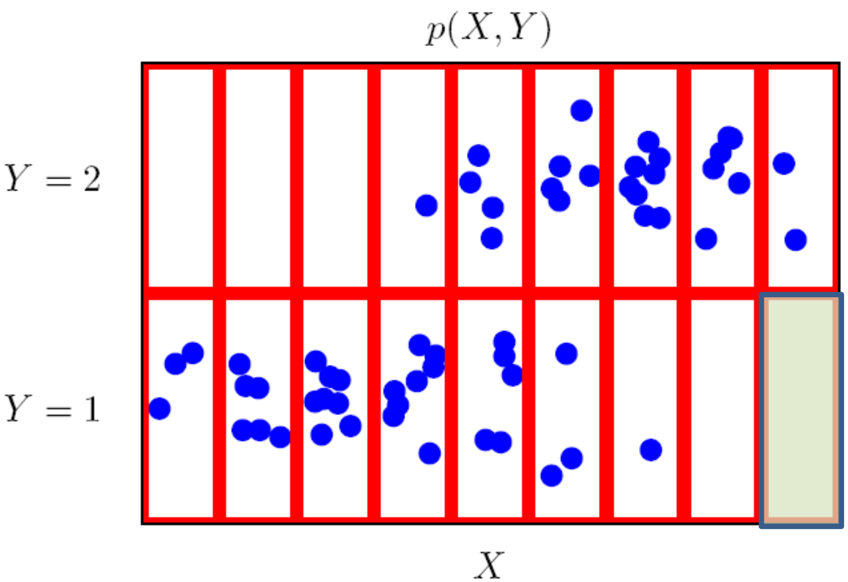
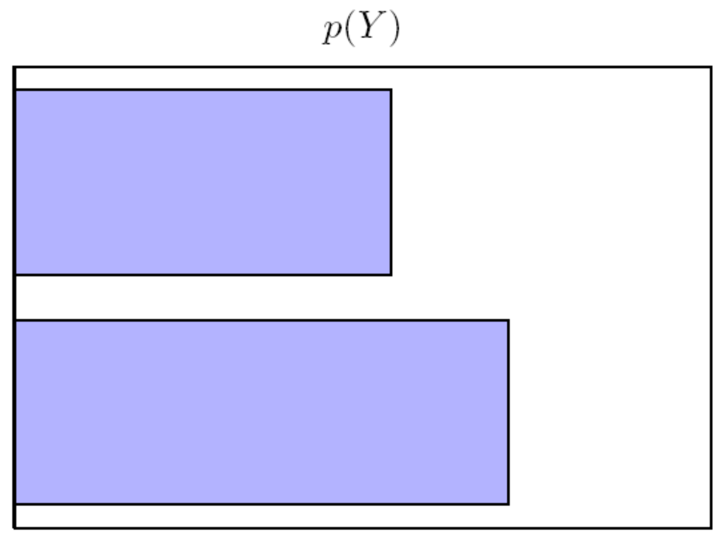
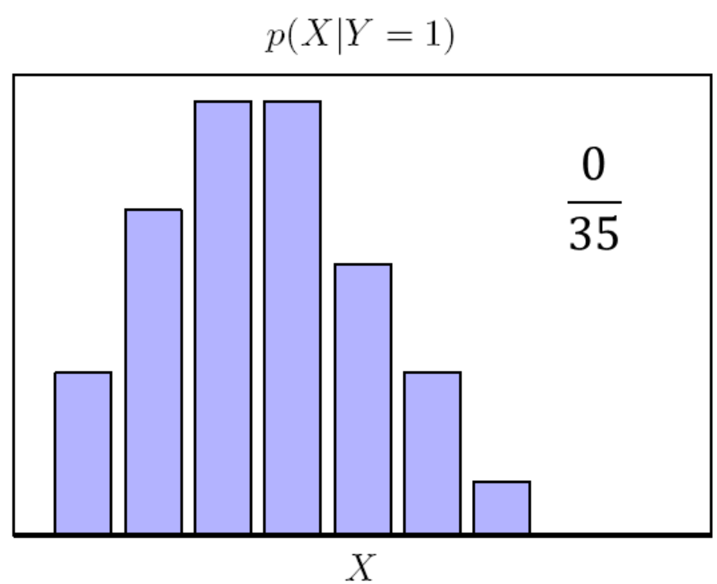






Given p(x,y) and p(x) we can compute p(x|y) using the product rule

$$p(x,y) = p(x|y)p(y)$$
$$p(x,y)/p(y) = p(x|y)$$

Thomas Bayes (1701–1761)

Thomas Bayes was born in Tunbridge Wells and was a clergyman as well as an amateur scientist and a mathematician. He studied logic and theology at Edinburgh University and was elected Fellow of the Royal Society in 1742. During the 18th century, issues regarding probability arose in connection with gambling and with the new concept of insurance. One particularly important problem concerned so-called inverse probability. A solution was proposed by Thomas Bayes in his paper ‘Essay towards solving a problem in the doctrine of chances’, which was published in 1764, some three years after his death, in the Philosophical Transactions of the Royal Society. In fact, Bayes only formulated his theory for the case of a uniform prior, and it was Pierre-Simon Laplace who independently rediscovered the theory in general form and who demonstrated its broad applicability.

Derive Bayes' Rule

Sum Rule $$p(X) = \sum_Y p(X,Y)$$

Product Rule $$p(X,Y) = p(Y|X)p(X)$$

$$p(X,Y) = p(Y|X)p(X) \text{ with } p(X,Y) = p(Y,X)$$

$$p(X,Y) = p(Y|X)p(X) = p(X|Y)p(Y)$$

$$p(Y|X) = \frac{p(X|Y)p(Y)}{p(X)}$$

$$\boxed{p(Y|X)} = \frac{\boxed{p(X|Y)}\boxed{p(Y)}}{p(X)}$$

$$p(X) = \sum_Y p(X|Y)p(Y)$$

posterior $\propto$ likelihood × prior

using $\quad p(X) = \sum_Y p(X,Y) \qquad p(X,Y) = p(Y|X)p(X)$

$$p(X) = \sum_Y p(X,Y) = \sum_Y p(X|Y)p(Y)$$

Q

Derive Bayes using the sum and product rule

$$p(X) = \sum_Y p(X, Y) \qquad p(X, Y) = p(Y|X)p(X)$$

Timer (5min): Start Stop

Derive Bayes' Rule

Sum Rule $$p(X) = \sum_Y p(X,Y)$$

Product Rule $$p(X,Y) = p(Y|X)p(X)$$

$$p(X,Y) = p(Y|X)p(X) \text{ with } p(X,Y) = p(Y,X)$$

$$p(X,Y) = p(Y|X)p(X) = p(X|Y)p(Y)$$

$$p(Y|X) = \frac{p(X|Y)p(Y)}{p(X)}$$

Suppose that we have three colored boxes ***r (red), b (blue),*** and ***g (green)***. Box r contains 3 apples, 4 oranges, and 3 limes, box b contains 1 apple, 1 orange, and 0 limes, and box g contains 3 apples, 3 oranges, and 4 limes. If a box is chosen at random with probabilities p(Y=r) = 0.2, p(Y=b) = 0.2, p(Y=g) = 0.6, and a piece of fruit is removed from the box (with equal probability of selecting any of the items in the box), then what is the probability of selecting an apple?

- We look for marginal prob. of X=apple
- We know marginal prob. of the box color p(Y)
- We can compute both the joint and conditional prob form the table.

	App.	Org.	Lim.
r	***3***	***4***	***3***
b	***1***	***1***	***0***
g	***3***	***3***	***4***

Suppose that we have three colored boxes ***r (red), b (blue),*** and ***g (green)***. Box r contains 3 apples, 4 oranges, and 3 limes, box b contains 1 apple, 1 orange, and 0 limes, and box g contains 3 apples, 3 oranges, and 4 limes. If a box is chosen at random with probabilities p(Y=r) = 0.2, p(Y=b) = 0.2, p(Y=g) = 0.6, and a piece of fruit is removed from the box (with equal probability of selecting any of the items in the box), then what is the probability of selecting an apple?

- We look for marginal prob. of X=apple
- We know marginal prob. of the box color p(Y)
- We can compute both the joint and conditional prob form the table.

$$p(X = apple) = \sum_{y} p(X = apple, Y)$$

$$p(X = apple) = \sum_{y} p(X = apple|Y)p(Y)$$

	App.	Org.	Lim.
r	***3***	***4***	***3***
b	***1***	***1***	***0***
g	***3***	***3***	***4***

Suppose that we have three colored boxes ***r (red), b (blue),*** and ***g (green)***. Box r contains 3 apples, 4 oranges, and 3 limes, box b contains 1 apple, 1 orange, and 0 limes, and box g contains 3 apples, 3 oranges, and 4 limes. If a box is chosen at random with probabilities p(Y=r) = 0.2, p(Y=b) = 0.2, p(Y=g) = 0.6, and a piece of fruit is removed from the box (with equal probability of selecting any of the items in the box), then what is the probability of selecting an apple?

$$p(X = apple) = \sum_y p(X = apple|Y)p(Y)$$

$$p(X = apple|Y = red) = 3/10$$

$$p(X = apple|Y = green) = 3/10$$

$$p(X = apple|Y = blue) = 1/2$$

	App.	Org.	Lim.
r	***3***	***4***	***3***
b	***1***	***1***	***0***
g	***3***	***3***	***4***

Suppose that we have three colored boxes ***r* (red), *b* (blue),** and ***g* (green)**. Box r contains 3 apples, 4 oranges, and 3 limes, box b contains 1 apple, 1 orange, and 0 limes, and box g contains 3 apples, 3 oranges, and 4 limes. If a box is chosen at random with probabilities p(Y=r) = 0.2, p(Y=b) = 0.2, p(Y=g) = 0.6, and a piece of fruit is removed from the box (with equal probability of selecting any of the items in the box), then what is the probability of selecting an apple?

$$p(X = apple) = \sum_y p(X = apple|Y)p(Y)$$

$$p(X = apple|Y = red) = 3/10$$
$$p(X = apple|Y = green) = 3/10$$
$$p(X = apple|Y = blue) = 1/2$$

$$\begin{aligned} p(X = apple) = {} & p(X = apple|Y = red)p(Y = red) + \\ & p(X = apple|Y = blue)p(Y = blue) + \\ & p(X = apple|Y = green)p(Y = green) \end{aligned}$$

$$\begin{aligned} &= \frac{3}{10} * 0.2 + \frac{3}{10} * 0.6 + \frac{1}{2} * 0.2 \\ &= \frac{6}{100} + \frac{18}{100} + \frac{10}{100} = \frac{34}{100} \end{aligned}$$

Questionnaire

Suppose that we have three colored boxes r (red), b (blue), and g (green).

Box r contains 3 apples, 4 oranges, and 3 limes,
box b contains 1 apple, 1 orange, and 0 limes,
and box g contains 3 apples, 3 oranges, and 4 limes.

If a box is chosen at random with probabilities p(r) = 0.2, p(b) = 0.2, p(g) = 0.6, and a piece of fruit is removed from the box (with equal probability of selecting any of the items in the box), then **what is the probability of selecting an apple?**

You may want to use this:

$$p(X) = \sum_{Y} p(X, Y)$$

$$p(X, Y) = p(Y|X)p(X)$$

Q

Start

Timer

Stop

Suppose that we have three colored boxes ***r* (red), *b* (blue),** and ***g* (green)**. Box r contains 3 apples, 4 oranges, and 3 limes, box b contains 1 apple, 1 orange, and 0 limes, and box g contains 3 apples, 3 oranges, and 4 limes. If a box is chosen at random with probabilities p(Y=r) = 0.2, p(Y=b) = 0.2, p(Y=g) = 0.6, and a piece of fruit is removed from the box (with equal probability of selecting any of the items in the box), then what is the probability of selecting an apple?

$$p(X = apple) = \sum_y p(X = apple|Y)p(Y)$$

$$p(X = apple|Y = red) = 3/10$$
$$p(X = apple|Y = green) = 3/10$$
$$p(X = apple|Y = blue) = 1/2$$

$$\begin{aligned} p(X = apple) = {} & p(X = apple|Y = red)p(Y = red) + \\ & p(X = apple|Y = blue)p(Y = blue) + \\ & p(X = apple|Y = green)p(Y = green) \end{aligned}$$

$$= \frac{3}{10} * 0.2 + \frac{3}{10} * 0.6 + \frac{1}{2} * 0.2$$
$$= \frac{6}{100} + \frac{18}{100} + \frac{10}{100} = \frac{34}{100}$$

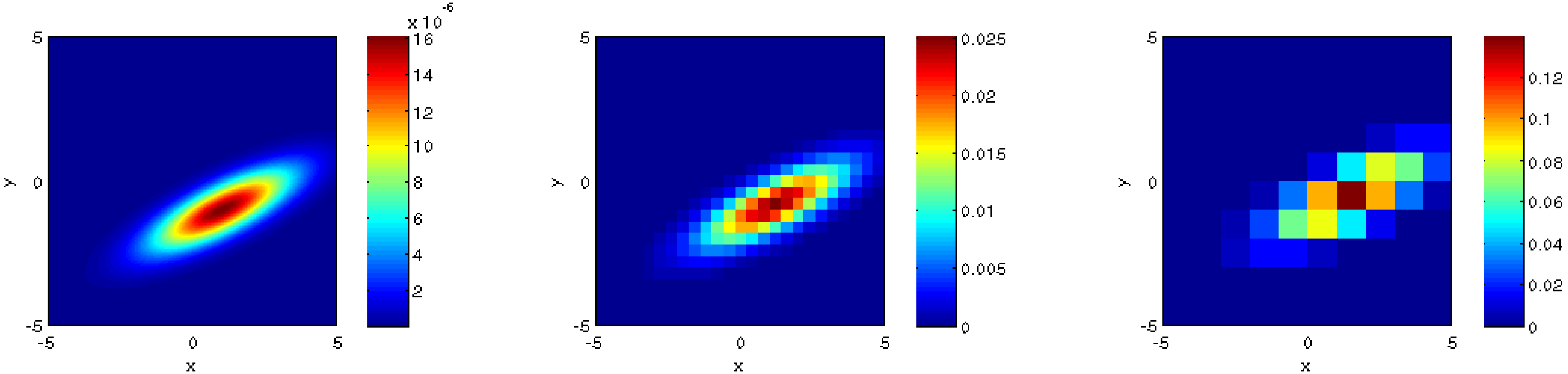
	App.	Org.	Lim.
r	***3***	***4***	***3***
b	***1***	***1***	***0***
g	***3***	***3***	***4***

Neuroinformatics Lecture

Topics:

Continuous and Discrete random variables

Probability Densities and Probability of Discrete Events



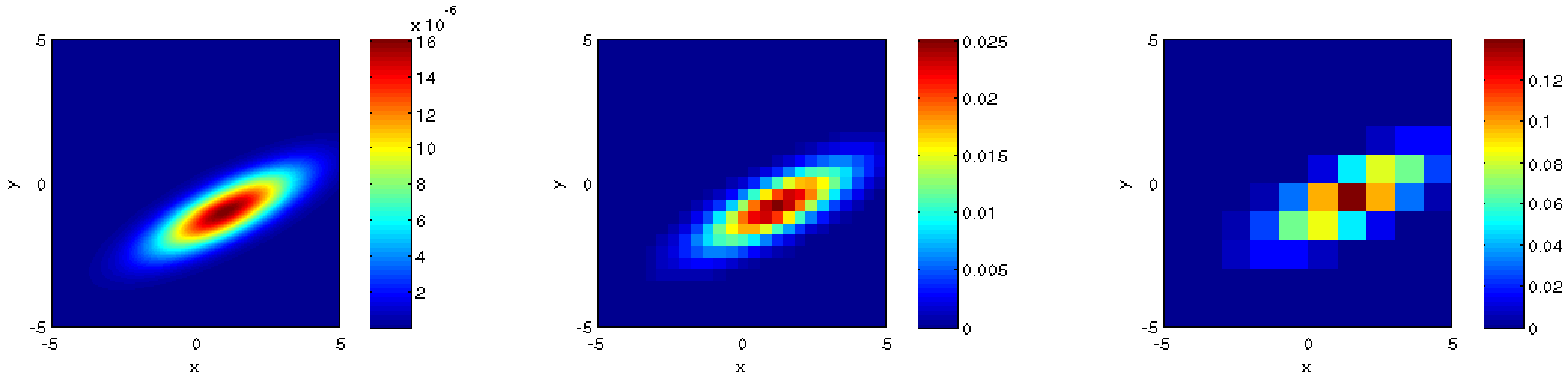
We introduced probabilities for discrete events.

Making the bins arbitrarily small leads to a probability density

PDF (probability density function) $p(x) \geqslant 0$ $\int_{-\infty}^{\infty} p(x)\,\mathrm{d}x = 1$

See example source code Prob_Density.m to reproduce the figures

Probability Densities and Probability of Discrete Events



This implies that, having a probability density, we need to define an interval to define a probability.

Probability

$$p(x \in (a,b)) = \int_a^b p(x)\,\mathrm{d}x$$

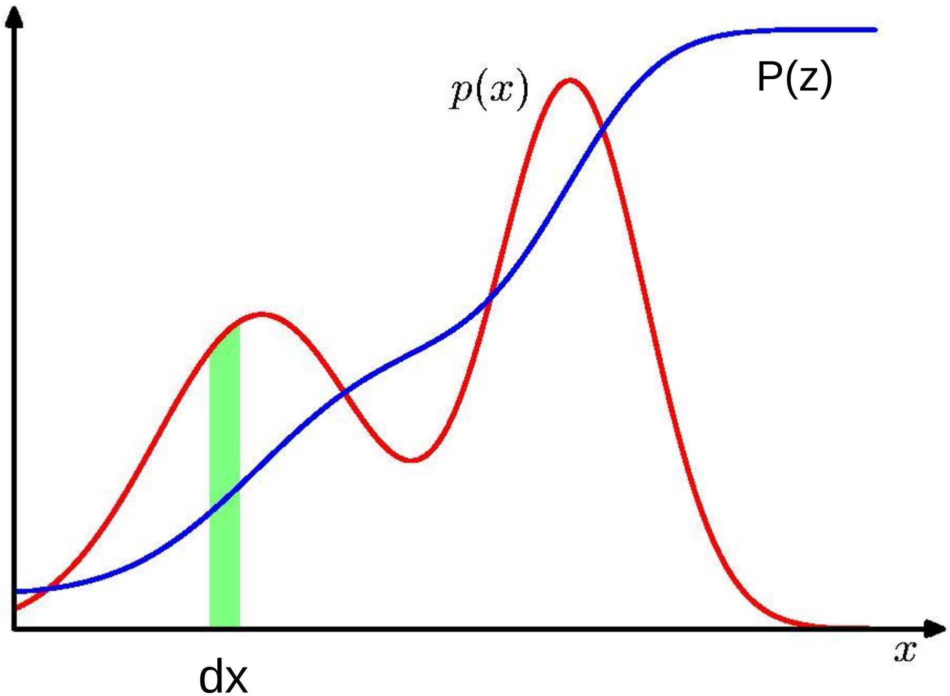
Definitions:

- **A Discrete Random Variable:**

  A random variable X is called discrete of the range of X is finite or countably infinite.

- **A Continuous Random Variable:**

  A random variable X is called continious of the range of X is uncountably infinite.



p(x) is a density

P(z) the CDF

PDF (probability density function)

$$p(x) \geqslant 0$$

$$\int_{-\infty}^{\infty} p(x)\,\mathrm{d}x = 1$$

Probability

$$P(x \in (a,b)) = \int_a^b p(x)dx$$

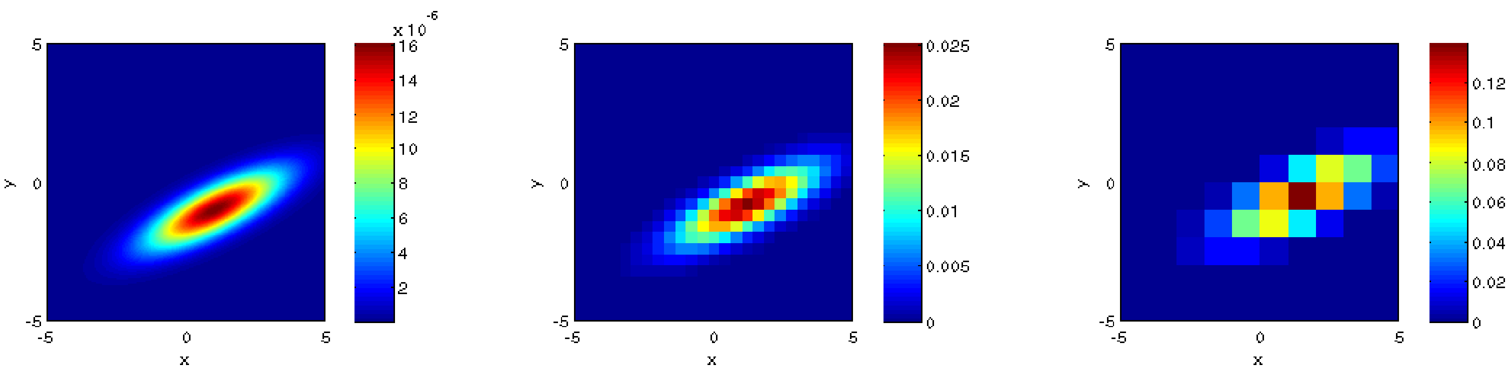
CDF (cumulative density function)

$$P(z) = \int_{-\infty}^{z} p(x)\,\mathrm{d}x$$

Questionnaire

- What is the difference between a continuous and discrete random variable.

- How can we compute the probability that a continuous random variable takes a value in the range between a and b given that you know its probability density

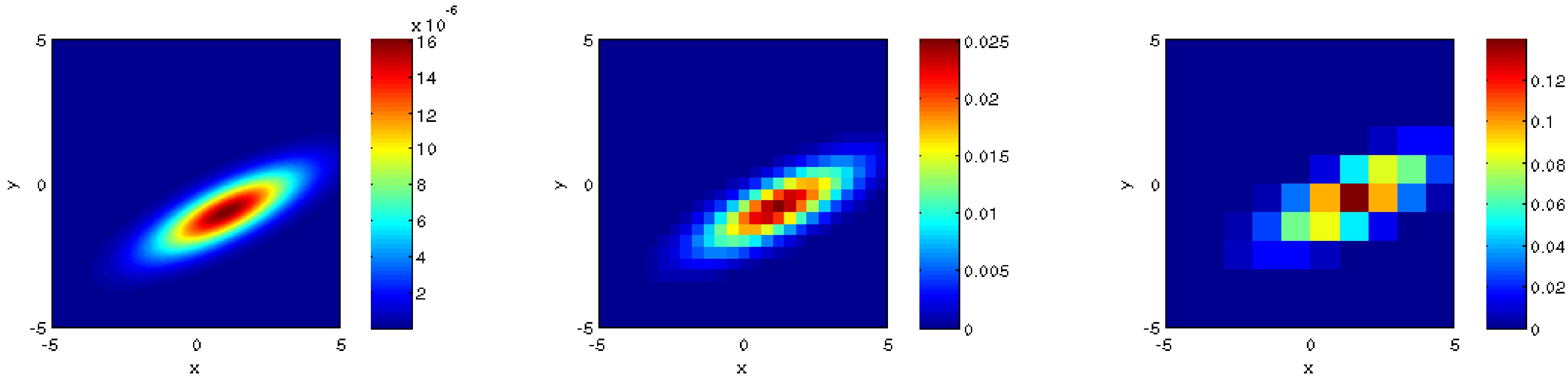


Start

Timer

Stop

Probability Densities and Probability of Discrete Events



This implies that, having a probability density, we need to define an interval to define a probability.

Probability

$$p(x \in (a,b)) = \int_a^b p(x)\,\mathrm{d}x$$

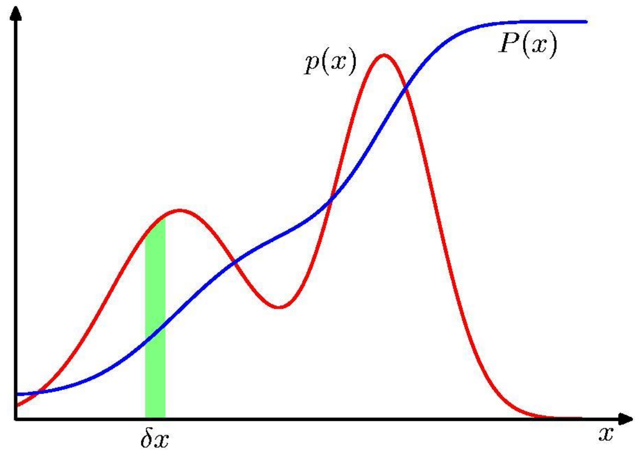
A Discrete Random Variable:

A random variable X is called discrete of the range of X is finite or countably infinite.

A Continuous Random Variable:

A random variable X is called continious of the range of X is uncountably infinite.

Probability: $P(x \in (a, b) = \int_a^b p(x)dx$



The 4W question session

What is this it all about ?

What can I use it for ?

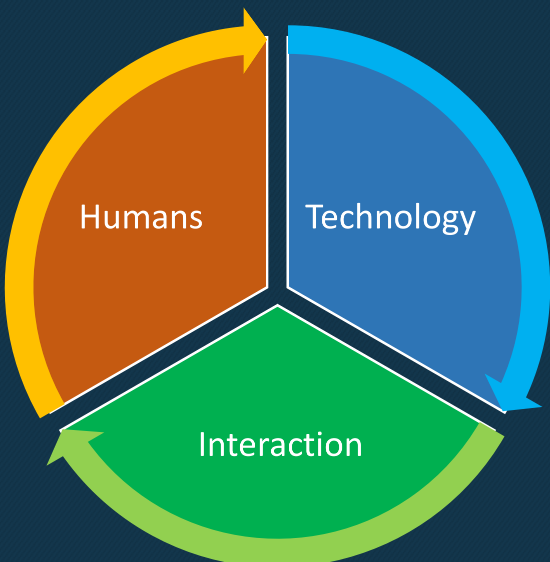
Why should I learn it ?

What are potential Bachelor and Master thesis topics ?

You can find this session at: https://youtu.be/JEqVbuUnuno

Cognitive Computing – (The new AI)

Institute of
Cognitive Science



Symbiotic fusion of the intelligent system, the user, and the expert.

Dialog between machine and human (natural language, intuitive graphics, and gestures)

The machine is the super assistant that enables the human to make truly intelligent decisions in complex scenarios.

At the core of Cognitive Computing since 15 years

10 full professors

~ 600 BSc
~ 200 MSc
~ 45 PhD students

Case 1

Institute of Cognitive Science

Cognitive Computing to predict and manage infectious outbreaks

Prof. Dr. Gordon Pipa, Osnabruck University

Prof. Dr. Kai-Uwe Kühnberger, Osnabruck University

Prof. Dr. Dr. Bertram Scheller, University Hospital Frankfurt

UNIVERSITÄTS KLINIKUM FRANKFURT GOETHE-UNIVERSITÄT

Relevance of Cognitive Computing

„For the ***Robert Koch Institute*** the machine learning and cognitive computing are very important topics for the future. The project ***flu-prediction*** of university Osnabrück demonstrates and highlights the huge potential of these technologies for public health“

ROBERT KOCH INSTITUT

Assessment by
Prof. Dr. Lothar H. Wieler
President of the
Robert Koch Institute

Institute of Cognitive Science

www.flu-prediction.com

Influenza matters

Prediction is important

Delayed and too little data

Data science methods

Social media analysis

Watson as medical expert

Cognitive Computing

flu prediction

A one year project by a core team of three master's students

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www.flu-prediction.com

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Watson as medical expert

Better prediction

Fully informed user

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Identify Causal Interactions

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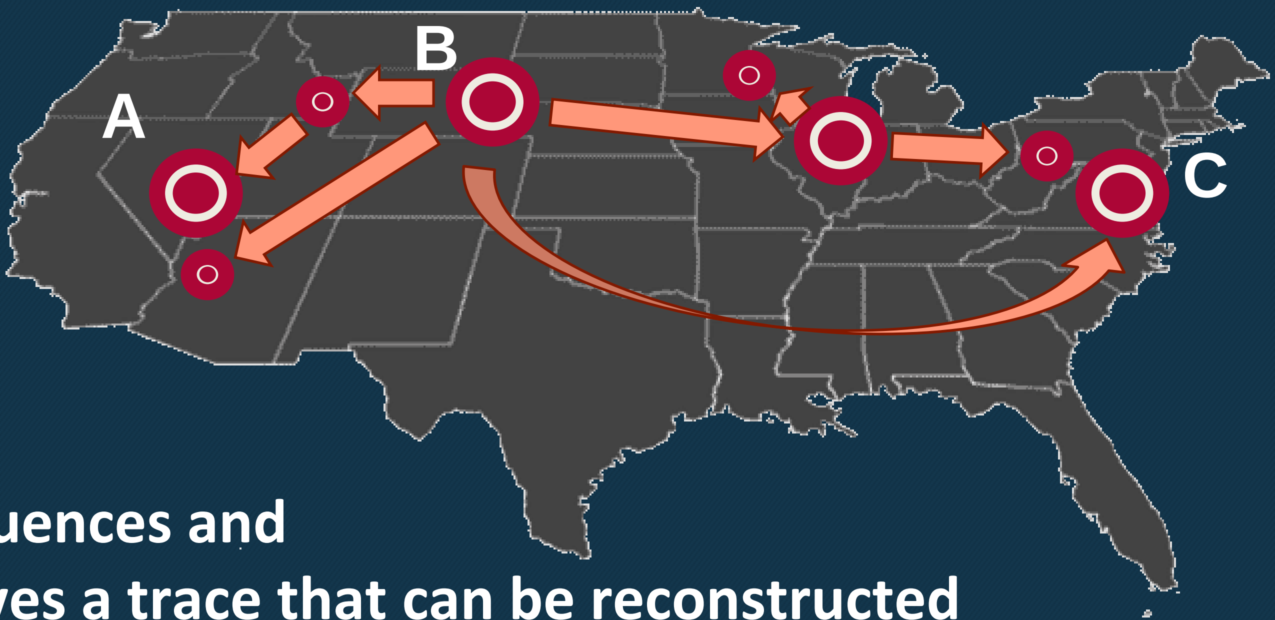
flu prediction



A driver influences and thereby leaves a trace that can be reconstructed

- Schumacher et al. (2015) - A Statistical Framework to Infer Delay and Direction of Information …
- Sugihara et al. (2012) - Detecting Causality in Complex Ecosystems

www.flu-prediction.com

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Fully informed user

Close the Gap by Fusing Data

Institute of Cognitive Science

flu prediction

Realtime fuzzy social media

+

Slow but reliable CDC data

Twitter activity (geo tag + Tweet)

CDC – delayed influenza data

Use the best from both worlds to improve prediction

Sample Tweets from 29/09/16

Institute of Cognitive Science

chaos tK @WhosChaos ·
Really hope I'm not getting the **flu** 🤒

himself worried

Kim @nanosounds
Anyone had any experience of getting better from **flu**,then getting worse?I was up and about yesterday, but today I'm exhausted and **sick** again

herself sick

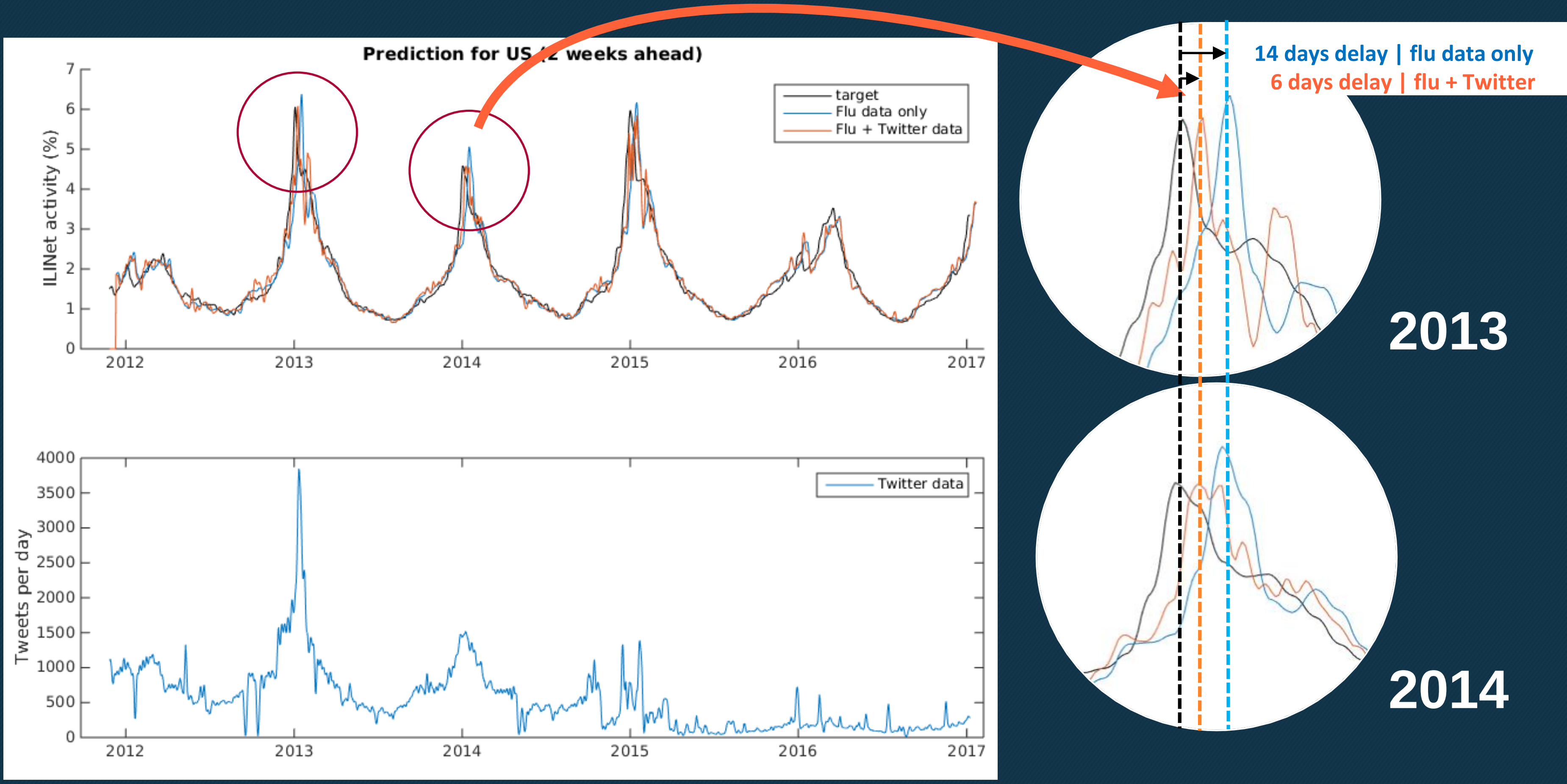
Rob Sinclair @RSinclairAuthor
It's that time of the year again...the school/nursery **flu** merry-go-round - both boys **sick** tonight! 😷 See you on the other side in April...

familiy is sick

Halen Sumner @haysum10
The Centenary **flu** has started making its way around campus. For those who don't wish to die: cover yo mouth, wash yo hands, & shun the **sick**

friends are sick

Delay Reduction with Twitter Data



www.flu-prediction.com

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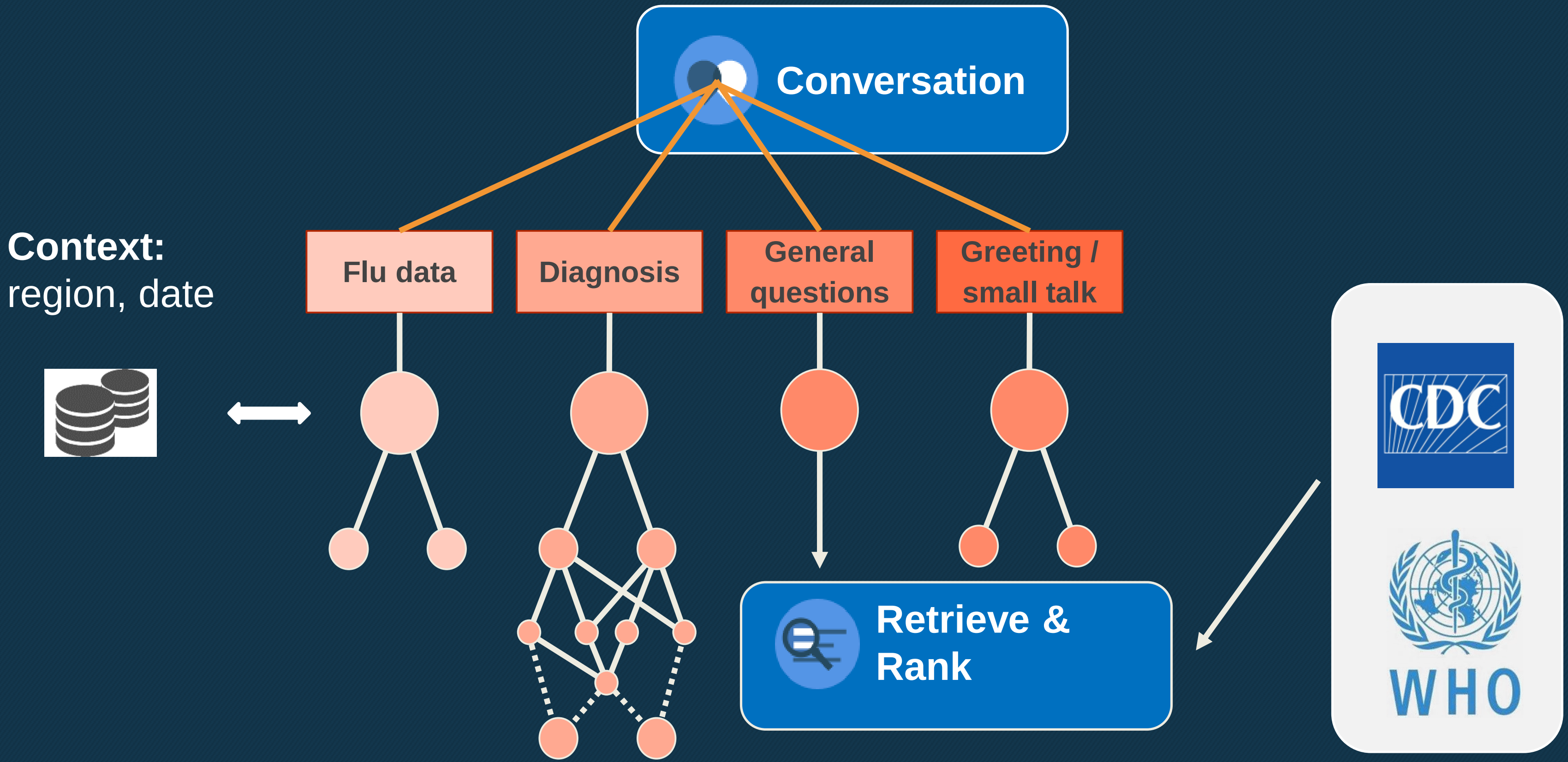
Conversation
Context:
region, date
Flu data
Diagnosis
General questions
Greeting / small talk
Retrieve & Rank
CDC
WHO

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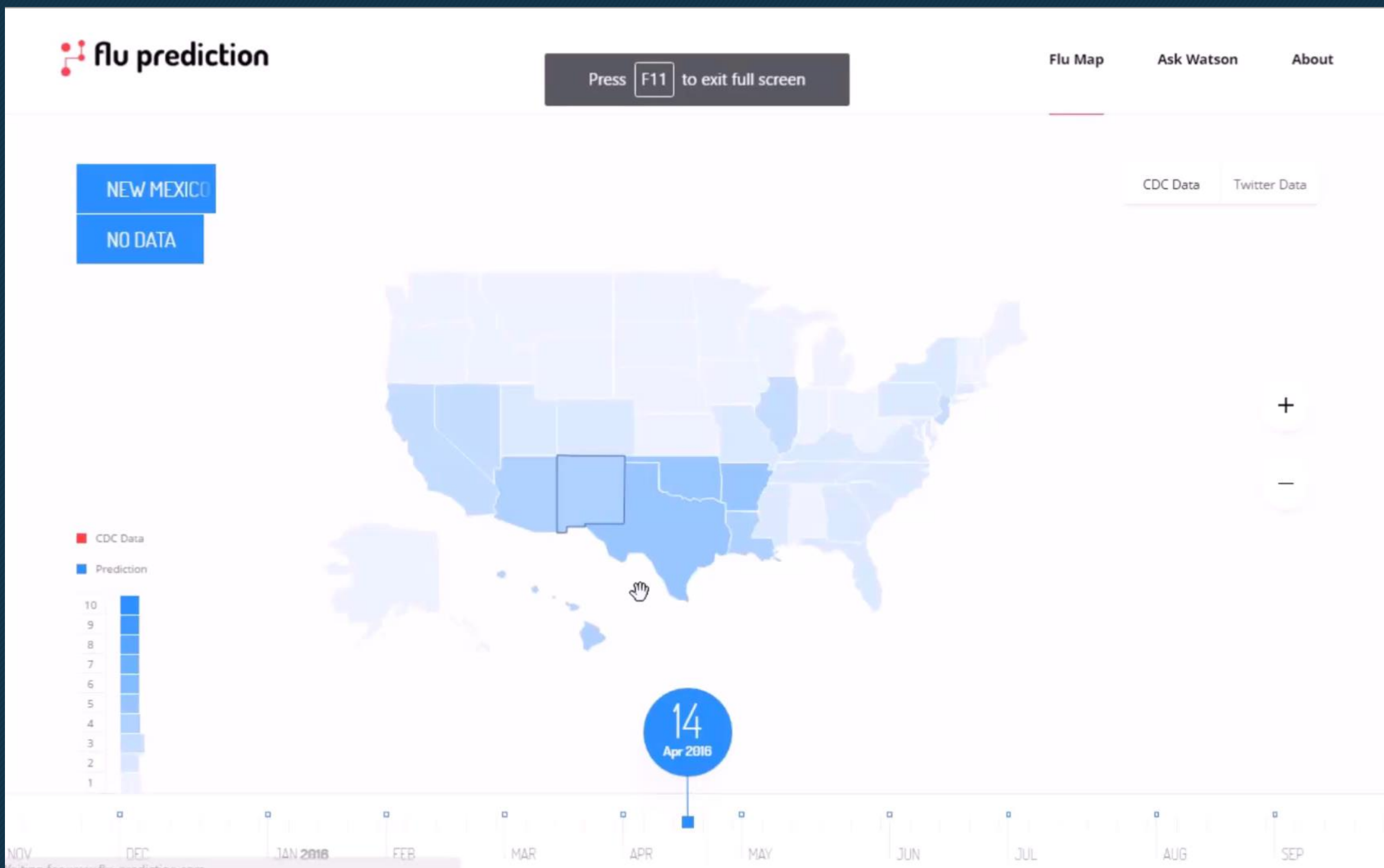
flu prediction



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Speak with Watson Flu

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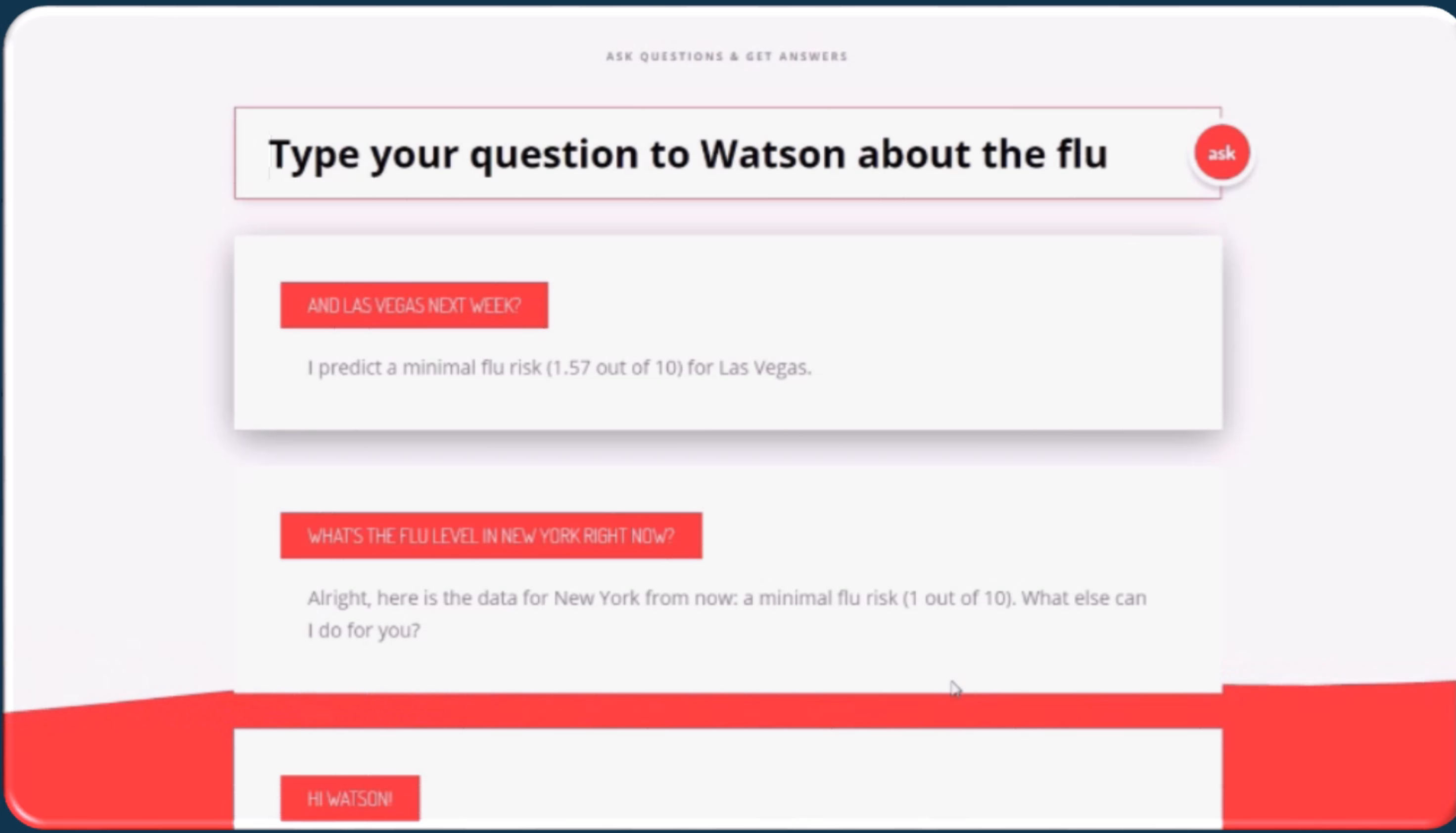


Supported by:

IBM Academic Initiative

IBM Bluemix™

Case 2

Institute of Cognitive Science

ALP – Mobile Cloud Diagonsis

Prof. Dr. Gordon Pipa, Osnabruck University

Prof. Dr. Dr. Bertram Scheller, University Hospital Frankfurt

UNIVERSITÄTS KLINIKUM FRANKFURT
GOETHE-UNIVERSITÄT

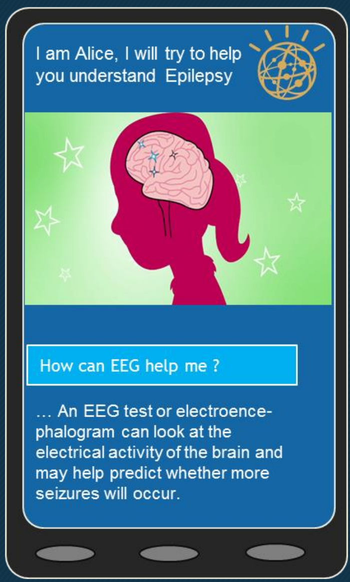
ALP: A Proposal for the use case epilepsy

- 50 million people worldwide, with 80% in developing regions
- There, mostly older AEDs are administered by non-physician health care workers (~10$ a month)
- Sustainable service since the social and economic problems outweigh investment for treatment by far

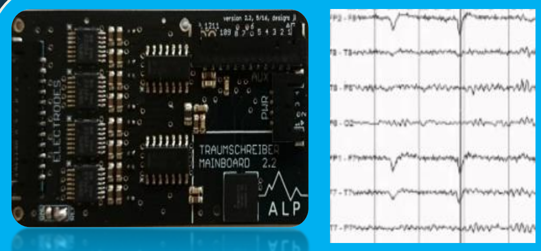
→ The crucial step is the diagnosis and crowd support by experts

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2912535/
https://www.youtube.com/watch?v=lhC0zCcUV3E

ALP: A CLOUD IOT/AI System for treating epilepsy



IoT



EEG using mobil phones

Cloud Services for

- Artificial Intelligence
- Distributing Data
- Managing Human Resources, Patients, and Devices

ALP: A CLOUD IOT/AI System for treating epilepsy

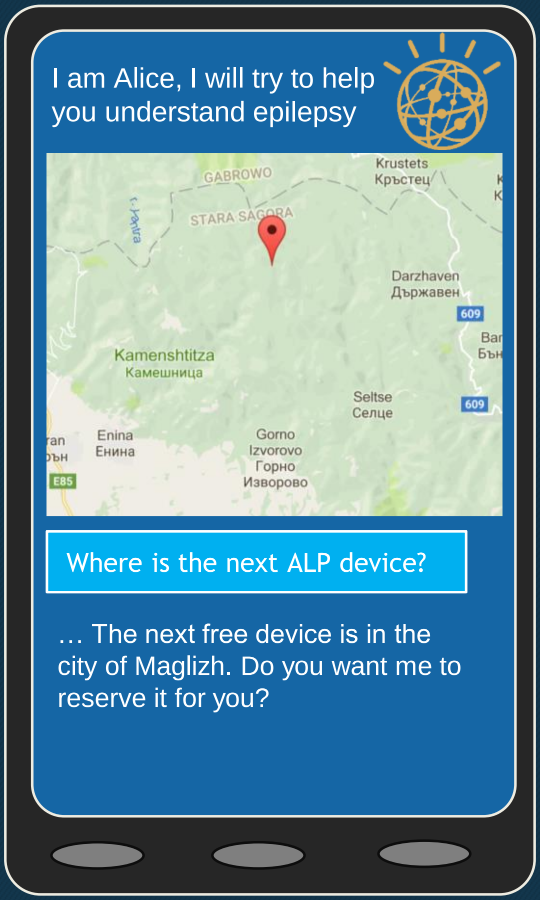
Institute of Cognitive Science

- Simple App for generating awareness and informing patients and relatives in spoken natural language

https://www.youtube.com/watch?v=LS4_jwVY3mc
from Epilepsy Action. The UK's leading epilepsy charity

ALP: A CLOUD IOT/AI System for treating epilepsy

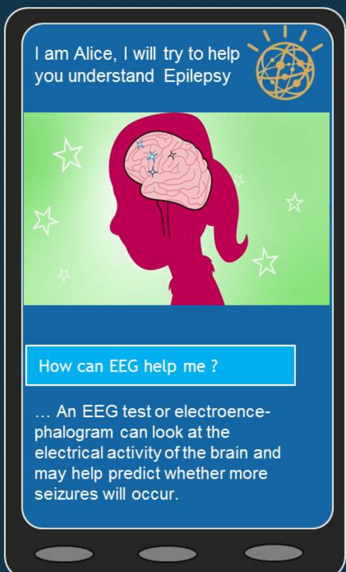
Institute of Cognitive Science



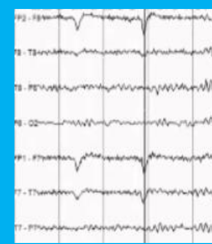
- It helps in locating ALP crowd EEG devices
- It establishes a network of patients and medical care

Institute of Cognitive Science

ALP: A CLOUD IOT/AI System for treating epilepsy



IoT



EEG using mobil phones

Cloud services for

- Artificial Intelligence
- Distributing Data
- Managing Human Resources, Patients, and Devices

Cloud Doctor

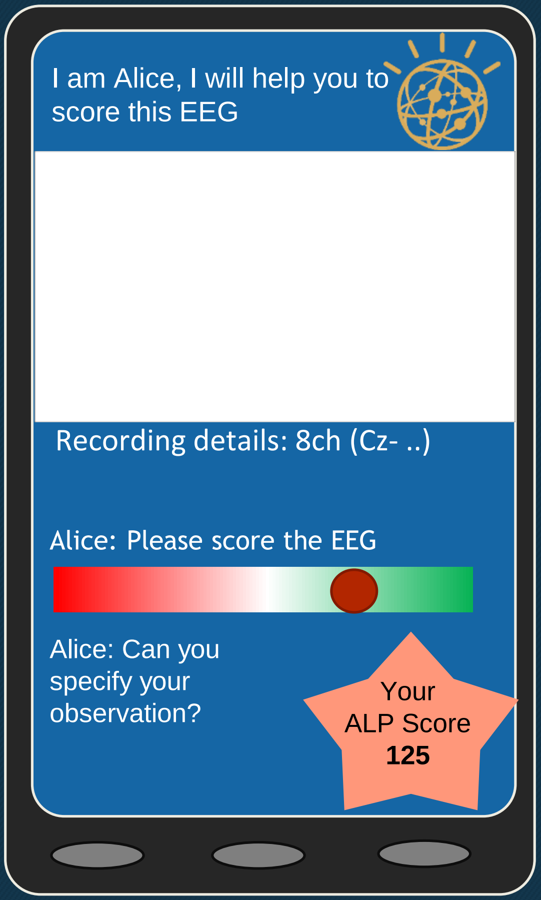
EEG will be scored automatically and by cloud doctors.

Treatment Support

Expert assessment by cloud doctors supports the local teams

ALP: A CLOUD IOT/AI System for treating epilepsy

Institute of Cognitive Science



- Simple App for CLOUD scoring the EEG and videos.
- AI to support treatment with recommendations
- Gamification for CLOUD doctors by ALP Score.

(You contributed to helping 125 children already)