Neuroinformatics Lecture (L2)

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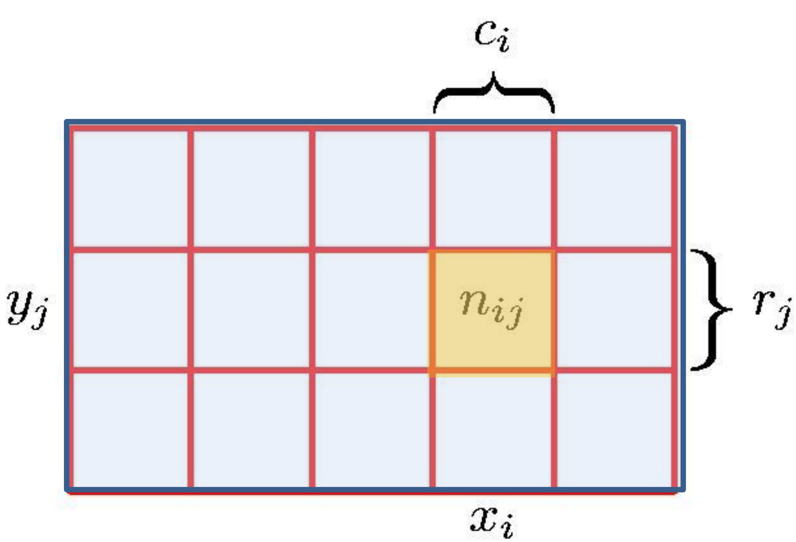
Classes of events x and y i.e. :

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

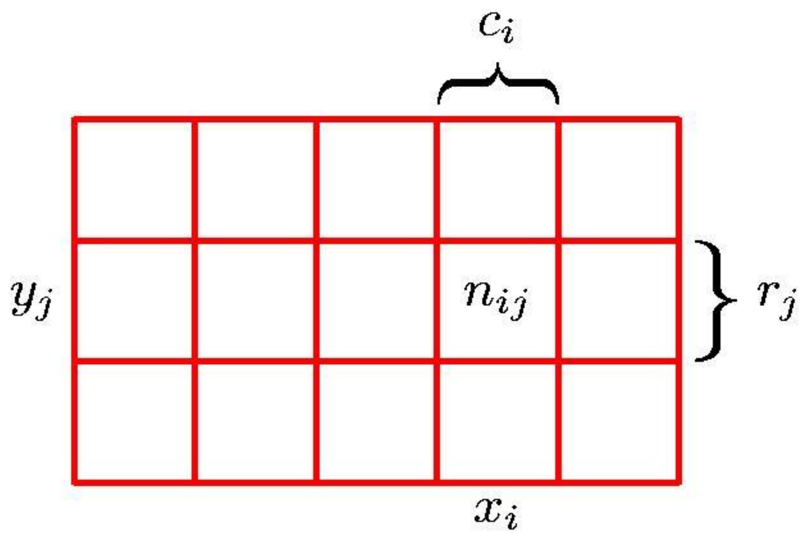
(Probability of Y=y given class X=x)

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

Joint Probability

(Probability of X=x and Y=y)

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



marginal probability

Sum Rule

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

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

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

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

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.

Bayes' Theorem

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

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

posterior ∝ likelihood × prior

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

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

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***
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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

Q

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:

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

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

Start

Timer

Stop

S

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?

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

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

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

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

	App.	Org.	Lim.
r	***3***	***4***	***3***
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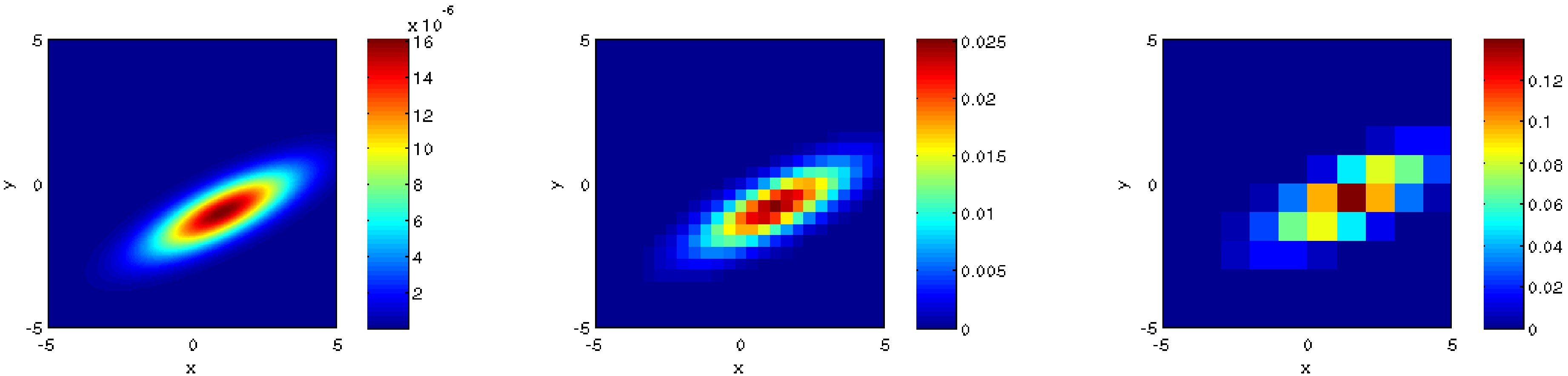
Neuroinformatics Lecture

Topics:

Continuous and Discrete random variables

Probability Densities and Probability of Discrete Events



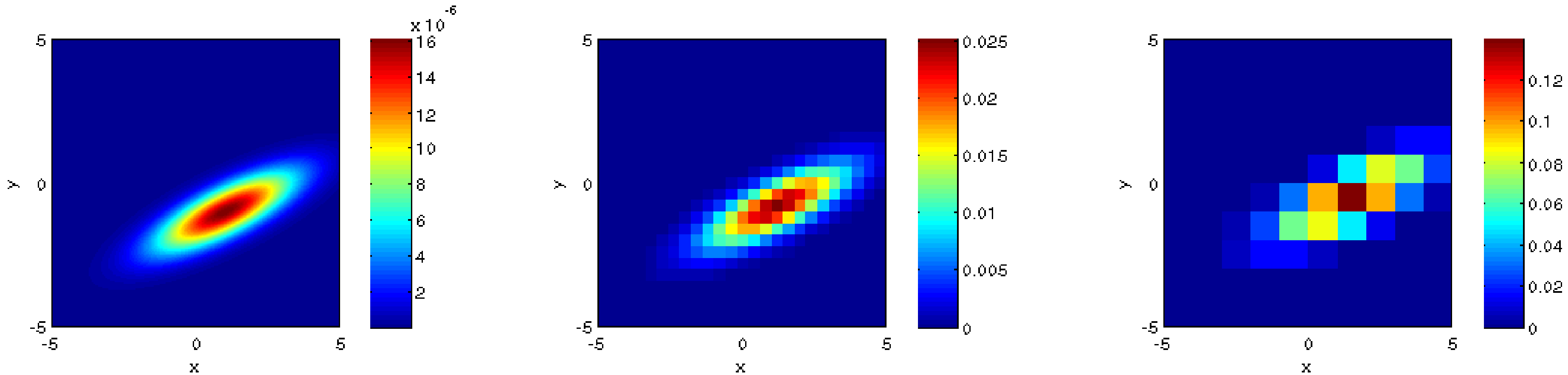
We introduced probabilities for discrete events.

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

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

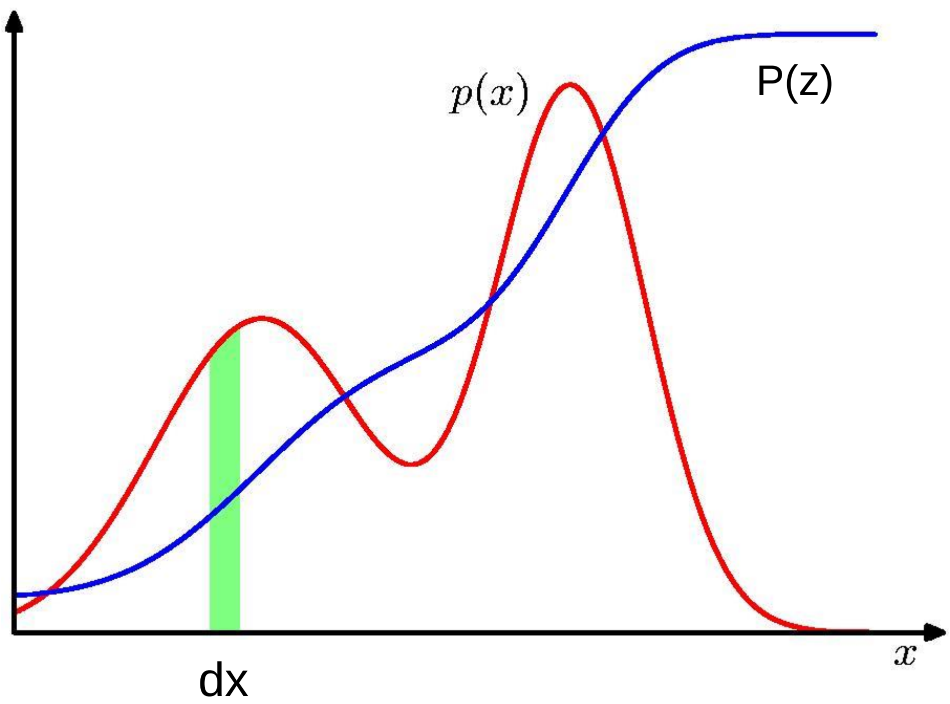
Definitions:

- **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)

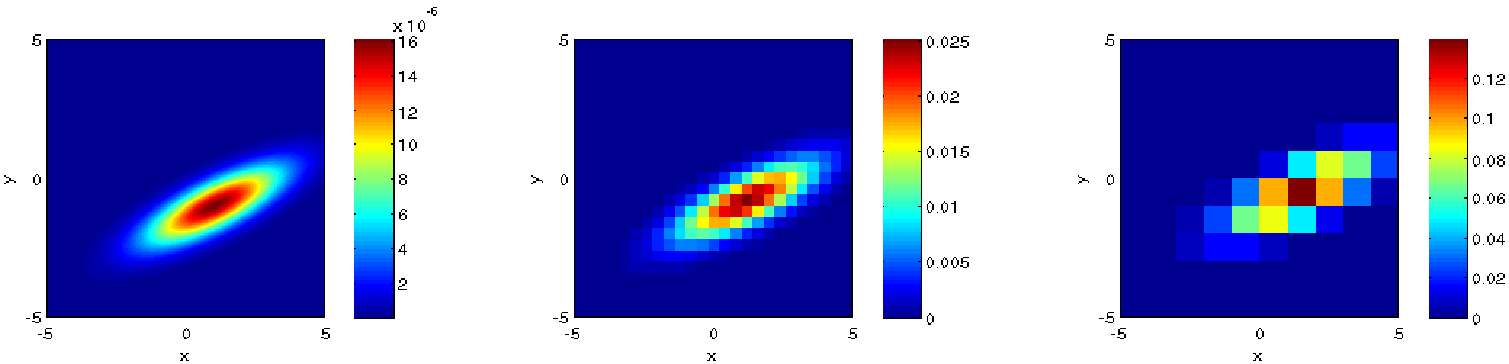
$$P(z) = \int_{-\infty}^{z} p(x)\,\mathrm{d}x$$

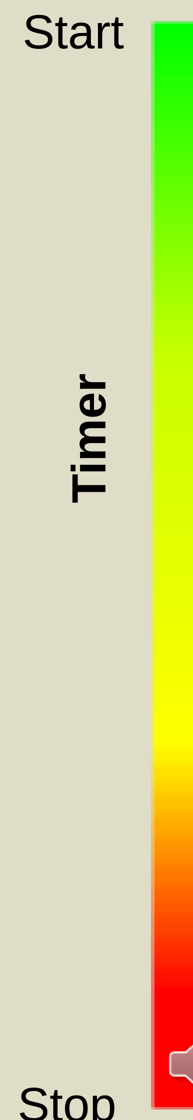
Questionnaire

Q

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

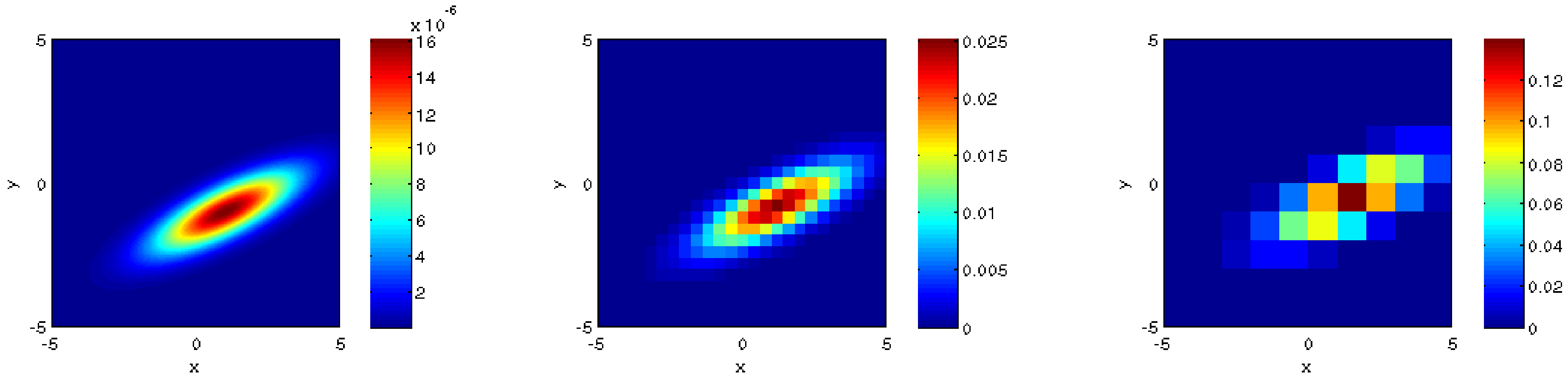
- How can we compute the probability that a continuous random variable takes a value in the range between a and b given that you know its probability density





freemusicarchive.org/music/Kai_Engel/

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

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

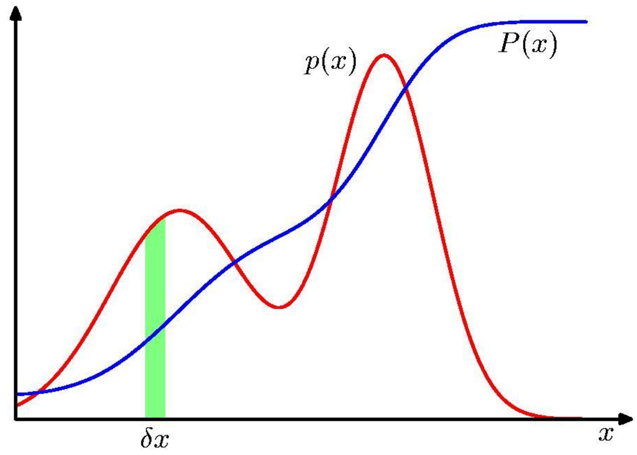
A Discrete Random Variable:

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



Example HIV Testing:

Suppose:

- A blood test gives a false negative result with p=0.1
  (false negative: negative test if patient is HIV infected)
  (→ test power p=0.9 to detect HIV if patient has HIV)

$$p(negative\ test|has\ HIV) = 0.1 \quad and\ \ p(positive\ test|has\ HIV) = 0.9$$

- A blood test gives a false positive result with p=0.1
  (false positive: positive test if patient is not HIV infected)

  $p(positive\ test|has\ no\ HIV)$=0.1

- HIV infection is rare: p(has HIV)=0.006

What is the probability that a patient has HIV in the case that he receives a positive test result ?   p(has HIV | positive test)

Suppose:

- A blood test gives has a test power
- False positive
- HIV infection is rare:

$p(positive\ test|has\ HIV) = 0.9$

$p(positive\ test|has\ no\ HIV)$=0.1

$p(has\ HIV)$=0.006

What is the probability that a patient has HIV in the case that he receives a positive test result ? p(has HIV | positive test)

$$p(has\ HIV\ |positive\ test) = \frac{p(positive\ test|has\ HIV)p(has\ HIV)}{p(positive\ test)}$$

We used Bayes

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

Suppose:

- A blood test gives has a test power
- False positive
- HIV infection is rare:

$p(positive\ test|has\ HIV) = 0.9$

$p(positive\ test|has\ no\ HIV)$=0.1

$p(has\ HIV)$=0.006

What is the probability that a patient has HIV in the case that he receives a positive test result ? p(has HIV | positive test)

$$p(has\ HIV\ |positive\ test) = \frac{p(positive\ test|has\ HIV)p(has\ HIV)}{p(positive\ test)}$$

We use sum rule (‚we marginalize‘): Add all p for a positive test

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

Suppose:

- A blood test gives has a test power
- False positive
- HIV infection is rare:

$p(positive\ test|has\ HIV) = 0.9$

$p(positive\ test|has\ no\ HIV)$=0.1

$p(has\ HIV)$=0.006

What is the probability that a patient has HIV in the case that he receives a positive test result ? p(has HIV | positive test)

$$p(has\ HIV\ |positive\ test) = \frac{p(positive\ test|has\ HIV)p(has\ HIV)}{p(positive\ test)}$$

We use sum rule (‚we marginalize‘): Add all p for a positive test

$$p(positive\ test) = p(positive, HIV) + p(positive, no\ HIV) \qquad \text{sum rule}$$

$$= \underbrace{p(positive|HIV)p(HIV)}_{\text{product rule}} + \underbrace{p(positive|no\ HIV)p(no\ HIV)}_{\text{product rule}}$$

Suppose:

- A blood test gives has a test power
- False positive
- HIV infection is rare:

$p(positive\ test|has\ HIV) = 0.9$

$p(positive\ test|has\ no\ HIV)$=0.1

$p(has\ HIV)$=0.006

What is the probability that a patient has HIV in the case that he receives a positive test result ? p(has HIV | positive test)

$$p(has\ HIV\ |positive\ test) = \frac{p(positive\ test|has\ HIV)p(has\ HIV)}{p(positive\ test)}$$

$$p(has\ HIV\ |positive\ test) = \frac{p(positive|HIV)p(HIV)}{p(positive|HIV)p(HIV) + p(positive|no\ HIV)p(no\ HIV)}$$

$$p(has\ HIV\ |positive\ test) = \frac{(1-0.1)\cdot 0.006}{(0.9)\cdot 0.006 + 0.1\cdot(1-0.006)} = \frac{0.0054}{0.0054 + 0.0994}$$

Suppose:

- A blood test gives a false negative result with p=0.1 → test power 0.9
- A blood test gives a false positive result with p=0.1
- HIV infection is rare: p=0.006

What is the probability that a patient has HIV in the case that he receives a positive test result ?

$$p(has\ HIV\ |positive\ test) = \frac{(1-0.1)\cdot 0.006}{(1-0.1)\cdot 0.006 + 0.1\cdot(1-0.006)} = 0.0515$$

The probability that you have HIV when you get a positive test result is p=0.05. (Keep in mind the numbers a not real !)

Consequence: The HIV test alone is not sufficient but an important marker that indicates further medical check ups !

The 4W question session

What is this it all about ?

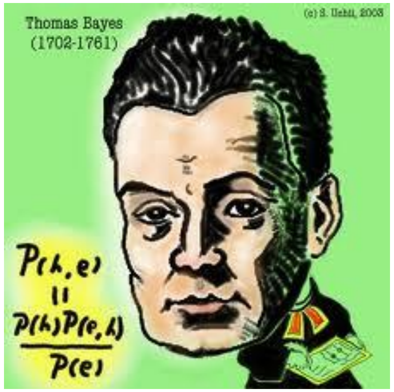
What can I use it for ?

Why should I learn it ?

What are potential Bachelor and Master thesis topics ?

The Brain is Bayesian

4W



Review

TRENDS in Cognitive Sciences Vol.10 No.7 July 2006

Full text provided by www.sciencedirect.com

ELSEVIER

Special Issue: Probabilistic models of cognition

Bayesian decision theory in sensorimotor control

Konrad P. Körding[1] and Daniel M. Wolpert[2]

[1]Brain and Cognitive Sciences, Massachusetts Institute of Technology, Building NE46-4053, Cambridge, Massachusetts, 02139, USA
[2]Department of Engineering, University of Cambridge, Trumpington Street, Cambridge, CB2 1PZ, UK

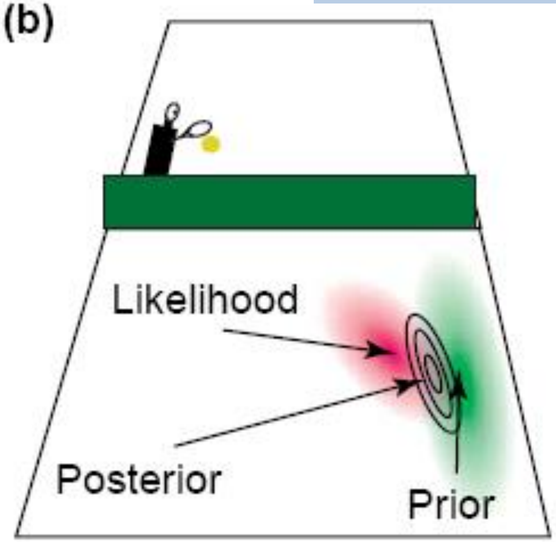
Paper is uploaded in Studip

Decision theory quantifies how people should choose in the context of a given utility function and some partial knowledge of the world. The expected utility is defined as:

$$E[\mathit{Utility}] \equiv \sum_{\substack{\text{possible} \\ \text{outcomes}}} p(\mathit{outcome}|\mathit{action})\,U(\mathit{outcome})$$

where $p(\mathit{outcome}|\mathit{action})$ is the probability of an outcome given an action and $U(\mathit{outcome})$ is the utility associated with this outcome.

(b)



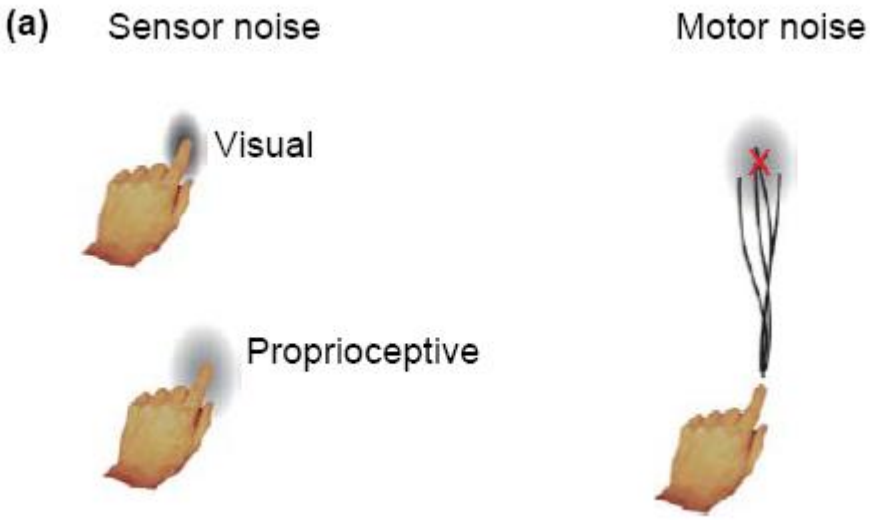
Outcome defined by:

- Prior of ball position
- Likelihood of ball position
- Prior of success in making a point dependent on the position

Is the brain really Bayesian ?

Experiment :

- A subject needs to point to a target.
- There are three types of noise leading uncertainty



4W

Box 2. Bayesian statistics

When we have a Gaussian prior distribution $p(x)$ and we have a noisy observation o of the position that leads to a Gaussian likelihood (red curve, Figure I) $p(o|x)$ it is possible to use Bayes rule to calculate the posterior distribution (yellow curve, Figure I; how probable is each value given both the observation and the prior knowledge):

$$p(x|o) = p(o|x)\frac{p(x)}{p(o)}$$

This equation assigns a probability to every possible location. If we assume that the prior distribution $p(x)$ is a symmetric one dimensional Gaussian with variance σ_p^2 and mean $\hat{\mu}$ and that the likelihood $p(o|x)$ is also a symmetric one dimensional Gaussian with variance σ_o^2 and mean o, it is possible to compute the posterior that is then also Gaussian in an analytical way. The optimal estimate $\hat{x}$, that is the maximum of the posterior is:

$$\hat{x} = \alpha o + (1-\alpha)\hat{\mu}$$

where

$$\alpha = \frac{\sigma_p^2}{\sigma_p^2 + \sigma_o^2}$$

Moreover we can calculate the width of the posterior as $\sigma^2 = \alpha\sigma_o$. The parameter α is always less than 1. This Bayesian approach leads to a better estimate of possible outcomes than any estimate that is only based on the sensory input.

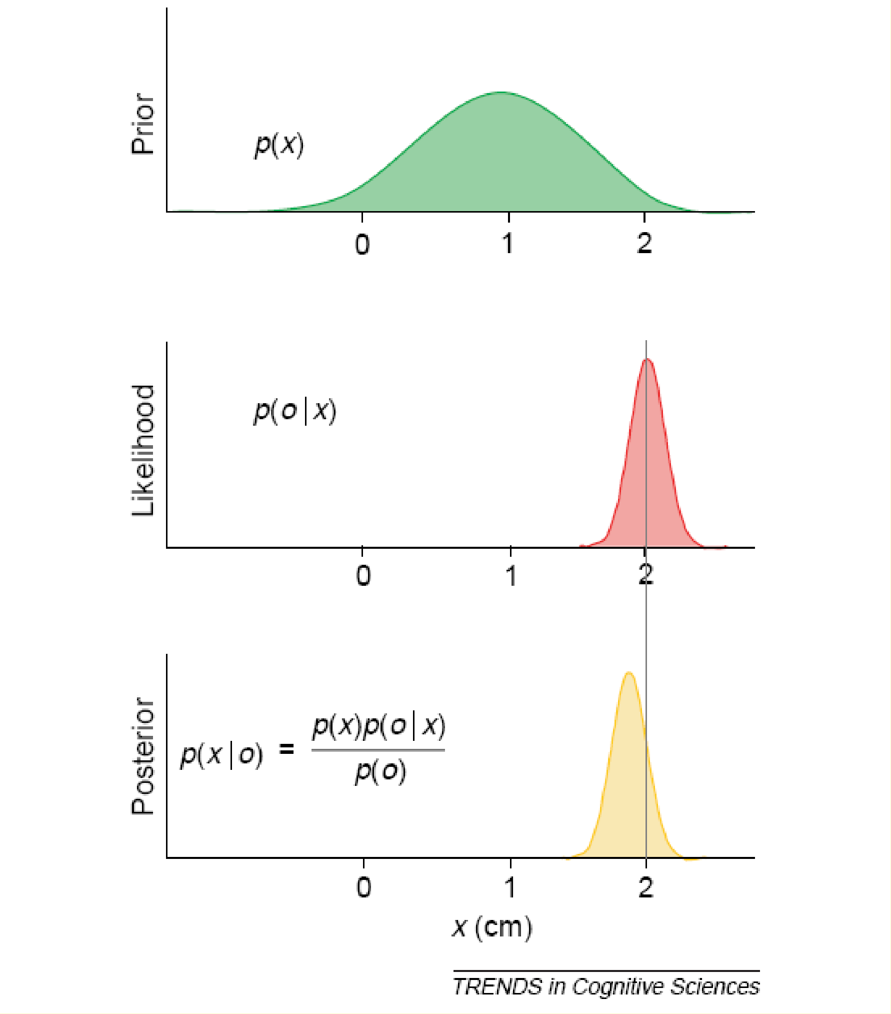


Figure I. Bayesian integration. The green curve represents the prior and red curve represents the likelihood. The yellow curve represents the posterior, the result from combining prior and likelihood.

4W

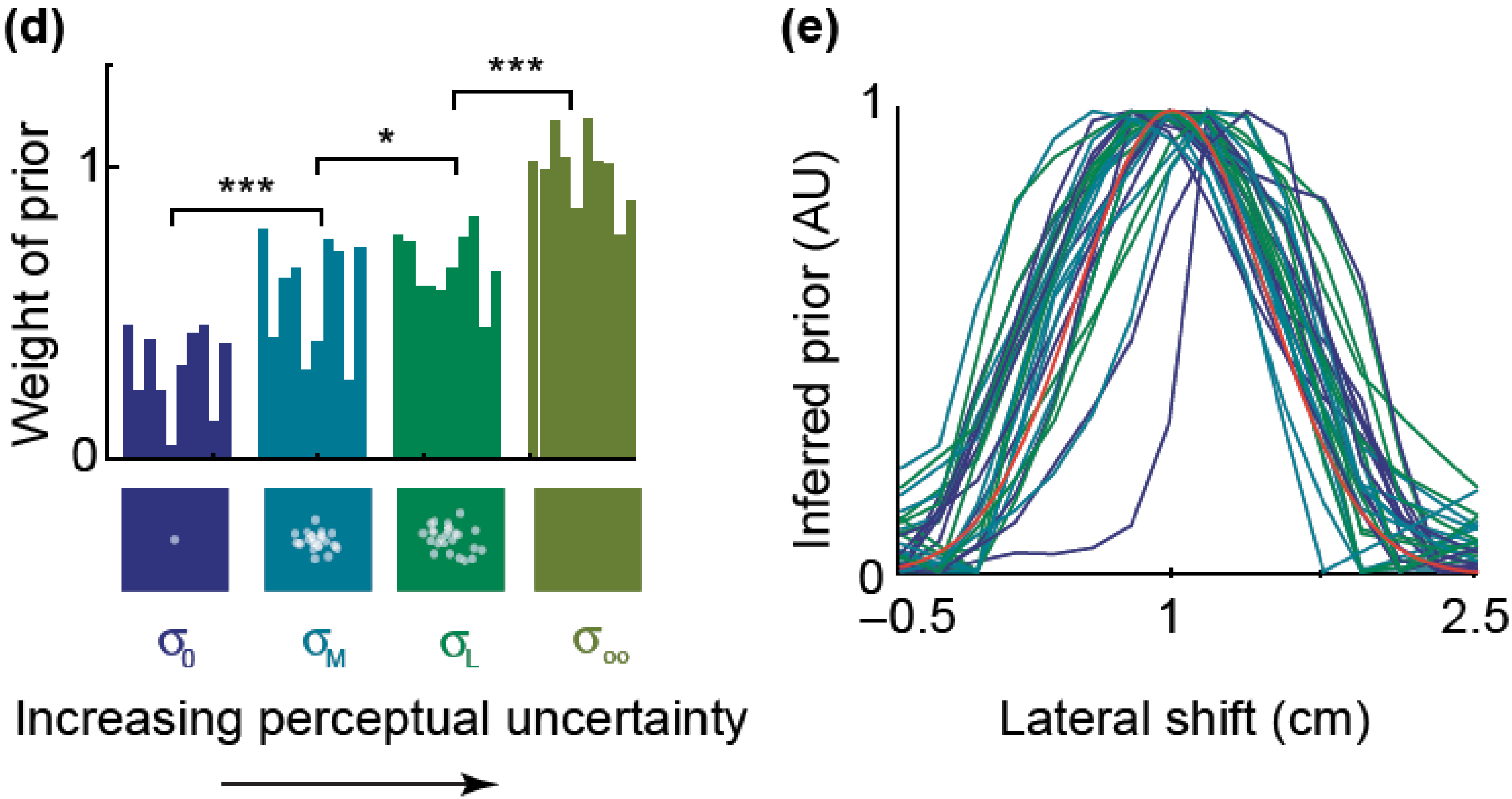
Is the brain really Bayesian ?

Experiment :

- A subject needs to point to a target.
- There are three types of noise leading uncertainty

Test:

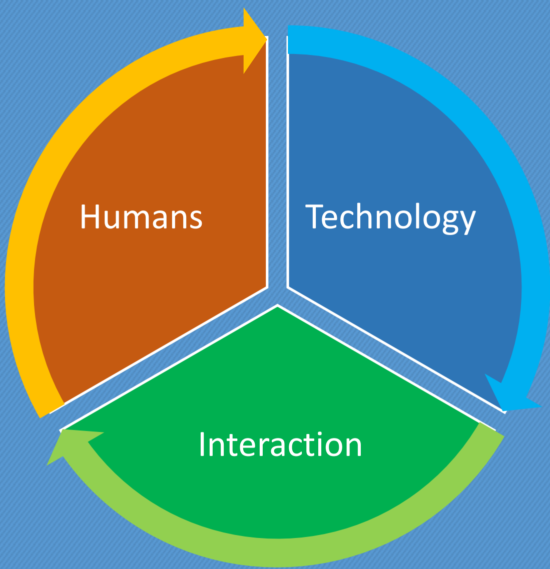
- Can the subject learn the uncertainty of the indiviudal sources to estimate the width of the likelihood?
- Can the subject learn a prior?
- Can it combine the prior and likelihood such that it makes a decision that is maximizing the posterior?



Yes we can, actually for this example it is Baysian optimal!

Cognitive Computing

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)

Neuro-inspired hardware for fault-tolerant new computing devices

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

Why Cognitive Computing?

Institute of Cognitive Science

Influenza matters

Prediction is important

Delayed and too few data

flu prediction

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



Why Cognitive Computing?

Institute of Cognitive Science

flu prediction

Influenza matters

Data science methods

Prediction is important

Social media analysis

Delayed and too few data

Watson as medical expert

Why Cognitive Computing?

Institute of Cognitive Science

flu prediction

- Influenza matters
- Prediction is important
- Delayed and too few data

Cognitive Computing

- Data science methods
- Social media analysis
- Watson as medical expert

- Better prediction
- Fully informed user

Why Cognitive Computing?

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flu prediction

Influenza matters

Prediction is important

Delayed and too few data

Data science methods

Social media analysis

Watson as medical expert

Better prediction

Fully informed user

Structured Causal Models

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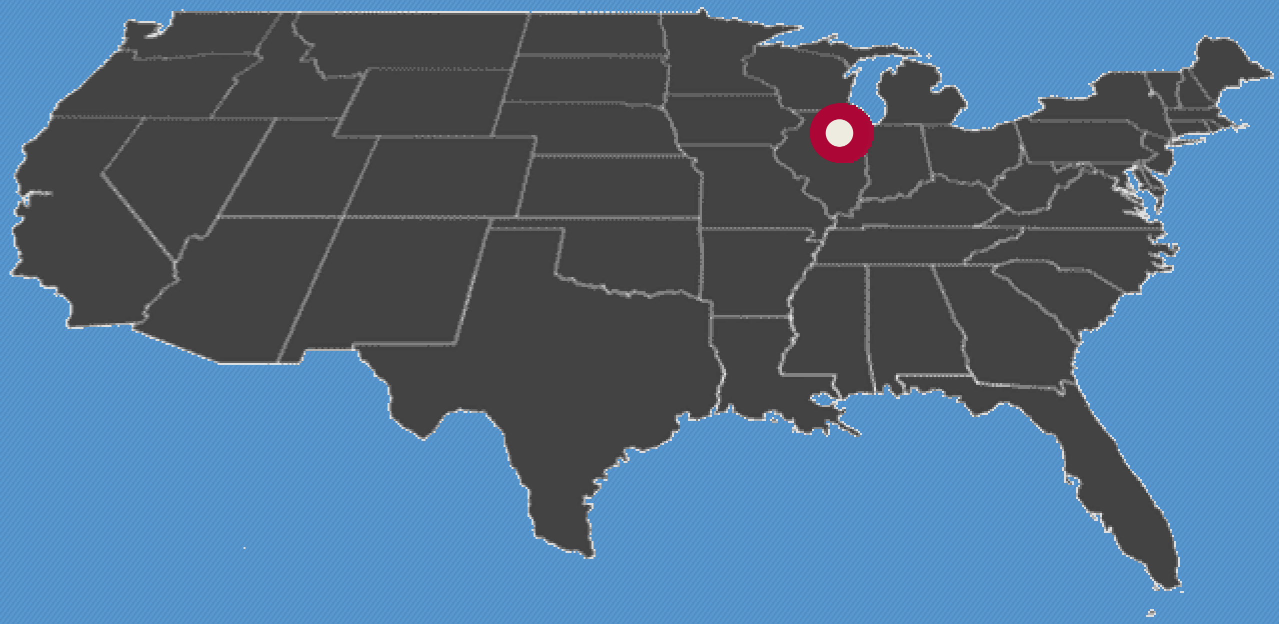
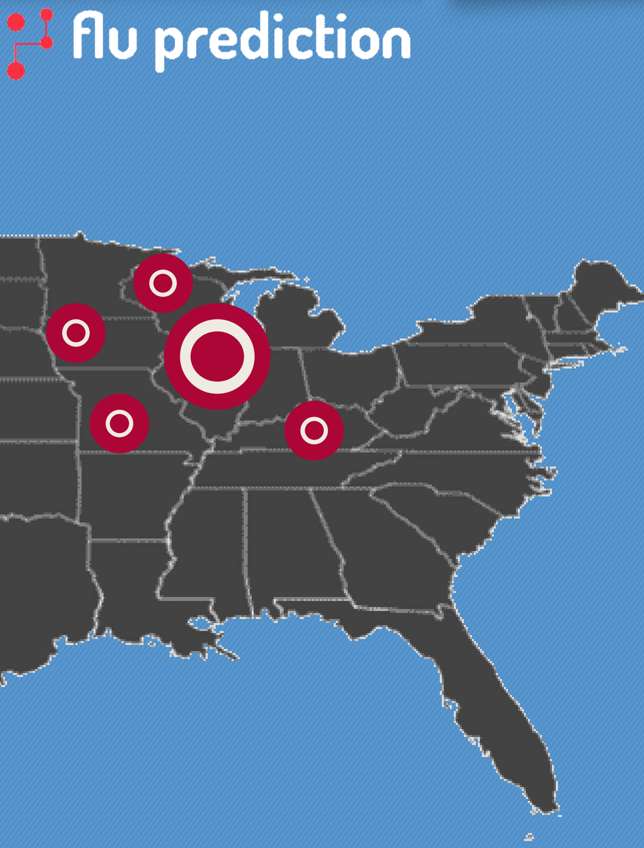
flu prediction



- **Disease spreads locally and via transportation hubs**
- **Weather, vaccination, and seasonal events change spreading**

Structured Causal Models



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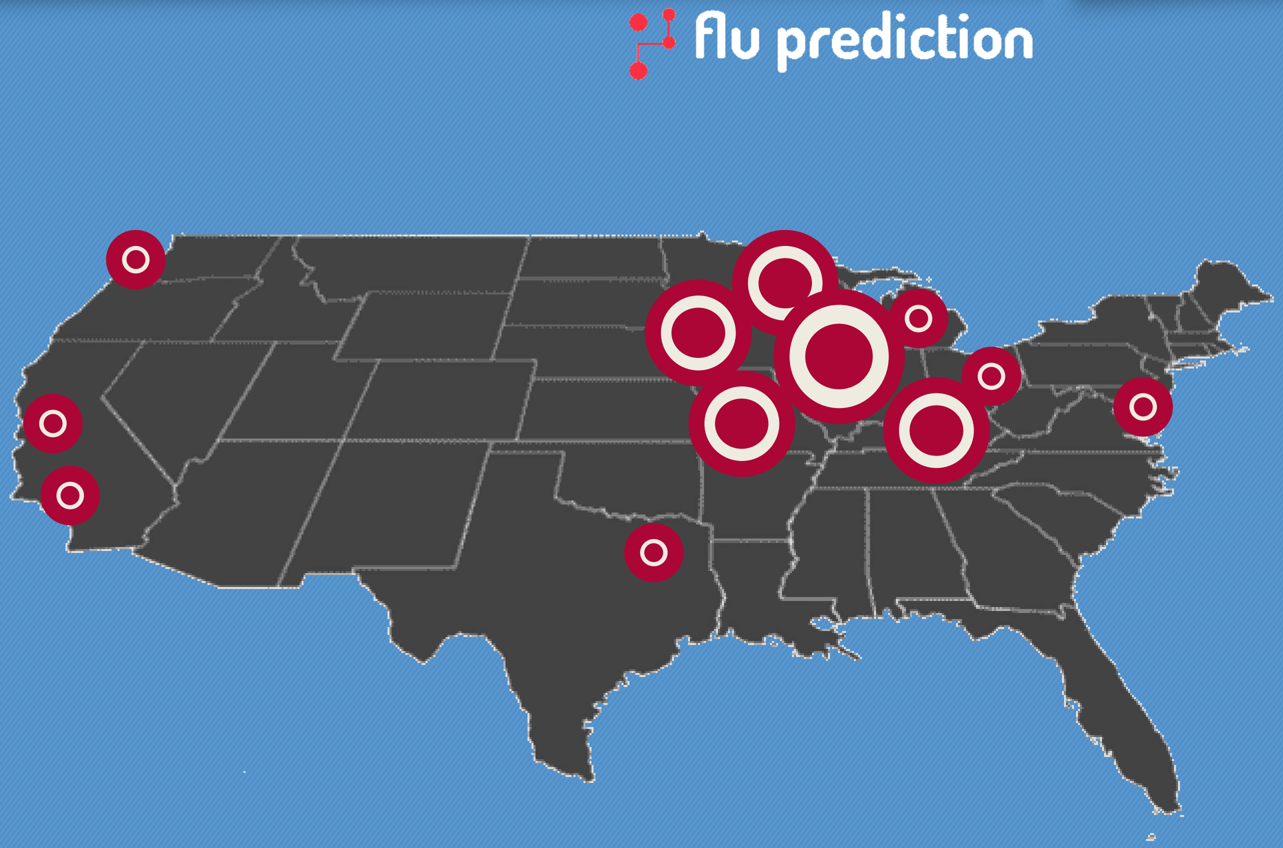
Structured Causal Models



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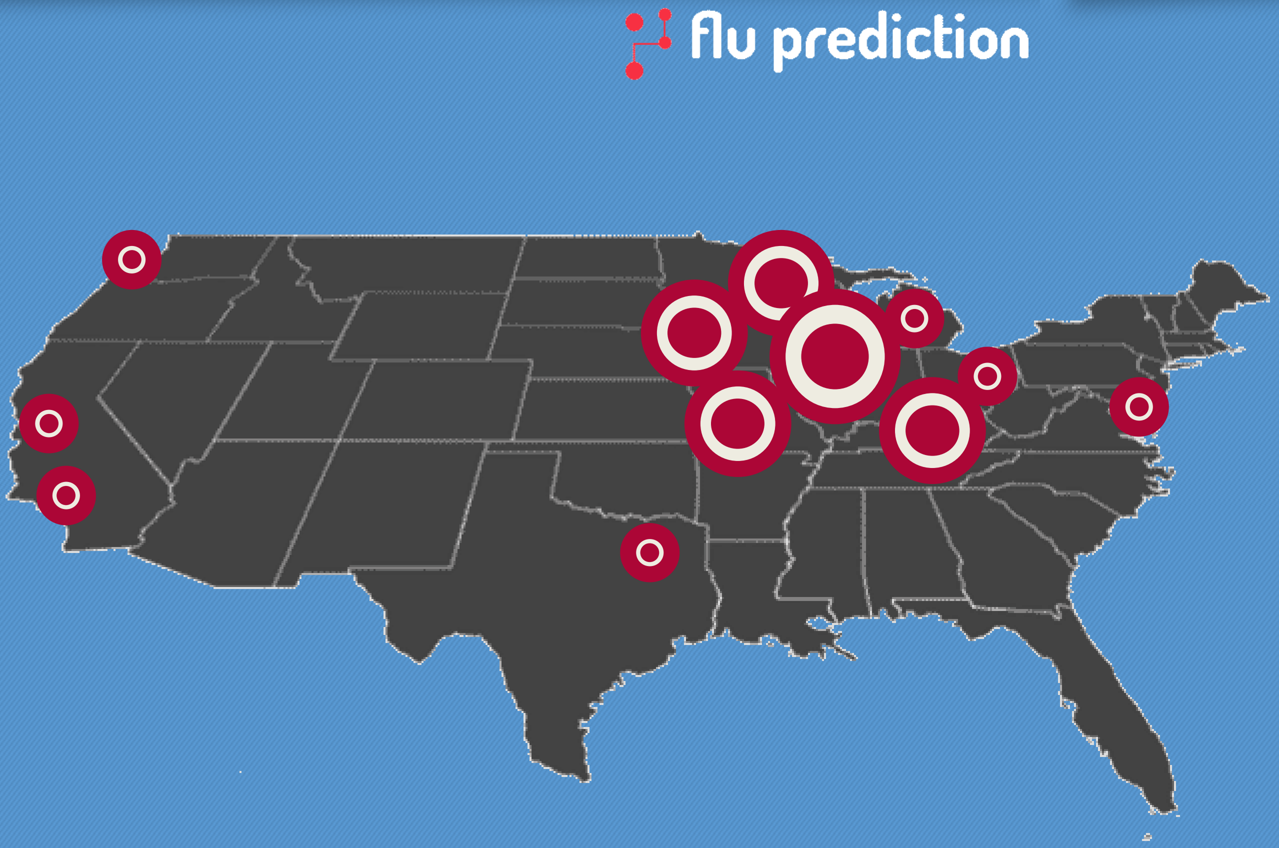
Structured Causal Models



Direction and speed of spread NEEDS to be identified from data

Identify Causal Interactions

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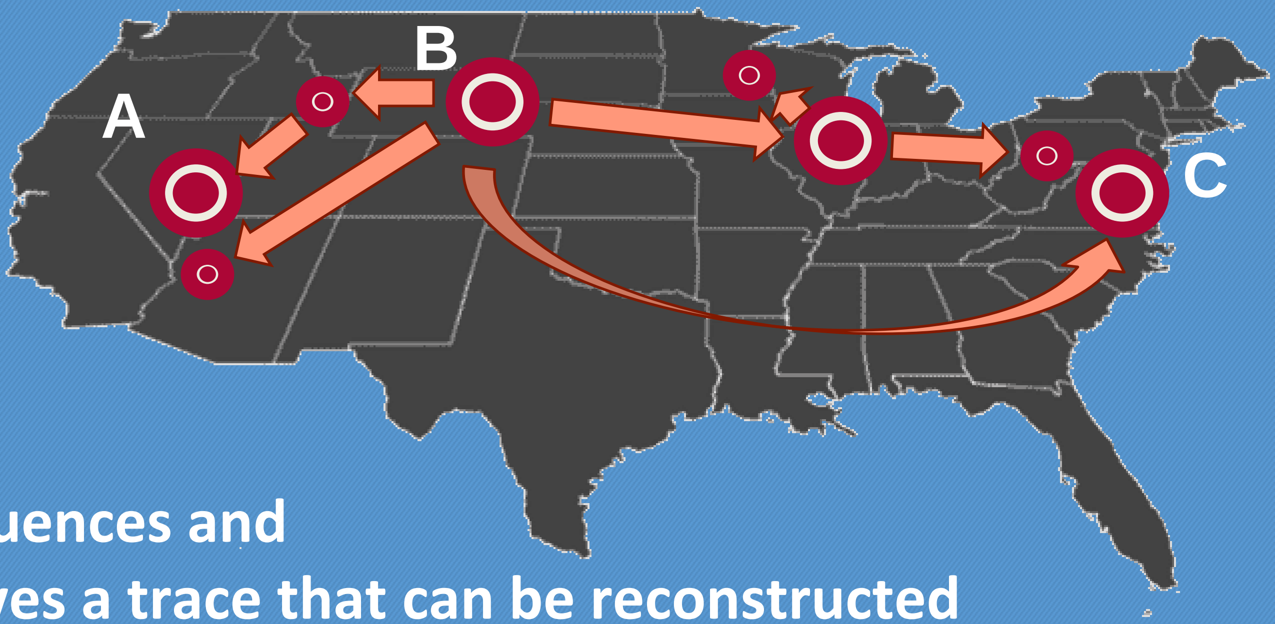
flu prediction



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

Identify Causal Interactions

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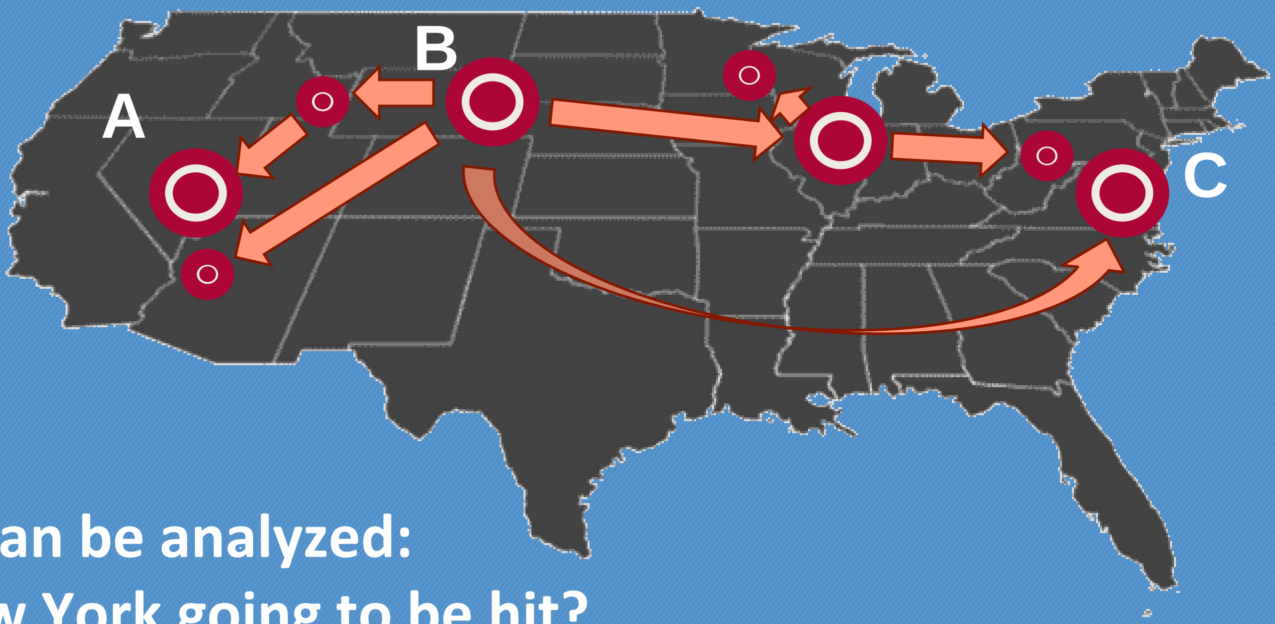
flu prediction

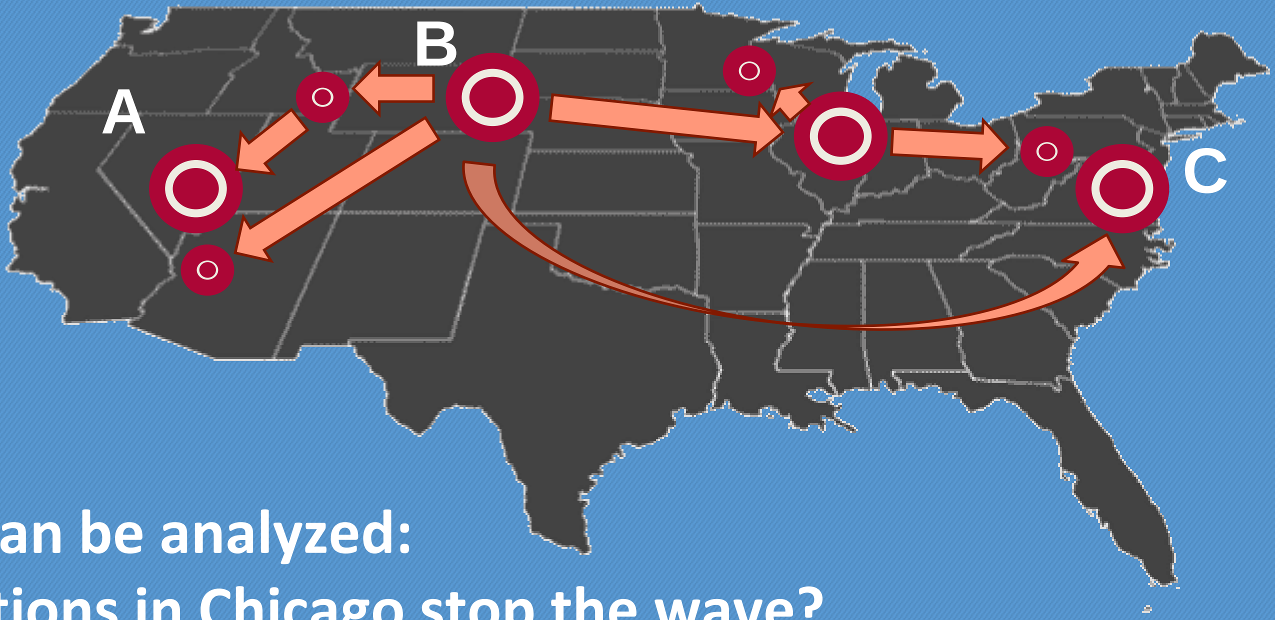


The model can be analyzed:
When is New York going to be hit?

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

Identify Causal Interactions

flu prediction



The model can be analyzed:
Can vaccinations in Chicago stop the wave?

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

IBM Blue Mix & Watson at work

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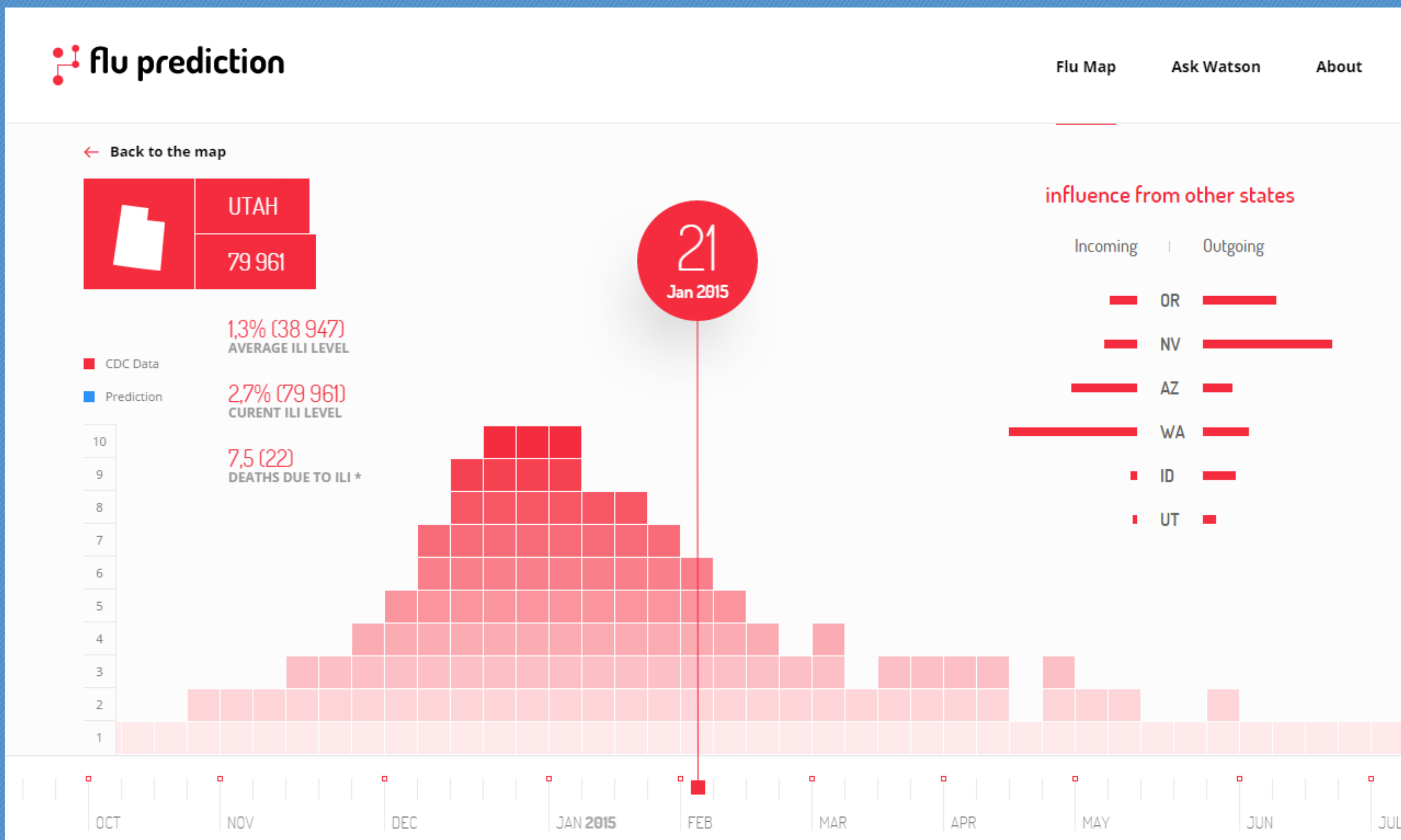

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Why Cognitive Computing?

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Influenza matters

Prediction is important

Delayed and too few data

Data science methods

Social media analysis

Watson as medical expert

Better prediction

Fully informed user

Sample Tweets from 29/09/16

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chaos tK @WhosChaos · 10 Std.
Really hope I'm not getting the **flu** 🤒

himself worried

Kim @nanosounds · 1. Okt.
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 · 29. Sep.
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 · 29. Sep.
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

Social Media

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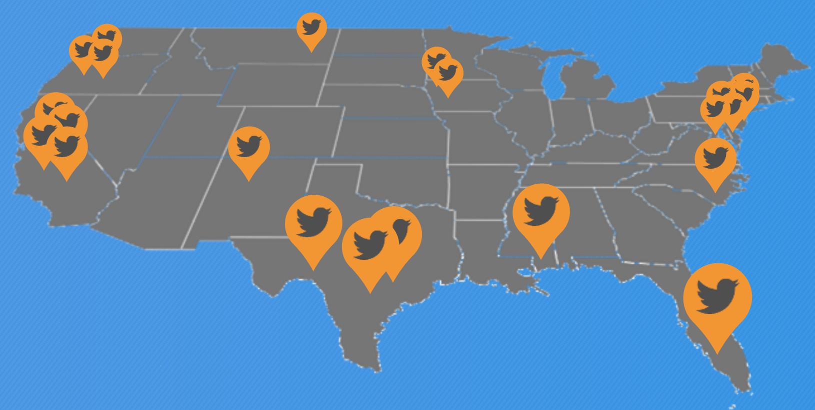

Twitter activity
(geo tag + tweet)

Twitter gives realtime and anytime available data
IBM Insights contains tweets since 2014

Close the Gap by Fusing Data

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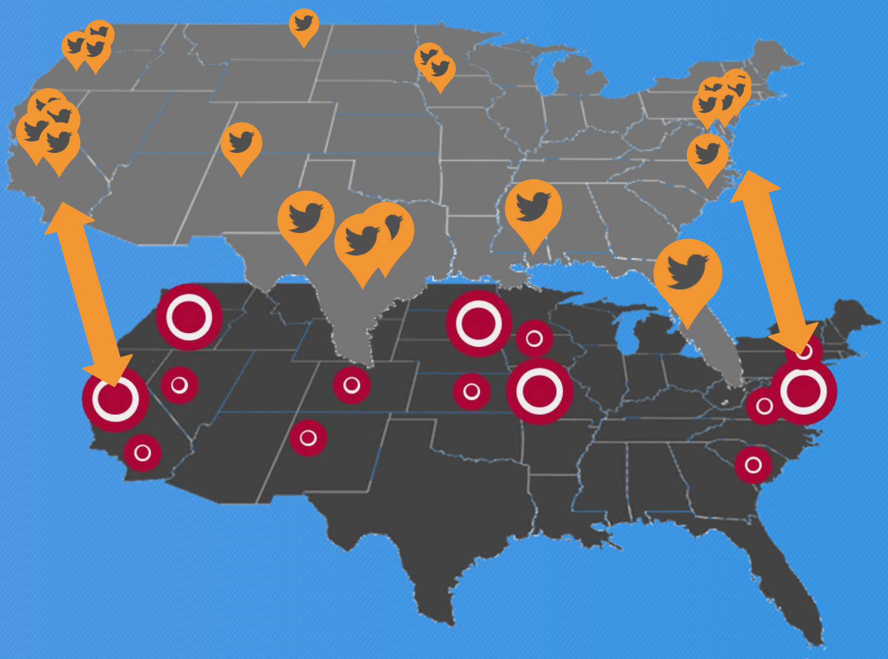
flu prediction

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

IBM Blue Mix & Watson at Work

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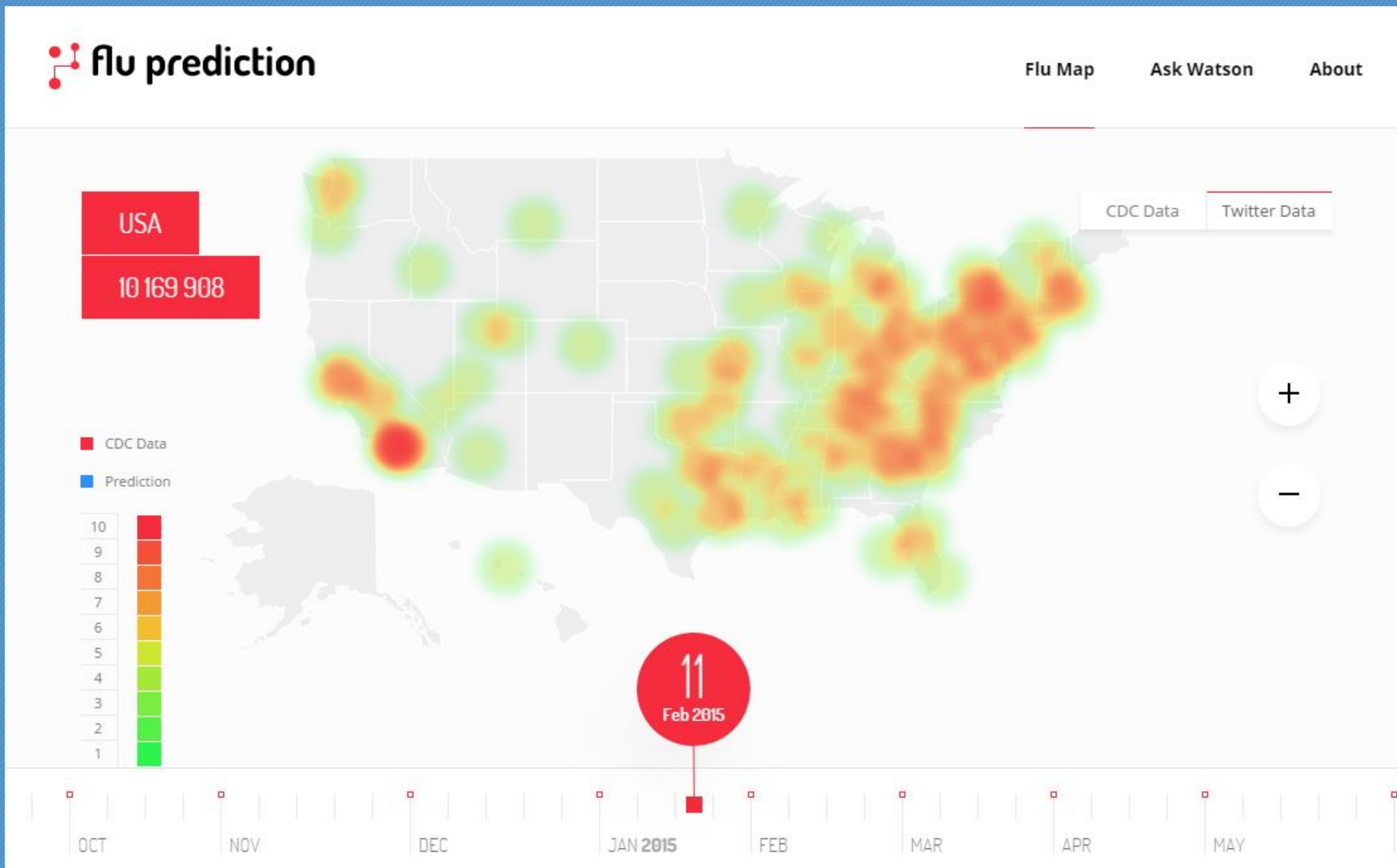

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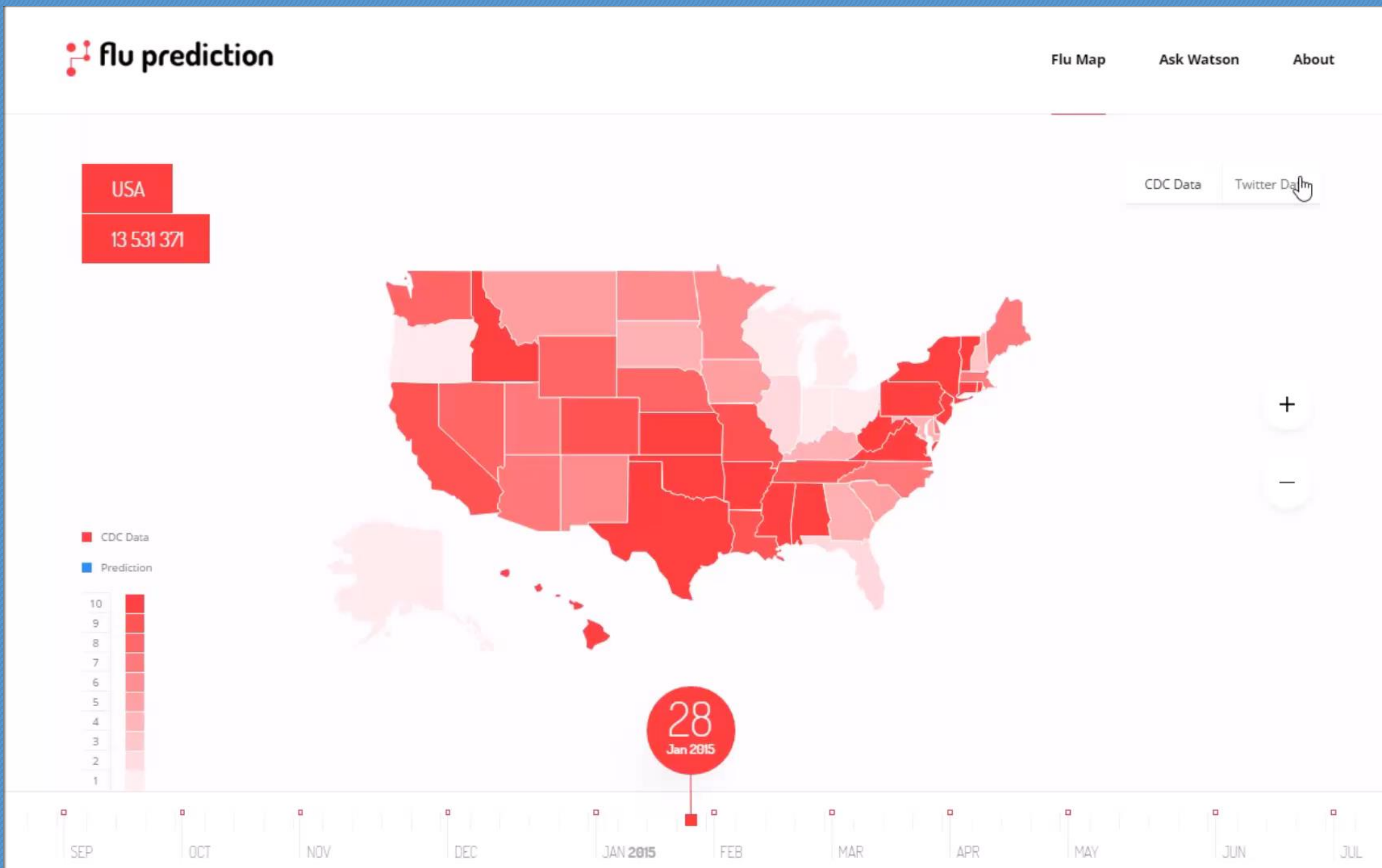

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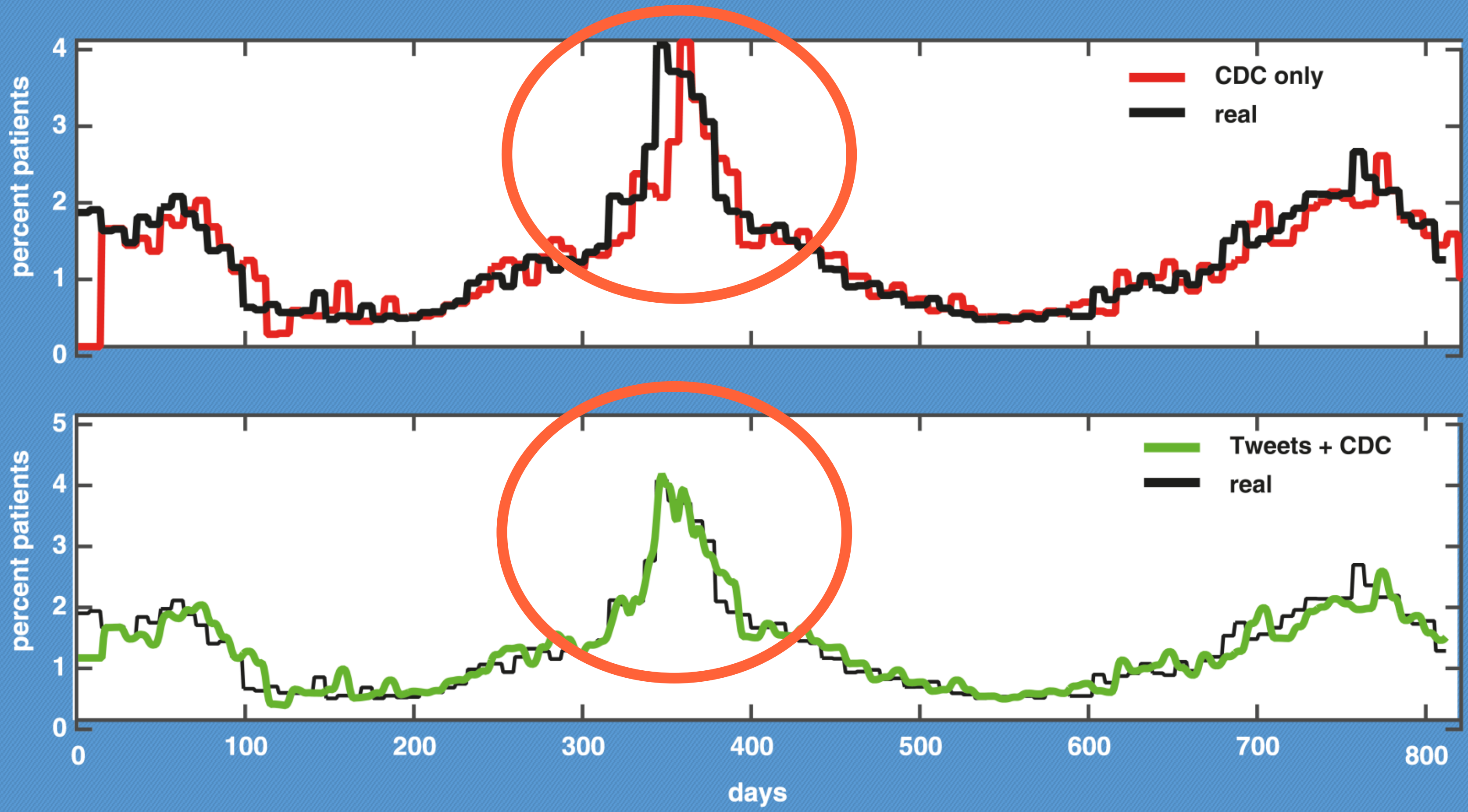
Performance – One Region USA



Why Cognitive Computing?

flu prediction

- Influenza matters
- Prediction is important
- Delayed and too few data
- Data science methods
- Social media analysis
- Watson as medical expert
- Better prediction
- Fully informed user

Why Cognitive Computing?

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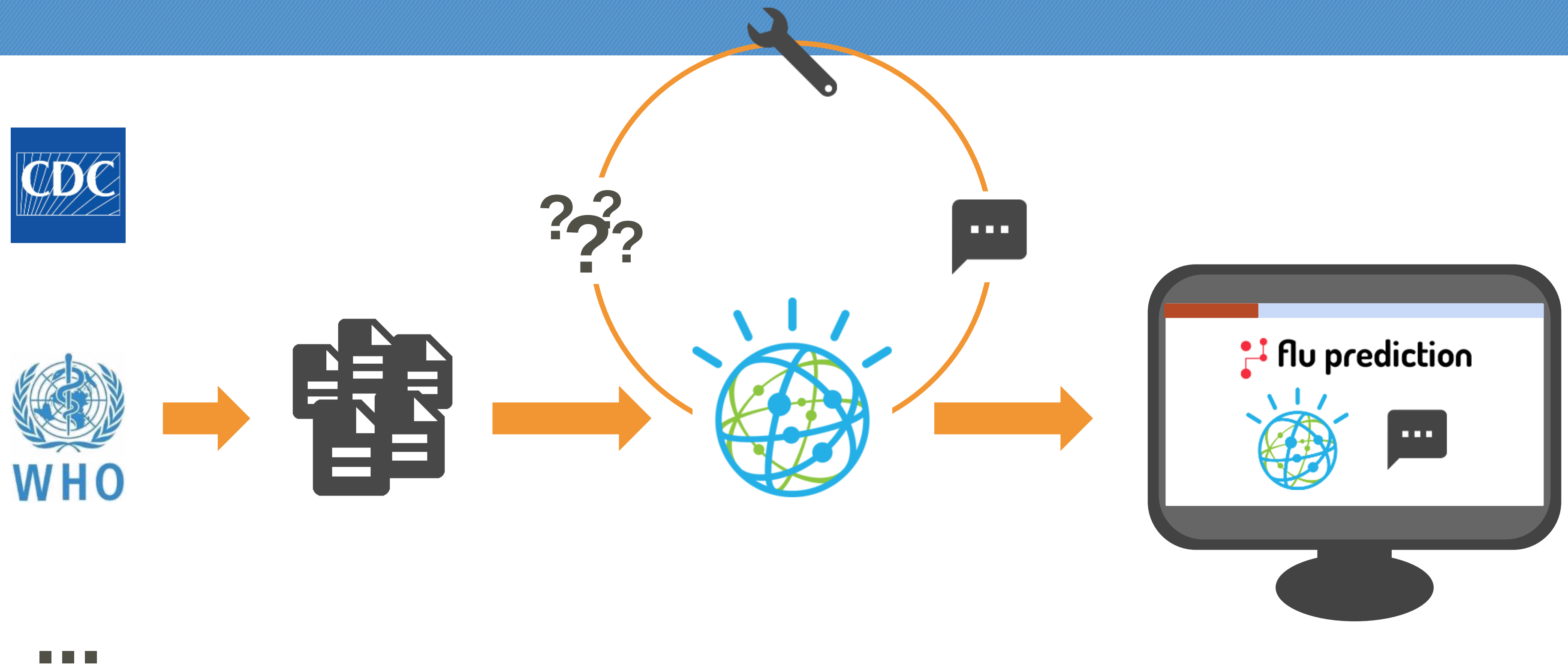
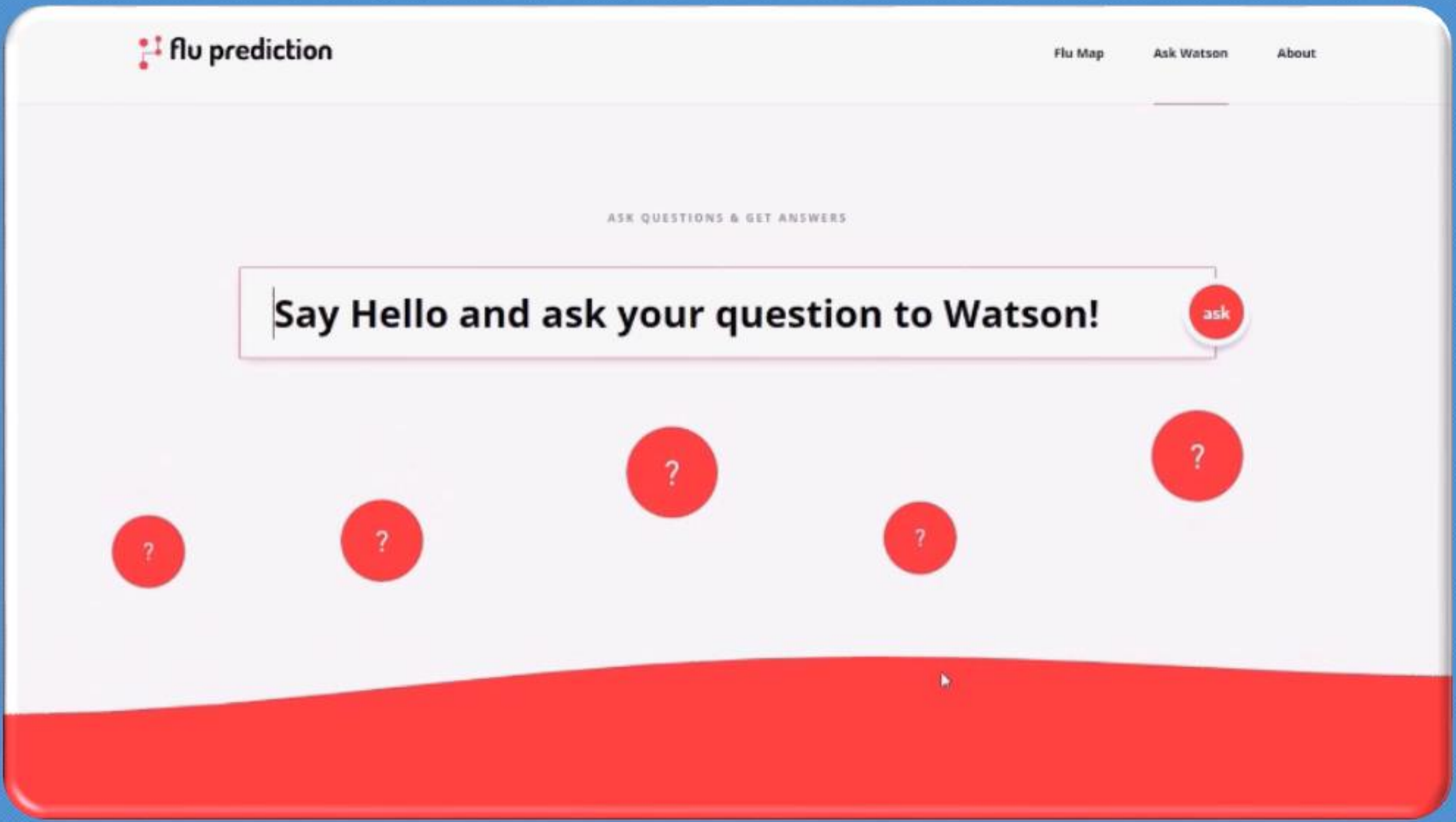


Speak with Watson Flu



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Summary

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Data science methods

- Data science allows identification of very complex causal relations
- Efficient use of BLUE Mix and Watson services

Social media analysis

- Combine social media with other conventional data to get the best of both worlds → realtime and reliable

Watson as expert

- Use large corpora to identify structure and relationships in your problem
- Use natural language interface for easy to use HCI

Try It Yourself **www.flu-prediction.com**

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Prof. Dr. Dr. Scheller
University Hospital
Frankfurt

Study Projcet - Pepper TA

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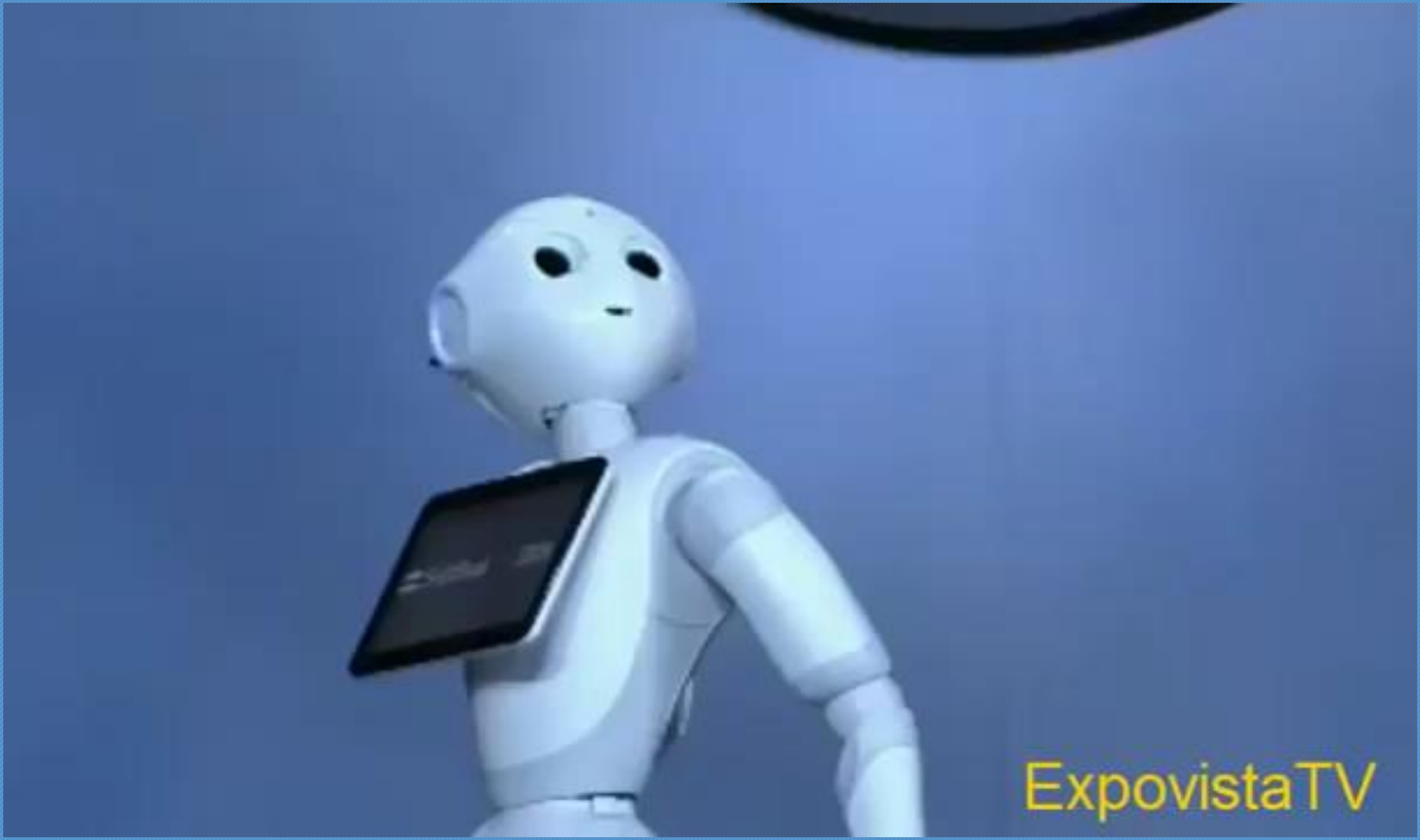

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Building skills for a smarter planet

AMAZONE

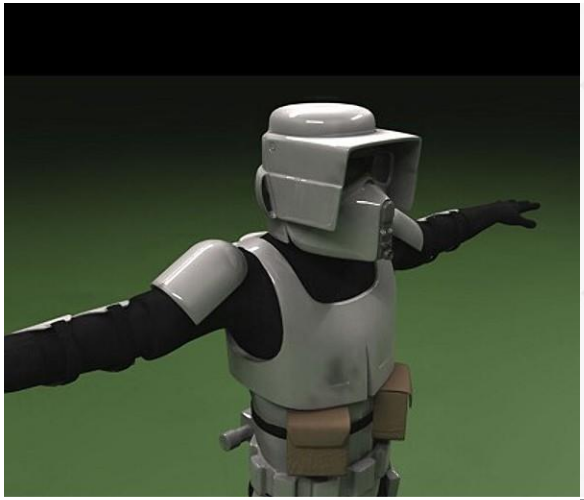
Our Lab

4W

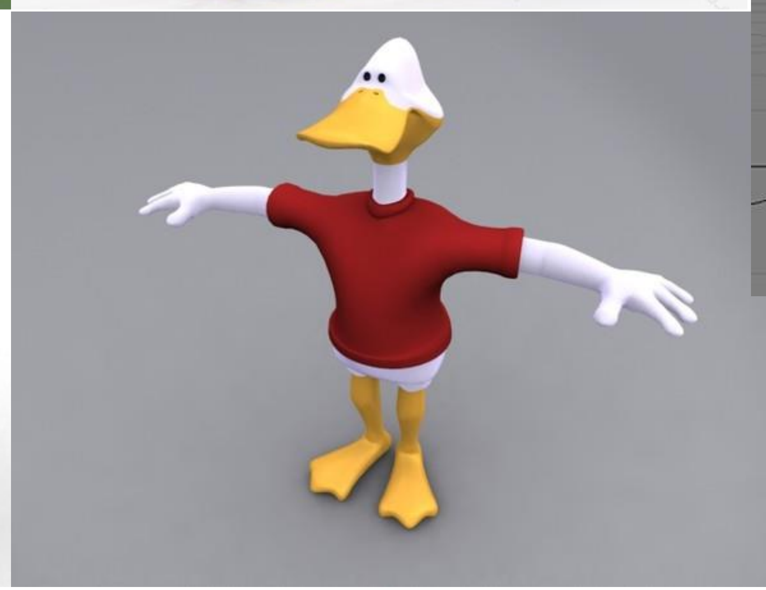
- HMD with see through option for argumented reality
- Optical and inertia tracking
- Live Characters
- Eye tracking integrated in the HMD

4W

Free Databases for 3D models: http://custom-3d.turbosquid.com/





4W

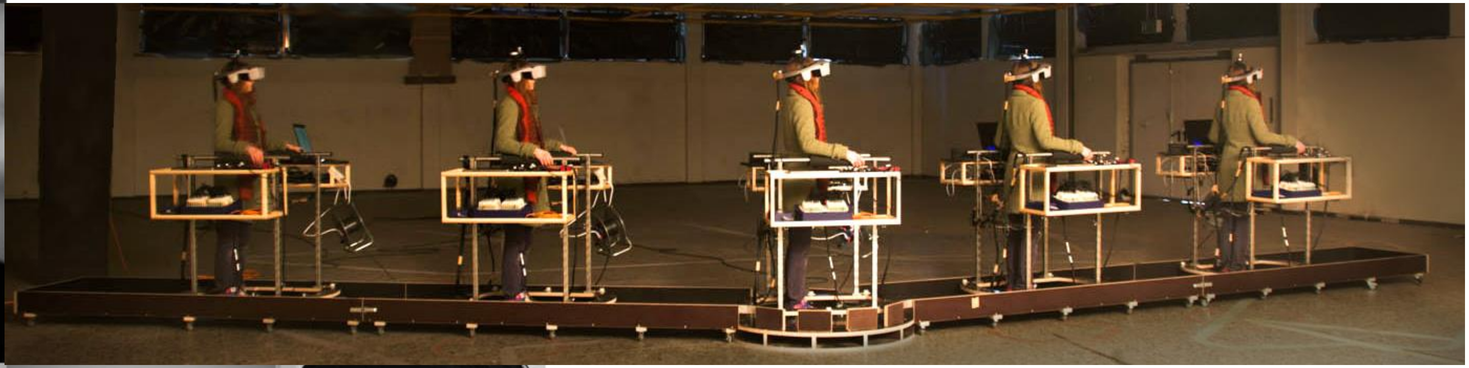

Virtual Reality Lab
Example Workflow
AG Neuroinformatik
Universität Osnabrück


move

Mobile EEG in Virtual Environments

P. Fischer, B. Ehinger, A. Gert, L. Kaufhold
F. Weber, M. Marchante Fernandez






By Felix Breuniger and Gordon Pipa (The Ultimate Game in VR - neuroeconomics)