Personalized Health with Gaussian Processes

Neil D. Lawrence

University of Sheffield

19th August 2015

What is Machine Learning?

data

- data: observations, could be actively or passively acquired (meta-data).

What is Machine Learning?

data +

- data: observations, could be actively or passively acquired (meta-data).

What is Machine Learning?

data + model

- data: observations, could be actively or passively acquired (meta-data).
- model: assumptions, based on previous experience (other data! transfer learning etc), or beliefs about the regularities of the universe. Inductive bias.

What is Machine Learning?

data + model =

- data: observations, could be actively or passively acquired (meta-data).
- model: assumptions, based on previous experience (other data! transfer learning etc), or beliefs about the regularities of the universe. Inductive bias.

What is Machine Learning?

$$\text{data} \quad + \quad \text{model} \quad = \quad \text{prediction}$$

- data: observations, could be actively or passively acquired (meta-data).
- model: assumptions, based on previous experience (other data! transfer learning etc), or beliefs about the regularities of the universe. Inductive bias.
- prediction: an action to be taken or a categorization or a quality score.

What's Changed (Changing) for Medical Data?

- Try Googling for: "patient data "...

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Driver and Vehicle Licensing Agency

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A brief history *of Registration*

For more information go to: **www.direct.gov.uk/motoring**

A brief history of registration

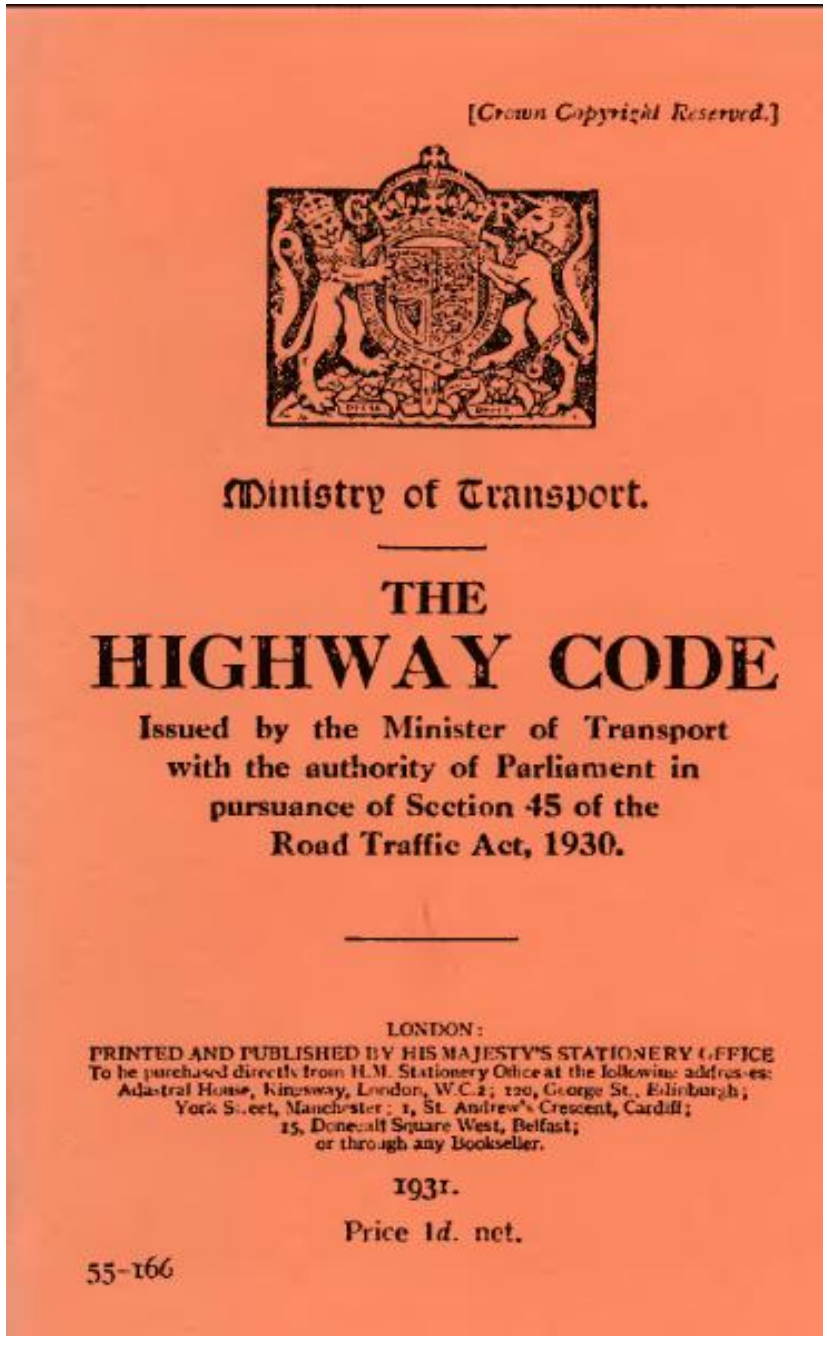
The early days

Prior to the appearance of the first railways in Britain, there was a brief development and interest in steam powered road going vehicles. In 1834, a Mr Hancock started a steam coach called the "Era", carrying up to 14 passengers from Paddington to Regents Park and the City at 6d a head. And in the following year, a Mr Church built an omnibus capable of carrying 40 passengers for the London and Birmingham Steam Carriage Company.

However, the success of the railway movement drove all such traffic off the roads.
A Parliamentary Commission of Enquiry in 1836 reported "strongly in favour of steam carriages on roads", but subsequent Acts of Parliament tended to have a discouraging and restrictive effect. **The Locomotive Act 1861** limited the weight of steam engines to 12 tons and imposed a speed limit of 10 mph.

The Locomotive Act 1865 set a speed limit of 4 mph in the country and 2 mph in towns. The 1865 Act also provided for the famous "man with a red flag". Walking 60 yards ahead of each vehicle, a man with a red flag or lantern enforced a walking pace, and warned horse riders and horse drawn traffic of the approach of a self propelled machine.

The Locomotive Amendment Act 1878 made the red flag optional under local regulations, and



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What are the Issues?

- Who owns our data?
- Is it ‘finders keepers’?
- Does ownership proliferate?
- What does data protection offer?
- Who has the right to share our data?
- Can we withdraw this right?

Moral Panics: Perhaps Rightly

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Cyclists look at a Ferrari parked illegally and blocking the bicycle lane off a main road in Beijing, on April 7, 2011.

Frederic J. Brown/AFP/Getty Images

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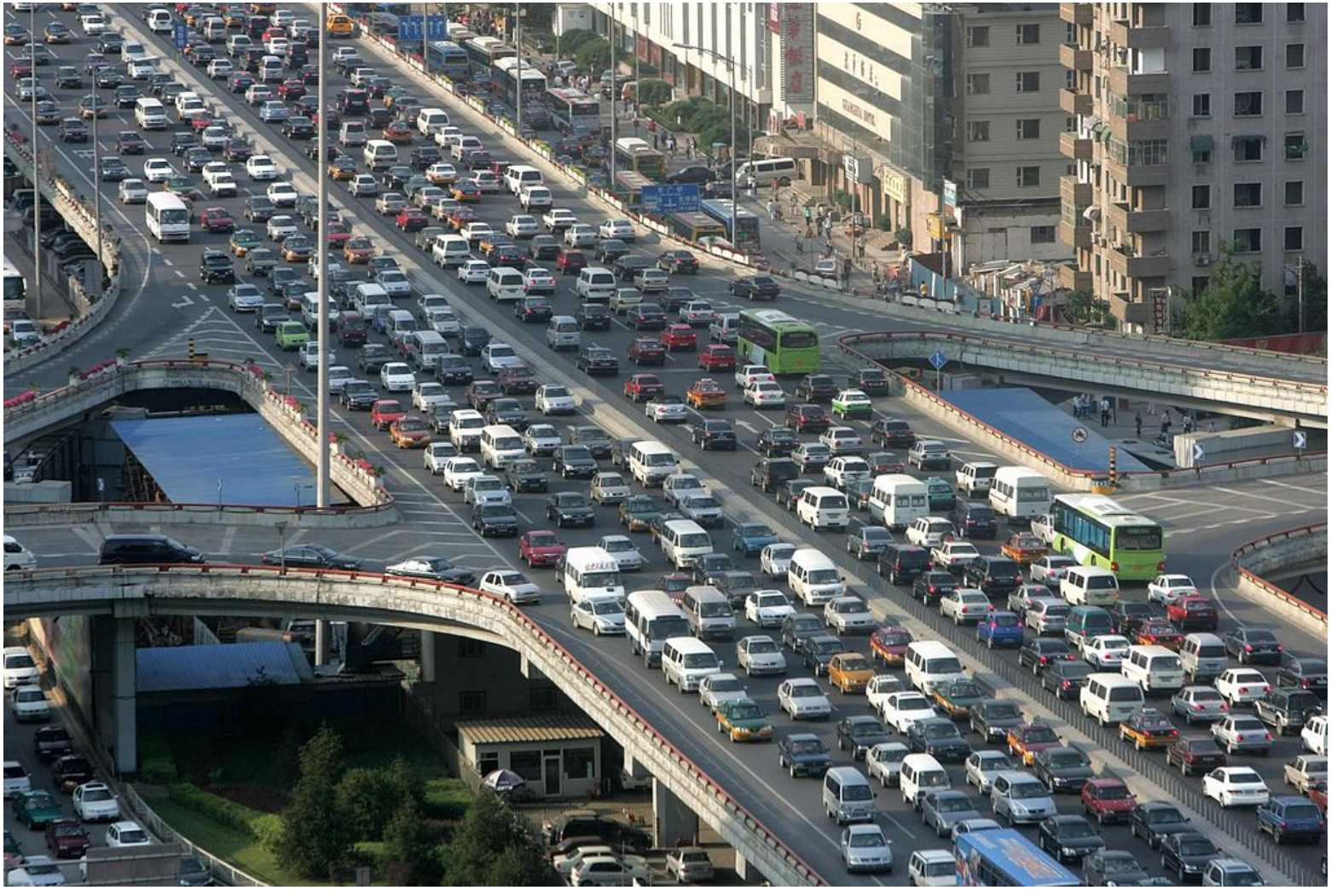
Before it became China's capital in 1949, Beijing was a fairly provincial little city of 2 million people.



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What's Changed (Changing) for Medical Data?

- Genotyping.
- Epigenotyping.
- Transcriptome: detailed characterization of phenotype.
  - Stratification of patients.
- Massive unstructured data sources.

Open Data

- Automatic data curation: from curated data to curation of publicly available data.
- Open Data: http://www.openstreetmap.org/?lat=53.38086&lon=-1.48545&zoom=17&layers=M.

Open Data

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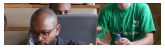
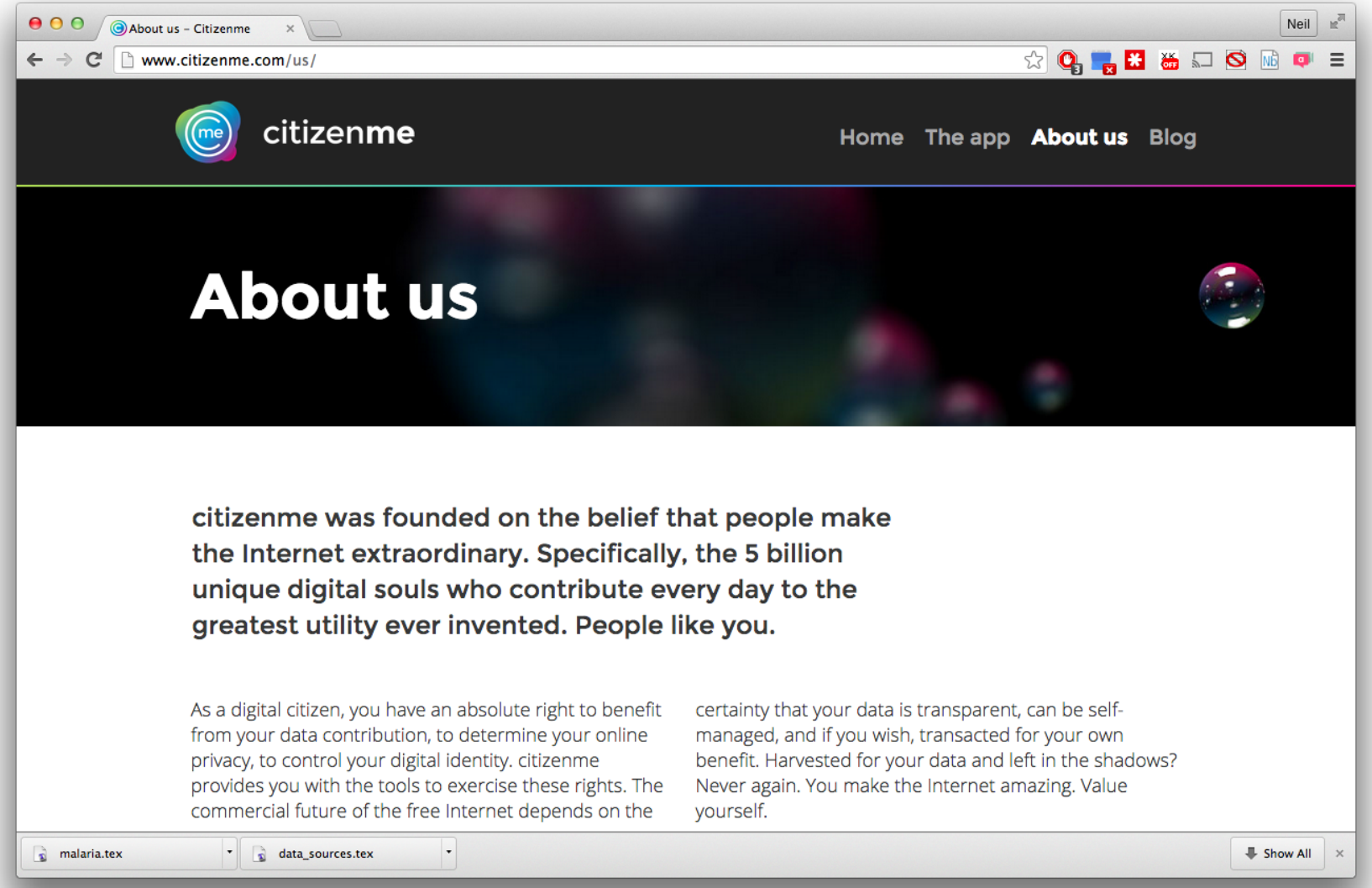
- Open Data: http://www.openstreetmap.org/?lat=53.38086&lon=-1.48545&zoom=17&layers=M.

- Social network data, music information (Spotify), exercise.



Why Africa?

- Short circuit the process.
  - For UK—infrastructure paralysis.
  - For Africa—potential for distributed architectures.
  - User-centric models of data management.
- Store personal data on mobile phone within control of individual.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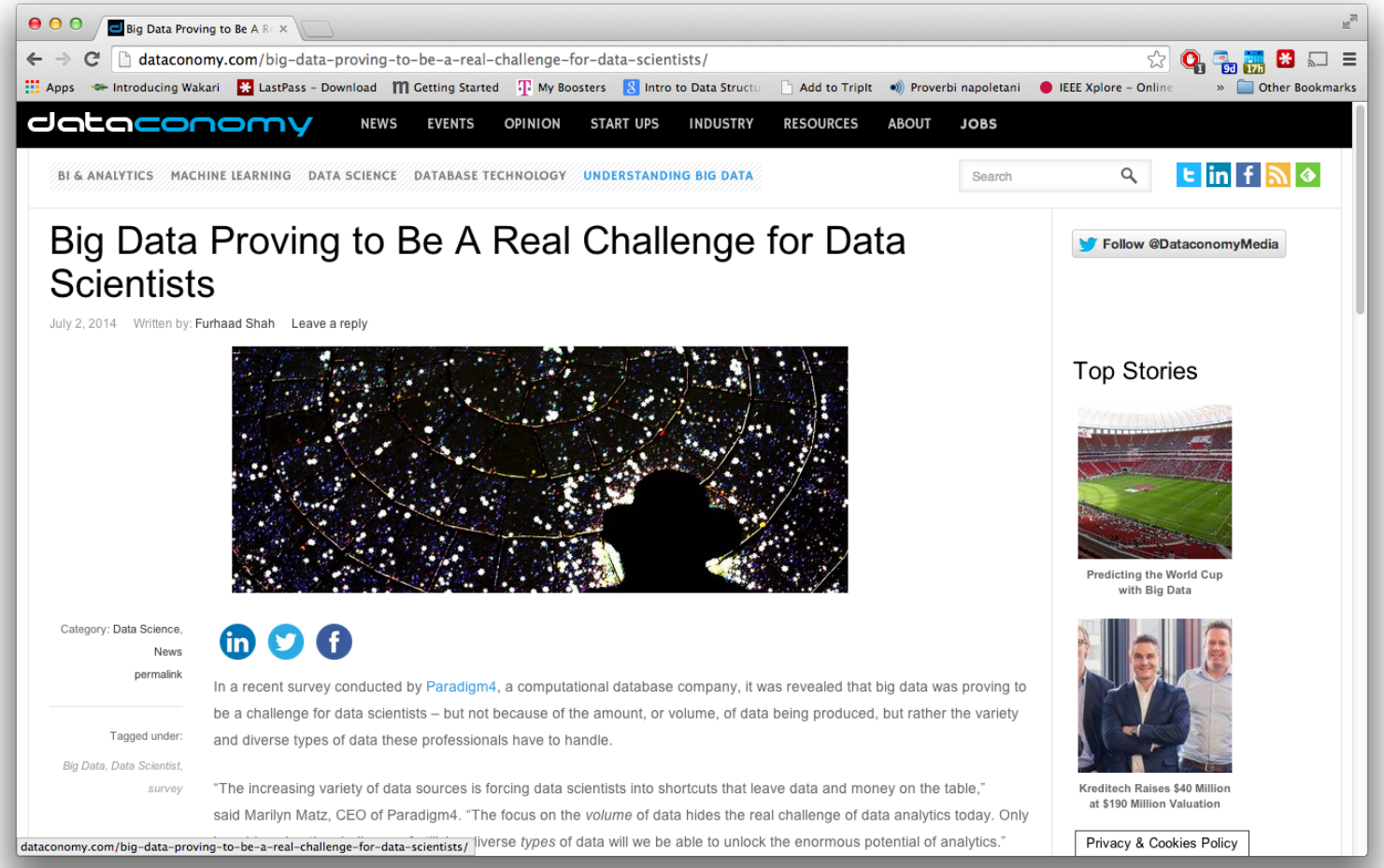
Outline

Diversity of Data

Massively Missing Data

Not the Scale it's the Diversity



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Scientists See Promise in Deep-Learning Programs

Hao Zhang/The New York Times

A voice recognition program translated a speech given by Richard F. Rashid, Microsoft's top scientist, into Mandarin Chinese.

By JOHN MARKOFF
Published: November 23, 2012

Using an artificial intelligence technique inspired by theories about how the brain recognizes patterns, technology companies are reporting startling gains in fields as diverse as computer vision, speech recognition and the identification of promising new molecules for designing drugs.

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The advances have led to widespread enthusiasm among researchers who design software to perform human

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NOVEMBER 25, 2012

IS "DEEP LEARNING" A REVOLUTION IN ARTIFICIAL INTELLIGENCE?

POSTED BY GARY MARCUS

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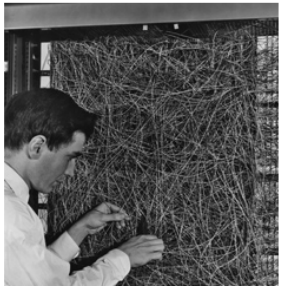

Can a new technique known as deep learning revolutionize artificial intelligence, as yesterday's front-page article at the New York *Times* suggests? There is good reason to be excited about deep learning, a sophisticated "machine learning" algorithm that far exceeds many of its predecessors in its abilities to recognize syllables and images. But there's also good reason to be skeptical. While the *Times* reports that "advances in an artificial intelligence technology that can recognize patterns

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Google To Expand Knowledge Graph Through Hire Of Geoffrey Hinton

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Mar 14, 2013 • 8:23 am | (10)
by Barry Schwartz | Filed Under Google Search Engine

If I had to place one search priority above all else, I'd say right now, Google's most ambitious project is the knowledge graph. Yea, they are pushing Google+ big time, but the knowledge graph is a level above all of that technically.

Of course, Google has an outstanding team working on this project lead by one of the smartest people I've ever met Amit Singhal.

To take the knowledge graph to the next level, Google has hired/acquired Geoffrey Hinton and his team at DNNresearch. Geoffrey posted a note on his Google+ page about it:

> Last summer, I spent several months working with Google's Knowledge team in Mountain View, working with Jeff Dean and an incredible group of scientists and engineers who have a real shot at making spectacular progress in machine learning. Together with two of my recent graduate students, Ilya Sutskever and Alex Krizhevsky (who won the 2012 ImageNet competition), I am betting on Google's team to be the epicenter of future breakthroughs. That means we'll soon be joining Google to work with some of the smartest engineering minds to tackle some of the biggest challenges in computer science. I'll remain part-time at the University of Toronto, where I still have a lot of excellent graduate students, but at Google I will get to see what we can do with very large-scale computation.

I know we just scratched the surface of the knowledge graph and I am excited to see where it takes us in the future.

I am just glad I don't have to figure out how to get us there. I get to just sit and enjoy the ride.

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BY ROBERT MCMILLAN 03.13.13 6:30 AM

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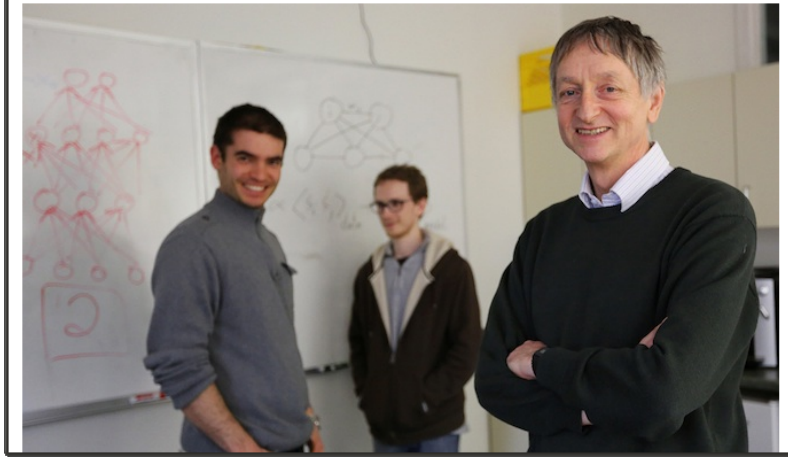

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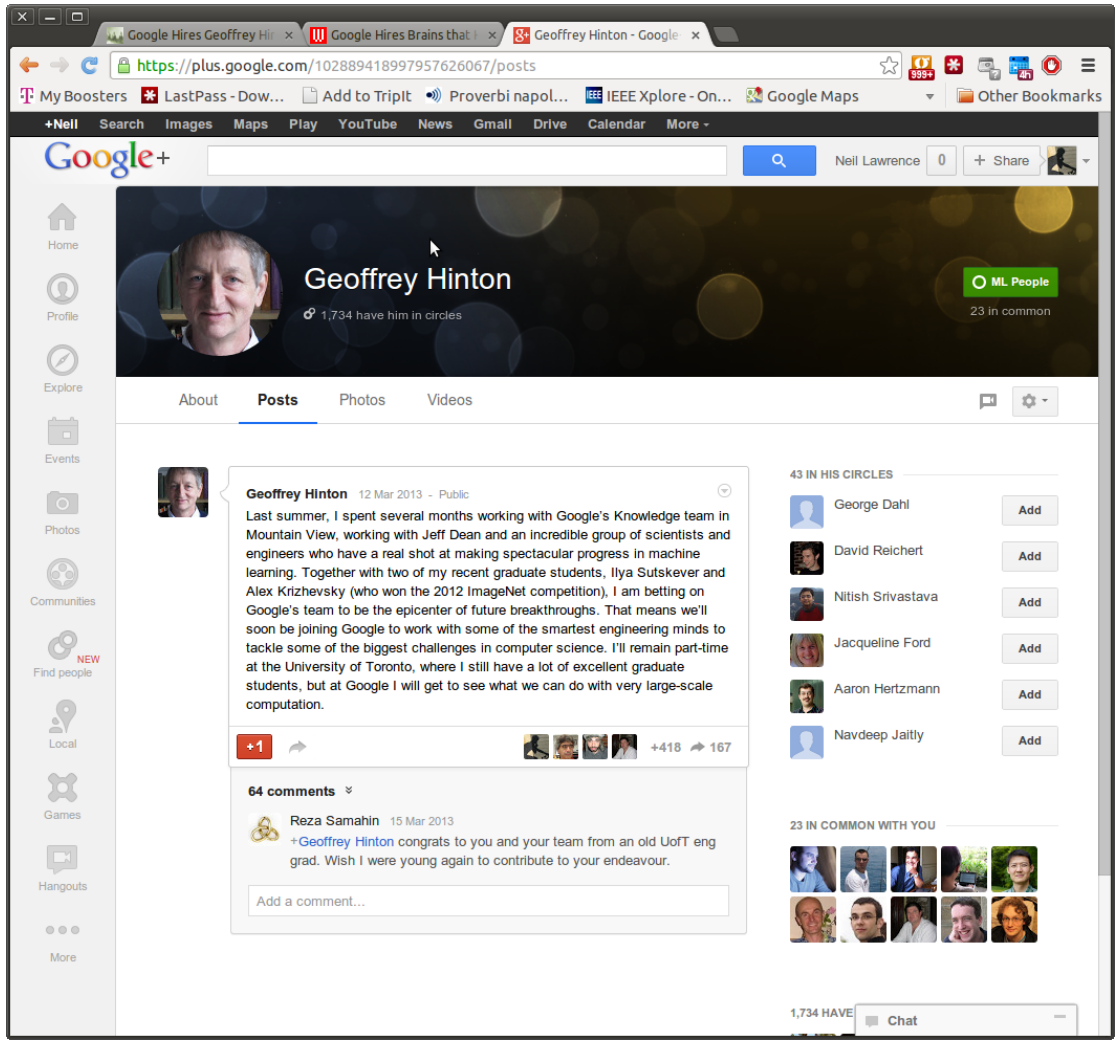
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Last summer, I spent several months working with Google's Knowledge team in Mountain View, working with Jeff Dean and an incredible group of scientists and engineers who have a real shot at making spectacular progress in machine learning. Together with two of my recent graduate students, Ilya Sutskever and Alex Krizhevsky (who won the 2012 ImageNet competition), I am betting on Google's team to be the epicenter of future breakthroughs. That means we'll soon be joining Google to work with some of the smartest engineering minds to tackle some of the biggest challenges in computer science. I'll remain part-time at the University of Toronto, where I still have a lot of excellent graduate students, but at Google I will get to see what we can do with very large-scale computation.
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+Geoffrey Hinton congrats to you and your team from an old UofT eng grad. Wish I were young again to contribute to your endeavour.
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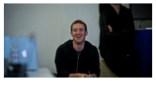

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12 December 2013, 2.41pm GMT

Are you an expert in machine learning? Facebook is hiring

AUTHOR

Neil Lawrence
Professor of Machine Learning and Computational Biology at University of Sheffield

DISCLOSURE STATEMENT

Neil Lawrence does not work for, consult to, own shares in or receive funding from any company or organisation that would benefit from this article, and has no relevant affiliations.

Do you know anything about machine learning? newyork

The University Of Sheffield.

"Move fast and break things." That is the Facebook motto plastered all over their California headquarters to remind engineers never to stop innovating. This week, the company

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AI ‘cheating’ scandal makes machine learning sound like a sport – it isn’t

June 12, 2015 5.31am BST

Author

Neil Lawrence
Professor of Machine Learning at University of Sheffield

Disclosure statement

Neil Lawrence does not work for, consult, own shares in or receive funding from any company or organization that would benefit from this article, and has disclosed no relevant affiliations

Emmulated Intelligence

- There is a common thread to the applications that are 'falling over' in the face of deep learning.
- Massive data, massive compute 'perceptual' tasks.
- We are merely building algorithms that *emmulate* human intelligence.
- This gives a misleading impressing of achieving intelligence.

Outline

Diversity of Data

Massively Missing Data

Massive Missing Data

- If missing at random it can be marginalized.
- As data sets become very large (39 million in EMIS) data becomes extremely sparse.
- Imputation becomes impractical.

Imputation

- Expectation Maximization (EM) is gold standard imputation algorithm.
- Exact EM optimizes the log likelihood.
- Approximate EM optimizes a lower bound on log likelihood.
  - e.g. variational approximations (VIBES, Infer.net).
- Convergence is *guaranteed* to a local maxima in log likelihood.

Expectation Maximization

Require: An initial guess for missing data

Expectation Maximization

Require: An initial guess for missing data
repeat

Expectation Maximization

Require: An initial guess for missing data
  repeat
    Update model parameters (M-step)

Expectation Maximization

Require: An initial guess for missing data
  repeat
    Update model parameters (M-step)
    Update guess of missing data (E-step)

Expectation Maximization

Require: An initial guess for missing data
  repeat
    Update model parameters (M-step)
    Update guess of missing data (E-step)
  until convergence

Imputation is Impractical

- In very sparse data imputation is impractical.
- EMIS: 39 million patients, thousands of tests.
- For most people, most tests are missing.
- M-step becomes confused by poor imputation.

Direct Marginalization is the Answer

- Perhaps we need joint distribution of two test outcomes,

$$p(y_1, y_2)$$

- Obtained through marginalizing over all missing data,

$$p(y_1, y_2) = \int p(y_1, y_2, y_3, \ldots, y_p) \mathrm{d}y_3, \ldots \mathrm{d}y_p$$

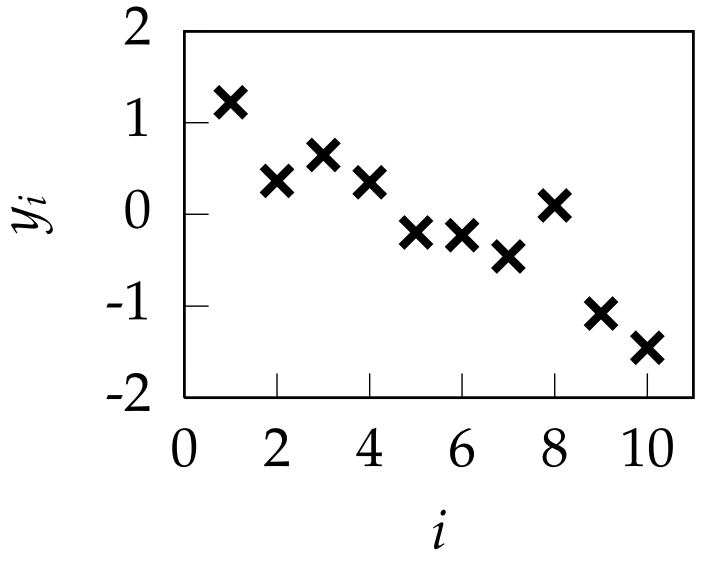
- Where $y_3, \ldots, y_p$ contains:
  1. all tests not applied to this patient
  2. all tests not yet invented!!

Magical Marginalization in Gaussians

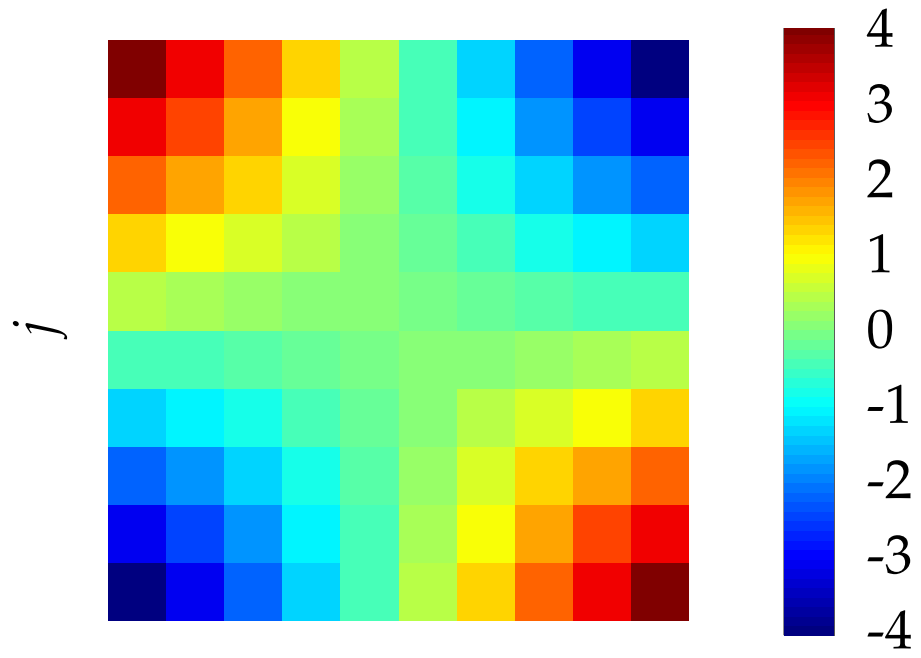
Multi-variate Gaussians

- Given 10 dimensional multivariate Gaussian, $\mathbf{y} \sim \mathcal{N}(\mathbf{0}, \mathbf{C})$.
- Generate a single correlated sample $\mathbf{y} = [y_1, y_2 \dots y_{10}]$.
- How do we find the marginal distribution of y_1, y_2?

Gaussian Marginalization Property



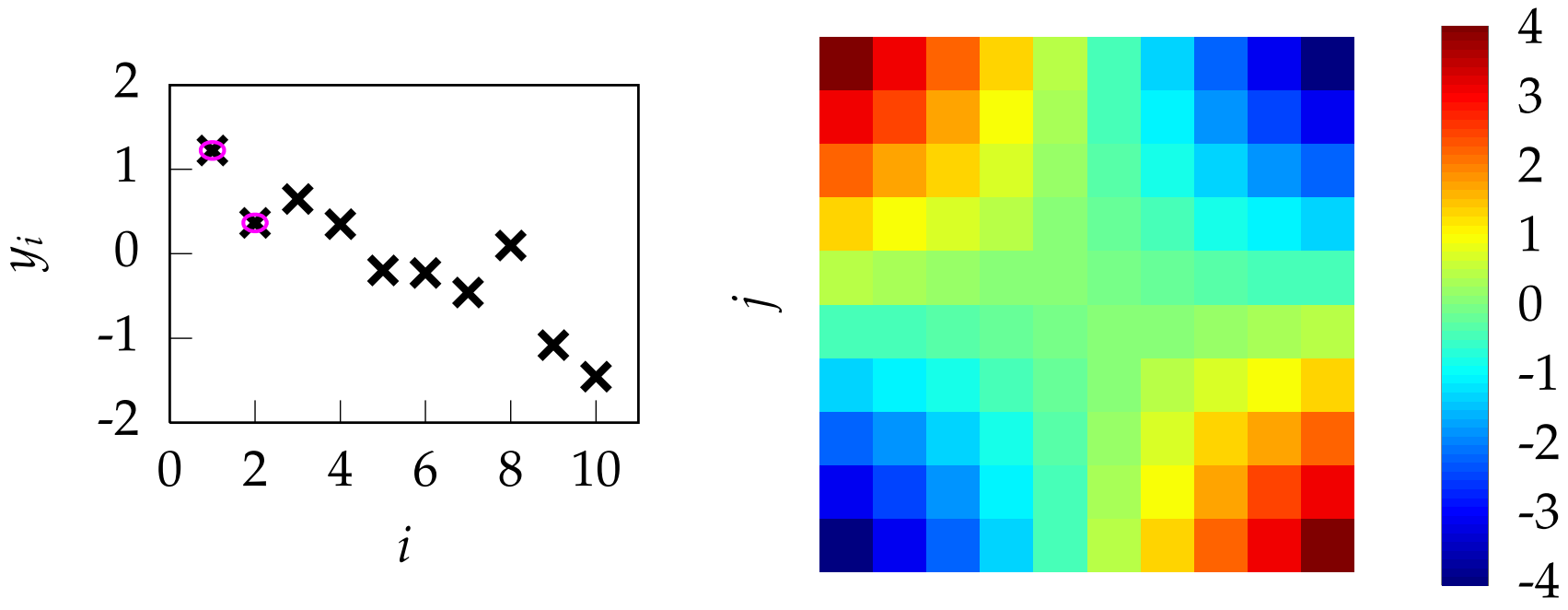
(a) A 10 dimensional sample



(b) colormap showing covariance between dimensions.

Figure: A sample from a 10 dimensional correlated Gaussian distribution.

Gaussian Marginalization Property



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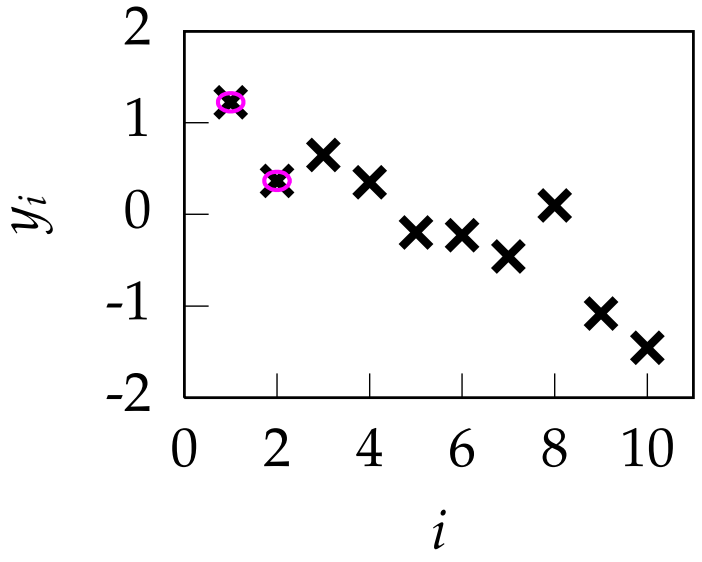

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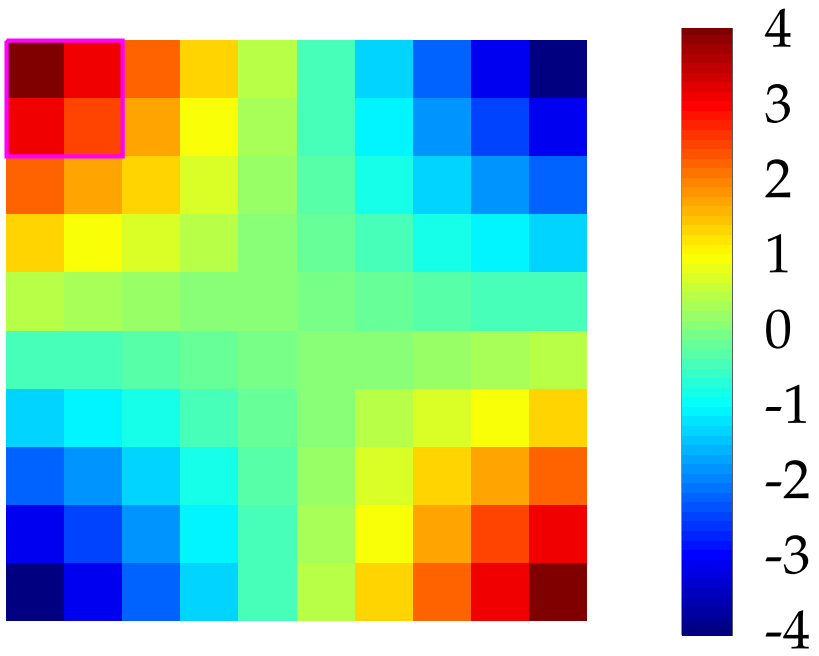

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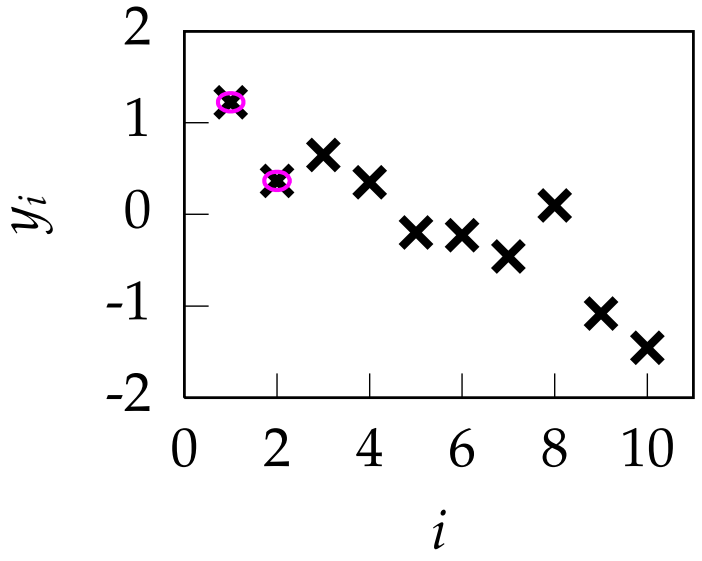

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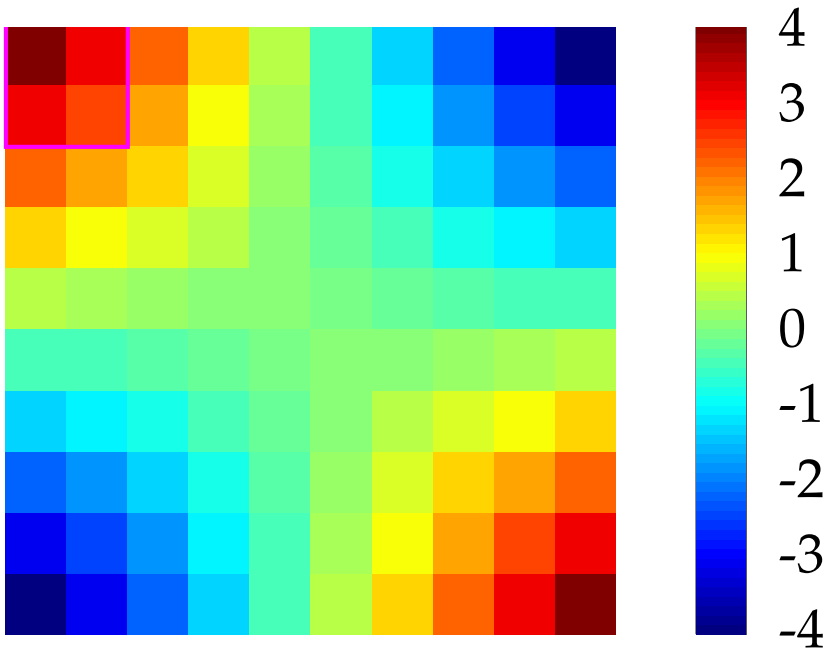

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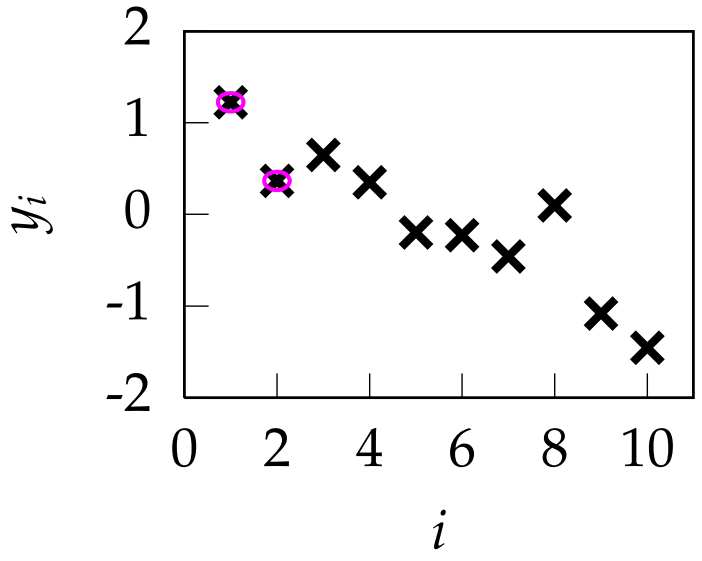
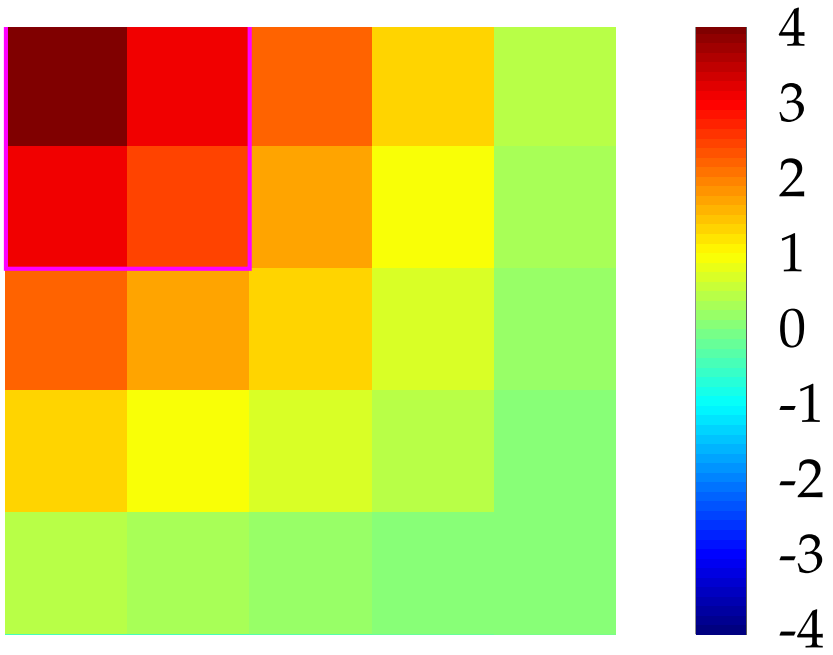


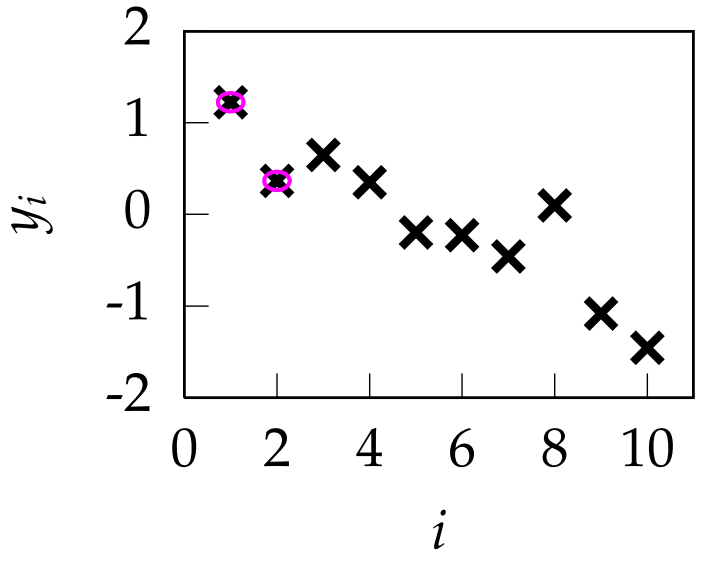
(a) A 10 dimensional sample



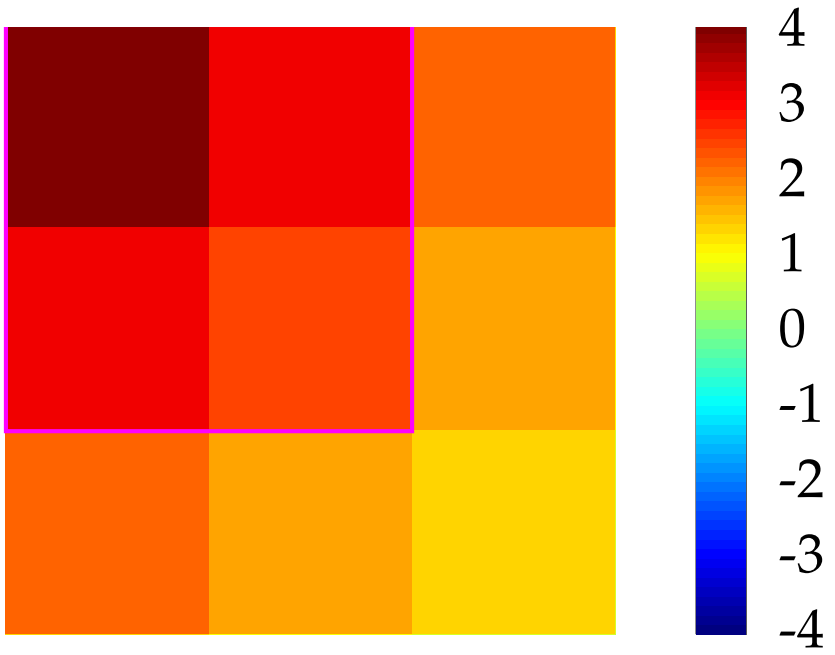
(b) colormap showing covariance between dimensions.

Figure: A sample from a 10 dimensional correlated Gaussian distribution.

Gaussian Marginalization Property



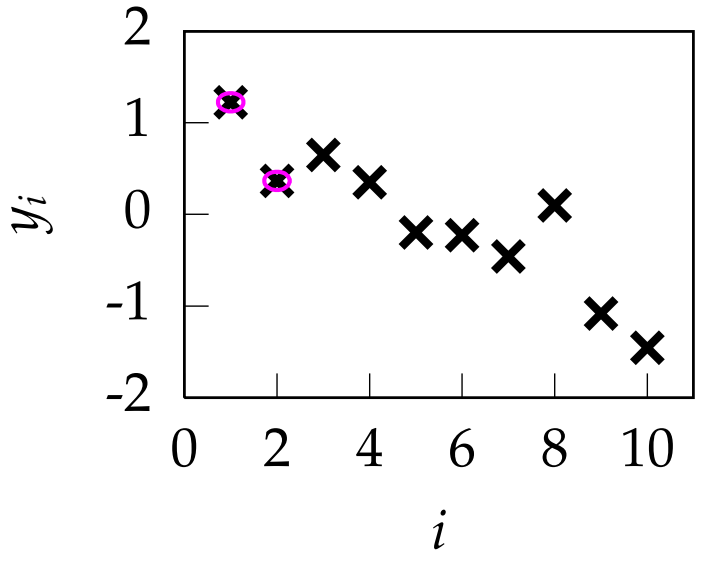
(a) A 10 dimensional sample



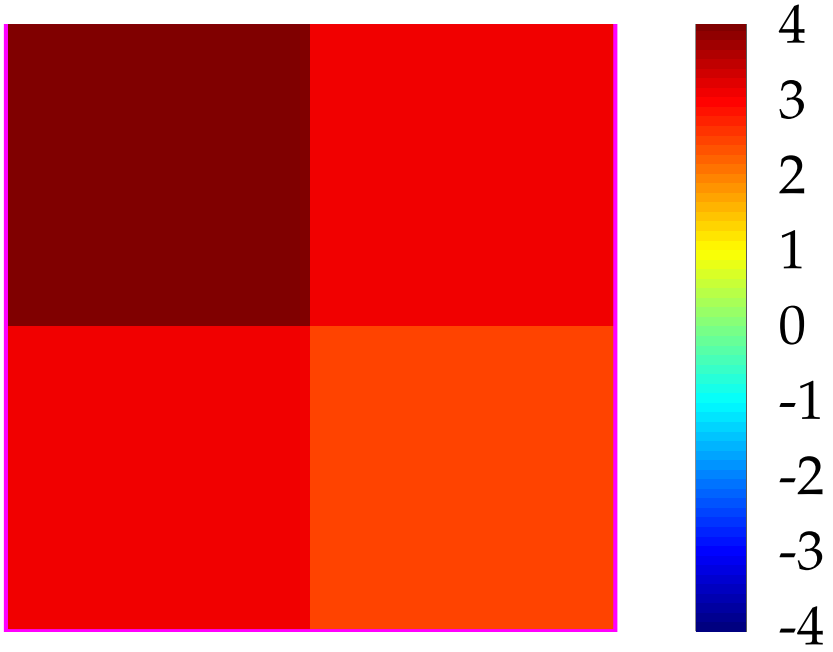
(b) colormap showing covariance between dimensions.

Figure: A sample from a 10 dimensional correlated Gaussian distribution.

Gaussian Marginalization Property



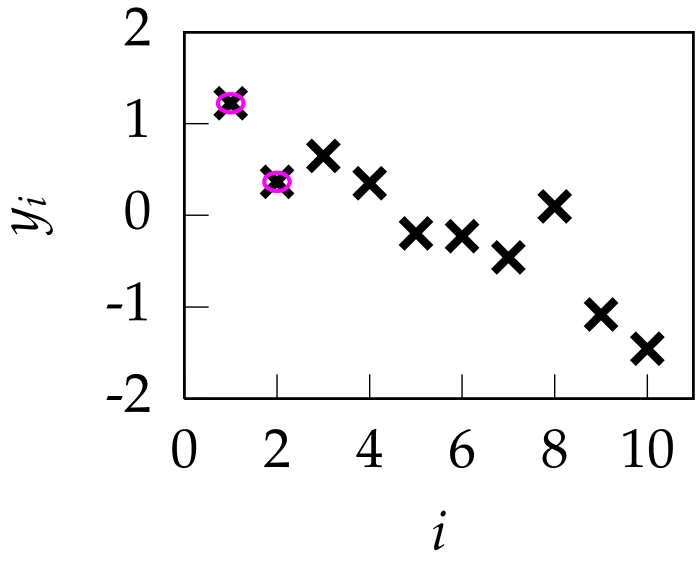
(a) A 10 dimensional sample



(b) colormap showing covariance between dimensions.

Figure: A sample from a 10 dimensional correlated Gaussian distribution.

Gaussian Marginalization Property



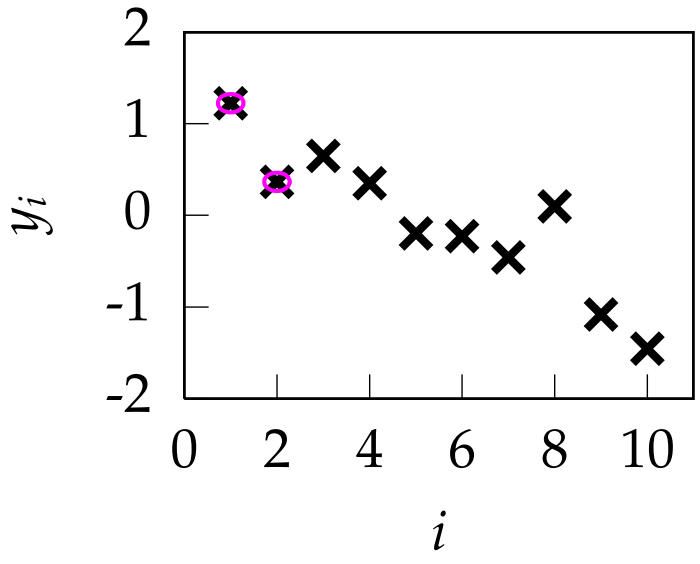
(a) A 10 dimensional sample

$$\begin{bmatrix} 4.1 & 3.1111 \\ 3.1111 & 2.5198 \end{bmatrix}$$

(b) covariance between y_1 and y_2.

Figure: A sample from a 10 dimensional correlated Gaussian distribution.

Gaussian Marginalization Property



(a) A 10 dimensional sample

$$\begin{bmatrix} 1 & 0.96793 \\ 0.96793 & 1 \end{bmatrix}$$

(b) correlation between y_1 and y_2.

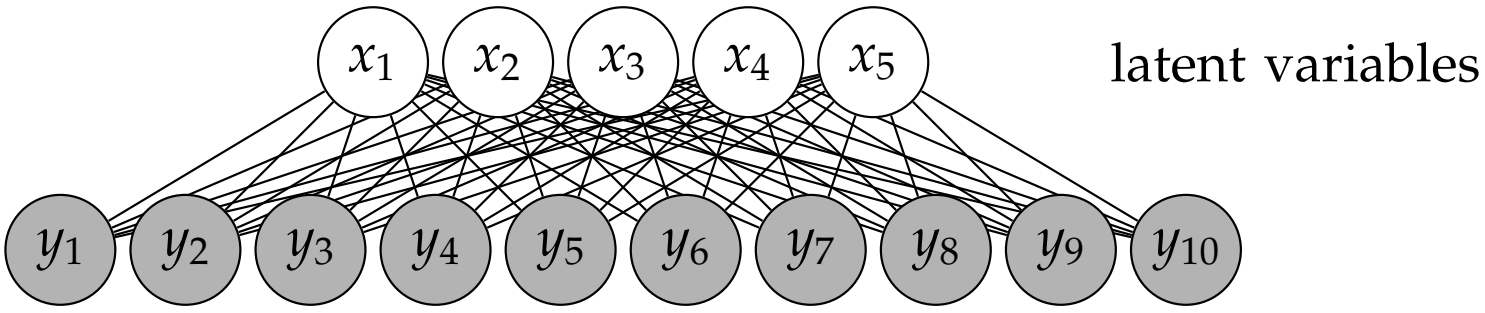
Figure: A sample from a 10 dimensional correlated Gaussian distribution.

Avoid Imputation: Marginalize Directly

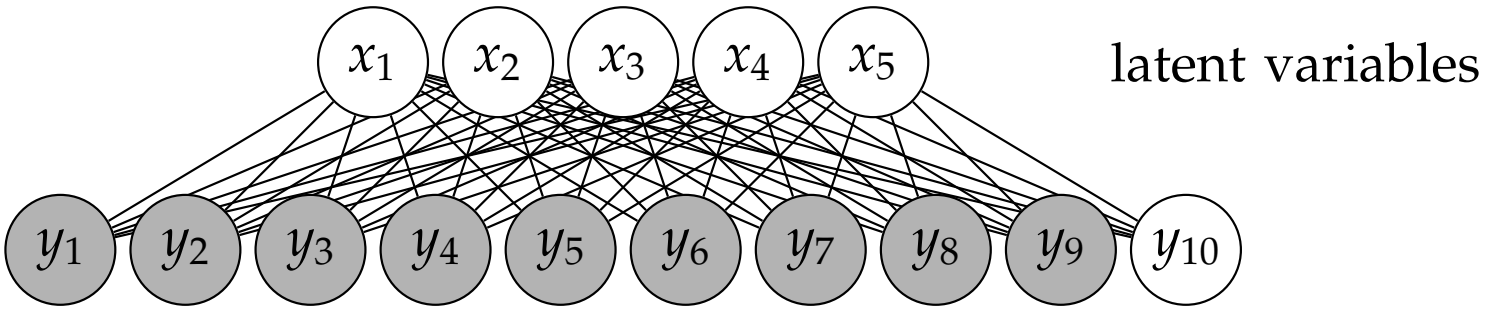
- Our approach: Avoid Imputation, Marginalize Directly.
- Explored in context of Collaborative Filtering.
- Similar challenges:
  - many users (patients),
  - many items (tests),
  - sparse data
- Implicitly marginalizes over all future tests too.

Work with Raquel Urtasun (Lawrence and Urtasun, 2009) and ongoing work with Max Zwießele and Nicoló Fusi.

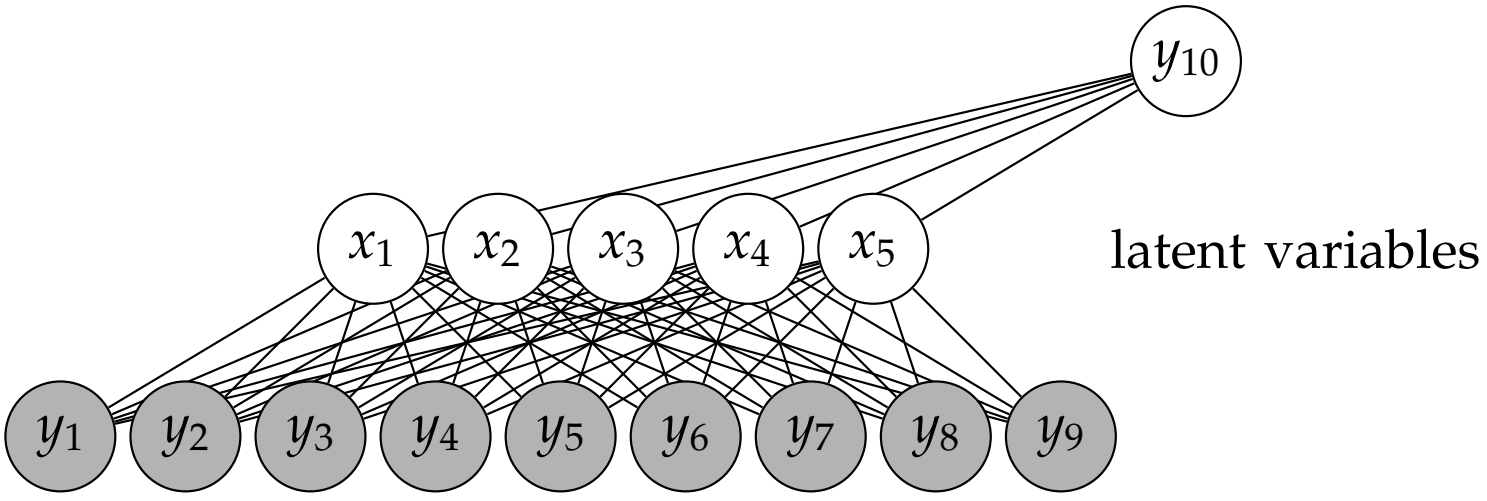
Marginalization in Bipartite Undirected Graph



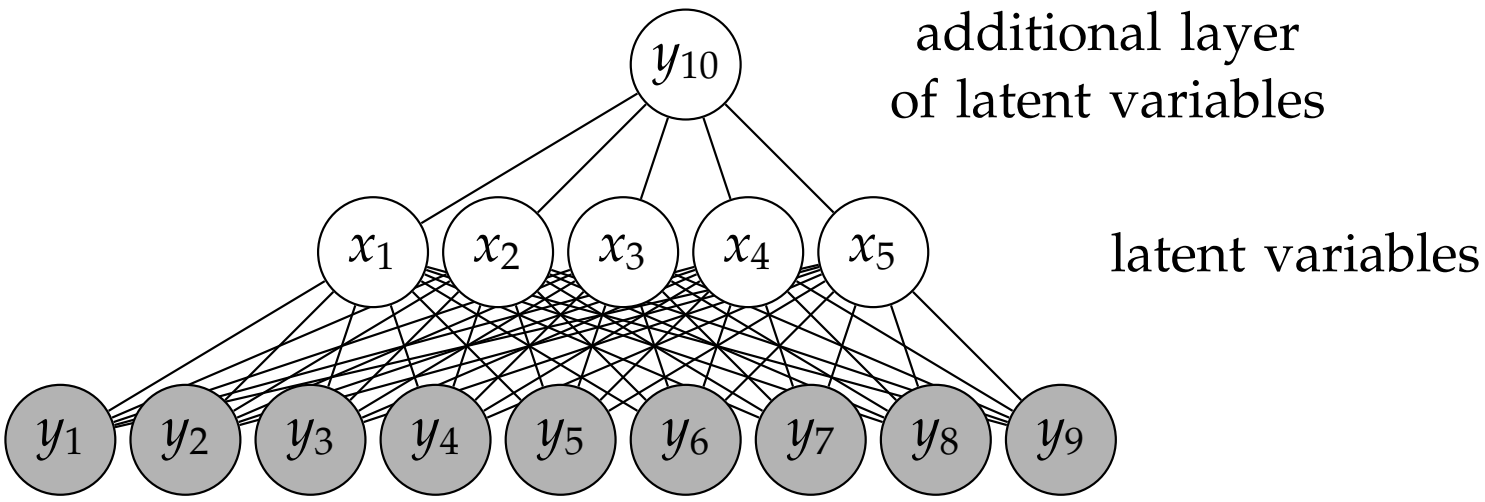
Marginalization in Bipartite Undirected Graph



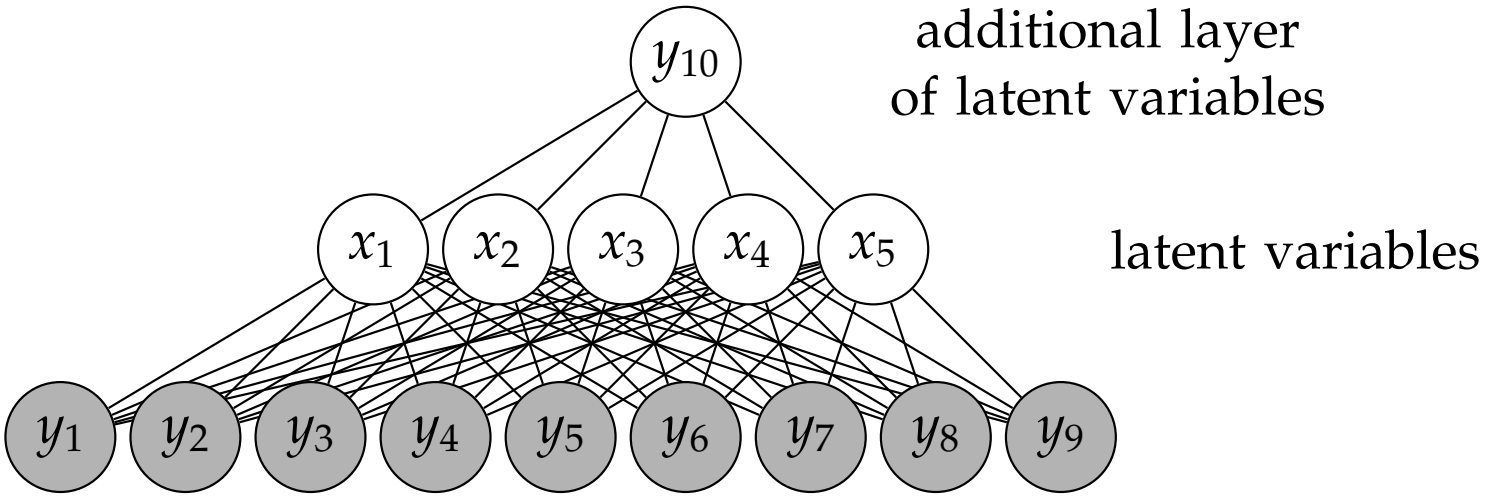
Marginalization in Bipartite Undirected Graph



Marginalization in Bipartite Undirected Graph



Marginalization in Bipartite Undirected Graph



For *massive missing data,* how many additional latent variables?

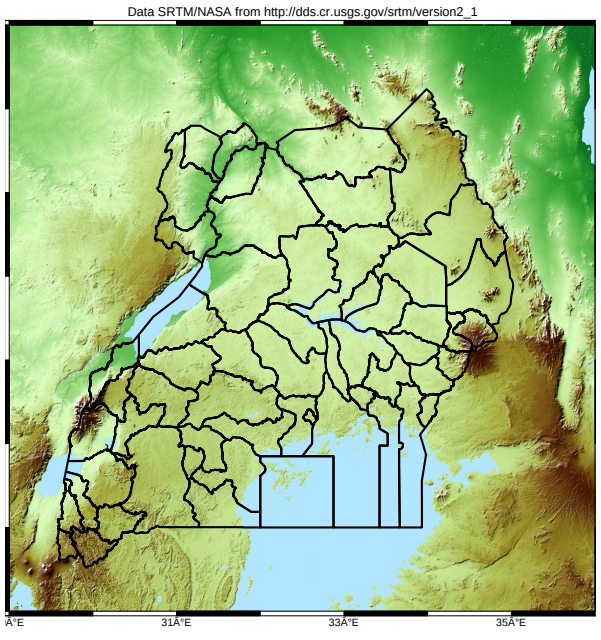
Methods that Interrelate Covariates

- Need Class of models that interrelates data, but allows for variable p.
- Common assumption: high dimensional data lies on low dimensional manifold.
- Want to retain the marginalization property of Gaussians but deal with non-Gaussian data!

Example: Prediction of Malaria Incidence in Uganda

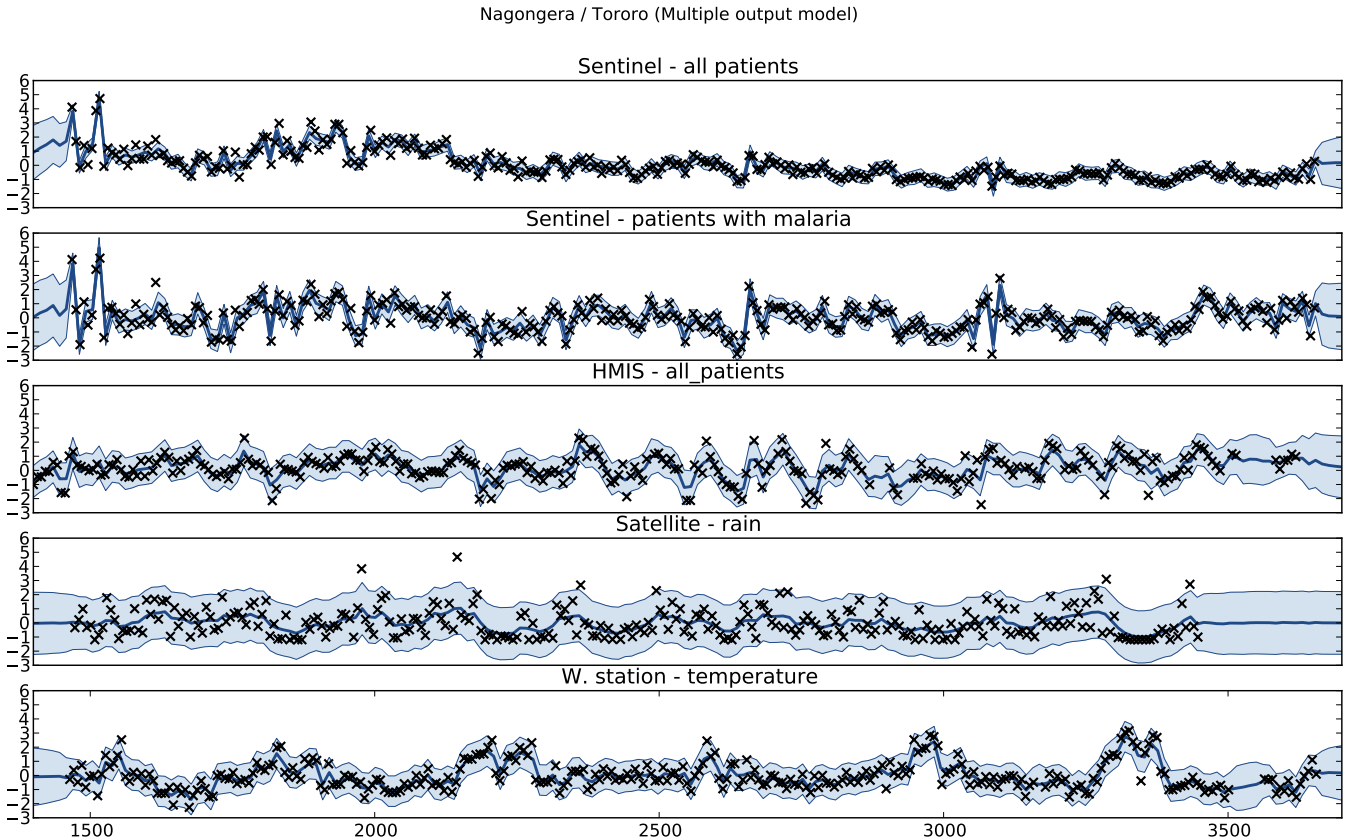
- Work with John Quinn and Martin Mubaganzi (Makerere University, Uganda)
- See http://air.ug/research.html.

Malaria Prediction in Uganda

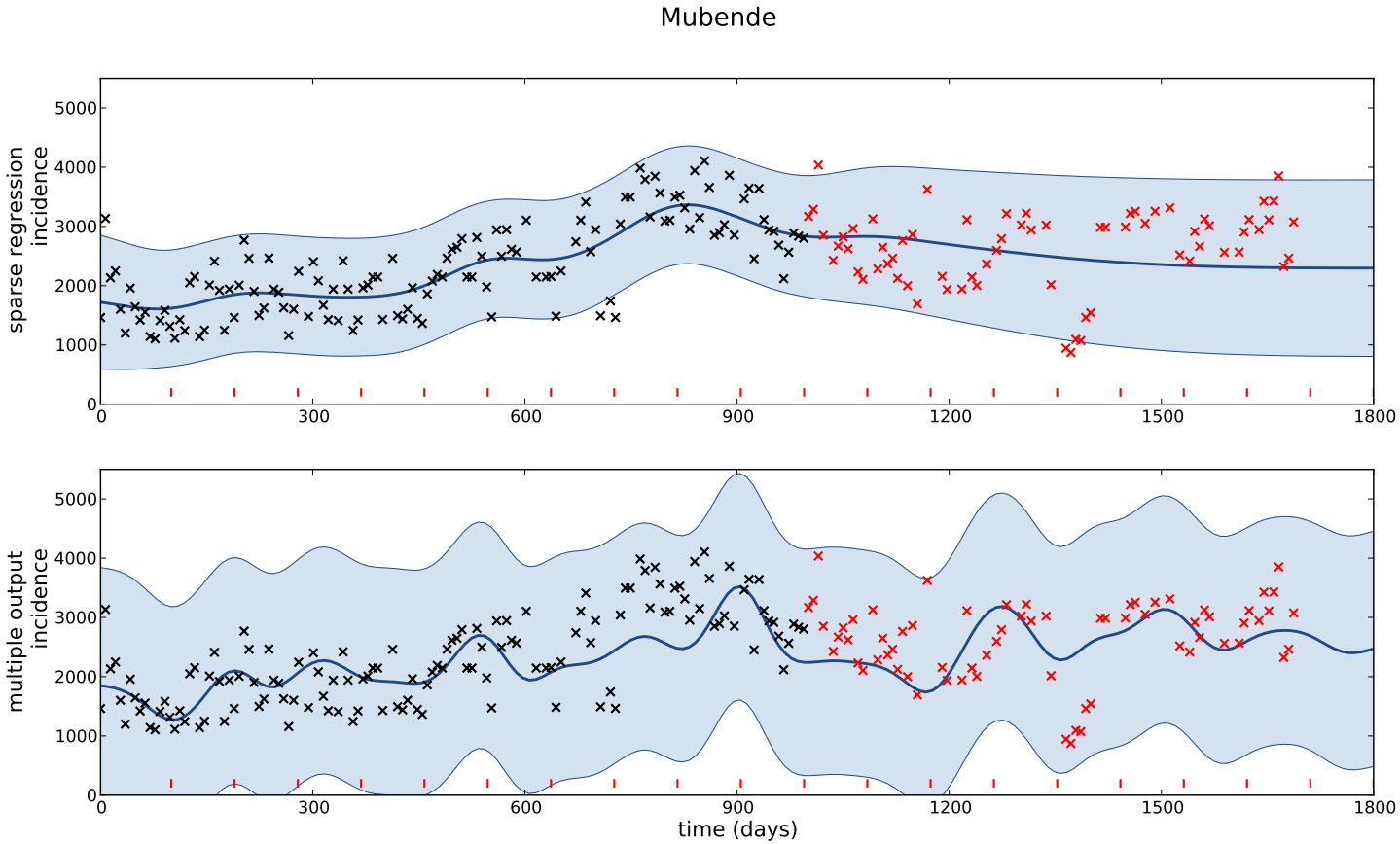


(Andrade-Pacheco et al., 2014; Mubangizi et al., 2014)

Malaria Prediction in Uganda

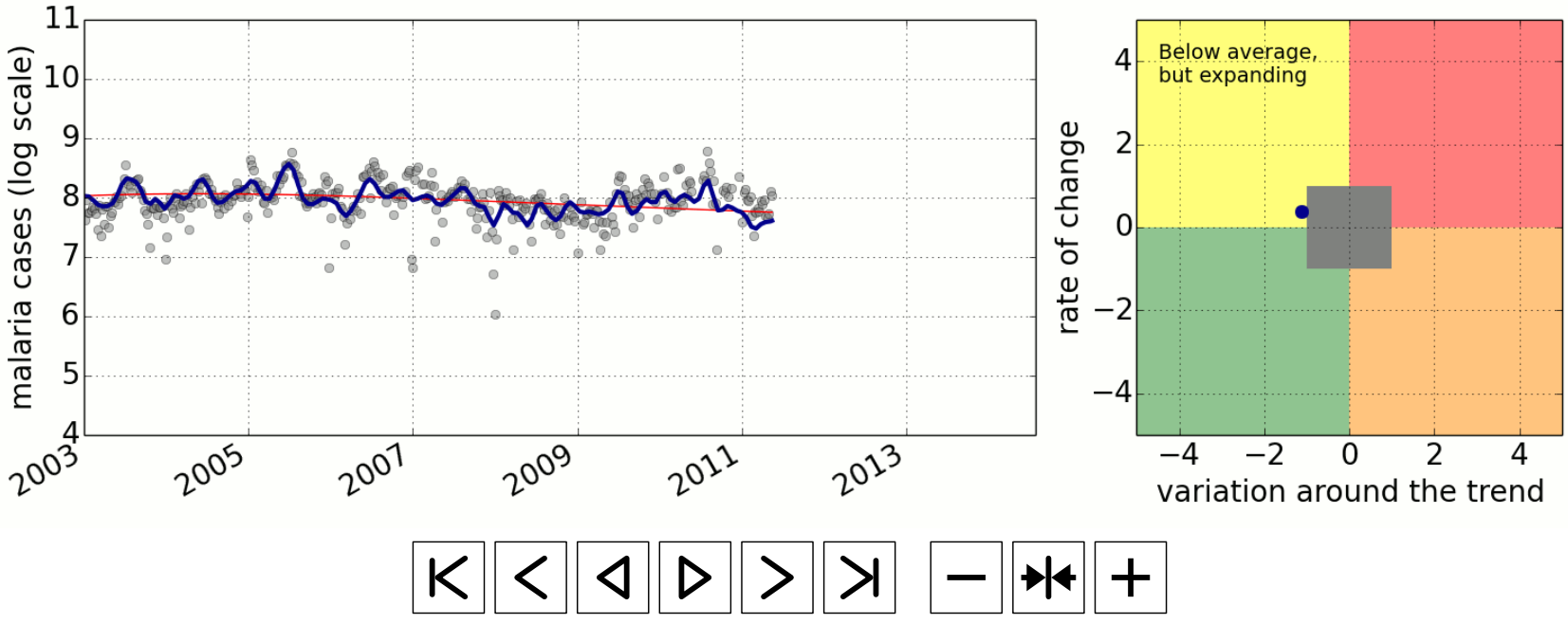


Malaria Prediction in Uganda

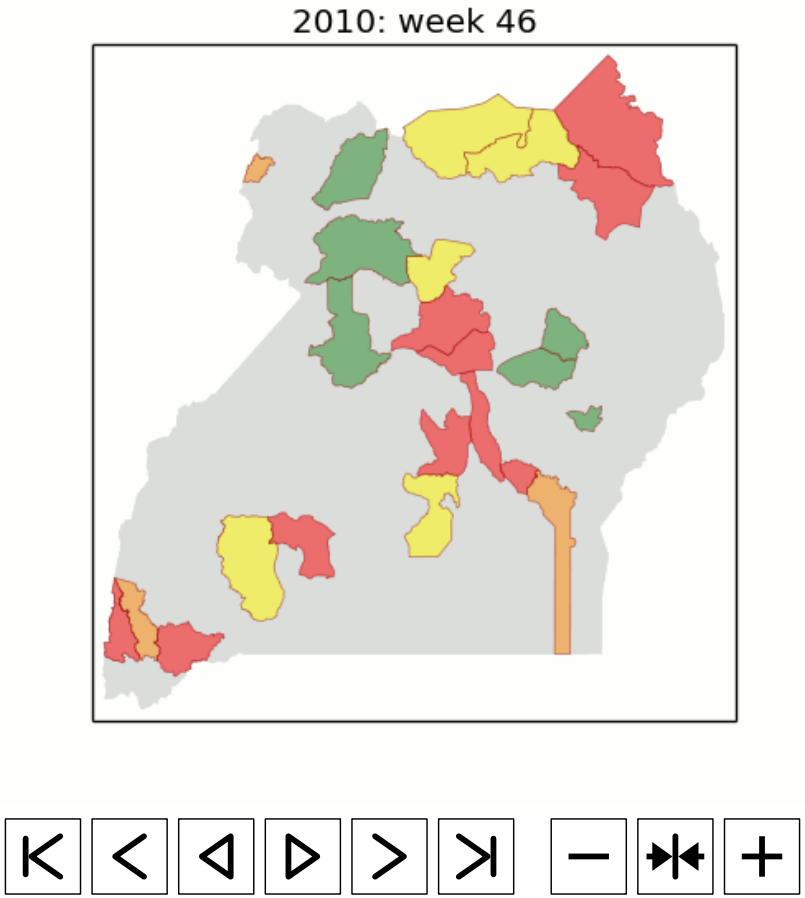


GP School at Makerere

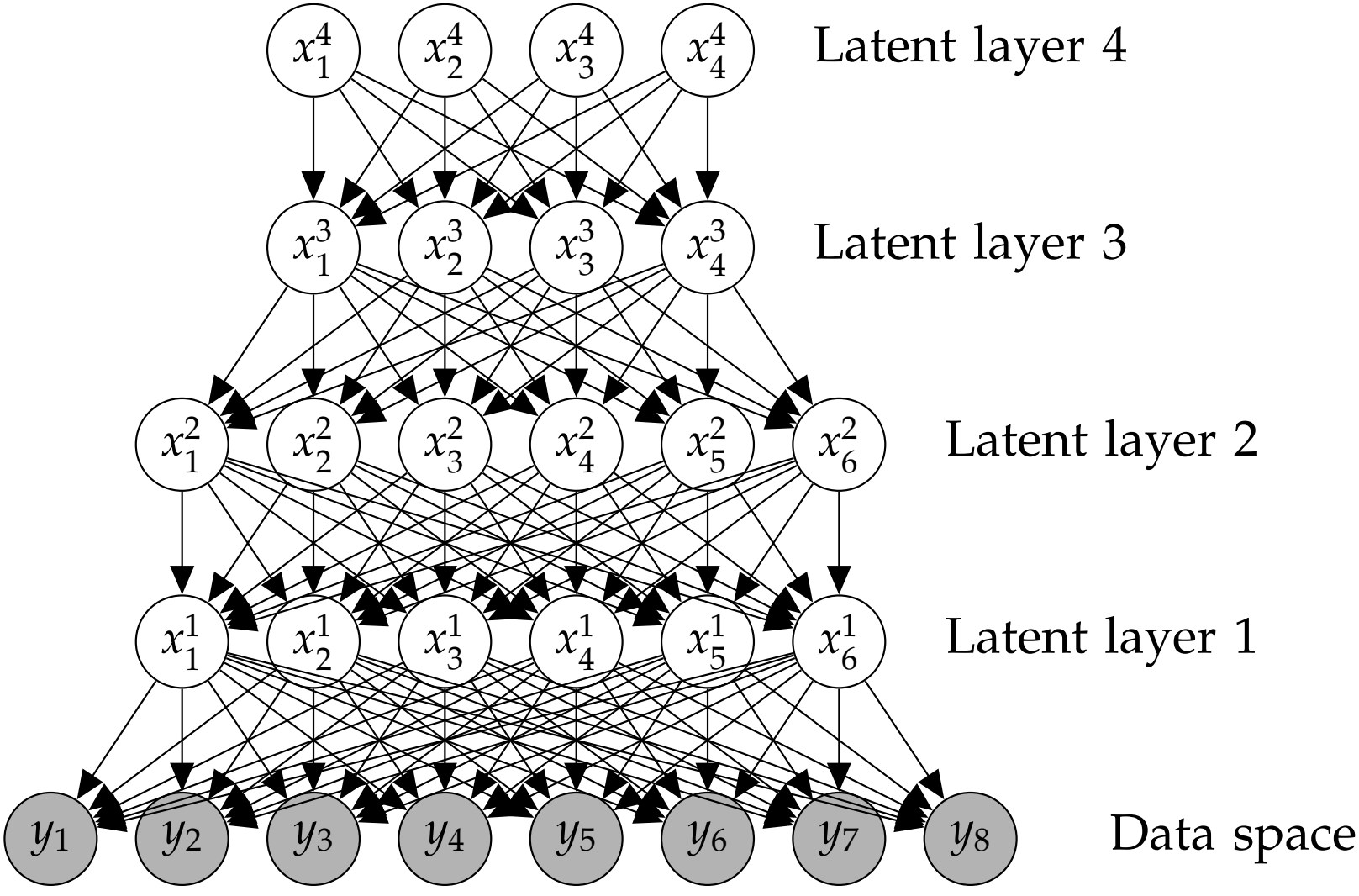
Early Warning Systems



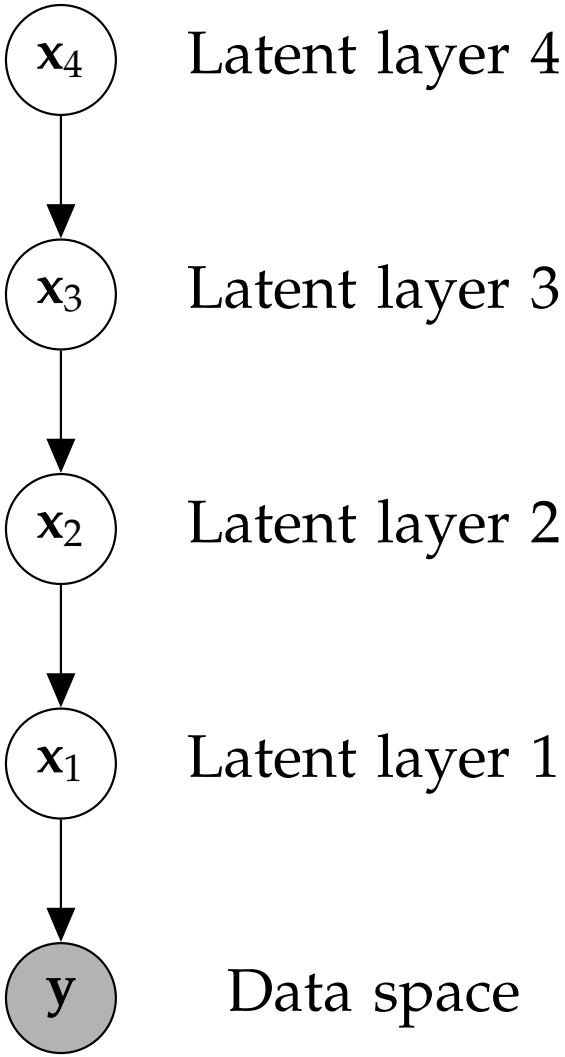
Early Warning Systems



Deep Models


x_1^4 x_2^4 x_3^4 x_4^4
Latent layer 4
x_1^3 x_2^3 x_3^3 x_4^3
Latent layer 3
x_1^2 x_2^2 x_3^2 x_4^2 x_5^2 x_6^2
Latent layer 2
x_1^1 x_2^1 x_3^1 x_4^1 x_5^1 x_6^1
Latent layer 1
y_1 y_2 y_3 y_4 y_5 y_6 y_7 y_8
Data space

Deep Models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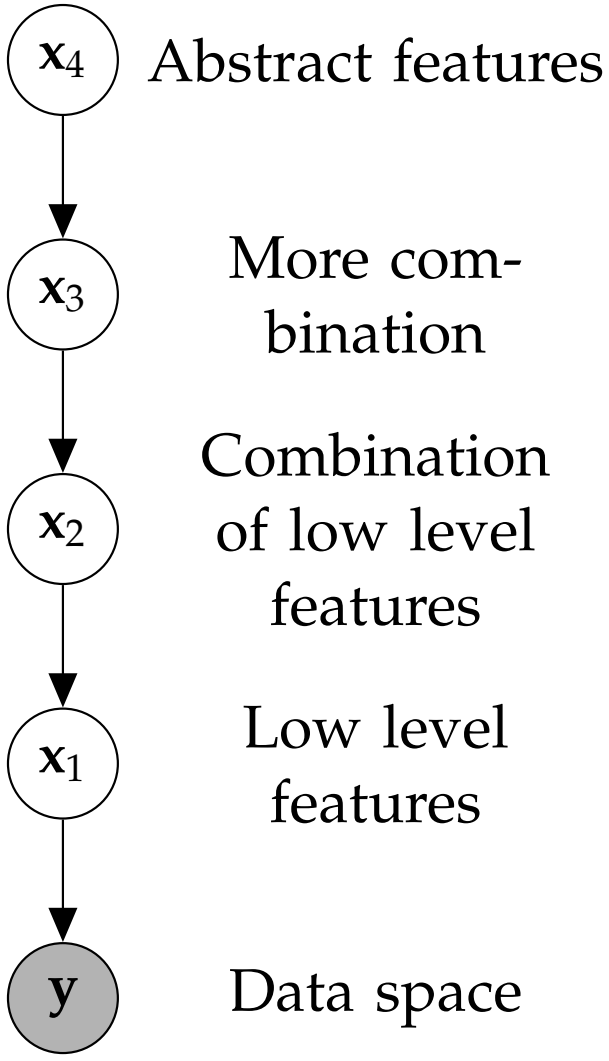
Latent layer 4
$\mathbf{x}_3$
Latent layer 3
$\mathbf{x}_2$
Latent layer 2
$\mathbf{x}_1$
Latent layer 1
$\mathbf{y}$
Data space

Deep Models

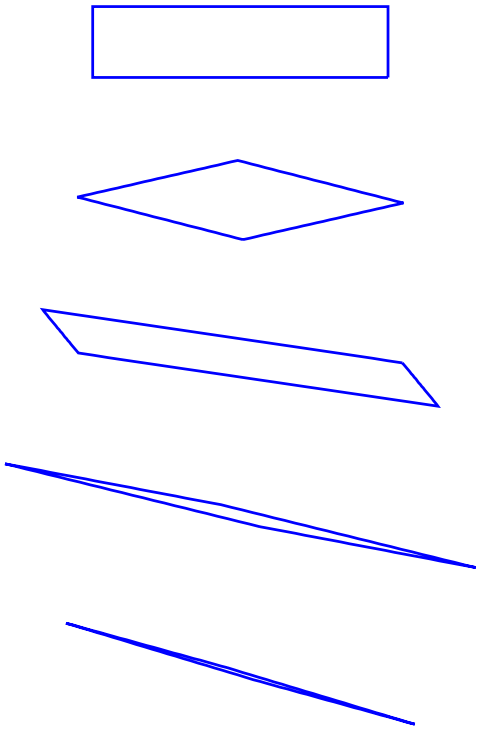

$\mathbf{x}_4$
Abstract features
$\mathbf{x}_3$
More combination
$\mathbf{x}_2$
Combination of low level features
$\mathbf{x}_1$
Low level features
$\mathbf{y}$
Data space

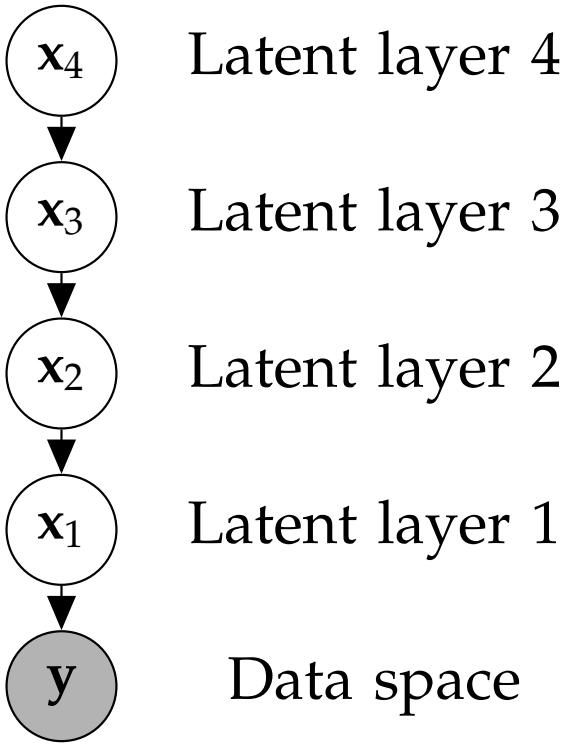
Deep Gaussian Processes

Damianou and Lawrence (2013)

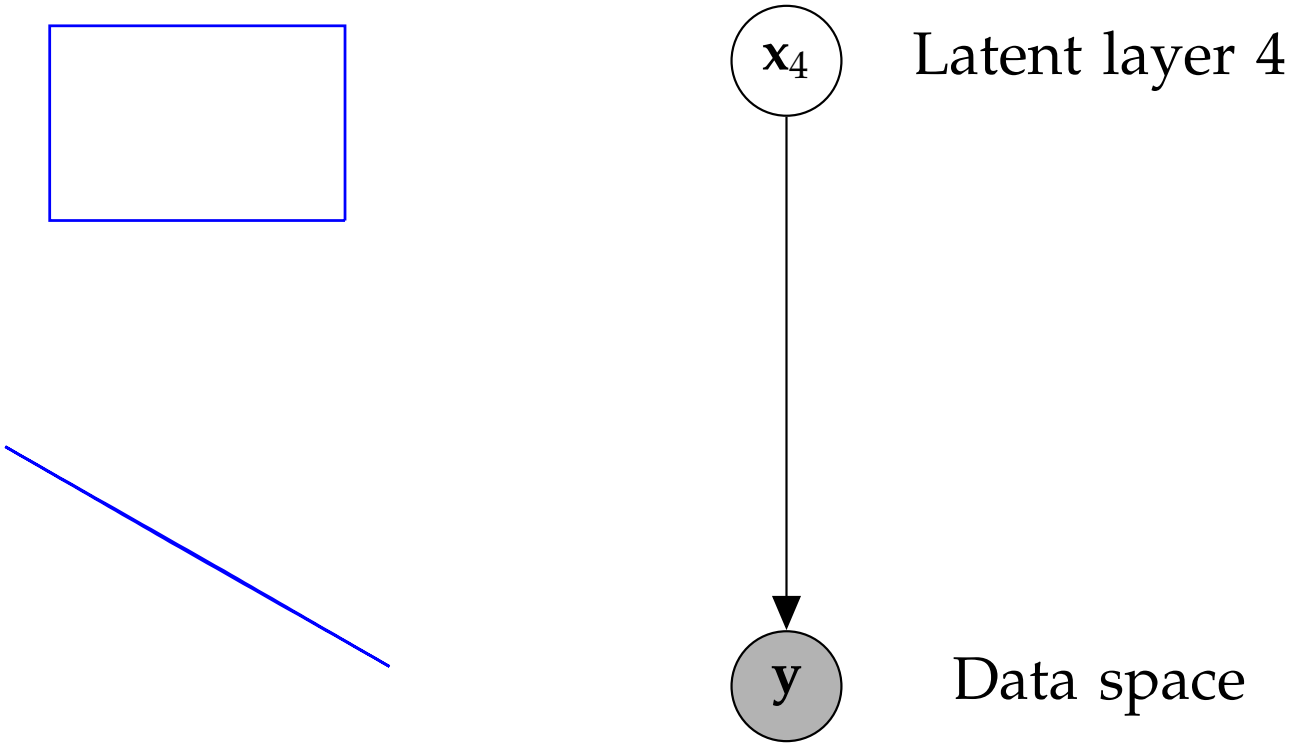
- Deep architectures allow abstraction of features (Bengio, 2009; Hinton and Osindero, 2006; Salakhutdinov and Murray, 2008).
- We use variational approach to stack GP models.

Stacked PCA

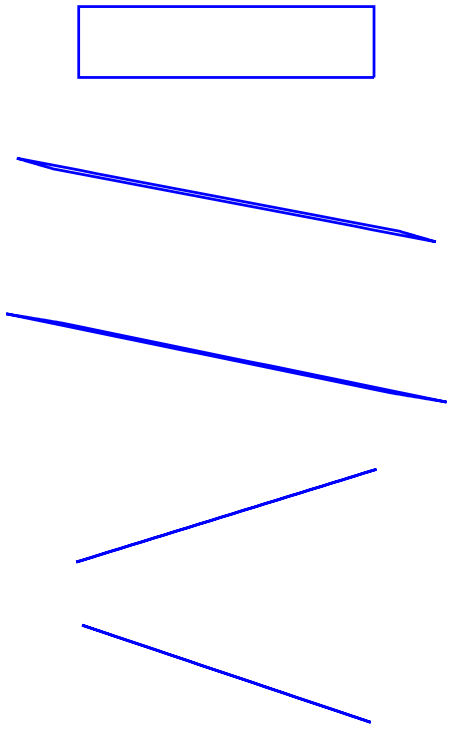


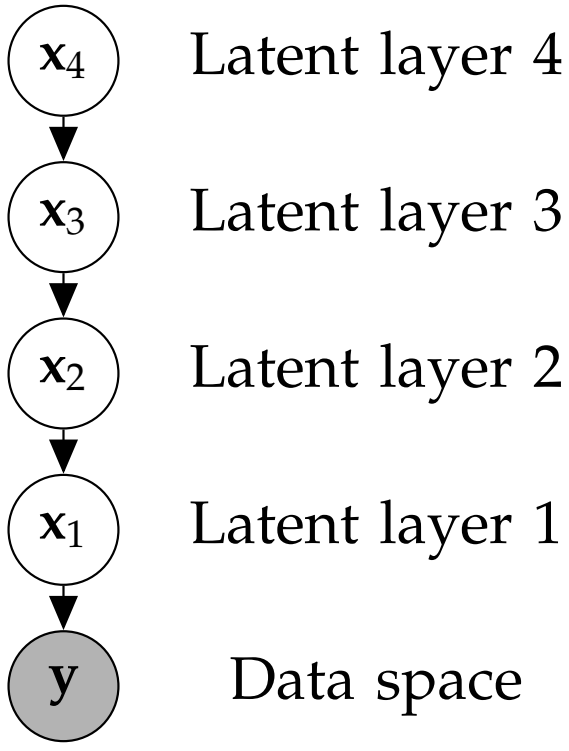

$\mathbf{x}_4$
Latent layer 4
$\mathbf{x}_3$
Latent layer 3
$\mathbf{x}_2$
Latent layer 2
$\mathbf{x}_1$
Latent layer 1
$\mathbf{y}$
Data space

Stacked PCA

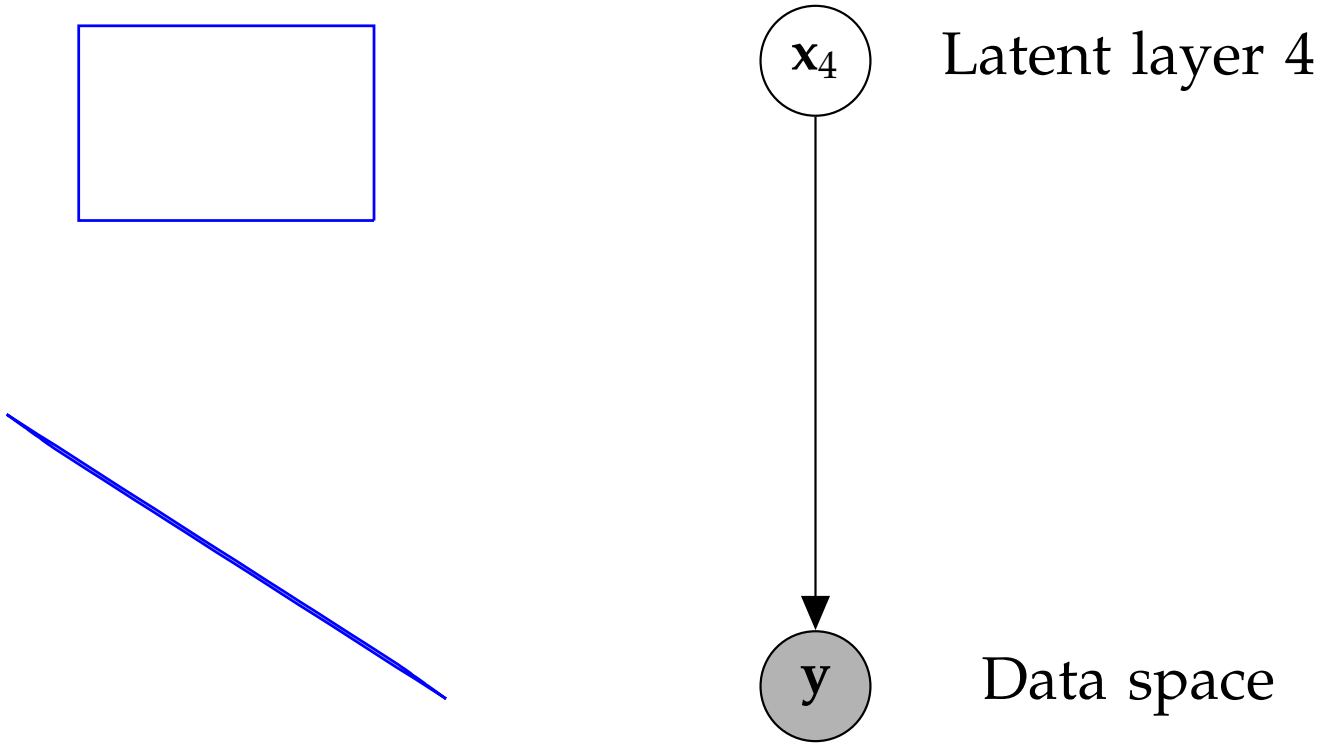


Stacked PCA

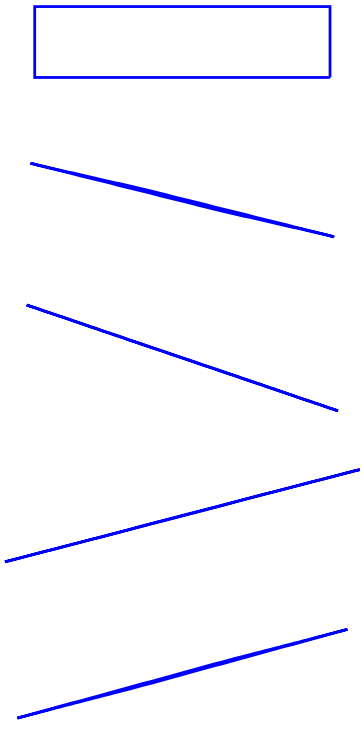


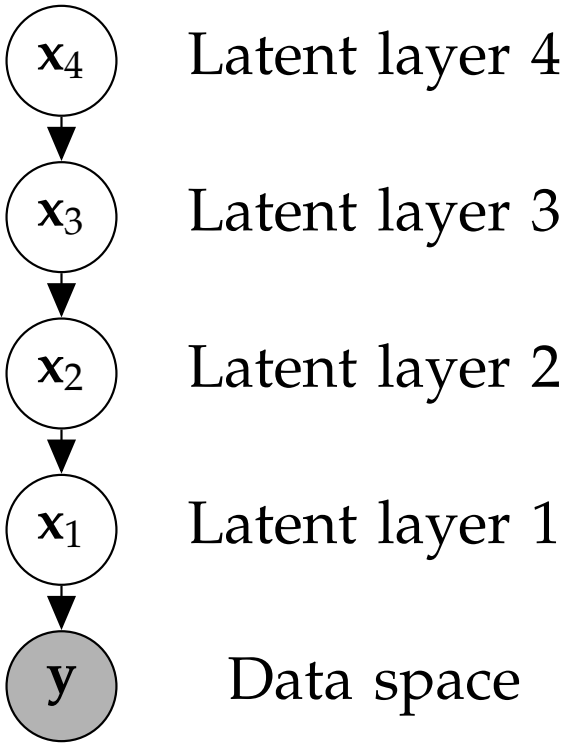

$\mathbf{x}_4$
Latent layer 4
$\mathbf{x}_3$
Latent layer 3
$\mathbf{x}_2$
Latent layer 2
$\mathbf{x}_1$
Latent layer 1
$\mathbf{y}$
Data space

Stacked PCA

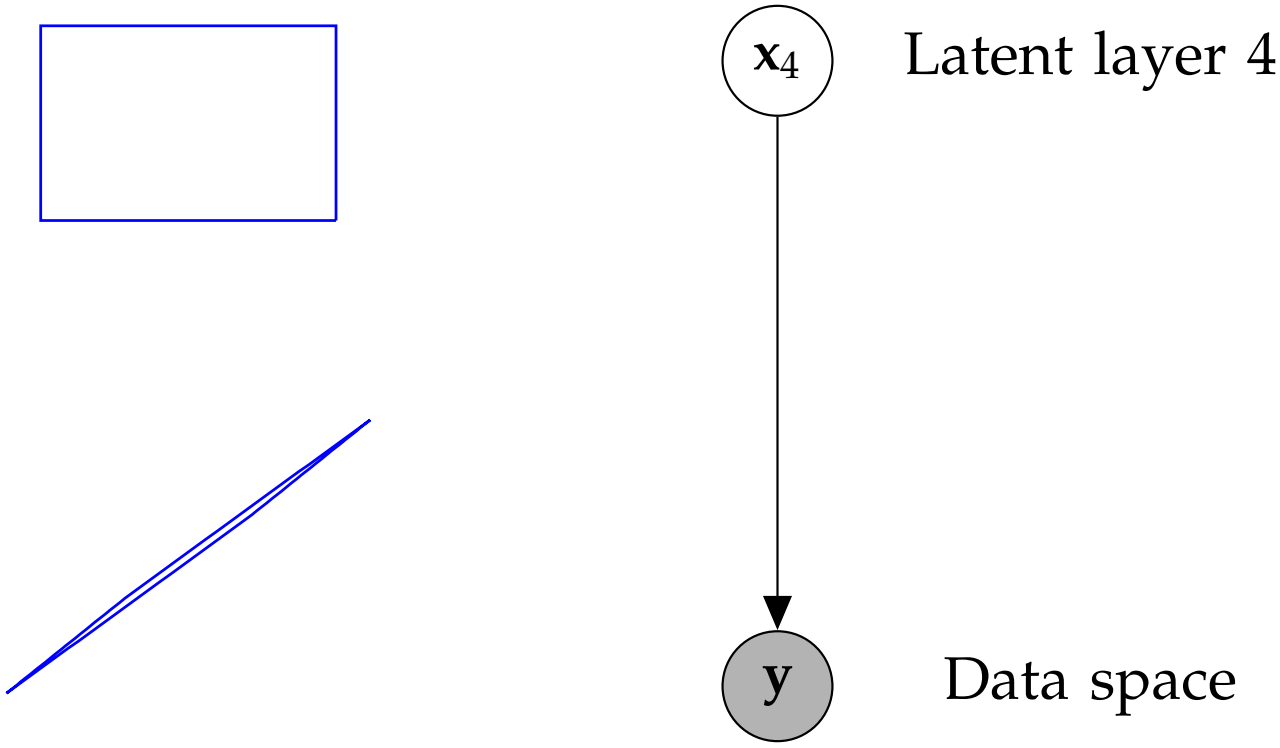


Stacked PCA

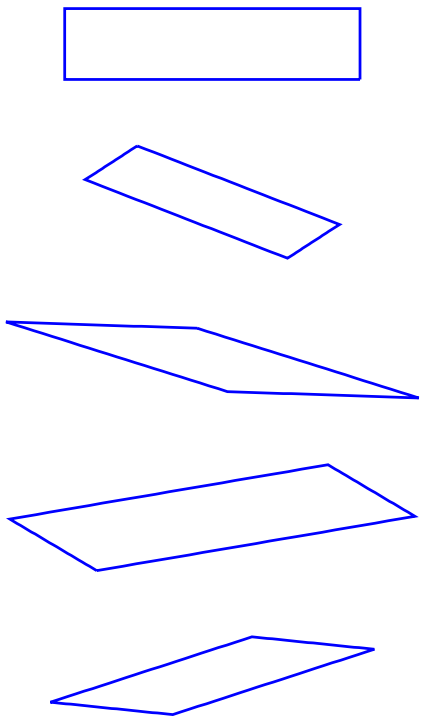


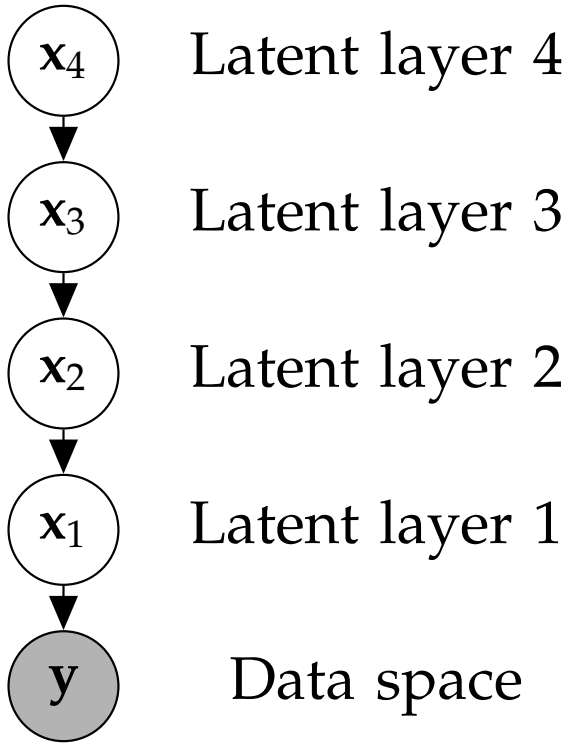

$\mathbf{x}_4$
Latent layer 4
$\mathbf{x}_3$
Latent layer 3
$\mathbf{x}_2$
Latent layer 2
$\mathbf{x}_1$
Latent layer 1
$\mathbf{y}$
Data space

Stacked PCA

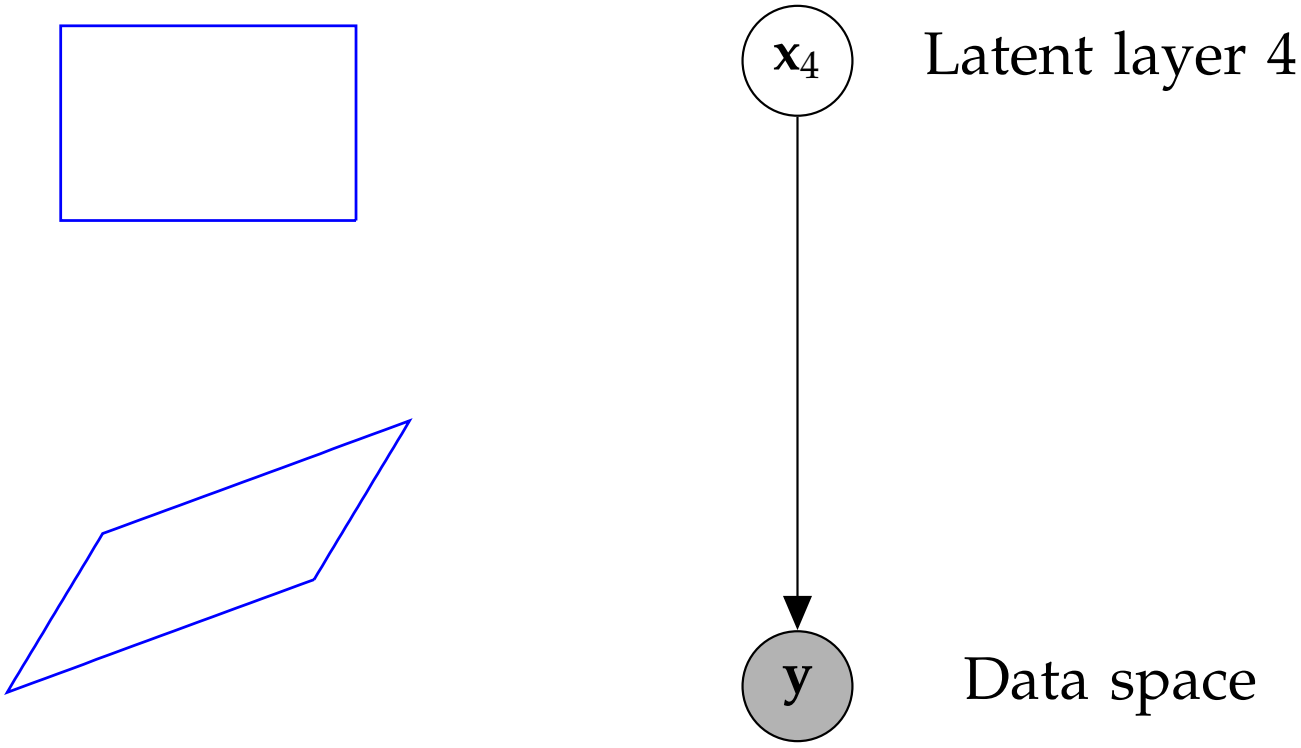


Stacked PCA

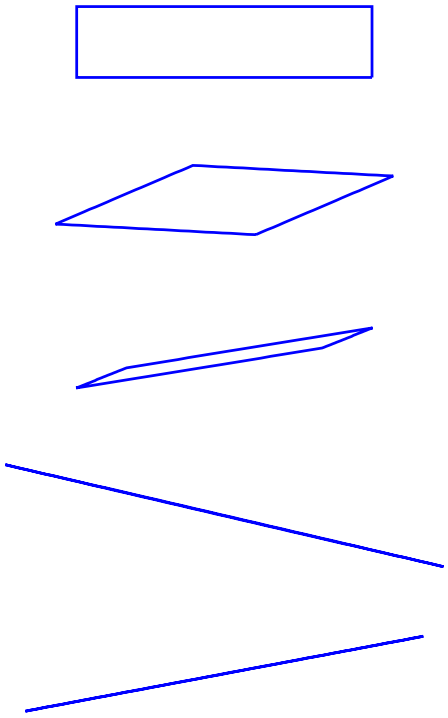


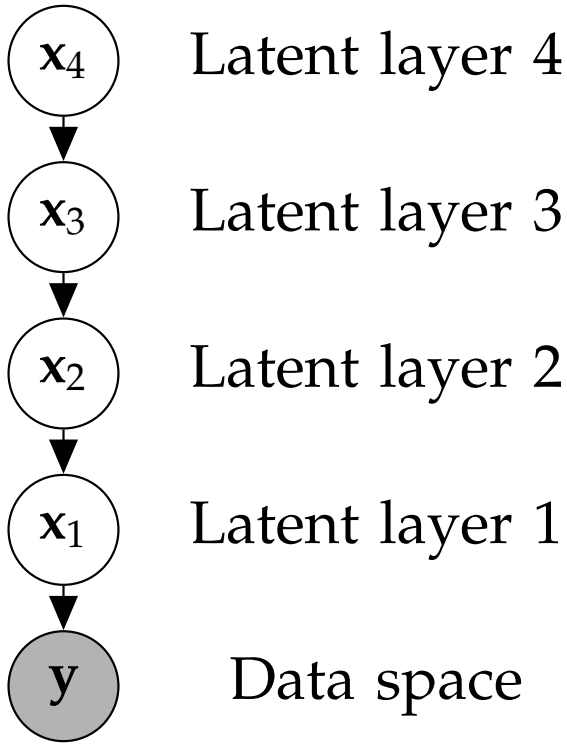

$\mathbf{x}_4$
Latent layer 4
$\mathbf{x}_3$
Latent layer 3
$\mathbf{x}_2$
Latent layer 2
$\mathbf{x}_1$
Latent layer 1
$\mathbf{y}$
Data space

Stacked PCA



Stacked PCA

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Latent layer 4
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$\mathbf{x}_2$
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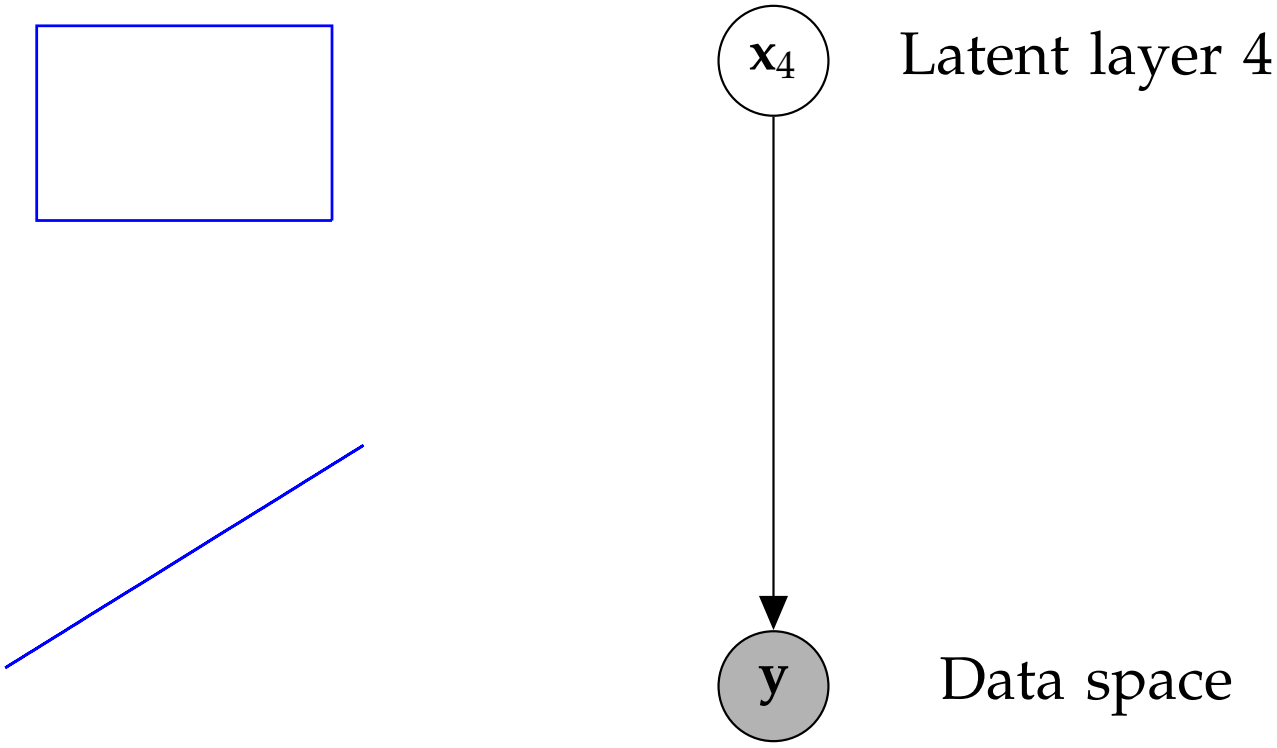
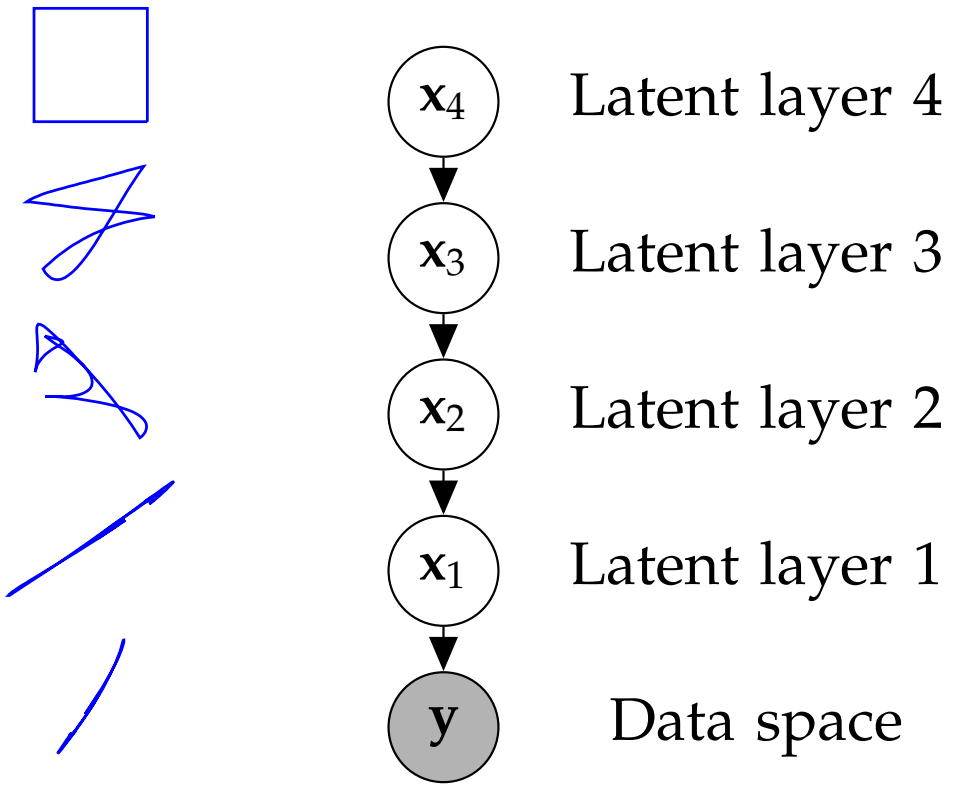
Latent layer 1
$\mathbf{y}$
Data space

Stacked PCA



Stacked GPs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Latent layer 4
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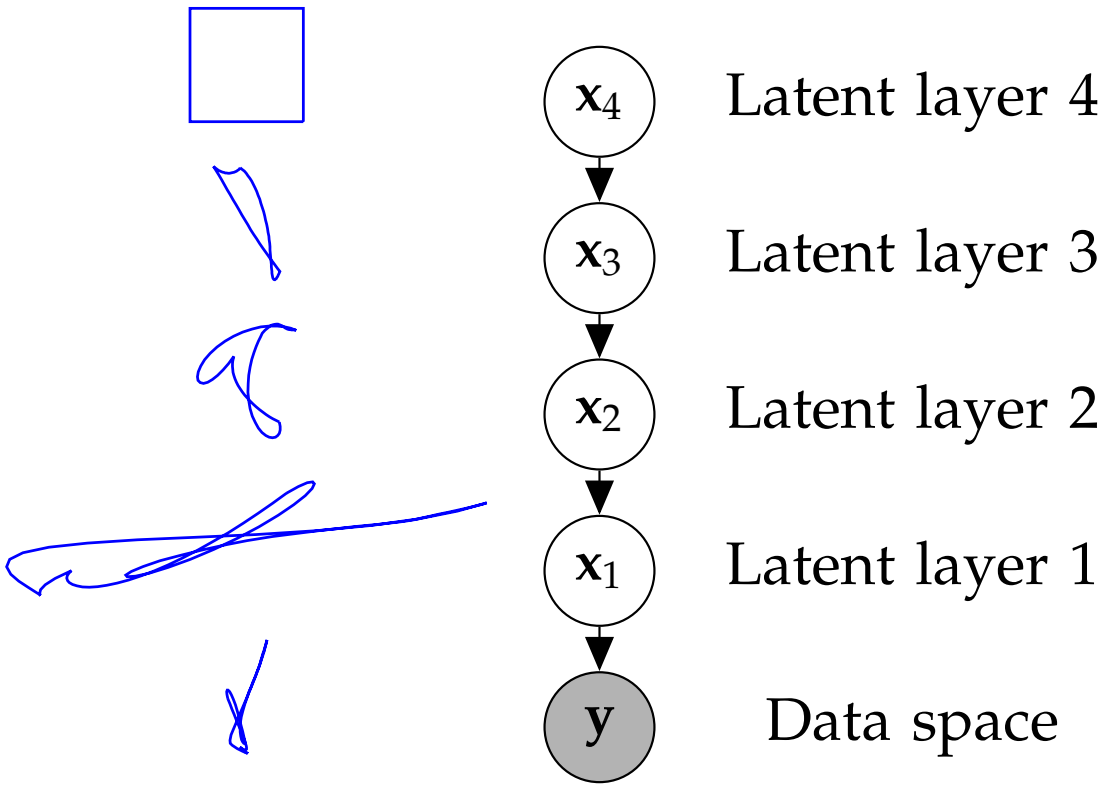
Latent layer 1
$\mathbf{y}$
Data space

Stacked GPs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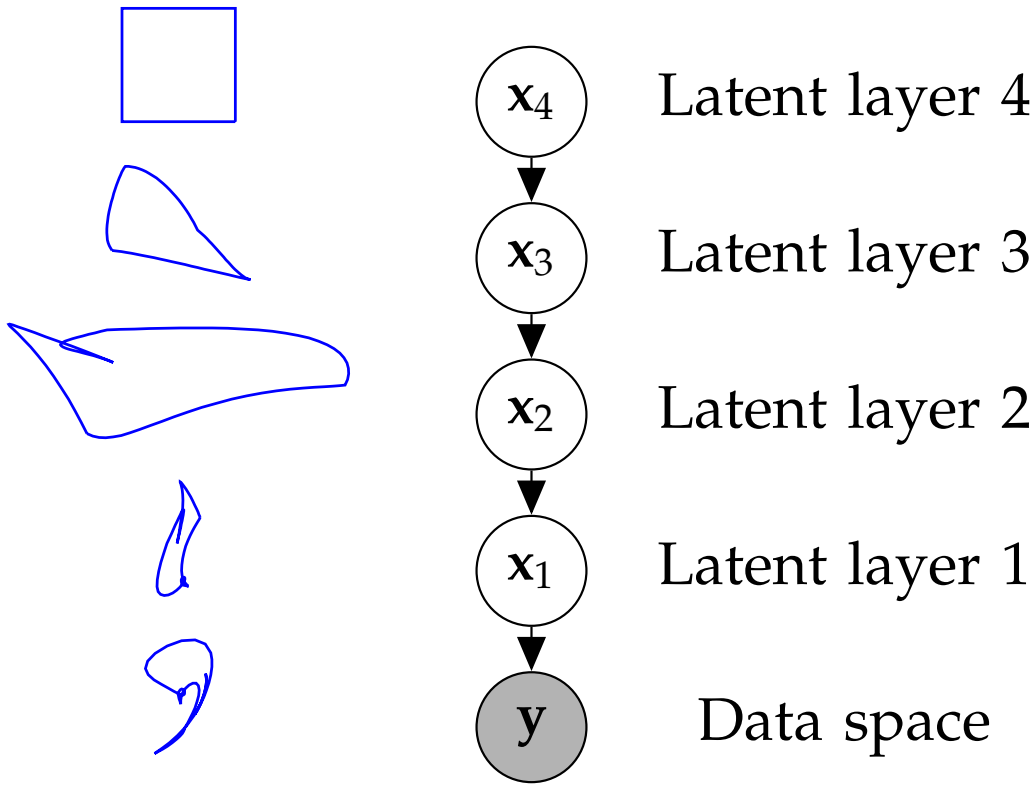
Data space

Stacked GPs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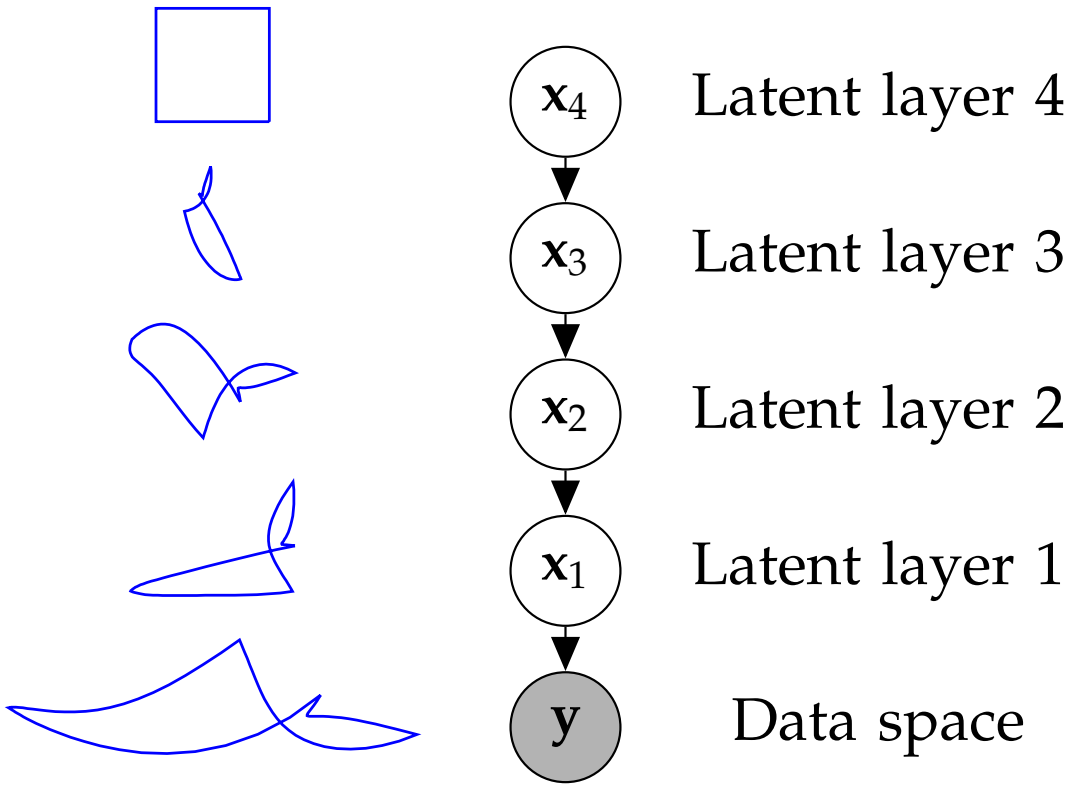
$\mathbf{y}$
Data space

Stacked GPs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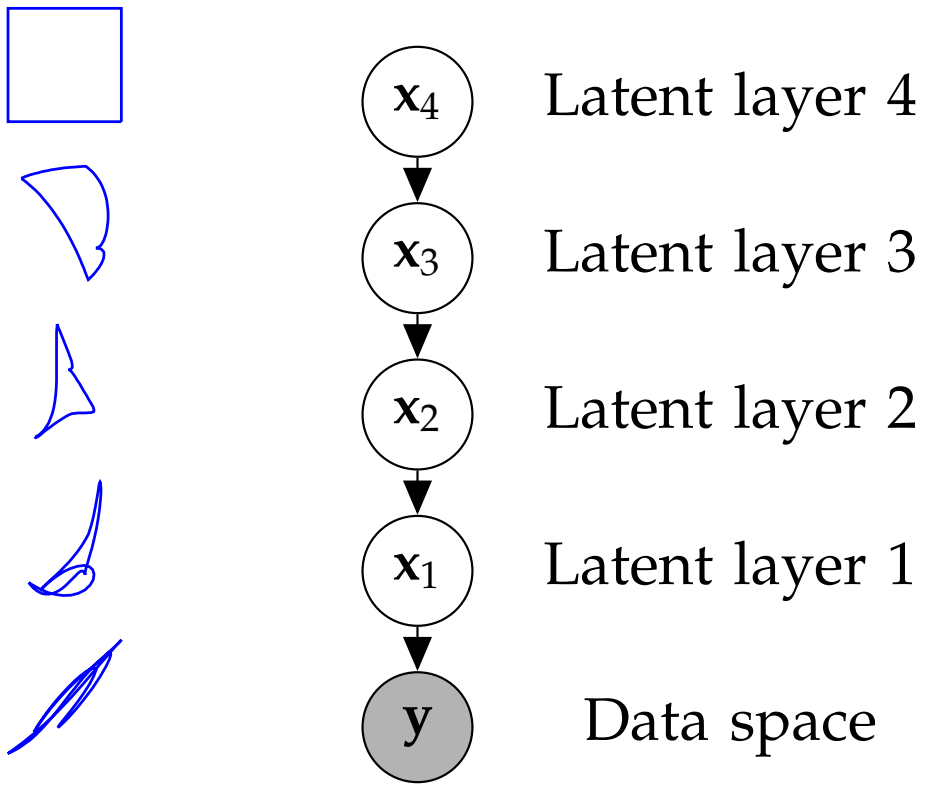
Data space

Stacked GPs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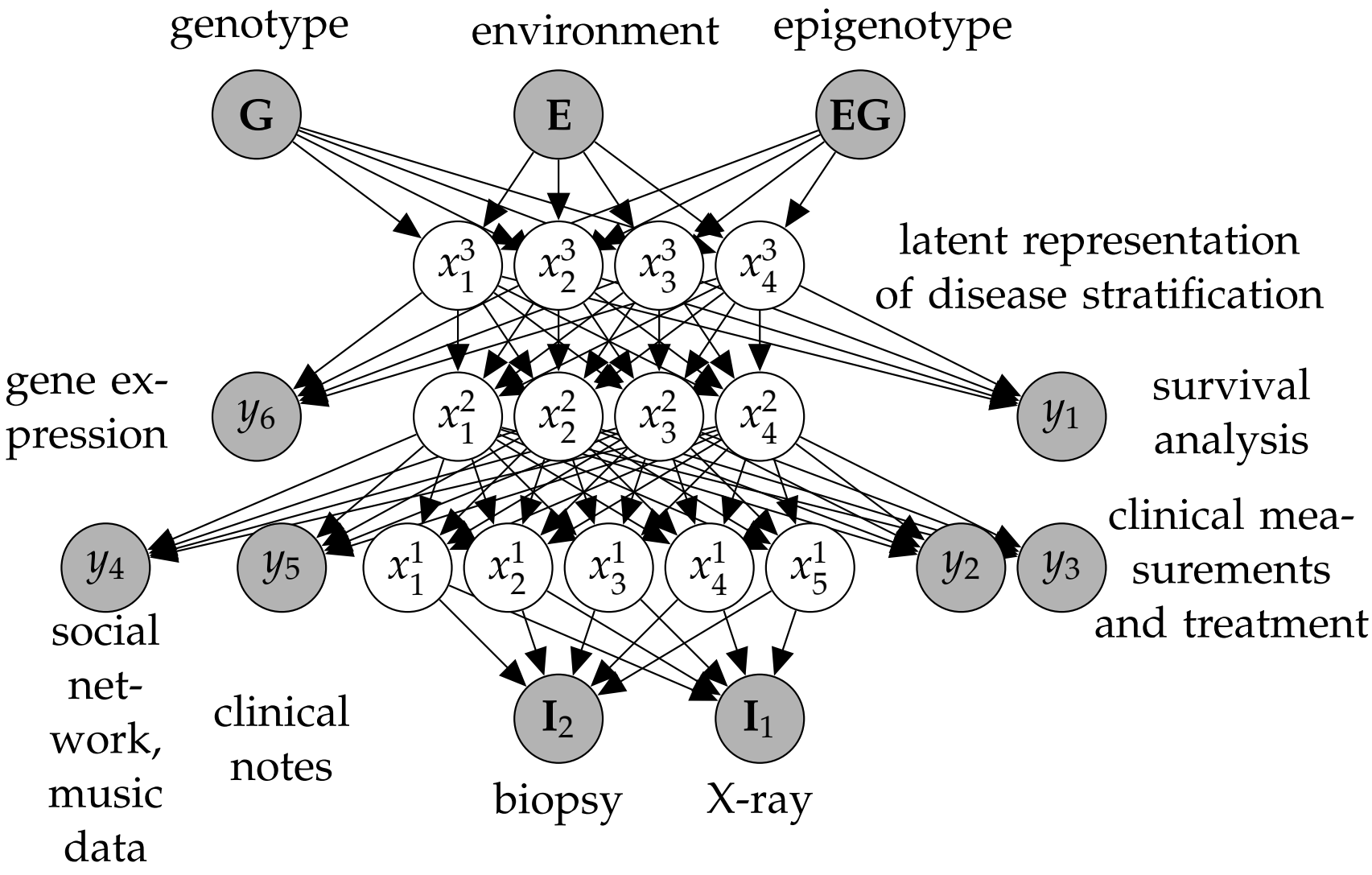
Latent layer 3
$\mathbf{x}_2$
Latent layer 2
$\mathbf{x}_1$
Latent layer 1
$\mathbf{y}$
Data space

What Can Academics Do that Google Can't?

- Google's resources give them access to volumes of data (or Facebook, or Microsoft, or Amazon).
- Is there anything for Universities to contribute?
- Assimilation of multiple views of the patient: each perhaps from a different patient.
- This may be done by small companies (with support of Universities).
- A Facebook app for your personalised health.
- These methodologies are part of that picture.

Deep Health


genotype
environment
epigenotype
G
E
EG
x_1^3 x_2^3 x_3^3 x_4^3
latent representation of disease stratification
gene expression
y_6
x_1^2 x_2^2 x_3^2 x_4^2
y_1
survival analysis
y_4
y_5
x_1^1 x_2^1 x_3^1 x_4^1 x_5^1
y_2
y_3
clinical measurements and treatment
social network, music data
clinical notes
I_2
I_1
biopsy
X-ray

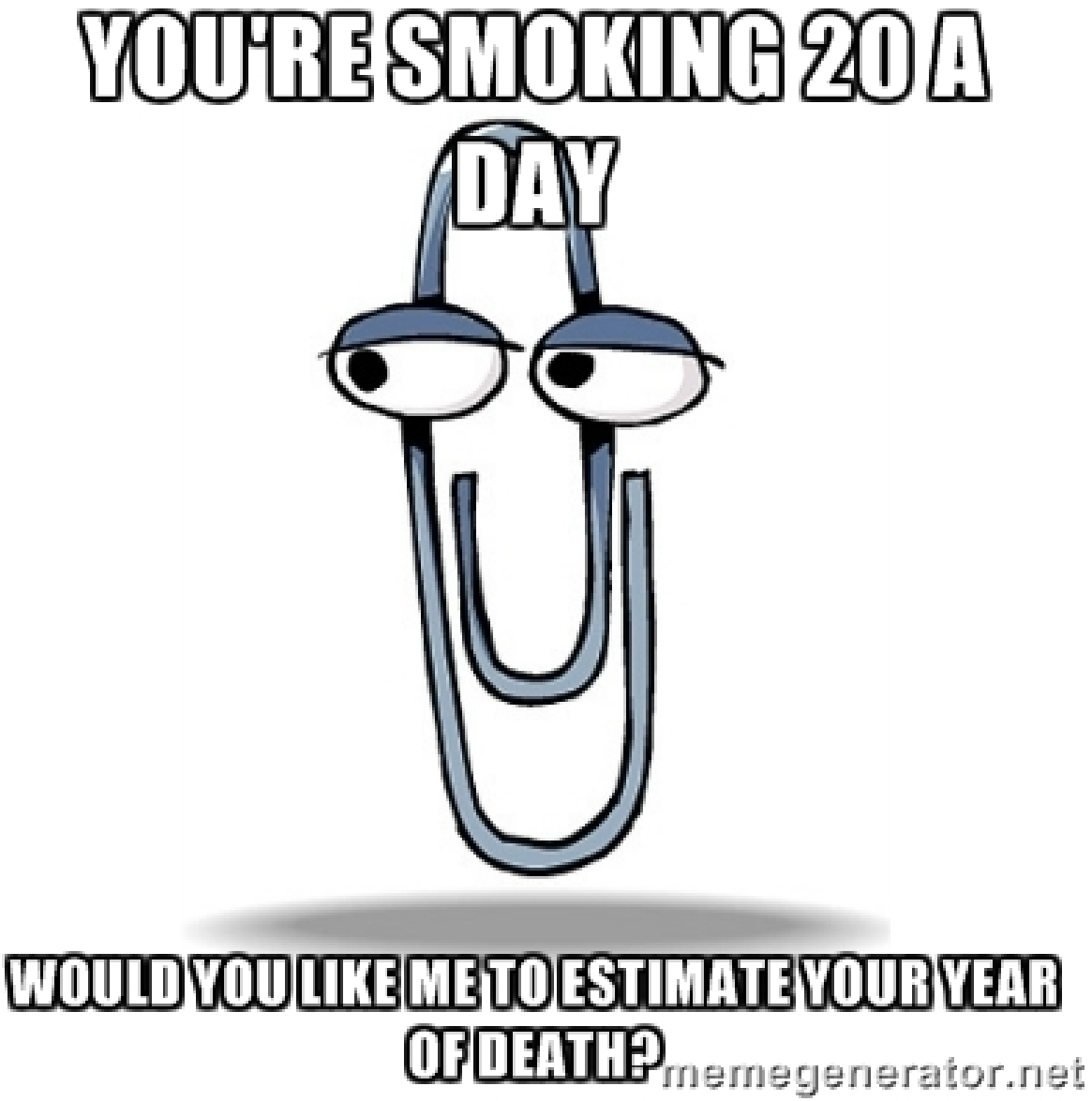
The Patient Experience: Bedside Manner

- A good bedside manner is a key part of the patient experience.
- How can information be delivered to patients?
- Public health significantly changed: tailored health advice.

Bedside Manner

Steen: Doctor and His Patient, Image from Wikimedia Commons.

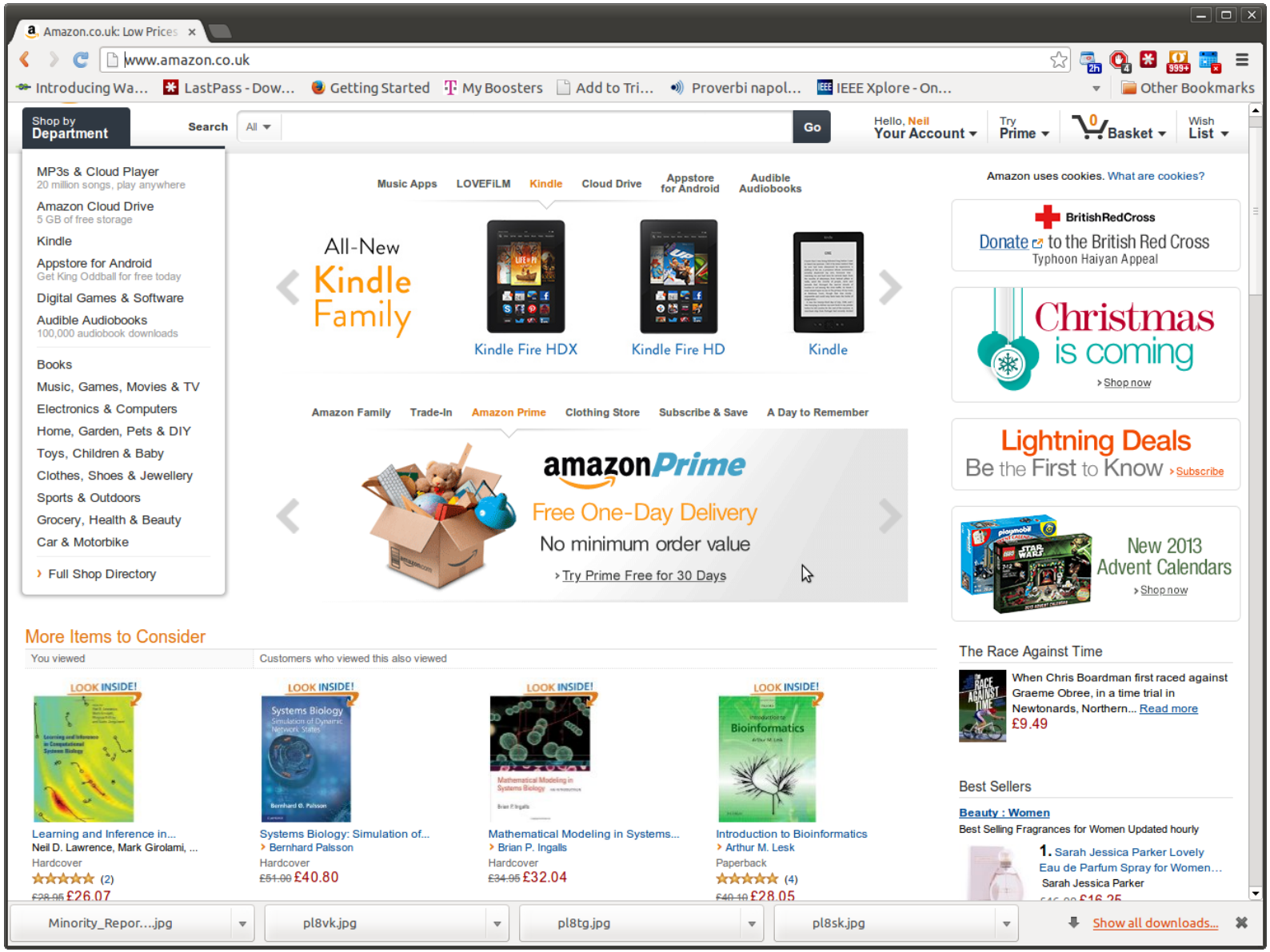
Interface


YOU'RE SMOKING 20 A DAY
WOULD YOU LIKE ME TO ESTIMATE YOUR YEAR OF DEATH?
memegenerator.net

Interventions?

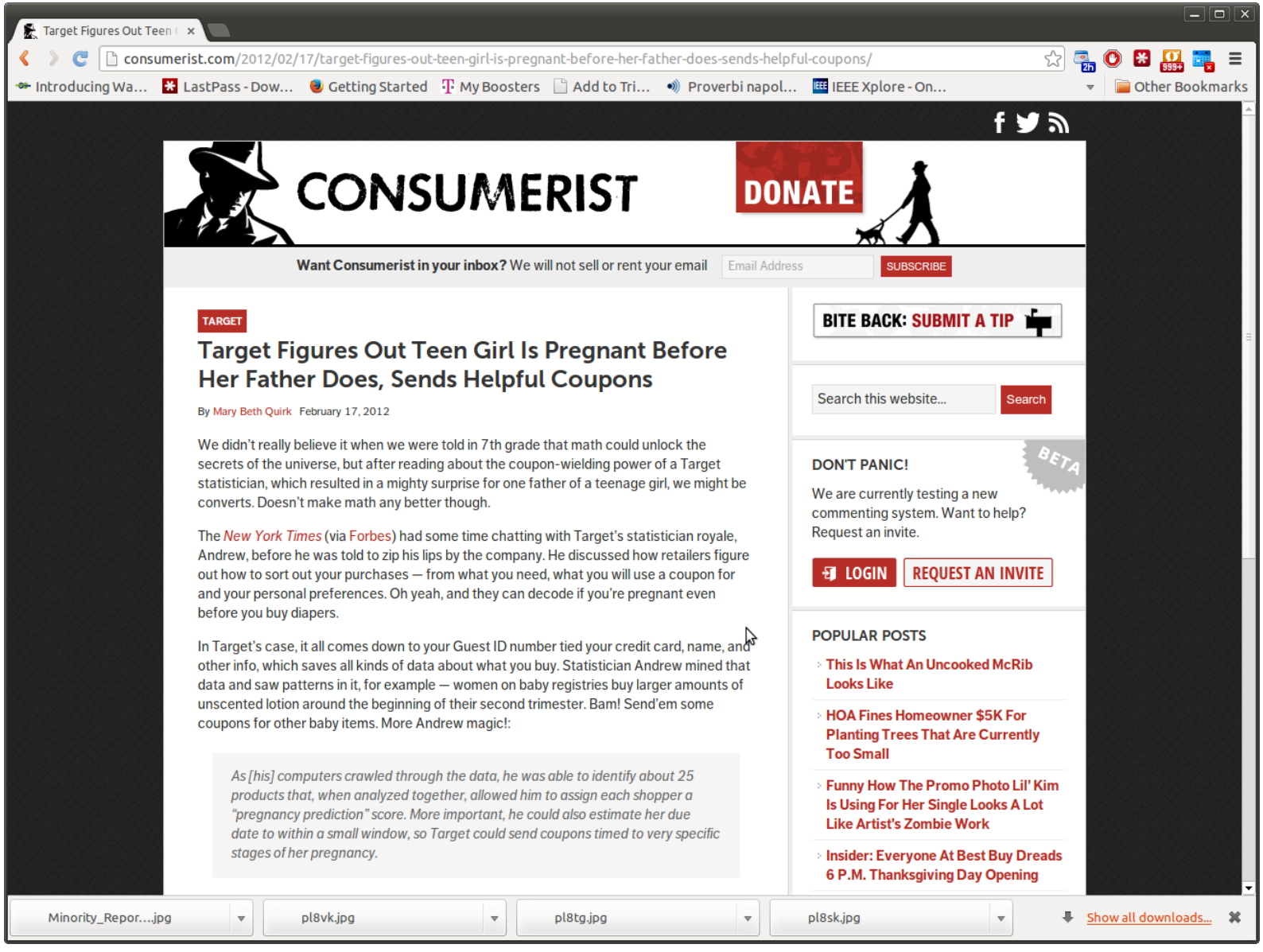
Poster shown under US fair use. Copyright DreamWorks Pictures

Guided Behaviour

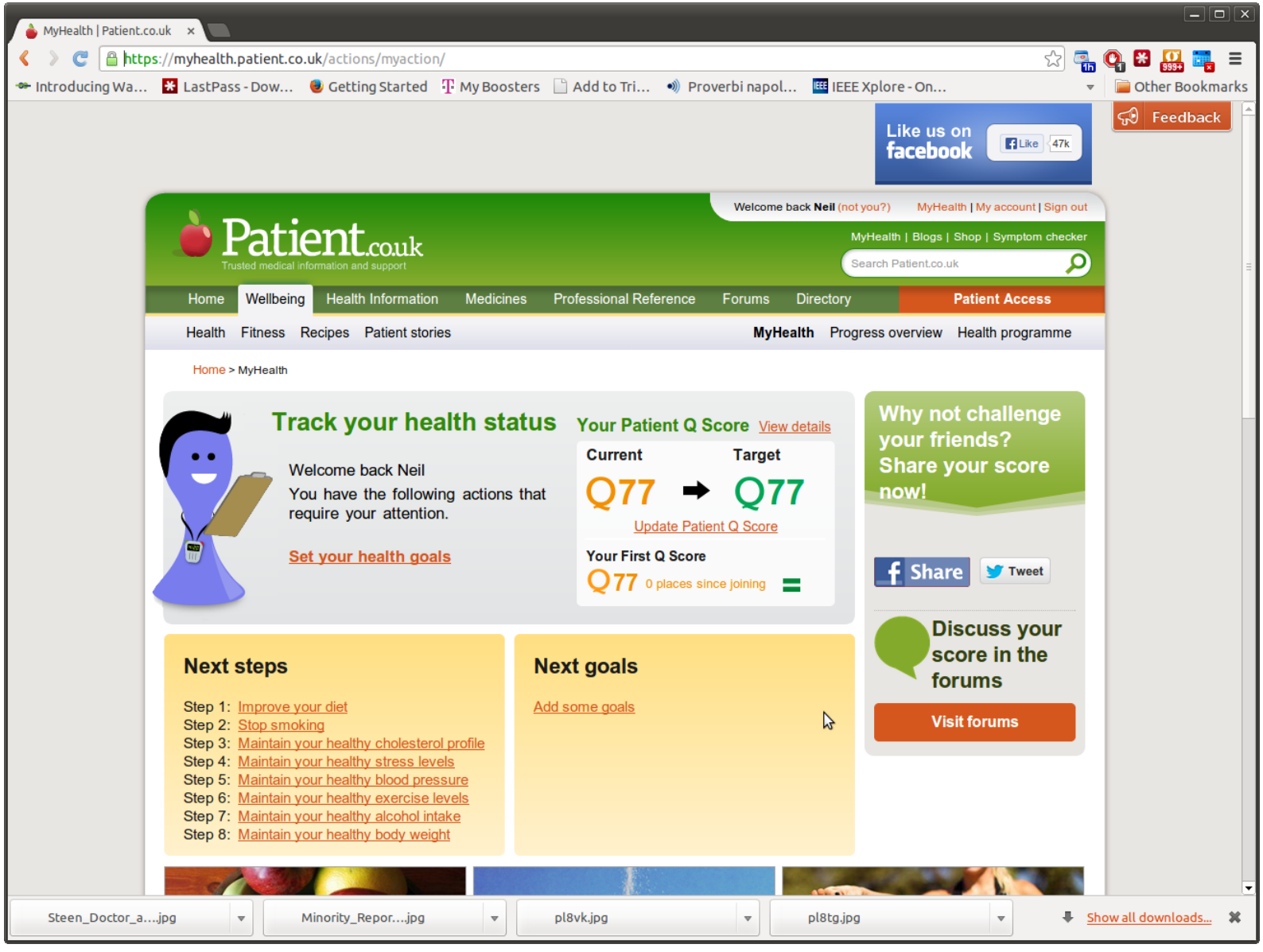


Facebook Knew I was Gay

Target told my Dad I was Pregnant



EMIS myHealth



How to Handle this?

- A *potential* answer.
  - Give the patients control of their own data.
  - Make patients the gatekeeper of what can be cross-linked.

Summary

- Intention is to deploy probabilistic machine learning for assimilating a wide range of data types in personalized health:
  - Social networking, text (clinical notes), survival times, medical imaging, phenotype, genotype, mobile phone records, music tastes, Tesco club card
- Requires population scale models with millions of features.
- May be necessary for early detection of dementia or other diseases with high noise to signal.
- Major issues in privacy and interfacing with the patient.
- But: the revolution *is* coming. We need to steer it.

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