Unravelling the Big Data Revolution

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Talk @ Leeds Maths Teaching Away Day

18th December 2013

Laplace on Rationality

of nature.

It is to the influence of the opinion of those whom the multitude judges best informed and to whom it has been accustomed to give its confidence in regard to the most important matters of life that the propagation of those errors is due which in times of ignorance have covered the face of the earth. Magic and astrology offer us two great examples. These errors inculcated in infancy, adopted without examination, and having

Laplace on Rationality

in infancy, adopted without examination, and having for a basis only universal credence, have maintained themselves during a very long time; but at last the progress of science has destroyed them in the minds of enlightened men, whose opinion consequently has caused them to disappear even among the common people, through the power of imitation and habit which had so generally spread them abroad. This power, the richest resource of the moral world, establishes and conserves in a whole nation ideas entirely contrary to those which it upholds elsewhere with the same

Laplace on Rationality

those which it upholds elsewhere with the same authority. What indulgence ought we not then to have for opinions different from ours, when this difference often depends only upon the various points of view where circumstances have placed us! Let us enlighten those whom we judge insufficiently instructed; but first let us examine critically our own opinions and weigh with impartiality their respective probabilities.

Laplace on Rationality

hoped for, by its probability. We can judge by this of the immorality of games in which the sum hoped for is below this product. They subsist only by false reasonings and by the cupidity which they excite and which, leading the people to sacrifice their necessaries to chimerical hopes whose improbability they are not in condition to appreciate, are the source of an infinity of evils.

The disadvantage of games of chance, the advantage

Gap

- Gap own: Gap, Bannana Republic, Old Navy, Piperline, Athleta.
  - They do this to sell us coats.
- They aim to exploit the lack of rationality in humans for money.
  - This is fine for coats, but not so good for medicine.

What is Machine Learning?

data

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

What is Machine Learning?

data +

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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 =

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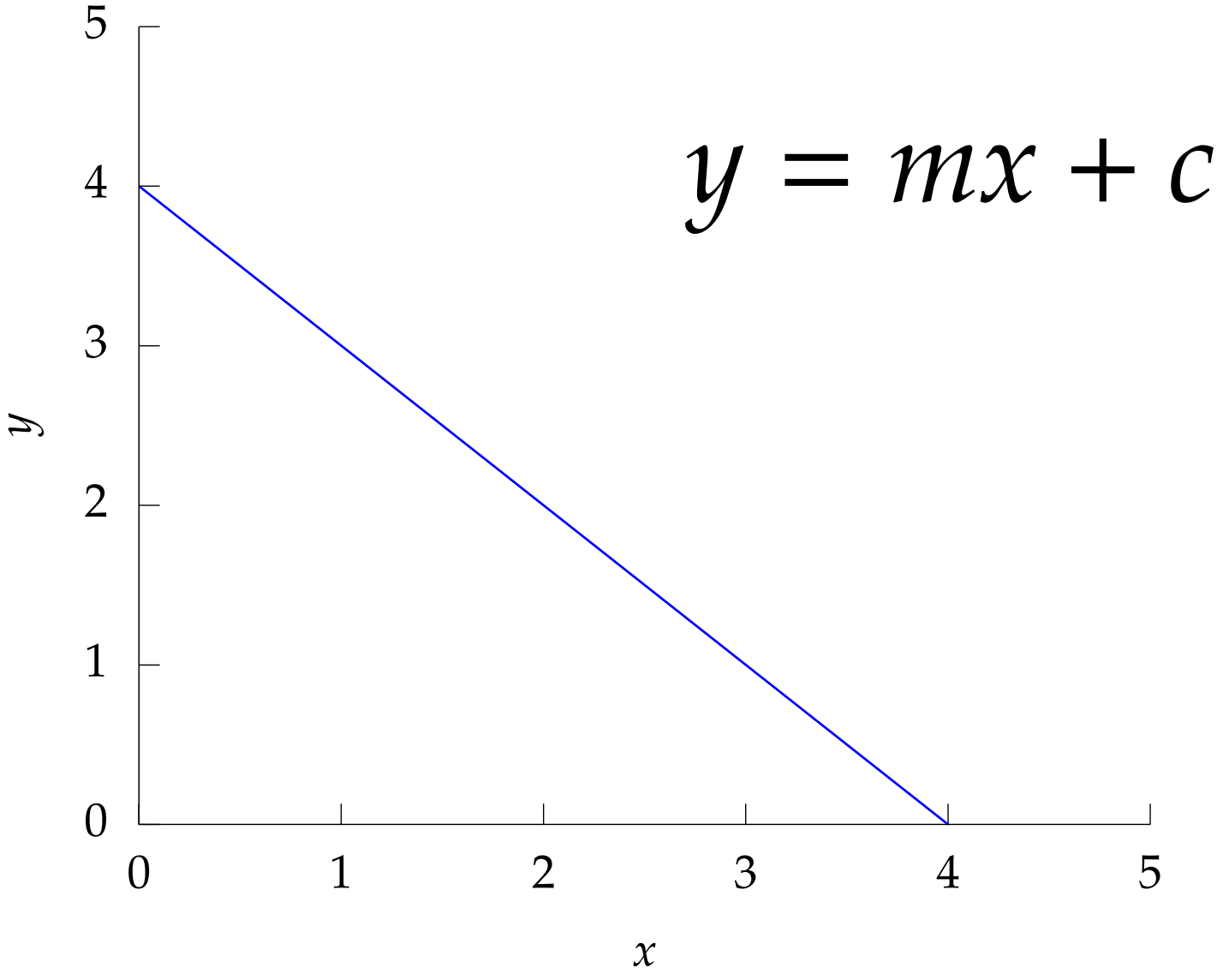
What is Machine Learning?

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

- 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.

$$y = mx + c$$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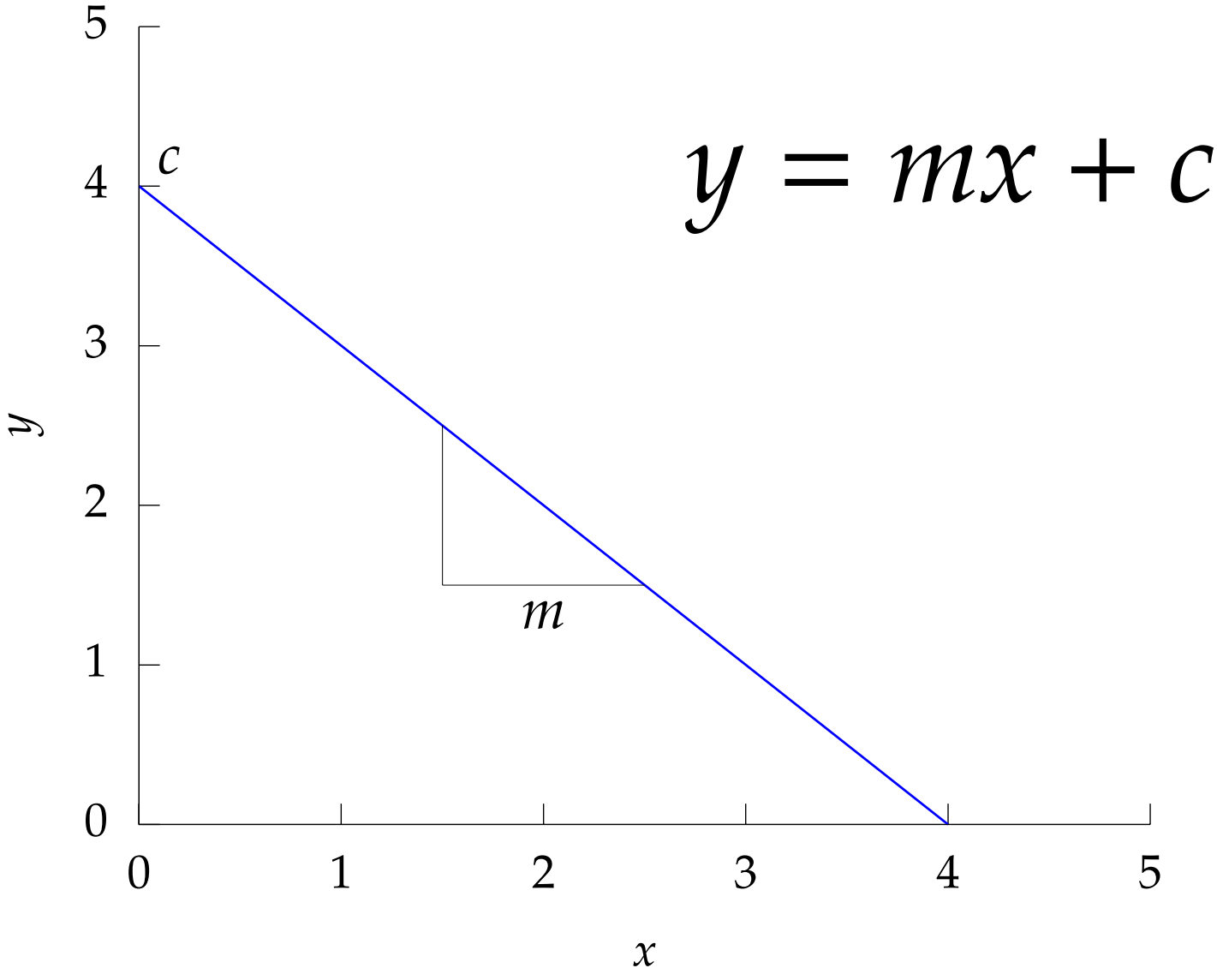
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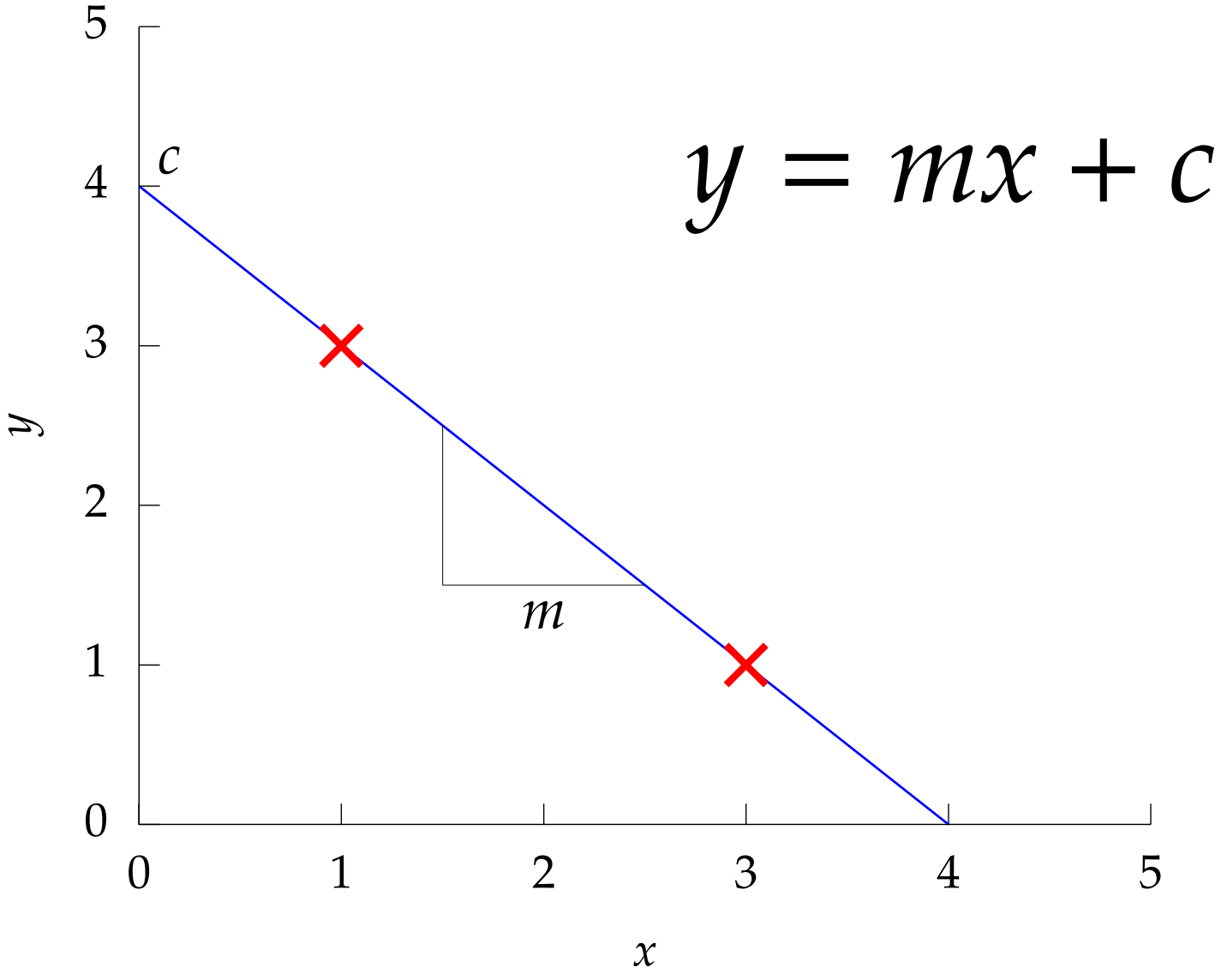
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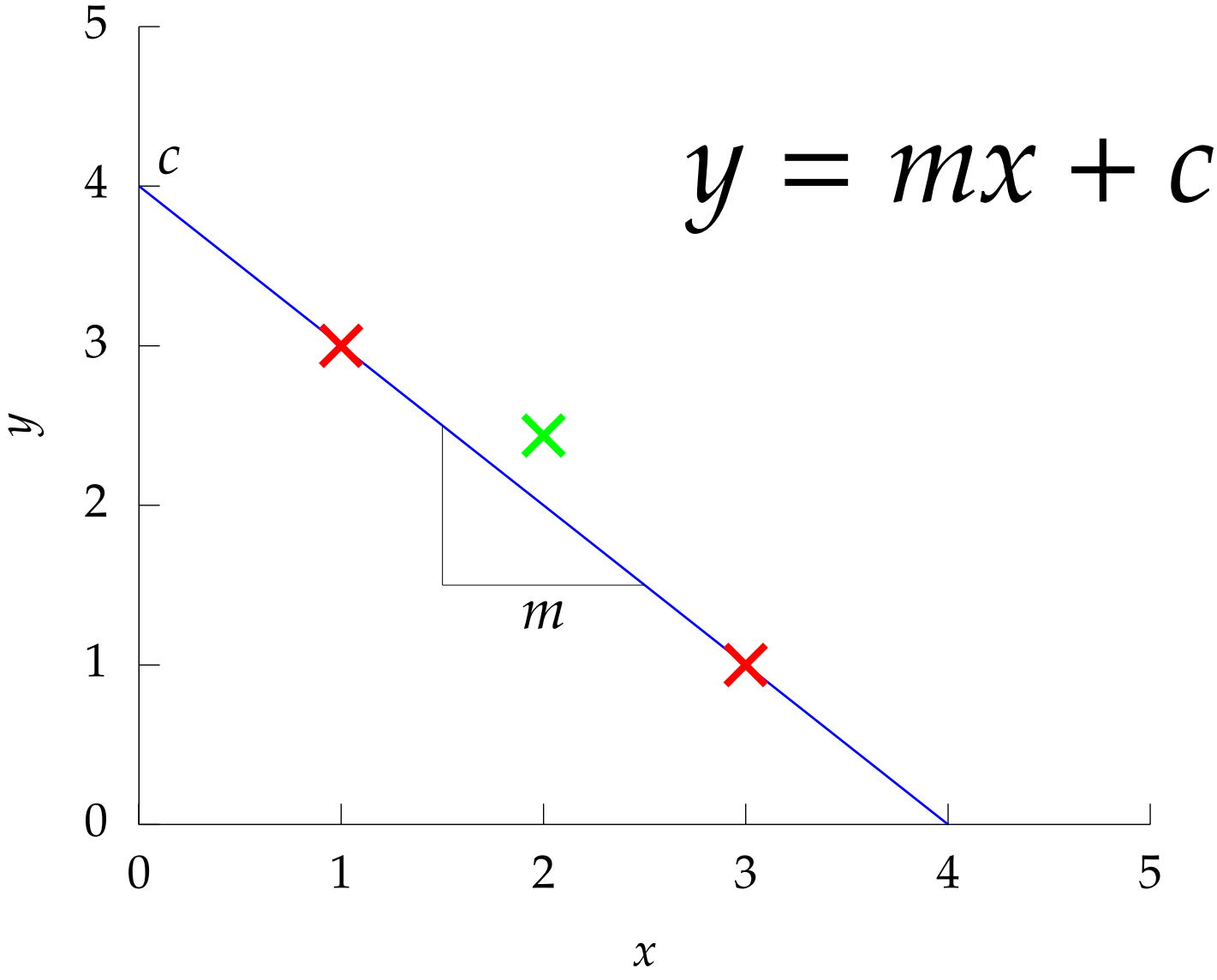
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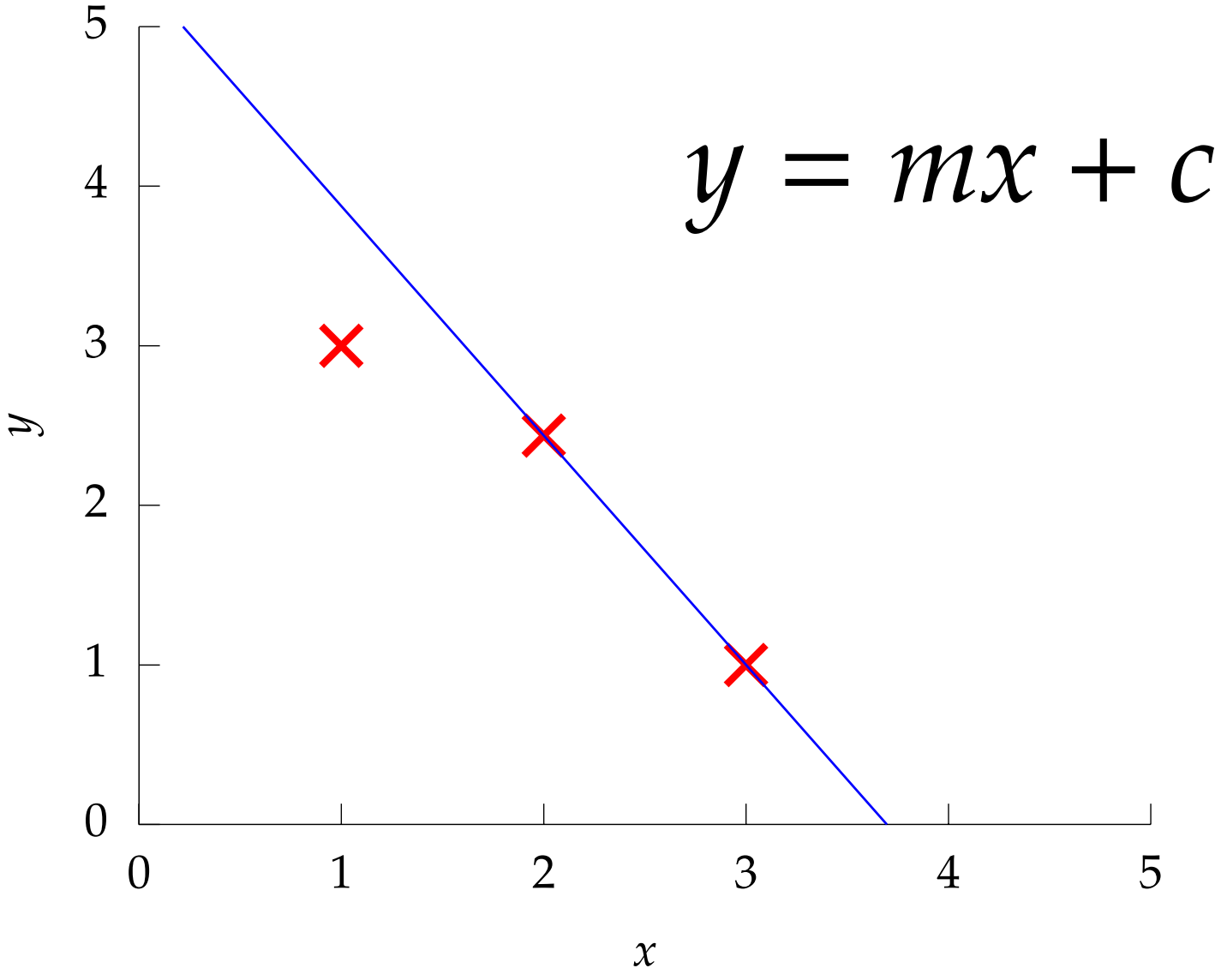
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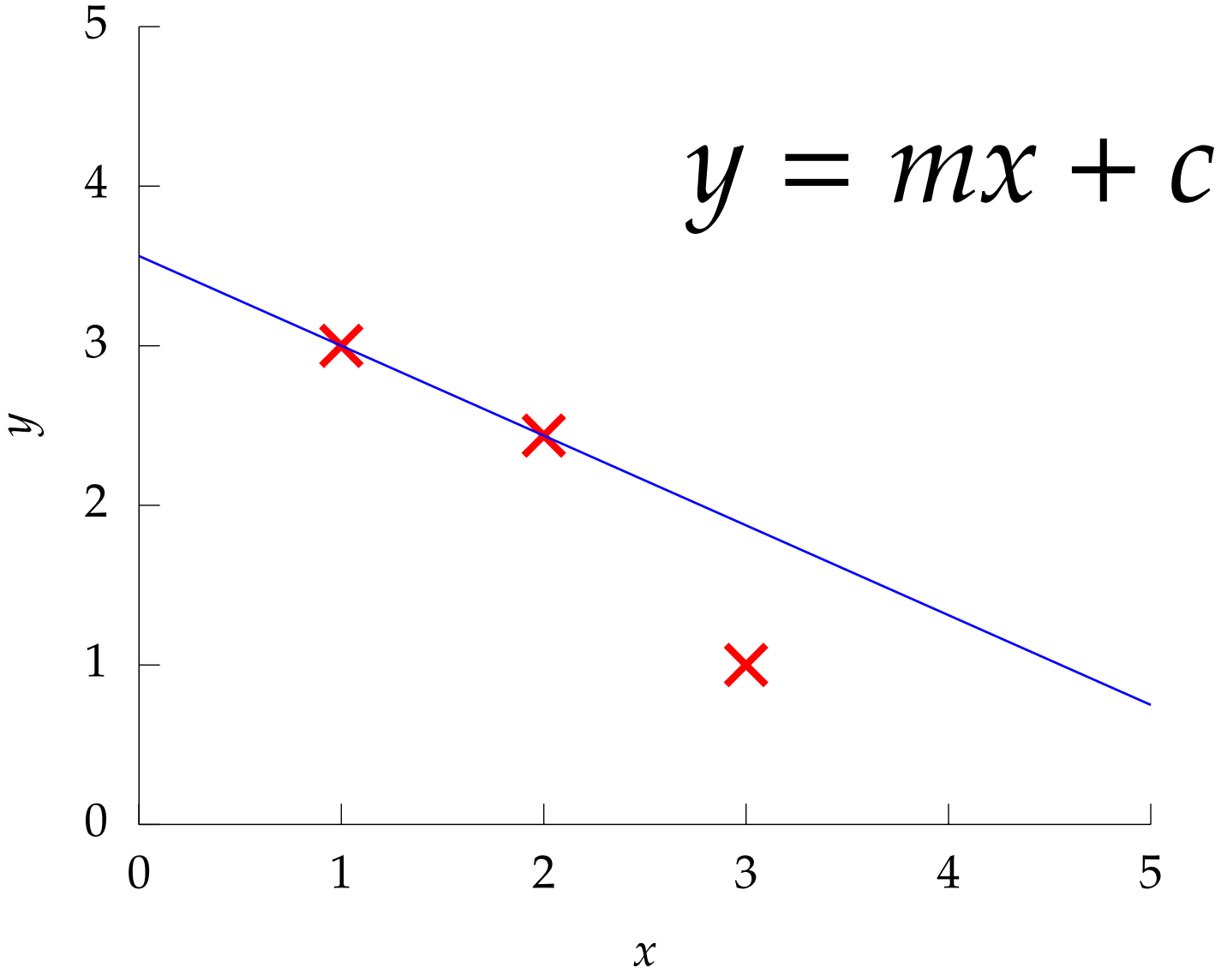
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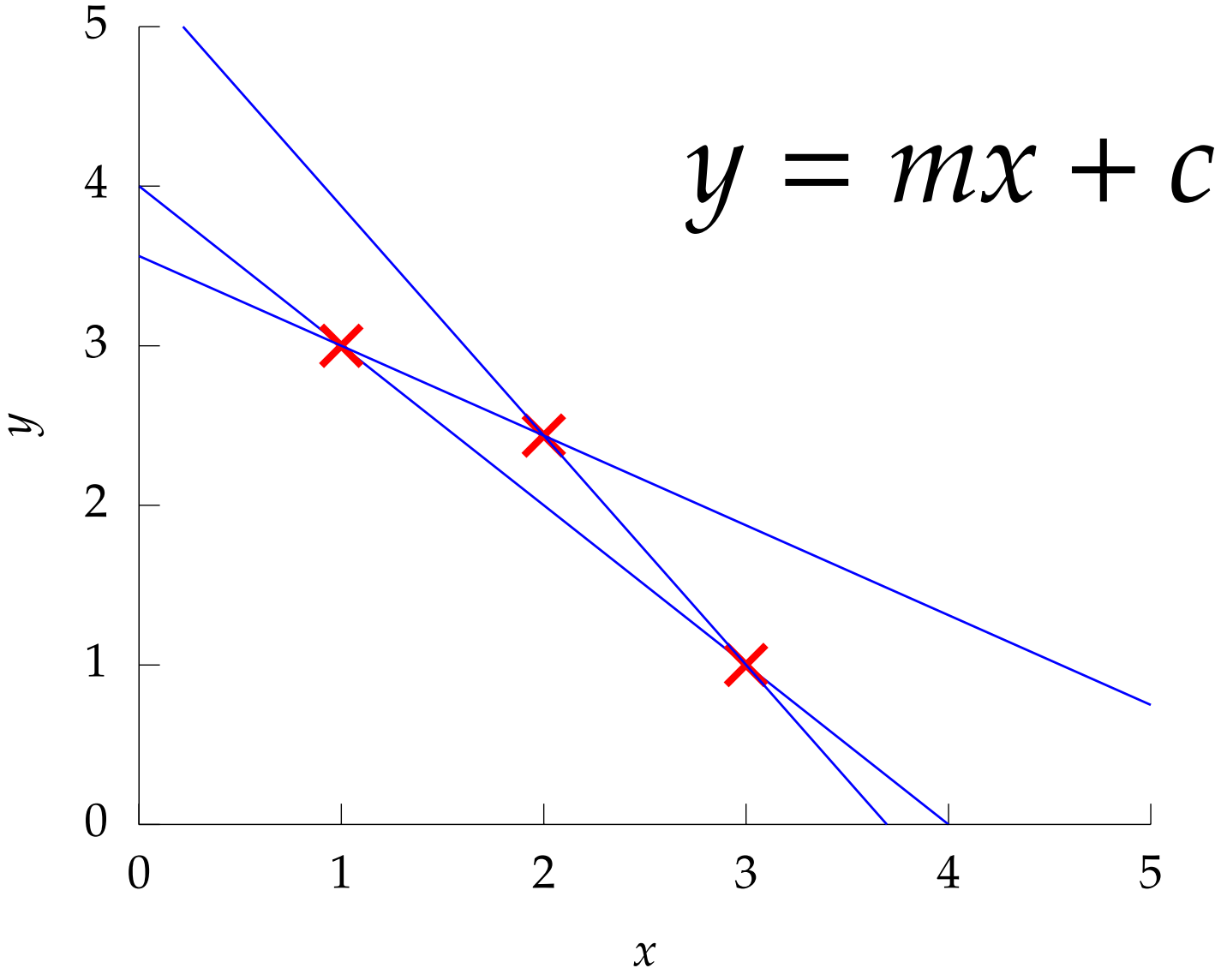
$y = mx + c$
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5
x
y

point 1: $x = 1, y = 3$

$$3 = m + c$$

point 2: $x = 3, y = 1$

$$1 = 3m + c$$

point 3: $x = 2, y = 2.5$

$$2.5 = 2m + c$$

point 1: $x = 1, y = 3$

$$3 = m + c + \epsilon_1$$

point 2: $x = 3, y = 1$

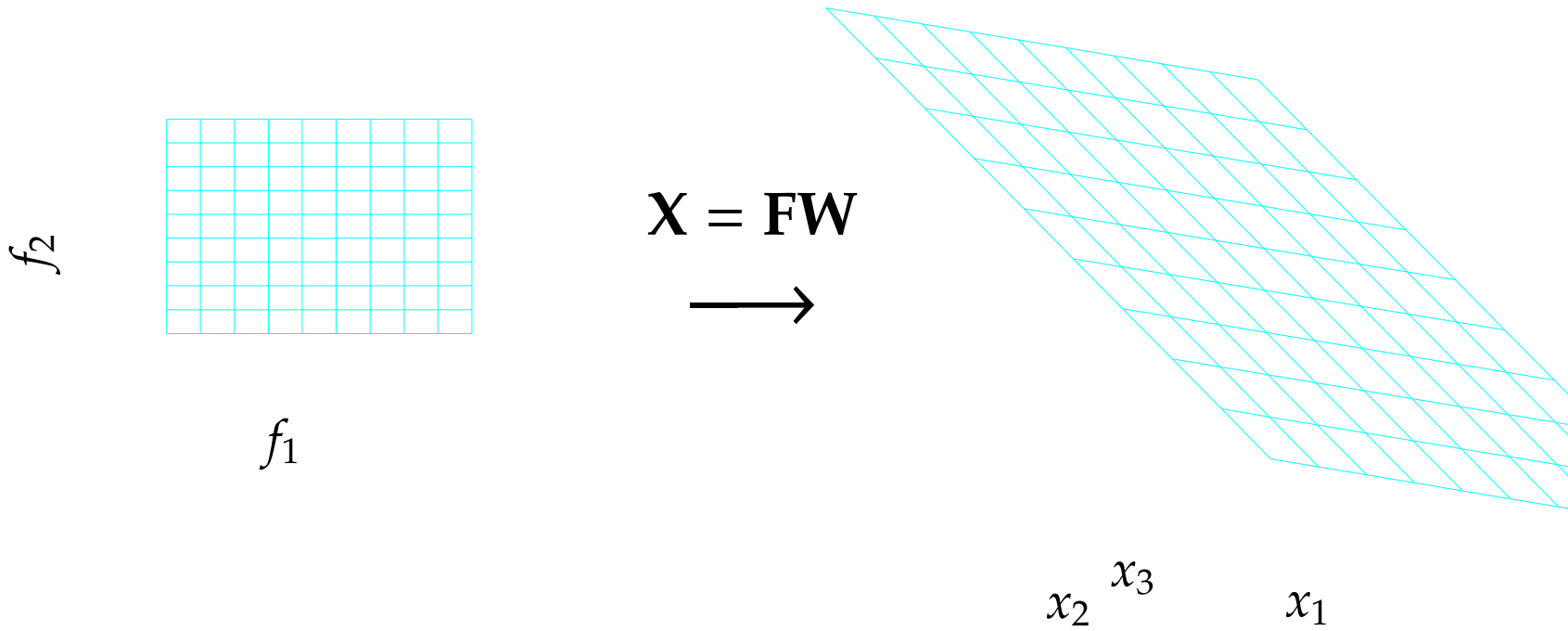
$$1 = 3m + c + \epsilon_2$$

point 3: $x = 2, y = 2.5$

$$2.5 = 2m + c + \epsilon_3$$

Linear Dimensionality Reduction

- Find a lower dimensional plane embedded in a higher dimensional space.
- The plane is described by the matrix $\mathbf{W} \in \Re^{p \times q}$.



Dimensionality Reduction

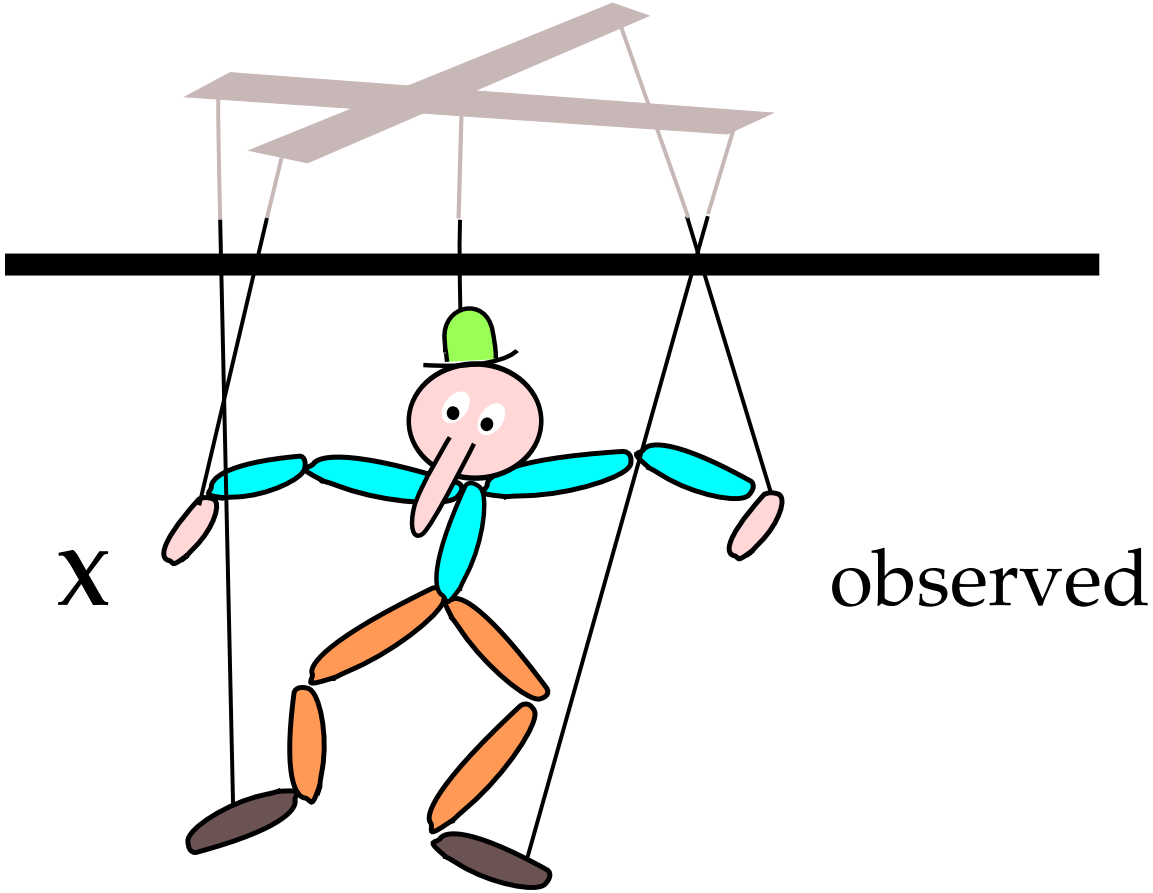
- Linear relationship between the data, $\mathbf{X}$, and a reduced dimensional representation, $\mathbf{F}$.

$$\mathbf{X} = \mathbf{F}\mathbf{W} + \epsilon,$$

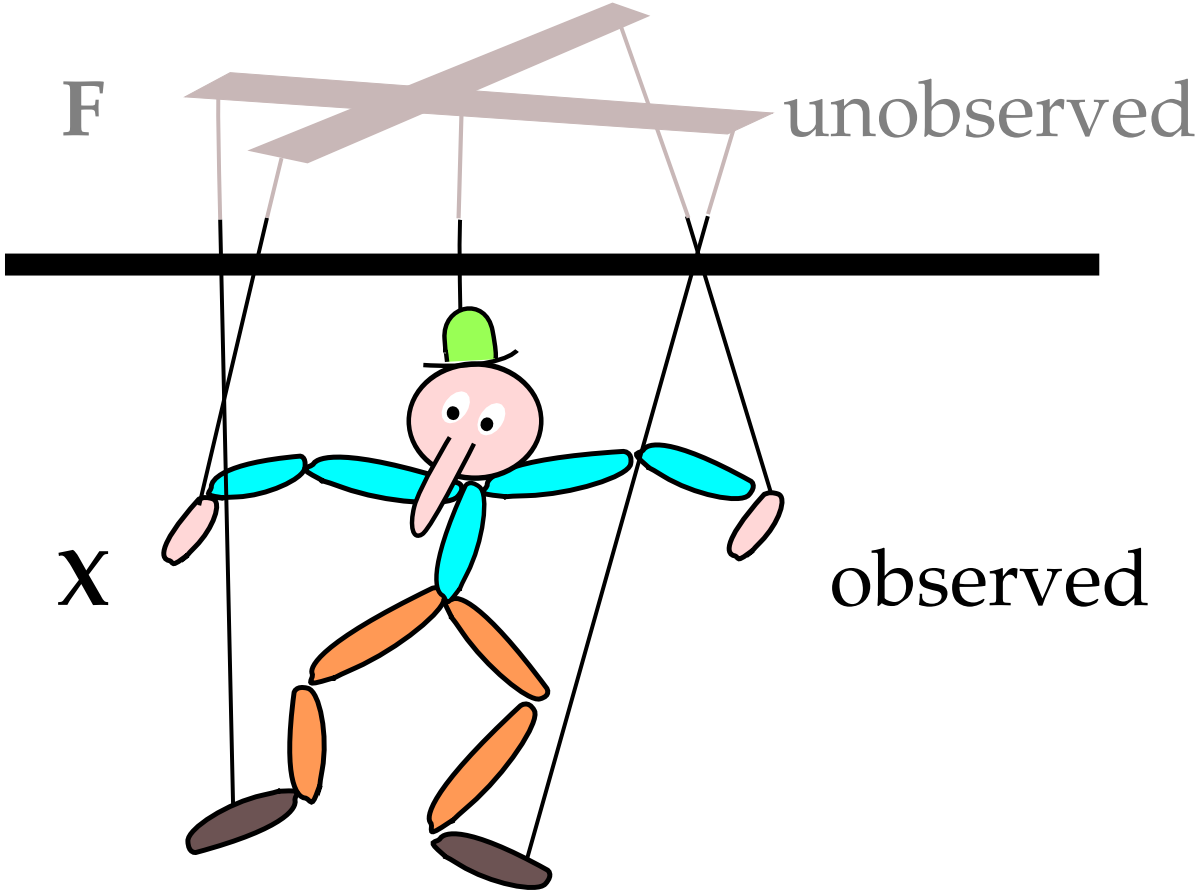
$$\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma})$$

- Problem is we don't know what $\mathbf{F}$ should be!

Marionette Analogy



Marionette Analogy



$\mathbf{F}$ is a Latent Variable

- Define a *probability distribution* for $\mathbf{F}$.
- Marginalize out $\mathbf{F}$ (integrate over).
- Optimize with respect to $\mathbf{W}$.
- For Gaussian distribution, $\mathbf{F} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
  - and $\Sigma = \sigma^2\mathbf{I}$ we have probabilistic PCA (Tipping and Bishop, 1999; Roweis, 1998).
  - and Σ constrained to be diagonal, we have factor analysis.

Dimensionality Reduction: Temporal Data

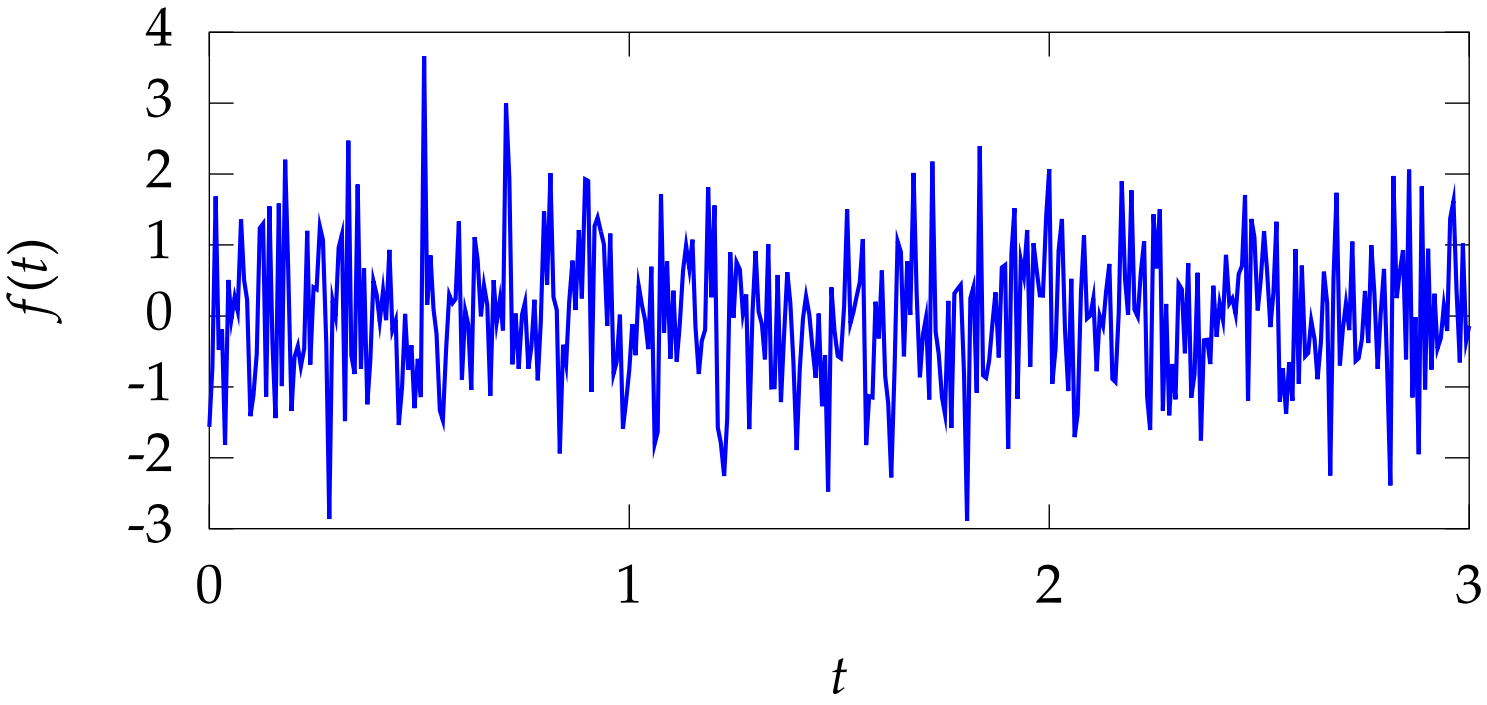


Figure : PCA: Pure sampling from a Gaussian does not retain temporal effects.

Dimensionality Reduction: Temporal Data

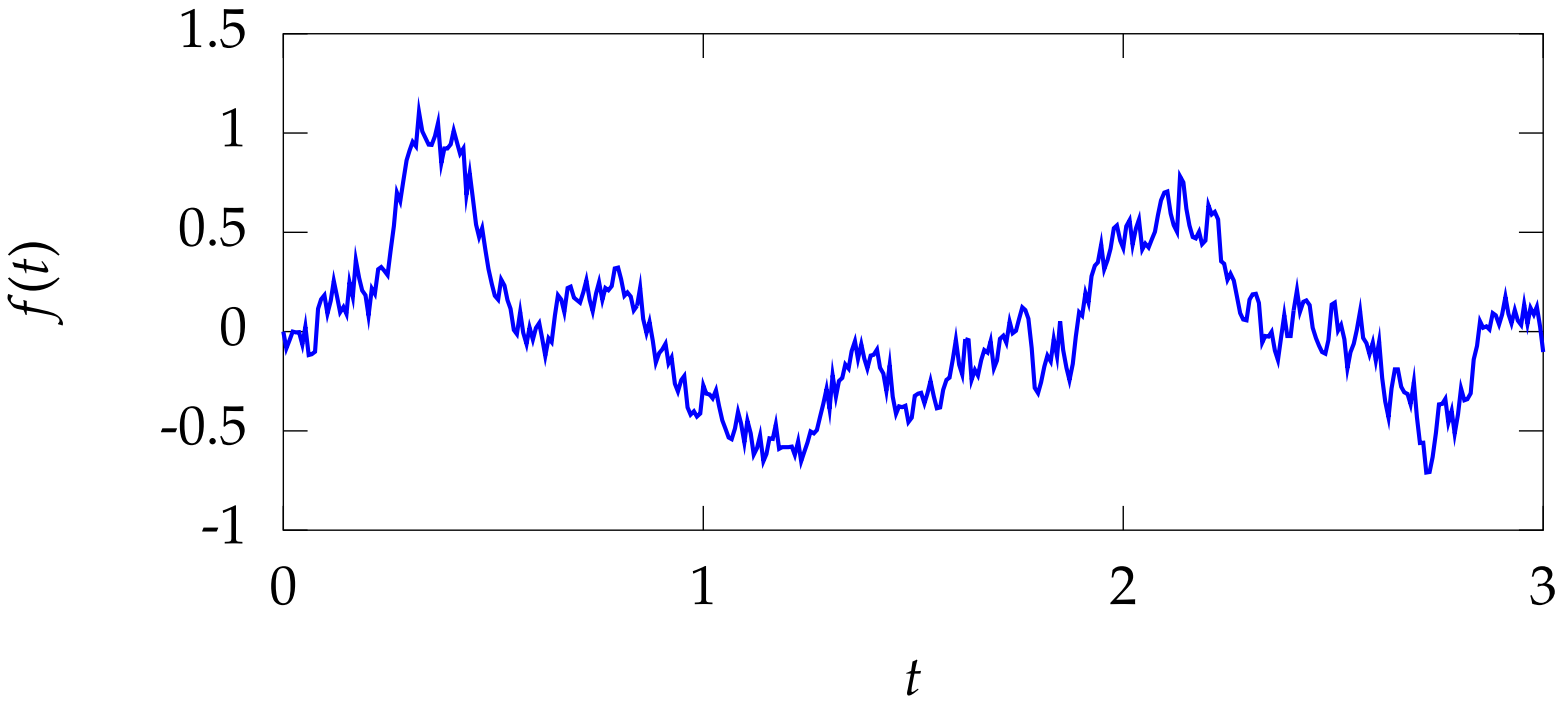


Figure : Kalman filter (Rauch-Tung-Striebel smoother) is Markov-Gaussian (non smooth).

Dimensionality Reduction: Temporal Data

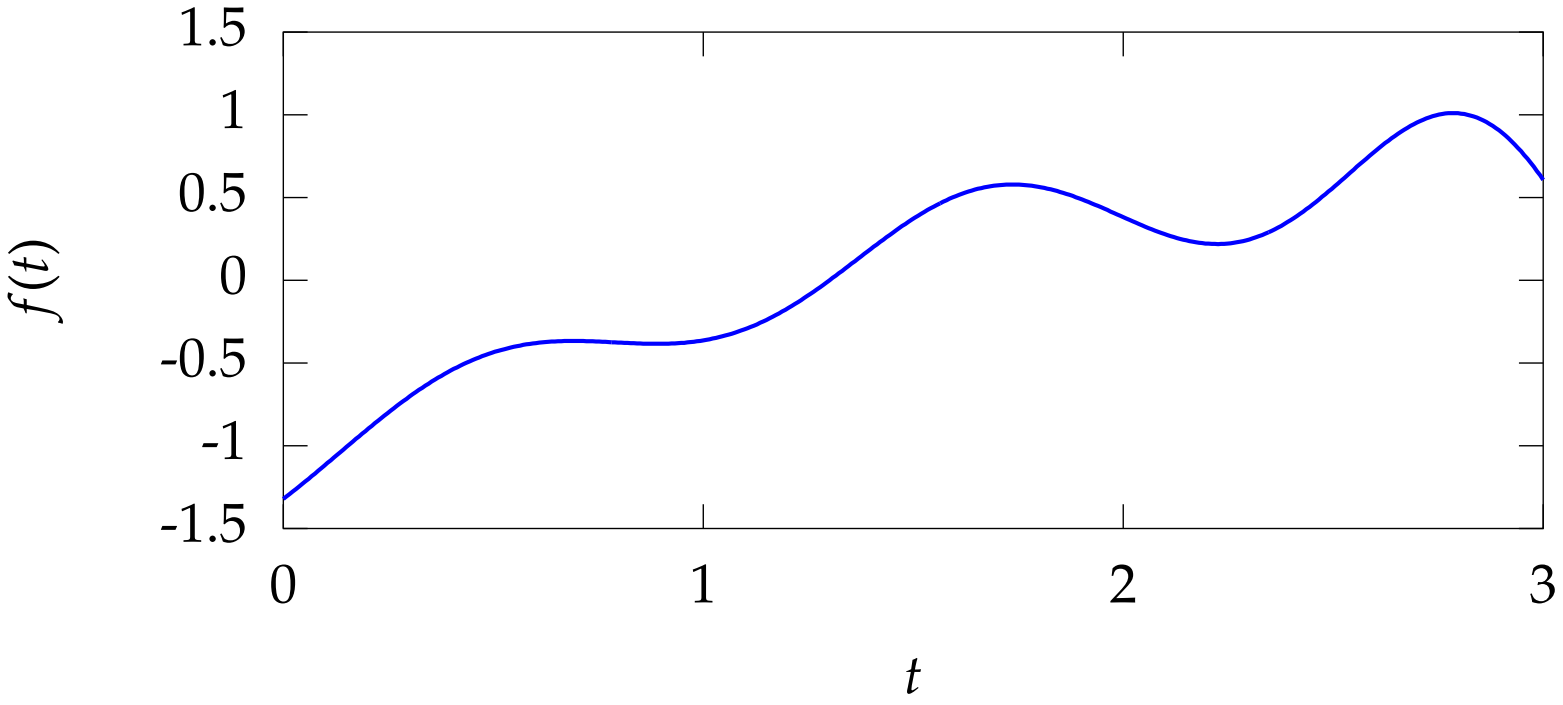
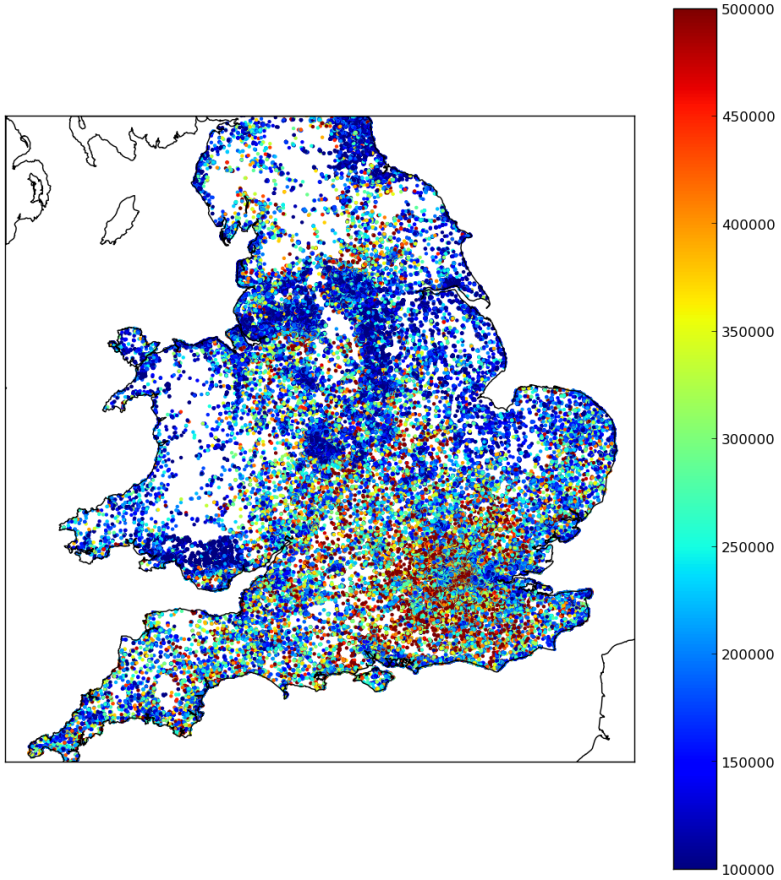


Figure : General Gaussian processes allow for priors over *smooth* functions.

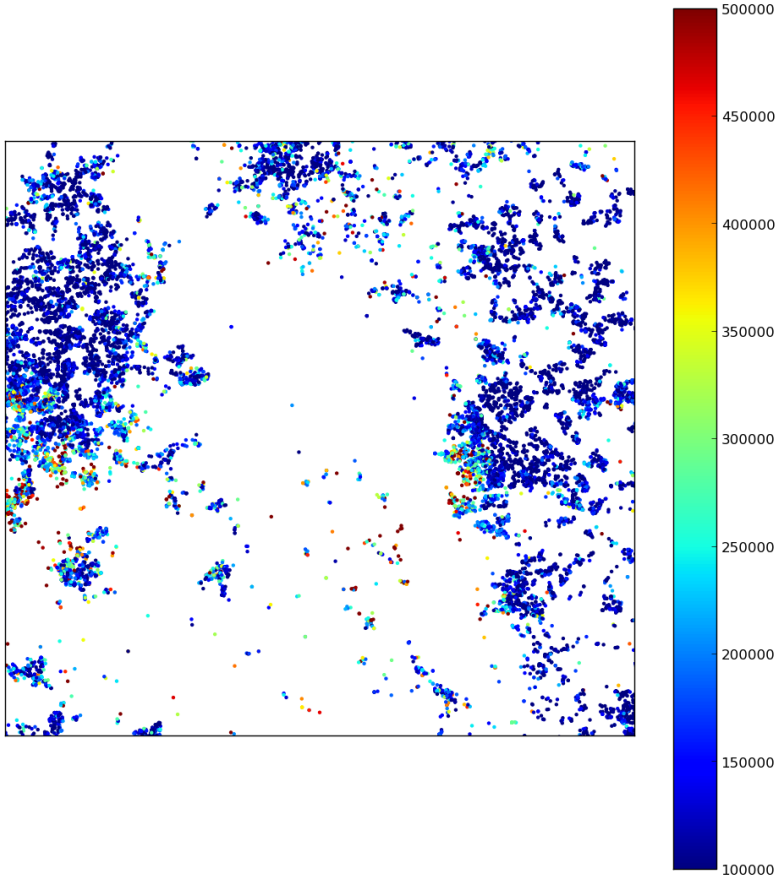
What's Changed (Changing) for Medicine?

Modern data availability



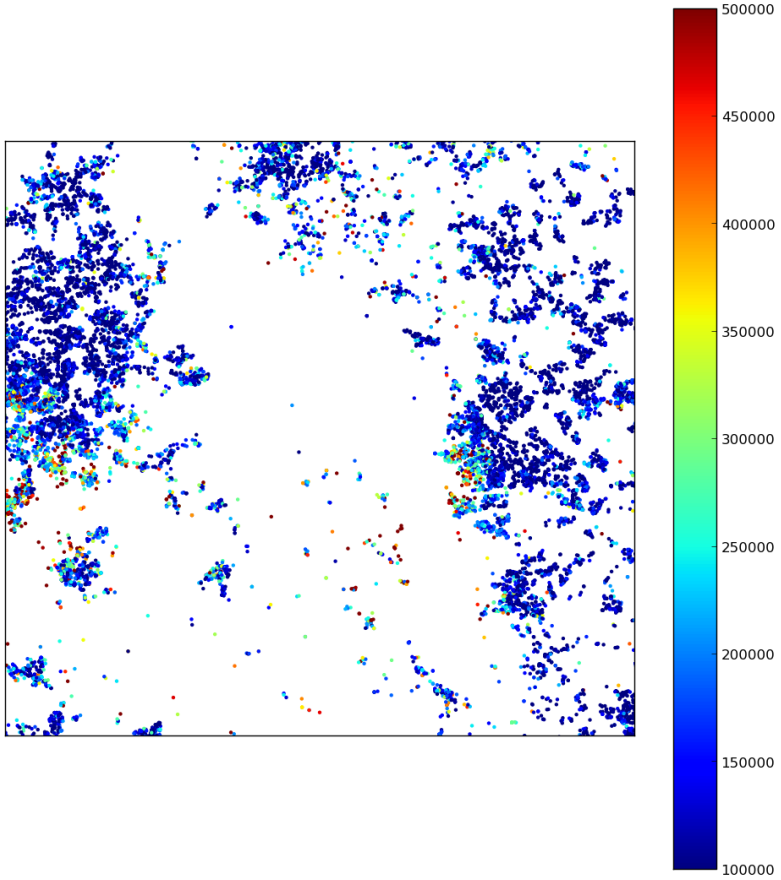
What's Changed (Changing) for Medicine?

Proxy for index of deprivation?



What's Changed (Changing) for Medicine?

Actually index of deprivation is a proxy for this ...



Hensman et al. (2013)

Gaussian Processes for Big Data

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Abstract

We introduce stochastic variational inference for Gaussian process models. This enables the application of Gaussian process (GP) models to data sets containing millions of data points. We show how GPs can be variationally decomposed to depend on a set

Even to accommodate these data sets, various approximate techniques are required. One approach is to partition the data set into separate groups [e.g. Snelson and Ghahramani, 2007, Urtasun and Darrell, 2008]. An alternative is to build a low rank approximation to the covariance matrix based around 'inducing variables' [see e.g. Csató and Opper, 2002, Seeger et al., 2003, Quiñonero Candela and Rasmussen, 2005, Tit-

Hensman et al. (2013)

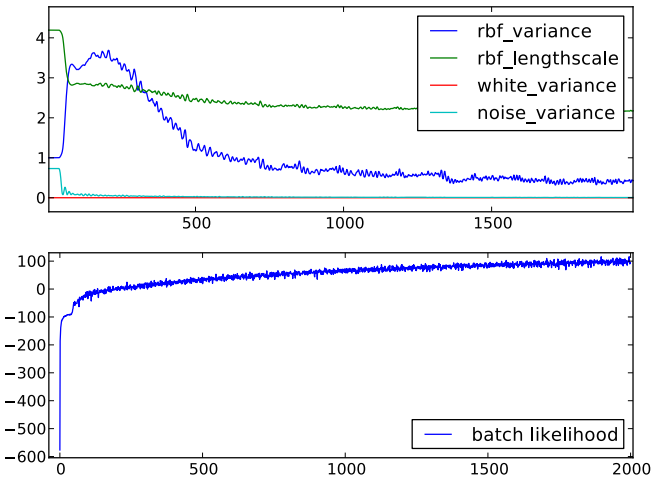

Figure 4: Convergence of the SVIGP algorithm on the two dimensional toy data

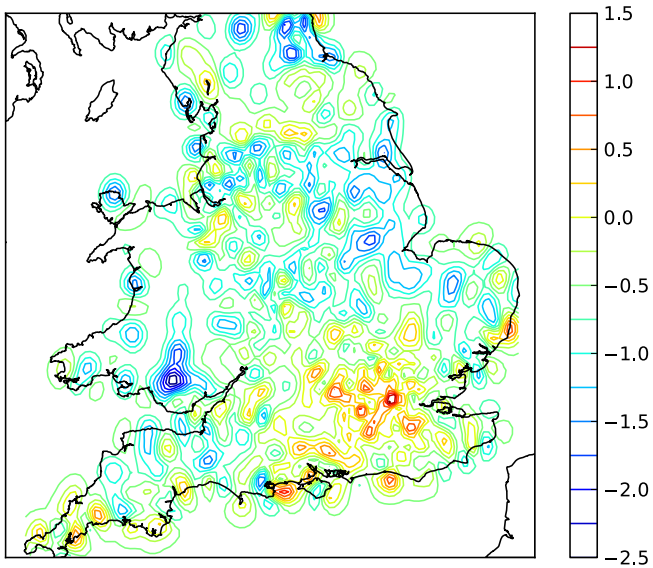

Figure 5: Variability of apartment price (logarithmically!) throughout England and Wales.

`land-registry-monthly-price-paid-data/`, which covers England and Wales, and filtered for apartments. This resulted in a data set with 75,000 entries,

ted a GP with the same covariance function as our

What's Changed (Changing) for Medicine?

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

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A brief history *of Registration*

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

A brief history of registration

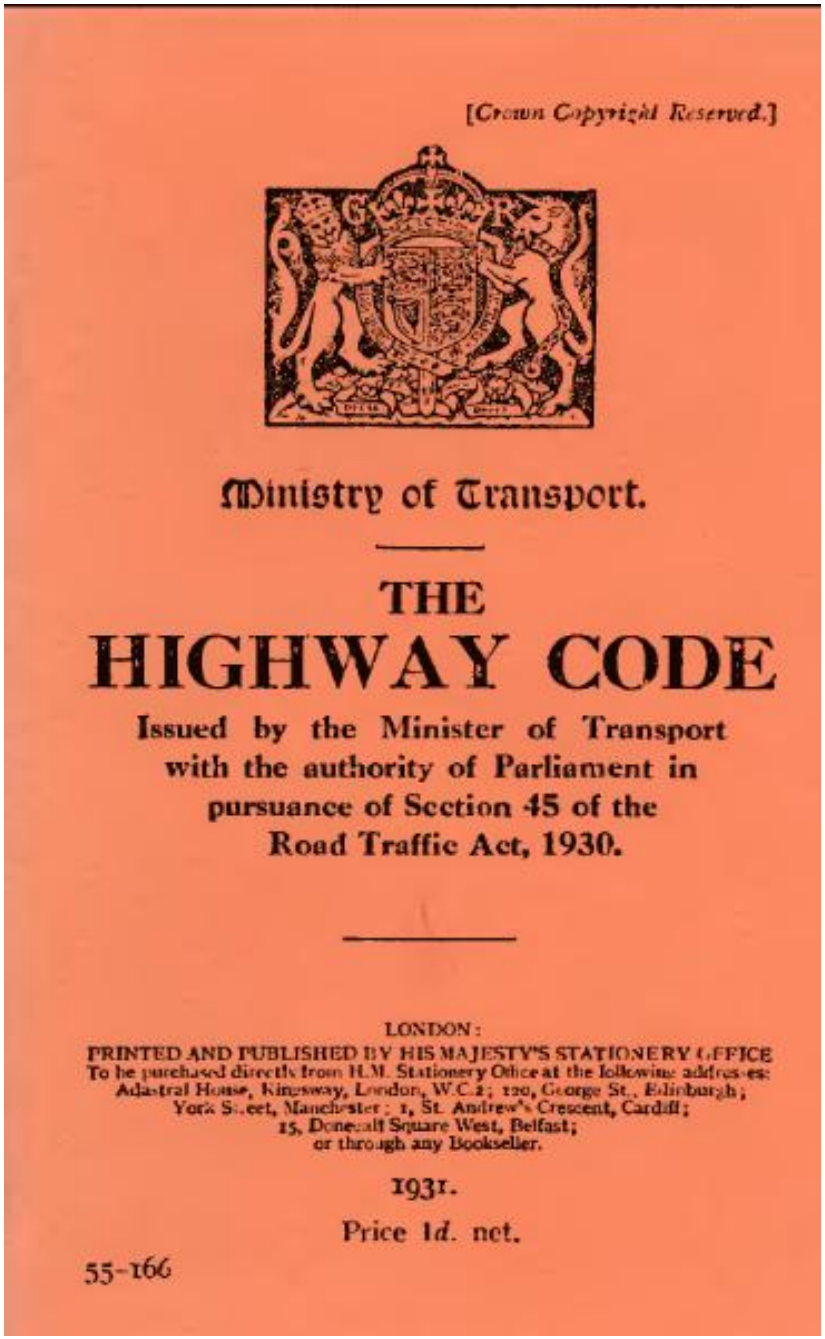
The early days

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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Ministry of Transport.

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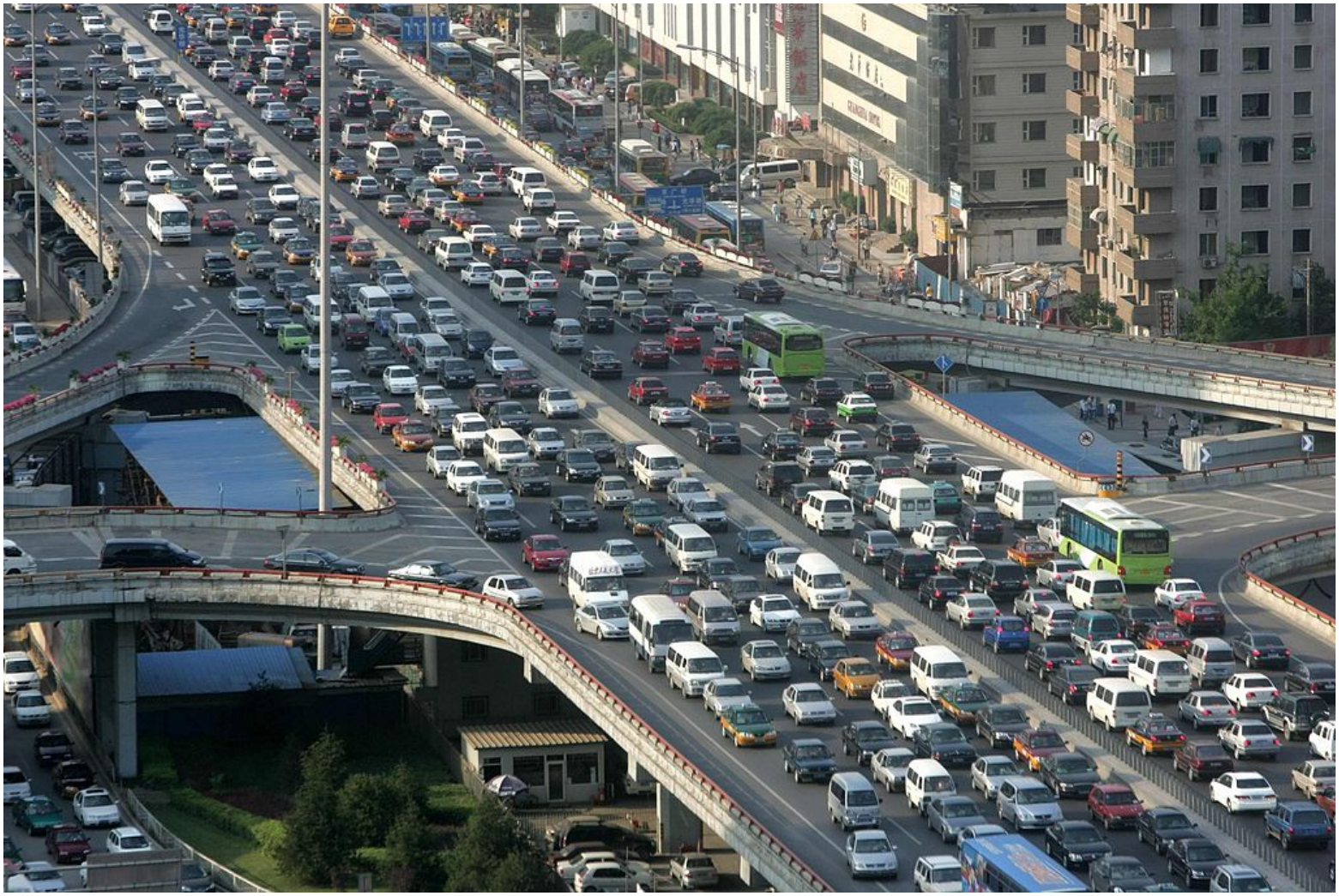

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What's Changed (Changing) for Medicine?

- 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

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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.

UK Government Stipulation on Data Availability

Patients will view their NH

www.telegraph.co.uk/health/healthnews/9673802/Patients-will-view-their-NHS-records-online-in-three-years.html

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Patients will view their NHS records online in three years

NHS patients will be given online access to their health records in the next three years under plans to be announced by the Government today.

The move for online health records comes despite the decision by Andrew Lansley, the previous health secretary, to cancel a massive NHS national database Photo: ALAMY

By Robert Winnett, Political Editor
7:00AM GMT 13 Nov 2012

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Patient Online: Roadmap

Patient Online: the route

www.rcgp.org.uk/news/2013/march/patient-online-launch-with-secretary-of-state.aspx

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Patient Online launch with Secretary of State

Publication date: 06 March 2013

Patient Online: the route to electronic access

(Left-right) Dr Peter Short, GP; Chris Ghush, Head of RCGP CIRC; Dr Imran Rafi, Chair of CIRC, who led the programme; Jeremy Hunt, Secretary of State for Health; Dr Clare Gerada, Chair of RCGP; and Dr Arvind Madan, GP

Patient Online: the route to electronic access

New guidance to support GP practices in providing online access for

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RCGP rules out full online access to GP records for most patients

6 March 2013 | By Madlen Davies

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GPs should not be forced to give patients retrospective access to information in their medical records as it would pile work on practices and risk destabilise the doctor-patient relationship, says the RCGP in its road-map for Government plans for online records access by 2015.

The Department of Health-commissioned report says that online access to records should be 'prospective' by default and that practices should be able to set an 'access from' date for all records.

The college recommends practices assess whether access to information entered prior to this date should be allowed for patients with complex diseases and only on a 'case-by-case' basis.

The report, *Patient Online: The Road Map*, also warns of the 'unintended consequence' of an increase in queries from patients when allowing access to patient records online. It also recommends practices should be able to specify which patients were able to see their test results before the GP had reviewed them.

The GPC said the report was a blow to the Department of Health's plans to give all patients online access to their full patient record by 2015.

According to the report, while 75% of practices have the capability to provide electronic access to medical records, less than 1% of practices- 63 in total- have

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EMIS Patient Access

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How do I view my medical record?

← Patient Access - Medical Record

New and returning users may **sign in**

If your practice offers this service there is a link called View your medical record in the Medical Record section of the home page after you have signed in. This area of the site requires an extra sign in process so you will have to request details from your practice to gain access.

Appointments Book an appointment

Date	Time	Clinician	Location	Action
You have no appointments booked				

Medical Record

View your medical record

This link will open in another window and you will need to sign in there to view your record. Use your Access user details and security word. When finished remember to sign out and close the window.

Repeat Prescriptions Make a request See your repeat prescriptions See requests detail

Watch a video on how to view your medical record

Patient Access - Medical Record

How do I view my medical record?

Why can't I view my medical record?

Why do I have to sign in again to view my medical record?

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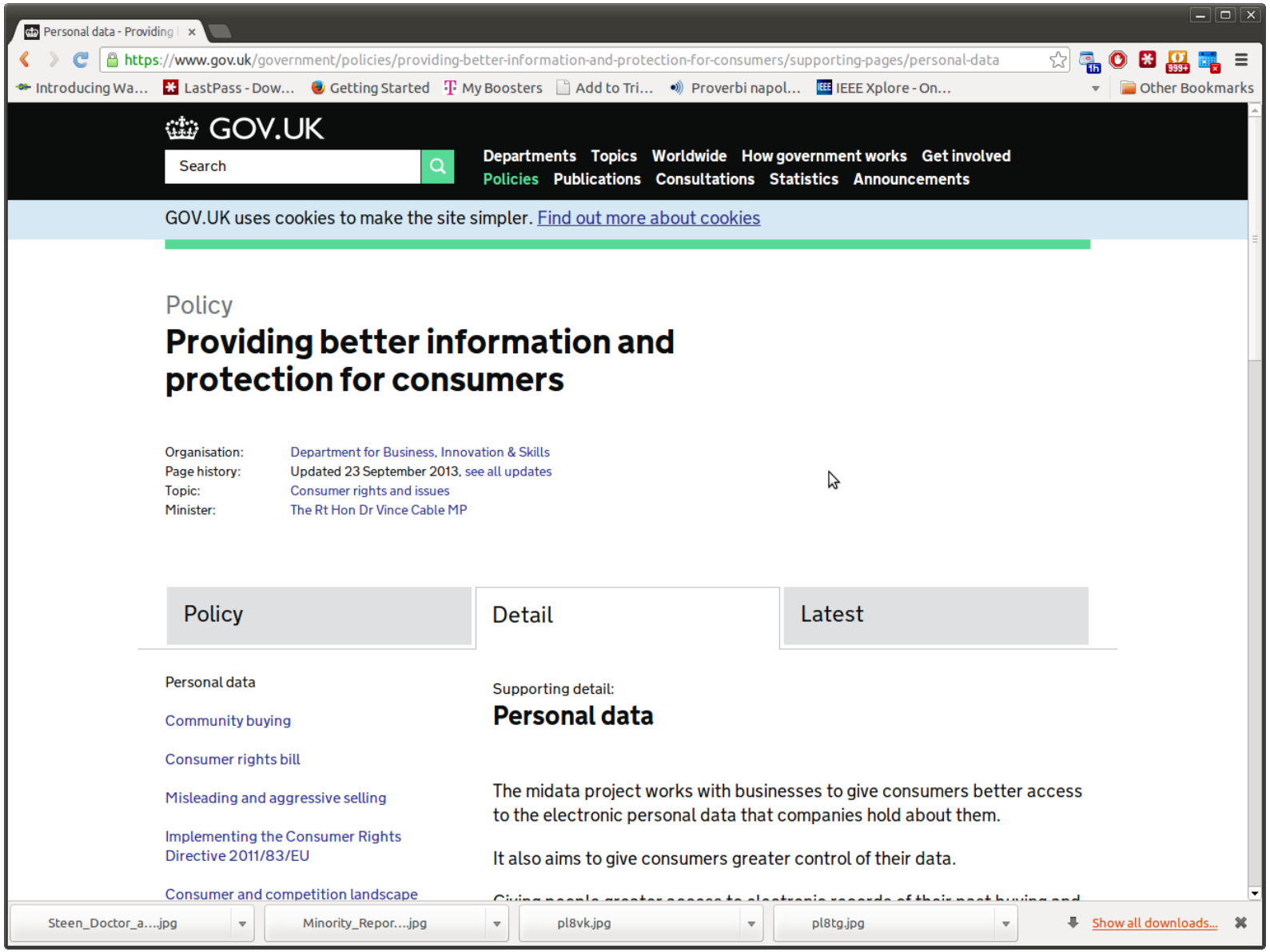

Outline

Data Heterogenity

Deep Learning

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.

Missing Data

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- As data sets become very large (39 million in EMIS) data becomes extremely sparse.
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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,

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

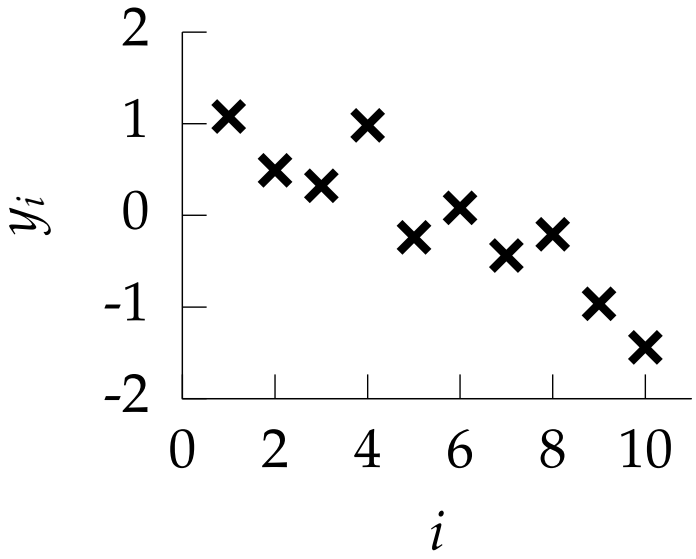
- Where $y_3, \ldots, y_p$ contains:
  1. all tests not applied to this patient
  2. all tests not yet invented!!

Magical Marginalization in Gaussians

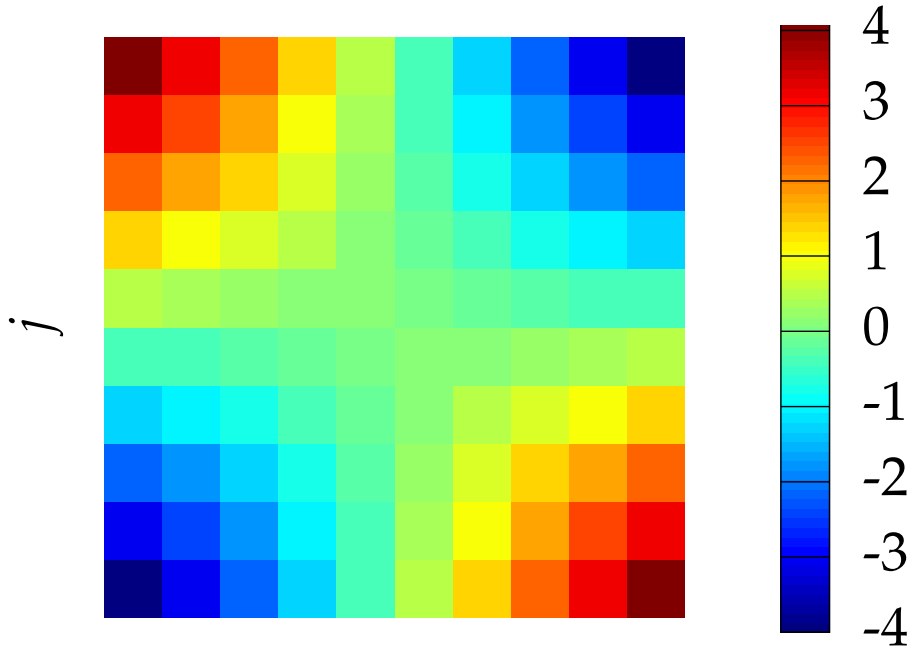
Multi-variate Gaussians

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

Gaussian Marginalization Property



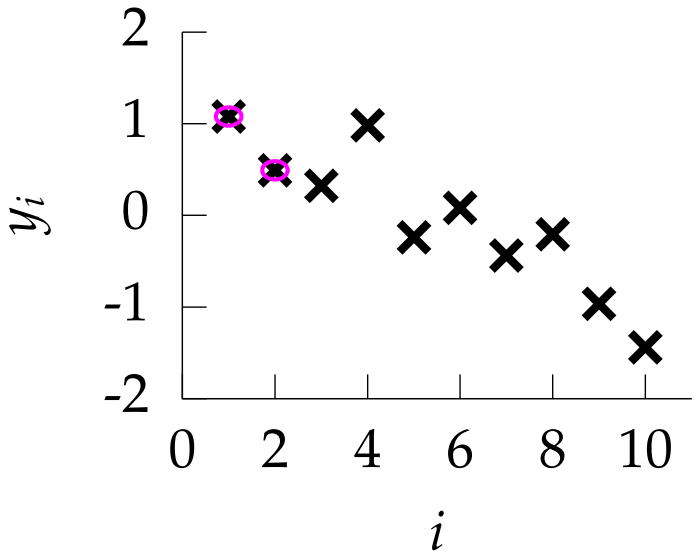
(a) A 10 dimensional sample



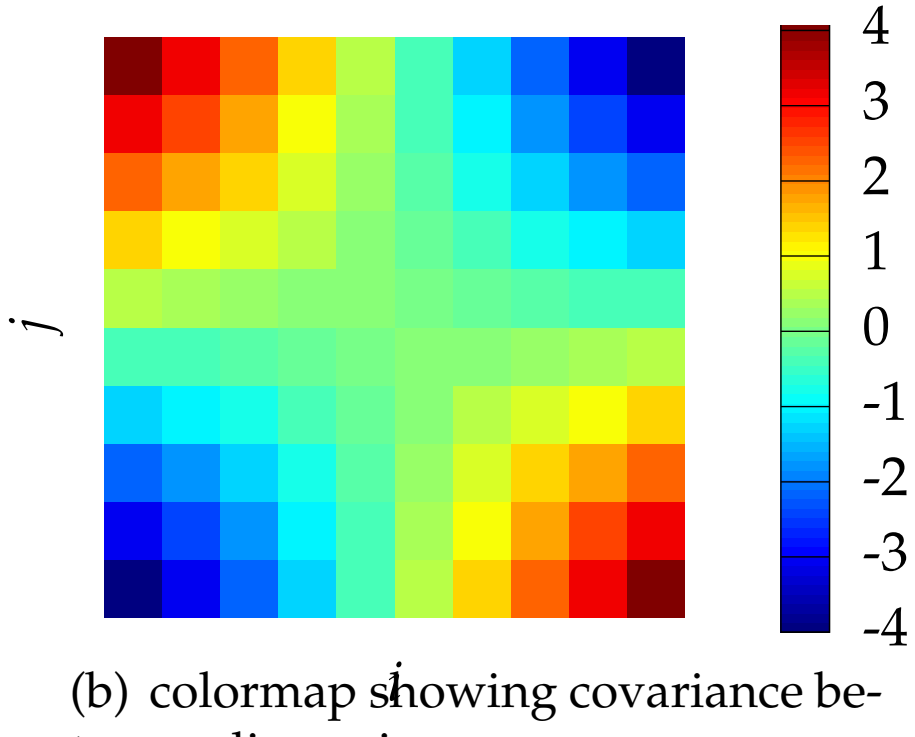
(b) colormap showing covariance between dimensions.

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

Gaussian Marginalization Property



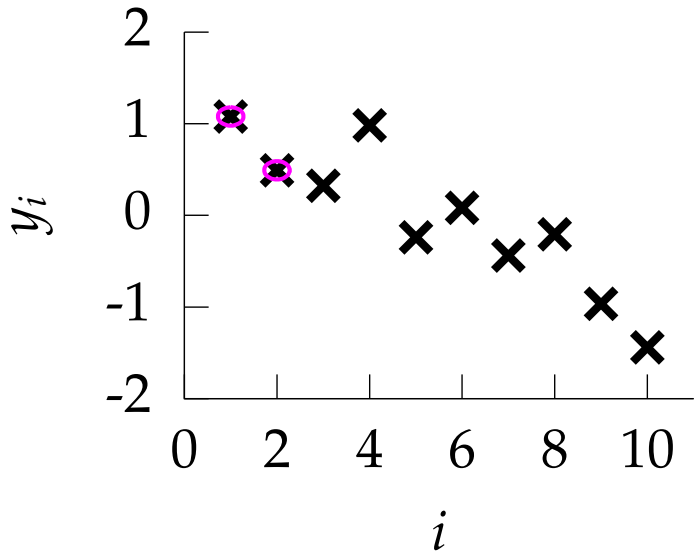
(a) A 10 dimensional sample



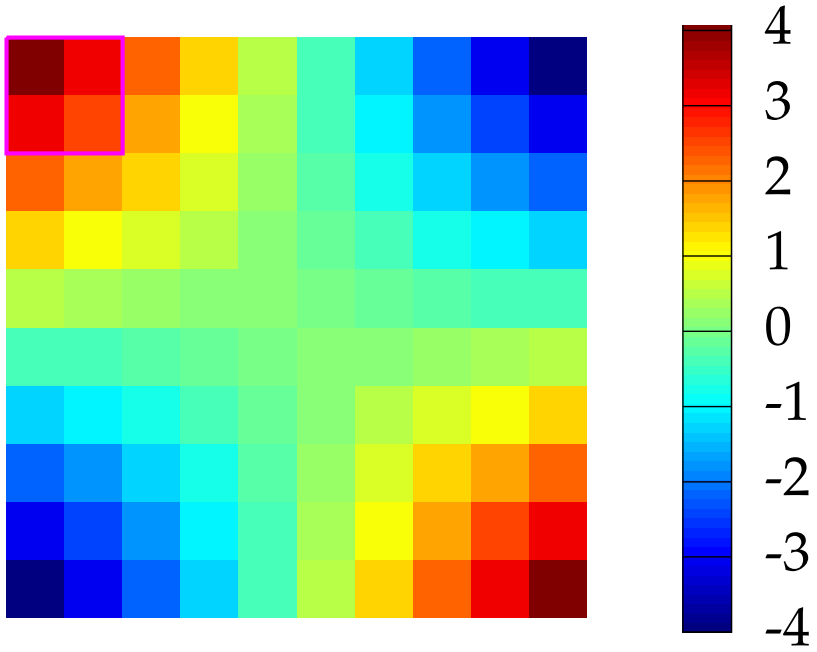
(b) colormap showing covariance between dimensions.

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

Gaussian Marginalization Property



(a) A 10 dimensional sample



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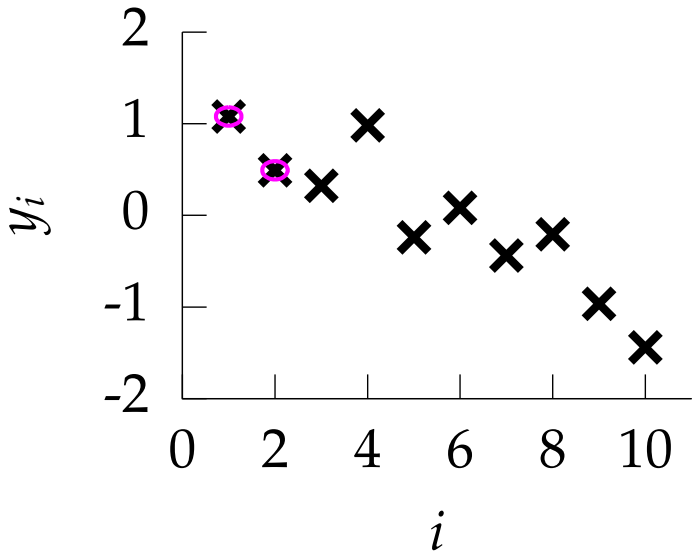
Gaussian Marginalization Property



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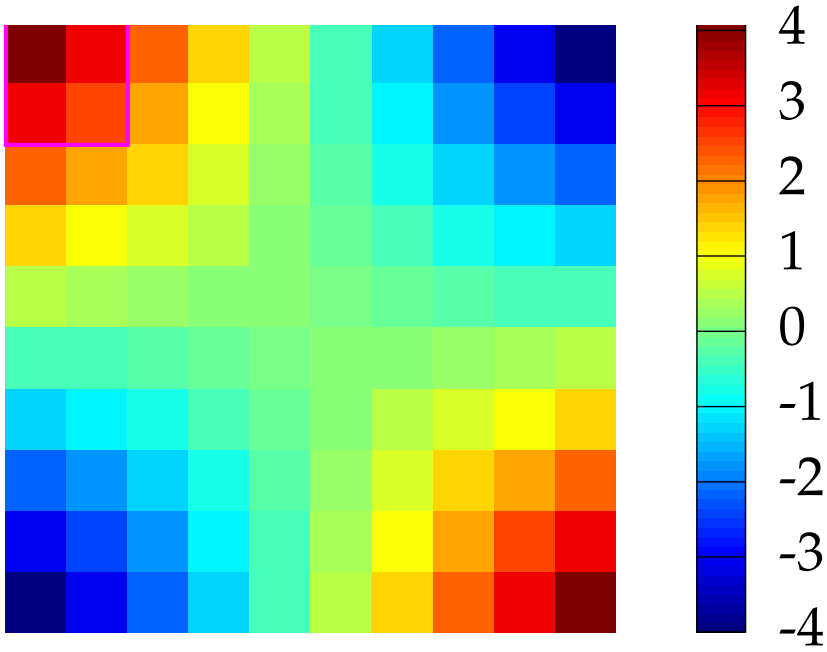
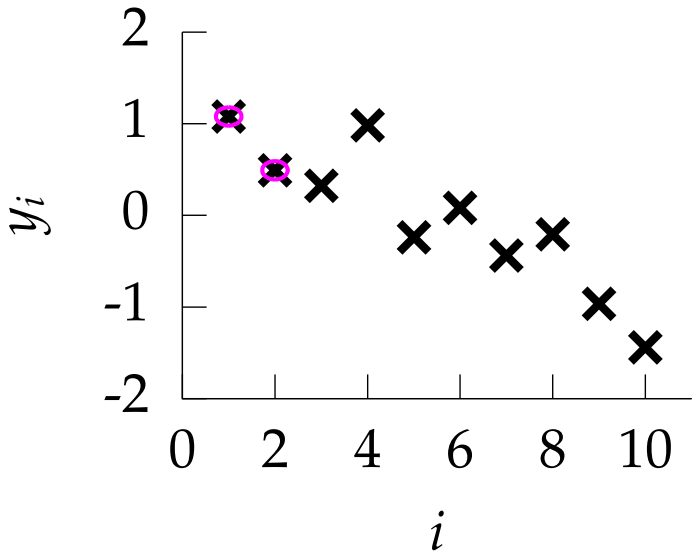


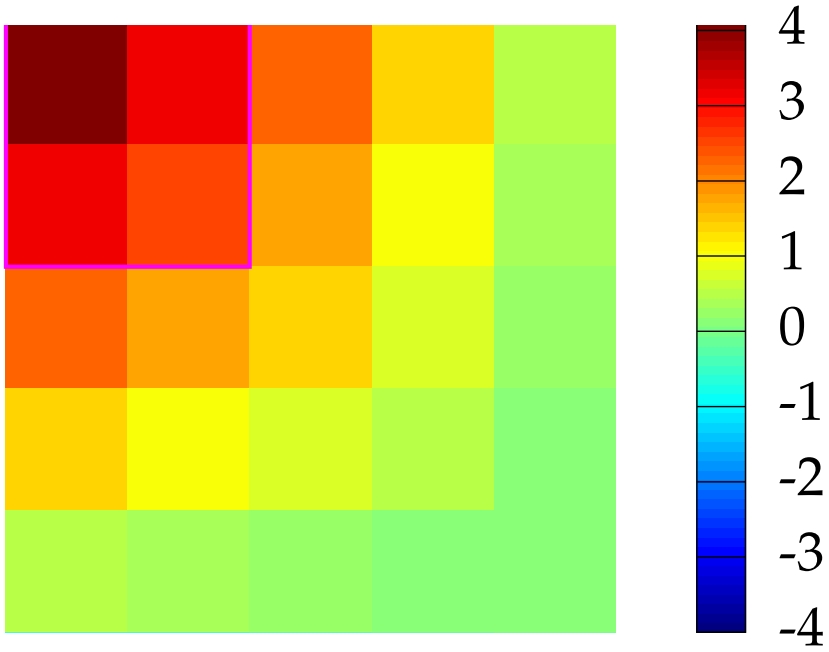
(b) colormap showing covariance between dimensions.

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

Gaussian Marginalization Property



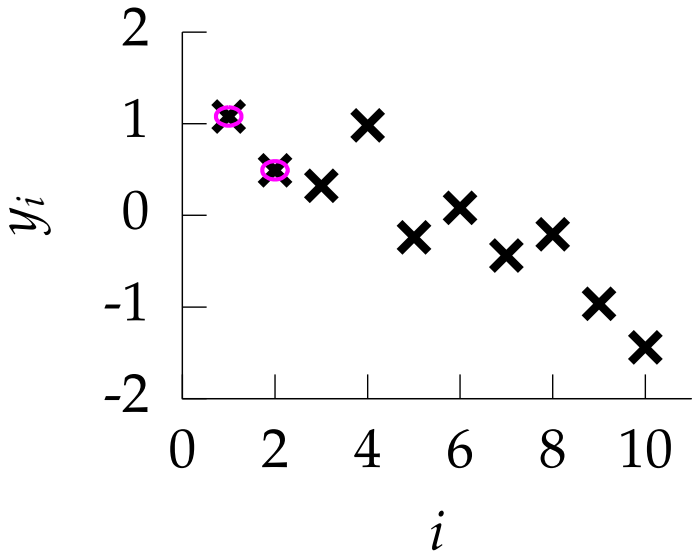
(a) A 10 dimensional sample



(b) colormap showing covariance between dimensions.

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

Gaussian Marginalization Property



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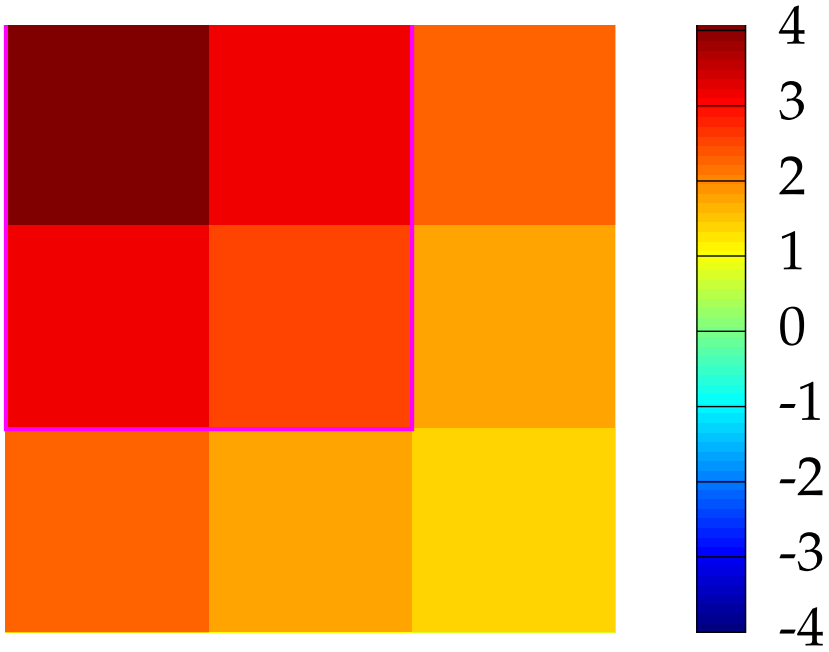
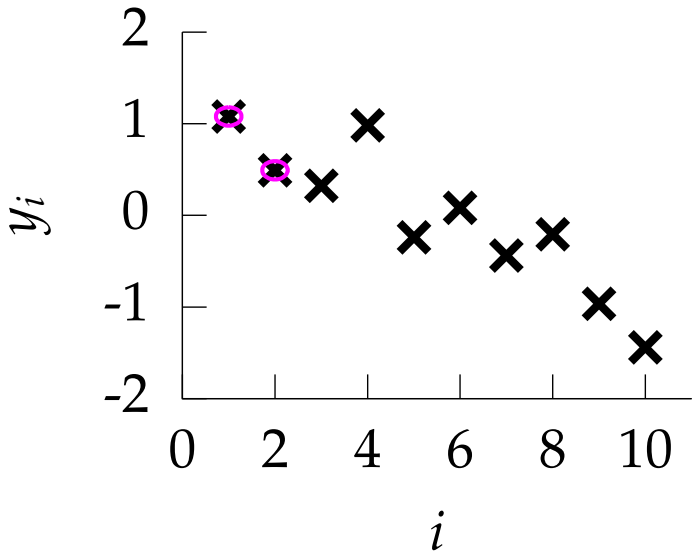


(b) colormap showing covariance between dimensions.

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

Gaussian Marginalization Property



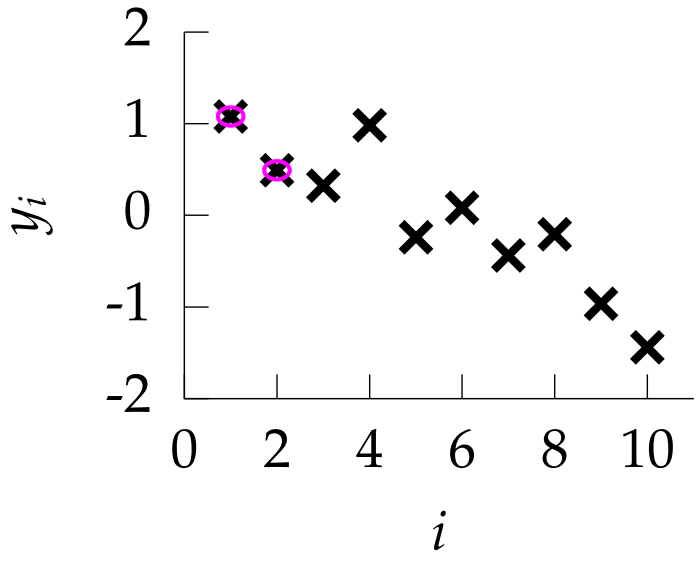
(a) A 10 dimensional sample

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

(b) colormap showing covariance between dimensions.

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

Gaussian Marginalization Property



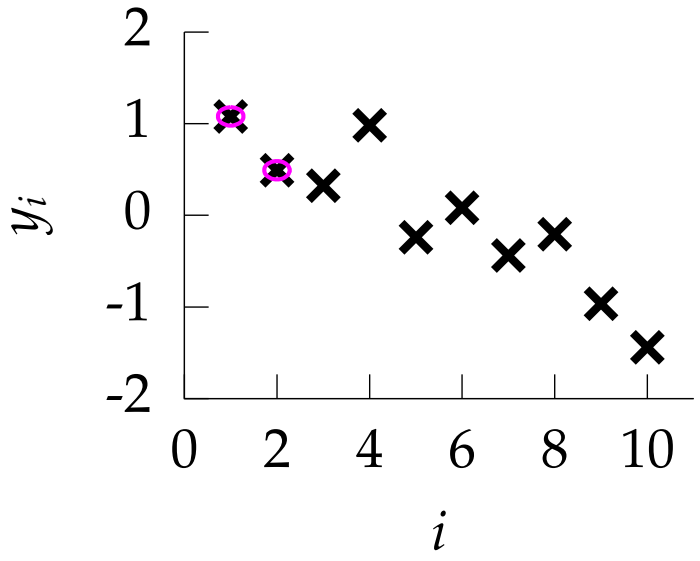
(a) A 10 dimensional sample

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

(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 recent submission with Nicoló Fusi.

Methods that Interrelate Covariates

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

Linear Dimensionality Reduction

Linear Latent Variable Model

- Represent data, $\mathbf{Y}$, with a lower dimensional set of latent variables $\mathbf{X}$.
- Assume a linear relationship of the form

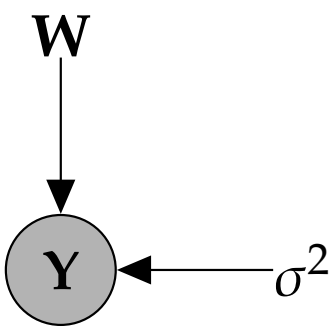
$$\mathbf{y}_{i,:} = \mathbf{W}\mathbf{x}_{i,:} + \boldsymbol{\epsilon}_{i,:},$$

where

$$\boldsymbol{\epsilon}_{i,:} \sim \mathcal{N}\left(\mathbf{0}, \sigma^2\mathbf{I}\right).$$

Linear Latent Variable Model II

Probabilistic PCA Max. Likelihood Soln (Tipping and Bishop, 1999)



$$p\left(\mathbf{Y}|\mathbf{W}\right) = \prod_{i=1}^{n} \mathcal{N}\left(\mathbf{y}_{i,:}|\mathbf{0}, \mathbf{W}\mathbf{W}^{\top} + \sigma^2\mathbf{I}\right)$$

Linear Latent Variable Model II

Probabilistic PCA Max. Likelihood Soln (Tipping and Bishop, 1999)

$$p\left(\mathbf{Y}|\mathbf{W}\right) = \prod_{i=1}^{n} \mathcal{N}\left(\mathbf{y}_{i,:}|\mathbf{0}, \mathbf{C}\right), \quad \mathbf{C} = \mathbf{W}\mathbf{W}^{\top} + \sigma^2\mathbf{I}$$

$$\log p\left(\mathbf{Y}|\mathbf{W}\right) = -\frac{n}{2}\log|\mathbf{C}| - \frac{1}{2}\mathrm{tr}\left(\mathbf{C}^{-1}\mathbf{Y}^{\top}\mathbf{Y}\right) + \text{const.}$$

If $\mathbf{U}_q$ are first q principal eigenvectors of $n^{-1}\mathbf{Y}^{\top}\mathbf{Y}$ and the corresponding eigenvalues are $\mathbf{\Lambda}_q$,

$$\mathbf{W} = \mathbf{U}_q\mathbf{L}\mathbf{R}^{\top}, \quad \mathbf{L} = \left(\mathbf{\Lambda}_q - \sigma^2\mathbf{I}\right)^{\frac{1}{2}}$$

where $\mathbf{R}$ is an arbitrary rotation matrix.

Dealing with Non Gaussian Data

- Marginalization property of Gaussians very attractive.
- How to incorporate non-Gaussian data?
  - Data which isn't missing at random.
  - Binary data.
  - Ordinal categorical data.
  - Poisson counts.
  - Outliers.

Project Back into Gaussian

- Combine non-Gaussian likelihood with Gaussian prior.
- Either:
  - Project back to Gaussian posterior that is nearest in KL sense.
  - Expectation propagation.
- Or:
  - Fit a locally valid Gaussian approximation.
  - Laplace Approximation.

Ongoing work with Ricardo Andrade Pacheco (EP) and Alan Saul (Laplace) also James Hensman.

Gaussian Noise

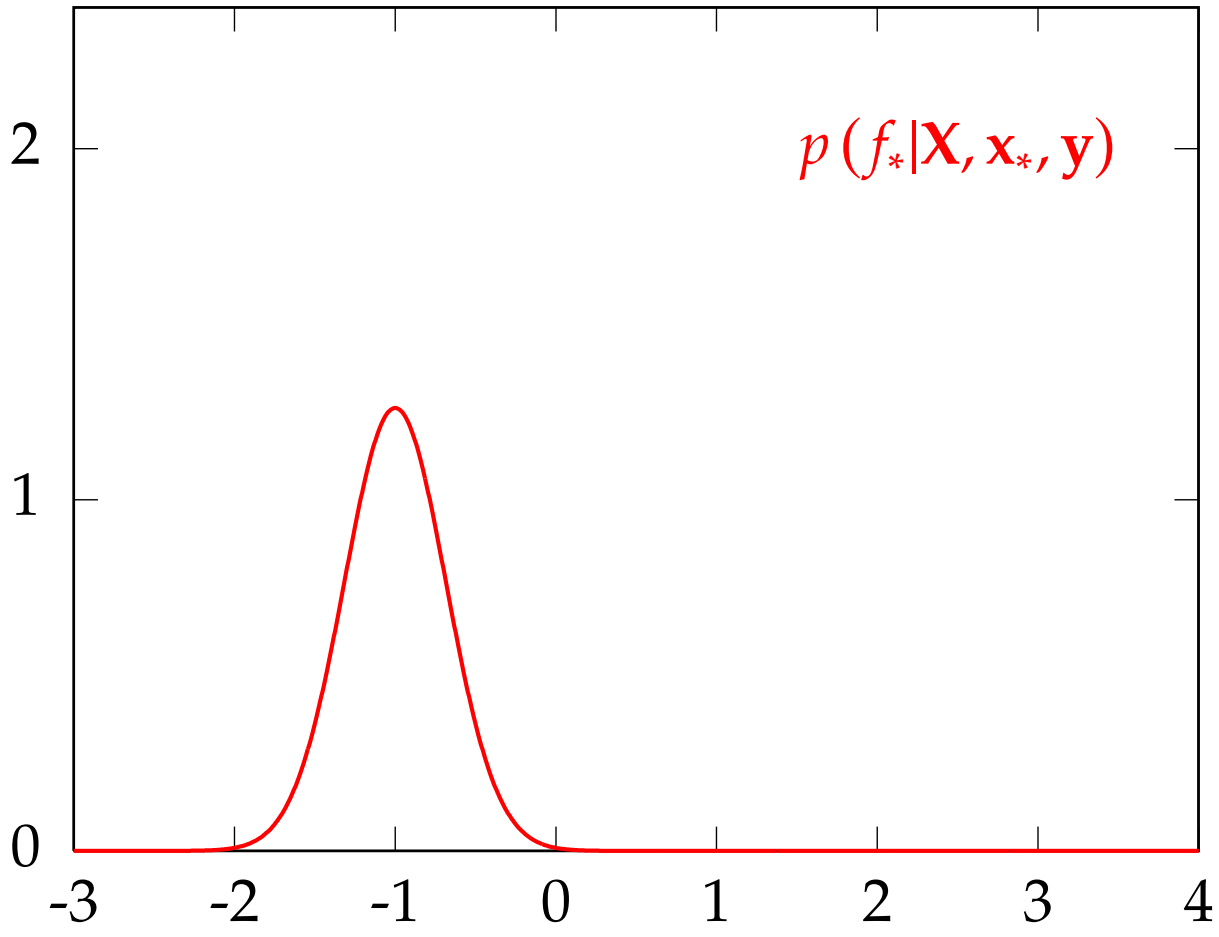
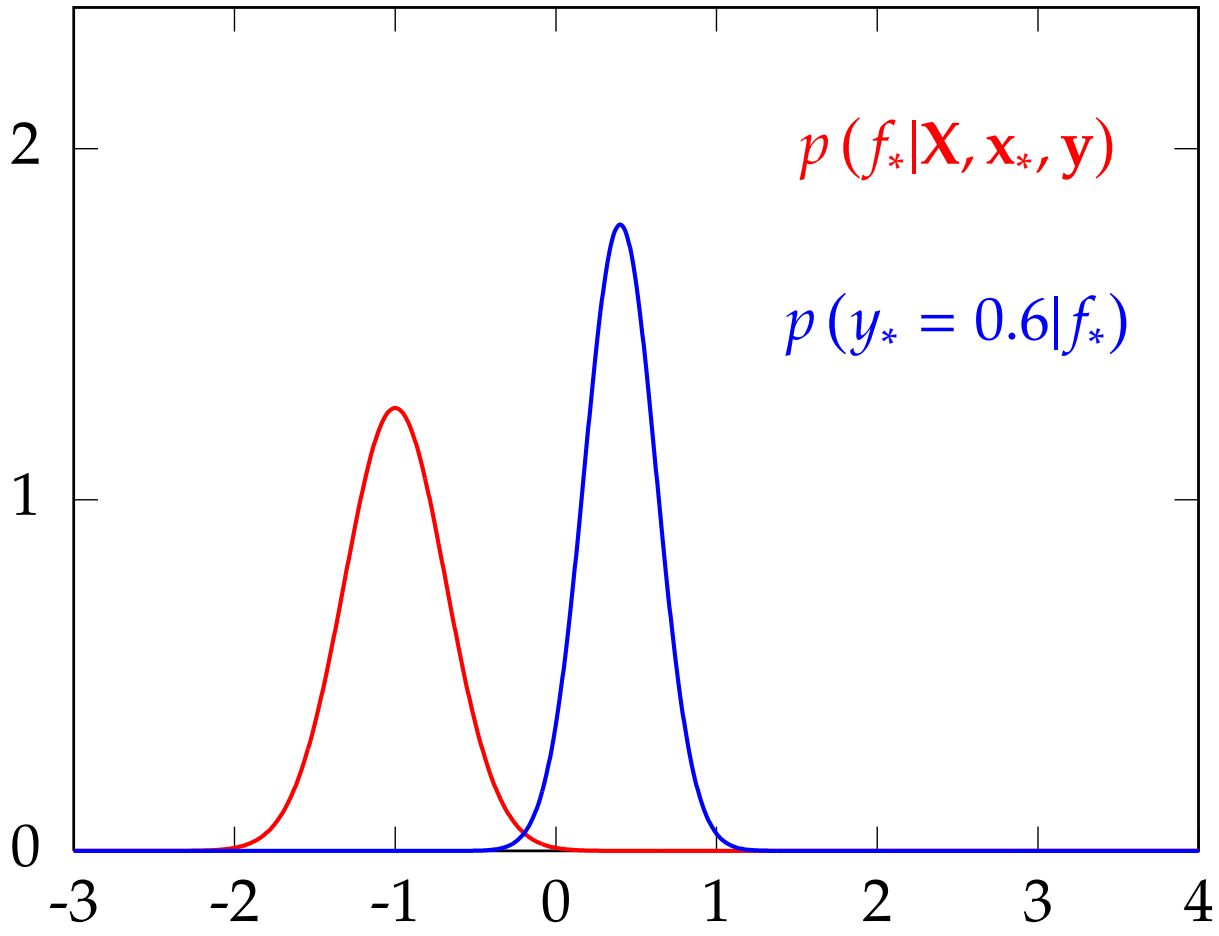


Figure : Inclusion of a data point with Gaussian noise.

Gaussian Noise



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Gaussian Noise

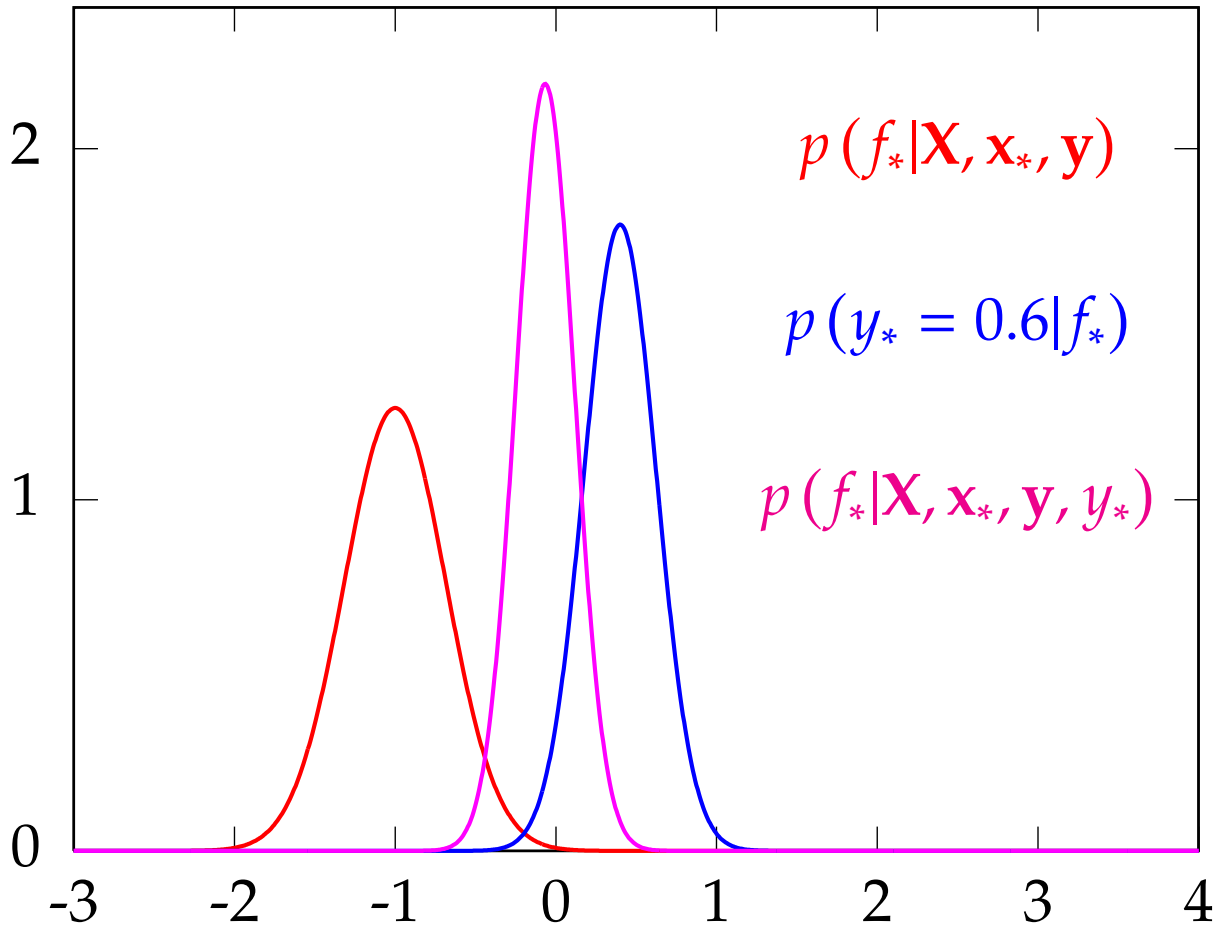


Figure : Inclusion of a data point with Gaussian noise.

Classification Noise Model

Probit Noise Model

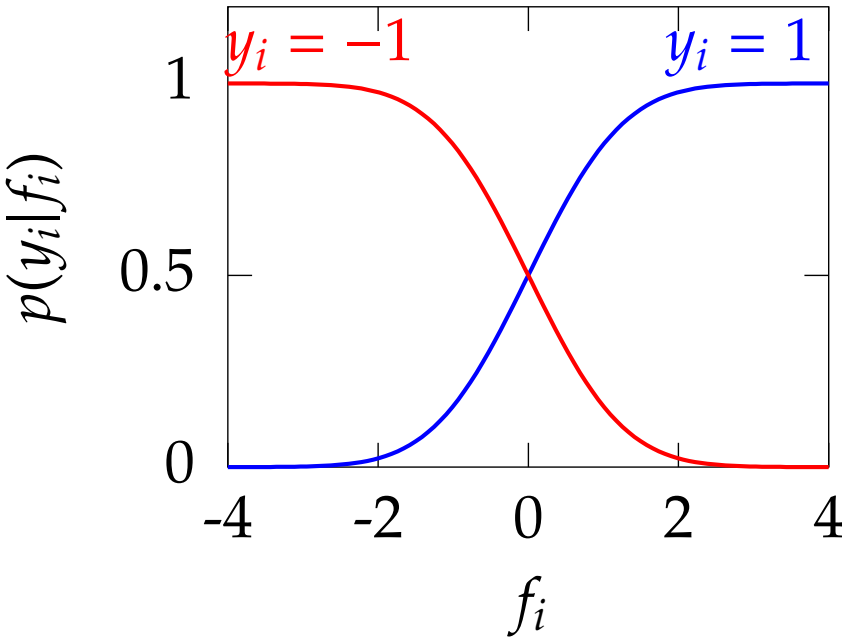


Figure : The probit model (classification). The plot shows $p(y_i|f_i)$ for different values of y_i. For $y_i = 1$ we have $p(y_i|f_i) = \phi(f_i) = \int_{-\infty}^{f_i} \mathcal{N}(z|0,1)\,\mathrm{d}z$.

Classification

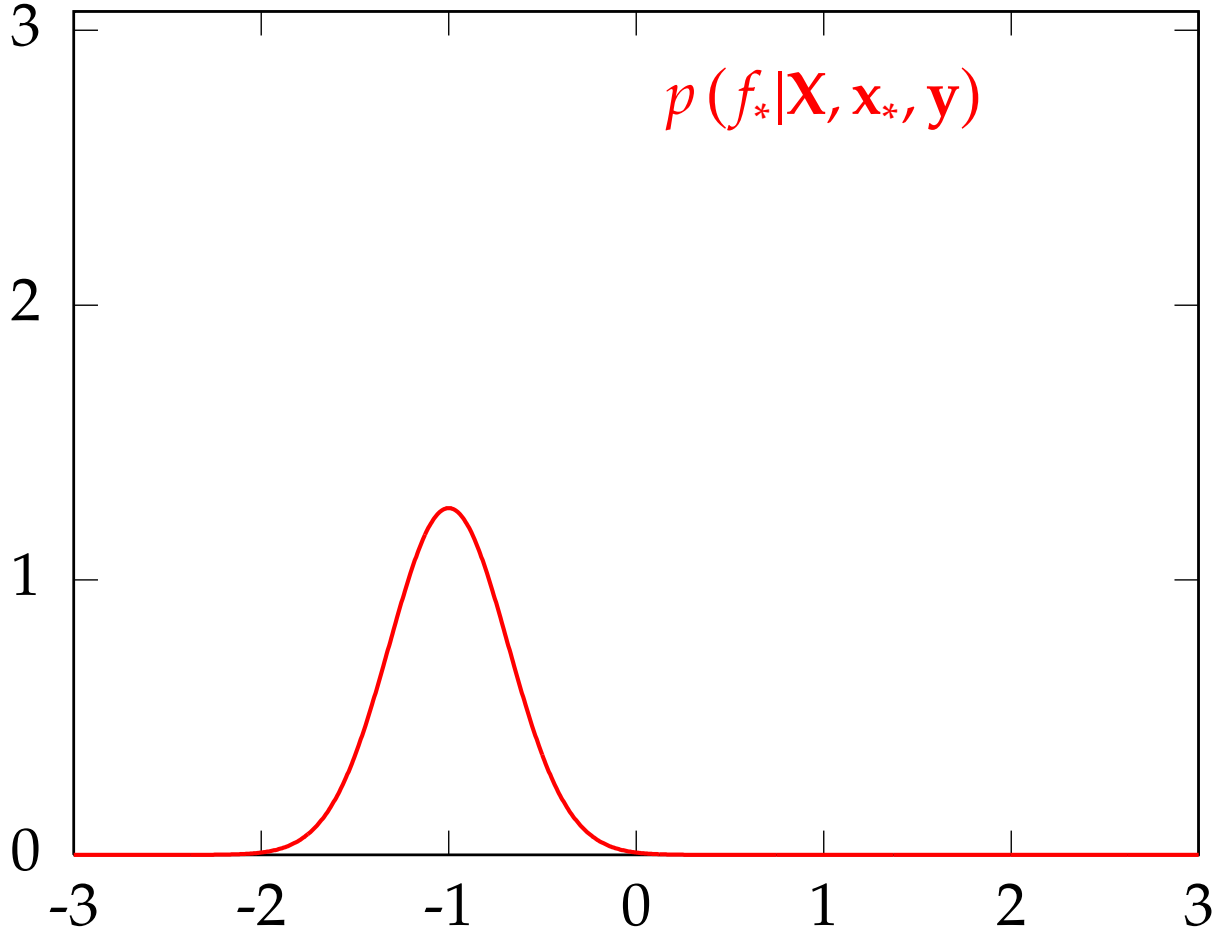
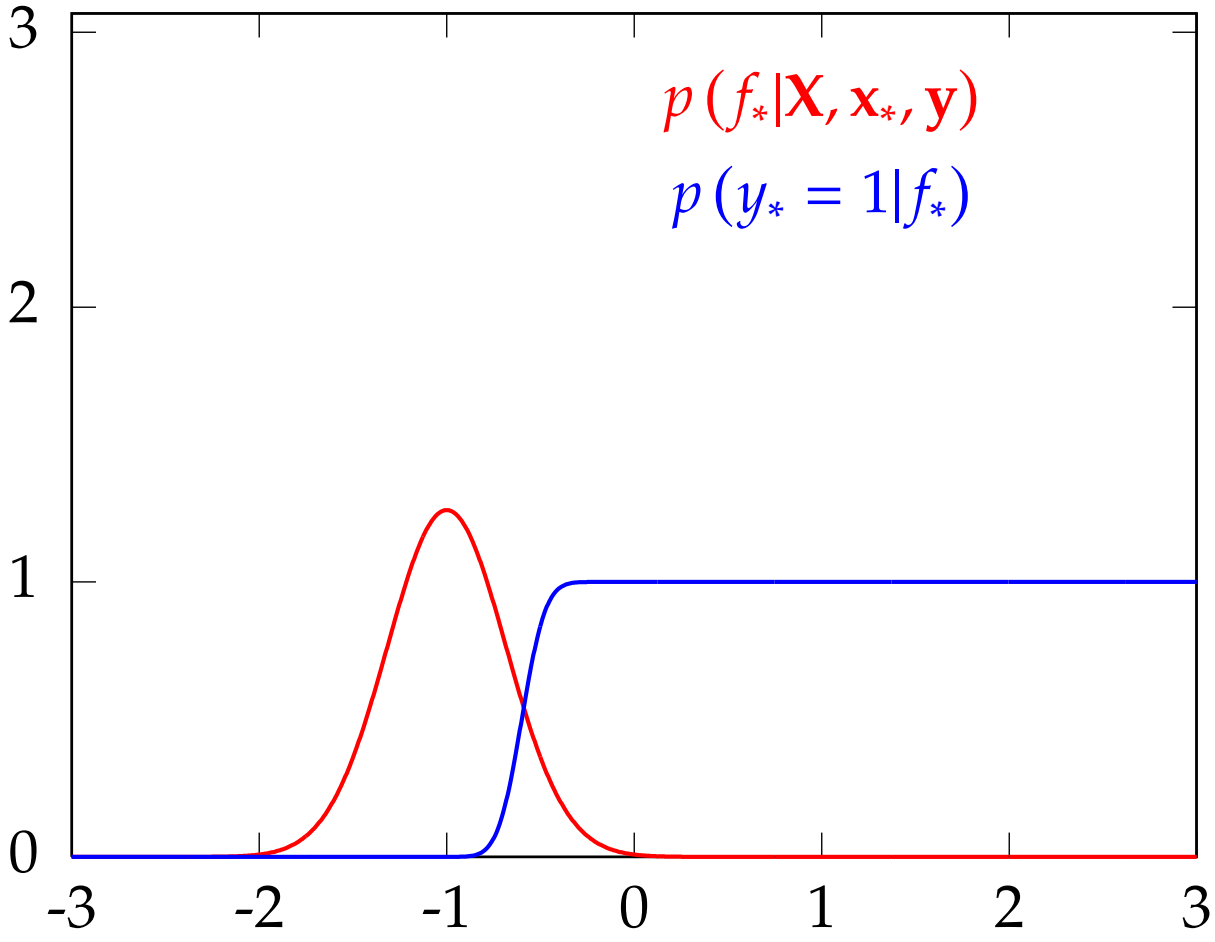


Figure : An EP style update with a classification noise model.

Classification



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Classification

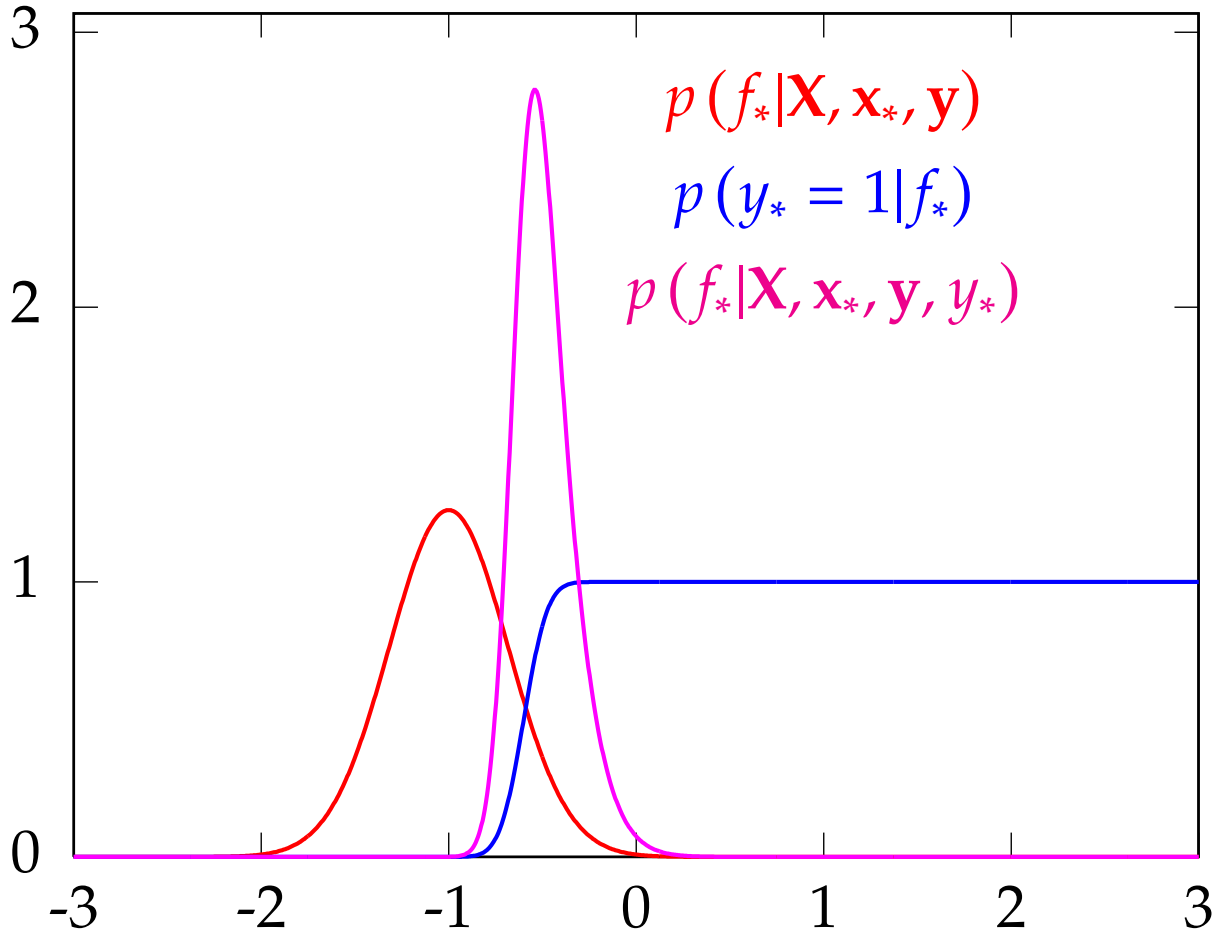


Figure : An EP style update with a classification noise model.

Classification

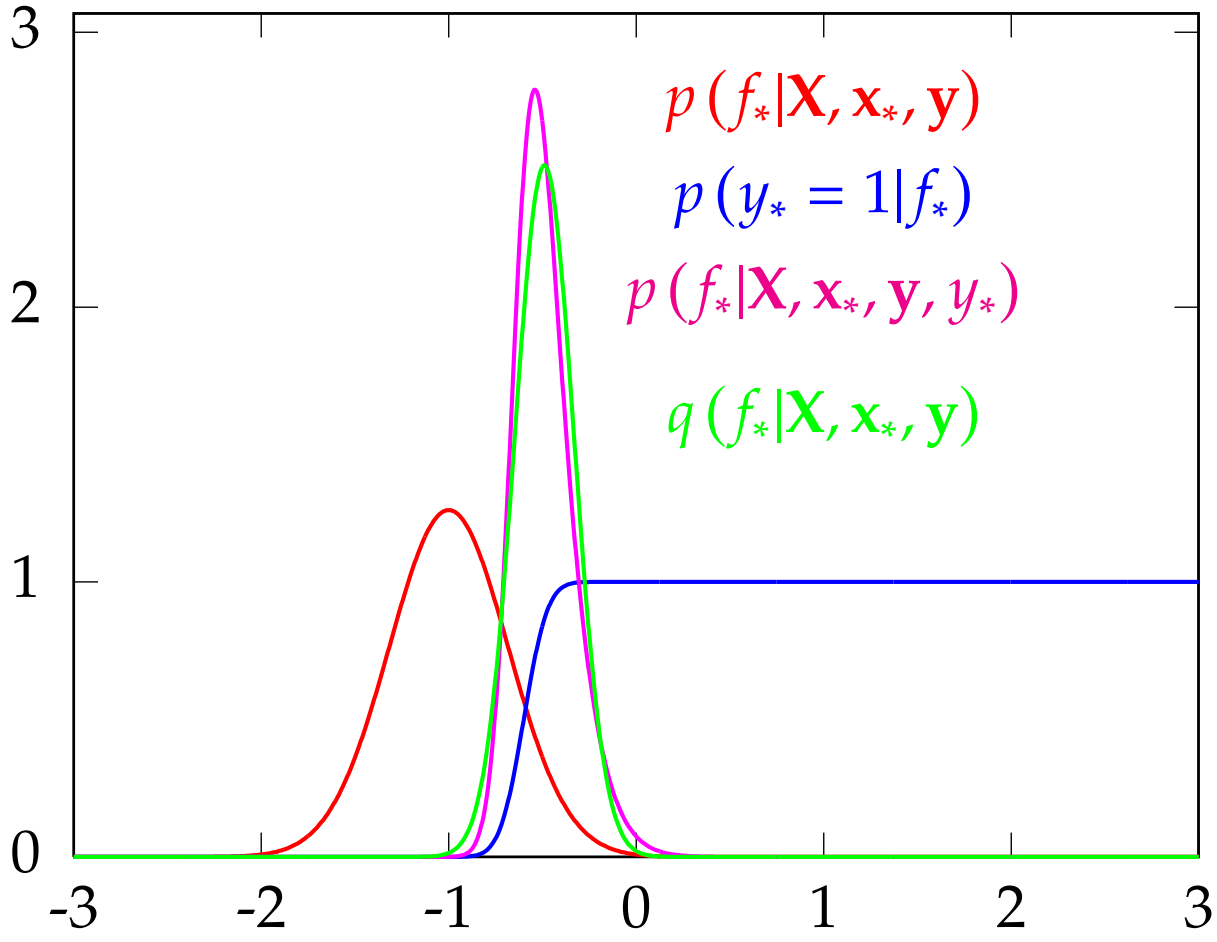


Figure : An EP style update with a classification noise model.

Ordinal Noise Model

Ordered Categories

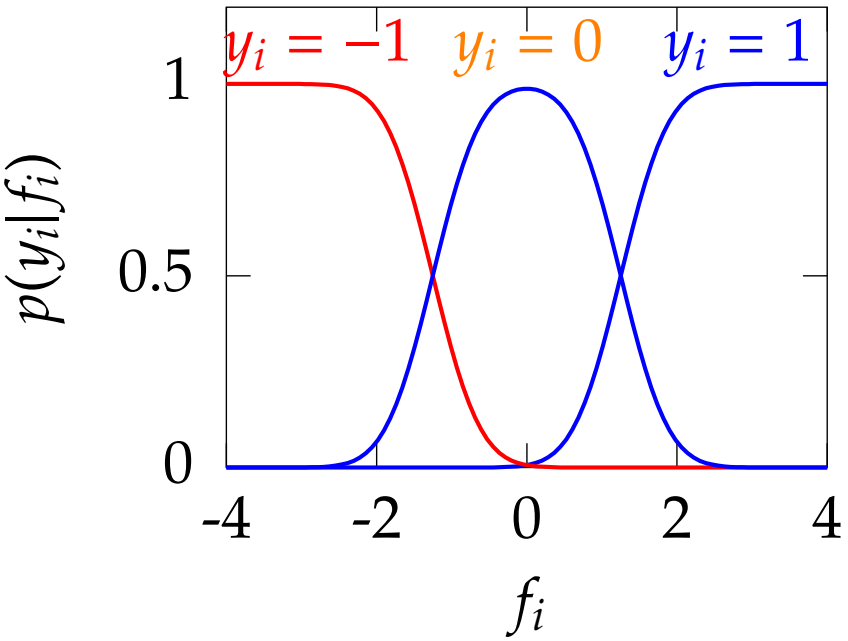


Figure : The ordered categorical noise model (ordinal regression). The plot shows $p(y_i|f_i)$ for different values of y_i. Here we have assumed three categories.

Ordinal Regression

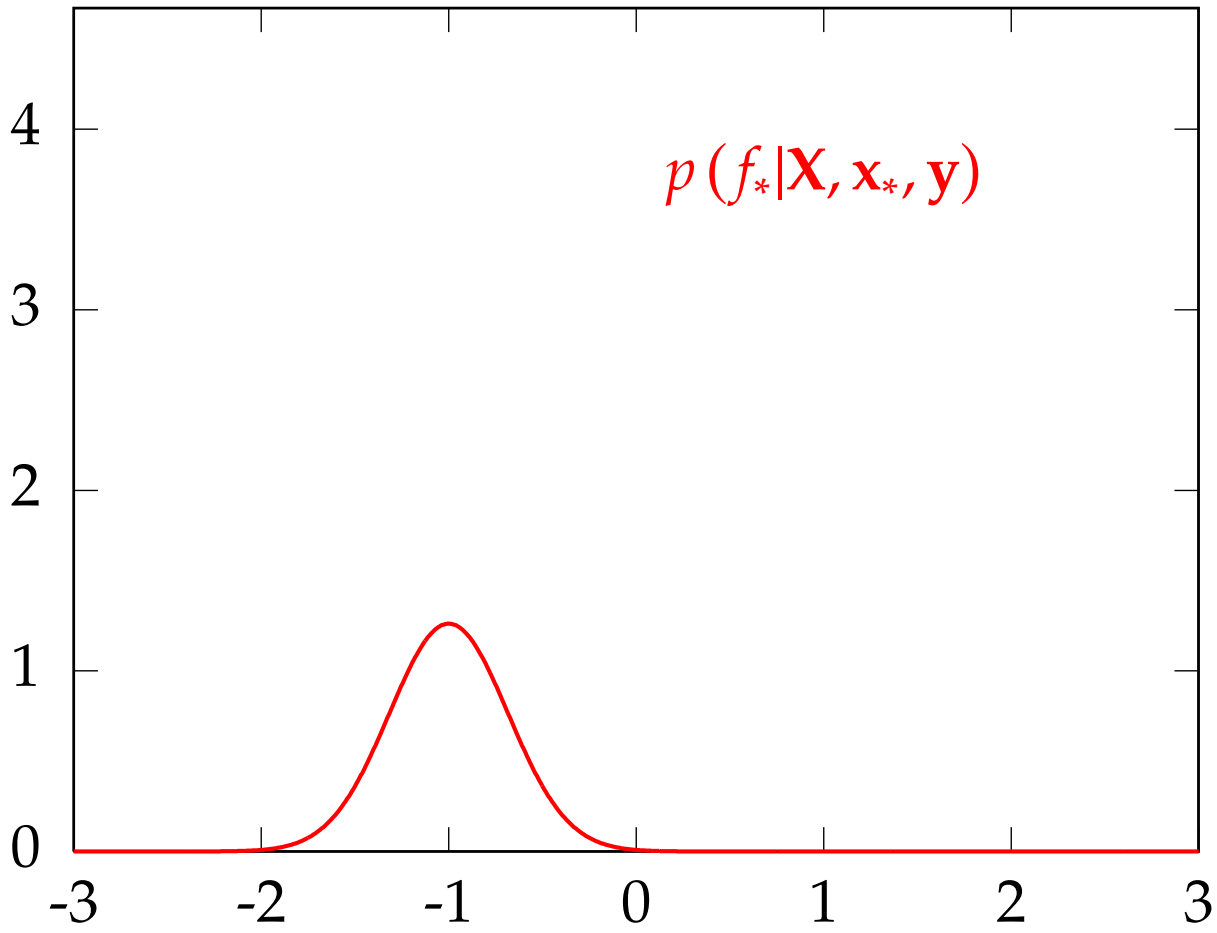


Figure : An EP style update with an ordered category noise model.

Return

Ordinal Regression

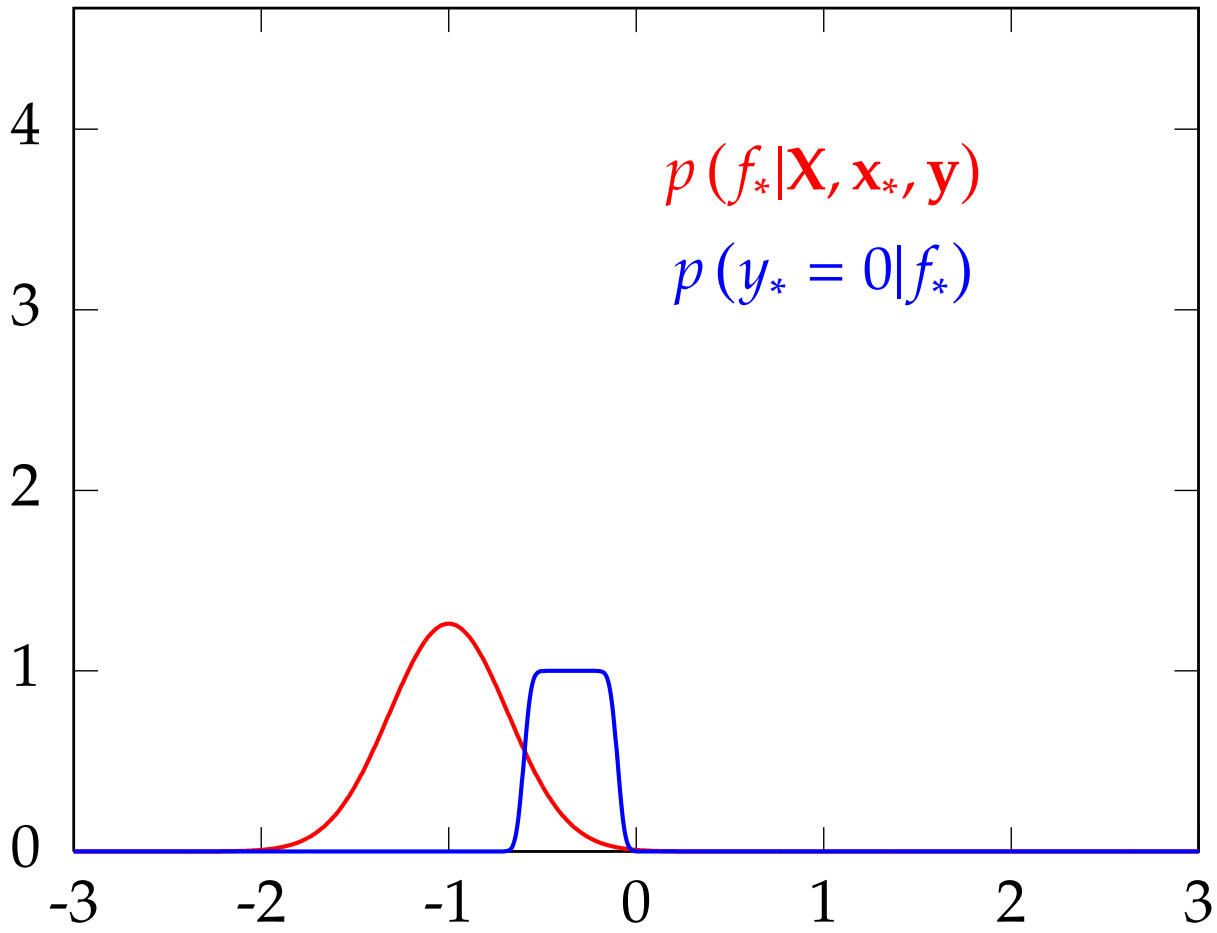


Figure : An EP style update with an ordered category noise model.

Return

Ordinal Regression

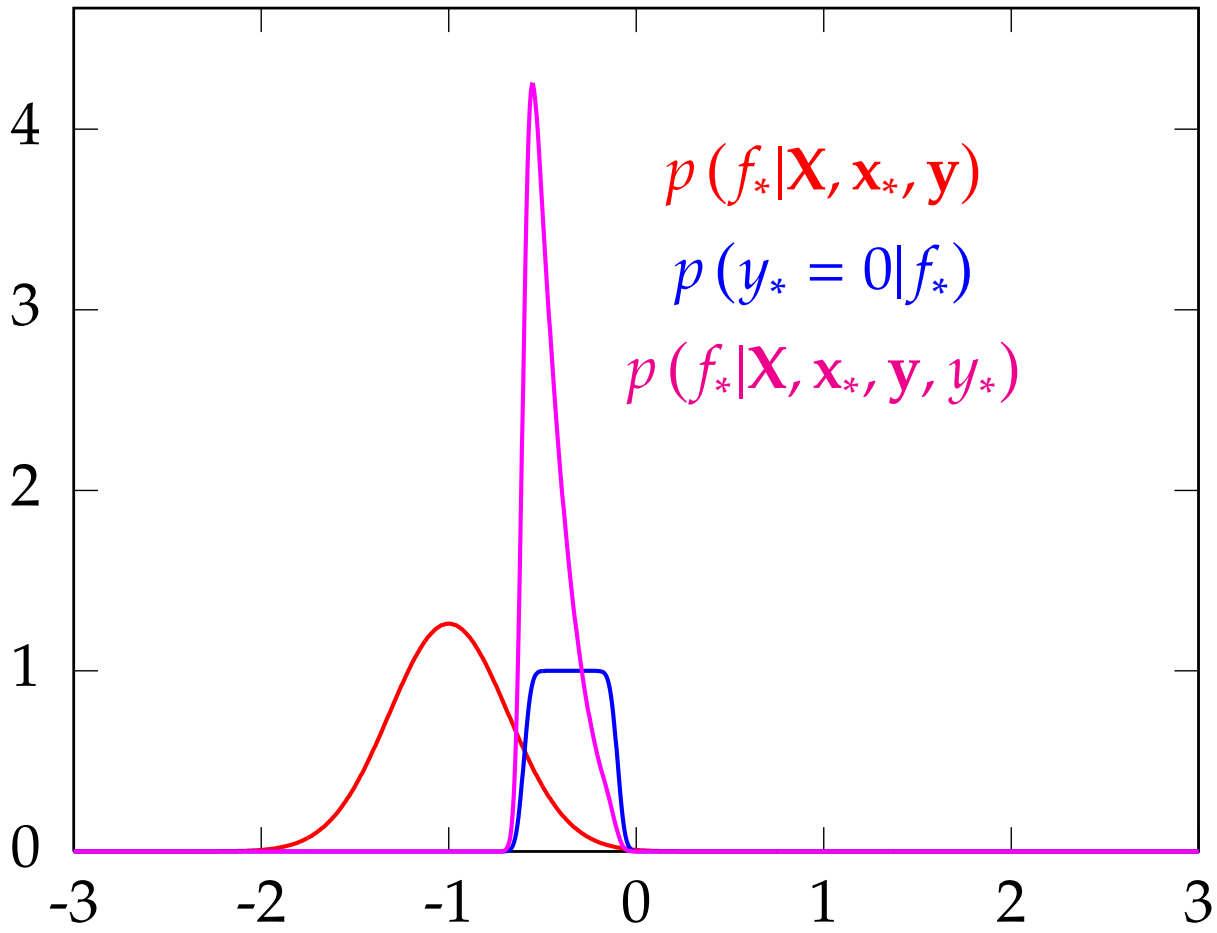


Figure : An EP style update with an ordered category noise model.

Return

Ordinal Regression

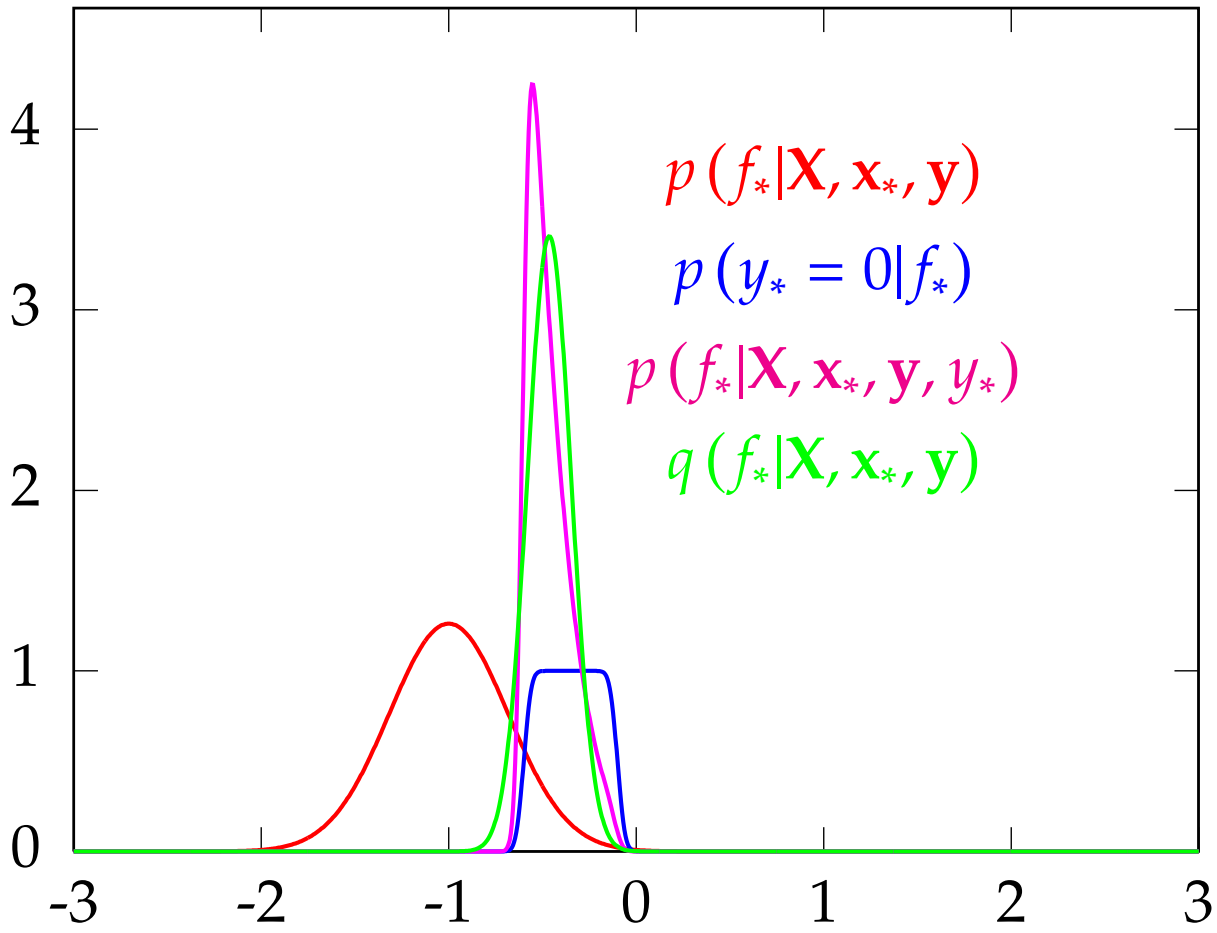


Figure : An EP style update with an ordered category noise model.

Return

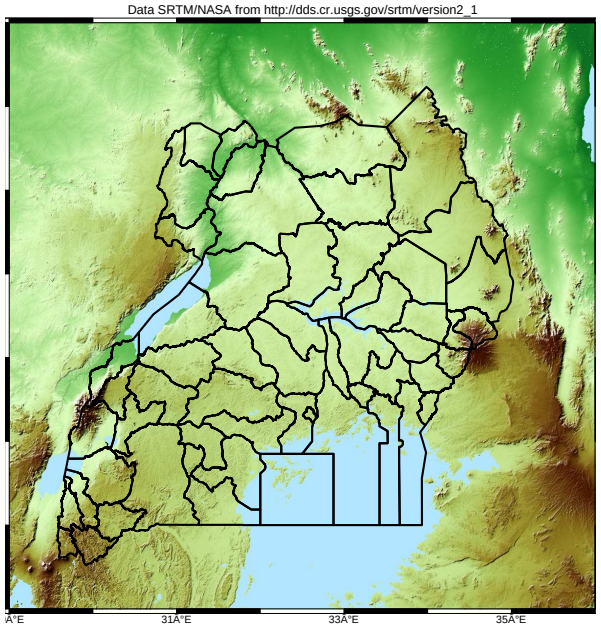
Other Challenges

- Spatial Data (workshop in November with Peter Diggle, work with Ricardo Andrade Pacheco and John Quinn's group).
- Survival Data (work with Alan Saul and Aki Vehtari's group and HeRC).
- Image Data (work with Teo de Campos, Violet Snell and imminent arrival of Zhenwen Dai)
- Text Data (planned collaboration with Trevor Cohn)

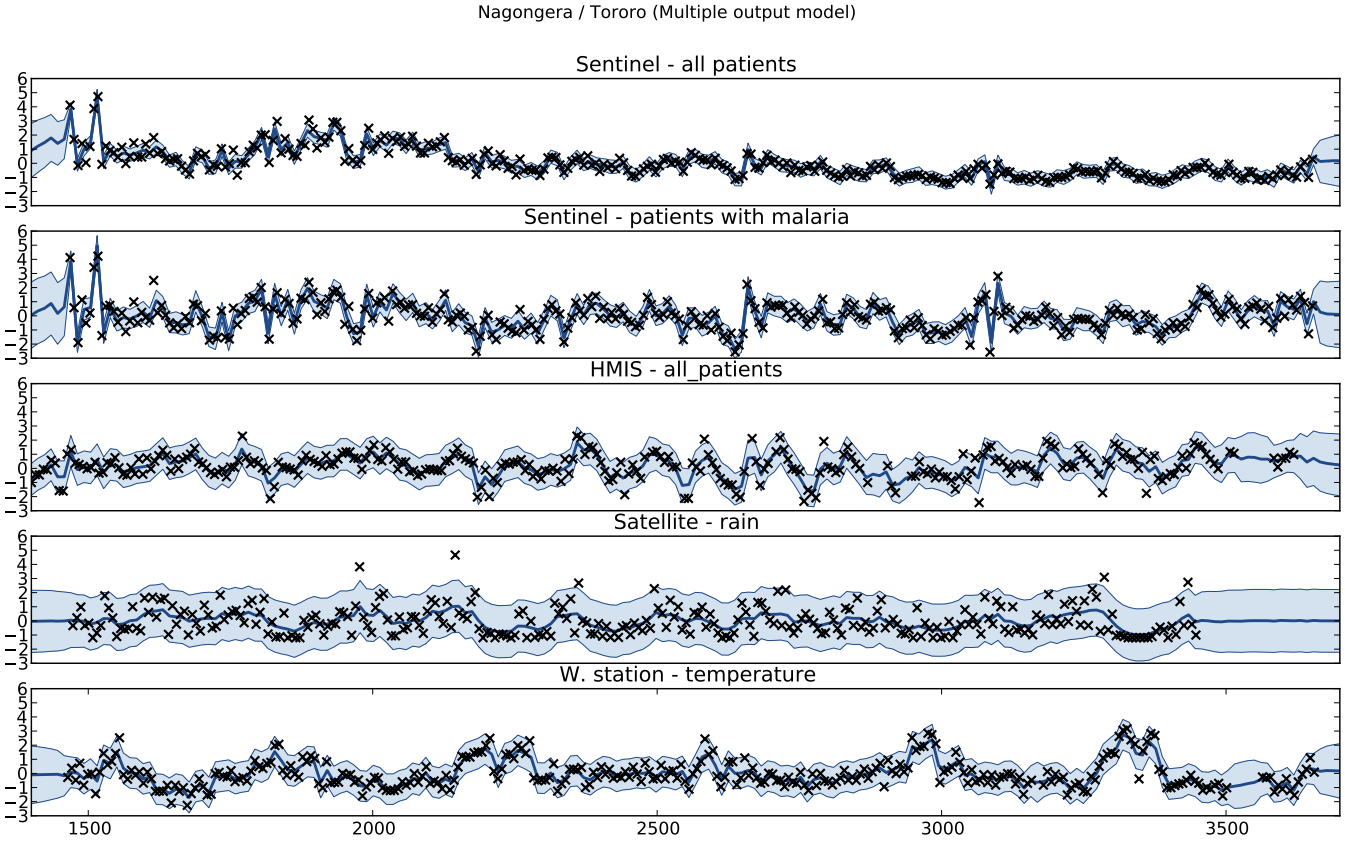
Example: Prediction of Malaria Incidence in Uganda

- Work with John Quinn and Martin Mubaganzi (Makerere University, Uganda)
- See http://cit.mak.ac.ug/cs/aigroup/.

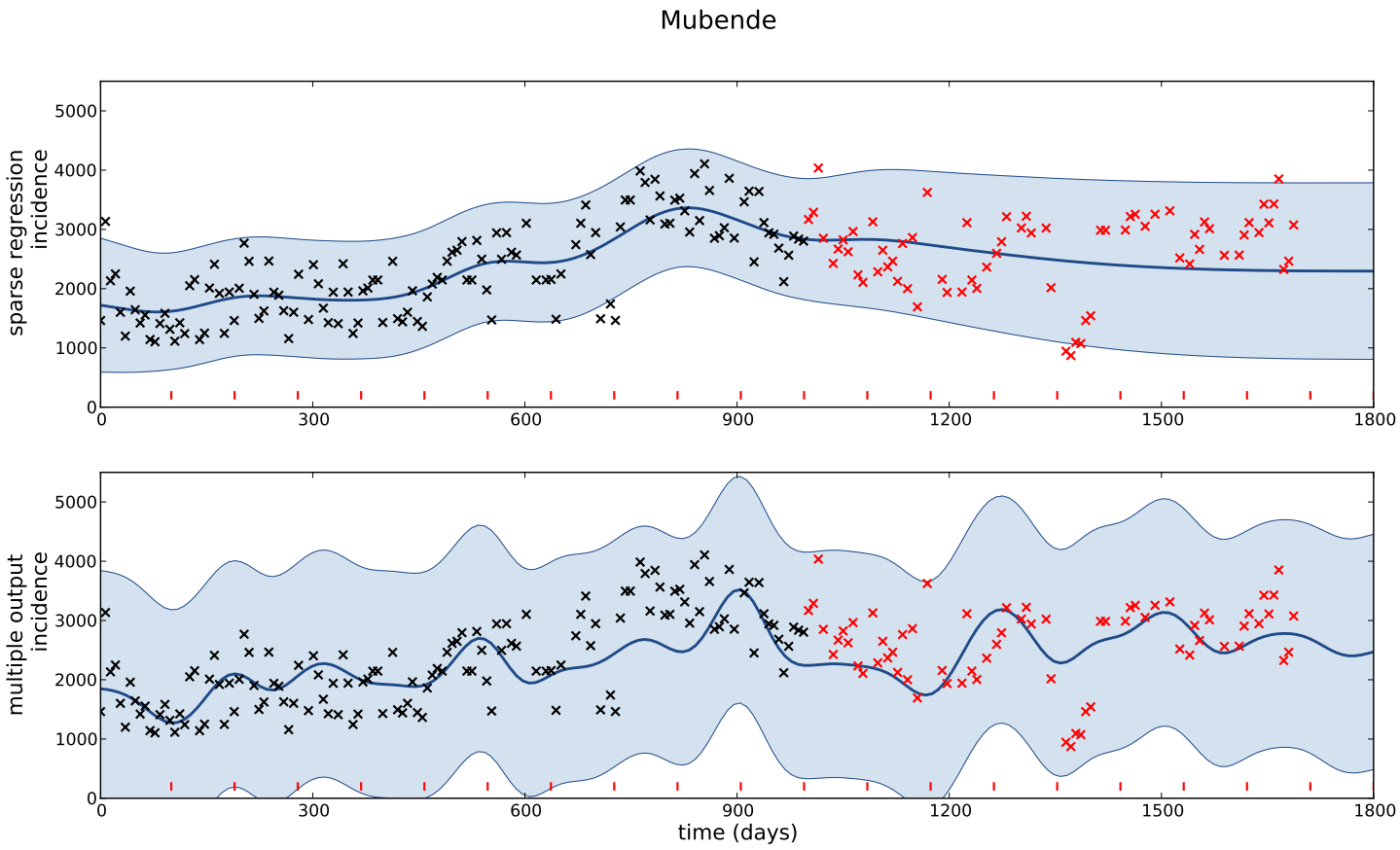
Malaria Prediction in Uganda



Malaria Prediction in Uganda



Malaria Prediction in Uganda



Visit to Uganda

Outline

Data Heterogenity

Deep Learning

direction for further research.

11.1. HAVE WE THROWN THE BABY OUT WITH THE BATH WATER?

According to the hype of 1987, neural networks were meant to be intelligent models which discovered features and patterns in data. Gaussian processes in contrast are simply smoothing devices. How can Gaussian processes possibly replace neural networks? What is going on?

I think what the work of Williams and Rasmussen (1996) shows is that many real–world data modelling problems are perfectly well solved by sensible smoothing methods. The most interesting problems, the task of feature discovery for example, are not ones which Gaussian processes will solve. But maybe multilayer perceptrons can't solve them either. On the other hand, it may be that the limit of an infinite number of hidden units, to which Gaussian processes correspond, was a bad limit to take; maybe we should backtrack, or modify the prior on neural network parameters, so as to create new models more interesting than Gaussian processes. Evidence that this infinite limit has lost something compared with finite neural networks comes from the observation that in a finite neural network with more than one output, there are non–trivial correlations between the outputs (since they share inputs from common hidden units); but in the limit of an infinite number of hidden units, these correlations vanish. Radford Neal has suggested the use of non–Gaussian priors in networks with multiple hidden layers. Or perhaps a completely fresh start is needed, approaching the problem of machine learning from a paradigm different from the supervised feedforward mapping.

Structure of Priors

MacKay: NIPS Tutorial 1997 "Have we thrown out the baby with the bathwater?" (Published as MacKay, 1998) Also noted by (Wilson et al., 2012)

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.

The advances have led to widespread

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NOVEMBER 25, 2012

IS "DEEP LEARNING" A REVOLUTION IN ARTIFICIAL INTELLIGENCE?

POSTED BY GARY MARCUS

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

Google To Expand Knowledge Graph Through Hire Of Geoffrey Hinton

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.

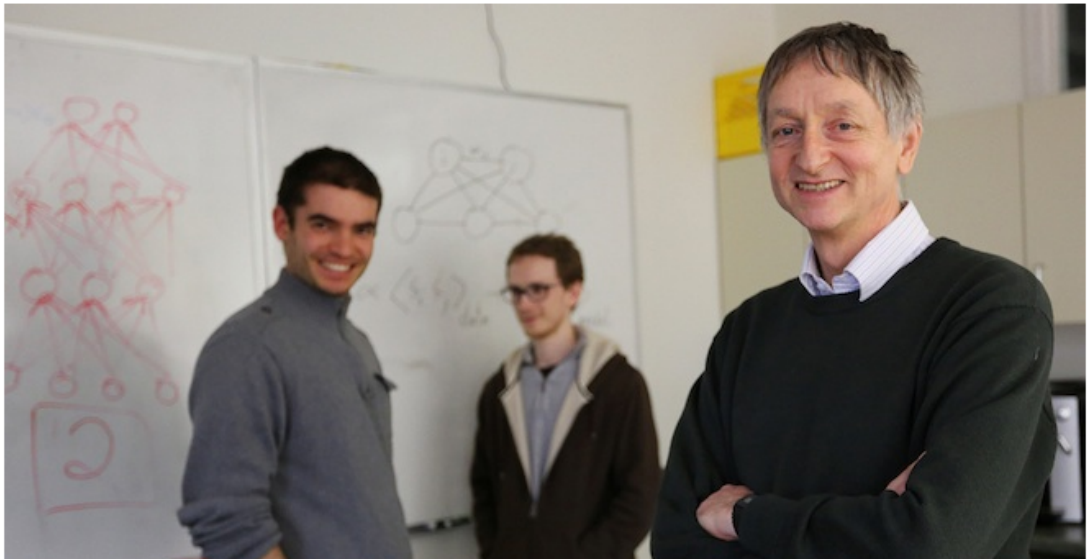
To take the knowledge graph to the next level, Google has hired/acquired Geoffrey Hinton and his team at DNNresearch. Geoffrey posted a note on his Google+ page about it:

> 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.

Google Hires Brains that Helped Supercharge Machine Learning

BY ROBERT MCMILLAN 03.13.13 6:30 AM



Google Hires Geoffrey Hir | Google Hires Brains that | Geoffrey Hinton - Google

https://plus.google.com/102889418997957626067/posts

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More

Geoffrey Hinton

1,734 have him in circles

ML People
23 in common

About **Posts** Photos Videos

Geoffrey Hinton 12 Mar 2013 - Public

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.

+1 +418 167

64 comments

Reza Samahin 15 Mar 2013
+Geoffrey Hinton congrats to you and your team from an old UofT eng grad. Wish I were young again to contribute to your endeavour.

Add a comment...

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Aaron Hertzmann Add
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23 IN COMMON WITH YOU

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Facebook's 'Deep Learnin

www.wired.com/wiredenterprise/2013/12/facebook-yann-lecun-qa/

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Facebook's 'Deep Learning' Guru Reveals the Future of AI

BY CADE METZ 12.12.13 6:30 AM

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Yann LeCun. *Photo: WIRED/Josh Valcarcel*

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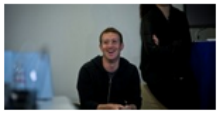
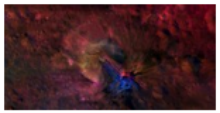


Facebook Forces Video Ads on You Because Marketers Told It To

Obama Taps Ex-Microsoft Exec to Fix Site That's Ruining His Presidency



WIRED Space Photo of the Day: Vesta's Aelia

What Improves Every Party? Giant

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

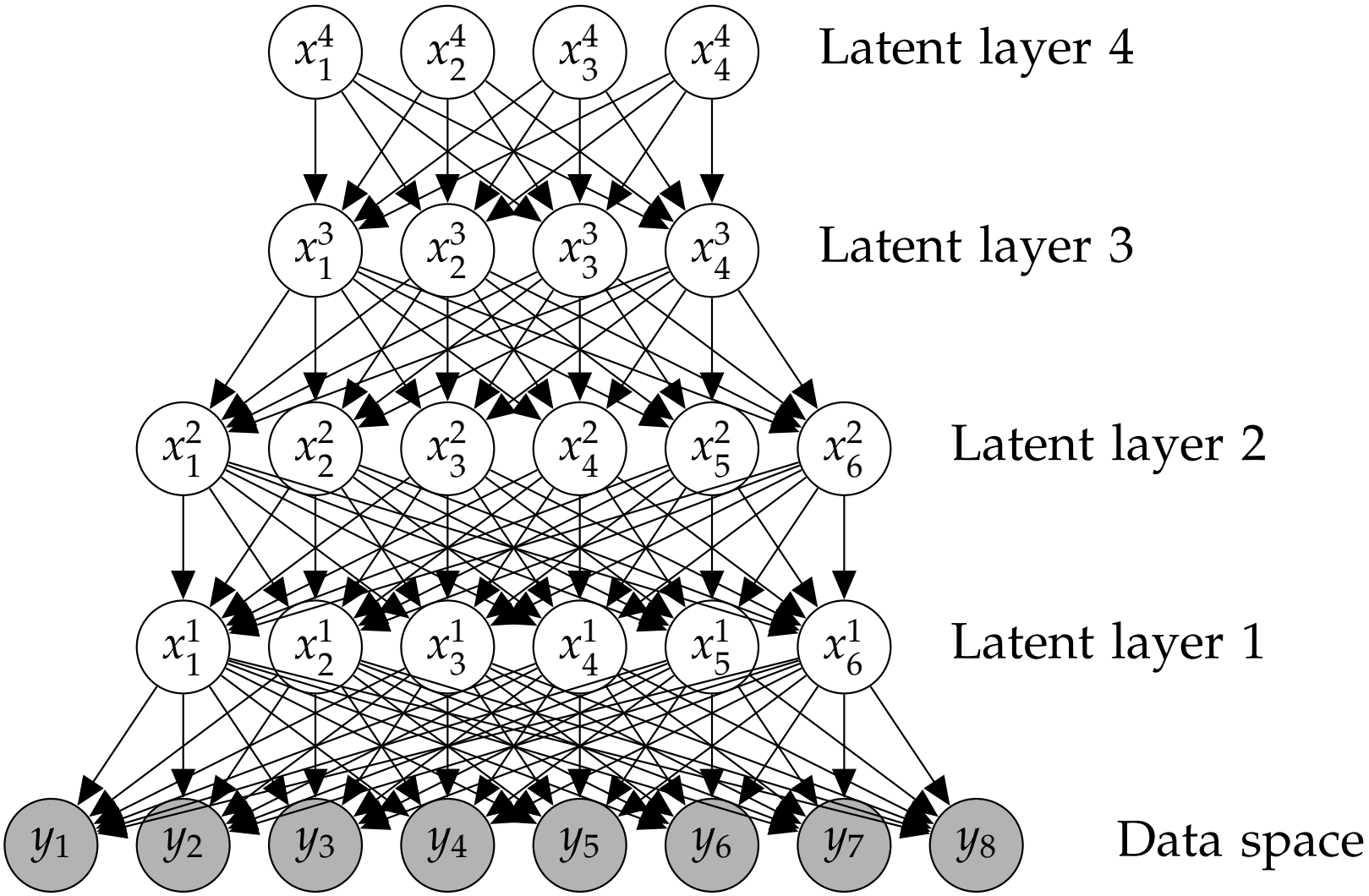
DISCLOSURE STATEMENT

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

"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

Deep Models


x_1^4 x_2^4 x_3^4 x_4^4
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Latent layer 2
x_1^1 x_2^1 x_3^1 x_4^1 x_5^1 x_6^1
Latent layer 1
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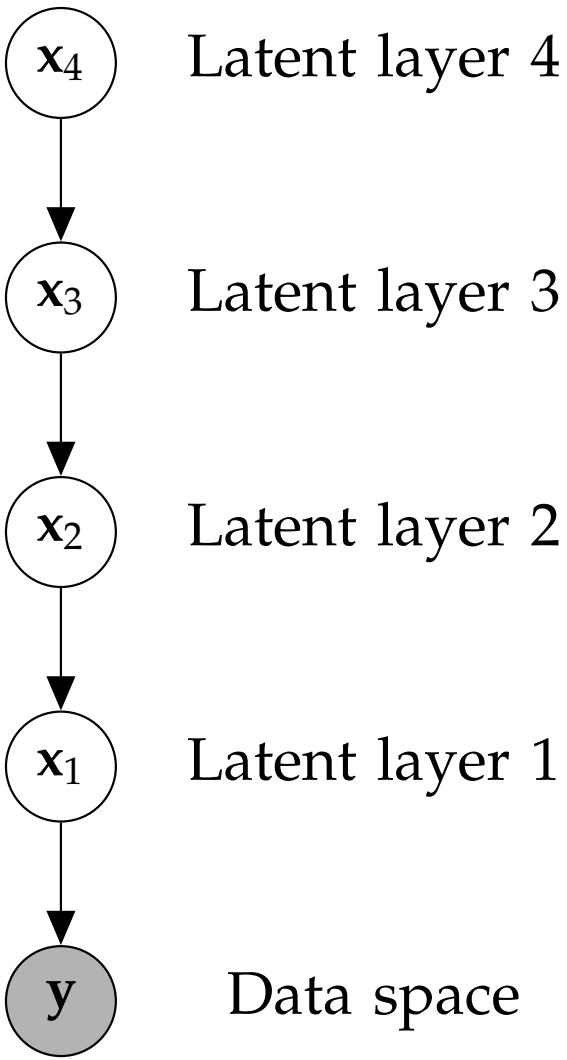
Data space

Deep Models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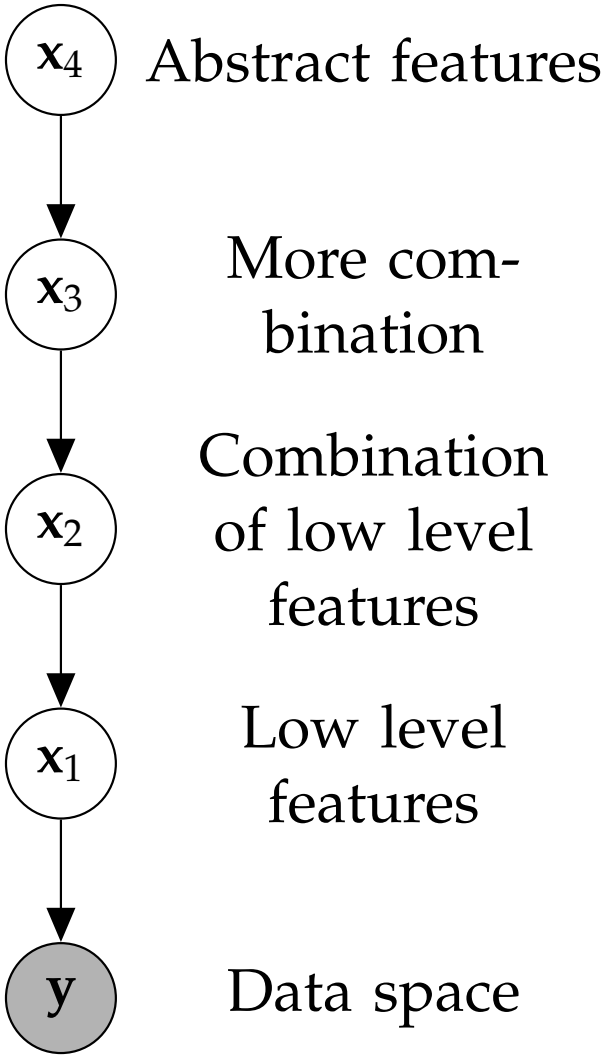
Data space

Deep Models

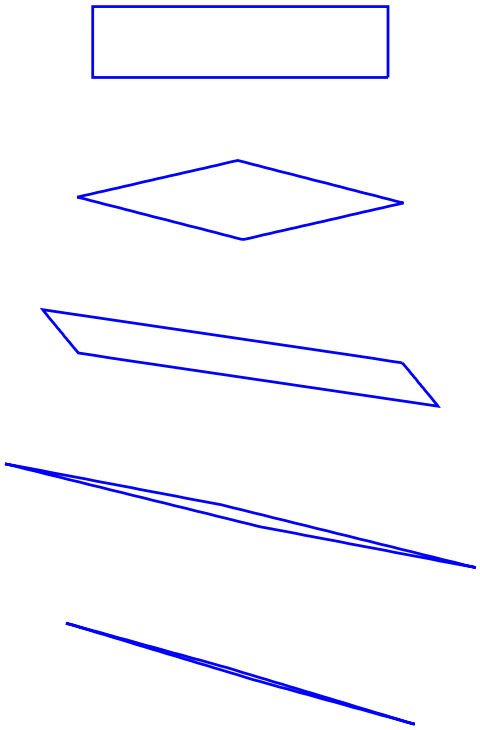

$\mathbf{x}_4$
Abstract features
$\mathbf{x}_3$
More combination
$\mathbf{x}_2$
Combination of low level features
$\mathbf{x}_1$
Low level features
$\mathbf{y}$
Data space

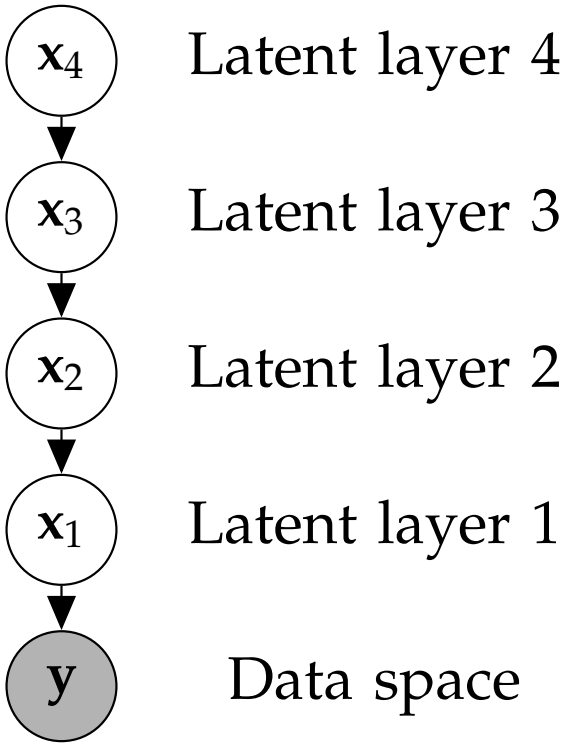
Deep Gaussian Processes

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

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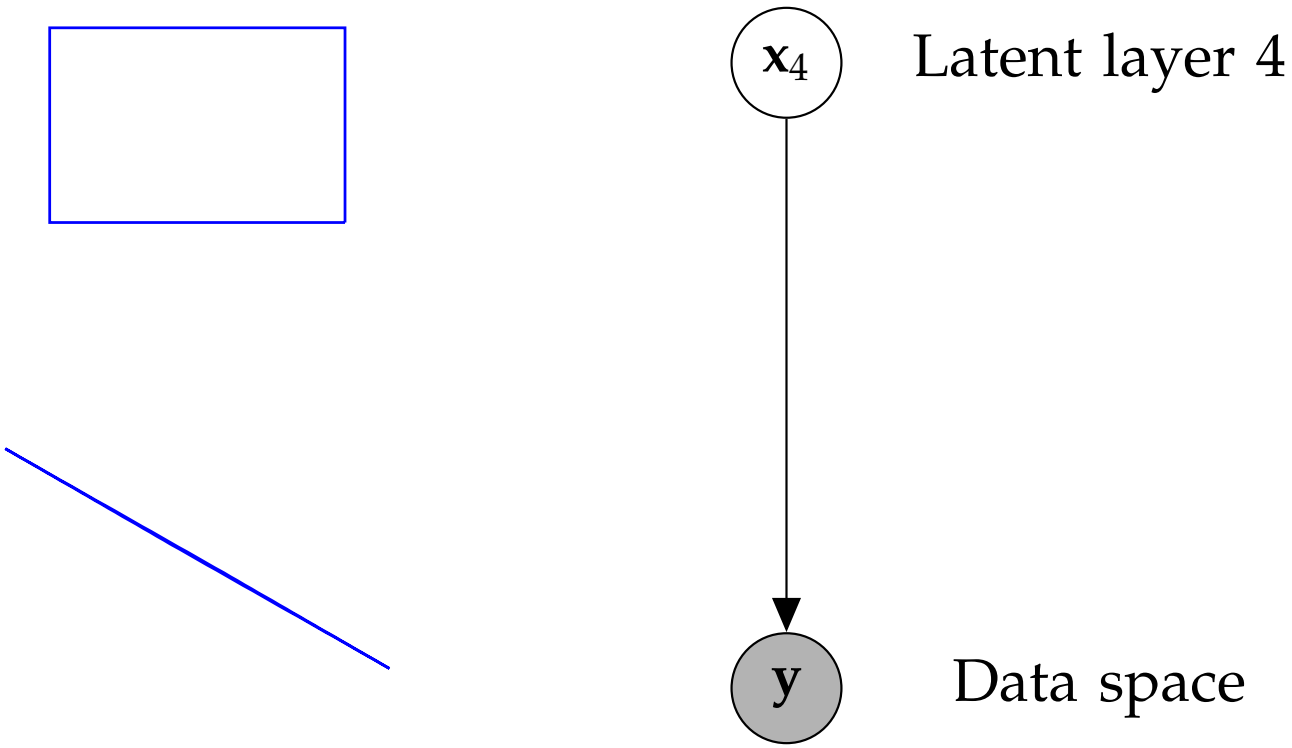
Data space

Stacked PCA



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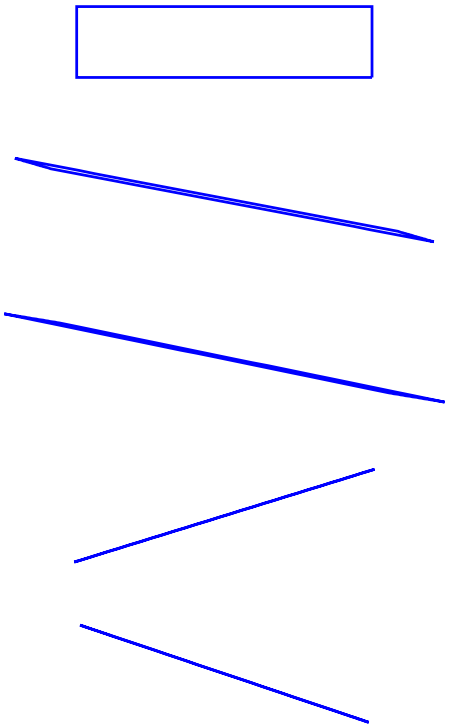

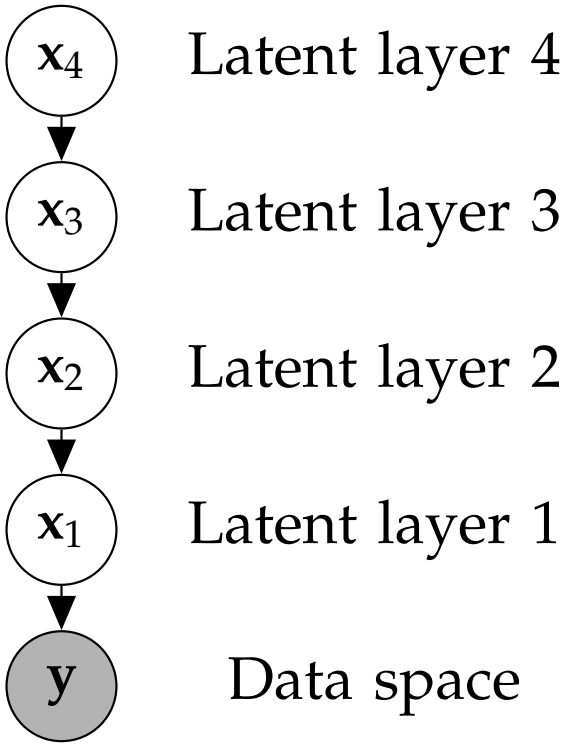
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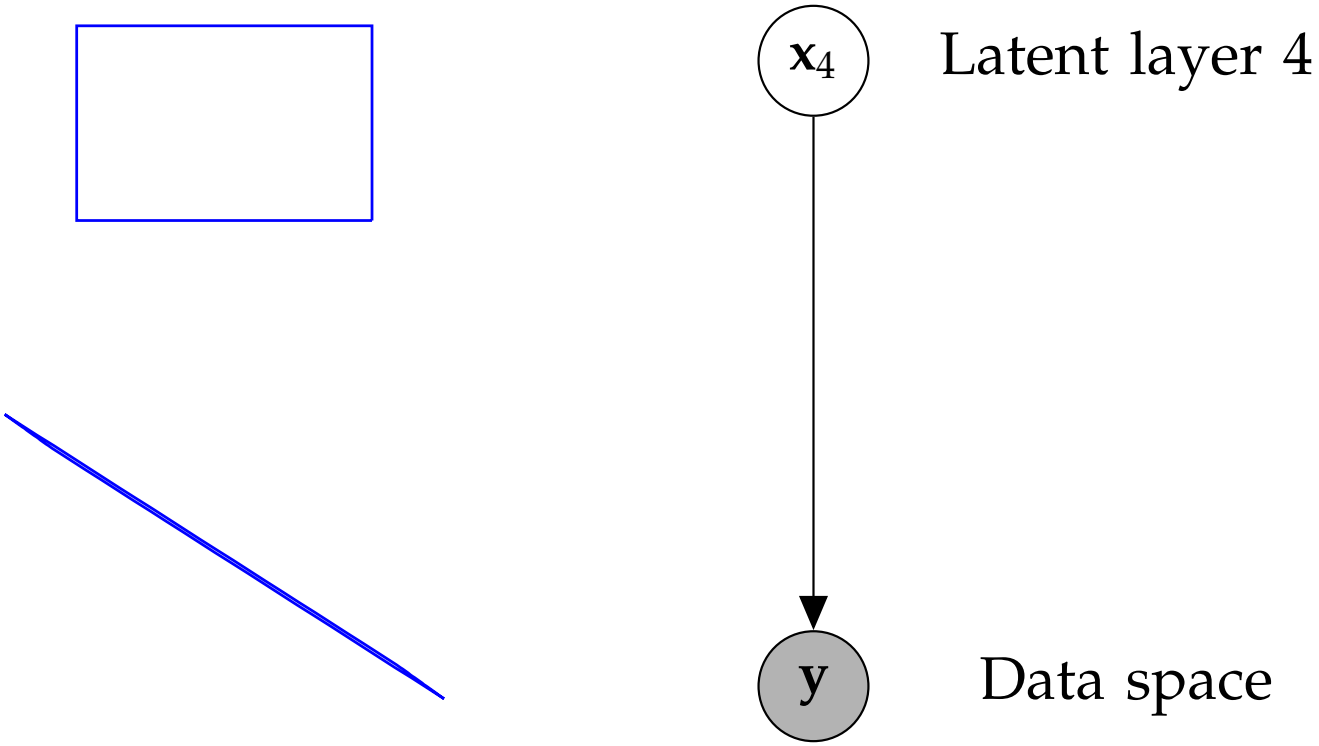
Data space

Stacked PCA



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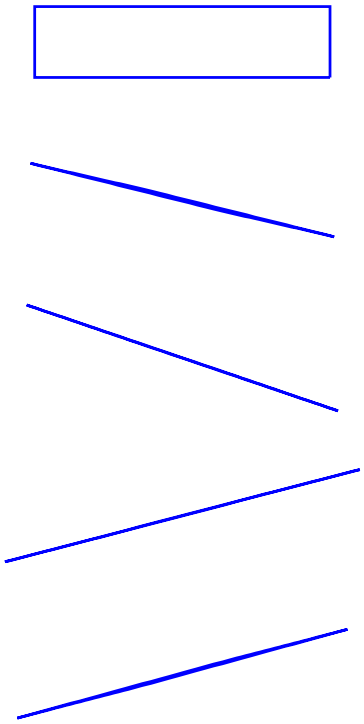

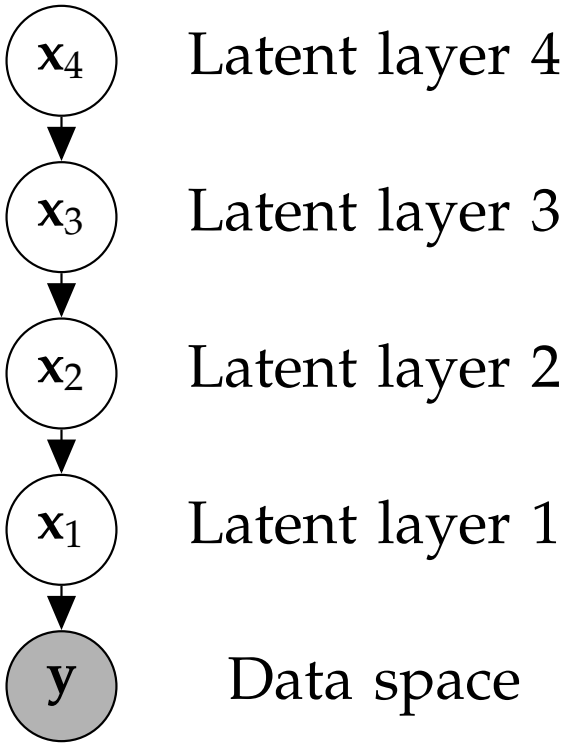
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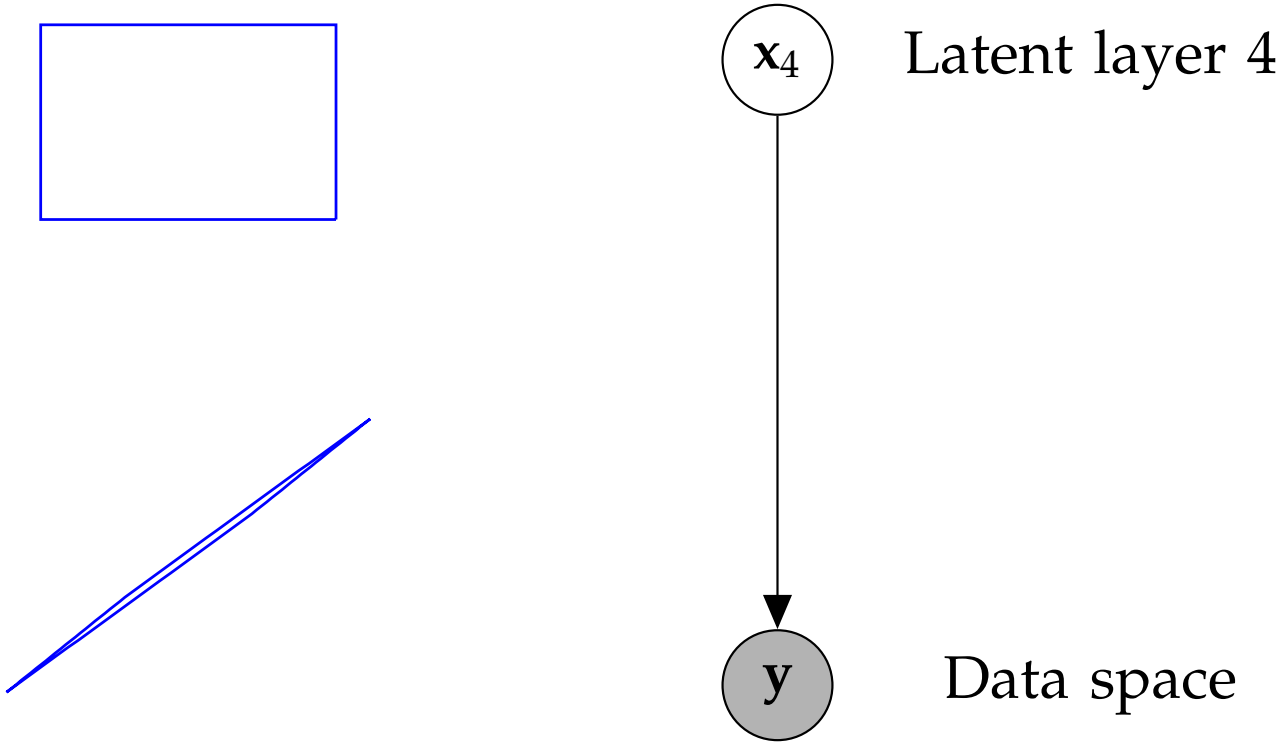
Data space

Stacked PCA



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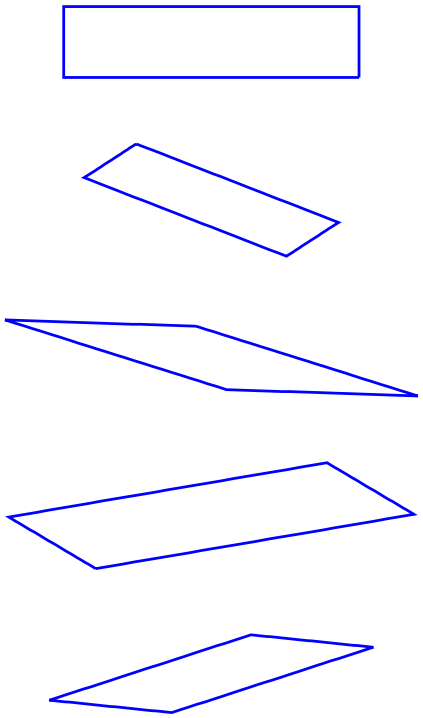

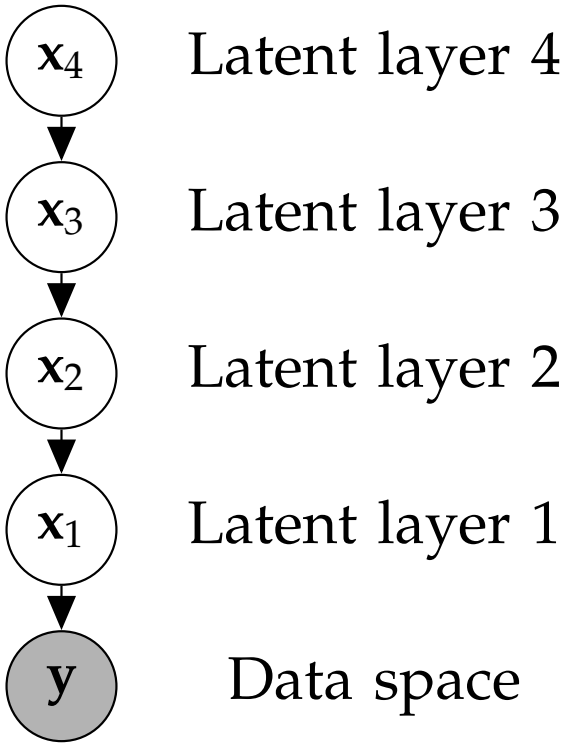
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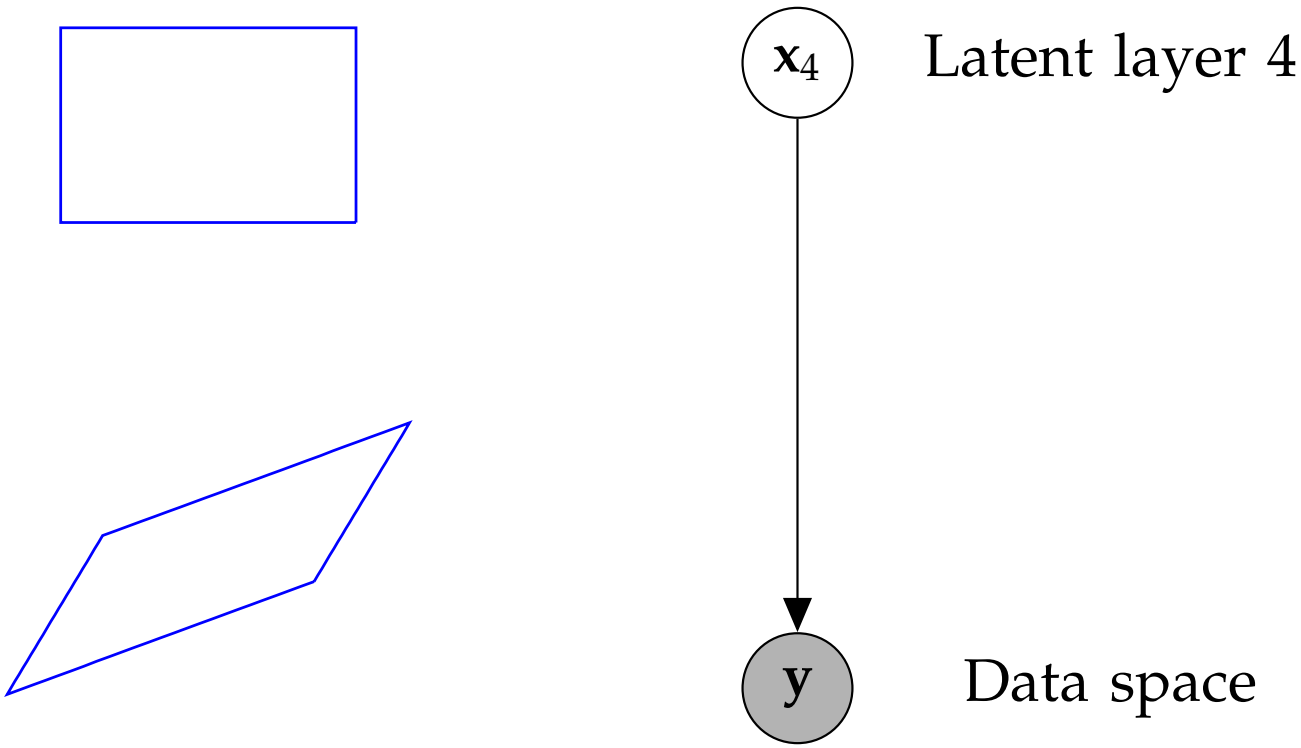
Data space

Stacked PCA



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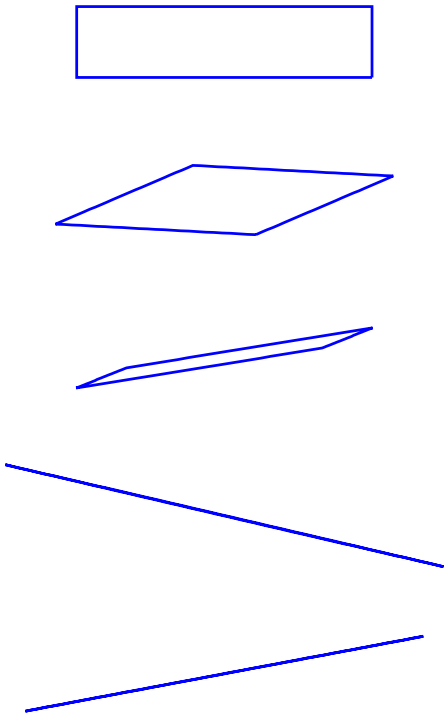

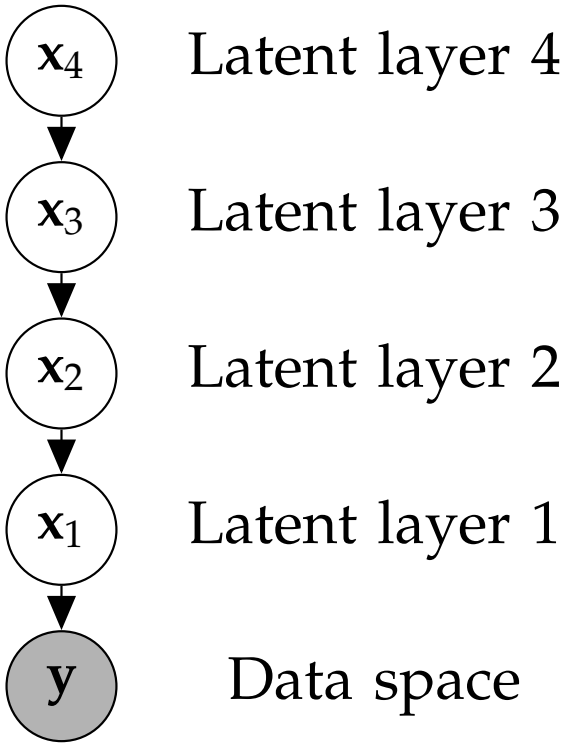
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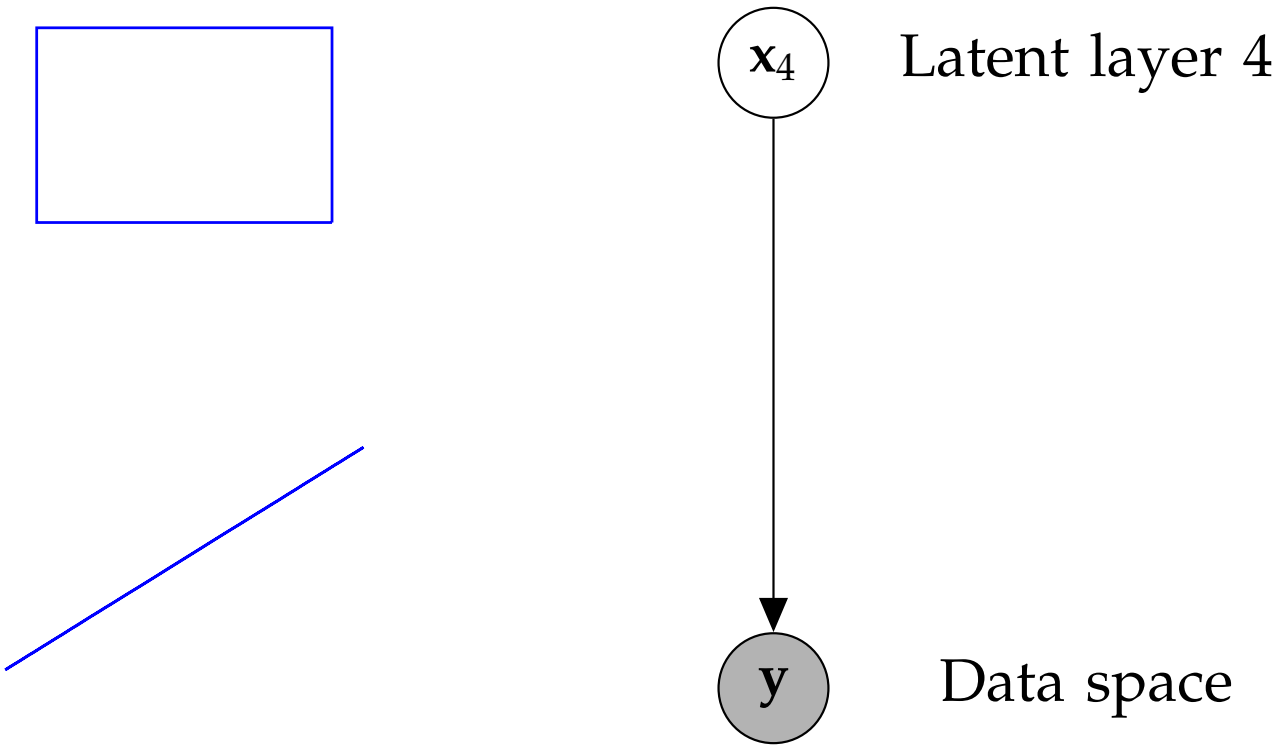
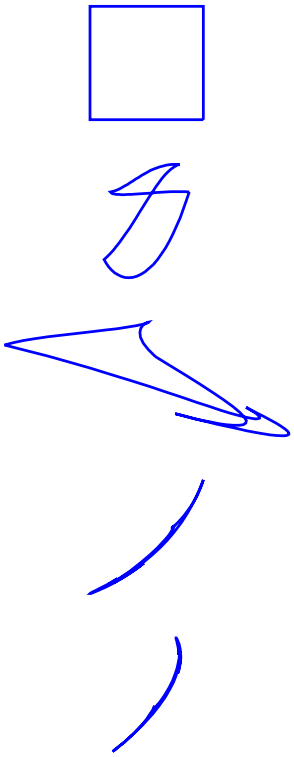
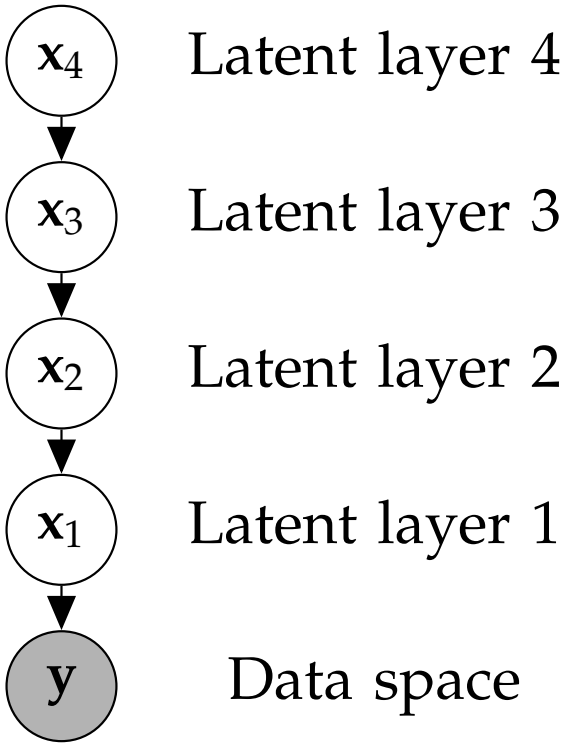
Data space

Stacked PCA



Stacked GPs

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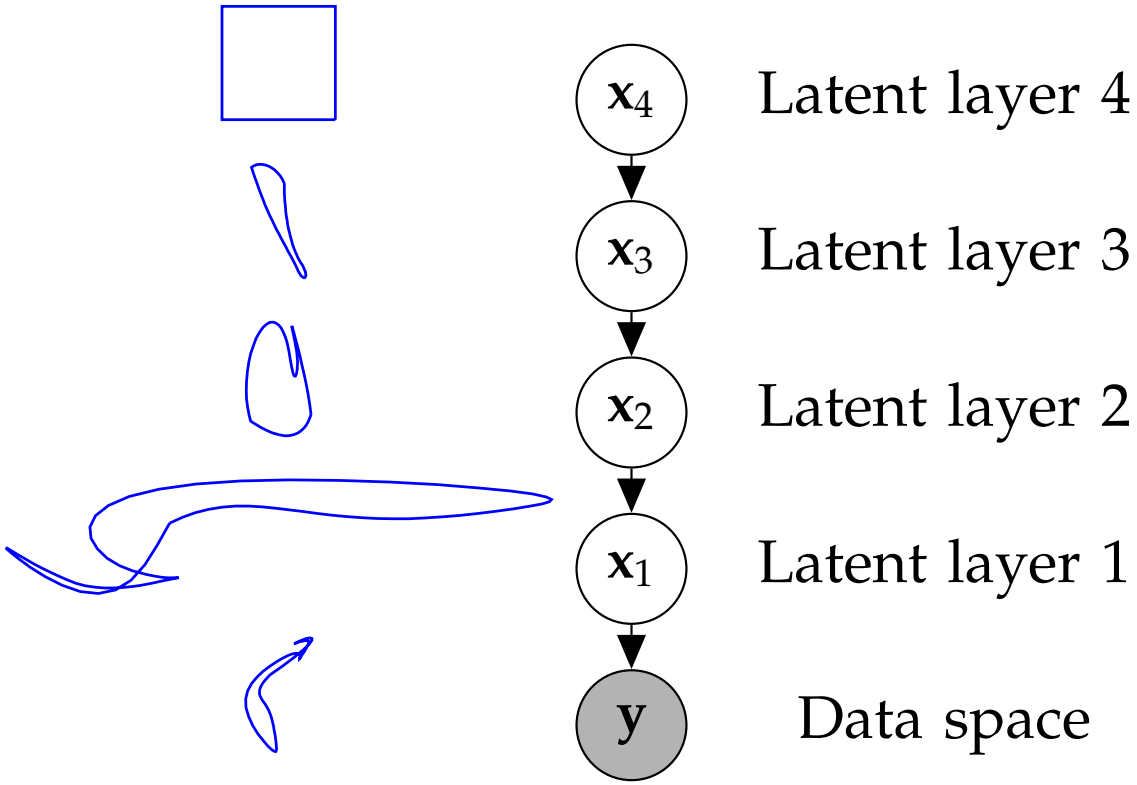
Data space

Stacked GPs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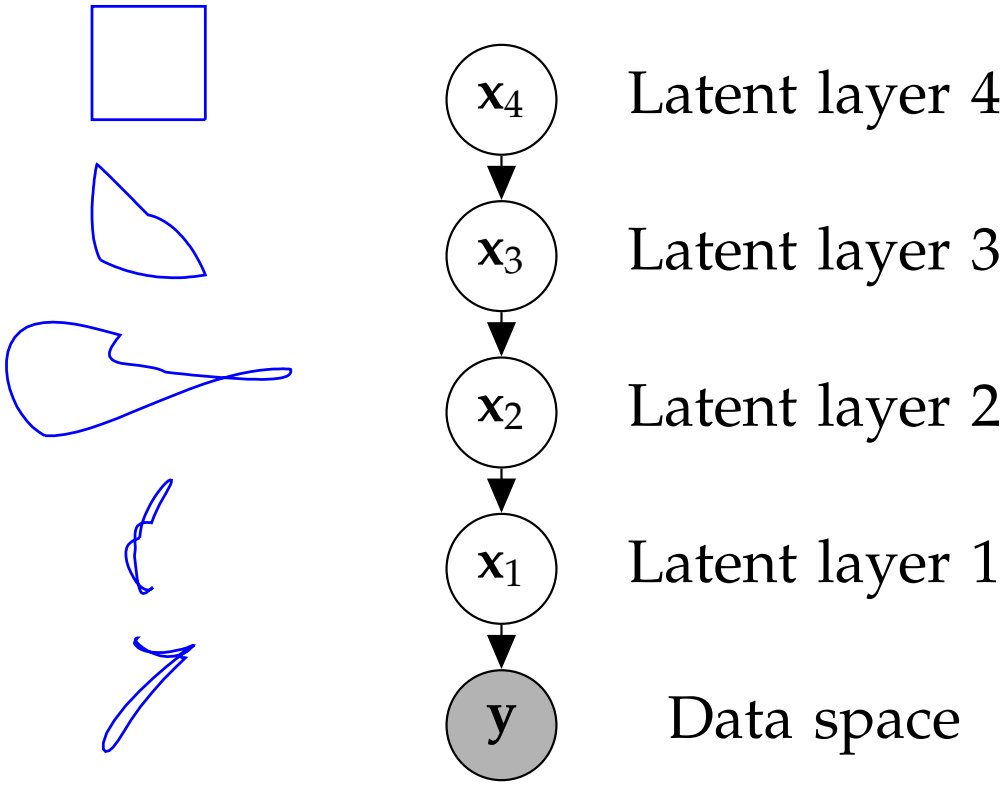
Stacked GPs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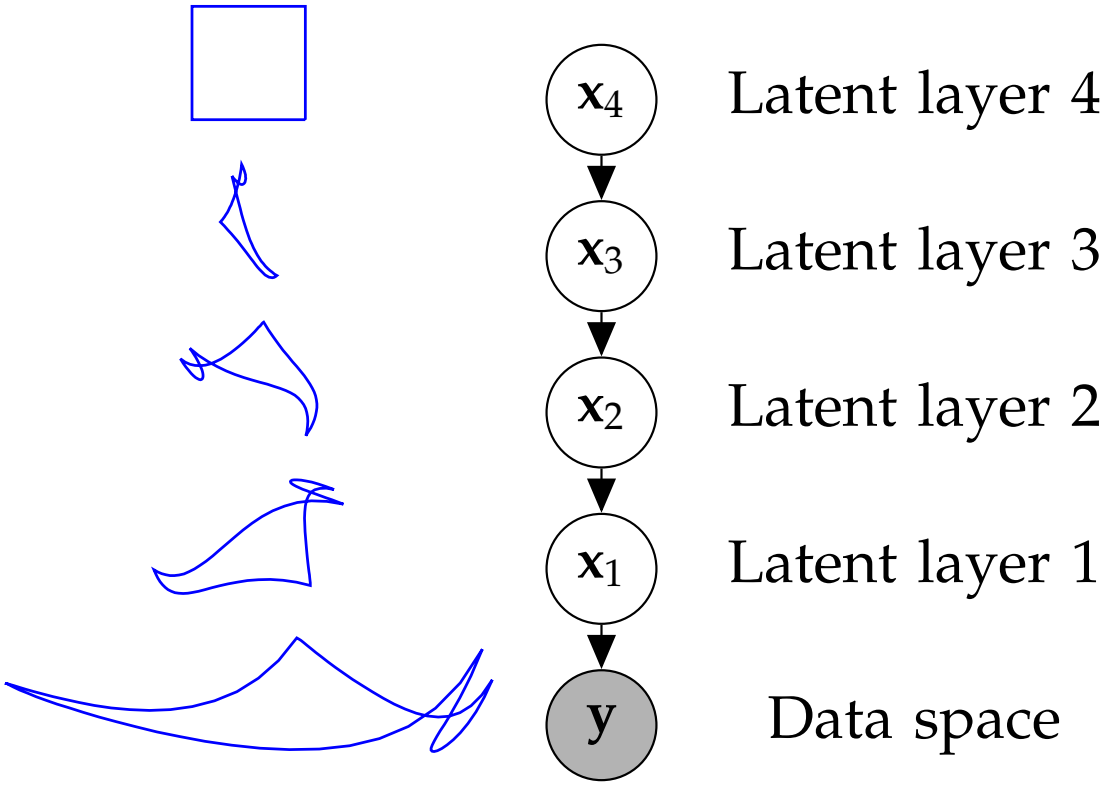
Data space

Stacked GPs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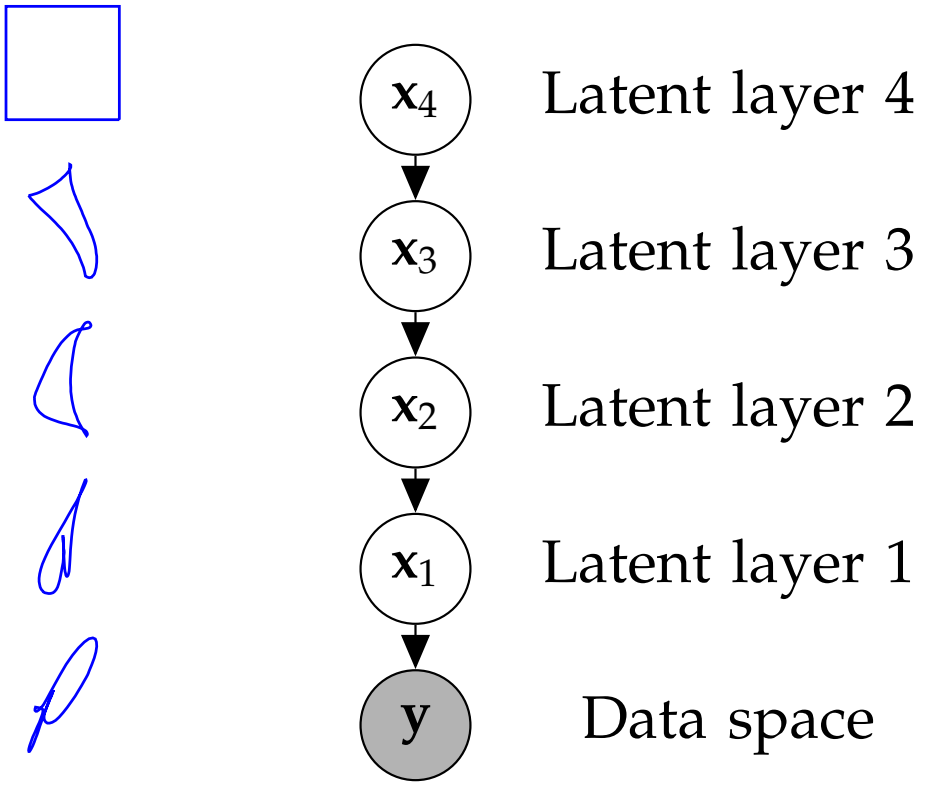
Data space

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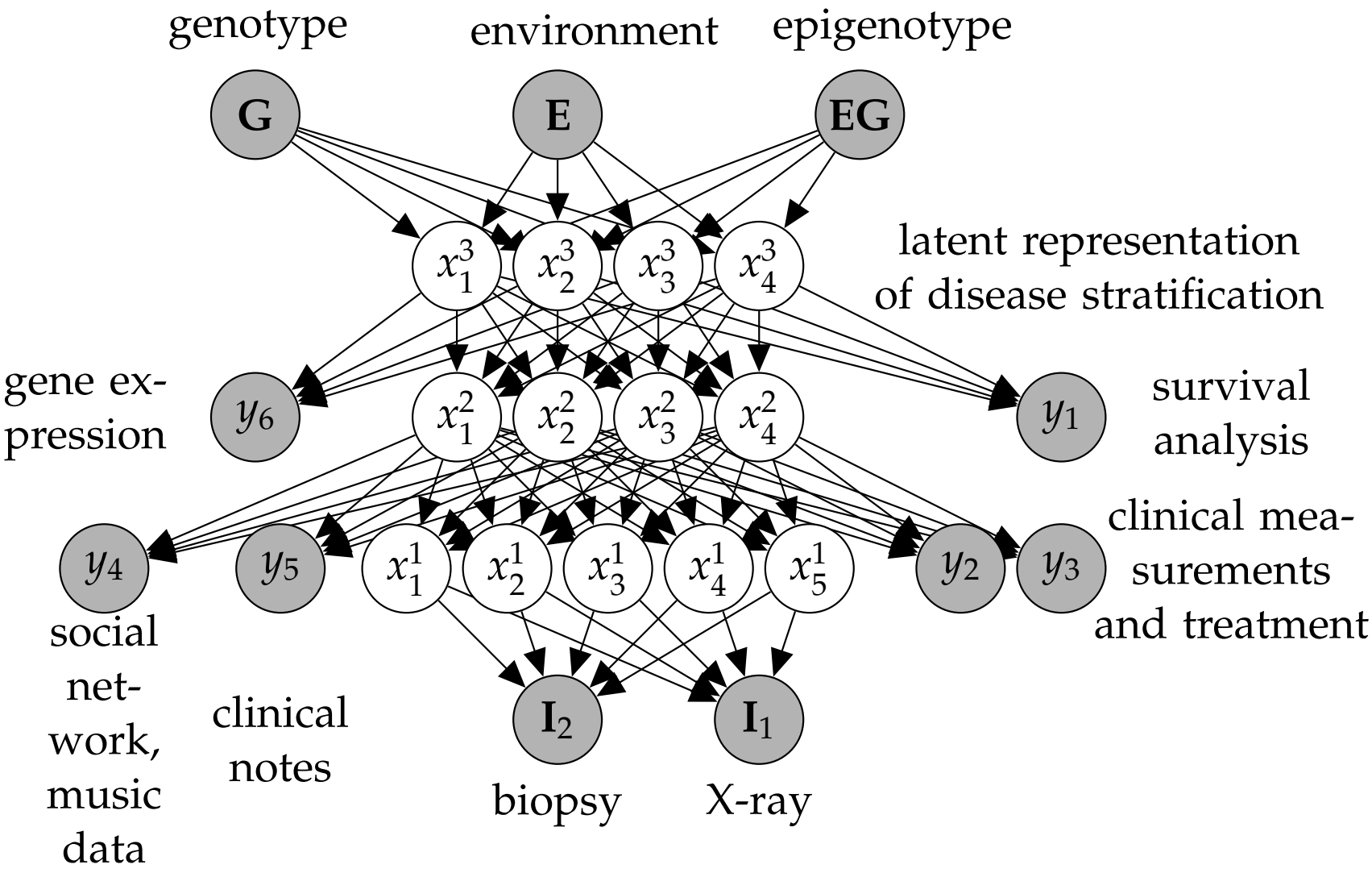
Latent layer 1
$\mathbf{y}$
Data space

What Can We 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
$\mathbf{I}_2$
$\mathbf{I}_1$
biopsy
X-ray

Deep Health: Power Ranger Model of Research

Thanks to Alan Saul for creating the image.

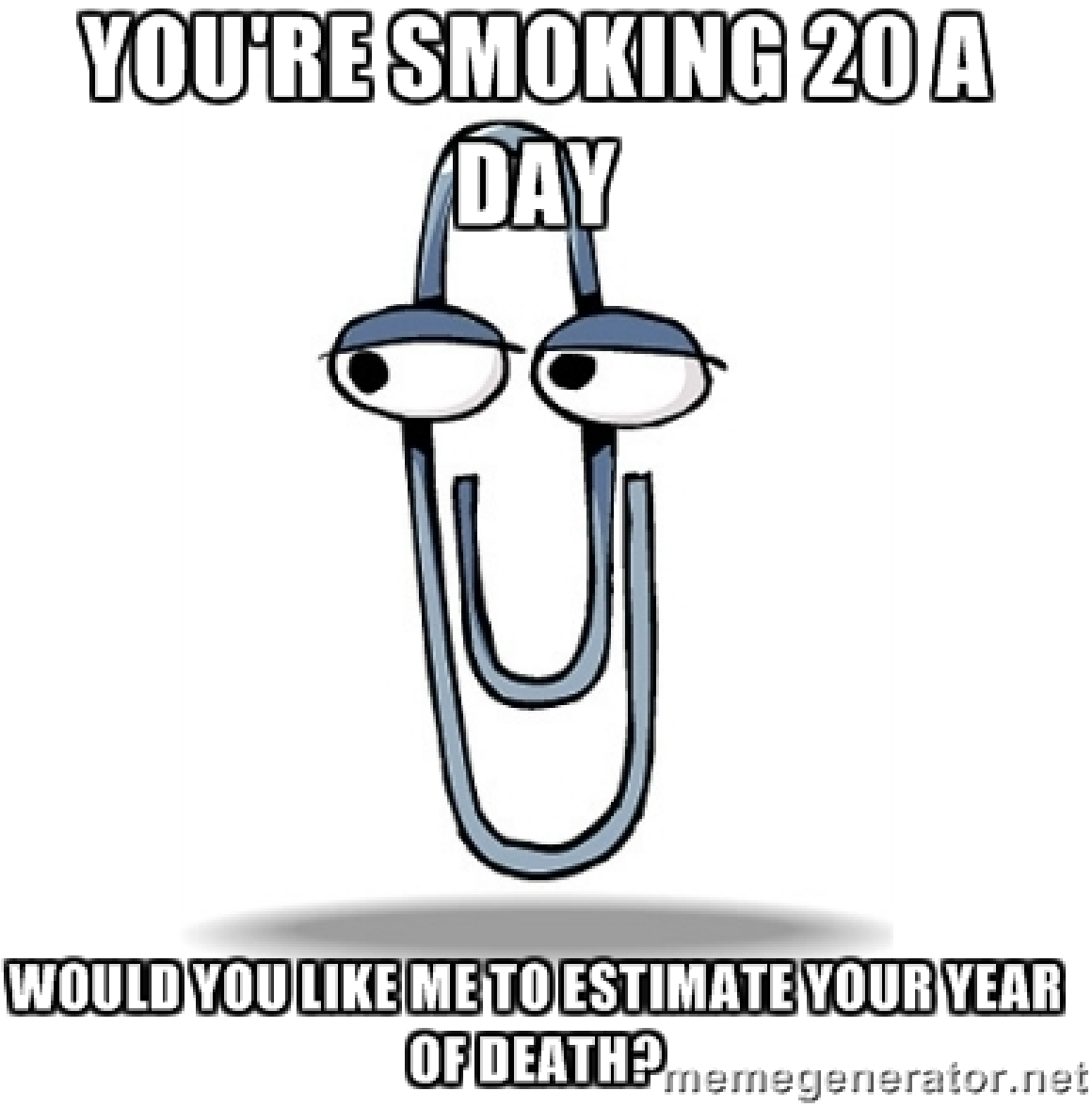
The Patient Experience: Bedside Manner

- 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.

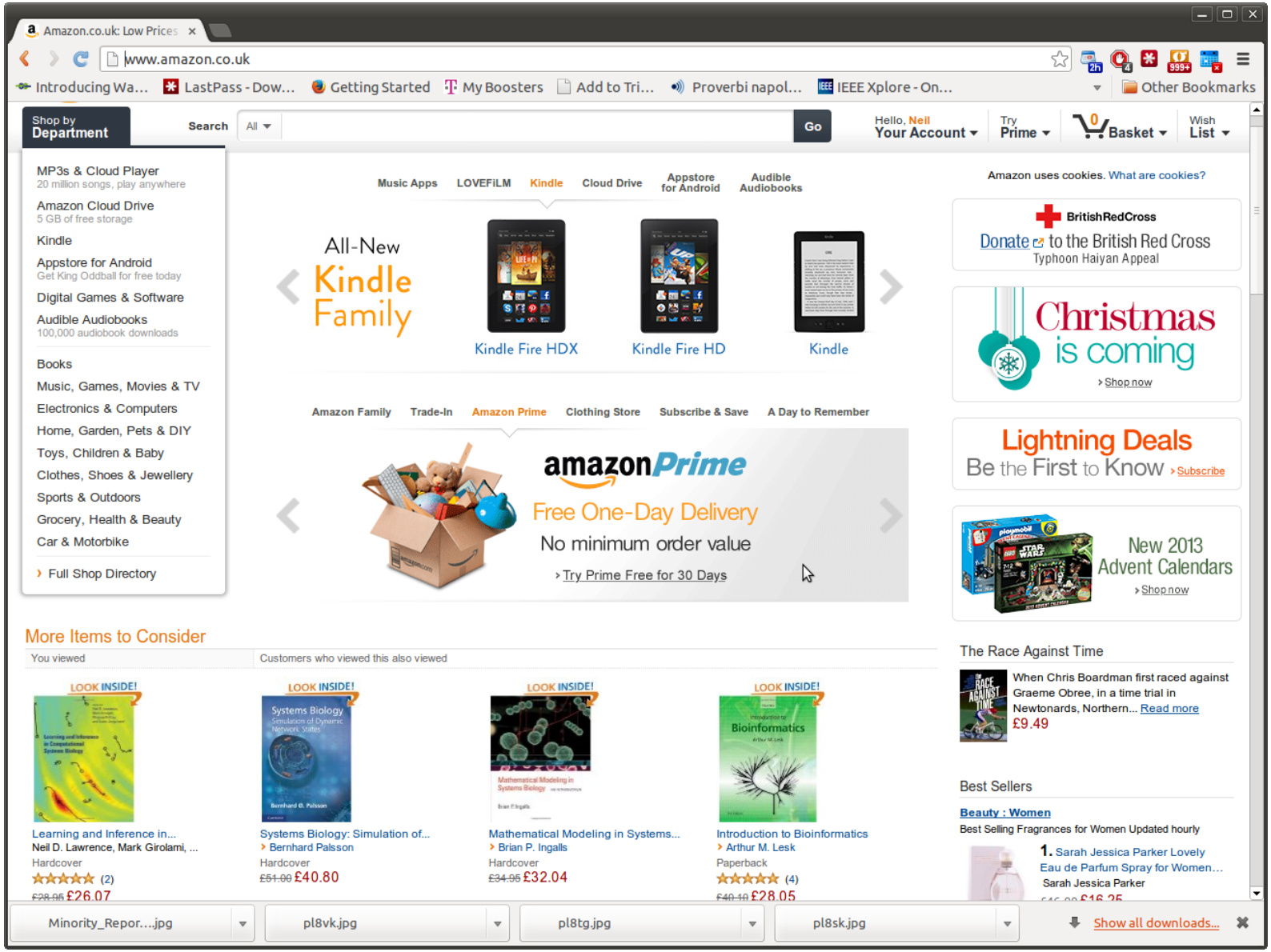
Interface


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

Target Figures Out Teen

consumerist.com/2012/02/17/target-figures-out-teen-girl-is-pregnant-before-her-father-does-sends-helpful-coupons/

Introducing Wa... LastPass - Dow... Getting Started My Boosters Add to Tri... Proverbi napol... IEEE Xplore - On... Other Bookmarks

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TARGET

Target Figures Out Teen Girl Is Pregnant Before Her Father Does, Sends Helpful Coupons

By Mary Beth Quirk February 17, 2012

We didn't really believe it when we were told in 7th grade that math could unlock the secrets of the universe, but after reading about the coupon-wielding power of a Target statistician, which resulted in a mighty surprise for one father of a teenage girl, we might be converts. Doesn't make math any better though.

The *New York Times* (via Forbes) had some time chatting with Target's statistician royale, Andrew, before he was told to zip his lips by the company. He discussed how retailers figure out how to sort out your purchases — from what you need, what you will use a coupon for and your personal preferences. Oh yeah, and they can decode if you're pregnant even before you buy diapers.

In Target's case, it all comes down to your Guest ID number tied your credit card, name, and other info, which saves all kinds of data about what you buy. Statistician Andrew mined that data and saw patterns in it, for example — women on baby registries buy larger amounts of unscented lotion around the beginning of their second trimester. Bam! Send'em some coupons for other baby items. More Andrew magic!:

> *As [his] computers crawled through the data, he was able to identify about 25 products that, when analyzed together, allowed him to assign each shopper a "pregnancy prediction" score. More important, he could also estimate her due date to within a small window, so Target could send coupons timed to very specific stages of her pregnancy.*

BITE BACK: SUBMIT A TIP

Search this website... Search

DON'T PANIC! BETA

We are currently testing a new commenting system. Want to help? Request an invite.

LOGIN REQUEST AN INVITE

POPULAR POSTS

- This Is What An Uncooked McRib Looks Like
- HOA Fines Homeowner $5K For Planting Trees That Are Currently Too Small
- Funny How The Promo Photo Lil' Kim Is Using For Her Single Looks A Lot Like Artist's Zombie Work
- Insider: Everyone At Best Buy Dreads 6 P.M. Thanksgiving Day Opening

Minority_Repor....jpg pl8vk.jpg pl8tg.jpg pl8sk.jpg Show all downloads...

EMIS myHealth

MyHealth | Patient.co.uk

https://myhealth.patient.co.uk/actions/myaction/

Introducing Wa... | LastPass - Dow... | Getting Started | My Boosters | Add to Tri... | Proverbi napol... | IEEE Xplore - On... | Other Bookmarks

Feedback

Like us on facebook Like 47k

Welcome back Neil (not you?) MyHealth | My account | Sign out

Patient.co.uk
Trusted medical information and support

MyHealth | Blogs | Shop | Symptom checker

Search Patient.co.uk

Home | Wellbeing | Health Information | Medicines | Professional Reference | Forums | Directory | Patient Access

Health | Fitness | Recipes | Patient stories | MyHealth | Progress overview | Health programme

Home > MyHealth

Track your health status

Welcome back Neil
You have the following actions that require your attention.

Set your health goals

Your Patient Q Score

View details

Current		Target
Q77	→	Q77

Update Patient Q Score

Your First Q Score
Q77 0 places since joining =

Next steps

Step 1: Improve your diet
Step 2: Stop smoking
Step 3: Maintain your healthy cholesterol profile
Step 4: Maintain your healthy stress levels
Step 5: Maintain your healthy blood pressure
Step 6: Maintain your healthy exercise levels
Step 7: Maintain your healthy alcohol intake
Step 8: Maintain your healthy body weight

Next goals

Add some goals

Why not challenge your friends? Share your score now!

Share | Tweet

Discuss your score in the forums

Visit forums

Steen_Doctor_a....jpg | Minority_Repor....jpg | pl8vk.jpg | pl8tg.jpg | Show all downloads...

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.

Implications for Curricula

- Computer science doesn't have enough maths.
- Maths doesn't have enough computer science.
- 'Data science' needs researchers that can use both.
- Maths and Computer Science duals specialize in 'Data Science'?

Maths

- Any ‘mature’ subject subdivides Poincaré as “The Last Universalist” (Bell, 1937).
- Sometimes these divides are very artificial Probabilists/statisticians.
- Sometimes long histories can ossify ways of thinking.
- However, it *doesn't* mean we should throw everything away and start again.

Proposed Solution

- New department would be ridiculous.
- Shared Computer Science/Stats institutes.
- Mike Jordan at Berkeley.
- Like that but different.
- Break down boundaries: become responsible for computer science/maths duals.
- Launch MSc programms in areas such as 'data science' (also 'food cooking', 'book reading').
- Data Science: despite problems with such terms, we *do* need to brand.
- Physiologists vs Systems Biologists.

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.

References I

E. T. Bell. *Men of Mathematics*. Simon and Schuster, New York, 1937.

Y. Bengio. Learning Deep Architectures for AI. *Found. Trends Mach. Learn.*, 2(1):1–127, Jan. 2009. ISSN 1935-8237. [DOI].

A. Damianou and N. D. Lawrence. Deep Gaussian processes. In C. Carvalho and P. Ravikumar, editors, *Proceedings of the Sixteenth International Workshop on Artificial Intelligence and Statistics*, volume 31, AZ, USA, 2013. JMLR W&CP 31. [PDF].

J. Hensman, N. Fusi, and N. D. Lawrence. Gaussian processes for big data. In A. Nicholson and P. Smyth, editors, *Uncertainty in Artificial Intelligence*, volume 29. AUAI Press, 2013.

G. E. Hinton and S. Osindero. A fast learning algorithm for deep belief nets. *Neural Computation*, 18:2006, 2006.

N. D. Lawrence and R. Urtasun. Non-linear matrix factorization with Gaussian processes. In L. Bottou and M. Littman, editors, *Proceedings of the International Conference in Machine Learning*, volume 26, San Francisco, CA, 2009. Morgan Kauffman. [PDF].

References II

D. J. C. MacKay. Introduction to Gaussian Processes. In C. M. Bishop, editor, *Neural Networks and Machine Learning*, volume 168 of *Series F: Computer and Systems Sciences*, pages 133–166. Springer-Verlag, Berlin, 1998.

S. T. Roweis. EM algorithms for PCA and SPCA. In M. I. Jordan, M. J. Kearns, and S. A. Solla, editors, *Advances in Neural Information Processing Systems*, volume 10, pages 626–632, Cambridge, MA, 1998. MIT Press.

R. Salakhutdinov and I. Murray. On the quantitative analysis of deep belief networks. In S. Roweis and A. McCallum, editors, *Proceedings of the International Conference in Machine Learning*, volume 25, pages 872–879. Omnipress, 2008.

M. E. Tipping and C. M. Bishop. Probabilistic principal component analysis. *Journal of the Royal Statistical Society, B*, 6(3):611–622, 1999. [PDF]. [DOI].

A. G. Wilson, D. A. Knowles, and Z. Ghahramani. Gaussian process regression networks. In J. Langford and J. Pineau, editors, *Proceedings of the International Conference in Machine Learning*, volume 29, San Francisco, CA, 2012. Morgan Kauffman.