A Brief Introduction to Deep Learning and Bayesian Approach in Disease Prediction

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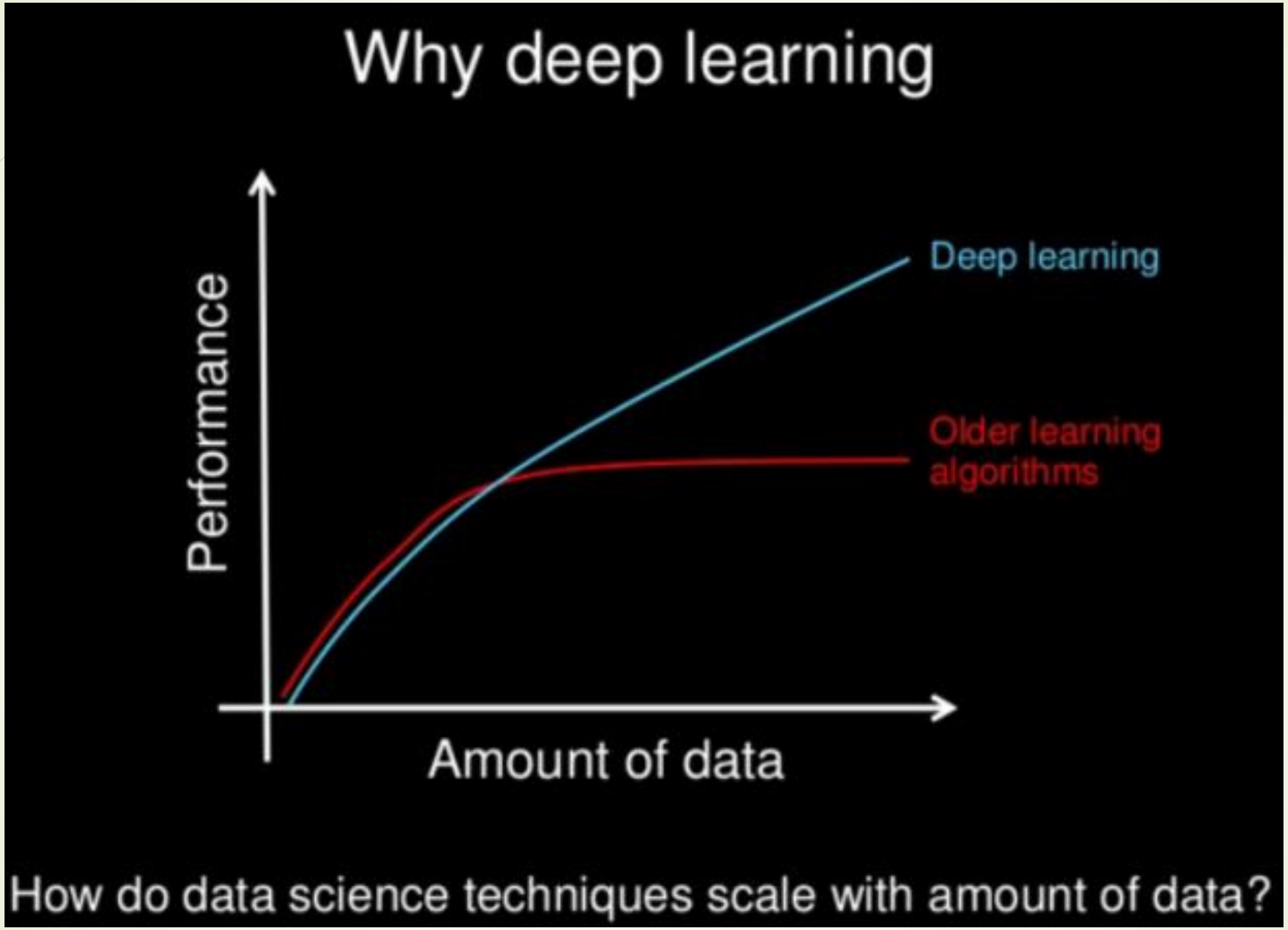
Outline

- Part 1:
  - Motivation
  - Three deep learning architectures
- Part 2:
  - Disease Prediction using Bayesian Network and Latent variable
  - Inductive Causation* algorithm
  - History of Bayesian Deep Learning
  - Bayesian deep Learning

Motivation

Deep Learning is a machine learning technique based on big data and aims to learning representations.

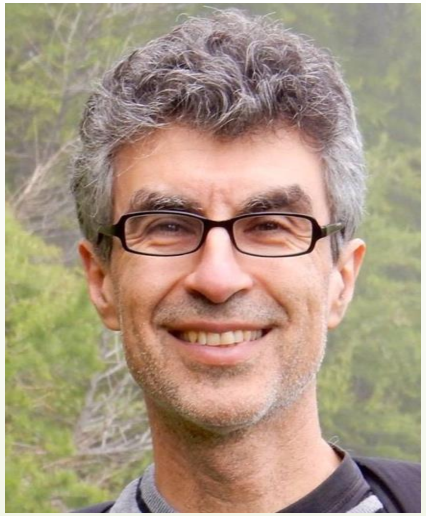
Since the proposal of a fast learning algorithm for deep belief networks in 2006, the deep learning techniques have drawn ever-increasing research interests.

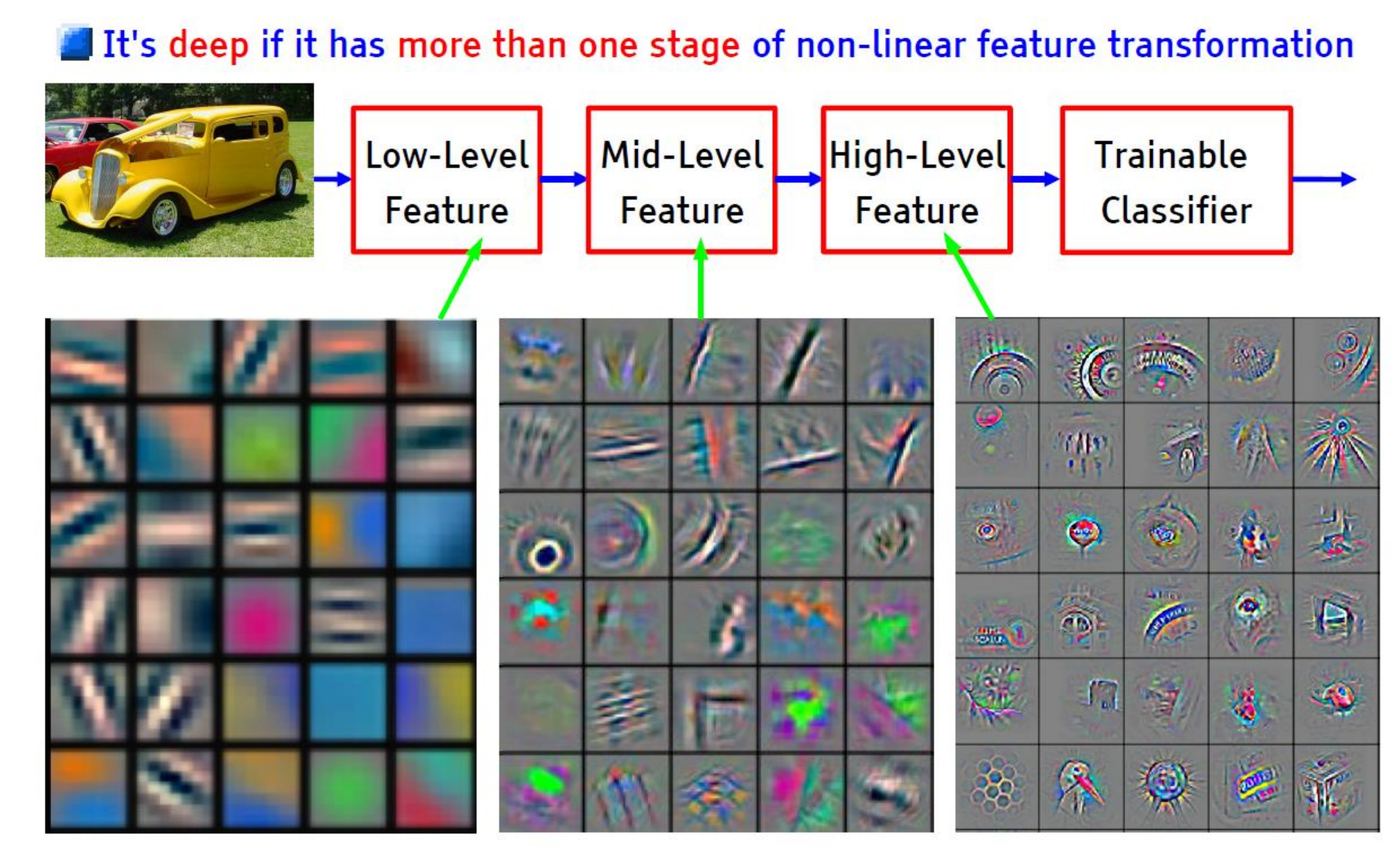


(Source: Andrew Ng, "Deep Learning, Self-Taught Learning and Unsupervised Feature Learning", 2013)

The Breakthrough in 2006:

1. Geoffrey E. Hinton, “A fast learning algorithm for deep belief nets”, University of Toronto.
2. Yoshua Bengio, “Greedy layer-wise training of deep networks”, University of Montreal.
3. Yann LeCun, “Efficient learning of sparse representations with an energy-based model”, New York University.





Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

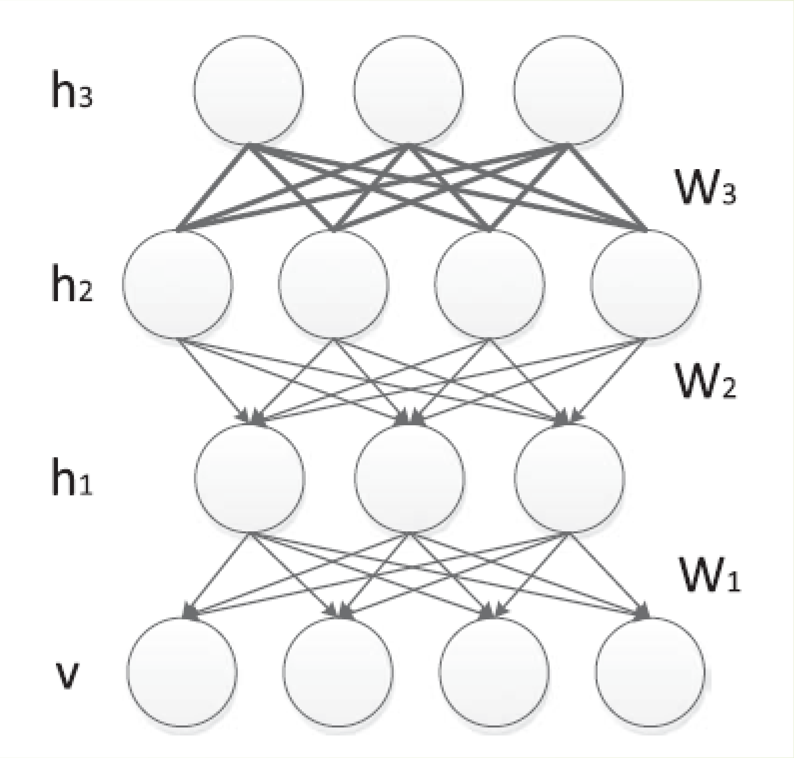
(Source: Yann LeCun, Deep Learning Tutorial, ICML, Atlanta, 2013-06-16)

Three deep learning architectures

1. Deep Belief Net

- The DBNs are composed of multiple layers of stochastic and latent variables and can be regarded as a special form of the Bayesian probabilistic generative model.

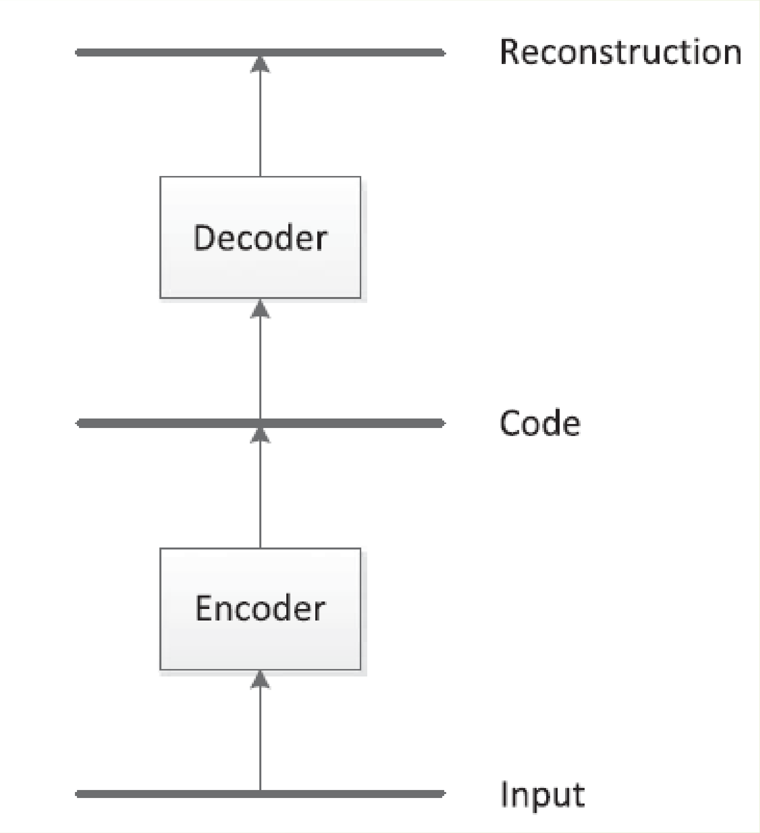
- Compared with ANNs, DBNs are more effective, especially when applied to problems with unlabeled data.



Three deep learning architectures

2. Autoencoder

- AE is an unsupervised learning algorithm used to efficiently code the dataset for the purpose of dimensionality reduction.
- The AE is a one-hidden-layer feed-forward neural network similar to the multilayer perceptron.



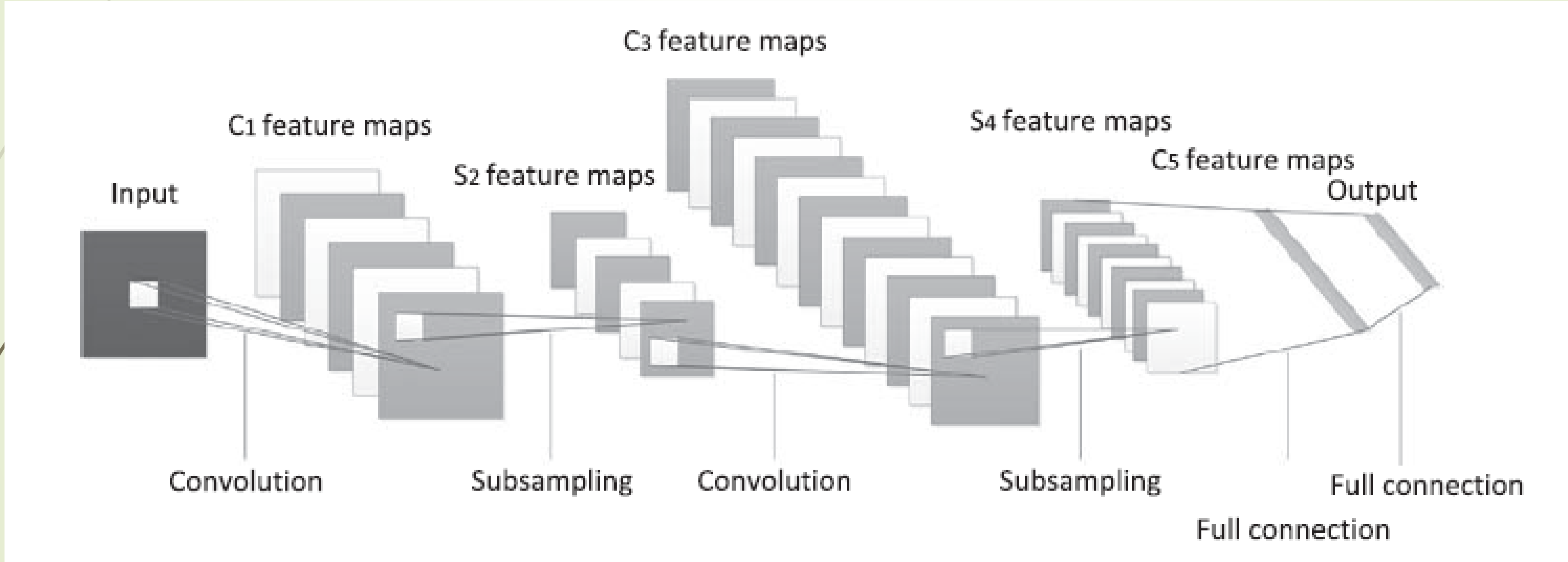
Three deep learning architectures

3. Deep Convolutional Neural Network

- CNNs are a subtype of the discriminative deep architecture and have shown satisfactory performance in processing two-dimensional data with grid-like topology, such as images and videos. The architecture of CNNs is inspired by the animal visual cortex organization.
- In CNNs, the convolution has replaced the general matrix multiplication in standard NNs. As such, the number of weights is decreased, thereby reducing the complexity of the network.

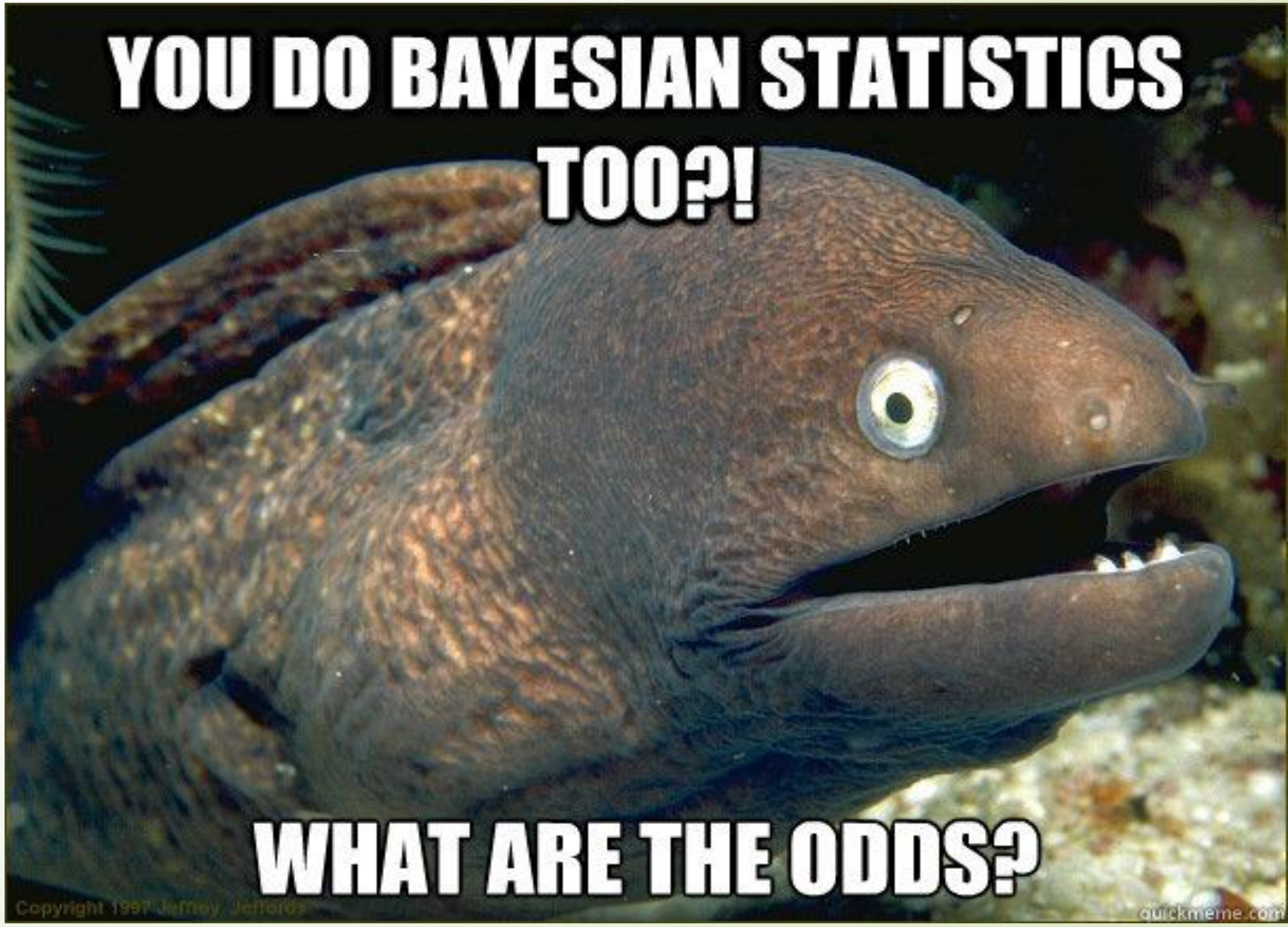
Three deep learning architectures

- Deep Convolutional Neural Network



Predicting Disease Complications

Using Hidden Variable Discovery for Learning Dynamic Bayesian Networks and Bayesian Deep learning



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History of Bayesian Neural Network (BNN)

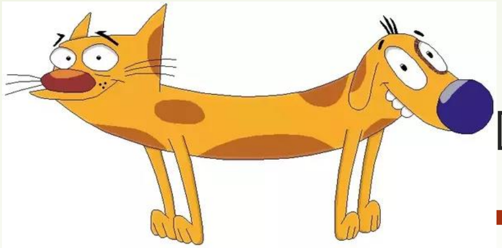
Approximate Inference in Bayesian Neural Networks

- Laplace Approximation (David MacKay-1992)
- Minimal Description Length (Hinton and Van Kamp-1993)
- Hamiltonian Monte Carlo (Radford Neal-1995)
- Ensemble Learning (Barber and Bishop-1998)
- Gal and Ghahramani :
  - Approximate Dropout NN and reparameterised posterior ad normal priors over network weights.
  - Optimising any Neural Network with dropout is equivalent to a form of approximate Bayesian Inference.
  - A network trained with dropout already is a Bayesian Neural Network!

Dropout is a regularization technique for reducing overfitting in NN by co-adaptations on training data. (Dropping out Hidden and observed units)

We need to approximate the weight of posterior in BNN

Bayesian Deep Learning



Bayesian Reasoning

Pros.

- A framework for inference and

decision making

- Unified framework for building,

Inference, prediction and decision making

- Explicit accounting for uncertainty and

variability outcomes.

- Robust to overfitting, tools for model

selection and composition.

Cons.

- Many coupled and linear models
- Potentially intractable inference, computationally expensive or long simulation time.

Deep Learning

- Rich non-linear models for classification and sequence prediction.
- Scalable learning using stochastic approximation and conceptually simple.
- Easily compostable with other gradient-based methods.
- Only estimates the points over confidently.
- Require large amount of labelled data.
- Hard to score models,

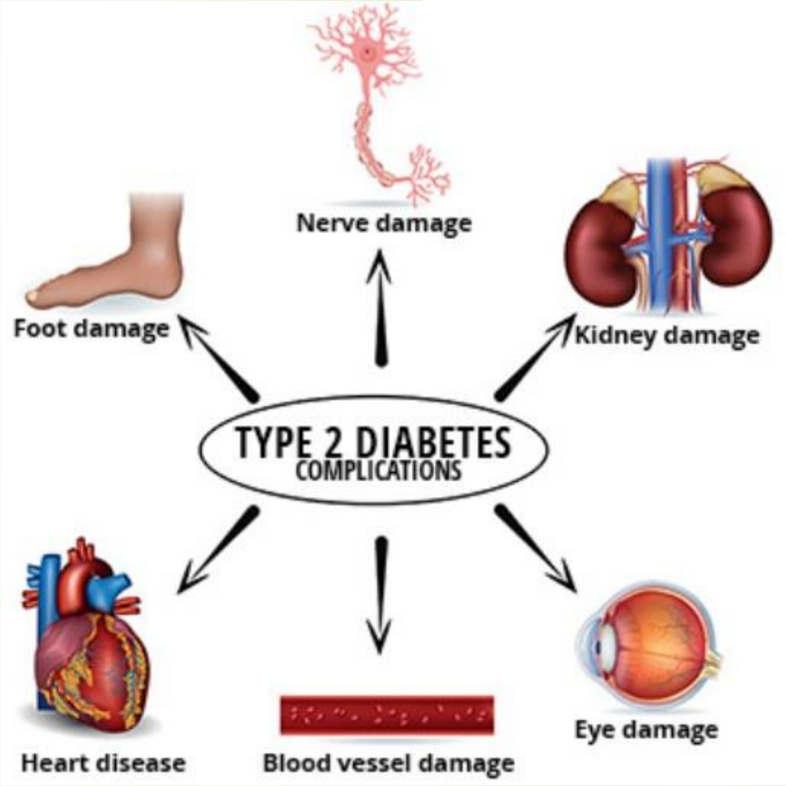
do selection and complexity

penalisation.

Natural to marry these approaches

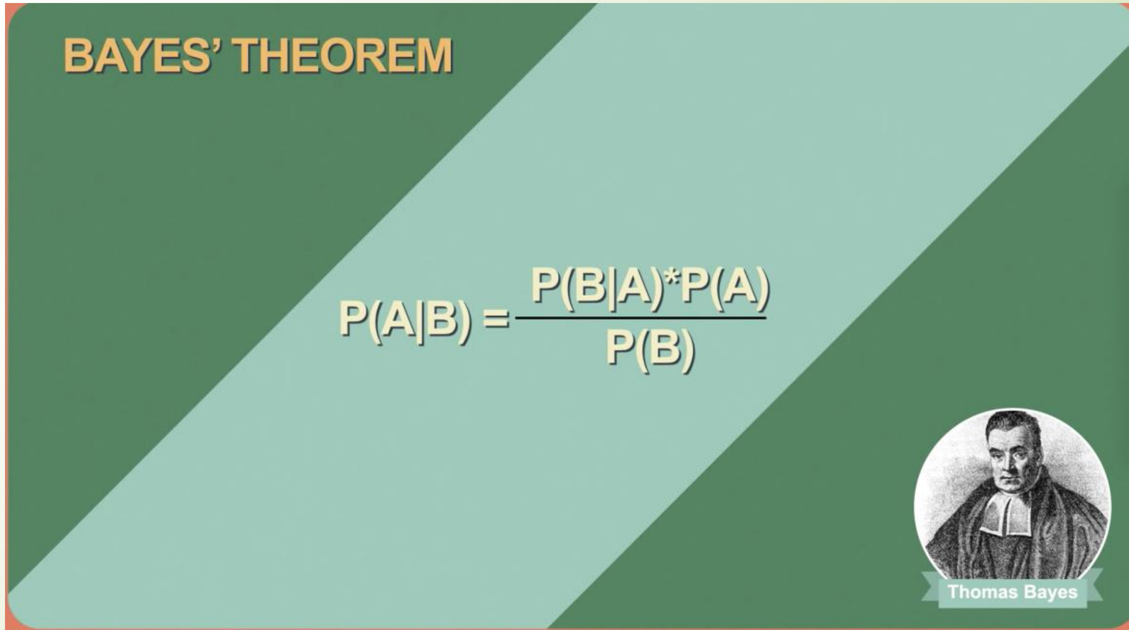
Diabetes & Its Complications

- Type 2 Diabetes Mellitus (T2DM), which is a non-insulin dependent diabetes or adult-onset diabetes.
- Type 2 Diabetes Mellitus (T2DM) most common form.
- Accounting for at least 90% of all cases.
- The World Health Organization (WHO) estimates that by 2030 ~550 million people suffering.
- Complications such as Eye and Liver Disease are common in Diabetes.
- Predicting these earlier very valuable but difficult.
- Using Latent variable to capture.



Introduction to Bayesian Modeling

- The theorem was invented by an english reverend Thomas Bayes (1701-1761) and published posthumously (1763).
- Given a prior state of knowledge or belief, it tells how to update beliefs based upon observations (current data).



Bayesian and what is Odds?

Likelihood ratio = the probability that a test is correct divided by the probability that it is incorrect

Positive Likelihood

$$LR- = \frac{1 - \text{sensitivity}}{\text{specificity}}$$

Positive Likelihood

$$LR+ = \frac{\text{sensitivity}}{1-\text{specificity}}$$

	Disease Positive	Disease Negative
Test Positive	A (True Positive)	B (False Positive)
Test Negative	C (False Negative)	D (True Negative)

	Disease Positive	Disease Negative
Test Positive	610	13,212
Test Negative	118	127,344
	Sensitivity = 83.8%	Specificity = 90.6%

From the study it was determined:
0.5% of women have breast cancer
99.5% of women do not have breast cancer

$$\text{Odds} = \frac{\text{P(something is true)}}{\text{P(something is false)}}$$

$$= \frac{0.005}{0.995}$$

$$= 0.005$$

BAYES' THEOREM
(applied to mammograms)

Post-test odds = Pre-test odds * LR+
= 0.43 * 8.9
= 3.8

Probability = Odds / (1+Odds)
= 3.8 / (1+3.8)
= 79%

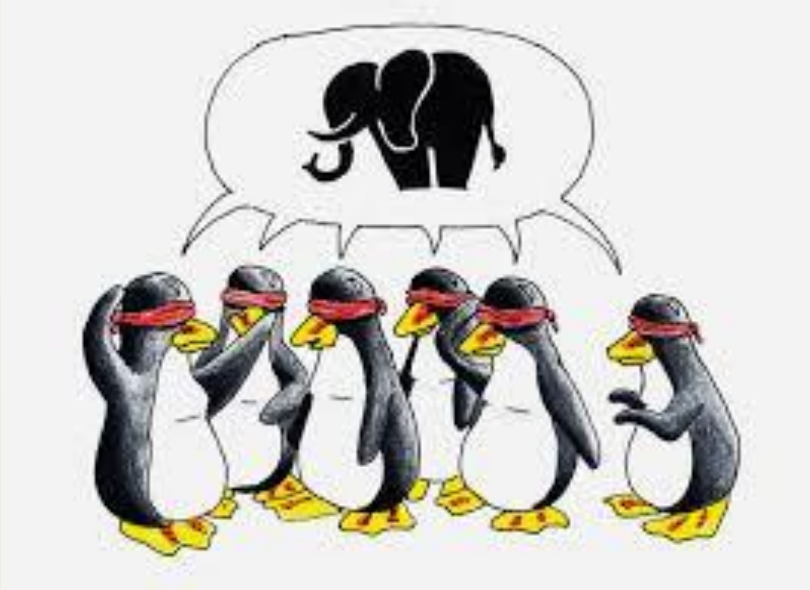
IC* (inductive causation) algorithm

- In the framework of Pearl's causality, algorithms IC and IC* provide a procedure to determine which causal connections among nodes in a network can be inferred from empirical observations.
- Even in the presence of latent variables, indicating the limits of what can be learned without active manipulation of the system.
- Established to analyze causal influences (effective connectivity) among T2DM features.
- Learn a partially oriented DAG (pattern) with latent variables
- The output P is an adjacency matrix, in which:
- P(i,j) = -1 if there is either a latent variable L such that i <-L-> j OR there is a directed edge from i->j.
- P(i,j) = -2 if there is a marked directed i-*>j edge.
- P(i,j) = P(j,i) = 1 if there is and undirected edge i—j.
- P(i,j) = P(j,i) = 2 if there is a latent variable L such that i<-L->j.

See Pearl, "Causality: Models, Reasoning, and Inference", 2000, p52 for more details.

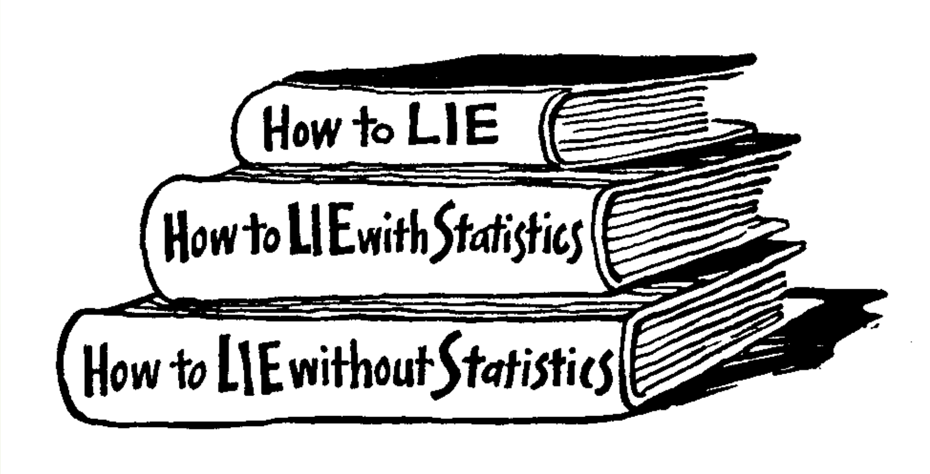
Latent Variable discovery

- IC* algorithm is a constraint based methods with an informative graph, which applies conditional independence analysis to infer casual structures.
- The learned DAG will not be unique
- Latent variable:
  - Some variables are unmeasured, called hidden or latent variables
  - The space of possible structures with latent variables is unbounded.

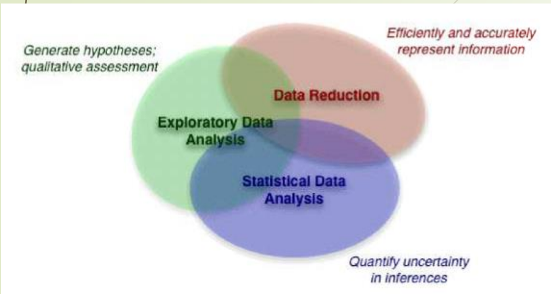


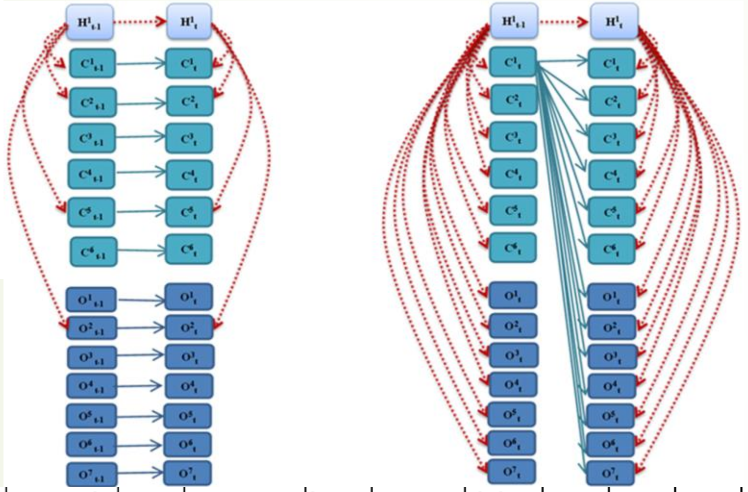
Step-wise Approach

- For all undiagnosed patients for a specific comorbidity Randomly chosen two consecutive time points of data [0 0].
- For all patients diagnosed with a specific comorbidity selected the two consecutive time points that represent the switch from no comorbidity to comorbidity [0 1].
- Randomly resample from the undiagnosed patients so that the same number of pairs appear as for diagnosed patients.

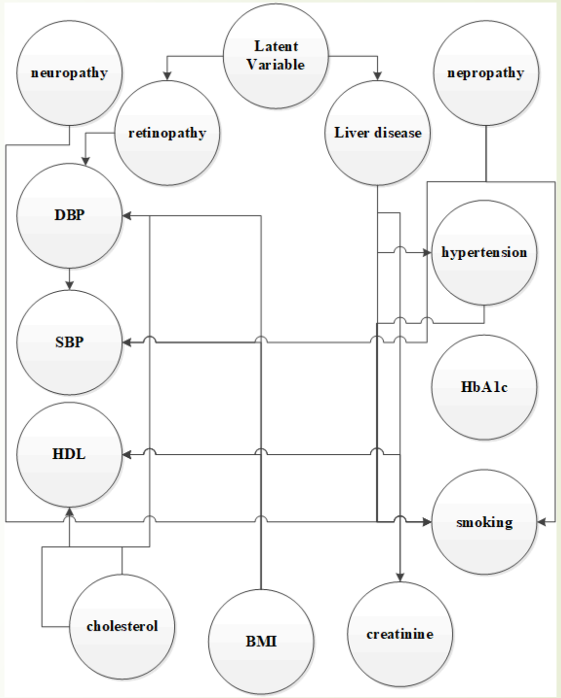


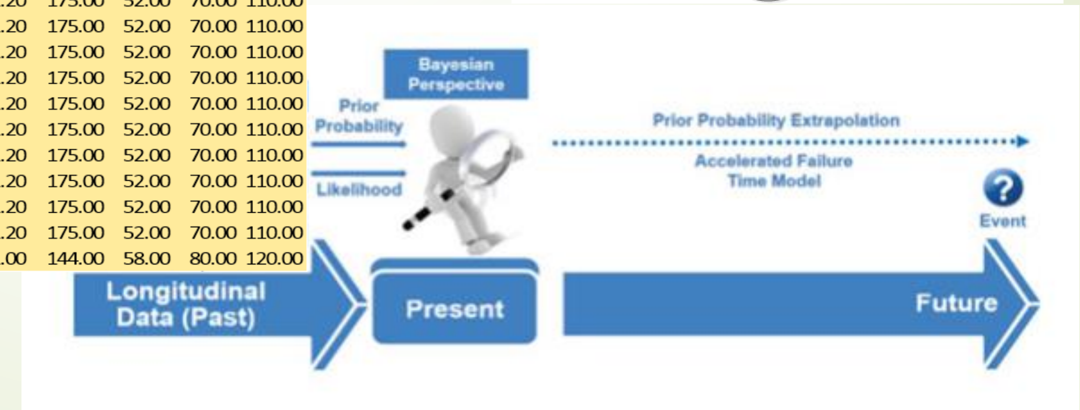
Dynamic Bayesian Network and Latent variable Data and structure





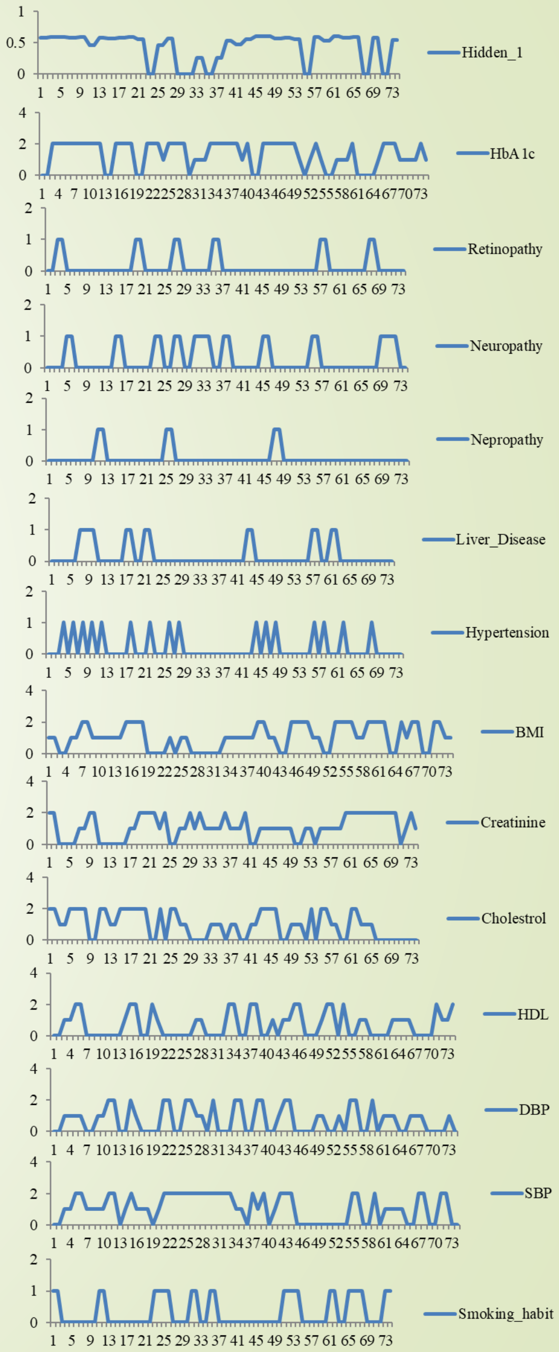
patient_id	HbA1c	Retinopathy	LIVER	Hypertention	bmi	creatinine	chol_tot	HDL	DBP	SBP
182.00	9.60	0	0	0	34.60	0.90	190.00	59.00	70.00	120.00
182.00	9.60	0	0	1	34.60	0.90	190.00	59.00	70.00	120.00
182.00	9.60	1	0	1	34.60	0.90	190.00	59.00	70.00	120.00
182.00	9.60	1	0	1	34.60	0.90	190.00	59.00	70.00	120.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.70	1	0	1	34.60	1.20	175.00	52.00	70.00	110.00
182.00	9.40	1	0	1	35.88	1.00	144.00	58.00	80.00	120.00





prediction Results for Liver Disease

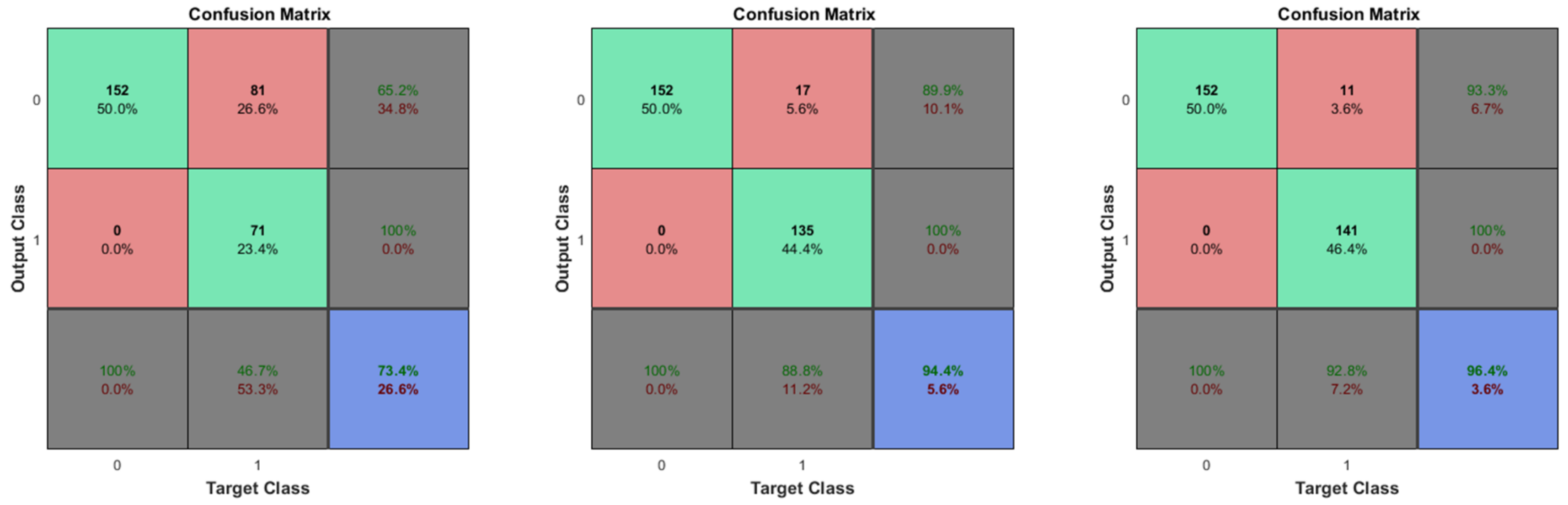
Predicted Latent variable
pattern VS T2DM
complication and Features



No Latent variable

First Step using IC*

Second Step Using IC*



Thank you for listening!

Any Question?