ALCIDION

DEEP LEARNING FOR PATIENT FLOW

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OVERVIEW

- Why are smart machines are important for health care
- The emergence of deep learning
- Deep learning vs existing methods
- Some early results
- Practical tips on getting started
- Future directions

ABOUT ALCIDION

- Health informatics company with products in
  - Patient flow & bed management
  - Emergency Department
  - Outpatient and referrals management
  - SmartForms, clinical decision support (CDS)
- A health informatics approach
  - Computers should play a more active role in health care
  - Assist clinical staff so that the right thing to do is the easier thing to do
- We want to turbo charge our products using advances in smart machines (AI)

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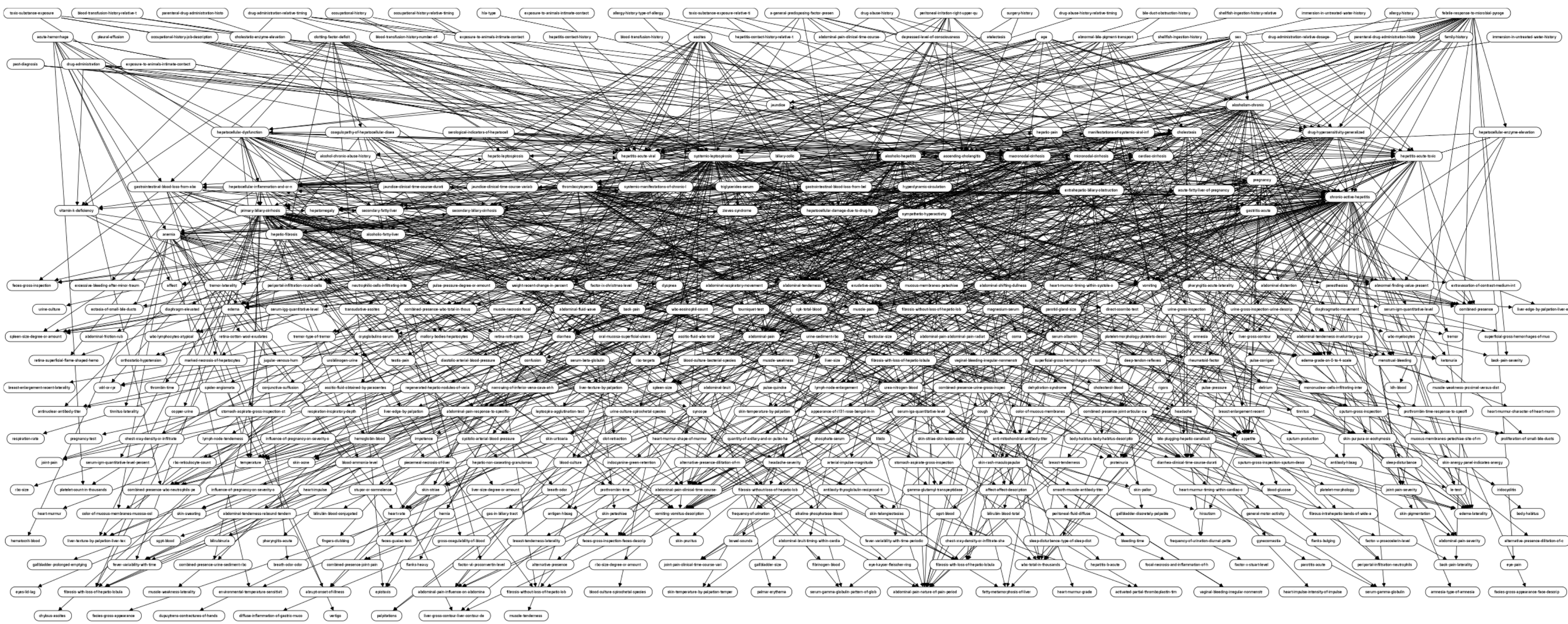
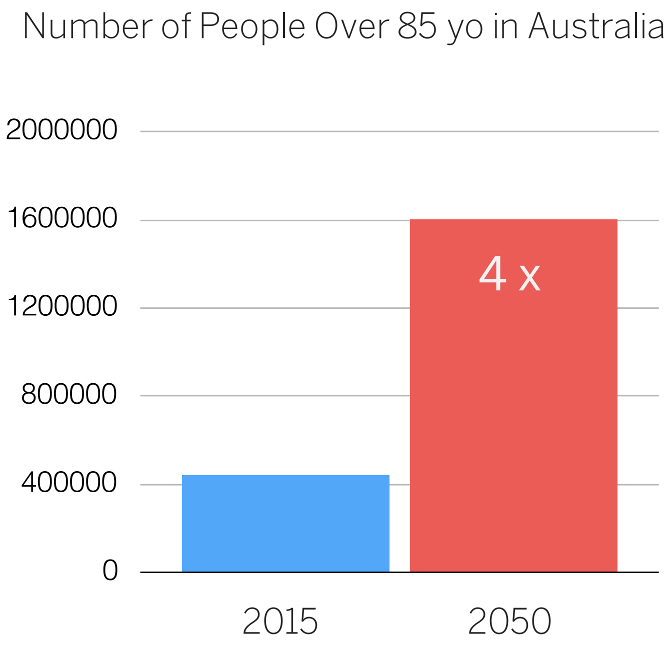
BACKGROUND

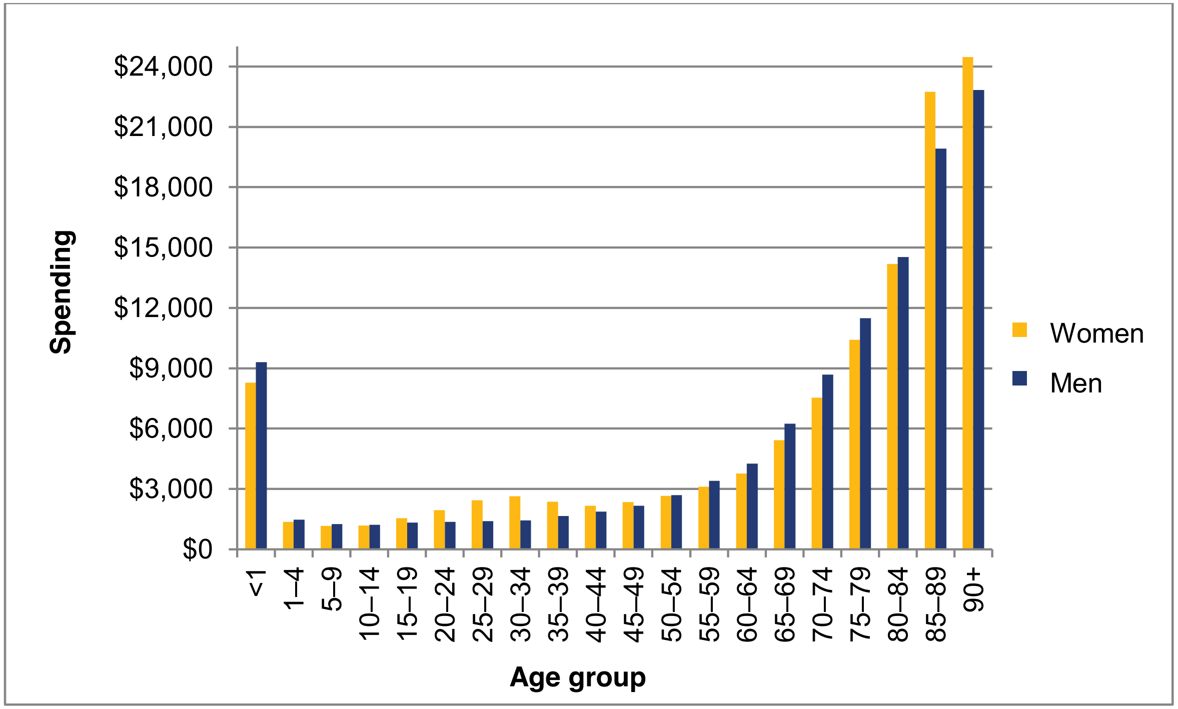
- I started research into AI in the early 1990's
- Focused on decision theory and complex models (uncertainty in AI)
- Probabilistic networks based on knowledge and data
  - 448 nodes, > 900 connections, > 90m probabilities



SMART MACHINES IN HEALTH CARE

- With an aging population the demand for health care is increasing rapidly





- Problems of safety, productivity, variation
- How else do we scale health care?

CHALLENGES IN PATIENT FLOW

- Increasingly complex patients
  - Increased referrals to allied health and other specialties
  - Higher resource utilization, difficult to predict ahead of time
- Current models
  - Predict ED admissions and future admissions
- Challenges
  - Predicting detailed resource needs ahead of time
  - Early detection of variation
  - Logistical support for bed management
  - Using clinical context to better understand patient needs
- AI has been around for ages, why hasn’t it helped us?

ALCIDION A (VERY) BRIEF HISTORY OF AI IN HEALTH

- Expert level performance since 1970's
- Clinical Decision Support for
  - Diagnosis
  - Management
  - Safety

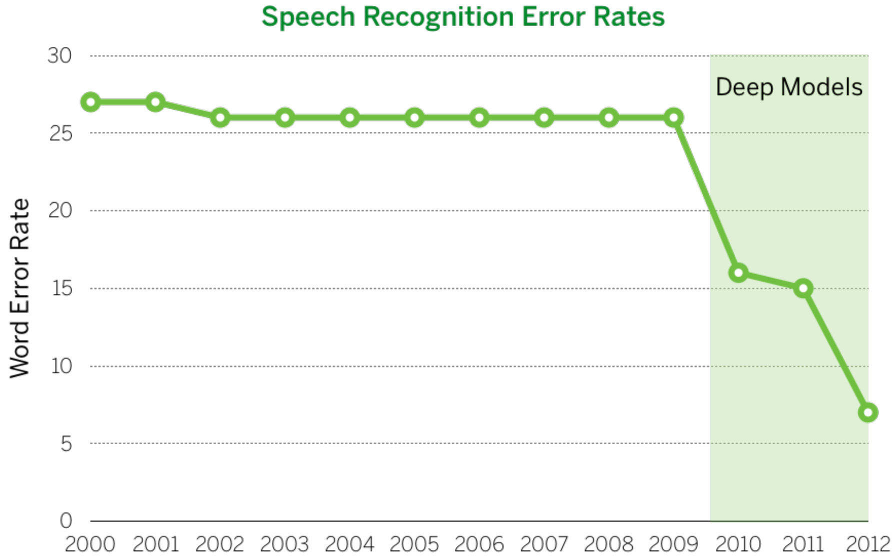
AAPHelp, Internist-1, Mycin, Casnet, PIP, Oncocin, DxPlain, QMR

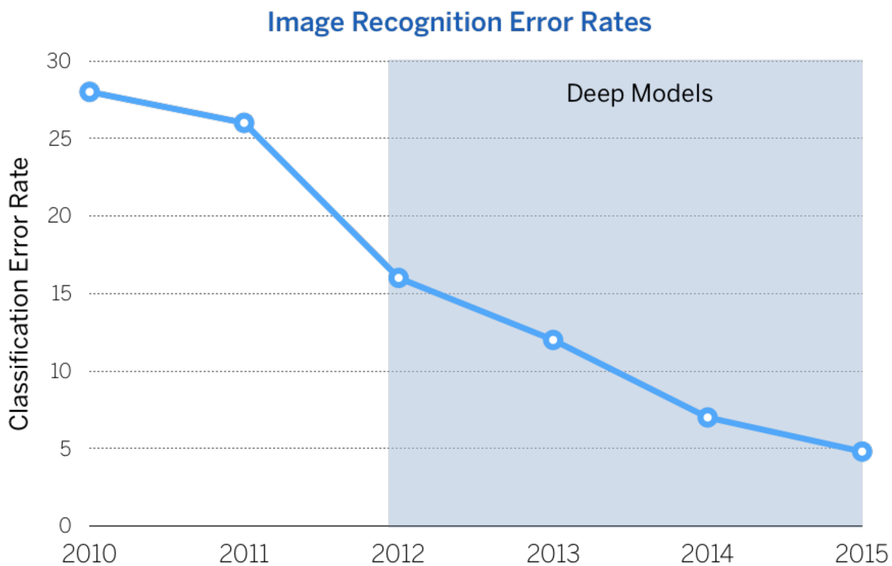
- Difficult to integrate into workflows
- Not integrated with IT systems
- Brittle
- Difficult to maintain over time
- Not easy to localize
- Descriptive, based on expert opinion

Traditional 'AI': Expertise → Model & structure (Knowledge base) → Algorithms to update model

Neural Networks: Data* → Learning algorithms, simple update

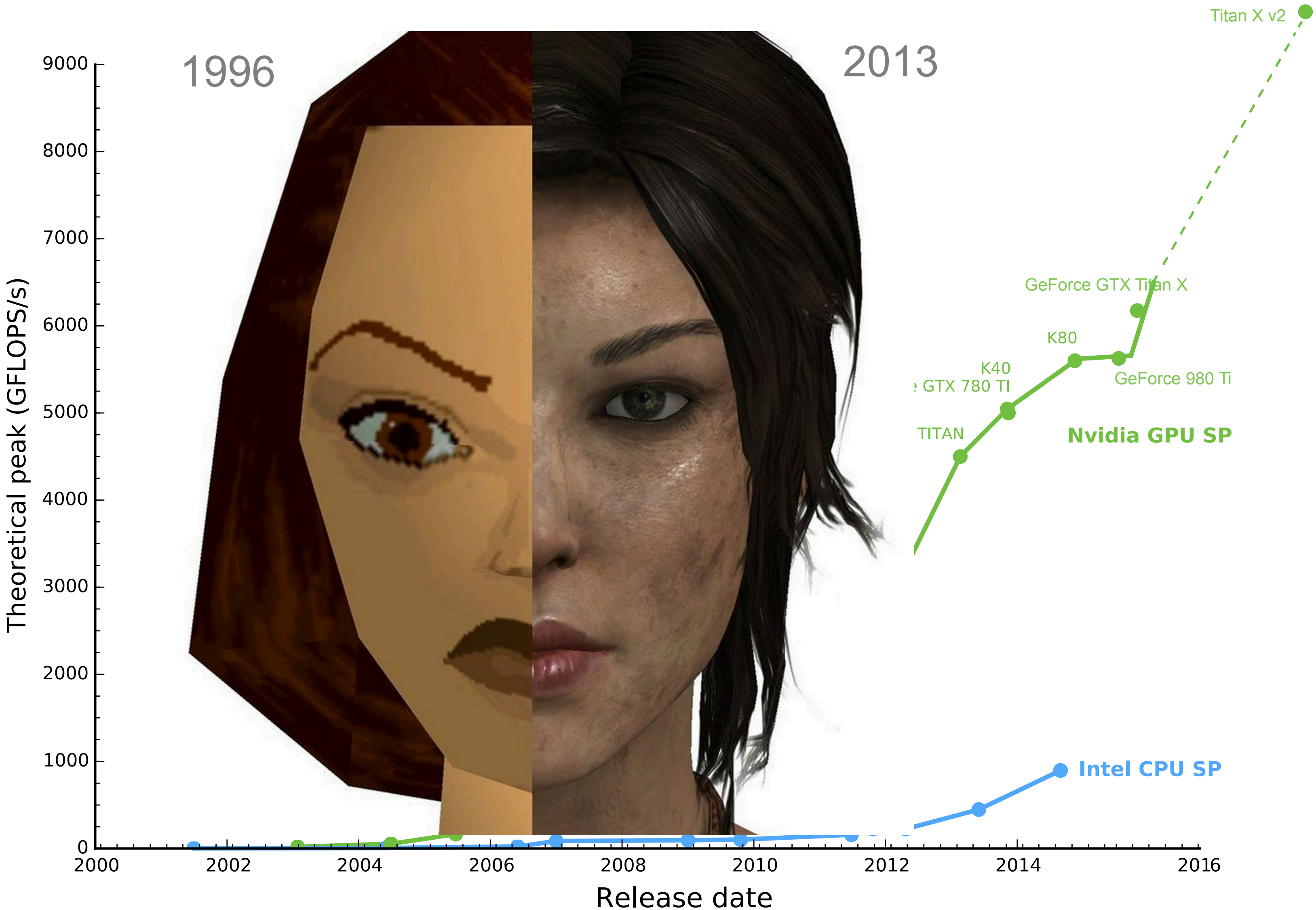
THE 3RD WAVE OF NEURAL NETWORKS





1. Technical improvements to deal with deep networks
2. Large data sets e.g. ImageNet has >14m annotated images
3. GPU

CPU VS GPU



1996
2013
Theoretical peak (GFLOPS/s)
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
2000
2002
2004
2006
2008
2010
2012
2014
2016
Release date
Titan X v2
GeForce GTX Titan X
K80
K40
GTX 780 Ti
GeForce 980 Ti
TITAN
Nvidia GPU SP
Intel CPU SP

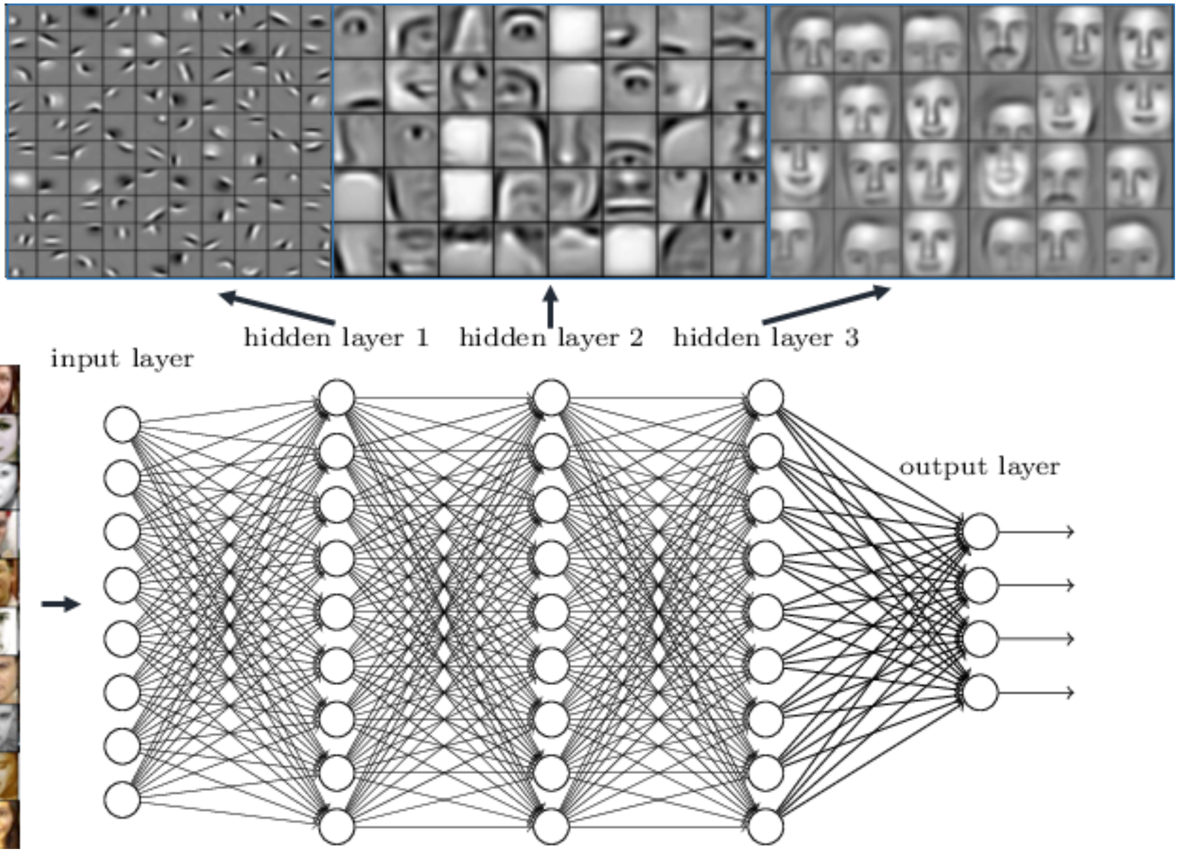
WHAT CAN THEY DO?

- Image description
- Text generation
- Self-driving cars
- Playing complex games
- Early work in demonstrating
  - Radiology
  - Histopathology
  - Risk detection

A close up of a child holding a stuffed animal.

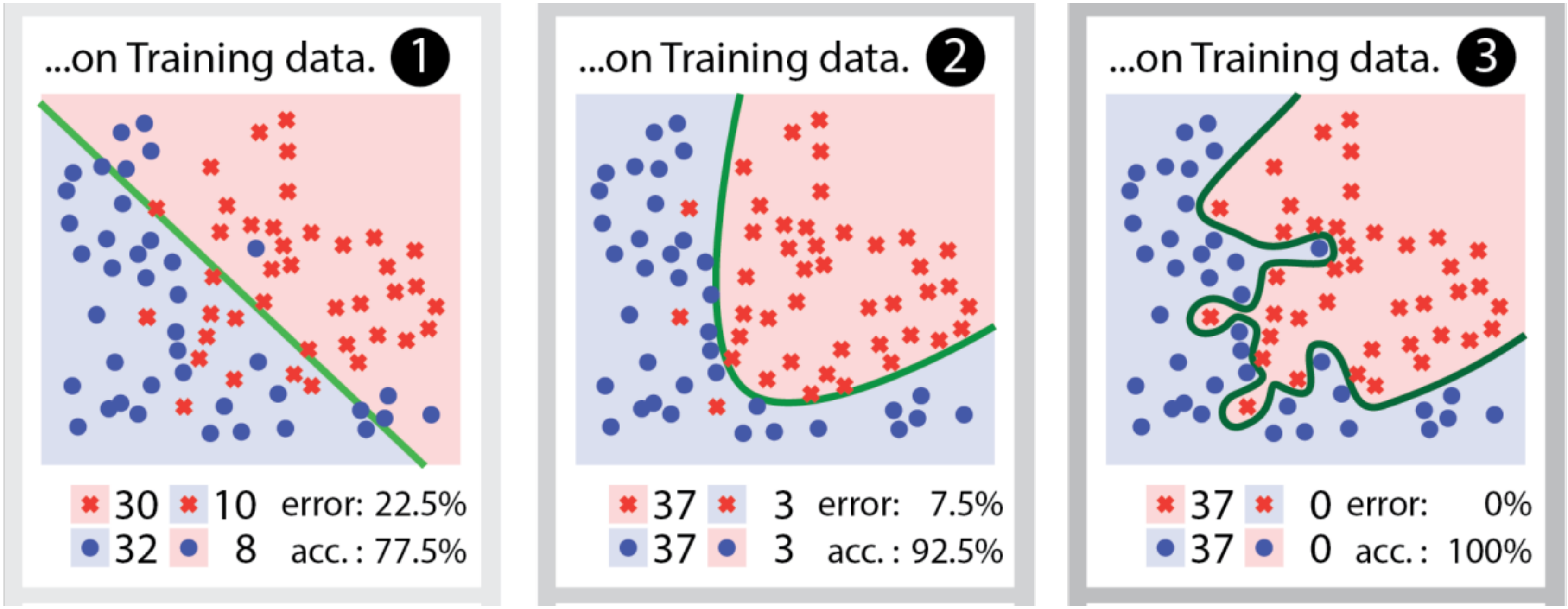
DEEP NETWORK INTUITION

Deep neural networks learn hierarchical feature representations



Lee, H. et. al. Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations. ICML 09
www.rsipvision.com/exploring-deep-learning/

WHY DO THEY WORK?



Latysheva N., Ravarani C. Misleading modelling: overfitting, cross-validation, and the bias-variance trade-off.

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METHODS

- Data generated from anonymised HL7 feeds
  - Admissions, readmissions, ICDs, DRGs
  - Later adding labs, radiology reports, OPD
- Multilayer perceptrons (MLP)
  - Tested 2-5 layers, many variations
  - Significant work in encoding categorical variables such as DRGs and ICDs
  - Approx 8,000 x 200,000 matrix of data
- Hardware & software
  - Linux based PC with Nvidia 980 Ti
  - Keras using Theano back-end
  - Python for running experiments and data transformation

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EARLY RESULTS

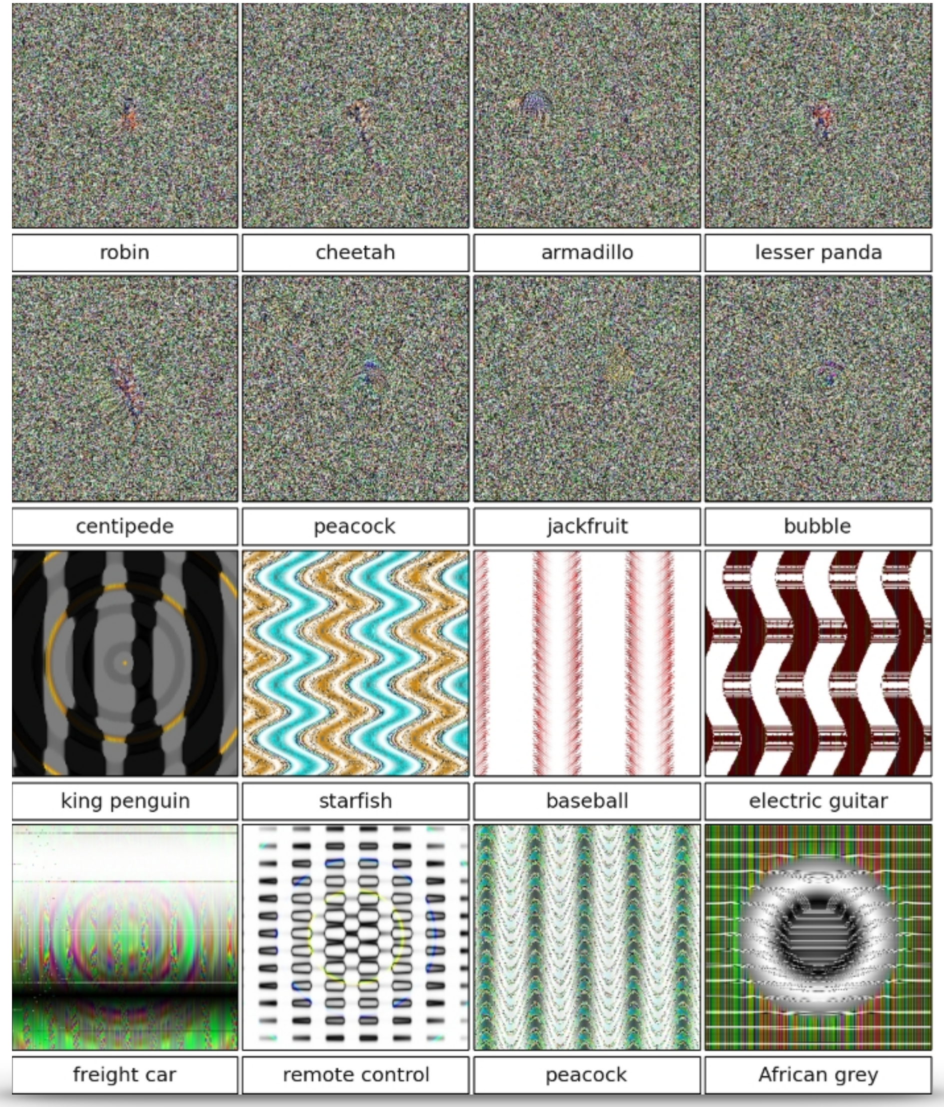
- Readmission
  - Detection of readmission < 30 days against
  - Usually for COPD, Heart failure, Pneumonia, AMI, Total hip/knee arthroplasty
  - On par with best published algorithms based on ICDs and LACE tool approx. 0.65 AUC (better than traditional models on this data set)
  - 3 layers seems to work well, 4-5 have increased training times with minor performance benefits
  - We are exploring an ensemble approach with multiple disease based models for major conditions
- General hospital demand prediction
  - Similar performance to time series models (approx 9% error 1 month prediction) compared to about 15-20% error from historical average methods
  - Require much more data to learn
  - Good performance from ARIMA models

Futoma, K. et. al. A comparison of models for predicting early hospital readmissions. Jof Bio Inform 56 (2015) 229–238

Kim, K. et. al. Predicting Patient Volumes in Hospital Medicine: A Comparative Study of Different Time Series Forecasting Methods

DL ISSUES FOR HEALTH CARE

- Very data hungry
  - Can't provide hints about the domain
- Confidently make errors
  - Recognised with > 99.6% probability
- Not explainable, hard to debug
- Embed probabilities, making them less portable to new settings
- Still descriptive, learn from what has been done



PRACTICALITIES

- Large volumes of data required
  - 100,000+ cases
- Non-image methods are still being developed
  - Representation of categorical data
- Research moves ahead fast using a direct publish model (arxiv)
- Many experiments required over hours – days
  - Configurations, epochs, batch sizes, etc.
- Hardware & software
  - You will need a powerful Nvidia GPU and configured Linux machine
  - Open source software is available: Theano, Tensorflow (Google), Torch (Facebook), CNTK (Microsoft), Keras

FUTURE DIRECTIONS

- Collaboration
  - Aim to create Health Informatics Machine Learning group, currently discussing with UniSA, University of Adelaide
  - Working to integrate more data sources e.g. community
- Improved models
  - Further incorporation of clinical data such as labs
  - Research to incorporate histopathology reports, radiology reports using unsupervised techniques
- Building smart machines
  - Make software part of the health care team, rather than a barrier to productivity
  - Allow patients to monitor their own health and navigate health care