McKinsey&Company

Using Artificial Intelligence to prevent healthcare errors from occurring

SECOND GLOBAL MINISTERIAL SUMMIT ON PATIENT SAFETY

Presentation | 29th March 2017

Agenda for today

1 **Why is Artificial Intelligence/Machine Learning different, and why now?**

2 **Where is the opportunity in patient safety/patient care?**

3 **How can we enable change?**

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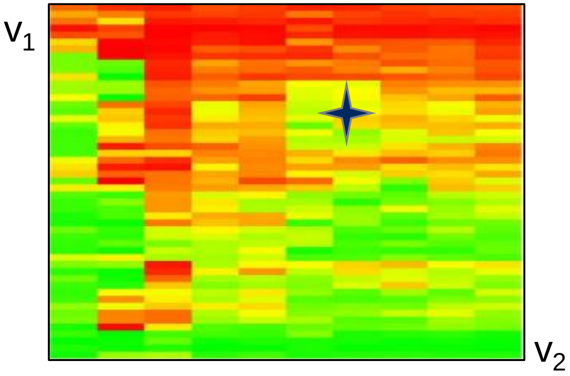
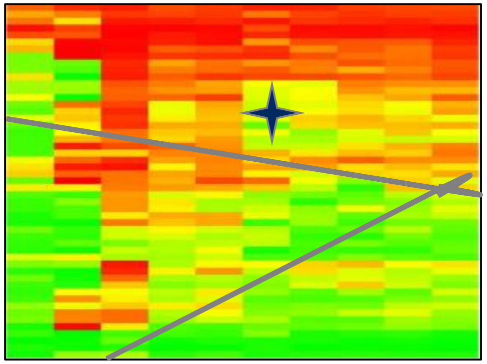
Why is machine learning different?

The actual phenomenon (real historical data)



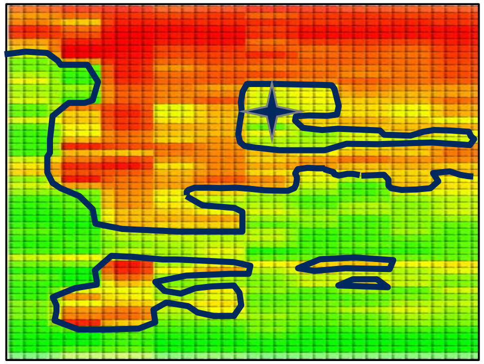
Real life phenomenon come in “all shapes and flavors” – showing patterns that are usually complex, non-linear and apparently disorganized

How Traditional stats sees it



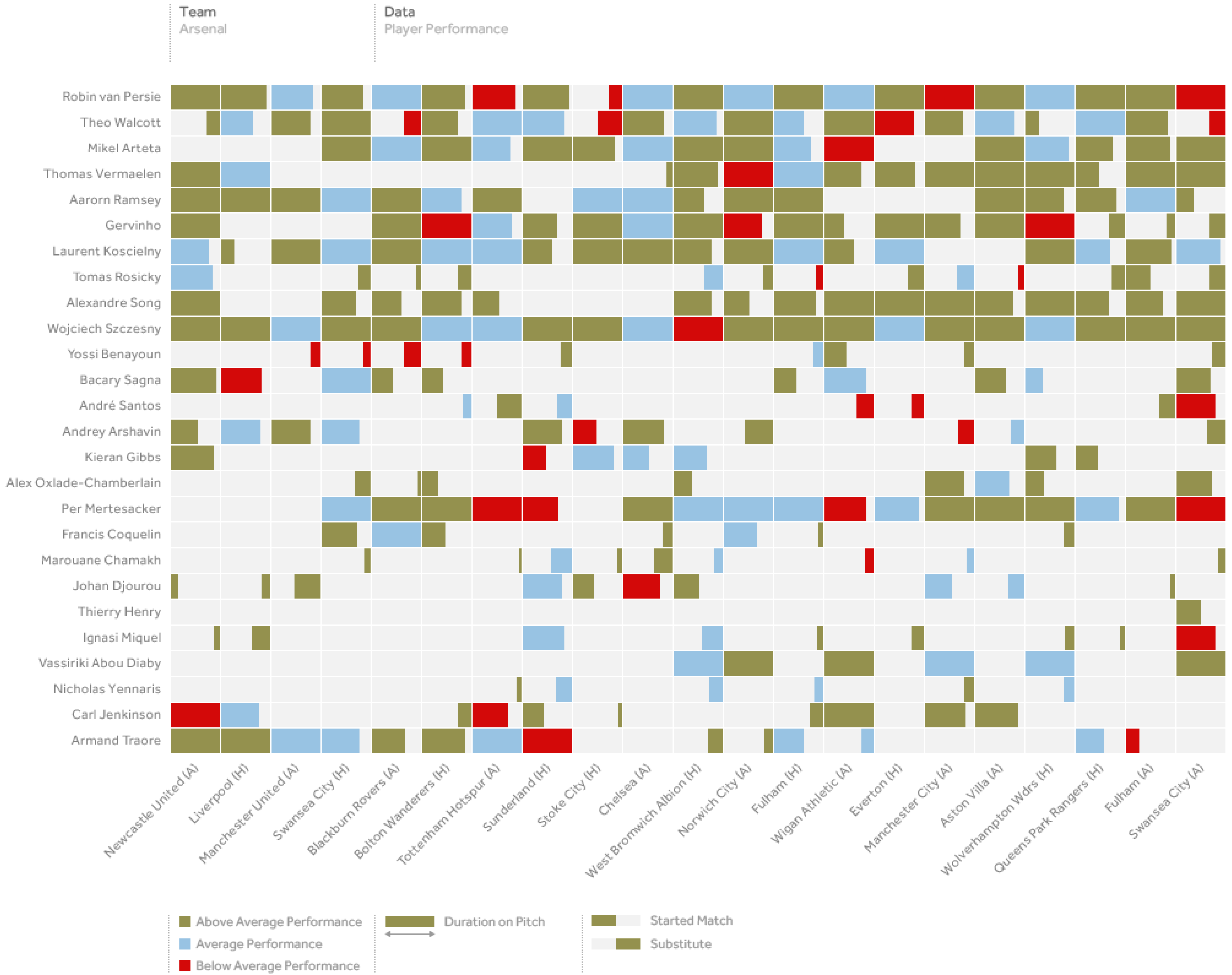
Traditional stats will fit a predetermined “shape” into the phenomenon (e.g. linear, quadratic, logarithmic models) – the square peg into the round hole!

How Machine Learning sees it



While ML algorithms are adapting themselves by spotting & recording patterns without clinging to any predetermined corset

Improving injury prediction in premiership football



90 %

Improvement in accuracy of forecasting non-impact injuries:

Forecast 170 of 184 non-impact muscle injuries across four squads and two years

SOURCE: QuantumBlack

Telecoms

Improving fault rate

Situation

Leading European telecoms and broadband provider needing to improve faults

Approach

Full data capture of all network activities, customer and geolocation data to predict faults

Impact

75 %	90 %	60 %
Faults predicted	Predicted faults prevented	Inbound service calls reduction

❯ Industry leading customer satisfaction score

Predictive maintenance at a coal fired power station helped to reduce mill downtime by >50%

Situation

- Station was suffering from low availability, unplanned maintenance was >3x the global average
- Three components found to be key drivers of failure
- Goal to reduce unplanned losses due to mill failures

Approach

Collected data 7 **different data bases and logs**

Identified key failures and validated failure events

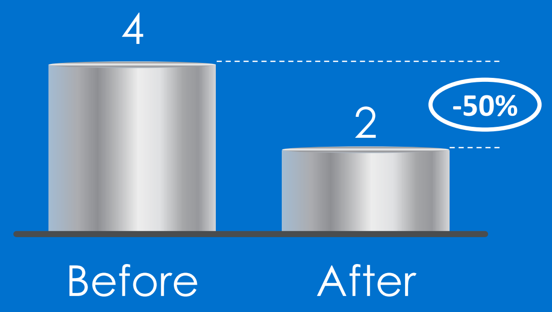
Used machine learning to define and predict failures

Developed user interface to **plan maintenance on time and implemented to shop floor**

Impact

Model predicts failure 3 months in advance with >75% **accuracy**

Down time reduced by >50%



Agenda for today

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3 How can we enable change?

US healthcare has seen increased adoption but only captured ~10% of 2011 value estimate

Categories	Levers	2011 Value potential, $B	2016 Adoption rate, %	Average value realized by adopters %	Value potential realized, $B
Clinical Ops	▪ Comparative effectiveness research ▪ Clinical decision support tools ▪ Transparency about medical data ▪ Remote patient monitoring ▪ Adv. analytics applied to patient profiles	164	25 - 70	10 - 30	12
Accounting/ Pricing	▪ Automated systems ▪ HEOR and performance-based pricing plans	47	10 - 20	20 - 30	2
R&D	▪ Predictive modeling ▪ Statistical tools and algorithms to improve clinical trial design ▪ Analyzing clinical trials data ▪ Personalized medicine ▪ Analyzing disease patterns	108	30 - 50	35 - 50	16
New business models	▪ Aggregating and synthesizing patient clinical records and claims datasets ▪ Online platforms and communities	5	90 - 100	40 - 100	2
Public Health	▪ Public health surveillance	9	60 - 80	60 - 80	5
Total		**333**			**36**

~10% value captured

- Major changes in industry incentives brought about by the ACA and rapid uptake of EMRs from ~30% in 2011 to 90+% today has contributed to general opening of healthcare data
- Slow regulatory processes and monopolistic and segregated industry structure has resulted in only ~10% progress toward realizing BDAA value from 2011

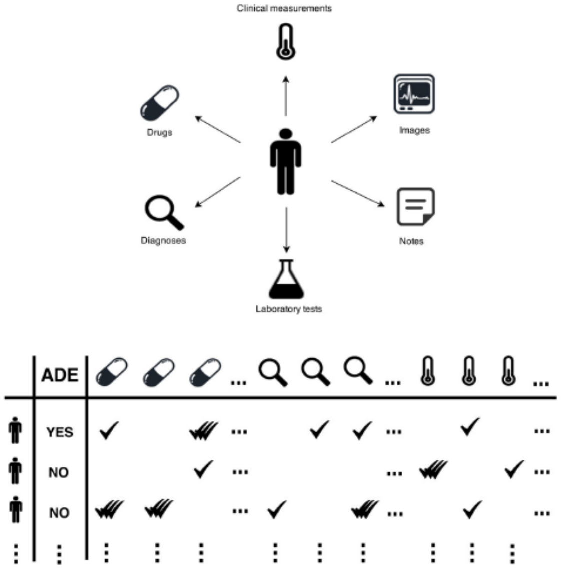
SOURCE: Expert interviews; industry surveys on HIT adoption; McKinsey Global Institute analysis

Proof of concept established for machine learning based predictive modelling to detect adverse drug events using EHR data

Summary

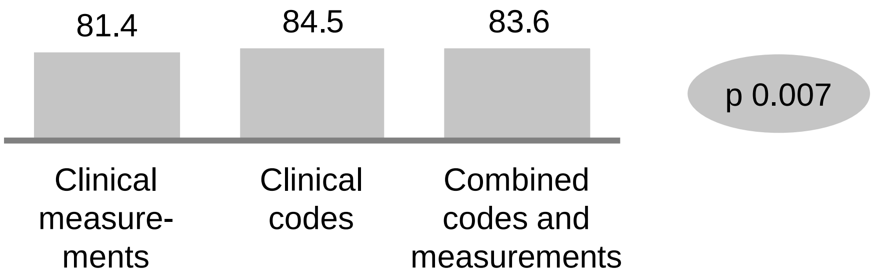
- Machine learning (random forest model) can be used to accurately predict ADEs (adverse drug events) using data from EHRs (electronic health records)
- Clinical coding data (used to record diagnoses and prescribed drugs) has higher predictive performance than clinical measurements – though both used in combination have higher predictive performance for certain ADEs
- Feature selection – to reduce dimensionality and sparsity – further improves predictive performance
- ADEs are responsible for ~5% of hospital admissions internationally
- Systems based on voluntary spontaneous reporting (pharma-covigilance) fail to capture ~94% of ADEs

Extracting data for machine learning from EHRs

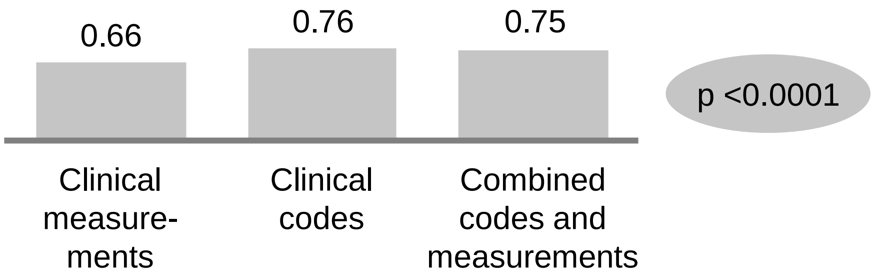


Impact

Accuracy score



AUC (area under curve)[1]



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[1] Standard statistical measure of diagnostic accuracy

SOURCE: Zhoa et al, Predictive modeling of structured electronic health records for adverse drug event detection, 2015, BMC Medical Informatics and Decision Making, 15 (Supplement 4):S1

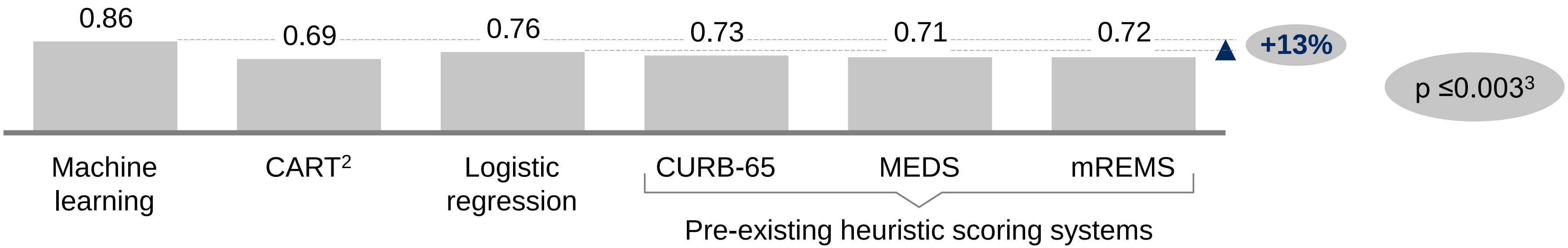
Proof of concept established for machine learning based predictive modelling to identify patients in ER with sepsis

Summary

- ER patients with sepsis have a 5% mortality risk
- Machine learning (random forest model) can be used to accurately identify patients with sepsis in the ER using data from the Electronic Health Record
- The machine learning approach has significantly greater predictive performance than other clinical decision rules based models
- The method developed can be automated and applied to EHRs to predict other clinical outcomes of interest
- Machine learning methods have potential advantages over traditional heuristic methods as they have greater generalizability, can be developed quickly, and may automatically update as new information becomes available

Impact

Accuracy – AUC (area under the receiver operating characteristic curve)[1]



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[1] Standard statistical measure of diagnostic accuracy

[2] CART = Classification and regression tree

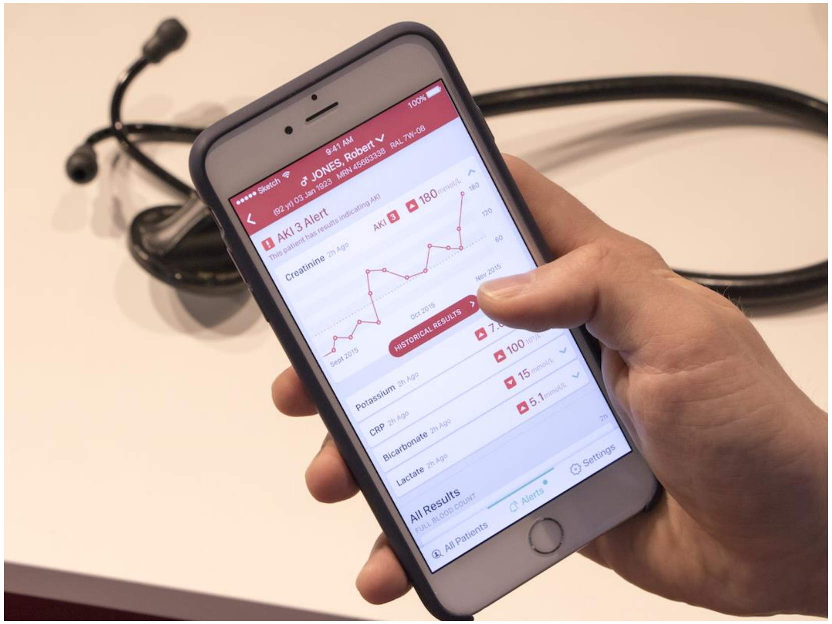
[3] Difference between the random forest model and all other models

SOURCE: Taylor et al, Prediction of In-hospital Mortality in Emergency Department Patients With Sepsis: A Local Big Data–Driven, Machine Learning Approach, 2016, Academic Emergency Medicine, Volume 23, Issue 3, 269–278

DeepMind and the Royal Free hospital in London have developed an AI-based instant alerting tool to identify patients at risk of AKI

Summary

- The Royal Free NHS Foundation Trust and Google's DeepMind artificial intelligence venture have created a real-time alerting system for Acute Kidney Injury (AKI)
- AKI affects 1 in 6 hospital patients are can lead to:
  - Longer length of stay (LOS)
  - Increased critical care (CCU) utilization
  - Higher risk of mortality – estimated at ~40,000 deaths/year in England
  - Higher costs – estimated at £1bn/year across the NHS in England
- The *Streams* app monitors patients' blood test results, combined with information from the patient's EHR, and sends an instant AKI alert to the most appropriate clinician when it identifies signs of deterioration – allowing clinicians to intervene sooner
- The data sharing agreement underlying this venture has been subject to significant scrutiny and criticism[1] – and may be subject to an investigation by the Information Commissioner's Office (ICO), which has yet to report any findings publicly, and the National Data Guardian (NDG) is also continuing to look into the arrangement[2]
- The app took around 18 months to develop



Impact

- Full service evaluation currently in progress
- DeepMind report positive feedback from early staff users with anecdotal evidence that:
  - App saves up to 2 hours/day of nursing time (in some settings/wards)
  - AKI identified in up to 11 patients/day through the alerting system

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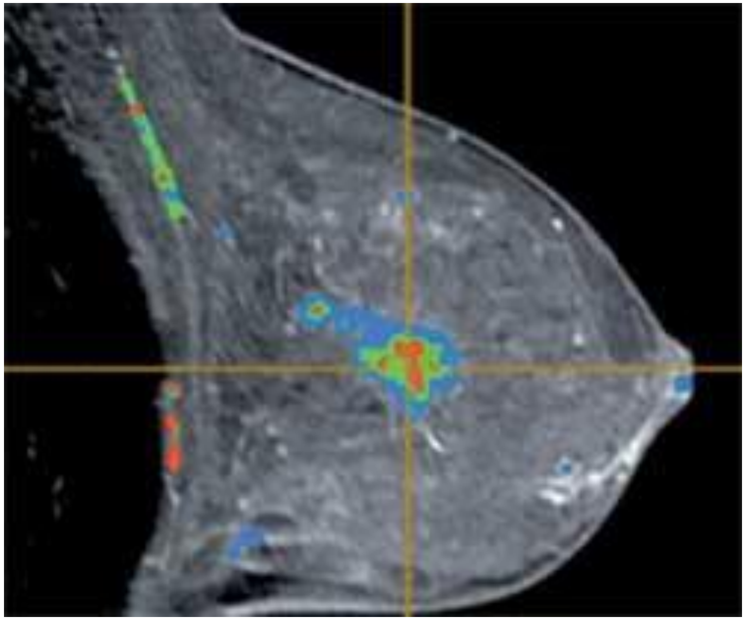
[1] https://link.springer.com/article/10.1007%2Fs12553-017-0179-1; [2] http://www.cam.ac.uk/research/news/deepmind-royal-free-deal-is-cautionary-tale-for-healthcare-in-the-algorithmic-age

SOURCE: Royal Free, https://www.royalfree.nhs.uk/news-media/news/google-deepmind-qa/ , https://www.royalfree.nhs.uk/news-media/news/new-app-helping-to-improve-patient-care/; DeepMind Health, https://deepmind.com/blog/milestone-deepmind-health-and-streams/

Novel approach proposed for computer-aided MRI-based detection of breast cancer

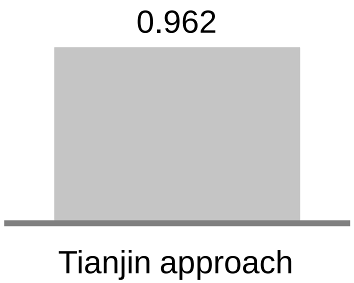
Summary

- Medical imaging plays an important role in the early detection and diagnosis of breast cancer
- Researchers at Tianjin University in China have proposed an automated computer-aided diagnosis (CADx) framework for MRI in breast cancer
- The approach combines several machine learning-based techniques, including:
  - Ensemble under-sampling (EUS) for imbalanced data processing
  - Relief algorithm for feature selection
  - Subspace method for providing data diversity
  - Adaboost for improving the base classifier performance
- Feature subsets' physical meaning subspaces were built by combining morphological features with each kind of texture or Gabor feature
- Proposals were tested using a manually segmented Region of Interest (ROI) data set, containing 438 images of malignant tumours and 1898 images of normal tissues or benign tumours
- The approach outperforms most other state-of-the-art CADx MRI diagnostic systems, significantly reducing the rate of false positive classification



Impact

Accuracy – AUC (area under curve)[1]



- Outperforms most other state-of-the-art CADx MRI diagnostic systems
- Significantly reduces rate of false positives

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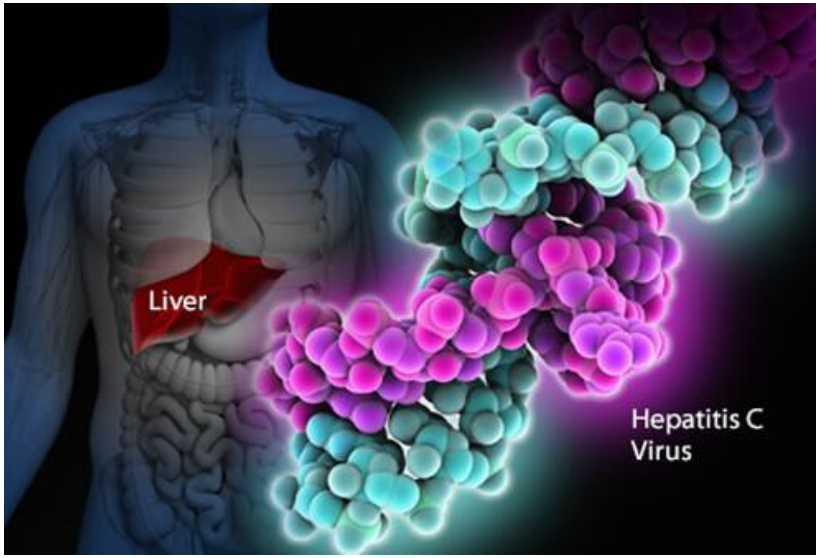
1 Standard statistical measure of diagnostic accuracy

SOURCE: Wei Lu et al, A novel computer-aided diagnosis system for breast MRI based on feature selection and ensemble learning, 2017, Computers in Biology and Medicine, Volume 83, Pages 157–165

Machine learning models predict patients at risk of Hep C progression

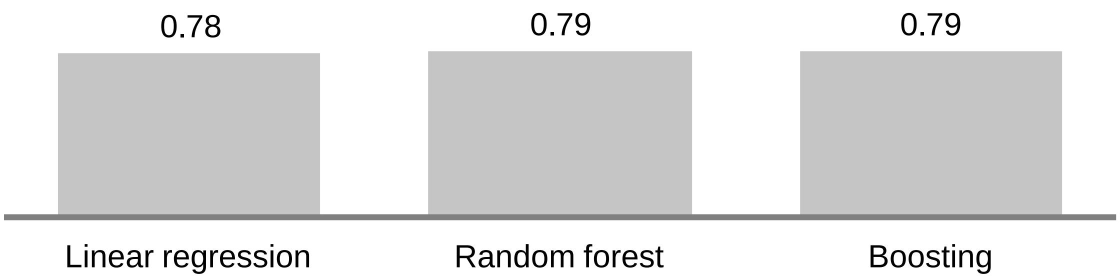
Summary

- Prediction models that incorporate longitudinal clinical data can capture non-linear disease progression in chronic hepatitis C
- The approach uses two outcomes measures (fibrosis progression, and liver-related clinical outcomes) and a range of predictive variables based on longitudinal clinical, laboratory and histological data
- The model was constructed using logistic regression and two machine learning methods, random forest and boosting, to predict an outcome in the next 12 months
- The model can help target costly therapies to patients with the most urgent need, guide the intensity of clinical monitoring required, and provide prognostic information to patients



Impact

Accuracy – AUC (area under the receiver operating characteristic curve)[1]



- **94% negative predictive value** – the proportion of patients identified as not at risk of progression, that do not progress
- **p <0.0001** – probability that longitudinal predictive model is superior to baseline (pre-existing) prediction models

[1] Standard statistical measure of diagnostic accuracy

SOURCE: Konerman M et al, Improvement of predictive models of risk of disease progression in chronic hepatitis C by incorporating longitudinal data, 2015, Hepatology, 61, 1832-1841

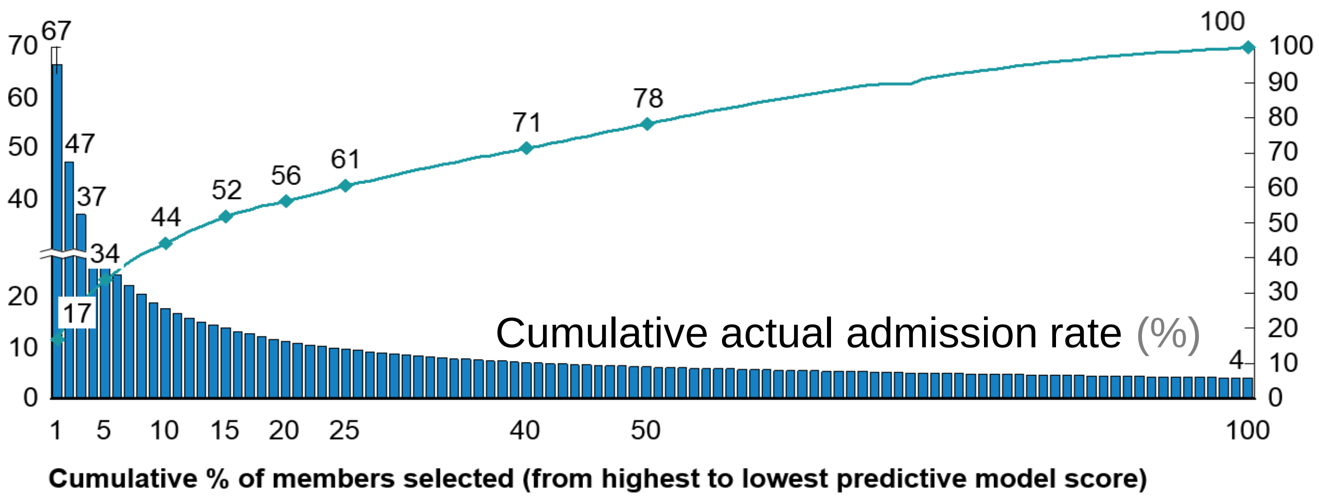
Machine learning tool can predict a patient's hospital re-admission risk in the next 6 months

Summary

- Machine learning to aggregate historical data and understand risk of individual patients of being re-admitted
- Segment patients to understand re-admission rates and develop predictive capabilities

Impact

Cumulative % of total admissions captured

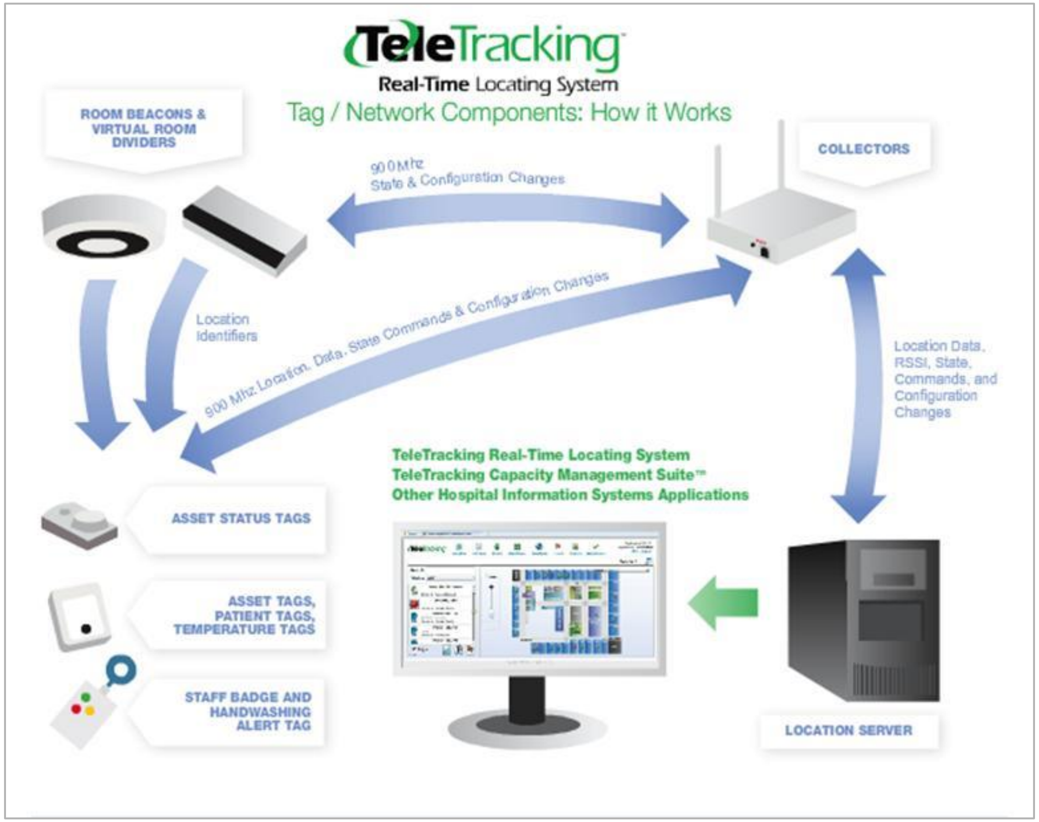


- Top **1%** patients identified are expected to have **67%** admission rate and account for **17%** of total admissions

Tracking hospital operations in real-time allows automation, reducing A&E headcount by up to 50% and cutting patient waiting times in half

Summary

- Real-time tracking improves data availability and accuracy, allowing for better capacity utilization and automation of routine administration activities



Impact

- Up to 50% fewer FTEs in A&E
- 40-50% shorter patient waiting time

Data-driven employee management can allow companies to identify the root causes of absenteeism and reduce related costs

Summary

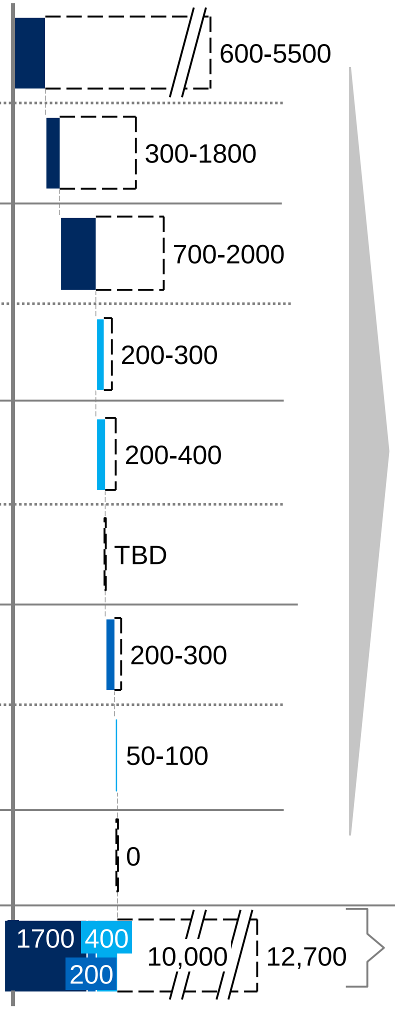
- Leading European financial institution was facing above-industry employee absenteeism
- Significant loss of value estimated at 20m USD yearly for 2k employees
- Strict regulatory environment prohibiting sanctions around absenteeism

Impact

- €15-20M saved in absenteeism costs
- Root cause drivers of attrition by cohort/ cluster
- Tailored interventions based on individual risk lists

Outlook: Significant further value at stake

■ Life extension
■ Quality of life
■ Cost savings
⬚ Additional



	Levers	**Global Value created,** $B
A **Right Living**	1 Improve treatment efficacy by assessing health risks and adherence through monitoring	600-5500
	2 Improve overall wellness through tailored programs	300-1800
B **Right Care**	3 Deliver the right treatment and optimize the dose	700-2000
	4 Eliminate treatments that are ineffective for that individual	200-300
C **Right Provider**	5 Proactive risk assessment to anticipate complications and reduce hospital care	200-400
	6 Refer patients to the right provider and care setting	TBD
D **Right Value**	7 Personalize the patient experience	200-300
	8 Direct patients to the highest value care and reduce costs through pricing transparency	50-100
E **Right In-novation**[1]	NOT SIZED	0
	TOTAL	1700 400 200 10,000 12,700

Impact

Increase in life expectancy

Global	+ 0.2 – 1.3 years
High Income	+ 0.5 - 2 years
Mid/Low Income	+ 0.1 – 1.1 years

Additional hours per person:

High Income:	+ 0.5 – 1 hour

Worldwide consumer value per person:

High Income	$100 - $300 pp
Mid/Low Income	$20 - $40 pp

Worldwide reduction in National Health Exp.:

Global	5 - 11% of NHE

Healthcare cost savings per person:

United States	> $600 pp
Non-US High Income	> $240 pp

% of Global GDP in 2016: 3 - 13%

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1 Not sized given focus on analytics in healthcare delivery only

2 National Health Expenditures

SOURCE: McKinsey Global Institute analysis

Barriers in healthcare vs. location based services

■ Internal Organizational barriers
□ External barriers to data

● Major barrier
◐ Minor barrier
○ Not a barrier

	Barrier	Location based data	Healthcare
A Analytical talent and organizational change	Leadership within the organization lack a vision for how to use the insights	○	●
	Mindsets within the organization resist change	○	◐
	Organizations need more analytical talent	○	◐
	Companies do not face high competitive pressure (including from data-natives)	○	●
	Insights from analytics have not been embedded into business processes	○	●
B Technology and IT infrastructure	Data is siloed in different parts of the organization within legacy IT systems	○	●
	Infrastructure lacks functionality and flexibility to perform the right analyses	○	●
C Data Access	External datasets lack interoperability	○	●
	Major data owners are disincentivized to share data	○	◐
	Existing data source(s) do not create a profit-making differentiation	○	●
D Data Policies	Privacy concerns and restrictions on data usage	◐	●
	Cybersecurity concerns hamper investment and discourage use	○	◐
	Concerns around liability and proper use of new data and analytical insights	◐	●

SOURCE: McKinsey Global Institute analysis

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1 Why is Artificial Intelligence/Machine Learning different, and why now?

2 Where is the opportunity in patient safety/patient care?

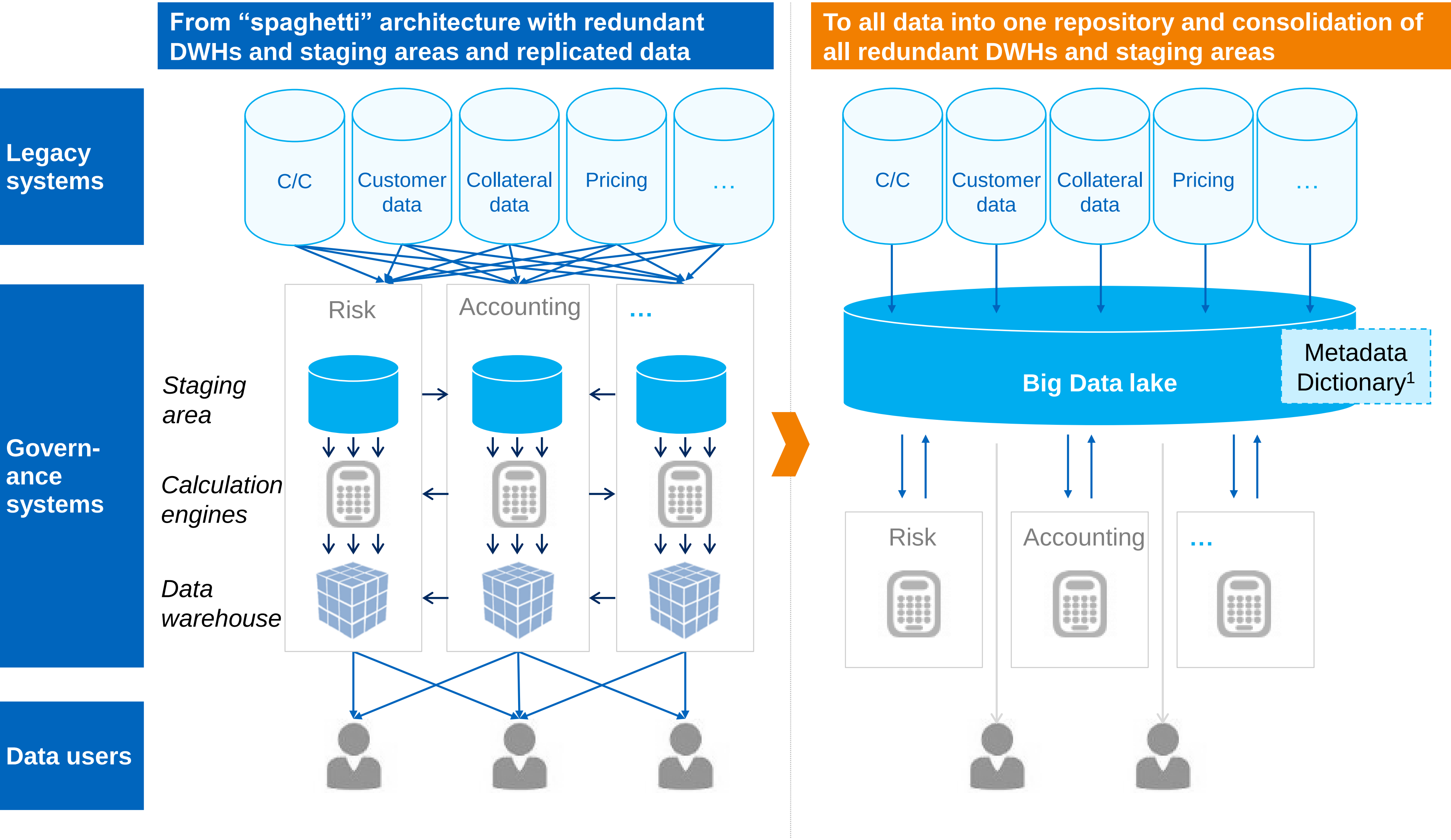
3 **How can we enable change?**

Advanced analytics capabilities and change management are key to a successful AA transformation

■ Key focus areas

	Key questions we hear
1	What is my vision and strategy?
2	How do I identify and prioritise use cases?
3	What kind of data infrastructure do I require?
4	Which skills and capabilities do I need?
5	What are the processes required for data management?
6	What are data quality principles and policies?
7	What organizational model do I need?
8	What are other innovative data technologies?
9	How do I manage the transition effectively?
10	How do I ensure an agile way of working?

3 “Data lake” is an indispensable enabler of the analytics transformation



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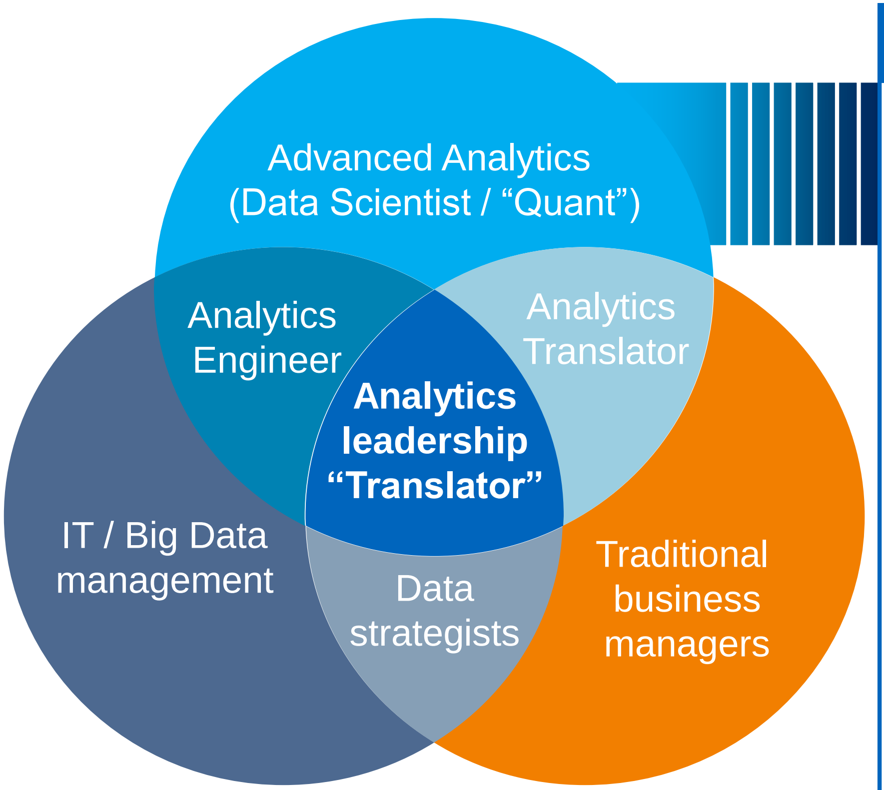
[1] Fundamental instrument to use data in a structured way and derive insights

4 Data analytics teams needs different skills to be successful

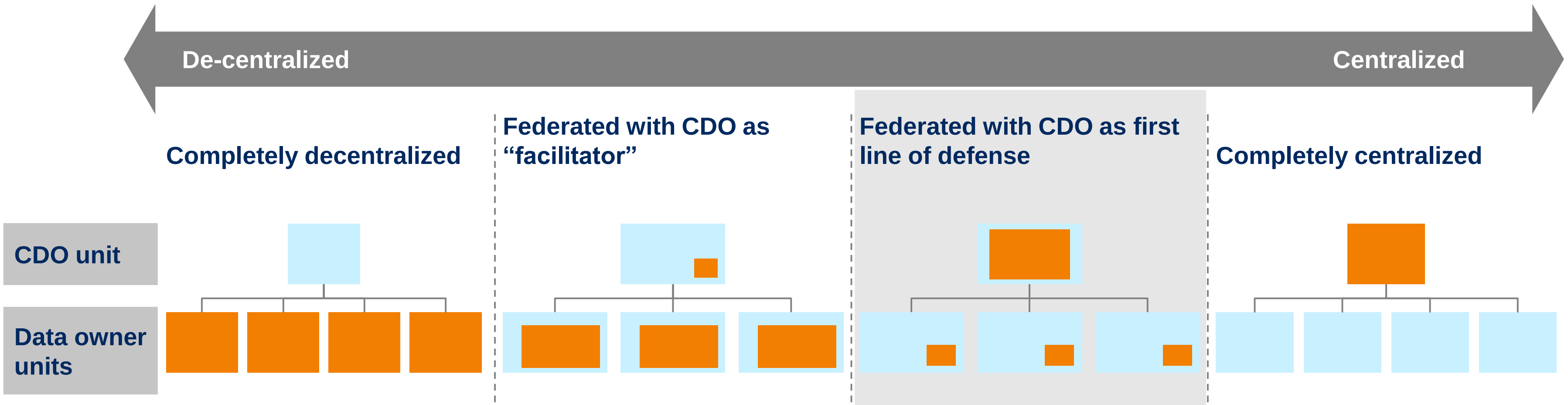


Roles and typical profiles needed

Data Scientist – "Quant"	▪ Background in (Applied) Mathematics, Data Mining, Statistics, Machine Learning, Computer Science, Physics ▪ Builds the mathematical algorithms
Analytics Engineer	▪ Data Scientist background with more focus on Computer Science and programming ▪ Takes Data Scientist's algorithms and makes them more efficient
Analytics Translator	▪ Data Scientist background + additional background and experience in business ▪ Understands business problem and translates into technical language and vice versa

7 Choosing the right organizational archetype is essential for managing data governance

🟦 Organizational unit
🟧 Data organization
⬜ Potentially applicable for SBAB



	Completely decentralized	Federated with CDO as "facilitator"	Federated with CDO as first line of defense	Completely centralized
Description	▪ Business units and functions define data management independently ▪ No overall data strategy ▪ Very limited alignment/ coordination	▪ Small CDO unit serving as facilitator and coordinator ▪ Responsibility for data assets within individual business units ("heavy" data owners units)	▪ CDO with larger team for data operations and responsible for data governance at Bank level ▪ Business units manage service data under strong guidance of CDO ("light" data owners units)	▪ CDO unit as official data owner of all data ▪ All data-related requests managed by enterprise team ▪ Highly prescriptive in definition and control
Evaluation	⊕ Highly agile in data changes and innovation ⊖ Potential inefficiencies in data operations ⊖ Strong danger of data inconsistencies	⊕ Keeps responsibility for data in business ⊕ Prioritizes for enterprise data needs ⊖ Difficult to establish mandate	⊕ Simplifies access to data ⊕ Improves data quality for enterprise data ⊖ Danger of overloading CDO organization	⊖ Difficult to implement in federated organization ⊖ Data change becomes slow in large organization

Advanced analytics capabilities and change management are key to a successful AA transformation

Key questions we hear

1 What is my vision and strategy?

2 How do I identify and prioritise use cases?

3 What kind of data infrastructure do I require?

4 Which skills and capabilities do I need?

5 What are the processes required for data management?

6 What are data quality principles and policies?

7 What organizational model do I need?

8 What are other innovative data technologies?

9 How do I manage the transition effectively?

10 How do I ensure an agile way of working?

Key take away messages

1. Huge progress to predict and prevent risk/faults across industries.
2. AI in healthcare is overhyped by stories about replacing doctors and making decisions, and under used for crucial safety and efficiency interventions
3. The longer term opportunity could be worth 3-13 % of GDP
4. Healthcare is a laggard in adoption, as opposed, for example to geolocation sector.
5. Most common mistakes/barriers include: lack of enabling data integration / interoperability, lack of investment into skills eg translators, and ineffective organizational set up
6. Ministers of Health and medical profession have an important role to create the regulatory context and conditions for the barriers to be overcome