

Leading the Future of Health Care Industry with Advanced Analytics, Artificial Intelligence, and Machine Learning

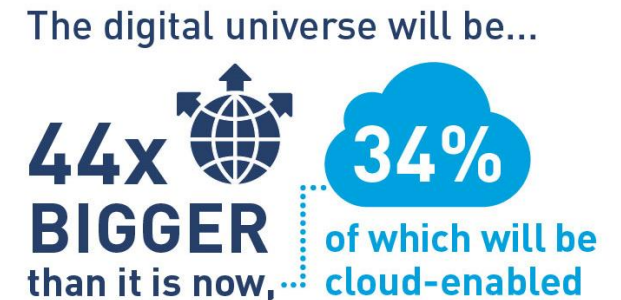
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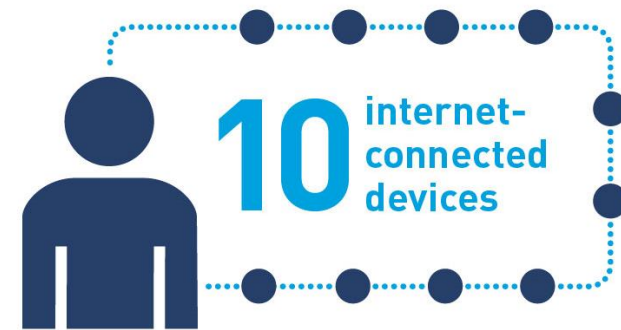
In next 5 years ...



A conventional smartphone will have the processing power of a...



A middle class person will have...



Almost every...

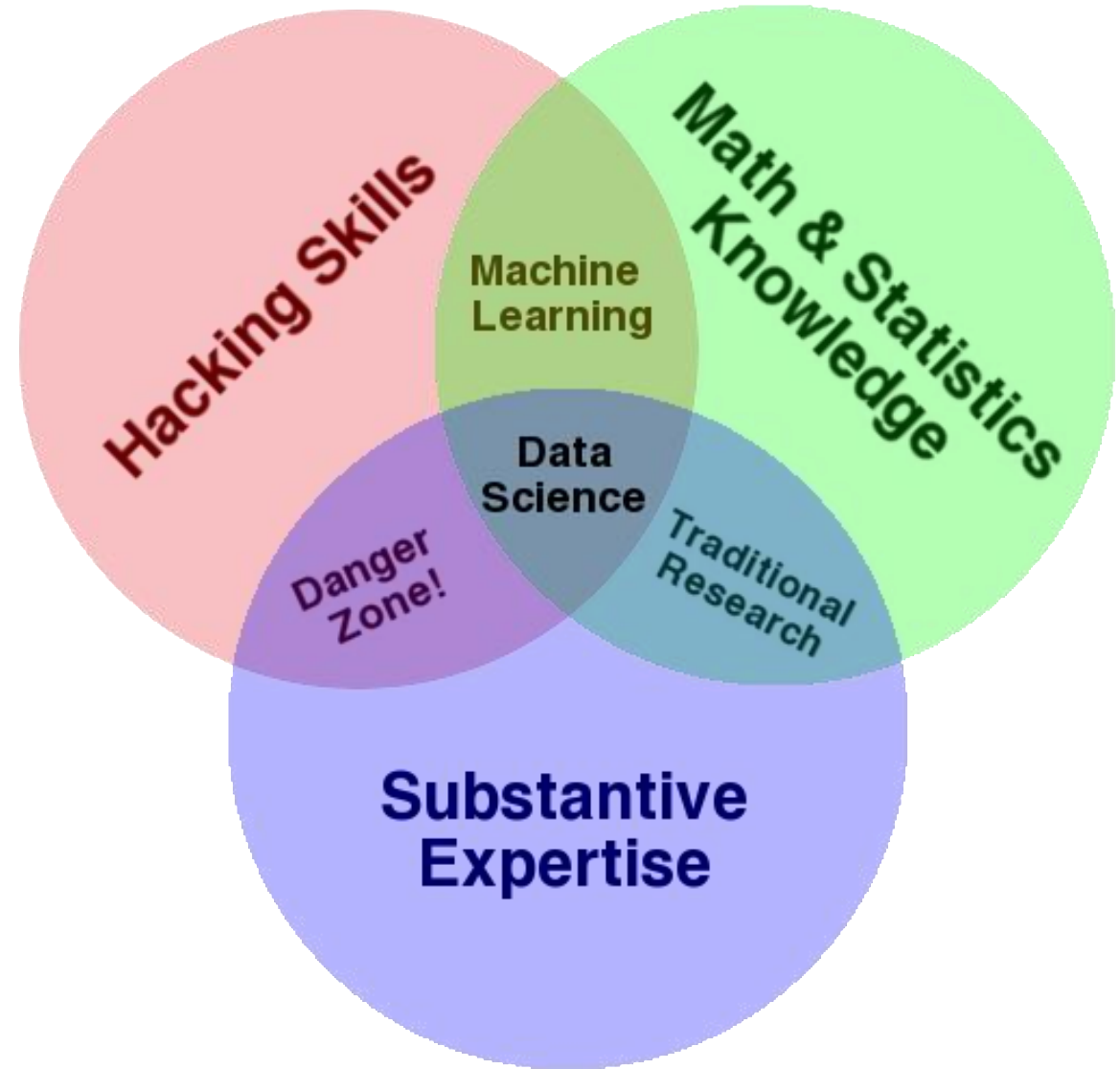


Trends, Challenges and Opportunities

- Technology revolution
- Alternative data sources and volume of the data
- Need for automation
- Beyond pills – digital health and connected care
- Slow adoptions with bottom up innovation vs fast pace environment
- Data access and data quality
- Talent recruiting and development

Potential Data Analytics Pitfalls

- Causality vs association
- Bias and confounding
- Missing data and missing mechanism
- Overfitting
- Multiplicity
- Convergence
- Efficiency – Design and Analytics
- Variance and bias trade off
- ...



Different Data Types



Output (outcomes)

Continuous

Binary

Time to event/recurrent events

Longitudinal data

...



Input (covariates)

Continuous

Categorical

Networks

Trees

Unstructured

A Journey at Eli Lilly and Company



Global Statistics



Advanced Analytics



Enterprise AADS – Advanced
Analytics and Data Sciences

Digital Health



Contextual Information (Input)



Action (Deep Learning/AI/Statistical Analytics)

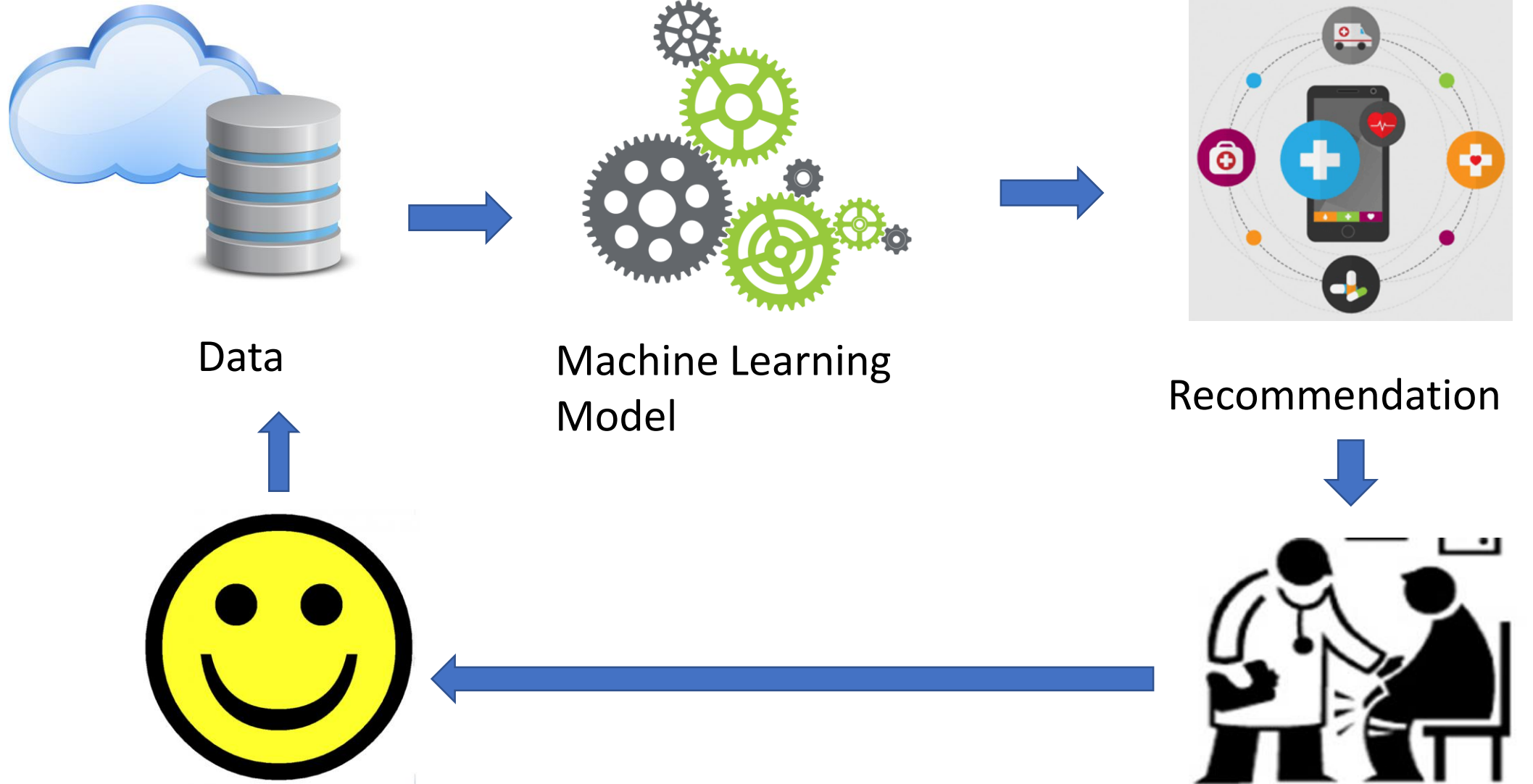


Outcome

Digital Health Analytics

- Digital Technology: Enables collection of detailed individual information
- Deep learning: Enables generation of *actionable insights*
- Analytics: Work hand-in-hand with technology to identify “replicable” actions to optimize patient outcomes.

Example in Diabetes: **What treatment assignment regimen** would lead to the best outcome on average?



Individualized Treatment Recommendation (ITR^{1,2})

ITR^{1,2} is a value function machine-learning algorithm that utilizes **RCT** and **RWD** to determine optimal treatment selection at the patient level to optimize an outcome

ID	Outcome	Action	Covariates			
	Δ HbA1c	Treatment	Age	Baseline HbA1c	Sex	...
1	-1.5	1	34	8.3	F	...
2	-1.2	2	25	9.2	F	...
3	-2.3	3	29	9.1	M	...
4	-0.9	2	55	7.8	F	...
5	-1.4	3	47	8.7	M	...
⋮	⋮	⋮	⋮	⋮	⋮	⋮

RCT, randomized controlled trials; RWD, real-world data

1. Fu, Haoda, Jin Zhou, and Douglas E. Faries. "Estimating optimal treatment regimes via subgroup identification in randomized control trials and observational studies." *Statistics in medicine* 35.19 (2016): 3285-3302.
2. Wang, Yuanjia, Haoda Fu, and Donglin Zeng. "Learning Optimal Personalized Treatment Rules in Consideration of Benefit and Risk: with an Application to Treating Type 2 Diabetes Patients with Insulin Therapies." *Journal of the American Statistical Association* 113.521 (2018): 1-13.

Single Optimization Framework

Lilly Value Function

Define,

$$E^{\mathcal{D}}(Y) = \int Y d\mathcal{P}^{\mathcal{D}} = \int Y \frac{d\mathcal{P}^{\mathcal{D}}}{d\mathcal{P}} d\mathcal{P} = E \left[\frac{Y}{I\{a = \mathcal{D}(x)\}} \right]$$

where we use the fact that,

$$\frac{d\mathcal{P}^{\mathcal{D}}}{d\mathcal{P}} = \frac{p(y|x, a) I\{a = \mathcal{D}(x)\} p(x)}{p(y|x, a) p(a|x) p(x)}$$

Our objective is to find $\mathcal{D}(\cdot)$ to maximize the

Value function

$$D_o \in \operatorname{argmax}_{D \in R} E^{\mathcal{D}}(Y) = E \left[\frac{Y}{I\{a = \mathcal{D}(x)\}} \right]$$

where R is a space of possible treatment recommendations.

Lilly ITR.ABC

Original objective function,

$$D_o = \operatorname{argmin}_{D \in R} n^{-1} \sum_{i=1}^n \frac{Y_i}{p(A_i|X_i)} I\{A_i \neq \mathcal{D}(X_i)\}.$$

ITR.ABC objective function,

$$\operatorname{minimize}_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n \frac{Y_i}{\Pr(A_i|X_i)} \ell\{f(x_i), W_{a_i}\} + \lambda J(f).$$

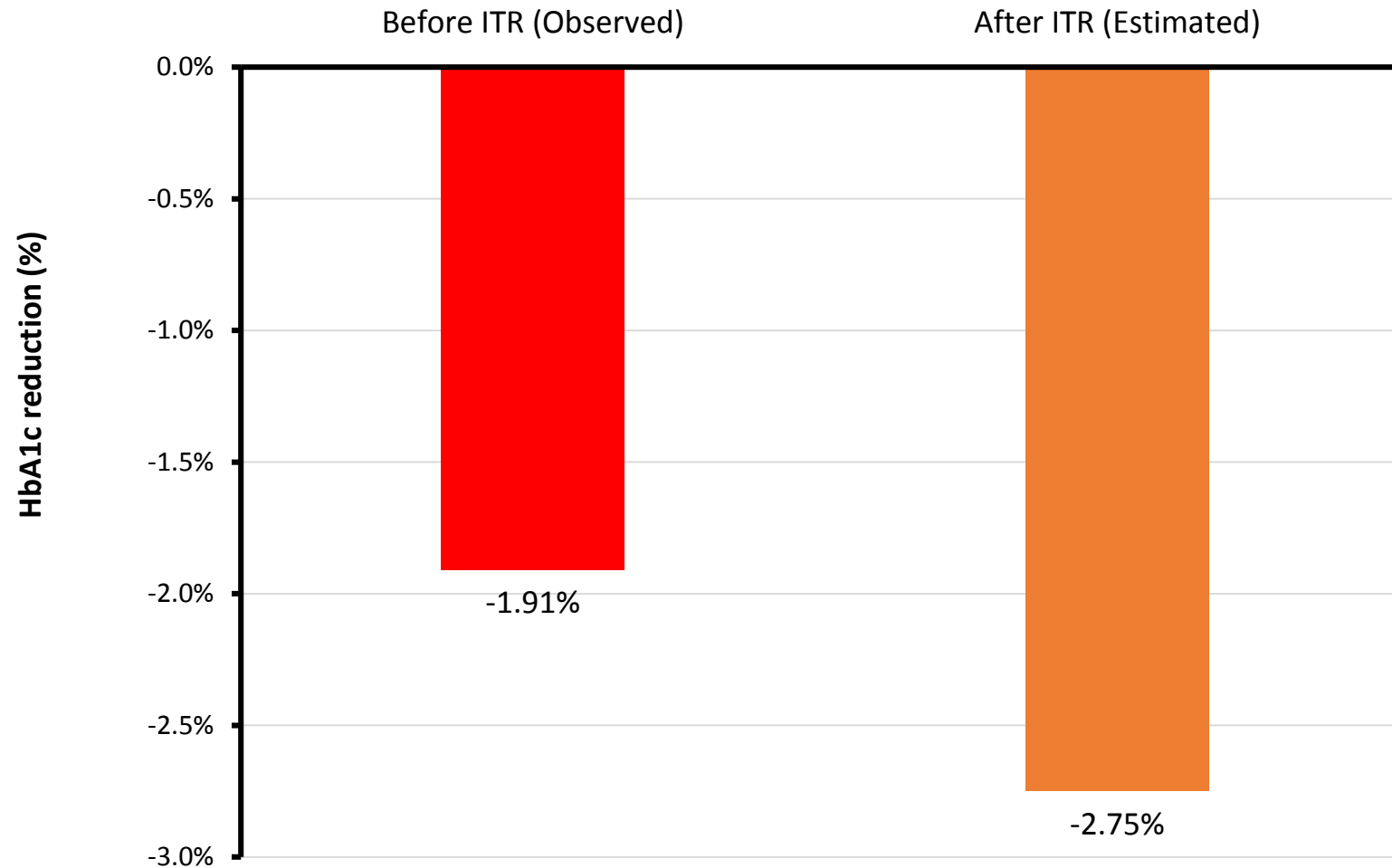
Theorem (Fisher consistency for ITR.ABC)

A classifier $f^*(\cdot)$ is called Fisher's consistency if it satisfies that, $\forall x$,

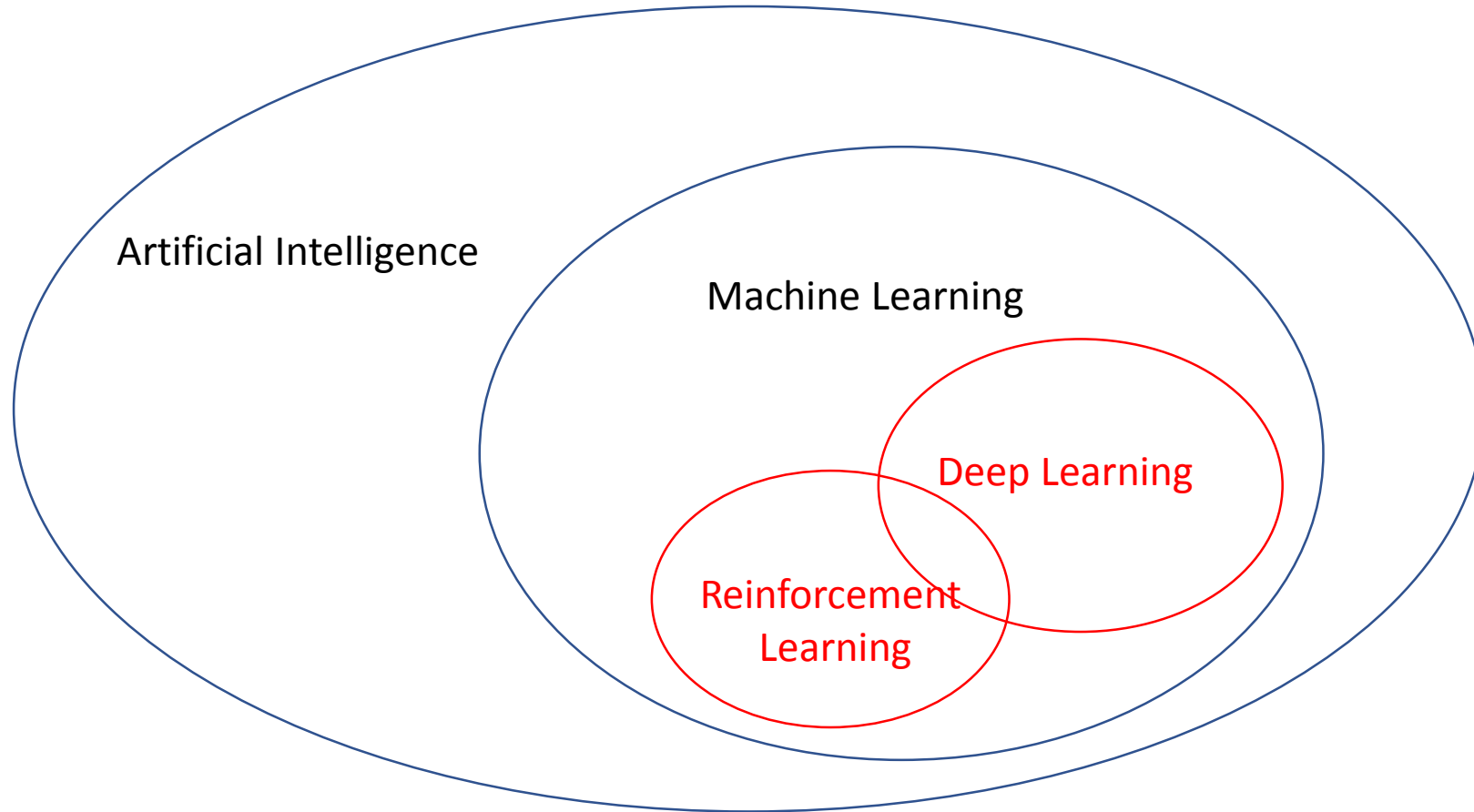
$$\operatorname{argmax}_{\forall j} \langle f^*(x), W_j \rangle = \operatorname{argmax}_{\forall j} E(Y|A=j, x)$$

ITR.ABC is Fisher consistency if ℓ is a convex, the derivative ℓ' exists and $\ell'(x) < 0, \forall x$.

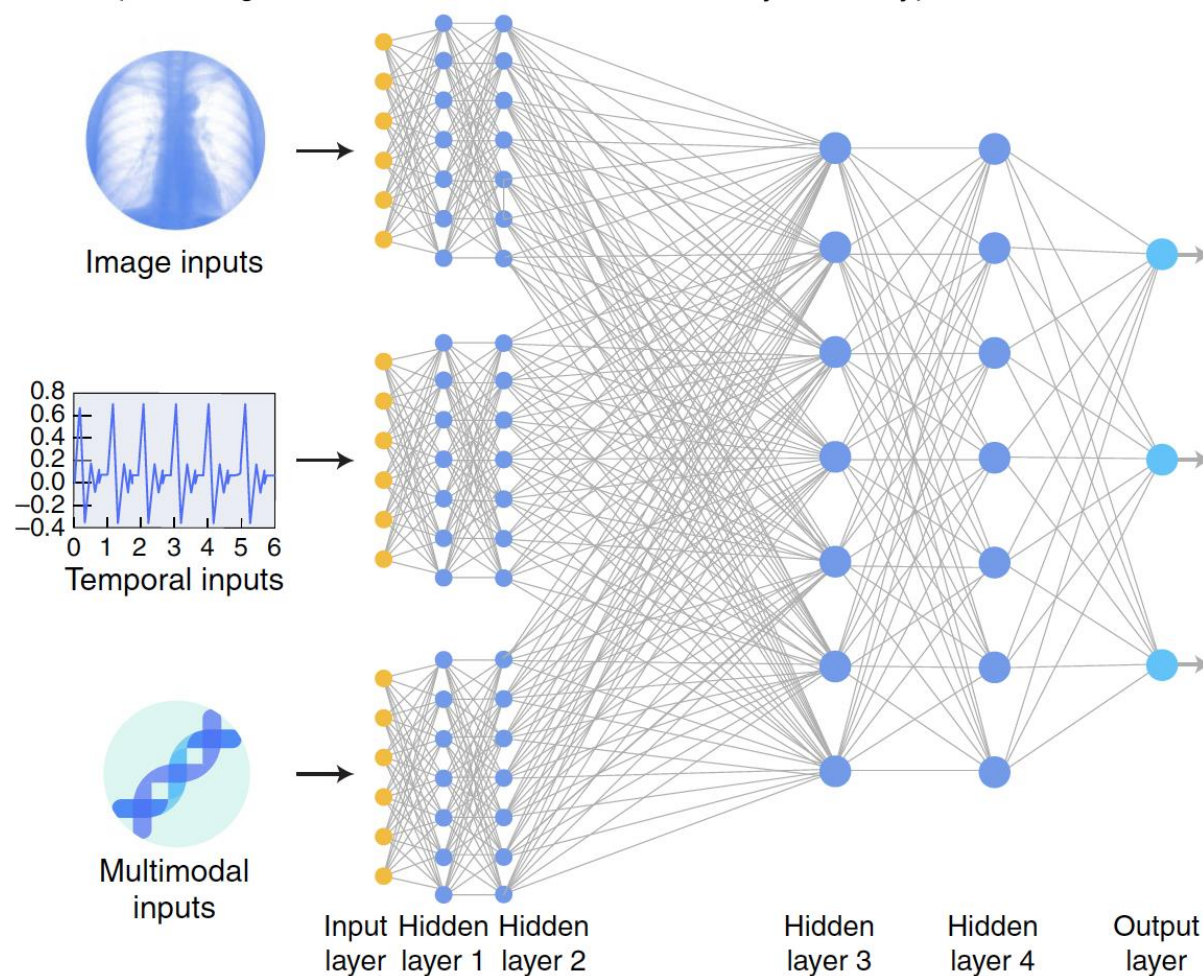
HbA1c reduction before and after ITR



AI – Machine Learning – DL & RL



What's new: using multiple data sources



Medical Image Diagnostic - Diabetes

Research

JAMA | **Original Investigation** | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD; Martin C. Stumpe, PhD; Derek Wu, BS; Arunachalam Narayanaswamy, PhD; Subhashini Venugopalan, MS; Kasumi Widner, MS; Tom Madams, MEng; Jorge Cuadros, OD, PhD; Ramasamy Kim, OD, DNB; Rajiv Raman, MS, DNB; Philip C. Nelson, BS; Jessica L. Mega, MD, MPH; Dale R. Webster, PhD

IMPORTANCE Deep learning is a family of computational methods that allow an algorithm to program itself by learning from a large set of examples that demonstrate the desired behavior, removing the need to specify rules explicitly. Application of these methods to medical imaging requires further assessment and validation.

 [Editorial pages 2366 and 2368](#)

 [Supplemental content](#)





Medical Image Diagnostic - Oncology

MENU ▾


nature
International journal of science

Letter | Published: 25 January 2017

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva , Brett Kuprel , Roberto A. Novoa , Justin Ko, Susan M. Swetter, Helen M. Blau & Sebastian Thrun 

Nature **542**, 115–118 (02 February 2017) | [Download Citation](#) ↓

 A Corrigendum to this article was published on 28 June 2017

Predict CV risk

nature
biomedical engineering

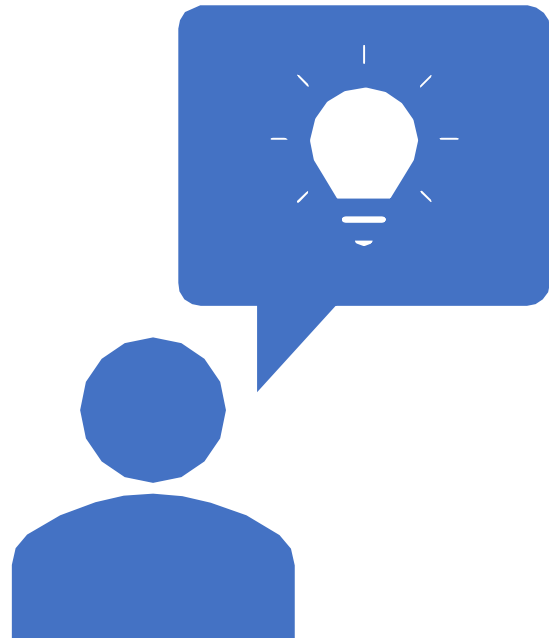
ARTICLES

<https://doi.org/10.1038/s41551-018-0195-0>

Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning

Ryan Poplin^{1,4}, Avinash V. Varadarajan^{1,4}, Katy Blumer¹, Yun Liu¹, Michael V. McConnell^{2,3},
Greg S. Corrado¹, Lily Peng^{1,4*} and Dale R. Webster^{1,4}

Summary



- New technology is here and exploding
- Data explosion in health care is a dream come true for Statisticians (of course dream also means there will be nightmares!!!)
- Statisticians have a phenomenal opportunity to collaborate and lead the science forward