Staying Ahead of the Hype Cycle:

Medicine in the Era of Big Data

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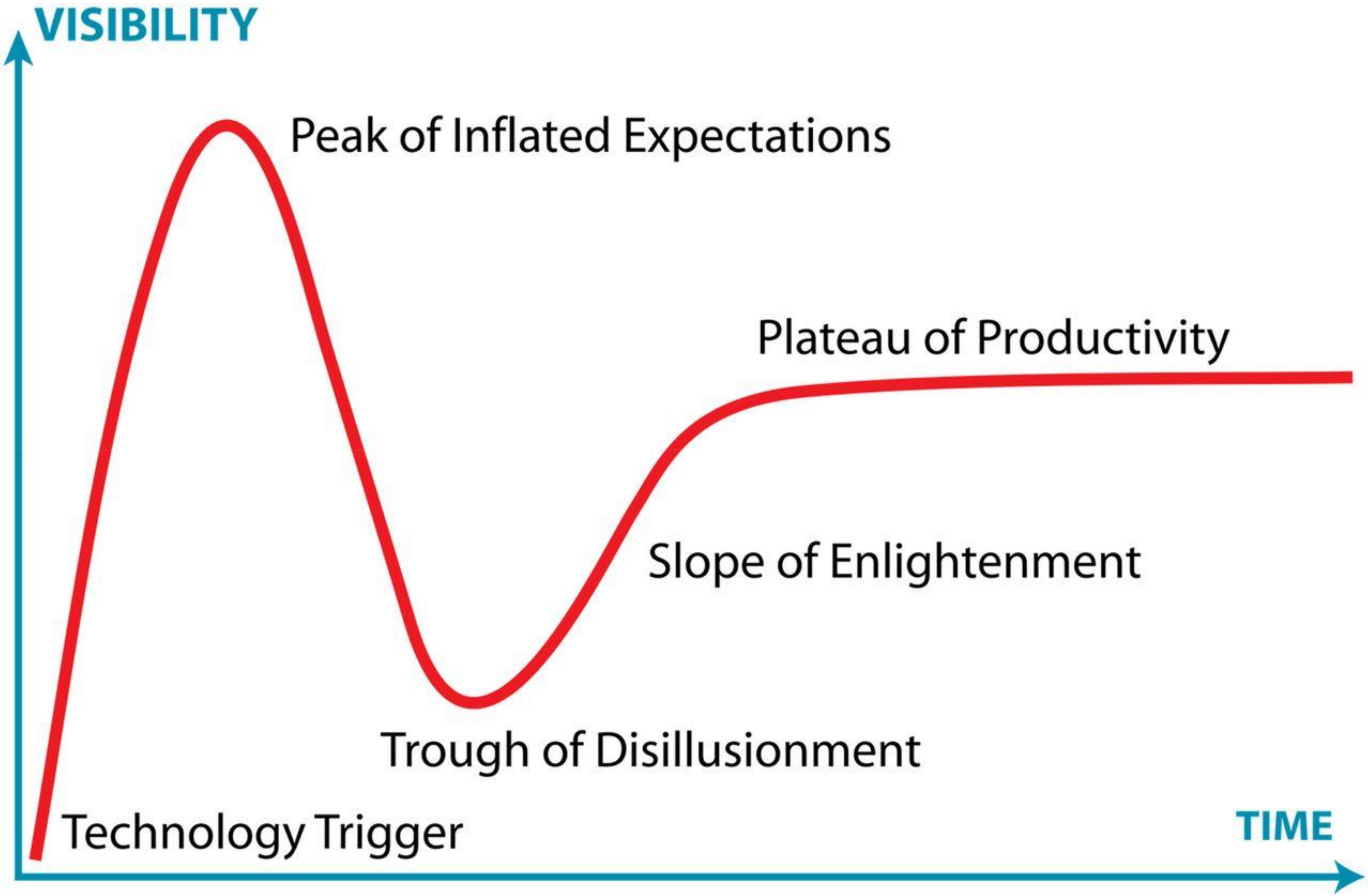
“An intellect which at a certain moment would know all forces that set nature in motion, and all positions of all items…were also vast enough to submit these data to analysis…nothing would be uncertain and the future just like the past would be present before its eyes”

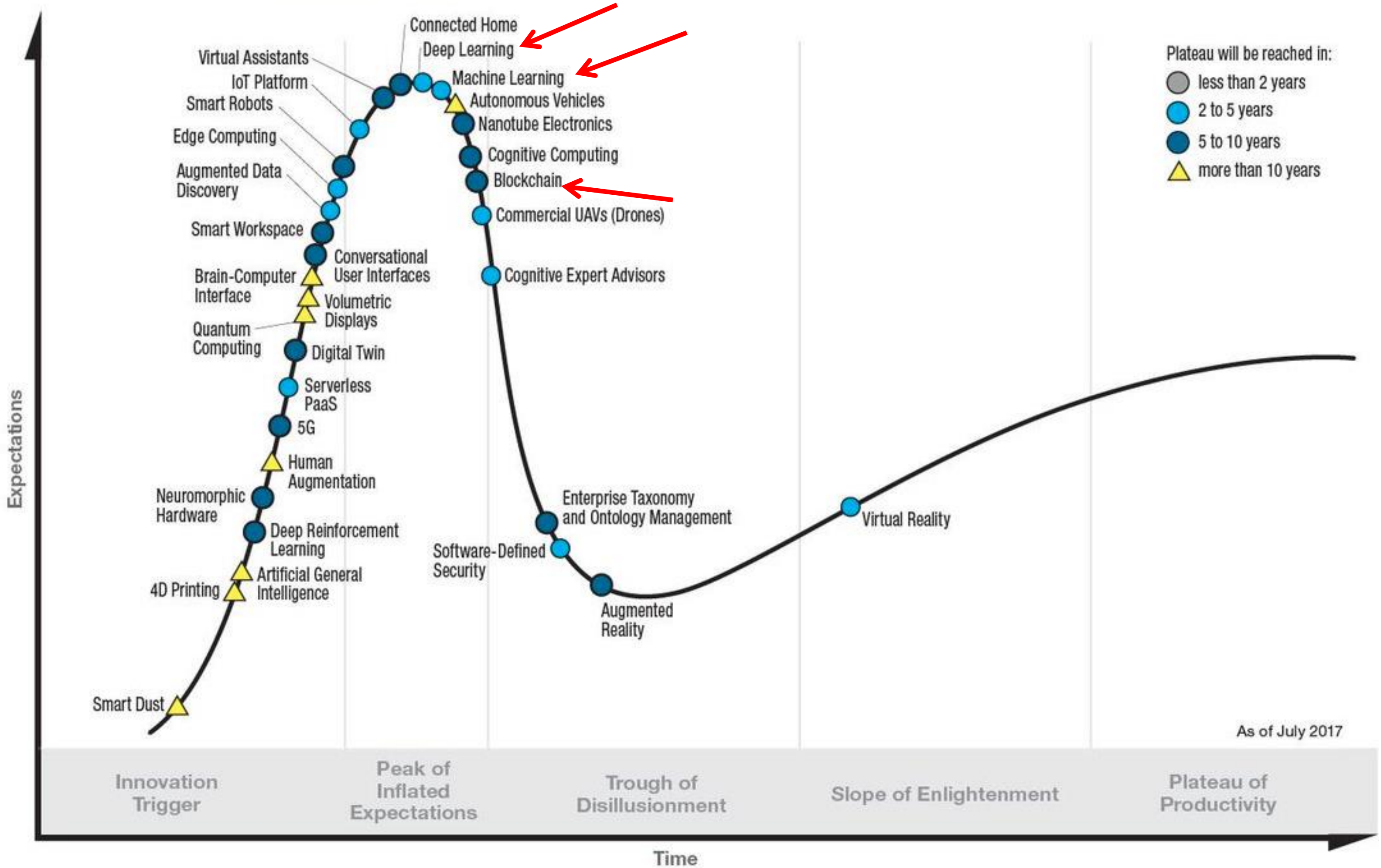
"An intellect which at a certain moment would know all forces that set nature in motion, and all positions of all items…were also vast enough to submit these data to analysis…nothing would be uncertain and the future just like the past would be present before its eyes"

DATA + COMPUTATION = PREDICTION

The Hype Cycle



The Hype Cycle



A Problem

Table 1.4. Nu

Centre

England
B Heart
B QEH
Basldn
Bradfd
Brightn
Bristol
Camb[c]
Carlis
Carsh
Chelms
Colchr
Covnt
Derby
Donc
Dorset
Dudley
Exeter
Glouc
Hull
Ipswi
Kent
L Barts
L Guys
L Kings
L Rfree
L St.G
L West

UK area	CCG/HB	population (2016)	2011 O/E	2012 O/E	2013 O/E	2014 O/E	2015 O/E	O/E	rate pmp	O/E	LCL	UCL	rate pmp[a]	non-White
London	**NHS Barking & Dagenham**	**206,500**	**1.65**	**2.03**	**1.60**	**1.94**	**1.91**	**1.69**	**140**	**1.80**	**1.56**	**2.09**	**141**	**41.7**
	NHS Barnet	**386,100**	**1.41**	**1.46**	**1.23**	**1.29**	**1.41**	**1.27**	**130**	**1.34**	**1.20**	**1.50**	**129**	**35.9**
	NHS Camden	246,200	1.11	1.06	1.32	1.16	1.28	0.99	93	1.15	0.98	1.35	103	33.7
	NHS City and Hackney	**282,900**	**1.68**	**2.02**	**1.83**	**2.11**	**1.13**	**1.84**	**148**	**1.76**	**1.55**	**2.01**	**134**	**44.6**
	NHS Enfield	**331,400**	**1.98**	**1.59**	**1.58**	**1.53**	**1.55**	**1.59**	**157**	**1.63**	**1.46**	**1.83**	**151**	**39.0**
	NHS Haringey	**278,500**	**1.69**	**2.27**	**2.21**	**1.64**	**1.56**	**1.94**	**172**	**1.88**	**1.66**	**2.12**	**157**	**39.5**
	NHS Havering	252,800	1.20	1.04	0.83	0.92	1.08	0.78	91	0.97	0.83	1.13	106	12.3
	NHS Islington	**232,900**	**1.53**	**2.05**	**1.44**	**1.11**	**1.60**	**1.06**	**90**	**1.46**	**1.25**	**1.70**	**117**	**31.8**
	NHS Newham	**341,000**	**2.12**	**1.86**	**2.14**	**2.24**	**2.31**	**2.44**	**191**	**2.19**	**1.97**	**2.44**	**161**	**71.0**
	NHS Redbridge	**299,200**	**1.38**	**2.15**	**1.98**	**1.45**	**1.45**	**1.73**	**167**	**1.68**	**1.50**	**1.90**	**153**	**57.5**
	NHS Tower Hamlets	**304,900**	**1.61**	**1.82**	**2.02**	**2.26**	**2.33**	**1.84**	**134**	**1.99**	**1.76**	**2.25**	**137**	**54.8**
	NHS Waltham Forest	**275,800**	**1.81**	**1.26**	**1.62**	**2.08**	**1.70**	**1.51**	**138**	**1.66**	**1.47**	**1.89**	**143**	**47.8**
	NHS Brent	**328,300**	**2.08**	**2.43**	**1.95**	**2.51**	**2.23**	**2.02**	**195**	**2.20**	**1.99**	**2.43**	**200**	**63.7**
	NHS Central London (Westminster)	178,400	1.29	1.17	1.37	1.08	0.97	1.09	112	1.16	0.97	1.38	112	36.2
	NHS Ealing	**343,200**	**1.91**	**2.26**	**1.68**	**1.78**	**2.25**	**1.77**	**175**	**1.94**	**1.76**	**2.15**	**181**	**51.0**
	NHS Hammersmith and Fulham	**179,700**	**1.43**	**1.49**	**0.99**	**1.44**	**1.13**	**1.80**	**167**	**1.38**	**1.16**	**1.64**	**121**	**31.9**
	NHS Harrow	**248,800**	**2.23**	**1.59**	**1.06**	**1.54**	**1.43**	**1.70**	**185**	**1.59**	**1.40**	**1.80**	**162**	**57.8**
	NHS Hillingdon	**302,500**	**1.46**	**1.50**	**1.42**	**1.00**	**1.08**	**1.16**	**116**	**1.26**	**1.10**	**1.44**	**118**	**39.4**
	NHS Hounslow	**271,100**	**1.83**	**1.73**	**2.02**	**1.28**	**1.29**	**1.65**	**159**	**1.62**	**1.43**	**1.84**	**147**	**48.6**
	NHS West London (Kensington and Chelsea, Queen's Park and Paddington)	226,000	1.20	0.91	0.98	1.50	0.67	1.23	128	1.08	0.92	1.27	106	33.4
	NHS Bexley	**244,800**	**1.17**	**0.87**	**1.01**	**1.11**	**1.24**	**1.65**	**184**	**1.19**	**1.03**	**1.37**	**124**	**18.1**
	NHS Bromley	326,900	0.69	0.72	0.85	0.99	1.50	0.82	95	0.94	0.82	1.08	102	15.7
	NHS Croydon	**382,300**	**1.26**	**2.00**	**1.95**	**1.79**	**1.93**	**1.64**	**167**	**1.76**	**1.60**	**1.95**	**169**	**44.9**
	NHS Greenwich	**279,800**	**1.03**	**1.15**	**2.38**	**1.23**	**1.68**	**1.62**	**147**	**1.52**	**1.33**	**1.74**	**130**	**37.5**
	NHS Kingston	176,100	0.96	1.08	1.11	1.11	0.78	0.96	97	1.00	0.82	1.21	95	25.5
	NHS Lambeth	**327,900**	**1.76**	**1.68**	**1.39**	**1.87**	**1.95**	**1.38**	**116**	**1.67**	**1.48**	**1.89**	**132**	**42.9**
	NHS Lewisham	**301,900**	**1.78**	**1.85**	**1.47**	**1.52**	**1.48**	**1.31**	**116**	**1.56**	**1.37**	**1.77**	**130**	**46.5**
	NHS Merton	**205,000**	**1.57**	**1.78**	**1.30**	**1.44**	**1.61**	**1.73**	**171**	**1.57**	**1.36**	**1.82**	**146**	**35.1**
	NHS Richmond	*195,800*	*0.69*	*0.79*	*0.98*	*0.78*	*0.60*	*0.65*	*71*	*0.74*	*0.61*	*0.92*	*77*	*14.0*

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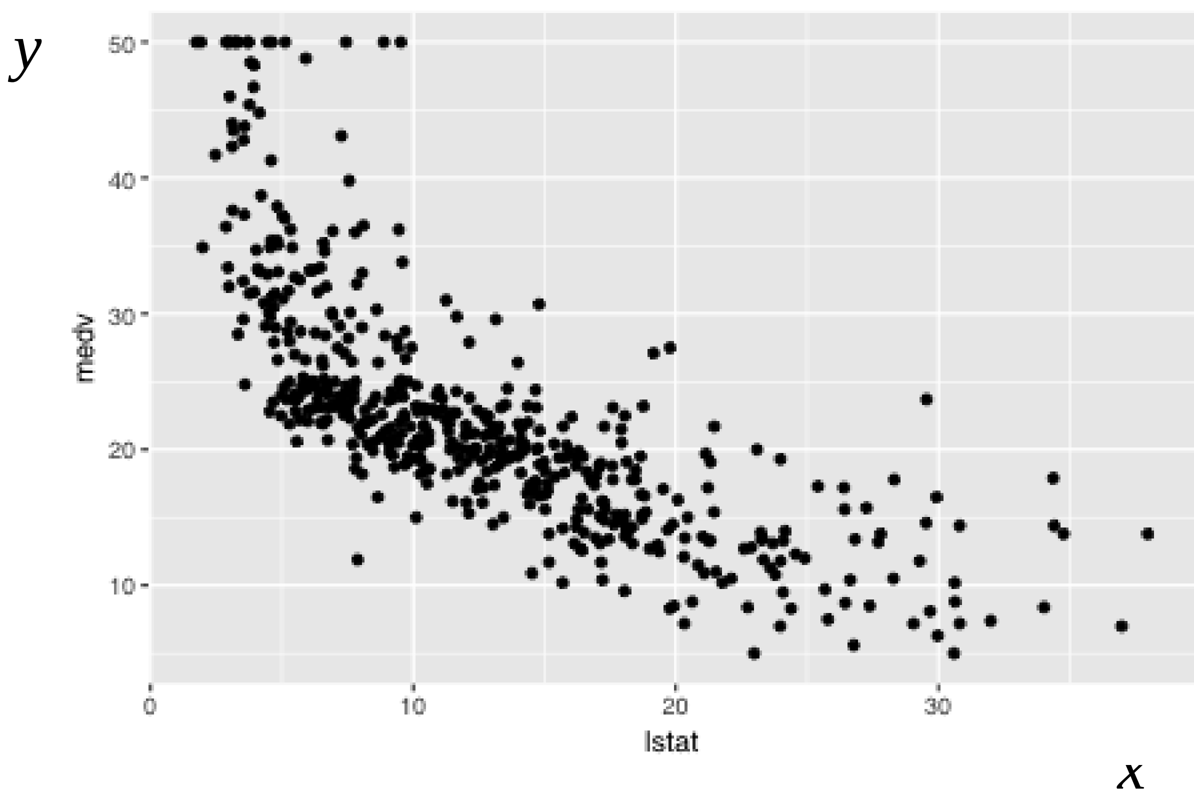
Caution

Images of statistical concepts and light mathematics approaching

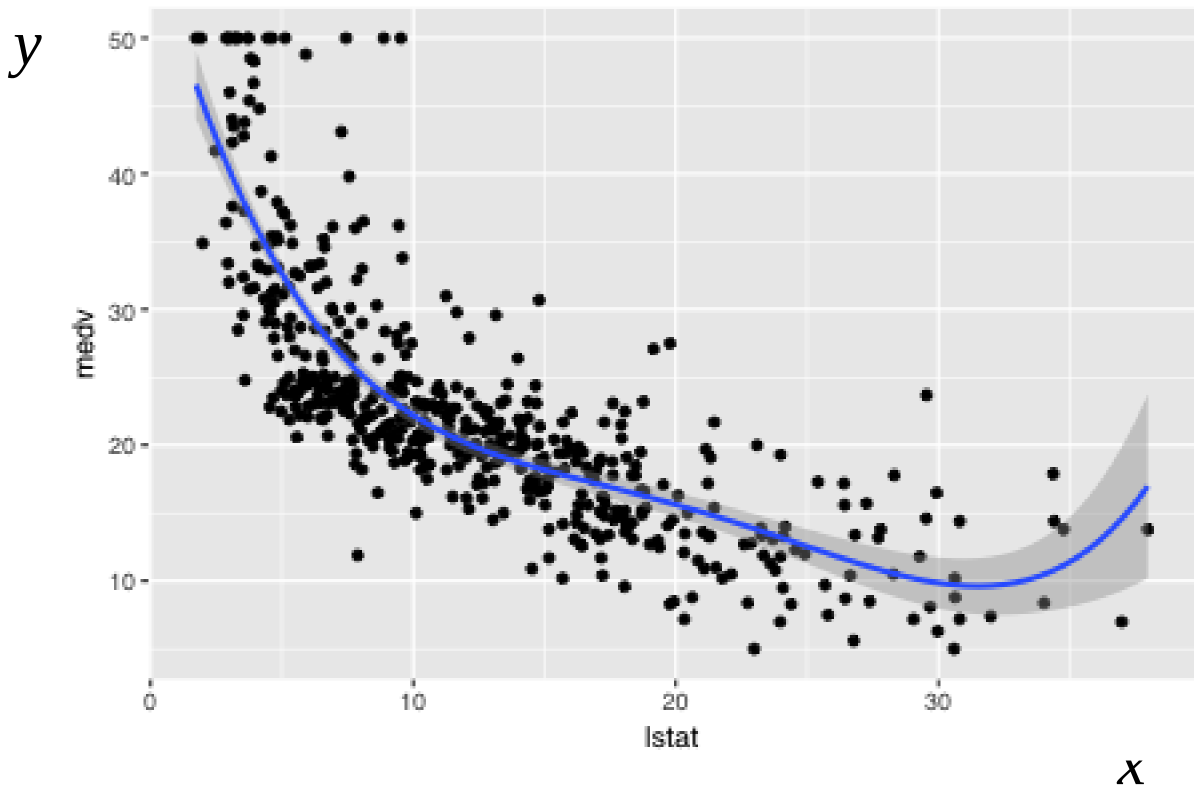
Viewers of a sensitive disposition are advised to proceed with caution

Using Data to Predict



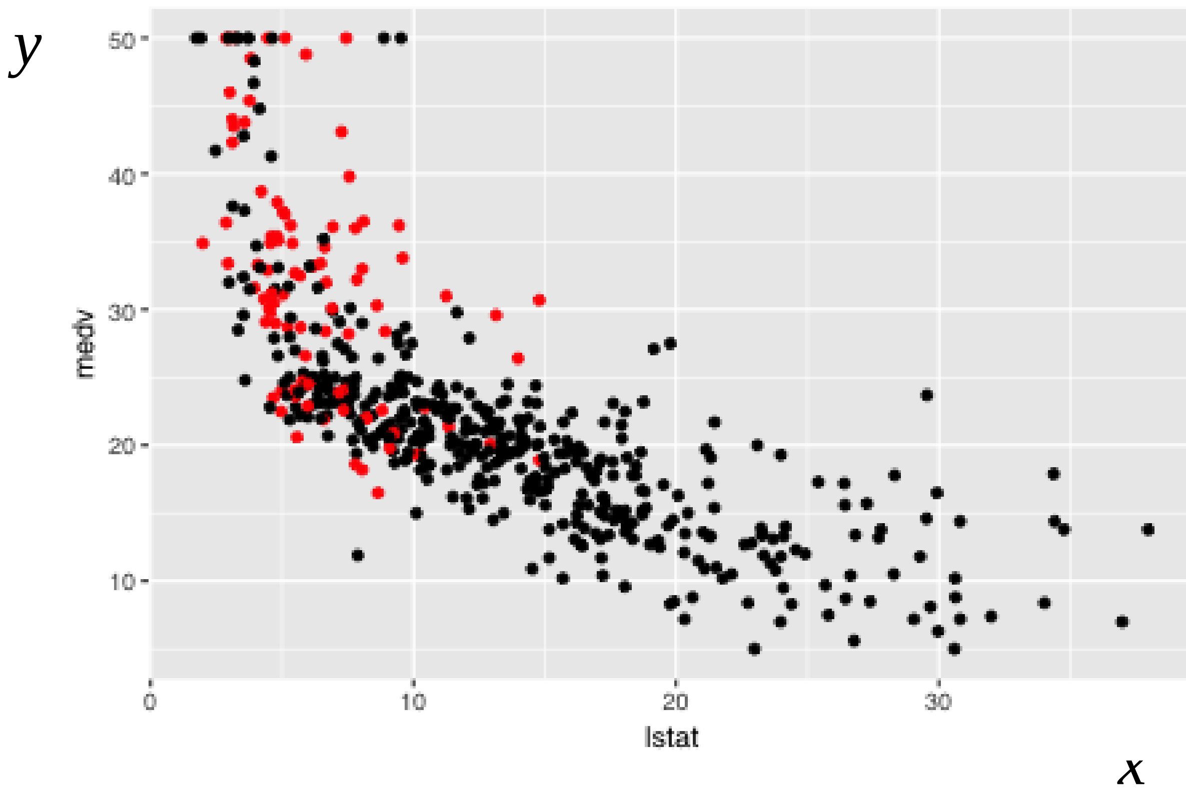
Using Data to Predict

$$y = f(x) + \varepsilon$$



Using Data to Classify

Machine Learning deals in overall prediction



Technology that allows computers to perform specific tasks by learning from data & not following pre-programmed rules

Clinical Medicine isn't Classification

Medical decisions are:

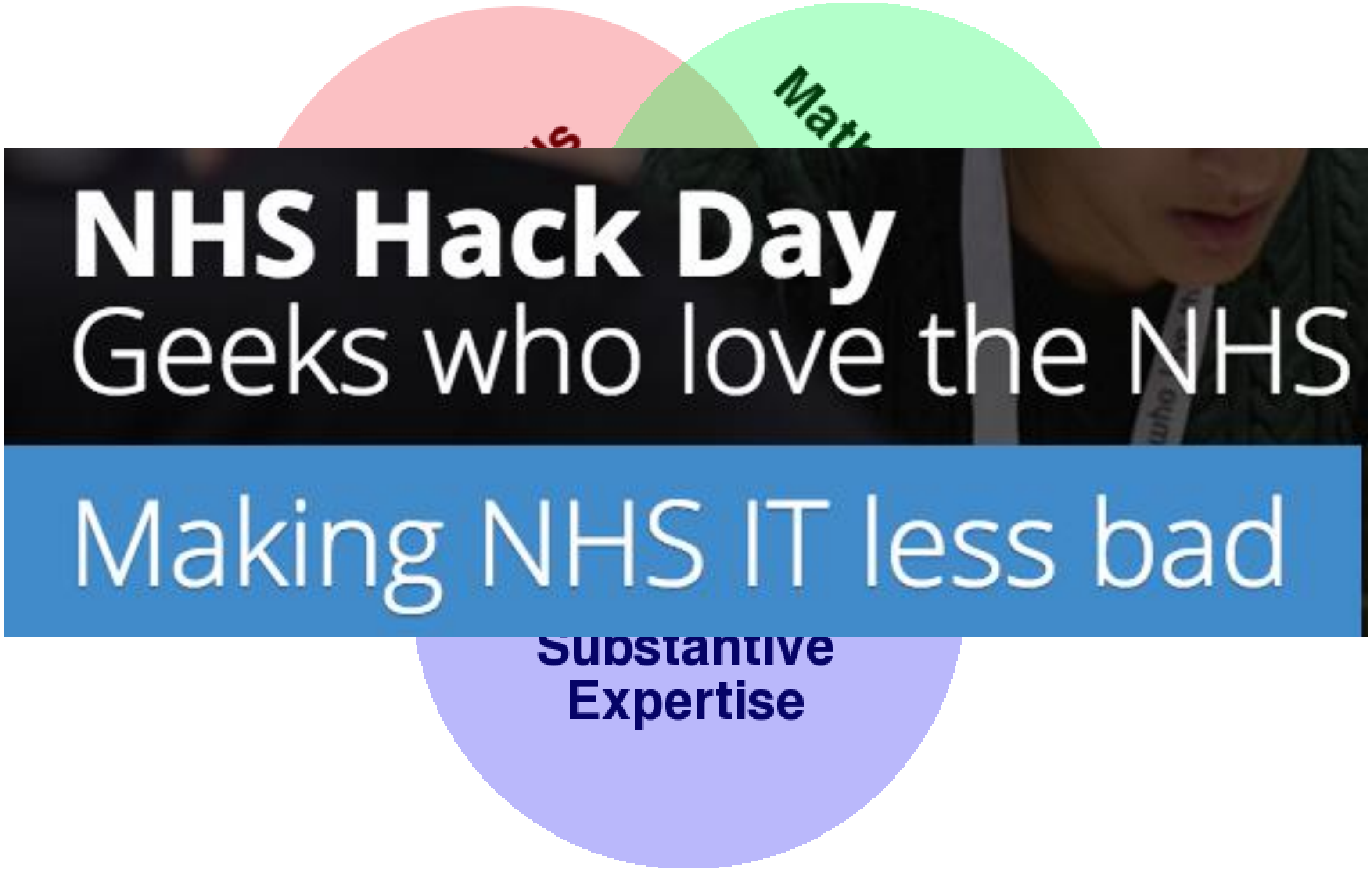
- not classification problems
- made at the point of care
- subject to change

Medical data has:

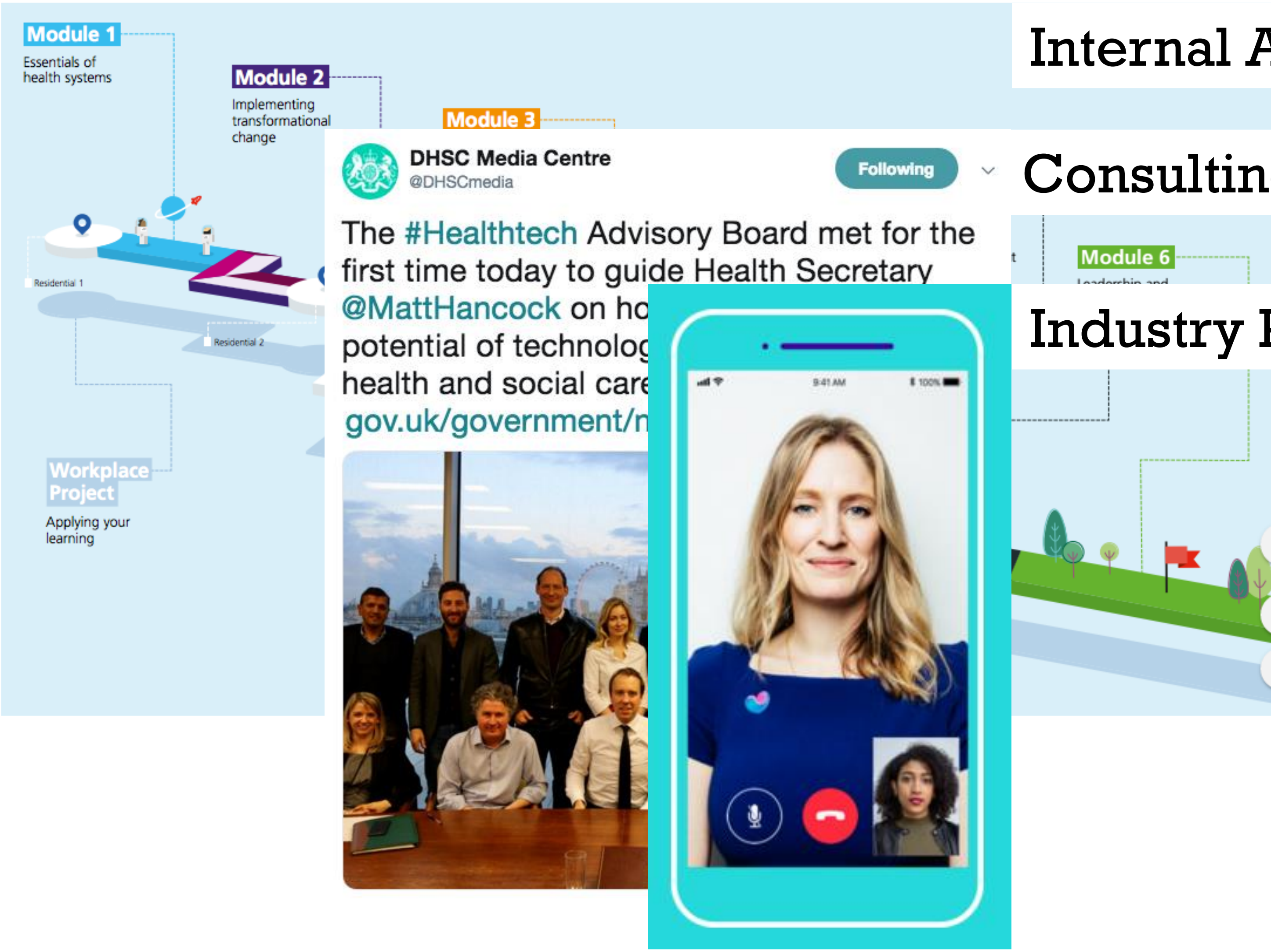
- Biological variation
- Sampling Variability
- Measurement Errors
- Different Treatments

Specialty	Images	Publication
Radiology/Neurology	CT head, acute neuro events	Titano, Nature Medicine, 2018
	CT head for brain hemorrhage	Arbabshirani, NPJ (Nature) Digital Medicine, 2018
Pathology	Breast cancer	Bejnordi, JAMA, 2017
	Brain tumors (+ methylation)	Capper, Nature, 2018
Dermatology	Skin cancers	Esteva, Nature, 2017
	Melanoma	Haenssle, Annals of Oncology, 2018
	Skin lesions	Han, Journal of Investigative Dermatology
Ophthalmology	Diabetic retinopathy	Gulshan, JAMA, 2016
	Diabetic retinopathy	Abramoff, NPJ (Nature) Digital Medicine, 2018
	Congenital cataracts	Long, Nature Biomedical Engineering, 2017
	Retinal diseases (OCT)	De Fauw, Nature Medicine, 2018
	Macular degeneration	Burlina, JAMA Ophthalmology, 2018
	Retinopathy of Prematurity	Brown, JAMA Ophthalmology, 2018
	AMD and diabetic retinopathy	Kermany, Cell, 2018
Gastroenterology	Polyps at colonoscopy	Mori et al, Annals Internal Medicine, 2018
Cardiology	Echocardiography	Madani, NPJ (Nature) Digital Medicine, 2018

So What Should the NHS do?



What is the NHS doing?

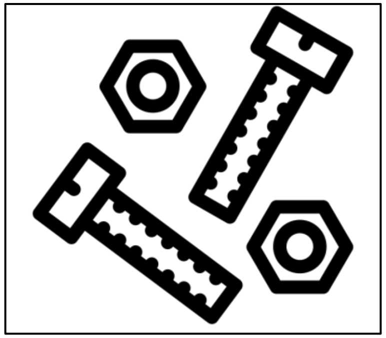


Internal Appointments

Consulting Expertise

Industry Partners

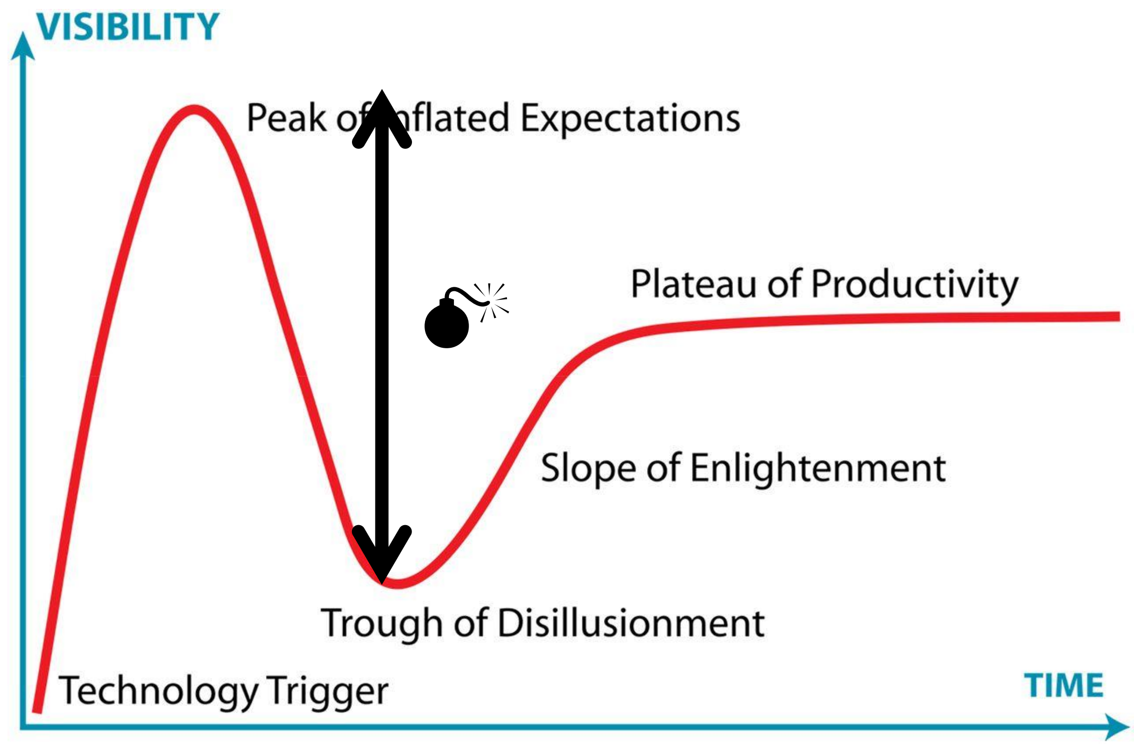
Is This Going to Work?



Technological Innovation Requires Practical Ability

Is This Going to Work?

Scope
Revenue
Maturity
Funding



Layoffs at Watson Health Reveal IBM's Problem With AI

Summary

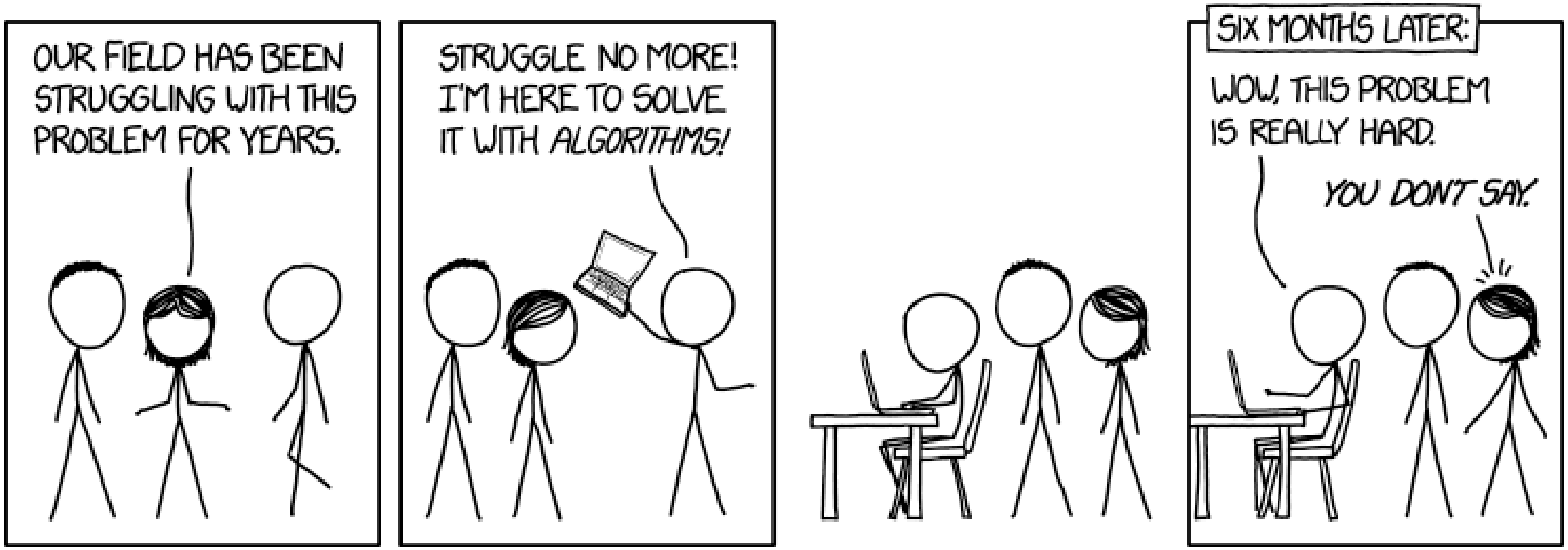
"A medical device with a plausible sales pitch is a very hard thing to counter with mere evidence" Richard Lehman June 2018

Many technological advances in healthcare are yet to achieve maturity

AI/ML approaches probably will change how we do highly replicable things

Big data usage in healthcare requires statistical rigour

Watch The Social Network



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