IBM Watson Health

Personalized, Evidence-based, Outcome-driven Healthcare Empowered by IBM Cognitive Computing Technologies

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IBM Research - China

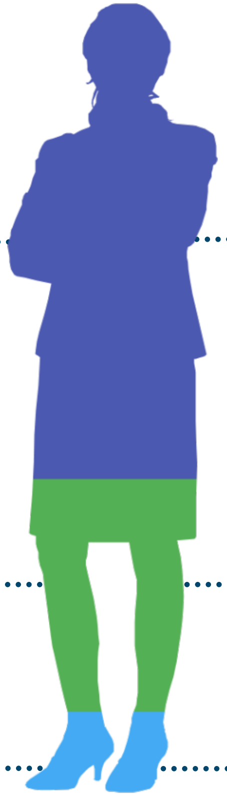
IBM

Explosion of Healthcare Data

Exogenous data
1,100 Terabytes
Generated per lifetime

Genomics data
6 TB
Per lifetime

Clinical data
0.4 TB
Per lifetime



Influence on outcomes

60%

30%

10%

Source: "The Relative Contribution of Multiple Determinants to Health Outcomes", Lauren McGover et al., *Health Affairs, 33, no.2 (2014)*

Watson Health Offerings – Cloud, Analytics and Solutions

Data

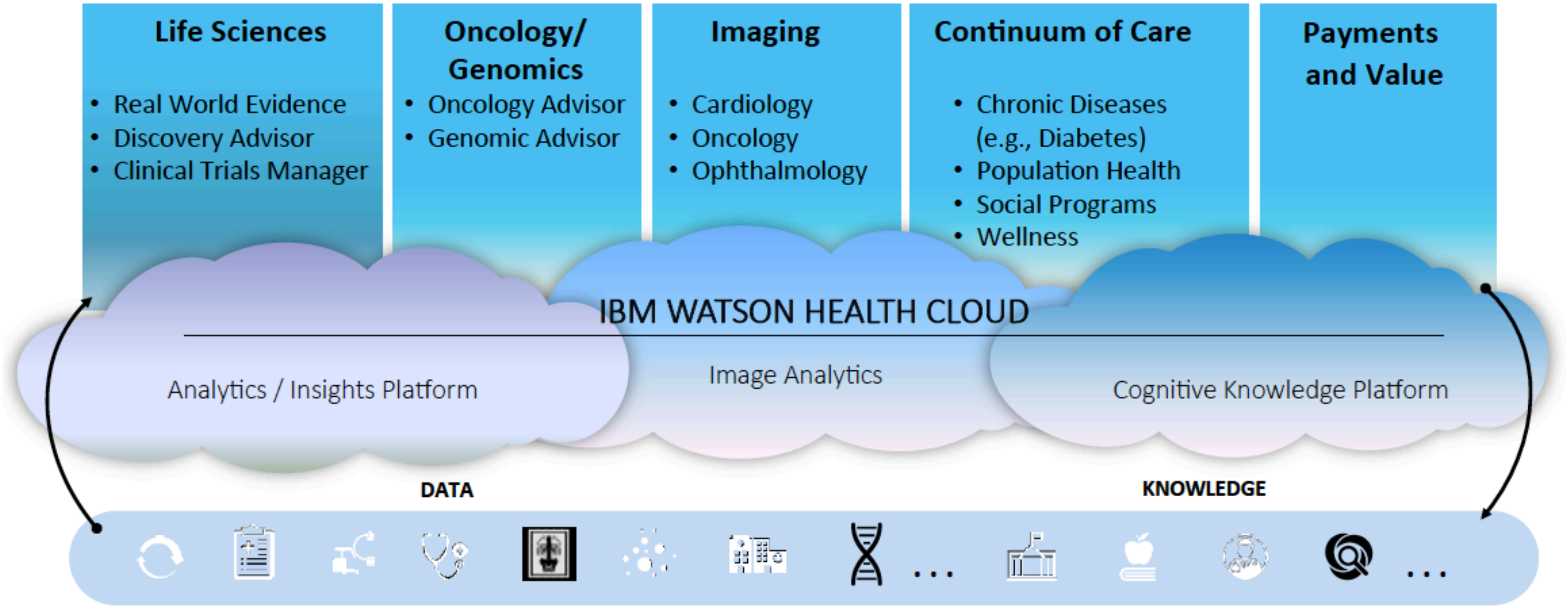
standards based, massively scalable, open repository of data on all dimensions of health for research

Insights as a Service

knowledge and actionable information through advanced analytics and cognitive capabilities

Solutions

from IBM an ecosystem of partners, designed to improve the overall experience and increase the quality of healthcare

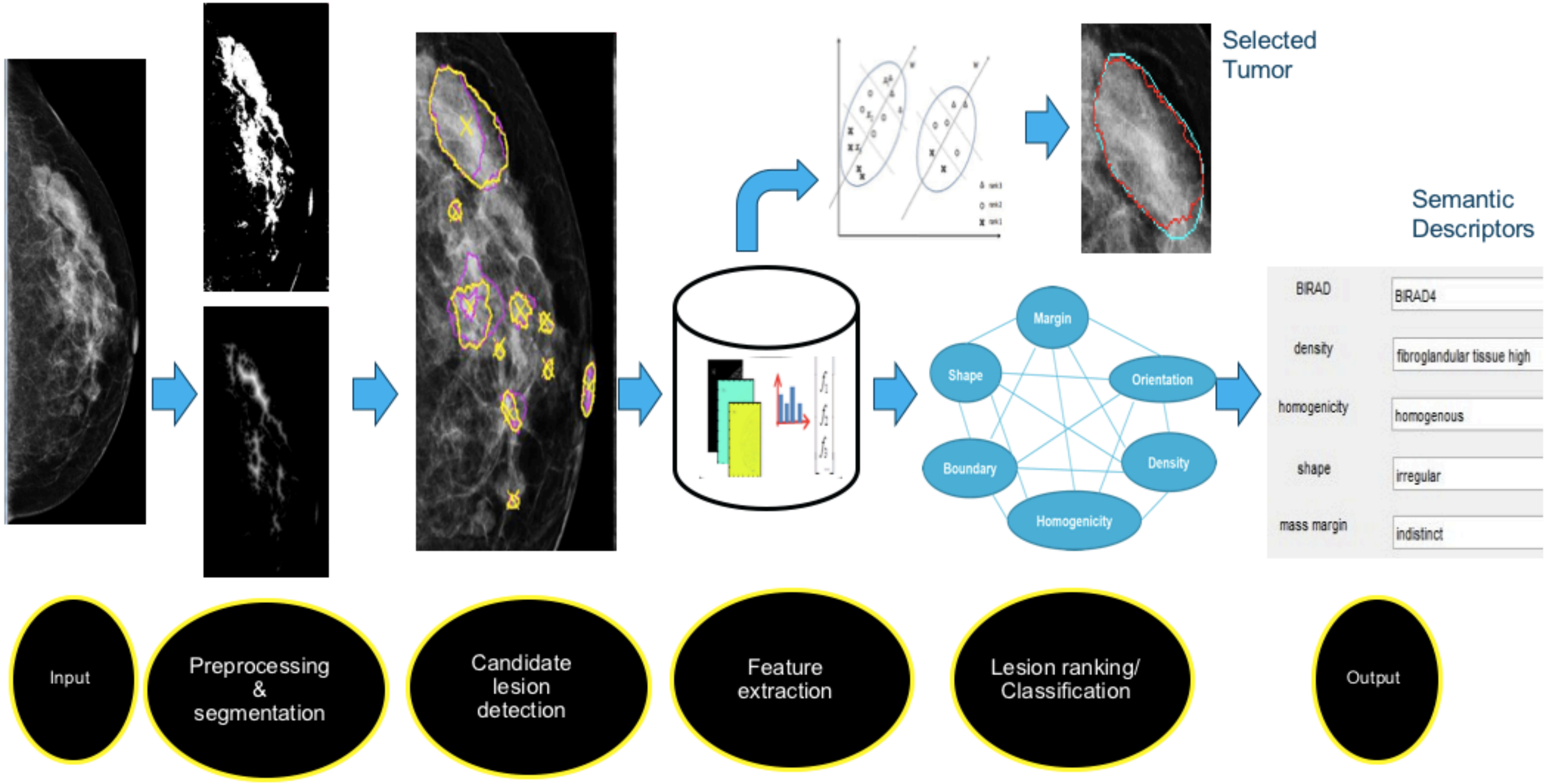


Watson Decision Advisor for Oncology

- Capability
  - Helps Oncologists make more informed, evidence-based patient treatment decisions
  - Provides a panel of confidence-weighted suggestions with full transparency of evidence

- Evidence Source
  - 600K+ pieces of evidence from 2M+ pages of text from 42 publications curated by Memorial Sloan Kettering Cancer Center (MSKCC) including NCNN guidelines, medical journals, text books, and documented best practices

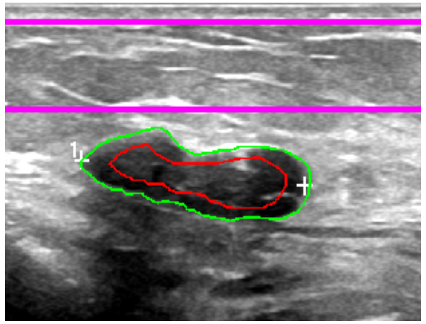
Tumor Detection and Classification

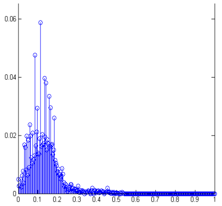


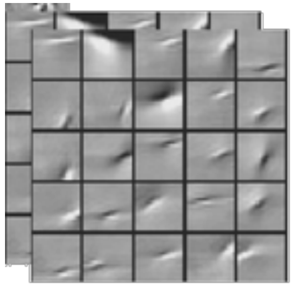
IBM Watson Health

Clinical and Visual Data Fusion

Visual Descriptor





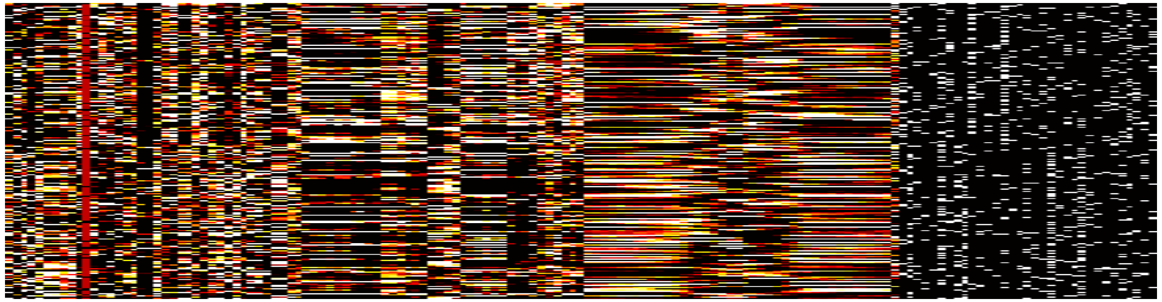


Clinical descriptor

"A 70 year old woman with a history of previous DCIS has a firm lump in the right breast. Ultrasonic scan acquired"

[… 0 1 0 0 0 1 1…]

based on predefined vocabulary



Applying proposed Multi-Kernel Learning method improves diagnosis accuracy by 5-10%

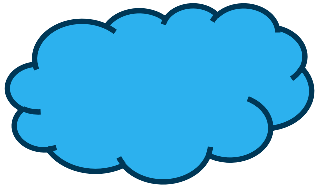
(compared to image-based only diagnosis)

Watson Genomics Analytics (WGA) Overview

WGA Service Analysis, Reports, & Visualizations

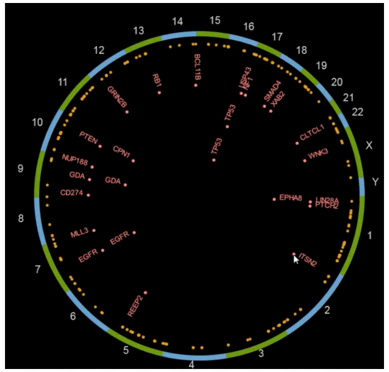
Case Sequenced

VCF / MAF, Log2, Dge Encryption



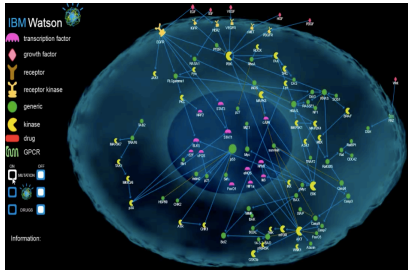
Molecular Profile Analysis

Gene		
NF2 *heterozygous loss*	Driver Score	0.898
	Expression Score	0.898
	Copy Number Heterozygous Loss	log2=-0.579
	Evidence	[TSGene_TSG], [Vogelstein_TSG], [IBM2020_TSG], [TAG_DB_TSG]
SMARCB1 *heterozygous loss*	Driver Score	0.898
	Expression Score	0.898
	Copy Number Heterozygous Loss	log2=-0.579
	Evidence	[TSGene_TSG], [Vogelstein_TSG], [IBM2020_TSG], [TAG_DB_TSG]
PTEN *heterozygous loss*	Driver Score	0.898
	Expression Score	0.898
	Copy Number Heterozygous Loss	log2=-0.553
	Evidence	[TSGene_TSG], [Vogelstein_TSG], [Zack_DEL], [IBM2020_TSG], [TAG_DB_TSG]
CDKN2A *heterozygous loss*	Driver Score	0.898
	Expression Score	0.898
	Copy Number Heterozygous Loss	log2=-1.627
	Evidence	[TSGene_TSG], [Vogelstein_TSG], [Zack_DEL], [IBM2020_TSG], [TAG_DB_TSG]



Pathway Analysis

Target	Reason for Identification	Pathway Distance	
PIK3CG	PIK3CG is downstream of EGFR.	4	PubMed: 10913131, 19233262, 8903320
	PIK3CG is downstream of PTEN.	1	PubMed: 12149650
PRKCA	PRKCA is downstream of EGFR.	2	PubMed: 1689310, 2 8290562, 2153914,
EGFR	EGFR is a possible driver.	0	
BRAF	BRAF is downstream of EGFR.	5	PubMed: 17563371, 17486115, 1049952



Drug Analysis

Actionable Alteration	D/P	Approved for Glioblastoma	Investigational for Glioblastoma	Approved for other cancers
PTEN *heterozygous loss*	P	Everolimus	Veliparib (ABT-888)	Olaparib (AZD-2281), Temsirolimus
EGFR *amplification*	D			etuximab, Erlotinib, Panitumumab, Gefitinib, patinib, Afatinib, Vandetanib
	P			Dabrafenib, Trametinib, Vemurafenib

Everolimus	MTOR	In kidney transplant rejection prophylaxis, everolimus inhibits antigenic and interleukin (IL-2 and IL-15) the FK506 binding protein, and the complex binds to and inhibits mTOR. In the presence of everolimus inhibited. As a result, phosphorylation of the ribosomal S6 protein and subsequent protein synthesis an
		Astrocytoma: [1] Phase III: (NCT00789828)
		Breast Carcinoma: [1](Citation: Bourgier C, Ray-Coquard I, Provencal J, et al. Exploratory subgroup analysis of the TAMR alone in patients with hormone-receptor-positive, HER-negative metastatic breast cancer (mBC) with p presentation at the European Society for Medical Oncology 36th Congress - ECCO 16 and ESMO 36.

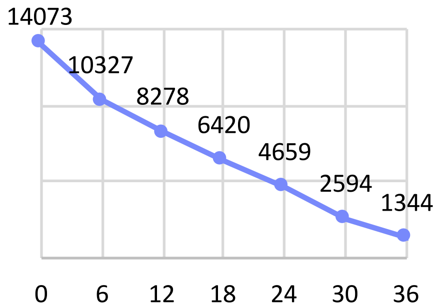
WGA Content

- 20+ Content Sources Including:
  - Medical Articles (23Million)
  - Drug Information
  - Clinical Trial Information
  - Genomic Information

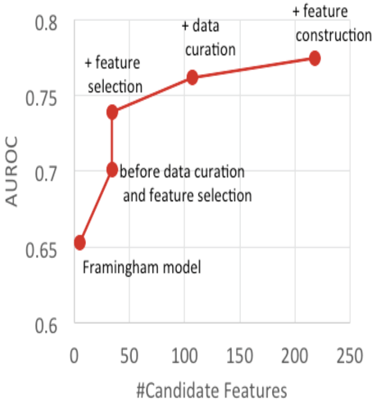
IBM Watson Health

Risk Prediction – Stroke-onset Risk for AF Patients

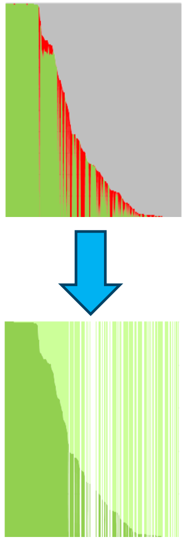
IBM



A Talk at GW-ICC 2015



Data Curation → Feature Construction → Feature Selection → Predictive Modeling



12

167

Base: 107 Derived: 111

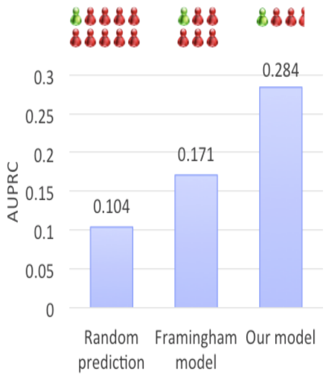
Feature Discovery:
- Feature Grouping: 7
- Co-occurrence Pattern : 93
- Knowledge: 11

27 Newly Discovered Risk Factors

Risk factor	Contr.	OR	P
颅内出血	+	5.780	<0.001
短暂性脑缺血发作 & 高脂血症	+	2.267	0.181
心肌梗死 & 高脂血症	+	1.992	0.038
血管栓塞	+	1.949	0.002
年龄 per 10	+	1.948	<0.001
目前吸烟	+	1.912	0.017
高血压 & 阵发性室上速	+	1.845	0.366
控制心室率药物	+	1.615	0.04
糖尿病患病年数: 0-5年	+	1.589	0.1
5-10年	-	0.535	0.166
>10年	-	0.843	0.594
高血压 & 心衰	+	1.557	0.149
缺血性脑卒中 & 冠心病	+	1.552	0.291
左室壁厚度	+	1.246	0.001
缺血性脑卒中 & 呼吸系统疾病	+	1.160	0.738
充血性心力衰竭	+	1.119	0.662
血红蛋白 per 10	+	1.082	0.191

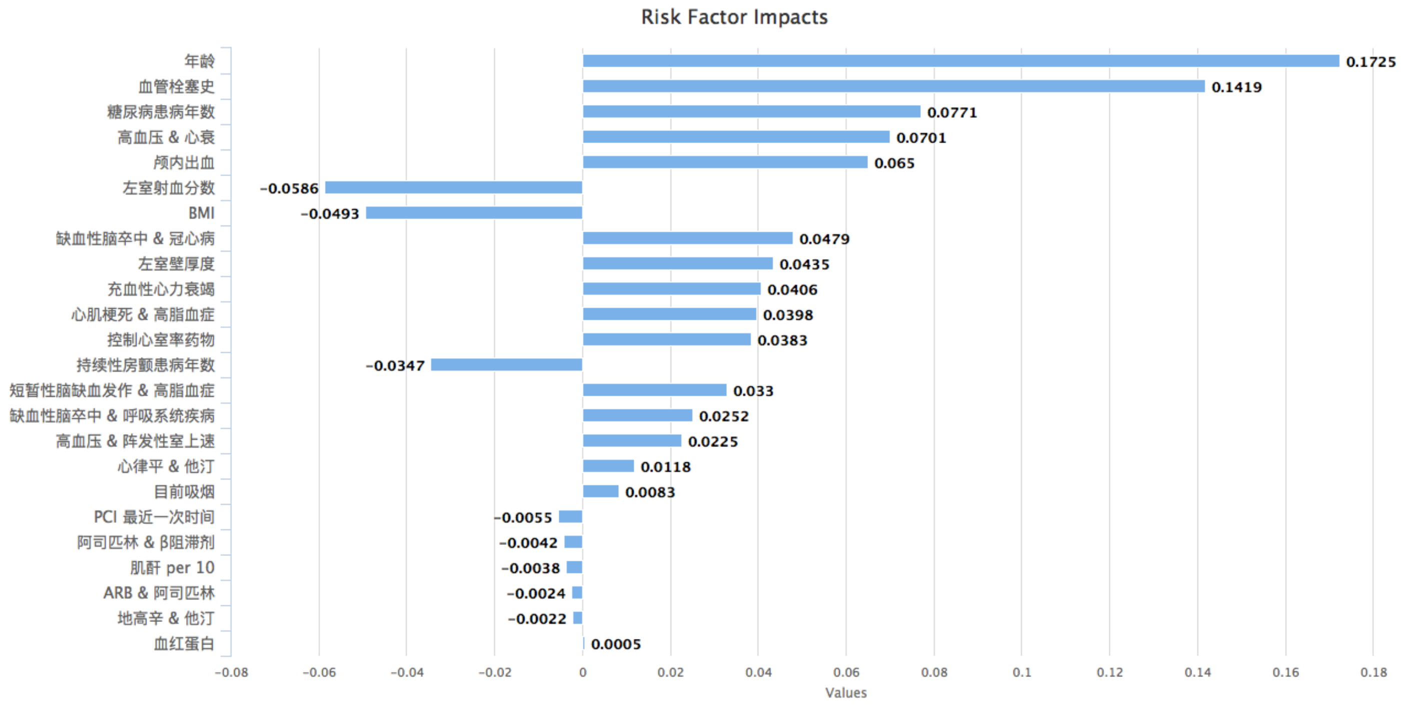
Risk factor	Contr.	OR	P
心律平 & 他汀	-	0.225	0.16
PCI 最近一次时间: 0-5年	-	0.579	0.134
5-10年	-	0.314	0.141
地高辛 & 他汀	-	0.451	0.071
持续性房颤患病年数: 0-5年	-	0.969	0.891
5-10年	-	0.632	0.17
>10年	-	0.788	0.38
ARB & 阿司匹林	-	0.715	0.092
左室射血分数 per 10	-	0.745	0.005
阿司匹林 & β阻滞剂	-	0.765	0.202
BMI	-	0.948	0.039
肌酐 per 10	-	0.904	0.027

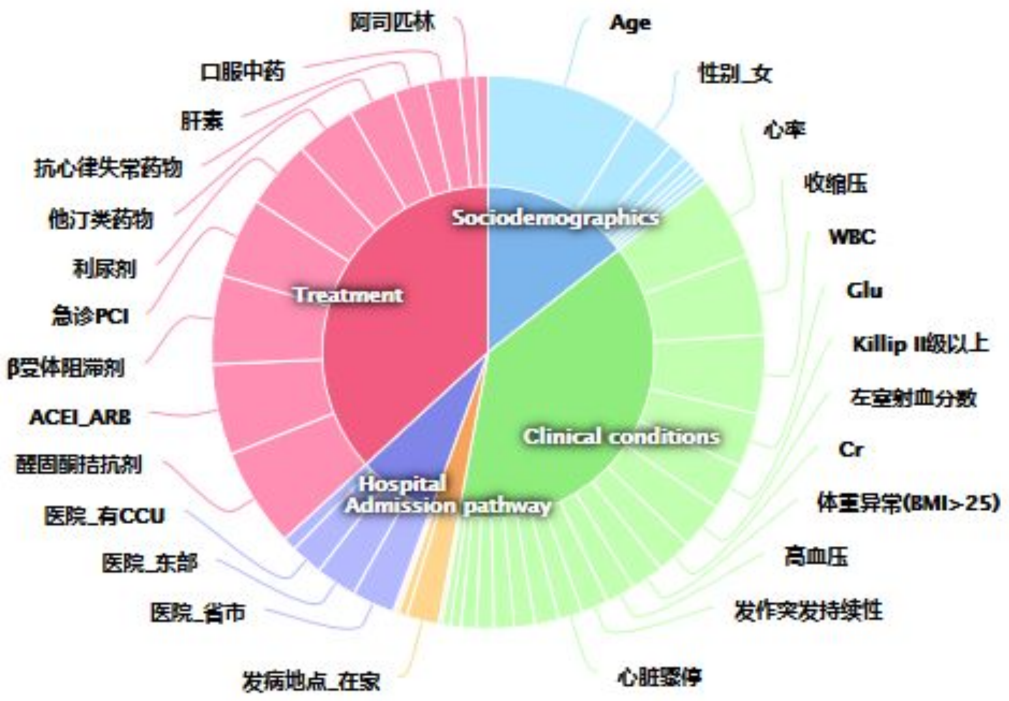
Imbalanced Learning



Improve average prediction precision by 66%

Real World Evidence – Risk Prediction





Patient Similarity – Treatment Efficacy Analysis

Much larger in-between group differences regarding the outcome

K	2	3	4	5	6
PCA(0.2)	[877, 58, 6.6%], [826, 101, 12.2%]	[457, 28, 6.1%], [420, 30, 7.1%], [826, 101, 12.2%]	[457, 28, 6.1%], [420, 30, 7.1%], [401, 42, 10.5%], [425, 59, 13.9%]	[457, 28, 6.1%], [190, 13, 6.8%], [230, 17, 7.4%], [401, 42, 10.5%], [425, 59, 13.9%]	[457, 28, 6.1%], [190, 13, 6.8%], [230, 17, 7.4%], [230, 22, 9.6%], [401, 42, 10.5%], [195, 37, 19.0%],
LDA(2)	[1255, 87, 6.9%], [448, 72, 16.1%]	[607, 39, 6.4%], [648, 48, 7.4%], [448, 72, 16.1%]	[413, 23, 5.6%], [648, 48, 7.4%], [194, 16, 8.2%] [448, 72, 16.1%],	[269, 8, 3.0%], [413, 23, 5.6%], [194, 16, 8.2%], [379, 40, 10.6%], [448, 72, 16.1%]	[269, 8, 3.0%], [413, 23, 5.6%], [194, 16, 8.2%], [379, 40, 10.6%], [227, 33, 14.5%], [221, 39, 17.6%]

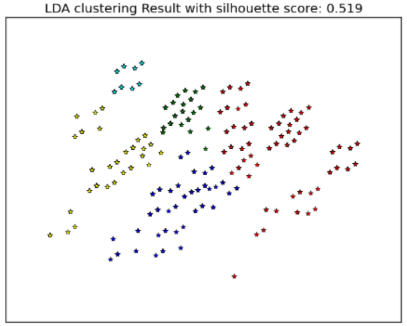
Significant risk factor heterogeneity among groups

	Group0 (269, 3%)	Group1 (413, 5.6%)	Group2 (194, 8.2%)	Group3 (379, 10.6%)	Group4 (448, 16.1%)
Cha2ds2-vasc	3	2	3	4	6
CHF	0 (0%)	14 (3%)	116 (60%)	77 (20%)	277 (62%)
Hypertension	269 (100%)	218 (53%)	104 (54%)	369 (97%)	426 (95%)
Age>=75	0 (0%)	88 (21%)	40 (21%)	297 (78%)	350 (78%)
Stroke	0 (0%)	0 (%)	78 (40%)	5 (1%)	290 (65%)
Vascular diseases	55 (20%)	101 (24%)	48 (25%)	112 (30%)	169 (38%)
Age [65,74]	269 (100%)	90 (22%)	8 (4%)	82 (22%)	90 (20%)

1,703 AF patients

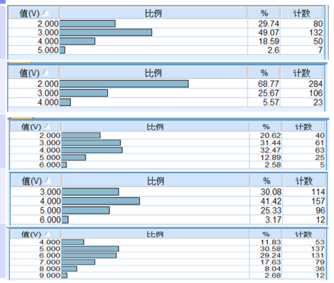
Outcome-Driven Similarity Metric Learning → Patient Clustering → Patient Group Phenotyping → Treatment Efficacy Analysis

LDA clustering Result with silhouette score: 0.519



Clustering Result with Supervised-Learning Metric (LDA)

	Size	Stroke_Onset	CHA2DS2-VASc
Group 0	269	8 (3%)	3
Group 1	413	23 (5.6%)	2
Group 2	194	16 (8.2%)	3
Group 3	379	40 (10.6%)	4
Group 4	448	72 (16.1%)	6



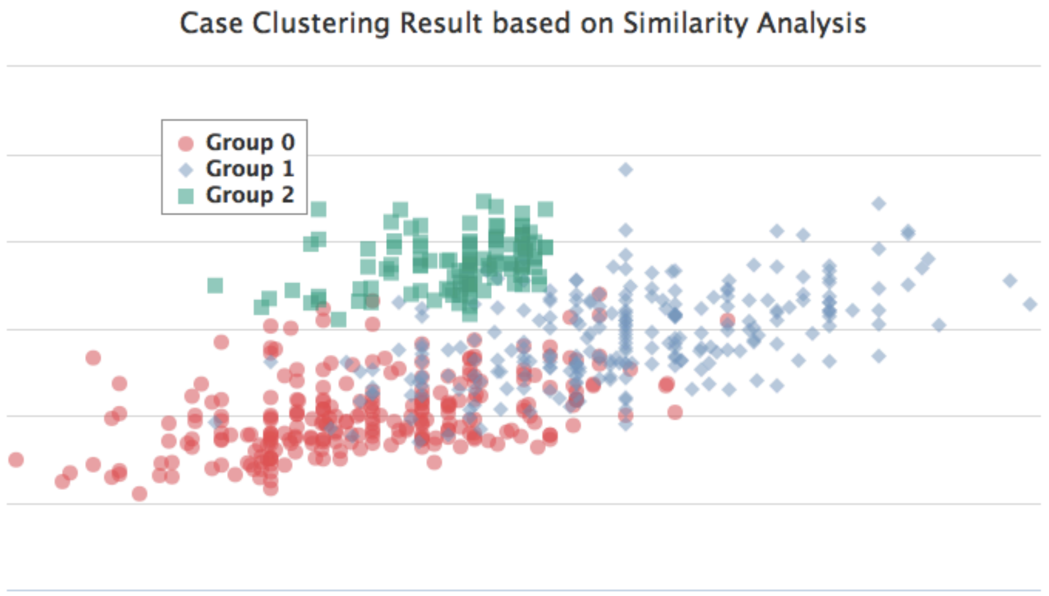
Count of patients using CCB (Percentage of patients using CCB within the group)

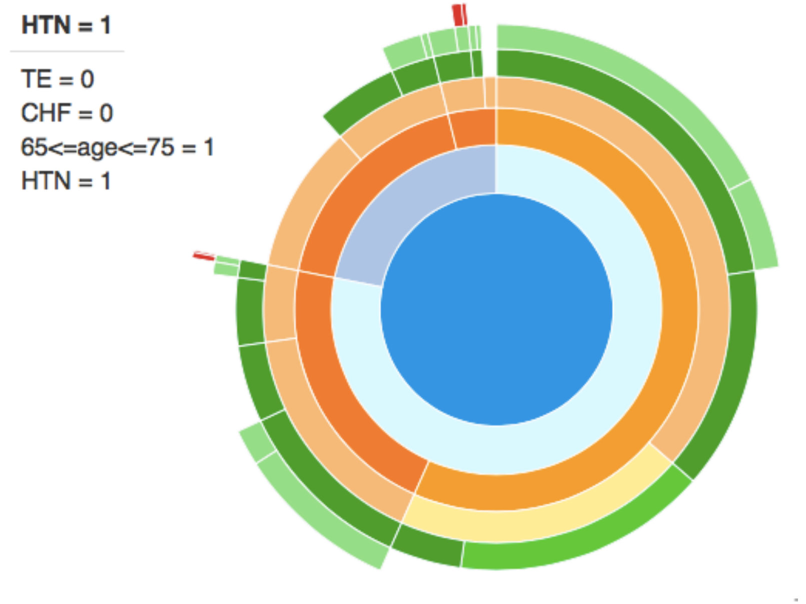
(stroke-onset percentage when using CCB: stroke -onset perdcentage when not-using CCB), p-value

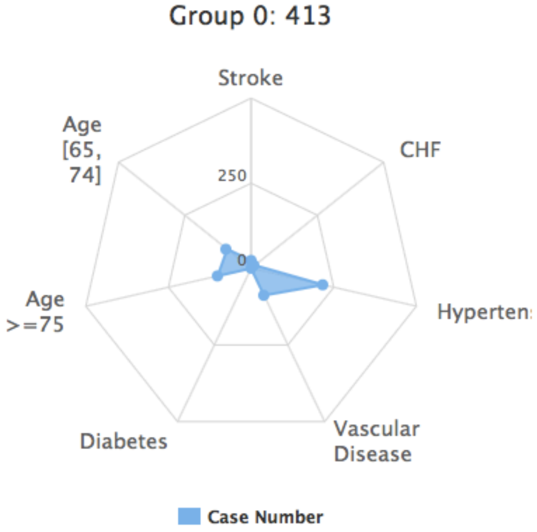
	All (1386, 9.9%)	Group0 (269, 3%)	Group1 (218, 4.6%)	Group2 (104, 10.6%)	Group3 (369, 10.3%)	Group4 (426, 16.4%)
Use_CCB	345 (24.5%)	66(25%)	62(28.4%)	25(24.0%)	92(24.9%)	100 (23.5%)
CCB-Outcome	(8.7%:10.3%), 0.393	(3.0%: 3.0%), 0.975	(3.2%: 5.1%), 0.545	(16.0%: 8.8%), 0.312	(14.1%: 9.0%), 0.163	(9.0%: 18.7%), 0.022

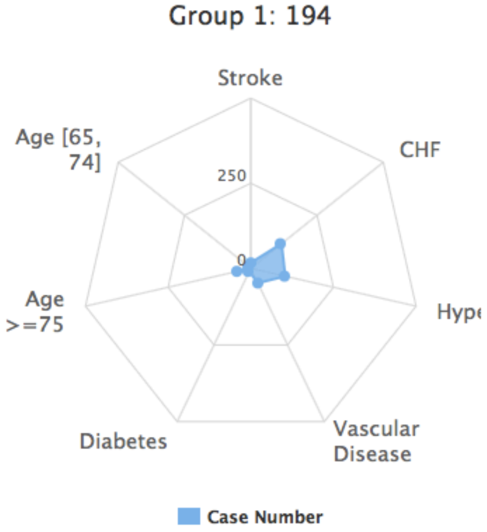
Identify target patient cohort whose risks might be reduced by 50% after using CCB

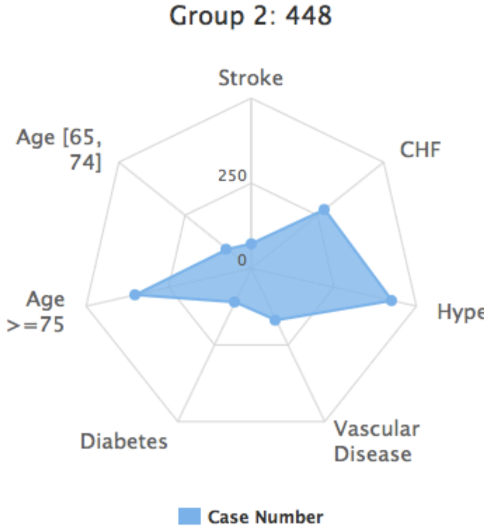
Real World Evidence – Patient Similarity







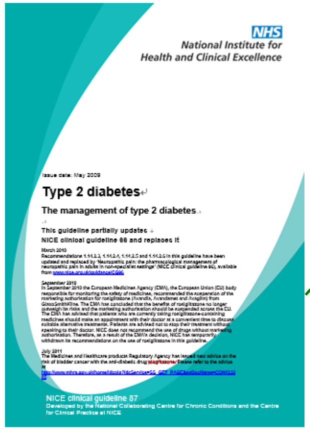




Cognitive Advisor for Type II Diabetes Management

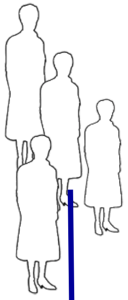
Knowledge-driven

Data-driven


NHS
National Institute for Health and Clinical Excellence
Type 2 diabetes
The management of type 2 diabetes
NICE clinical guideline 87

Clinical guidelines with medical ontologies from the literature

Clinically similar to



Best Treatment =
Metformin 0.40
Sulfonylureas 0.31
…

Outcomes Analysis
Treatment Comparison
Disease Progression

Decision Options

Goal	Care Pathway	Drug used	Drug recommended	Drug information	Data evidence*
Blood sugar management	Blood sugar badly controlled -> oral hypoglycemic drug combination	Metformin	Metformin + Sulfonylureas	Glucophage + Glimepiride	52% : 67%
Blood pressure management	Blood pressure abnormally high -> life style intervention	/	Life style intervention	Life style intervention	86% : 65%
Blood lipid management	Blood lipid abnormal -> Statin	/	Atorvastatin	Lipitor	72% : 87%

* : the first is the percentage for similar patients who used this treatment, and the second is the percentage for similar patients who used this treatment and got good outcome

IBM Watson Health Hypoglycemia Prediction Using Sensor Data

Can Watson predict Hypoglycemia in patients, post bolus?

Experimental Setup:	Data was derived from 2000 randomly selected T1 diabetic patients on Medtronic Pump and CGM therapy, with 3-9mos of data per patient. Patient demographic profile varied, as did their history with the disease and Insulin therapy.		
Feature Selection	Demographic Profiles, Patient diabetes history and years with Insulin therapy	Short-term trends in sensor glucose, and delivered boluses	— Long-term temporal patterns in patient insulin and usage profiles
Classification Method	— Combination of Predictive Feature-based Segmentation and Static Demographic-based clustering — Measures information-theoretic relationship between features and outcomes, and derive statistical p-values to cluster patients — Provides insights into statistical relationship between user behavior and outcomes — Allows discovery of “interesting” patient groups		
Results	Data was split into 80%-20% (train-test ratio). Historical patient data (more than 3-9 months old) was used to train the classifier. Once trained, the classifier was tested on the test patients over the same period.		
	HypoGlycemia (<70mg/dl)	Sensitivity	Specificity
	3hrs*	85%*	75.5%*
	4hrs*	85%*	66.3%*

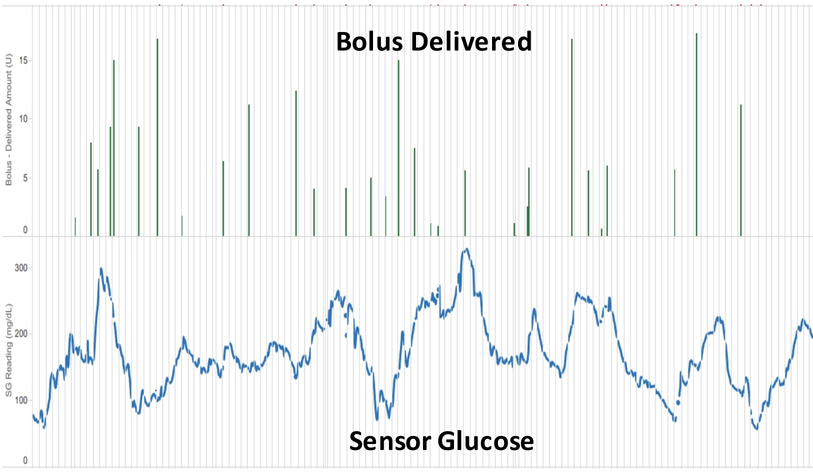
Device Alarms

Prior Hypos

Time of Day, Day of Week

Prelunch, Postlunch, Evening, Weekday

Pump Usage

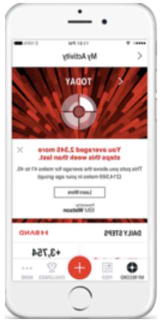


IBM Watson Health Cognitive Coaching for Fitness

RECORD

Personalized lifestyle insights using outcome-driven patterns from people like me

Under Armour



- Biggest digital fitness owner:
  - MapMyFitness
  - MyFitnessPal
  - Endomondo
- Total 160 million registered fitness app users
- Rich data from multiple apps with matched UA ID
- Personal profile, Weight log, Workout log, Food entries, Activity log, Sleep log

Population Based Predictions

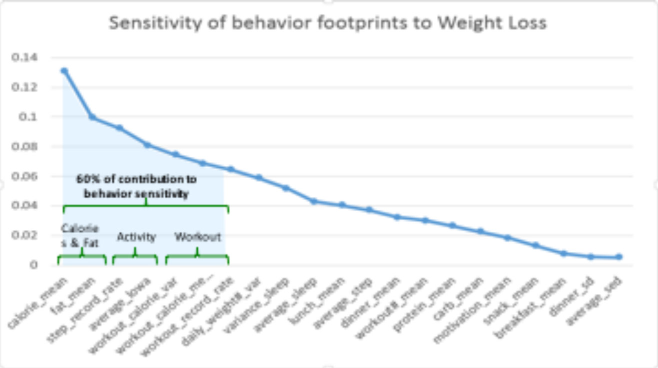
Identify behavioral features with highest impact on weight loss

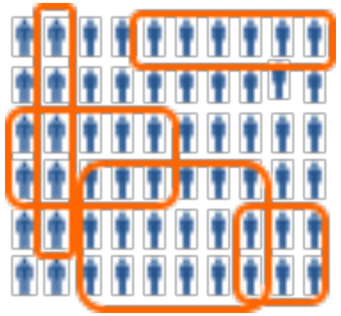
Similarity Analytics

Identify cohort with similar characteristics to Person A

Personalized Outcome Modelling

Identify most desirable behavioral changes to meet goal





For Person A, the following factors in a sub-cohort of 300, will impact ability to achieve weight loss goal:

- Total calories consumed
- Lunch nutrition
- Ave. # steps
- Step recording rate
- Ave. amount of sleep
- Sleep variance

IBM Watson Health

Data-driven Insights for Personalized Healthcare