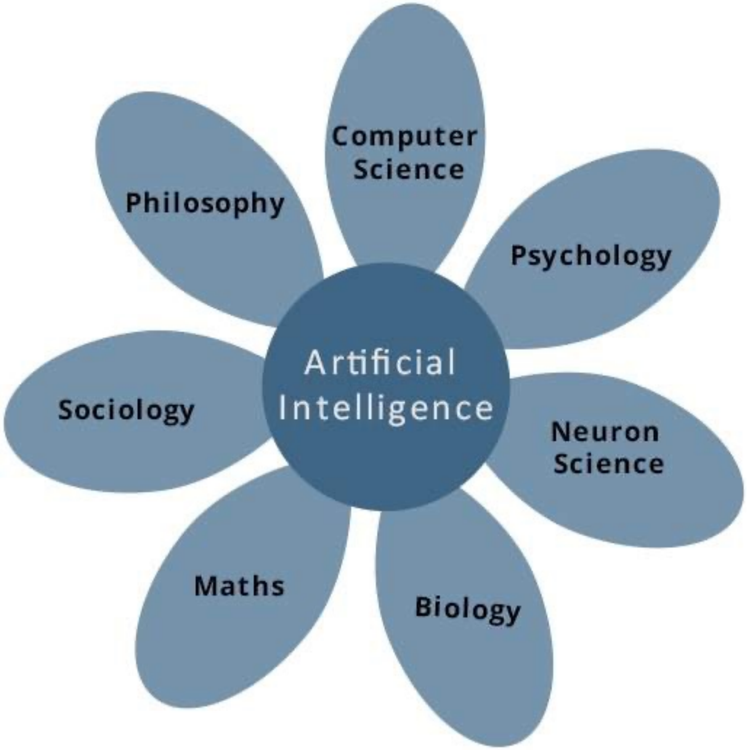
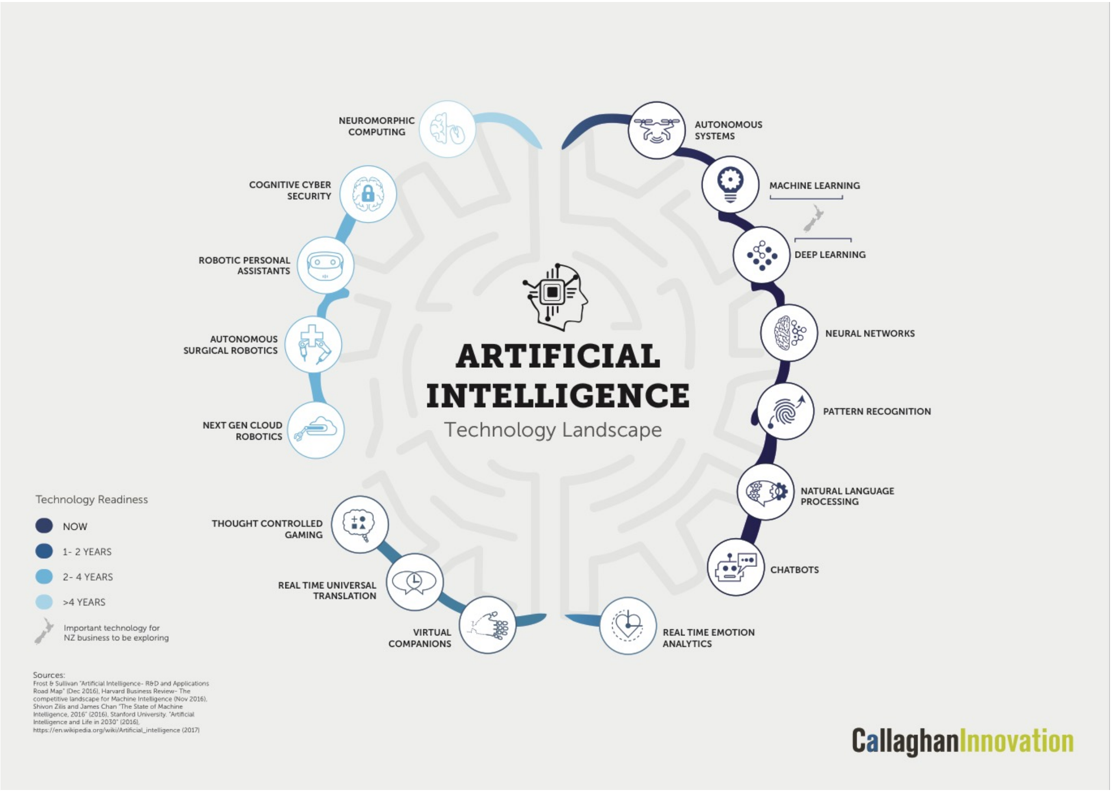
Medicina ed Intelligenza Artificiale
Esperienze e considerazioni

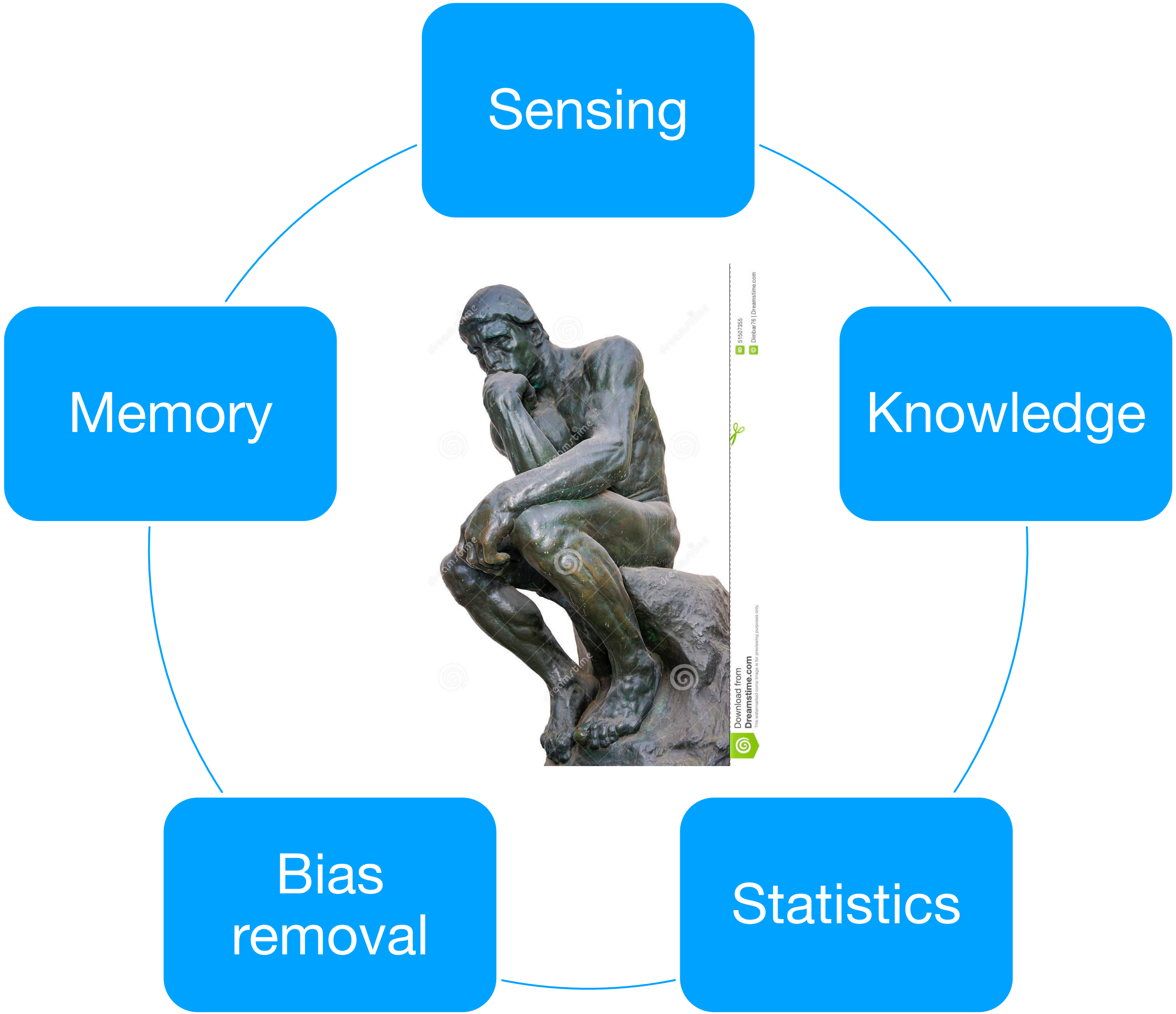
Robert Alexander – 4 Maggio 2021

bob@ralexander.it

AI sciences applied as technology



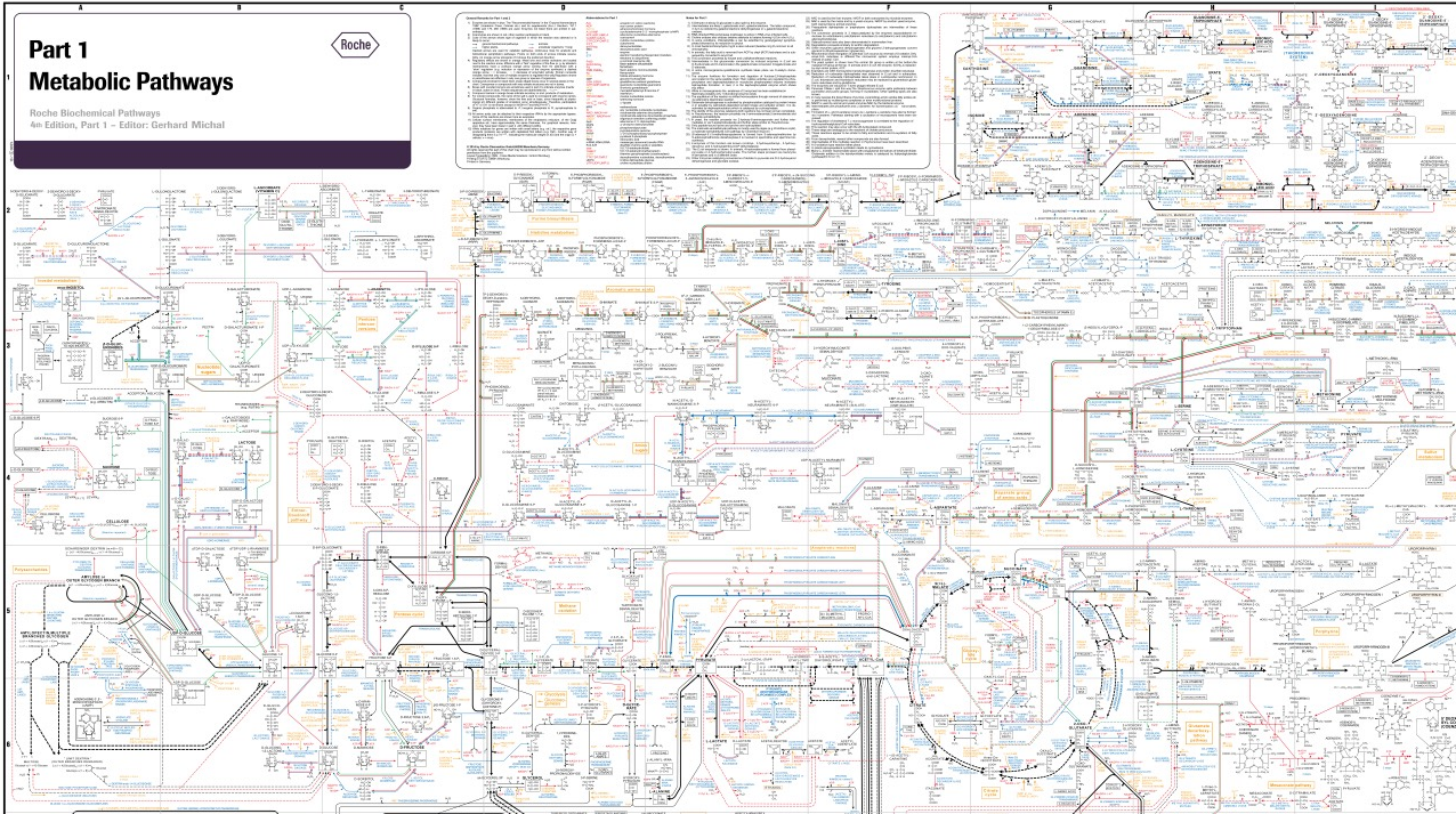



Sensing
Knowledge
Statistics
Bias
removal
Memory
Download from
Dreamstime.com

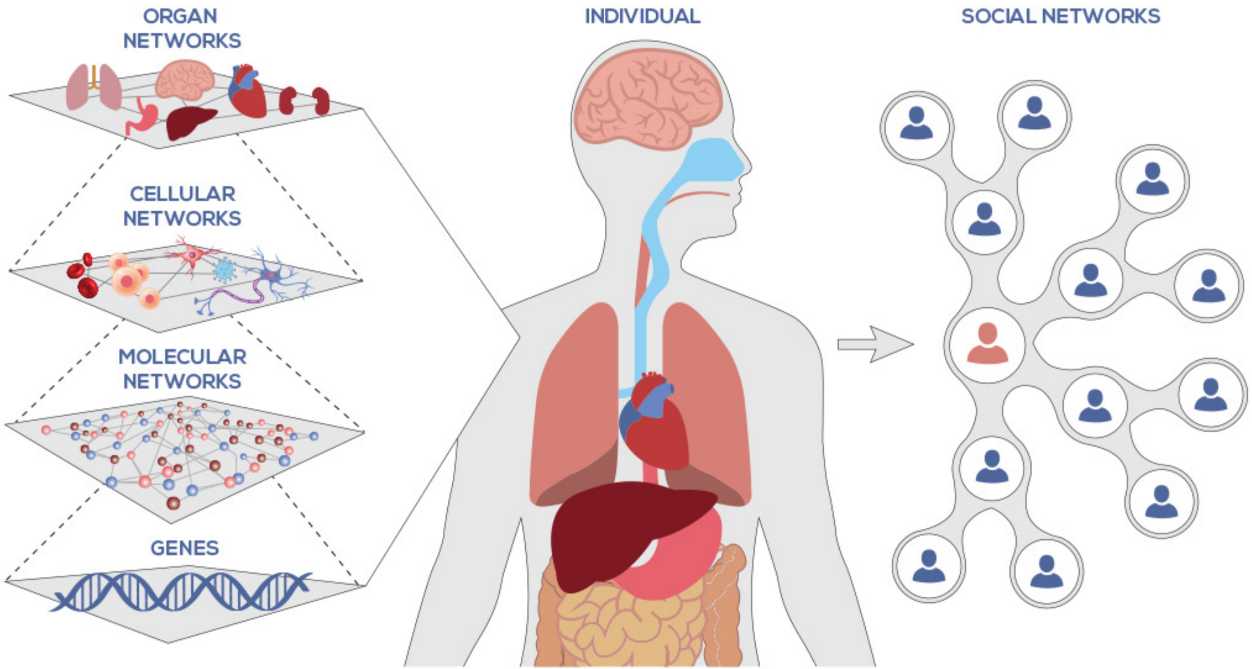

Colerick ·
Sanguine ·
Flewmatik ·
Melancoly ·
The Colerick p
son ys hote, drye,
lene, slend, cone
tous, yrefull, ha
stiv, deceitfull, &
The Sanguine
pson ys hote, mo
ist, liberall, plen
teous, mery, m
ddy, he drawith
The flegmatik
pson is cold, and
moist, hevy, slow
slepy, ingenious
he spitteth when
The melancoly
pson is cold, drye
hevy, coveitous
backbit, malicious
& slowe, he loveth

Part 1
Metabolic Pathways

Roche Biochemical Pathways
4th Edition, Part 1 – Editor: Gerhard Michal

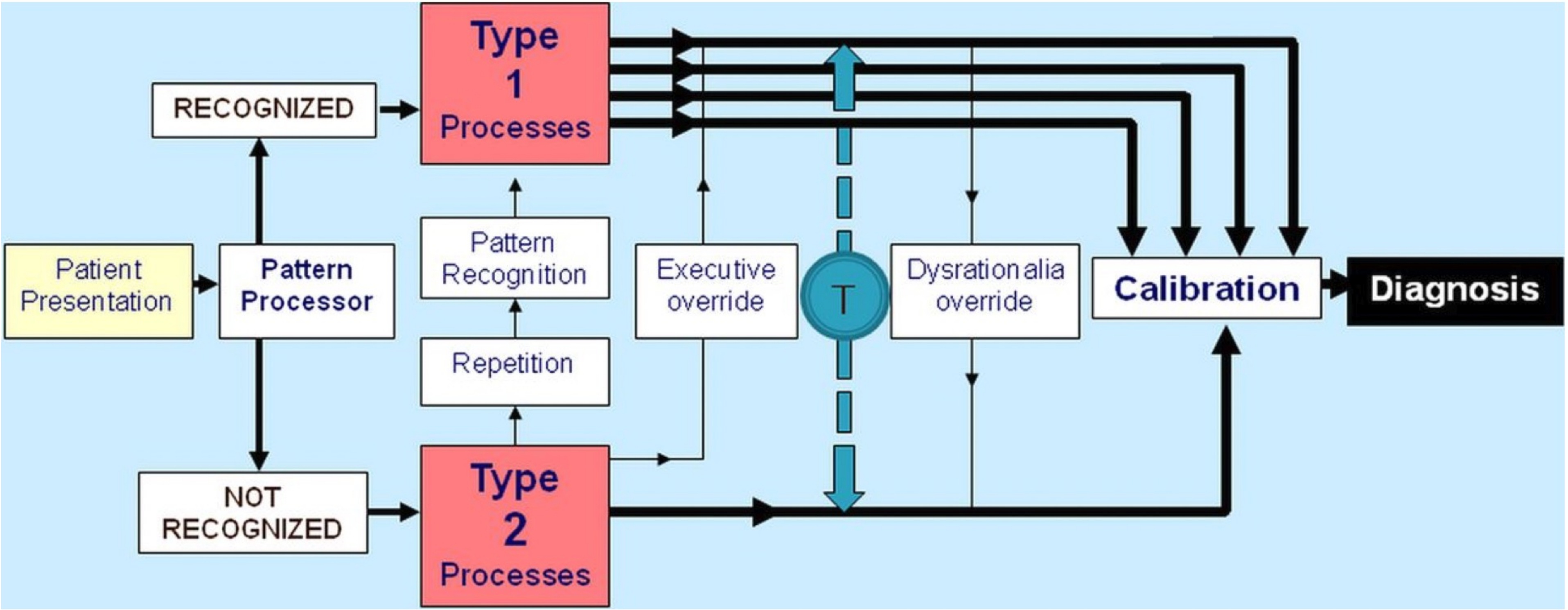


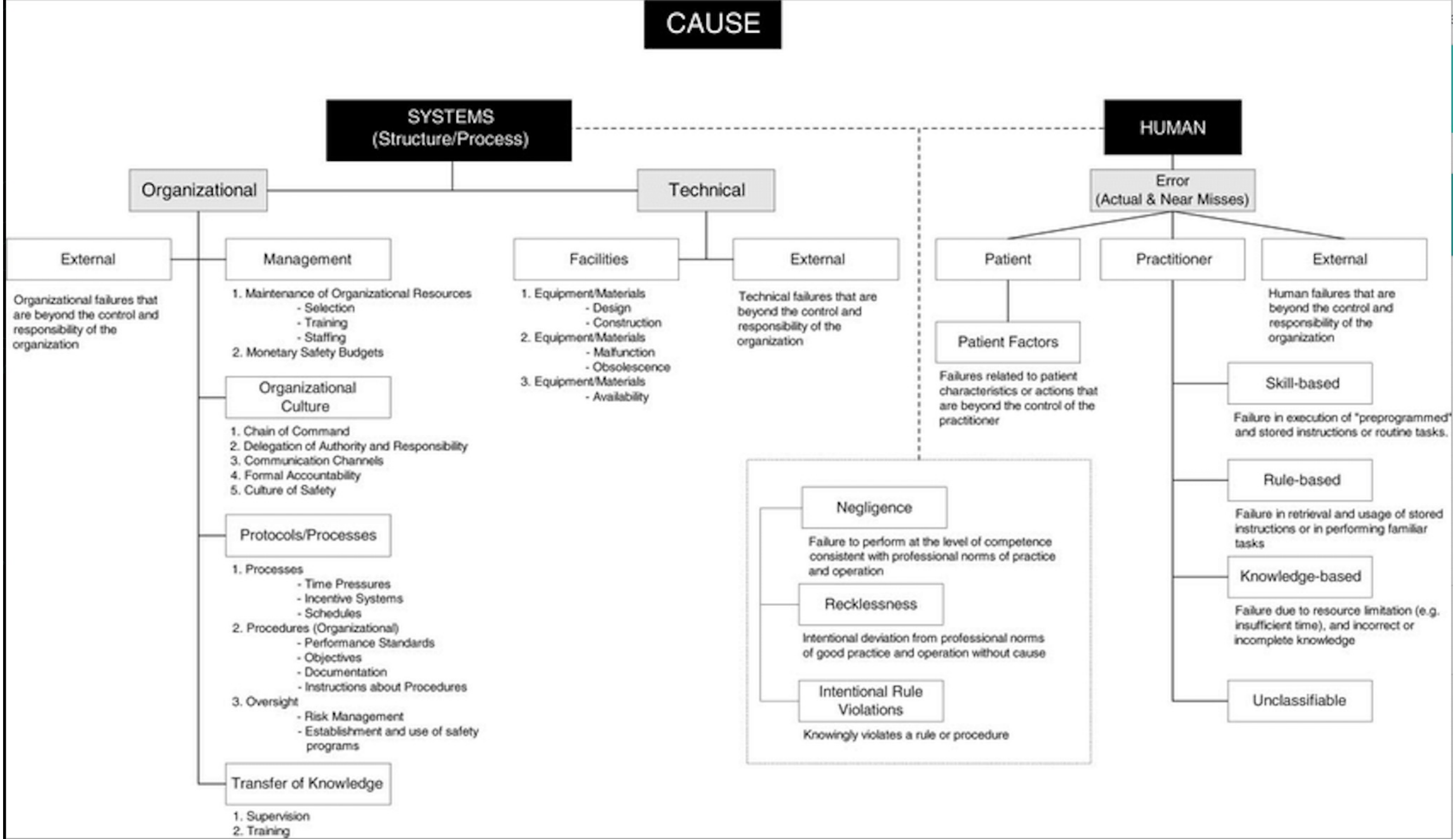
Humans are defined by a multilevel complex system: to socio-ecology



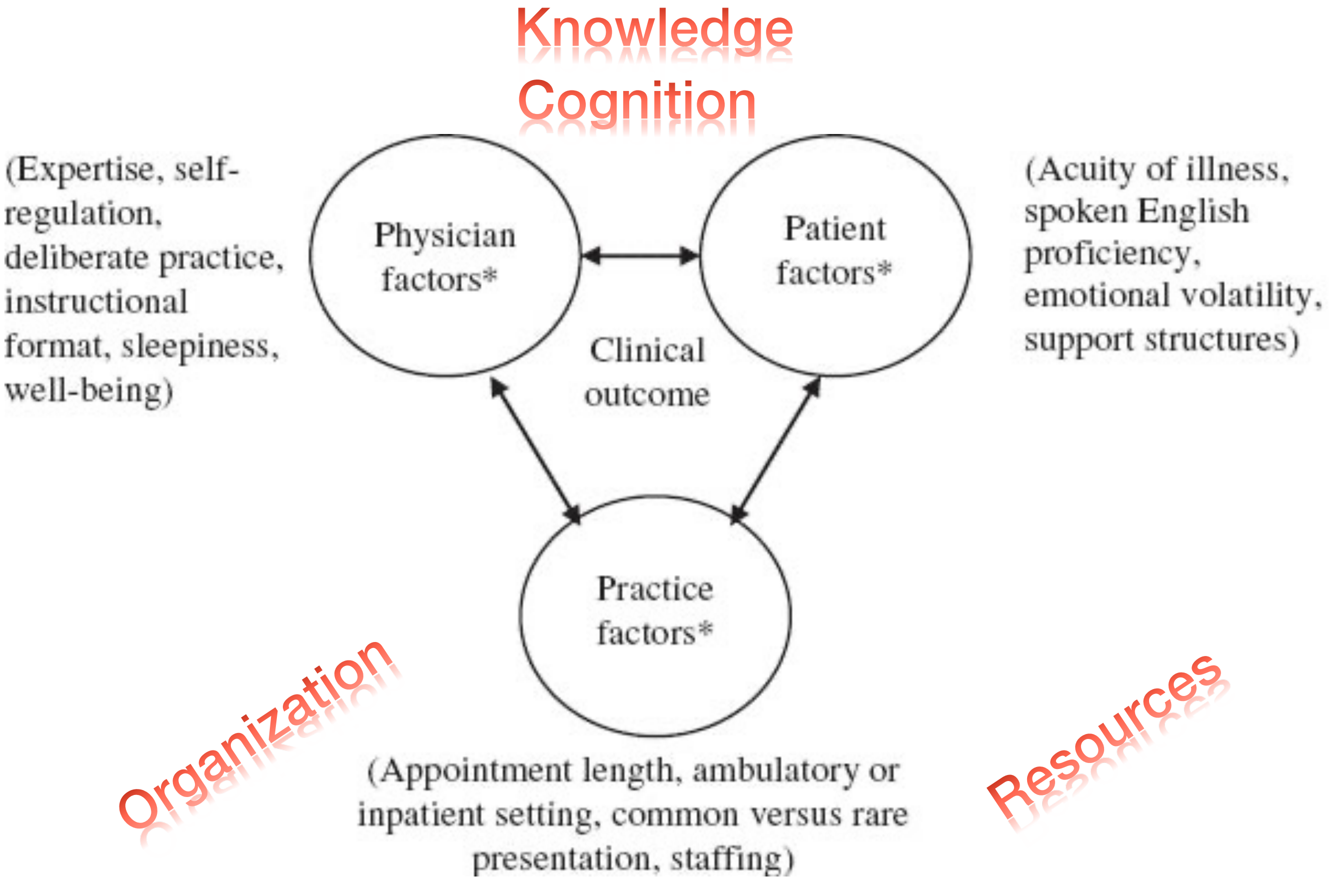
Health -> Systems science

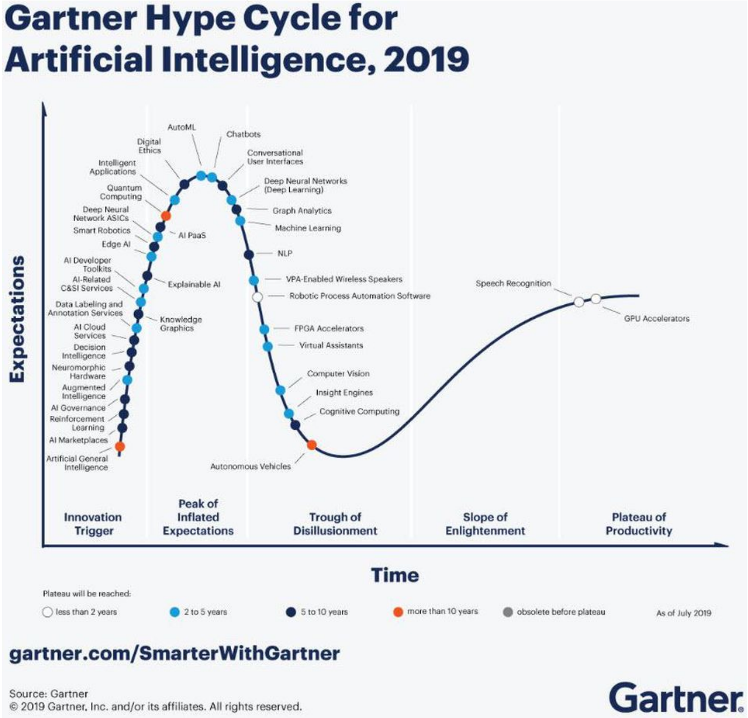
Medical cognition model: experience vs analysis
Dual processing theory in action




CAUSE
SYSTEMS (Structure/Process)
HUMAN
Organizational
Technical
Error (Actual & Near Misses)
External
Organizational failures that are beyond the control and responsibility of the organization
Management
1. Maintenance of Organizational Resources
- Selection
- Training
- Staffing
2. Monetary Safety Budgets
Organizational Culture
1. Chain of Command
2. Delegation of Authority and Responsibility
3. Communication Channels
4. Formal Accountability
5. Culture of Safety
Protocols/Processes
1. Processes
- Time Pressures
- Incentive Systems
- Schedules
2. Procedures (Organizational)
- Performance Standards
- Objectives
- Documentation
- Instructions about Procedures
3. Oversight
- Risk Management
- Establishment and use of safety programs
Transfer of Knowledge
1. Supervision
2. Training
Facilities
1. Equipment/Materials
- Design
- Construction
2. Equipment/Materials
- Malfunction
- Obsolescence
3. Equipment/Materials
- Availability
External
Technical failures that are beyond the control and responsibility of the organization
Patient
Patient Factors
Failures related to patient characteristics or actions that are beyond the control of the practitioner
Practitioner
External
Human failures that are beyond the control and responsibility of the organization
Skill-based
Failure in execution of "preprogrammed" and stored instructions or routine tasks.
Rule-based
Failure in retrieval and usage of stored instructions or in performing familiar tasks
Knowledge-based
Failure due to resource limitation (e.g. insufficient time), and incorrect or incomplete knowledge
Unclassifiable
Negligence
Failure to perform at the level of competence consistent with professional norms of practice and operation
Recklessness
Intentional deviation from professional norms of good practice and operation without cause
Intentional Rule Violations
Knowingly violates a rule or procedure

Factors impacting clinical outcomes




Gartner Hype Cycle for Artificial Intelligence, 2019
Expectations
AutoML
Chatbots
Digital Ethics
Intelligent Applications
Conversational User Interfaces
Quantum Computing
Deep Neural Networks (Deep Learning)
Deep Neural Network ASICs
Graph Analytics
Smart Robotics
Machine Learning
AI PaaS
Edge AI
NLP
AI Developer Toolkits
AI-Related C&SI Services
Explainable AI
VPA-Enabled Wireless Speakers
Robotic Process Automation Software
Speech Recognition
GPU Accelerators
Data Labeling and Annotation Services
Knowledge Graphics
AI Cloud Services
FPGA Accelerators
Decision Intelligence
Virtual Assistants
Neuromorphic Hardware
Computer Vision
Augmented Intelligence
Insight Engines
AI Governance
Cognitive Computing
Reinforcement Learning
AI Marketplaces
Artificial General Intelligence
Autonomous Vehicles
Innovation Trigger
Peak of Inflated Expectations
Trough of Disillusionment
Slope of Enlightenment
Plateau of Productivity
Time
Plateau will be reached:
less than 2 years
2 to 5 years
5 to 10 years
more than 10 years
obsolete before plateau
As of July 2019
gartner.com/SmarterWithGartner
Source: Gartner
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Gartner

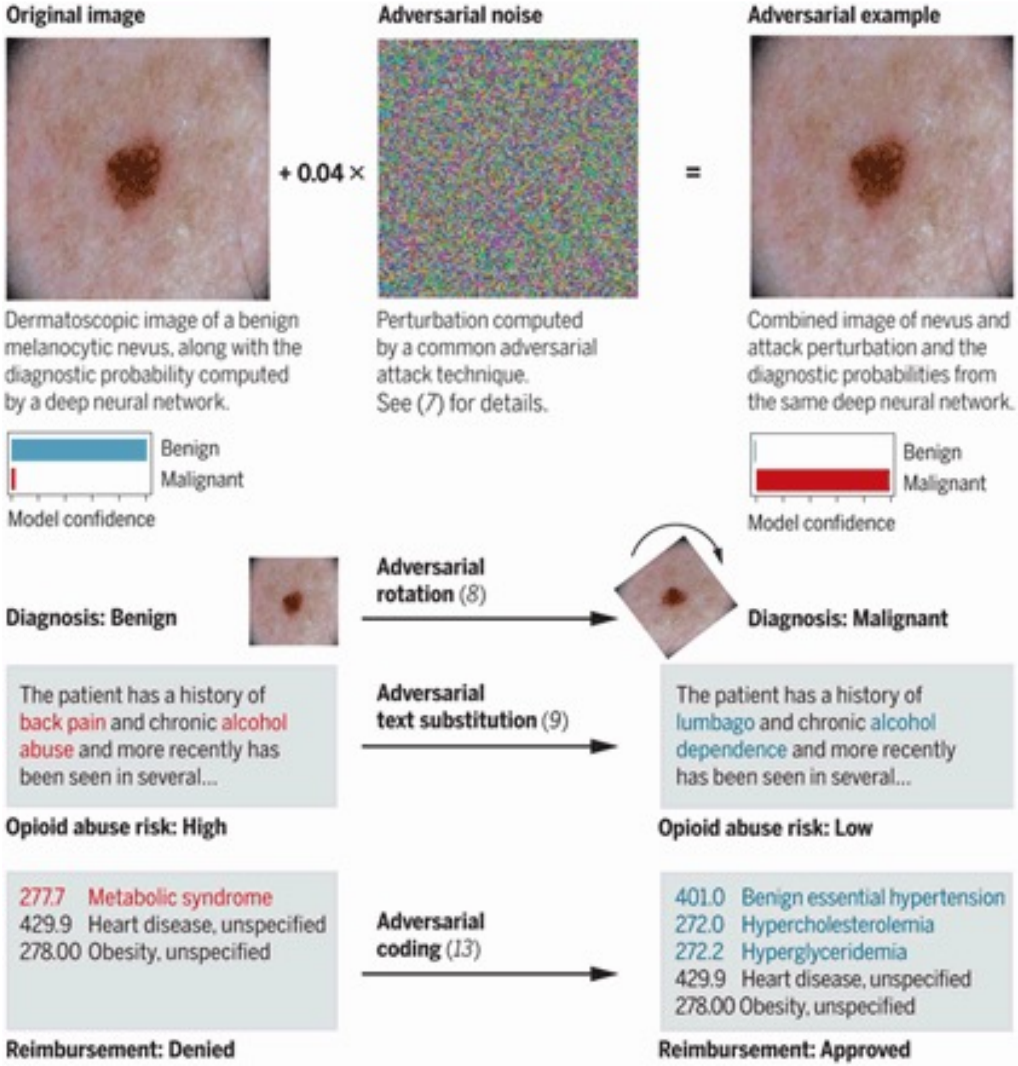
[Submitted on 6 Nov 2020 (v1), last revised 24 Nov 2020 (this version, v2)]

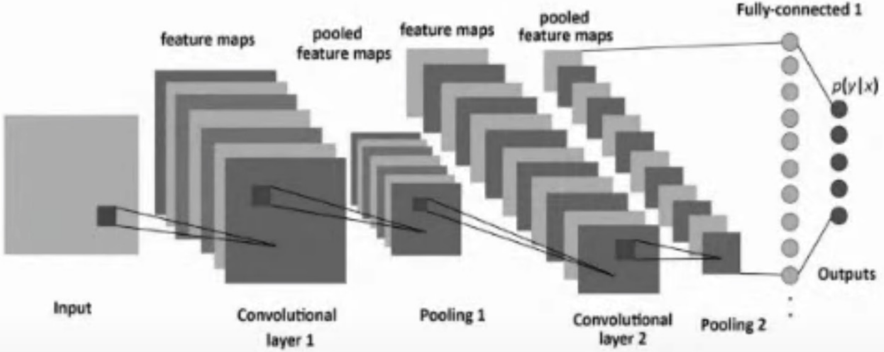
Underspecification Presents Challenges for Credibility in Modern Machine Learning

Alexander D'Amour, Katherine Heller, Dan Moldovan, Ben Adlam, Babak Alipanahi, Alex Beutel, Christina Chen, Jonathan Deaton, Jacob Eisenstein, Matthew D. Hoffman, Farhad Hormozdiari, Neil Houlsby, Shaobo Hou, Ghassen Jerfel, Alan Karthikesalingam, Mario Lucic, Yian Ma, Cory McLean, Diana Mincu, Akinori Mitani, Andrea Montanari, Zachary Nado, Vivek Natarajan, Christopher Nielson, Thomas F. Osborne, Rajiv Raman, Kim Ramasamy, Rory Sayres, Jessica Schrouff, Martin Seneviratne, Shannon Sequeira, Harini Suresh, Victor Veitch, Max Vladymyrov, Xuezhi Wang, Kellie Webster, Steve Yadlowsky, Taedong Yun, Xiaohua Zhai, D. Sculley

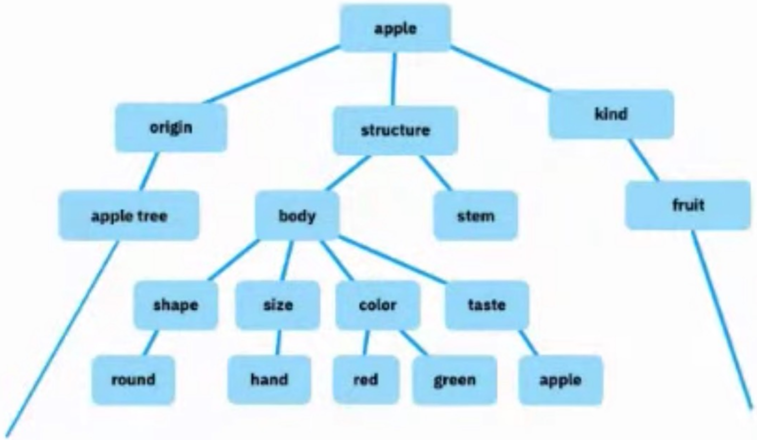
ML models often exhibit unexpectedly poor behavior when they are deployed in real-world domains. We identify underspecification as a key reason for these failures. An ML pipeline is underspecified when it can return many predictors with equivalently strong held-out performance in the training domain. Underspecification is common in modern ML pipelines, such as those based on deep learning. Predictors returned by underspecified pipelines are often treated as equivalent based on their training domain performance, but we show here that such predictors can behave very differently in deployment domains. This ambiguity can lead to instability and poor model behavior in practice, and is a distinct failure mode from previously identified issues arising from structural mismatch between training and deployment domains. We show that this problem appears in a wide variety of practical ML pipelines, using examples from computer vision, medical imaging, natural language processing, clinical risk prediction based on electronic health records, and medical genomics. Our results show the need to explicitly account for underspecification in modeling pipelines that are intended for real-world deployment in any domain.


TEMPE
SELF-DRIVING VEHICLE HITS BICYCLIST
abc 15
ARIZONA


Original image
+ 0.04 ×
Adversarial noise
=
Adversarial example
Dermatoscopic image of a benign melanocytic nevus, along with the diagnostic probability computed by a deep neural network.
Perturbation computed by a common adversarial attack technique. See (7) for details.
Combined image of nevus and attack perturbation and the diagnostic probabilities from the same deep neural network.
Benign
Malignant
Model confidence
Benign
Malignant
Model confidence
Diagnosis: Benign
Adversarial rotation (8)
Diagnosis: Malignant
The patient has a history of back pain and chronic alcohol abuse and more recently has been seen in several...
Adversarial text substitution (9)
The patient has a history of lumbago and chronic alcohol dependence and more recently has been seen in several...
Opioid abuse risk: High
Opioid abuse risk: Low
277.7 Metabolic syndrome
429.9 Heart disease, unspecified
278.00 Obesity, unspecified
Adversarial coding (13)
401.0 Benign essential hypertension
272.0 Hypercholesterolemia
272.2 Hyperglyceridemia
429.9 Heart disease, unspecified
278.00 Obesity, unspecified
Reimbursement: Denied
Reimbursement: Approved



+

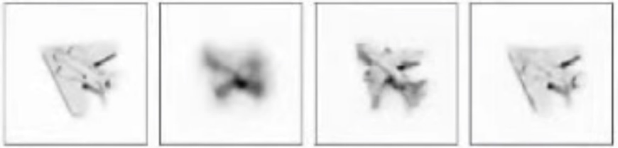



```
(:action pickup

 :parameters (?b1 ?b2 - block)

 :precondition (and (on ?b1 ?b2)
                    (hand-clear))

 :effect (and (not (hand-clear))
              (not (on ?b1 ?b2))
              (holding ?b1))
)
```

NEURAL NETWORKS

SYMBOLIC AI

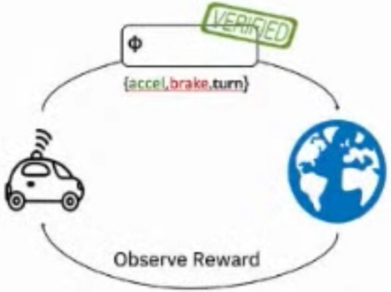
Neurosymbolic
Generative Models



(a) Target (b) β-TCVAE (c) DS-VAE with perturbed Z (d) DS-VAE

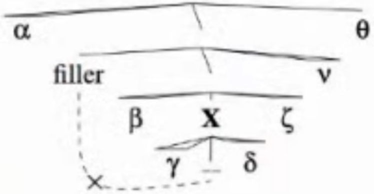
Srivastava et al. 2020 (submitted)

Neurosymbolic
Safe ML/RL



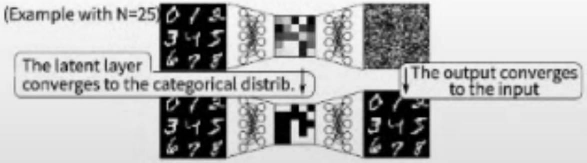
Fulton et al AAAI 2018

Neurosymbolic
NLU



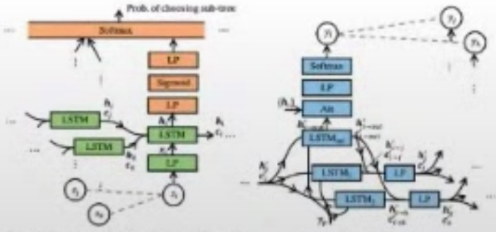
Wilcox et al. NAACL 2019

Neurosymbolic
Planning



Asai et al. AAAI 2018

Neurosymbolic
Code Optimization

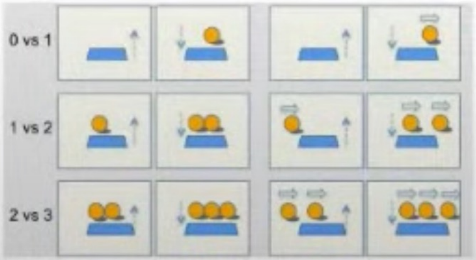


(a) The tree encoder (green) and subtree selector (orange).

(b) The tree decoder.

Shi et al. ICLR 2019

Neurosymbolic
Machine Common Sense



Smith et al. NeurIPS 2019

EMERGENZA SANITARIA

Coronavirus Covid-19: Campus Biomedico Roma, acquisito sistema di intelligenza artificiale per diagnosi precoce utilizzato a Wuhan

18 marzo 2020 @ 18:44

"Il sistema di intelligenza artificiale – si legge in una nota – è in grado di fornire una risposta in 20 secondi partendo dall'analisi delle immagini della Tc polmonare". "Il tasso di attendibilità – viene spiegato – è del 98,5% ed è stato testat[o su] pazienti anonimizzati in cieco dai medici radiologi del Policlin[ico]

THE LANCET
Digital Health

CORRESPONDENCE | VOLUME 2, ISSUE 5, E225, MAY 01, 2020

Cautions about radiologic diagnosis of COVID-19 infection driven by artificial intelligence

Andrea Laghi

Open Access • Published: May, 2020 • DOI: https://doi.org/10.1016/S2589-7500(20)30079-0

References

Article Info

Linked Articles

I read with interest the piece by Becky McCall[1] in *The Lancet Digital Health*. The author interviews several experts from different health-care sectors about the possible role of artificial intelligence (AI) in tackling coronavirus disease 2019 (COVID-19).

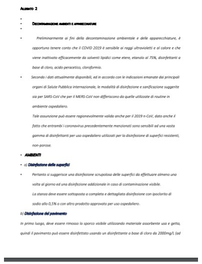
On the one hand, I agree that because AI is causing a paradigm shift in health care there could be many possible uses of AI during this COVID-19 outbreak.[1]

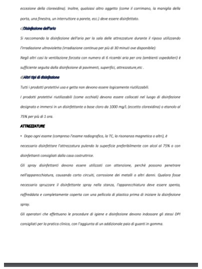
• View related content for this article

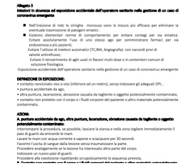
On the other hand, as a radiologist, I disagree with some of the optimistic expectations about the diagnostic value of a particular algorithm applied to lung CT images as outlined by McCall because, in my opinion, this is not yet supported by scientific evidence.

Unfortunately, the little evidence that has been reported shows that approximately 50% of patients with COVID-19 infection have a normal CT scan, if scanned early after the onset of symptoms.[2] This evidence is the main reason why the American College of Radiology does not consider CT imaging as a useful screening test in asymptomatic individuals.[3]

One of the experts that McCall interviewed states that "while a manual read of a CT scan can take up to 15 minutes, AI can finish reading the image in 10 seconds". I don't think this is in line with the daily diagnostic reality. To detect a diffuse lung parenchyma abnormality, a non-specialised radiologist takes a few seconds to scroll the entire image dataset and there is also no risk of not identifying the lesion because it is extremely obvious.



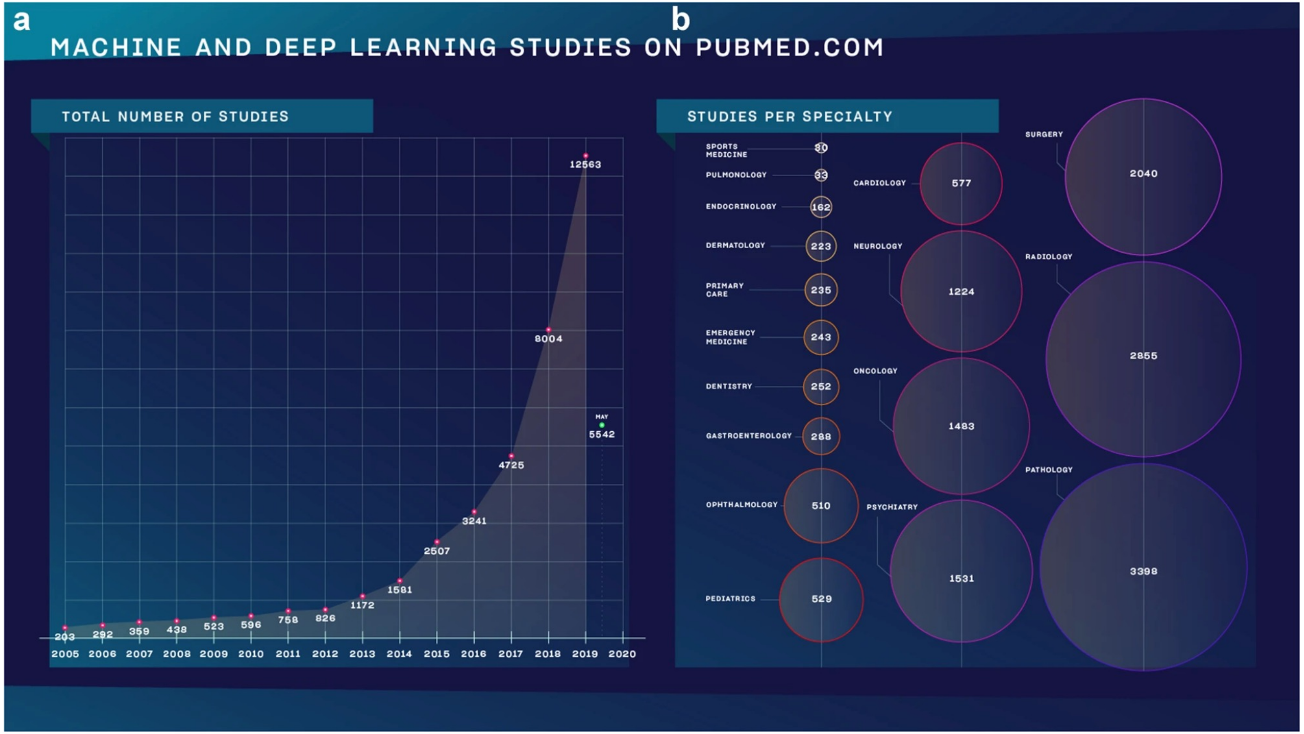




Cambi d'aria per ora	Minuti richiesti per la rimozione contaminanti 99%	99,9%
1	276	414
6	46	69
10	28	41
15	18	28
20	14	21
50	6	8

CDC 1993

From: A short guide for medical professionals in the era of artificial intelligence

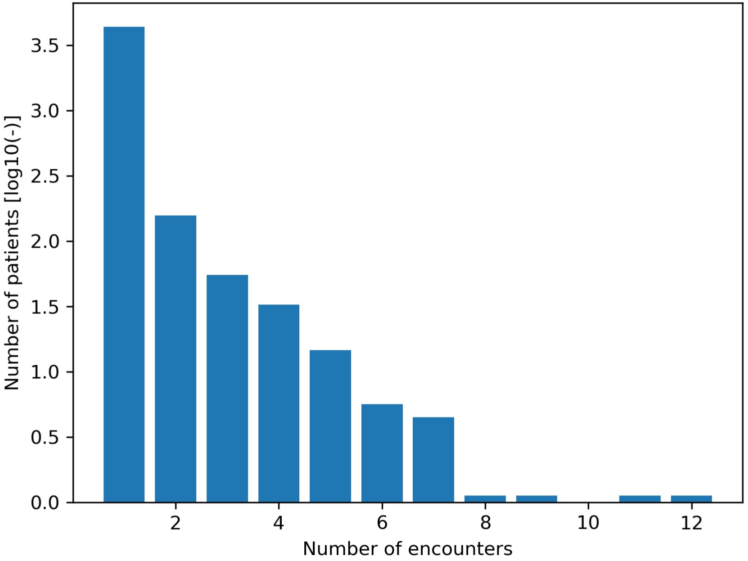


a The number of studies as found on Pubmed.com using the search term)“machine learning” OR “deep learning”) and choosing a year in advanced search. **b** The same search method was used followed by (AND specialty) without specifying a time frame. The number in the circles determine how many studies we found.

Back to article page ›

Distribution of the number of encounters for the selected cohort to go from “Aortic valve disorder (disorder)” to “Aortic stenosis, non-rheumatic (disorder)”

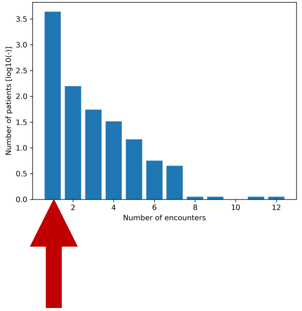
In the majority of the patients both features are found during the same hospital encounter, however for some patients the journey is longer and takes up to 12 encounters considering a maximum temporal window of 60days.



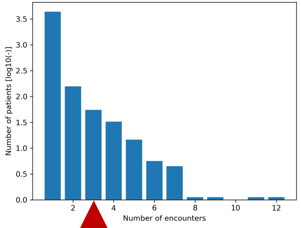
All the pathways of all the patients are computed and aggregated to show the cohort Sankey diagram

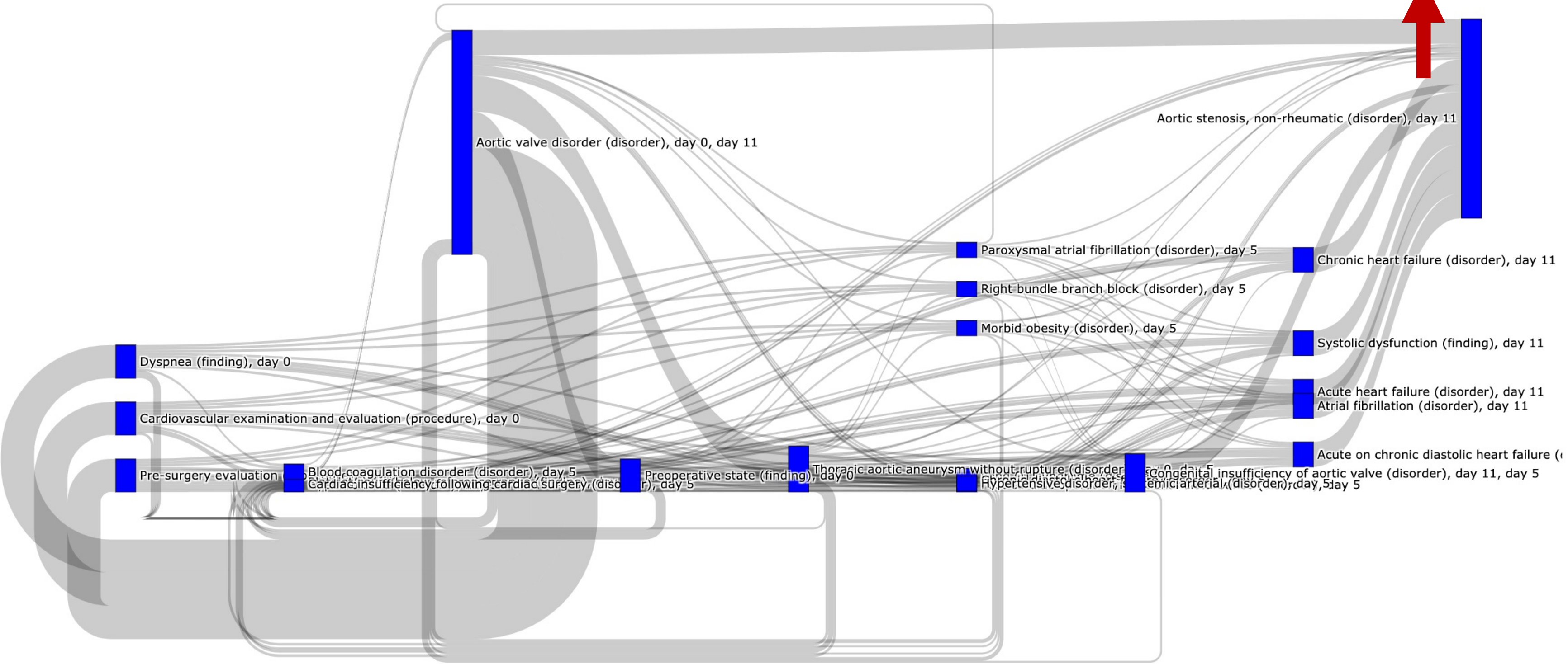
The next 3 slides show the pathways of selected patients at a glance with 1, 3, and 12 encounters

1 patient from the base query with temporal evolution along a maximum of 60 days
The patient with least encounters: the same day both start and end events happened

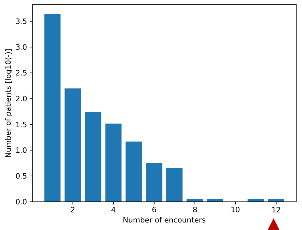


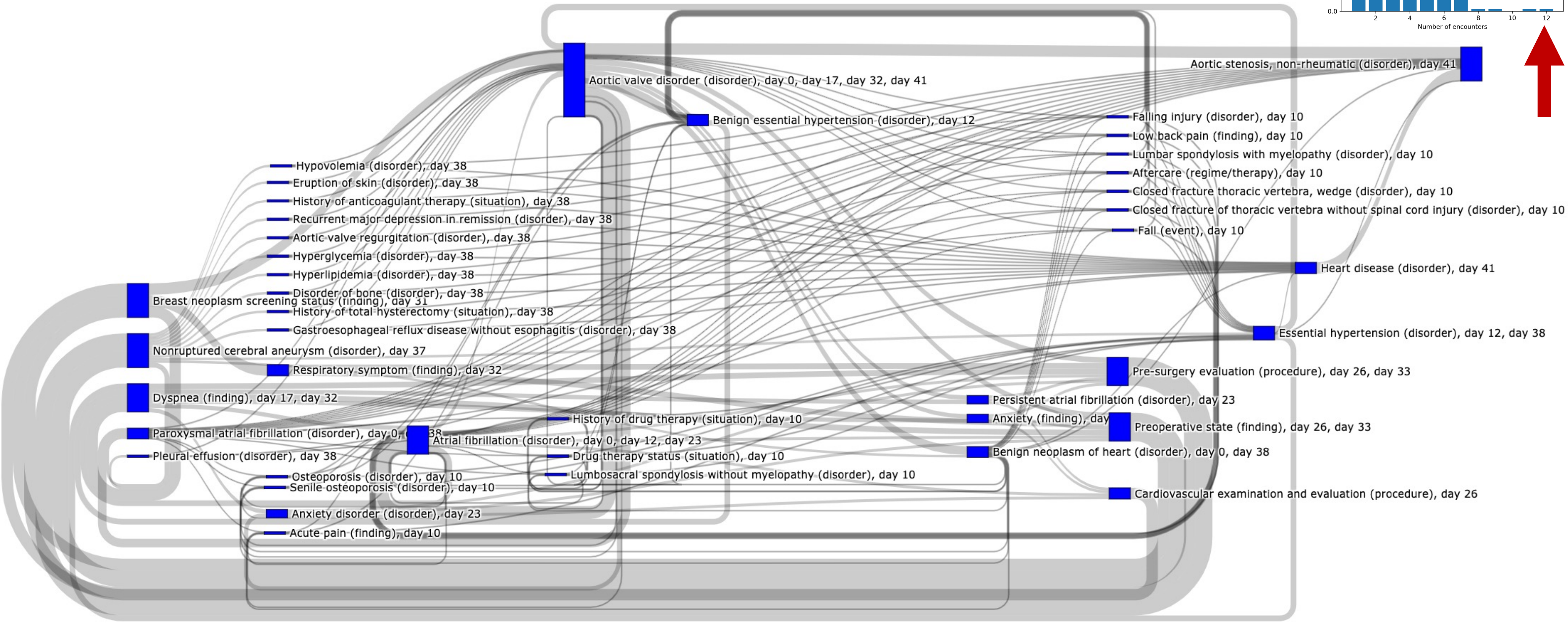
1 patient from the base query with temporal evolution along a maximum of 60 days
A patient with 3 encounters over 11 days





1 patient from the base query with temporal evolution along a maximum of 60 days
The patient with most encounters in the cohort with maximum time window of 60 days





Uomo 89 anni
-ipertensione arteriosa labile;
- '94 episodio di diplopia (indagato con TAC e Doppler dei vasi epiaortici); da allora seguito dal dott.Alberti per riscontro di soffio da insufficienza aortica non severa;
- '95 ECO: dilatazione ed ipertrofia ventricolare sinistra; insufficienza aortica di media severità, normale funzione ventricolare sinistra;
- '96 segnalata disfunzione Vsin; indagine emodinamica: FEVS ai limiti (58%), coronarie normali, IAo grado 2. fibrillazione atriale parossistica durante la degenza.
- '99 sincope verosimilmente vasovagale. ECO e HOLTER negativi.
- successivi controlli c/o il CCV;
-2005 visita cardiologica per episodi di dispnea da sforzo ed edemi arti inferiori: riscontro ECG ed Holter di bradicardia sinusale, BAV I grado , BAV II M1 ed M2, BAV avanazato con episodi di dissociazione AV; all'ECO: Vsin con ipocinesia infero settale ed inferiore con FE conservata, Vdx normocinetico. Moderata dilatazione atriale sinistra e lieve destra. Stenosi aortica lieve ed insufficienza aortica moderata.
Trattato con impianto di PM DDD 4 /2005.
-3-2008 ricovero in medicina d'urgenza e dimesso con diagnosi di IMA Broncopolmonite destra, disfunzione Vsn severa, Ipertensionea rteriosa . BBsn completo. malattia da reflusso gastroesofageo . Morbo di Parkinson.
-successivo controllo presso la Pineta del carso per edemi importanti e episodi di oppressione toracica.
5-2008 visita cardiologica per persistenza di edemi declivi ed episodi di oppressione toracica: Dorme con un cuscino alto, non riferisce dispnea parossistica notturna. non dispnea da sforzo. Episodi di oppressione toracica a destra forse atipici.
EO: Dolore (0-10): 0 Moderati edmi declivi, polsi distali sembrano pesenti, Addome trattabile. Attività caridaca ritmica, 3° tono, soffio da IM , IT e soffio aortico sistolico. Non soffi carotidei. PA 155/70 mmHg.
5-2008 ECG RS 68 /min. occasionali extrasistoli ventricolari. BBsn completo. Modificata la terapai con introduzione di digitale
-06/06/2008 ECG Ritmo sinusale 61/min, Blocco di branca sinistra completo
-13/06/2008 AGGIORNAMENTO
In considerazione alla modificazioni della terapia con aggiunta della digitale l'ECG mostra buone frequnze senza evidenza di ritardi di conduzione.
Continui con la terpia in atto.
-22-1-09 visita CCV: asintomatico/paucisintomatico per dispnea (NYHA I-II,), sporadici episodi notturni a riposo di fastidio all'emitorace dx di tipo oppressivo a risoluzione spontanea in minuti, PA 140/62, problemi di deambulazione per m di Parkinson
EO: peso 70,100Kg (stabile)x175cm, PV =0, RAG assente, Attività cardiaca ritmica, soffio da IM 1-2/6 e soffio aortico sistolico 2/6 e protodiastolico PS3. Non soffi carotidei. PA 140/60 mmHg, edemi malleolari ++
E.C.G. : ritmo indotto da pacemaker (atrioguidato) 60 bpm deviazione assiale sinistra
blocco di branca sinistra
-1-10-09 visita CCV: asintomatico, PA ben controllata
EO: PV =0, RAG assente, Attività cardiaca ritmica, soffio da IM 1-2/6 e soffio aortico sistolico 2/6 e protodiastolico PS3, edemi malleolari ++
Altezza: 170 cm Peso: 69,5 Kg FC: 60 B/min PA: 140 / 80mmHg BSA: 1,8 BMI: 24,05 E.C.G. : ritmo indotto da pacemaker con stimolazione atriale , fc 60 bpm, ben funzionante
-13-4-10 visita CCV: asintomatico
EO PV =0, RAG assente, Attività cardiaca ritmica, soffio da IM 1-2/6 e soffio aortico sistolico 2/6 e protodiastolico PS3, edemi malleolari ++
Altezza: 172 cm Peso: 70,0 Kg FC: 65 B/min
PA: 140 / 55 mmHg BSA: 1,83
E.C.G. ritmo sinusale e talora indotto da pacemaker, occasionali extrasistoli ventricolari con occasionali extrasistoli sopraventricolari
blocco di branca sinistra completo
-30-12-10 visita CCV pauci/asintomatico dal punto di vista cardiologico, deambula con difficoltà per Parkinson invalidante, viene in visita in carrozzina accompagnato dal nipote

Esame obiettivo

Esame Obiettivo: PV =0, RAG assente, Attività cardiaca ritmica, soffio da IM 1-2/6 e soffio aortico sistolico 2/6 e protodiastolico PS3, edemi malleolari ++

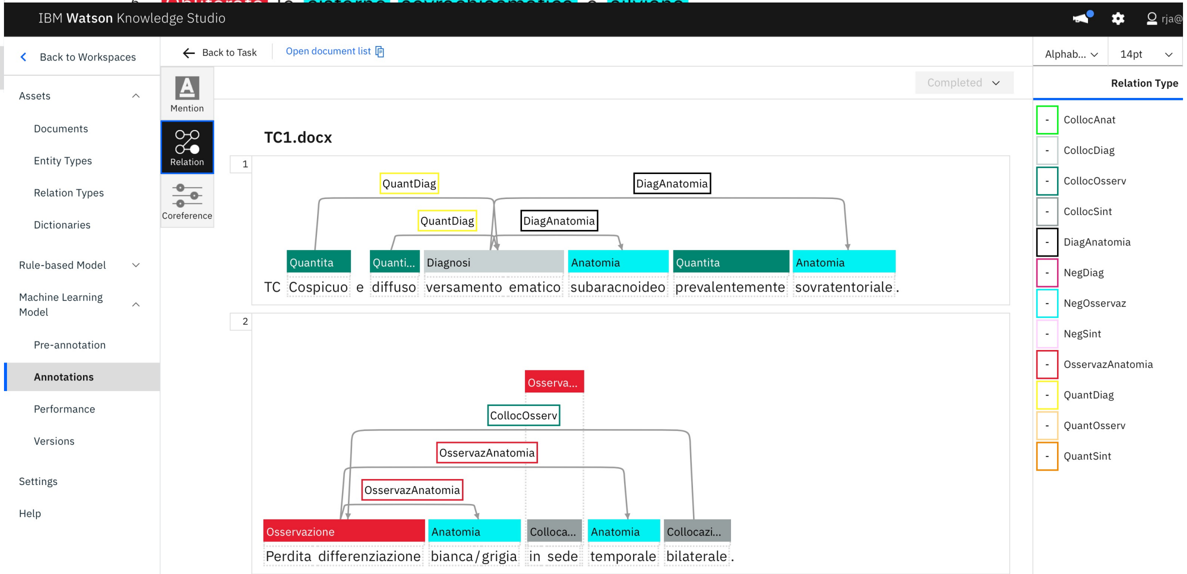
Parametri funzionali
Altezza: 170 cm FC: 60 B/min
PA: 120 / 80 mmHg

Esami Strumentali:
E.C.G. 30-12-2010
Referto: ritmo indotto da pacemaker bicamerale 60bpm

Diagnosi
Cardiopatia ipertensiva e valvolare
Cardiopatia ischemica con severa disfunzione ventricolare sinistra
Ipertensione Arteriosa controllata in terapia
Insufficienza della Valvola Aortica di grado moderato
Blocco Atrioventricolare avanzato con dissociazione AV.
Blocco di Branca Sinistra completo
Fibrillazione atriale parossistico/a
Scompenso Cardiaco Cronico congestizio controllato in terapia
Dislipidemia mista di grado lieve
Aneurisma vascolare dell'aorta ascendente (radice aortica 4.1cm)

Prescrizione
LASIX 25 MG 1-2 cp die da adeguare secondo peso, diuresi ed edemi declivi.
MESALAZINA "400 MG COMPRESSE GASTRORESISTENTI" 50 COMPRESSE GASTRORESISTENTI 1 cp ore 8.
CARDIOASPIRIN 100 MG 1 cp ore 13 (a stomaco pieno).
LANSOPRAZOLO DOC - 30MG 14CPS 30MG 14CPS 1 cp ore 8.
MONOKET "MULTITAB" 60 MG 1 cp ore 8.
STALEVO - 100+25+200MG 100CPR 100+25+200MG 100CPR 1 cp x 5 dì
ENALAPRIL ACV - 5MG 28CPR 5MG 28CPR 1 cp x 2 (ore 8-20)

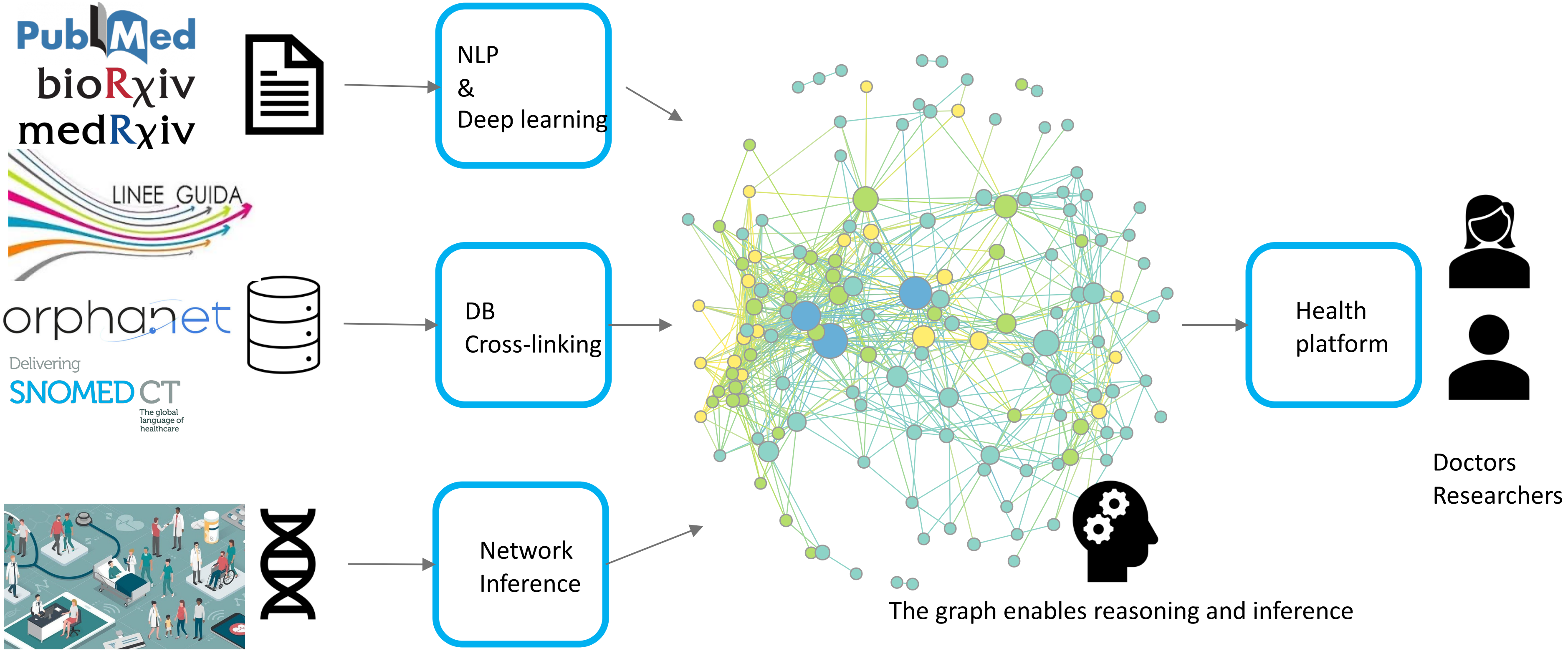
Raccomandazioni al paziente (inutile)
Si raccomanda la profilassi dell'endocardite infettiva
La profilassi antibiotica dell'endocardite batterica e' altamente raccomandata in pazienti con protesi valvolari cardiache, pregressa endocardite batterica, cardiopatie congenite e valvulopatie prima di eseguire procedure dentarie (estrazioni, procedure periodontali, implantologia, pulizia dentale e rimozione del tartaro e comunque tutte le procedure in cui si puo' verificare sanguinamento), procedure chirurgiche del tratto respiratorio (inclusa broncoscopia con broncoscopio rigido), del tratto gastrointestinale (incluse le procedure endoscopiche se associate a prelievo bioptico) e urinario (inclusa cistoscopia).
Non necessitano generalmente di profilassi antibiotica procedure di intubazione endotracheale, broncoscopia con broncoscopio flessibile, ecocardiogramma transesofageo, esofagogastroduodenoscopia (senza prelievo bioptico), cateterismo cardiaco, compresa angioplastica. Un'alimentazione corretta ed equilibrata è molto importante. Al posto di cibi troppo grassi, preferite alimenti che contengono fibre e carboidrati (pane, pasta, cerali, riso, patate). Preferire ai grassi saturi (burro, derivati animali), i grassi monoinsaturi (olio d'oliva) o polinsaturi (olio di semi). Ottima la frutta e verdura ma attenzione a non assumere troppi liquidi. Cucinate con poco sale e non aggiungetene dopo la cottura, evitate di abusare dei cibi conservati (insaccati, scatolette, ecc). Pesatevi ogni giorno. Una variazione di peso oltre 1 kg in 2-3 giorni che state trattenendo (se aumentate) o perdendo (se calate) troppi liquidi. Sarà quindi necessario o ridurre la quantità di liquidi introdotti (acqua, bevande varie, frutta, minestre, verdura) o variare la dose del diuretico (ad esempio LASIX-



5) Are only english terms found in the FMA?

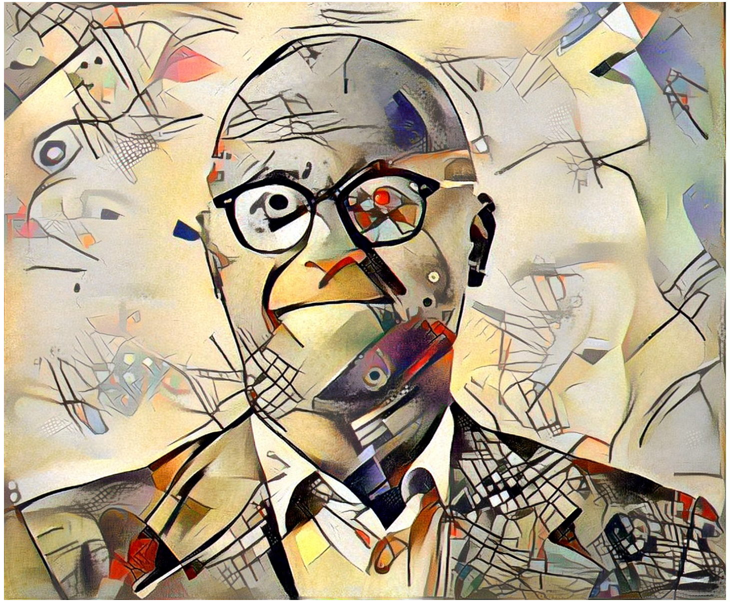
The FMA contains 8,500 Latin, 4,700 French, 500 Spanish, 350 German terms.

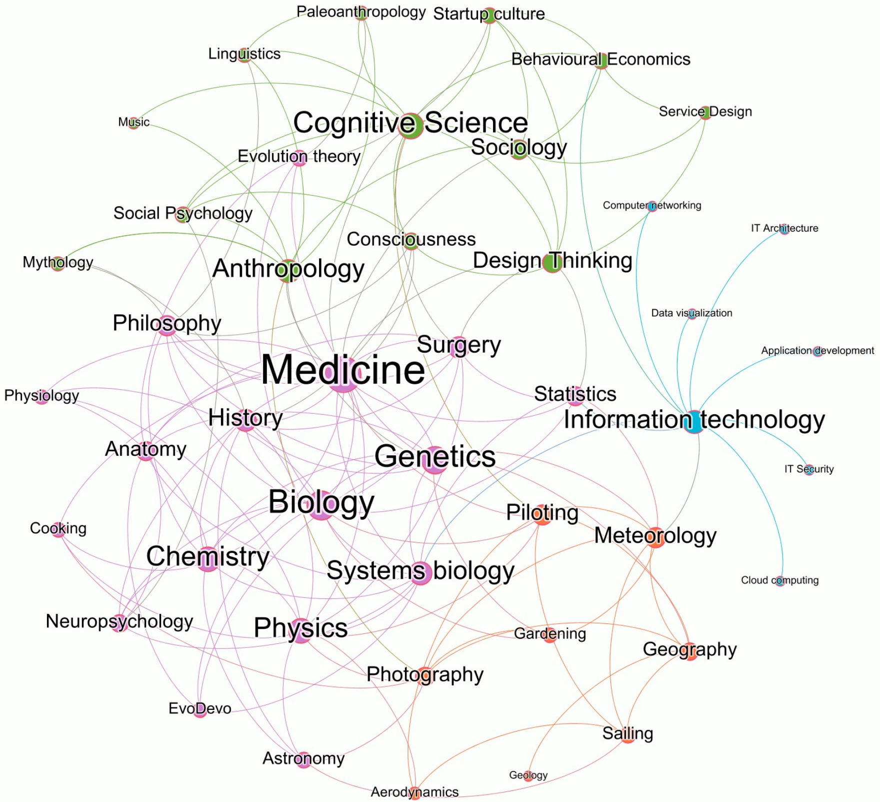
AI for dynamic healthcare and medical knowledge



The system is continuously updated in a dynamic fashion, to untap newest findings

Thank you for your attention





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