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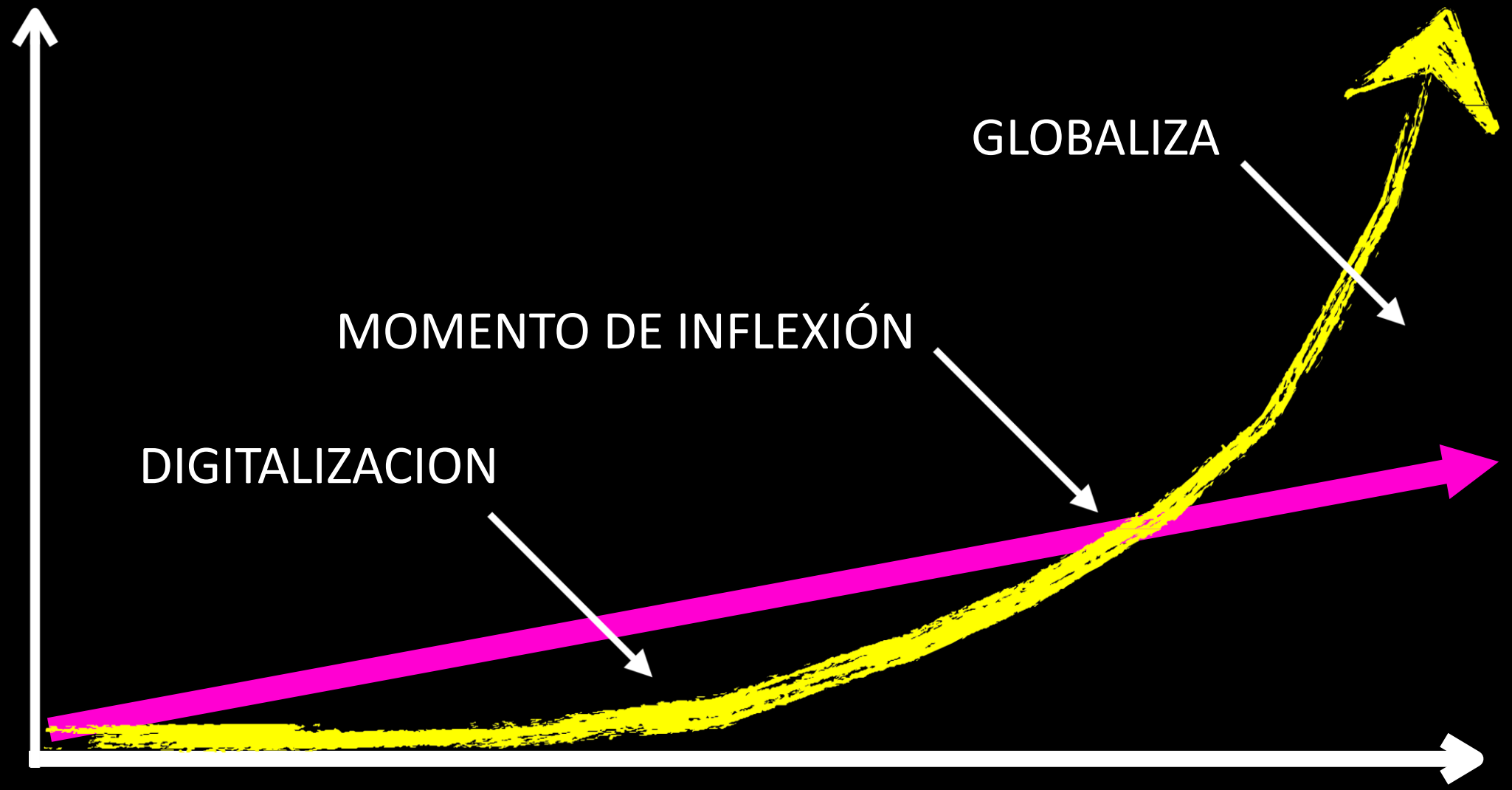
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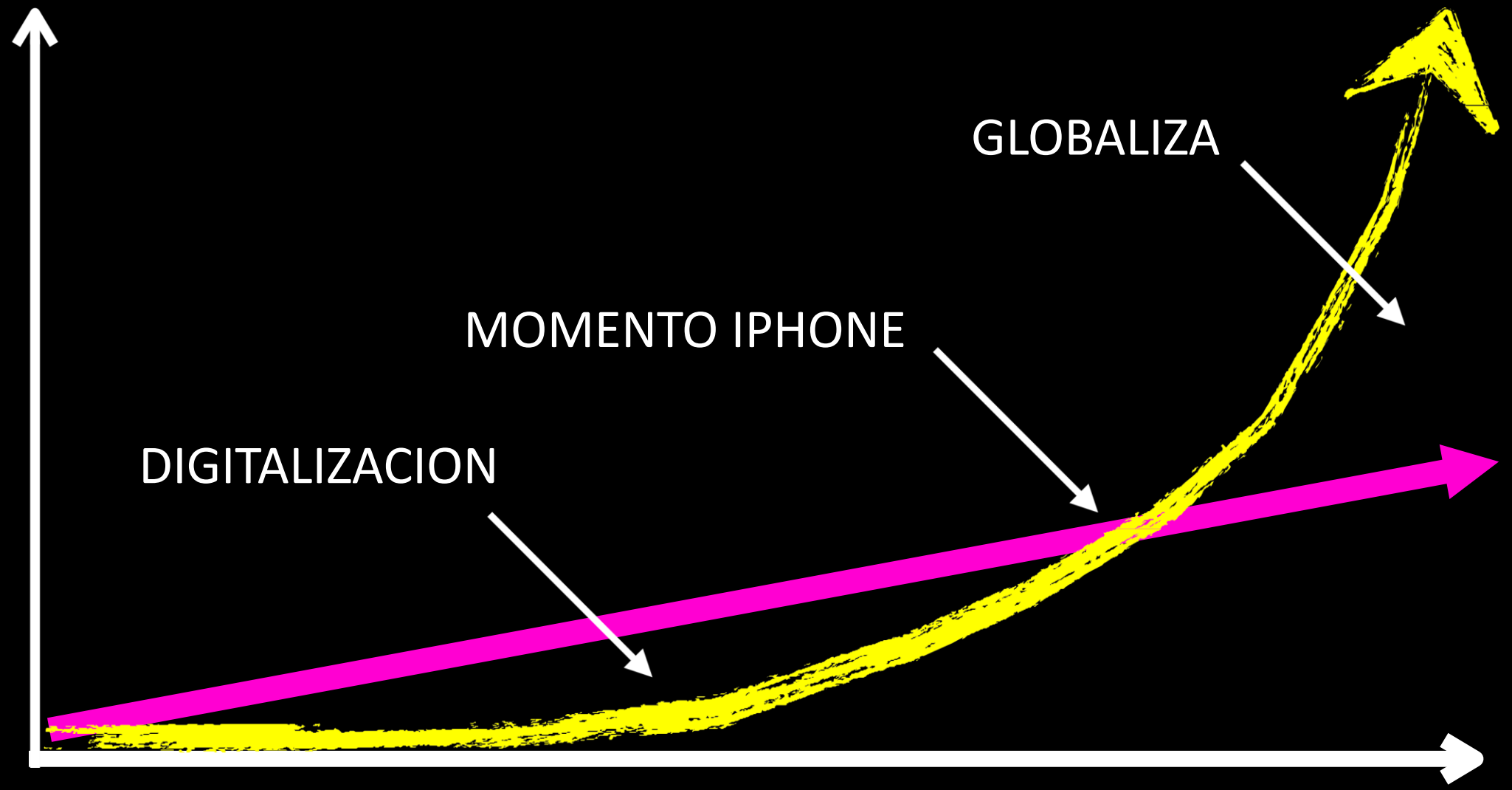
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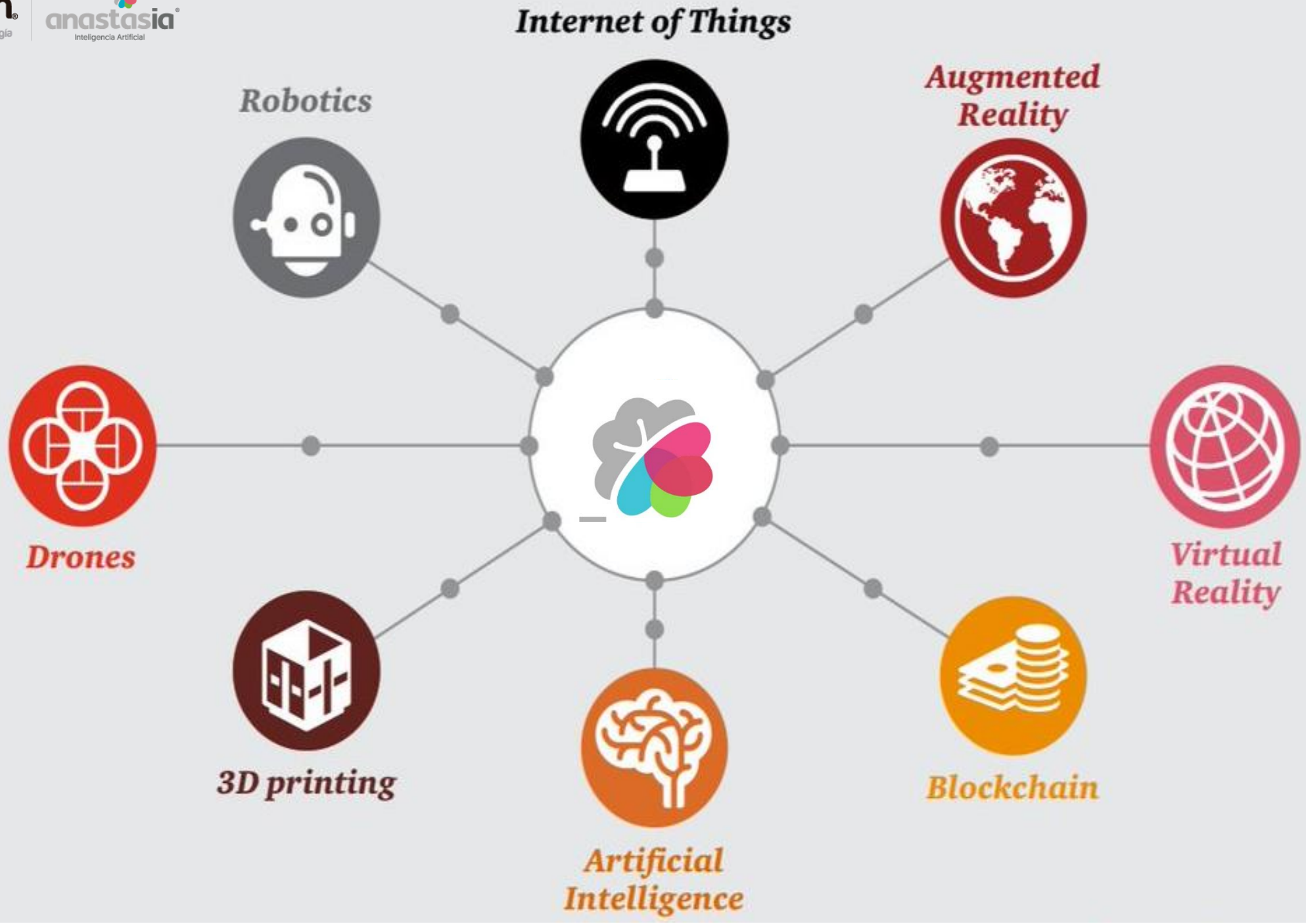

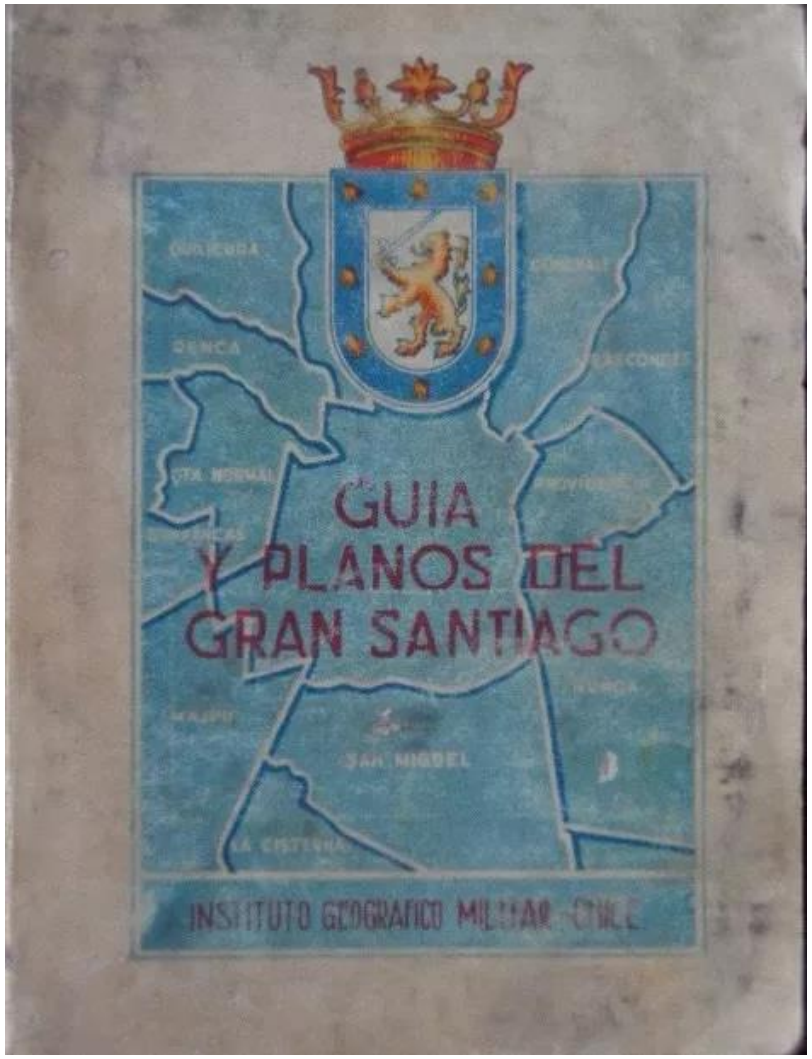

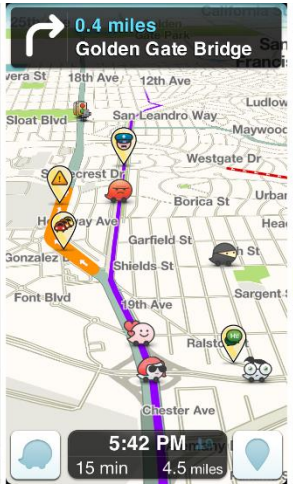

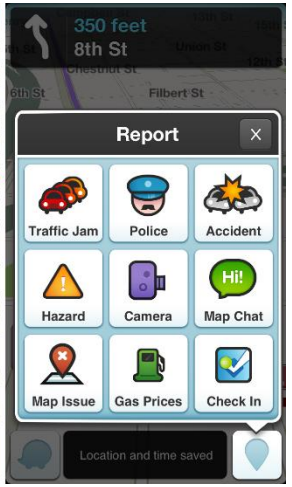

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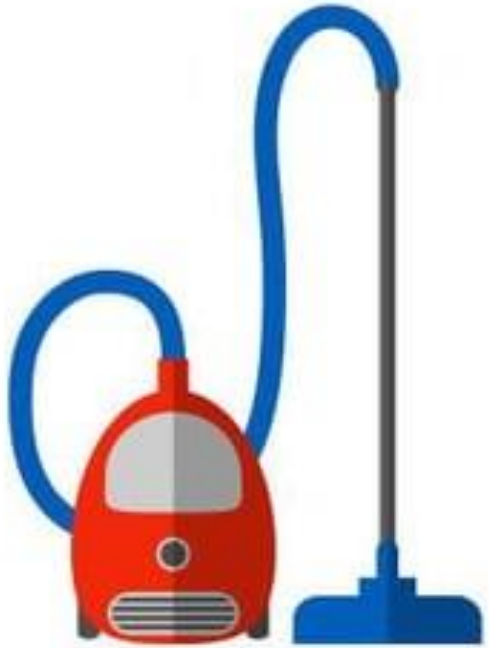

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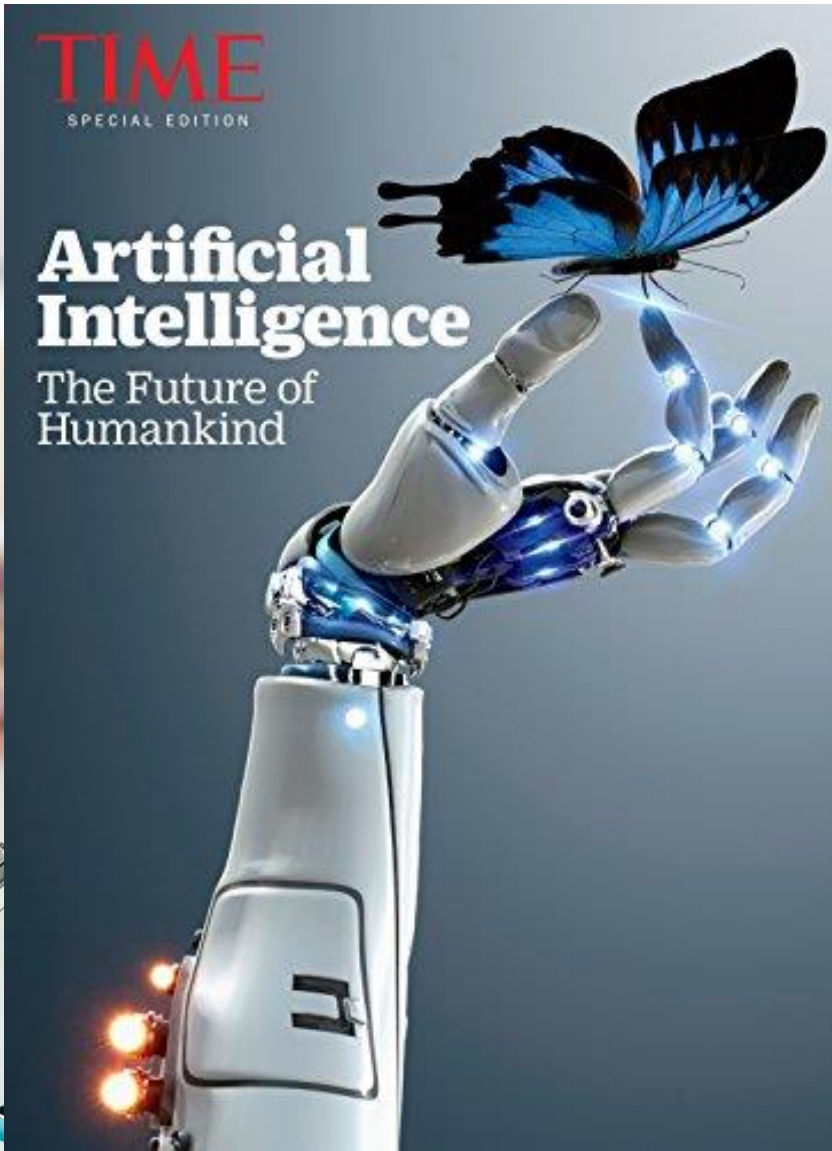

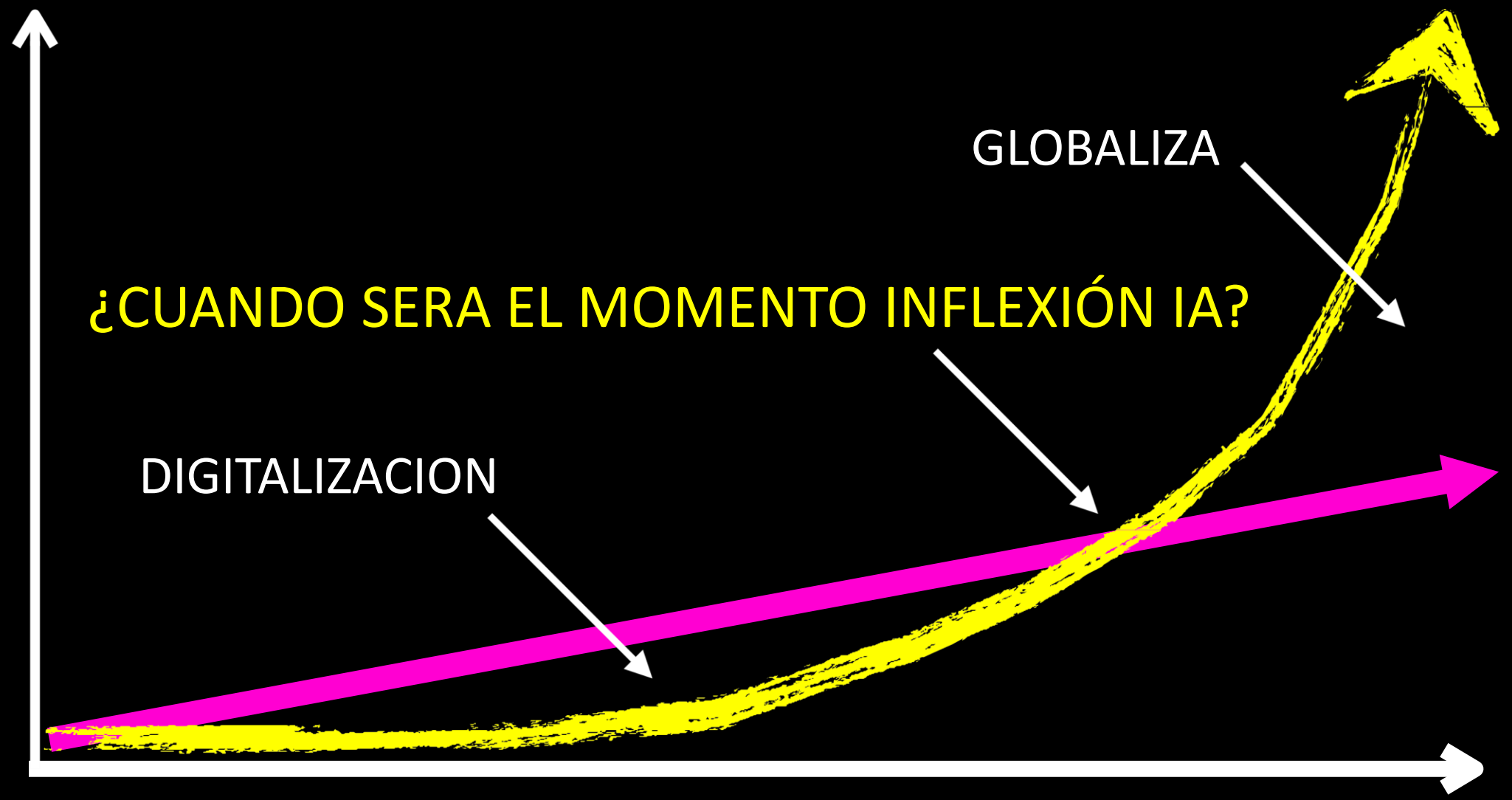
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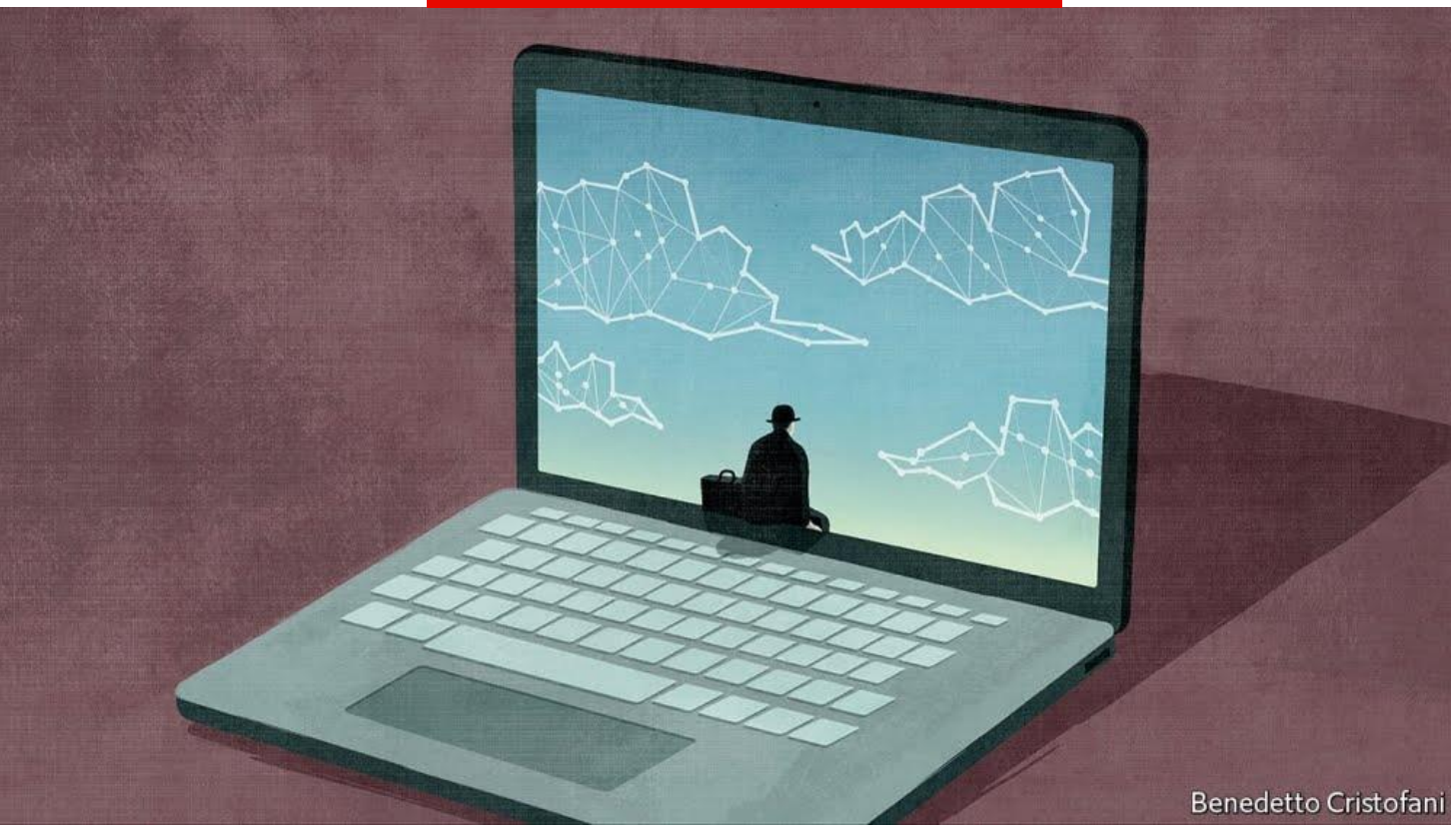
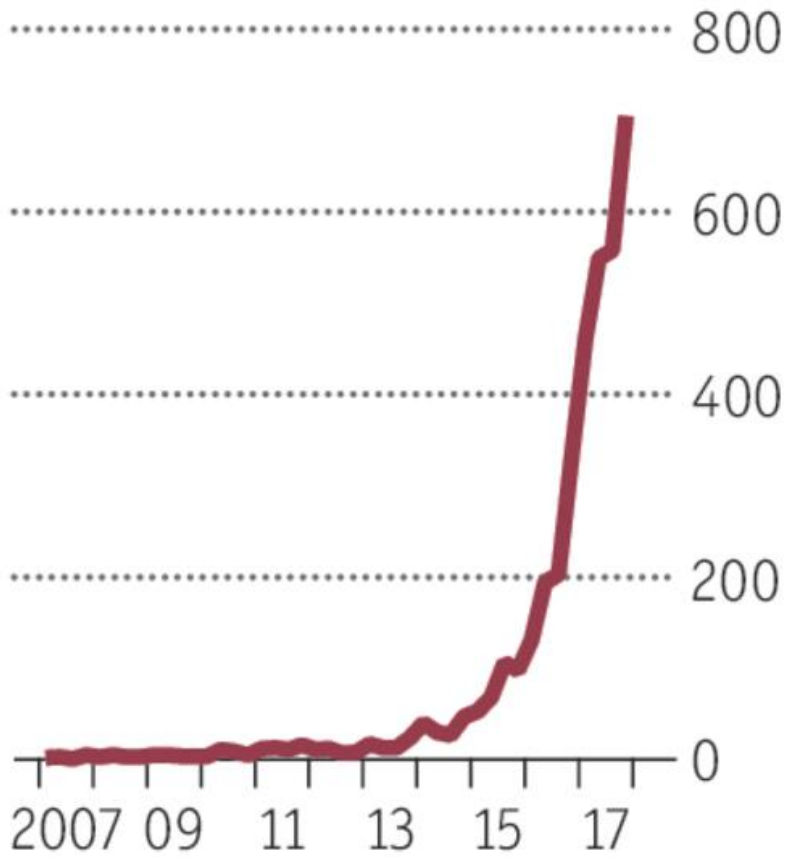


https://www.economist.com/special-report/2018/03/28/non-tech-businesses-are-beginning-to-use-artificial-intelligence-at-scale

Machine earning

Mentions of AI and machine learning on earnings calls of public companies



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[v:1703.00810v1 [cs.LG] 2 Mar 2017

Opening the Black Box of Deep Neural Networks via Information

Ravid Shwartz-Ziv [1] Naftali Tishby [1 2]

Abstract

Despite their great success, there is still no comprehensive theoretical understanding of learning with Deep Neural Networks (DNNs) or their inner organization. Previous work [Tishby & Zaslavsky (2015)] proposed to analyze DNNs in the *Information Plane*; i.e., the plane of the Mutual Information values that each layer preserves on the input and output variables. They suggested that the goal of the network is to optimize the Information Bottleneck (IB) tradeoff between compression and prediction, successively, for each layer.

In this work we follow up on this idea and demonstrate the effectiveness of the Information-Plane visualization of DNNs. We first show that the stochastic gradient descent (SGD) epochs have two distinct phases: fast empirical error minimization followed by slow representation compression, for each layer. We then argue that the DNN layers end up very close to the IB theoretical bound, and present a new theoretical argument for the computational benefit of the hidden layers.

1. Introduction

In the last decade, deep learning algorithms have made

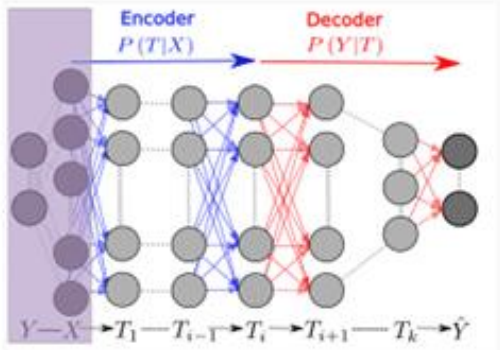
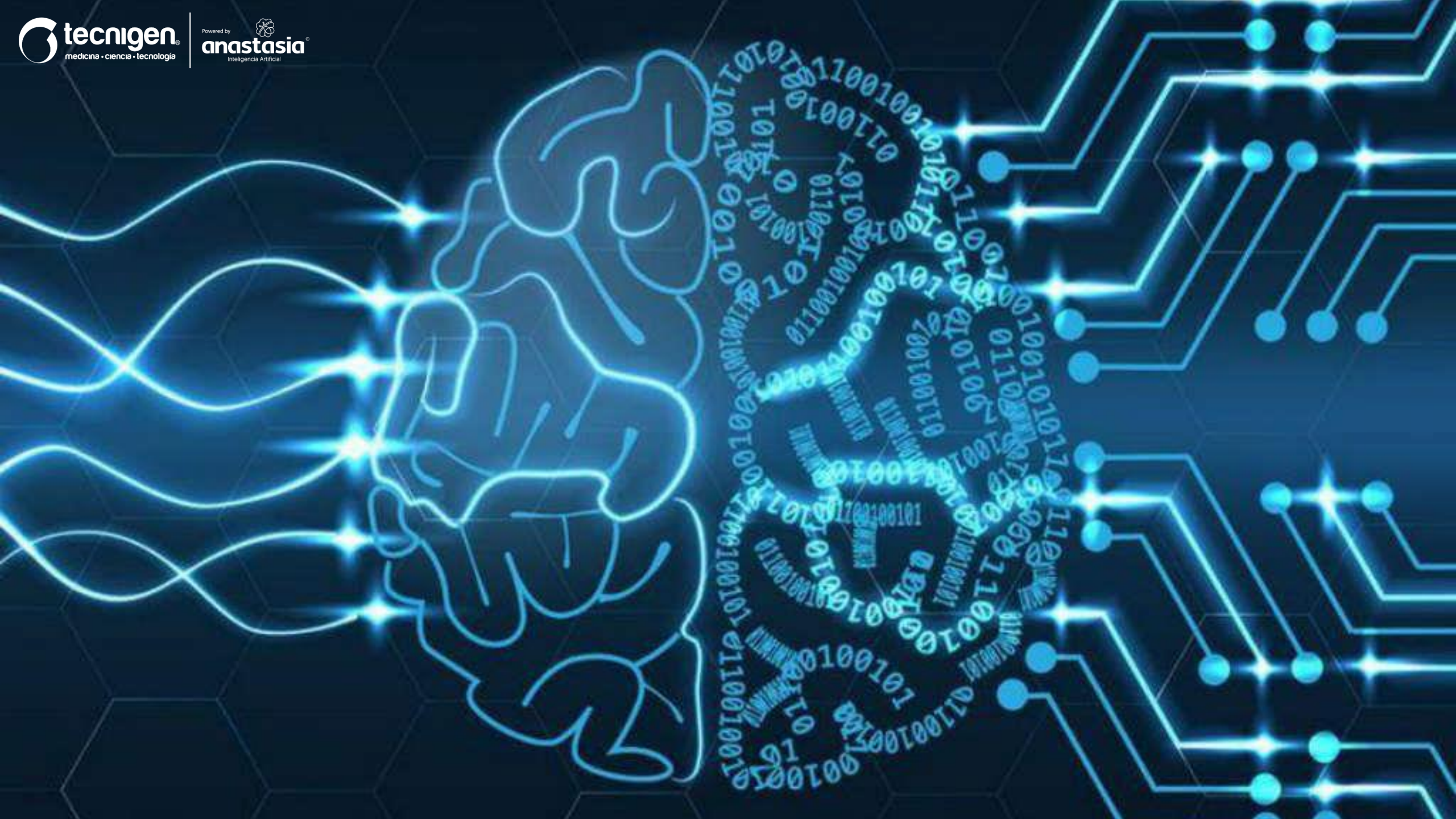


Figure 1. The DNN layers form a Markov chain of successive internal representations of the input layer X. Any representation of the input, T, is defined through an encoder, $P(T|X)$, and a decoder $P(\hat{Y}|T)$, and can be quantified by its *information plane* coordinates: $I_X = I(X;T)$ and $I_Y = I(T;Y)$. The Information Bottleneck bound characterizes the optimal representations, which maximally compress the input X, for a given mutual information on the desired output Y.

In Tishby & Zaslavsky (2015), the authors noted that layered neural networks form a Markov chain of successive representations of the input layer and suggested studying them in the *Information Plane* - the plane of the Mutual Information values of any other variable with the input variable X and desired output variable Y (Figure 1). The ra-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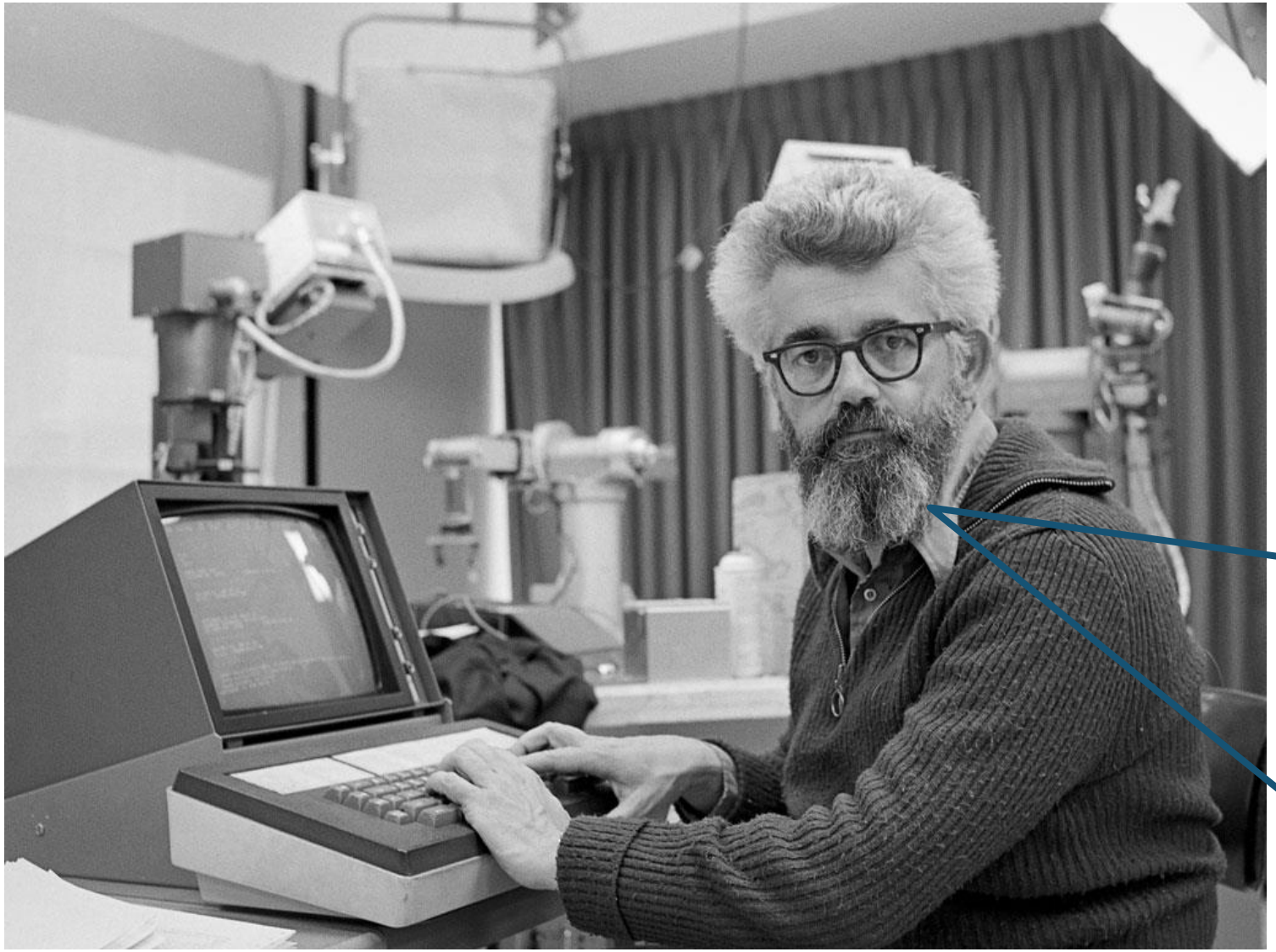

"descubrir cómo hacer que las máquinas utilicen el lenguaje, formen abstracciones y conceptos, resuelvan tipos de problemas que ahora están reservados para los humanos y mejoren por sí mismas. Creemos que se puede lograr un avance significativo en uno o más de estos problemas si un grupo de científicos cuidadosamente seleccionados trabajan en conjunto por un verano"

John McCarthy Científico computacional y cognitivo. Ph.D. en Matemáticas (1927 – 2011)

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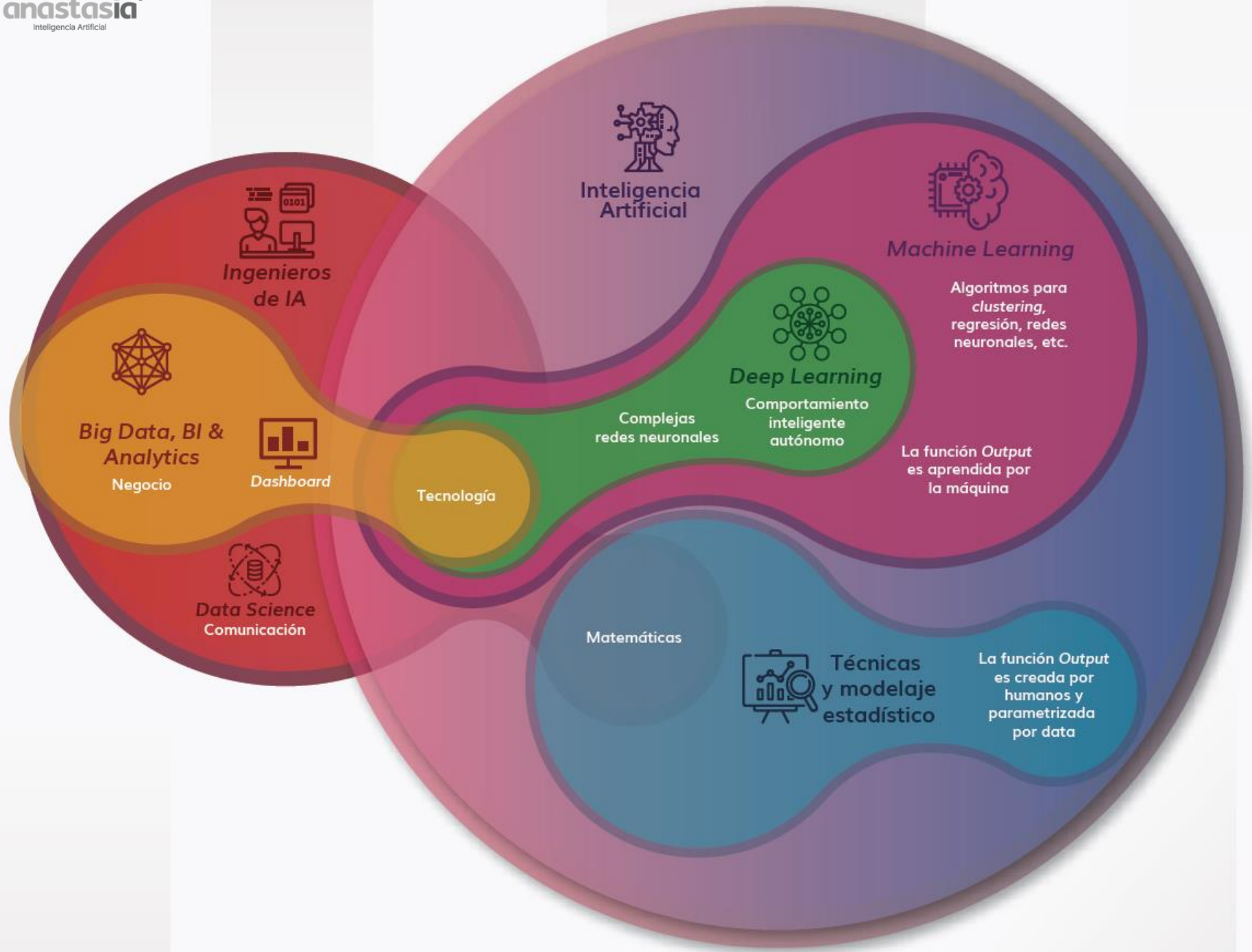
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Algoritmos para clustering, regresión, redes neuronales, etc.
Deep Learning
Comportamiento inteligente autónomo
Complejas redes neuronales
La función Output es aprendida por la máquina
Ingenieros de IA
Big Data, BI & Analytics
Negocio
Dashboard
Tecnología
Data Science
Comunicación
Matemáticas
Técnicas y modelaje estadístico
La función Output es creada por humanos y parametrizada por data

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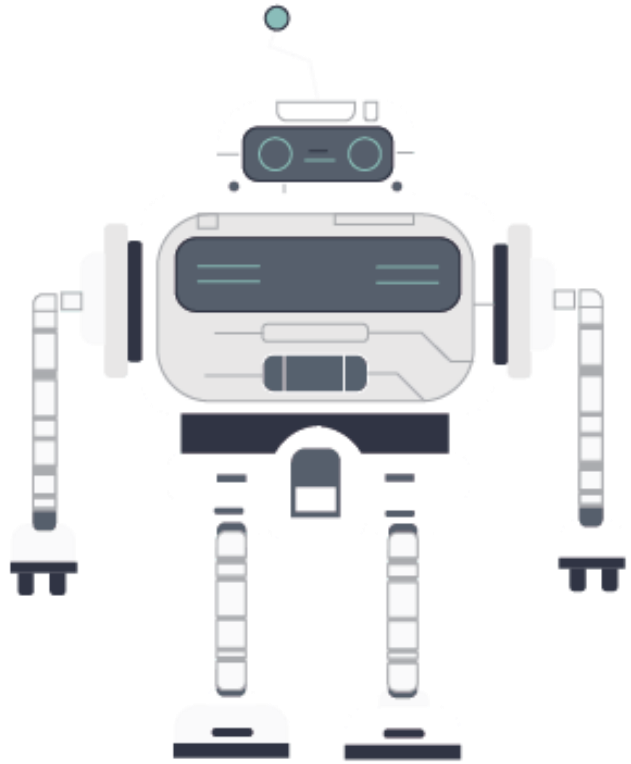

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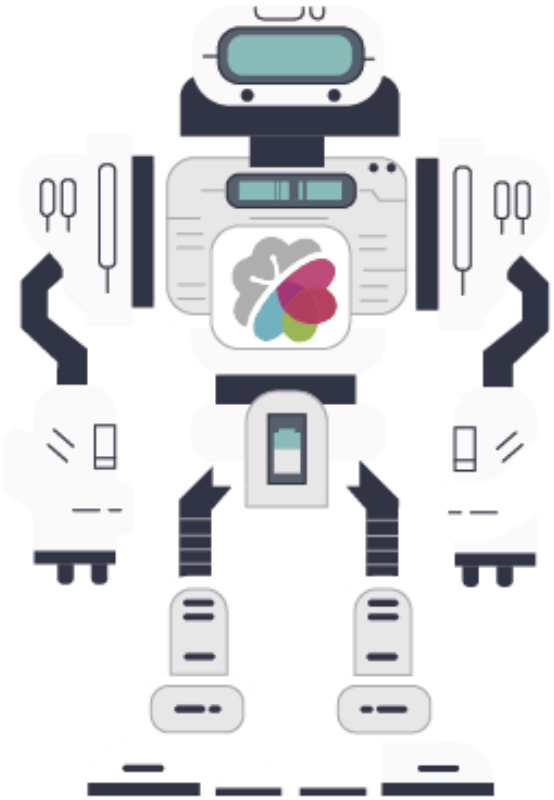

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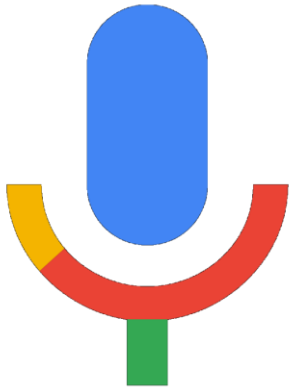

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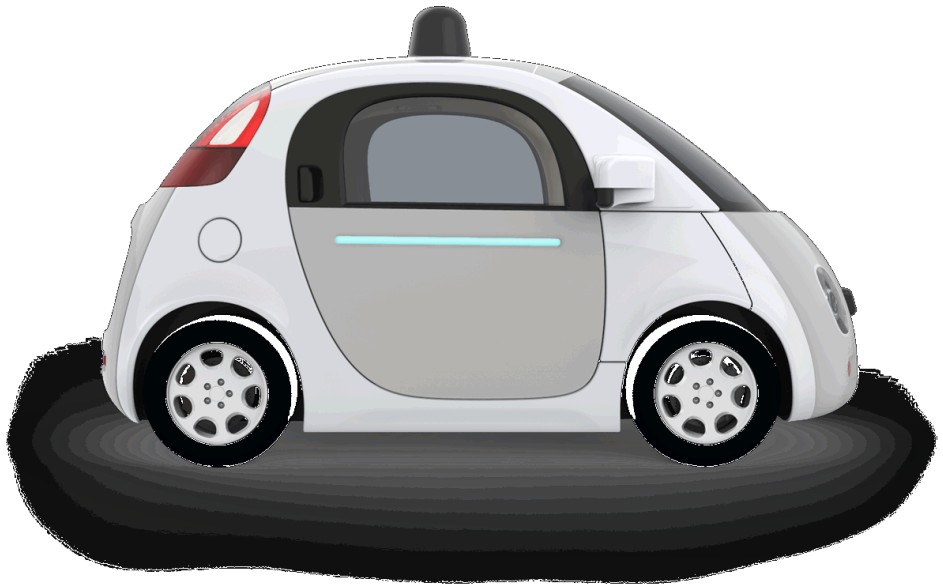

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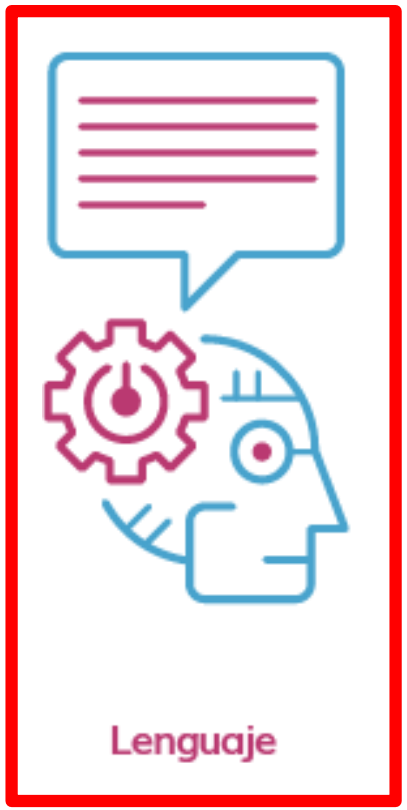

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A Deep Reinforced Model for Abstractive Summarization

Romain Paulus, Caiming Xiong & Richard Socher
Salesforce Research
172 University Avenue
Palo Alto, CA 94301, USA
{rpaulus,cxiong,rsocher}@salesforce.com

arXiv:1705.04304v3 [cs.CL] 13 Nov 2017

Abstract

Attentional, RNN-based encoder-decoder models for abstractive summarization have achieved good performance on short input and output sequences. For longer documents and summaries however these models often include repetitive and incoherent phrases. We introduce a neural network model with a novel intra-attention that attends over the input and continuously generated output separately, and a new training method that combines standard supervised word prediction and reinforcement learning (RL). Models trained only with supervised learning often exhibit "exposure bias" – they assume ground truth is provided at each step during training. However, when standard word prediction is combined with the global sequence prediction training of RL the resulting summaries become more readable. We evaluate this model on the CNN/Daily Mail and New York Times datasets. Our model obtains a 41.16 ROUGE-1 score on the CNN/Daily Mail dataset, an improvement over previous state-of-the-art models. Human evaluation also shows that our model produces higher quality summaries.

1 Introduction

Text summarization is the process of automatically generating natural language summaries from an input document while retaining the important points. By condensing large quantities of information into short, informative summaries, summarization can aid many downstream applications such as creating news digests, search, and report generation.

There are two prominent types of summarization algorithms. First, extractive summarization systems form summaries by copying parts of the input (Dorr et al., 2003; Nallapati et al., 2017). Second, abstractive summarization systems generate new phrases, possibly rephrasing or using words that were not in the original text (Chopra et al., 2016; Nallapati et al., 2016).

Neural network models (Nallapati et al., 2016) based on the attentional encoder-decoder model for machine translation (Bahdanau et al., 2014) were able to generate abstractive summaries with high ROUGE scores. However, these systems have typically been used for summarizing short input sequences (one or two sentences) to generate even shorter summaries. For example, the summaries on the DUC-2004 dataset generated by the state-of-the-art system by Zeng et al. (2016) are limited to 75 characters.

Nallapati et al. (2016) also applied their abstractive summarization model on the CNN/Daily Mail dataset (Hermann et al., 2015), which contains input sequences of up to 800 tokens and multi-sentence summaries of up to 100 tokens. But their analysis illustrates a key problem with attentional encoder-decoder models: they often generate unnatural summaries consisting of repeated phrases.

We present a new abstractive summarization model that achieves state-of-the-art results on the CNN/Daily Mail and similarly good results on the New York Times dataset (NYT) (Sandhaus, 2008). To our knowledge, this is the first end-to-end model for abstractive summarization on the NYT dataset. We introduce a key attention mechanism and a new learning objective to address the repeating phrase problem: (i) we use an intra-temporal attention in the encoder that records previous attention weights for each of the input tokens while a sequential intra-attention model in the decoder

Table 2: Quantitative results for various models on the New York Times test dataset

Source document
Jenson Button was denied his 100th race for McLaren after an ERS prevented him from making it to the start-line. It capped a miserable weekend for the Briton; his time in Bahrain plagued by reliability issues. Button spent much of the race on Twitter delivering his verdict as the action unfolded. 'Kimi is the man to watch,' and 'loving the sparks', were among his pearls of wisdom, but the tweet which courted the most attention was a rather mischievous one: 'Ooh is Lewis backing his team mate into Vettel?' he quizzed after Rosberg accused Hamilton of pulling off such a manoeuvre in China. Jenson Button waves to the crowd ahead of the Bahrain Grand Prix which he failed to start Perhaps a career in the media beckons... Lewis Hamilton has out-qualified and finished ahead of Nico Rosberg at every race this season. Indeed Rosberg has now beaten his Mercedes team-mate only once in the 11 races since the pair infamously collided in Belgium last year. Hamilton secured the 36th win of his career in Bahrain and his 21st from pole position. Only Michael Schumacher (40), Ayrton Senna (29) and Sebastian Vettel (27) have more. *(...)*
Ground truth summary
Button denied 100th race start for McLaren after ERS failure. Button then spent much of the Bahrain Grand Prix on Twitter delivering his verdict on the action as it unfolded. Lewis Hamilton has out-qualified and finished ahead of Mercedes team-mate Nico Rosberg at every race this season. Bernie Ecclestone confirms F1 will make its bow in Azerbaijan next season.
ML, with intra-attention (ROUGE-1 41.58)
Button was denied his 100th race for McLaren. ERS prevented him from making it to the start-line. The Briton. He quizzed after Nico Rosberg accused Lewis Hamilton of pulling off such a manoeuvre in China. Button has been in Azerbaijan for the first time since 2013.
RL, with intra-attention (ROUGE-1 50.00)
Button was denied his 100th race for McLaren after an ERS prevented him from making it to the start-line. It capped a miserable weekend for the Briton. Button has out-qualified. Finished ahead of Nico Rosberg at Bahrain. Lewis Hamilton has. In 11 races. . The race. To lead 2,000 laps. . In. . . And. .
ML+RL, with intra-attention (ROUGE-1 44.00)
Button was denied his 100th race for McLaren. The ERS prevented him from making it to the start-line. Button was his team mate in the 11 races in Bahrain. He quizzed after Nico Rosberg accused Lewis Hamilton of pulling off such a manoeuvre in China.

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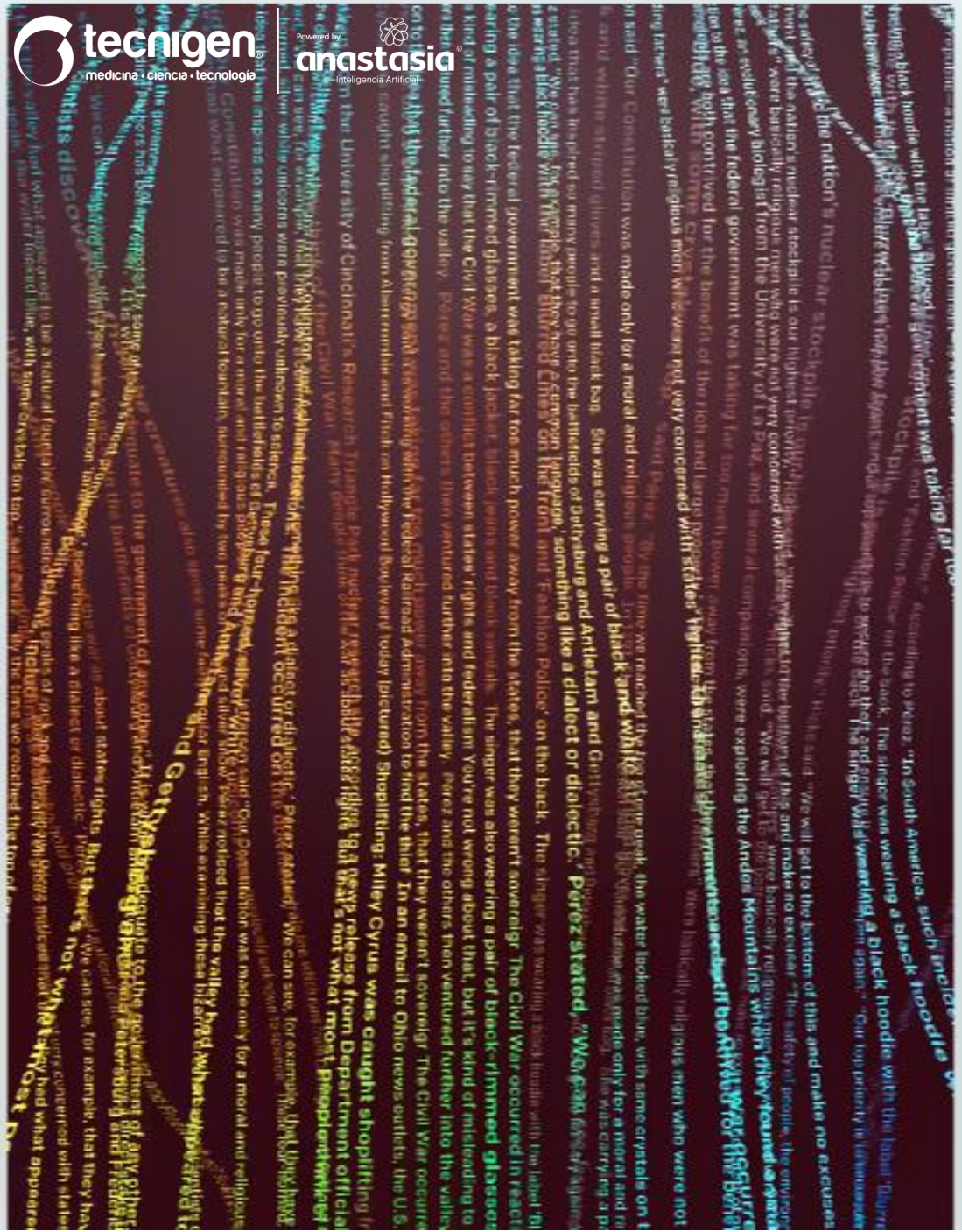

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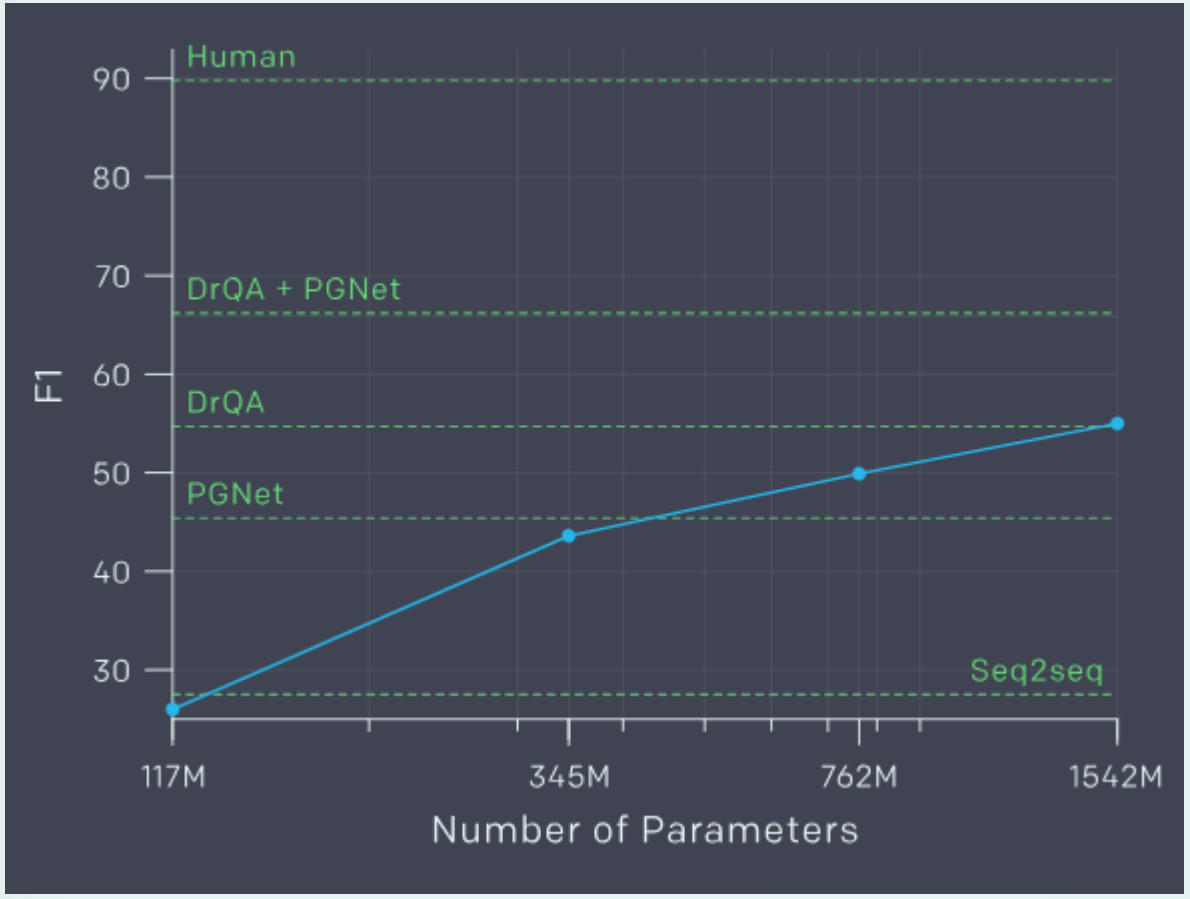
Better Language Models and Their Implications



Texto escrito por humanos

En un hallazgo impactante, un científico descubrió una manada de unicornios que viven en un valle remoto, previamente inexplorado, en las montañas de los Andes. Aún más sorprendente para los investigadores fue el hecho de que los unicornios hablaban un inglés perfecto.

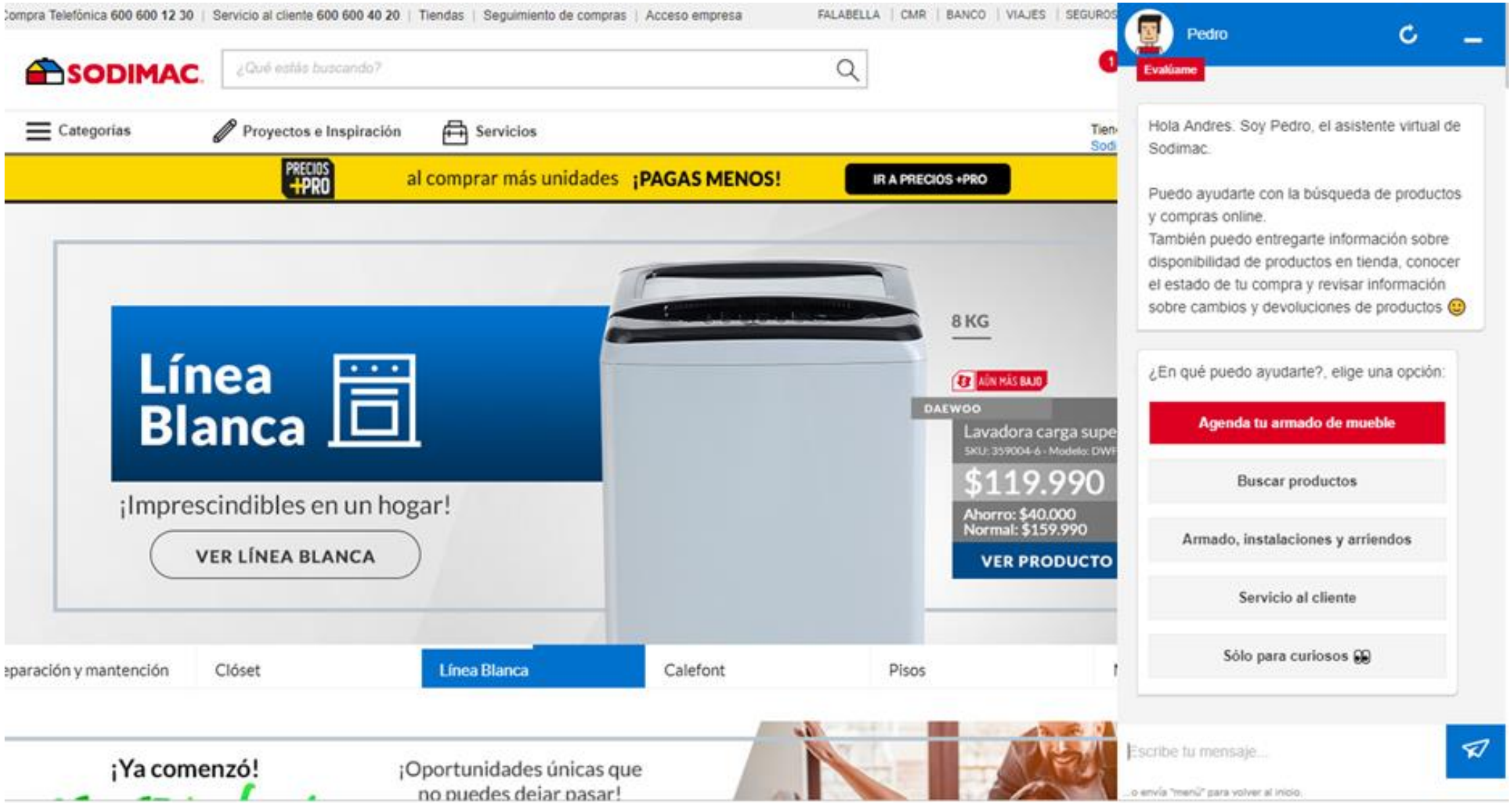
Texto escrito por IA

El científico nombró a la población, por su distintivo cuerno, Unicornio de Ovidio. Estos unicornios de cuatro cuernos y blanco plateado eran previamente desconocidos para la ciencia.

Ahora, después de casi dos siglos, el misterio de lo que provocó este extraño fenómeno se resuelve finalmente.

El Dr. Jorge Pérez, un biólogo evolutivo de la Universidad de La Paz, y varios compañeros, estaban explorando las montañas de los Andes cuando encontraron un pequeño valle, sin otros animales o humanos. Pérez notó que el valle tenía lo que parecía ser una fuente natural, rodeado por dos picos de roca y nieve plateada.

Pérez y los demás se aventuraron más lejos en el valle. "Cuando llegamos a la cima de un pico, el agua se



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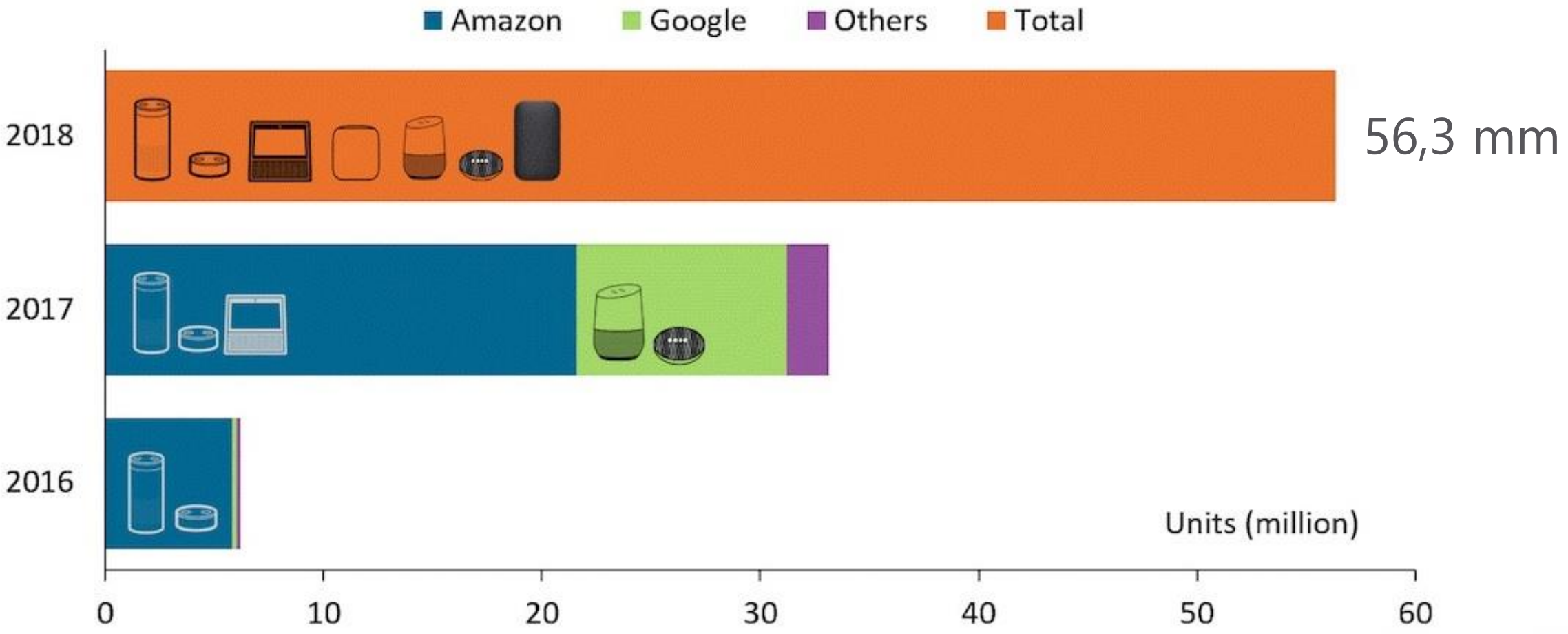
Ventas de Smart Speaker 2016 al 2018



Source: Canalys estimates and forecasts, Smart Speaker Analysis, December 2017

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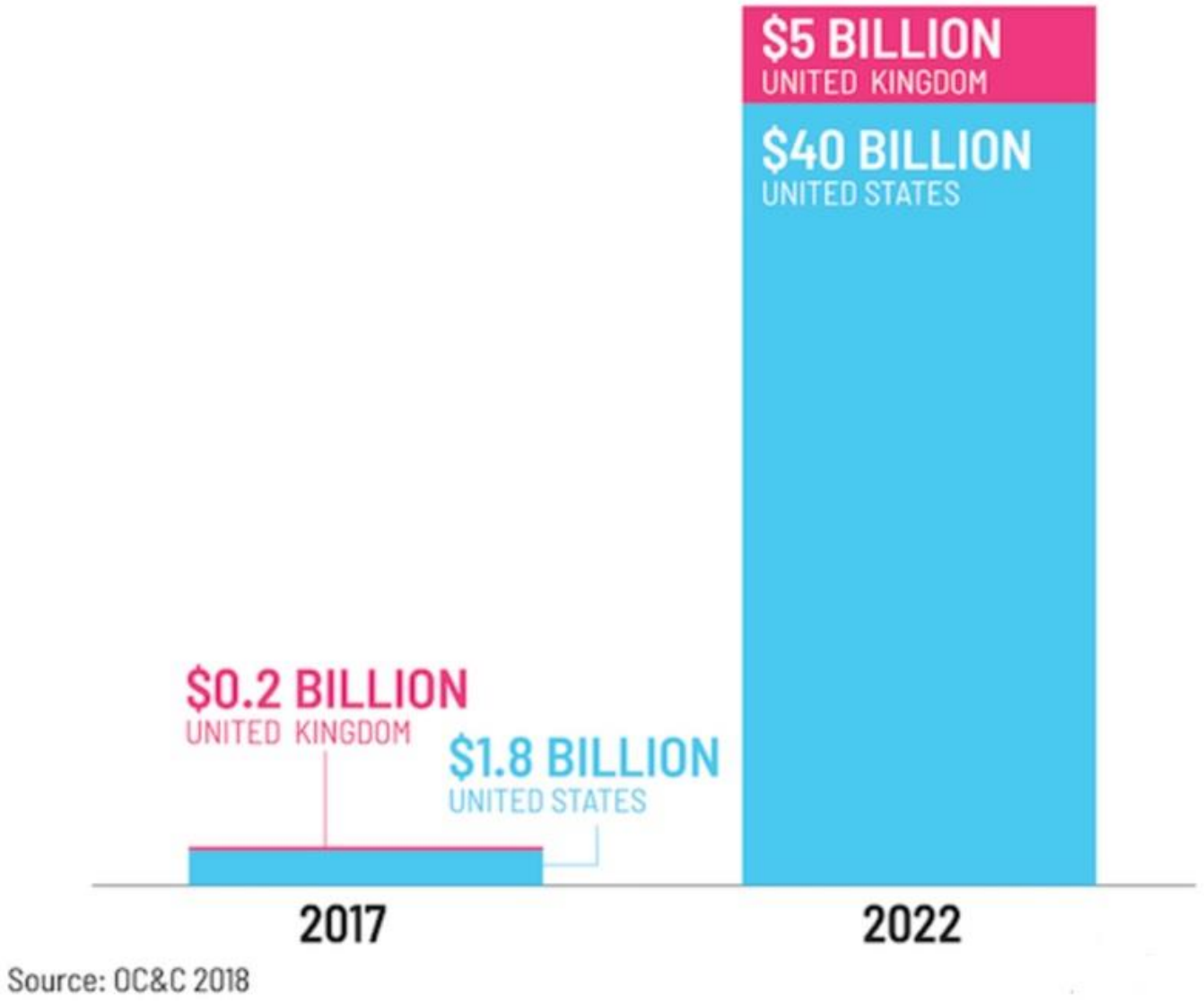

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Deep Visual-Semantic Alignments for Generating Image Descriptions

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Abstract

We present a model that generates natural language descriptions of images and their regions. Our approach leverages datasets of images and their sentence descriptions to learn about the inter-modal correspondences between language and visual data. Our alignment model is based on a novel combination of Convolutional Neural Networks over image regions, bidirectional Recurrent Neural Networks over sentences, and a structured objective that aligns the two modalities through a multimodal embedding. We then describe a Multimodal Recurrent Neural Network architecture that uses the inferred alignments to learn to generate novel descriptions of image regions. We demonstrate that our alignment model produces state of the art results in retrieval experiments on Flickr8K, Flickr30K and MSCOCO datasets. We then show that the generated descriptions significantly outperform retrieval baselines on both full images and on a new dataset of region-level annotations.

1. Introduction

A quick glance at an image is sufficient for a human to point out and describe an immense amount of details about the visual scene [14]. However, this remarkable ability has proven to be an elusive task for our visual recognition models. The majority of previous work in visual recognition has focused on labeling images with a fixed set of visual categories and great progress has been achieved in these endeavors [45, 11]. However, while closed vocabularies of visual concepts constitute a convenient modeling assumption, they are vastly restrictive when compared to the enormous amount of rich descriptions that a human can compose.

Some pioneering approaches that address the challenge of generating image descriptions have been developed [29, 13]. However, these models often rely on hard-coded visual concepts and sentence templates, which imposes limits on their variety. Moreover, the focus of these works has been on reducing complex visual scenes into a single sentence, which we consider to be an unnecessary restriction.

In this work, we strive to take a step towards the goal of generating dense descriptions of images (Figure 1). The primary challenge towards this goal is in the design of a model that is rich enough to simultaneously reason about contents of images and their representation in the domain of natural language. Additionally, the model should be free of assumptions about specific hard-coded templates, rules or categories and instead rely on learning from the training data. The second, practical challenge is that datasets of image captions are available in large quantities on the internet [21, 58, 37], but these descriptions multiplex mentions of several entities whose locations in the images are unknown.

Figure 1. Motivation/Concept Figure: Our model treats language as a rich label space and generates descriptions of image regions.

Our core insight is that we can leverage these large image-sentence datasets by treating the sentences as weak labels, in which contiguous segments of words correspond to some particular, but unknown location in the image. Our approach is to infer these alignments and use them to learn a generative model of descriptions. Concretely, our contributions are twofold:

- We develop a deep neural network model that infers the latent alignment between segments of sentences and the region of the image that they describe.

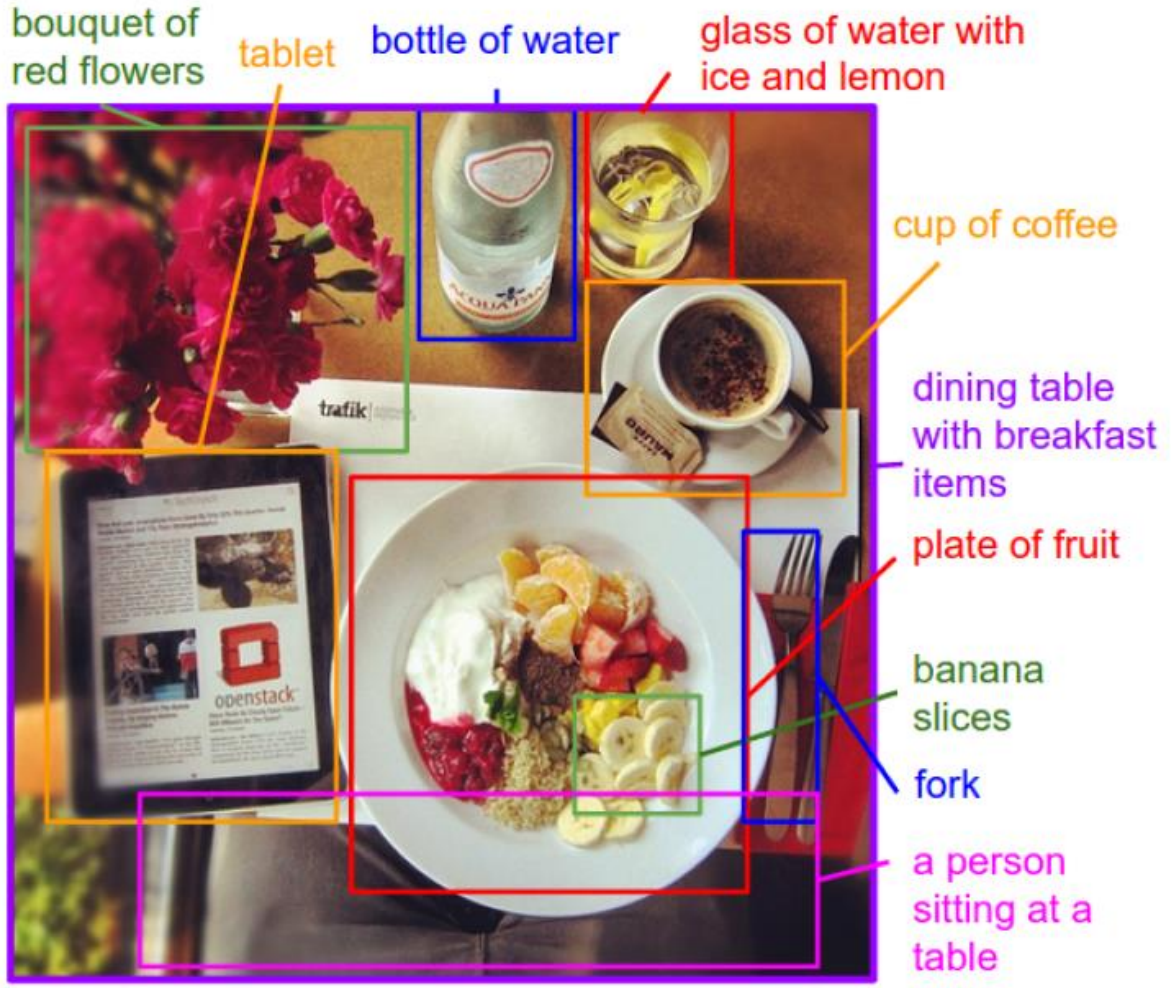

Figure 1. Motivation/Concept Figure: Our model treats language as a rich label space and generates descriptions of image regions.

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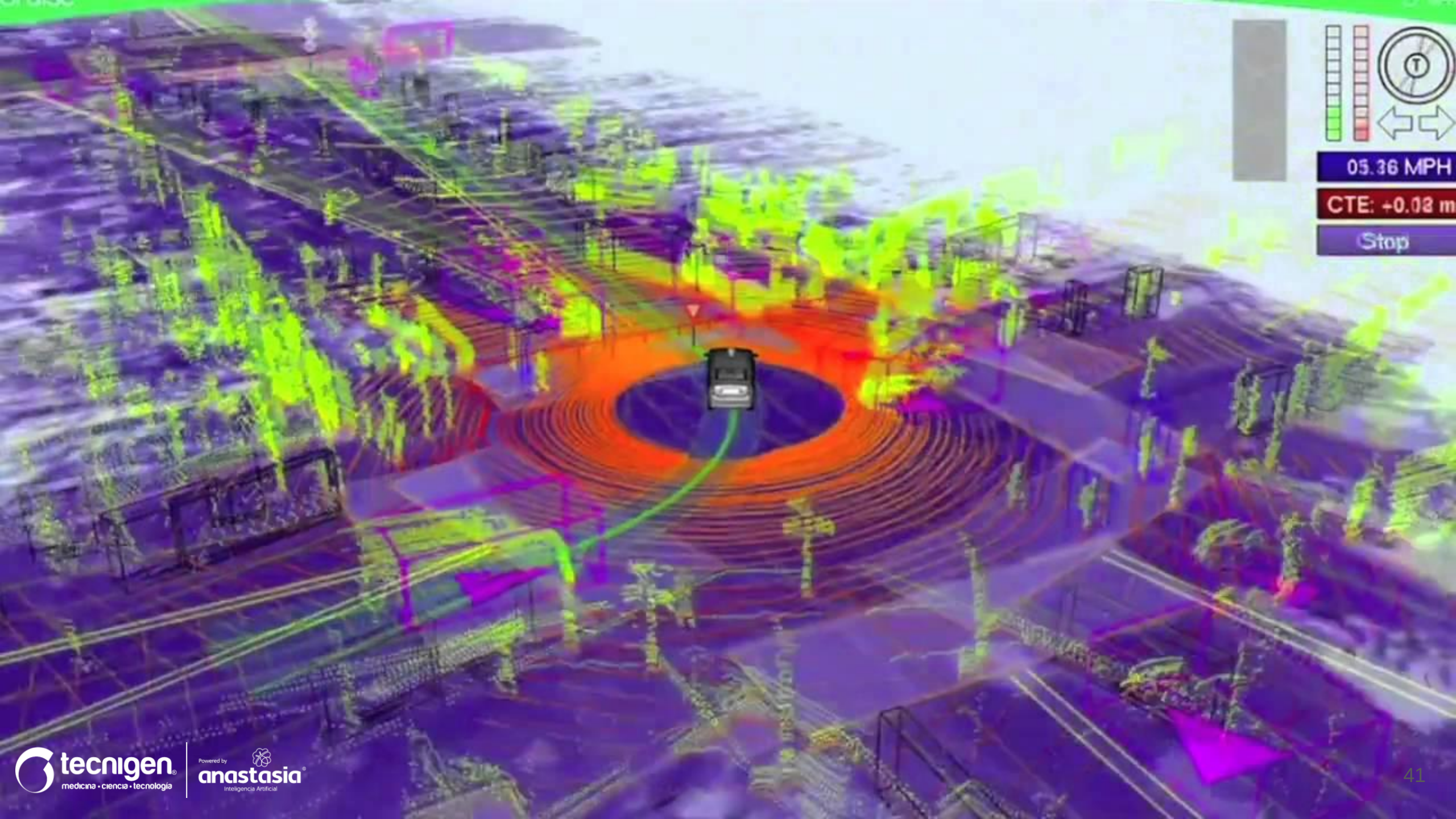
05.36 MPH
CTE: +0.08 m
Stop

arXiv:1808.07371v1 [cs.GR] 22 Aug 2018

Everybody Dance Now

CAROLINE CHAN, UC Berkeley
SHIRY GINOSAR, UC Berkeley
TINGHUI ZHOU, UC Berkeley
ALEXEI A. EFROS, UC Berkeley

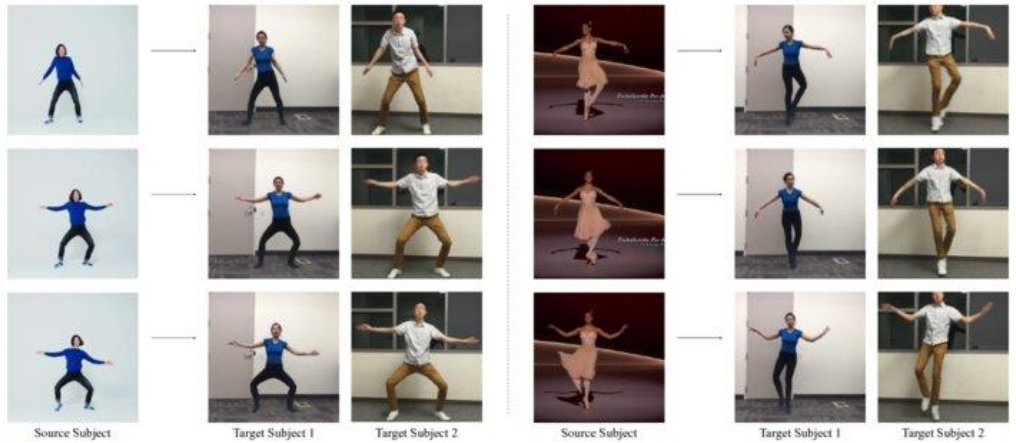

Fig. 1. Motion transfer from a source onto two target subjects.

This paper presents a simple method for "do as I do" motion transfer: given a source video of a person dancing we can transfer that performance to a novel (amateur) target after only a few minutes of the target subject performing standard moves. We pose this problem as a per-frame image-to-image translation with spatio-temporal smoothing. Using pose detections as an intermediate representation between source and target, we learn a mapping from pose images to a target subject's appearance. We adapt this setup for temporally coherent video generation including realistic face synthesis. Our video demo can be found at https://youtu.be/PCBTZh41Ris.

Additional Key Words and Phrases: Motion transfer, Video generation, Generative adversarial networks

1 INTRODUCTION

We propose a method to transfer motion between human subjects in different videos. Given two videos – one of a *target* person whose appearance we wish to synthesize, and the other of a *source* subject whose motion we wish to impose onto our target person – we transfer motion between these subjects via an end to end pixel-based pipeline. This is in contrast to approaches over the last two decades which employ nearest neighbor search [4, 9] or retarget motion in 3D [7, 13, 26, 30]. With our framework, we create a variety of videos, enabling untrained amateurs to spin and twirl like ballerinas, perform martial arts kicks or dance as vibrantly as pop stars.

To transfer motion between two video subjects in a frame-by-frame manner, we must learn a mapping between images of the two individuals. Our goal is therefore to discover an image-to-image translation [14] between the source and target sets. However, we do not have corresponding pairs of images of the two subjects performing the same motions to supervise learning this translation directly. Even if both subjects perform the same routine, it is still unlikely to have an exact frame to frame body-pose correspondence due to body shape and stylistic differences unique to each subject.

We observe that keypoint-based pose, which inherently encodes body position but not appearance, can serve as an intermediate representation between any two subjects. Compatible with our objective, poses preserve motion signatures over time while abstracting away as much subject identity as possible. We therefore design our intermediate representation to be pose stick figures such as in Figure 2. From the target video, we obtain pose detections [5, 27, 35] for each frame yielding a set of *(pose stick figure, target person image)* corresponding pairs. With this aligned data we are able to learn an image-to-image translation model between pose stick figures

Authors' addresses: Caroline Chan, UC Berkeley; Shiry Ginosar, UC Berkeley; Tinghui Zhou, UC Berkeley; Alexei A. Efros, UC Berkeley.

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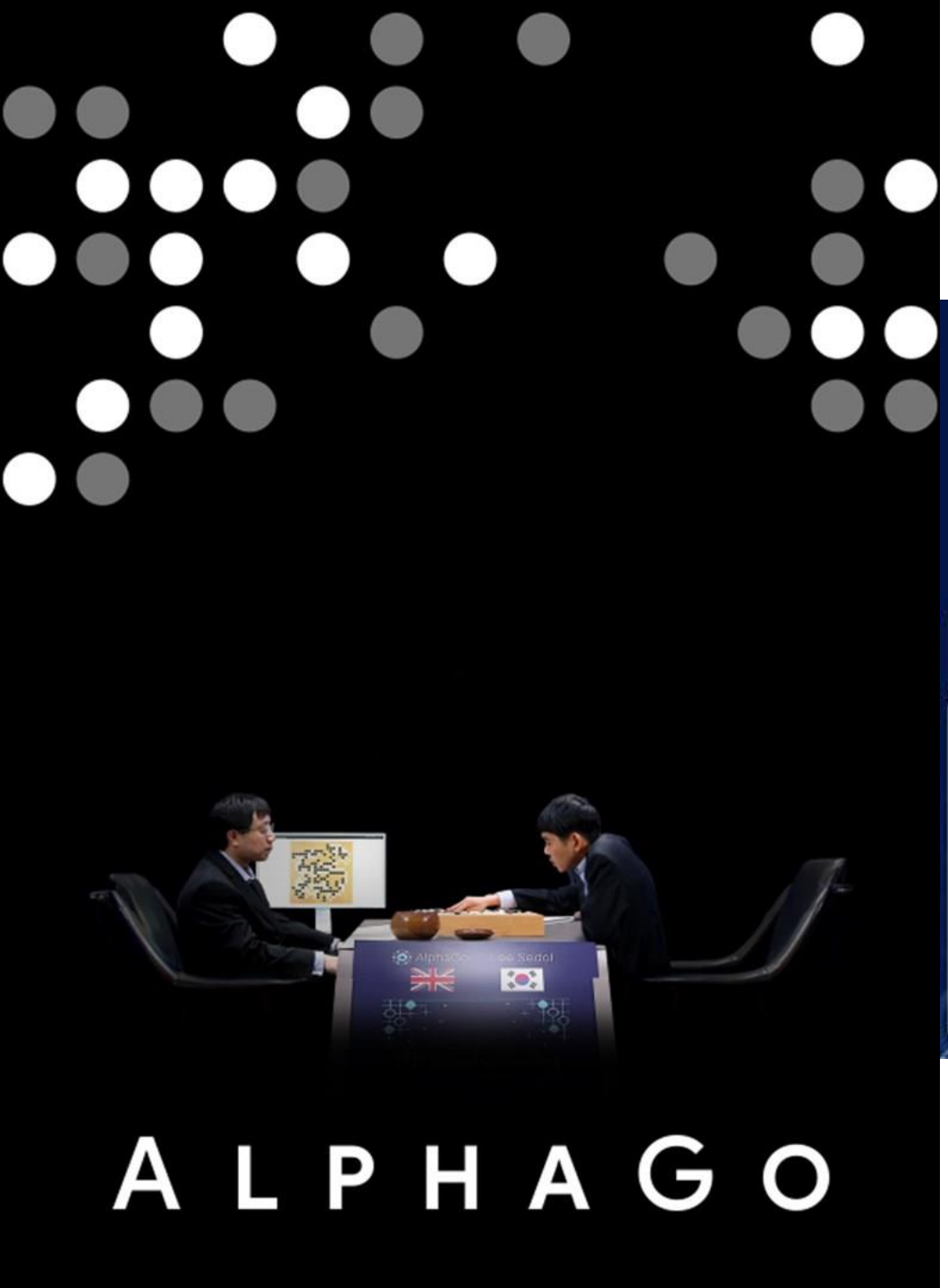
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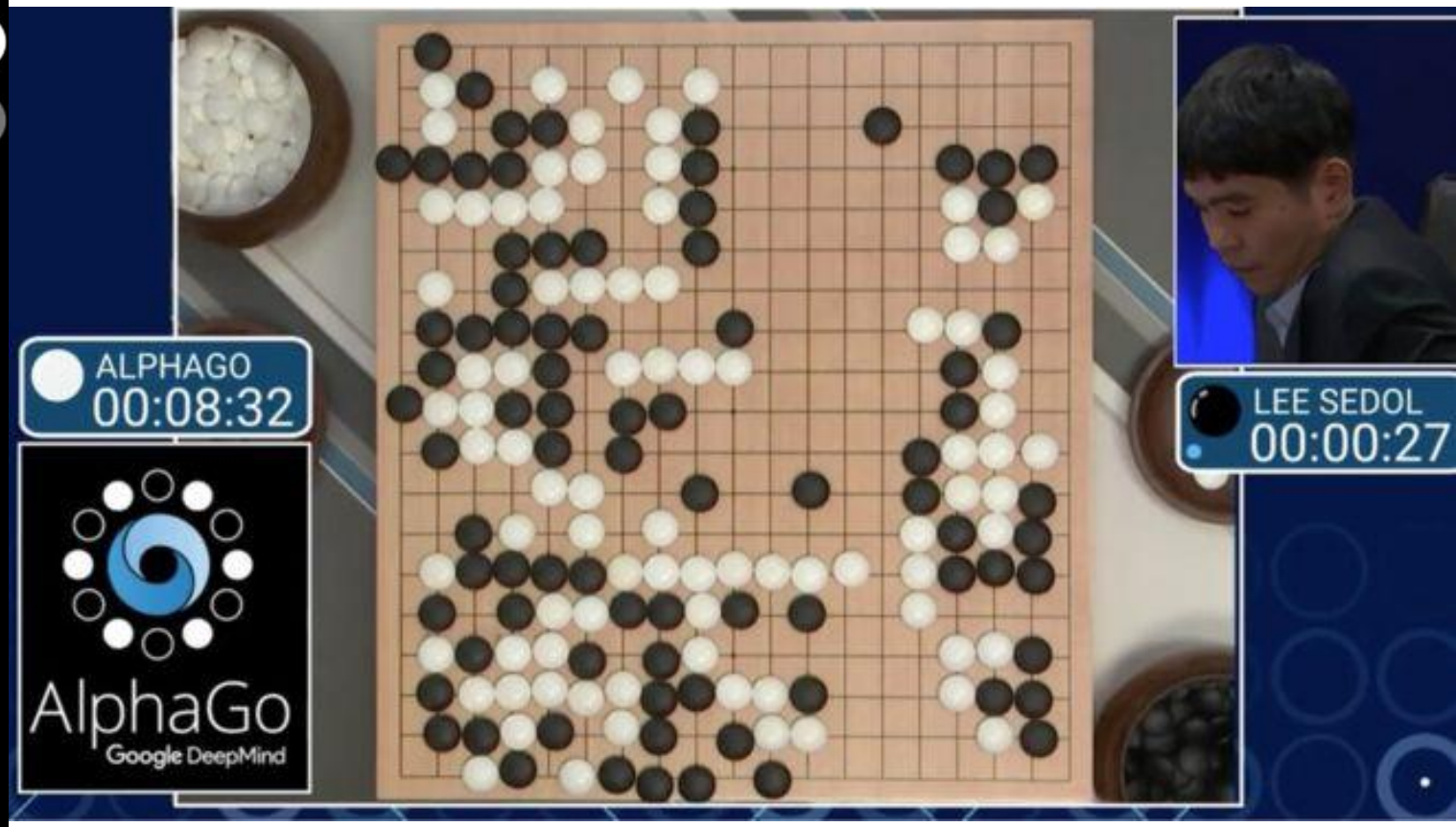
ALPHAGO
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AlphaGo
Google DeepMind
LEE SEDOL
00:00:27

AlphaZero AI beats champion chess program after teaching itself in four hours

Google's artificial intelligence sibling DeepMind repurposes Go-playing AI to conquer chess and shogi without aid of human knowledge

arXiv:1712.01815v1 [cs.AI] 5 Dec 2017

Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm

David Silver,[1*] Thomas Hubert,[1*] Julian Schrittwieser,[1*]
Ioannis Antonoglou,[1] Matthew Lai,[1] Arthur Guez,[1] Marc Lanctot,[1]
Laurent Sifre,[1] Dharshan Kumaran,[1] Thore Graepel,[1]
Timothy Lillicrap,[1] Karen Simonyan,[1] Demis Hassabis[1]

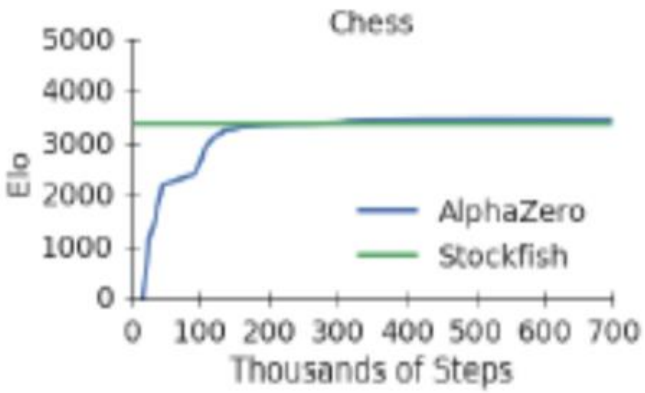
[1]DeepMind, 6 Pancras Square, London N1C 4AG.
*These authors contributed equally to this work.

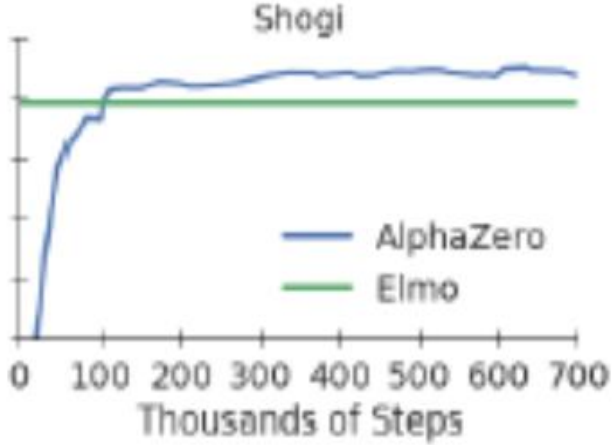
Abstract

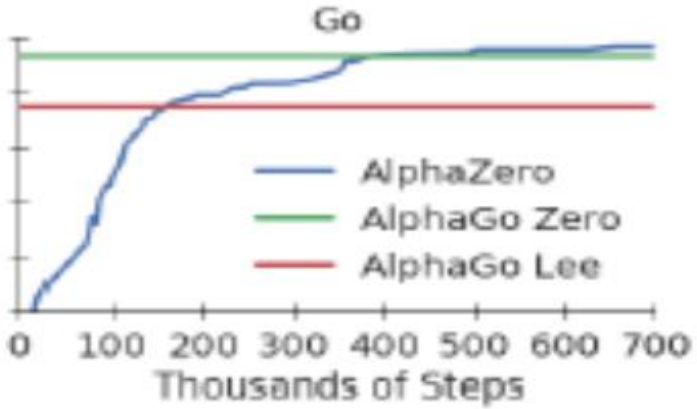
The game of chess is the most widely-studied domain in the history of artificial intelligence. The strongest programs are based on a combination of sophisticated search techniques, domain-specific adaptations, and handcrafted evaluation functions that have been refined by human experts over several decades. In contrast, the *AlphaGo Zero* program recently achieved superhuman performance in the game of Go, by *tabula rasa* reinforcement learning from games of self-play. In this paper, we generalise this approach into a single *AlphaZero* algorithm that can achieve, *tabula rasa*, superhuman performance in many challenging domains. Starting from random play, and given no domain knowledge except the game rules, *AlphaZero* achieved within 24 hours a superhuman level of play in the games of chess and shogi (Japanese chess) as well as Go, and convincingly defeated a world-champion program in each case.

The study of computer chess is as old as computer science itself. Babbage, Turing, Shannon, and von Neumann devised hardware, algorithms and theory to analyse and play the game of chess. Chess subsequently became the grand challenge task for a generation of artificial intelligence researchers, culminating in high-performance computer chess programs that perform at superhuman level (*9, 13*). However, these systems are highly tuned to their domain, and cannot be generalised to other problems without significant human effort.

A long-standing ambition of artificial intelligence has been to create programs that can instead learn for themselves from first principles (*26*). Recently, the *AlphaGo Zero* algorithm achieved superhuman performance in the game of Go, by representing Go knowledge using deep convolutional neural networks (*22, 28*), trained solely by reinforcement learning from games of self-play (*29*). In this paper, we apply a similar but fully generic algorithm, which we



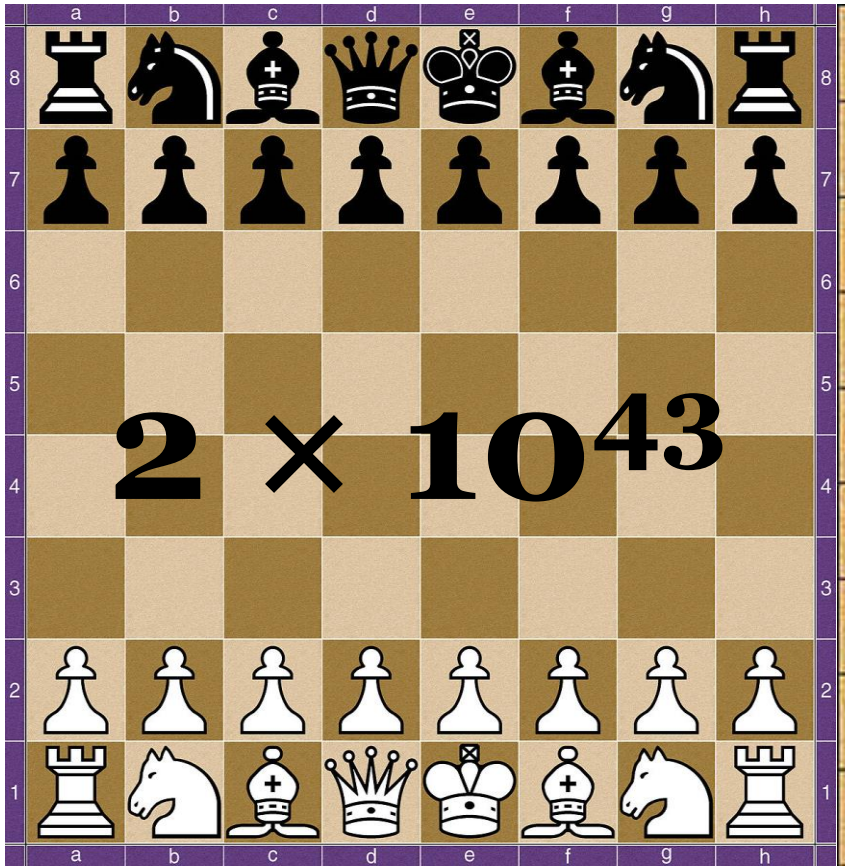


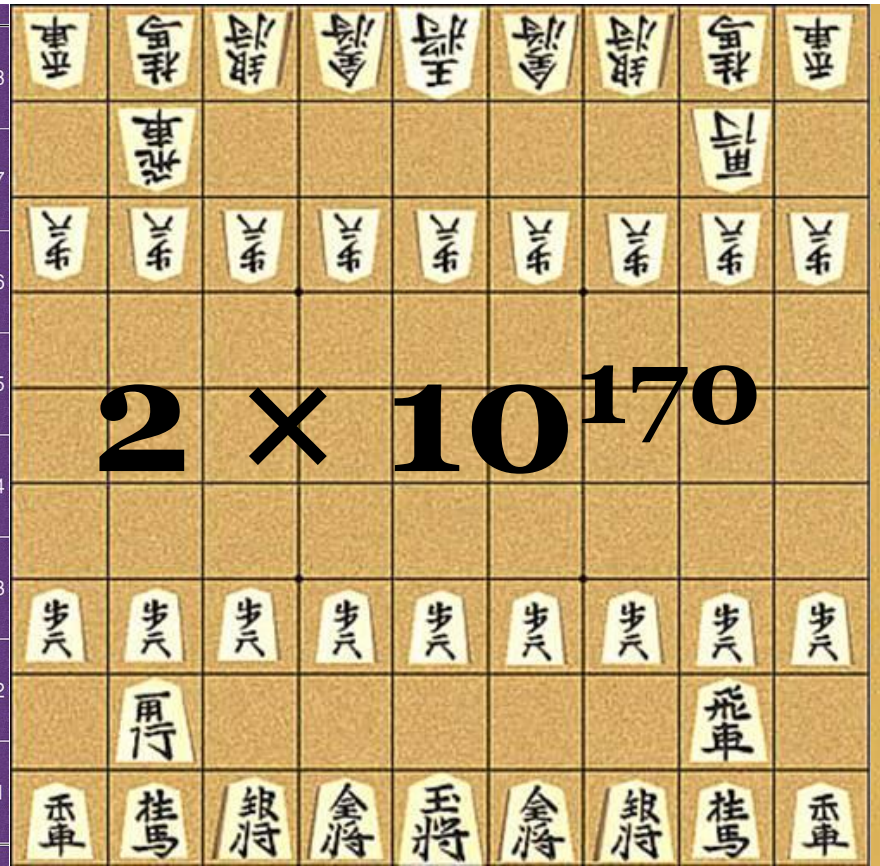


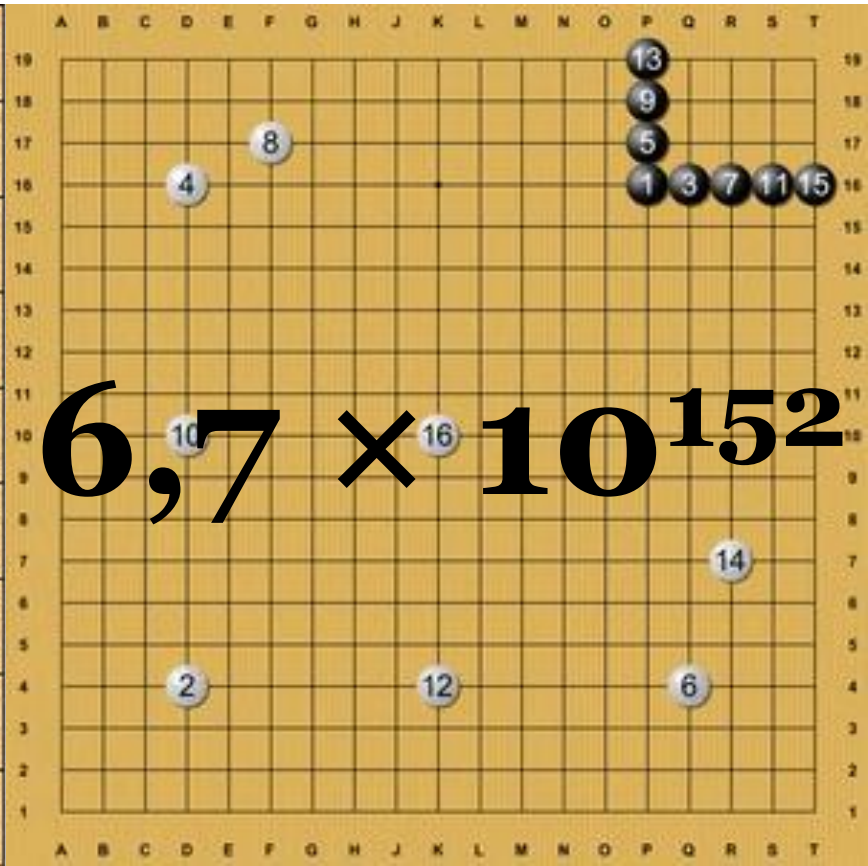
AJEDREZ= 8 X 8

SHOGI= 9 X 9

GO= 18 X 18







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JUST FOR MEN
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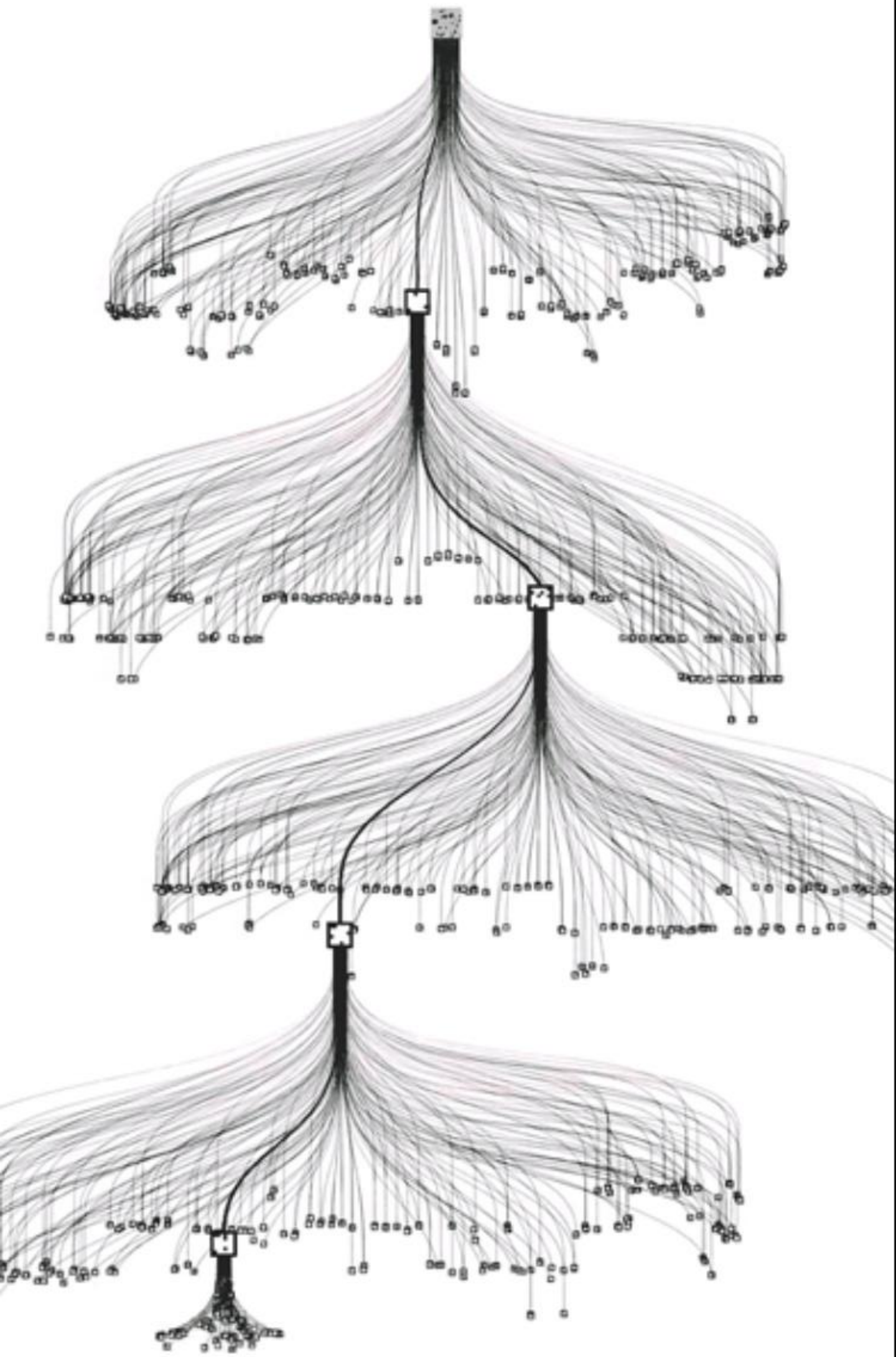

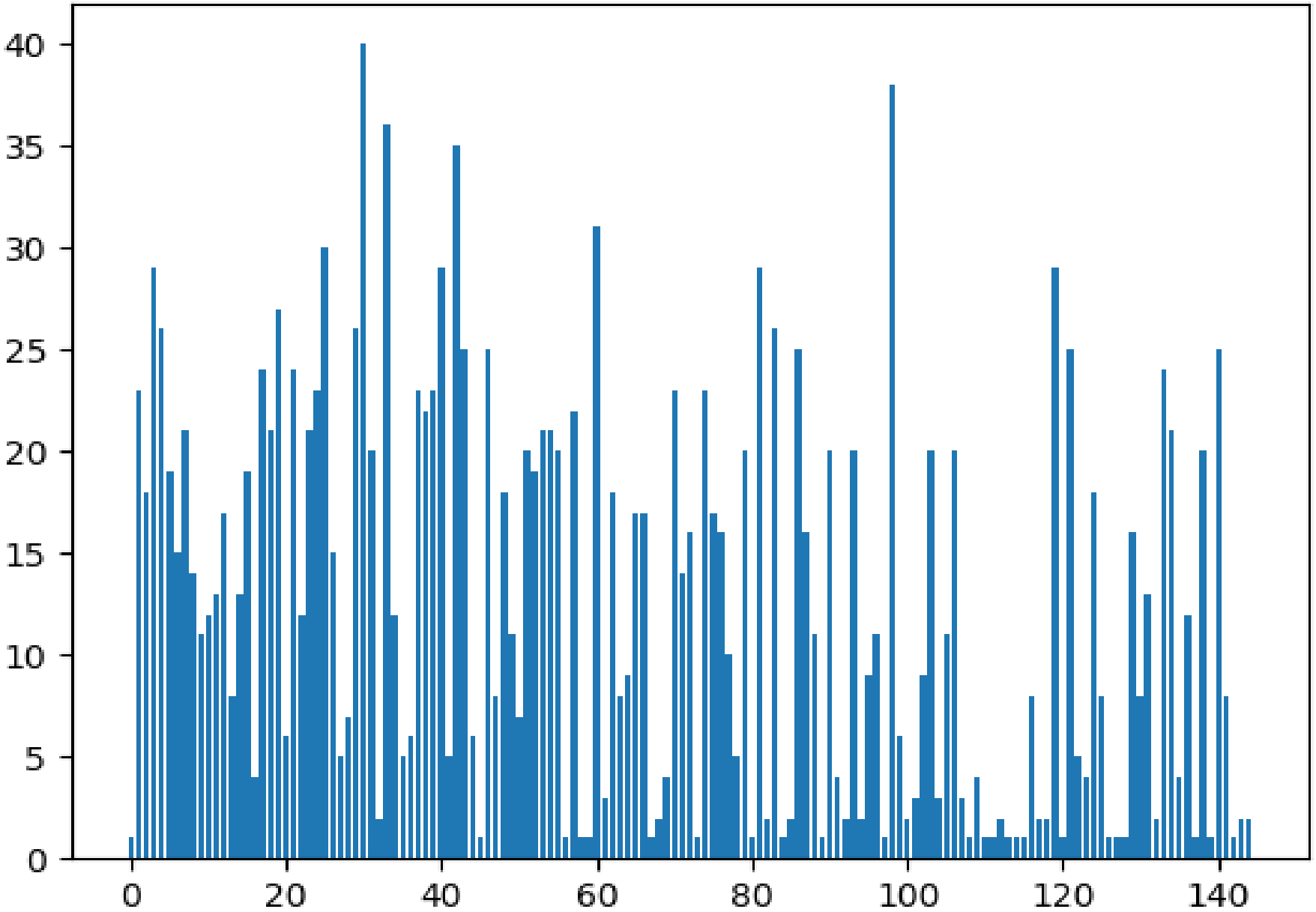
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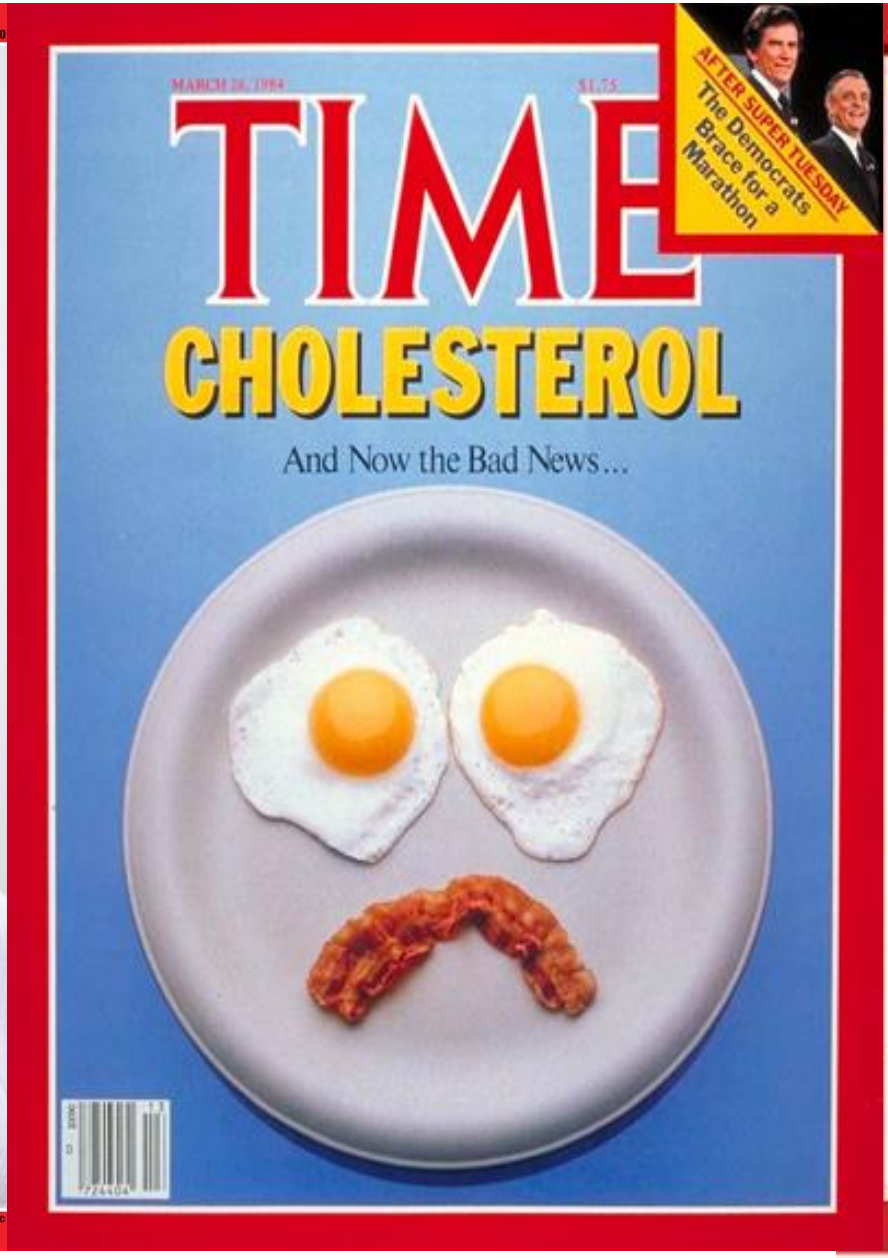
FEBRUARY 23 / MARCH 2, 20
TIME
SPECIAL
HEALTH
DOUBLE
ISSUE
THIS BABY COULD LIVE TO BE 142 YEARS OLD
Dispatches From the Frontiers of Longevity


TIME
CHOLESTEROL
And Now the Bad News...
AFTER SUPER TUESDAY
The Democrats Brace for a Marathon

THE HEALTH ISSUE
TIME
How Can This Be Profitable Again?
Special Report: Can Insurers Fill The Void Left By Big Pharma? You Betcha
It's All About Prevention.
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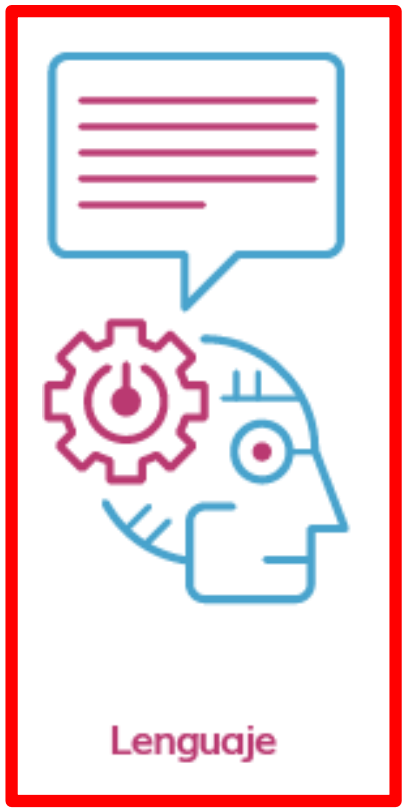

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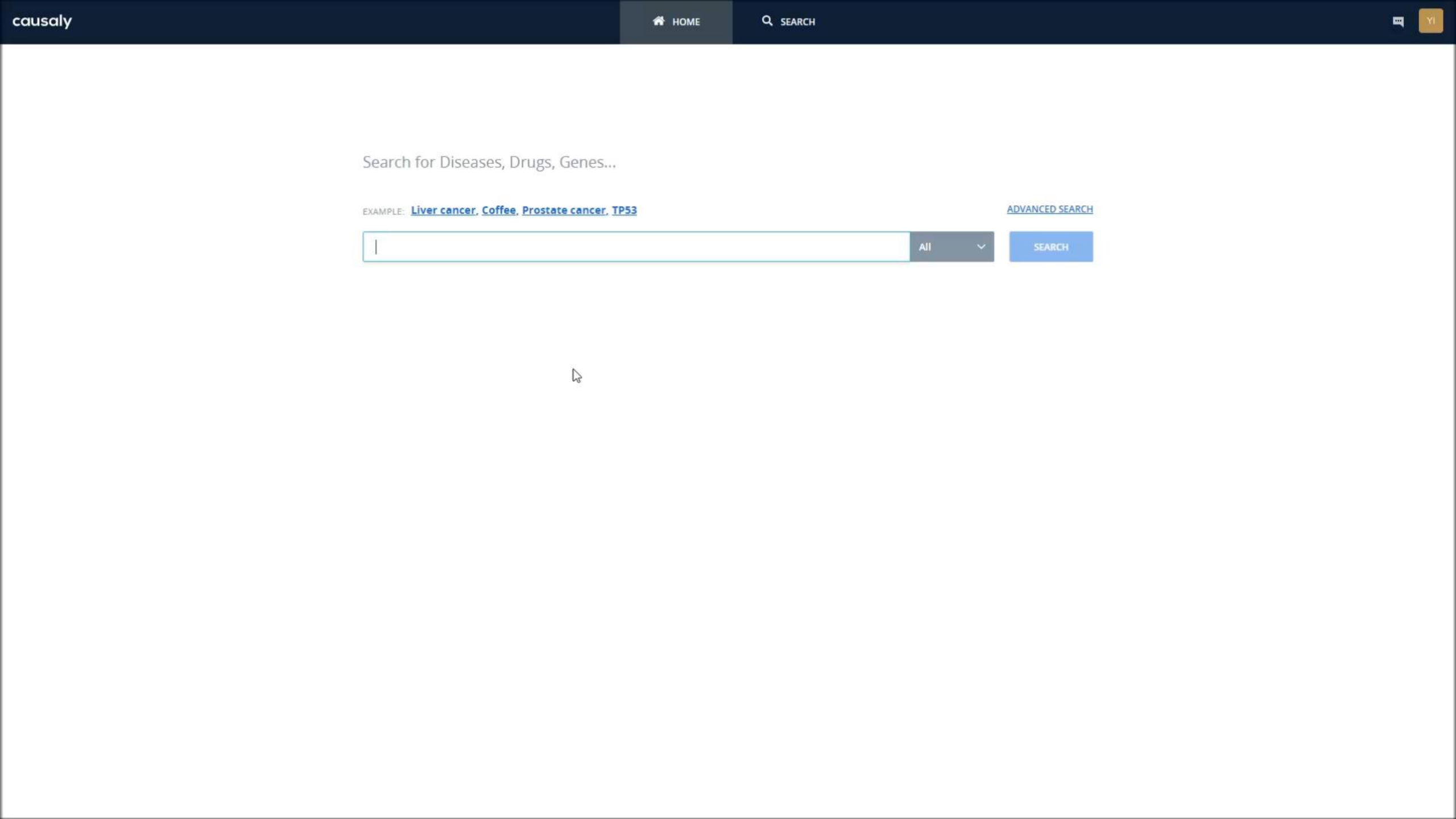
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HOME
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Search for Diseases, Drugs, Genes...
EXAMPLE: Liver cancer, Coffee, Prostate cancer, TP53
ADVANCED SEARCH
All
SEARCH

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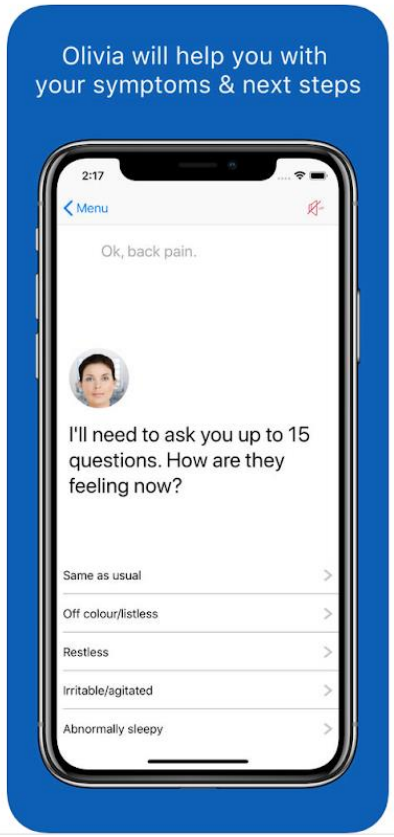
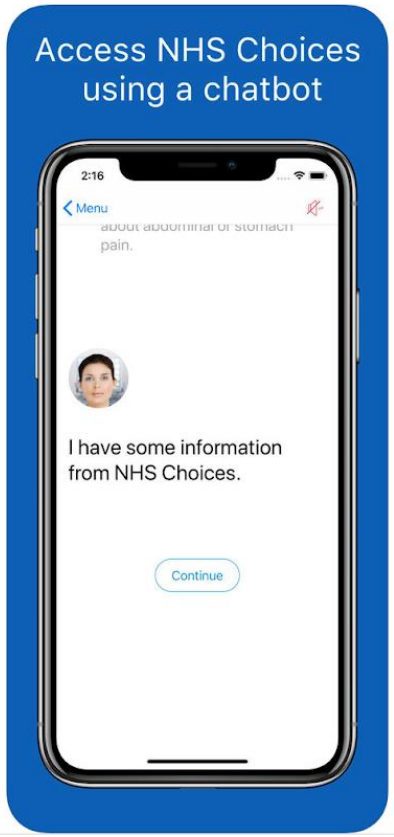
Your health assistant

GYANT

NLP

ASK NHS





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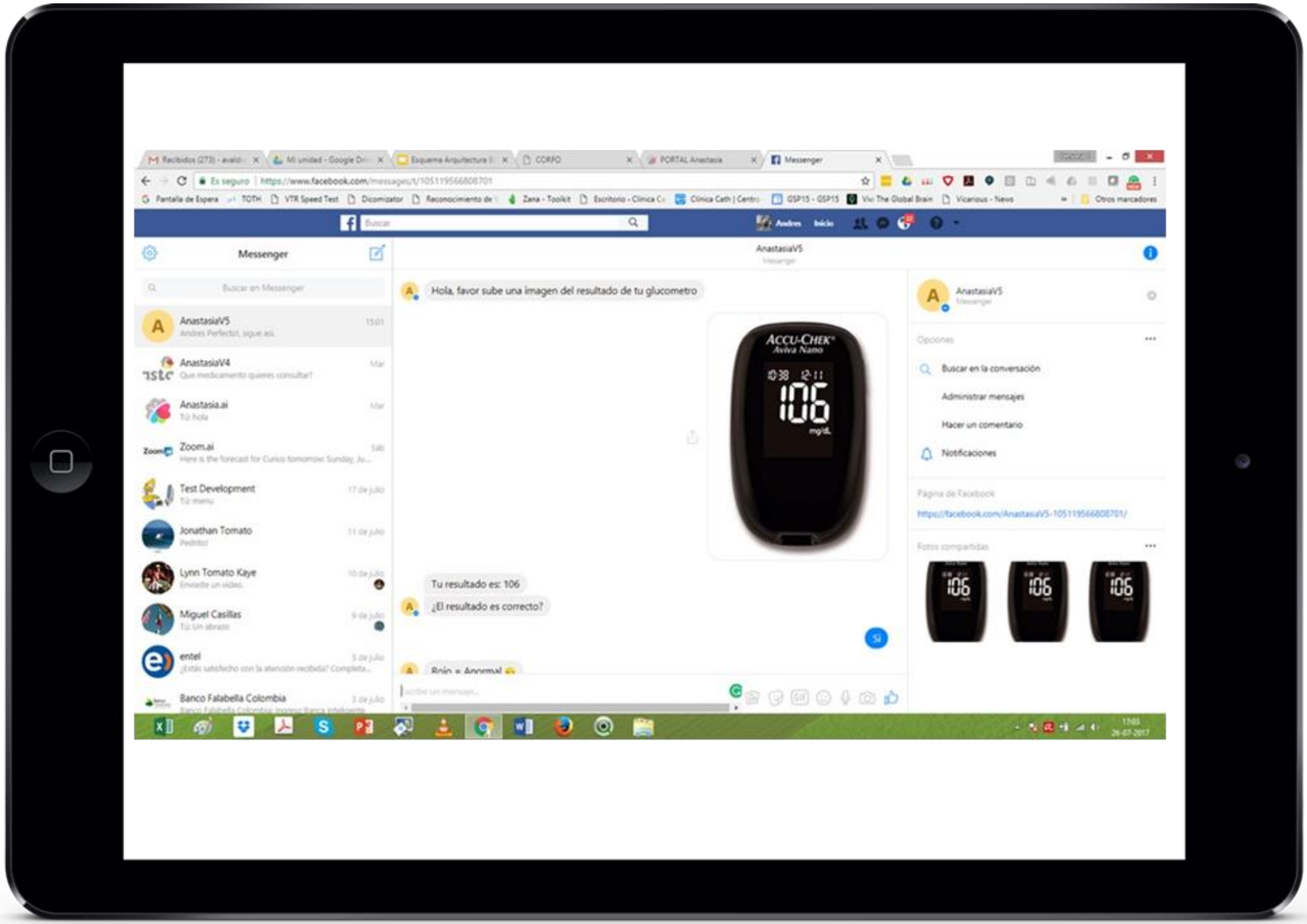

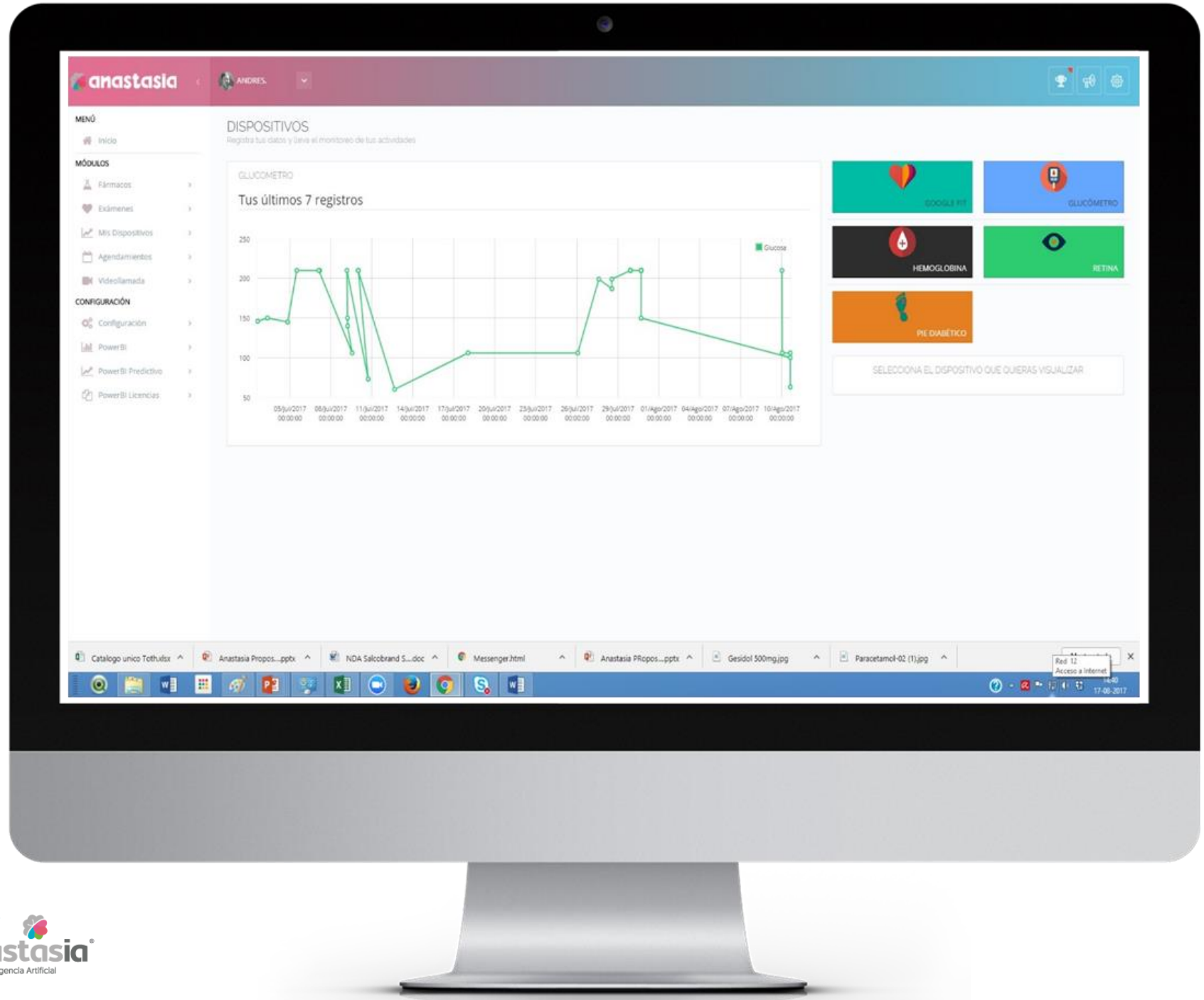

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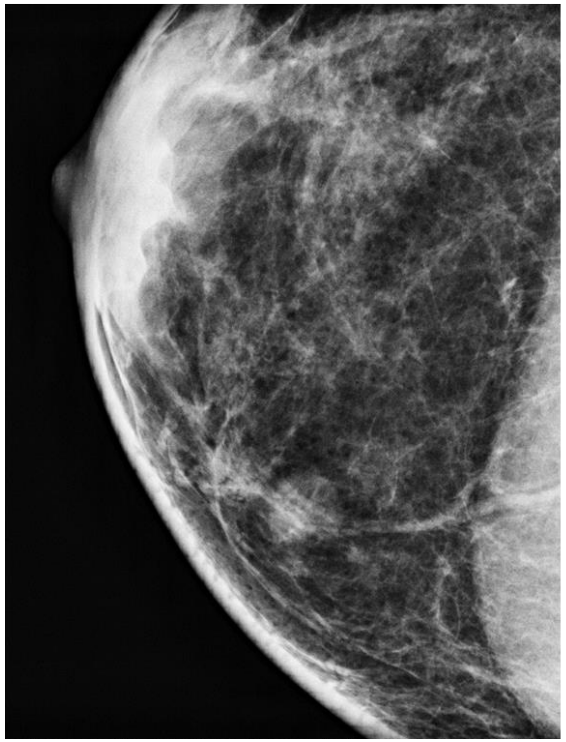
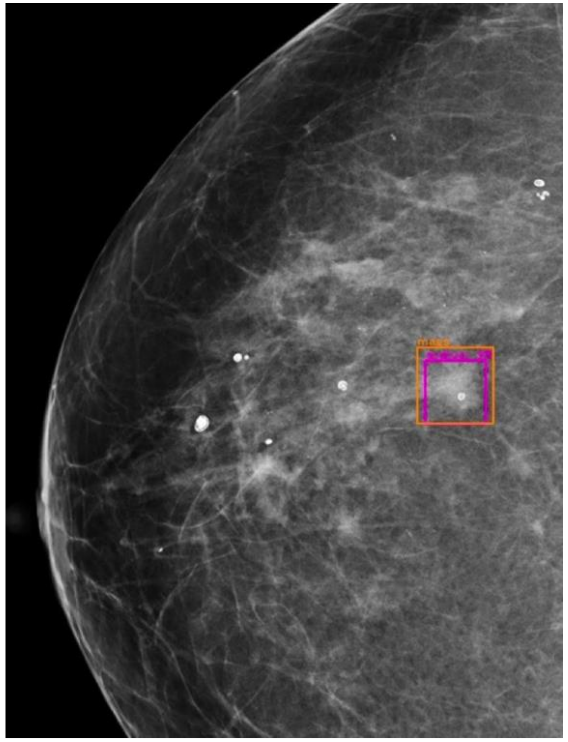




Estimado Dr:
Presente

El examen realizado al (a) paciente ,
57 años, 1 meses y 9 días, ha arrojado el siguiente resultado:

MAMOGRAFÍA BILATERAL:

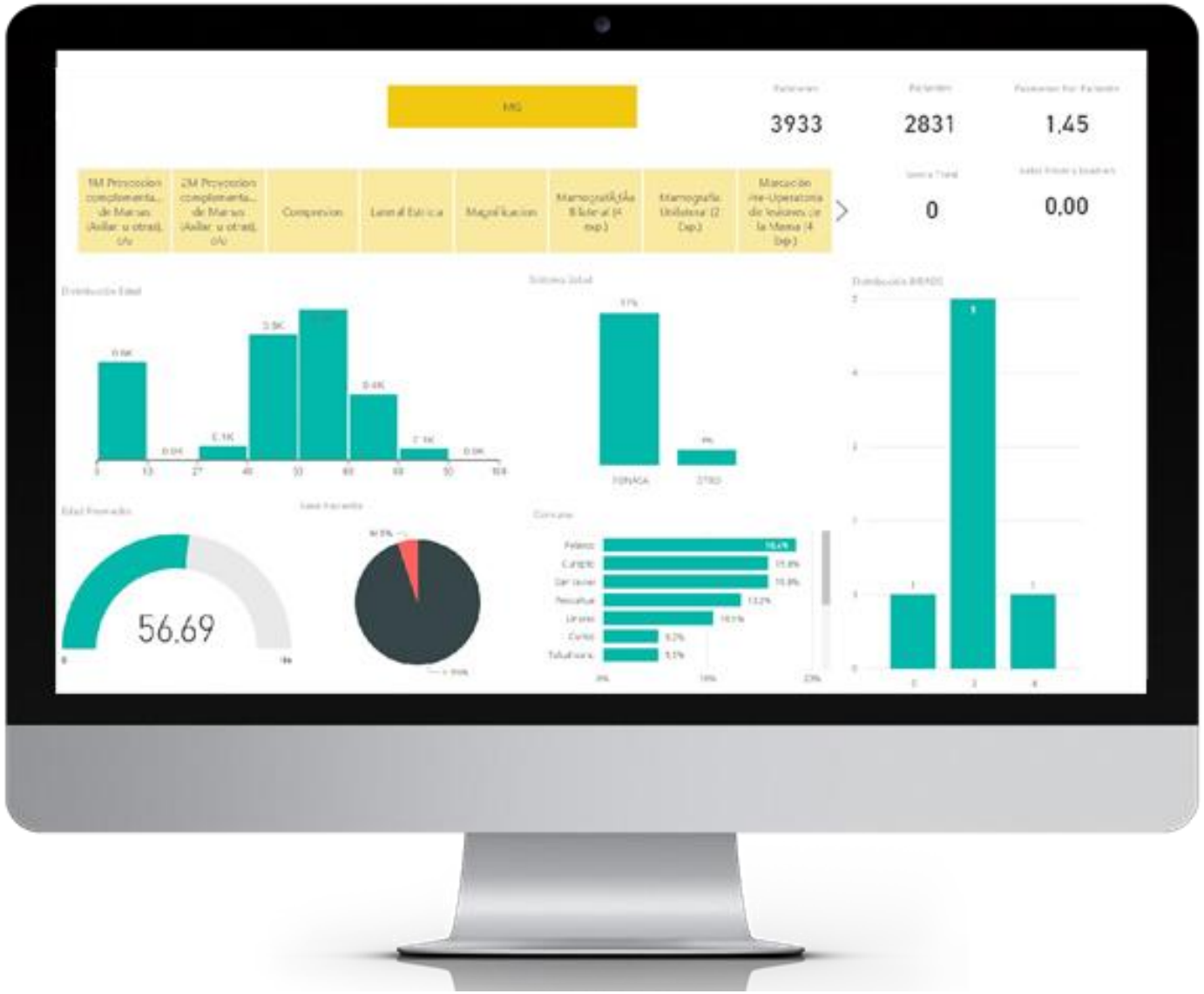
HALLAZGOS:

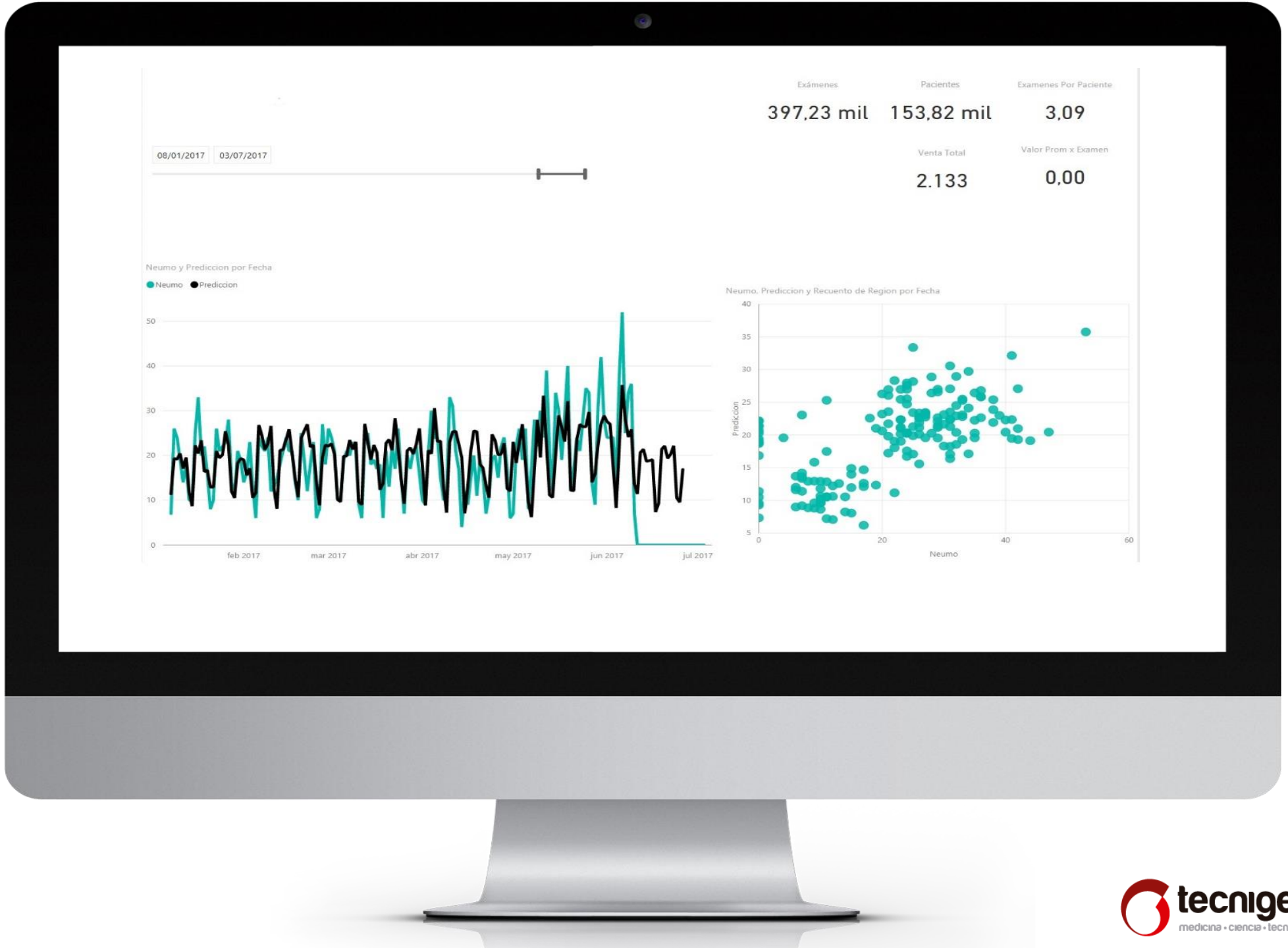
Piel, tejido celular subcutáneo y pezones conservados.
Mamas con densidades fibroglandulares dispersas.
Se observan contornos nodulares bilaterales, más evidentes en mama derecha. En ecografía anterior, se correlacionar con con formaciones quísticas.
Espacios retromamarios libres.
Regiones axilares libres.

IMPRESIÓN MAMOGRÁFICA:

Contornos nodulares bilaterales.
BIRADS 2
ACR B
Se sugiere actualizar Ecotomografía mamaria de alta resolución.

Saludo atentamente:





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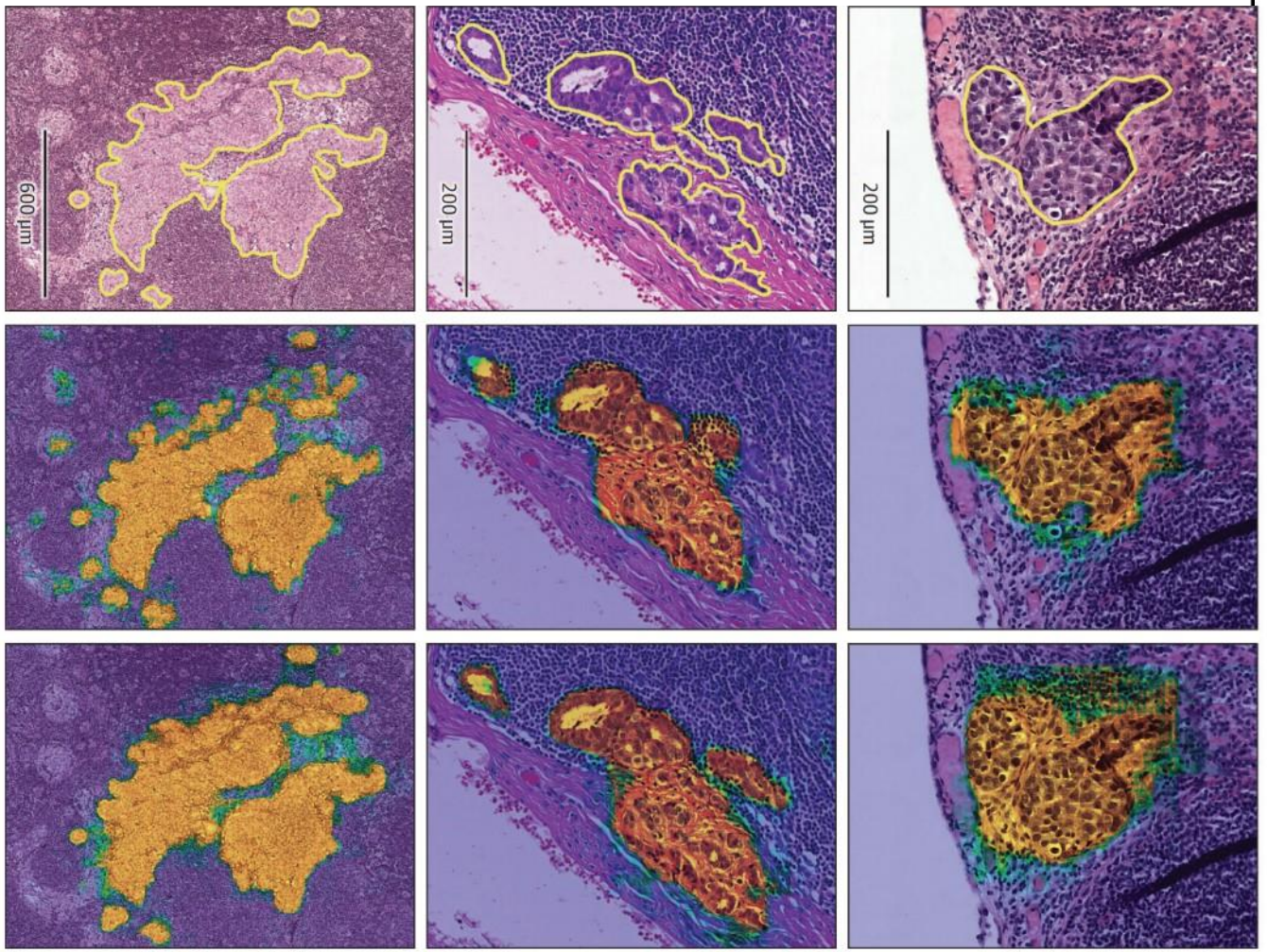
JAMA | Original Investigation

Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer

Babak Ehteshami Bejnordi, MS; Mitko Veta, PhD; Paul Johannes van Diest, MD, PhD; Bram van Ginneken, PhD; Nico Karssemeijer, PhD; Geert Litjens, PhD; Jeroen A. W. M. van der Laak, PhD; and the CAMELYON16 Consortium



CAMELYON16 Consortium JAMA (2017)

Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer

BioMind
CHAIN 1
CHAIN 2

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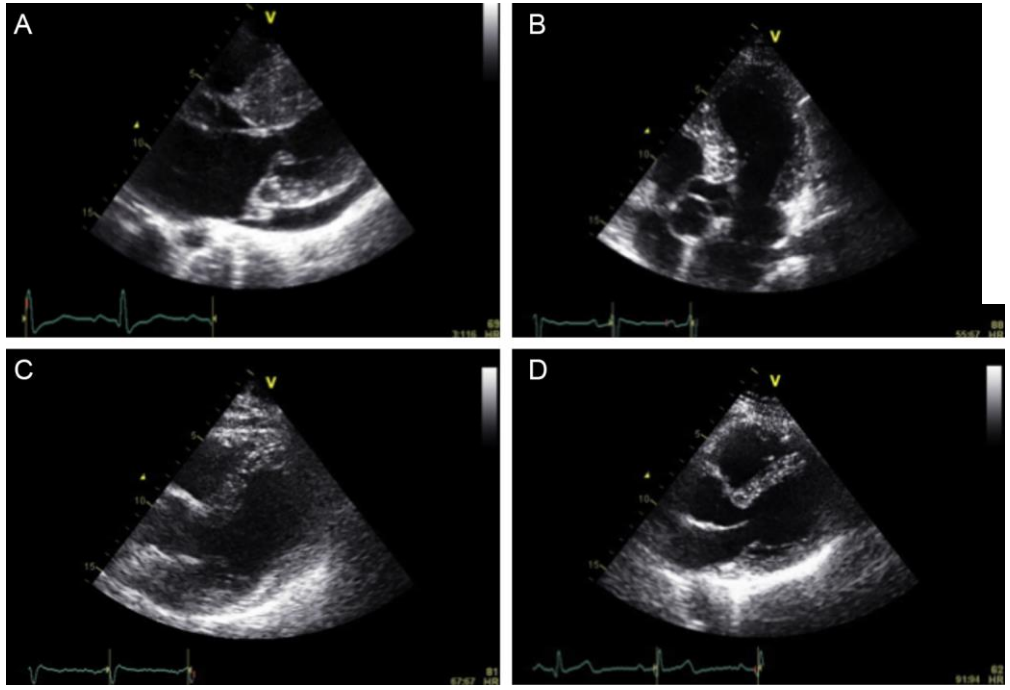


Doctores = 79%

AI= 92%

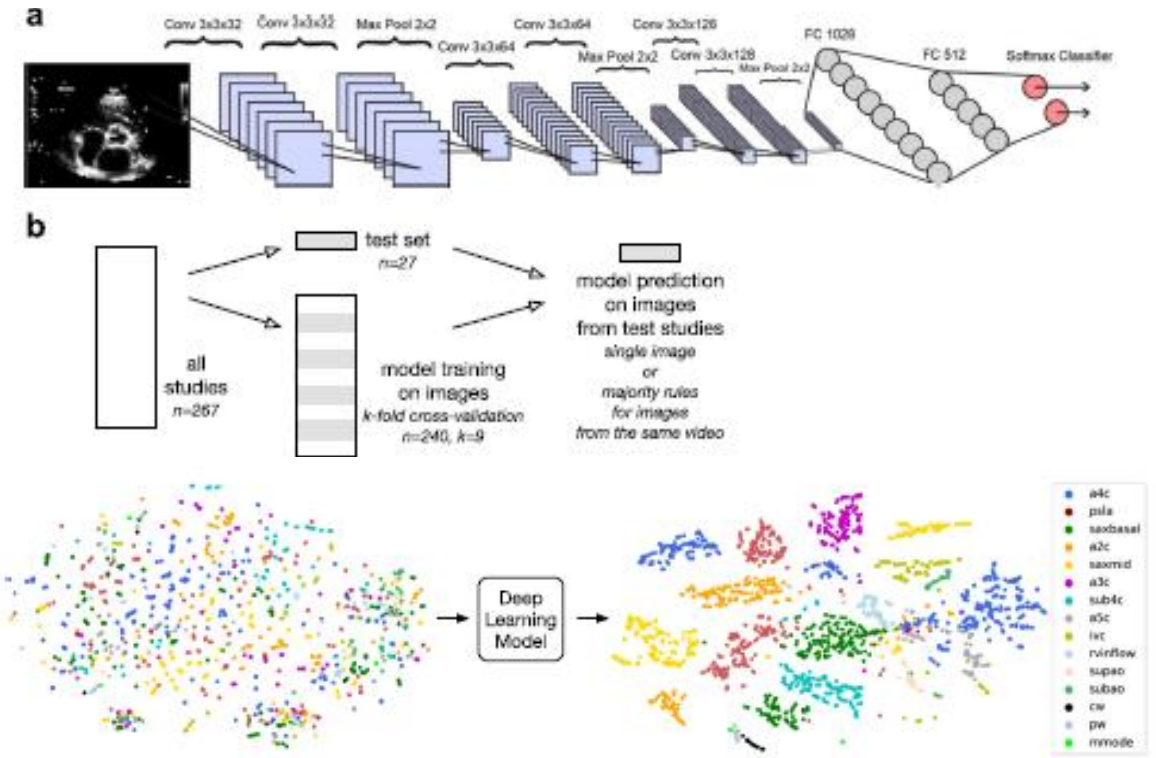
ARTICLE OPEN

Fast and accurate view classification of echocardiograms using deep learning

Ali Madani[1], Ramy Arnaout[2], Mohammad Mofrad[1] and Rima Arnaout[3]

Echocardiography is essential to cardiology. However, the need for human interpretation has limited echocardiography's full potential for precision medicine. Deep learning is an emerging tool for analyzing images but has not yet been widely applied to echocardiograms, partly due to their complex multi-view format. The essential first step toward comprehensive computer-assisted echocardiographic interpretation is determining whether computers can learn to recognize these views. We trained a convolutional neural network to simultaneously classify 15 standard views (12 video, 3 still), based on labeled still images and videos from 267 transthoracic echocardiograms that captured a range of real-world clinical variation. Our model classified among 12 video views with 97.8% overall test accuracy without overfitting. Even on single low-resolution images, accuracy among 15 views was 91.7% vs. 70.2–84.0% for board-certified echocardiographers. Data visualization experiments showed that the model recognizes similarities among related views and classifies using clinically relevant image features. Our results provide a foundation for artificial intelligence-assisted echocardiographic interpretation.

npj Digital Medicine (2018)1:6 doi:10.1038/s41746-017-0013-1



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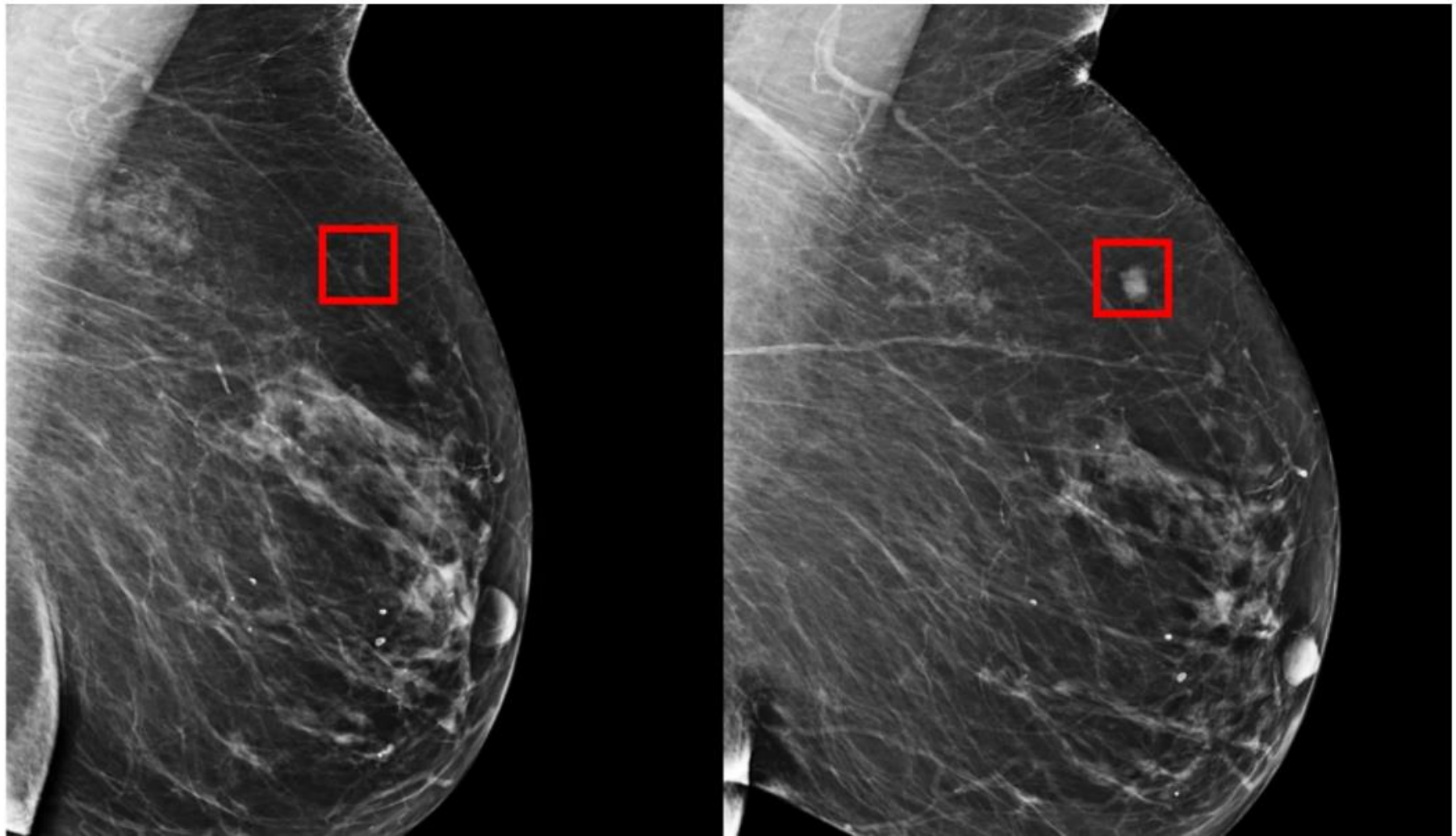
MIT AI tool can predict breast cancer up to 5 years early, works equally well for white and black patients

Darrell Etherington @etherington / 10:31 am -04 • June 26, 2019

Comment



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DART

by TELEDX.org

MARKET INSIGHT IN ASSOCIATION WITH GlobalData.

FDA APPROVES FIRST AI DEVICE TO DETECT DIABETIC RETINOPATHY

On 11 April the US Food and Drug Administration (FDA) announced the marketing approval of the first medical device to use artificial intelligence (AI) to detect more than a mild level of diabetic retinopathy, the most common cause of vision loss among diabetic patients and the leading cause of vision impairment among the US working-age population.

IDx-DR, the device developed by IDx LLC, is able to produce screening decisions without the need for clinician interpretation of retinal images, allowing the device to be used outside specialist centres, such as by primary care physicians.

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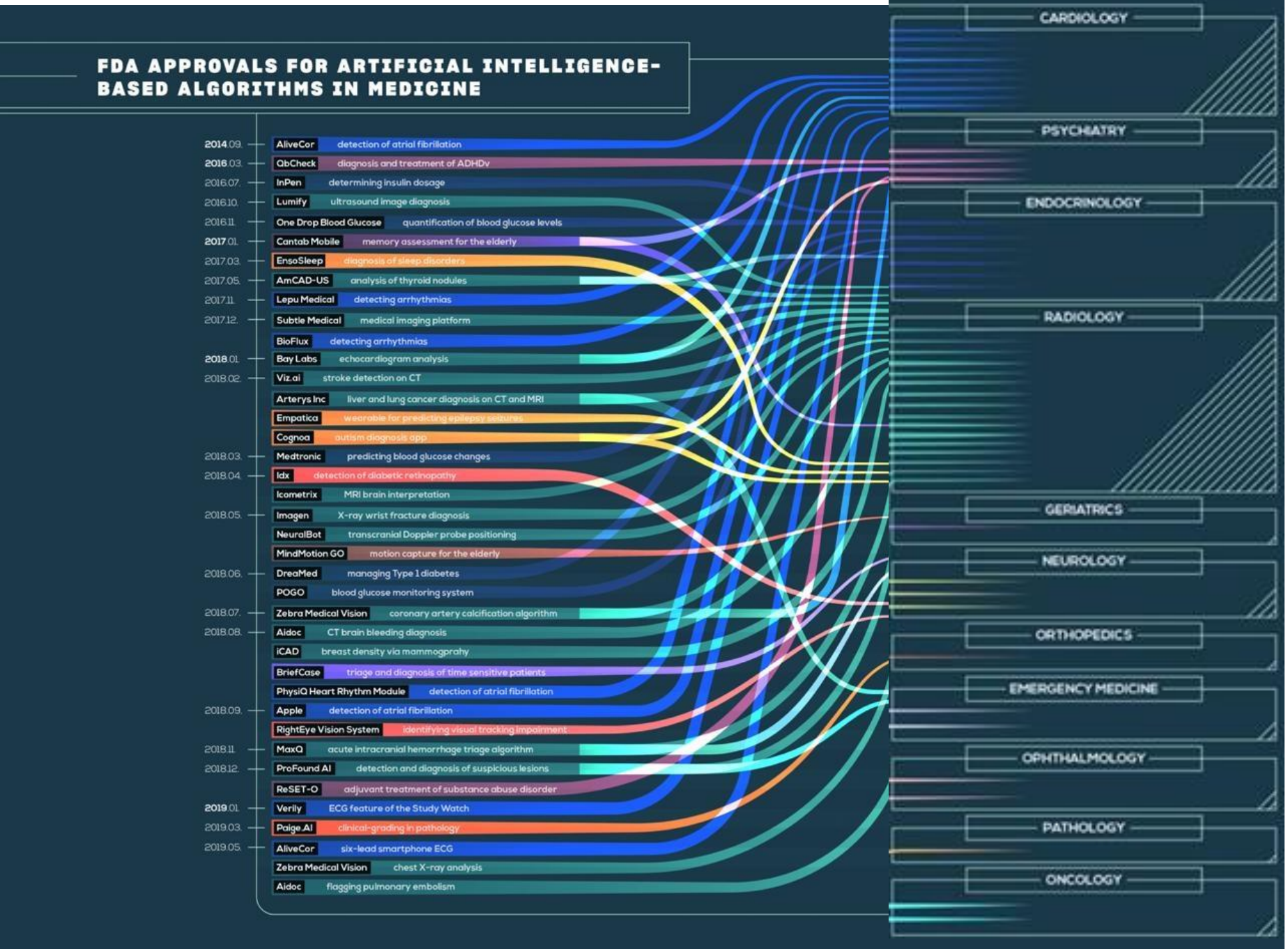

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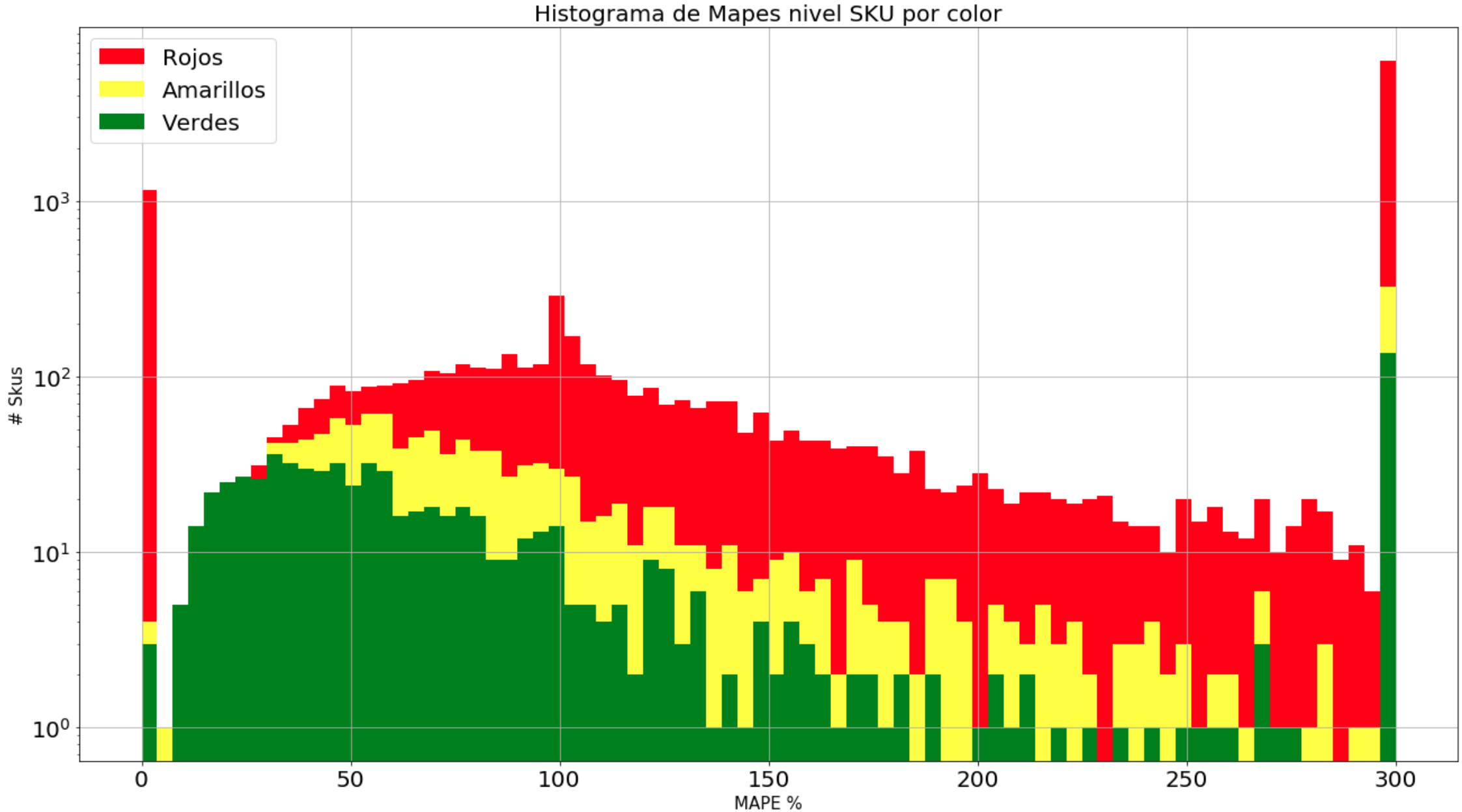

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ANASTASIA AI

INICIO

PANEL DE CONTROL

MODULOS

PREDICTOR

Subida de datos

Generar series de tiempo

Listado Series de tiempo

Resultados

MODULO DE SALUD

Información Paciente

Información Administrativa

PREDICTOR

Predictor / Indicadores relacionados

SERIES DE TIEMPO

Generar Indicadores relacionados

Buscar

ID	Nombre	Generado	Tipo de Agrupación	Rango Información	Periodicidad	Selección
737	auto_sku	24-05-2018	SKU	20/05/2017-16/02/2018	Mensual	◉
443	por planta	24-05-2018	GE3	20/05/2017-16/02/2018	Mensual	○
128	por región	13-07-2018	GE4	20/05/2017-16/02/2018	Mensual	○
937	prueba	13-07-2018	SKU	20/05/2017-16/02/2018	Mensual	○

← Prev 1 2 3 4 Next →

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Seleccione SKU

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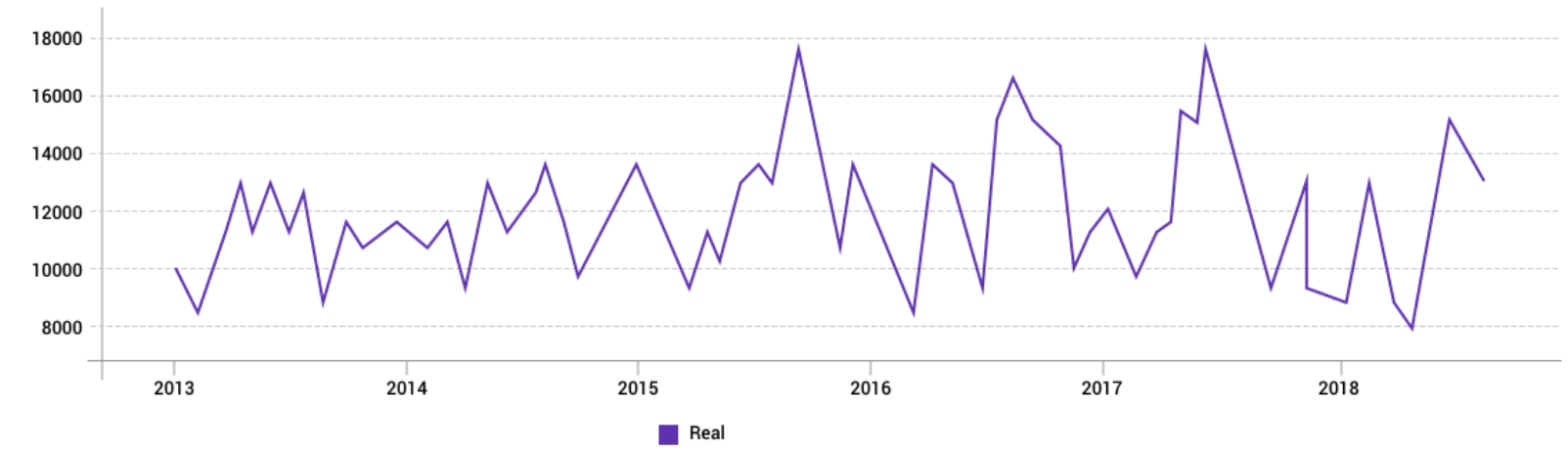

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Fecha

2/2/2019 3/31/2019

Género

- (Blank)
- Femenino
- Masculino

Count of IdCliente by Año

50K
0K

Atenciones por Género

Femenino

Tabaquismo

Moderado

Social

Atenciones Epidemiología

Enfermedades respiratorias
Gastroenterología
Aparato genital y urinario
Infecciones Ap. digestivo
Otorrinolarin...
Otros
Muscu...
Examen médi...
Nutri...
San...
S.N.C
Infecciones Vi...
Dermatología
Traumatism...
Enf.Mentales

Atenciones por Diagnostico

Faringitis aguda
Rinofaringitis aguda [resfriado com£n]
Amigdalitis aguda
Diarrea y gastroenteritis de presunto ...
Infecci¢n de v¡as urinarias, sitio no esp...
Faringitis aguda, no especificada
Bronquitis aguda
Infecci¢n aguda de las v¡as respiratori...
Faringitis estreptoc¢cica
Colitis y gastroenteritis al,rgicas y diet,...
Rinitis, rinofaringitis y faringitis cr¢nicas
Otitis externa

0K 2K 4K 6K 8K 10K 12K 14K

Atenciones por Sucursal

TANTOYUCA
LAS TORRES
LUCERO
ANTONIO MADRAZO
JARDIN REAL
JUPITER II
LAS FUENTES REYN...
PLAZA VISTA DEL SOL
PLAZA DEL SOL
MODAL ROSARIO
LERDO
CUMBRES MADEIRA
TINAJAS
LAGO ALBERTO
PASEO DEL TRIUNFO
BELLAS ARTES
PLAZA SAUCES (SOBE)
FELIX CUEVAS
FRESNO
CHAPALA
JARDINES DEL VALLE...
TCHAIKOVSKI
PASEO DE LOS VERD...

0 200 400 600 800

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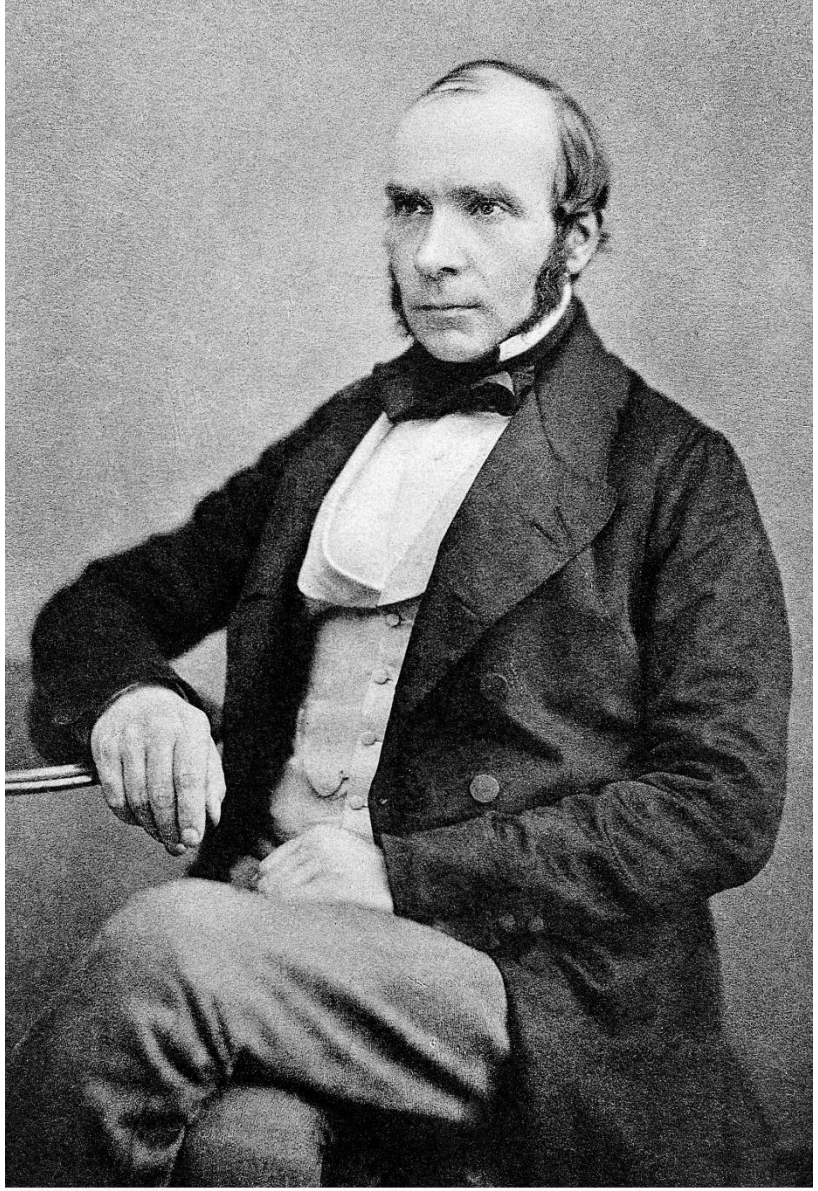

John Snow

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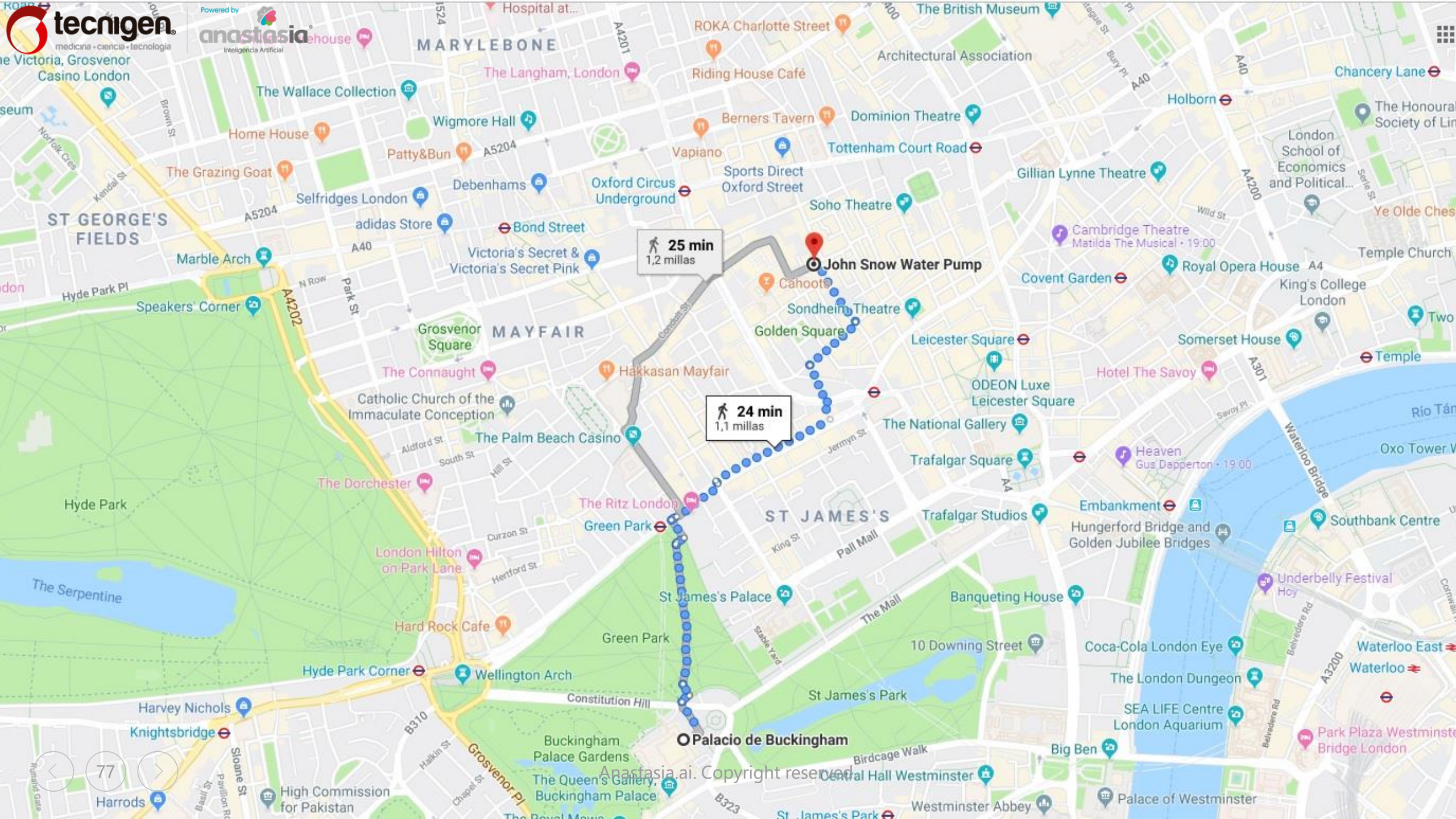

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Diabetes

NO | SI

Sexo

F | M

Pais

CHILE | MEXICO

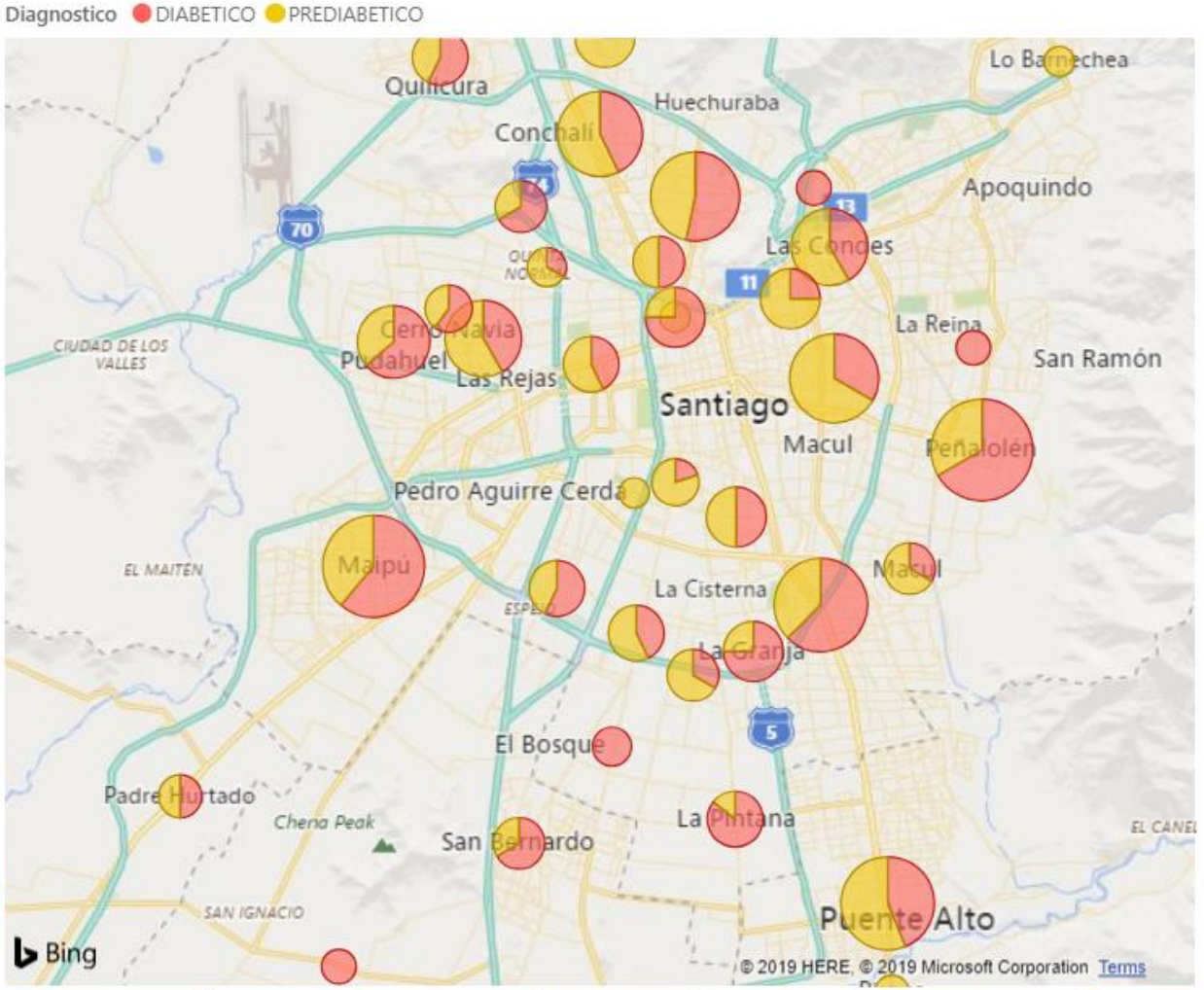
Edad

0 — 99

Fecha

Mexico DF | Chile X Región | Chile VII Región | Chile V Región | Chile Metropolita... | Chile IV Reg... | Chile III Reg...

Chile XI Región | Chile VIII Región | Chile VI Región | Chile Otra | Chile IX Región | Chile II Región



VITACURA | SANTIAGO CE... | SAN MIGUEL | RENCA | PUENTE ALTO | POLPAICO | PENAFLOR | PADRE HURT... | MAULE | LO PRADO | LAMPA | LA FLORIDA | ESTACION CE... | CONCH... | COLINA | CERRO ...

TIL TIL | SANTIAGO | SAN JOSE DE ... | RECOLETA | PUDAHUEL | PIRQUE | PELLUHUE | NUNOA | MALLOA | LO ESPEJO | LA REINA | LA CISTERNA | EL MONTE | CERRILLO... | CALER... | BUIN

TALAGANTE | SAN VICENTE | SAN JOAQUIN | QUINTA NOR... | PTE ALTO | PEUMO | PEDRO AGUI... | NO SE | MAIPU | LO BARNECH... | LA PINTANA | INDEPENDEN... | EL BOSQUE | CARTAGE...

STGO | SAN RAMON | SAN BERNAR... | QUILICURA | PROVIDENCIA | PENALOLEN | PAINE | MELIPILLA | MACUL | LAS CONDES | LA GRANJA | HUECHURABA | CURACAVI | BATUCO

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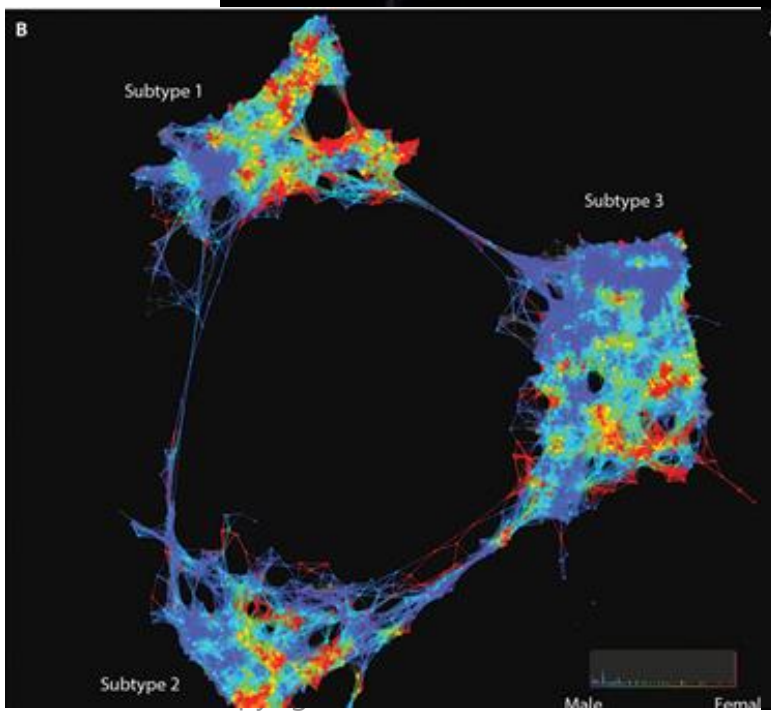
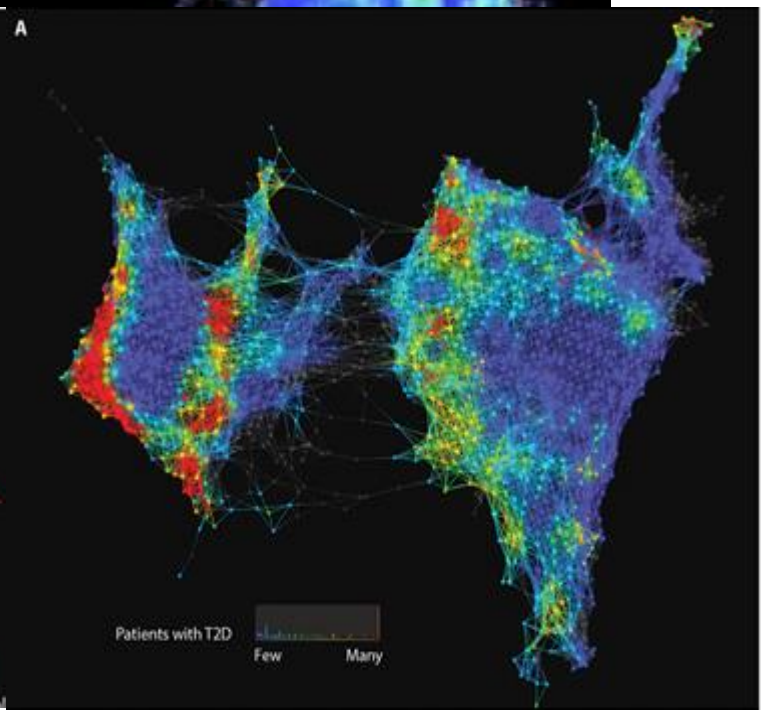
Identification of type 2 diabetes subgroups through topological analysis of patient similarity

Li Li[1], **Wei-Yi Cheng**[1], **Benjamin S. Glicksberg**[1], **Omri Gottesman**[2], **Ronald Tamler**[3], **Rong Chen**[1], **Erwin P. Bottinger**[2], and **Joel T. Dudley**[1,4,*]

Abstract

Type 2 diabetes (T2D) is a heterogeneous complex disease affecting more than 29 million Americans alone with a rising prevalence trending toward steady increases in the coming decades. Thus, there is a pressing clinical need to improve early prevention and clinical management of T2D and its complications. Clinicians have understood that patients who carry the T2D diagnosis have a variety of phenotypes and susceptibilities to diabetes-related complications. We used a precision medicine approach to characterize the complexity of T2D patient populations based on high-dimensional electronic medical records (EMRs) and genotype data from 11,210 individuals. We successfully identified three distinct subgroups of T2D from topology-based patient-patient networks. Subtype 1 was characterized by T2D complications diabetic nephropathy and diabetic retinopathy; subtype 2 was enriched for cancer malignancy and cardiovascular diseases; and subtype 3 was associated most strongly with cardiovascular diseases, neurological diseases, allergies, and HIV infections. We performed a genetic association analysis of the emergent T2D





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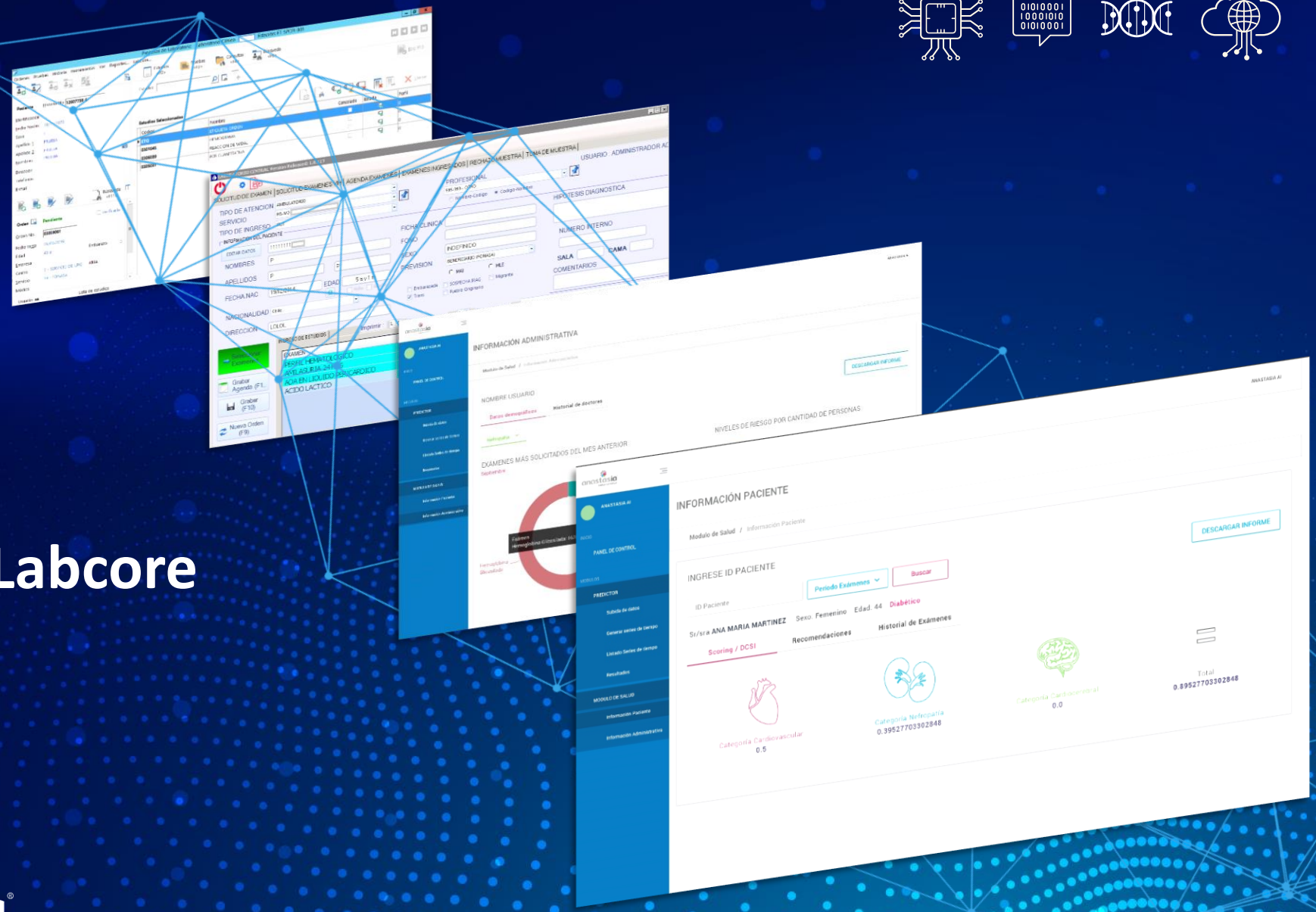

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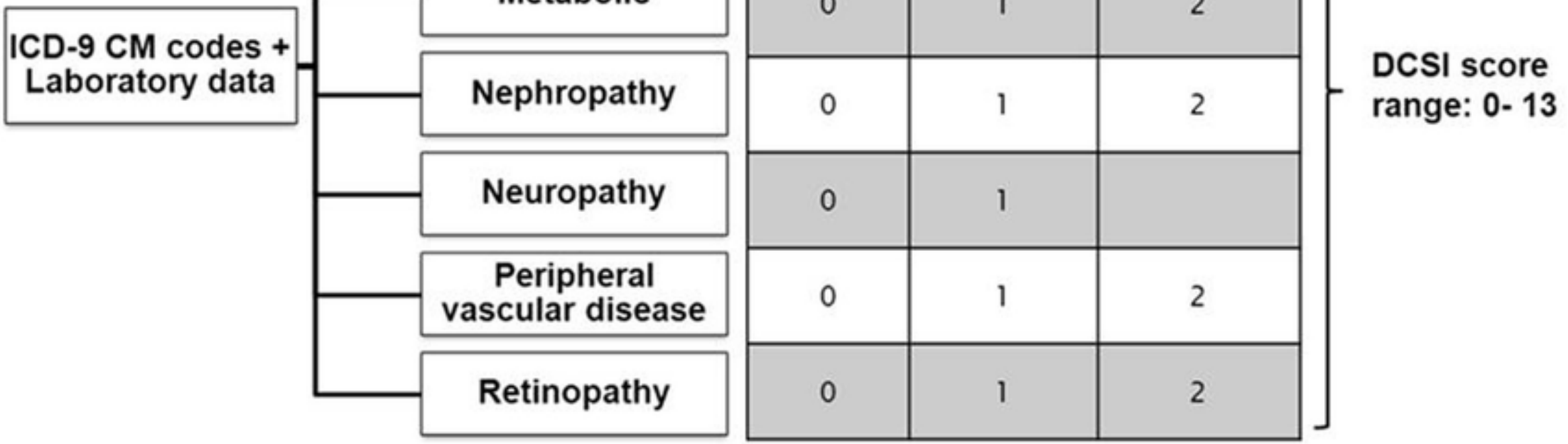

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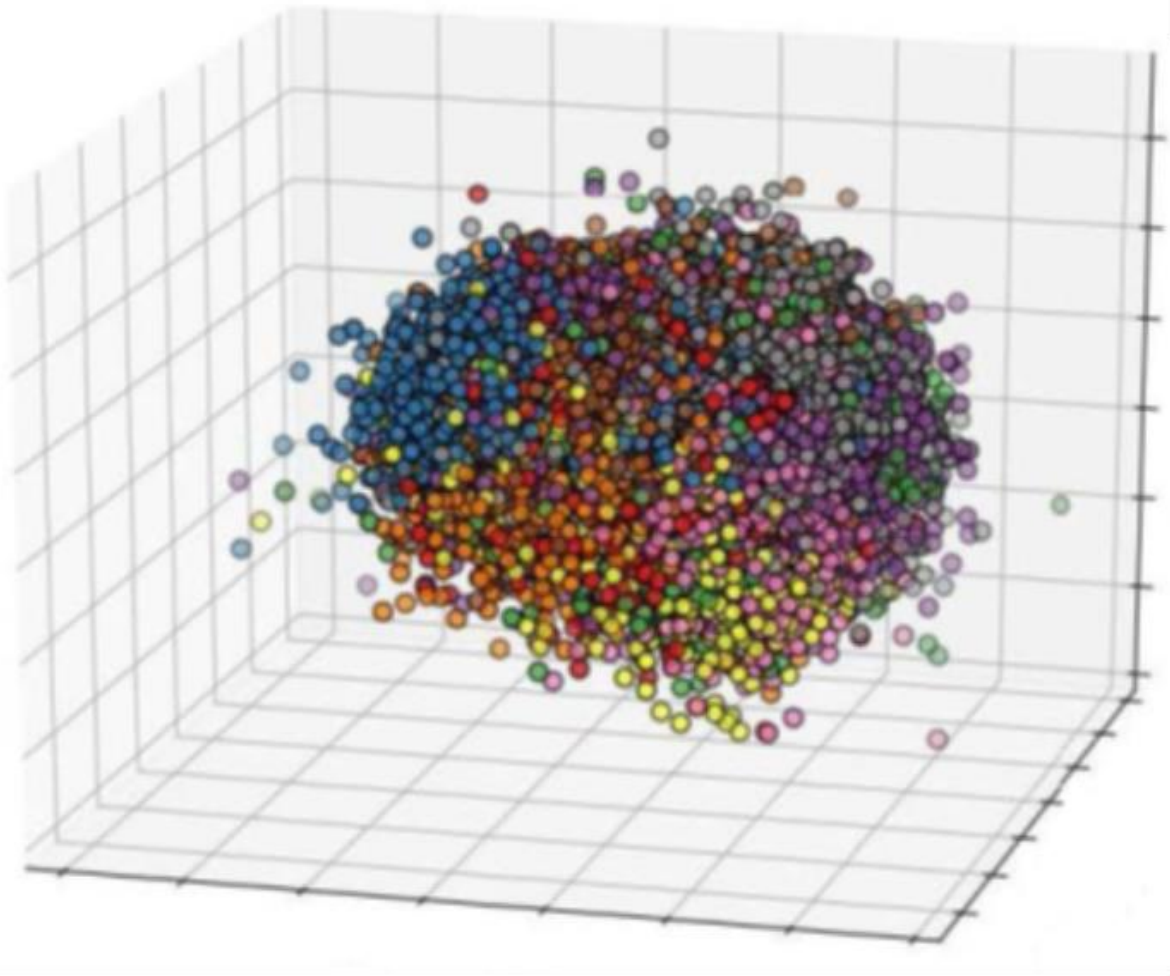

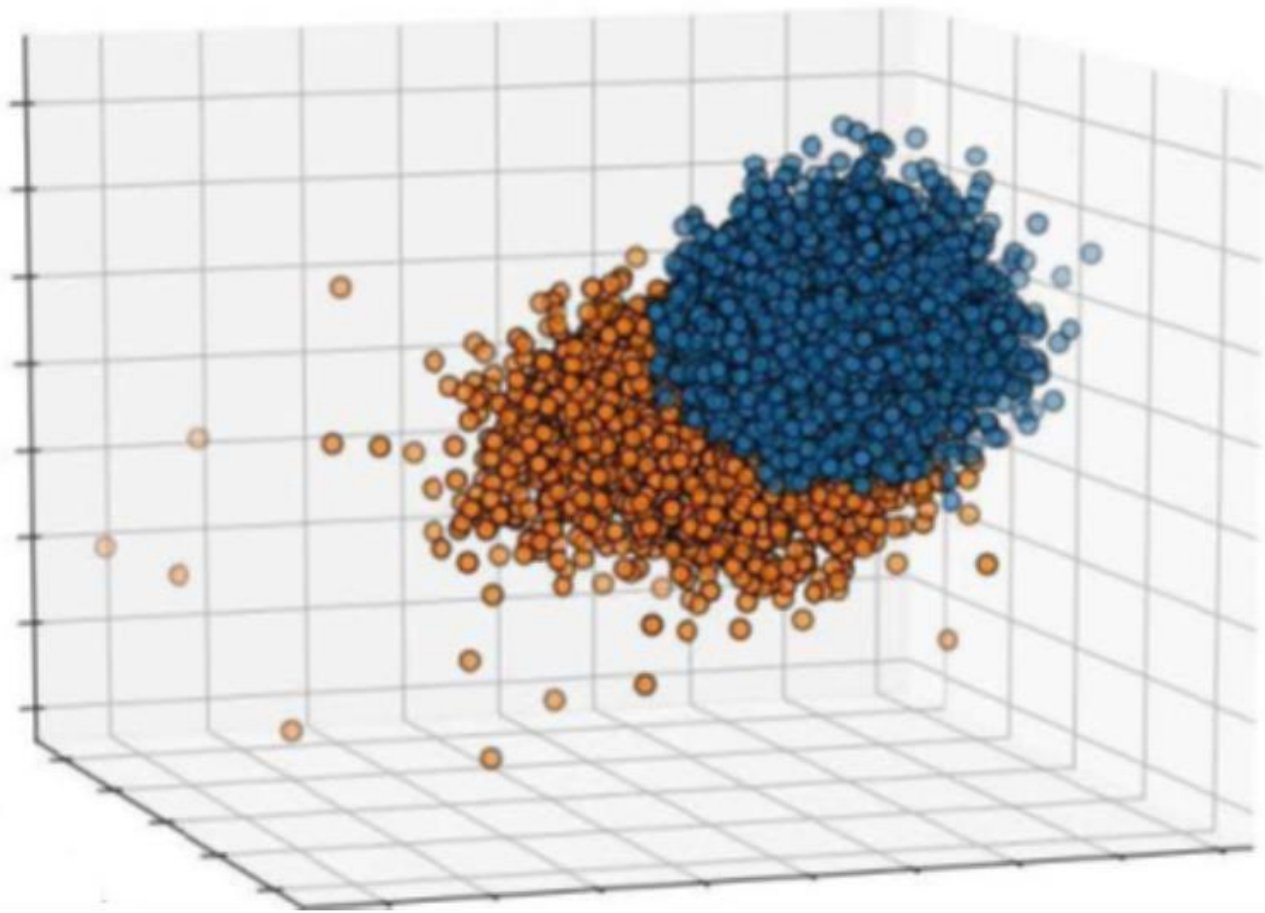

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0 104

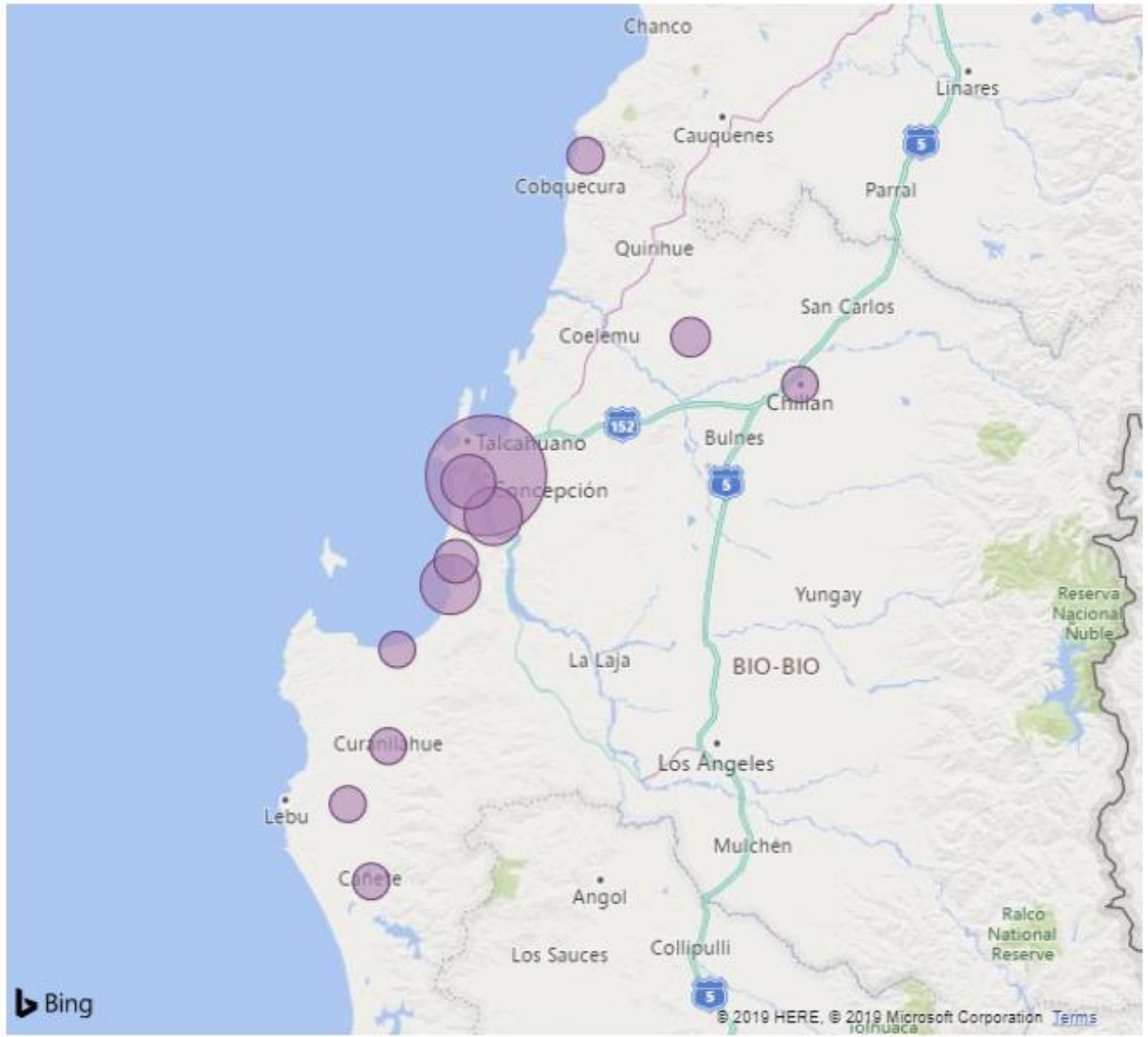
Diagnostico di...
- [ ] Diabetico
- [ ] Normal
- [ ] Pre-Diabetico

- [ ] FEMENINO
- [ ] MASCULINO

Edad (grupos)
- [ ] (Blank)
- [ ] 0 - 15
- [ ] 16 - 30
- [ ] 31 - 45

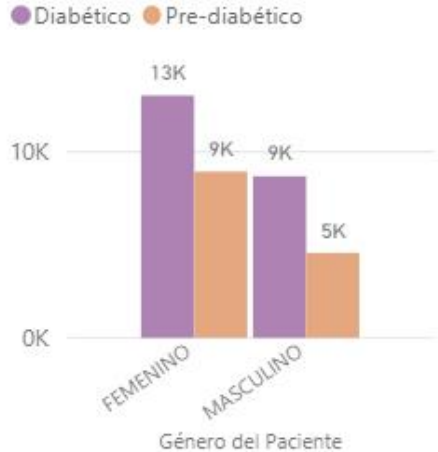
Normal	Pre-diabético	Diabético
422,257	13,502	21,710

Ubicación geográfica de pacientes diabéticos



Pacientes diabéticos y pre-diabéticos por rango de Edad

Pacientes diabéticos y pre-diabéticos por género



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0 104

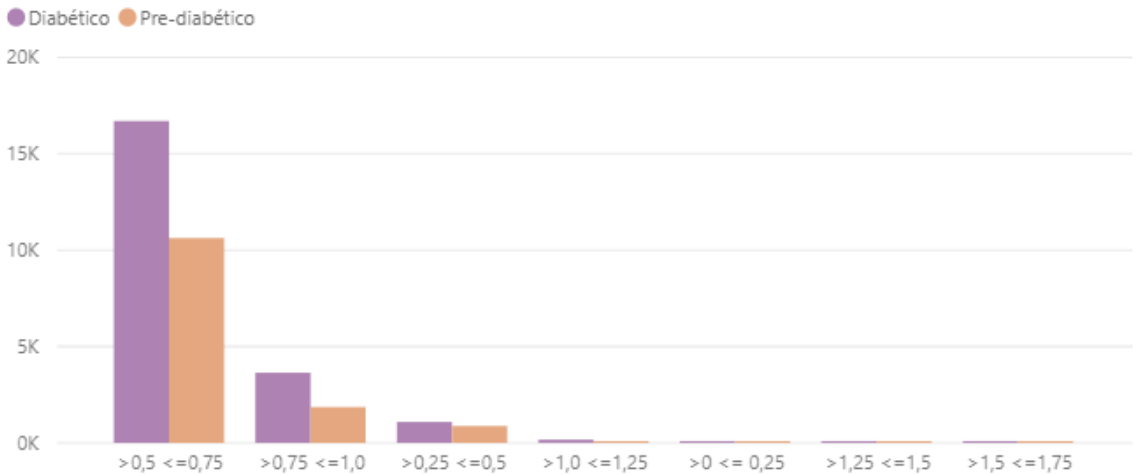
Diagnostico diabe...
- Diabetico
- Normal
- Pre-Diabetico

- FEMENINO
- MASCULINO

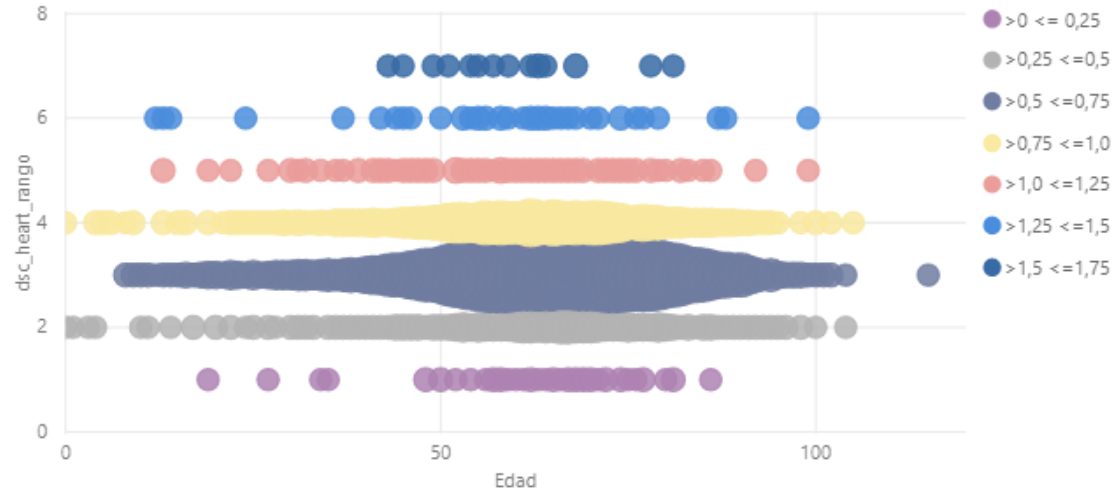
Edad (grupos)
- (Blank)
- 0 - 15
- 16 - 30
- 31 - 45

dsci_heart (ubicaciones)
0.06 1.55

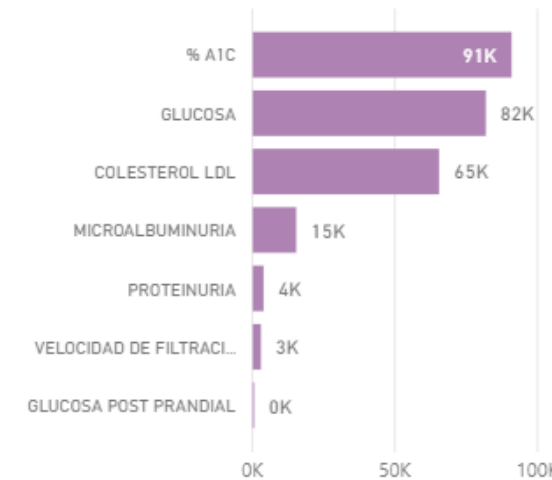
Diabético y Pre-diabético por Rango dsci cardíaco



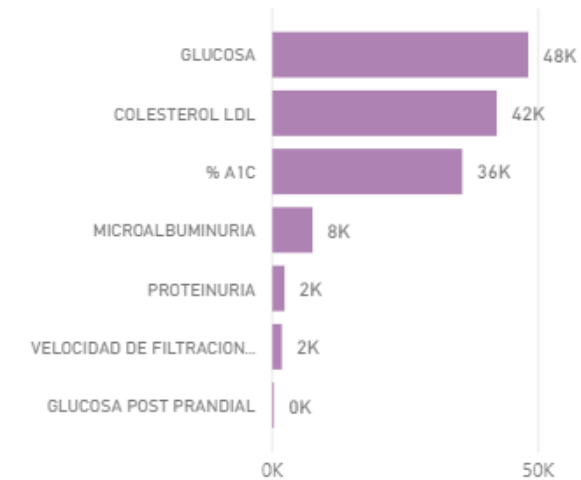
Cantidad de Pacientes por edad y por Rango de dsci cardíaco



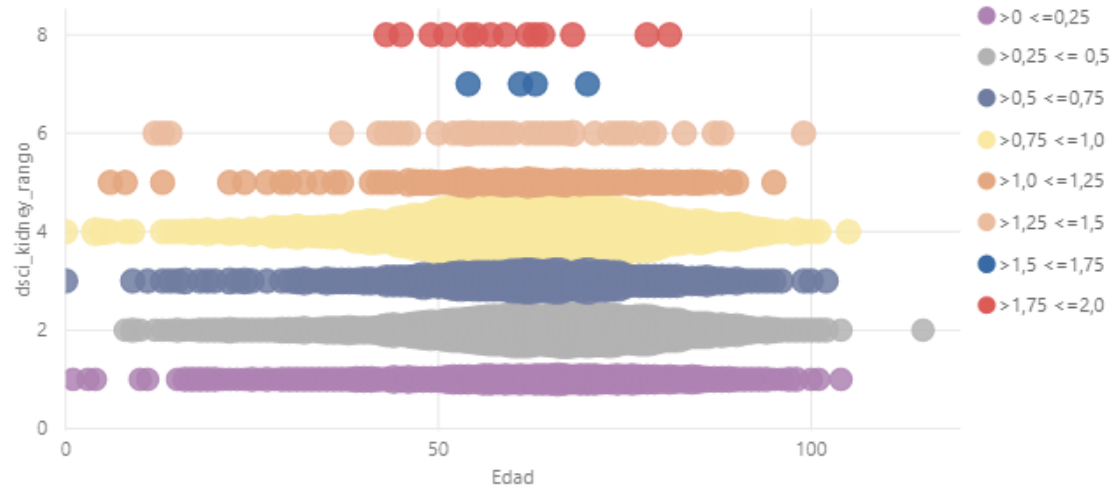
Cantidad de Exámenes por paciente diabético



Cantidad de Exámenes por paciente pre-diabético



Cantidad de Pacientes por edad y por Rango de dsci pulmonar



INGRESE ID PACIENTE

1

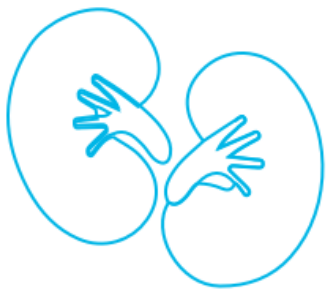
Últimos 12 meses

BUSCAR

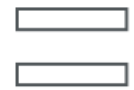
Sr./Sra. : Sexo : I Edad : **Diabetico (Riesgo cardiovascular alto)**

Scoring / DCSI | Recomendaciones | Historial de Exámenes

Categoria Cardiovascular
0.8105487124822411



Categoria Nefropatía
0.7107127445962931



Total
1.521261457078534

Sr./Sra. : Sexo : Edad : **Diabetico (Riesgo cardiovascular alto)**

Scoring / DCSI | Recomendaciones | Historial de Exámenes

Se recomienda que el/la paciente realice los siguientes exámenes :

MICROALBUMINURIA

VELOCIDAD DE FILTRACION GLOMERULAR (CKD-EPI)

Se recomienda evaluar :

Evaluar si existe algun grado de neuropatía, insuficiencia arterial periferica y/o pie diabético. Evaluar si existen alteraciones retinales. Preguntar por eventos de urgencia diabéticas como cetoacidosis o coma. Tomar presión arterial, medir circunferencia de cintura, calcular IMC, corroborar si está en postmenopausia, evular tabaquismo, evaluar actividad fisica.

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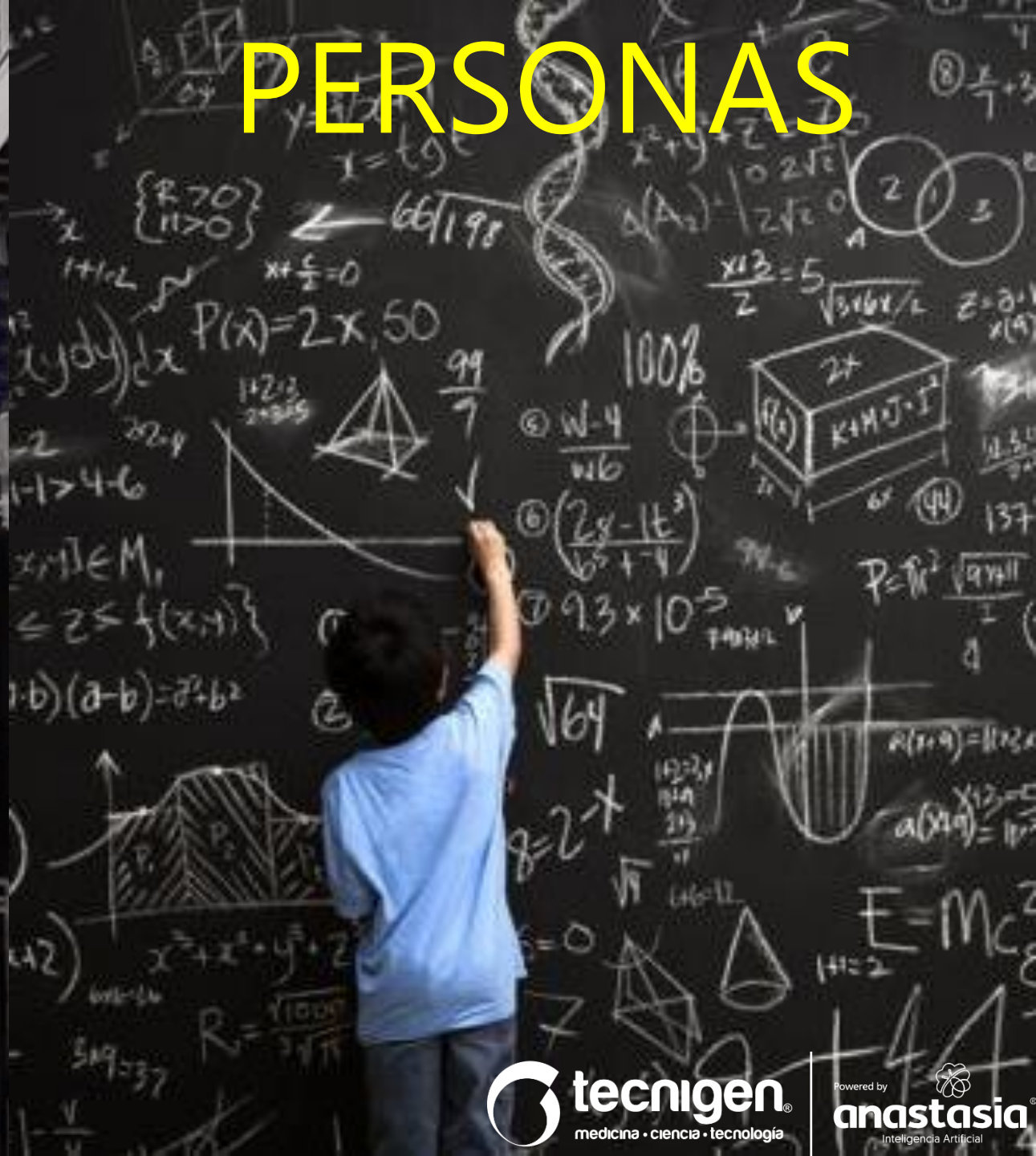

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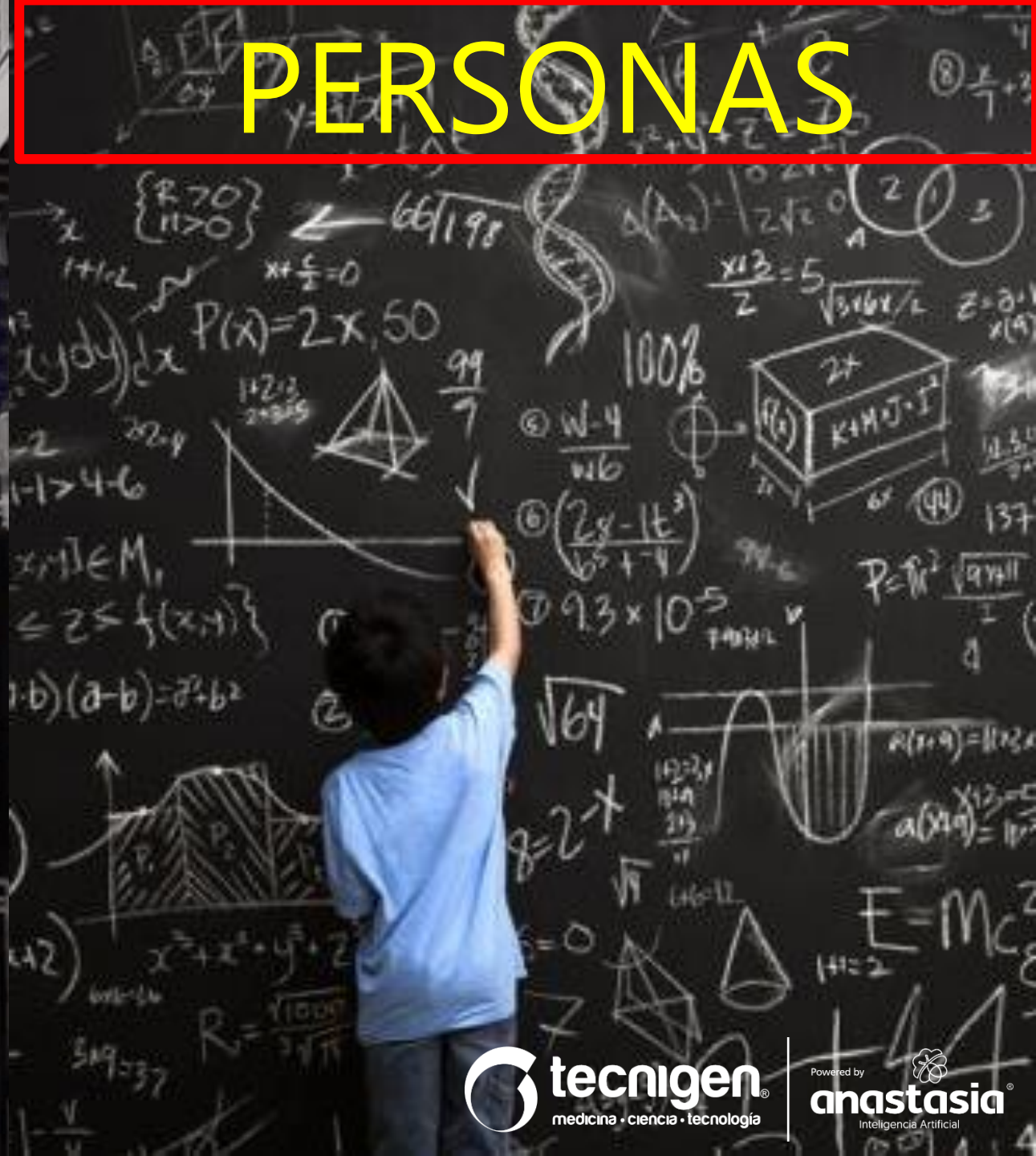
PERSONAS



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OCDE destaca el alto costo del país para enfrentar los desafíos de la automatización:

42% de los chilenos no tiene competencias básicas para la economía digital

> *Este es un desafío mayor que no solo puede ser resuelto por el Gobierno: las empresas deben dejar de ser consumidoras de trabajo para pasar a ser formadoras de talento".*
>
> **SARA MOSK,** PRESIDENTA DE AGEST

> *Responder a la exigencia de aprendizaje continuo que imponen los nuevos tiempos es imposible sin una reforma profunda al sistema de capacitación".*
>
> **JUAN BRAVO,** ECONOMISTA DE CLAPES UC

dustria ha desaparecido de una zona geográfica, por ejemplo". Smok dice que en esto hay una combinación de factores, dado por un sistema educacional que no está alineado para la adaptabilidad.

El desafío de capacitar

En este sentido, la OCDE destaca el desafío de los países para capacitar a sus trabajadores y facilitar su transición desde trabajos con altos riesgos de ser automatizados hacia mejores empleos de mejor calidad.

"Vemos que se están haciendo esfuerzos en esta área, como el proyecto para modernización de la franquicia tributaria ingresado al Congreso en marzo de este año, que tiene elementos positivos, pero que no aborda la problemática de la capacitación de manera integral", dice Juan Bravo, economista de Clapes UC. "Responder a la exigencia de aprendizaje continuo que imponen los nuevos tiempos

débiles estructuras educacionales se suman a que en Chile una gran proporción de los empleados están en puestos que pueden desaparecer. "Chile es de los países con mayor proporción de sus trabajadores en puestos de trabajos con alto riego de ser automatizados", dice el reporte.

Estas características hacen que Chile sea el país donde sería más caro capacitar a la masa de trabajadores con alto riesgo de perder sus trabajos a puestos con bajo riesgos de ser reemplazados por la automatización, contabilizando los costos directos (el pago de la instrucción) así como los indirectos (el salario perdido por tener que educarse). Mientras en Noruega este costo es de 0,3% del PIB anual, en Chile esto sería de 2,3% del PIB, el valor más alto en los países de la muestra. "Chile, Grecia y Turquía se están

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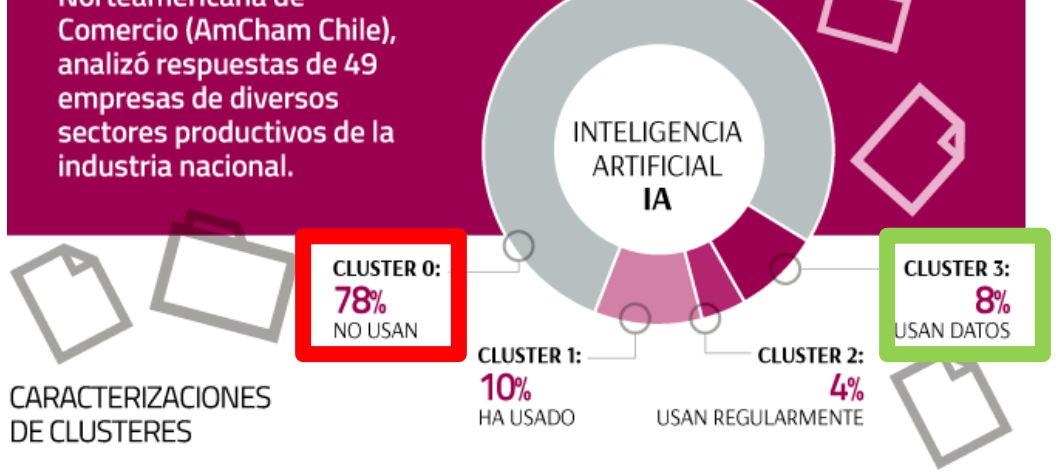
Comercio (AmCham Chile), analizó respuestas de 49 empresas de diversos sectores productivos de la industria nacional.



CARACTERIZACIONES DE CLUSTERES

USO DE DATOS, TECNOLOGÍAS INCORPORADAS Y POLÍTICAS	CLUSTER 0	CLUSTER 1	CLUSTER 2	CLUSTER 3
PARA TOMAR DECISIONES	NO	A VECES	SÍ	SÍ
DATOS DE SENSORES IOT	NO	NO	SÍ	SÍ
DATOS NO ESTRUCTURADOS	NO	NO	NO	SÍ
USO DE INTELIGENCIA ARTIFICIAL (IA)	BAJO	BAJO	BAJO	SÍ
PROTOCOLO PARA MANEJO DE DATOS SENSIBLES	NO	SÍ	NO	SÍ
SOFTWARE PARA INCORPORAR IA	NO	SÍ	SÍ	SÍ
ESPECIALISTAS PARA INCORPORAR IA	N/A*	NO	SÍ	SÍ
ESTRUCTURA PARA INCORPORAR IA	N/A*	NO	NO	SÍ
ANALÍTICA DESCRIPTIVA	BAJO	SÍ	SÍ	SÍ
ANALÍTICA PREDICTIVA	NO	BAJO	SÍ	SÍ
POLÍTICA EMPRESARIAL PARA USO DE IA	NO	SÍ	SÍ	SÍ

(*) NO APLICA

IMPACTO DE USO DE IA EN LAS EMPRESAS	CLUSTER 0	CLUSTER 1	CLUSTER 2	CLUSTER 3
ELIMINAR ROLES	NO	SÍ	SI	SI
REDUCIR COSTOS	NO	NO	SÍ	SI
AUTOMATIZAR TAREAS	NO	NO	SI	SI
AUMENTAR LA PRODUCTIVIDAD	NO	SÍ	SI	SI

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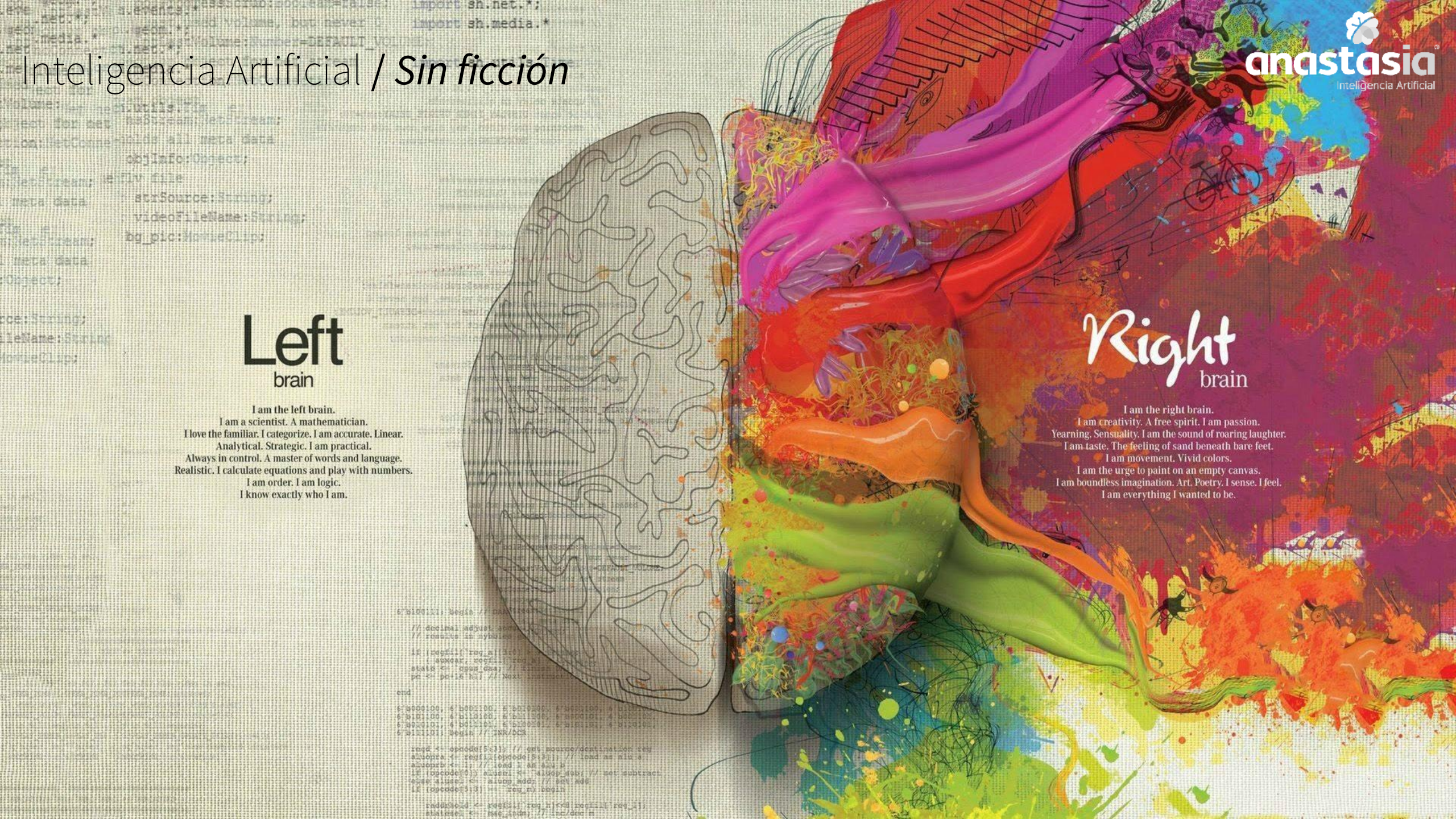
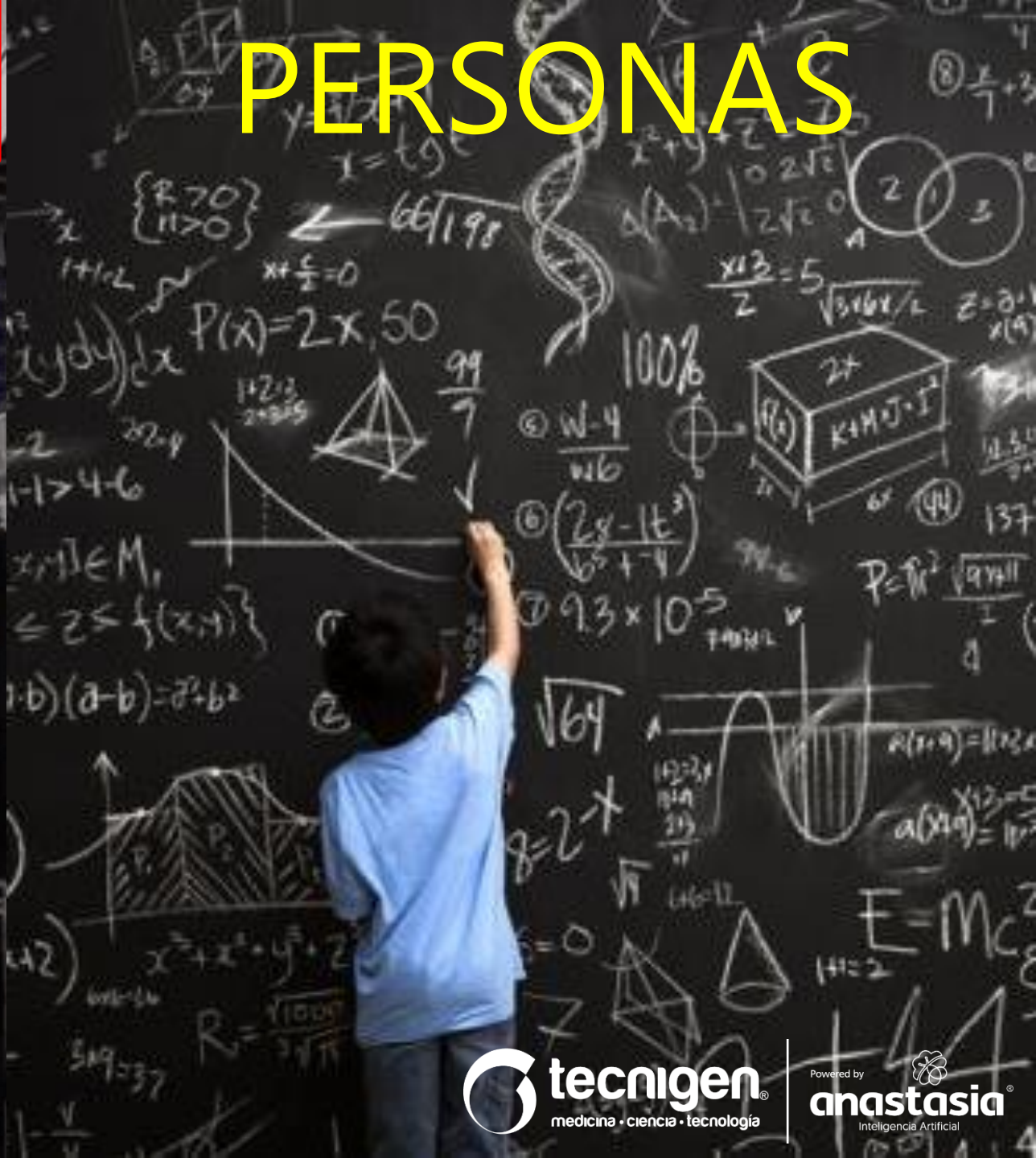


TECNOLOGÍA

PERSONAS



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Datos

Entropia

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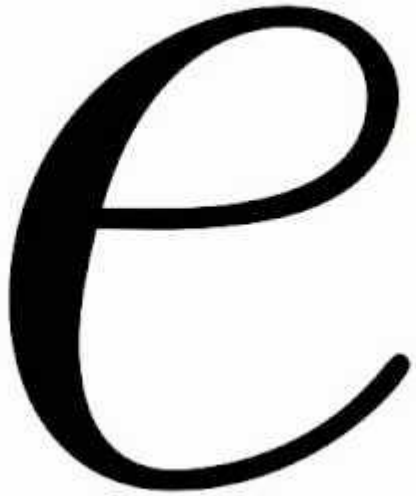

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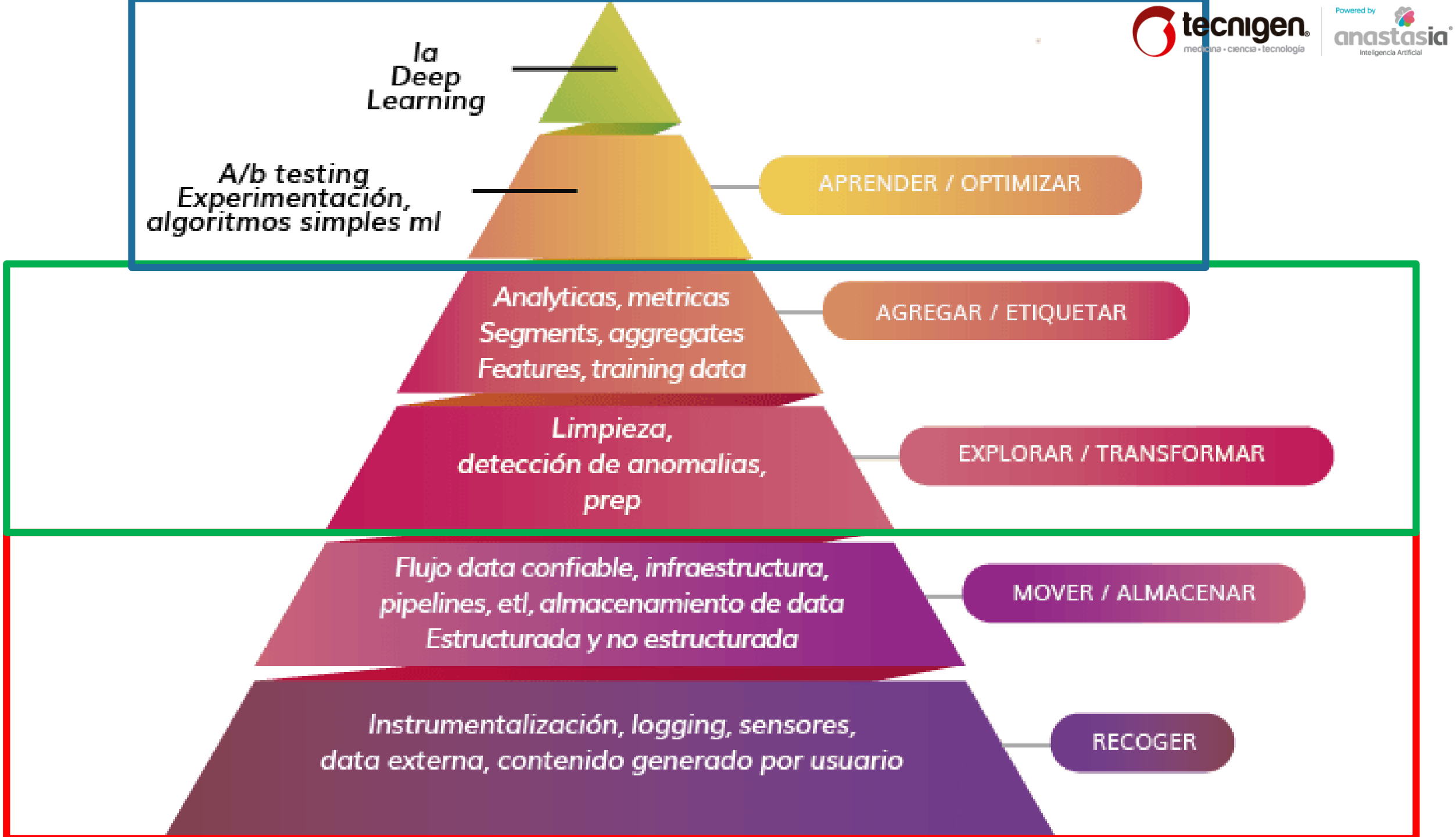
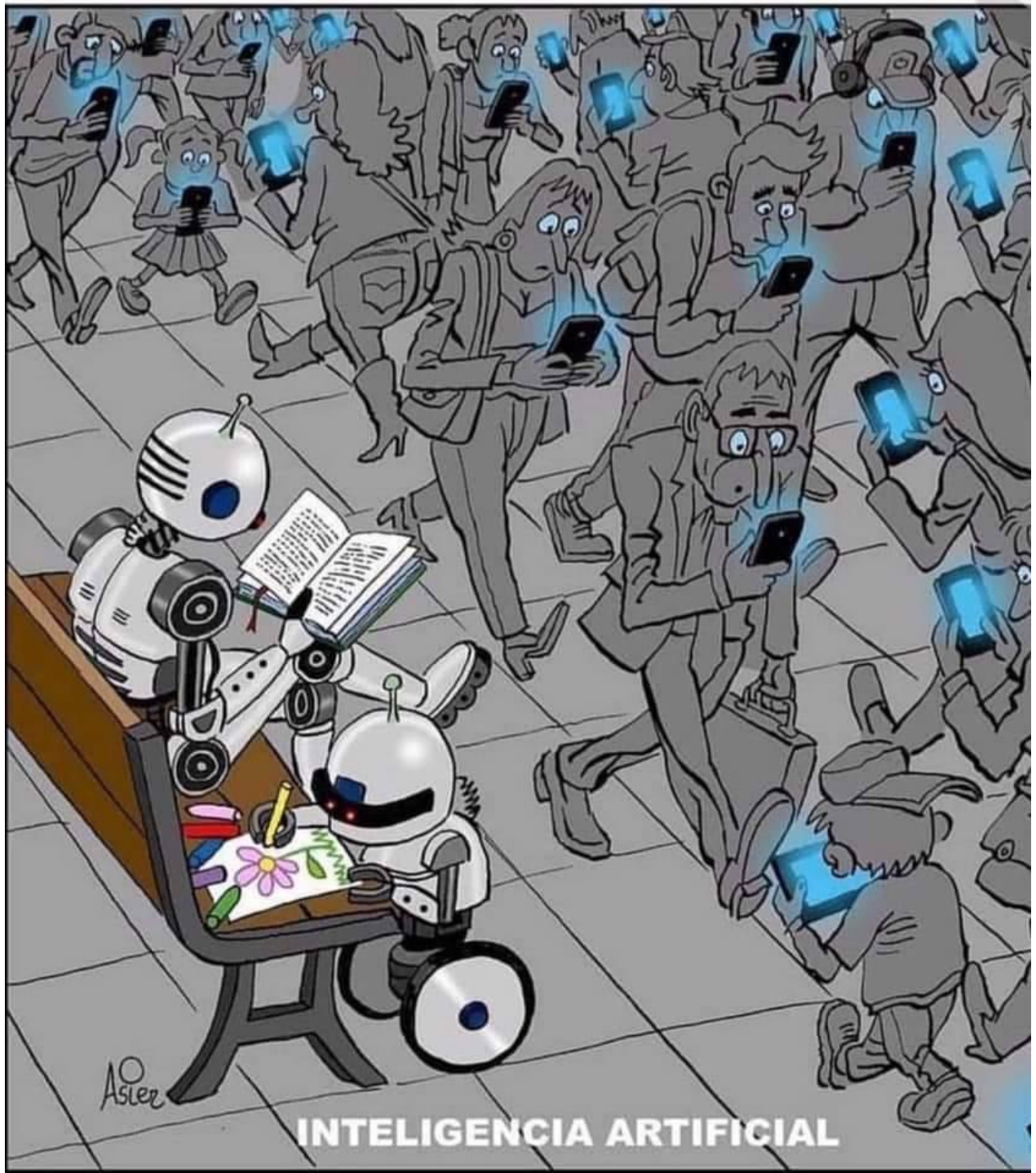

la
Deep
Learning
A/b testing
Experimentación,
algoritmos simples ml
APRENDER / OPTIMIZAR
Analyticas, metricas
Segments, aggregates
Features, training data
AGREGAR / ETIQUETAR
Limpieza,
detección de anomalias,
prep
EXPLORAR / TRANSFORMAR
Flujo data confiable, infraestructura,
pipelines, etl, almacenamiento de data
Estructurada y no estructurada
MOVER / ALMACENAR
Instrumentalización, logging, sensores,
data externa, contenido generado por usuario
RECOGER



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