

Inteligencia Artificial

Una Revolución

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Presentación

Científico y Emprendedor, Enfocado en Inteligencia Artificial



- No es una ciencia más, es una **meta ciencia**.
- **Inteligencia Artificial**
 - Aprendizaje de Máquinas
 - Aprendizaje Profundo (*Deep Learning*)
- **Robótica**, IA en un sistema físico capaz de interactuar con el mundo físico.

- A partir del 2011, sorpresivamente y en contra del sentido común, las **redes neuronales profundas resolvieron problemas difíciles con facilidad**.
- Schwartz-Ziv and Tishby, el 29 of April of 2017, **demuestran en “Opening the black box of Deep Neural Networks via Information”, ArXiv, que se cruzó un umbral matemático, hasta el momento desconocido, que permitió diseñar con facilidad IAs complejas.**

Inteligencia Artificial

Estado del Arte

arXiv:1611.08235v2 [cs.CV] 6 Dec 2016

Full-Resolution Residual Networks for Semantic Segmentation in Street Scenes

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Abstract

Semantic image representation is an essential component of modern autonomous driving systems, as an accurate understanding of the surrounding scene is crucial to navigation and action planning. Current state-of-the-art approaches to semantic image segmentation rely on pre-trained networks that were initially developed for classifying images as a whole. While these networks exhibit outstanding recognition performance (i.e., what is visible?), they lack localization accuracy (i.e., where precisely is something located?). Therefore, additional processing steps have to be performed in order to obtain pixel-accurate segmentation results at the full image resolution. To achieve this, we propose a novel ResNet-like architecture that exhibits strong localization and recognition power. We combine multi-scale context with pixel-level accuracy by using two processing streams: while our network does semantic segmentation at the full image resolution, enabling precise adherence to object boundaries. The other stream undergoes a sequence of pooling operations to obtain coarse features for recognition. The two streams are coupled at the full image resolution using residual units. Without additional processing steps and without pre-training, our approach achieves an intersection-over-union score of 77.2% on the Cityscapes dataset.

1. Introduction

Recent years have seen an increasing interest in self-driving cars and in driver assistance systems. A crucial aspect of autonomous driving is to acquire a comprehensive understanding of the surroundings in which a car is moving. Semantic image segmentation [1, 2, 3, 4, 5, 6], the task of assigning a set of predefined class labels to image pixels, is an important tool for modeling the complex relationships of the semantic content usually found in street scenes, such as cars, pedestrians, road, or sidewalks. In autonomous navigation it is used to estimate metrics, e.g., to open processing steps to discard image regions that are unlikely to contain objects of interest [7, 8] to improve object detection [9, 10, 11, 12].



Figure 1. Example output and the abstract structure of our full-resolution residual network.

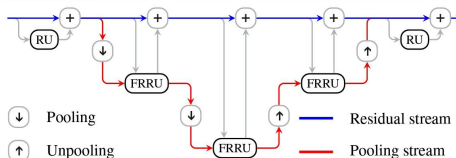


Figure 1. Example output and the abstract structure of our full-resolution residual network. The network has two processing streams. The residual stream (blue) stays at the full image resolution, the pooling stream (red) undergoes a sequence of pooling and unpooling operations. The two processing streams are coupled using full-resolution residual units (FRRUs).

2016-12-6

Learning Dexterous In-Hand Manipulation



Figure 1: A blue fingered humanoid hand trained with reinforcement learning manipulating a block from an initial configuration to a goal configuration using vision for sensing.

Abstract

We use reinforcement learning (RL) to learn dexterous in-hand manipulation policies which can perform vision-based object manipulation on a physical Shadow Hand. The training is performed in a simulated environment to learn a combination many of the physical properties of the system like friction coefficients and an object's appearance. Our policies transfer to the physical robot despite being trained entirely in simulation. Our method does not rely on any human demonstrations, but more reliance toward human manipulation energy naturally including finger posing, wrist finger coordination, and the controlled use of gravity. Our results were obtained using the same distributed RL system that was used to train OpenAI Five [15]. We also include a video of our results. Images: /papers/2019/04/01/0101010101

1 Introduction

While dexterous manipulation of objects is an fundamental everyday task for humans, it is still challenging for autonomous robots. Modern-day robots are typically designed for specific tasks in controlled settings and are largely unable to adjust, adapt, and effectively. In contrast, people are able to perform a wide range of dexterous manipulation tasks in a diverse set of environments, making the human hand a generalist source of inspiration for robotic in-hand manipulation. The Shadow Handcrafter Hand (SH) is an example of a robotic hand designed for human-level dexterity. It has five fingers with a total of 38 degrees of freedom. The hand has been commercially available since 2015 (<http://www.shadow-robot.com>) and is open to OpenAI in alphabetical order.

Shao-An Huang, Benoit Bonet, Michael Chen, Rishi Desai, Bob D'Amico, Clark Doornik, Andrew Engel, Markéta Filipová, Shuang Gao, Alex Hays, James Henshaw, Norman Hou, Bob Kahn, Peter Kohler, Liheng Wang, Wojciech Zarembki

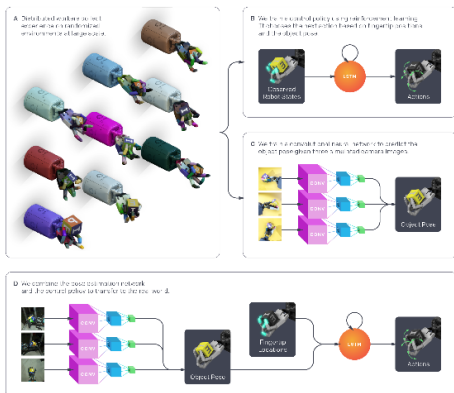


Figure 2: System Overview. (a) We use a large distribution of simulations with randomized parameters and appearances to collect data for both the control policy and vision-based pose estimator. (b) The control policy receives observed robot states and rewards from the distributed simulations and learns to map observations to actions using a recurrent neural network and reinforcement learning. (c) The vision based pose estimator renders scenes collected from the distributed simulations and learns to predict the pose of the object using a convolutional neural network (CNN), trained separately from the control policy. (d) To transfer to the real world, we predict the object pose from 3 real camera feeds with the CNN, measure the robot fingertip locations using a 3D motion capture system, and give both of these to the control policy to produce an action for the robot.

2018-7-30

A Deep Reinforced Model for Abstractive Summarization

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Abstract

Attentional, RNN-based encoder-decoder models for abstractive summarization have achieved good performance on short input and output sequences. However, for longer documents and summaries, these models often include repetitive and incoherent phrases. We introduce a neural network model with reinforcement and a new training method. This method combines standard supervised word prediction and reinforcement learning (RL). Models trained only with the former often exhibit “stoppage bias” – they assume good truth is provided at each step during training. However, when standard word prediction is combined with the global reward provided by testing 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 41.6 BLEU-4 score on the CNN/Daily Mail dataset, a 5.7 absolute points improvement over previous state-of-the-art models. It also performs well as the first abstractive model on the New York Times corpus. 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 parts.

By combining large quantities of information into short, informative summaries, summarization can aid many downstream applications such as

creating news digests, tweets, and report generators.

There are two prominent types of summarization algorithms. First, extractive summarization extracts facts summaries by copying parts of the input (Nee et al., 2002; 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; Zeng et al., 2016).

Recently, neural network models (Nallapati et al., 2016; Zeng 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 BLEU-4 scores. However, these systems have typically focused on summarizing short input sequences (one or two sentences) to generate even shorter summaries. For example, the summaries on the DUC-2000 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 to the CNN/Daily Mail dataset (Ramesh et al., 2015), which contains input sequences of up to 500 tokens and multi-sentence summaries of up to 100 tokens. The analysis by Nallapati et al. (2016) illustrates a key problem with attentional encoder-decoder models: they often generate redundant 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) (Stanford, 2006). To our knowledge, this is the first model for abstractive summarization on the NYT dataset. We introduce a key attention mechanism and a new training objective to address the repeating phrase

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. He also became only the sixth F1 driver to lead 2,000 laps. Nico Rosberg has been left in the shade by Lewis Hamilton who celebrates winning his third race of the year Kimi Raikkonen secured a record seventh podium finish in Bahrain following his superb late salvo, although the Ferrari driver has never won in the Gulf Kingdom. It was the Finn's first trip to the rostrum since the 2013 Korean Grand Prix, but his triumph brought a typically deadpan response: 'You're never happy when you finish second... I'm a bit pleased to get a result.' Sparks fly off the back of Kimi Raikkonen's Ferrari en route to finishing second in Bahrain Bernie Ecclestone was in the Bahrain paddock this weekend. He denied trying to engineer a deal for Hamilton, out of contract at the end of the season, to join Ferrari despite earlier insisting that such a move would be "great" for the sport. The 84-year-old also confirmed that F1 would be in Azerbaijan for the first time next year, even with concerns surrounding the country's human rights record. 'I think everybody seems to be happy,' Ecclestone said. 'There doesn't seem to be any big problem there. There's no question of it not being on the calendar. It's going to be another good race. Formula One supremo Bernie Ecclestone speaks to Nico Rosberg ahead of the Bahrain Grand Prix

Ground truth summary

Button denied 100th race start for McLaren after ERS failed. 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.

ML₁ 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.

RL₁ 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+RL₁ 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 has 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.

Table 3: Example from the CNN/Daily Mail test dataset showing the outputs of our three best models after de-tokenization, re-capitalization, replacing anonymized entities, and replacing numbers. The ROUGE score corresponds to the specific example.

2017-5-19

Inteligencia Artificial

Estado del Arte

arXiv:1412.2306v2 [cs.CV] 14 Apr 2015

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 distant supervision 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 Multiresolution Recurrent Neural Network architecture that uses the regional alignments to learn to generate natural descriptions of image regions. We demonstrate that our alignment model produces state-of-the-art results in several experiments on Flickr3K, Flickr30K and MSCOCO datasets. We also show that the generated descriptions significantly outperform textual baselines on both full images and on a new dataset of region-level annotations.



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

generating these descriptions of image regions (Fig. 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. Ideally, the model should be free of assumptions about specific hand-crafted templates, rules or capacities 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 [1, 76, 77], but these descriptions analyze variations of several hundred visual instances in the images on captions. One core insight is that we can leverage these large image-sentence datasets by treating the sentences as weak labels, to which candidate regions of words correspond to some particular, but unknown location in the image. Our approach is to learn 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 learns the latent alignment between segments of sentences and the regions of the image that they describe.

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 [10]. However, the remarkable ability has proven to be a herculean 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 concepts and prior progress has been achieved on these endeavors [4, 11]. However, while closed vocabularies of visual concepts contain a convenient modeling assumption, they are overly restrictive when compared to the immense amount of rich descriptions that a human can compose.

Some pioneering approaches that address the challenge of generating image descriptions have been developed [70, 13]. However, these models rely only on learning natural 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

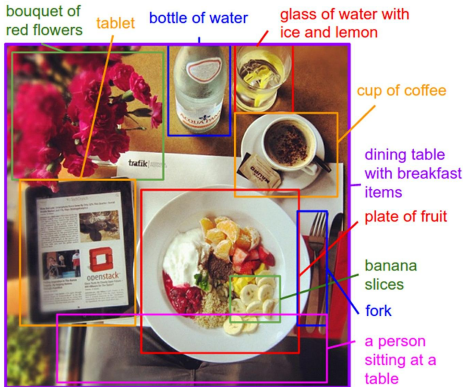
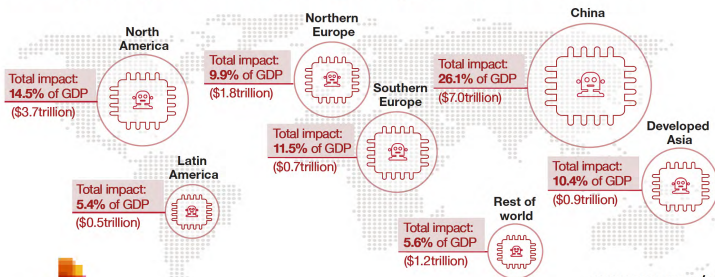


Figure 1. Motivation/Concept Figure: Our model treats language as a rich label space and generates descriptions of image regions.

Inteligencia Artificial

Creación de US \$15,7 Millones de Millones de Valor Económico

Sizing the prize – Which regions gain the most from AI?

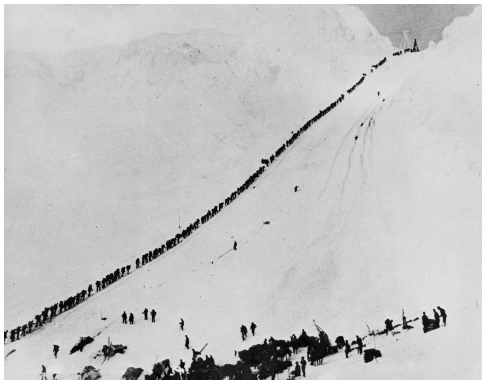


www.pwc.com/ai
#AIrevolution

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Inteligencia Artificial

La Fiebre de la Inteligencia Artificial



Personas caminando por el Sendero Chilkoot durante la Fiebre del Oro en Yukon, Alaska, a fines del siglo XIX (Wikipedia).

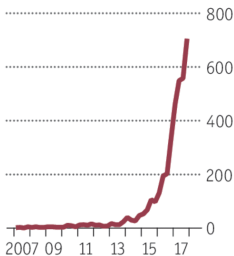
- Incide en **todas las actividades humanas**, no es sobre un producto o servicio.
- Afecta a **donde sea que haya personas**, no está localizada geográficamente.
- Produce una **reacción de empresas y gobiernos** que tiene como fin asegurar posiciones en este nuevo escenario.

Adaptaciones de las Empresas

Reacciones

Machine earning

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



Source: Bloomberg

Economist.com

Non-tech businesses are beginning to use artificial intelligence at scale, The Economist, 31 de marzo de 2018.

- ▶ Mercados horizontales compuestos por consumidores generales están dominados por **Alibaba, Amazon, Apple, Baidu, Facebook, Google, IBM, Microsoft y Tencent.**
- ▶ El resto son **silos aislados.**
- ▶ **Quién tiene la gente y los datos domina.**
- ▶ Los algoritmos se están transformando en un **commodity.**

Adaptaciones de las Empresas

IA en la Internet



Adaptaciones de las Empresas

IA en la Empresa



AI Lanscape 2018, Topbots, septiembre de 2018.

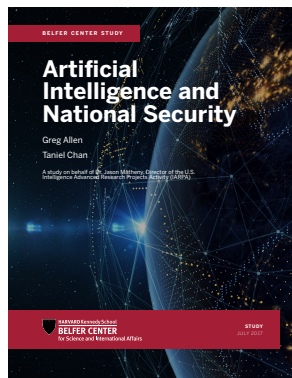
Adaptaciones de las Empresas

IA en el Mundo Físico



YuMi de ABB.

- ▶ **El último paso.**



● Executive summary

- Researchers in the field of Artificial Intelligence (AI) have demonstrated significant technical progress over the past five years, **much faster** than was previously anticipated.
- Most AI research advances are occurring in the **private sector and academia**.
- **Existing capabilities in AI have significant potential for national security.**
- Future progress in AI has the potential to be a transformative national security technology, **on a par with nuclear weapons, aircraft, computers, and biotech.**
- Advances in AI will affect national security by driving change in three areas: **military superiority, information superiority, and economic superiority.**
- We analyzed four prior cases of transformative military technologies—nuclear, aerospace, cyber, and biotech—and generated “**lessons learned**” for AI.
- Taking a “whole of government” frame, **we provide three goals for U.S. national security policy toward AI technology and provide 11 recommendations.**

Reacciones de los Gobiernos

Fuerzas Armadas



Reacciones de los Gobiernos

Capacidad de Manipulación

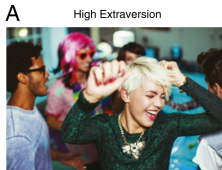
Psychological targeting as an effective approach to digital mass persuasion

L. C. Madar*, M. R. Meindl[†], G. Nava[‡], and J. S. Bailly^{§¶}

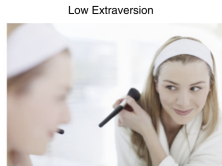
*Columbia Business School, Columbia University, New York City, NY 10027; [†]Yale School of Management, Yale University, New Haven, Connecticut, CT 06510; [‡]Yale School of Public Health, Yale University, New Haven, Connecticut, CT 06510; [§]Yale School of Forestry and Environmental Studies, Yale University, New Haven, Connecticut, CT 06510; [¶]Yale School of Applied Psychology, Yale University, New Haven, Connecticut, CT 06510

People are exposed to persuasive communication across many contexts, including in-person, television, and online. However, our previous research suggests that such exposure appears to be most effective in influencing behavior when they are subjected to a social and/or psychological characteristic. However, the emergence of large-scale psychological persuasion in the real world has been limited by the opportunities afforded by digital technologies, such as their feedback loop or timing. Capitalizing on this form of psychological persuasion from digital behaviors, we had the effects of psychological persuasion on people's actual behavior in an experimentally valid setting, in three field experiments. The first two studies used an experimentally valid setting, in which we used a large-scale digital advertisement to influence the behavior of a large group of people in a real-world setting. The third study used an experimentally valid setting, in which we used a large-scale digital advertisement to influence the behavior of a large group of people in a real-world setting. The results suggest that psychological targeting is an effective approach to digital mass persuasion, and that such targeting is most effective when it is used to influence the behavior of a large group of people in a real-world setting. The results suggest that psychological targeting is an effective approach to digital mass persuasion, and that such targeting is most effective when it is used to influence the behavior of a large group of people in a real-world setting.

Significance
Building on recent advancements in the treatment of people based on their digital behaviors, this paper demonstrates the effectiveness of psychological mass persuasion—that is, the use of large-scale digital advertising to influence the behavior of a large group of people in a real-world setting. The results suggest that psychological targeting is an effective approach to digital mass persuasion, and that such targeting is most effective when it is used to influence the behavior of a large group of people in a real-world setting. The results suggest that psychological targeting is an effective approach to digital mass persuasion, and that such targeting is most effective when it is used to influence the behavior of a large group of people in a real-world setting.



Dance like no one's watching
(but they totally are)



Beauty doesn't have to shout



Aristoteles? The Seychelles? Unleash your creativity and challenge your imagination with an unlimited number of crossword puzzles!

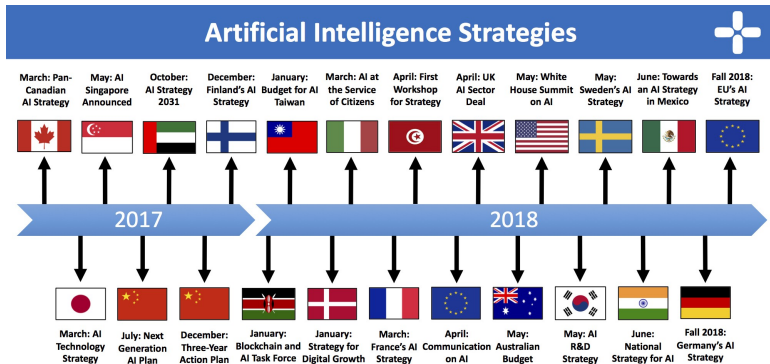


Settle in with an all-time favorite! The crossword puzzle that has challenged players for generations.

- **"Some countries are already moving in this direction. China has begun to construct a digital authoritarian state by using surveillance and machine learning tools to control restive populations, and by creating what it calls a "social credit system." Several like-minded countries have begun to buy or emulate Chinese systems. Just as competition between liberal democratic, fascist, and communist social systems defined much of the twentieth century, so the struggle between liberal democracy and digital authoritarianism is set to define the twenty-first."** (*How Artificial Intelligence Will Reshape the Global Order*, Foreign Affairs, 10 de julio de 2018)

Reacciones de los Gobiernos

Planes Gubernamentales



2018-07-13 | Politics + AI | Tim Dutton

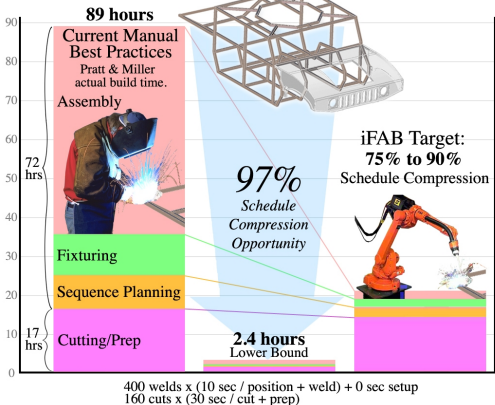
La Sociedad Humana

Predicciones sobre la Automatización del Trabajo

When	Where	Jobs Destroyed	Jobs Created	Predictor
2016	worldwide		900,000 to 1,500,000	Metra Martech
2018	US jobs	13,852,530*	3,078,340*	Forrester
2020	worldwide		1,000,000-2,000,000	Metra Martech
2020	worldwide	1,800,000	2,300,000	Gartner
2020	sampling of 15 countries	7,100,000	2,000,000	WEF
2021	worldwide		1,900,000-3,500,000	IFR
2021	US jobs	9,108,900*		Forrester
2022	worldwide	1,000,000,000		Thomas Frey
2025	US jobs	24,186,240*	13,604,760*	Forrester
2025	US jobs	3,400,000		ScienceAlert
2027	US jobs	24,700,000	14,900,000	Forrester
2030	worldwide	2,000,000,000		Thomas Frey
2030	worldwide	400,000,000-800,000,000	555,000,000-890,000,000	McKinsey
2030	US jobs	58,164,320*		PWC
2035	US jobs	80,000,000		Bank of England
2035	UK jobs	15,000,000		Bank of England
No Date	US jobs	13,594,320*		OECD
No Date	UK jobs	13,700,000		IPPR

Every study we could find on what automation will do to jobs, in one chart, Erin Winick, Technology Review, 25 de enero de 2018.

iFab Opportunity



Instruction Generation

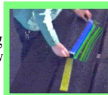
Robotic Assembly

MACHINE INSTRUCTION



Augmented Fixturing

HUMAN INSTRUCTION



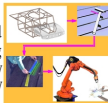
Virtual Layout

HUMAN INSTRUCTION



Automated Process Planning

MACHINE & HUMAN INSTRUCTION



Robots and People Can Work Faster Together, David Bourne, Director del Rapid Manufacturing Lab, Robotics Institute, Carnegie Mellon University, 25 de julio de 2013. Leer *Collaborative Intelligence: Humans and AI Are Joining Forces*, Harvard Business Review, Julio-Agosto, 2018.

La Sociedad Humana

Máquinas Viviendo en un Mundo ético

- La IA detecta que alguien compra **insulina**.
- La máquina establece que es **diabética**.
- Para aumentar la venta el algoritmo descubre que lo mejor es ofrecerle comprar un **dulce**.
- **¿Está bien?**

Conclusión

¿Preguntas?