A Roadmap for AI in Latin America

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Abstract

If we want ensure that AI in the upcoming years is a positive factor of the development of Latin America we need to start acting now and stop doing the same thing over and over again. The recent past and the current context in the region clearly indicates that it is unlikely that we see any improvements in the resources and support that AI has, instead, it will probably be aggravated by the impact of the COVID-19 pandemic. Consequently, it is our role as researchers to visit this issue and attempt to propose a road map towards a solution.

The driving motivation for this paper is to plant the seeds of a discussion on how to create a bottom-up and inclusive positive momentum for AI in the region, given the existing conditions, while, at the same time, reducing the potential negative impacts that it might have. We present this in the form of a roadmap or workflow that identifies the main obstacles that should be addressed and how they can be overcome by a combination focusing the work AI practitioners on particular research topics and that of decision markers and concern citizens.

Note: This is a live document. We are aware of the incompleteness, feel free to reach out the authors with suggestions and comments.

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1 INTRODUCTION

Cognition has enabled humankind to succeed as specie and extend ourselves to all climates and latitudes, from the depths of the oceans to space and, eventually, to other planets. Therefore, it is not surprising that since early ages of humanity we have been puzzled by the very feature that defines and differentiates us from the rest of the natural kingdom: our capacity to think, act intelligently, learn and adapt our behavior.

The coming of age of digital computing in the 1940s and 1950s provided the perfect canvas to at last formalize, express in algorithmic terms and be able to replicate *in silico* the processes that define intelligence. That is why in the dawn of computer science, back in the summer of 1956 at the Dartmouth College, computer scientists of the time gathered to reflect on how to bring cognition into computers creating the field denominated as artificial intelligence (AI).

AI is a disruptive technology that is transforming society behavior and its well-being. Specially for developing countries, it brings the opportunity to jump into a new economic equilibrium, increasing economic growth, and speeding agricultural, industrial and services development. AI is the technology differentiating countries. It is still time to jump in this boat and use it as a leverage to reach development, or it might increase the economic and social disparities among countries and people.

How to land the potential benefits of AI in a Latin America has been getting more and more attention. This is urgent for the following reasons:

- AI can have a decisive impact on increasing the quality of life of the people of the region,
- AI can also serve to give a viable alternative for escaping the apparently infinite loop of underdevelopment,
- the region's intrinsic characteristics actually pose important research questions to AI, and
- as researchers we are called to look at all the implications of our work.

Doing science in Latin America is not an easy feat (Ciocca & Delgado, 2017; Valenzuela-Toro & Viglino, 2021). However, it does not look like we should keep waiting for a top-down solution to this issue. It is our call to reflect and propose what we, as computer scientists, can do to be a positive impact.

That is the motivation for this paper. We do not intend to give a descriptive account of AI in Latin America, nor to give a reflection on the long-term impact of AI. Instead, we discuss what short- to mid-term actions we can take.

The paper is organized as follows. Subsequently, Section 2 provides a general context on AI at the time of writing. After that, Section 3 provides a brief panorama if the AI-related policy making. Then, in Section 4 we layout the roadmap and the reasoning behind it. Section 5 serves as colophon.

2 CONTEXT OF AI AND MACHINE LEARNING

AI and, in particular, machine learning (ML) has seen an important success in the last 15–20 years. These methods work under the principle that knowledge can be directly elucidated or learned from data, thus requiring less-to-none *a priori* domain knowledge.

As of year 2021 we are experiencing a turning point in AI and ML (Clark et al., 2021). Progress in ML has made it feasible to address problems like computer vision or natural language processing (NLP) that before were deemed intractable or just were not even envisioned. This fast-paced progress has been led by a group of ML techniques commonly denominated as deep learning (DL). DL methods use multiple layers to progressively extract higher-level features from the raw input.

Therefore, we have reached a current state where sufficient data is available and accessible in many domains. ML/DL frameworks and computational power, either on the cloud or on-premises, together with data, allow us to use ML/DL technology to solve complex problems. This raise can be attributed to the progress in four interrelated pillars:

- the emergence of better hardware substrate to host the algebraic operations of neural networks, in particular the emergence of general-purpose computing on graphics processing units (GPGPUs) and tensor processing units (TPUs),
- the proposal and consolidation of ML/DL approaches and models like convolutional neural networks, deep recurrent neural networks (like long short-term memories (LSTMs), gated recurrent units (GRUs), etc.), attention mechanisms and transformers, adversarial learning, language models, AutoML, etc. that have made possible to scale up regarding both in terms of representation capacity as well as dimensions of the learning data,
- the consensus on the importance of reproducibility and replicability of scientific results, and
- the creation of datasets that pose challenges to the state of the art at the time.

The ML/DL revolution has been compared with the discovery of electricity, the internal combustion engine or even fire. This progress has brought important advantages and has served as a conveyor belt to the creation of whole new business sectors.

This has led two the oversimplification of the understanding of the current status of that can be summarized in two groups of opinions:

- The first group has an overenthusiastic and simplified perception that claims that current results in AI, ML and DL are sufficiently solid such that the upcoming challenges lie only on how these results are packaged, transferred and deployed to industry.
- The second pessimistic trend has gained track stating that we are approaching a new AI winter, where progress in the field will be stagnated or even should be stopped, because of limits of our understanding of AI, the negative ethical issues and the resistance to adoption of AI.

We find both opinion groups are wrong. We are not close to the end of the loop, but we are in the adolescence of AI and ML. In the next decade we will need new AI science and engineering to be able to overcome challenges and deadlocks.

The ultimate objective of AI is to understand the nature of intelligence itself. Simply put, AI is a moving target, and once a given task that was once deemed as "intelligent" is solved, immediately it is perceived as just a piece of technology. That is the case of character and voice recognition and many image classification and segmentation tasks, to mention a few that are no longer perceived as 'AI'.

Consequently, as new problems are solved the horizon of challenges automatically moves forward only to bring more and bigger challenges. These new challenges will be of exponentially increasing complexity as we move towards the realm of self-awareness, reasoning, consciousness and, ultimately, artificial general intelligence. Therefore, these new challenges will require more deep AI/ML research.

Key AI and ML issues like improved representation, reasoning and neuro-symbolic systems, better learning algorithms, adaptation, self-configuration, causality, etc. that can be envisioned that will take a big role in the next 10 years.

To handle the current challenges of AI (the need for a new AI; the need for a good AI; the need to address underspecification in AI and ML; the need to tackle the "innate vs acquired knowledge" and "symbolic vs connectionist" dichotomies; the need for automatic, adaptive, autonomous, efficient, and "learning to learn" learning methods; the big data/small data scenarios; the need for a scalable AI, Latin America puts forward a multidisciplinary virtuous cycle where research lines are interconnected between them and to application domains.

However, this is a naive perception since the data guiding the machine learning are produce by humans and hides humans' biases, preferences and decision-making strategies. So, machine learning consolidates the moral values of a society implicitly recorded in the data.

This is one of the reasons why AI systems should be evaluated in a broader sense to understand the moral values built in the systems from other countries or companies. For example, a full autonomous car will have built-in preferences of how to act in a dilemma situation. The MIT Moral code experiment (Awad et al., 2018) surveyed more than 40 million opinions from more than 150 countries concerning whom an autonomous car should avoid running over in an unavoidable accident.

This experiment has shown that different societies may accept different attitudes. France would spare children over senior citizens, while Japan and China would prefer the other way around. The experiments' results varied among different cultures showing the preferences depending on gender, number of people involved or even the economic status of the passersby.

Maybe the most difficult challenge to address is how to deal with the impact on social inequalities and countries economic disparities caused by the introduction of AI technology. Although there is a high demand for AI workers all over the world, specially in the developing countries including Brazil, these amounts represent just a few percentages of a country population. Wealthy concentration to machine owners tends to increase. As machines get better performance than humans, companies tend to substitute AI for workers. What will happen with employment?

Freeman claims, it is not a matter of employment, but income. People will find something to do, but what will be the remuneration for that? There are different possibilities requiring actions from the government, private sector and customers (citizens). Universal Basic Income (UBI) could be an answer in which the government would provide a basic income for all citizens, so survival is guaranteed. Currently, there is no country that has implemented UBI. It has been experimented in some US states, such as Alaska. Nevertheless, UBI requires increasing taxes that might face citizen's resistance.

3 CHARACTERISTICS AND STATUS OF AI IN LATIN AMERICA

It is not in the spirit of this paper to make a detailed account of the status of AI in Latin America or globally. Nevertheless, for the sake of completeness and in order to support the subsequent discussion it is necessary to provide an overview of the situation.

In this regard, it is important to discuss the roles the different stakeholders, meaning the government, the private sector, and the citizens, should play in this new society setting. There are formulators major issues that must be addressed here:

- the country AI strategy in terms of public and private investment to foster AI development and use,
- the laws regulating AI, laying the principles, rights, duties and penalties for AI developers and users,
- the educational measures to allow society to understand, inspect the use and take advantages of the technology, and
- last, but not least, the actions to deal with the soaring inequalities that AI technology may foster.

Latin America has still a timid embrace of the AI scenario, with less than 0.5% of private investment dedicated to AI development. The number of Latin American AI companies in 2018 was around 260, this number more than double in 2 years, reaching 490 in 2020. In this scenario, Brazil is currently the leading LA country holding 42% of all AI companies, followed by Mexico and Chile. What is behind the Brazilian performance?

Massive governmental investment might be the answer. While the private sector is still timid, the Brazilian government has a clear strategy to foster AI.

Situation in Argentina

Argentina began the study of an Artificial Intelligence Strategy in 2018[1]. The 'ARGENIA' National Artificial Intelligence Plan[2] was delivered, informally, during the month of December 2019 and was never published due to the change of government in that country.

Since the new government there have been no new versions of the Strategy, probably due to the importance given to the COVID-19 pandemic in the country. Among what stands out is that it has the largest number of pages (242), the largest number of axes (11) and the largest number of measurements (76).

However, it does not present a funding policy, governance, detailed action plans, or periodic review structure.

Situation in Brazil

Brazil is the last country that has officially published its Brazilian Strategy for Artificial Intelligence (EBIA)[3] in June 20218 and has been able to take advantage of the maturity of the sector and perhaps that of the other countries that have published before it. The strategy was led by the Ministry of Science, Technology and Innovation and the Secretary of Entrepreneurship and Innovation.

The strategy was built in 3 stages: i) hiring a consultancy specialized in AI, ii) carrying out a national and international comparison, and iii) public consultation process, 9 which was carried out between December 12, 2019 and March 3, 2020 and more than 1,000 contributions were received.

This can be seen because although it has a limited number of pages, a large part of them are dedicated to the strategic axes and these axes are among the most repeated in the analysis carried out.

However, it is also missing the part of governance, detailed action plans, financing and the way to carry out revisions to the strategy.

Brazilian government seems committed to AI development. The EBIA policy lays the thematic axes that guides Brazil's approach to trustworthy AI in compliance with the OECD directive. EBIA was elaborated by the Ministry of Science, Technology, and Innovations (MCTI) and it took 2 years to be elaborated from initial evaluation from an external private consulting firm to a public consultation open from December 2019 to March 2020 to the final approval in July 2021. EBIA stimulates research, innovation, and development of AI in the country mostly by promoting governmental grants for research, tax reduction for companies that invest in AI projects, a promise to remove barriers for innovation in AI and a strong fostering to projects that consolidate the triple helix: public sector, private sector, and academia. AI area was even included as a major strategic area to be considered in any public investment.

Brazilian researchers have also understood the importance of AI research. The number of official research groups certified by the national research agency (CNPq) has also grown since 2015 from X to Y in 2021. The number of centers in computer science and engineering grew, but also grew the number of research groups in other areas, such as, law and medicine, that apply AI in their studies. Looking at the distribution per state, as shown in Figure 1, we note a concentration of research centers in São Paulo state. The much higher state investment, when compared to other states, might explain the results. It seems there is a high correlation between investments and the number of AI research groups and start-ups.

1 https://uai.edu.ar/ciiti/2019/buenos-aires/downloads/B1/JA-Plan-Nacional-IA.pdf
2 https://ia-latam.com/wp-content/uploads/2020/09/Plan-Nacional-de-Inteligencia-Artificial.pdf
3 https://www.gov.br/mcti/pt-br/acompanhe-o-mcti/transformacaodigital/inteligencia-artificial

Table 1: Summary metrics of the AI strategies proposed by Latin American countries.

Country	Name	Pub. date	Total pages	Number of axes	Axes content (% pages)	Pages per axis	Actions	Pages per action	Actions per axis	Exec. Period
Argentina	ARGENIA, Plan nacional de Inteligencia Artificial (not official)	12.2019	242	11	72%	15.8	76	2.3	6.9	until 2030
Brazil	Estratégia Brasileira de Inteligência Artificial (EBIA)	06.2021	52	9	62%	3.6	73	0.4	8.1	
Chile	Política Nacional de Inteligencia Artificial	10.2021	78	10	58%	4.5	80	0.6	8.0	10 years
Colombia	Política Nacional para la Transformación Digital e Inteligencia Artificial	11.2019	63	4	25%	4.0	63	0.3	15.8	5 years
México	Agenda Nacional Mexicana de Inteligencia Artificial	09.2020	143	6	83%	19.7	62	1.9	10.3	N/A
Perú	Estrategia Nacional de Inteligencia Artificial, Documento de Trabajo para la Participación Ciudadana	05.2021	88	6	35%	5.02	75	0.4	12.5	5 years
Uruguay	Estrategia de Inteligencia Artificial para el Gobierno Digital - Documento para Consulta Pública Versión 0.2	01.2020	16	4	31%	1.03	18	0.3	4.5	N/A

The grants that have been awarded have been to research, grants for universities and research centers, and to innovation, grants for university-companies partnership, for start-ups and for young PhD willing to implement their ideas and put into market. It still early to evaluate the results from the government investment. But strong investment seems in the right track

Other important, but controversial measure, governmental action was to centralize AI development fostering the creation, by providing seed money, of 8 national centers for AI development. In one hand, since the resources are finite and AI development needs expensive resources, it makes sense not to pulverize. On the other hand, investment centralization might prevent actual innovation that may come from all over Brazil.

The government seems in the right direction, but the public sector is still waiting for playing a more active role. It might be a matter of culture or economic policy instability or even strategic complementarity meaning that everybody waits for everybody else to move first.

Additionally, Brazil as in most LA countries have still unstable political systems that let the market in its tiptoe to make major investments. Although all the signs for major investments I. AI, Brazilian government just announced (November 2021), 90% cuts on research investment. The reasons may vary, but as we get closer to the presidential elections, that will happen in 2022, money tend to go to where the votes are. Brazilian politics are prone to populist measures. Science and technology don't seem to bring many votes, investments in AI and other technology are at risk.

Situation in Chile

As of the date of this study, the final "National Policy on Artificial Intelligence",[4] which has been completed since the end of June 2021, has not yet been published, and the document analyzed was the draft for public consultation released at the end of December 2020.[5]

The strategy brings together about 70 priority actions and 180 initiatives that will be developed in the period 2021–2030. The document has been created by the Ministry of Science, Technology, Knowledge and Innovation and provides a vision of both the public and private sectors, academia and civil society. Although there was a massive participation process, it is not indicated in the document how the indications made by the different actors have influenced or not the published text.

Situation in Colombia

Colombia has the merit of having officially published the first national policy for Digital Transformation and Artificial Intelligence in Latin America in November 2019, the Colombian government approved through Conpes 3975.[6]

However, and perhaps due to this, the document is not exclusive to Artificial Intelligence but also has various elements of Colombia's Digital Transformation Policy, producing in some sense a certain confusion of some issues.

On the positive side, Colombia is the only Latin American country that delivers a budget of USD 31.6 million, even associated with public agencies, governance, a detailed plan of action and subsequent reviews on a regular basis.

In addition to the above, Colombia has continued to work on the issue and this is reflected in the Ethical Framework documents for Artificial Intelligence in Colombia,[7] with a first version in August 2020 and a second discussion document in May 2021 and Task Force for development and implementation of Artificial Intelligence in Colombia November 2020,[8] and The International Council of Artificial Intelligence for Colombia in February 2021.[9]

4 https://minciencia.gob.cl/politica-nacional-de-inteligencia-artificial/
5 https://www.minciencia.gob.cl/legacy-files/borrador_politica_nacional_de_ia.pdf
6 https://colaboracion.dnp.gov.co/CDT/Conpes/Econ%C3%B3micos/3975.pdf
7 https://dapre.presidencia.gov.co/TD/Marco-Etico-IA-Colombia-2021.pdf
8 https://dapre.presidencia.gov.co/AtencionCiudadana/Documents/TASK-FORCE-para-desarrollo-implementacion-Colombia-propuesta-201120.pdf
9 https://dapre.presidencia.gov.co/TD/CONSEJO-INTERNACIONAL-INTELIGENCIA-ARTIFICIAL-COLOMBIA.pdf

Situation in Mexico

Back in 2018, Mexico was one of the first 10 countries in the world to present a multi-sectorial proposal for an artificial intelligence strategy, which was consigned in a draft.[10] From there, the IA2030MX[11] citizen coalition was created, founded by nine institutions from all sectors, which after more than a year of work presented the Mexican National Agenda for Artificial Intelligence in September 2020.

In the process of creating the agenda, more than 400 people participated in the public consultation and in six Working Groups. There was also a consultation period between August 15 and September 15, 2018[12] and the results were an input for the final document.

However, despite the length of the document (143 pages), there is no mention of the budget, governance, detailed action plan or how the periodic reviews will be carried out.

Situation in Peru

Peru is in full public consultation of its National Artificial Intelligence Strategy[13] having published in May 2021[14] an 88-page document in MS PowerPoint format and in a launch through digital media.[15]

The document has the characterization of "Working document for citizen participation during the period 2021-2026" and is the result of an articulated work between the Secretary of Government and Digital Transformation of the Presidency of the Council of Ministers (PCM), the public sector, academia, private sector and civil society, and will be updated every 2 years as part of the National Policy for Digital Transformation. For its latest edition, the ENIA Committee of experts collected and analyzed the contributions sent by those involved up to June 4, 2021.

Although it is indicated that the execution period will be 5 years, no financing, governance or detailed execution plans are specified. It is noted that as part of the document various cases of use of Artificial Intelligence relevant to Peru are shown, such as local governments, mining, agriculture, fishing and aquaculture, forest protection, among others.

Situation in Uruguay

The Strategy establishes among its objectives the implementation of digital services based on the application of emerging technologies, such as AI.[16]

To carry out this initiative, a public consultation[17] was carried out with the objective of reaching a National Artificial Intelligence Strategy for Digital Government. The four stages of the consultation process were between April 2019 and September 2020.[18]

The publication of the document "Artificial Intelligence Strategy for Digital Government" was in public consultation format in January 202025 and to date no later or final version has been published.

The main difference with the other strategies of the Ibero-American countries is that the document is dedicated almost entirely to the state's relationship with AI, not having points or activities in the private environment.

In fact, page four of that document reads verbatim *"The general objective of the strategy is to promote and strengthen the responsible use of AI in the Public Administration, identifying objective pil-*

10 https://ia-latam.com/portfolio/hacia-una-estrategia-de-ia-en-mexico-aprovechando-la-revolucion-de-la-ia/
11 https://www.ia2030.mx/
12 https://www.ia2030.mx/consulta
13 https://www.gob.pe/13517-participar-de-la-estrategia-nacional-de-inteligencia-artificial
14 https://www.gob.pe/institucion/pcm/informes-publicaciones/1929011-estrategia-nacional-de-inteligencia-artificial
15 https://www.youtube.com/watch?v=jS9h8BwlCoE
16 https://www.gub.uy/agencia-gobierno-electronico-sociedad-informacion-conocimiento/comunicacion/noticias/inteligencia-artificial-para-gobierno-digital-hay-estrategia
17 https://www.gub.uy/participacionciudadana/consultapublica
18 https://www.gub.uy/participacionciudadana/consultapublica/legislation_proposals?is_proposal=false

lars and specific lines of action.".[19] It also says it clearly in *"the purpose of the document is to capture the strategy for the Public Administration to use Artificial Intelligence in the development of public services and in the improvement of its internal processes."*

Uruguay has defined the goals and objectives for its digital development in the Uruguay Digital Agenda 2021[20] and in the Digital Government Plan 2018–2022.

Finally, on page 8 of the document, it shows the transversal principles for the development of AI in the digital government of Uruguay: *"The responsible use of AI involves four dimensions: ethical, normative, technical and social. Which must be present from the design to the implementation of its various applications."*

4 AN ROADMAP FOR ACTION FOR AI IN LATIN AMERICA

A famous quote, widely used by Albert Einstein (Wilczek, 2015), poses that "Insanity is doing the same thing over and over and expecting different results." Consequently, if we want ensure that AI in the upcoming years is a positive factor of the development of Latin America we need to start acting now and stop doing the same thing over and over again.

The recent past and the current context in the region clearly indicates that it is unlikely that we see any improvements in the resources and support that AI has, instead, it will probably be aggravated by the impact of the COVID-19 pandemic. Consequently, it is our role as researchers to visit this issue and attempt to propose a road map towards a solution.

The driving motivation for this paper is to plant the seeds of a discussion on how to create a bottom-up and inclusive positive momentum for AI in the region, given the existing conditions, while, at the same time, reducing the potential negative impacts that it might have.

We present this in the form of a roadmap or workflow (see Figure 1). We have organized it first reviewing the main obstacles that are contributing for the widening the the development gap with respect to AI. After that, we outline a number of scientific, technical, educational and institutional actions that we think that could serve to overcome these obstacles. These actions are to be consolidated in a new AI culture and ecosystem. It may be argued that some of these recommendations require the convergence of different forces. We hope that our discussion would serve accelerate that convergence.

Therefore, the question of how to ensure a positive socio-economic impact is not whether AI could have that impact or not, but how to scale, extend, and accelerate this impact. This is not a trivial task and, to make things worse, the recent success of AI has led to the oversimplified understanding of this problem and its inherent complexity. There are two trends that particularly disconcerting [3]:

1. The first trend has to do with an overenthusiastic and simplistic perception that claims that current results in AI, ML and DL are sufficiently solid such that the upcoming challenges lie only on how these results are packaged, transferred and deployed to industry.

2. The second trend is a pessimistic view that has gained track stating that we are approaching a new "AI winter," where progress in the field will be stagnated or even should be stopped, because of limits of our understanding of AI, the negative ethical issues and the resistance to adoption of AI.

In fact, there is still a lot of work to do in AI to make it reach its full potential . There is still work ahead to make AI usable to everyone and in a safe and effective way, but it is also the right moment to think about how to ensure that the benefits of AI reach all corners of Latin America and the planet.

19 https://www.gub.uy/agencia-gobierno-electronico-sociedad-informacion-conocimiento/sites/agencia-gobierno-electronico-sociedad-informacion-conocimiento/files/documentos/noticias/Estrategia%20IA%20-%20consulta%20p%C3%BAblica%20vf%201.pdf

20 https://www.gub.uy/uruguay-digital/

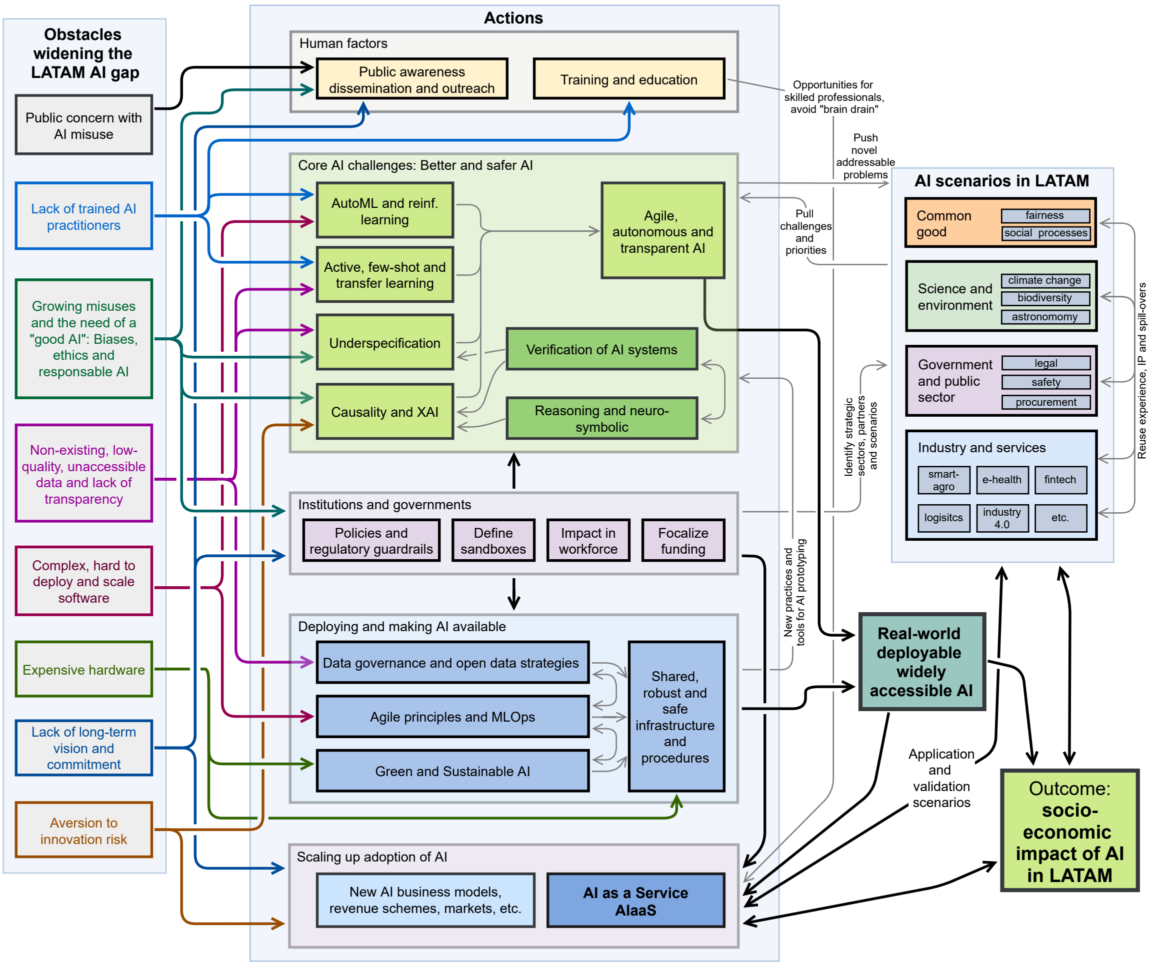

Figure 1: A roadmap for action of AI in Latin America. It identified the main obstacles, the actions to overcome those obstacles and the high-potential impact areas.

4.1 Obstacles and factors contributing to the widening AI gap

In order to improve and accelerate the positive impact of AI in Latin America it is first necessary to identify and analyze the different issues and obstacles that might be hampering a positive outcome. We will not present the ones that we have identified.

4.1.1 *Public concerns, reservations and objections regarding AI*

There is a generalized public concern and, very frequently, a simplistic negative perception of the impact of AI. With the advances on facial recognition, marketing has aggressively used it to understand user's reactions to ads as an indirect way to measure and adjust the ad to increase people consume.

In this sense, the Brazilian data protection law, approved in 2020, has provided the legal basis for consumers to sue the company for the unauthorized use of their image. In May 2021, a judge from São Paulo state fined the São Paulo metro company for using cameras located close to ads to count the number of people to look at the ad and to extract their reactions to the as. This is an example of the way AI might be used to harm society, and it was good to have a law that could provide the means to restrict the bad usage.

So far, researchers all over the world have faced the technology challenge to improve performance, but there must be regulation to delimit the reach of the automation, the responsibility and accountability when problems happen, transparency on the machine decision-making and the challenges for building auditable algorithms respecting trading secrets.

Recently, March 2021, the Federal Legislative approved the legal framework for development and use of AI (law 21/2020). The objective was to provide legal safety for developers and users, reducing the barriers, in terms of bureaucracy for startups, and signalizing the world that Brazil is for ethical AI.

The law needs to be improved, but it is the beginning. The law defines the role of AI agents as developers and deployers of AI systems. AI agents are legally accountable for any harm caused by the AI systems they developed or deployed.

The law also enforces the compliance of AI developers with citizens' data privacy as regulated by the Brazilian Law for Personal Data Protection (LGPD) and the obligation of informing people an AI system in place, for instance, informing Bank clients that their credit applications has been analyzed by an AI system developed by a specified company. The law formulators may have misunderstood the "human-in-the-loop" prerogative. There are many situations in which humans are unreachable to make the final call or simply the task does not lead to harm, so it would be better to allow autonomy. The law was approved too fast and there should have been a more thorough debate by the society including the Brazilian AI community. The law is still generic and leave the executive with the burden to define how it will be implemented. Given the fast development for the area and the nonexistence of legal basis, a more generic law seems adequate as a starting point.

In addition to the federal law, there are also some state laws, such as the Rio de Janeiro's and Minas Gerais's laws, that were open for public discussion at the time of writing (November 2021).

The important lesson learned is that each country must discuss and define AI regulation.

4.1.2 Lack of trained practitioners and professionals

The vast majority of applications of AI in Latin America and globally —even under different formal frameworks— can be reduced to a sort of consultancy where (highly-trained, scarce and expensive) AI practitioners and domain stakeholders work side-by-side. Hence, the number of applications is caped by the availability of AI practitioners.

Training and education, to create more AI practitioners and accelerate research is obviously required, but given the current conditions that is unlikely to happen.

In the other hand, AI itself can be used to automate important parts of the application of AI in a better and safe way, and thus, break the linear applications/AI practitioner relation and reach an exponential escalation. That is why we can identify as interesting lines:

- Learning to learn and AutoML, tackling underspecification, efficient learning, etc., to reduce and eventually eliminate human intervention for designing a solution.
- Causality, explainable AI (XAI) and reasoning should be in charge of offering understandable, human-readable and verifiable information about the models being created, so the domain can validate the solution.
- Formal verification of AI is also needed to ensure consistency and Agile ML approaches must consolidate the outcomes and make them production-ready.

4.1.3 Growing misuses and the need for a good AI

AI disruptivity with respect to the fabric of life (travel, education, entertainment, social networks, politics, to name a few) became unavoidable [6], together with its expected impacts on the nature and amount of jobs. As of now, it seems that the risk of a new AI Winter might arise from legal and societal issues.

While privacy is now recognized as a civil right in most countries, tech companies can already capture a sufficient fraction of human preferences and their dynamics to achieve their commercial and other goals, and build a Brave New Big Brother (BNBB), a system that is openly beneficial to many, covertly nudging, and possibly dictatorial.

The ambition here is to mitigate the BNBB risk along several intricate dimensions, by addressing causal and explainable models, fair data and models, and provable robust models. AI and ML can be misused -even not on purpose- and its results can be aggravated by its capacity amplifying biases and errors and scaling their harm to millions of people. This, on its time, has reduced the acceptance by the general-public and authorities.

This calls for the for incorporation features like explicability, accountability, bias elimination, etc., and create safety guardrails, both regulatory and technological such that the interests of citizens are protected.

In the same lines, the region has seen already numerous attempts to apply AI fake news, public opinion manipulation, and other forms of misuse.

4.1.4 *Non-existing, low-quality, unaccessible data and lack of transparency*

It is not a new fact that the region has a long-time issue around transparency data accessibility and availability. The big data/small data scenarios. Probably the main hurdle AI/ML practice is the need for large annotated datasets suitable for supervised learning limits the applicability and adoption of these recent advances.

In many practical scenarios, obtaining such data can be expensive or impossible. In most real-life situations is it most common a small-data scenario or a hybrid case where there are very limited amounts of quality data and, in some cases, lots of noisy, partially invalid or non-annotated data.

This situation around data impacts also at what point current state to the art results can be "imported" into local application scenarios. Recent pre-trained data-hungry models are generally not directly usable (Poblete & Pérez, 2020).

4.1.5 *Lack of scalable and accessible AI software and hardware*

There is an important computational hurdle when turning AI/ML systems into production-ready applications. The cost of deploying and scaling AI/ML models, in particular those related to deep learning, has kept growing exponentially and, thus, requiring expensive computing hardware and becoming very energy demanding. This fact hinders the access to this technology by academics, small and medium-sized enterprises (SMEs), governments and society, even if the algorithms and their source code are available.

To ensure a true democratization of AI in Latin America it is necessary to address how AI software projects themselves are planned, engineered, programmed, tested, formally verified from the ground-up. Therefore, another big challenge for AI systems in the coming decade is to go over a transformation from custom/local solutions to replicable, easily deployable, secure and trustable solutions.

This could be seen up to a certain point as a homologous process as cloud computing and modern software engineering have rendered complex, high-performance, scalable and on-demand computing facilities at the reach of anyone under the paradigms of infrastructure as a service (IaaS), platform as a service (PaaS) or software as a service (SaaS).

4.1.6 *Aversion to innovation risk*

Even if the potential of AI is at this point generally accepted, the outcome of the application of AI is not guaranteed. This, combined with the high upfront costs and uncertainties (D'Amour et al., 2020) makes that many potential applications are not addressed thus limiting many promising outcomes. For instance, in 2020 only 58% of companies invested in AI, where the average in the region is 73%.

4.2 Addressing the AI challenges: Better and safer AI

Science, and in this case AI, can be

4.2.1 *Automatic, adaptive, efficient learning and "learning to learn" methods*

This can be summarized as the AutoML issue of automatically selecting and configuring an algorithm portfolio for a problem instance. This issue governs the knowledge transfer from research labs to industry, all the more so as massive computational resources are at stake. In the medium term, it would be needed to integrate hyper-parameters and model structure in the learning criteria, using information theory and/or bi-level programming. In the long-term, our goal is to establish a phase diagram of the learning landscape.

4.2.2 Learning and adaptation in small data contexts

Progress in machine learning has made it feasible to address problems in areas of computer vision or natural language processing that only 10 years ago were deemed as intractable of just were not even envision. This raise can be attributed to the progress in three interrelated pillars:

1. the emergence of better hardware substrate to host the operations of neural networks, in particular the emergence of general-purpose computing on graphics processing units (GPGPUs) and tensor processing units (TPUs),
2. the proposal and consolidation of approaches and models like convolutional neural networks, recurrent neural networks, attention mechanisms, transformers, etc., and
3. the creation of datasets that posed important challenges to the state of the art at that time.

However, the need for large annotated datasets suitable for supervised learning limits the applicability and adoption of these recent advances. Furthermore, in many practical scenarios, obtaining such data can be expensive or plainly impossible. That is why it is crucial to address how machine learning models are trained and adapted to meet this small data scenario. These actions are consolidated as the work in the following directions:

- *Complex data representation* Data representation is a key element in the success of any computational system. Natural language or relational information has started to be able to be handled by neural networks opening a wide range of important applications. Arguably, much of the progress in machine learning in recent years comes from being able to handle more complicated forms of input data than pure tabular data. However, there is an increasing number of applications where data are represented in the form of graphs. Even in contexts like NLP where the information is structured as a sequence, there is an implicit graphical internal representation, such as a syntactic dependency tree, discourse, or semantic parse. Causality relations and explainability, another important goal package of the center rely on dependency graphs. Complex relationships, like spatio-temporal relationships, are hard to capture using current representations.
- *Transfer learning (TL) and domain adaptation* Here we propose to study how models trained or adjusted for one application and domain can be re-purposed for other applications with minimal impact. In our case, for example, to study how existing models can be applied to new species, other regions, etc. Transfer learning addresses the issue of how to adapt and re-purpose the internal representations of a model that has been trained on a given task to address a similar problem.

  On the other hand, domain adaptation is the capacity to cope with changes in the environment because of the natural evolution of the system and/or the need to particularize a general model to a particular instance. For instance, in a previous work (Santana et al., 2019) we have addressed how to apply Genetic Programming to adapt general brain-computer interfaces to a particular user.
- *Active and few-shot learning* In problems with limited data and/or high uncertainty, like the ones to be dealt here, it is necessary to apply methods that direct the measurements to the areas of the domain where they are most necessary. Guided sampling using active learning and Bayesian principles. However, due to the limited resources available, few-shot learning methods relying on TL must take care of producing actionable products with minimal data. An alternative is to combine deep learning with stochastic search approaches like Genetic Programming.
- *Multi-source and multi-task learning deep neural models* It can be stated that ML methods are about optimizing a model's parameters with regard to a particular metric. This metric can

be a score on a certain benchmark or even a business KPI. A process generally denominated as 'training' adjusts a single model or an ensemble of models to perform our desired task. It is then possible to fine-tune and tweak these models until their performance no longer increases.

While these methods generally achieve acceptable performance, by being laser-focused on our single task, sometimes they ignore information that might help the model to do even better on the metric. Specifically, when this information comes from the training signals of related tasks. Sharing representations between related tasks, enable the model to generalize better on the original task. This approach is called multi-source or multi-task learning (MTL).

MTL effectively increases the sample size that is being used for training. MTL also biases the model to prefer representations that are useful for other tasks. This will also help the model to generalize to new tasks in the future (transfer learning) as a hypothesis space that performs well for a sufficiently large number of training tasks will also perform well for learning novel tasks as long as they are from the same environment.

4.2.3 *Addressing underspecification in AI and ML*

This is a cornerstone and severe problem that has been often left aside in ML practice (D'Amour et al., 2020). ML models often exhibit unexpectedly poor behavior when they are deployed in real-world domains even after a properly designed and curated optimization (training) phase. An ML pipeline is underspecified when it can return a number of different predictors with equivalently strong performance in the training dataset.

Underspecification is common in modern ML/DL pipelines. Because of underspecification, ML models often exhibit unexpectedly poor behavior when they are deployed in real-world 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 scenarios. This phenomenon has been shown to occur in application domains like computer vision, medical imaging, natural language processing, clinical risk prediction based on electronic health records, medical genomics among others (D'Amour et al., 2020).

4.2.4 *The need to tackle the "innate vs acquired knowledge" and "symbolic vs connectionist" dichotomies*

How to best combine available human knowledge, and data-based knowledge-agnostic machine learning? We need to examine this question focusing on domains with spatial and temporal multi-scale structure, as pervasive in natural sciences (for example, where domain knowledge is expressed using PDEs, or through powerful compact representations as in signal processing), or by making progress in hybrid neural-symbolic systems. This also by taking advantage of the multidisciplinary expertise and scientific collaborations of the AI experts in the region but also worldwide.

4.3 Deploying and making AI widely available

The development and deployment of ML systems can be executed easily with modern software and programming tools, but the process is typically rushed and means-to-an-end and ultimately, much of the code would have been used for exploratory analysis and failed experiments and, therefore, disregarded. This lack of diligence generally leads to technical debt, creepled scope and misaligned objectives, model misuse and failures, and expensive consequences. Computing engineered systems, on the other hand, follow well-defined processes and testing standards to streamline development for high-quality, reliable results. Both worlds need to necessarily reconnect. First, new agile processes should be conceived to raise the code quality of the AI experimentation.

4.3.1 *Open data, governance and sandboxes*

One of the big technological challenges in ML is to access the available data in a consistent and robust form. It is therefore necessary to govern and curate the data. The need for defining access policies and curation processes has been clearly established on the field, however, it remains an open issue. The result of this process will be a curated data hub -or data lake- containing or providing transparent and homogeneous access to a diverse set of data sources. This would be an important asset for the research community globally.

4.3.2 Agile principles and MLOps

Continuous monitoring and performance optimization are keys to properly manage resources consumption (e.g., CPU, memory, or energy), as well as being essential factors that directly impact the value of an AI model, which largely depends on its deployment and enactment. The prevalence of AI-based techniques in modern software systems calls for programming and verification supports that are observable, testable, and formally expressible. It is known that testing and verifying software components based on machine learning is challenging and still remains open.

4.3.3 Green and Sustainable AI

The current climate crisis calls for the use of all available technology to try to understand, model, predict and hopefully work towards its mitigation. There is, however, an area that has been neglected by researchers and industry: the ecological impact of artificial intelligence itself. The amount of resources necessary for applying state-of-the-art ML/DL results have increased 300,000 times and the situation is even worse in areas like NLP (Sanchez-Pi & Marti, 2021; Schwartz et al., 2020).

BETTER/CUSTOM HARDWARE Alternatives to be considered include FPGAs and ASIPs and the use of low-precision computing. Energy-aware high-performance and cloud computing self-scaling computing facilities made available as a pool of shared resources.

BETTER LEARNING ALGORITHMS AND AUTOML Model self-adaptation, transfer learning and domain adaptation in this context: to the use of evolutionary approaches, or to look for methods that adapt their complexity (ART or GNG) to the complexity of the problem being solved.

ACTIVE LEARNING AND SAMPLE EFFICIENCY We can also take advantage of the active learning algorithm. Active learning can attain accuracy with fewer training labels if it carefully selects the data from which it learns.

4.4 Scaling up adoption of AI

An essential element to reach this acceleration is to consolidate the efforts and lessons learned on each particular project -as long as IP regulations and agreements allow. Relying on this accumulated experience we propose to create an AI value as a service (AIVaaS) platform. It would allow potential clients to easily apply AI and ML with minimal knowledge (hence the "AI value as a service" concept). From a business model perspective it would follow a "value as service" approach where simply, commercial users pay for the use of the platform part of the revenue they get from the system.

To the best of our knowledge, this concept has not been put forward before. From a technical point of view, this platform will be constructed by the center engineers. It should evolve and consolidate under a unique framework the experience obtained across domains, incorporating results from work in different domains. This platform as it becomes more robust and stable along the years has the potential to become one important asset.

4.5 Seeking high-impact AI applications in Latin America

4.5.1 AI for the common good

Computational social sciences are making significant progress in the study of social and economic phenomena thanks to the combination of social science theories and new insight from data science.

Bias and prejudices, algorithmic errors, and actions morally unacceptable are risks that come with the technology. Human in the loop is an approach that let humans with the final decision and with the power to make machines to adjust the technology to accomplish humans' needs and preferences. AI is a powerful tool and should be used with care.

While the simultaneous advent of massive data and unprecedented computational power has opened exciting new avenues, it has also raised new questions and challenges. Studies are to be conducted around labor (labor markets, platform micro-work, quality of life and economic performance), about nutrition (health, food, and socio-demographic issues).

UNDERSTANDING SOCIAL PROCESSES Traditional modeling approaches in this context consider linear interactions, a small number of variables characterizing the event being modeled, and data generated through focus groups and/or a limited number of surveys. Through these approaches, we have witnessed significant failures to predict (to a certain level) the outcome (or at least the trend) of events like presidential elections, referendums, political and social polarization, immigration effects, social-ecological impacts, and effects of natural disasters on society. In these cases, we argue that ML methods can capture nonlinear interactions, thereby improving our capacity to anticipate social trends and prepare for their complex effects. This aspect gains ground in major, data-rich private companies; on the other hand, public researchers around the world are engaging in an effort to use it for the benefit of society as a whole. This does not only regard scientists: it is essential that civil society participate in the science of society.

HUMAN–AI INTERACTION AND AUGMENTED HUMAN INTELLIGENCE Undoubtedly one of the main concerns regarding AI is how this new form of intelligence will interact and relate with humans. Consequently, an important strategy to address this issue is to explore how humans and AI systems can interact and complement each other in a mutually beneficial cycle. This has led to a new research direction called human-AI interaction (HAII) that consists of the overlap of the computer sciences fields of human-computer interaction (HCI) and AI. Another form of posing this interaction is in the context of ambient intelligence where AI, sensors and wearables are combined to provide an intelligent enhanced reality experience.

4.5.2 Science, nature, the environment and the universe

AI is not only the ultimate problem-solving and modeling tool but also a research and discovery tool. The application of causality and explainable AI has the potential not only to model correctly many challenging phenomena but also to express these models in a human-readable way in such a way that can be converted into new scientific knowledge in the application area.

The current climate crisis calls for the use of all available technology to try to understand, model, predict and hopefully work towards its mitigation.

UNDERSTANDING CLIMATE CHANGE: IMPACT, ADAPTATION AND MITIGATION The ocean is key to understanding our planet and climate change. We identified two main challenges concerning the modeling of the ocean symbiome system and its relation with climate change. All of them have an intrinsic need for the development of computer science theory, computational tools and ideas to bring us beyond the state of the art and strengthen the accumulated area of expertise.

- Biodiversity and ecosystem functioning: Biodiversity supports important functions, such as primary productivity and carbon fixation and sequestration, that are directly or indirectly used and affected by humans. Understanding the processes driving these functions is fundamental from a basic science and policy perspective.

- Understanding plankton communities using AI, ML, and vision: Self-learning and anomaly detection computer vision techniques are called for to help to identify individuals in an automated way.

- Indirect plankton identification: instead of quantifying the presence of different microscopic organisms, it would be possible to detect some large dimension objects that indicate the presence of such organisms.
- Connecting images and genomic features: oceanographic datasets provide an extensive overview of plankton images. Both images and genomics provide a lot of diversity to investigate.
- Anomaly detection and explainable AI for automatic plankton discovery: how to identify unknown or out of context species automatically and, at the same time, provide explanations of why that organism is an interesting specimen?
- Tracking and predicting marine pollution.

ASTROCOMPUTING The astrocomputing area has three main dimensions of interest:

1. *AI and ML for astronomical observatory operations* The operations monitoring and control is what has been called "mission-critical contexts" which extend to emergency response and management, and critical infrastructure operations. Astronomical observatories can be viewed as "data factories" where data analysis, high-performance computing, human-computer interaction, have played a predominant role. More recently, it has been established the need for machine learning and logistic support to both automate the operation of the installation by incorporating elements of predictive maintenance, anomaly detection, process scheduling and logistics. One is prescriptive maintenance using operational data from different domains such as astronomical observatories like the Atacama Large Millimeter/submillimeter Array (ALMA) and the Vera C. Rubin observatory (LSST) in Chile.
   - Performance monitoring, predictive maintenance and anomaly detection.
   - Smart radio-telescope monitoring system.
   - Data governance models for operational systems.
   - Design, construction and deployment of secure and robust collaborative self-service infrastructures for data engineering processes, analytics and machine learning workflows, for operational data analysis and visualization.
   - Tracking and improvement of maintenance plans combining metaheuristics and predictive maintenance for engineering maintenance.
2. *Automatic discovery of relevant astronomical events* One of the objectives of survey telescopes like Vera C. Rubin is to discover transients, objects that change brightness over time-scales of seconds to months. These changes are due to a plethora of reasons; some may be regarded as uninteresting while others will be extremely rare events, which cannot be missed. These challenges are even greater if we pose the use of computer science not just as a descriptive and modeling tool but as an analytical and predictive tool capable of becoming a primary source of knowledge and understanding of the phenomena and not just a modeling tool. This is aligned with the current hot topics of ML and AI like causal inference, explainable AI, model visualization, etc.
   - Unsupervised anomaly detection approaches applied to images and light curves to transient astronomical events: detect truly unknown events.
   - Active learning for assisted semi-supervised learning and transfer learning for reusing models across conditions.
   - Generative adversarial approaches for anomaly detection, generalizing models for interesting events.
   - Causality and explainable AI for reducing false positives by going beyond plain detection by providing a theory and reasoning behind a detection.
3. astrophysics and cosmology.

4.5.3 *Government and public sector*

Many governments and public institutions of the region are undergoing a process of digital transformation. In this context, AI can serve as a catalyzer for this process and also rely on it to provide citizens with added-value services. For example,

1. reduce bureaucracy overheads and processing times,
2. expedite access to justice and law in an unbiased manner,
3. mitigate fake news and misinformation,
4. enhance resilience to natural disasters,
5. automate procurement, requests for work and other public solicitation processes,
6. data protection,
7. etc.

4.5.4 *Industry and productive sector*

Recent advances in sensors, data management, and cloud computing are transforming the environment for operations managers in these industries. Large, rich datasets can be readily assembled from diverse sources with substantial computational power available for analytics. This creates a fertile environment for the application of computational intelligence. Prediction, classification and optimization algorithms can support decision-makers in the management of highly expensive resources, where even small percentage cost reductions can amount to millions of dollars. The application of computational intelligence can be transformative, leading to large-scale efficiency and major changes in operations.

As already expressed, we think we should render AI as available to society as another utility service. Therefore, these application scenarios also have the aggregated value of validating the shared lessons and using AI as a cornerstone for inter-sectorial collaboration.

SMART AGRICULTURE Modern agriculture relies more and more on digital technologies in what is known as smart or precision agriculture. The goal of smart agriculture research is to define a data-informed decision system for agricultural management with the goal of optimizing returns while preserving resources and ensuring a long-term activity. Current population growth coupled with processes like climate change, El Niño or La Niña put additional stress on agriculture that must have substantial yields while adapting to changes and unexpected events. This change not only renders useless centuries of human experience but also challenges AI/ML methods as poses a small data scenario with high risks of underspecification.

- Micro-localized climate prediction via downscaling and fusion using open meteorological and macro/micro-scale forecasting.
- Crop detection and evaluation (i.e. pest detection, health, etc.) based on near and remote sensing. Disease detection and prediction in blueberry orchards. Early detection of botrytis or other diseases, how they spread and the impact on postharvest life of fruit.
- Deep learning and AI models for estimating harvest productivity. Harvest estimation using computer vision: counting models and ripeness.
- Remote sensing (via drones and/or satellite) and application of machine vision and ML to remotely manage agricultural plots.
- Optimization and logistics for the production chain: care, harvest, transportation, and export. Predictive maintenance.

- Research in transfer, active and few-shot learning and hybrid forecasting models using AI and modeling tools to generalize results across different fields, species, etc.
- Estimation of effective pollination in blueberries: hive monitoring, visited flower monitoring, correlation with climate data, extrapolation to total surface.

RETAIL, LOGISTICS AND TRANSPORTATION The location of many countries in the region, relatively withdrawn from the major trade routes combined with its extreme geography and challenging natural features like desert, mountains, etc. render the area of transportation sector to be of paramount strategic importance.

This sector is also undergoing an important transformation with the introduction of passive public transportation solutions, electric transportation, green hydrogen, city logistics, etc. all meant to alleviate the burden of transportation while also making it consistent with ecological long-term goals. Both in the current and in futures scenarios, the use of AI is essential.

INDUSTRY 4.0 Industries in the region are essential. For example, the mining industry is an asset for the Chilean economy and society. A majority of mines still use legacy technology. Easily attainable cost and productivity are getting harder to obtain. Productivity in mining operations worldwide continues to decline—despite continuous improvements to operations and even after adjusting for declining ore grades.

Because of the combination of different industrial processes and labor location it is highly susceptible to improvement thanks to the use of AI, IoT and related technologies. Experiences in this industry can also be extrapolated to other sectors.

Some of the problems that we can point out are:

- Automated on-the-fly truck routing based on crowd-sourced road data.
- Automatic road assessment using drones and computer vision.
- Truck fleet management and predictive maintenance.
- Optimal fiscalization and inspection of mining facilities.
- Accident risk estimation, causal inference and explainable AI for improving health and safety environment

HEALTH Health and AI have a long-dated relationship and, more recently, it has been argued that "AI can make healthcare human again" [35]. The researchers of the center have important experience in this sector. This experience had undergone an important bump because of the recent COVID-19 pandemic. Researchers of the center have worked during this period on bringing the state of the art of AI to assist in the different aspects of the medical processes, from diagnosis, management, and research.

- NLP methods for automatic understanding of electronic health records.
- Natural language understanding and graph-based neural networks for assisting in biomedical research bibliographic management.
- Data-driven management of hospitals, critical beds, respirators, etc.
- Automatic interpretation and diagnosis of medical images.

FINTECH Access to finance services is another important social divide in Latin America (Gershenson et al., 2021). The expansion of fintech activities is widely viewed as having the potential to alleviate financial frictions and improve financial inclusion. AI is a critical part of the fintech space in terms of collecting data, analysing information, safeguarding and facilitating transactions, creating customer-centric products, and streamlining processes. But with great technology comes great responsibility and the application of AI and data collection in financial services is one that raises many questions in terms of management, security and regulation. For instance, the European Union recently introduced rules that will begin to shape the way AI is used, with a particular focus on the financial services sector.

The regulatory aspect of AI and the need of explainable, auditable methods in the financial sector will likely include more thorough analyses of training data and algorithms to identify areas where bias is treating people unfairly or blocking people from certain products. In one hand, this sector uses algorithmic decision-making is to discriminate —-to judge people according to certain criteria like where they live, their age, their occupation.

5 FINAL REMARKS

This paper consolidates the preliminaries discussions that the authors had in preparation for the "AI in Latin America" side event of the of the 2021 Global Partnership for AI (GPAI) Paris Summit. We have focused these discussions on how AI research and policy making can be directed towards topics and applications that can lead to the socioeconomic progress of the region and an improvement of the quality of life understood in broad terms.

This is an urgent discussion that should not be postponed or left out of the academic circles. Key issues like social gaps, impact on labour force, health and equality are at stake.

We expect this work to serve to ignite a wider community-wide conversation that consolidates and extends the arguments being put forward here.

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