# Artificial intelligence ESG stakes

Discussion paper

Building a better working world

# INTRODUCTION

The convergence of artificial intelligence (AI) and environmental, social and governance (ESG) factors is a pivotal development in today's rapidly evolving business landscape. In this paper we provide an in-depth analysis of the symbiotic relationship between AI and ESG, outlining how AI technologies can be applied to enhance ESG management and mitigate related risks.

EY teams discuss ESG's significance in today's world and its synergy with AI technologies. It also scrutinizes how AI can be a catalyst in achieving ESG objectives, from environmental sustainability to social responsibility and governance. We conclude with a critical evaluation of AI's impact on ESG metrics and offer actionable insights for mitigating potential challenges.

By integrating AI into ESG risk management and strategies, organizations can not only achieve their sustainability goals, but also unlock new avenues for driving both sustainable development and organizational innovation.

# AGENDA



# In today's rapidly evolving business landscape, CEOs are placing AI and sustainability at the pinnacle of their strategic agendas

According to EY CEO Outlook Pulse Report, CEOs across the globe are incorporating AI technology and sustainability into their growth agenda.

- While most CEOs are positively adopting AI in their future strategy, the journey towards sustainability is fraught with challenges, since the benefits of ESG initiatives tend to lie in the long term.

**88%**

of CEOs reported existing or planned capital investments to AI-driven products or service innovations.

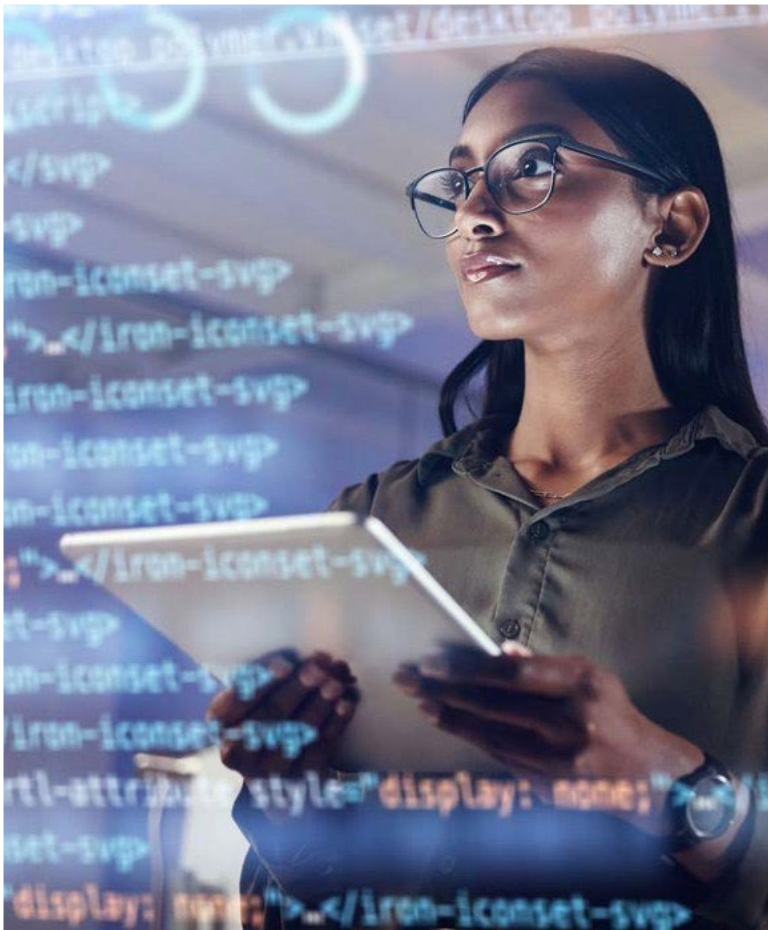
**38%**

of CEOs reported they prioritize sustainability issues when making capital allocation decisions.

- While the promise of AI is undeniable, the exciting new technology is bringing along new sustainability challenges.

**65%**

of CEOs say more work is needed to address the social, ethical and criminal risks in the new AI-fueled future.




The convergence of AI and sustainability offers a compelling solution to both challenges. Businesses are increasingly using AI to expedite their sustainability initiatives, particularly at a time when there is growing pressure from investors, regulators and broader society for greater transparency in ESG practices. The alignment of AI and sustainability is not just a strategic move, but a critical response to meet the diverse demands of today's stakeholders.

# Background

The promise of AI offers innovative tools to tackle ESG priorities. The rise of AI highlights the urgency to examine AI ESG stakes

## AI adoption drivers

- AI systems are machine-based systems with varying levels of autonomy that can, for a given set of objectives, produce an output (predictions, recommendations or decisions) using massive amounts of data sources and data analytics (big data).

- In recent years, AI models have been increasingly deployed in various domains, such as medicine, finance and education due to:

Abundance of available data

Increase in computational capacity

Advancements in AI methods and technology

## AI in support of ESG priorities

- AI systems are rapidly providing new benefits and efficiencies to organizations around the world through new automation capabilities, greater ease of use and accessibility and a wider variety of well-established use cases.
- Organizations are also applying AI to tackle far-reaching challenges with greater social and environmental impact. For example, organizations are addressing skills or labour shortages or helping advance ESG-related initiatives and reducing their environmental impact.

- Climate challenges: AI models can be used to enhance climate actions through energy management and climate change monitoring.
- Financial crimes: AI-driven technology has been extensively used in fraud detection and anti-money laundering system designs.

## AI impact on ESG factors

- As the deployment of AI systems around the world is expected to grow in importance in the coming years, the potential challenges and risks emerging from its application are becoming more concerning.
- The rise in popularity of AI systems also raises concerns about ESG factors because of the potential impacts of AI algorithms on ESG factors.

- Large AI models such as deep learning (DL) and gen AI generally consume a significant amount of energy and generate large carbon emissions, since the process of training and operating large AI models requires vast amounts of energy. This results in increased air pollution, water usage and carbon emissions that can accelerate climate change.

**600,000 lbs**

The process of training a single deep learning natural language processing (NLP) model can lead to approx. 600,000 lbs of carbon dioxide emissions, similar to the amount produced by five cars over the cars' lifetime.[1]

**96 tonnes**

Google's AlphaGo Zero generated 96 tonnes of CO2 over 40 days of research training, which amounts to 1,000 hours of air travel or a carbon footprint of 23 American homes.[2]

# ESG and AI overview

# What is ESG?

The term environmental, social and governance (ESG) is often used interchangeably with sustainability and corporate responsibility. It refers to the three main factors used to evaluate a company's sustainability and ethical impact.

## ENVIRONMENTAL

Environmental criteria evaluate how sustainable a company's operations are. It captures an organization's overall impact on the environment and the potential risks and opportunities it faces because of environmental issues, such as climate change and measures to protect natural resources.

Examples of environmental factors that can be ESG criteria include energy consumption and efficiency, carbon footprint (including greenhouse gas emissions), waste management, air and water pollution, biodiversity loss, deforestation, natural resource depletion, clean energy and technologies.

## SOCIAL

Social criteria assess how a company treats different groups of people – its employees, customers, suppliers and communities – and its efforts to promote diversity, equity and inclusion.

The criteria used include employee safety, product safety, human rights, child labour and the diversity agenda.

## GOVERNANCE

Governance factors examine how a company polices itself, focusing on internal controls and practices to maintain compliance with regulations, industry leading practices and corporate policies.

Examples include executive compensation policies, financial transparency and business integrity, regulatory compliance and risk management initiatives, ethical business practices and financial reporting.

# Why is ESG so important today?

Helpful to achieve the United Nations Sustainable Development Goals

By incorporating ESG factors in the decision-making process, organizations significantly contribute to achieve the United Nations (UN) Sustainable Development Goals (SDGs). On the corporate side, ESG considerations can be broadly mapped to SDGs.

### What are the SDGs?

- The UN 17 SDGs consist of a global call to action to end poverty, protect the planet and ensure that all people enjoy peace and prosperity.
- They cover environmental sustainability, social inclusion and economic growth.
- There is also a focus on health, education, gender equality and climate action.

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### By adopting ESG practices, businesses can contribute towards the SDGs

#### Ethical supply chain practices

Companies that establish and enforce ethical supply chain practices, ensuring fair labour conditions, responsible sourcing and transparency, align with SDG 8 - Decent Work and Economic Growth. These practices promote sustainable economic development, decent working conditions and fair trade.

#### Waste management

Organizations that implement waste reduction strategies, prioritize recycling and promote circular economy principles align with SDG 12 - Responsible Consumption and Production.

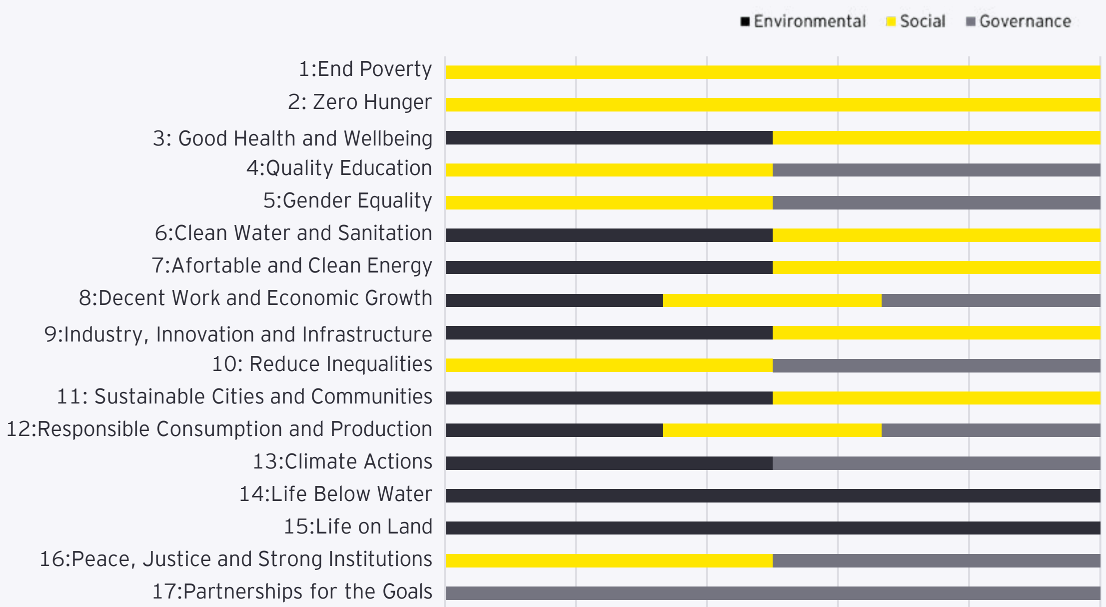
#### Water management and conservation

Businesses that implement sustainable water management practices, reduce water consumption and promote water conservation initiatives align with SDG 6 - Clean Water and Sanitation. Their efforts help ensure access to clean water and contribute to the overall preservation of water resources.

#### Carbon footprint

When a company focuses its efforts to reduce carbon emissions and promote renewable energy, this strategy aligns with SDG 7 - Affordable and Clean Energy and SDG 13 - Climate Action.

Relating ESG Components to the 17 SDGs



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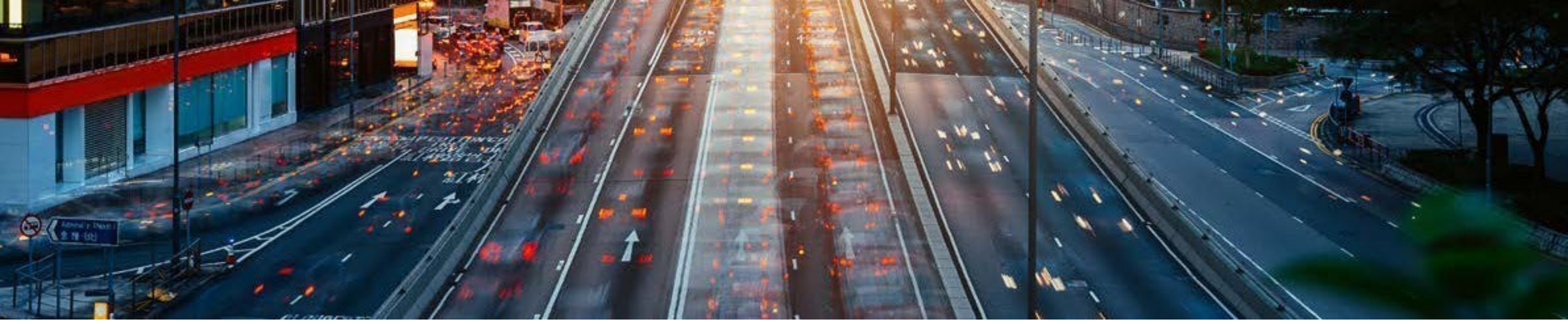


## The Canadian Government has a comprehensive and aggressive 2030 emissions reduction plan

### Aggressive sector decarbonization

**BUILDING**

**$150 million**

Investment for net-zero buildings strategy by 2050

**OIL & GAS**

**75%**

Target reduction in emissions below 2012 levels

**TRANSPORTATION**

**100%**

Light-duty vehicle (LDV) zero-emission vehicles (ZEV) sales by 2035

**AGRICULTURE**

**$950 million**

Investment to climate mitigation, carbon sequestration, adaption and agricultural clean technology

### Increased use of carbon pricing mechanisms

**Carbon price**

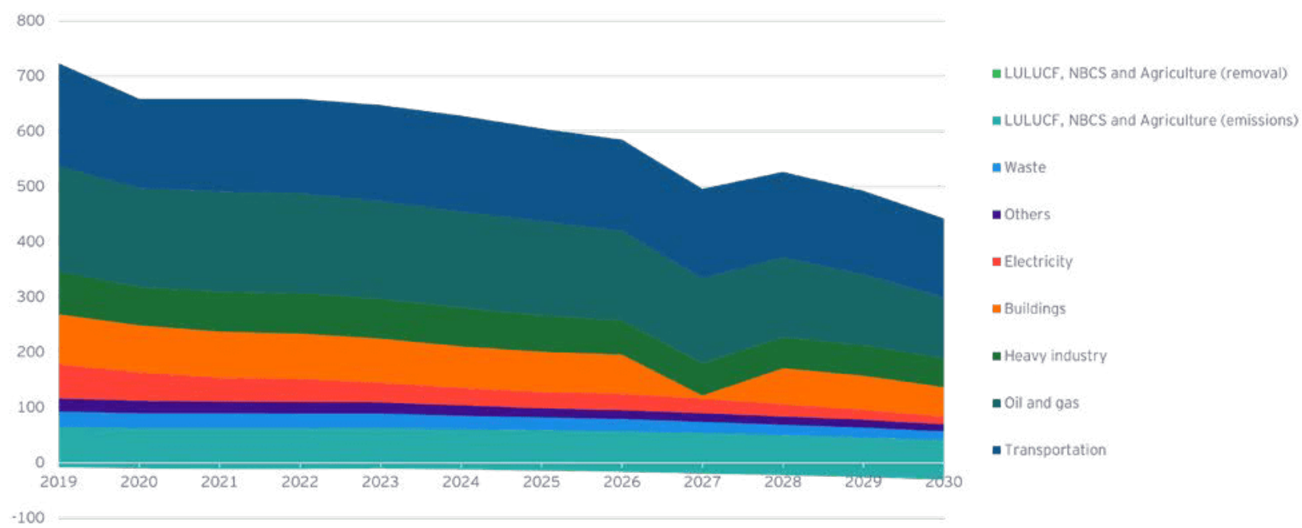
rising **$15** per tonne annually, reaching **$170** in 2030

### Clean, reliable, affordable electricity supply

**Renewable energy**

Enhance support for the deployment of commercially ready renewable energy technologies with over **$850 million** investment

**Canada's greenhouse gas emissions pathway to 2030 [3] (Mt CO2 eq)**



# How AI systems are related to ESG factors

What is AI?

## AI models

AI models consist of the application of computational tools to build models from examples, data and experience, rather than following pre-programmed rules.

**1** Programs that attempt to simulate the behaviour of the human brain by learning from large amounts of data.
e.g., deep learning

**2** Programs that allow machines to learn from data and make decisions/predictions on their own.
e.g., machine learning techniques

**3** Programs that enable computers to understand text and spoken words in much the same way human beings can.
e.g., large language models

**4** Programs that help computers process, analyze and interpret visual data (e.g., digital images or video).
e.g., computer vision

The adoption of AI models provides the ability to treat large amounts of unstructured and structured data for better decision-making and to address sustainability issues (climate issues, education, health). For example:

- Use in medicine to diagnose diseases, develop drugs faster, improve gene editing, personalize treatment
- Use for environmental management: climate change modeling, monitoring deforestation through satellite imagery analysis, energy management

In the absence of proper controls, adoption of AI may have significant environmental, social and governance impacts.

- An AI model is an energy consumer through its lifecycle, yielding carbon emissions.
- AI models are exposed to regulatory, reputational and business risks (e.g., data privacy and transparency issues).

# How AI systems are related to ESG factors

## Potential link with ESG factors

Some of the common technical, regulatory and practical challenges through the AI lifecycle

May affect different aspects of →

ESG criteria as illustrated in the following diagram with few technical, regulatory and practical considerations when using AI models

**E**

**AI sustainability**

The importance of assessing the environmental impact of AI throughout its lifecycle and its supply chain: meaning the sustainable development and use of the technology by taking into consideration its environmental impact.

**S G**

**AI transparency**

The degree to which a human can understand the cause of the prediction and the model outcome and can consistently predict the model's result.

**E S**

**AI for sustainability problems**

The potential of AI to solve complicated environmental and societal issues and help to meet the United Nations SDGs (e.g., quality education, reduce inequalities, climate actions, innovation, infrastructure).

**S G**

**Data privacy**

AI systems must prioritize and safeguard privacy and data rights and provide explicit assurances about how personal data will be used and protected.

**S G**

**AI resilience**

The ability of the AI system to continue functioning even when it encounters unexpected inputs, errors or other forms of disruptions (environmental). The idea is to create robust AI systems that can maintain their functionality even in the face of unforeseen circumstances, such as hardware failures, cyberattacks or environmental changes. This is crucial for safety-critical applications, where system failures can lead to severe consequences.

**S G**

**Compliance**

AI-powered systems must comply with all applicable laws and regulations. For example, the data used to train AI systems should be collected and used legally and ethically.

**G**

**Explainability/interpretability**

Can a human understand, challenge and validate the inner workings and results produced by the AI system?

**E S G**

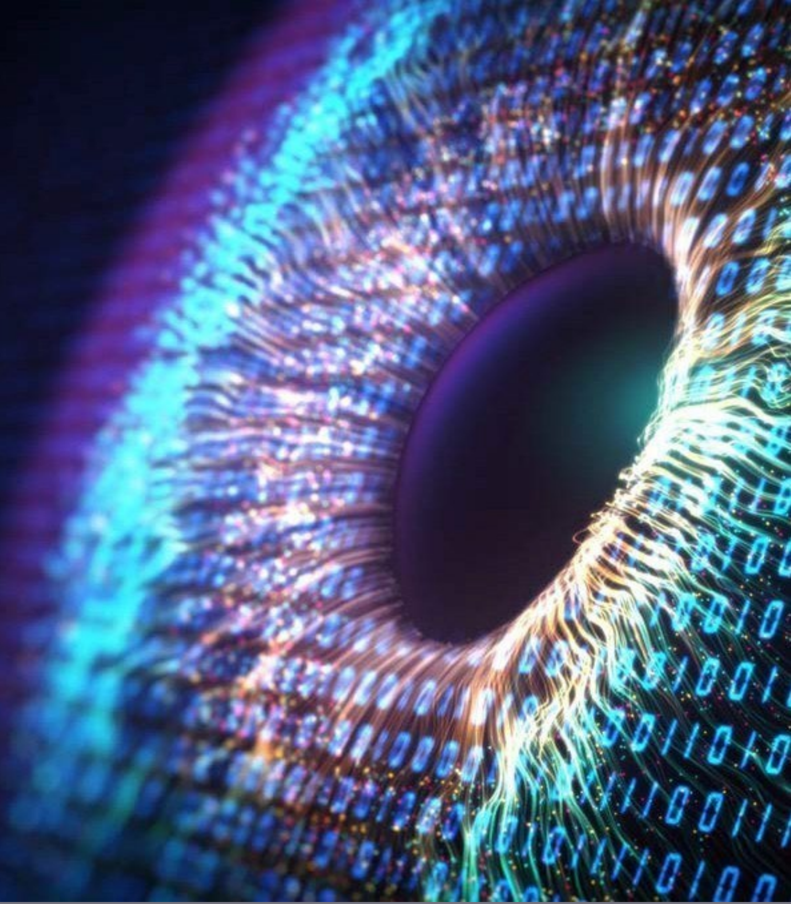
**AI ethics**

A set of guidelines that advise on the design and outcomes of AI systems.

The direction of the impact (+/-) of AI on ESG criteria depends on whether the AI system is responsibly used and sustainable over its lifecycle.

# How does AI enable ESG management?

# How can AI promote ESG?



AI has the potential to **revolutionize** the way we approach and address global challenges.

With **ESG** gaining prominence over recent years **and** the **increasing use of AI** in various domains of society, it is **critical to understand** how **AI** can help **build a sustainable** future by promoting **environmental, social and governance** (ESG) practices.

## E

### Energy management

Energy use and consumption can be monitored through the use of AI models, which in turn can provide optimized usage settings to result in **reduced greenhouse emissions**.

### Climate change monitoring

AI models can assist in providing accurate predictions to assist policy- and decision-makers in implementing more effective strategies to **mitigate the impact of climate change**.

### Deforestation monitoring

Satellite imagery can **detect illegal deforestation in real time**. AI models using image/video annotation can be used in conjunction with this to identify patterns of forest loss. This will enable conservation organizations to take timely action.

## S

### Financial inclusion

AI can help FinTech companies **provide affordable financial services to unbanked and excluded individuals** by performing alternative credit checks.

### Health & wellbeing

AI can help health care providers **improve access to quality health care for underprivileged communities (e.g.,** use of delivery drones).

### Employment discrimination:

AI can assist companies in analyzing hiring and promotion data and **correcting for any potential biases** and ensure a more inclusive, fair and objective workforce.

## G

### Corporate governance

AI can assist in analyzing corporate governance data to **assess organizations' ESG performance** and identify possible enhancements and efficiencies.

### Public sector efficiency

AI can assist in streamlining public sector processes and ultimately **improve service delivery**.

### Regulatory compliance

AI can assist in monitoring large amounts of regulatory data to identify potential breaches in a timely manner. This will **allow organizations to take proactive measures** instead of being reactive.

# How can AI make the environment more sustainable?

### Biodiversity

When paired with satellite imagery, AI can assist in identifying changes in land use, vegetation, forest cover and the effect of natural disasters. Further, AI can improve waste management through better AI-enabled sorting across the entire waste management lifecycle.

### Energy

Using neural networks, pattern recognition and fuzzy logic models, AI can assist in reducing consumption of natural resources and energy demands associated with human activities. For example, Chen et al. (2021) introduced an effective evaluation model based on AI techniques that can be used for predicting energy efficiency and conservation. The proposed model exhibits a significant energy efficiency rate of around 97.32% [4].

### Water

AI can forecast stream flow and examine water quality. It can assist in predicting droughts, as well as soil and subsurface water conditions.

### Transportation

Computer vision techniques can aid decision-making in traffic management, public transportation and urban mobility.

### Air

AI can collate data from sensors and satellites and assist scientists in mixing climate models. AI-enhanced purifiers can continually record air quality data and modify their filtering performance as needed. In addition, AI can be used to better qualify localized emissions from satellite remote-sensing data.

### Agriculture

Farmers can use drones and satellite imagery to assess soil quality and crop productivity. This can increase efficiency, productivity and yields. AI can also be used to monitor illegal fishing.

# How can AI potential be unlocked for social good?

New developments in **AI can spur democratization of access to services and work opportunities,** which could **improve the lives of many** around the world.  However, these **advances** could be used for **good or ill.** They could result in creating new commercial opportunities for business, increased fairness, increased access to health care solutions, but they could also lead to new inequalities, biases and exclusions. Below are **some of the potential benefits that AI can unlock for social good**.

## Human augmentation

- Also known as biohacking , human augmentation technologies can enhance human performance for good or evil.
- When used for good, these AI technologies can improve the lives of people with disabilities, using AI-powered exoskeletons.
- These exoskeletons can allow disabled people to perform physical tasks that were previously impossible for them.
- AI algorithms used with a sign language glove can enable people communicating in sign language to verbalize their signs by converting the signing patterns to electrical signals and spoken words.

## Sensory imbalance

- The five human senses offer rich territory for AI technologies and applications.
- AI technology could be used to detect a person's physical and mental wellbeing by analyzing pitch, tone, timbre and vocabulary.
- AI technology can currently analyze large amounts of data sets to predict melanomas and be as accurate as dermatologists (see Tri-Cong Pham et al. (2021) for more details)[5].

## Geographic tracking

- AI technology in conjunction with Google street view  can be used to analyze large amounts of images of a city landscape to identify patterns of inequality and urban deprivation.
- AI technology can analyze and derive results that can be used to complement official statistics such as government census programs.
- AI technology can be used for tracking and controlling infectious diseases.
- By analyzing travel data, news reports and other data points, a Canadian-based company sounded the alarm early around the spread of the coronavirus in the city of Wuhan.

# How can AI benefit governance?

1

## FRAUD DETECTION

Financial institutions are required to monitor their customers on an ongoing basis to identify potentially fraudulent or criminal activity between normal customer review cycles. Using AI-based solutions, they can construct comprehensive customer profiles by leveraging additional data sources, which more accurately pinpoint suspicious activities and assess risk across various domains. This reformed underlying detection logic leads to the enhancement of screening and monitoring tools. Implementing robust AI modeling techniques, such as unsupervised learning and outlier detection models, can fine-tune thresholds for rule-based monitoring systems, leading to more resilient thresholds supported by extensive data. Consequently, this can diminish false positives and enhance the efficiency of the investigation process[6].

2

## MONITORING AND COMPLIANCE AUTOMATION

AI's application in monitoring and compliance automation is streamlining processes in financial institutions. Employing natural language models, firms can efficiently scan regulatory sources, producing consolidated and relevant summaries for senior management review. By facilitating first drafts of policy documents, AI solutions offer a foundation for human refinement, reducing costs and enhancing procedural efficiency. Furthermore, automating tasks with AI allows compliance officers to focus on strategic matters, exemplifying AI's role in identifying potential fraud or errors, akin to its function in safeguarding data against cyber threats.[7]

3

## DATA GOVERNANCE

Data governance entails using a set of metrics, standards, policies and processes to ensure companies use customer data correctly and responsibly. In data governance, AI can be used for various purposes. Businesses can train an AI-based solutions to help detect anomalies such as breach in data centres as well as cyberattacks by identifying patterns of cyber threats, ensuring their customer data is protected 24/7. AI is also useful in secure data transmission through monitoring data traffic, leveraging advanced encryption methods and anomaly pattern recognition techniques to safeguard against interception by cybercriminals.[8]

4

## BOARD REPORTING AND GOVERNANCE ANALYTICS

Presenting accurate and concise information is paramount for the board's effective decision-making. However, the process of preparing reports to the board and making sure all the information is correct and up to date can be a time-consuming task. AI technologies can be introduced to streamline this process, linking directly to databases to generate real-time, accurate board reports. Further, AI's potential extends to personalizing reporting dashboards per board member, emphasizing distinct key areas of focus, thereby enhancing efficiency and responsiveness in governance analytics.[9][10]

# How does AI impact ESG?

# Environmental impact of AI models

## Negative environmental impact of using AI

The major environmental impacts of AI are primarily related to **energy consumption**, **greenhouse gas (GHG) emissions** and **water consumption**, which can occur throughout the **model lifecycle,** from the development to the deployment phases.

- Model development **phases** over the **AI system lifecycle** are illustrated below.

**Data processing**

Extract features from data

- Transform features using weights based on features importance

**Experimentation**

Design, test and evaluate the quality of:

- The feature selection process
- The modeling techniques
- The model architecture
- Training method to determine the model parameters

**Training**

Finalize the model selection and refine the model:

- Performance comparison
- Refinement of the selected model
- Preparation for deployment

**Inference (deployment)**

The best model is deployed

- To produce trillions of daily predictions
- To serve billions of users

- Each phase of the AI model lifecycle is **computationally demanding** and will **use energy/water**, so it will have some **carbon footprint** on the environment.
  - E.g.: The experimentation phase **needs a lot of energy** to calibrate the model parameters, similarly in the training phase to evaluate several candidate models' performance for appropriate model selection.

- The **quantity of energy** used and the carbon footprint will **depend** on the **type of model.**
  - E.g.: **Deep learning**, **natural language processing (NLP)** and **generative AI** models are **strongly computationally demanding** and hence **more energy consuming** than some **classification models.**

# Environmental impact of AI models

## Negative environmental impact of using AI

Two different carbon emissions will be considered throughout the AI system lifecycle:

- Embodied carbon emissions from data processing and model experimentation phases
- Operational carbon emissions from training and inference phases

### Embodied carbon emissions

- Data processing: Model developers will extract features from data during this phase and apply weights to individual features based on feature importance to the model optimization objective.
  - This will consume some energy and hence produce carbon emissions.
  - The quantity of energy (carbon emission) needed (produced) during this phase will largely depend on the complexity of the available data set, the volume and the type of data set.
- Experimentation: During this phase, model developers design, implement and evaluate the quality of proposed algorithms, model architectures, modeling techniques and/or training methods for determining model parameters.
  - The quantity of energy consumed will depend on the complexity and the type of the use case.
  - e.g., a deep learning/NLP/RL model may consume more energy than a regression-based or classification model.

### Operational carbon emissions

- Training phase where several AI models' performance is evaluated using extensive production data with the aim of selecting an appropriate candidate. The selected model will then be refined to prepare it for deployment. The process often requires additional hyper-parameter tuning.
  - This phase is largely computationally based. It demands a significant quantity of energy, which depends on several factors, including model complexity, precision of the algorithm, data complexity and the number of models to evaluate.
- Inference: the best-performing model is deployed, producing trillions of daily predictions to serve billions of users worldwide.
  - This phase requires energy during the full model deployment timeline.
  - The total compute cycles for inference predictions are expected to exceed the corresponding training cycles for the deployed model.

# Environmental impact of AI models

## Quantifying the carbon emissions of AI models: strategies for AI use cases

- Before proposing a way to reduce carbon emissions over an AI system lifecycle, you should first be able to assess the carbon emission generated by the models and understand the factors impacting the carbon footprint.
- The energy used and the carbon emission will be essential to understand the potential climate impacts of machine learning models.
- Several methods have been proposed to quantify or to estimate the carbon footprint of AI models.

**The metric** to quantify the carbon emission: CO2-equivalents (CO2eq), a standard metric used to evaluate the environmental impact.

**Factors that could affect the metric:**

- The geographical zone of the server (provide information about the energy grids used): the distribution and variation in carbon emissions depends on the location of the server.
- The type of graphics processing units (GPU) (computing infrastructure) and the training time: models such as NN often use multiple GPU for several weeks/months, which requires more energy.
- The calculator uses those factors and outputs the approximate amount of CO2eq produced to inform model developers/users about the model's potential environmental impact.

Carbon emission calculator[11]: an alpha version has been proposed by Alexandre et al. (2019).


Carbon-tracker to track and predict the energy and carbon footprint of training DL models [12].

- Carbon-tracker is an open-source tool written in Python for tracking and predicting the energy consumption and carbon emissions of training DL models.
- It is available through the Python Package Index (PyPi).
- Carbon-tracker uses several metrics for tracking carbon footprint.
  - Power usage effectiveness (PUE): This is defined as the ratio of the total energy used in a data centre facility to the energy used by the IT equipment such as the computing, storage and network equipment.
  - Energy consumption (E) obtained by combining PUE and average power consumed and training duration.
  - Carbon footprint obtained with E and the carbon intensity.
  - The carbon intensity is forecasted using application programming interfaces (API). It refers to how many grams of carbon dioxide (CO2) are released to produce a kilowatt hour (kWh) of electricity. This is specific to each region.

# Environmental impact of AI models

## Quantifying the carbon emission of AI models: strategies for AI use cases

Example of the default setup added to training scripts for tracking and predicting with Carbon-tracker.

```
from carbontracker.tracker
  ↪  import CarbonTracker

tracker
  ↪  = CarbonTracker(epochs=<your epochs>)

for epoch in range(<your epochs>):
    tracker.epoch_start()

    # Your model training.

    tracker.epoch_end()

tracker.stop()
```

Example output of using Carbon-tracker to track and predict the energy and carbon footprint of training a DL model.

```
CarbonTracker: The following components
  ↪  were found: GPU with device(s) TITAN
  ↪  RTX. CPU with device(s) cpu:0, cpu:1.
CarbonTracker: Carbon intensity
  ↪  for the next 1:54:54 is predicted to
  ↪  be 54.09 gCO2/kWh at detected location:
  ↪  Copenhagen, Capital Region, DK.
CarbonTracker:
Predicted consumption for 100 epoch(s):
        Time:   1:54:54
        Energy: 1.159974 kWh
        CO2eq:  62.744032 g
        This is equivalent to:
        0.521130 km travelled by car
CarbonTracker: Average
  ↪  carbon intensity during training
  ↪  was 58.25 gCO2/kWh at detected location:
  ↪  Copenhagen, Capital Region, DK.
CarbonTracker:
Actual consumption for 100 epoch(s):
        Time:   1:55:55
        Energy: 1.334319 kWh
        CO2eq:  77.724065 g
        This is equivalent to:
        0.645549 km travelled by car
CarbonTracker: Finished monitoring.
```

# Leading practice to mitigate AI's environmental impact

Through developing sustainable AI solutions

## 1 MULTI-OBJECTIVE OPTIMIZATION

Energy and carbon footprint can be directly incorporated into the cost function as optimization objectives to enable discovery of environmentally friendly models.

## 2 REDUCE WASTED RESOURCES

Replacing **grid search** with **random search** can significantly accelerate **hyperparameter search,** consequently reducing carbon emissions (it reduces training time during the experimental and training phases).

Also, while **failed experiments** are a common part of ML research and are sometimes unavoidable, their number **can often be reduced** with **careful design** such as unit tests, integration tests and extensive and early debugging.

## 3 DEVELOP EFFICIENT TRAINING ALGORITHMS

Evaluations of optimization methods should account for all experimentation efforts required to tune optimizer hyperparameters, not just the method performance after tuning. Efficiently scale training by reducing communication cost via **compression**, **pipelining** (the processor performs an instruction in multiple steps) and **shading** (database partitioning that separates large databases into smaller, faster, more easily managed parts). Hyperparameter tuning may be improved by substituting grid search for random search using Bayesian optimization or other optimization techniques like Hyperband.

## 4 CARBON-EFFICIENT SCHEDULING FOR AI COMPUTING AT SCALE

Using carbon-free energy to neutralize operational carbon footprint during training and experimentation.

## 5 DATA UTILIZATION EFFICIENCY

**Data scaling and sampling** should be well designed to improve the competitive analysis of AI algorithms by affecting the size and quality of the training data[13]: intelligent data sampling with only 10% of data subsample can significantly reduce training time for similar performance, leading to significant operating carbon footprint reduction.

**Data perishability** Understanding the rate at which data loses its predictive value has strong implications on the resulting carbon footprint (e.g.: natural language data sets can lose half of their predictive value in less than 7 years). This data value amortization rate will help provide effective sampling strategies to subset data. By doing so, the resource requirement for the data storage and ingestion pipeline can be significantly reduced leading to lower training time as well as storage needs.

# Social impact of AI models

### AI FAIRNESS AND BIAS

- Public training data can reflect societal biases, resulting in AI systems unintentionally favouring or discriminating against specific sub-groups.
- Inherent bias in algorithmic design and model selection can perpetuate unfair outcomes across various business applications.
- AI systems, especially interactive ones, may generate or amplify toxic responses, necessitating continuous oversight and moderation to ensure respectful user interactions.

### DATA PRIVACY AND SECURITY

- AI's ability to process large data volumes can lead to potential misuse or mishandling of sensitive data.
- AI algorithms, particularly in machine learning, often require extensive data, which can intrude on privacy if not adequately managed.
- AI systems can be vulnerable to cyberattacks, risking data breaches.
- Gen-AI models are subject copyright litigation. While the copyright law of fair use allows sufficiently differentiating "derivative work," defining its boundaries is challenging. In addition, the intricate nature of generative AI makes tracing the specific training data for outputs difficult.[14]

### JOB DISPLACEMENT

- AI integration disrupts roles with repetitive tasks (e.g., manufacturing, data entry, customer service).
- AI's impact is task based rather than job based, indicating a workforce shift towards higher-value tasks. [15]
- While immediate impacts of AI can lead to substantial job displacement, the long-term outlook hints at a potential adaptation of the workforce and the emergence of new job opportunities.



EY

# Mitigating AI's impact on social

## 1 DATA SECURITY AND PRIVACY

- Implement robust encryption and anonymization techniques to safeguard data; ensure sufficiency of consent management for privacy and confidentiality; adhere to the AI Acts and any other regulations that may be violated by using AI.

## 2 AI FAIRNESS AND BIAS

- Use diverse and representative data for training to minimize biased outcomes; promote transparent algorithms and interpretability to shed light on the decision-making process.

## 3 JOB DISPLACEMENT

- Initiate reskilling and upskilling programs to prepare workers for AI-related job transformations; establish social safety nets, including unemployment benefits, to support displaced workers.

# Governance impact of AI models

## TRANSPARENCY

AI has a serious transparency problem. In fact, due to the complexity of most AI algorithms, its outcomes are difficult to explain and its processes impossible for lay users to understand. Hence, it becomes difficult for end users to have knowledge about and control over what data is being captured and how it is used. This is due to:

- Limited understanding of bias in training datasets
- Lack of visibility into training datasets
- Lack of visibility into the method of data selection
- Some difficulties to explain algorithms

## EXPLAINABILITY

AI models, in general, are highly complex and lack inherent explainability, unlike traditional mathematical/statistical models. Explainability is crucial to understand the underlying mechanisms that drive the operation of AI systems useful to produce a trusted AI output.

## BIAS ISSUES

The inherent biases arising from the composition of the development team, data and training methods are difficult to identify due to the structure of the model. So the performance comparison with alternative models should be done with caution. This will also limit the model trust since end users do not have clear idea about the importance of the bias.

## PERFORMANCE ISSUES

AI models tend to have higher complexity, higher data consumption and dependency, lower explainability and lower stability than traditional models. As a result, an appropriate model performance monitoring plan is needed (model performance monitoring challenges) to ensure the performance is compatible with end users' expectations.

# Mitigating AI's impact on governance

Through responsible development of AI solutions in organizations using the following steps

| | KEY ACTIVITIES | OUTCOMES |
|---|---|---|
| BUILD | Build an AI governance framework to enable AI adoption and manage emerging risks.<br>Set up AI policies, procedures and guidelines to streamline people, process and technology pillars. | Consistent definition of AI and AI system risk tiering<br>Clearly defined roles and responsibilities across the AI model lifecycle (RACI matrix)<br>Model inventory framework<br>Ethics and privacy assessments framework<br>AI standards for model development and validation |
| OPERATIONALIZE | Enable the technology supporting AI model inventory, privacy and ethics questionnaires.<br>Log the institution's AI systems in the model inventory.<br>Set up cadences for executive committees, escalation forums.<br>Vet current AI systems, including remediation plans for issues identified. | Operationalization of the AI governance framework across pillars<br>Vetting of AI systems across principles of trusted AI to ensure performance, lack of bias, transparency, resilience and explainability<br>Remediation of risks and issues identified in validation against standards |
| SCALE | Support institution-wide enablement of trusted AI principles.<br>For example, deploy fairness toolkit or ongoing monitoring toolkit.<br>From a technology point of view, support enablement of trusted AI through an end-to-end XOps framework. | Consistent, streamlined adoption of trusted AI principles across functions (e.g. fairness, ongoing monitoring)<br>Acceleration of trusted AI enablement through technology |

# Generative AI models and ESG factors

## AI drivers - emergence of generative AI models


- Generative AI (gen AI) is a branch of AI that uses ML techniques to generate a wide variety of new contents in the form of images, text, audio, etc., instead of simply analyzing and regenerating existing data.
- Gen AI uses sophisticated algorithms to assess data and derive novel and unique insights, thereby improving decision-making and streamlining operations.
- Gen AI is becoming very popular and is increasingly used in various domains because of the multiple benefits associated with these models in terms of creating new contents, process automation, efficiency improvement, etc.
- However, the adoption of gen AI models gives rise to various challenges and risks that could significantly affect ESG factors.

### A few examples of how gen AI can impact ESG factors

#### ENVIRONMENTAL IMPACTS

- These models require substantial computing power and energy consumption compared to other AI models (classification, regression-based models).
- Hence, they significantly contribute to global carbon emissions, exacerbating climate change concerns.
  - A study by Strubell et al. 2019 among others estimates that training a LLM can emit over 626,000 lbs of carbon dioxide, similar to the amount of carbon dioxide emissions produced by five cars over the cars' lifetime.

#### SOCIAL IMPACT

- Gen AI may produce biased or discriminatory output, perpetuating stereotypes or promoting harmful narratives.
  - Such incidents can harm an organization's reputation, violate ethical standards and impact social harmony.
- Gen AI such as LLMs relies on large amounts of data for training and generating outputs and may expose an organization to data privacy and security (cybersecurity exposure) issues.
  - Data breaches or unauthorized access to AI models can lead to severe reputational damage and legal repercussions.
- Moreover, the integration of gen AI can reshape the workforce landscape, potentially leading to job displacement and socioeconomic challenges.
  - Due to their ability to automate repetitive tasks and generate content, specific job roles may become obsolete or require significant reskilling and upskilling efforts.

#### GOVERNANCE CHALLENGES

- Explainability issue: The large number of model parameters (~100b) makes most gen AI models such as LLMs a black box lacking explainability.
  - This makes it difficult for model users to understand the logic behind certain decisions and may affect trust in these decisions.
- Cyberattack and adversarial attack: Training data and trained LLMs may be leaked out of the institution or vendor platform due to cyberattack or adversarial prompt engineering.

**To mitigate these risks, organizations should develop a responsible and sustainable Gen AI**

# How do AI models contribute to an organization's overall carbon footprint?

## AI models emission impact

### Scope 2

- Scope 2 emissions are indirect emissions from **energy purchased.**

**AI model training and deployment**

- Training often involves iterating over large datasets multiple times, requiring vast **computational resources** with high energy usage.
- **Deployment environments**, such as cloud servers or edge devices, also require power to host and run these AI models.

**Data storage**

- Data for AI modelling purposes is stored in **data centres**, consuming vast amount of energy.

### Scope 3

- Scope 3 emissions are other indirect emissions **upstream and downstream**

**Hardware production**

- **AI hardware** such as GPUs and TPUs have an energy-intensive production process

**End user impact**

- **AI-driven features**, especially those backed by resource-heavy algorithms, can lead to increased device workloads, consuming more power.
- **Inefficient AI software** frameworks or algorithms might require end users to run their devices for longer periods or at higher intensities, indirectly leading to increased energy use.

## AI models emission quantification

**DATA CENTRE**

A physical facility organizations use to house their critical applications and data

**TENANT**

An individual client or organization accessing specific parts of the cloud environment

**CONTAINER**

Packages of software that contain all of the necessary elements to run in any environment

**WORKLOAD**

A resource running on the cloud consuming compute and possibly storage

1. Start with a comprehensive look at emissions on the data centre's aggregated scale.
2. Dive into container-specific energy uses to further break down the emission composition of data centres.
3. Deriving from the aggregated power consumption at hardware levels, identify the granular energy usage at the software/workload level for specific AI-related tasks.

# How can AI assist when selecting ESG investments?

AI

allows investors to collect and analyze large amounts of information and can help sustainable investors process data that contains essential ESG information.

By nature, ESG data is very different from traditional financial data since there is no standardization and the data is highly unstructured. This makes data retrieval difficult and impossible to retrieve via traditional NLP approaches. AI models can assist with retrieval of ESG data.

AI models can be trained to analyze tone (sentiment analysis) and content and digest all information to form a holistic view point on an organization's commitment and approach to ESG initiatives.

1 Allows detailed analysis of large amounts of data, which previously was very time consuming and resource heavy.

2 Using improved algorithms and tools such as sentiment analysis and natural language processing, AI can unearth key data and filter out irrelevant data.

3 Consumers and portfolio managers can now have access to companies' ESG investing statistics and make informed decisions when selecting their investments.[16]

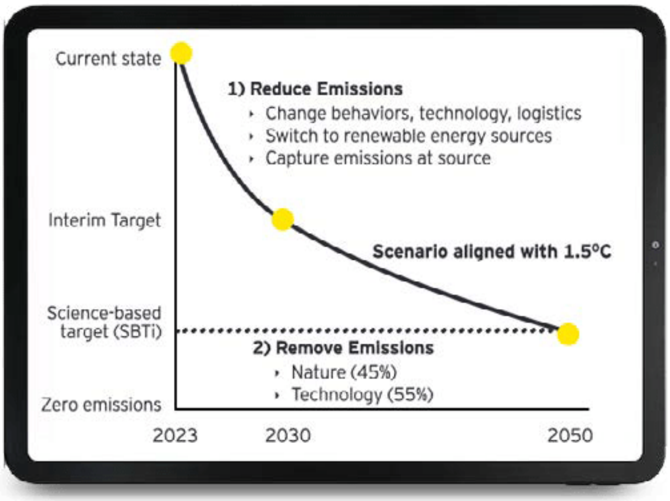
4 Allows companies to view their current ESG position and make strategic decisions to create improvements where needed.

# Net zero: science, finance and policies in support of a just transition

Why commit to net zero and how do we pave the path towards it?

## Climate science

- The world is rapidly warming, leading to a rise in sea levels and increased droughts, floods and wildfires. Alongside these tangible consequences, there is also the destruction and alteration of natural habitats and drastic changes in local temperatures. Climate science shows these effects will become significantly worse if we continue on this path.
- According to climate science, compared to a 1.5°C world, in a 2°C world we would experience 1.7 billion more people facing heatwaves annually, several hundred million more people would be exposed to climate-related risks and poverty, global fishery catches could decline by another 1.5 million tonnes, and there would be a drastic increase in drought risk for the Mediterranean region. [17]
- Limiting global warming to 1.5 °C will require the global economy to release zero greenhouse gas emissions by 2050, and nearly half of those reductions must have happened before 2030. This highlights the imperative to achieve net-zero carbon emission for the global temperature to stabilize and provide a guideline of actions to be undertaken by policymakers and organizations around the world.
- To ensure a seamless and orderly transition towards a sustainable future, the role of policymakers and financial institutions is paramount. Their support, guidance and initiatives not only lay the foundation for a greener and more sustainable tomorrow, but also to establish the framework within which businesses and individuals can operate. Their proactive involvement makes the path to sustainability not only aspirational but also actionable, creating a balance between the organization's current needs and the future it aims to shape.




## Financial institutions

Financial institutions play a pivotal role in driving sustainability through their funding and investment decisions. Economic activities (assets and revenues) are classified based on their alignment with the 1.5°C scenario to be able to access green finance or transition finance.

- Green: Provide dedicated financial support for economic activities that are aligned with the 1.5°C scenario by positively contributing to eco-friendly initiatives. Financial institutions can design and promote financial instruments that cater to green projects, including green bonds and green loans.
- Transition: Recognizing that not all industries can switch to green alternatives immediately, financial institutions can provide transition financing. This supports companies in the interim period to gradually shift from brown to green practices.
- Brown: To actively discourage non-sustainable practices, financial institutions can divest from, or reduce, their exposure to brown practices, which are often plagued by high transition costs, limited clean energy access or high exposure to physical risk.

## Policymakers

As global economies gear up for a sustainable transition in line with the net-zero initiative, regulators' role becomes increasingly indispensable. Their involvement can shape the trajectory of this transition by regulating the financial markets, providing incentives and facilitating collaborations.

- Regulation of financial markets: Policymakers set guidelines for the financial sector to promote sustainability. This includes crafting clear green taxonomies for financial products, imposing disclosure requirements for transparency and laying down risk management parameters for key financial players like banks, insurers and asset managers.
- Public sector incentives and enablers: Harnessing the public sector's influence, regulators drive the green transition by investing in sustainable infrastructure and promoting green innovation. They use subsidies and tax incentives to encourage sustainable practices, while also introducing disincentives for environmentally detrimental activities.
- Facilitate collaborations: Policymakers prioritize collaboration across government departments. By combining insights and weighing both environmental and societal factors, they develop comprehensive policies aiming for a balanced transition.

# Glossary

### CARBON REDUCTION

Carbon reduction refers to the act of decreasing or mitigating the emission of greenhouse gases, particularly carbon dioxide ($CO_2$), into the atmosphere. It is a crucial strategy to combat climate change and achieve a more sustainable and low-carbon future.

### DISTILLATION

Distillation in AI refers to the process of transferring knowledge from a large model to a smaller one. The objective of distillation is to reduce the size of the training dataset to improve accuracy.

### MODEL PRUNING

AI model pruning refers to the process of removing unneeded parameters or connections from a model in order to simplify it. This results in performance improvement by reducing its complexity and making it easier to train and deploy. In addition, pruning can help prevent overfitting by reducing the number of parameters that can be tuned.

### QUANTIZATION

AI quantization refers to the method of reducing computational demands. It is a model size reduction technique that converts model weights from high-precision floating point to low-precision floating point. This results in improved performance and power efficiency by reducing memory access and increasing computing efficiency.

### GRID SEARCH

Grid search is an exhaustive search technique used to identify the optimal hyperparameters for a given model. The process involves evaluating the model performance for every combination of specified hyperparameters.

### RANDOM SEARCH

Random search is a strategy in machine learning that employs random combinations of hyperparameters to identify the optimal solution for a given model. Unlike grid search, which exhaustively explores all possible combinations, random search samples points from a bounded domain of hyperparameter values.

### NET ZERO

Net zero refers to a state in which the greenhouse gases going into the atmosphere are balanced by removal out of the atmosphere. To "go net zero" is to reduce greenhouse gas emissions and/or to ensure that any ongoing emissions are balanced by removals.

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