ARTIFICIAL INTELLIGENCE AND ITS ECONOMIC OUTCOME

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ABSTRACT. This article weights up the significance of Articial Intelligence (AI) and its impact on economic market sector namely on labour jobs. The paper was based on a secondary research materials derived from previous publications on AI from various sources, which are highlighted throughout the article and summed up at the end in Bibliography section. The paper contemplates that while AI is on rise it impacts on our everyday life and causes reduction of human work force in industries. The effectiveness of AI depend on various factors like technological advancements, environment in which it is used and for reason it is employed. The paper concludes that AI is developed in line with its ability to generate profit.

ABSTRAKT. Tento článok posudzuje umelú inteligenciu (AI) a jej dopad na hospodárske odvetvia trhu práce a na zamestnanosť. Príspevok je založený na sekundárnom výskume materiálov získaných z predchádzajúcich publikácií o AI z rôznych zdrojov, ktoré sú zdôraznené v celom článku a zhrnuté na konci v sekcii Bibliografia. V príspevku sa zvažuje, že aj keď AI je na vzostupe, jej vplyv na náš každodenný život je vysoký a spôsobuje zníženie ľudskej pracovnej sily v priemysle. Účinnosť AI zavisí od rôznych faktorov, ako je napríklad technologický pokrok, prostredie v ktorom je AI použitá, aj z dôvodu jej zamestnanosti. Príspevok zhrnie, že AI je vytvorená v súlade s jej schopnosťami vytvárať zisk.

KEY WORDS

Artificial Intelligence (AI). Intelligence Quotients (IQ). Emotional Quotients (EQ). Social Quatients (SQ). Economic Prosperity of AI.

INTRODUCTION

This paper will contemplate on artificial intelligence, reinforcement learning, supervised learning, and evolutionary learning, and will highlight three fundamental problems of AI namely the (1) symbol-grounded problem, (2) situatedness problem, and (3) homunculus problem. This section will further examine intelligence that is the IQ, EQ, and SQ, as well as, touch on analytical and synthetic approach. This part will, highlight common problems that AI is lacking and how can intelligence be educated and evaluated.

The article will in addition, look at AI and it impact on economic market with a particular focus on owning machines and its impact on labor jobs.

The paper will end with conclusion and bibliography.

AN INTRODUCTION TO ARTIFICIAL INTELLIGENCE (AI)

[1]**Artificial Intelligence (AI)** can be attributed to **John McCarthy,** a well-know computer scientist, who received a Turning Award in 1971 for his major contributions to the fields of Artificial Intelligence (AI). "He was responsible for the invention of the term "Artificial Intelligence" in his 1965 Dartmouth Conference and the invention of the Lips programming language". However, in the Dr. Hanson's 1998 paper, "Economic Growth Given Machine Intelligence", he suggested that when machines achieve adequate intelligence, it would become a complete substitute rather than an addition to Human.

[2]In Economic managements requires complex reasoning and problem solving, which Artificial Intelligence mimics such activities thus defining how human work out problems.

In contrast, it is well known that learning from interaction is a foundational idea underlying nearly all theories of learning and intelligence. Learning can be accomplished in this example by (1) reinforcement learning, and by (2) supervised learning, or through (3) evolutionary learning. **Reinforcement learning,** is the learning based on what to do and how to map situations to actions, in order to maximize a numerical reward signal. Here, the learner is not told which action to take, as in most forms of machine learning, but instead the learner must discover which actions yields the most reward by trying them. Whereas, **supervised learning** is learning from examples provided by knowledgeable external supervisors. Finally, **evolutionary learning** means that their operation is analogous to the way biological evolution produces organisms with skilled behavior even when they do not learn during their individual lifetime.

Moreover, to obtain many rewards, a reinforcement-learning agent must favor actions that it tried in the past and found to be effective in producing reward. However, to discover such actions, it has to try actions that it has not selected before. Therefore, the agent has to exploit what it already knows in order to obtain rewards; also, it has to explore in order to make better action selections in the future. The dilemma is that neither exploration nor exploitation can be pursued exclusively without failing at the task. The agent must therefore, try a variety of actions and progressively favor those that appear to be best. In this respect, a stochastic task, each action must be tried many times to gain a reliable estimate of its expected reward. Furthermore, when reinforcement learning involves planning, it has to address the interplay between planning and real-time action selection, as well as the question of how environmental models are acquired and improved. When reinforcement learning involves supervised learning, it does so, for specific reasons that determine which capabilities are critical and which are not.

In addition, there are four main sub elements of a reinforcement learning system i.e. a policy, a reward function, a value function, and, optionally, a model of the environment. A **policy** is referred to as mapping from perceived states of the environment to actions to be taken when in those states. In some cases, the policy may be a simple function or lookup table, whereas in others, it may involve extensive computation such as a search process. Whereas, a **reward function,** maps each perceived state of the environment to a single number, a reward, indicating

[1] (Wikipedia, 2007)

[2] (Some Thoughts on Economuc Theory and Artificial Intelligence, 2007)

the intrinsic desirability of that state. Its sole objective is to maximize the total reward it receives in the end. In general, reward functions may be stochastic. On the other hand, a **value function** specifies what is good in the end. Whereas rewards determine the immediate, intrinsic desirability of environmental states, values indicate the long-term desirability of states after taking into account the states that are likely to follow, and the rewards available in those states. Nevertheless, action choices are made based on value judgments.

In contrast, modern **artificial intelligence** researchers accept statistical and control algorithms, for instance, as relevant competing methods or simply as tools of their trade. However, there are also some fundamental problems with AI, namely: (1) symbol-grounded problem (2) problems with embodiment, and Situatedness, and (3) homunculus and underlying problems.

The (1) **symbol grounded problem**, referrers to how symbols relate to the real world. In addition, AI symbols are typically districted in a purely syntactic way by how they relate to other symbols and how some interpreter processes them, thus the relation of the symbols to the outside world is rarely discussed explicitly. For example, if the robot is programmed with symbols representing objects and has to interact with its environment on its own, it has to be able to map the sensory stimulation (from e.g. the cup itself) onto its internal symbolic representation (the world "cup") a very hard problem. On the other hand, symbol systems, such as computer programs, in which symbols refer only to other symbols, are not grounded because they do not connect the symbols they employ to the outside world. Thus, the symbols have only meaning to a designer or a user, not to the system itself.

(2) The **problem of embodiment** refers to the fact that abstract algorithms do not interact with the real world. It should be noted, that only if a system is personified do we know for sure that it is able to deal with the real world. Moreover, systems that are not embodied all suffer from the symbol-grounding problem. As embodied systems, robots have the potential to "solve" the symbol-grounding problem, but this requires them to have "**Situatedness**". An agent is "situated" if it can acquire information about the current situation through its sensors in interaction with the environment. A situated agent interacts with the world on its own, without an intervening human. In designing situated agents, adopting the agent's actions is based on the sensor data the robot gets. It should be noted, that embodiment does not automatically imply Situatedness. Agents can be equipped with detailed models of their environment to be used in the planning processes. If these plans are employed significantly in controlling the agent's behavior, it will not be situated. If the real world changes, one of the main problems is keeping the models in tune with the environment. Inspections of the problem of behaving in the real world shows that it is neither necessary nor desirable to develop very comprehensive and detailed models that is, the more comprehensive and the more detailed the models, the more strongly the agent is going to be affected by the frame problem. The situated agent can interact with the current situation: the real world is, in a sense, part of the "knowledge" the agent needs to behave appropriately.

(3) In the **homunculus and underlying problems,** the **homunculus problem**, or the homunculus fallacy, as it is also called, refers to circular accounts of psychological processes. These processes are circular because they ascribe to some internal mechanism (the homunculus) the very psychological properties being investigated in the first place. In a sense, a homunculus is required to perform the function that the formal system is intended to explain. In other words,

the homunculus problem and the symbol grounding problem are closely related: a system containing ungrounded symbols will always require a homunculus giving meaning to them. Whereas, the problem of **underlying substrate** is referred to a biological substance i.e. "the true intelligence requires biological substance as a basis", thus only natural brains can, in this tradition, exhibit "true intelligence". [3]Table 5: shows how Gary Kasparow playing the Deep Blue chess playing supercomputer developed by IBM in 1996, and in 1997.

Table 1: Gary Kasparov playing against Deep Blue computer

(Wikipedia, Deep Blue, 2007)

Likewise, in AI it is important to build a **model of the environment**, this somewhat that mimics the behavior of the environment. For example, given a state and action, the model might predict the resultant next state and next reward. Models are used for planning, by which we mean any way of deciding on a course of action by considering possible future situations before they are actually experienced. To select our moves, in this modeled environment, we examine the states that would result from each of our possible moves, and look up their current values in the table. Most of the time, we move greedily, selecting the move that leads to the state with greatest value that is with the highest estimated probability of winning. Occasionally, however, we select randomly from among the other moves instead. These are called **exploratory moves** because they cause us to experience states that we might otherwise never see. While we are playing, we change the value of the states in which we find ourselves during the game. We accept to make them more accurate of the probabilities of winning. To do this, we "back up" the value of the state after each greedy move to the state before the move. More precisely, the current value of the earlier state is adjusted to be closer to the value of the later state.

The examination of intelligence

Humans, animals, and robots have to interact with the real world, whereas the computer metaphor has focused on abstract virtual or computational worlds and has neglected their relationship to the real world. What we consider intelligent depends also on our expectations. What intelligence is or is not depends on what people find interesting or what they do not.

[3] (Wikipedia, Deep Blue, 2007)

Intelligence is a descriptive term: it describes certain properties of individuals or groups of individuals. Thus, descriptive terms are largely arbitrary, and it is therefore unlikely that descriptive definitions of intelligence have a common denominator related to novelty and adaptively. Cognitive science has closer ties to empirical sciences like psychology, biology, and neurology, whereas AI (Artificial Intelligence) is more closely associated with computer science, algorithms, and logic. Most people when asked to define intelligence almost universally mention abstract thinking as stated Rene Descartes “Cogito ero sum”. Many people regard creativity as the highest form of human intelligence. On the other hand, an **Emotional intelligence**, refers to the ability to recognize emotions in others, using emotions to support thinking and actions, understanding emotions, and regulating emotions. The general idea is that if you recognize your own emotions, you are better able to perceive the emotions in others and to react appropriately in social situations.

Additionally, there are other types of intelligence e.g. (**IQ**) Intelligence Quotient, (**EQ**) Emotional Quotients, and (**SQ**) Social Quotients, where the original IQ test was invented in 1905 by French psychologist Alfred Binet, essentially to find out whether children with certain learning deficiencies would be better off in a special schools. German psychologist William Stern in 1912 turned the test into a general intelligence test for children, and David Wechesler in 1939 developed it into one for adults. He proposed the Gaussian distribution of test results: two third should be between 85 and 115 (100 being the mean), and only 2.3 percent above 130 and below 70.

According to Gardner, there is not a single intelligence, or factor but multiple ones: linguistic intelligence, musical intelligence, logical-mathematical intelligence, special intelligence, bodily-kinetic intelligence, and personal intelligences (for perceiving yours own and other people’s moods, motives, and intentions). Very roughly, the main idea is that intelligence thinking can be understood in terms of computer programs: input is provided, the input is processed, and finally an output is generated.

By analogy, the human brain is viewed in some sense as a very powerful computer. It receives inputs from the outside world through sensors (e.g. eyes, ears, skin). These inputs are processed: for example, stimulation received through the eyes is mapped onto an internal representation or model, and you recognize a cup of coffee standing in front of you. Depending on your internal state, your motivation, this percept generates the intention or plan to drink coffee: the processing phase. Finally, the action is executed: the output.

Furthermore, the intelligence is in differentiated between analytic and synthetic approaches. The **analytic approach** is generally applied in all empirical sciences. Typically, experiments are performed on an existing system, e.g. a human, a desert ant, or a brain region, and the results are analyzed in various ways. Often the goal is to develop a model to predict the outcome of the future experiments. The **synthetic approach**, on the other hand, works by creating an artificial system that reproduces certain aspects of a natural system. Such models are typically computer models that, when run, are expected to reproduce the experimental result. The synthetic modeling approach can be characterized as “understanding by building”. In the study of intelligence, AI and cognitive science have supported this approach. In addition, it is useful to note a **synthetic methodology** (i.e. an autonomous agent), which can be extended to include not only simulations, but also physical systems, artificial creatures, behaving in the real world. Normally, these autonomous agents have the form of a mobile robot and can be used as models of biological systems, humans, or animals. The autonomous agents actually behave in the real world without the intervention of a human: they have sensors to perceive the environment, and they perform actions that change the environment. This is why they are also well suited to explore issues in the study of intelligence in general, not only of biological systems. We can perform experiments with our robots as we like, creating artificially intelligent systems. Moreover, because the robots physically interact with the real world, they can be used for applications, to perform tasks that humans cannot or do not want to do themselves. Thus, we can pursue three potential goals with the synthetic methodology: we can model biological systems, we can explore principles of intelligence in general, and we can develop applications. However, there are three agents (1) **Biological agents** exist in nature-we do not have to build them, then (2) **robotic agents,** which is further divided by **research agent,** here research agents are used to model natural agents and to explore general principles of intelligence and **industrial agent,** which are used for practical applications and finally (3) **computational agents** which is also divided to **simulated agents, artificial life agents** and **software agents,** which are computer programs that perform a certain task and interact with real-world software environments and humans by issuing commands and interpreting the environment's feedback. These agents are used in various **modeling** e.g., it is known that the control mechanisms of animals are based on neural structures. Biological neural systems have inspired artificial neural network models. Thus, neural architectures can be understood only in the context of the physical system in which they are embedded. A second application of autonomous agents in cognitive science is to explore principles of intelligence e.g. through **experiments**. Experiments can be conducted using any type of sensors, even that do not exist in nature (like laser scanners, or radio emitted-receivers. What's more, high intellectual ability resulting in a high IQ score may well be due to a complex mix of sensory-motor abilities than in turn depend on the particular social environment.

Then again, it is also important to note, that AI has its **fundamental problems**. The main reason for difficulties and the reason for the fundamental problems of AI in general is that the models do not consider the real world. Much work in AI has been devoted to abstract, virtual worlds with precisely defined states and operations, quite unlike the real world, for instance:

(a) Chess is a formal game. It represents a virtual world with precisely defined states, board positions, and operations, that is, the legal moves.

(b) Soccer is an example of a normal game. There are no precisely defined states and operations. In contrast to chess, two situations in soccer are never identical.

In other words, information gathered from the sensors is therefore always subject to errors. It follows that the real world is only partially knowable, and this in turn implies that it is predictable only to a limited extent.

Thus, **AI is lacking** in the following:

(1) **Robustness and generalization:** traditional AI systems often lack robustness, which means that they lack tolerance of noise (i.e. fluctuation of data) and fault tolerance and cannot behave appropriately in new situations. If a situation arises, that has not been predefined in its programming, a traditional system breaks down, or stops operating.

(2) **Real time processing:** because the real world has its own dynamics, systems must be able to react quickly in order to survive and perform their tasks. Systems based on the classical paradigm embedded in real robots are typically slow, because they process information centrally.

(3) **Sequential nature of programs:** the architecture of today's AI programs is essentially sequential, and they work on a systematic basis. By contrast, the human brain's processing is massively parallel, with activity occurring in many parts of the brain at all times.

(4) **Other problems:** classical systems are goal-based, which are hierarchical.

(5) **The frame problem** was originally pointed out by McCarthy and Hayes in 1969. The central point concerns how to model change and how can a model of a continuously changing environment be kept in tune with the real world? Thus, the problem is about the **system environment interaction:** how models of changing environment can be kept in tune with the environment

Principles of educating intelligence

[4]Knowledge takes part in the brain, in other words the brain works in a parallel level i.e. the brain processes wholes and parts simultaneously, as well as, the search for meaning comes through patterning.

Besides, there are three instructional techniques connected with the **brain-based learning** namely:

(1) **Orchestrated immersion**, happens where learning environments are formed which fully immerse students in a learning experience;
(2) **Relaxed alertness**, here an effort is made to get rid of the fear while sustaining a highly demanding environment; and
(3) **Active processing**, where the learner establish and internalizes information, by strongly, processing it.

What's more, the learning should be intended to be developed around the student's interest by also making it contextual. Thus, there must be a personally meaningful challenge. Besides that, students should be placed in groups, where they can easily interact, and the learning should be focused on real problems, thus if it is possible encourage the settings to be outside the classrooms and school buildings. Moreover, students should be assessed according to their learning styles and preferences, a so-called "active processing of experience"; by continuous monitoring, this is due to allowing students to maximize their own learning processes.

Furthermore, in **AI systems**, the learning is mainly done by a passive data-driven process of applying a single learning algorithm to training examples installed to the system. On the other hand, in a **goal-driven learning**, the learning happens through an active and strategically process driven by analyzing information, using alternative learning strategies, and finding opportunities in the environment. Besides, the goal driven learning is additionally separated into the classes centered in the region of **task goals, learning goals,** and **specifications, policies** and **constraints.** Where, task goals determine why the reasoner is learning in the first place, the learning goals, on the other hand, specify what the reasoner needs to learn specification, policies,

[4] (Horn P. S., Teaching the Human Brain - Brain Based Learning, 2007)

and constraints influence how learning occurs. In this respect, the task goals force the search for relevant plans in memory and trigger learning of new guides for plan retrieval when failures arise. Learning goals differ from task goals in that, while they too specify a desired state, the specified state is an internal or mental state, that is, a state of knowledge or belief that the learner is attempting to achieve. Task goals, on the other hand, are satisfied through problem solving in the external (physical) world, while learning goals are satisfied through a learning process that, in the goal-driven learning framework, is viewed as problem solving in the “informational” world. In addition, reasoning goals span the broad range of predetermined activities, including activities such as retrieval of relevant information and similarity assessment. Learning goals or knowledge goals, on the other hand, refer solely to goals that acquire or formulate particular types of knowledge.

Conversely, in AI systems, reinforcement learning that satisfies the Markov property is called a **Markov Decision Process (MDP).** Whereas, if the state and action spaces are finite, then it is called a **finite Markov Decision Process (finite MDP)**. A particular finite MDP is defined by its state and action sets and by the one-step dynamics of the environment. Given any state and action, **s** and **a,** the probability of each possible next state, **s’,** is:

$\mathbf{P}^{(a)}_{(Ss')} = \mathbf{Pr\ \{st = 1 = s', st = s, at = a}\}$ these qualities are called transition probabilities.

For example, when an agent makes a decision at times determined by external events (or by other parts of the robots control system). At each such time, the robot decides whether it should (1) actively search for e.g. a Can, (2) remain stationary and wait for someone to bring it a Can, or (3) go back to home base to recharge its battery. The **Bellman equation**, in contrast, expresses a relationship between the value of a state and the values of its successor states. In other words, it states that the value of the start state must equal the (discounted) value of the expected next state, and the reward expected along the way. What’s more, Bellman optimality equation provides one route to finding an optimal policy, and thus to solving the reinforcement learning problem. The solution relies on at least three assumptions that are rarely true in practice: (1) we accurately know the dynamics of the environment; (2) we have enough computational resources to complete the computation of the solution, and (3) the Markov property. However, for the kinds of tasks in which we are interested, one is generally not able to implement this solution exactly because various combinations of these assumptions present no problems for the game of backgammon; the second is a major impediment.

What is more, reinforcement learning method also uses a **Backup diagrams**, which in other words is a diagram relationships that form the basis of the update or backup operations. These operations transfer value information back to a state (or a state action pair) from its successor states (or state-action pairs).

Besides, backup diagrams, one may use a **grid world, golf, Monte Carlo, or a temporal difference method** to illustrate value functions. It, however, should be noted that, even if we have a complete and accurate model of the environment’s dynamics, it is usually not possible to simply calculate an optimal policy by solving the Bellman optimality equation. For example, board games such as chess (see also Appendix 4), are a tiny fraction of human experience, yet large, custom-designed computers still cannot compute the optimal moves. A critical aspect of the problem facing the agent is always the computational power available to it, in particular, the amount of computation it can perform in a single time step. The memory available is also an important constraint. A large amount of memory is often required to build up approximations of value functions, policies, and models.

Goal based evaluation

[5]Both in psychology and in AI, goal based evaluation theories, either, tend to look at the evaluation process as context-independent, or to examine it within a single fixed context. This is then followed by an investigation of how a specific aspect of context (i.e. the overreaching goal of the explainer to use an explanation), determines the information that the explainer requires when confronted with an anomalous situation. Moreover, the researcher also argued that effectiveness of any explanations satisfies the needs for information that arise from system goals. In contrast, **Attribution theory,** investigates how people decide whether to explain an action in terms of features of its actor, or features of the environment. Most work in attribution theory assumes either that personal or those situational factors will apply, but not both. On the other hand, a **co-variation principle** maintains, that people look at co-variation across different time, people, and other entities in order to decide which type of factor applies. Although attribution theory gives criteria for deciding which class of factors to implicate, it does not suggest how to decide which particular personal or environmental factors are important.

Excuse theory studies how the desire to form excuses makes people manipulate the types of factors to use in attribution, to blame external influences for their own bad performance. Besides excuse theory, in AI, the question of explanation's goodness has been investigated in three main areas. Research in expert system explanation has concentrated on the question of explanation's goodness for explaining system behavior, for the benefit of the system user. On the other hand, research in explanation for text understanding has concentrated on how to select valid explanations from a range of hypotheses, and explanation-based learning research has primarily considered the problem of determining explanations' goodness for learning to improve performance on concept recognition and search.

[6]Conversely, according to psychometric views, human intellectual competence appears to divide along three dimensions, **(1) fluid intelligence, (2) crystallized intelligence, and (3) visual-spatial reasoning**. **Fluid intelligence** is the ability to develop techniques for solving problems that are new and unusual, from the perspective of the problem solver. **Crystallized intelligence** is the ability to bring previously acquired often culturally defined, problem-solving method to bear on the current problem. **Visual-spatial reasoning** is the specialized ability to use visual images and visual relationships in problem solving

An Economic prosperity of AI

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[5] (Horn P. S., Memory, 2007)
[6] (Bapi, 1990)

[7]It has been suggested, that extensive use of machine intelligence will decrease their cost and could increase economic growth, but will substitute human workers, and thus wages would fall below acceptable level. This is due to human being also the technology consumers and hence reduction in wages would naturally reduce the purchase of intelligent machines. This would lead to the situation where buyers would be not able to afford to pay for the new technology, which would result in falling revenues and business would collapse.

On the other hand, by owning intelligent machines it also encompasses the possessing part of the interest in the economy of the future, which would be sufficient to make up for the decline in wages allowing the population to consume.

On problem with this theory is that the asset values of investments are not determined by the investors' perception about the technology but by their expectation of future cash flow. This inclines that the investors has to have a logical reason to invest and as asset value would increase, due to good investments, it would generate investment income, which would be used to further consume generating future cash flow.

What is more, when firms compete with each other, price would have to fall, thus AI is responsible for the fall in human labor jobs. In this scenario, human labor does not determines the output profitability, but considers how much more AI can be added to the production in order to generate more profit in the same market. Although, there can be a situation where a well established firm adopts the new technology but its customer might not support such investment such as the GPS firm like Garmin which is jeopardized by mobile phones GPS devices. This lead to a theory in economics evolution, which suggests that there are two processes namely a (1) creative destruction and (2) complimentary leveraging.

CONCLUSSION

The paper focused on Artificial Intelligence (AI) and how AI can learn through reinforced learning, supervised learning and through evolutionary learning. This part also touched on fundamental AI problems such as symbol-based problems, situatedness problem, and on homunculus problem. The following part of the paper centered on examination of intelligence through analytical approach and synthetic approach with the use of three agents namely (1) biological agents, (2) robotic agents and (3) computational agents. The paper further demonstrated that AI is lacking in robustness and generalization, real time processing, sequential nature of programs, other problems, and frame problems.

The subsequent section, the principles of educating intelligence was discussed, touching on Markov Decision Process (MDP), and on goal-based evaluation of AI, and Intelligence.

However, it support the main argument that productivity impovemets will not ease up purchasing power for other consumptions, but instead it would cumulate more investment.
Moreover, the economic prosperity of AI took into consideration Dr. Hanson's points of view with a specific focus on labour market. In this section, the article assumed that due to technological inovations human labour work will be in decline, but only when it cost-effective for a corporation to do so.

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[7] (Hanson, 2009)

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