RESEARCH PAPER

Towards Non-Reductionist AI: Reformational Philosophy Perspective on Current Machine Learning Implementation

Hendrik Santoso Sugiarto, Indonesia

hendriksantososugiarto@gmail.com

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1. Introduction

The recent advances in artificial intelligence (AI) have widely impacted humanity. Their technological penetration is not only reserved for future imagination such as self-driving cars, but also in our day to day activities from search engine to social media. The progress of AI may benefit humans in repetitive work that require stable concentration, especially in dangerous environments such as in mining or space. On the other hand, AI capabilities to shape culture on a global scale may amplify the rationalization-technologization of society by mechanical-rational rules(35). Nevertheless, as AI-empowered technologies will become an everyday naive experience, since our plastic temporal horizon will be opened and deepened by the progress of technology(26). Especially, in anticipation of industry 5.0 where AI is expected to collaborate with humans[1].

Defining AI is difficult because this field has a moving target. But one common definition is a system that can act like a human(67). Contemporary AI generally employs massive amounts of big-data (BD) and expressive machine learning (ML) algorithms with a lot of parameters(41). In contrast to the previous approaches[2], this data-centric approach is preferred in AI design, because of their success in outperforming humans on many different ranges of tasks. ML provides AI with the capability to directly acquire knowledge by extracting patterns. At the same time, BD will align this acquisition process according to the observed reality. Therefore, this approach can be summarized as AI=ML+BD[3]. However, this approach originated from several scientific traditions with competing presuppositions. In this particular theme, reformational philosophy

[1] http://ec.europa.eu/info/research-and-innovation/research-area/industrial-research-and-innovation/industry-50_en

[2] The previous approach in AI is known as knowledge engineering, which was advocated by the CYC project(56). According to this approach, all knowledge must be hard-coded by human experts. This approach ended up in disappointment because the interactions grow exponentially and there is no unifying concept to handle them. After that, machine learning became a popular approach, which enables the machine to learn new knowledge directly from the observed data, without the hard-coded knowledge from human experts.

[3] The scope of this paper is focusing on this specific AI approach.

may offer substantial critique to this technological trend.

In the era of cloud technology, computational resources are abundant and usually many kinds of data will be collected. However, we need to distinguish between the collection of a large dataset and the original reality. Data is recorded using certain devices and methods, which are created by specific assumptions. Data is also not neutral, in the sense that observed patterns in the society actually involve psychological, cultural, and ethical decisions. In this case, data collection is some kind of filtered reality for AI, in which some aspects of reality can be magnified or ignored by the theoretical attitudes of the designers and users.

Reformational philosophy through transcendental critique already showed that a neutral position is not only impossible, but certain supra-theoretical commitment is always required(17). Therefore, non-neutrality is not necessarily wrong as long as we remain critical with assumptions and limitations of each position. Moreover, in order to be understood by AI, the data must be processed by ML model and this modeling is always conceptually mediated (or at least inspired) by contingent sociocultural contexts of specific research community or tradition(53). Therefore, the AI knowledge acquisition is a kind of paradigm-relative interpretation. What AI learnt is what AI's been trained to see.

2. ML Paradigms

There are several competing ML paradigms that originated from different scientific traditions. It will be difficult to discuss all developments and nuances of each tradition in a short paper. Nevertheless, I will briefly summarize their underlying assumption and its manifestation in ML models.

2.1. *Logic*

The inquiry on logic can be traced back to Aristotle(49). This paradigm reduces intelligence into the ability to do deduction and induction of several logical statements. In the past *foundationalism* project, there are efforts to reduce mathematics into logical operation(68). Since ML algorithms utilize data, mostly induction methods are used in this paradigm. However, as Hume already pointed out the problem of inductions, there is no basis to choose any kind of generalization from stream of facts(43). Since there is no way to choose multiple competing hypotheses, the Occam razor is often used(24). The most popular choice is decision tree induction by ordering the logical rules from the most certain distinction to the least. Some famous algorithms to construct these rules are CHAID(50), CART(12), ID4.5(66). This paradigm is popular in early machine learning because the output can be explained through logical rules.

2.2. *Mathematics (geometry)*

Geometricism can be traced back to the enlightenment science-ideal period[4]. Various different phenomena can be explained through geometry through the work of Descartes(21) and Leibniz(55) in mathematics, Keppler(51) and Galileo(20) in astronomy. Many problems in mathematics can be reduced into geometrical problems such

[4] science-ideal period refers to the deterministic polar of nature-freedom ground-motive dialectic in Dooyeweerd historical schema (27)

as complex numbers, functional analysis, and algebra. Even physics problems such as quantum mechanics can be expressed in spatial representation(23). This paradigm believes in the geometrical nature of truth. Therefore it is natural for mathematicians to reduce anything (including intelligence) into multidimensional spatial representations. By reducing all concepts and entities into spatial representations, the similarity of different entities can be measured by the distance between them. Similar entities will be clustered in close proximity and opposite entities will be far apart. KNN(19), SVM(18), and PCA(45) are some famous models in this paradigm. By manipulating geometrical properties, a much richer algorithm can be constructed such as embedding(59).

2.3. *Statistics*

This tradition consists of Bayesian and frequentist interpretation, but the underlying principle is similar and converges into similar results in a large population. Laplace realized that Bayes theorem can be used to learn anything in the universe by updating our belief through new facts(57). Therefore he believes intelligence can be reduced into statistical calculation. On the frequentist side, positivist social science also shows promising results of using statistical inference to describe social phenomena(58). Naive-Bayes(36), Markov Model(3), and Monte-Carlo(37) are some famous models of this paradigm. The statistical nature of this paradigm makes it flexible to be incorporated with many different hypotheses across various problems. For example probabilistic models such as LDA can be used to find topical groupings based on re-occurrences of words(6).

2.4. *Evolutionary Biology*

Modern evolutionary biology is the synthesis between Mendelian genetics and Darwinian natural selection by Fisher(31). The study of evolution through genetic mechanism was progressed after the discovery of DNA molecular structure by Watson and Crick(81). According to central dogma of molecular biology, functionality of every living thing (including the brain) is controlled by its genes. Hence, this paradigm believes intelligence is hidden in the genetic information, and AI can be generated by re-simulating the evolutionary process. Genetic algorithms is the most popular model within this paradigm(34). Some variation of this algorithm eventually generated a device that managed to fool the US patent office[5]. Nevertheless, this paradigm is currently not popular because of its learning inefficiency[6].

2.5. *Psychology*

The psychological theory of behavior can be traced back in psychoanalytic tradition. In which, human decision was explained through unconsciousness, whether through Freudian personal id(32) or Jungian collective archetype(46). On behaviorism tradition, Skinner attempts to understand human decision in terms of conditioned response to the external stimulus(76). Modern formulation of this ML paradigm is inspired by observation on animal learning(80). This ML paradigm, known as reinforcement

[5] https://www.popsci.com/scitech/article/2006-04/john-koza-has-built-invention-machine/

[6] Although time is the best friend for evolution in creating various magnificent species, paradoxically time is also the hindrance for this paradigm for creating efficient products. In the end, other ML paradigms develop faster and outperform this paradigm in many different tasks.

learning(79), believes intelligence can be achieved through modifying the internal unconscious and conscious mental state of an agent through stimulus-response in a conditioned environment. Through reward-punishment mechanisms, the machine will eventually learn how to function correctly in the world. Famous model from this paradigm is AlphaGo-Zero that can learn Go without human knowledge(74).

2.6. *Neuroscience*

The foundation of modern neuroscience is started by detailed experimental demonstration of individual neurons in the brain by Cajal(14). Human brain consists of 86 billions neurons, and each neuron can have thousands of connections(40). Each neuron has different concentrations of potassium and sodium ions, creating voltage differences for electrical spark. If many neurons fire close together, the electrical signals suddenly spike. Electrical stimulation of hypothalamus and amygdala is shown affecting emotional response(4). Neurotransmitter imbalances such as serotonin is also shown affecting behavior(29). In this paradigm, intelligence is reduced into neuron electrical activities. Perceptron is the first algorithm to imitate the single neuron activity(65). However, only after the discovery of emergent phenomena in physics, many statistical physicists proposed physical mechanisms for cognition such as Hopfield network(42) and Boltzmann machine(1). Furthermore, the discovery of backpropagation enabled the construction of multilayer-perceptrons(64). The availability of GPU framework also enhances the efficiency of a very deep neural network significantly. Hence, the recent research on deep neural network architecture (such as CNN) is progressing very fast(52).

2.7. *Linguistics*

This paradigm measures intelligence by the ability to articulate knowledge. Initially, Turing also used a linguistic test (whether a text-generated by AI can fool humans) to determine whether AI exhibits behavior equivalent to humans(78). In the beginning, the relation between linguistics and ML was in opposition because Chomsky believes that language must be innate (known as universal grammar)(16). However, the progress of computational linguistics opens the possibility of grammatical and semantic representations. Contemporary ML such as transformers architectures can learn expressive representations which enable them to learn the hidden structure of language by observing huge amounts of text data(15). Natural language processing (NLP) is the field that focuses on this task(33). BERT(22) and GPT-3(13) are some famous transformer-based algorithms that can learn the language structure and solve general NLP tasks such as generating text, machine translation, answering questions.

2.8. *Ecology*

The starting point of this tradition is the relationship between living organisms. Bees are well-known for their high level of organization and division of labor(44). Chimps can form a hierarchy and even cooperate to overthrow their leader(47). Although many animals show apparent intelligent cooperation, some argue that social behavior in animals is qualitatively different with human[7]. Nevertheless, this paradigm believes

[7] Studies show that animals can do simple communication because they can form signals and symbols. However the memory span of even the smartest primate is relatively short, and hence all their communication remains

that intelligent phenomena cannot be explained by individual species but by the self-organized relationship of the entire ecological system. Although a single AI may not be intelligent, intelligence may emerge from the overall interaction of a lot of AI. Ensemble models are popular algorithms under this paradigm. The ensemble decision is achieved by incorporating different learned perspectives of several simple learners through voting mechanisms known as bagging(11). Another more advanced ensemble model is known as boosting, in which the next learners are designed to focus on the mistakes of previous learners(69). Another variation of ensemble models is known as stacking(60), in which there is a meta-learner that is trained to combine different kinds of ML algorithms. Recently, researchers are developing a new model known as swarm intelligence(84). This model is inspired by the sophisticated formation of schooling fish evading the predators as a group, although each individual fish just reacts to the nearby fishes' movement.

3. Reductionism

From a brief survey of each paradigm, we can observe that each paradigm has a certain theoretical attitude that absolutizes a specific aspect of reality. The distinctiveness of each paradigm is summarized in Appendix A. The illustration on reasoning mechanisms of different ML paradigms are described in Appendix B.

Any reductionism has limitations. Some of the paradigm limitations have been analyzed extensively by various thinkers. For example, evolutionism-naturalism incompatibility argument by Plantinga(62). Becker also showed that psychoanalysis failed where it pretended to be a total world-view in itself(5). Moreover, Adorno already mentioned the limit of statistical thinking in the famous "positivist dispute"(54). Wittgenstein also realized that language is not about referentiality between meaning and object, but language is always embedded in communal practice (language games)(83).

Additionally, the underlying assumptions may somehow deny the paradigm itself (self-referential incoherences(17)). If intelligence emerges from neuron electrical activity, the paradigm itself is just a product of physical activity. If intelligence emerges from the overall interaction, this paradigm itself is merely an interaction. Furthermore if stimulus-response can explain intelligence, this paradigm itself is merely a product of stimulus-response. Similar weak self-referential incoherences can also be found in other paradigms.

Moreover, In order for an algorithm from a certain paradigm to exist, it required the existence of various other aspects (self-performative incoherences(17)). Imagine we want to construct a decision tree model (Logic paradigm). Paradoxically to calculate certain induction, the algorithm needs to count the frequency of such occurrences which already presupposes the numerical aspect. Moreover, designing such an algorithm already presupposes a formative aspect. Similar aspectual presupposition can also be found in various algorithms from other paradigms.

Some advocate that different paradigms are only instrumental tools to simplify the reasoning process of AI. Even if the paradigm is only pragmatically used, "ideas have consequences"[8]. For example in ML models from geometric paradigm (which are frequently used in many recommender systems), the users will be introduced to their preferred items (connections, contents, advertisements, products, etc.). To achieve this

in the present. In contrast, human memory spans almost the whole lifetime. The connection between the past and future is the basis of accumulating culture and forming genuine society(72).

[8]The phrase is taken from the title of the famous philosophical work by Richard Weaver(82).

purpose, this algorithm usually recommends the items with closer distance (including fake news) and hides the items with far distance to them. Hence, it often creates polarization in society(8). Moreover, the algorithm is surprisingly sensitive enough to identify the location of users' deepest desires[9]. By feeding users with the desired content, it creates an addiction problem. It is designed to captivate the users to keep using the apps. Since human activity is merely a tensor operation, social and ethical aspects will be ignored.

4. Towards Non-Reductionist AI?

As ML research progresses, different research communities are not only developing their own paradigm but also comparing it with other paradigms. However, comparison between different paradigms usually are evaluated on the practical level such as efficiency or performance on specific problems(63). Some attempts of cross-paradigms discussion have been done, but mostly reducing one paradigm into another(25). Furthermore, since different paradigms employ different starting points, polar oppositions often occur between competing paradigms. For example: nature-nurture debate, deterministic-fuzzy debate, explainable-tacit debate. There will be no solutions for those dialectical tensions because the problem is deeper than the particular surface issue.

In the previous section we've shown that the AI=ML+BD approach is not really neutral and objective, but consists of several competing paradigms (with their various contingencies and limitations). Suppose we utilize all paradigms on a case by case basis. For instance, applying specific paradigms for specific problems or even combining multiple paradigms. Subsequently another meta-paradigm is still needed to choose or synthesize different paradigms, and this meta-paradigm is also not immune to reductionism. For example meta-paradigm that optimize profit (absolutize economic aspect) or optimize control (absolutize formative aspect).

Reformational insight potentially provides the guiding principle for constructing an alternative paradigm with a genuine non-reductionist starting point. First, it recognized that a paradigm-less starting point is impossible. Second, alternative paradigm does not necessarily mean a single universal unifying ML paradigm, but a new paradigm that can cohere with all aspectual reality. Moreover, that paradigm should be able to connect with all previous paradigms to enrich each other. Finally, the theory of individuality-structure and enkapsis from reformational philosophy can be used to situate AI with various aspects of reality and other individuality-structures coherently.

In reformational perspective, the reality consists of unbreakable coherence of aspectual diversity before any attempt of specific theoretical abstraction[10]. In this aspectual order, the latent potential for any technology (including AI) is already available and can be unfolded by cultural activities(70). In order to function meaningfully, AI must refer to various aspectual diversity[11]. Reformational perspective can also flexibly

[9] https://www.wsj.com/video/series/inside-tiktoks-highly-secretive-algorithm/investigation-how-tiktok-algorithm-figures-out-your-deepest-desires

[10] "If I consider reality as it is given in the naïve pre-theoretical experience" (NC,I, 3)(26). Following Husserlian tradition, Dooyeweerd took this pre-theoretical experience as his starting-point. It doesn't mean that he is not uncritical towards naive experience, but he concerns more on the coherence relationship between naive experience and any theoretical attitudes.

[11] Intelligence does not suddenly emerge from a void. In order to function properly, AI basically utilizes various aspects of reality. Any computer is a Turing Machine, which is designed by humans to perform specific operations (formative) as efficiently as possible (economic). The transistor is arranged in such a way to handle logical

utilize many insights from various paradigms as part of cosmonomic diversity. This cosmonomic order is also the basis for AI normative practice. Furthermore, reformational philosophy describes humans can naturally function as a subject in all aspects of reality(73). Since AI is expected to mimic various cultural activities, AI should also meaningfully function in all aspects of reality(2). But the functioning depends on the associated communal practices (including its theoretical attitude)[12]. Therefore as a human-like individuality-structure, AI can be used to augment human functioning capability. Hence, societal potential can be opened-up through AI according to the technological-historical norms of differentiation and integration[13]. Since it is the extension of human capability, the aspectual functioning of an AI can be oriented towards deterioration or flourishment of civilization.

Furthermore, AI can be incorporated to any communities. AI can bind enkaptically to any specific qualifying function in the plurality of relationships. Self-driving cars and IoTs, for example, should be qualified by the judicial aspect (obey traffic rules) but at the same time must be enkaptically bound with the sensitive aspect because they need to react fast to their environment (to avoid crashes with other objects and stay on their lane). AI for corporations is qualified by the economic aspect to drive business and may integrate multiple aspects to support it. AI for social media is qualified by the social aspect to facilitate online community. As institution qualified by public justice, the legal authority should then regulate AI practices of each community (including utilizing AI to capture unjust algorithms or data violations), to prevent any intrusion to different spheres-sovereignty. Therefore, data collection and algorithm paradigms cannot be synthesized arbitrarily, but should be guided by the associate qualifying aspect of individuality-structures. In this way, reformational perspective not only criticizes the AI=ML+BD approach, but also enriches it.

In this perspective, the basis of non-reductionist AI is the cosmonomic order and communal sphere-sovereignty in which different AIs obtain their structural diversity and function meaningfully[14]. Diverse AIs should cohere with spheres-sovereignty of individuality-structures interdependence. AI receives data from a community and its intelligence can only be functioned meaningfully in the practical context of a specific community (Appendix C for more elaboration). Therefore we should reject omniscience AI that transcends its creaturehood[15] Because AI (similar to individual man), is only meaningful in relation to specific practical embeddedness in community[16]. Since AI receives communal insight, the aggregate intelligence may surpass individual man. This communal perspective also open the possibility of interdisciplinary conversation with other area (such as hermeneutics(61)). Reformational framework allows

statements (logical), arithmetical operations (numerical), and symbolic manipulation (lingual). All the data is recorded through different sensors (sensitive). There is electricity and physical alteration in the digital memory (physical). The data often record observed patterns in the society (social) actually involve psychological (sensitive), cultural (formative), legal (law), ethical (ethics) and calculated (analytical) decisions.

[12] An AI definitely lacks a supra-aspectual ego. Therefore the designers will decide the specific theoretical attitude of an AI based on a certain scientific paradigm. The users behaviors also shape the training data. The interaction between these two elements direct the AI towards certain orientation

[13] Technology (including AI) may foster differentiation in the typical individuality-structures of social relationships. Introducing diverse technology to society will open-up and enrich the diversity of typical cultural spheres. However, the process of cultural differentiation must be balanced by cultural integration(75).

[14] The differentiation and integration that is capable of maintaining sphere-sovereignty requires a detailed consideration of enkapsis, the intertwinement of entities with their own individuality-structure (NC,III, 653-693)(26), including the enkapsis between specific technology with specific community.

[15] This kind of AI is known as Artificial Super Intelligence. After achieving technological singularity, an AI is hypothesized capable of recursive self-improvement without limit(7).

[16] Pragmatist philosopher Robert Brandom also proposed a pragmatic version of artificial intelligence which is the ability to engage in some autonomous discursive practice(10).

decentralization of AI, rather than manipulating AI for centralization of power (such as surveillance capitalism and totalitarian technocracy)[17]. In this way, reformational perspective liberates AI from any paradigm without undermining the contribution of specific paradigm.

This proposal is very brief and certainly not a fully developed non-reductionist AI paradigm. This project will still be a challenge for reformational scholars in order to be able to engage with AI researchers in a meaningful direction. Nevertheless, we can start with interdisciplinary conversation, where presuppositions of different paradigms can be critically examined. In the midst of current competing scientific paradigms (which are dominated by lower aspectual perspectives), reformational philosophy potentially offers meaningful integration of various interdisciplinary perspectives (especially from higher aspectual perspectives).

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[17] Egbert Schuurman noticed that absolution or centralization of specific aspects in technology will potentially create dialectical opposition (meaning-disturbance) that paradoxically hinder the natural development, rather than create harmonious natural progress (meaning-disclosure) according to diverse normativity of creation(71).

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Appendix A. ML Paradigms and Aspectual Reduction

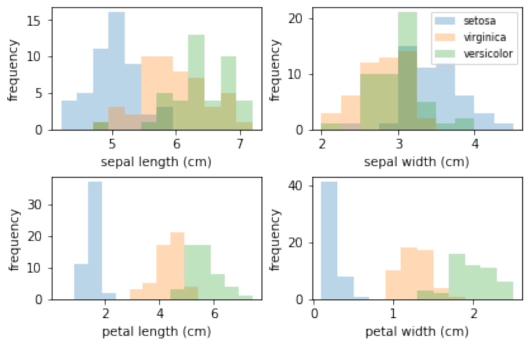
Table A1 summarizes aspectual reduction, learning process, and model examples from each scientific traditions in section 2

Scientific Tradition	Aspectual Reduction	Learning Process	Supervised Learning	Unsupervised Learning
Statistics	Numerical	Likelihood Maximization	NB, HMM	LDA, GMM
Mathematics	Spatial	Constraint Optimization	KNN, SVM	K-means, PCA
Neuroscience	Physical	Backpropagation	DNN, CNN	VAE, GAN
Biology	Biotic	Genetic Search	Genetic Algorithms	GAC
Logic	Analytic	Inverse Deduction	Decision Tree	Dendrogram
Psychology	Sensitive	Rewards-Punishments	Q-Learning	Adaptive Clustering
Linguistic	Lingual	Autoregressive	LSTM, BERT	Encoder-Decoder
Ecology	Social	Metaheuristic	Ensemble Models	Self-Organization

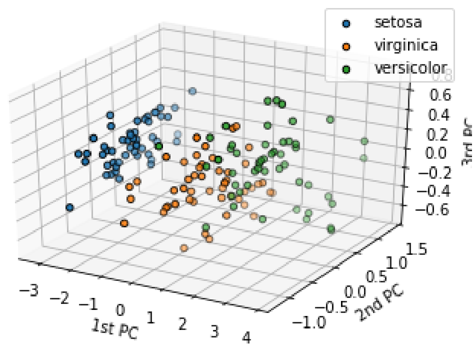
Table A1.: Comparison of Different ML Paradigms

Appendix B. Paradigm-Relative ML Learning Process

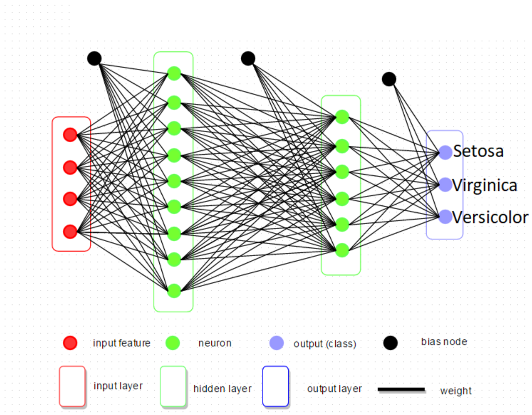
To illustrate how different paradigms construct the reasoning process, 4 models from different paradigms are trained on the identical data to perform a very simple task, classifying correct species. The Iris flower dataset is a multivariate dataset introduced by Fisher(30). There are only 3 species (iris-setosa, iris-virginica, iris-versicolor) and 4 features (petal width, petal length, sepal width, sepal length). Several models from different competing paradigm with different reasoning process will classify iris species based on their available features[18]. The comparison below is only for an illustrative purpose and not for technical comparison such as evaluating performance and efficiency.



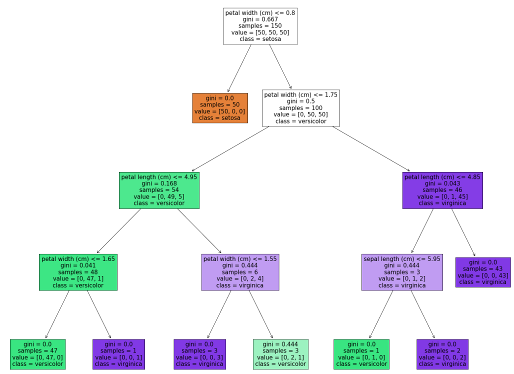
(a) Statistics Paradigm



(b) Geometry Paradigm



(c) Neuroscience Paradigm



(d) Logic Paradigm

Figure B1.: These figures illustrate different reasoning mechanism of 4 models from competing paradigms on the identical data (iris dataset) and task (species classification).

For the paradigm in Figure B1a, the conditional probability between species and features is estimated through counting the frequency of such occurrences. This frequency usually is assumed following a certain parametric statistical distribution. Based on the choice of the statistical hypothesis, the parameters are estimated through log-likelihood maximization as its learning process. These parameters then can be used

[18] Only 4 different paradigms (logic, statistics, neuroscience, geometry) are compared here, because the reasoning mechanisms in other paradigms are difficult to be visualized

to calculate the probability of specific species given the observation data. Therefore by inputting new observation data of unknown species, this paradigm can assign the final probability of the new observation belonging to specific species. It then predicts the new observation as the species with highest probability.

For the paradigm in Figure B1b, the data is projected into a certain spatial representation. This projection depends on the spatial encoding that we choose. For example in that figure, linear principal component analysis (PCA) is used. The nonlinear spatial relationship encoding can also be used in complex cases such as network embedding. All different spatial projections usually require estimation of spatial transformation parameters through constraint optimization as its learning process. By projecting all data into low dimensional spatial relationships, all AI reasoning can be done geometrically. The distance between data can be measured for other analysis. Two data that are near to each other indicates they are similar, and two data that are far apart indicates they are different. Therefore this spatial distance can be used for distinguishing different species through certain models. For example using k-nearest-neighbors (KNN) to decide the species based on their closest neighboring species, or using support-vector-machine (SVM) to find several hyperplanes that separate different species groups). Similarly all these models require estimation of parameters through constraint optimization. For example in SVM, we need to estimate the parameters that specify the location of hyperplanes.

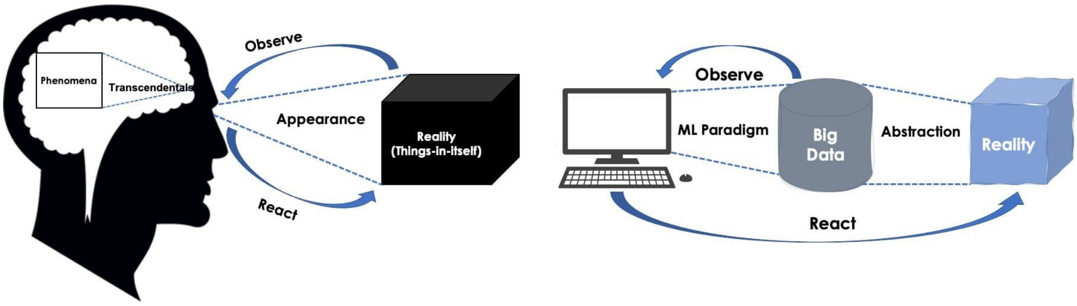
For the paradigm in Figure B1c, the data is translated into signals, then the signal is multiplied by the weight of that particular neural connection. The total signal weights are then aggregated to activate the next neuron. If the weight aggregation is above a certain non-linear threshold, the next neuron will be activated and interact with next connection weights. All these signals will keep propagating forward to the next neural connection. The accumulation of signal propagation across multiple neuron layers will be used for distinguishing different species. The final signal is then compared with the data and the error is propagated backward through backpropagation as its learning process. The connection weights between all neural connections are then adjusted to find the best fit with the data. Therefore the neural weights are the parameter that will be optimized in this paradigm. The new observation data then go through all weighted connections and the accumulation of signals can be used to predict the species.

For the paradigm in Figure B1d, a certain induction process is performed on the data, then it is translated into a logical rule such as decision tree. The rule is then adjusted based on a specific inverse deduction mechanism until it is optimized according to observation data as its learning process. The optimization mechanism depends on specific criteria. For example CHAID algorithm uses Bonferroni testing, CART algorithm uses gini index, and ID.3 or ID4.5 use information measure. The final decision tree is in the form of if-else logical statements and can be used for distinguishing different species in new observation data. For example in that figure, if the petal width is smaller than certain value it will be assigned as setosa, if not it will go through the next if-else logical statements until it reaches the final logical statement.

Although all of them use the same data and have the same task, they operate on very different reasoning processes that utilize different aspectual reality. Moreover, all these ML paradigms are generic enough to handle different kinds of data across a wide range of problems. This genericity can be explained by inter-aspectual analogies. In which the same problems can be analogized by multiple different aspectual perspectives to a certain extent. For example in previous examples on the species assigning problem, we can use spatial analogy or physical analogy or any other analogies to solve it.

Appendix C. Non-Reductionist AI

The reductionist reasoning assumes the existence of subjects (whether human or AI) that can observe phenomena neutrally. Kant held the dogma autonomy of theoretical thought by locating the central reference point of the theoretical synthesis in the transcendental logical subject or ego(28). The Figure C1a describes the reductionist reasoning proposed by Kant using transcendental critiques on theoretical reason. In Kantian perspective, the reality (as things-in-itself) is unknown. However, the appearance that is correlated with reality can be obtained through human intuition via transcendental categories(48). Similarly, in reductionist ML reasoning (Figure C1b), the big data as the abstraction of reality is processed via ML model with specific theoretical attitude given by the scientific paradigm. This kind of reasoning is problematic as described in the section 3 above.



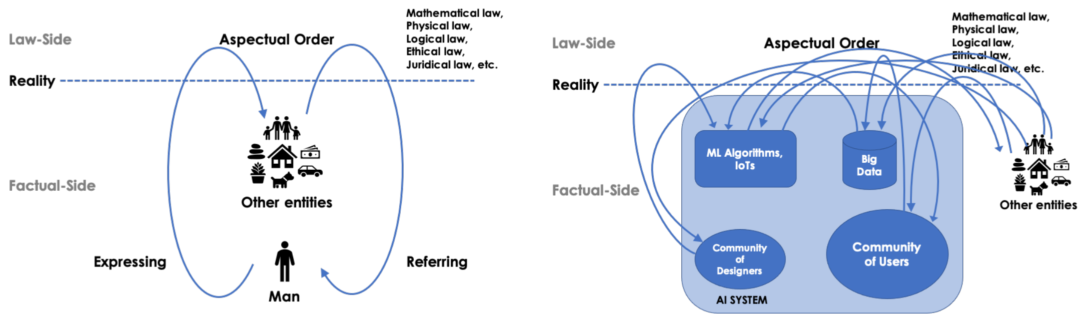
(a) Kantian Reductionist Reasoning (b) Reductionist ML Reasoning

Figure C1.: These figures describe the reductionist reasoning in both Kantian perspective and ML paradigm

In contrast, the non-reductionist reasoning based on reformational philosophy assumes the existence of aspectual law order with its unbreakable coherence in which each individual entity (including human and AI) find their meaningfulness. In this perspective, man (and AI) is not observing reality but functioning meaningfully in coherent relationships with all aspects of reality. Man reasoning is therefore always mediated by cosmonomic order in which he is expressing and referring toward a certain orientation (Figure C2a). Moreover, we can always distinguish the law-side (as the basis for normativity in Appendix E) and factual-side (as the basis for individuality-structures in Appendix D) of reality.

Moreover, AI reasoning is also contingent to a sociocultural context of that community, where all interactions and functionings are made possible by and through the cosmonomic order (Figure C2b). The cosmonomic order not only ensures the machine and designer operate in the same mathematical law, physical law, logical law, etc; but also ensures both community of users and designers operate in the same mathematical law, logical law, juridical norm, ethical norm, etc. Furthermore, the same cosmonomic order will ensure that particular AI system not only cohere internally, but also with other spheres-sovereignty (for instance with the legal authority).

And similar to individual man, AI decisions are only meaningful in that specific community of users and designers. The context can be a search engine which is qualified by lingual aspect, or social media which is qualified by social aspect, or e-commerce which is qualified by economic aspect. Each context should maintain their own sphere-sovereignty. The aggregate intelligence as a whole AI system (including community of



(a) Non-Reductionist Man (b) Non-Reductionist AI

Figure C2.: Non-reductionist proposal based on reformational philosophy.

designers and users in specific context) can be better than an individual user or even several users. For example the product recommendation of AI in the e-commerce context can be better than the sales manager. Because AI utilizes all insights and intelligence from both designers (through ML Algorithms, IoT, Sensors) and users (through Big Data). This perspective also demystifies AI from its appearance as a seemingly magical being with independent mysterious intelligence that suddenly emerges from a void.

In contrast to other technologies (such as computers and smartphones) which are purely human artifacts. I prefer to describe the individuality-structure of an AI system as both a human artifact and a social community (with a unique enkaptical relationship). This communal view of AI also liberates it from the domination of natural science paradigms (which focus more on scientific and technological development) and opens new paths for rich conversations with humanities and social science. The situatedness of an AI as *being-in-the-world* can open conversation with Husserl-Heideggerian phenomenological tradition(39). The investigation on *verstehen* and *fusion-of-horizons* of an AI can open conversation with Dilthey-Gadamerian hermeneutics tradition(61). The examination of systemic influence and power relationship within the community can open conversation with critical theorists in Frankfurt tradition(35). The analysis of AI practice in the community can open conversation with Rorty-Brandomian pragmatics tradition(9). The exploration of community-relative reasoning in AI can open conversation with postmodernist tradition.

Appendix D. Individuality-Structures and Enkapsis

In this section, the AI as previously defined by AI=ML+BD approach will be reinterpreted and enriched through reformational view. In a non-reductionist reformational perspective, AI can be considered as an *Umwelt* in the concept of reformational correlative enkapsis(77). There are at least 4 interdependent individuality-structures that influence each other (big-data, machine-learning, community of designers, community of users). Both big-data and machine learning are founded on information technology which is qualified by the formative aspect. But they can be qualified by various possible aspects depending on the various modeling paradigms. Both community of users and designers are founded on historical norms which are qualified by the formative aspect. But they can be qualified by various possible aspects depending on the

AI application. The choice of the paradigm better should be compatible with the AI application. Moreover, the socio-cultural context of the users will shape the big-data and the socio-cultural context of the designers will shape the machine-learning model. The machine learning model will influence the interpretation of big-data and big-data will influence the machine-learning output. The output will influence the community of users and designers. The entire feedback loop among all interacting elements makes AI as an *Umwelt* not static but dynamic.

Big-data and Machine-learning models (including their physical components such as sensors, actuators, devices, computers, servers, etc) are human artifacts. The community of designers and the community of users are social communities. This structural relationship of an AI as both artifact and community is analogous to the body and soul metaphor in philosophy (but we need to take note that both body and soul function in all aspects to avoid dualist reductionism). The apparent personality or soul of an AI can be explained by the aggregate behavior of the entire community that is estimated through its physico-conceptual base (big-data and machine-learning). This aggregate personality metaphor can be analogous to *volksgeist* in Hegelian perspective(38). Additionally, machine-learning through the community of designers is the structure of the learning process. In contrast, big-data through the community of users is the state of affairs or situation of the learning process. This rich enkaptical interdependence (*Umwelt*, body-soul metaphor, structure-situation metaphor) indicates that the AI can be comparable to man in many ways.

Reformational perspective also guarantees the sphere-sovereignty of that *Umwelt* that distinguishes it from different *Umwelt*. For example a search engine as an AI is qualified by the lingual aspect, it will be supported by the search pattern data of the users and specific lingual model by the designers. The input and output of that AI is only meaningful in the context of information searching practice. Therefore, it can be distinguished with other AI with different individuality structures (with different data, model, and purpose). In this way, enkaptical relationship of multiple different AIs can be formed to support specific organizations with various radical types (state, enterprise, university, research center, museum, gallery, hospital, free association, etc).

For illustration, suppose in the future there will be self-driving taxi companies. As an enterprise that is qualified by economic aspect, it can use a specific AI (search engine) to automate typing location, different AI (recommender system) to suggest place, alternative AI (path finder) to find the fastest road, another AI (pricing system) to estimate the optimized price, another AI (object detection) to observe traffic situation, another AI (self-driver) to automate driving, etc. In this case, different AI is unique with different data and different models which maintains their own sphere-sovereignty. But multiple AIs also form rich enkaptical interdependencies which are led by the qualifying function of specific organization (in this case is the economic aspect). Specific AI can also form enkaptical interdependencies with other members in that organization (e.g. helping sales, marketing, customer service, engineer, etc).

Appendix E. Normativity

The multi-aspectual paradigm through reformational perspective presuppose plurality of aspectual law as the basis of AI diverse normativity. In contrast with standard reformational views that assign sharp distinction between law and norm(77), I prefer recognizing the normative characters of all aspects with increasing degrees of freedom from lower to higher aspects. Even the physical aspect has a certain degree of freedom such as non-deterministic properties of quantum mechanics, which should be carefully designed in a certain normative manner for an AI with quantum computing principle. I just list a few possible examples and this list can be expanded along with the progress and capability of AI.

Normative consideration of the numerical aspect such as rounding should be considered especially when the data consist of thousands of variables or the algorithm consists of log function. Normative consideration of the spatial aspect such as number of dimensions and spatial properties should be considered if we borrow ML models from the spatial paradigm. Normative consideration of the physical aspect such as bandwidth and latency of data extraction and computational process should be planned properly. Regarding the sensitive aspect, we should estimate how sensitive an AI reacts towards external stimuli, if the AI is too sensitive it will create an overreaction for any random noise, if the AI is too insensitive it will ignore many important decisions. Normativity of the analytical aspect should also be planned, whether the AI uses strict logical reasoning that can be understood by humans or flexible tacit reasoning that can adapt with various unexplainable situations.

The normativity considerations are even more crucial in higher aspects. In the formative aspect such as systemic influence and power relation that is created by specific algorithms to the entire society. In the lingual aspect such as how AI should communicate with the community of users and whether AI will alter the mode of communication in the community. In the social aspect, the situatedness of AI and its practice in the community. In the economic aspect, AI is not only about maximizing profit but also whether the AI is efficient and uses less energy. Furthermore, what will happen to the labor market if this AI is introduced should be carefully thought through. In the juridical aspect, the preservation of public justice should be considered through careful legal drafting. For example the anticipation of certain AI intrusion towards other spheres-sovereignty such as surveillance capitalism and social credit. In the ethical aspect, whether the AI causes polarization, fake news transmission, addiction, overconsumption, and other unethical consequences. Moreover, the other paradigms in section 2 can also be flexibly employed on specific problems, but the consequences of their presuppositions should be anticipated and integrated with other aspectual normativity.