Using General Collective Intelligence to Optimize the Process of Evolutionary Optimization

Andy E. Williams, Nobeah Foundation, Nairobi, Kenya

Abstract
In the study of logic, state spaces have been used to define semantic representations of theories for the purpose of abstract problem-solving. This paper explores the use of a variety of state space (a functional state space) defined through the emerging technique of Human-Centric Functional Modeling, in a thought experiment to model all information required in the process of problem-solving using evolutionary computing, and all the information required to index evolutionary computing solutions and the problems they are meant to solve, so those problems and solutions can be uniquely identified and compared, in order to move towards automation of the process of evolving such evolutionary computing solutions by applying such solutions to the design of the solutions themselves.

Background

While Evolutionary Computation (EC) might be applied to a wide range of problems, for simplicity this paper considers only problems in connecting concepts, that is problems that can be defined through text based information, as opposed to problems in the visual recognition of objects, which requires semantic recognition of objects that might not even have a conceptual representation. The example to be used in this thought experiment is email spam detection. Activities by spammers and scammers pose major concerns because even though a vast majority of users are able to identify spam e-mails and are aware of threats posed by them, a significant amount of users who receive spam e-mails are vulnerable [1]. In this problem domain the entire set of fields representing the data of the email in whatever message format the email client uses, might be part of the relevant feature set for detecting whether or not the message is spam.

One of the main problems tackled in this paper is the invisible alignment of EC problem definitions and solutions, whether intentional or unintentional, where that alignment is with aims that undermine the public good. Where this problem has in the past been defined as a problem of ethics, it might also be seen as a problem of capacity. Assuming that the rate of change of evolutionary computing is R_{EC}, which includes the rate at which new algorithms and types of algorithms are introduced, assuming the rate at which solutions become aligned with the aims of some entity can be characterized as R_A, and assuming the rate at which solutions can be aligned with some broadly defined public good can be characterized as R_G, where “public good” can be taken as the collective fitness of all users to achieve all outcomes they might targeted with those solutions, then if $R_{EC}*R_A$ is greater than R_G, whatever policies or other means used to ensure the design of such solutions are “ethical” in this sense of serving the broad public good must be deemed ineffective. The question is then how to increase R_G significantly enough that it is always reliably greater than $R_{EC}*R_A$. Since this ethical problem-solving effort might involve any EC problem in general, and since it involves the group of all problem-solvers, it requires an increase in the collective general problem-solving ability of the group, which has been described as being characterized by the general collective intelligence or c factor [2], which is assumed to be aligned with collective interests (the public good). Assuming that the rate at which problems might be solved by some single entity or some subset of individuals, in a way that aligns with their interests, is correlated with the general problem-solving of that individual or subset of individuals, this implies that the collective intelligence must be greater than this intelligence for an increase in the invisible and unwitting alignment of solutions to be reliably avoided despite ever emerging new agendas and new technologies through which those agendas might be promulgated.

Introduction

Evolutionary computation (EC) techniques are well-known for their global search ability/potential and it is likely that the number of EC solutions are rapidly growing. In only one area, namely EC for feature selection in classification, it has been estimated that there have been over 500 papers published in the last five years [3]. At the same time however, there are no comprehensive guidelines on the strengths and weaknesses of alternative approaches along with their most suitable application areas. This leads to progress in the field being disjointed, shared best practice becoming fragmented and, ultimately, opportunities for improving performance and successful applications being missed [3].

Lists of popular machine learning algorithms certainly exist, as do surveys and lists of existing types of learning algorithms such as evolutionary algorithms [4], [5]. Although such lists of learning algorithms exist, the fact that there is no readily available list of all known learning algorithms points to what is both an unfortunate truth and a tremendous opportunity. The unfortunate truth is that the process of improving the effectiveness of machine learning algorithms faces a number of barriers that are fundamentally human limitations since the underlying processes have not yet been automated. These include the fact that optimal algorithms for a given problem can only be reliably selected where humans are aware of all algorithms that might be optimal, where humans have the capacity to test all such candidates to find the one that works best for each specific problem, where that testing methodology itself can be assured to select the optimal algorithm, and where use of that testing methodology can be assured rather than it possibly being circumvented.

The tremendous opportunity is that if it is possible to define a unique identifier for each learning algorithm, a unique identifier for each problem a learning algorithm might be applied to, a metric for the fitness of each learning algorithm in solving each problem within each given context, and an algorithm for applying all of these, then selection of optimal algorithms might be automated, making it useful to enumerate all existing learning algorithms so this automated evolution might be implemented.

Human-Centric Functional Modeling or HCFM [6] postulates that the behavior of potentially all systems can be represented in terms of functional state spaces. In the case of intelligent systems such as AI, HCFM postulates that all such computing programs are an automation of human pattern recognition processes (type 1 reasoning) and/or an automation of human logical processes (type 2 reasoning). In HCFM all sets of concepts are represented as also being a concept, therefore human reasoning is represented in terms of the transition from one concept to another. The graph of all concepts existing within the cognition at any one time (to which new concepts might be added or removed), connected by all reasoning processes, then forms a space of concepts (a "conceptual space") that the cognition moves through, or that intelligent systems move through while executing the cognitive processes they have automated.

All transitions between functional states in any functional state space are of two types. Type 1 consists of direct transitions from one functional state to another, and type 2 consists of step by step transitions between intermediate functional states. In the conceptual space these two types correspond to the type 1 and type 2 reasoning which human cognition has been determined to consist of [7]. Type 1 transitions are used to solve uncomputable problems, that is problems that are not computable in terms of known path segments. These problems must be solved through pattern recognition, that is, through recognizing patterns identifying cases in which the same solution has been applied to solve the problem in the past. Type 2 transitions are used to solve problems that are computable in terms of such known path segments (i.e. in the case of conceptual space computable in terms of logical steps). Where all possible transition processes can be represented in terms of a combination of some basic set of functions, those functions are said to "span" the functional state space, thereby enabling every possible process or functional state to be represented.

Functional Modeling to Index all Instances of Problems

In any functional state space problems are defined as the lack of a path allowing the system described by the functional state space to transition from one functional state to another. Problems in the conceptual space that has been defined as the functional state space of the cognitive system, or problems in the collective conceptual space that has been defined as the functional state space of the collective cognition, are thus defined as the lack of reasoning processes allowing the system to transition from one concept to another.

However, defining such a set of two concepts (an initial concept and a target concept) as an index to describe problems might not accommodate all problems. Some problems are distinguished not by their inputs (initial concept in conceptual space) or by their outputs (final concept in conceptual space), but by the context in which the problem occurs. This context is defined by other concepts that might be distributed around the region of the problem in conceptual space, or that might be distributed over the entire conceptual space. Put another way, for a function F = Ax + By, the values for the variables [x, y] are inputs, and the constants [A, B] might be seen as the context.

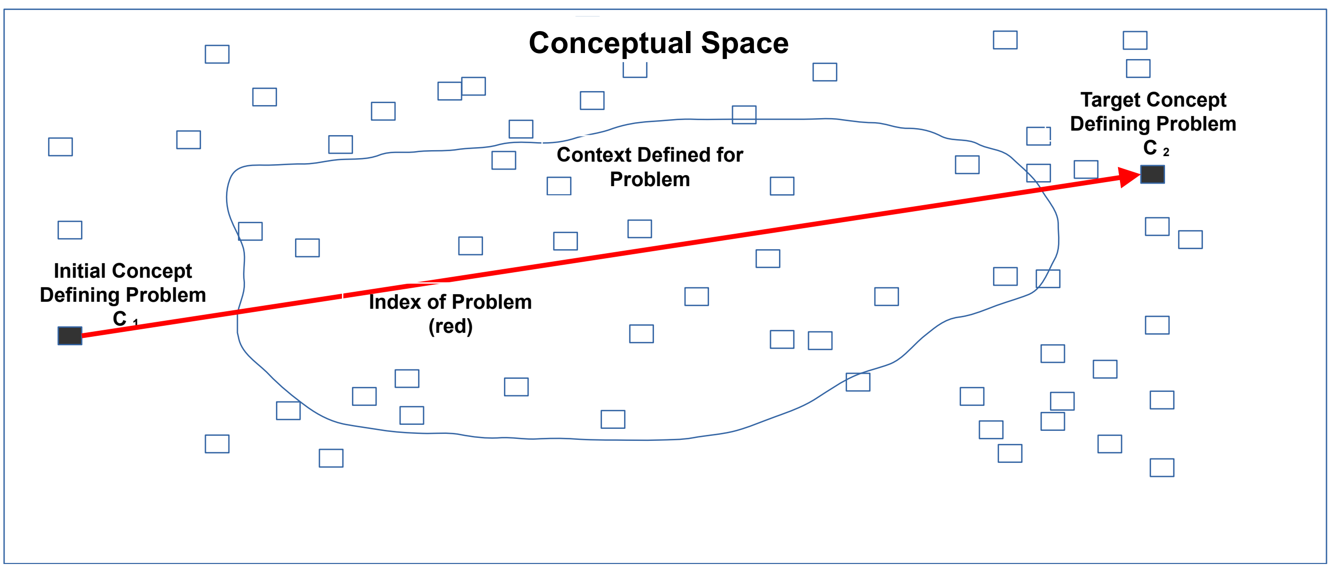

Figure 1: *Region of the graph of conceptual space defining the context of a problem and line defining the index by which the problem might be uniquely identified.*

A more complete functional model of a problem is then comprised of an input concept, an output concept, each of which might represent a set of concepts, and a region of the graph of conceptual space containing a set of concepts defining the context. Both the problem and this subset of the graph of conceptual space defining the context must be uniquely identified. Because the path through conceptual space is hypothesized to be unique for each problem, it might then serve as a unique index by which record of the problem might be stored and retrieved. In order for this path to be well-defined however, the position in the collective conceptual space of each concept defining the problem must be determined.

If all problems are defined by an initial concept and a final concept, in the case of our problem of determining whether an email is spam, the initial concept might be the generalized concept of email (thereby defining a set containing every email message), and the target concept might be the determination of whether or not that email is spam. The context of the problem is less straightforward. What is spam to one individual might be a helpful message to another. This reveals a fundamental issue with the problem of spam detection itself that is also potentially a fundamental issue with all pattern detection problems. That problem is that there are underlying ambiguities with the definition of such problems that don't become clear until one takes a Human-Centric Functional Modeling approach. Namely, there are potentially four quadrants of categorization related to spam detection due to human beings having both type 1 (intuitive) reasoning, and type 2 (rational methodical) reasoning with which they might make the determination of whether an email is spam or not. Since computation can be seen as the automation of human reasoning, this means there are four quadrants within which any such programs should operate. As in figure 2, type 1 reasoning is based on pattern detection, and might make the determination that an email is spam based on patterns such as whether others say it is spam. Type 2 reasoning is based on some logical process which might make the determination that an email is not spam even if everyone else says it is.

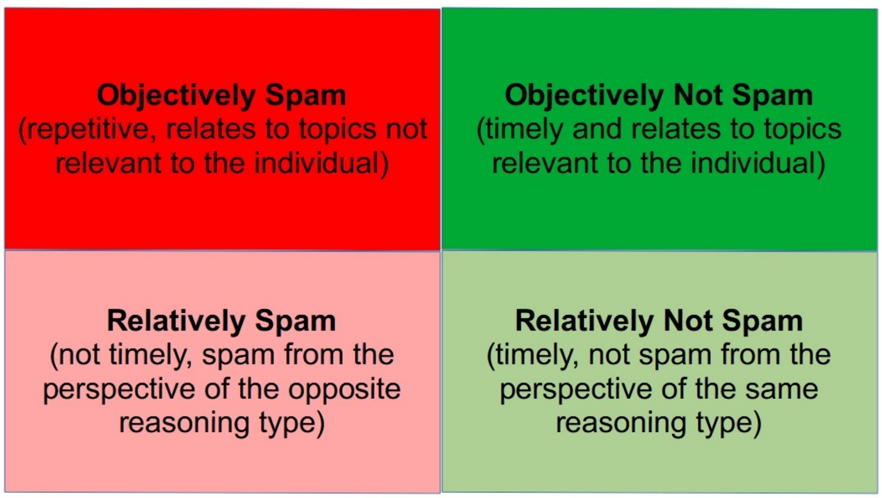

Figure 2: *Quadrants defining spam.*

As an example of email that is relatively spam, an individual might be targeted for weight loss email as a result of cookies accumulated in their browser while searching on the web for weight loss programs. An algorithm on the online search provider's server might identify the ideal weight loss program for that individual based on this search history, and since the user indicated on some website that they were interested in receiving related offers, that algorithm might target that individual with an offer that is a significantly better deal than they might otherwise have found. But if that individual perceives the suggestion as an unwelcome intrusion into their very private search concerning sensitive matters about their personal health, then it is relatively spam since many individuals predisposed to the same intuitive reasoning process might find it to be, even if it is not objectively so.

Furthermore, where the set of recipients targeted by advertising messages is defined by some search engine provider, as opposed to the set of recipients being gathered by the sender from targeted web searches conducted on their own, those sets of interests don't align. The interests of that search engine provider who targets their users with advertising messages through the search engine website, through social media, or through other browser based adverting are different from the interests of senders who target users with advertising messages through email, social media, or other platforms. Where those search engine providers are responsible for designing and deploying spam detection algorithms in their widely used free email services, are they equally motivated to eliminate the unwanted messages they receive advertising revenue for sharing as they are for the messages sent through channels they don't receive revenue for? Does this constitute a conflict of interest?

By contrast with the assignment of email to the category of spam based on type 1 reasoning, other individuals predisposed to evaluate each email by some set of metrics, and therefore according to type 2 or logical reasoning, such as according to whether it is timely, topical, and otherwise relevant even if the recipient can't remember having opted in for it, might evaluate the email as relatively not spam, though others of the opposite reasoning type find it to be.

A more accurate model of what is or what is not spam from the type 1 perspective would be one that considers all the patterns by which a message might be detected to be spam or not to be spam, and that considers all the type 1 patterns by which one determination as spam or as not spam might override another. Some examples are listed in table a.

Determination	Type 1 Pattern
Spam	Other key influencers say the message is spam.
Spam	Key influencers have not made a determination of whether or not the message is spam, but it aligns with perspectives, activities, or roles that others key influencers reject as spam.
Override Determination of Not Spam to Categorize as Spam	Message relates to perspectives, activities, or roles that some key influencers view as legitimate, but user has expressed that those views, activities or roles are illegitimate.
Not Spam	Other key influencers say its not spam.
Not Spam	It aligns with views that key influencers have not declared to be spam, or have declared not to be spam.
Override Determination of Spam to Categorize as Not Spam	Message relates to perspectives, activities, or roles that some key influencers view as illegitimate, but user has expressed that those views, activities or roles are legitimate.

Table a: *Some intuitive (pattern detection based) criteria for the determination of email as spam or not spam, and for overriding that determination.*

A more accurate model of what is or what is not spam from the type 2 perspective would be to consider all the logic by which a message might be determined to be spam or not to be spam, and to consider all the logic by which one determination might override another. Some examples are in table b:

Determination	Type 2 Logic
Spam	Message relates to activity of a role that user does not have and is not foreseen to have.
Spam	Message relates to activity of a role that user has or is foreseen to have, but message is repeated with similarity and frequency that disrupts other user activities.
Override Determination of Not Spam to Categorize as Spam	Message relates to activity of a role that user has or is foreseen to have in one context, but message is sent within a different context to a role (e.g. sent to the individual's professional email) that the message is not relevant to, or that the message might be banned from.
Not Spam	Message relates to activity of a role that user has or is foreseen to have, and message is not repeated with such similarity and frequency that it disrupts other user activities.

Not Spam	Message relates to activity of a role that user has or is foreseen to have in the current context (e.g. is relevant to work and is sent to the individual's professional email).
Override Determination of Spam to Categorize as Not Spam	Message relates to activity of a role that user has or is foreseen to have, and message is repeated with similarity and frequency that disrupts other user activities, however, repetition is determined to have happened by mistake.

Table b: *Some logical criteria for the determination of email to be spam or not spam, and for overriding that determination.*

To make this determination, it is not only necessary to model the email in the collective conceptual space, it is also necessary to model the conceptual space of the individual user in order to detect the activities they are involved in, their roles within those activities, as well as their perspective on various issues related to the content of the email. This might be achieved through observing the user over time, and constructing a map of their conceptual space. A private intelligent agent working on the user's sole behalf might then use that conceptual space to simulate the user in making that determination of spam or not spam.

This model has introduced a number of what might seem like additional complexities into the problem of spam detection. But this highlights the point about EC having hidden impacts. Anecdotally, there are few if any individuals with an email account who have not lost legitimate email to their spam folder until the time window for response had passed. And there are few if any individuals with email accounts who have any say beforehand in what is or what is not considered spam by those email services. In practice, since the predisposition towards a given reasoning type is highly correlated with political views, views regarding disruptive innovation, and views in a very wide range of other key areas, what this means is that in effectively hiding certain content, spam detection software might actually function to achieve a very different goal than protecting users from spam. For example, if being knowledgeable users don't click on links in potentially malicious email, and if being conscientious users review at least the title of all the email in their spam folder in any case, then deleting an email from their spam folder after reading the title doesn't save any time over deleting the email from their inbox after reading the title. In fact it might take more time to go to the spam folder and delete the email. What the spam folder might actually accomplish for such users is effectively delaying the receipt of certain classes of email. The assignment of those classes might be assumed to align with the email service provider's definition of the problem and with their chosen solution, but can it be assumed to align with what is optimally functional for each individual? While this potential misalignment or any other potential misuse of machine learning has in the past been framed as a question in ethics, it cannot be effectively solved as a question of ethics without an adequate functional model that permits an understanding of the fundamental issues (such as the existence of the four quadrants of decision-making), and therefore which permits the ethics to be understood.

Functional Modeling to Index all Algorithms for Solving the Problems

Where problems in functional state space are defined in HCFM as the lack of a path allowing the system described by the functional state space to transition from one functional state to another, solutions are defined as the paths which accomplish those transitions. The functional model of the solution is then comprised of an input concept, an output concept, each of which might represent a set of concepts, a region of the graph of conceptual space containing a set of concepts defining the context, and a path through conceptual space. This unique path defines a unique identifier by which each solution might be identified. Having defined a unique identifier for each problem, the unique identifier for the solution can then be used as a unique index for all the algorithms which might be used to solve that problem.

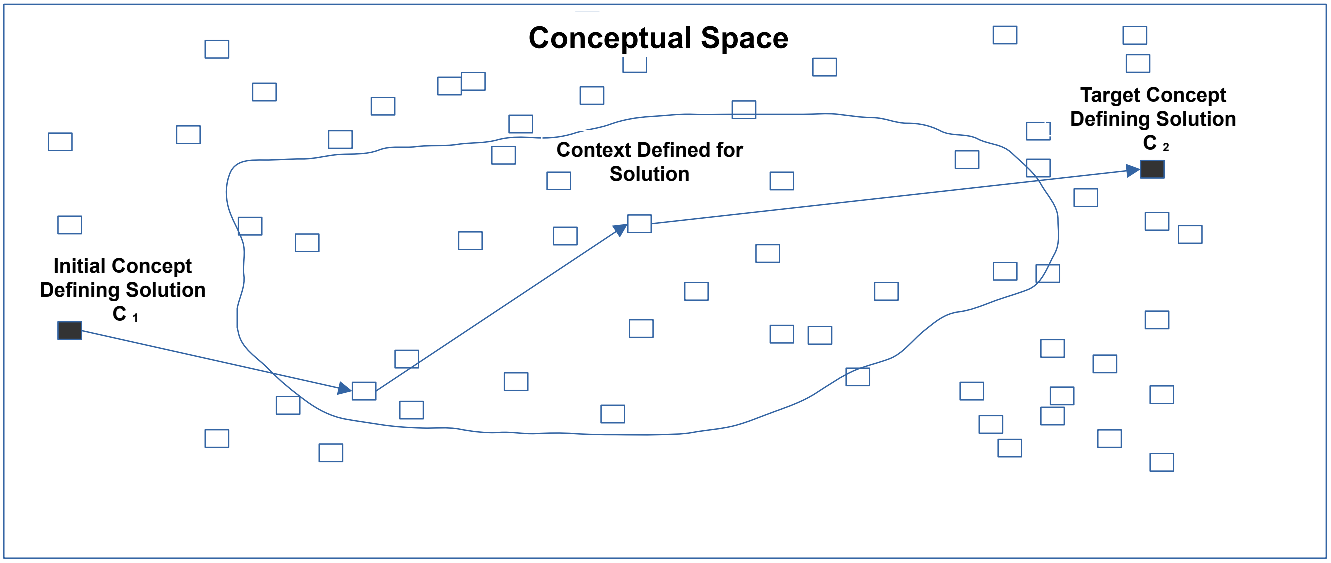

Figure 3: *Region of the graph of conceptual space defining the context of the problem used by the solution.*

The goal of this analysis is to define a model for EC solutions that is able to store all the parameters and other configuration information with which any method of evolutionary computation might be executed, in order to be able to uniquely represent all such solutions for each specific problem. Take Genetic Algorithms (GA) as applied to this spam detection problems. The parameters for such algorithms as applied to spam detection are assumed to be [8]:

Assumed Parameters for Genetic Algorithms
Crossover probability p
Fitness function F
Sets of Words or Phrases Discarded from Consideration D_i
Sets of Categories of Words or Phrases C_i
Sets of Weights W_i
Sets of Chromosomes and their Length S_i

Table c: *Some logical criteria for the determination of spam or not spam, and for overriding that determination.*

The only format for this information that can’t be broken by missing or extra information is a semantic representation. This information is not part of the semantic model of the problem, but instead is part of the semantic model of the solution. This suggests that each solution has an additional subset of some conceptual space consisting of the concepts and reasoning relationships between them which define the context of the solution. How can any region of conceptual space (any subset of conceptual space) be uniquely identified so that two regions (two subsets of the graph of conceptual space) can reliably be identified as the same or different from each other? How can differences be approximated as insignificant in the case that they are irrelevant as in figure 1? Assuming it is possible to uniquely identify a subset of a graph, then this unique identifier defining the context of the solution is part of the solution.

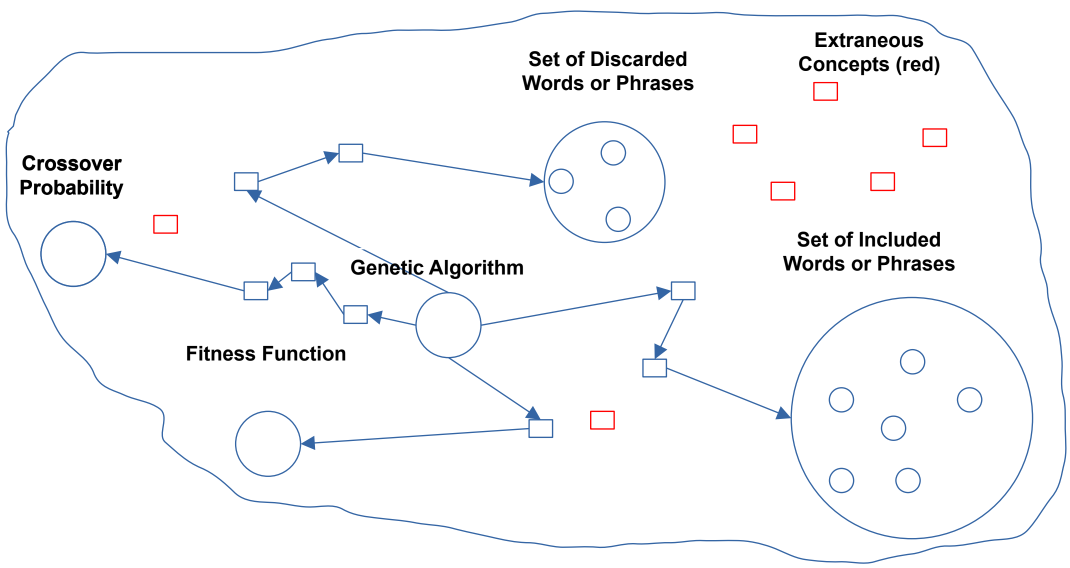

Figure a: *Region of the graph of conceptual space defining the context of the solution. Extraneous concepts included in the graph (red) should not affect the unique index defined for the graph.*

Functional Modeling of Performance

Once problems and their prospective solutions have been identified, they must be compared. An automated process must be capable of accommodating any possible metrics for the fitness of the solution in achieving its targeted outcome. This fitness might also be stored in the context of the solution. As an example, one general metric of performance fitness is volume of outputs per volume of inputs, where the term "volume" is used to metaphorically to describe the product of N measurements selected as relevant to performance in this context such as: accuracy, and speed, and where N is equal to or greater than one. Here volume of inputs describes the product of M selected measurements relevant to cost such as: required memory, and required processing power.

In the context of one problem accuracy might be much more important. In the context of another problem speed might be much more important. The relative importance of each property in performance would need to be stored in some property such as a weight factor. The properties and weight factors would also need to be stored in the context of the solution in order to be available for automated comparison.

Functional Modeling to Index all Algorithms for Evolving the Solutions

In more precise terms, most reasoning processes described by paths through the conceptual space are functions which take a set of inputs and produce a set of outputs. Others are processes which are defined as taking multiple sets of inputs at potentially different stages of processing. Reasoning processes can also be defined at a number of levels of abstraction as in table 1.

Process	**Outcome**
Specific Activity	Targets a Specific Outcome
Policy	Targets the Identification of a Set of Specific Activities and their Specific Outcomes.
Tactic	Targets the Identification of Activities, Policies, Lower-Level Tactics, and their Outcomes.
Strategy	Targets the Identification of Activities, Policies, Tactics, Lower-

Level Strategies, and their Outcomes.

Table 1: *Hierarchy of processes.*

An algorithm for evolving algorithms is itself a solution that must be modeled in conceptual space in order for all instances of that solution to be indexed so that applying that solution might be automated. This second order modeling is not considered in detail here as the complexity might not warrant the insight to be gained.

Implementing the Algorithms in an Intelligent System of Individual Optimization

Measured in terms of outcomes per unit of resources for some set of decision-makers restricted to a minority and potentially one individual, all problems of achieving collective impact can be seen as individual or minority optimization problems. In the case of spam detection, this means optimally solving the problem of spam for that minority of individuals or potentially that one individual or entity. Given that the aspects of spam detection that can potentially change for each individual are the definition of the problem, and the method for determining fitness of the solution, this in turn means solving whatever definition of the problem that is optimal for that individual or minority of individuals, to achieve whatever definition of fitness that is optimal for them. If the individual entity also has other roles within the group (for example is responsible for Internet searches), then this optimization for the individual might align with that individual's interests in a way that creates a conflict of interests which undermines the collective outcomes for the group. The hypothetical drift of all technologies towards the interests of the largest technology companies as they continue to grow has been called the "technology gravity well".

Assuming that an Artificial General Intelligence (AGI) is possible and eventually exists, and that the general problem-solving ability of this AGI is significantly greater than that of a human, the general problem-solving ability of this hypothetical AGI suggests the ability to explore the fitness of every combination of different solution in implementing every evolutionary computing operation, and suggests the capacity to explore interactions between computing operations that are much higher order (much more complex) than currently possible, and to do so at vastly greater speed and scale, in order to achieve vastly greater impact on any targeted metric of performance. Solving this problem of evolving evolutionary computing on behalf of any individual or entity makes this an individual optimization exercise that can potentially align outcomes with individual interests.

Implementing the Algorithms in an Intelligent System of Collective Optimization

Measured in terms of collective outcomes per person per unit of resources for some set of decision-makers that includes the majority and potentially all individuals, all problems of achieving collective impact can be seen as collective optimization problems. In the case of spam detection, this in turn means solving whatever definition of the problem that is optimal for that majority or entire group of individuals, to achieve whatever definition of fitness that is optimal for them.

Assuming that a General Collective Intelligence (GCI) [9] is possible and eventually exists, and that the general problem-solving ability of this GCI is significantly greater than that of a human, the general problem-solving ability of this hypothetical GCI suggests the capacity to collectively store information about which combination of different solutions is most fit in implementing every evolutionary computing operation, so that the computing operations executed by any one individual benefit from intelligence gained from the execution of any computing operation by any other individual. If all possible solutions are represented by unique indexes in conceptual space, this entails the capacity to divide the task of exploring that conceptual space as efficiently as possible between all those involved in this collective problem-solving. Meaning that if there are N individuals exploring that conceptual space for optimal EC solutions, each with intelligence factor g_i, then the volume of conceptual space each one explores might be assigned intelligently, perhaps being partitioned into contiguous regions of volume proportional to g_i for each individual. To create the potential to enable higher order interactions between computation operations managed by group processes, and to do so at vastly greater speed and scale in order to achieve vastly greater impact on targeted collective outcomes of computation for all users, this GCI might also divide the conceptual space of such higher order interactions in the same way.

In a GCI orchestrated evolutionary computation process for spam detection, users or intelligent agents based on some subset of AGI working behalf of each user might negotiate the problem definition, the type of evolutionary computation solution used to solve it, and every other function of spam detection for each user, in order to optimize collective spam detection outcomes for all users. In order to do so a GCI might orchestrate that cooperation to adaptively learn which implementation of each function is most fit in each context from all possible occurrences of spam detection use by each user. The usefulness of doing so would be expected to be significantly increased collective outcomes that benefit every member of the group, including an increase in quality of spam detection across all messaging uses. One reason is that new forms of spam resulting in spam detection tools that are no longer effective would be expected to disappear where the need to upgrade or install new spam detection software does not serve the public good. Since a GCI must optimize fitness to achieve collective outcomes for all users, being constructed in a way that maximizes the public good implies the modularity to adapt with any new functionality added by any vendor.

Discussion

The usefulness of leveraging Human-Centric Functional Modeling to define functional state spaces that might be used to index machine learning problems as well as to index evolutionary computing solutions in order to move towards the automated evolution of those solutions, remains to be explored in practice. The usefulness of leveraging Human-Centric Functional Modeling to define functional models to clarify aspects of pattern recognition problems that are currently obfuscated (e.g. the difference between type 1 and type 2 reasoning) also remains to be explored in practice.

A few concrete issues have emerged through this analysis however. One is the lack of intuitive functional models for machine learning algorithms that remove the need to understand the complexities of machine learning when using such algorithms. The resulting predisposition to design algorithms in ways that force ourselves and others to understand more and more technology, is a problem of both technology and awareness. It’s a problem of technology because the human-centric technologies required to provide an alternative strategy simply did not exist before. This absence of a visible alternative might have led to the predisposition to believe that the solution to technological complexity is memorizing more, or creating more for others to remember, well past the point at which individuals can reliably manage their technology choices, as opposed to making technology more and more human-centric in not requiring any specialist expertise at all, so that as long as one has an understanding of the problem domain, one can easily and reliably select the best of such human-centric tools and use it to help solve the problem. It’s also a problem of awareness of the underlying problem, and awareness of the technologies themselves.

The key issue of awareness is that all of the Human-Centric Functional Modeling techniques described in this paper rely on researchers being able to validate these ideas based on first person observation of their own cognition, and awareness must be created about the strong predisposition anecdotally observed of individuals in the machine learning community to reject first person methods. Other key issues are creating awareness about the problems that potentially can’t reliably be solved without a first person approach (such as the problem of automating the evolution of machine learning), and creating awareness about how the emerging science of HCFM provides that first person approach in order to solve these problems. In the study of logic and semantic representation within the discipline of philosophy, constructs known as "state spaces" [10] have been used for decades to conceptualize the semantic representation of specific information. These state spaces are critical to understanding cognitive constructs that at this point only be understood by first person observation (self-reflection) of our own cognition, since there are not yet any external tools capable of connecting measurable phenomena to specific thoughts. However, science has not historically been capable of measuring the validity of first person observation, and so has not been reliably capable of treating first person observation as anything but subjective and non-scientific. As discussed in this paper, some fundamental aspects of problems in machine learning remain out of reach of understanding as long as models based on first person observation remain out of the reach of science. HCFM however enables all of human perception to be represented in terms of "functional state spaces" that potentially enable all the properties of first person observation to be quantified. As mentioned for example, cognition can be represented in terms of the mind using reasoning to navigate a space of concepts or a "conceptual space", that serves as the functional state space of the mind. In this functional state space, truth is believed to be a property that has a well-defined representation in terms of a signal that can be transmitted by a reasoning process as a channel with an ability to transmit truth that is given by information theory, so that the truth of any first person observations made through such reasoning might be objectively assessed, thereby making first person observations accessible to science for the first time.

Research Limitations

A number of elements of conceptual space need to be elaborated before it can be effective in modeling and indexing problems as well as the algorithms used to solve them. Most importantly, distances in conceptual space have as of this writing only been approximated. Furthermore, the application to the modeling of systems in a number of different domains has only begun to be explored. This exploration is critical to ensure the models of thinking about the systems for which problems are being solved, matches the models for the behaviors those systems are actually capable of [11].

Conclusions

As machine learning comes to be used more and more throughout industry and society, the numbers of algorithms used can only increase. This has implications regarding a number of areas of research. Questions concerning the ethics of one algorithm or another quickly become meaningless when the pace at which the number of algorithms is increasing, or at which algorithms change is beyond the rate that any human-defined policies can manage. Furthermore, questions regarding which algorithm is optimal for a given application become meaningless when the number of algorithms to choose from is greater than any individual can evaluate, and the differences between all the different algorithms becomes a problem too large in scope for any individual to understand. Use of Human-Centric Functional Modeling to index such algorithms and the problems they are meant to solve, and the use of General Collective Intelligence to coordinate problem-solving is one approach towards finding a solution.

References

[1] Jai Batra, Rupali Jain, Vinay A. Tikkiwal, Amrita Chakraborty, A comprehensive study of spam detection in e-mails using bio-inspired optimization techniques, International Journal of Information Management Data Insights, Volume 1, Issue 1, 2021, 100006, ISSN 2667-0968, https://doi.org/10.1016/j.jjimei.2020.100006.

[2] Woolley, Anita Williams, et al. "Evidence for a collective intelligence factor in the performance of human groups." science 330.6004 (2010): 686-688.

[3] B. Xue, M. Zhang, W. N. Browne and X. Yao, "A Survey on Evolutionary Computation Approaches to Feature Selection," in IEEE Transactions on Evolutionary Computation, vol. 20, no. 4, pp. 606-626, Aug. 2016, doi: 10.1109/TEVC.2015.2504420.

[4] G. Yu, L. Ma, Y. Jin, W. Du, Q. Liu and H. Zhang, "A Survey on Knee-oriented Multi-objective Evolutionary Optimization," in IEEE Transactions on Evolutionary Computation, doi: 10.1109/TEVC.2022.3144880.

[5] Li, Jian-Yu, Zhi-Hui Zhan, and Jun Zhang. "Evolutionary Computation for Expensive Optimization: A Survey." Machine Intelligence Research 19.1 (2022): 3-23.

[6] Williams, Andy E. "Human-Centric Functional Modeling and the Unification of Systems Thinking Approaches: A Short Communication." Journal of Systems Thinking (2021): 5-5.

[7] Kahneman, Daniel. Thinking, fast and slow. Macmillan, 2011.

[8] Chowdhary, Mandeep, and V. S. Dhaka. "E-mail Spam Filtering Using Genetic Algorithm: A Deeper Analysis." International Journal of Computer Science and Information Technologies 6.3 (2015): 2272-2276.

[9] Williams, A. E. (2021. Defining a continuum from individual, to swarm, to collective intelligence, to general collective intelligence. International Journal of Collaborative Intelligence, In press (2022)

[10] Suppe, Frederick. The semantic conception of theories and scientific realism. University of Illinois Press, 1989.

[11] Williams, A. E. (n.d.). Selecting Between Semantic Modeling of Intelligence and Semantic Modeling of Systems. Retrieved from osf.io/preprints/africarxiv/gdn5y