Chapter 7

Human-AI Synergy in Creativity and Innovation

Tony McCaffrey

Additional information is available at the end of the chapter

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Abstract

In order to maximize creative behavior, humans and computers need to collaborate in a manner that will leverage the strengths of both. A 2017 mathematical proof shows two limits to how innovative a computer can be. Humans can help counteract these demonstrated limits. Humans possess many mental blind spots to innovating (e.g., *functional fixedness, design fixation, analogy blindness*, etc.), and particular algorithms can help counteract these shortcomings. Further, since humans produce the corpora used by AI technology, human blind spots to innovation are implicit within the text processed by AI technology. Known algorithms that query humans in particular ways can effectively counter these text-based blind spots. Working together, a human-computer partnership can achieve higher degrees of innovation than either working alone. To become an effective partnership, however, a special interface is needed that is both human- and computer-friendly. This interface called *BrainSwarming* possesses a linguistic component, which is a formal grammar that is also natural for humans to use and a visual component that is easily represented by standard data structures. Further, the interface breaks down innovative problem solving into its essential components: a goal, sub-goals, resources, features, interactions, and effects. The resulting human-AI synergy has the potential to achieve innovative breakthroughs that either partner working alone may never achieve.

Keywords: creativity, innovation, human-computer interface, artificial intelligence, intelligence augmentation

1. Introduction

Recent critiques of IBM Watson in the business world (*Forbes* and *Fortune*) and technical world (*MIT Technical Review* and *Wired*) suggest concerns about Watson's abilities and potential [1–5]. One critique is based on Watson's inability to draw conclusions beyond the corpus it has been trained on. Another critique is that it cannot make connections, or draw analogies, between different domains of data—such as between oncology and heart disease [1]. Yet another critique argues that AI, including IBM Watson, is still several breakthroughs away from being really intelligent, but this critique does not specify the particulars of these needed breakthroughs [5]. Our theory is that IBM Watson is exhibiting the limitations demonstrated in a 2017 mathematical proof of the limits to a computational approach to innovation and analogical thought [6]. No matter how many academic journal articles Watson processes about its topic of choice, it cannot overcome the proven limits. Further, human blind spots, such as *functional fixedness*, are implicit within the human-produced text and data used by Watson. Unless IBM Watson and other AI technologies face these limits and address them properly, they will continue to experience frustration over the uneven results that these technologies produce.

More generally, any computational approach to innovation and creativity (e.g., Machine Learning, Deep Learning, AI in general) has limits to how creative or innovative it can be. The 2017 mathematical proof details two of these limitations [6]. Humans can help counter these limits. On the other hand, humans have many known mental blind spots to innovation, including *functional fixedness* [7], *design fixation* [8], and *analogy blindness* [9, 10]—to name a few. For every known mental obstacle to innovation, there now exists an effective counter-technique, which can be implemented in software [11]. These counter-techniques help humans be more innovative as well as improve the AI technologies that operate on the text and data produced by humans.

From these findings, it makes sense to create a human-computer interface for innovation that is both human- and computer-friendly so that the computer can help humans be more innovative and humans can return the favor for the computer. The overall result thus far has been a human-computer partnership that has already found novel solutions to such tough problems as how to significantly reduce concussions in American football players and how to adhere a coating to the non-stick surface Teflon [11, 12]. This human-computer synergy has the potential to achieve even greater innovative breakthroughs.

This chapter first articulates new definitions of creativity, innovation, feature, and effect. These definitions permit quantified arguments about the innovation process. Next, the main points of the proof will be presented. All the proof's details are contained in Ref. [6]. The main conclusion is that no computational approach can fully take over the creative or innovative process.

Then, several of the weaknesses to human innovation will be presented along with their effective algorithmic counter-techniques. A full description of human weaknesses and programmable counter-techniques are contained in Ref. [11]. How these human weaknesses become computer weaknesses is explained with an emphasis on how the programmable counter-techniques can also improve the innovation of any AI technology. Finally, the human-computer interface that permits humans to counter computer limits and the computer to counter human weaknesses will be presented. This interface called *BrainSwarming* has the potential to result in greater innovative behavior than either humans or computers can achieve working alone.

2. Proven computer limits to innovation

Section 2.1 articulates the new definitions for creativity/innovation, feature, and effect, which then permit the quantification of the size of the space of innovation for physical objects. The

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space of innovation for a given object is shown to consist of all possible effects that the object could produce when interacting with every other possible object, material, force, energy, and condition (e.g., barometric pressure and gravity strength). Section 2.2 quantifies the number of interactions that are possible between an object of interest and all other objects, materials, forces, and energies in the world. Section 2.3 builds on Section 2.2 by exploring all the ways that two given objects could interact within various conditions to produce interesting effects. The number of possible interactions and possible effects is so astronomically large that the fastest supercomputer today could not examine them even it started working from the invention of the first computer. Section 2.4 articulates other reasons why a computer could not predict certain effects of an interaction. Finally, Section 2.5 shows how humans can help counteract the challenges that computers have when innovating.

2.1. New definitions

Any creative/innovative solution to a problem is built upon at least one commonly overlooked or new feature of the problem. A feature that is commonly overlooked or new is called obscure. The above description is called the *Obscure Features Hypothesis of Innovation* [13].

If the solution was based upon a commonly noticed feature, then it would get a low rating on originality and a high rating on obviousness [11]. For example, if a scented jar candle company came out with a new scent called *Bag of Halloween Candy*, people might enjoy it and buy this new scent but it still might not receive very high creativity scores. The feature of scent has been explored a great deal in the context of candles. In contrast, if a candle company devised a self-snuffing candle that could be set to extinguish itself after a desired amount of time, then this would receive high creativity scores [11]. The feature of self-snuffing in the world of candles has been under-explored.

Given that features are a crucial aspect of creativity, a definition adapted from the philosopher Nietzsche permits the number of features of an object to be quantified [6]. Nietzsche states: "The features of a 'thing' are its effects on other 'things': if one removes other 'things,' then a thing has no features" [14]. From this perspective, every feature emerges from interactions and is not intrinsic to the object itself. Certainly, color is not intrinsic to an object, but results from light interacting with the object and our retinas, which results in processing in the human visual cortex. Change the circumstances of the interaction and the color changes. Change the lighting. Put on sunglasses. Experience trauma in the visual cortex. These and other changes can result in a change in color.

As a further example, the mass of an object now appears to be the result of the object interacting with Higgs bosons [15]. Mass and length of an object change as its speed increases as it nears the speed of light [16]. Even the size of an object depends on the gravitational field that it is experiencing. A table of a certain size might be stable within one gravitational field but collapse in another gravitational field because its legs cannot hold up the weight of its tabletop. Any feature of an object, in fact, can be described as the effect of interactions.

Given these definitions of creativity and feature, we are able to quantify the number of features, interactions, and effects by defining a feature as an effect that results from interacting the object of interest with other objects, materials, forces (e.g., centripetal and centrifugal), and energies (acoustic, magnetic, chemical, biological, human, thermal, electrical, hydraulic, pneumatic, mechanical, electromagnetic, and radioactive: [17]). Given that some amount of a material (e.g., a patch of velvet or a chunk of steel) can be considered an object, we can leave out material from the definition of feature above. Also, the lists of forces and energies may increase someday, especially as we better understand dark matter and dark energy, but these lists are currently stable but potentially dynamic in the future.

2.2. Interactions

For our calculations, let us estimate that there are 10 million objects in the world. In April 2015, the US Patent Office issued its nine millionth patent [18], and this number does not include the patents unique to patent offices of other countries or the trade secrets contained in no patent databases. Further, this estimate leaves out natural objects (e.g., stone) and common objects (e.g., ball) that are also excluded from all patent databases. Further, the number of patented objects grows everyday as new patent applications are submitted on a daily basis. However, 10 million is a reasonable estimate for the present time, and it is an easy number with which to do calculations.

Given an object of interest, how many interactions are possible with 10 million objects? Strictly speaking, there are $2^{10,000,000}$ possible subsets of 10 million things, which is approximately 10^{80}, so our object of interest could interact with every possible subset of objects. More realistically, however, an engineer might interact their object of interest with between one and five other objects, which would result in on the order of 10^{27} subsets. Computers have existed for on the order of 10^{9} seconds, so to examine all subsets of five or fewer objects would require examining $10^{27}/10^{9} = 10^{18}$ subsets per second since the 1950s. The fastest supercomputer as of June 2015, the Tianhe-2, computes on the order of 10^{16} floating-point operation per second [19]. So, if the Tianhe-2 existed since the first computer existed, it could still not examine all the possible interactions of our object of interest with a reasonable number of subsets of possible objects. This calculation only allows one floating-point operation to process each subset. Further, it does not take into account all the possible conditions that these interactions could take place in: differing barometric pressures, humidity, temperature, lighting intensity, radiation, magnetic fields, strength of gravitational field, and so on.

In sum, even with our conservative estimates, the current fastest supercomputer could not fully explore the space of possible interactions for our object of interest in a reasonable amount of time.

2.3. Many ways to interact

The assumption made in the previous section is that, given two or more objects, it is obvious how they should interact. A spoon is used to stir the contents of a coffee cup, for example. That is what *functional fixedness* would dictate, which is the tendency to fixate on the designed use of an object, including when it is interacting with another object, and ignore the plethora of other possible uses [7]. But the spoon and the coffee cup could interact in an almost incalculable number of ways to achieve many different effects. For example, rest the spoon across the opening of a steaming cup of coffee. Place an ice cube in the spoon and watch the ice cube melt. Or, place a marble in the spoon as it rests across the cup's opening. Slap down on the handle part of the spoon hanging over the edge of the cup and launch the marble across the room. Or, place the coffee cup on one side of the room and take the spoon to the other side of the room. Make the coffee cup into a target by trying to throw the spoon into the cup. Or, play golf with the spoon as the putter, a marble as the golf ball, a table top as the putting green, and a sideways coffee cup as the hole.

Or, again set the coffee cup upright on the counter and place the spoon horizontally so it rests across the opening of the cup. Turn the spoon over so the curved part is facing upward and play a game of trying to balance various objects on the curved surface so they do not fall into the cup. Or, shake a spoon around in an empty cup to make a rattling sound. Or, turn a coffee cup over so that the open end is facing down. Place a spoon into the open end of the empty coffee cup and set the contraption on the counter. The spoon will force one side of the coffee cup to elevate a bit, forming a trap. When the spoon is disturbed by a mouse, for example, the coffee cup will fall and flatten, possibly trapping the mouse.

These are just a few of the ways to interact the spoon and the coffee cup to achieve an interesting effect. To consider all the ways that these two objects could interact, we would have to take into account every possible spatial relation between the two objects; every possible speed, acceleration, and deceleration of the two objects with respect to each other; every possible type of movement (linear, nonlinear, spinning at various angles and speeds); every possible surface that they may rest upon; every possible lighting condition, wind condition, heat condition, radiation level, magnetic field strength, electrical current flow, barometric pressure, humidity, earthquake or turbulence condition, and gravity strength; every possible extra object involved in the interaction (e.g., ice cube, marble, liquid coffee, and a human); as well as other conditions that we are probably overlooking.

If any of these conditions is actually measured by a continuous variable, then the number of different interactions between the spoon and coffee cup is truly computably nonenumerable. Even if all these conditions are measured by discrete variables that extend to a finite number of decimal places, then the number of possible interactions is outlandishly large. All these digits of precision on a variable are probably unnecessary in most cases, but when one is approaching a phase transition (e.g., liquid coffee approaching gas or the ceramic coffee cup possibly becoming superconductive), then many decimal places might be necessary to understand the onset of the transition. If one is approaching a previously unknown phase transition, then the slightest change in one condition, as measured by a change in the 100th decimal place for that variable, for example, could produce a radically different effect.

In sum, although we calculated that there may be about 10^{18} possible interactions between one object and up to five other objects out of 10 million possible objects, taking into account the incredible number of ways that any two objects can interact with each other plus all the possible conditions that those interactions could take place in, raises our number of interactions at least several orders of magnitude and quite possibly many orders of magnitude [6]. The overall result is a number of possible interactions that becomes increasingly beyond the ability of current and projected supercomputers to explore even if they were running since the invention of the first computer.

When quantum computers come fully into being, then all the above calculations will need to be redone. There has been work showing how quantum computers could handle certain computably enumerable sets [20]. However, if any of the conditions (e.g., heating, humidity, radiation, etc.) actually requires a continuous variable for its measurement, then the number of possible interactions is truly continuous and thus not computably enumerable. If all the conditions can be measured with discrete variables, then it is possible yet unclear whether the set of interactions is the type of set that is computably enumerable by a quantum computer, according to the specifications in Ref. [20]. Even if the set of possible interactions were computably enumerable, however, any gaps in the theories involving those interactions—as described in the next section—would make the set of derived effects from the set of interactions uncomputable.

2.4. Predicting effects computationally

Can a computer compute the effects of a set of objects or entities that are interacting? It depends on whether a theory exists that derives the particular effects under consideration. Sometimes, theory is ahead of empirical measurement and sometimes empirical measurement is ahead of theory. For the former, Einstein's General Relativity, developed between 1907 and 1915, predicted that light would bend around massive objects such as our Sun [16]. It took until 1919, however, until Arthur Eddington verified this prediction by measuring starlight that moved around a total solar eclipse [21]. For the latter, empirical measurement determined that galactic clusters did not have sufficient mass to account for their rotational speeds, so the existence of dark matter was posited as a way to increase gravitational effects present in galactic clusters [22].

If no theory exists to predict a particular effect of an interaction, then no algorithm exists to compute that effect. Given our previous example of a coffee cup interacting with a spoon, if there are gaps in the theories for how the interaction would proceed in a possible condition (e.g., lighting, wind, heat, radiation level, magnetic field strength, electrical current flow, barometric pressure, humidity, earthquake or turbulence condition, and gravity strength), then no computer could predict the effects within that particular configuration. That particular combination of conditions would have to be empirically measured. Thus, a computer's ability to list out a particular combination of conditions does not mean that the computer could successfully predict the effects of the interaction taking place within that amalgam of conditions.

2.5. Humans countering computer limits

Humans are needed to carry out the empirical measurements that neither a computer can carry out nor a robot has not been set up to execute. Further, with our vast experience of interacting with the physical world, humans already know many effects of interactions but have yet to encode them for a computer. If humans have not yet experienced the interaction, often we can comfortably predict the main effects of that interaction after running a mental simulation in the sensorimotor cortices of our brain [23, 24].

In this way, humans can help flesh out and teach the computer many effects that the computer does not currently know and is presently unable to derive. Further, humans are good at crafting theories that make predictions of effects that then can be empirically tested. So, humans can encode their theories that a computer can then use to derive effects. Although a computer will continue to learn new effects taught to it by humans and derive effects based on new theories, given the computable nonenumerability of effects, humans will continue to maintain their rightful place in innovation—even with the onset of quantum computers (see previous Section 2.3 M*any Ways to Interact*).

3. Human weaknesses to innovation and counter-techniques

In this section, we present five human blind spots to being creative and innovative (i.e., *functional fixedness* [7], *design fixation* [8]; *analogy blindness* [9, 10], *goal fixedness* [11], *assumption blindness* [11]) as well as the effective algorithms, several of them patented, that can guide humans out of these creative dead ends. For a more complete discussion, we refer the reader to [11], which includes the treatment of other human creative blind spots.

3.1. Functional fixedness

Functional fixedness is the tendency to fixate on the common use of an object or one of its parts [7]. In 2012, the first highly effective counter-technique, the *generic parts technique* (GPT), was developed [13]. Consider the *Two Rings Problem* [26], in which you have to fasten two steel rings together in a figure-eight configuration. The rings are each about 6 inches in diameter and weigh about three pounds. All you have to work with is a long candle, a strike-anywhere match, and a two-inch cube of steel.

Most people first try to light the candle and drip wax around the rings. However, the rings are too heavy to be fastened securely with a wax bond. The key is to notice that the candle's wick is a string. Remove the string by scraping the wax away on the steel cube and tie the rings together.

People who used the GPT solved 67% more problems than a control group [13]. The idea is to break an object into its parts while you ask two questions. First, can the object be broken down further into smaller parts? For example, in **Figure 1**, *candle* can be broken down into *wax* and *wick*. Second, does the description imply a use? If so, re-describe it generically in terms of its shape, material, or size. For example, a wick implies burning to give off light. When re-described in terms of its material (i.e., string), this new more generic description opens up new possibilities for uses—especially, tying things together. In this case, this use is sufficient to solve the *Two Rings Problem,* but if an even more generic description is needed then perhaps *long, interwoven fibrous strands* would be about the next level of generic description.

Software that exists can find the solution to the *Two Rings Problem* and other problems requiring the discovery of obscure features if the key obscure features are either already known in a corpus or dataset or they have been articulated by a human in a targeted query [27]. For example, if a corpus/dataset "knows" that the verb *tie* is a synonym of *fasten, string* is a material for *wick*, and *tie* is a use of *string*, then software has generated the following solution to the *Two Rings Problem*: "a candle's wick is made of string, which might be able to tie ring to ring" [27]. If any of these connections is missing in the text/data, then the solution is difficult to reach. For example, if your data source is ConceptNet 5.5 [28], for example, then *tie* is a way to *fasten* things, *wick* is a part of *candle*, but *wick* is not a type of *string*, so it is difficult to

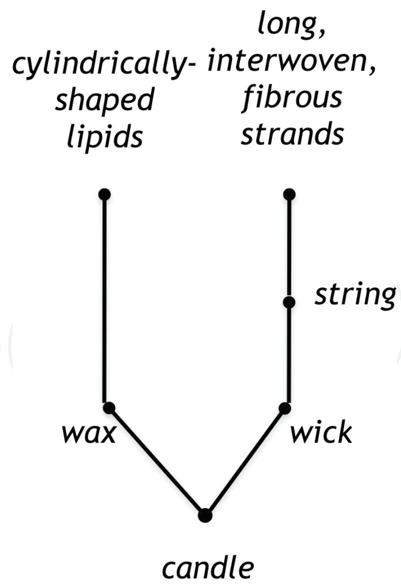

Figure 1. Generic parts technique.

reach the conclusion that you can use the wick to tie things together. In order to obtain this information, either a human must intervene to answer the questions of the *generic parts technique*, another text or data source is used to obtain the crucial information, or you find another possible route through ConceptNet 5.5 such as *wick* being a type of *cord,* which can be used to *tie* things. I chose ConceptNet 5.5 as an example because its information comes from multiple good sources [28]: including Open Mind Common Sense contributors, DBPedia 2015, OpenCyc 2012, and Open Multilingual WordNet.

3.2. Design fixation

Design fixation occurs when a designer attempts to create a novel design but fixates on the features of known designs they have seen [8, 29, 30]. For example, people instructed to create a novel candle might think up a new scent for a candle or add multiple wicks to the candle. In the context of candles, however, scent and number of wicks have been frequently explored. To be truly innovative, you need to manipulate a commonly overlooked (or perhaps new) feature of a candle. But how does one notice something that is rarely noticed?

Although the number of features of a candle (or any object) is intractable and not computably enumerable, classifying the types of features that any object could possess into an extensive category system has been a highly effective method for overcoming *design fixation* [11].

We initially listed 32 categories of feature types for objects, but now use a 50-category system [11]. We asked people to list as many features as they could for many common objects (e.g., candle, umbrella, etc.). We then categorized their answers based on our 32-category system. On average, people overlooked 20.7 of the 32 categories (67.4%) for each of the objects [11]. For each object, they overlooked different types of features. For example, for a rocking chair, they would notice motion—that the chair was designed to move in a certain way. For a candle, however, no one we tested ever noticed that a candle is motionless when it burns. Its flame flickers, but the candle itself does not move.

To be innovative, you need to build upon a feature that has been commonly overlooked and, based upon our findings, the majority of feature types of common objects are overlooked. Therefore, there is plenty of room to create novel variations for even the most common of objects.

For example, a candle that moves from its own dynamics is an under-explored type of candle. Examining the other overlooked features for a candle, we found that no one noticed that a candle loses weight when it burns. Thus, we leveraged weight loss to produce a candle in motion. By placing a candle on one side of a scale-like object and a counterweight on the other side, the candle moved upward slowly as it burned down. For fun, we placed a snuffer above the candle so that it eventually moved into the snuffer and extinguished itself. The *self-snuffing candle* was born [11]. A constructed prototype revealed that the *self-snuffing candle* works as described.

Computationally, in ConceptNet 5.5 [28], a candle has no connection with being motionless or losing weight while burning, while a rocking chair has many connections related to motion. ConceptNet 5.5, as an example of many textual and data sources, would not be a good source for noticing overlooked features that could become the basis of a novel design. The overlooked features need to be uncovered through another method such as using the extensive category system of feature types discussed above.

3.3. Goal fixedness

Goal fixedness occurs when a solver stays close to the original phrasing of the problem's goal and does not notice the various ways to phrase the goal in synonymous ways [11]. Any goal can be phrased in the following form: *verb noun-phrase prepositional-phrases*. The verb describes the change that is desired (e.g., *increase profits in the New England area during the holiday season*). In some cases, you want something to stay the same that is trying to change (e.g., *maintain altitude with one damaged engine*). The *noun-phrase* names what needs changing (e.g., *profits*) or maintaining (e.g., *altitude*). The prepositional phrases describe the important constraints and relations that need to hold true (e.g., *in the New England area during the holiday season*).

Focusing on the verb, people are able to list between 5 and 11 synonyms of a verb [11]. Humans drastically underperform when compared to the synonyms that are present in a good thesaurus. In *WordNet* [31], for example, the number of synonyms for the verbs we tested ranged between 24 and 172. Each synonym has nuances that may lead to new solutions.

For example, suppose a person was working on fastening the rings together in the *Two Rings Problem* [26] and used *WordNet* [31] to explore the synonyms of *fasten*. *WordNet* has a hierarchical structure to its synonyms. More specific synonyms are called *hyponyms*, while more general synonyms are called *hypernyms*. The hyponyms of a verb often name specific ways to achieve the change. There are 61 hyponyms of *fasten*, and they describe many ways to fasten things together, including *tie, weld, staple, velcro, clip, glue, buckle, pin, sew, clamp, chain, garter, clinch, strap, grout, lodge, cement, hasp, bind, button, latch,* and *rivet.* In this case, *tie* is the verb that names how to solve the *Two Rings Problem*. A computer program can easily solve the *Two Rings Problem* when it is revealed that *tie* is a hyponym of *fasten* and *string* is the material from which a wick is composed [27]. For countering *goal fixedness*, both *WordNet* and ConceptNet 5.5 are effective datasets.

3.4. Assumption blindness

Any phrasing of the goal belies many assumptions [11]. For example, a company was stuck on trying to adhere a coating to the nonstick surface Teflon. Everything they tried failed. However, some analysis of the verb *adhere* revealed some of its assumptions.

The verb *adhere* assumes a chemical solution often involving some type of adhesive. The verb *adhere* also assumes that two things are being adhered to each other, that the adherence is probably meant to be permanent, that the two things being adhered are in direct contact with each other, that the direct contact is playing an important causal role in the adherence, and so on.

Noticing three of the assumptions was crucial to a solution: (1) using a chemical process between (2) two surfaces where (3) contact is crucial to the solution. Exploring alternatives to these assumptions led to a novel solution: (1) using a magnetic process among (2) three surfaces where (3) contact is not crucial to the solution. Specifically, a magnetic surface is placed behind the Teflon surface, while the coating with some ferrous content is placed in front of the Teflon surface. The coating sticks through the Teflon to the magnetic surface and forms a kind of *Teflon sandwich*.

In general, there is a master list of 50 types of features that any physical solution might possess [11]: including size, shape, material, quantity, type of energy used (e.g., chemical, magnetic, etc.), spatial relations among the parts, symmetry, and motion. To uncover some important assumptions, simply proceed through the list and ask if the verb under consideration assumes anything about each of these feature types.

These types of assumptions are contained in neither ConceptNet 5.5 nor, most likely, any other current text or data source. These assumptions need to be unearthed carefully through a method such as the one described above.

3.5. Analogy blindness

Gick and Holyoak [9, 10] were the first to show experimentally how difficult it is for humans to notice by themselves how an idea from one area could be adapted as a solution in another area. For example, they had participants read a brief military story that held the crucial idea for solving a surgery problem [9, 10]. Thirty percent solved the surgery problem after mere exposure to the military problem, but 80% solved it after being told to use the military problem to help solve the surgery problem.

Building upon the work of Julie Linsey and colleagues [32–36], who focused upon looking at synonyms of the main verb expressing the goal of the problem, McCaffrey and Krishnamurty [11] went one step further to explore the synonyms of both the verb and noun phrase of the goal. For example, consider the goal *reduce concussions in American football players*. The goal is in the form *verb noun-phrase prepositional-phrase*. Focusing upon *reduce concussions*, we explored the synonyms of both words and took into consideration some basic engineering knowledge. This process led to an extensive list of alternative phrasings:

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including *diminish trauma, lessen impact, reduce energy, soften collision, minimize force, decrease momentum,* and *repel energy*.

Next, we entered each of the phrases into Google in the form "concussions diminish trauma" [12]. This step helped us determine which phrases were under-explored in the context of concussions. We found that *repel energy* was almost completely ignored. The word *repel* is closely associated with magnets, and this connection quickly triggered the creation of a possible solution. Magnetize all football helmets with the same pole so they do not want to be near each other. Tests with models showed that potential head-on collisions were turned into glancing blows as the helmets slowed down and slightly veered when approaching each other at high speeds [12].

In the *BrainSwarming* graph for *reduce concussions* (**Figure 2**), the goal was placed at the top and the alternative goal phrasings grew downward from the top. The resources were divided into two types: *objects* and *energies*, and placed across the bottom. A solution was constructed in the middle showing an interaction between the two helmets and magnetic energy. This interaction satisfied the subgoal *repel energy*, which satisfied the main goal *reduce concussions.*

Obtaining synonyms from *WordNet*, ConceptNet 5.5, or other sources can definitely uncover nuanced phrasings of the goal that may illuminate novel solutions to a problem. These data sources and the process of creating alternative goal phrasings could potentially help any AI technology that is focused on the task of problem solving.

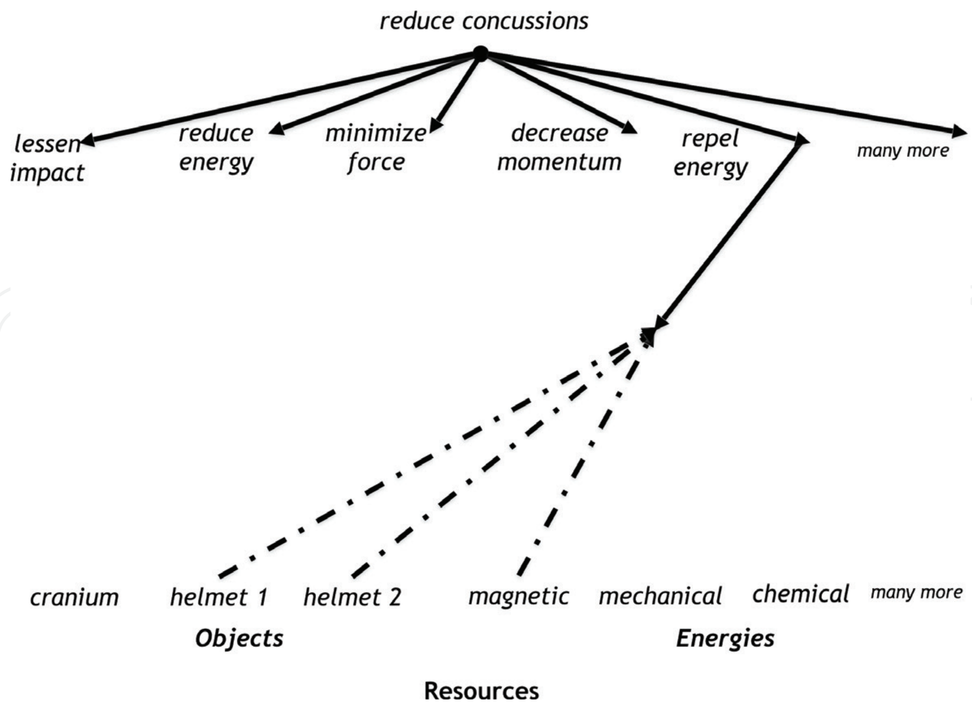

Figure 2. BrainSwarming graph for reduce concussions.

4. Human-computer interface to achieve synergy

In order for humans to counter computer limits and computers to counter human weaknesses, an interface is needed, which is comprised of data structures that both humans and computers can easily populate. In order to make the human-computer interaction efficient, the interface needs to be both human- and computer-friendly. Building upon our new definitions, we can define a problem as a set of desired effects and define a solution as a sequence of interactions that ultimately produces the desired effects named in the problem.

We define the problem solving grammar for innovation in Extended Backus-Naur Form (EBNF: [37]), which is a compact notation mostly used for defining the syntax of computer programming languages. For our grammar, we only need a few of EBNF's symbols: "::=" means "is defined as," a superscripted "+" means there can be one or more of the preceding item, and a superscripted "*" means there can be zero or more of the preceding item.

The bidirectional *BrainSwarming* graph has been tested with various age groups and has been found to be easy to understand [25]. As illustrated in **Figure 3**, a goal is placed at the top, and the refinements of the original goal grow downward below it. The resources to solve the problem are placed across the bottom, and the parts and features grow upward above the resources. The two directions grow toward each other until they connect, at which point you have your first candidate solution. The solution is comprised of a sequence of interactions between resources, features, and parts until the goal's effects are satisfied. Humans find the graph intuitive, and the computer can easily represent the bidirectional graph as a set of trees.

A goal is a set of desired effects. Any effect can be described as an action verb that describes a change (or a nonchange), a noun phrase to name that which needs changing (or should be kept from changing), and a list of prepositional phrases that describe important constraints and

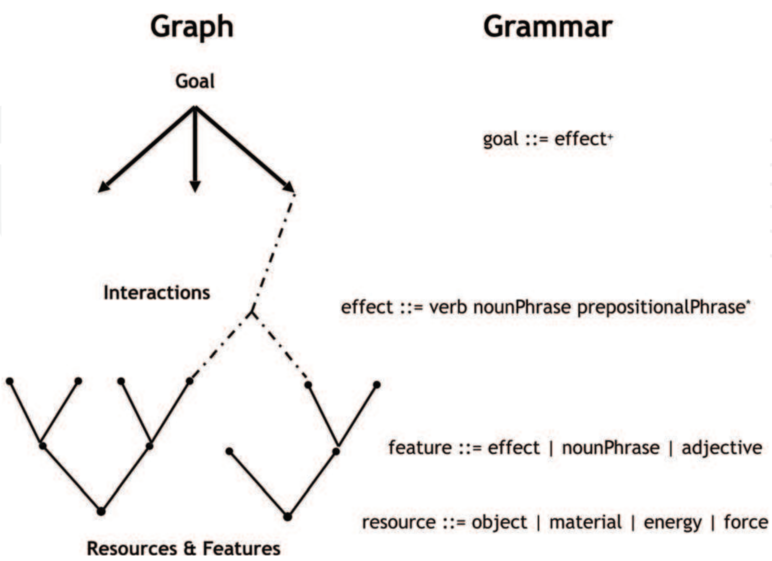

Figure 3. BrainSwarming graph and grammar.

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relations. A feature is synonymous with an effect, but sometimes a shorthand can be used: an adjective (e.g., heavy) or a noun phrase (e.g., a heavy, metal rectangle). A resource is either an object (e.g., hammer), a material (e.g., velvet), an energy (e.g., magnetic), or a force (e.g., centrifugal).

Each of these grammatical forms is both human- and computer-friendly. Each phrase has a natural English form, and each phrase is regular so that it is easy for a computer to parse.

5. Current implementation and applications

The current implementation of *BrainSwarming* (brainswarming.io) includes the visual graph and grammar of **Figure 3**, as well as software to counteract *functional fixedness*, *design fixation*, *goal fixedness*, and *analogy blindness* [11]. The counter-technique for *assumption blindness* has not been implemented at this time. *BrainSwarming's* visual graph is simultaneously updatable online by multiple users working from different locations. *Analogy Finder* [11, 38], the counter-technique to *analogy blindness*, currently searches the U.S. Patent database for analogous solutions from different fields (i.e., solutions that achieve the same basic effect and can be adapted to the particulars of the problem at hand). The user of *Analogy Finder* enters the verb and noun-phrase of a goal (e.g., *reduce concussions*). *Analogy Finder* then explodes the phrase into many synonymous phrases. The user selects which phrases to use in the search and *Analogy Finder* finds patents that achieve the desired effect expressed in many different ways (jargons) across all domains of the U.S. Patent database. *Analogy Finder* could easily be made to search any dataset or corpus (e.g., academic journals, *Wikipedia, etc.*).

In *BrainSwarming's* current implementation, it has helped humans create a novel, magnetic solution to reduce concussions [12, 39], an original way to stick a coating to Teflon [11], as well as several other new solutions to proprietary problems. For the Teflon problem, the *assumption blindness* technique was executed by hand, as it has not yet been implemented, although the synonym generation and analogous search were conducted by the software.

Because *BrainSwarming* allows multiple users to remotely access it, one of *BrainSwarming's* users could be a software program—specifically, an AI program such as IBM Watson or a machine learning program. Of course, the AI program would need to be able to communicate through an API to join the *BrainSwarming* team that is working on a particular problem. In this way, the humans on the team could help the AI program overcome the proven limits that hold for any computational approach to innovation. While *BrainSwarming's* software explicitly counteracts certain human obstacles to creativity (e.g., *functional fixedness*), the contributing AI program could help the team of human users overcome such things as noticing patterns that humans have trouble noticing (e.g., machine learning programs), revealing relevant information that a user has not yet read (e.g., IBM Watson), revealing information that is outside a user's expertise, or making connections that a user has yet to make. Finally, *BrainSwarming's* software can help counteract the obstacles to innovation (e.g., *functional fixedness* or *analogy blindness*) that are implicit in the corpora and datasets being used because humans produced these sources of information.

In this way, *BrainSwarming* counteracts the known cognitive obstacles to innovation in the human users as well as in the human-produced corpora and datasets. It also provides a highly visual interface that humans and any contributing AI program can access. The interaction among the human users, the visual interface, *BrainSwarming's* software that counteracts obstacles to creativity, and any contributing AI programs has the potential to achieve great innovative breakthroughs. Much testing is required to test the innovative power of the *BrainSwarming* platform when an AI program such as IBM Watson interacts with it as one of its users. The crucial comparison would be the innovativeness of IBM Watson (or another AI program) on its own compared to IBM Watson interacting with the *BrainSwarming* platform and some human users. Even without a contributing AI program, *BrainSwarming* helped human users become more innovative by coming up with novel solutions to some very difficult problems [11, 12, 39].

6. Conclusions

Every innovative solution is built upon an obscure (i.e., commonly overlooked or new) feature of the problem [13, 27]. Both computers and humans tend to overlook different sets of obscure features based on their differing search biases. These differences are somewhat complementary so that computers and humans can help each other uncover obscure features that the other partner would miss [6, 11]. The result is significantly more unearthed features of the problem, resulting in a higher chance of unearthing the key obscure features required for a novel solution to the problem. Further, computers cannot completely take over the creative and innovative process due to the fact that the set of features of any object is not computably enumerable, so it cannot be fully explored by a computational device [6]. Working together through a computer- and human-friendly interface called *BrainSwarming* permits computers and humans to easily innovate together. This human-computer synergy has already produced innovative solutions to some difficult industry problems [11, 12, 39]. Adding an AI program such as IBM Watson to the team innovating together through *BrainSwarming* has the potential to produce innovative breakthroughs that neither IBM Watson nor the human team could achieve on its own.

Specifically, imagine IBM Watson plugged into the *BrainSwarming* interface. It populates the bi-directional graph and reads information placed in the graph by the human users. In this way, it dynamically informs the human users of its insights as well as learns of the insights from the human users. Specifically, humans' implicit knowledge of many features and effects that have yet to be encoded can be communicated to Watson. New empirical results from tests conducted by humans can be entered for Watson to use. Further, Watson can learn obscure features from the *generic parts technique* in order to overcome *functional fixedness*. It can use overlooked features uncovered from the 50-category feature type list in order to overcome *design fixation*. It can capitalize on the 50-category feature type list to unearth assumptions hidden behind the main goal verb in order to counter *assumption blindness*. Watson can also leverage the synonyms of *WordNet* and ConceptNet 5.5 in order to overcome *goal fixedness* and *analogy blindness.* In turn, IBM Watson can offer its considerable knowledge and insight to the *BrainSwarming* graph. Overall, IBM Watson, or any AI technology, can interact with humans

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through the *BrainSwarming* interface to uncover crucial obscure features for the problem at hand. Because innovative solutions are built upon obscure features, any AI technology using the *BrainSwarming* interface can potentially achieve higher levels of innovativeness than either the human users or the AI technology can achieve on its own. We look forward to testing this exciting hypothesis.

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Conflict of interest

This research is associated with my company, Innovation Accelerator, Inc. (www.innovationaccelerator.com), and may lead to the development of software products, in which I have a business and/or financial interest. I have in place an approved plan for managing any potential conflicts arising from this arrangement.

Author details

Tony McCaffrey

Address all correspondence to: tony@innovationaccelerator.com

Innovation Accelerator, Inc., West Brookfield, Massachusetts, United States

References

[1] Bloomberg J. Is IBM Watson a 'Joke'? [Internet]. 2017. Available from: https://www.forbes.com/sites/jasonbloomberg/2017/07/02/is-ibm-watson-a-joke/#76e55bb8da20 [Accessed January 5, 2018]

[2] Freedman D. A Reality Check on IBM's AI Ambitions [Internet]. 2017. Available from: https://www.technologyreview.com/s/607965/a-reality-check-for-ibms-ai-ambitions/ [Accessed: January 5, 2018]

[3] Schank R. The Fraudulent Claims Made by IBM about Watson and IBM [Internet]. 2017. Available from: http://www.rogerschank.com/fraudulent-claims-made-by-IBM-about-Watson-and-AI [Accessed: January 5, 2018]

[4] Darrow B. Has IBM Watson's AI Technology Fallen Victim to Hype? [Internet]. 2017. Available from: http://fortune.com/2017/06/28/ibm-watson-ai-healthcare/ [Accessed: January 5, 2018]

[5] Frank B. AI is Still Several Breakthroughs Away from Reality [Internet]. 2017. Available from: https://venturebeat.com/2017/06/23/ai-is-still-several-breakthroughs-away-from-reality/ [Accessed: January 5, 2018]

[6] McCaffrey T, Spector L. An approach to human–machine collaboration in innovation. Artificial Intelligence for Engineering Design, Analysis and Manufacturing. 2017:**32**:1-15. DOI: 10.1017/S0890060416000524

[7] Duncker K. On problem-solving. Psychological Monographs. 1945;**58**(5):1-113

[8] Jansson D, Smith S. Design fixation. DES Studies. 1991;**12**(1):3-11

[9] Gick M, Holyoak K. Analogical problem solving. Cognitive Psychology. 1980;**12**:306-355

[10] Gick M, Holyoak K. Schema induction and analogical transfer. Cognitive Psychology. 1983;**15**(1):1-38

[11] McCaffrey T, Krishnamurty S. The obscure features hypothesis in design innovation. International Journal of Design Creativity and Innovation. 2014:**3**(1):1-28

[12] McCaffrey T, Pearson J. Find innovation where you least expect it. Harvard Business Review. 2015;**93**(12):82-89

[13] McCaffrey T. Innovation relies on the obscure: A key to overcoming the classic *functional fixedness* problem. Psychological Science. 2012;**23**(3):215-218

[14] Nietzsche F. Will to Power (Translated by Kaufmann W, Hollingdale R). New York: Random House; 1968 (Original work published 1901)

[15] Ellis J, Gaillard M, Nanopoulos D. An Updated Historical Profile of the Higgs Boson [Internet]. 2015. Available from: http://arxiv.org/pdf/1504.07217.pdf [Accessed: January 5, 2018]

[16] Einstein A. Relativity: The Special and the General Theory (Translated by Lawson R). New York: Barnes & Noble; 2004 (Original work published 1920)

[17] Hirtz J, Stone R, McAdams D, Szykman S, Wood K. A functional basis for engineering design: Reconciling and evolving previous efforts. Research in Engineering Design. 2002;**13**(2):65-82

[18] USPTO Patent Full-Text and Image Database [Internet]. Washington, DC: US PatentDatabase; 2016. Available from http://patft.uspto.gov/netacgi/nph-Par-ser?Sect1=PTO1&Sect2=HITOFF&d=PALL&p=1&u=%2Fnetahtml%2FPTO%2Fsrchnum.htm&r=1&f=G&l=50&s1=9000000.PN.&OS=PN/9000000&RS=PN/9000000 [Accessed: February 11, 2016]

[19] Top500 Lists. Top 500 [Internet]. 2015. Available from: http://www.top500.org/lists/2015/06/ [Accessed: February 11, 2016]

[20] Calude C, Tadaki K. Spectral Representation of Some Computably Enumerable Sets with an Application to Quantum Provability [Internet]. 2013. Available from: https://arxiv.org/abs/1303.5502 [Accessed: January 5, 2018]

[21] Kennefick D. Testing relativity from the 1919 eclipse—A question of bias. Physics Today. 2009;**62**(3):37-42

[22] Zwicky F. On the masses of nebulae and of clusters of nebulae. Astrophysical Journal. 1937;**86**:217

[23] Battaglia P, Hamrich J, Tennenbaum J. Simulation as an engine of physical scene understanding. Proceedings of the National Academy of Sciences of the United States of America. 2013;**110**(45):18327-18332 Available from: http://www.pnas.org/content/110/45/18327.full

[24] Hegarty M. Mechanical reasoning by mental simulation. Trends in Cognitive Sciences. 2004;**8**(6):280-285

[25] McCaffrey T. Overcome any Obstacle to Creativity. Washington, DC: Rowman & Littlefield; 2018

[26] McCaffrey T. The obscure features hypothesis for innovation: one key to improving human innovation [unpublished doctoral dissertation]. University of Massachusetts, Amherst. 2011

[27] McCaffrey T, Spector L. How the obscure features hypothesis leads to innovation assistant software. In: Proceedings of the 2nd International Conference of Comput Creativity (ICCC). Mexico City, Mexico: ICCC; 2011. pp. 120-122

[28] ConceptNet 5.5 [Internet]. 2017. Available from: conceptnet.io [Accessed: January 5, 2018]

[29] Smith S. Getting into and out of mental ruts: A theory of fixation, incubation and insight. In: Sternberg R, Davidson J. The Nature of Insight. Cambridge, MA: MIT Press; 1995. pp. 229-251

[30] Smith S, Ward T, Schumacher J. Constraining effects of examples in a creative generation task. Memory & Cognition. 1993;**21**:837-845

[31] Miller G. WordNet: A lexical database for English. Communications of the ACM. 1995; **38**:39-41

[32] Linsey J. Design-by-analogy and representation in innovative engineering concept generation [dissertation]. The University of Texas at Austin, Austin, TX. 2007

[33] Linsey J, Laux J, Clauss E, Wood K, Markman A. Increasing innovation: A trilogy of experiments towards a design-by-analogy method. In: Proceedings of ASME Des Engineering and Technical Conference (IDETC). Las Vegas, NV: IDETC; 2007. pp. 1-15

[34] Linsey J, Markman A, Wood K. WordTrees: A method for design-by-analogy. In: Proceeding of the 2008 Amer Soc Eng Educ Ann Conf (ASEEAC). Pittsburg, PA: ASEEAC; 2008. pp. 1-13

[35] Linsey J, Wood K, Markman A. Increasing innovation: Presentation and evaluation of the WordTree design-by-analogy method. In: Proceedings of the ASME 2008 International

Design Engineering Technical Conferences & Computers and Information in Engineering Conferences. New York, NY: ASME; 2008. pp. 21-32

[36] Linsey J, Markman A, Wood K. Design by analogy: A study of the WordTree method for problem re-representation. ASME Transactions, Journal of Mechanical Design. 2012; **134**:041009-041012

[37] Aho A, Sethi R, Ullman J. Compilers: Principles, Techniques, and Tools. New York: Addison Wesley; 1986

[38] McCaffrey A. Analogy Finder. U.S. Patent US9501469B2. Washington, DC: USPTO; November 22, 2016

[39] Marks P. Eureka machines. New Scientist. 2015;**227**(3036):32-35